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Data-Driven Audiovisual Art Focused on the Uncertainty in the Human-Data-Machine Loop

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Data-Driven Audiovisual Art Focused on the Uncertainty in the Human-Data-Machine Loop

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by

Sihwa Park

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PROFESSIONAL EXPERIENCE

Jan 2016-Jul 2016	Freelance iOS Developer, Alleys Wonderlab, Inc., South Korea
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SELECT PUBLICATIONS

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Sihwa Park. ARLooper: Collaborative Audiovisual Experience with Mobile Devices in a Shared Augmented Reality Space. In Extended Abstracts of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI EA). ACM, Honolulu, HI, USA, 2020

Sihwa Park. ARLooper: a Mobile AR Application for Collaborative Sound Recording and Performance. In Proceedings of International Symposium on Computer Music Multidisciplinary Research (CMMR), Marseille, France, 2019

Sihwa Park. Multimodal Data Portrait for Representing Mobile Phone Use Behavior. In Proceedings of the International Symposium on Electronic Art (ISEA), Gwangju, Korea, 2019

Sihwa Park. BeHAVE: a Heatmap-based Audiovisual Representation of Personal Data. In Proceedings of the International Computer Music Conference (ICMC), Daegu, Korea, 2018

Sihwa Park and Woohun Joo. FormSound: A Particle Formation- Based Audiovisual Interface. In Proceedings of the International Computer Music Conference (ICMC), Shanghai, China, 2017

Jiho Choi, Junhee Yeo, Hyeonchoel Lee, Saehun Jang, Kyunging Yang, **Sihwa Park**, and Jinhae Choi. Designing Interaction for Conversational TV using Extended CFA Model. In Proceedings of HCI Korea 2013, Gangwon, Korea, 2013

Sihwa Park, Seunghun Kim, Samuel Lee, and Woon Seung Yeo. Composition with Path: Musical Sonification of Geo-referenced Data with Online Map Interface. In Proceedings of the International Computer Music Conference (ICMC), New York, NY, USA, 2010

Sihwa Park, Seunghun Kim, and Samuel Lee. COMPath: A Music-Making Environment with Interactive Map Interface. In Emille, the Journal of the Korean Electro-Acoustic Music Society (KEAMS), 2009

SELECT EXHIBITIONS

Nov 2021	Uncertain Facing at the 22nd Advanced Imaging International Festival 2021 (Online)
Dec 2020	Uncertain Facing at the NeurIPS 2020 Workshop on Machine Learning for Creativity and Design AI Art Gallery (Online)
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Jun 2019	ARLooper at the MAT 2019 End of Year Show: MADE [at] UCSB, California NanoSystems Institute
Aug 2018	BeHAVE at the International Computer Music Conference 2018, Daegu Art Factory

Jun 2018	BeHAVE at the MAT 2018 End of Year Show: Invisible Machine, California NanoSystems Institute
May 2017	InstaSynth: Listen to Your Colors at the MAT 2017 End of Year Show: Re-habituation, California NanoSystems Institute
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SELECT PERFORMANCES

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Spring 2021	Teaching Associate, MUS 109IA Introduction to Sound Synthesis and Audiovisual Composition, Music Department, UCSB
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Oct 2019	Data-driven Audiovisual Art: Multimodal Representation of Data at the IEEE VIS 2019 Arts Program

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Abstract

Data-Driven Audiovisual Art Focused on the Uncertainty in the Human-Data-Machine Loop

by

Sihwa Park

Along with the increasing digitization of society, our personal data has been explicitly or implicitly collected and shared through a plethora of digital devices and online social media services. This personal data has become of vital importance for researchers, designers, and artists to represent an impression of our datafied society and to depict the images of data subjects through various forms of data representations. Meanwhile, the explosive increase of personal data has also been accelerated by commercial or governmental entities behind services or technologies to monetize the customer data or surveil citizens. These entities use the data to categorize and predict our behaviors, preferences, and identities through machines that are designed for services or applications, such as content recommendation and facial recognition.

As our society is increasingly datafied, we see ourselves through our data, which is collected and processed by the machines, for self-representation and self-understanding. Moreover, responses from the machines also affect how we behave and understand ourselves. Within this data-centered human-machine interrelationship, the Human-Data-Machine Loop, the machines see us through available, measurable data obtained from us and through stochastic, algorithmic processes to generalize individuals. Here, uncertainty exists because personal data is not an objective representation of oneself, and the machines are not perfect; they can be erroneous and biased upon the data or humans. These issues of uncertainty are difficult to estimate and represent, and they are problems to be solved, especially in scientific domains. But, this uncertainty perspective can be a creative force or theme in data art. This dissertation proposes an artistic approach to reflecting the uncertainty in the Human-Data-Machine Loop through data art. To this end, this dissertation defines the Human-Data-Machine (HDM) Loop as the main conceptual research framework for viewing our datafied society, along with possible types/sources of uncertainty in the Loop. Second, I propose three types of data art practice based on the HDM framework: Artist-Centered Practice, Artist-Machine Collaborative Practice, and Machine-Centered Generative Practice. Last, this dissertation explains and evaluates the author's data-driven audiovisual art projects as an empirical case study of each data art practice.

This dissertation aims to contribute to expanding data art practice with the perspective of uncertainty in data practice and to raising the audience's awareness of uncertainty in data practice through artistic approaches.

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Chapter 1

Introduction

1.1 Background

We live in an environment surrounded by tons of digital devices and online social media and services, the prevalence of which is accelerated by advances in computing power and Internet connectivity. Personal data, such as selfies, blogs, tweets, check-in locations, heart rates, etc., has been explosively generated, collected, and shared with these devices and media in our daily lives.

We use our personal data to express our thoughts, emotions, and personalities as forms of digital self-representation. Also, as the Quantified Self movement [1] has shown a concept of "Self-knowledge and -discovery through Numbers", we measure our behaviors, activities, and health information through a variety of sensors for quantification on mobile devices to understand, and ultimately, improve ourselves.

While the use of personal data is seemingly for the interest of individuals who generate the data, this datafication has also been amplified by companies to monetize their customer data and affect consumers' decisions and by authorities and governmental entities to surveil citizens and address social issues. For these purposes, the data is used to categorize or predict our behaviors, preferences, and identities through machines that are devised for services or applications, such as content recommendation and face recognition

[2].

Once data is collected, we need to make sense of our data to utilize it. In Computer Science, Data Science, Statistics, and Personal Informatics, research on data processing, analysis, and visualization has been a significant area of interest for finding meaningful patterns and for drawing insights from data. Many researchers and designers in Graphic Design have put their efforts into making data more visually perceivable and understandable with various representation approaches. Data Journalism has become a domain that uses data with interactive visualizations for immersive, compelling storytelling. Artists have also shown their increasing interests in and have developed practices to use data as an art material to make aesthetic storytelling, express artistic messages about datafied society, or depict images of data subjects via multimodal data transformation visually, audibly, or physically.

It is generally accepted by artists and visualization researchers that data can reveal social phenomena or the subject of data through appropriate representation. The general practice in data art or data visualization has an assumption that "the numbers tell us objective truth", which is called *dataism*[3]. Under this assumption, their focus lies in finding ways to represent data and the context of the data as objectively as possible. What data practitioners expect from their representational approaches is that data is the subject itself from which the data is gained.

1.2 Problem Statement

However, there is uncertainty in the belief in data objectivity described above. Especially, personal data is not as objective as we believe. The personal data can be subjectively collected, not rigorously obtained. The representation of the data can also be too abstract or subjective, making it difficult to find indexicality between the data and the representation. Besides, the types, resolution, and granularity of personal data we can obtain are limited by measurable metrics made from available sensors and algorithms of machines. This also means that when we try to see ourselves through our data, we actually see ourselves through the machines' experience and vision [4].

The machines also give us responses that affect us in shaping our behaviors and understanding ourselves. It is common for us to use the machines' prediction and recommendation when we make decisions. This data-centered human-machine interrelationship that I define as the Human-Data-Machine Loop has appeared more frequently due to advances in machine learning and artificial intelligence. However, since the machines see us through stochastic, algorithmic processes to generalize individuals based on available personal data, other forms of uncertainty also exist. The machines are not perfect, and they can be erroneous and biased upon the data or humans. And due to the complexity of deep neural networks, one of the most popular machine learning techniques, it is difficult to understand how the machines with deep neural networks work [5].

Our reliance on data and the algorithms of machines continues to become more pervasive. Hence it is important to be aware of uncertainty in the Human-Data-Machine Loop. These issues of uncertainty are difficult to estimate and represent, and they are problems to be solved, especially in scientific domains. However, I argue that this uncertainty perspective can be a creative force or theme in data art. In particular, data art can reflect this uncertainty perspective in art practice and thus make a unique form of data art. With proper interaction design for the audience, data art also can raise the audience's awareness of uncertainty in data practice.

In this regard, this research has three main questions:

1. How can data art reflect uncertainty in data practice?

2. How can data art practice deal with uncertainty in data practice?

3. In what ways can data art raise the audience's awareness of uncertainty in data practice?

1.3 Methodology

This dissertation proposes an artistic approach to reflecting uncertainty in data practice through data art. To this end:

- First, this dissertation defines the Human-Data-Machine Loop as the main conceptual research framework for viewing our datafied society along with possible types/sources of uncertainty in the Loop.
- Second, I propose three data art practices based on the framework: Artist-Centered Practice, Artist-Machine Collaborative Practice, and Machine-Centered Generative Practice. A description of each practice includes types of uncertainty and representation approaches.
- Last, based on the suggested data art practices, the dissertation explains and evaluates the author's data-driven audiovisual art projects as empirical case studies.

1.4 Structure of the Dissertation

Including this introductory chapter, the dissertation comprises five chapters. Chapter 2 explains the background research in detail, discussing the definition of uncertainty, the implications of uncertainty in sciences and the arts, the meaning of data, increasing personal data in our datafied society, and a brief history of data visualization as well as data art. With existing discourses and perspectives on uncertainty in data visualization and machine learning, Chapter 3 describes the definition of the main research framework, the Human-Data-Machine Loop in addition to the types and sources of uncertainty in the Loop, and proposes three data art practices based on the framework, delineating the roles of the artist and the machine in each practice. In Chapter 4, the detailed description and analysis of the author's three data-driven audiovisual artworks are presented as empirical case studies of the suggested data art practices. Finally, Chapter 5 concludes by answering the research questions with the evaluation of the research framework and case studies and describing the future directions of work.

Chapter 2

Literature Review

2.1 Definition of Uncertainty

In general, uncertainty is when we are not certain about something. There are various definitions of uncertainty according to disciplines. Thomson et al.[6] explains uncertainty as follows:

> "Uncertainty has been defined as the degree to which the lack of knowledge about the amount of error is responsible for hesitancy in accepting results and observations without caution. In other definitions, the term uncertainty represents a broader range of doubt or inconsistency than is implied by the term error and error is just one component of uncertainty. Other definitions, including accuracy, reliability, ignorance, precision, clearness, distinctiveness, are also used in the literature. More generally, definitions of uncertainty imply that there is imperfection in the users' knowledge about a dataset, process or result."

In Bonneau et al. [7]'s article, uncertainty is described as below:

> "Uncertainty is the lack of information. It can be due to randomness, such as results by chance, for example the roll of the dice or knowing the exact daily

quantity of rain in Seattle. This type of uncertainty is called aleatoric and is objective in that results differ each time an experiment is run. These types of phenomenon are truly random in that the results depend on chance, and thus use probabilistic modeling to describe."

Researchers in machine learning also define uncertainty in a similar manner [8]:

> "In general, uncertainty is interpreted as 'what is not known precisely', but it can be characterized differently, e.g., by also considering its impact or causes. Thus, various taxonomies and classifications of uncertainty exist that provide different points of view on uncertainty, such as aleatoric vs. epistemic, irreducible vs. reducible, or the different kinds of inference that introduce them (e.g., predictive, statistical, or proxy)."

2.2 Uncertainty in Sciences and the Arts

How has uncertainty been understood and accepted in sciences and the arts? and how has the uncertainty perspective contributed to different fields? This section briefly looks into the domains of Information Theory, the Physical Sciences, the Visual Arts, and Music since it is not the goal to comprehensively cover all the fields related to uncertainty.

2.2.1 Information Theory

Information theory is about how digital information is transmitted, processed, extracted, and used. One of the famous quotations about information theory is "information is the resolution of uncertainty." This abstract concept is believed to be said by Claude Shannon who is an American mathematician also known as a father of information theory, although there is no provenance of the quotation. Shannon, in his paper

"A Mathematical Theory of Communication" [9] in 1948, made a concrete concept of communication of information over a noisy channel. Information can be thought of as a set of messages. The data source of a data communication system sends messages over a communication channel. The receiver of the communication system then needs to rebuild the messages. In the reconstruction process, the main problem is to reduce the probability of error because of the channel noise. In this regard, Shannon established the noisy-channel coding theorem that it is possible to communicate digital information nearly without error up to a computable maximum rate through the communication channel over which the messages are sent.

In the same paper [9], Shannon established another important theorem, the source coding theorem (or noiseless coding theorem) that it is impossible to have the code rate for compressing the data less than the Shannon entropy of the data source. The entropy in the source coding theorem represents an absolute mathematical limit up to which the data of the source can be compressed without loss onto a perfectly noiseless channel.

Entropy is a key measure in information theory. Entropy is the average level of information or "uncertainty" inherent to the possible outcomes of a random variable or process. The entropy of a discrete random variable X, with possible outcomes $x_1, ..., x_n$, is defined as below:

$$\mathrm{H}(X) = -\sum_{i=1}^{n} \mathrm{P}(x_i) \log_2 \mathrm{P}(x_i)$$

where $\mathrm{P}(x_i)$ is the probability of occurrence of x_i and Σ means the sum over the variable's possible values. Base 2 for the logarithm gives the unit of bits. But the choice of base can be different according to applications.

Information theory has affected various research domains and applications including data compression, error detection and correction, the development of the compact disc and the Internet, statistical inference, cryptography, machine learning, etc.

2.2.2 Physical Sciences

Scientists in the physical sciences closely work with uncertainty. Their primary interests are to measure things to find the 'truth' of a given circumstance in nature. They need to overcome or accept that every measurement involves an error or uncertainty which can affect the accuracy of the measurement result. With the efforts of physical scientists to reduce uncertainties in measurements and accurately quantify these uncertainties, the concept of measurement uncertainty plays a significant role in understanding our natural world [10].

One of the most important principles in quantum mechanics is Heisenberg's uncertainty principle, which involves the measurement of the position x and momentum p of a particle. In the world of quantum mechanics appeared in the mid-1920s, it is impossible to accurately measure x and p at the same time. This concept cannot be explained with classical physics that allows us to know both position and momentum exactly. Heisenberg's principle is also used to explain the relationship between energy E and time t. These uncertainty relations are defined as below [10]:

$$\Delta x \Delta p \approx \hbar \tag{2.1}$$

$$\Delta E \Delta t \approx \hbar \tag{2.2}$$

$\hbar$ is the reduced Planck constant, $\hbar = h/2\pi$, where h is the Planck constant, (6.6×10^{-34} Joule seconds). Delta (Δ) represents the uncertainty associated with each variable.

In quantum mechanics, the energy of a photon is equal to its frequency multiplied by the Planck constant. The expressions above indicate that if the uncertainty in one quantity decreases, the uncertainty of the other variables increases. This relationship is generally considered an intrinsic property of the particle [10].

Heisenberg's uncertainty principles challenges the 'deterministic' view in classical physics where the exact prediction of the motion of a particle is possible based on the present position and momentum of the particle along with the forces applied to the particle. In the indeterministic quantum mechanical world, the fundamental particles such as electrons, protons, and atoms can have more than one quantum state simultaneously, behaving in a probabilistic manner. However, if we try to determine the state of a particle with a discrete measurement, the result is always a particular value or state for the particle instead of the mixed states [10].

In the physical sciences, uncertainty is a widespread concept that drives quantum mechanics, and influences virtually all significant results of physics about the nature of things [10].

2.2.3 Visual Arts

Whereas uncertainty in sciences is generally seen as a hindrance to objective quantification or observation, uncertainty is perceived as a creative force in the visual arts [11]. Grishin [11] locates written evidence for this relationship from one of Leonardo da Vinci's notes titled "A way to stimulate and arouse the mind to various inventions":

> "I will not refrain from setting among these precepts a new device for consideration which, although it may appear trivial and almost ludicrous, is nevertheless of great utility in arousing the mind to various inventions. And this is that if you look at any walls spotted with various stains or with a mixture of different kinds of stones, if you are about to invent some scene you will be able to see in it a resemblance to various different landscapes adorned

> with mountains, rivers, rocks, trees, plains, wide valleys and various groups of hills. You will be able to see diverse combats and figures in quick movement, and strange expressions of faces, and outlandish costumes, and an infinite number of things which you can then reduce into separate an well-conceived forms. With such walls and blends of different stones it comes about as it does with the sound of bells, in whose clanging you may discover every name and word that you can imagine." [12]

Leonardo da Vinci had the principle of uncertainty as a source of creative inspiration along with certainty in techniques necessary for being a painter, such as anatomical representation skills, understanding of perspective, mathematics, and characteristics of color and optics [11].

By the early 20th century, uncertainty and the concept of "the law of chance" influenced art movements, such as Dada and surrealism. Dadaist and abstract artist Hans Peter Wilhelm Arp, better known as Jean Arp in English wrote about his collage working process as below:

> "The law of chance, which comprises all other laws and surpasses our understanding (like the primal cause from which all life arises), can be experienced only in a total surrender to the unconscious." [13]

Later, chance as a principle for creativity in Dadaism continued to the new techniques of art making, such as collage, photomontage, and the ready-mades [11].

In the latter half of the 20th century, many artists still adopted the concept of chance and uncertainty as a liberating force, although there were radical stylistic changes to combine certainty and uncertainty within the context of Abstract Expressionism, conceptual art, performance art, and happenings [11].

Grishin [11] concludes that "today uncertainty in the visual arts is seen as a creative energy with a huge potential and is something to be harnessed and cultivated, rather than something to be feared or contained."

2.2.4 Music

In jazz, uncertainty is a catalyst for improvisers to seek creative note choices and rhythmic changes out of their personal clichés [14]. Soloists could incorporate wide intervals of melodies in their common use of narrow intervals. Improvisers may use the limited number of notes on their instrument to be away from personal clichés.

In music, improvisation is a way to spontaneously create music based on musical structures or materials that improvisers are already familiar with, such as a set of chord sequences and melodies. Jazz improvisation was born in New Orleans in the late 1800s and generally means "improvising a solo" that combines musical elements, such as accentuation, articulation, tempo, ornamentation, melody and rhythm. In jazz improvisation, it is often expected to spontaneously build melodies based on a chord sequence that is generally not written down. A jazz soloist within an ensemble constructs their solo by musically interacting with the other members of the group. Uncertainty can arise depending on the soloist's response to unfamiliar musical ideas and structures. To reduce uncertainty, improvisers need to practice over many years to obtain abilities for improvisation, such as a well-developed ear, recognition of unfamiliar chord progressions, and pre-hearing improvised melodies [14].

2.3 Meaning of Data

2.3.1 Epistemological Change of Data

Some data researchers begin with the origin of the term "data" to explain the definition of data [15, 16, 17]. Data is the plural form of *datum* that is the past participle of the Latin word *dare*, which means "to give" in English. Thus, datum naturally means something *given*.

Many researchers including Freeman [16] and Rendgen [17] refer to Euclid's book of geometrical axioms, *Data* as one of the earliest scientific use of the term data. In his book, data is a tool for the mathematical deduction or inference of new data. In propositions, for example, when a geometrical object is given as a datum, another object can be inferred as a new datum. It is analog to the use of data by contemporary data practitioners to draw new information or insights from existing data.

It was not until the 17th century that data was first used in English. In his article [15], Rosenberg draws a connection between the conceptual emergence of data in English and the development of modernity with concepts of knowledge and argumentation that led to innovations in information technology in the 20th century. With an analysis of word-frequency trends of "data" by using Eighteenth-Century Collections Online (ECCO) [1], an online archive that contains English-language and foreign-language titles printed in the United Kingdom between the years 1701 and 1800, Rosenberg found how the meaning of data has shifted in scientific contexts. According to his research, in the 17th century, data was mainly used in mathematics but it was not a common term in English. By the end of the 18th century, the concept of the term data was used to refer to the result of an investigation and to facts in evidence drawn by experiment or collection. After undergoing a latent period for broad cultural acceptance in the 19th century, the term

[1]https://www.gale.com/primary-sources/eighteenth-century-collections-online

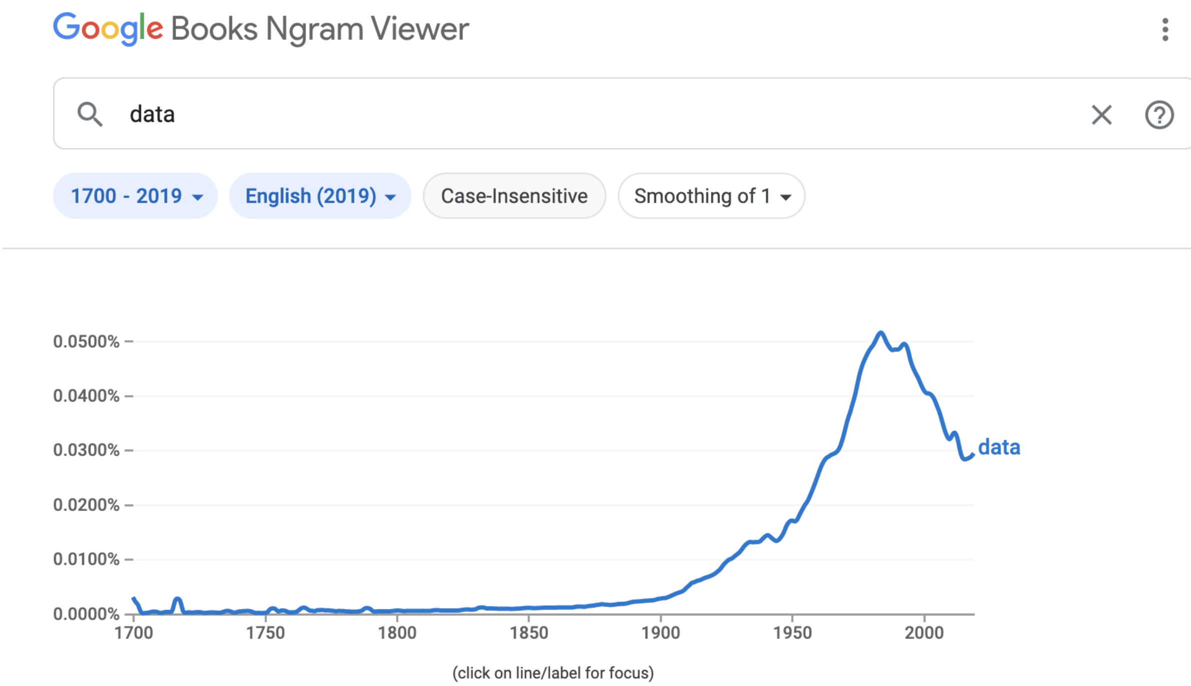


Figure 2.1: A search result of Google Ngram Viewer produced by the author. The result shows the relative frequency of "data" appeared in English books from 1700 and 2019 collected by Google.

data as the result of statistical observation and scientific experiment became a well-established concept in the 20th century. With the emergence and evolution of computer technology and information theory, our notion of data as digitally encoded information in numerical form has pervaded.

Figure 2.1 illustrates the relative word frequency of "data" that I generated with Google Ngram Viewer. As with Rosenberg's analysis, the appearance of "data" peaks in the 20th century.

As it is generally accepted that the existence of data as digital information is determined by the machine, Rendgen [17] reminds us of the importance of the role of humans in the process of data creation:

"The notion that data begins to exist when it is recorded by the machine completely obscures the role that human decisions play in its creation. Who decided which data to record, who programmed the cookie, who built the sensor? And more broadly – what is the specific relationship of any digital data set to reality?"

2.3.2 Types of Data

To better understand data as digital information, it is imperative to understand what types of data exist. The classification of data also influences the process and methodology needed for being able to find patterns or draw insights, including data analysis and visualization. This data classification varies according to how we define the classification of knowledge, as Ware [18] points out.

Table 2.1: Qualitative and quantitative data.

Type	**Form**	**Examples**
Qualitative	Verbal	Smells, tastes, textures, color, etc.
Quantitative	Number	Width, height, length, temperatures, humidity, prices, area, etc.

As Table 2.1 illustrates, data can be classified as *qualitative* or *quantitative* [19]. What makes this distinction is whether data is numerical or not. Qualitative data is usually in verbal form and can be thought of as characteristics and descriptors of the subject being observed. Examples of qualitative data include smells, tastes, textures, and color. On the other hand, quantitative data is numeric. Dimensions, such as width, height, length, temperatures, humidity, prices, area, and volume, fall into this type. In general, it is believed that quantitative data can be measured more objectively compared to qualitative data.

In 1946, the statistician Steven [20] created a classification of scales of measurement in science and his taxonomy has been widely used to explain types of data [18, 19].

According to Steven's taxonomy, data also can be described with four scales: *nominal*, *ordinal*, *interval*, and *ratio* (see Table 2.2).

"Nominal" is coined from the Latin nomenclature "Nomen", which means name. Nominal data is a categorization or classification of objects to be measured and called labeled or named data. Names of people, gender, and nationality are examples of nominal data. Nominal data can be numerical values but they are only used to identify group membership, such as football players' numbers and bus numbers. On the other hand, ordinal data uses numbers to represent a meaningful order. However, the distance between ordinal data values has no meaning. Examples of ordinal data include the Likert scale [21], ranking of things, and socio economic status (e.g. low income, middle income, high income). Data on an interval scale gives meaning to both the order and the difference between data points. Temperature with the Celsius or Fahrenheit scale, date, location in Cartesian coordinates, and direction measured in degrees from true or magnetic north are examples of interval data. In the same manner, the ratio type possesses the characteristic of both meaningful order and meaningful distances between points on the scale. A zero value on a ratio scale is used as a reference. Objects measured on ratio scales can be described as, for example, an object that has "twice the length". Examples of ratio data include weight, length, temperature in Kelvin, duration, energy, plane angle, and

Table 2.2: Nominal, ordinal, interval, and ratio data.

Type	**Meaning**	**Examples**
Nominal	Classification, label	Name, gender, nationality, identification number, etc.
Ordinal	Order, sequence	Likert scale, ranking, letter grade for coursework, etc.
Interval	Order with the meaningful difference between points	Temperature (Celsius or Fahrenheit), date, etc.
Ratio		Weight, length, temperature in Kelvin, duration, energy, etc.

electric charge.

Table 2.3: Category, integer, and real-number data.

Type	**Relationship with Steven's taxonomy**
Category	Nominal class
Integer	Ordinal class in that it is discrete and ordered
Real-number	The combined properties of interval and ratio scales

As Table 2.3 shows, Ware [18] explains three data classes as most often considered data types in data visualization based on computer programming, drawing a connection from Steven's scales of measurement explained above.

Numerical data can also be categorized as *discrete* or *continuous* [19] (see Table 2.4). Discrete data represents discrete pieces of information, such as events or samples, by counting them. Discrete data can only take certain values, for example, the number of students in a class and the results of rolling a dice. Continuous data takes any values within a range by measuring a continuous form of information. Examples of continuous data include height, time, weight, and length.

Table 2.4: Discrete and continuous data.

Type	**Method**	**Examples**
Discrete	Counted	Number of students, results of rolling a dice, etc.
Continuous	Measured	Height, weight, time, length, etc.

One of the other ways to describe data is to consider how well the structure of data is defined in terms of data processing and analytics [22]. With regard to this perspective, data can be either *structured* or *unstructured* (see Table 2.5).

Table 2.5: Structured and unstructured data.

Type	**Format**	**Examples**
Structured	Row-column format	Relational database, spreadsheet
Unstructured	No particular format	Photo, video, audio, text, PDF, etc.

Structured data has a definite format and length and enables the convenient analysis and storage of data. The identifiable structure of the data helps with organizational use and tasks, such as query-based information retrieval. A common example of structured data is Structured Query Language (SQL), a relational database in which the data consists of a combination of numbers, dates, strings, and text. Structured data is usually organized in row-column format and the well-organized structure of the database enables the data searchable along with simple search algorithms. Structured data has been the main source with which conventional information and data analytics have been conducted.

As its name alludes, unstructured data has no specific structure like structured data. Text, video, audio, photo, and PDF files are typical examples of unstructured data. Since there is no pre-defined model for unstructured data, it is difficult to organize the data in relational databases. With a variety of sources, such as social media, digital devices, and sensors, the majority of the data currently generated on a daily basis is unstructured data and it has been growing exponentially. Data scientists and practitioners in machine learning and artificial intelligence have been devising algorithms that make information in unstructured data accessible and automatically processed.

2.4 Datafied Society and Personal Data

2.4.1 Big Data and Datafication

According to a report by the International Data Corporation in 2018 [23], the world generated 33 zettabytes of data from all sources, and the amount of data is expected to increase to 175 zettabytes by 2025. A zettabyte is a billion terabytes or ten to the twenty-first power bytes. As the bar chart in Figure 2.2 illustrates, enormous amounts of

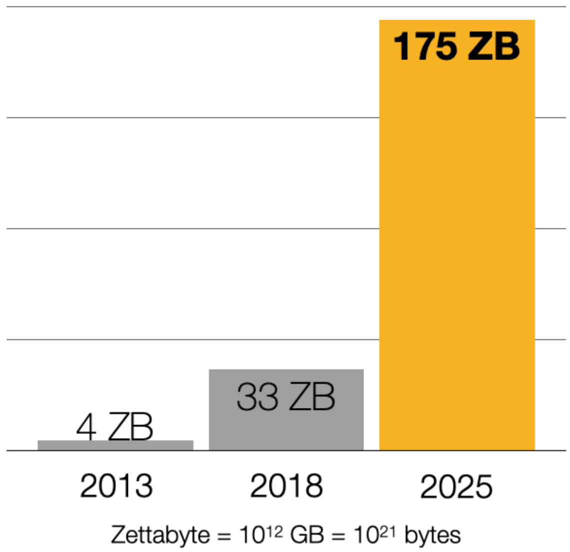


Figure 2.2: Data by 2025 created by the author based on a report by the International Data Corporation [23].

data in the world have been generated as much as the human senses can hardly imagine. When it comes to the contribution of humans to the data analyzed in another article [24] based on the same report [23], about 3.7 zettabytes of data are created by people and an average of about 117 gigabytes of data per person are stored per year. It is also expected to reach almost 300 gigabytes of data by 2025. Gröne et al. [24] infer that the average person will produce one datum every 18 seconds and this data is collected, analyzed, and monetized by many industry sectors, producing the value of $227 billion in the data economy.

The explosive increase of data also has been explained as a concept of Big Data that appeared in the 1990s. John Mashey who was Chief Scientist at Silicon Graphics (SGI) used the term "Big Data" for the first time in an SGI slide deck entitled "Big Data and the Next Wave of InfraStress" [25]. Since its origin, Big Data had been an abstract concept and used as an advertising hook and a unifying theme for technical seminars within the SGI community. As the concept has become more generally and broadly accepted, Big Data is used to explain data practices including the collection, processing and analysis of large data sets [26].

One of the social changes that have contributed to the rise of Big Data is the increasing use of social media. As van Dijck [3] points out, sharing a variety of personal information, such as eating habits, running routes, watched movies, etc. through social media became the new norm. The data people share on social media becomes the interest of businesses and government agencies also known as Big Business and Big Brother [3]. Tech companies like Google, Facebook, Twitter, YouTube, etc. which run social networks and communication platforms, utilize their users' data for target marketing. Many governments over the world also use these personal data as practices of surveillance. The general acceptance of using personal information aggregated online in many parts of our society is explained as the term "Datafication", the transformation of social action into online quantified data for the real-time tracking and predictive analysis of people's behaviors [27].

2.4.2 Personal Data

In general, the definition of personal data can be found in privacy laws:

> "Information which can be used to distinguish or trace an individual's identity, such as their name, social security number, biometric records, etc. alone, or when combined with other personal or identifying information which is linked or linkable to a specific individual, such as date and place of birth, mother's maiden name, etc." - In the United States [28]

> "Personal data shall mean any information relating to an identified or identifiable natural person ('Data Subject'); an identifiable person is one who can be identified, directly or indirectly, in particular by reference to an identifica-

> tion number or to one or more factors specific to his physical, physiological, mental, economic, cultural or social identity." - In the European Union [29]

From the definitions above, we can find that personal data in privacy laws is concerned with identifiable and linkable attributes of an individual and these attributes can be a combination of analog and digital formats.

There has been an explosive increase of personal data in digital format. For example, selfies, blogs, tweets, check-in locations, running routines, heart rates, etc. This is partly because of advances in computing power, Internet connectivity, and the prevalence of digital mobile and wearable devices, and the Internet of things. Also, our use of online social media and mobile applications contributes to this increase.

Our personal data is generated and used for digital self-representation to express our thoughts, emotions, and personalities with activities via social media, such as posting, sharing, liking, and curating. And it is also used for self-understanding to better understand and improve ourselves, as it can be found in the Quantified Self movement which has a slogan of "Self-knowledge through numbers." [1]

On the other hand, the increase of personal data has been also amplified by companies that monetize the customer data and affect their customers' decisions and by governmental entities that try to surveil citizens and address social issues based on citizens' data. Examples of this case include face recognition/identification, job screening, crime prediction, etc.

Yau [30] describes personal data according to the five main categories of applications where personal data are generated, collected, or used: journaling, personal informatics, identity, crowdsourcing, and citizen science (see Table 2.6).

It is necessary to have the definition of personal data that is relevant to the goals and scope of this study. This dissertation focuses on four key types of personal data based

Table 2.6: Five main categories of personal data applications [30].

Type	Data	Purpose
Journaling	Photographs (of memorable events), diary	To reflect, remember, and increase awareness of one's actions
Personal Informatics	About the self, health-related in particular	To estimate change, modify behavior, and optimize performance
Identity	Profile information and posts on social networking services	To provide an image of who or what an individual or group is by framing data and visualization as a form of expression
Crowdsourcing	Aggregated personal data	To gain insights and make important decisions in public domains such as urban planning and health
Citizen Science	Aggregated personal data	To lead to more scientific results with experts' data analysis and management

on Rettberg's classification of digital self-representation modes [4] as below:

- Visual (Images, e.g. selfies)
- Written (Text, e.g. posts on social media like blog, Twitter, and Facebook)
- Quantitative (Numbers, e.g. self-tracking data, listening/watching history)
- Curation (Preference info, e.g. "Likes" on social media, music list, watch history)

2.5 Data Visualization and Data Art

2.5.1 What is Data Visualization?

As we generate and use more data, making sense of data has also become important. In Computer Science, Data Science, Statistics, Information Design, Personal Informatics, and many other disciplines, research on data processing, analysis, and visualization has been a significant topic to find meaningful patterns and draw insights from data.

Then what is data visualization? In general, data visualization is to communicate information through graphical representations of data. The definitions of data visualization interestingly have slightly different nuances according to scholars or disciplines.

Bertin [31], a French cartographer and theorist, explains data visualization from the perspective of our perception of information:

> "The entire problem is one of augmenting this natural intelligence in the best possible way, of finding the artificial memory that best supports our natural means of perception."

Bertin [31] says that information processing has improved along with the computer, but in terms of simplification, which is a process of reducing a large amount of data to smaller categories of information we can utilize in dealing with a given problem, the computer cannot decide what level of simplification is best and cannot recognize the pertinence of data in regard to the problem being considered. These issues require our natural intelligence –our own knowledge and intuition– to imagine data and relationships about which the machine has not yet been instructed. The quote above alludes that data visualization is to find the artificial memory in which a large number of data is transcribed into visual objects, enabling us to use our ability of visual perception to resolve logical problems.

McCormick et al. [32] define data visualization as "the transformation of the symbolic into the geometric":

> "Visualization is a method of computing. It transforms the symbolic into the geometric, enabling researchers to observe their simulations and computations. Visualization offers a method for seeing the unseen. It enriches the process of scientific discovery and fosters profound and unexpected insights.

> In many fields it is already revolutionizing the way scientists do science. ··· That is, visualization is a tool both for interpreting image data fed into a computer, and for generating images from complex multi-dimensional data sets."

Table 2.7: Working definitions of external cognition, information design, data graphics, visualization, scientific visualization, and information visualization by Card et al. [33].

Concept	**Definition**
External cognition	Use of the *external world* to accomplish cognition. It is concerned with the interaction of cognitive representations and processes across the external/internal boundary in order to support thinking.
Information design	(The explicit attempt to) Design of *external representations* to amplify cognition.
Data graphics	Use of *abstract, nonrepresentational* visual representations of data to amplify cognition.
Visualization	Use of *computer-based, interactive* visual representations of data to amplify cognition. (i.e., Uses the computer for data graphics)
Scientific visualization	Use of interactive visual representations of *scientific data*, typically *physically based*, to amplify cognition.
Information visualization	Use of interactive visual representations of *abstract, nonphysically based data* to amplify cognition.

With an emphasis on the important role of visual metaphors in our cognitive processes between what we see and what we think, Card et al. [33] define information visualizations as "the use of computer-supported, interactive, visual representations of abstract data to amplify cognition." Card et al. [33] also point out the difference between scientific visualizations and information visualizations in terms of data physicality:

> "Scientific visualizations tend to be based on physical data – the human body, the earth, molecules, or other. The computer is used to render visible some properties. While visualizations may derive from abstractions on this physical

> space, the information is nevertheless inherently geometrical. ⋯ Nonphysical information such as financial data, business information, collections of documents, and abstract conceptions may also benefit from being cast in a visual form, but this is information that does not have any obvious spatial mapping. ⋯ there is the more fundamental problem of mapping nonspatial abstractions into effective visual form."

Card et al. [33] clarified the relationships among different concepts related to information visualization, such as external cognition, information design, data graphics, visualization, and scientific visualization, as shown in Table 2.7. Also, Card et al. [33] use the term *perceptualization* to generalize visualization in a broader design context to include systems for *information* sonification or *tactilization* of data for multiple perceptualizations.

It is worth noting that Unwin [34] draws a distinction between Information Visualization and Data Visualization, insisting one of the goals of the latter is to represent raw data to reveal the variability and uncertainty inherited in the data:

> "⋯ Information Visualization, which is concerned with the visualization of information of all kinds. Data Visualization is related to Information Visualization, but there are important differences. Data Visualization is for exploration, for uncovering information, as well as for presenting information. It is certainly a goal of Data Visualization to present any information in the data, but another goal is to display the raw data themselves, revealing the inherent variability and uncertainty."

While the definitions above are from cartographic, scientific, or computing research domains, Manovich [35] defines another trend of information visualization as *media visualization*, from the perspective of digital humanities and media studies. With the conventional definition of information visualization as a mapping between data and a visual representation, Manovich [35] first explains two principles of information visualization to draw the main difference that resides in the new definition: *data reduction* and *privileging of spatial variables*. Data reduction in information visualization is to employ graphical primitives, such as points, lines, curves, and geometric shapes, to represent objects of data and relations between them for the purpose of revealing hidden patterns and structures in the data objects. Here, in representing more important properties and patterns of data via graphical primitives, it is common to give preference to spatial variables, such as position, size, shape, line curvature, and movement, over other visual dimensions, such as the tones, textures, colors, transparency, and shape of the graphical elements.

Manovich [35] then points out the necessity of a new term to call certain new visualizations that create visual representations from the original visual data without rigidly following the two principles above, preserving a much richer set of properties of data objects:

> "However, it seems to longer adequately describe certain new visualization techniques and projects developed since the middle of the 1990s. Although these techniques and projects are commonly discussed as 'information visualization,' is it possible that they actually represent something else ... that can be called *media visualization*: creating new visual representations from the actual visual media objects, or their parts. Rather than representing text, images, video or other media though new visual signs such as points or rectangles, media visualizations build new representations out of the original media. Images remain images; text remains text. In view of our discussion of data reduction principle, we can also call this method *direct visualization*, or

visualization without reduction. In this method, the data is reorganized into a new visual representation that preserves its original form."

This definition of media visualization enables us to expand the preoccupied concept of data visualization into a concept of data representation that does not rely on the use of graphic elements mapped to data as a required qualification in the definition.

2.5.2 A Brief History of Data Visualization

Along with understanding the definitions of data visualization, it is meaningful for practitioners to comprehend how the field of data visualization has evolved. This section provides a brief overview of the history of data visualization, describing some significant milestones in the development of data visualization from medieval to modern times, based on an article written by Friendly [36].

Before the 17th century, early data visualizations generally appeared in the forms of city maps, geometric diagrams, and tables of the positions of stars and celestial bodies, which were developed along with advances in techniques and instruments for precise observation and measurement used in obtaining physical quantities and geographic and celestial position [36].

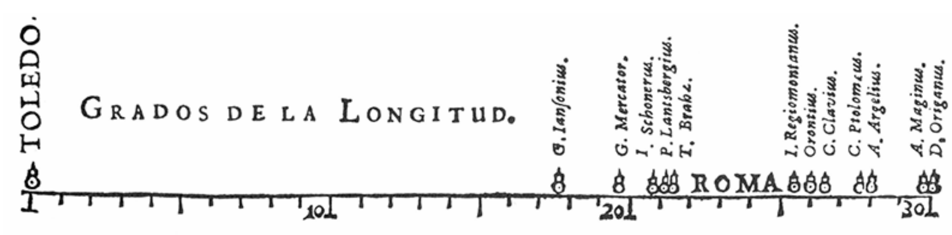


Figure 2.3: The first known statistical graph created by Michael Florent van Langren in 1644. The image is in the public domain.

Figure 2.3 shows a visualization created by van Langren in 1644, which is believed to be the first visual representation of statistical data [37]. This line graph represents the twelve known estimates at the time of difference in longitude between Toledo and Rome and the name of the astronomer. What is noteworthy about this invention at that time is that instead of providing the same information in a table, van Langren used the graph to show the wide variation in the estimates.

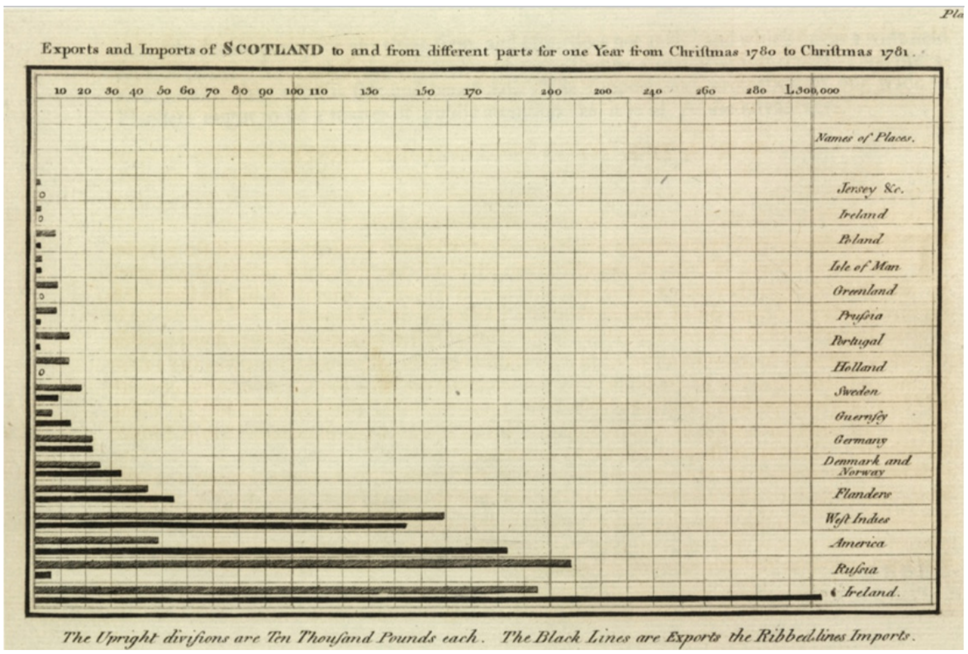


Figure 2.4: The first bar chart invented by William Playfair in 1786 [38]. The chart shows exports and imports of Scotland to and from seventeen countries in 1781. The image is in the public domain.

In the 18th century, the thematic mapping and new data representations of geologic, economic, and medical data were introduced and developed. Scottish engineer and political economist Playfair invented many of the most popular graphical forms used today, such as line, bar, circle, and pie charts [36]. Figure 2.4 shows Playfair's invention of the bar chart, which was first published in Playfair's *Commercial and Political Atlas* in 1786 [38].

After the invention of all of the modern forms of statistical graphics in the first half of the 19th century, such as histograms, time-series plots, contour plots, and scatterplots, the latter half of the 19th century is defined as "the Golden Age of Statistical Graphics"

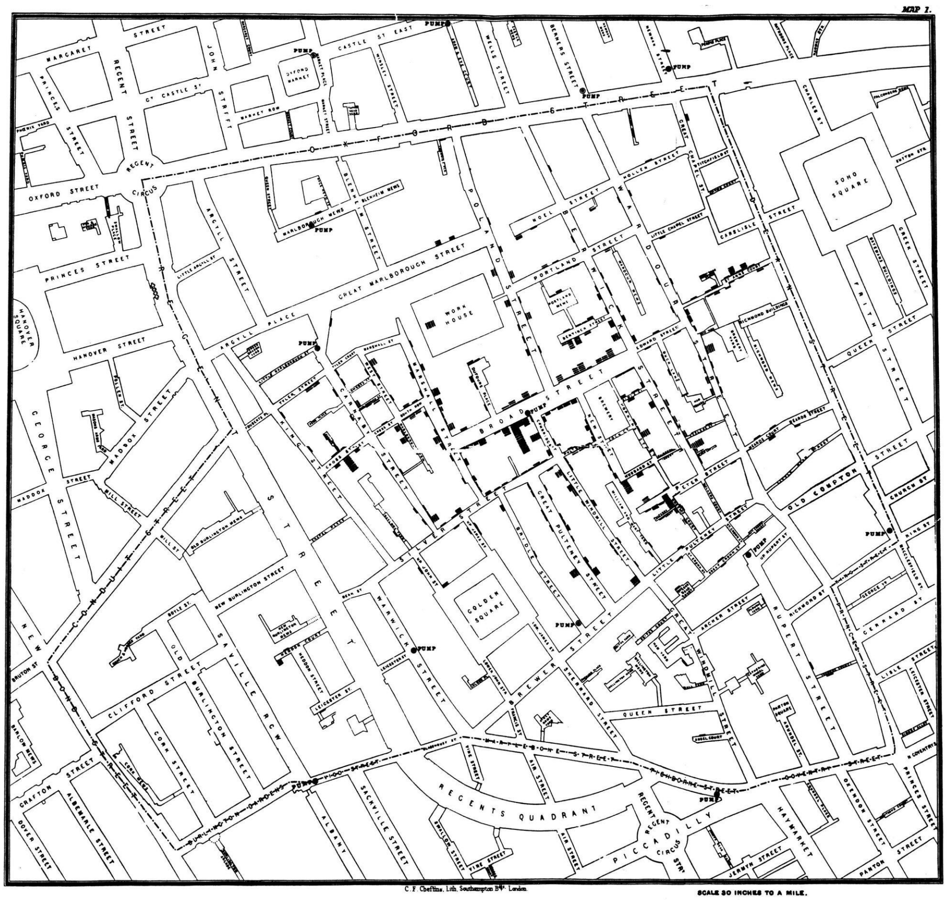


Figure 2.5: John Snow's map of cholera outbreaks in the London epidemic of 1854. The image is in the public domain.

[36]. Several factors contributed to the rapid development of statistical graphics: official government statistical offices; a growing recognition of the importance of numerical data in social planning, industrialization, commerce, and transportation; statistical theory which provided the means to make sense of large datasets [36].

In particular, some graphical innovations enabled professionals to understand complex social data and phenomena during this period. For example, Snow's dot map visualizing deaths from cholera outbreaks in the London epidemic of 1854 was one of the remarkable inventions [39]. As shown in Figure 2.5, with small bar graphs representing the number of cholera deaths per household and black circles representing wells, the map provided the insight that contaminated water from a well on Broad Street could be the main source of the outbreak.

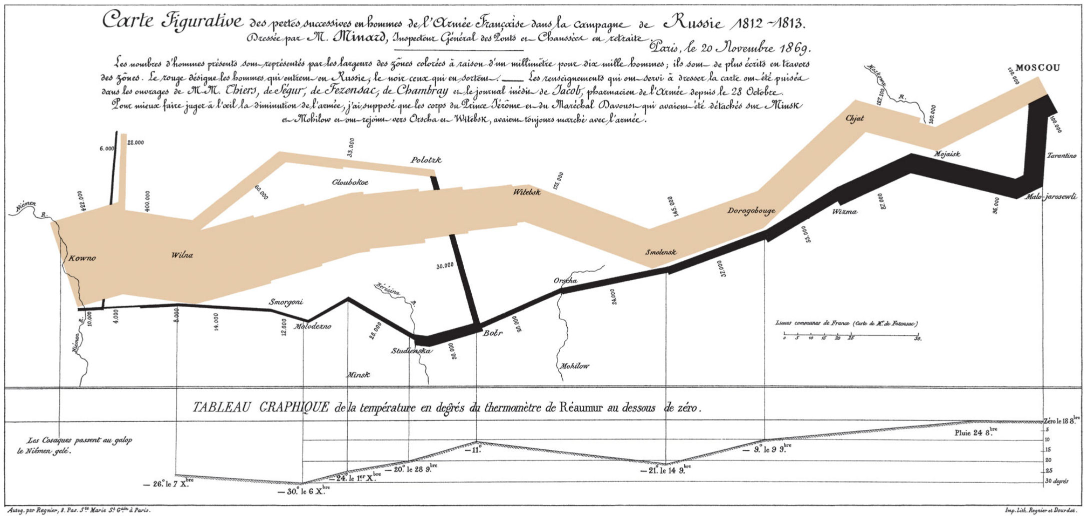


Figure 2.6: The visualization of Napoleon's 1812-1813 Russian campaign created by Charles Minard in 1869. The image is in the public domain.

Another renowned example is Minard's flow map illustrating successive losses of men of the French Army in the Russian campaign of 1812 (see Figure 2.6). In this flow map, six types of data are displayed in two dimensions: the number of Napoleon's troops, distance, temperature, latitude and longitude, direction of travel, and location relative to specific dates. The widths of lines represent the size of the Army at specific geographic locations. The map is now recognized as the best statistical graphic ever drawn by modern information scientists and designers including Tufte [40].

Figure 2.7 shows a new visualization called the Rose Chart or coxcomb, which Nightingale [41] invented during this time. This polar area diagram illustrates seasonal sources of the mortality of soldiers in the military hospital Nightingale managed, representing preventable disease in blue and battle wounds in red. Nightingale's invention contributed to improving sanitary conditions in the treatment of soldiers on the battlefield [36].

Contrary to the "golden age" of data visualization, the early 20th century is described

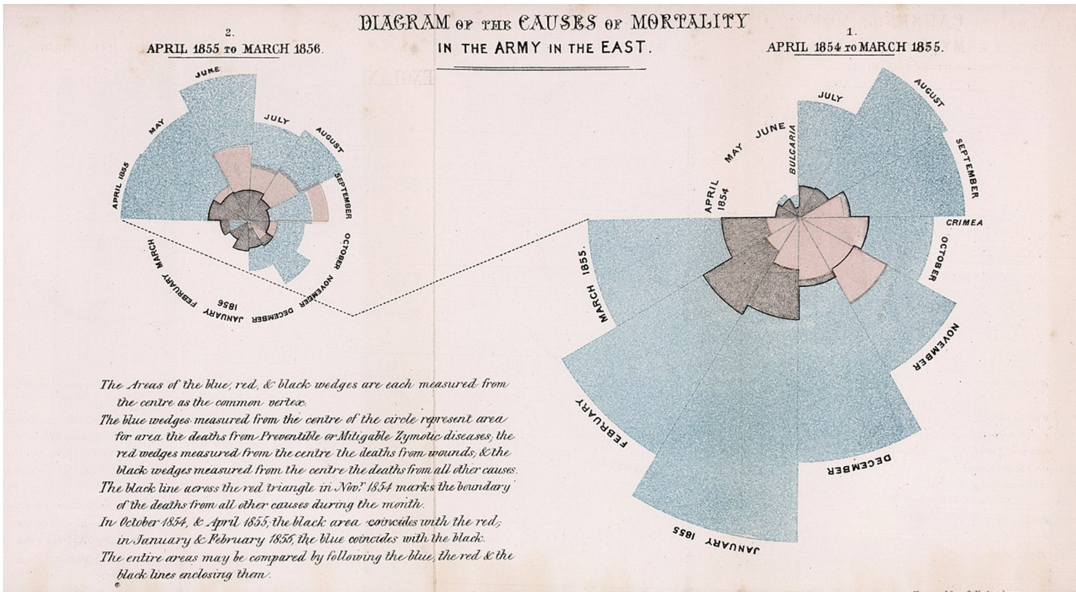


Figure 2.7: The Rose Chart, diagram of the causes of mortality created by Florence Nightingale in 1858. The image is in the public domain.

as the "modern dark ages" of visualization [36]. It was because many statisticians preferred exact numbers and parameter estimates along with standard errors over visualized images that were considered inaccurate. Nevertheless, this period was a time of popularization for data visualization. Charts and graphical methods were adopted into textbooks and curricula and their use became standard in government, commerce, and science.

With advances in computing power, statistical processing methodology, and display devices, the latter half of the 20th century saw the "rebirth of data visualization" [36]. Increasing computing power enabled statisticians to collect large datasets and visualize information more efficiently and conveniently. Developments in data analysis and human-computer interaction technology also contributed to a growth in new visualization methods and techniques. Several important figures in data visualization research emerged during this period. For example, Tukey [42] in the USA and Bertin [31] in France published significant research results on the science of information visualization in the fields of statistics and cartography, respectively. Tufte's seminal work, the first edition of *The Visual Display of Quantitative Information* [40] was published in 1985, which is still widely used today in the curriculum of data visualization and statistical analysis in universities.

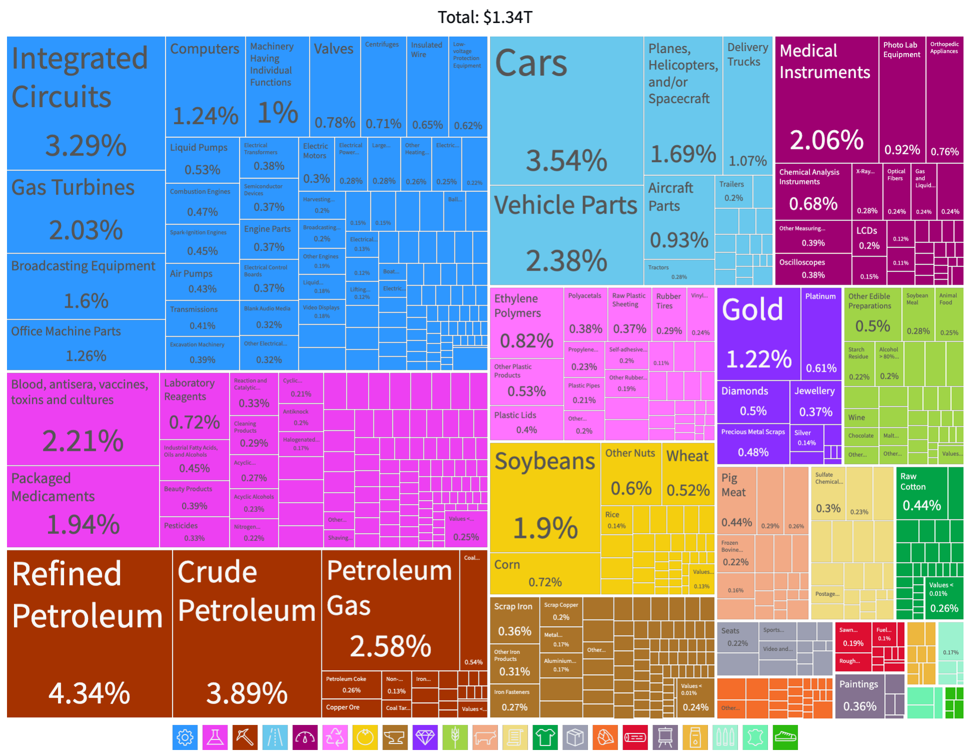


Figure 2.8: An example of Treemap that shows the USA's exports by product category in 2020. The imaged is generated from the Observatory of Economic Complexity website [43] and is in a Creative Commons CC0 public domain license.

During the last three decades of the 20th century, research on data visualization became more mature and multidisciplinary along with widely available visualization methods and software tools for personal computers [36]. Two significant aspects among many of the advances in statistical graphics are: the development of data visualization and analysis techniques for multi- and high-dimensional data, and the development of new paradigms and methods for interactive data visualization that supports the immediate and direct manipulation of graphic elements as well as related data properties. The increased computer processing speed and capacity that enables handling vast high-dimensional datasets, led researchers to further develop and utilize dimensionality reduction techniques such as principal component analysis. One of the remarkable visualization methods invented during this period is *Treemap* by Shneiderman in 1992 [44]. As Figure 2.8 shows, a treemap is a data visualization that represents the hierarchical data as nested rectangles. In other words, a treemap means the visual transformation of a tree-structured dataset into a planar space-filling map in a recursive way. Since its invention, many variations of treemaps have been developed with interactive techniques for filtering and modifying treemaps.

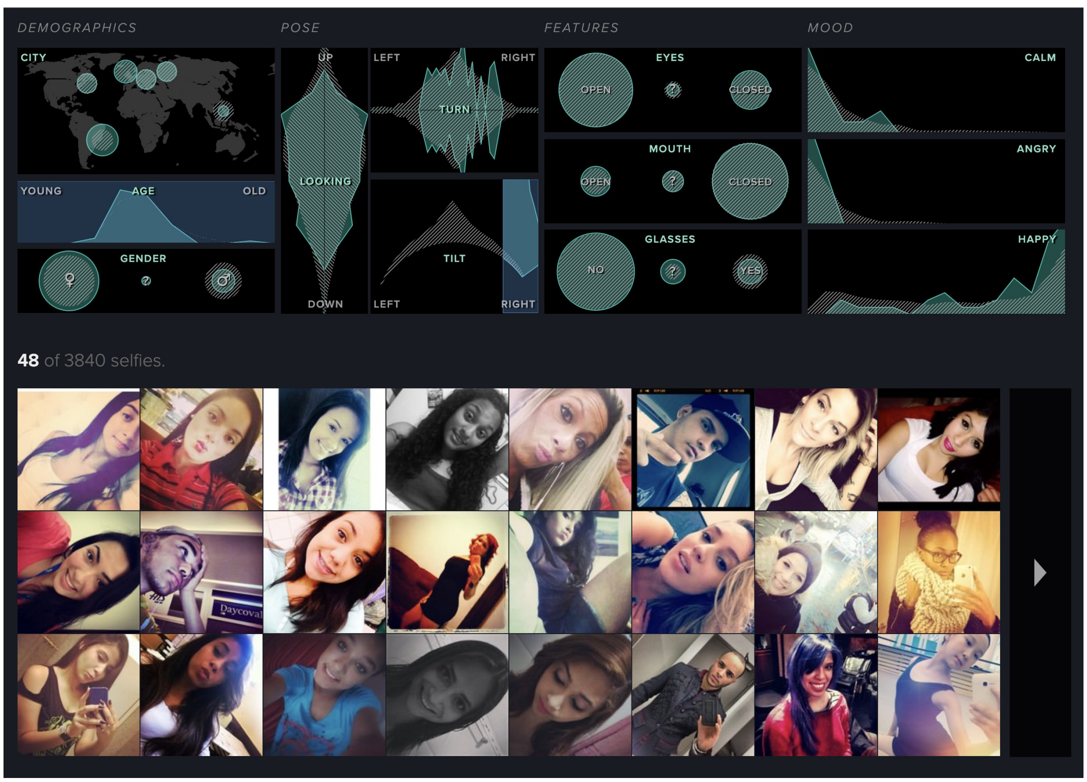


Figure 2.9: A screenshot of the website of Selfiecity[2]by Lev Manovich et al. [45]. The image is used by permission.

Since the middle of the 2000s, the popular use of social media, such as Tumblr, Twitter, Facebook, Flickr, YouTube, and Instagram, and the explosive increase of personal

[2]https://selfiecity.net/selfiexploratory/

data shared online have paved a new way that pushes the boundaries of data visualization for cultural data analysis [35]. Selfiecity [45] shown in Figure 2.9, is one of the examples that aim to understand social phenomena and find how people behave online through the visualization and analysis of social media data. Selfiecity [45] is an interactive web visualization for exploring 3,200 selfie photos on Instagram in 5 global cities, New York, Bangkok, Berlin, Moscow, and São Paulo. The dataset was chosen from about 20,000 images taken in each city by human judgment and analyzed by using software for face analysis that generates 20 measurements such as the size and orientation of each face, the presence of smile and glasses, the detection of eyes, and the guessed gender, age, and emotion of a person in each photo. Through the computational analysis and various visualizations of a large set of images, Tifentale and Manovich [45] presented selected findings of the selfie phenomenon, for example, "There are significantly more women selfies than men selfies in every city."

As a reflection of the Quantified Self movement [1], some researchers and graphic designers have explored various quantitative self-representations to make self-tracking data more visually perceivable, understandable, or meaningful [4], as shown in Figure 2.10. Since 2005, Graphic designer Nicholas Felton had self-tracked his habits and interests, such as music listening habits, visited locations, the categories and amounts of physical activity, sleep, weight, computer usage, etc., and had annually published his self-tracking data as a set of graphic representations, *The Felton Annual Report* in an attempt to reveal the connections, context, and correlations of the data. Felton continued to publish the annual report until 2015 [46].

Looking at the history of data visualization, it is obvious that research on data visualization has been contributing to a multitude of aspects of our lives and society, and its impact has been increasing along with advances in computing technology.

[3] http://feltron.com/FAR14.html

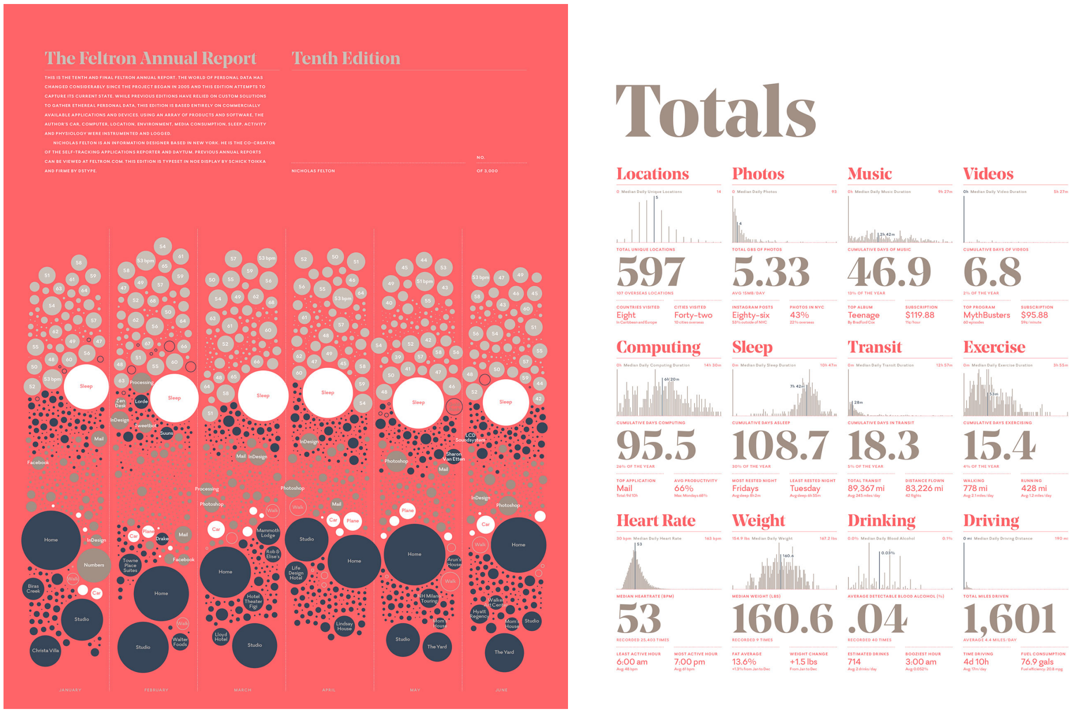


Figure 2.10: Nicholas Felton's 2014 Annual Report. The images are from Felton's website[3]by permission.

2.5.3 From Data Visualization to Data Art

Along with the increasing research on data visualization, data practitioners have begun to show their interest in expanding the domains and boundaries of scientific and information visualization. Pousman et al. called this transition *Casual Information Visualization* [47], giving the motivation of the domain expansion as follows:

> "Workers in widely varying domains from finance to government to journalism use information visualization tools to explore data, generate, refine and test hypotheses, and ultimately to produce insight. ⋯ Some information visualization systems are however not designed for these user populations and these work situations. Instead, the systems are designed for more casual uses and without the same degree of task focus. Systems for visualizing this personal data certainly have some of the properties of an infovis system."

Posuman et al.'s types of *Casual Information Visualization* include *artistic information visualization* [47], recognizing that the term artistic infovis was first coined by Viegas and Wattenberg [48]. The main impact of artistic infovis is explained with the perspective of reflective insight:

> "They (artistic infovis) 'problematize' our everyday conceptions. ⋯ Data-driven artworks may challenge some of our notions of visualization and computer-mediated understanding, our notions of what constitutes data, and may even question our ideas about the infrastructure of computer systems. ⋯ Artistic infovis systems can make computer networks, algorithms, and data itself objects for reflection. Because these systems may evoke curiosity, puzzlement, or even frustration, they depart from just being aesthetically pleasing or well-designed. Of course, as art, many of them are beautiful. ⋯ Reflective insight is insight about oneself, the world, and one's place in it. One of the ways that reflection can be prompted is by defamiliarization, making the mundane and everyday strange. Artistic infovis systems often use defamiliarization to help users make reflective insights." [47]

Viegas and Wattenberg [48] define artistic data visualizations as "visualization of data done by artists with the intent of making art." They also emphasize the two key differences of artistic data visualization compared to generic data visualization:

> "First, the artworks must be based on actual data, rather than the metaphors or surface appearance of visualization. ⋯ Underlying mapping between data and image is required. ⋯ Second, our definition avoids the issue of beauty: we do not contend that beautiful scientific visualizations are automatically artistic, or that visualization art must be pretty. ⋯ focusing on intent rather than surface aesthetics."

Two reasons why the new type of visualization has emerged are followed:

> "First is the emergence of software tools that are appropriate for artistic production of data visualizations. ··· (Second,) Data has become part of the cultural discourse on several levels. Government and corporate collections of data now play a critical role in the lives of citizens of many nations. As a result, it is natural that artists want to grapple with the issues raised by the controlling power of data." [48]

Besides Viegas and Wattenberg's definition of artistic data visualization focusing on artists' intent rather than surface aesthetics applied to actual data, Kosara [49] gives an interesting distinction between pragmatic visualization and artistic visualization along with the concept of data as a raw material:

> "The goal of pragmatic visualization is to explore, analyze, or present information in a way that allows the user to thoroughly understand the data. ··· The goal of artistic visualization is usually to communicate a concern, rather than to show data. The data is used as the basis, the raw material. It also provides a proof that the concern in question is, in fact, real."

In the same year when the terms, artistic information visualization and artistic data visualization, were used to describe a different branch of data visualization research, Lau and Moere [50] proposed a model of information aesthetics in the context of information visualization as a cross-disciplinary conceptual link between information visualization and visualization art. The model whose domains are defined according to data, aesthetics, and interaction, is constructed from two perspectives: one is an information visualization perspective regarding functionality and effectiveness and the other is the perspective of artistic influence and meaningfulness in visualization art. They draw two factors from these two perspectives, mapping technique and data focus, that define the model. The mapping technique factor describes the degree to which visualization methods to represent an abstract dataset are direct or interpretive, whereas the data focus represents whether applied visualization techniques are intrinsic or extrinsic in facilitating knowledge acquisition and communicating the meaning of data (see Figure 2.11).

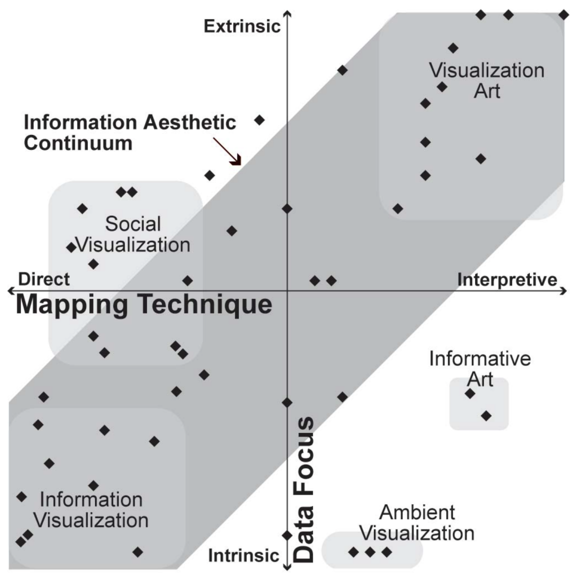


Figure 2.11: Categories within the model of information aesthetics [50]. The black diamond geometric shapes represent existing data visualization applications that have been analyzed and placed on the model by the authors of [50]. The image is used by permission.

According to the analysis of Lau and Moere [50], these two factors are qualitatively correlated. For example, mapping techniques used in information visualization are generally direct mapping focusing on revealing intrinsic patterns. Visualization art, meanwhile, uses more interpretive mapping emphasizing extrinsic data meaning. They point out that information visualization is based on visual cognition research to increase the effectiveness and efficiency of the user's ability to detect data patterns and visualization art mapping techniques tend to be highly subjective and arbitrary, aiming to provoke personal reflection and facilitate the expression of meaning underlying data. They conclude that information aesthetic visualization techniques can utilize conventional visualization techniques, which are generally direct and accurate, for alternative purposes in stylistic and artistic ways as in visualization art, facilitating both intrinsic insights into patterns and extrinsic meaning underlying the data.

In addition to the emergence of artistic data visualization, Donath [51] suggests the term "data portraits" in explaining the representations of personal data. Compared to artistic data visualization, data portraits more focus on depicting individuals through their digital archives as illustrated in Figure 2.12, and function as data mirrors, showing patterns in data as a tool for self-understanding and evoking the impression of its subject like traditional portraits.

Within the spectrum between data visualization and data art, Freeman [16] posits her practice as a more comprehensive data art. She defines data art as "translations of digital data to create cognitive, physical and/or sublime artworks", to describe data as an art material, rather than part of a process in the data visualization, even artistic data visualization domain. This conceptual expansion of data art enables the forms of data art to include various representations in addition to screen and print-based visualization, such as Sonification, Physicalization, Olfactory/Tactile/Taste Experiences, Performance, etc.

Data representation also can take advantage of our multimodal perception abilities by encoding data into multiple sensory channels as Hogan and Hornecker [52] define multimodal data representation as below:

> "Multisensory data representation is a class of data representation that has a clear intent to reveal insight by encoding data in more than one representational modality and requires at least two sensory channels to fully interpret and understand the underlying data."

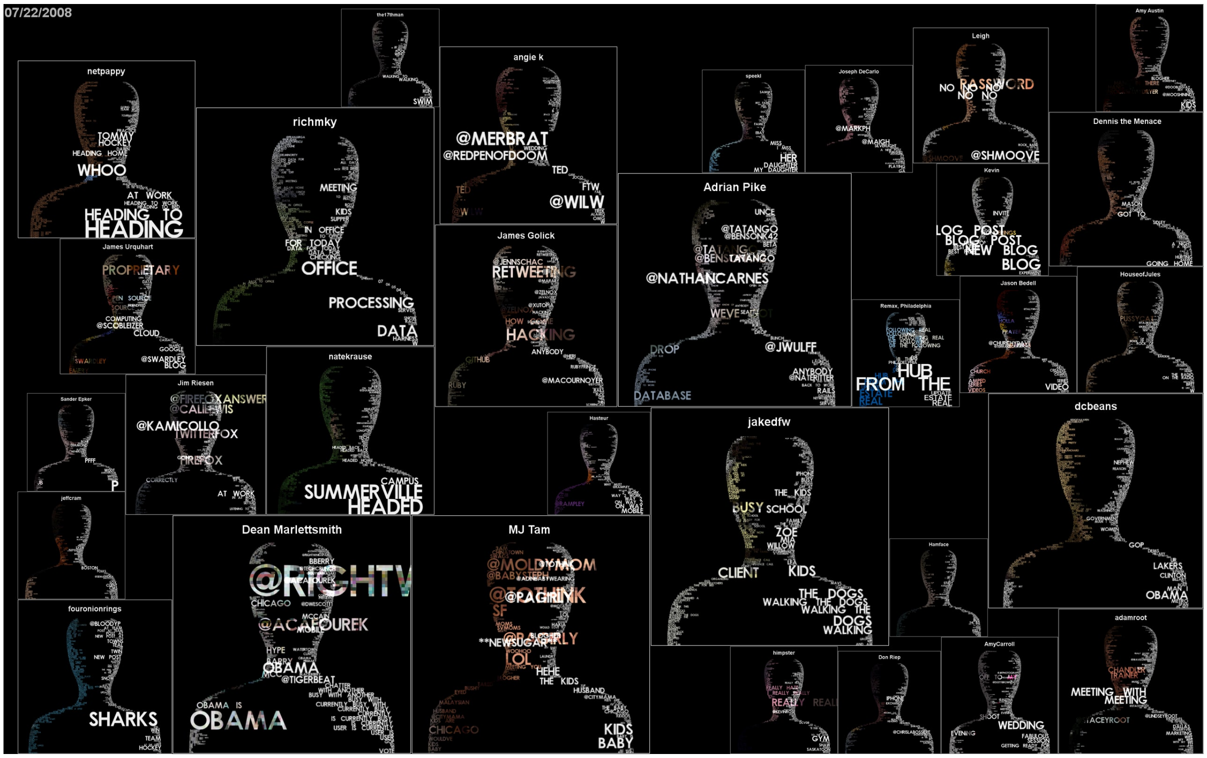


Figure 2.12: Lexigraphs I. © 2009 Alex Dragulescu and Judith Donath. The image is used by permission.

Hogan and Hornecker [52] suggest the design space of multimodal data representation along with three categories: *use of modalities*, *representation intent*, and *human-data relations*. Interestingly, representational intent is explained as the lines of *Utilitarian* and *Casual* in a similar manner as a model of information aesthetics constructed by Lau and Moere [50]. *Utilitarian* representations are defined as works that aim at revealing data insight with regard to an explicit task to a specific audience, whereas *Casual* data representations are not task-oriented and intended for more open-ended data exploration for a much broader audience. Hogan and Hornecker [52] insist *Casual* data representations with multiple modalities can have more potential to evoke personal meaning and hedonic responses:

> “We believe that expanding the perceptual field of representation beyond the

> visual modality offers practitioners more scope to create representations that evoke personal meaning in their audience."

Hogan and Hornecker [52] conclude that while having more than one modality in representing data may increase the cognitive load needed to interpret a multimodal representation, it can facilitate "a more holistic sensory experience":

> "Whether the intention of the creator is to support a utilitarian task or draw attention to a concern, data representations that stimulate more than one sensory channel, we argue, facilitate a more holistic sensory experience and allow the user/audience to interpret the data in a manner that is personal to them."

As Freeman [16] and Hogan and Hornecker [52] indicate, Data Sonification is considered one of the ways for data representation. An umbrella term and research field of data sonification is Auditory Display which uses sound to communicate information, whereas data sonification is a subtype of auditory display that uses non-speech audio to represent data [19]. Research interests in sonification have arisen in scientific domains, such as seismology, astronomy, and geography, in the 1990s with increasing computing power to generate sound in real time, mainly focusing on the use of sound as an alternative or complement to the visual representation of scientific data, as Lenzi and Ciuccarelli [53] reviewed its literature. As Hermann [54] identifies the necessary conditions of sonification, scientific sonifications are required to have data-dependency, objectivity, systematicness, and reproducibility. With the intensifying datafication of our society, however, there has been also an increasing practice to use sonification in other domains, such as information design and art. Taking account of the intentionality of communicating the complexity of social issues in a data-intensive society through data sonification, Lenzi and Ciuccarelli [53] explain the expanded use of data sonification in two directions:

> "complementing data visualization in the representation of specific, invisible dimensions of a phenomenon to wider publics, and fostering the engagement of non-experts through a captivating and compelling experience."

My research mainly focuses on multimodal data representation based on a combination of data visualization and sonification to create data-driven audiovisual art. Both visualization and sonification can be used as the main tools in making data arts. Visualizing data can help a person reveal a story of data and perceptualize data for others, meanwhile, data sonification can generate knowledge about the subject of data, using non-speech sound to convey data. Whereas visualization exploits our visual perception that is more spatially adapted and optimized for understanding static phenomena, sonification takes advantage of the ability of acoustic perception to recognize temporal changes and patterns [55]. Simultaneously presenting these two representations, multimodal data representation can enhance the perception and understanding of data with multisensory stimuli. If aesthetics is about sensuous perception, the multimodal data representation can be seen as a form of data art that pursues an aesthetic goal, besides its pragmatic purpose in terms of information design [56].

Chapter 3

The Human-Data-Machine Loop

3.1 Uncertainty in Data Visualization

3.1.1 Dataism and a Fantasy of Knowing

The general practice in datafication and data visualization is carried out based on the assumption that "data tells us objective truth [4]." Census data, which is used to produce the classificatory standards of people's personal attributes and behaviors, such as gender, race, and citizenship [57], is an exemplary case of datafication in the public domain.

As the affordances of self-tracking technologies and an increasing desire for self-improvement through self-tracking data have permeated into society since the emergence of the Quantified Self movement, the use of personal data visualizations provided by self-tracking services and applications has become a norm in our digital culture, as shown in Figure 3.1. Self-trackers try to understand their behaviors by looking at their data as forms of the graphical representations generated by the applications either on mobile phones or desktop personal computers. It is observed that self-tracking practitioners use the generated visualizations to obtain insights to improve their health and other aspects of life and to find new life experiences [58].

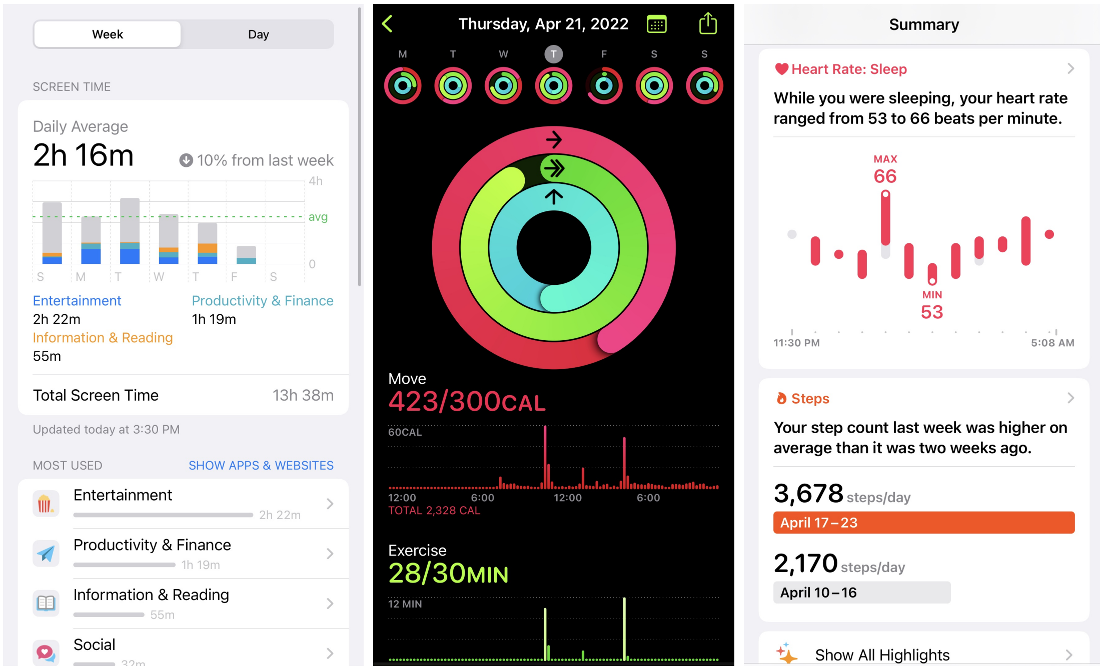


Figure 3.1: Examples of the self-tracking data visualizations generated by using Apple's Screen Time (left), Fitness (middle), and Health (right) apps, respectively. Screen Time shows the usage of the author's mobile phone, Fitness visualizes different types of the author's physical activities, and Health shows some highlights of the author's health information.

Big Data research has an ideal perspective: the more data, the more objective. boyd and Crawford [59] explain this ideal as the mythology of Big Data, which is "the widespread belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy."

The belief in data as the objective truth is also found in data art practice. Donath [51] calls the representations of personal digital data "portraits" instead of "visualizations" by borrowing the concept of traditional portraits in Renaissance paintings that depict the subject's character or role in society through highly symbolic garments and possessions. Although Donath's intention of using the term "portrait" is to highlight the importance of subjective interpretation of the artist in depicting the subject, Donath expects data portraits to function as the "data mirror", a tool for self-understanding that helps us discover and represent our identities entangled with data depictions [51]. This expectation is similar to what self-trackers expect from visualizations of their self-tracking data.

However, we need to be aware of what aspects our personal data cannot reflect who we are in reality. van Dijck [3] criticizes a common belief in the objective quantification and self-tracking of human behavior with the term *dataism*, emphasizing the necessity of understanding the different reasons for and contexts in which data is gathered as well as who interprets the data:

> "I will argue that in many respects datafication is rooted in problematic ontological and epistemological claims. However compelling some examples of applied Big Data research, the ideology of *dataism* shows characteristics of a widespread *belief* in the objective quantification and potential tracking of all kinds of human behavior and sociality through online media technologies. Besides, dataism also involves *trust* in the (institutional) agents that collect, interpret, and share (meta)data culled from social media, internet platforms, and other communication technologies."

In industry, as van Dijk [3] states, data is believed as "raw material" that can be mined for the purpose of the analysis and prediction of human behaviors. However, Gitelman [60] argues that "raw data" is an oxymoron because "data is given prior to argument, given in order to provide a rhetorical basis."

Rettberg [4] points out that personal data can be subjectively collected, not rigorously:

> "Our quantitative self-representations are not entirely objective, though the numbers, checkboxes and graphs give them that appearance. ⋯ Sometimes

> we fudge the data to make ourselves look better (even just to ourselves) and other times we fudge it to represent ourselves in a way that feels more accurate, although it may not be exactly true."

What kinds of data we can obtain and measure are determined by available sensors and algorithms of the machines. Moreover, the representations of the data gathered from our devices might not be about our experiences but the experiences of the devices, *the machine vision*, as Rettberg [4] writes:

> "When we use devices to represent ourselves, we rely on what the devices are able to measure. The step monitor doesn't really measure how many steps I take, it measures how often it moves in a way that tends to correlate to the way the device would move if a human, wearing it, took a step. ⋯ Even if we are creating something for ourselves or for other humans, we have to mould our expression to what the devices we are using can perceive."

Therefore, "uncertainty" exists in the belief of data objectivity. In this regard, Drucker [61] suggests the use of the term *capta* instead of *data* which to reflect the subjectivity of data which is measured from our devices:

> "Differences in the etymological roots of the terms data and capta make the distinction between constructivist and realist approaches clear. Capta is 'taken' actively while data is assumed to be a 'given' able to be recorded and observed. From this distinction, a world of differences arises. ⋯ knowledge is constructed, *taken*, not simply given as a natural representation of pre-existing fact."

As McCosker and Wilken (2014) [62] argue that the visualization of Big Data represents "a fantasy of knowing, or total knowledge", data representation is also subject to uncertainty. This uncertainty can be caused by filters, randomness, subjective programming, or biased algorithms. The surface aesthetic of the work can change meaning derived from the data as Freeman [16] points out the "uncertainty" in data representation:

> "Data visualization often focuses on the portrayal of precise objective messages which emerge from the data. ⋯ Obfuscation can take place within code through filters, randomness, subjective programming, or biased algorithms. The aesthetic of the work can conceal or alter meaning derived from the data if it is over-bearing or has some strong characteristics."

quoting Drucker [63]:

> "The rendering of statistical information into graphical form gives it a simplicity and legibility that hides every aspect of the original interpretive framework on which the statistical data were constructed."

Manovich [35] contends that the data reduction to graphic primitives cannot comprehensively reveal the characteristics of data objects:

> "We throw away 99 percent of what is specific about each object to represent only 1 percent in the hope of revealing patterns across this 1 percent of objects' characteristics."

In addition to the uncertainty in data visualization, Freeman [16] mentions that data art practice is still under the influence of the objectivity-based practice in data visualization, although data artists can open up the boundaries of objectivity.

3.1.2 Types of Uncertainty in Data Visualization

As Figure 3.2 illustrates, the widely used pipeline in data visualization is comprised of data processing (data transformation), visual mapping (encoding), and presentation

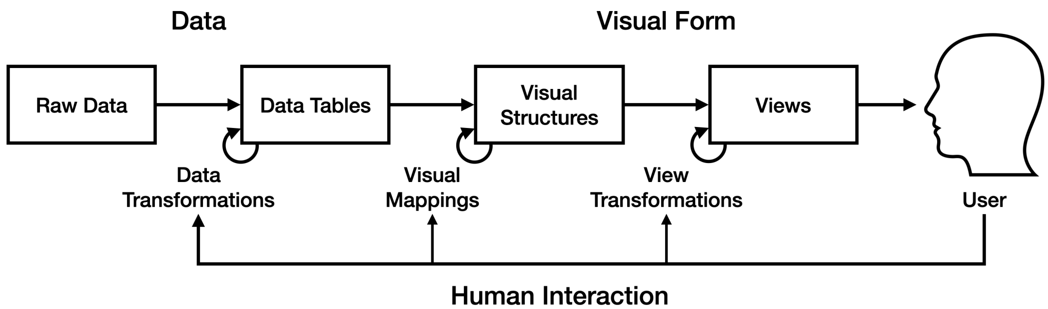


Figure 3.2: Data visualization pipeline (adapted from Card et al. [33]).

(view transformation) [33]. Human interaction is possibly involved in each step. Data collection can be added before data processing to extend the pipeline, as Thudt et al. [64] point out that data collection can be an integral part of data visualization to reflect the subjective perspective of data in the pipeline.

Figure 3.3 shows one of the uncertainty examples in data visualization generated from inefficient representation of data. In this example, there are fifteen different charts, yet each has the same summary statistics. In addition to uncertainty in data representation, there are possible factors or sources in the whole pipeline that can cause uncertainty.

Explaining uncertainty in the data visualization pipeline was first proposed by Pang et al. in their preprint version of the paper entitled "Approaches to Uncertainty Visualization" [66]. Figure 3.4 illustrates that different forms of uncertainty exist within the pipeline: data uncertainty from models and measurements, derived uncertainty from the transformation process, and visualization uncertainty from the visualization process.

An updated version of Pang et al.'s uncertainty diagram in 1997 [67] includes possible sources and types of uncertainty in detail, as shown in Figure 3.5. Defining types of uncertainty to include statistical variations or spread, errors and differences, minimum-maximum range values, and noisy or missing data, Pang et al.[67] review the sources of uncertainty in three stages: acquisition, transformation, and visualization.

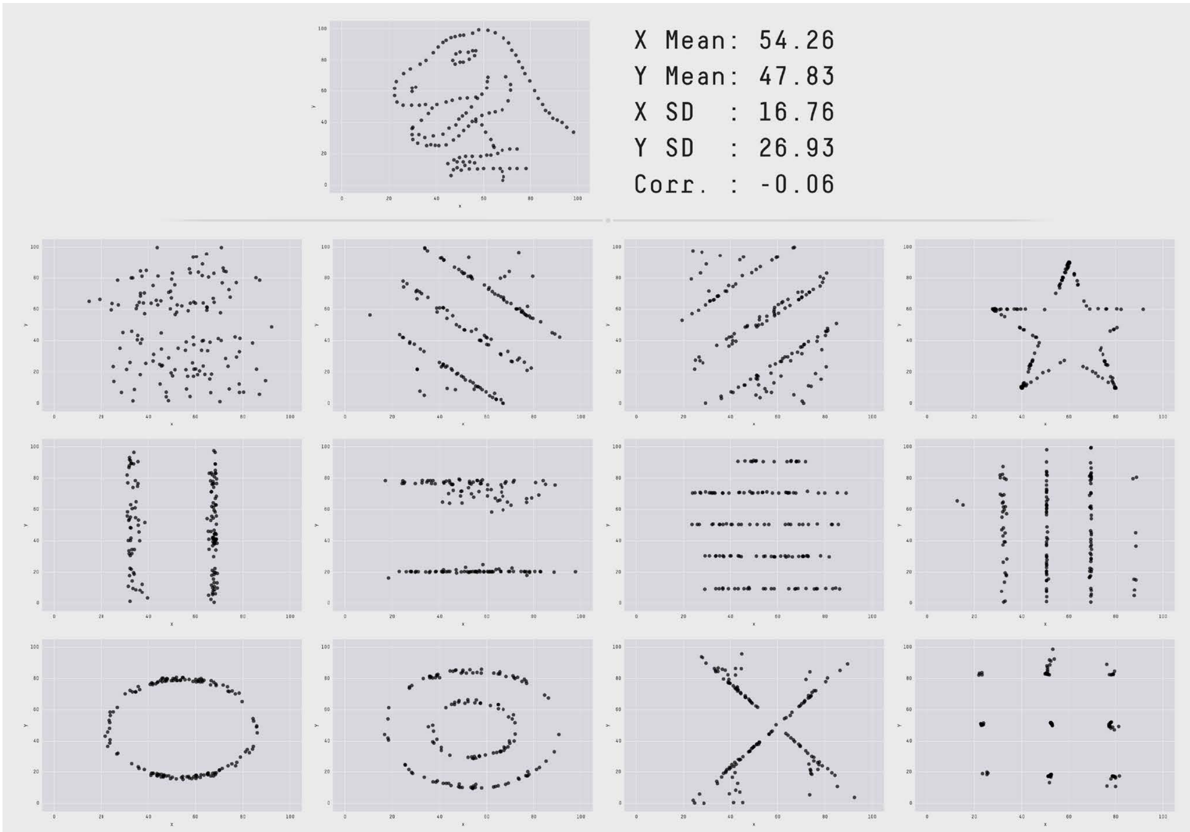


Figure 3.3: An example of visualization uncertainty [65]. The image is used by permission.

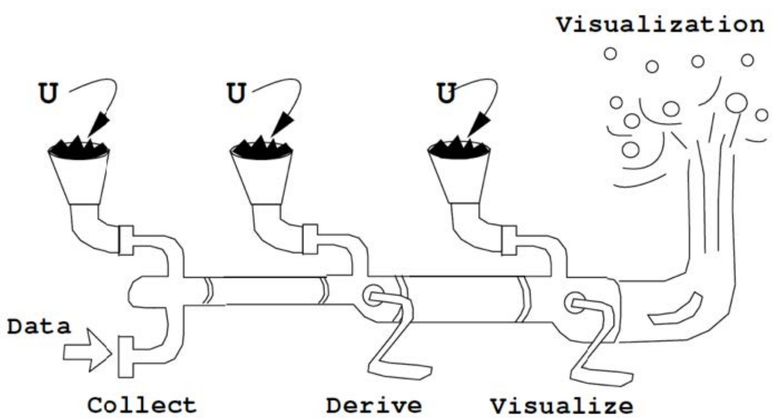


Figure 3.4: Pang et al. [66]'s diagram of uncertainty in the data visualization pipeline (A preprint version in 1996). The image is used by permission.

At the data acquisition stage, data uncertainty can be caused by a statistical variation in instrument measurements, numerical models, and human observations or inputs.

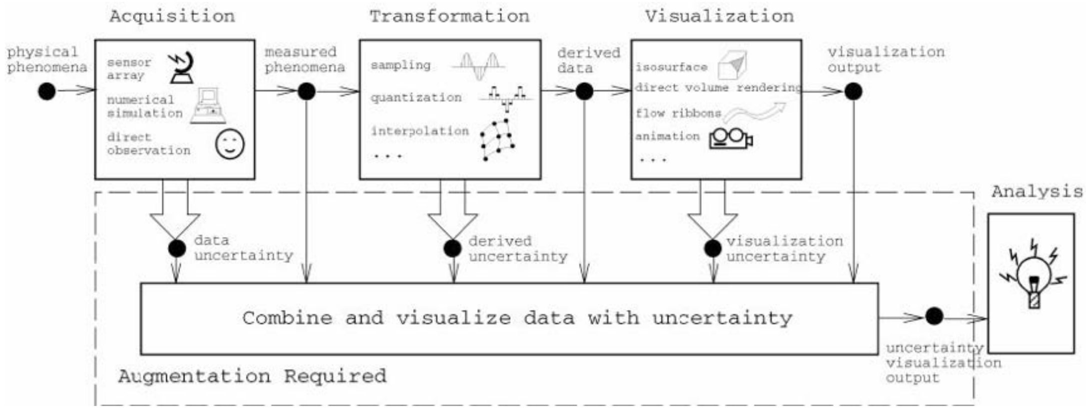


Figure 3.5: Pang et al. [67]'s diagram of uncertainty in the data visualization pipeline (A revised version in 1997). The image is used by permission.

Algorithms and the limited precision of the machinery can introduce errors in numerical calculations on the models. Variability in human observations can be a source of uncertainty due to individual differences in perception and task performance [67].

Data transformation involves a set of operations, such as sampling, quantization, interpolation, measurement unit conversion, etc., in order to derive a new type of data by fusing one or more types of data. These operations can introduce some uncertainty by altering the original form of the data [67].

Finally, at the data visualization stage, uncertainty can arise from differences in rendering techniques. For example, approximations in the lighting simulation can be one cause of visualization uncertainty. There may be different volume renderings of the same 3D data set according to different approaches, such as ray traversal methods, filter functions for splatting, resampling processes, or the tradeoffs between speed and image quality. In slicing, contouring or isosurface algorithms, surface approximation and interpolation for scattered data sets can introduce uncertainty because of various tradeoffs between performance and accuracy existing in the choice of parameters for these operations. The different integration methods, step sizes, orders, and seeding strategies of flow visualization can produce uncertainty. Animation, which includes time as an additional parameter in visualization, can result in slight variations according to methods, such as interpolation of positions or orientations, along with a choice between quaternions and Euler angle [67].

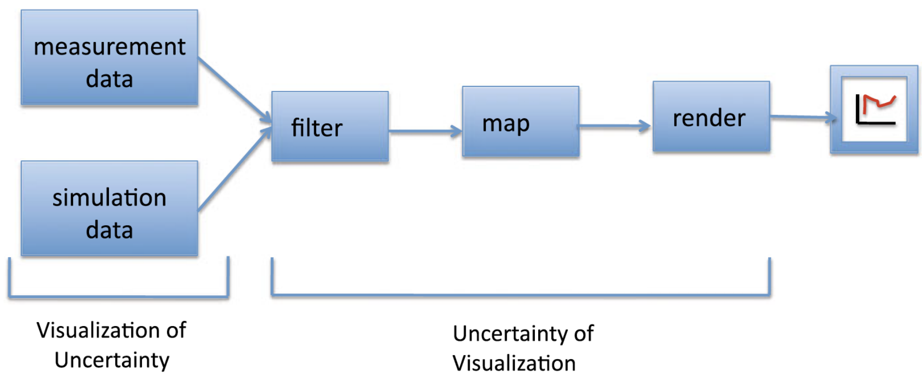


Figure 3.6: Brodlie et al. [68]'s diagram referring to Haber and MCNabb's visualization model [69]. The image is used by permission.

Brodlie et al. [68] attempt to explain uncertainty in data visualization based on Haber and McNabb's visualization reference model [69], as Figure 3.6 illustrates. The concern about the general practice based on dataism is also pointed out:

> "Visualization is now well accepted as a powerful means to allow scientists to explore large datasets, and to present their results to a wider audience. Yet most visualization techniques make the assumption that the data they are displaying are exact." [68]

Brodlie et al. [68] insist that "uncertainty occurs at all stages - visualization of uncertainty focuses on the data stage, while the uncertainty of visualization begins at the filter stage and passes through to the render stage."

With different taxonomies, Bonneau el al. [7] explain sources of uncertainty in scientific visualization (see Figure 3.7). Compared with Brodlie et al. [68], the difference that this pipeline has is that "modeling uncertainties" are included in the *filter* stage.

Bonneau et al. [7] say:

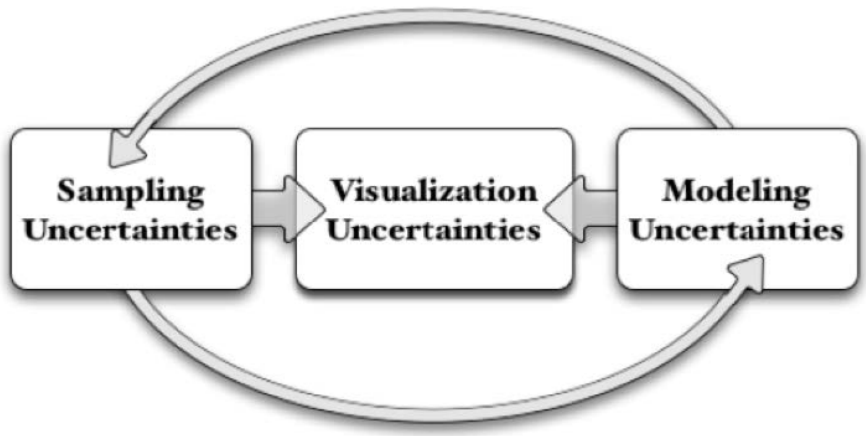


Figure 3.7: Bonneau el al. [7]'s sources of uncertainty. The image is used by permission.

> "As technological advances lead to better data acquisition methods, higher bandwidth, fewer memory limits, and greater computational power, scientific data sets are concurrently growing in size and complexity; scientists to become increasingly reliant on data processing, feature and characteristic extraction, and visualization as tools for managing and understanding large, highly complex data sets; there is becoming a greater accessibility to the error, variance, and uncertainty not only in output results but also incurred throughout the scientific pipeline."

Sampling uncertainty is observed in sampled data. Lack of information can happen due to missing or incomplete data sets, filtering out incomplete data, or using estimation techniques such as interpolation or imputation to fill in missing values. On the other hand, the appearance of too much data can be caused by noisy data or instruments, human error in the data collection, or sampling at an inappropriate scale. Data trustworthiness is subject to sampling uncertainty depending on whether data is outdated, from an untrusted source, or collected via a non-standard process [7].

Modeling uncertainty (or the uncertainty or variability in the outputs of models) can be attributed to various sources. These sources include "residual variability from simplifying abstractions, variability in the mechanism or magnitude of causality and relationships, potential errors in model inputs, incorrect model parameters, or imprecision in tacit knowledge [7]."

The data processing or visualization process can introduce visualization uncertainty. Bonneau et al.[7] remind us that we need to understand the following: "computational sources of error and uncertainty in input values, perceptual or cognitive influences on the understanding of uncertainty visualization, effects of differences in audience abilities and cultures, requirements imposed by different application tasks or goals, and competing positive or negative consequences of showing uncertainty."

Table 3.1: Typology of uncertainty in geographic data visualization [6].

Category	**Definition**
Accuracy/error	Difference between observation and reality
Precision	Exactness of measurement
Completeness	Extent to which info is comprehensive
Consistency	Extent to which info components agree
Lineage	Conduit through which info passed
Currency/timing	Temporal gaps between occurrence, info collection & use
Credibility	Reliability of info source
Subjectivity	Amount of interpretation or judgment included
Interrelatedness	Source independence from other information

As shown in Table 3.1, there is also a typology of uncertainty in Geographic Visualization [6]. This typology has been developed to specifically deal with the types of uncertainty that intelligence analysts face and to draw on frameworks for uncertainty representation in scientific computing.

Based on the common taxonomies and sources of uncertainty described above, this dissertation summarizes three main types of uncertainty in data visualization: data uncertainty, derived uncertainty, and visualization uncertainty (see Figure 3.8). Each type has different sources that possibly cause uncertainty according to tasks in the pipeline.

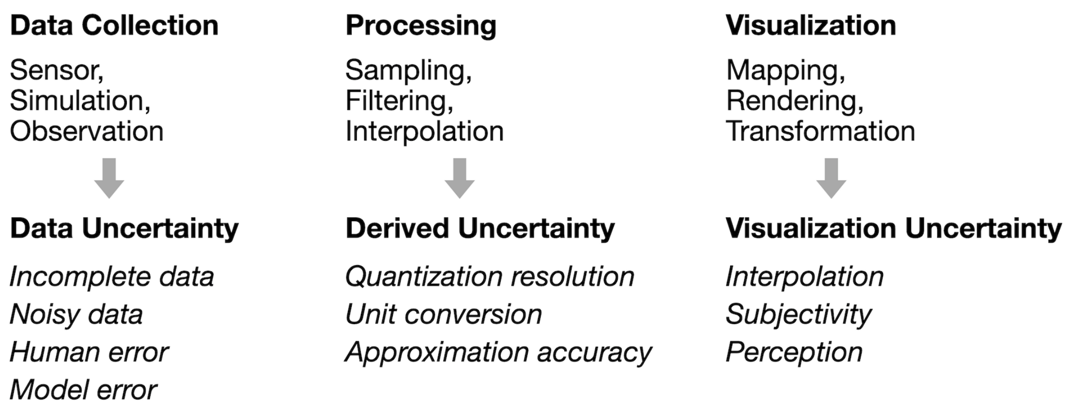


Figure 3.8: Types of uncertainty summarized by the author.

Data uncertainty can arise from incomplete data due to the lack of proper sensors or methods to completely observe phenomena or the subject. Data can also be noisy due to malfunctioning measurement devices. Humans' unrigorous or subjective data collection can be a reason for data uncertainty. Errors in simulation algorithms or prediction models can add uncertainty to the data being calculated.

The quantization of data can happen in data collection through the digitization process of sensors, which is one of the sources of data uncertainty. Quantization also contributes to derived uncertainty at the data processing or transformation stage. Operations for digital data processing on computers, such as the choice of precision or bit depth for floating point format and conversion between integer and floating point numbers, frequently accompany the change of a quantization resolution. The unit conversion of data, which usually happens when data sets with multiple units need to be combined or reduced to a new single data set, can cause derived uncertainty. The approximation of missing data based on existing data or simulation algorithms is one of the sources that give rise to derived uncertainty.

Visualization uncertainty can be caused by the operations of rendering techniques. For example, interpolation is indispensable for drawing continuous visuals across data points, such as lines, curves, contours, or isosurfaces, to fill in missing data between measured data points. Subjectivity also affects uncertainty at the visualization stage. The choice of data-to-visual mapping can be too abstract or subjective. The subjective representation of data can make it difficult to find indexicality between the data and its representation.

3.2 Uncertainty in Machine Learning

3.2.1 Personal Data and Machine Learning

> "There are only two industries which refer to their customers as *users*, drugs and computers." -Edward Tufte [70]

> "All models are wrong but some are useful." -George Box [71]

Our personal data is used by social media companies and communication services to analyze our behaviors, preferences, and characteristics, to create a more accurate understanding of who we are and what we like, and to ultimately make "users" use their platforms more, as Tufte [70] alludes in the above quote.

Social media platforms such as Facebook or Twitter collect data about their "users" with regard to online activities and behavioral traces, for example, writing posts, clicking "likes", or constantly scrolling on the platforms. The intelligent algorithms of the platforms utilize the data to feed us more content that will make their users stay more on the platforms, and expose commercial advertisements personalized to each user. In general, what we see on social media, the so-called "Timeline" is a kind of visualization of personal data showing a mix of other people's posts and commercials prioritized and filtered by the algorithms.

"Algorithm", in general, means a list of step-by-step instructions to solve a problem by a computer, and there are a tremendous number of different algorithms. Broadly speaking, four main categories of the real-world tasks that these intelligent algorithms are used to solve can be accounted for as below [2]:

- Prioritization: making an ordered list (e.g. Google Search's ranked search results, Netflix or YouTube's suggested videos to watch next)
- Classification: picking a category (e.g. Facebook's target advertisement or face labeling on photos)
- Association: finding relationships between things (e.g. Amazon's item recommendation by connecting each customer's interests to those of other customers)
- Filtering: isolating what's important (e.g. Twitter's personalized feed, Siri's speech recognition)

As Hannah [2] explains, the four categories above can cover a vast, complex area of algorithm study although there are other categories, such as mapping, reduction, regression, and clustering. In a real-world situation, it is common that computer algorithms are designed to conduct a combination of the tasks above.

Given our personal data as input, machine algorithms produce output in various forms according to tasks. The output can be recommendation, prediction, or just a new set of data created from the original data. We use these responses or results that the machines generate in many parts of our daily lives. The machines' responses affect us in understanding ourselves, shaping our behaviors, and making decisions. The impact of the machines has been accelerated by recent advances in machine learning and artificial intelligence. However, we have witnessed many failures that the machines make.

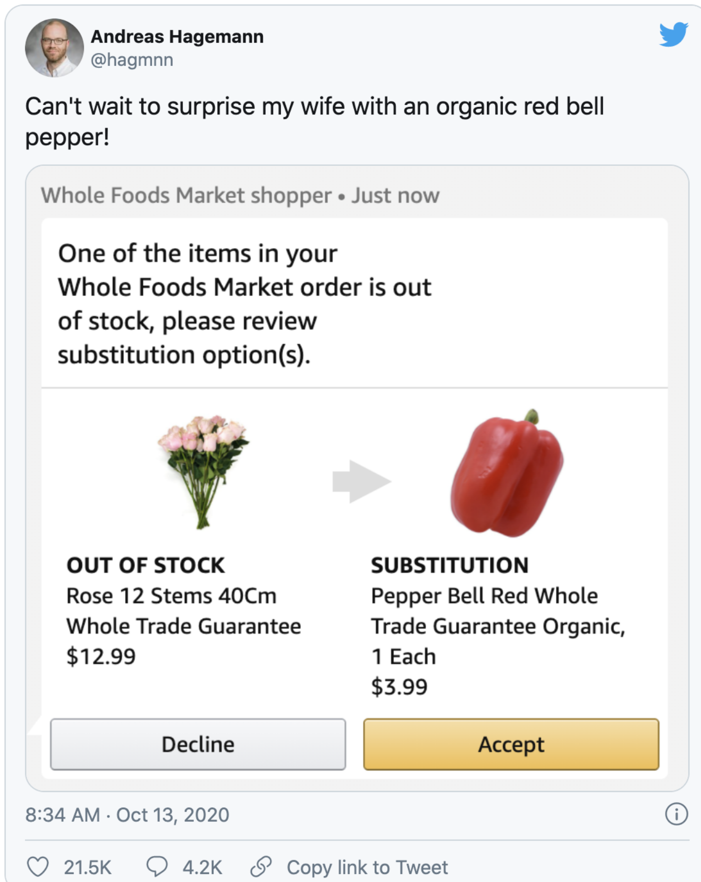


Figure 3.9: Amazon's irrelevant item recommendation shared on Twitter in 2020. Source: https://twitter.com/hagmnn/status/1316039640718155776

In 2015, for example, the Google Photos app wrongly identified two African Americans as "gorillas" [72], raising concerns of racial discrimination of AI systems. This fiasco was the result of a biased training data set that did not have enough tagged images of persons of color and lack of enough testing. Facebook showed the same failure of their AI system that labeled the video of Black men as content about "Primates" [73]. Microsoft's conversational AI bot, Tay was another example of racist AI systems, which was shut down 16 hours after its launch due to its racist and sexist posts on Twitter [74]. Figure

3.9 shows a failure in recommendation systems. Andreas Hagemann, a professor at the University of Michigan, tweeted a ridiculous failure of Amazon's item recommendation that suggested buying red bell peppers instead of out-of-stock roses. It is also known that recommendation systems like YouTube exhibit "an implicit bias towards the past because they are trained to predict future behavior from historical examples" [75] and "how to effectively and efficiently learn to reduce such biases for the systems is an open question." [76]

The examples above show that machines are not perfect. Machines see us through stochastic, algorithmic processes to generalize individuals based on available personal data. Machines can be erroneous and biased upon the data or humans. And due to the nature of deep neural networks, which are currently the most popular machine learning technique, it is difficult to understand how machines work [5]. Mappings of deep learning algorithms between high dimensional data to an array of outputs can be inaccurate. These issues of uncertainty that machines have are difficult to estimate and represent, and they are problems to be solved especially in scientific domains.

3.2.2 Types of Uncertainty in Machine Learning

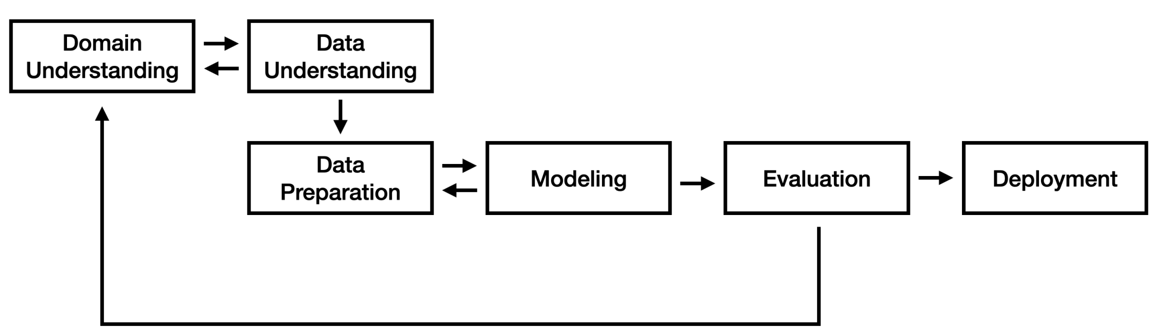


Figure 3.10: A general pipeline for the development of ML/AI models (adapted from Wirth [77]).

The development of machine learning (ML) models and artificial intelligence (AI) applications, in general, follows a variation of the CRISP-DM (CRoss Industry Standard Process for Data Mining) methodology [77], which was first introduced by IBM. Phases of the CRISP-DM consist of business/domain understanding, data understanding, data preparation, modeling, evaluation, and deployment, as shown in Figure 3.10. Kläs and Vollmer [8] explain key activities in the process as follows. With a specific goal or problem definition, the scope of the AI/ML model application is defined in the domain understanding phase. The collection of raw data based on the scope definition is conducted in the relevant context to build and test the model. In the following data preparation step, the raw data becomes cleaned with various techniques for filtering and preprocessing, such as image normalization. The cleaned data is divided into training and test data. The training data is used to build and cross-validate the model, and the test data is used to evaluate how well the model performs with unseen data. Depending on the result of the model evaluation, it is decided whether the model is deployed to actual use or the modeling process is reconducted from the beginning. This iterative process is repeated until the model is considered accurate enough to be deployed.

As Figure 3.11 illustrates, there are two main types of ML: discriminative modeling and generative modeling [78]. Discriminative modeling aims to learn a function that maps an input to an output using a labeled dataset to discriminate between different kinds of data instances. Discriminative modeling is supervised learning for an optimization task that finds boundaries that could divide categories of data instances. A discriminative model can make predictions on previously unseen data. Examples of discriminative modeling include image classification, speech recognition, translation, etc. Meanwhile, generative modeling is, in general, unsupervised learning that learns a probabilistic approximation of the distribution of a dataset to generate new data instances that look similar to but do not exist in the training dataset. Generative modeling is a

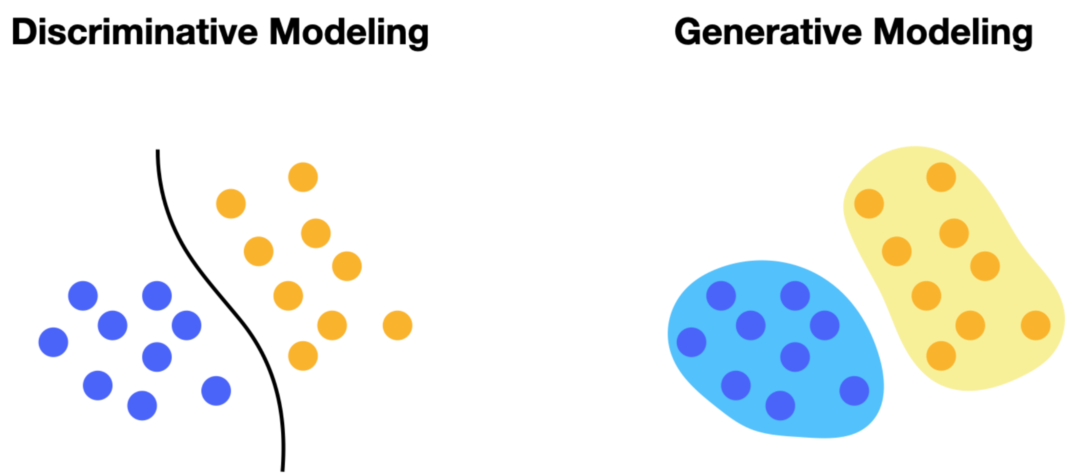


Figure 3.11: Two main types of machine learning.

density modeling task. Applications of generative modeling are new sample generation, data augmentation, input reconstruction, data compression, noise removal (denoising), anomaly input detection (outlier detection), etc. As Foster [79] explains, recent advancements in ML/AI since 2014 have been made through novel applications of deep learning [80] to generative modeling tasks.

The key point in ML is to learn the probabilistic distribution of a training dataset. As Figure 3.12 illustrates, there are two categories of uncertainty in ML from the probability perspective [82]: epistemic uncertainty and aleatoric uncertainty. Epistemic uncertainty results from limited, incomplete knowledge about the best model. In principle, epistemic uncertainty can be reduced, for example, by adding more parameters to the model or gathering more data. High epistemic uncertainty can arise in regions where there are fewer data instances for training a model. Aleatoric uncertainty arises from the natural stochasticity of observations. Aleatoric uncertainty is caused by class overlap or noise inherent in the observations. Noisy measurements of the underlying process such as sensor malfunction can lead to high aleatoric uncertainty. In contrast to epistemic uncertainty,

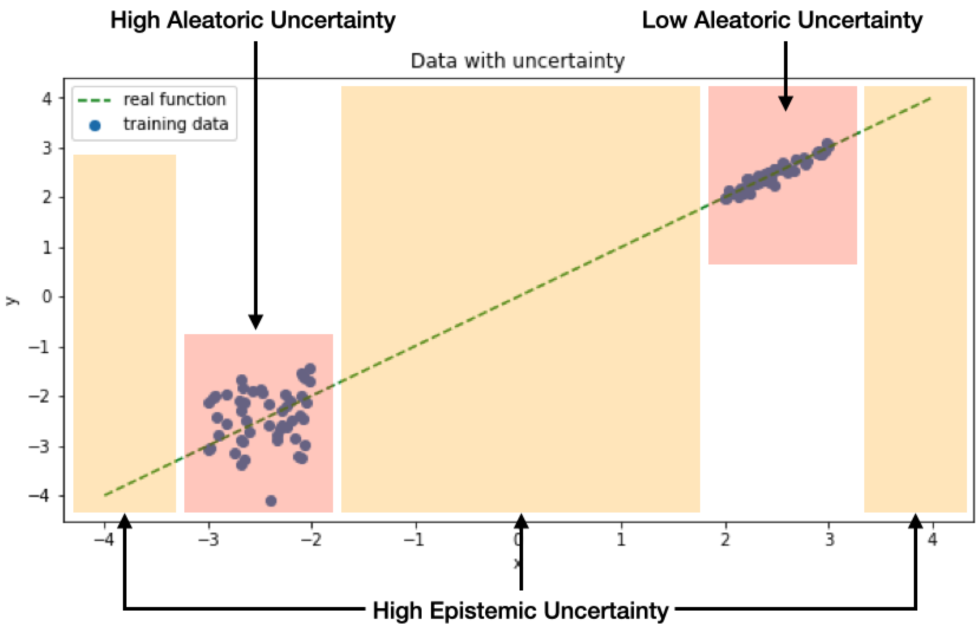


Figure 3.12: Two categories of uncertainty in ML (apapted from Kana [81]).

aleatoric uncertainty cannot be reduced by observing more data samples.

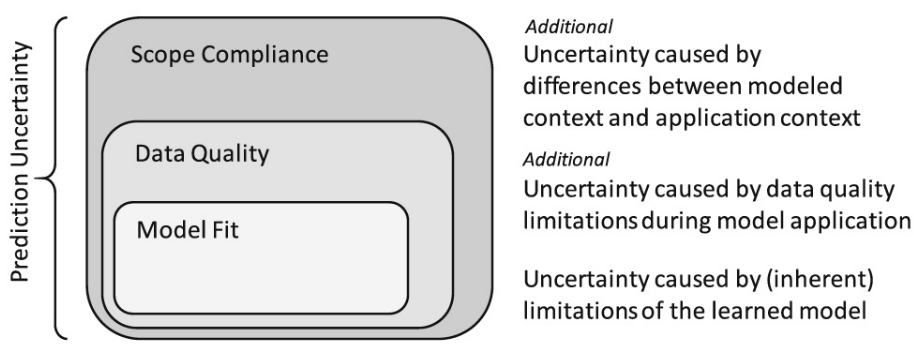


Figure 3.13: Prediction uncertainty [8]. The image is used by permission.

Kläs and Vollmer [8] propose a practice-driven classification of uncertainty in predictive models (see Figure 3.13). According to their classification, model fit uncertainty is "caused by the fact that AI/ML techniques provide empirical models that are only an approximation of the real (functional) relationship between the model input and its outcome." There are several factors that limit the accuracy of this approximation, for example, the limited number of model parameters, input variables, and available data points. One of two important underlying assumptions from which model fit uncertainty arises is that "the data appropriately represents a setting where the model is applied", which is similar to *dataism*. The other assumption is that "the data that the model is built and applied on does not suffer from quality issues". Model fit uncertainty is generally represented as the error rate the model calculates with the cleaned data split into a training dataset and a test dataset. Moreover, uncertainty in data quality appears as "the result of a delta between the quality of the cleaned data (for training) and the data on which the model is being applied." [8] Data quality is limited by various sources, such as the quality and resolution of sensors, differences in real environments, and the performance and accuracy of human input. As the last category, scope compliance uncertainty is defined as "the likelihood that a model is currently being applied outside the scope for which it was tested." [8] There are two sources that can cause scope compliance uncertainty. One is a circumstance where the model is applied outside the intended scope. The other is when the raw data is not sufficient enough to represent the intended scope.

Goodfellow et al. [80] summarize three possible sources of uncertainty. First, inherent stochasticity in the system being modeled. It can be also explained as noise in observations. Noise refers to variability or randomness in the observation, which could be a minimum-maximum value range in data or an error in data measurements. Second, incomplete observability. We cannot have all of the observations to represent the task for which the data or model will be used. There will always be some unobserved cases. Last, incomplete modeling. In other words, imperfect modeling of the problem. It can stem from an error of omission. To achieve the expectation that the model will generalize better to new cases and have better overall performance, we discard some of the information we have observed. The discarded information can be a reason for uncertainty in the model's predictions.

In addition to the types and sources of the uncertainty in ML above, which mainly appear in discriminative modeling, there is another type of uncertainty in generative modeling that I call *data authenticity*. Due to recent advances in generative modeling based on deep learning techniques, generative models are used to generate highly realistic new data samples. NVIDIA's StyleGAN series [83, 84, 85] is a representative example of the state-of-the-art generative modeling for hyper-realistic image generation of human faces. GPT-3 [86] created by OpenAI is a cutting-edge language model that can generate human-like text. However, these advances show various issues of fake content on the internet. As the quality of machine-generated synthetic data becomes more highly realistic, it is more difficult to distinguish between fake and real online content with regard to image and text data. There are some online websites, such as "This Person Does Not Exist" [87], "This X Does Not Exist" [88], and "Which Face Is Real" [89] that demonstrate the issue of fake images and content.

Furthermore, this uncertainty of data authenticity may be problematic for machines when the machines are trained with synthetic data. Data augmentation is one of the ways to deal with lack of data in ML [90]. For example, it is a common practice in ML to increase the number of data points of an image dataset by having different versions of the existing images through various image transformations, such as rotating, cropping, color shift, brightness change, scaling, etc. Generative models also can be used for data augmentation to increase dataset size [91]. The use of synthetic data for model training or prediction could introduce uncertainty because machine models, in general, are not designed to detect whether the data is fake or not. It also makes us consider whether we can trust the model which is trained with synthetic/fake data.

3.3 Uncertainty in the Human-Data-Machine Loop

> "Design is a solution to a problem. Art is a question to a problem." -John Maeda[1]

As our reliance on data and the algorithms of machines becomes more pervasive, how to deal with uncertainty in data practice is also an important topic. In data visualization, there have been various visualization techniques to address uncertainty information, such as confidence and variability, but the visualization of uncertainty is still an unsolved problem because uncertainty is considered an additional dimension to data visualization, and the addition of uncertainty complicates the visualization [7, 68]. Moreover, practitioners in data visualization are less interested in visualizing uncertainty [92].

Deep neural networks are currently one of the most popular techniques in ML. However, due to the complexity of deep layered architecture, it is difficult to understand how deep neural networks work [5]. Although methods for uncertainty quantification in ML have been studied, uncertainty quantification is still a challenging topic [93].

The issues of uncertainty in data practice are difficult to estimate and represent and are problems to be solved in scientific domains. However, I argue that this perspective on uncertainty can become a creative force or theme in data art. In particular, data art can reflect this uncertainty perspective in the art making practice to not only make a unique form of data art, but also raise the audience's awareness of uncertainty in data practice.

3.3.1 The Definition of the Human-Data-Machine Loop

To enable data art practice to reflect the uncertainty perspective, I first define the data-centered interrelationship between humans and machines in our datafied society as

[1] This quote is from Maeda's post on Twitter, https://twitter.com/johnmaeda/status/2057122807

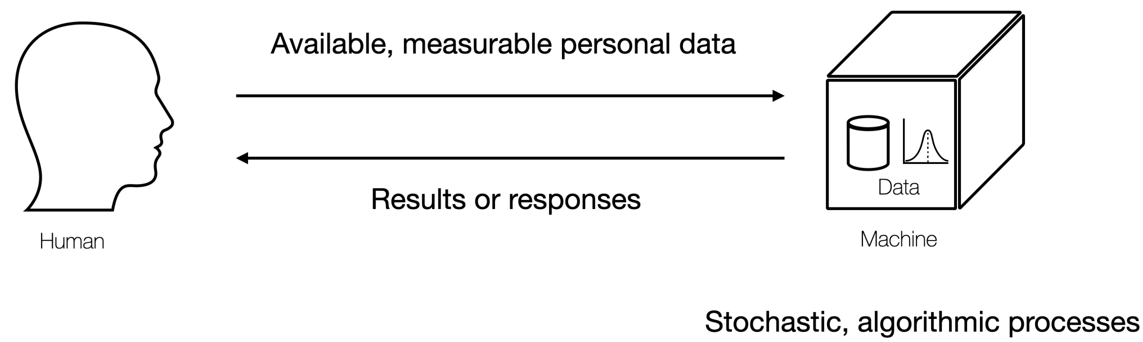


Figure 3.14: The Human-Data-Machine Loop.

the Human-Data-Machine (HDM) Loop along with input and output flows within entities (see Figure 3.14). The human's personal data is collected by or through the machine with the sensing functionality or data logging features. The machine processes the given data with various stochastic algorithms to find hidden patterns or required information from the data according to the tasks that the machine tries to solve. The results of the machine's processing then return to the human. The results can be predictions, recommendations, or just different representations, such as processed data with reduced dimensionality, synthetic data sampled from the machine, or generative visualizations of the latent representation that the machine learns from the data.

3.3.2 Types of Uncertainty in the Human-Data-Machine Loop

The machine sees us through available, measurable personal data obtained from us. We are affected by responses from the machine that generalize us through stochastic, algorithmic processes. These flows in the HDM Loop can be considered three parts: input, model, and output. Based on the taxonomies of uncertainty in data visualization and machine learning described in the previous sections, this framework includes possible types or sources of uncertainty in each step as shown in Table 3.2.

Table 3.2: Types/sources of uncertainty in the Human-Data-Machine Loop.

Input	**Model**	**Output**
• Subjective data collection • Quantization • Noise • Sensor limitations • Biased data	• Scope fit • Reduced dimensionality • Interpolation • Error estimation • Synthetic data detection	• Indexicality • Subjective visualization • Data authenticity • Latent representation • Prediction

I expect that the HDM framework can play a role for data artists in finding an inspirational theme for and in describing their works.

3.4 Data Art Practices in the Human-Data-Machine Loop

Based on this HDM Loop framework, this dissertation suggests three types of data art practice: Artist-Centered Practice, Artist-Machine Collaborative Practice, and Machine-Centered Generative Practice. The characteristics of each practice are determined by the roles of the artist and the machine along with types of uncertainty that each practice mainly can reflect.

3.4.1 Artist-Centered Practice

As shown in Figure 3.15, in the Artist-Centered Practice, the artist collects or generates data with the machine. Here the machine plays a role as a sensor or logging

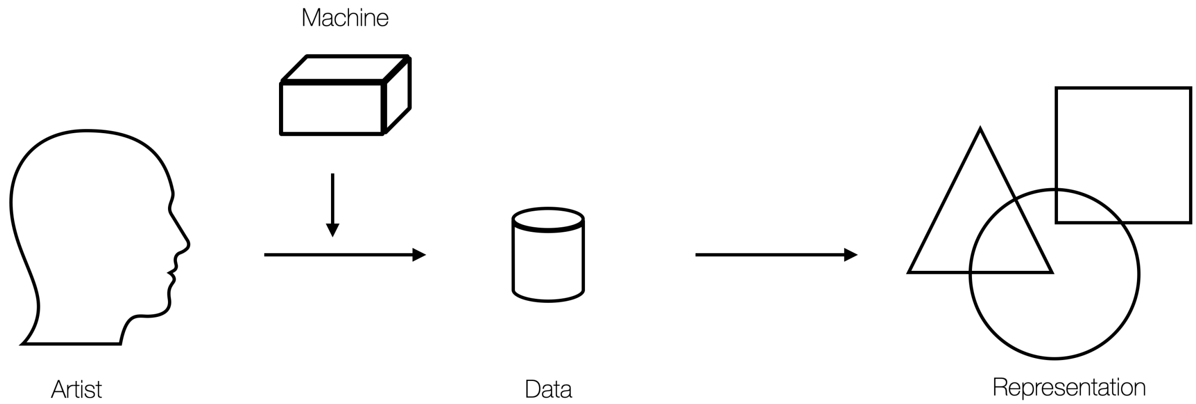


Figure 3.15: Artist-Centered Practice.

device.

Data processing in this practice can involve a simple level of data selection or filtering without complex algorithms running through the machine. Data representation is determined by how the artist encodes data into visible, physical, or sonic forms. The encoding result can be a uni-modal, cross-modal, or multi-modal representation. It is basically the same as the practice in data visualization.

The Artist-Centered Practice could mainly reflect input uncertainty in the HDM framework, such as quantization resolution, noisy data, and sensor limitations, since the artist uses the machine only to collect data.

The practice has the potential to reflect the necessity of alternative perspectives to represent the subjectivity of data [4, 61, 64].

While subjective data representation can be an artistic approach to representing subjective personal data, subjective data representation can be a cause of uncertainty. Highly abstract or subjective data representation that only focuses on surface aesthetics could conceal or mislead messages that the representation is intended to communicate. This conflict requires the artist to find a balance between indexicality and subjectivity in data representation. On one end of the spectrum of data representation, the artist can utilize artistic approaches found in the fine arts that convey a feeling of uncertainty or ambiguity as new ways of exhibiting uncertainty in data representation [94]. On the other end of the spectrum, the artist can consider the situatedness of data representation, focusing on contiguous relationships between the collected data, the context of the data, and generated data representations to evoke feelings of presence and familiarity in viewers [95].

3.4.2 Artist-Machine Collaborative Practice

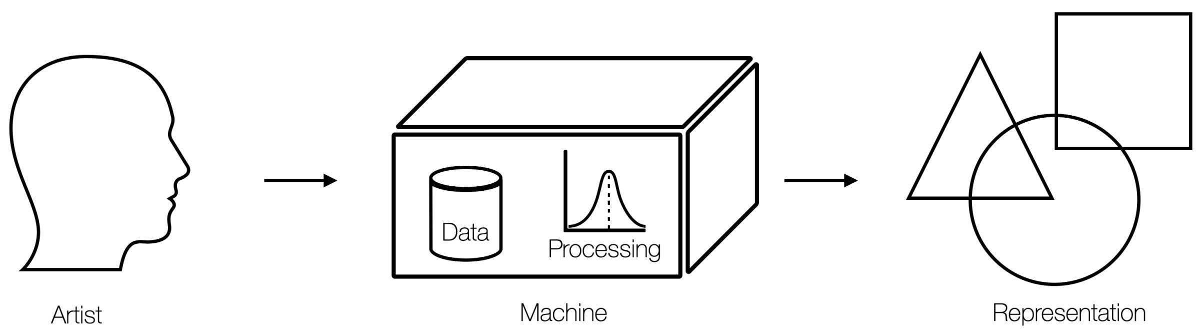


Figure 3.16: Artist-Machine Collaborative Practice.

In the Artist-Machine Collaborative Practice, the artist and the machine engage in both data acquisition and data representation (see Figure 3.16). The artist first collects data and obtains the post-processed or newly generated data through complex computational data processing, algorithms, or machine models, for example, synthetic data generated from a generative model or the data whose dimensional complexity is reduced by dimensionality reduction algorithms. The types of uncertainty this practice could deal with include quantization, interpolation, error estimation, reduced dimensionality, data authenticity, and prediction.

Data representation can be a combination of the artist's intention (of the representation) and choice (of variables of the representation) and the machine's algorithmic and computational process that affects representation results.

The machine's output can directly affect determining the main structure of data representation. For example, dimensionality reduction algorithms in data visualization are used to decide the dimension of representation space by reducing the N-dimension of data into 2D or 3D for the ease of human perception. Values of the reduced data calculated by an algorithm are totally new and do not exist in the original dataset. The artist cannot work with the original data for data representation until the machine produces the reduced data.

The artist determines how to represent the data and chooses what data attributes need to be highlighted on the representation according to the intention of the artist. For example, for a visual form built with a rendering technique and the given data, such as isosurfaces, curvy lines, ribbons, etc., the artist decides on the visual properties of the structure, such as color, texture, scale, and transparency, to represent calculated uncertainty values, such as error estimates, standard deviation, prediction confidence, etc. If the data is in multiple formats as a set of structured data (quantitative values) and unstructured data (text, images, sounds, or videos), the artist can use the original unstructured data to decorate the representation of the reduced quantitative data.

The artist can also employ existing approaches used in Scientific Visualization and Cartography to visualize uncertainty [67, 96, 7]. For example, the artist can adopt the methods developed for representing uncertainty in surfaces and animation applications [67]. The methods include adding glyphs, adding geometry, modifying geometry, modifying attributes, animation, sonification, and psychovisual approaches. In particular, animation is one of the appropriate approaches to representing the data in which the estimated variability or uncertainty changes over time. As Pang et al. [67] explain, the artist can utilize the parameters of animation such as speed, duration, motion blur, and the range or extent of motion, and can use animation along with geometry modification, such as translation and rotation. Sonification is another effective way to represent the temporality of uncertainty values. As a way of multimodal data representation, sonification can be helpful for representations suffering from an overloading visual channel by mapping some uncertainty variables to sound, as well as can validate data by providing the redundancy of representation [67].

3.4.3 Machine-Centered Generative Practice

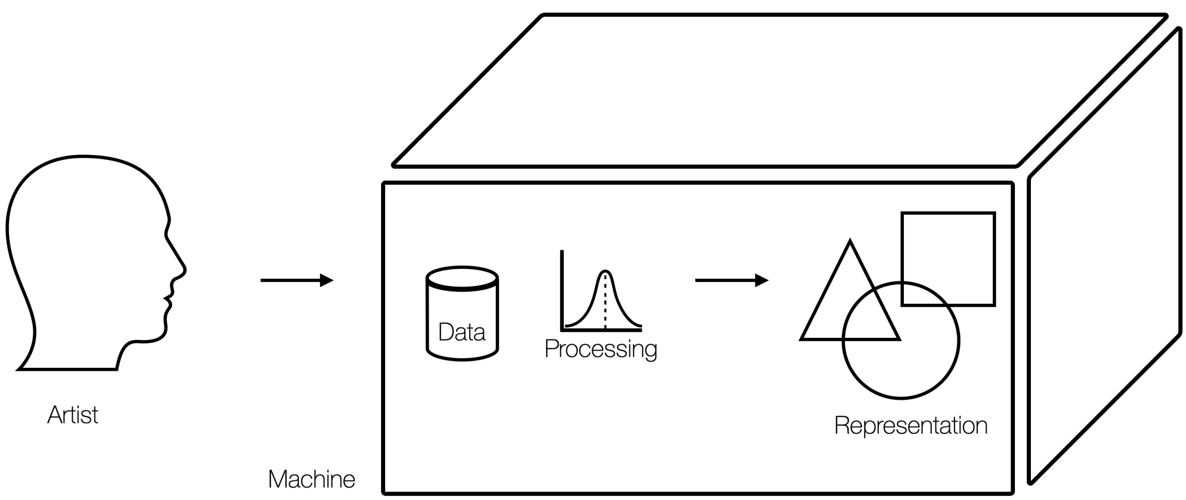


Figure 3.17: Machine-Centered Generative Practice.

The last practice is the Machine-Centered Generative Practice (see Figure 3.17). In this practice, data is collected or generated by the artist, and then the data is used to train the machine. Data representation is mainly accomplished by the machine's algorithms or the latent representation that the machine learns from the data. The types of uncertainty this practice could reflect are biased data, synthetic data detection, scope fit, and latent representation. The artist can be involved in input and output interaction flows that determine how the data representation is generated from the machine.

The Machine-Centered Generative Practice intends to include an emerging trend and transition in data art, broadly speaking, generative art that is explored by contemporary digital media artists and scholars. The use of algorithms and data for creative generativity remains the standard practice, but the role of deep learning models is becoming more popular due to increasing accessibility to advanced ML/AI tools and techniques, as Memo Akten [97], one of the pioneering computational, generative software artists described in an interview.

In the same interview [97], Akten explains "a spectrum of approaches to the practicalities of making AI-generated artwork with generative deep neural networks" as listed below:

- Train on your own data with your own (or heavily modified) algorithms
- Train on your own data with off-the-shelf (or lightly modified) algorithms
- Curate your own data and use your own (or heavily modified) algorithms
- Curate your own data and use off-the-shelf (or lightly modified) algorithms
- Use existing datasets and train with heavily modified algorithms
- Use existing datasets and train with off-the-shelf (or lightly modified) algorithms
- Use pre-trained models and algorithms

The most important aspect in the spectrum described above is that the output of a model depends on the data used to train the model. The collection and curation of the data affect how the machine understands the world where the data is from. This intrinsic relationship between the choice of the data and the machine has been causing an increasing concern for data bias.

Several methods for input data analytics in ML can be employed to represent data bias uncertainty. For example, a method for measuring and visualizing aleatoric and epistemic uncertainty in computer vision can be used in data representation to highlight areas where the model lacks information for semantic segmentation [98].

The artist can also utilize feature visualization techniques to visualize what features the model learns from the data at various levels of neural network architectures, such as neurons, channels, layers, and class output [99].

One of the ways to represent what the machine learned in the latent feature space from a limited set of data is to purposely deploy the model in a context different from the context of a training dataset, as Akten's approach to demonstrating biased models in his artwork [100]. In this way, the artist could address both scope fit uncertainty and biased data via the generative output of the machine.

Another way to represent the machine's understanding of the data is to navigate the latent space of the model by projecting seen/unseen data onto the latent space and by interpolating between latent vectors that are the corresponding values of data points within the latent space. The forms of the model output generated by the projection and the interpolation can be either real-time interactive applications [100, 101] or animating videos [102, 103].

Chapter 4

Empirical Case Studies

4.1 Preliminary Study: InstaSynth

This section introduces the InstaSynth project I made as a preliminary study on data-driven audiovisual art. This project was conducted before the HDM framework was designed. Thus, the goal of the project is not related to the uncertainty perspective. InstaSynth is an artistic exploration of how personal photo data can be represented as a form of audiovisual data art.

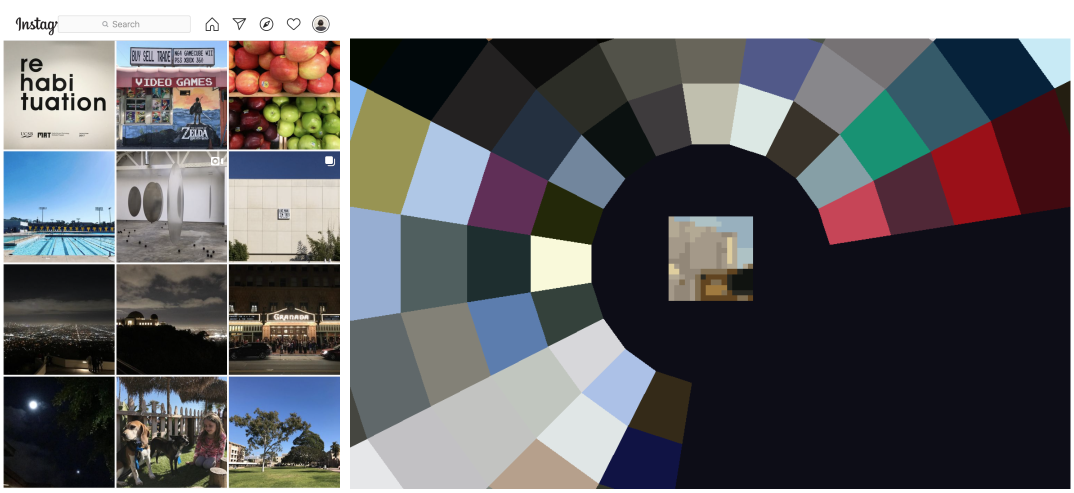


Figure 4.1: The author's personal photos on Instagram (left) and InstaSynth (right).

4.1.1 Project Description

InstaSynth is an image-based audiovisual data art project that transforms personal images on Instagram into a unique audiovisual piece. InstaSynth is an audiovisual representation of my color preference through the transformation of my Instagram photos in real time. The main goal of InstaSynth is to explore what colors I perceive and prefer through photos in daily life and to find the possible way of expressing my color preference as a form of data-driven audiovisual art. InstaSynth involves a color quantization process for dominant color extraction and a sonification based on extracted dominant colors. This project attempts to present the audience with a novel artistic experience by making an abstract visual and sound composition from real images.

4.1.2 Visualization Design

After gathering 20 recent photos from my Instagram account via the Instagram API, InstaSynth sequentially displayed each image while extracting the 12 dominant colors of the image and pixelating the image based on the dominant colors. The pixelated image was fragmented and dropped into a rotating transparent hemispheric structure in the background, which was comprised of 20 vertical bars. Each bar had 12 sections filled with the dominant colors of an image. As a result, InstaSynth generated the hemispheric color palette of 20 images in 3D space (see Figure 4.1).

4.1.3 Sonification Design

Each colored bar created a sound based on an additive synthesis technique. The hue values of a bar's 12 colors were mapped onto the frequencies of 12 sine oscillators respectively. Each oscillator's amplitude was determined by a mapped color's brightness value and the dominant degree of the color. The generated sound of each oscillator was also spatialized by the bar's position. InstaSynth triggered each bar's sound according to a specified BPM (beats per minute). As a result, InstaSynth used the hemispheric color palette as a color-based sound synthesis instrument.

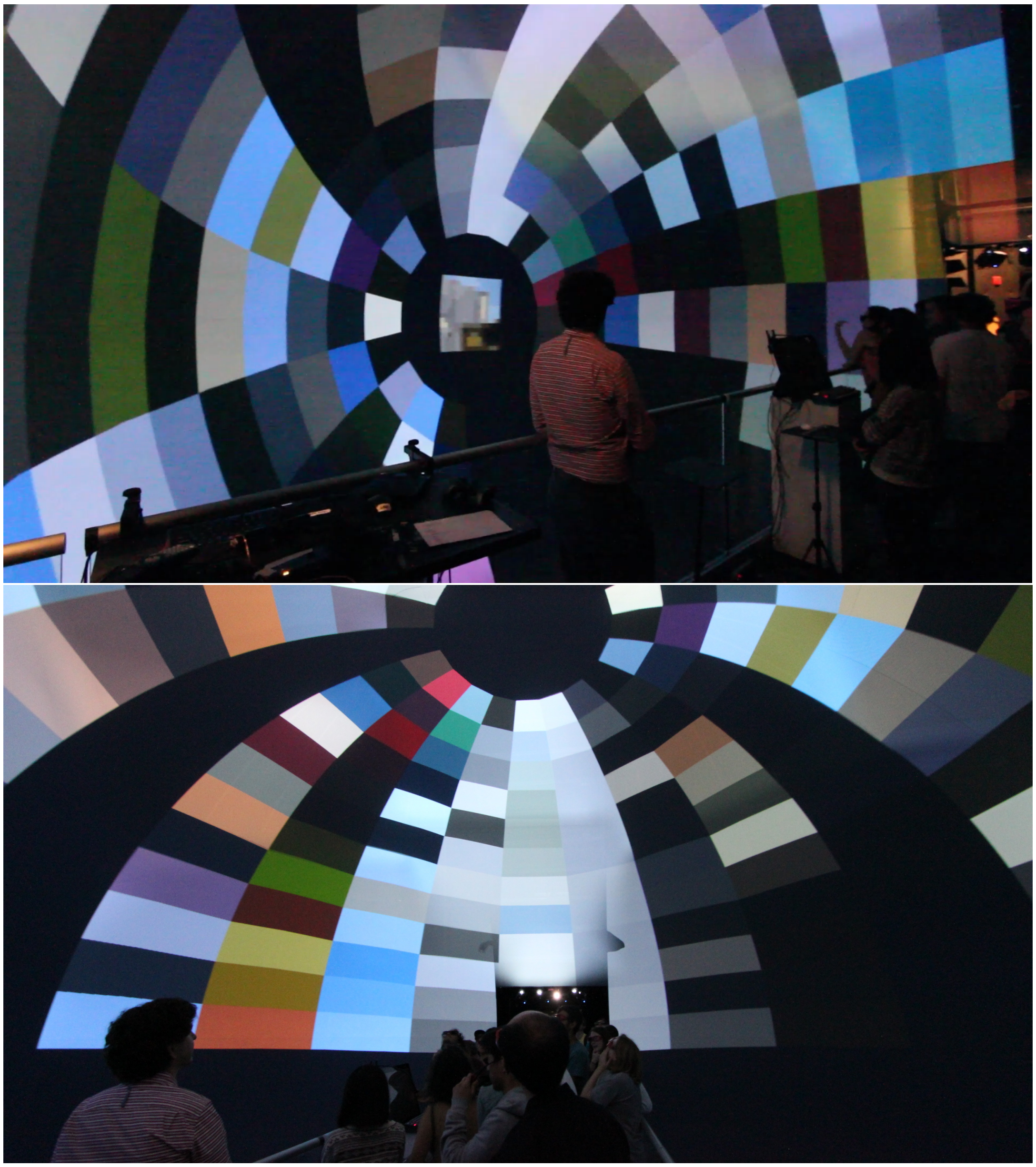


Figure 4.2: InstaSynth demonstration in the AlloSphere at the UCSB MAT 2017 End of Year Show: Re-habituation.

4.1.4 Implementation

The visualization and sonification of InstaSynth were written in the C++ programming language along with AlloSystem, a cross-platform suite of C++ components for building interactive multimedia tools and applications developed by the AlloSphere Research Group at the University of California, Santa Barbara [104]. For access to Instagram photos, InstaSynth used the Instagram API[1].

4.1.5 Demonstration and Discussion

InstaSynth was demonstrated in the AlloSphere[2] at the Media Arts and Technology (MAT) Program 2017 End of Year Show at the University of California, Santa Barbara (UCSB) as shown in Figure 4.2. The AlloSphere is a three-story facility that is used to represent large and complex data with multiple modalities including immersive visualization, sonification, and interactivity. Synthesized sounds were spatialized via the multichannel speakers of the AlloSphere. In consideration of the audience being positioned in the middle of the AlloSphere, the visualization of InstaSynth rotated around the audience. InstaSynth was able to provide the audience with an immersive audiovisual experience driven by personal photo data.

The video documentation of InstaSynth is available at `https://sihwapark.com/InstaSynth`.

[1] https://www.instagram.com/developer
[2] http://www.allosphere.ucsb.edu

4.2 BeHAVE

BeHAVE is a case study of the Artist-Centered Practice. The project focuses on indexicality and subjectivity in data representation. The description of BeHAVE in the following is excerpted from two papers of the project published at the International Computer Music Conference 2018 [105] (with open access permission) and the International Symposium on Electronic Art 2019 [106] (with the author's permission).

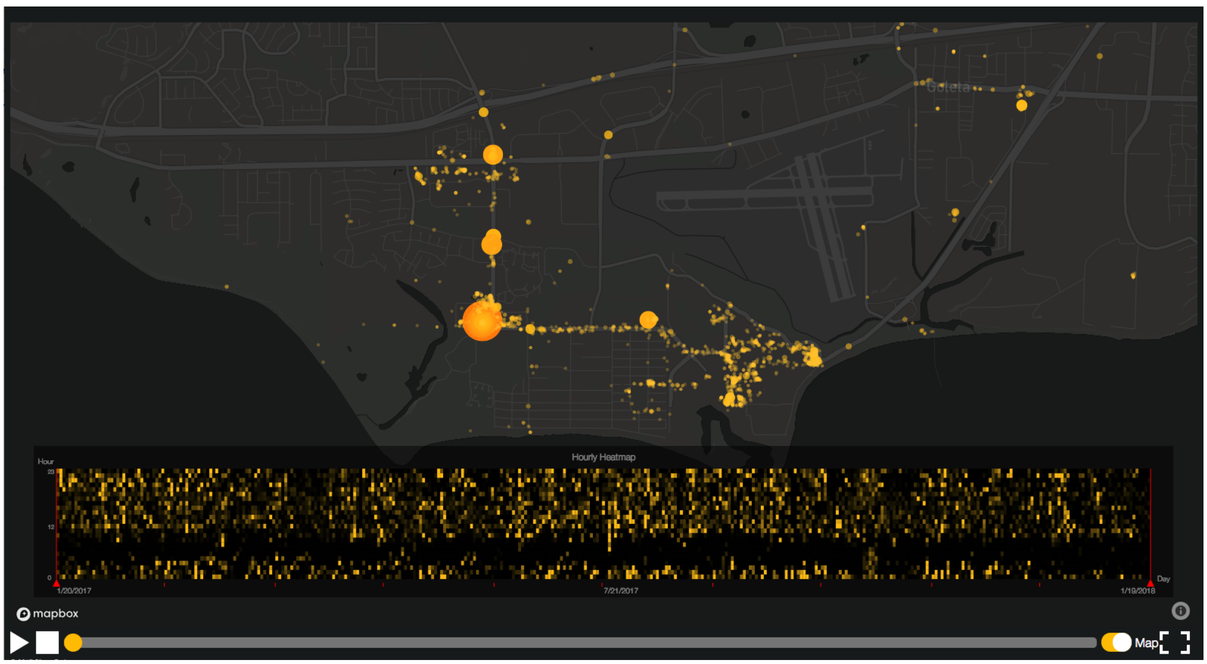


Figure 4.3: The interface of BeHAVE.

4.2.1 Introduction

We have been representing ourselves to understand personality, improve behavior, or share personal experiences with others in various forms, such as self-portraits, autobiographies, memoirs, and diaries. In a digital world, as Rettberg [4] insists, self-representations can be categorized into three modes: written, visual and quantitative. Blogs, selfies, and self-tracking data gathered from sensors can be considered an evidence for each mode.

Quantitative self-representation has been growing over a decade due to advances in self-tracking technology. As mobile and wearable devices have become more accessible to people, collecting data about oneself and one's daily activities has also become easy. This change has given rise to the Quantified Self (QS) movement[3] that has the slogan of self-knowledge through numbers [1]. In the era of QS, with the use of self-tracking devices and applications, automatically measuring our activities or status as numbers and sharing them are becoming commonplace. By looking at numbers about ourselves, we might be able to understand our lives better, become more productive and healthier, and feel the pleasure of control as Benjamin Franklin, before the digital era, tracked his habits with pens and papers based on 13 virtues for arriving at moral perfection [4, 107].

However, quantifying oneself can be a self-representational purpose in terms of making sense of self-tracking data. We can not only see ourselves through data but also express ourselves like a self-portrait by representing data in diverse ways. There has been an increasing number of researchers and artists that try to depict themselves by using self-tracking data and attempt to elicit aesthetic curiosity in representing data [107, 1, 108, 64]. Donath [51] suggests calling these representations 'data portraits' that function as data mirrors that show patterns in data as a tool for self-understanding and evoke the impression of its subject like traditional portraits.

Visualization and sonification can both be used as the main tool in making a data portrait. Visualizing data can help a person reveal a story of data and perceptualize data for others, while data sonification can generate knowledge about the subject of data, using non-speech sound to convey data. Whereas visualization exploits our visual perception that is more spatially adapted and optimized for understanding static phenomena, sonification takes advantage of the ability of acoustic perception to recognize temporal changes and patterns [55]. Simultaneously presenting these two representations, multimodal data

[3]http://quantifiedself.com

representation can enhance the perception and understanding of data with multisensory stimuli. If aesthetics is about sensuous perception, the multimodal data representation can be seen as a form of data art that pursues an aesthetic goal, not to mention its pragmatic purpose in terms of information design [56]. In light of this, multimodal representation of self-tracking data can not only disclose the unexpected aspects of ourselves but also express ourselves aesthetically as a data portrait.

In this regard, the web-based audiovisual piece BeHAVE (Behavioral data as Heatmap-based Audio-Visual Expression) explores a way of revealing the author's behavior, which is potentially inherent in personal data, through multimodal data representation. Based on the data set about the author's behavior of mobile phone use, which has been collected over a year by using a self-tracking app, BeHAVE visualizes and sonifies the geographic and temporal records of the phone use on an interactive online map.

This section also discusses the concept of indexicality in data representation to explore a way to depict the author's behavior of mobile phone use as a form of multimodal data portrait. Particularly, BeHAVE shows an indexical visualization approach that uses mobile phone screens as an additional channel to express the context of data and facilitate audience engagement.

4.2.2 Background

Mobile Phone as the Extended Self

Technologies have been affecting how we perceive the relationship between ourselves and media or devices, which are byproducts of technologies. For this relationship, McLuhan's pioneering interpretation that media are the extensions of human senses is still applicable in the digital era [109]. Especially, mobile technologies have become an important part of our lives as they are capable of representing an extension of our physical selves, functioning as comfort and intimate objects [110]. This psychological perception, causing mobile phone attachment and dependency in the technology-driven society, can be also explained by Belkin's Extended Self Theory that one's possessions can become an extension of oneself [111, 112].

In this context, representing mobile phone use behavior as a data portrait to understand and express ourselves can give an impression about our physical selves captured through an extended digital body although self-tracking data could be considered as just discrete snapshots of ourselves in time and space dimensions. As a self-experiment, BeHAVE attempts to portray my behavior through the multimodal representation of self-tracking data about mobile phone use, considering the data as a means of self-expression.

Behavior Data and Multimodal Representation

A variety of research has been conducted to represent phone usage data for an analytic purpose. Kang et al. [113] introduce 2D and 3D graphic representations of millions of raw mobile call records in a city in China to understand the dynamics of individual mobility patterns. Kaewoni et al. [114] present a visualization tool for mobile phone usage data of Portugal with flow and intensity modes that display a different 3D animation on the Portugal map according to each mode. Ville Vivante[4] is the City of Geneva's visualization project that illustrates 2 million mobile phone calls during a single day in Geneva for the purpose of citizen science and urban planning. However, these works only deal with the behavioral data of the anonymous public via merely a visual representation.

There have been various attempts to render temporal and geo-related data either visually or sonically. In terms of sonification, whereas iSonic [115] is a practical example that transforms georeferenced data into non-verbal sounds to make visually-impaired people recognize trends of data, COMPath [116] has a focus on the musical sonification

[4] https://villevivante.ch

of geo-related data which is plotted on an online map and converted into OSC or MIDI messages to create sound. Similarly, in one of his works, Two Trains[5], Foo attempts to reveal income inequality through musical sound by sonifying income data along with the New York City subway lines. Besides these works that focus on sonification, there are also several examples of multimodal data representation. Rosli [117] suggested a multimodal data representation approach that sonifies and visualizes NASA's lightning data, based on the principles of Gestalt Psychology. Han and Tiwari [118] explored a way to enhance the perception of California drought data by combining a sonification technique with diverse visualizations.

BeHAVE suggests an approach to represent phone use behavior data in a multimodal way that visualizes and sonifies the data simultaneously. On top of that, it represents the mobile phone use data via a mobile phone as an indexical visualization approach to frame the context of the data through the medium that generated the data itself and to allow audiences to take part in the piece and more closely experience the data. With these approaches, BeHAVE aims to depict the author's behavior as a form of data portrait and evoke the aesthetic perception of data through multimodal representation.

4.2.3 Data Collection and Preprocessing

For obtaining phone use data, an active screen time tracking iPhone application 'Moment'[6] has been used since January 20, 2017 (see Figure 4.4). Basically, this app detects a phone pickup, which means a phone use location and time when the user turns their phone screen on, and calculates use duration until the screen is turned off. The app can export all pickup data as a JSON format file that includes the location, date, and duration in seconds of a pickup, daily using times in minutes, pickup counts, and a daily

[5]https://datadrivendj.com/tracks/subway
[6]https://inthemoment.io

list of most used apps calculated based on battery usage.

The exported file size of a year of data was about 5.6 Mb including a total of 11,367 pickup records. By using Python in the Jupyter Notebook [7], this raw data changed into a GeoJSON format, which is a geographic data structure used in a map-based visualization, as shown in Table 4.1. The date information of each pickup was also converted into a single float value *time* starting from 12 AM on the first day of the data as zero. For example, the converted time of 10:30 AM on the second day is $1 + (10 + 30/60)/24 = 1.4375$. This value is used for exploring data in sequential order. The minimum, maximum, mean, and standard deviation values of the phone use duration are 0.017, 283.667, 6.243, and 14.465 minutes, respectively.

```json
{
  "type": "FeatureCollection",
  "features": [
    {
      "type": "Feature",
      "properties": {
        "lengthInMinutes": 2.1666666666666665,
        "time": 5.550694444444445,
        "date": "2017-01-25T13:13:32-08:00"
      },
      "geometry": {
        "type": "Point",
        "coordinates": [
            -119.84788839071086,
            34.41519673065517
        ]
      }
    },
    ...
  ]
}
```

Table 4.1: GeoJSON data example. It shows one record of phone pickups.

[7] https://jupyter.org/

Figure 4.4: Moment, a self-tracking app for mobile phone user behavior. The image is from the app's website (no longer exists).

4.2.4 Design

Indexicality and Subjectivity in Data Representation

As Donath [51] points out, data portraits could be difficult for the audience to infer meaning because of the abstract nature of data or its representation that has no everyday familiarity, compared to traditional portraits that use personal possessions and the structure and expression of faces as a visual language to evoke an impression. On the other hand, in the fields of data-driven art or artistic InfoVis, artists could emphasize this nature with the use of defamiliarization techniques in their works to prompt reflective insights [47]. A conceptual spectrum of representation proposed by Keefe et al. [119] also

Figure 4.5: A spectrum of data representation (adapted from Keefe et al [119]). The closer the data representation sits to the left end it is more driven by artistic freedom, whereas the closer it is placed to the right end it has more the focus on clear representation which tightly connected with data.

illustrates this subjectivity between data and its representation (see Figure 4.5).

In this regard, it is worth considering the concept of indexicality in designing data representations [95, 56]. Indexicality is a taxonomic concept in Charles Sanders Peirce's theory of semiology that proposes three categories of signs: icons, indices, and symbols. In data visualization, indexicality can be a measure of contiguity that shows how visual representations of data have a contiguous relationship with the physical world or the subject of data. As Schofield [95] insists, a physical contiguity to reality in visualization can impact audiences' understanding of the relationship between data and representation, framing a meaning through context. Also, indexical signs in visual representation may increase trust and support engagement as indexicality evokes a sensation of situatedness and temporality by revealing 'moments' of isolation in space and time, which mean that sensor data is taken from reality. In data sonification, Barrass and Vickers [56] also explain the indexicality as a measure of the arbitrariness in mapping data into sound. Direct data-to-sound mappings such as audification have high indexicality, whereas a sonification system using symbolic or interpretative mappings exhibits low indexicality.

Although it is hard to find a direct connection between the visual indexicality and the auditory indexicality, considering what data attributes can primarily contribute to both visualization and sonification is significant to arouse congruent visual and auditory perception simultaneously. BeHAVE aims to find a relevant position in the indexicality spectrum of data representation for making an impression about the phone use behavior and to present a strong correlation between visuals and sound for multimodal data perception. In this sense, BeHAVE has three layers of data representation: a symbolic heatmap visualization, a parameter mapping-based data sonification which exhibits somewhat high indexicality, and a temporal data visualization on the mobile phone screen to increase indexicality in visualization.

Heatmap Visualization

Considering temporal and geographic attributes of data, BeHAVE visualizes data with two types of heatmap representation, as shown in Figure 4.3: a geographic heatmap on an interactive online map and a heatmap chart at the bottom of the screen. For the geographical heatmap visualization, the raw data was pre-processed to change in GeoJSON format, a geographic data structure used in a map-based visualization, by using Python in the Jupyter Notebook[8].

A geographic heatmap is a typical representation to identify data location and depict data density in areas or at points by plotting geo-related data on an interactive or static map. As described above, the phone use data has spatial and temporal information. In this regard, an interactive map-based geographic heatmap, which is used as the main visualization frame of BeHAVE, is an appropriate way to represent the behavior of where and how long I used my phone. In the geographic heatmap visualization of BeHAVE, each phone pickup is expressed as a circle on a map according to the coordinates information of a phone pickup location. The radius and color of each circle are determined by a phone use duration value. Based on the maximum and minimum phone use duration in the data, which are 0.017 and 283.667 minutes, respectively, a circle's minimum and

[8]https://jupyter.org/

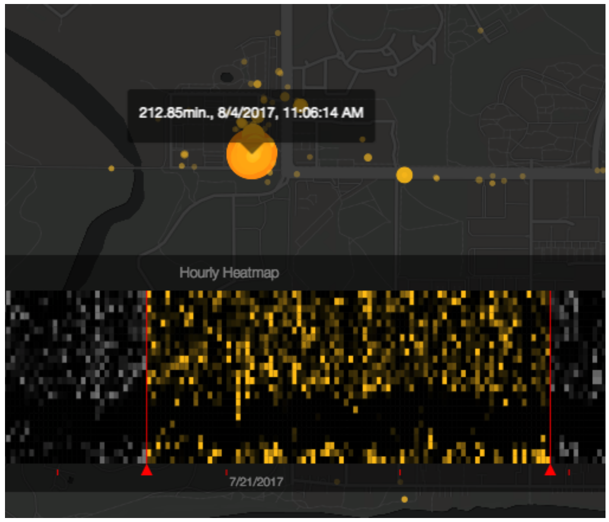


Figure 4.6: A close look of the BeHAVE interface. A tooltip on a circle shows a data record in detail. Red handlebars on the heatmap chart determine an active data range.

maximum radii are linearly interpolated. The change of a zoom level on the map also affects the interpolation of this value range; the lower the zoom level is, the wider the range is. Due to the radius interpolation, the user can catch the outline of data points at a lower zoom level, whereas a detailed shape of data on the map is revealed at a higher zoom level. Also, between a certain low zoom level and the minimum zoom level of 0, adjacent circles form a cluster like blobs to depict density as a heatmap representation.

In addition to the geographic heatmap, BeHAVE presents the heatmap chart at the bottom of the map, which visualizes all data grouped on an hourly basis to reveal the whole trend and pattern of my phone use behavior. The y-axis of the heatmap chart means hours for a day and the x-axis represents dates. The use duration of 60 minutes is mapped to the brightest yellow color. This heatmap graph also functions as a graphical user interface for trimming a data range, having start and end date selection bars at the left and right sides of it, respectively (see Figure 4.6).

However, both heatmap visualizations are symbolic, having an indirect or arbitrary relationship between size and color variant visual elements and the phone use behavior. It takes time to learn data-to-visual mappings and it may require an additional explanation about the mappings. It is hard to recognize the temporality of individual data points although the geographical heatmap reveals the spatial distribution of data well and the heatmap chart shows the overall trend. Exploring data in chronological order will be a key feature to reveal temporal characteristics of data and evoke aesthetic perception as a data portrait.

Temporal Data Exploration

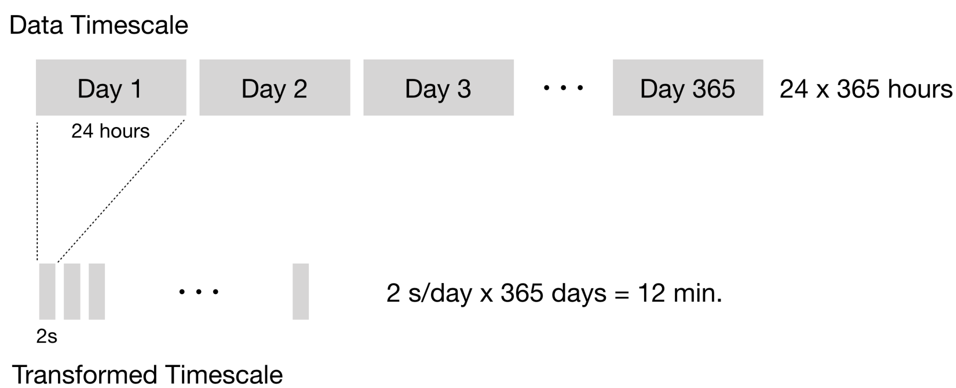


Figure 4.7: Time scale transformation.

In realizing a temporal data exploration mode, the original time scale of the data should be compressed into a smaller scale to sequentially read a year of records in a short period as Figure 4.7 illustrates. As a default setting, a day is scaled down to 2 seconds so that it is possible to navigate 365 days of data in 12 minutes but it is flexible to change the setting by adjusting a scale parameter. By this time scale transformation, the use duration and occurrence timing of phone pickup records are proportionally re-calculated. For example, if the use duration of a pickup is 1 minute, its transformed duration based on 2 seconds per day is $(1/(60 \times 24)) \times 2 = 0.0013\text{s}(= 1.3\text{ms})$. In this way, 238 minutes, which is the maximum value, is re-scaled to 383 ms.

During the temporal data exploration mode, which is triggered by clicking a play button on the interface (see Figure 4.3), the rendering of data points occurs over time according to calculated timing information based on the transformed time scale. Unlike the heatmap mode, if drawn circles are left on the screen in the exploration mode, it can cause visual ambiguity in perceiving instant and individual data occurrence. To enable audiences to catch the occurrence of data points, each drawn circle disappears according to the transformed phone use duration, resulting in a flickering visual effect (see Figure 4.8). Because the circles in this mode quickly disappear, a color variation according to phone use duration is not as effective as it is in the heatmap mode. So only white is used for simplicity and aesthetic purposes. Compared to the radius range of circles in the heatmap mode, a radius in the exploration mode is mapped to a bigger and constant range regardless of the zoom level.

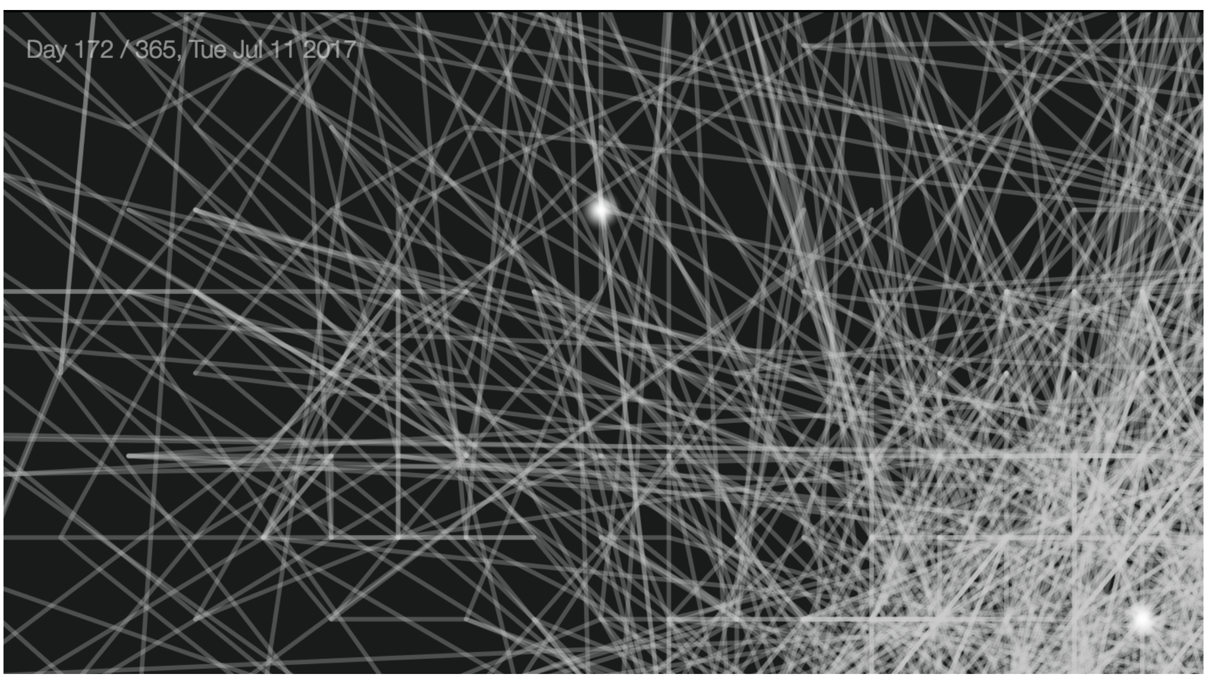


Figure 4.8: Visualization of the temporal data exploration mode. Flickering circles represent phone use at a location and overlapping lines express routes.

To depict a spatial change in the data over time, translucent lines are used. Whenever a circle is drawn, a line is drawn between the last data location and the current location of the circle. As Figure 4.8 illustrates, the translucent lines connecting data locations render a data route. The lines also reveal data density in a more abstract way compared to the clusters of the geographic heatmap because the degree of line overlap visually explains where data occurs the most. In case the next circle's location is out of a currently visible area, the center location of the current area is transposed to the next location before drawing the circle so that audiences can keep track of the data route without mouse manipulation. And it is possible to hide the background map and let audiences focus on the whole shape of the data route by toggling a map switch on the GUI.

In the temporal exploration mode, it is necessary to present time information as part of the data context, allowing audiences to understand an elapsed time and a remaining time. BeHAVE has a time progress bar at the bottom of the screen, revealing the time context of the temporal exploration mode as a graphical form. BeHAVE also has a text label at the top-left corner showing the date of a currently rendering data point and elapsed days.

Data Sonification

In data sonification for the temporal data exploration, it is important to reflect the main characteristics of data-to-visual mappings in sound mappings to evoke multimodal data perception. This means BeHAVE should generate sounds that reveal the temporal attribute and spatial change in the data, such as phone use duration and location. One of the appropriate approaches for this mapping requirement is parameter mapping sonification in which sound is closely derived from data, exhibiting somewhat high indexicality [56].

Because the data time scale is compressed into a shorter time scale for the exploration mode, data-to-sound mappings should be based on the time scale to reflect the temporality of the data. Based on the time scale transformation described above, sound can be dealt with on a microsound time scale, a duration threshold ranging from one to a hundred milliseconds, in which humans can perceive an acoustic event [120] .

Granular synthesis is a microsound synthesis technique [120]. A grain of sound is a building block for sound objects, shaping a waveform by using an amplitude envelope of which the duration is within the microsound time scale. The main sonification approach of BeHAVE is to map the re-scaled phone use duration onto the duration of the amplitude envelope with constant properties, such as attack time, decay time, sustain level, and release time (ADSR). During the temporal data exploration, this mapping irregularly triggers sounds. As a result, the sound of BeHAVE can be considered as *Quasi-Synchronous Granular Synthesis* in which sound grains follow each other at unequal intervals. Besides the envelope mapping, a reverberation effect is applied to make a sound with the longer duration of an envelope stay more in space.

As the visualization for temporal exploration represents the spatial property of the data as a form of overlapping lines, the sonification of BeHAVE also needs to reflect the spatial change of the data in sound. In this regard, BeHAVE maps the distance from the last data location to a data location currently being rendered, onto the frequency of a sound grain. This mapping can cause a dynamic pitch change of sound if the data locations frequently change. The mapping can also reveal the degree that how long the data continuously occurs at a point or an area through continuous low-frequency sounds. Compared to other ways to reflect the spatiality of data in sound, such as the use of a panning effect and directly mapping longitudes or latitudes to a frequency, this distance-to-frequency mapping can be effective even if the geographic data is not well distributed, representing the temporary density of data at an area.

Figure 4.9: Mobile-phone based visualization. The phone is syncing with flickering circles on the BeHAVE main projection screen behind.

Indexical Visualization via Mobile Phones

As a way to exhibit higher indexicality in visualization thereby giving a more intuitive impression of the phone use behavior to audiences, BeHAVE represents the phone use behavior data through a mobile phone that has a direct relationship with the data itself (see Figure 4.9). By accessing a mobile web page of BeHAVE, the mobile phone connects to the BeHAVE main web page via web-to-web communication established by the Web-Socket technology. During the temporal exploration mode, the connected phone's whole screen becomes white or black, syncing with flickering circles, as a metaphor for turning the screen on and off. This visualization reveals the data context, depicting an image of me as an invisible but real person who was using the phone at the moment. Due to the advanced WebAudio technology, the sound synthesized on the main web page can be generated through the mobile phone by using the same code for sonification. The indexical visualization of BeHAVE expects that using a mobile phone as a physical imprint for the phone use behavior data can expand channels for multimodal data perception as well as frame the context of the data.

User Interaction and Temporal Data Exploration

BeHAVE presents a user interface and interaction for data analysis and exploration. The UI of BeHAVE makes it possible to control the zoom level and navigate the map through mouse manipulation. By hovering a mouse cursor over a circle on the map or a cell in the heatmap chart, users can check each record in detail as a form of a tooltip (see Figure 4.6). Dragging the left or right red handlebar on the heatmap chart changes the start date or end date of a data range so that what data instances need to be visible is determined in real time. For the data exploration mode, play, pause, and stop buttons are given and users can control the position of the time progress bar to jump to a certain date. Users can also turn the background map on or off and toggle full-screen mode.

4.2.5 Implementation

MapBox for Geographic Data Rendering

For the web-based geographic data visualization, BeHAVE uses MapBox GL JS[9], a WebGL-based JavaScript library for rendering interactive maps. By adding the GeoJSON format data as a data source and layers that draw circles and heatmap blobs based on the data source, MapBox creates a geographic heatmap. Also, it is possible to set the steps of a circle's radius and color based on zoom levels, a phone use duration range, and an interpolation method. In the visualization for the temporal exploration mode, lines are added as another layer on the map. In this mode, a layer for flickering circles

[9]https://www.mapbox.com/mapbox-gl-js

is shown whereas the layer for drawing heatmap circles is hidden. A flickering effect is made by changing a circle's opacity with a JavaScript function, `setTimeout`.

The heatmap chart is drawn by using the HTML canvas element on top of the map. The chart plots hourly phone use as rectangles of the same size and the yellow color of each rectangle is linearly interpolated based on hourly phone use duration ranging from 0 to 60 minutes.

Gibberish for WebAudio Sound Synthesis

BeHAVE uses Gibberish [121], a JavaScript sound synthesis library. Gibberish can generate and synthesize sounds based on per-sample basis processing [122]. One sample in digital audio processing with the audio sampling rate of 44,100Hz is a sound signal of 0.02 milliseconds. In terms of microsound synthesis, BeHAVE can benefit from this sample-accurate timing feature of Gibberish.

Table 4.2: Parameters for sonification.

Parameter	Value
Envelope Duration	$transformedUseDuration \times 44100$
Attack Ratio	0.1
Decay Ratio	0.6
Sustain Ratio	0.2
Release Ratio	0.1
Sustain Level	0.6
Frequency	220 + distance

As the main sound source, Gibberish's `Synth` instrument, which has an oscillator connected to an ADSR amplitude envelope and a selectable resonant filter, is utilized. The envelope duration in samples is a value of transformed use duration multiplied by the audio sampling rate. The values for ADSR are also measured in audio sample units based on the multiplication of ADSR ratios and the envelope duration (see Table 4.2).

The resonant filter is set with a zero-delay 4-pole Moog-style ladder filter and the `Synth` is connected to `Freeverb` for a reverberation effect.

To calculate the distance between two data locations, the equirectangular projection [123] is applied. Due to the fact that a high frequency can cause an unpleasant or inaudible sound, it is necessary to limit the maximum distance up to a threshold, for example, 10 kilometers, to result in a frequency range from 220 Hz to 10,220 Hz.

WebSocket for Communication Browsers

WebSocket is a single Transmission Control Protocol (TCP) socket-based technology that enables full-duplex communication between a client and a server[10]. Because most modern web browsers, including mobile web browsers, support WebSocket, it is possible to develop a web application that provides real-time synchronization among multiple users via web browsers.

Communication between the main BeHAVE web page and the mobile web page is established through a server application, which is run by a server-side JavaScript environment, Node.js [124]. During the temporal data exploration, when the main web page is about to draw a new circle at a given data point, the main web page sends a phone use duration value and a frequency to a server. Then, the server transmits the received data to all connected mobile clients. The mobile web page changes the background color to white as soon as it receives a new message from the server and calls a color animation function that uses a given phone use time as an expiration time to change the background to black. To reduce a networking delay, BeHAVE uses a dedicated Wi-Fi router, to which a local computer and mobile phones connect. The local computer serves not only as a server handling client connections and messages but also as a client showing the main web page.

[10]https://tools.ietf.org/html/rfc6455

4.2.6 Exhibitions and Discussion

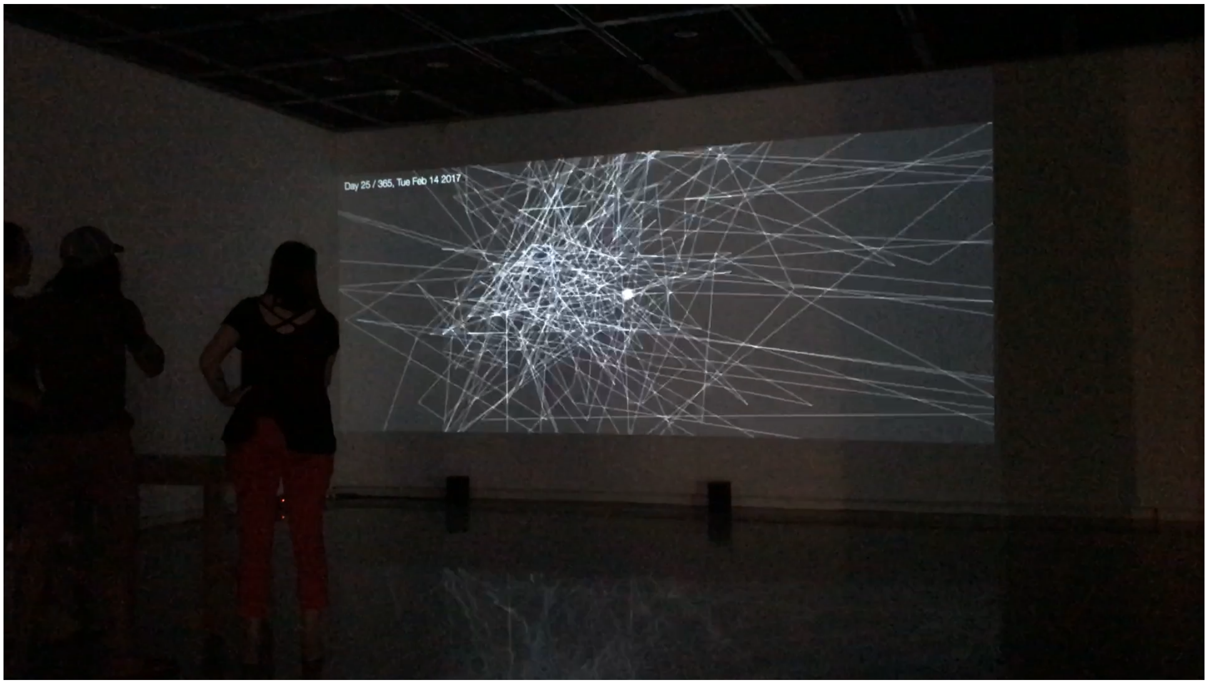


Figure 4.10: An installation of BeHAVE at the International Computer Music Conference (ICMC) 2018, Daegu Art Factory, Daegu, Korea.

The initial version of BeHAVE was presented as an installation as well as a conference paper [105] at the International Computer Music Conference (ICMC) 2018 as shown in Figure 4.10.

BeHAVE was also presented as an installation at the Media Arts and Technology (MAT) Program 2018 End of Year Show at the University of California, Santa Barbara (UCSB) as shown in Figure 4.11. As Figure 4.12 illustrates, the installation consisted of the projection on a wall screen and my mobile phone, from which the data was collected, on a pedestal. For simplicity and aesthetic purposes, the installation was set to show only the temporal exploration mode, looping the data. A trackpad was placed on the pedestal to allow audiences to navigate the visualized data. Audiences were also able to experience the behavior data through their mobile phones by following an instruction attached to an

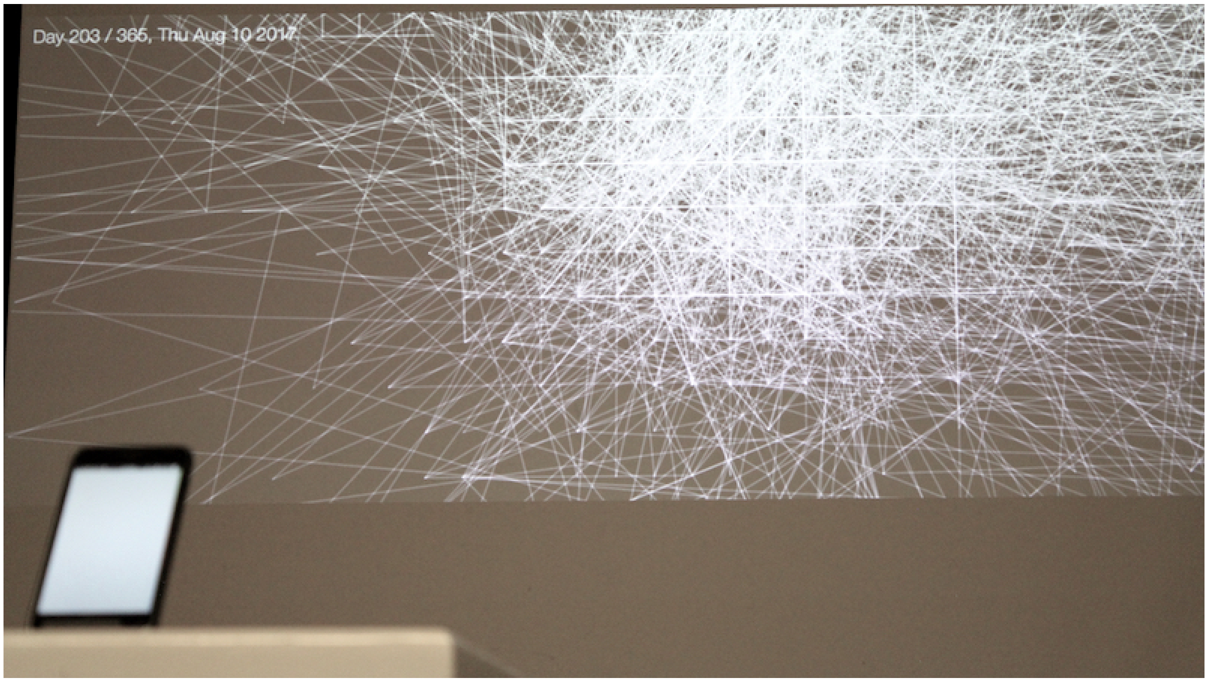


Figure 4.11: An installation of BeHAVE at the UCSB MAT 2018 End of Year Show: Invisible Machine.

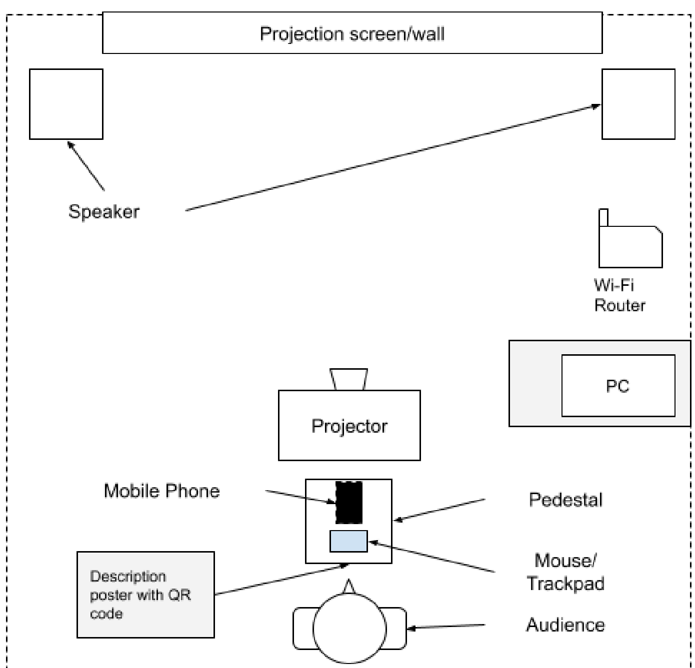


Figure 4.12: A floor plan of BeHAVE.

entrance wall (see Figure 4.13). The sound of the main screen was played through stereo speakers and the mobile phone was also set to play sound. However, generating sound through the audiences' mobile phones was not included to prevent a displeasing audience experience, which results from broken audio issues caused by a difference in versions of mobile web browsers.

Figure 4.13: Audience interaction. After accessing the mobile web page via a QR code or a URL with their mobile phone, the audience can see the user interface to connect or disconnect to the BeHAVE main web (top). The screens of the connected mobile phones are flickering (bottom).

BeHAVE received interesting and constructive feedback from audiences. Most audiences expressed a curiosity when they first looked at the installation that was drawing flickering circles and lines and generating short bursting or beeping sounds. After understanding what data was being represented, some audiences tried to guess locations where circles were frequently appearing and where lines were densely overlapping. There were some expectations that something might happen differently at the end of the data exploration of 365 days, such as showing the whole shape of visuals or a cinematic description of the piece. While some audiences enjoyed interactivity given through trackpad manipulation, such as zooming in and out the visual space, one of the audiences suggested that it would be better if the piece had different zoom levels according to events, dates, or times. Interestingly, a couple of the audiences asked if they could apply their own data after self-tracking with their mobile phones.

Figure 4.14: An image of the BeHAVE installation at the UCSB MAT 2018 End of Year Show: Invisible Machine.

Most of the audience recognized the sound aesthetically. One of the interesting feedback about the BeHAVE sonification was that the sound is perceived as more musical rather than just data. The intention of the pitch change was not intuitively perceived by some audiences without understanding the mapping although they were able to guess that a different pitched sound occurring with a visual change meant a different activity or state. However, when the distance-to-frequency mapping was explained to them, they acknowledged the effectiveness and relevance of the mapping.

The mobile phone-based indexical visualization was an impressive effect as a metaphor for phone use activities, exposing the behavior of how frequently I used my phone, in a more direct representation. After recognizing the synchronization between the mobile phone on the pedestal and the wall screen, audiences actively tried to engage in the piece through their mobile phones as shown in Figure 4.14. However, some of the connections were unstable because of the delay in the TCP-based WebSocket communication.

Overall, the main goal to give audiences an impression of me by depicting my phone usage behavior as a data portrait was delivered through multimodal representation maintaining high indexicality in both visualization and sonification. Although it is reasonable to raise a doubt whether the visual expression of BeHAVE that uses simple lines and circles in 2D space is the only visual language to uniquely reveal one's behavior, my choice of simplicity in representation was effective in enhancing data perception and enough to be considered as a style in generating a data portrait and evoking aesthetic curiosity. A video of the BeHAVE demo and installation version is available at `https://sihwapark.com/BeHAVE`.

4.2.7 Conclusion

BeHAVE is a web-based multimodal data representation that visualizes and sonifies my mobile phone use behavior, exploring a way to depict oneself as a data portrait of self-tracking data in the context of the extended digital self. BeHAVE shows an approach to represent the personal data with multiple layers of visualization and sonification, considering subjectivity and indexicality between data and representation. In terms of the concept of indexicality, BeHAVE attempts to reduce arbitrariness in the mapping between data and representation and enhance the perception of temporality and spatiality in data. In the temporal data exploration mode, the main expression for visual perception, which uses circles and lines, and the sonification approach based on a microsound time scale help audiences receive an impression of the behavior data. The synchronized mobile phone-based indexical visualization that exhibits a contiguous relationship between the data and the physical object, is an approach to not only allude to my behavior but also make audiences participate in the piece through their mobile phones.

4.3 Uncertain Facing

This section introduces the Uncertain Facing project that belongs to the second proposed data art practice, Artist-Machine Collaborative Practice, followed by the description of types of uncertainty in the HDM framework that Uncertain Facing aims to represent, and the representational approaches of Uncertain Facing as a data-driven audiovisual art installation.

4.3.1 Introduction and Background

The Curse of Dimensionality and Dimensionality Reduction

In machine learning (ML), most real-world problems, such as spam identification, image/voice recognition, demand forecasting, and product recommendation, require high-dimensional data that has thousands or millions of features. The high dimensionality of the real-world data involves a problem called *the curse of dimensionality* [125] that causes the issue of data sparsity. If a data space is equally divided into 4 regions per dimension,

Figure 4.15: An installation of Uncertain Facing.

the space becomes 4 regions in 1D space, 16 regions in 2D space, and 64 regions in 3D space. The exponential growth in data dimension space causes high sparsity in a data set. Thus, the amount of data needs to grow exponentially to accurately generalize and represent the data space.

The exponential growth of data size due to the problem of data sparsity increases data storage space and processing time, making the modeling process of ML inefficient. Moreover, in analyzing high-dimensional data, it is difficult to visualize the data in high-dimensional space. These issues caused by the curse of dimensionality have led to the development of dimensionality reduction algorithms [126]. Dimensionality reduction refers to the process of reducing the number of features/dimensions of data by obtaining a unique set of principal features/dimensions from the data and by ensuring that the data with reduced dimensions conveys similar information found in the original data.

t-distributed Stochastic Neighbor Embedding (t-SNE) developed by van der Maaten and Hinton [127] is one of the most popular dimensionality reduction techniques for visualizing high-dimensional data by "giving each data point a location in a 2D or 3D map." The t-SNE algorithm is a stochastic process that relies on probability distributions over data, such as the Gaussian distribution and the Student t-distribution, to find locations of data points and prevent the crowding problem of data points in a lower-dimensional space. The result of t-SNE reveals hidden clusters of data, keeping similar data points close to each other and dissimilar points apart. In training a model with a dataset, visualizing the clusters of the data, in general, helps with monitoring and evaluating the performance of the model.

However, uncertainty exists in the non-deterministic process of t-SNE that involves an initial random configuration of map points [127]. The clusters of the data are meaningful, but the positions of the data points are not. Whenever t-SNE is run with the same data set to visualize in 2D or 3D space, the coordinates of the data points are always different. Moreover, dimensionality reduction algorithms including t-SNE, in general, have an issue of interpretability [128]. When a large set of data features is reduced to a smaller set of key features, it is hard to understand what each feature means. If the data is about ourselves and used to categorize or predict our personalities, identities, or behaviors, this uncertainty in reducing dimensionality could ignore significant outliers that affect the inclusiveness or fairness of artificial intelligence.

Fake Face Generation, Face Data, and Face Recognition

There have been remarkable advances in Generative Adversarial Networks (GANs) since their development in 2014 [129]. Especially, the generation of realistic fake images has become more feasible. StyleGAN2 [84], which can produce fake human faces of high quality, is one of the examples that show the advancement of GANs. However, the availability of creating synthetic, fake data raises uncertainty issues for both human and machine vision. First, GAN models could generate biased synthetic output because of biased training data. For example, the researchers of StyleGANs state that the Flickr-Faces-HQ dataset used for training their models to generate human faces inherits all the biases of Flickr, a social media platform for uploading sharing photos and videos [83]. Second, in a situation where GAN-generated fake images are used with real images, it becomes harder for humans to discriminate what images are real or fake. This is also applied to machine vision. For example, in face recognition, deep neural networks such as FaceNet [130] are used to extract face embeddings or features. However, they are not designed to detect fake face images in both training and predicting. If a model for face embedding extraction is trained with fake face data, can we trust that model?

Uncertain Facing is a data-driven, interactive audiovisual installation that explores a way to raise concerns about the aspects mentioned above. Uncertain Facing aims to represent the uncertainty of face data and ML algorithms, such as FaceNet [130] for face recognition, StyleGAN2 [84] for fake face image generation, and t-SNE [127] for dimensionality reduction and data clustering, through abstract, probabilistic representations of the face data as opposed to the exactness that we expect from the use of scientific visualizations. Uncertain Facing also attempts to raise concerns about the possibility of the unintended use of ML with synthetic/fake data through audience participation.

4.3.2 Data Collection and Preprocessing

Pre-generated Face Images with StyleGAN2

The pre-trained models of StyleGAN2 and the Python source code to generate face images with StyleGAN2 are available on the GitHub repository of StyleGAN2 [131]. I was able to generate fake face images by providing a pre-trained StyleGAN2 model for face image generation with parameter values, such as a range of random seed values and a ψ (psi) value that determines the degree of image style variation.

However, instead of generating new fake face images, I downloaded the pre-generated face images that the StyleGAN2 researchers shared to showcase the performance of StyleGAN2. The links to the pre-generated face images are also available on the same StyleGAN2 GitHub repository [131]. After downloading 10,000 pre-generated face images in PNG (Portable Network Graphics) format, I decreased the size of the images from 1,024 x 1,024 to 256 x 256 pixels in dimension by using a custom Python program that I wrote.

Face Embeddings

To extract facial features from the face images, I used a pre-trained model based on FaceNet which is developed by Google [130]. FaceNet extracts a 128-element vector representation from a photo of a face. These 128 features are called a face embedding because the important information from a face image is embedded into a vector.

Based on an open-source online tutorial [132] for using FaceNet models, I extracted the 128-dimensional face embeddings of the downloaded face images and stored them as a CSV (Comma-Separated Values) file.

4.3.3 Design

Uncertain Facing consists of three major components: 1) face data including synthetic images of faces generated by StyleGAN2 and the face embeddings of the faces obtained from FaceNet, 2) t-SNE (t-distributed Stochastic Neighbor Embedding), a non-linear dimensionality reduction technique for the visualization of high-dimensional datasets, and 3) multimodal data representation based on metaball rendering, an implicit surface modeling technique in computer graphics [133], and granular sound synthesis [120].

Following the previous section that explains the face data, this section describes two other components: the use of t-SNE and the multimodal data representation of Uncertain Facing.

The Visualization of the t-SNE Process with Metaball Rendering

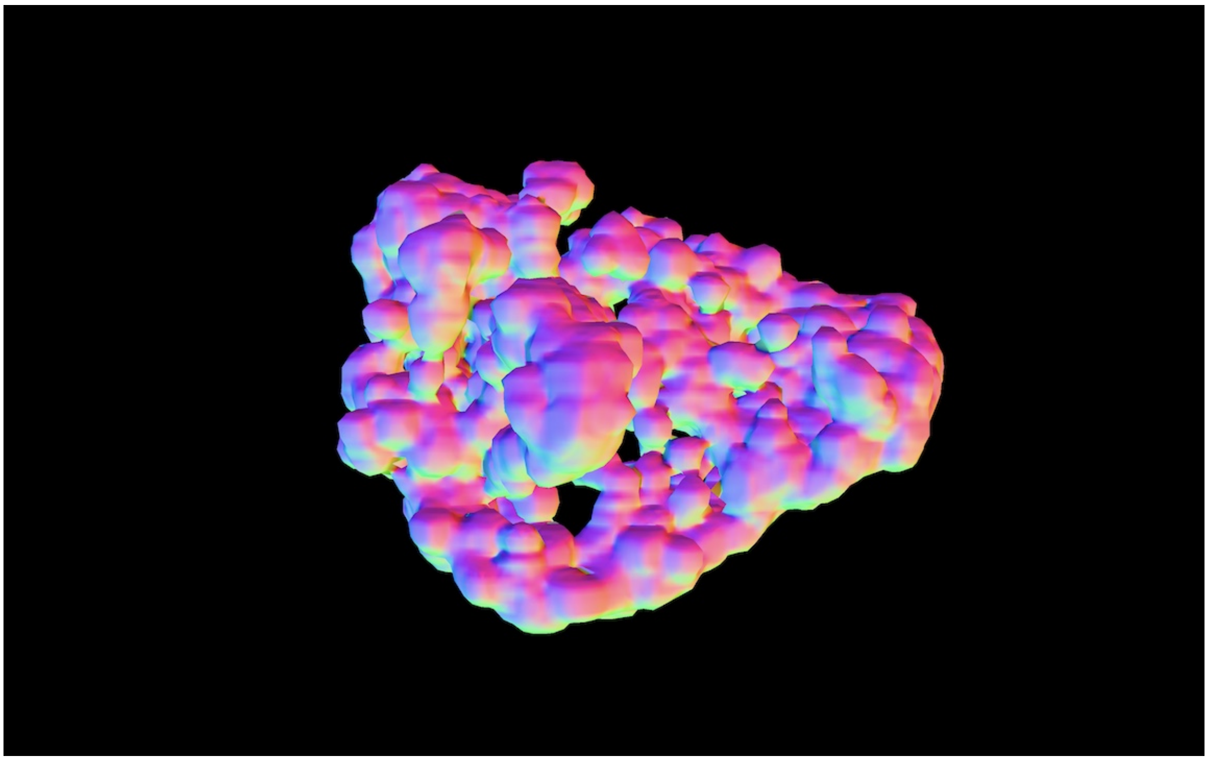


Figure 4.16: Metaball rendering. The face data points are rendered as metaballs during the t-SNE visualization process.

Uncertain Facing visualizes the real-time clustering of the fake face images in 3D space by using t-SNE with 128-dimensional face embeddings of the faces. This clustering reveals what faces are similar to each other based on a probability distribution over data points. However, unlike the conventional use of the t-SNE visualization that plots data points as a 3D scatter plot for the purpose of objective data exploration in ML, Uncertain Facing represents data points as metaballs to reflect the uncertain and probabilistic nature of data locations the t-SNE algorithm yields (see Figure 4.16). Metaball rendering is an implicit surface rendering technique used for volumetric 3D data rendering [133]. The metaball rendering algorithm can infer missing data points by interpolation to draw surfaces, in which the missing data points could exist.

Figure 4.17: Metaball rendering textured with face images. The fake face images are mapped to surfaces of metaballs as textures.

The idea of representing faces as metaballs was conceived with an understanding of the similar face search process in face recognition. In face recognition, a common way to find faces similar to a given face image is to calculate the Euclidean distance between face feature vectors. The closer the distance between two face feature vectors, the more similar the faces are. Revealing the clusters of face embeddings with t-SNE is another way to find similar faces. Between two faces positioned in space based on similarity, there is room to imagine that another possible face could exist between them. The imagined face could be a mixed or merged version of the two faces, but what the imagined face would look like is uncertain. Uncertain Facing represents this possibility or uncertainty by using metaball rendering for probabilistic face merging.

Figure 4.18: Similar faces being merged. By running t-SNE with face embeddings of the face images, similar faces are placed close to each other, forming the clusters of the face data (top). The similar faces become a merged metaball, creating a fragmented, combined face image (bottom).

As shown in Figure 4.17, the fake face images are mapped to surfaces of metaballs as textures. If the face data points become close to each other, their face images begin to merge, creating a fragmented, combined face as a means of an abstract, probabilistic representation of the face data as opposed to the exactness that we expect from the use of scientific visualizations (see Figure 4.18). Uncertain Facing also reflects an error value, which t-SNE measures at each iteration, between a data distribution in original high dimensions and a deduced low-dimensional data distribution, as the jittery motion of the data points.

The Sonification of the t-SNE Process

In addition to the metaball-based t-SNE visualization, Uncertain Facing has a sonification approach to representing the overall process of t-SNE with error values and the density of the face data in 3D space. Uncertain Facing sonifies the change of the overall data distribution in 3D space based on a granular sound synthesis technique [120]. The data space is divided into eight subspaces and the locations of the data points in the subspaces are tracked during the t-SNE operation. The density of data points in each subspace contributes to parameters of granular synthesis, for example, grain density and the number of sound grains. The error values are used to determine the frequency range, amplitude, and duration of sound grains. As a result, the higher the error value, the stronger and louder the generated sound. The error value sonification is designed to represent the uncertainty of data locations due to the stochastic process of t-SNE.

Audience Interaction and Participation

As an interactive installation, Uncertain Facing allows the audience to explore the data in detail or their overall structure through a web-based UI on an iPad. Moreover, the audience can take a picture of their face, and send it to the data space to see its relationship with the fake face data (see Figure 4.19). Given the new face image, Uncertain Facing re-starts t-SNE after obtaining face embeddings of the audience's face image in real time.

While the real audience face is being mixed, merged with the fake faces in 3D space, Uncertain Facing also shows the top nine similar faces on the UI, as shown in Figure 4.20. With the audience interaction and participation design, Uncertain Facing attempts to

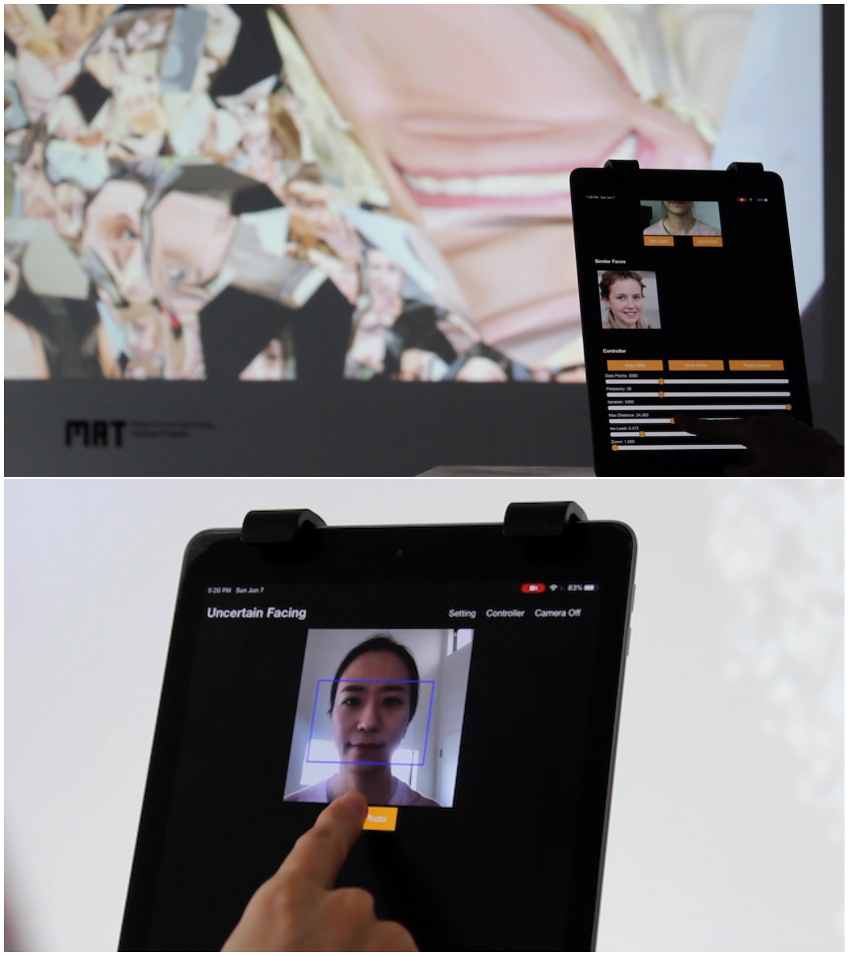


Figure 4.19: The UI of Uncertain Facing for audience participation. The audience can control parameters for the t-SNE and metaball-based visualization via the UI on the iPad (top) and take a photo of their face as new face data (bottom).

imply an aspect that ML algorithms could be misused in an unintended way as FaceNet does not distinguish between real and fake faces.

The video documentation of Uncertain Facing is available at `https://sihwapark.com/Uncertain-Facing`.

4.3.4 Implementation

Figure 4.21 illustrates a schematic diagram of Uncertain Facing including a main program for visualization and sonification, a face embedding extractor with FaceNet, a local

Figure 4.20: The UI of Uncertain Facing for similar face search. The UI shows the top nine faces similar to a photo of the audience's face.

web server, a data set, and an iPad. The diagram also shows the flows of UI and data that occur via Open Sound Control (OSC), a protocol for real-time message communication. The main program for visualization and sonification is written in the C++ programming language with AlloLib, a library for interactive multimedia application development created by the AlloSphere Research Group at the University of California, Santa Barbara [134]. The face embedding extractor is written in Python. As a component that bridges between the C++ main program and the Python program, Uncertain Facing uses TINC (Toolkit for Interactive Computation) developed by the AlloSphere Research Group [135].

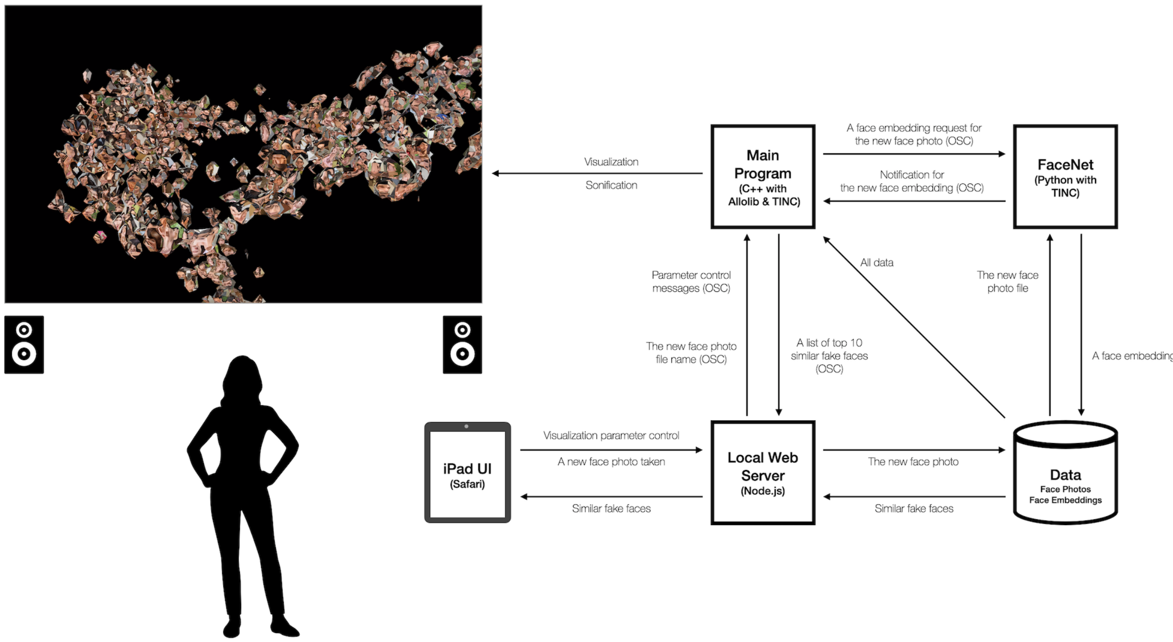


Figure 4.21: A diagram of Uncertain Facing.

The local web server is made with a server-side JavaScript environment, Node.js [124]. The UI on the iPad is written in HTML, CSS, and JavaScript and it only runs on the Safari web browser due to the iOS development policy that limits local web applications' access to cameras on the iPad.

The t-SNE Process Visualization in Real Time

The t-SNE implementation of Uncertain Facing is fundamentally based on the source code of the original t-SNE algorithm [127, 136] written in the C++ programming language. Since the original source code of t-SNE produces only the final reduced result of a data set after repeating the t-SNE process for the given number of iterations, it is impossible to obtain an interim result at each iteration. To visualize the t-SNE process in real time, the t-SNE implementation of Uncertain Facing adopted a modified version of the original t-SNE source code for iteration control [137]. In addition to that, the t-SNE implementation applied an optimization method for improving the performance of the original t-SNE version proposed in an article on the Microsoft Research Blog [138].

The Marching Cubes Algorithm for Metaball Rendering

To implement metaball rendering, Uncertain Facing uses the Marching Cubes algorithm [139], a computer graphics algorithm for extracting a polygonal mesh of an isosurface from a 3D discrete scalar field. The data space is divided into cube cells and data points determine values accumulated at the vertices of the cube cells. These values are scalar values in a density field, called isovalues. In each cube cell, the Marching Cubes algorithm extracts surfaces based on the isovalues of the vertices and repeats the same procedure over all the cube cells.

For a better performance in visualizing a large set of data points in real time, the Marching Cubes algorithm of Uncertain Facing was implemented based on a modified version of the Marching Cubes algorithm that runs on the GPU (Graphics Processing Unit) using a geometry shader [140].

An Octree for Sonification and Similar Face Search

To sonify the distribution of the face data in 3D space and find fake faces similar to a given new face, Uncertain Facing uses an octree, a data structure to manage data in 3D space [141]. An octree is a tree-based data structure in which each internal node has eight child nodes. While a binary search tree is used to decompose 1D point information, octrees are used to manage 3D spatial information. The implementation of the octree data structure for Uncertain Facing referred to a C# version tutorial of the octree implementation [142] but was heavily modified in order to work in C++.

With an octree, Uncertain Facing calculates how many data instances exist in the subspaces of the octree, recursively. As a result, each child node of the root node has

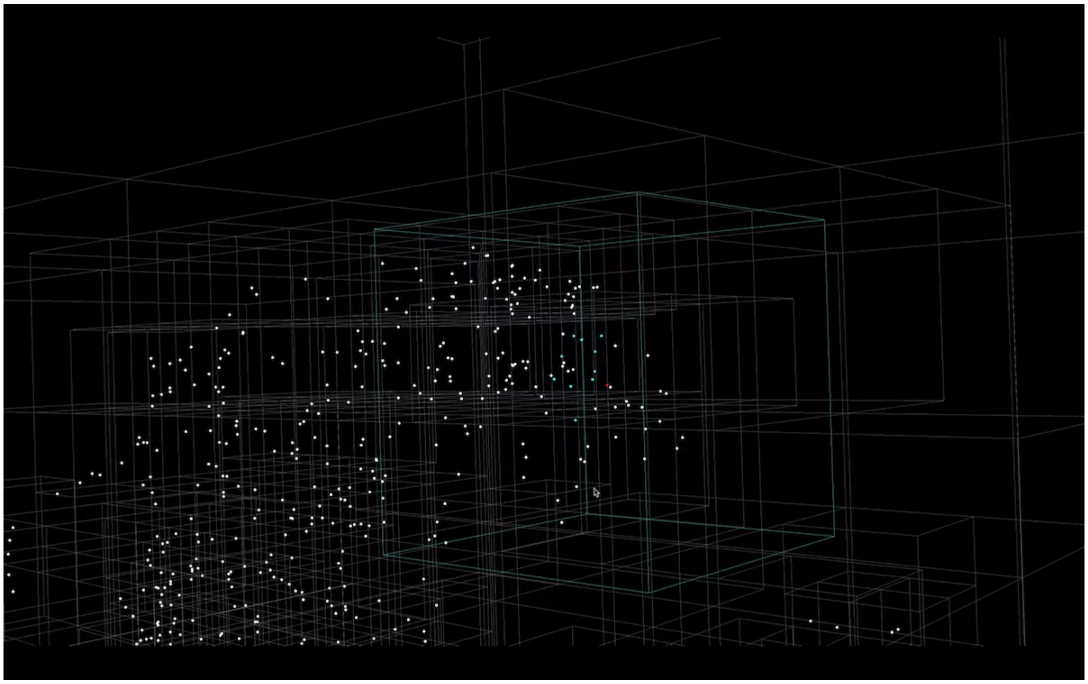


Figure 4.22: The visualized octree of Uncertain Facing. Cube boxes represent the child nodes of the octree and dots represents the face data points. The red point in the cyan colored box is being queried for searching for similar faces, and cyan dots are a search result that represents the top nine data points closest to the red data point.

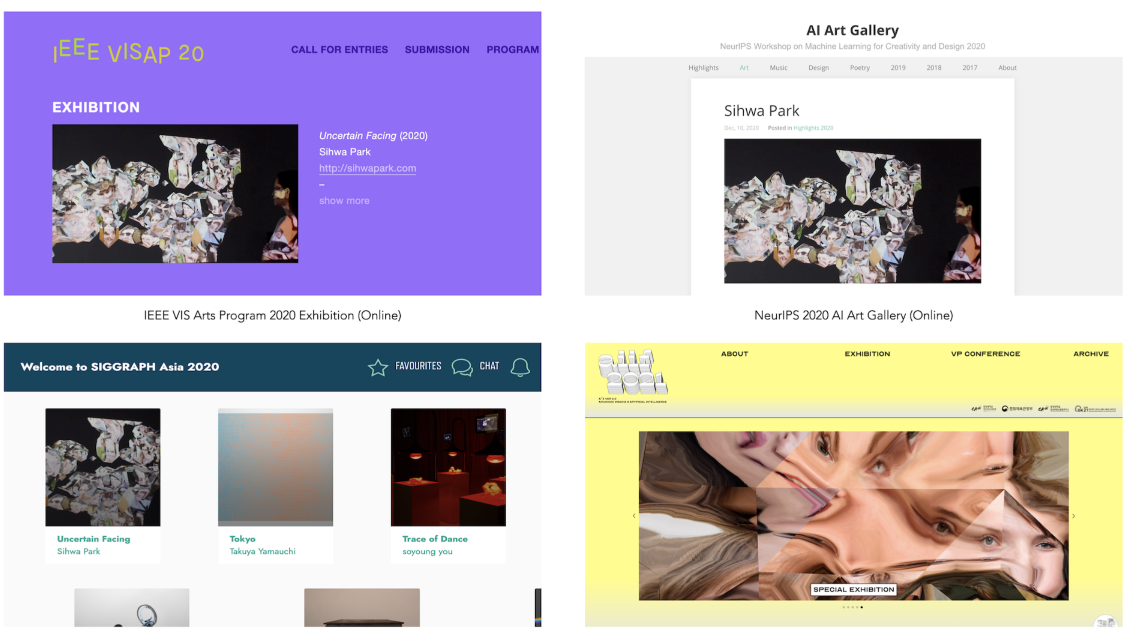
the accumulated number of data points in the subspace. The accumulated number of data points divided by total number of the face data is used as a density value of the subspace. Uncertain Facing treats each subspace as a sound cloud in granular synthesis [120], having eight sound clouds for eight subspaces. The grain size of each sound cloud is determined by the density value, while the duration, amplitude, and frequency range of sound grains are calculated based on an error value that the t-SNE algorithm produces at each iteration. Since the eight sound clouds that represent the eight subspaces of Uncertain Facing can be managed individually, the data sonification result can be spatialized through eight-channel speakers.

As Figure 4.22 illustrates, the octree is also used for searching for similar faces when a new face image is given to Uncertain Facing. First, Uncertain Facing locates a child node of the octree where the data point of the new face image belongs. Then, it calculates distances between the new face data point and other data points that are in the same node. Finally, it chooses the top nine shortest data points and sends that information to the UI.

Face Detection on the UI

The web-based UI of Uncertain Facing has a real-time face detection process that finds faces in images from a camera on the iPad. A button for taking a photo on the UI is activated only when the UI detects any faces. This face detection process prevents some possible errors that Uncertain Facing could have due to non-facial images. The face detection on the UI was implemented by using face-api.js, a JavaScript face recognition API for the browser [143].

4.3.5 Exhibitions and Discussion



IEEE VIS Arts Program 2020 Exhibition (Online)

NeurIPS 2020 AI Art Gallery (Online)

SIGGRAPH Asia 2020 Art Gallery (Online)

Advanced Imaging International Festival 2021 Advanced Imaging & AI (Invited to 'Special Exhibition', Online)

Figure 4.23: The online exhibitions where Uncertain Facing was presented in the form of a documentation video.

Due to the COVID-19 pandemic, Uncertain Facing had to be exhibited online. Since its first online presentation at the Media Arts and Technology (MAT) Program 2020 End of Year Show at the University of California, Santa Barbara (UCSB), Uncertain Facing had been exhibited as a form of video documentation at international conferences, as shown in Figure 4.23, including the IEEE Visualization Arts Program 2020, the SIGGRAPH Asia 2020 Art Gallery, and the NeurIPS Workshop on Machine Learning for Creativity and Design 2020 AI Art Gallery. Uncertain Facing was also invited as one of the six artworks for the online special exhibition of the 22nd Advanced Imaging International Festival 2021 Advanced Imaging & Artificial Intelligence.

Uncertain Facing was invited to the Ars Electronica Festival 2020 as one of two artworks to represent the UCSB MAT Program. For this event, Uncertain Facing was physically exhibited as an interactive installation. The interactive installation of Uncertain Facing consists of an LCD screen or projector, two speakers, a pedestal, and an iPad (see Figure 4.24). As shown in Figure 4.25, the installation of Uncertain Facing for the Ars Electronica Festival used an LCD TV screen instead of a projector. Since Uncertain Facing was remotely set up for this event, it was impossible to test a multi-channel speaker setup. Thus, the installation in this exhibition was presented with only stereo speakers of the TV for sonification.

For a real-time interactive installation, the number of face data that Uncertain Facing represented was set to 2,000 and the number of t-SNE iterations was set to 3,000. With these configurations, Uncertain Facing was able to render the t-SNE process at approximately 50 frames per second on a MacBook Pro (Retina, 15-inch, Early 2013) with NVIDIA GeForce GT 650M.

To help the audience better understand about the audience interaction and participation with Uncertain Facing, a detailed guideline explaining how to take a photo of their face and see the representation of the t-SNE process with their face photos as well

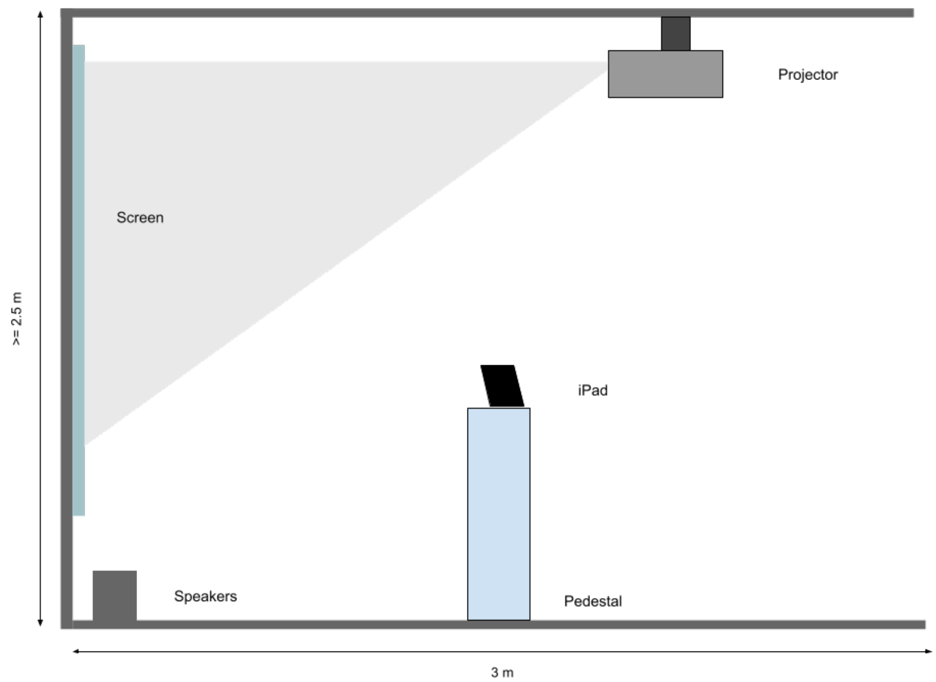


Figure 4.24: A floor plan of Uncertain Facing.

Figure 4.25: Uncertain Facing at The Wilde State: Networked Exhibition, Ars Electronica Festival 2020, Linz, Austria. Photo: Su-Mara Kainz

as similar fake faces was provided on the UI.

It was found from this exhibition that most audiences took photos of their face wearing a mask, which was unexpected but showed well about an unusual circumstance caused by the COVID-19 pandemic.

One of the curators for the exhibition provided interesting feedback after testing Uncertain Facing with his face photos. He said that "it doesn't detect a bearded face well." While he has a noticeable beard, the results of similar faces that Uncertain Facing showed for him would have not included faces with a beard. It is a known issue for some face recognition models such as FaceNet that certain facial features or trademarks, such as beards and glasses, are not considered as part of face embeddings [144, 145]. This issue could be understood as data bias because training data would have not included enough people with certain facial features. The issue could be the model uncertainty because the architecture of a facial recognition model would have not had a process to detect the specialized facial features.

4.3.6 Conclusion

Uncertain Facing is an interactive data art installation that represents the uncertainty of face data and ML algorithms, such as face recognition, fake face image generation, and dimensionality reduction, through the multimodal representation of the face data.

Uncertain Facing visualizes the process of t-SNE along with the data and sonifies the overall data distribution that changes by the t-SNE progress, to represent the non-deterministic locations of the face data that the t-SNE algorithm yields. To reflect the possibility or uncertainty of missing data points between similar faces, Uncertain Facing visualizes the face data as metaballs textured with face images, creating merged faces among similar, close faces. Error estimates that t-SNE calculates are expressed as the jittery motion of metaballs and sounds of which pitch and strength change according to error values to represent the uncertainty of the reduced dimensionality.

Uncertain Facing raises the audience's awareness of the uncertainty in data authenticity that the synthetic face data has via the UI design for audience interaction and participation. The audience can observe the variation of the face metaballs rendering by controlling parameters of the t-SNE and Marching Cubes algorithms on the UI. Through the UI element for taking a photo of a real human face, Uncertain Facing allows the audience to experience a situation where their real face image and the fake face images are mixed and merged in the same space. Showing a set of fake faces most similar to their face on the UI, Uncertain Facing allows the audience to evaluate how resemblant the shown fake faces are or to question the accuracy of facial recognition technology. In this regard, the feedback from the participant with a beard provided an insight into possible data bias and model uncertainty that facial recognition models would have.

4.4 YouTube Mirror

As a case study of the Machine-Centered Generative Practice, this section explains the YouTube Mirror project that shows how the artist can utilize the generativity of a machine in data-driven audiovisual art, what types of uncertainty in the HDM framework could be represented, and how the audience can interact with the generative machine.

4.4.1 Introduction and Background

Audiovisual Relationship and Implicit Bias of Video Recommendation

We try to understand the relationships between images and sounds when we watch videos. Along with the popularity and impact of video-based social media platforms such

Figure 4.26: An installation of YouTube Mirror.

as YouTube, we watch a plethora of videos and our video consumption affects how we see other people and the world. What videos we watch are not only determined by our choices but also hugely affected by the recommendation algorithms of the platforms that are intended to make their users remain longer on their platforms. The "watch-to-next" videos suggested by the algorithms are, in general, based on the user's previous watch history and other metadata related to the videos. Since these data could be implicitly biased or wrongly reflect the user's behavior or preference, the recommendation models could cause a feedback loop effect, narrowing down the choices of videos the user can find [75, 76]. This feedback loop will affect our understanding of audio-visual relationships that we unconsciously find in the videos we watch. This project tries to make a machine simulate these audio-visual associations and represent the world through the relationships the machine learned.

Cross-modal Generative Modeling for Audiovisual Art

Generative modeling in ML is an unsupervised learning technique to train a model with an unlabeled dataset and try to learn hidden patterns in the training dataset, which is called latent representation. Once a generative model learns the probabilistic distribution of a training dataset, we can generate new data that looks similar to but does not exist in the training dataset by sampling from the model. Variational Autoencoders (VAEs) [146] and Generative Adversarial Networks (GANs) [129] are representative deep learning architectures for generative modeling.

While the remarkable progress in machine learning for the arts has focused on uni-modal generative modeling, audiovisual art is a less explored genre in machine learning research, where sound is translated into visual forms or vice versa. Several noteworthy attempts have been made to generate sound from images and images from sound with generative machine models. Synesthetic Variational Autoencoder (SynVAE) [147] attempts to transform paintings into sounds. Jeong et al. [148] suggest a neural network architecture to generate videos that respond to music by using StyleGAN2 [84]. In both attempts, however, the image-music pairs for training a model are arbitrarily made. Adapting Neural Visual Style Transfer [149] to the audio domain, Odlen et al. [150] and Verma et al. [151] propose a generative model that learns from pairings of music and corresponding album cover art to make an artistically meaningful relationship between sound and image. Akten's *Ultrachunk* (2018) [152] shows a fresh perspective on cross-modal generative modeling that combines a singer's facial changes obtained while the singer was singing songs with her voice data, as the key components of the singer's identity.

Compared to the previous attempts explained above, such as the arbitrary image-sound pairing or the album cover art-music association, this project investigates the possibility of cross-modal generative modeling based on a more concrete sound-image relationship that can be found in video data.

YouTube Mirror is an interactive, audiovisual AI installation that generates images and sounds in response to the images of the audience captured through a camera in real time as a concept of data mirror. YouTube Mirror uses a cross-modal generative machine model that was trained in an unsupervised way to learn the association between images and sounds obtained from the YouTube videos I watched. The machine will see the world only based on this audio-visual relationship, and the audience can see themselves through the machine-generated images and sounds. YouTube Mirror is an artistic attempt to simulate my unconscious, implicit understanding of audio-visual relationships that can be found in and limited by the videos I watched. YouTube Mirror also attempts to represent the possibility of the machine's bias caused by implicit bias inherent in video recommendation algorithms as well as a small set of personal data.

4.4.2 Data Collection and Processing

YouTube Watch History

The video data of YouTube Mirror is based on the YouTube watch history of my Google account by using the Google Takeout [11] service that allows the user to export a copy of content in the user's Google account. The history includes the metadata of 14,315 videos that I watched from November 11th, 2018 to March 24th, 2022, including title, subtitle, URL, timestamp, etc. The watch history file is in JSON format as shown in Table 4.3. A substring after "`v=`" in a video URL represents a video ID. For example, the substring `pIjt_z4JHGM` is the ID of the video in Table 4.3.

[11] https://takeout.google.com/settings/takeout

```
{
  {'activityControls': ['YouTube watch history'],
  'header': 'YouTube',
  'products': ['YouTube'],
  'subtitles': [{'name': 'NBC News',
    'url': 'https://www.youtube.com/channel/UCeY0bbntWzzVIaj2z3QigXg'}],
  'time': '2022-03-24T04:56:20.343Z',
  'title': 'Watched Nightly News Full Broadcast - March 23',
  'titleUrl': 'https://www.youtube.com/watch?v=pIjt_z4JHGM'
    }
}
```


Table 4.3: An example of the YouTube watch history data.

By using the YouTube Data API [12] with extracted IDs of all the videos, it was found that there are only 12,183 videos that are available and non-redundant.

YouTube Video Data Collection and Preprocessing

Based on Dale's Cone of Experience [153], it is widely believed that "learners can generally remember 50 percent of what they see and hear." Although this argument was not scientifically justified, this project considers the argument as an artistic concept to choose the amount of data to be used for training a model. Thus, I decided to use 50 percentage of 12,183 videos, which is 6,091 videos. One second segment of each video was randomly extracted and stored by using *youtube-dl* [13], a command-line program to download videos from YouTube.

[12] https://developers.google.com/youtube/v3
[13] https://ytdl-org.github.io/youtube-dl

4.4.3 Design

Cross-modal Audiovisual Generative Modeling

YouTube Mirror attempts to simulate my unconscious, implicit understanding of audio-visual relationships found in the videos I watched. To this end, this project utilizes cross-modal generative modeling.

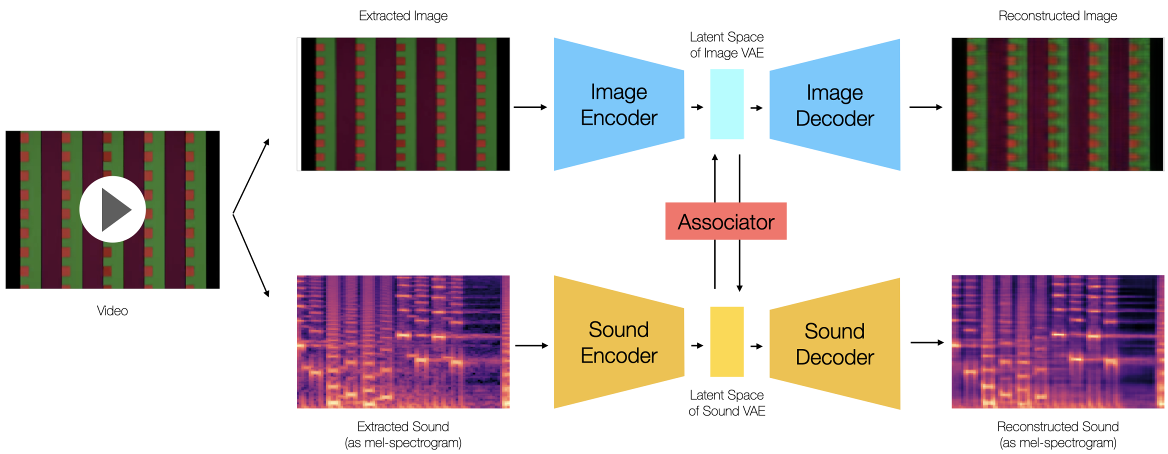


Figure 4.27: A diagram of cross-modal VAEs with associators.

Figure 4.27 illustrates the model architecture of the YouTube Mirror project, cross-modal Variational Autoencoders (VAEs) with associators. This model architecture is based on an architecture proposed by Jo et al. [154]. To briefly explain, VAEs are probabilistic, generative autoencoders. An autoencoder consists of an encoder, a decoder, and the same input and output data with no labels. The encoder reduces high-dimensional input data into low-dimensional latent variables which are called latent vectors. The decoder converts latent variables back into high-dimensional space. In this regard, autoencoders are used for dimensionality reduction. While autoencoders encode each data sample directly into latent space, the encoding of VAEs involves randomness based on a Gaussian distribution to generate new data instances similar to the training data set.

The model training of the YouTube Mirror project has two steps: intra-modal association and cross-modal association. In the intra-modal training phase, an image VAE and a sound VAE are trained with a set of image data and a set of corresponding sound data extracted from the same videos, respectively. An associator is trained in the cross-modal training phase with pairs of the images and corresponding sounds by using two VAEs previously trained. The associator is also a VAE, but the input and output data for the associator are the latent representation of the original data. The goal of the associator is to encode the latent space of the image VAE into the latent space of the sound VAE, and vice versa. For example, the associator that is trained with the encoder of the image VAE and the decoder of the sound VAE can generate a sound from a given input image. The image encoder produces a latent vector from the input image. Then, the associator maps the latent vector for the image to the latent vector for the sound VAE. The sound is reconstructed from the latent vector for the sound VAE via the sound decoder. The reconstructed sound here is a mel-spectrogram. Whereas a spectrogram is the time-frequency representation of a sound on a linear scale, a mel-spectrogram is based on the mel-scale that is analogous to human hearing [155]. At the final stage, the mel-spectrogram is transformed into the time-amplitude representation of the sound that can be heard. The latent vector for the image is also used to produce a reconstructed image via the image decoder of the image VAE.

One of the significant characteristics that VAEs have compared to GANs is that the generated results of VAEs tend to be blurry [80]. This project utilizes the blurry nature of VAEs to emphasize the uncertainty of the generative machine.

Interactive Audiovisual Mirror and Audience Interaction

YouTube Mirror aims to let the audience see themselves through the machine-generated images and sounds. For this goal, as its name alludes, YouTube Mirror represents the machine's output as a form of interactive mirror that can be found in digital media arts, such as Kyle McDonald's *Sharing Faces* (2013) [156] and Gene Kogan's *Cubist Mirror* (2016) [157].

Figure 4.28: An interactive model test with a camera.

As shown in Figure 4.26, the YouTube Mirror installation uses a web cam to capture images of the audience in real time and represents the reconstructed images of the audience via a vertical monitor. In this way, YouTube Mirror is designed to make the audience interact with the work as they explore how the reflected images on the monitor change. In addition, one unique aspect of YouTube Mirror as an interactive mirror is that the audience can hear generated sounds that respond to their images. This audiovisual representation of YouTube Mirror as an interactive mirror provides the audience a multisensory experience that requires active engagement to navigate provided audiovisual output.

Figure 4.28 is a screenshot taken during interactive model testing, showing a generated visual result responding to the image of the camera output at the top right corner.

The video documentation of YouTube Mirror is available at `https://sihwapark.com/YouTube-Mirror`.

4.4.4 Implementation

Data Processing and Model Training

All processes from data collection and model training were conducted with Google Colab [14], an online Python environment that runs the web browser. The video data for YouTube Mirror was stored in a Google Drive cloud storage that can be used in Google Colab.

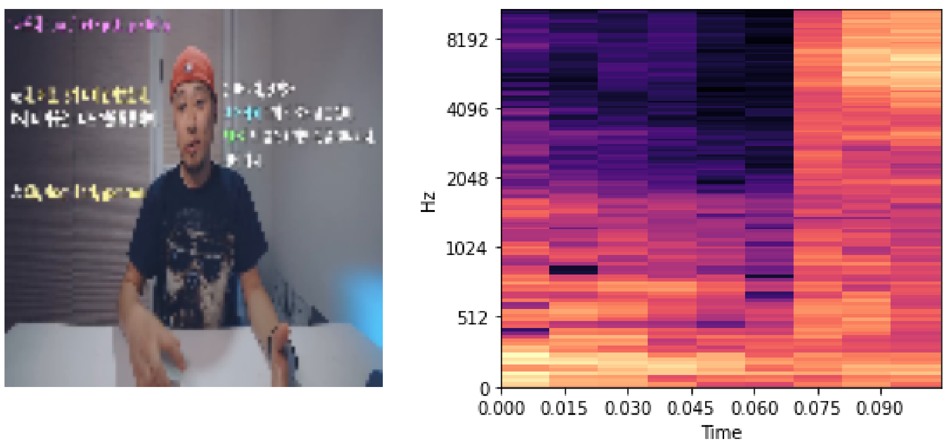


Figure 4.29: An example of a representative image frame of a video segment (left) and a mel-spectrogram of the same segment (right).

For all 6,091 videos, a 100-millisecond sound segment of each video was extracted. The sound segment was converted into a mel-spectrogram by using a Python audio processing package, librosa [15]. A representative image frame of each video was selected based on the strongest onset event detection [158]. Figure 4.29 shows an example of a pair of a representative image frame and a mel-spectrogram, extracted from the same video segment.

The model training of YouTube Mirror was conducted by using TensorFlow [16], an open-source Python library for machine learning and artificial intelligence. The model

[14]https://colab.research.google.com/
[15]https://librosa.org
[16]https://www.tensorflow.org

architecture of YouTube Mirror was implemented based on an architecture proposed by Jo et al. [154].

Interactive Audiovisual Mirror

YouTube Mirror has two main modules: a playback module written in C++ with AlloLib [134] and TINC [135] and an inference module created in Python with TINC. Given a real-time camera input, the inference module continuously produces images and sounds reconstructed from a trained cross-modal generative model. The inference sends the images to the playback module via the communication feature of TINC. And the sounds are sent to the playback module by using *mmap*, a method of memory-mapped file I/O to reduce latency in sound data communication.

The playback module displays the received images as a full-screen texture. Since the trained model is designed to generate images with 112 pixels in width and 112 pixels in height, the texture is linearly interpolated to be a full-screen size. The playback module plays sound sample data received by the *mmap* communication method at the sampling rate of 44,100 Hz. With some adjustment, the playback module can play the images and the sounds at approximately 20 frames per second.

4.4.5 Exhibition and Discussion

As Figure 4.30 illustrates, a YouTube Mirror installation consists of a camera, a wall-mounted or portrait mode LCD display, loud speakers, an audio mixer, and a PC. YouTube Mirror was exhibited as an installation at the Media Arts and Technology (MAT) Program 2022 End of Year Show at the University of California, Santa Barbara (UCSB). The installation used a vertical LCD monitor on a pedestal, as shown in Figure 4.31.

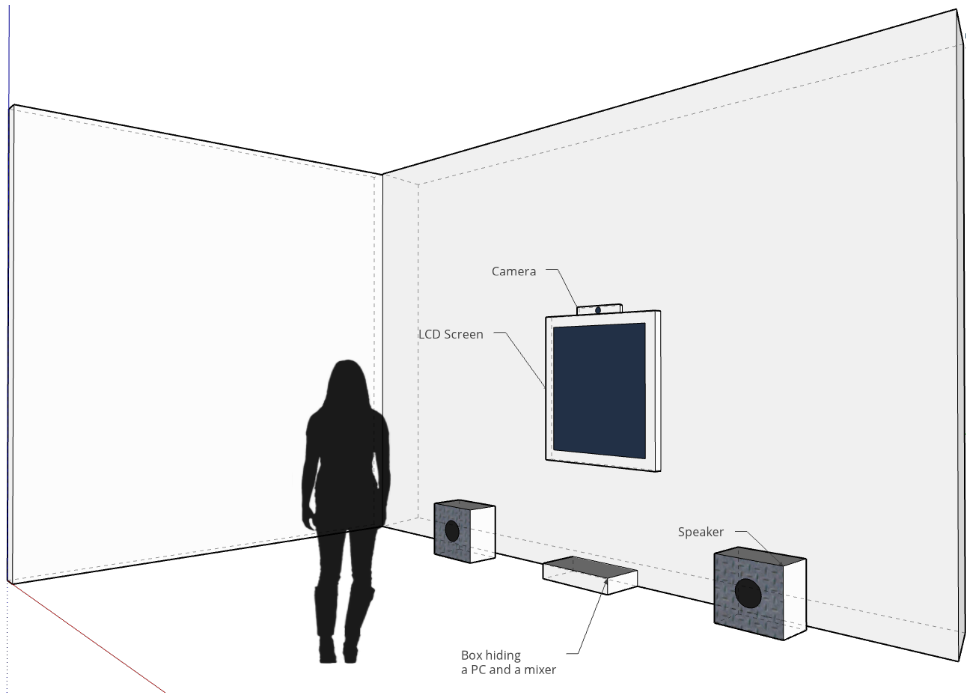


Figure 4.30: A floor plan of YouTube Mirror.

Figure 4.31: An installation of YouTube Mirror at the UCSB MAT 2022 End of Year Show: SYMADES.

After realizing that the installation generates sounds and visuals via the attached camera, the audience showed interesting behavior in front of the work. A few audiences

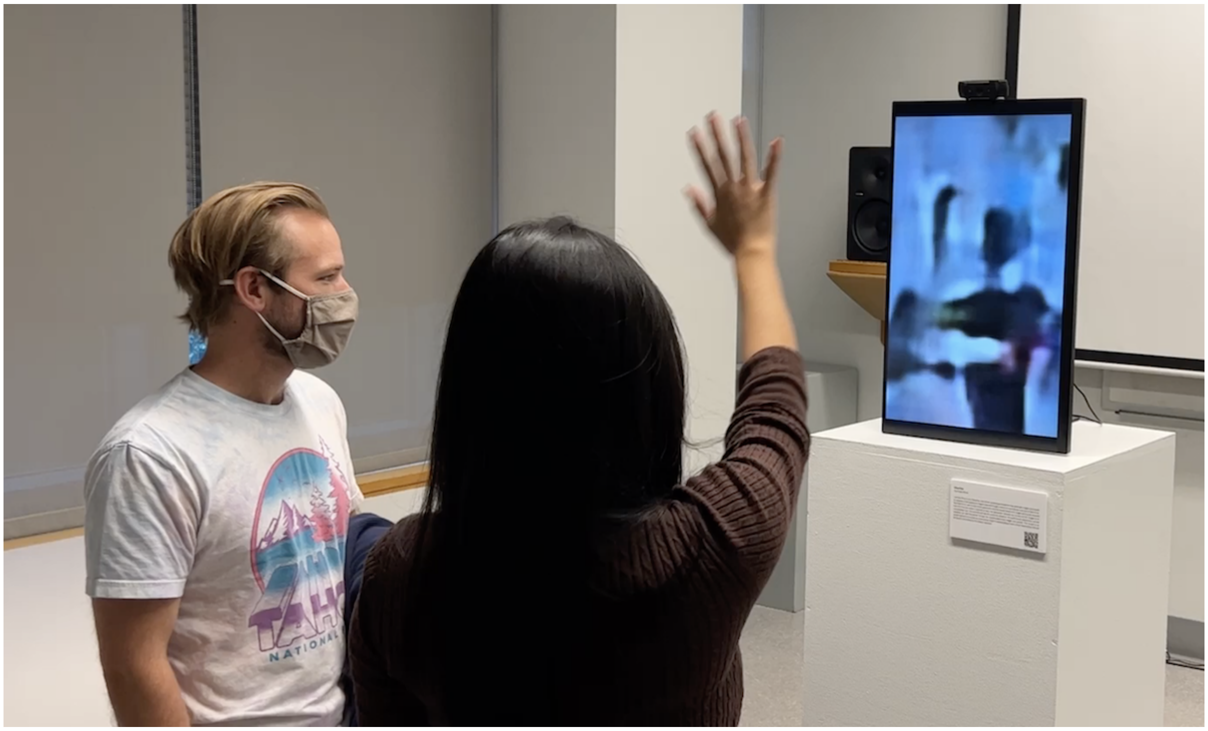


Figure 4.32: Audience interaction

just stood still, slightly swaying their head from side to side. As shown Figure 4.32, some audiences waved their hands or arms. There was a participant who waved his arm as if dancing. Some other audience members showed acting like movements.

4.4.6 Conclusion

YouTube Mirror is an interactive, audiovisual AI installation based on a cross-modal generative model that learned the implicit relationship between images and corresponding sounds extracted from the same videos that I watched on YouTube. YouTube Mirror is an artistic attempt to simulate my unconscious, implicit understanding of audio-visual association that can exist in the watched videos. YouTube Mirror utilizes the generativity of the machine in creating a unique form of interactive data art.

The real-time interactivity of YouTube Mirror invites the audience to explore the generative representation of the machine by navigating the latent space of the model with their own body. As a result, the audience showed various movements to interact with the YouTube Mirror installation that provides a multisensory, cross-modal experience.

YouTube Mirror exhibited the uncertainty of generative representation as the machine generated limited visuals and sounds. This representational uncertainty could be caused by implicit bias inherent in video recommendation algorithms, a small set of personal data, or the model's inaccuracy in generalizing unseen data.

Chapter 5

Conclusion and Future Work

5.1 The Human-Data-Machine Framework as a Creative Force in Data-Driven Audiovisual Art

Dealing with uncertainty in data practice is an important topic in our datafied society. While uncertainty is a difficult problem to estimate and represent in data visualization and data science, this dissertation argues that data art can utilize uncertainty in data practice as a creative force to make a unique form of data art and to raise the audience's awareness of uncertainty in data practice. This dissertation aims to propose an artistic approach to reflecting uncertainty in data practice through data art. To this end, this research explores three main questions.

First, how can data art reflect uncertainty in data practice? To answer this question, this dissertation first defines the Human-Data-Machine (HDM) Loop as a research framework that helps us view the data-centered interrelationship between humans and machines and understand what types of uncertainty in the HDM Loop exist. To enable data art practice to reflect the perspective of uncertainty, the dissertation proposes three data art practices based the HDM framework: Artist-Centered Practice, Artist-Machine Collaborative Practice, and Machine-Centered Generative Practice. I believe that the proposed data art practices can play a role for data artists in finding an inspirational theme and further defining their relationship to machines in data art making.

Second, how can data art practice deal with uncertainty in data practice? The empirical case studies show three insights into this question. As found in the indexical data visualization of BeHAVE, one of the ways to deal with uncertainty in the Artist-Centered Practice is to find representational approaches to reduce the uncertainty by considering contiguous relationships between data, data context, and data representation. As Uncertain Facing shows approaches to represent the issues of the non-deterministic t-SNE process and synthetic data, the artist in the Artist-Machine Collaborative Practice can treat the issues of uncertainty by revealing the processes of the machine's algorithms in a way that emphasizes the uncertainty and by exposing the audience to the uncertainty. The YouTube Mirror project shows that the Machine-Centered Generative Practice can utilize the uncertainty of the machine's generativity, which is largely determined by the artist's choice of data and model architecture, in creating unique data artworks.

Last, in what ways can data art raise the audience's awareness of uncertainty in data practice? The case studies show that the multimodal representation of uncertainty in data practice can be an answer to this question. Since information about uncertainty is considered an additional dimension to data visualization, it adds a burden to the visual channel in communicating the uncertainty as visual forms only. However, data art can utilize our multisensory perception to better communicate a concern or message of an artwork. Especially, a combination of visualization and sonification in data-driven audiovisual art helps enhancing the perception of uncertainty variables by providing the redundancy of representation or the complementation of representation. The multimodal representation of uncertainty in data practice could provide a more immersive experience in a way that makes the audience better understand what concerns the artwork tries to deliver. Another answer to this question is the design of audience interaction and participation that makes the audience experience the uncertainty that a work of data art represents. As found in the case studies, the interactive and participatory design can be a catalyst for raising the audience's awareness of uncertainty in data practice by allowing the audience to explore, participate in, and interact with the artwork. The indexical visualization of BeHAVE exhibits a passive interaction that makes the audience experience behavior data with their own device. The UI design of Uncertain Facing presents a procedural/exploratory interaction by which the audience can interact with the machine's algorithm and participate in the machine's process with their own data. The real-time interactivity of YouTube Mirror enables an active interaction and participation for the audience to navigate the latent space of the generative machine with their own body.

5.2 Limitations and Future Work

This research proposes an approach to expand data art practice with the Human-Data-Machine (HDM) framework to reflect the uncertainty perspective of data practice. However, there are still limitations that need further investigation.

First, the types of uncertainty in the HDM framework are not comprehensive. There may be some types of uncertainty the framework is missing. The HDM framework could be improved by adding more types of uncertainty according to additional case studies.

Second, the proposed data art practices are not mutually exclusive. They could be mixed or overlapped according to artists' intentions or artworks. A mixed practice could emerge to provide artists with more ideas in finding novel approaches to dealing with the uncertainty in the HDM framework.

Third, there will be more approaches to representing uncertainty. In addition to the approaches to representing uncertainty suggested in each data art practice and empirical case study, new ways could be developed accordingly.

Future work will involve additional case studies that could provide improvement for the limitations described above. In particular, the Machine-Centered Generative Practice has room to explore more ways to utilize the generativity of the machine upon the choice of modeling parameters or data. Possible research topics include the use of different modeling architectures, representation variations with data categorization, model accuracy, and the temporality of input data.

Bibliography

[1] P. Abend and M. Fuchs, *Introduction. The Quantified Self and Statistical Bodies*, *Digital Culture & Society* **2** (2016), no. 1 5–21.

[2] H. Fry, *Hello World: Being Human in the Age of Algorithms*. W. W. Norton & Company, 1st ed., 2018.

[3] J. van Dijck, *Datafication, dataism and dataveillance: Big Data between scientific paradigm and ideology*, *Surveillance & Society* **12** (2014), no. 2 197–208.

[4] J. W. Rettberg, *Seeing Ourselves Through Technology : How We Use Selfies, Blogs and Wearable Devices to See and Shape Ourselves*. Palgrave Macmillan UK, 2014.

[5] G. Marcus, *Deep Learning: A Critical Appraisal*, *arXiv:1801.00631 [cs.AI]* (2018).

[6] J. Thomson, E. Hetzler, A. MacEachren, M. Gahegan, and M. Pavel, *A typology for visualizing uncertainty*, in *Visualization and Data Analysis 2005*, vol. 5669, pp. 146–157, International Society for Optics and Photonics, 2005.

[7] G.-P. Bonneau, H.-C. Hege, C. R. Johnson, M. M. Oliveira, K. Potter, P. Rheingans, and T. Schultz, *Overview and State-of-the-Art of Uncertainty Visualization*, in *Scientific Visualization: Uncertainty, Multifield, Biomedical, and Scalable Visualization* (C. D. Hansen, M. Chen, C. R. Johnson, A. E. Kaufman, and H. Hagen, eds.), Mathematics and Visualization, pp. 3–27. Springer London, 2014.

[8] M. Kläs and A. M. Vollmer, *Uncertainty in Machine Learning Applications: A Practice-Driven Classification of Uncertainty*, in *Computer Safety, Reliability, and Security* (B. Gallina, A. Skavhaug, E. Schoitsch, and F. Bitsch, eds.), Lecture Notes in Computer Science, pp. 431–438, Springer International Publishing, 2018.

[9] C. E. Shannon, *A mathematical theory of communication*, *The Bell System Technical Journal* **27** (1948), no. 3 379–423.

[10] S. J. Buckman, *Uncertainty in the Physical Sciences: How Big? How Small? Is It Actually There At All?*, in *Uncertainty and Risk : Multidisciplinary Perspectives* (G. Bammer and M. Smithson, eds.), pp. 89–98. Routledge, 2012.

[11] S. Grishin, *Uncertainty as a Creative Force in Visual Art*, in *Uncertainty and Risk : Multidisciplinary Perspectives* (G. Bammer and M. Smithson, eds.), pp. 133–144. Routledge, 2012.

[12] E. MacCurdy, *The Notebooks of Leonardo da Vinci, Vol. 2*. Jonathan Cape, 1954.

[13] J. Arp, *Arp on Arp: Poems, Essays, Memories*. Viking Press, 1972.

[14] J. Mackey, *Musical Improvisation, Creativity and Uncertainty*, in *Uncertainty and Risk : Multidisciplinary Perspectives* (G. Bammer and M. Smithson, eds.), pp. 105–113. Routledge, 2012.

[15] D. Rosenberg, *Data before the Fact*, in *"Raw data" is an oxymoron* (L. Gitelman, ed.), Infrastructures series, pp. 15–40. The MIT Press, Cambridge, Massachusetts, 2013.

[16] J. Freeman, *Defining Data as an Art Material*. Ph.D dissertation, Queen Mary University of London, 2018 [Online]. Available: `https://qmro.qmul.ac.uk/xmlui/handle/123456789/31793`.

[17] S. Rendgen, "What do we mean by "data"?." `https://idalab.de/what-do-we-mean-by-data/`, 2018. Accessed on January 29, 2021.

[18] C. Ware, *Information Visualization: Perception for Design*. Interactive technologies. Morgan Kaufmann, Waltham, MA, 3rd ed., 2013.

[19] B. N. Walker and M. A. Nees, *Theory of Sonification*, in *The Sonification Handbook* (T. Hermann, A. Hunt, and J. G. Neuhoff, eds.), pp. 9–39. Logos Publishing House, Berlin, Germany, 2011.

[20] S. S. Stevens, *On the Theory of Scales of Measurement*, *Science* **103** (1946), no. 2684 677–680.

[21] R. Likert, *A technique for the measurement of attitudes*, *Archives of Psychology* **22 140** (1932) 55–55.

[22] A. C. Eberendu, *Unstructured Data: an overview of the data of Big Data*, *International Journal of Computer Trends and Technology* **38** (2016), no. 1. Publisher: Seventh Sense Research Group.

[23] D. Reinsel, J. Gantz, and J. Rydning, *The Digitization of the World from Edge to Core*. The International Data Corporation (IDC), 2018.

[24] F. Gröne, P. Péladeau, and R. A. Samad, "Tomorrow's data heroes." `https://www.strategy-business.com/article/Tomorrows-Data-Heroes?gko=7b095`. Accessed on Feburary 12, 2021.

[25] F. X. Diebold, *On the Origin(s) and Development of the Term 'Big Data'*, PIER Working Paper No. 12-037, Social Science Research Network, 2012.

[26] M. T. Schäfer and K. van Es, eds., *The Datafied Society. Studying Culture through Data.* Amsterdam University Press, 2017.

[27] V. Mayer-Schönberger and K. Cukier, *Big data: a revolution that will transform how we live, work, and think.* Houghton Mifflin Harcourt, Boston, 2013.

[28] E. McCallister, T. Grance, and K. Scarfone, *Guide to Protecting the Confidentiality of Personally Identifiable Information (PII)*, Tech. Rep. NIST Special Publication (SP) 800-122, National Institute of Standards and Technology, 2010.

[29] European Union Law, *Directive 95/46/EC of the European Parliament and of the Council of 24 October 1995 on the protection of individuals with regard to the processing of personal data and on the free movement of such data*, 1995.

[30] N. Yau, *An Online Tool for Personal Data Collection and Exploration.* PhD thesis, UCLA, 2013 [Online]. Available: `https://escholarship.org/uc/item/18h0j9xh`.

[31] J. Bertin, *Semiology of graphics.* University of Wisconsin Press, 1983.

[32] B. H. McCormick, T. A. DeFanti, and M. D. Brown, *Visualization in Scientific Computing*, *Computer Graphics* **21** (1987), no. 6.

[33] S. K. Card, *Readings in Information Visualization: Using Vision to Think.* Morgan Kaufmann Series in Interactive Technologies. Morgan Kaufmann Publishers, 1999.

[34] A. Unwin, *Introduction*, in *Graphics of Large Datasets: Visualizing a Million* (A. Unwin, M. Theus, and H. Hofmann, eds.), Statistics and Computing, pp. 1–27. Springer, New York, NY, 2006.

[35] L. Manovich, *Cultural Analytics.* The MIT Press, 2020.

[36] M. Friendly, *A Brief History of Data Visualization*, in *Handbook of Data Visualization* (C.-h. Chen, W. Härdle, and A. Unwin, eds.), Springer Handbooks Comp.Statistics, pp. 15–56. Springer, Berlin, Heidelberg, 2008.

[37] M. Friendly, P. Valero-Mora, and J. I. Ulargui, *The First (Known) Statistical Graph: Michael Florent van Langren and the "Secret" of Longitude*, *The American Statistician* **64** (2010), no. 2 174–184.

[38] W. Playfair, H. Wainer, and I. Spence, *Playfair's Commercial and Political Atlas and Statistical Breviary.* Cambridge University Press, 2005.

[39] J. Snow, *On the Mode of Communication of Cholera*. John Churchill, 1855.

[40] E. R. Tufte, *The Visual Display of Quantitative Information*. Graphics Press, 2001.

[41] Unknown, *Mortality of the British army: at home and abroad, and during the Russian war, as compared with the mortality of the civil population in England ; illustrated by tables and diagrams.* Harrison and Sons, Martin's Lane, London, 1858.

[42] J. W. Tukey, *Exploratory data analysis*. Addison-Wesley Pub. Co., Reading, Mass., 1977.

[43] "The Observatory of Economic Complexity | OEC." `https://oec.world/`. Accessed on April 22, 2022.

[44] B. Shneiderman, *Tree visualization with tree-maps: 2-d space-filling approach*, *ACM Transactions on Graphics* **11** (1992), no. 1 92–99.

[45] A. Tifentale and L. Manovich, *Selfiecity: Exploring Photography and Self-Fashioning in Social Media*, in *Postdigital Aesthetics: Art, Computation and Design* (D. M. Berry and M. Dieter, eds.), pp. 109–122. Palgrave Macmillan UK, London, 2015.

[46] N. Felton, *Tracing my life*, in *New Challenges for Data Design* (D. Bihanic, ed.), pp. 341–352. Springer London, London, 2015.

[47] Z. Pousman, J. Stasko, and M. Mateas, *Casual Information Visualization: Depictions of Data in Everyday Life*, *IEEE Transactions on Visualization and Computer Graphics* **13** (2007), no. 6 1145–1152.

[48] F. B. Viégas and M. Wattenberg, *Artistic data visualization: Beyond visual analytics*, in *Proceedings of the 2nd International Conference on Online Communities and Social Computing*, OCSC'07, pp. 182–191, Springer-Verlag, 2007.

[49] R. Kosara, *Visualization Criticism - The Missing Link Between Information Visualization and Art*, in *2007 11th International Conference Information Visualization (IV '07)*, pp. 631–636, 2007.

[50] A. Lau and A. V. Moere, *Towards a Model of Information Aesthetics in Information Visualization*, in *2007 11th International Conference Information Visualization (IV '07)*, pp. 87–92, 2007.

[51] J. Donath, A. Dragulescu, A. Zinman, F. Viégas, and R. Xiong, *Data portraits*, in *ACM SIGGRAPH 2010 Art Gallery*, SIGGRAPH '10, pp. 375–383, Association for Computing Machinery, 2010-07-26.

[52] T. Hogan and E. Hornecker, *Towards a Design Space for Multisensory Data Representation*, *Interacting with Computers* **29** (2017), no. 2 147–167.

[53] S. Lenzi and P. Ciuccarelli, *Intentionality and design in the data sonification of social issues*, *Big Data & Society* **7** (2020), no. 2.

[54] T. Hermann, *Taxonomy and Definitions for Sonification and Auditory Display*, in *Proceedings of the 14th International Conference on Auditory Display (ICAD 2008)*, 2008.

[55] G. Daurer, *Audiovisual Perception*, in *See this Sound: Audiovisuology: A Reader* (D. Daniels, S. Naumann, and J. Thoben, eds.), pp. 328–337. Verlag der Buchhandlung Walther König, Köln, 2015.

[56] S. Barrass and P. Vickers, *Sonification Design and Aesthetics*, in *The Sonification Handbook* (T. Hermann, A. Hunt, and J. G. Neuhoff, eds.), pp. 145–171. Logos Publishing House, Berlin, Germany, 2011.

[57] J. Cheney-Lippold, *We Are Data: Algorithms and The Making of Our Digital Selves*. NYU Press, 2017.

[58] E. K. Choe, N. B. Lee, B. Lee, W. Pratt, and J. A. Kientz, *Understanding quantified-selfers' practices in collecting and exploring personal data*, in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '14, p. 1143–1152, Association for Computing Machinery, 2014.

[59] d. boyd and K. Crawford, *Critical Questions for Big Data*, *Information, Communication & Society* **15** (2012), no. 5 662–679.

[60] L. Gitelman, ed., *"Raw data" is an oxymoron*. Infrastructures series. The MIT Press, Cambridge, Massachusetts, 2013.

[61] J. Drucker, *Humanities approaches to graphical display*, *Digital Humanities Quarterly* **5** (2011), no. 1 1–21.

[62] A. McCosker and R. Wilken, *Rethinking 'big data' as visual knowledge: the sublime and the diagrammatic in data visualisation*, *Visual Studies* **29** (2014), no. 2 155–164.

[63] J. Drucker, *Graphesis: Visual Forms of Knowledge Production*. Harvard University Press, 2014.

[64] A. Thudt, C. Perin, W. Willett, and S. Carpendale, *Subjectivity in personal storytelling with visualization*, *Information Design Journal* **23** (2017), no. 1 48–64.

[65] J. Matejka and G. Fitzmaurice, *Same Stats, Different Graphs: Generating Datasets with Varied Appearance and Identical Statistics through Simulated Annealing*, in *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pp. 1290–1294. Association for Computing Machinery, 2017.

[66] A. T. Pang, C. M. Wittenbrink, and S. K. Lodha, *Approaches to uncertainty visualization*, . [Preprint], Available: `https://www.researchgate.net/publication/2776724_Approaches_to_Uncertainty_Visualization`.

[67] A. T. Pang, C. M. Wittenbrink, and S. K. Lodha, *Approaches to uncertainty visualization*, *The Visual Computer* **13** (1997), no. 8 370–390.

[68] K. Brodlie, R. Allendes Osorio, and A. Lopes, *A Review of Uncertainty in Data Visualization*, in *Expanding the Frontiers of Visual Analytics and Visualization* (J. Dill, R. Earnshaw, D. Kasik, J. Vince, and P. C. Wong, eds.), pp. 81–109. Springer London, 2012.

[69] R. B. Haber and D. A. McNabb, *Visualization idioms: A conceptual model for scientific visualization systems*, *Visualization in scientific computing* (1990) 74–93.

[70] E. Tufte, "Computer Literacy Bookshops Interview, 1994-1997." `https://www.edwardtufte.com/tufte/complit_9497/`, 1997. Accessed on May 8, 2022.

[71] G. E. P. Box, *Science and Statistics*, *Journal of the American Statistical Association* **71** (1976), no. 356 791–799.

[72] J. Guynn, "Google Photos labeled black people 'gorillas'." `https://www.usatoday.com/story/tech/2015/07/01/google-apologizes-after-photos-identify-black-people-as-gorillas/29567465/`. Accessed on May 9, 2022.

[73] R. Mac, "Facebook Apologizes After A.I. Puts 'Primates' Label on Video of Black Men." `https://www.nytimes.com/2021/09/03/technology/facebook-ai-race-primates.html`, 2021. Accessed on May 9, 2022.

[74] P. Lee, "Learning from Tay's introduction." `https://blogs.microsoft.com/blog/2016/03/25/learning-tays-introduction/`, 2016. Accessed on May 9, 2022.

[75] P. Covington, J. Adams, and E. Sargin, *Deep Neural Networks for YouTube Recommendations*, in *Proceedings of the 10th ACM Conference on Recommender Systems*, pp. 191–198, 2016.

[76] Z. Zhao, L. Hong, L. Wei, J. Chen, A. Nath, S. Andrews, A. Kumthekar, M. Sathiamoorthy, X. Yi, and E. Chi, *Recommending what video to watch next: a multitask ranking system*, in *Proceedings of the 13th ACM Conference on Recommender Systems*, pp. 43–51, Association for Computing Machinery, 2019.

[77] R. Wirth, *CRISP-DM: Towards a standard process model for data mining*, in *Proceedings of the Fourth International Conference on the Practical Application of Knowledge Discovery and Data Mining*, pp. 29–39, 2000.

[78] A. Ng and M. Jordan, *On Discriminative vs. Generative Classifiers: A comparison of logistic regression and naive Bayes*, in *Advances in Neural Information Processing Systems* (T. Dietterich, S. Becker, and Z. Ghahramani, eds.), vol. 14, MIT Press, 2001.

[79] D. Foster, *Generative Deep Learning: Teaching Machines to Paint, Write, Compose, and Play.* O'Reilly Media, Inc., 2019.

[80] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning.* The MIT Press, Cambridge, Massachusetts, 2016.

[81] M. Kana, "Uncertainty in deep learning. how to measure?." `https://towardsdatascience.com/my-deep-learning-model-says-sorry-i-dont-know-the-answer-that-s-absolutely-ok-50ffa562cb0b`, 2020. Accessed on May 31, 2022.

[82] S. C. Hora, *Aleatory and epistemic uncertainty in probability elicitation with an example from hazardous waste management*, *Reliability Engineering & System Safety* **54** (1996), no. 2 217–223.

[83] T. Karras, S. Laine, and T. Aila, *A Style-Based Generator Architecture for Generative Adversarial Networks*, in *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 4396–4405, 2019.

[84] T. Karras, S. Laine, M. Aittala, J. Hellsten, J. Lehtinen, and T. Aila, *Analyzing and Improving the Image Quality of StyleGAN*, in *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 8107–8116, 2020.

[85] T. Karras, M. Aittala, S. Laine, E. Härkönen, J. Hellsten, J. Lehtinen, and T. Aila, *Alias-Free Generative Adversarial Networks*, in *Advances in Neural Information Processing Systems* (M. Ranzato, A. Beygelzimer, Y. Dauphin, P. Liang, and J. W. Vaughan, eds.), vol. 34, pp. 852–863, 2021.

[86] T. Brown, B. Mann, N. Ryder, M. Subbiah, J. D. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, S. Agarwal, A. Herbert-Voss, G. Krueger, T. Henighan, R. Child, A. Ramesh, D. Ziegler, J. Wu, C. Winter,

C. Hesse, M. Chen, E. Sigler, M. Litwin, S. Gray, B. Chess, J. Clark, C. Berner, S. McCandlish, A. Radford, I. Sutskever, and D. Amodei, *Language Models are Few-Shot Learners*, in *Advances in Neural Information Processing Systems* (H. Larochelle, M. Ranzato, R. Hadsell, M. Balcan, and H. Lin, eds.), vol. 33, pp. 1877–1901, 2020.

[87] P. Wang, "This Person Does Not Exist." `https://thispersondoesnotexist.com/`. Accessed on May 15, 2022.

[88] K. Hora, "This X Does Not Exist." `https://thisxdoesnotexist.com/`. Accessed on May 15, 2022.

[89] J. West and C. Bergstrom, "Which Face Is Real." `https://www.whichfaceisreal.com/`. Accessed on May 15, 2022.

[90] C. Shorten and T. M. Khoshgoftaar, *A survey on Image Data Augmentation for Deep Learning*, *Journal of Big Data* **6** (2019), no. 1 60.

[91] A. Antoniou, A. Storkey, and H. Edwards, *Data Augmentation Generative Adversarial Networks*, *arXiv:1711.04340 [stat.ML]* (2017).

[92] J. Hullman, *Why Authors Don't Visualize Uncertainty*, *IEEE Transactions on Visualization and Computer Graphics* **26** (2020), no. 1 130–139.

[93] M. Abdar, F. Pourpanah, S. Hussain, D. Rezazadegan, L. Liu, M. Ghavamzadeh, P. Fieguth, X. Cao, A. Khosravi, U. R. Acharya, V. Makarenkov, and S. Nahavandi, *A review of uncertainty quantification in deep learning: Techniques, applications and challenges*, *Information Fusion* **76** (2021) 243–297.

[94] A. Hill, C. Churchouse, and M. F. Schober, *Seeking New Ways to Visually Represent Uncertainty in Data: What We Can Learn from the Fine Arts*, in *2018 IEEE VIS Arts Program (VISAP)*, pp. 1–8, IEEE, 2018.

[95] T. Schofield, M. Dörk, and M. Dade-Robertson, *Indexicality and visualization: exploring analogies with art, cinema and photography*, in *Proceedings of the 9th ACM Conference on Creativity & Cognition - C&C '13*, pp. 175—-84, ACM Press, 2013.

[96] A. M. MacEachren, R. E. Roth, J. O'Brien, B. Li, D. Swingley, and M. Gahegan, *Visual Semiotics Uncertainty Visualization: An Empirical Study*, *IEEE Transactions on Visualization and Computer Graphics* **18** (2012), no. 12 2496–2505.

[97] R. Zachariou, "Machine Learning Art: An Interview With Memo Akten — Artnome." `https://www.artnome.com/news/2018/12/13/machine-learning-art-an-interview-with-memo-akten`, 2018. Accessed on May 19, 2022.

[98] A. Kendall and Y. Gal, *What uncertainties do we need in Bayesian deep learning for computer vision?*, in *Proceedings of the 31st International Conference on Neural Information Processing Systems*, NIPS'17, pp. 5580–5590, 2017.

[99] C. Olah, A. Mordvintsev, and L. Schubert, *Feature visualization*, *Distill* (2017). https://distill.pub/2017/feature-visualization.

[100] M. Akten, R. Fiebrink, and M. Grierson, *Learning to see: you are what you see*, in *ACM SIGGRAPH 2019 Art Gallery*, SIGGRAPH '19, pp. 1–6, Association for Computing Machinery, 2019.

[101] M. Klingemann, "Uncanny Mirror." `https://underdestruction.com/2020/08/29/uncanny-mirror/`. Accessed on May 22, 2022.

[102] J. Bailey, "Breeding Paintings With Machine Learning." `https://www.artnome.com/news/2019/8/25/breeding-paintings-with-machine-learning`, 2018. Accessed on May 22, 2022.

[103] M. Klingemann, "Memories of Passersby I." `https://underdestruction.com/2018/12/29/memories-of-passersby-i/`. Accessed on May 22, 2022.

[104] AlloSphere Research Group, "Allosystem C/C++ Library." `https://github.com/AlloSphere-Research-Group/AlloSystem`. Accessed on Jun 3, 2022.

[105] S. Park, *BeHAVE: a Heatmap-based Audiovisual Representation of Personal Data*, in *Proceedings of the 2018 International Computer Music Conference*, 2018.

[106] S. Park, *Multimodal Data Portrait for Representing Mobile Phone Use Behavior*, in *Proceedings of the 25th International Symposium on Electronic Art*, pp. 36–43, 2019.

[107] N. Young, *The Virtual Self: How Our Digital Lives Are Altering the World Around Us.* McClelland & Stewart, 2013.

[108] G. Neff and D. Nafus, *Self-Tracking.* The MIT Press, 2016.

[109] M. McLuhan, *Understanding media: the extensions of man.* The MIT Press, 1994.

[110] J. Harkin, *Mobilisation: The growing public interest in mobile technology.* Demos, 2003.

[111] R. W. Belk, *Possessions and the extended self*, *Journal of Consumer Research* **15** (1988), no. 2 139–168.

[112] R. W. Belk, *Extended self in a digital world*, *Journal of Consumer Research* **40** (2013), no. 3 477–500.

[113] C. Kang, S. Gao, X. Lin, Y. Xiao, Y. Yuan, Y. Liu, and X. Ma, *Analyzing and geo-visualizing individual human mobility patterns using mobile call records*, in *Geoinformatics, 2010 18th International Conference on*, pp. 1–7, IEEE, 2010.

[114] N. Kaewnoi, N. Suntiparadonkul, S. Phithakkitnukoon, and Z. Smoreda, *Visualizing mobile phone usage for exploratory analysis: A case study of portugal*, in *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*, UbiComp '16, pp. 1358–1362, ACM, 2016.

[115] H. Zhao, C. Plaisant, B. Shneiderman, and J. Lazar, *Data sonification for users with visual impairment: A case study with georeferenced data*, *ACM Transactions on Computer-Human Interaction* **15** (2008), no. 1 4:1–4:28.

[116] S. Park, S. Kim, S. Lee, and W. S. Yeo, *Composition with path : Musical sonification of geo-referenced data with online map interface*, in *Proceedings of the International Computer Music Conference*, pp. 5–8, 2010.

[117] M. H. W. Rosli and A. Cabrera, *Gestalt principles in multimodal data representation*, *IEEE Computer Graphics and Applications* **35** (2015), no. 2 80–87.

[118] Y. C. Han and S. Tiwari, *California drought impact: Multimodal data representation to predict the water cycle*, pp. 1–8, 2017.

[119] D. F. Keefe, D. B. Karelitz, E. L. Vote, and D. H. Laidlaw, *Artistic collaboration in designing vr visualizations*, *IEEE Computer Graphics and Applications* **25** (2005), no. 2 18–23.

[120] C. Roads, *Microsound*. The MIT Press, 2004.

[121] C. Roberts, "Gibberish." `https://github.com/gibber-cc/gibberish`. Accessed on June 14, 2022.

[122] C. Roberts, G. Wakefield, and M. Wright, *The web browser as synthesizer and interface*, in *Proceedings of the 13th Conference on New Interfaces for Musical Expression*, pp. 313—-318, 2013.

[123] J. Snyder, *Flattening the Earth: Two Thousand Years of Map Projections*. University of Chicago Press, 1997.

[124] S. Tilkov and S. Vinoski, *Node. js: Using javascript to build high-performance network programs*, *IEEE Internet Computing* **14** (2010), no. 6 80–83.

[125] R. Bellman, *Dynamic Programming*. Princeton University Press, Princeton, NJ, USA, 1st ed., 1957.

[126] L. van der Maaten, E. Postma, and J. van den Herik, *Dimensionality Reduction: A Comparative Review*, Tech. Rep. Technical Report TiCC-TR 2009-005, Tilburg University, 2009.

[127] L. van der Maaten and G. Hinton, *Visualizing Data using t-SNE*, *Journal of Machine Learning Research* **9** (2008), no. 86 2579–2605.

[128] A. Chatzimparmpas, R. M. Martins, and A. Kerren, *t-visne: Interactive Assessment and Interpretation of t-SNE Projections*, *IEEE Transactions on Visualization and Computer Graphics* **26** (2020), no. 8 2696–2714.

[129] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, *Generative Adversarial Nets*, in *Advances in Neural Information Processing Systems* (Z. Ghahramani, M. Welling, C. Cortes, N. Lawrence, and K. Weinberger, eds.), vol. 27, 2014.

[130] F. Schroff, D. Kalenichenko, and J. Philbin, *FaceNet: A unified embedding for face recognition and clustering*, in *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 815–823, 2015.

[131] NVIDIA Research Projects, "Stylegan2 — Official TensorFlow Implementation." `https://github.com/NVlabs/stylegan2`. Accessed on May 30, 2022.

[132] "Deep face recognition with Keras, Dlib and OpenCV." `https://nbviewer.org/github/krasserm/face-recognition/blob/master/face-recognition.ipynb?flush_cache=true`. Accessed on May 30, 2022.

[133] J. Menon, B. Wyvill, C. Bajaj, J. Bloomenthal, B. Guo, J. Hart, G. Wyvill, and C. Bajaj, *Implicit surfaces for geometric modeling and computer graphics*, *SIGGRAPH'96 Course Notes* (1996).

[134] AlloSphere Research Group, "Allolib C/C++ Libraries." `https://github.com/AlloSphere-Research-Group/allolib`. Accessed on May 31, 2022.

[135] AlloSphere Research Group, "Tinc (Toolkit for Interactive Computation)." `https://github.com/AlloSphere-Research-Group/tinc`. Accessed on May 31, 2022.

[136] L. van der Maaten, "Barnes-Hut t-SNE." `https://github.com/lvdmaaten/bhtsne`. Accessed on May 30, 2022.

[137] G. Kogan, "ofxtsne." `https://github.com/genekogan/ofxTSNE`. Accessed on May 30, 2022.

[138] T. Barnes, "Optimizing Barnes-Hut t-SNE." `https://www.microsoft.com/en-us/research/blog/optimizing-barnes-hut-t-sne`, 2018. Accessed on May 30, 2022.

[139] W. E. Lorensen and H. E. Cline, *Marching cubes: A high resolution 3D surface construction algorithm*, *ACM SIGGRAPH Computer Graphics* **21** (1987), no. 4 163–169.

[140] C. Kiefer, "Marching cubes gpu." `https://github.com/chriskiefer/MarchingCubesGPU`. Accessed on May 30, 2022.

[141] C. L. Jackins and S. L. Tanimoto, *Oct-trees and their use in representing three-dimensional objects*, *Computer Graphics and Image Processing* **14** (1980), no. 3 249–270.

[142] E. Nevala, "Introduction to Octrees." `https://www.wobblyduckstudios.com/Octrees.php`. Accessed on May 30, 2022.

[143] V. Mühler, "face-api.js." `https://github.com/justadudewhohacks/face-api.js`. Accessed on May 31, 2022.

[144] E. Vendrow, A. Singhal, and A. Dixit, "Ensemble Networks for Better Facial Recognition of Bearded Faces." `http://cs229.stanford.edu/proj2019aut`, 2019. Accessed on May 31, 2022.

[145] S. Mulholland, "No Beards Allowed: Exploring Bias in Facial Recognition AI." `https://www.ideo.com/blog/no-beards-allowed-exploring-bias-in-facial-recognition-ai`, 2019. Accessed on May 31, 2022.

[146] D. P. Kingma and M. Welling, *Auto-Encoding Variational Bayes*, *arXiv:1312.6114 [stat.ML]* (2013).

[147] M. Muller-Eberstein and N. van Noord, *Translating Visual Art Into Music*, in *2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)*, pp. 3117–3120, IEEE, 2019.

[148] D. Jeong, S. Doh, and T. Kwon, *Träumerai: Dreaming Music with StyleGAN*, *arXiv:2102.04680 [cs.SD]* (2021).

[149] L. A. Gatys, A. S. Ecker, and M. Bethge, *A Neural Algorithm of Artistic Style*, *arXiv:1508.06576 [cs.CV]* (2015).

[150] I. Odlen, P. Verma, C. Basica, and P. D. Kivelson, *Painting from Music using Neural Visual Style Transfer*, in *NeurIPS 2020 Workshop on Machine Learning for Creativity and Design*, 2020.

[151] P. Verma, C. Basica, and P. D. Kivelson, *Translating Paintings Into Music Using Neural Networks*, *arXiv:2008.09960 [cs.SD]* (2020).

[152] M. Akten, "Ultrachunk." `https://www.memo.tv/works/ultrachunk`, 2018. Accessed on Jun 2, 2022.

[153] S. J. Lee and T. C. Reeves, *A Significant Contributor to the Field of Educational Technology*, *Educational Technology* **47** (2007), no. 6 56–59.

[154] D. U. Jo, B. Lee, J. Choi, H. Yoo, and J. Y. Choi, *Associative Variational Auto-Encoder with Distributed Latent Spaces and Associators*, in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 34, pp. 11197–11204, 2020.

[155] S. S. Stevens, J. Volkmann, and E. B. Newman, *A Scale for the Measurement of the Psychological Magnitude Pitch*, *The Journal of the Acoustical Society of America* **8** (1937), no. 3 185–190.

[156] K. McDonald, "Sharing faces." `https://vimeo.com/96549043`, 2013. Accessed on Jun 2, 2022.

[157] G. Kogan, "Cubist mirror." `https://vimeo.com/167910860`, 2016. Accessed on Jun 2, 2022.

[158] J. Bello, L. Daudet, S. Abdallah, C. Duxbury, M. Davies, and M. Sandler, *A tutorial on onset detection in music signals*, *IEEE Transactions on Speech and Audio Processing* **13** (2005), no. 5 1035–1047.