Data Visualization - From a Human-Centered Perspective (Lecture Notes)

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2021-10-31

Contents

Preface

The current rapid technological development requires the processing of large amounts of data of various kinds to make them usable by humans. This challenge affects many areas of life today, such as research, business, and politics. In these contexts, decision-makers use data visualizations to explain information and its relationships through graphical representations of data. This course aims to familiarize students with the principles, techniques, and methods in data visualization and provide practical skills for designing and implementing data visualizations.

The master course «data visualization» is intended for students interested in better understanding how to critically engage with data visualization and how to design effective data visualizations reflectively.

Basic knowledge of programming (HTML, CSS, Javascript, Python) and data analysis (e.g., R) is helpful. In addition to participating in class discussions, students will complete several programming and data analysis assignments. In a mini-project, students work on a given problem. Finally, we expect students to document and present their assignments and mini-project in a reproducible manner.

Please note that the course will focus on how data is visually coded and presented for analysis after the data structure and its meaning are known. We do not explicitly cover exploratory analysis methods for discovering insights in data.

Text Book

This course is highly influenced bu the work of Tamara Munzner and her book (Visualization Analysis & Design)[https://www.routledge.com/Visualization-Analysis-and-Design/Munzner/p/book/9781466508910]. In our hand library, there are exemplars available.

Learning Goals & Objectives

This course gives students a solid introduction to the fundamentals of data visualization with current insights from research and practice. By the end of the course, students will be able to

- select and apply methods for designing visualizations based on a problem,
- know essential theoretical basics of visualization for graphical perception and cognition,
- know and to select visualization approaches and their advantages and disadvantages,
- evaluate visualization solutions critically, and
- have acquired practical skills for implementing visualizations.

Chapter 1

The Value of Data Visualization

In the following section, I highlight the value of data visualizations, which is caused by an increasing availability of data. I highlight these values by different typical examples from data visualizations.

When thinking about the value of data visualization we should consider the increasing importance of data in our society. Over the last century the availability of data in the world is growing exponentially. We now have data whose scope is no longer imaginable.

According to *statista*[1] the total amount of data reached almost 65 zettabytes in 2020 (Statista, Inc., 2021). This growth was higher than previously expected due to the COVID-19 pandemic, as more and more people work and study from home and make more use of home entertainment options. However, in 2020, the installed storage capacity reached 6.7 zettabytes, thus, only a small proportion of the created data was kept. During the forecast period from 2020 to 2025, *statista* states an average annual growth rate of 19.2 % in storage capacity (Statista, Inc., 2021).

Just to recall, a zettabyte is a unit of measurement for storage capacity and stands for 10^21 bytes. That's trillions of bytes, or in numbers, 1,000,000,000,000,000,000 bytes. This in turn is equal to 1,000 exabytes or one billion terabytes.

Besides the aforementioned data that are created by using social media, there are many other types of data that contributed to the need for higher storage capacity. Just to give you some examples of available data: there are geographical,

[1] *statistics* is a statistics database that makes data from market and opinion research institutions as well as from business and official statistics available in various Languages.

cultural, scientific, financial, statistical, meteorological, natural, and transport data.

Even though, we have all these data available, already in 1999 Edward O. Wilson concluded (Wilson, 1999): > "We are drowning in information, while starving for wisdom. > The world henceforth will be run by synthesizers, people able to put together the right information > at the right time, think critically about it, and make important choices wisely. > It went a lot faster with two people digging."

This quote nicely summarize the challenges we face in data visualization. Even though, we have a lot of data available it turns out that we need the ''right information" at the ''right time''. However, we need''think critically" about these data in order to be able to ''make important choices wisely". One of these important decisions concern how we represent the data.

We are especially concerned with ''the visual representation and presentation of data to facilitate understanding"(Kirk, 2016). Representation relates to the visual depiction of your data, whereas the presentation relates to specific design choices of your visual depiction, such as the composition, the colors used, the interactivity supported, and the annotations provided.

When people view your visualization, they go through a process consisting of perceiving, interpreting, and comprehending (Kirk, 2016). In reality, these steps occur in parallel. This first first is simply about perceiving, i.e. reading the chart. People try to understand the main features of the visualizations. In the phase interpreting, these observations are translated into meaning which also involves that people map their interpretation onto their own knowledge about this domain. Especially in situations, where people might not have enough knowledge in the visualized domain, a gap between the observation and the meaning might occur. This gap needs to be recognized and bridged. In the third phase of understanding people reflect on what the interpretation means to themselves. This phase depends especially on your viewers, since what might be a learning for one person, might be cryptic for another.

In the following, we use this framework to discuss three examples for well-received visualization examples.

1.0.1 Visualization Example: Napoleon's March

Napoleon's Russian campaign of 1812, after initial French successes, ended in one of the greatest military disasters in history. The French engineer Charles Minard (1781-1870) illustrated the disastrous outcome of Napoleon's failed Russian campaign. The graph (see Figure XXX) shows the size of the army by the width of the band across the map of the campaign on its outward and return legs, with the temperature on the retreat shown in the line graph below.

The graph starts at the Polish-Russian boarder in June 1812 by showing a thick tan band exhibiting the size of the Grand Army (422,000 men).The width of

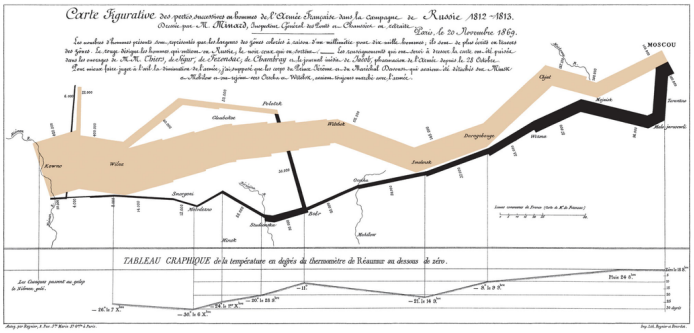


Figure 1.1: Snow's map shows cholera cases in London during the 1854 epidemic. Taken from https://commons.wikimedia.org/wiki/File:Minard.png (Charles Minard (1781-1870), Public domain, via Wikimedia Commons)

the line shows the size of the army at each place on the map. In September 1812 the army reached Moscow with 100,000 men. A darker lower band shows the retreat of the Grand Army. This lower band is also linked to temperature scale and dates at the bottom of the chart. It was a bitterly cold winter and the graphic shows the challenges of crossing rivers. Only 10,000 men arrived finally in Poland.

Minard's visualizations tell a story with multivariate data including the size of the army, its location on a two-dimensional surface, direction of the army's movement, and the temperature on various dates during the retreat from Moscow.

Many consider Minard's original to be the best statistical graph ever drawn.

1.0.2 Visualization Example: Cholera Epidemic in London

Cholera broke out in Broad Street, London, on the evening of August 31, 1854. This outbreak was one of the most severe outbreaks of cholera in London. One of the investigators of this outbreak, John Snow, suggested that water from the municipal pumps may have caused these deaths. Further investigation of the recorded deaths revealed a strong link between cholera and the Broad Street pump. This pump handle was removed by the authorities after being informed by Snow. How did he arrive at his conclusion and could end the epidemic?

In his book ''Visual Explanation" Edward R. Tufte (Tufte, 1997) traced Snow's investigation. He highlights that Snow had a hypothesis, ''a causal theory about how the disease spread". Snow developed this hypothesis from medical analysis and empirical observation. Tufte describes Snow's method by four characteristics. First of all, Snow placed the data in an appropriate context for assessing cause and effect. For this, he created lists ordered by the data of death with the victim's name and the circumstances of their death. However, plotting a time series would not support his reasoning, thus he decided to use a map. He

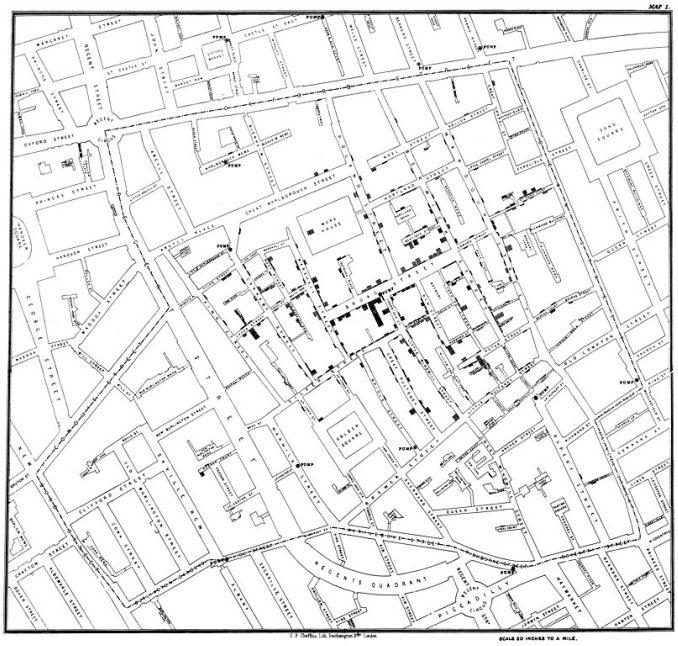


Figure 1.2: Snow's map shows cholera cases in London during the 1854 epidemic. Taken from https://commons.wikimedia.org/wiki/File:Snow-cholera-map-1.jpg (John Snow, Public domain, via Wikimedia Commons)

marked the deaths from cholera by black rectangles and existing pumps by black circles with a white corona. Based on this map, Snow could show determine a relation between cholera and the proximity to the Broad Street pump. Second, Snow also made quantitative comparisons, for getting the whole image, he also investigated who escaped the disease. For this, he interviewed people at tow sides - the workhouse and the brewery. As opposed to the neighborhood, no or little deaths were reported. The workhouse had its own pump, and the employees in the brewery were allowed to drink beer. Third, Snow also thought about alternative explanations and contrary cases, thus, Snow traced deaths of people with no obvious link to the Broad street pump. In a number of cases, he could make connections to these cases and the Broad street pump. Finally, Snow assessed possible errors in the reported numbers, thus, he disclosed how he collected or received the data, and discussed possible deficiencies.

Snow's study was a major event in the history of public health and the founding event of the science of epidemiology.

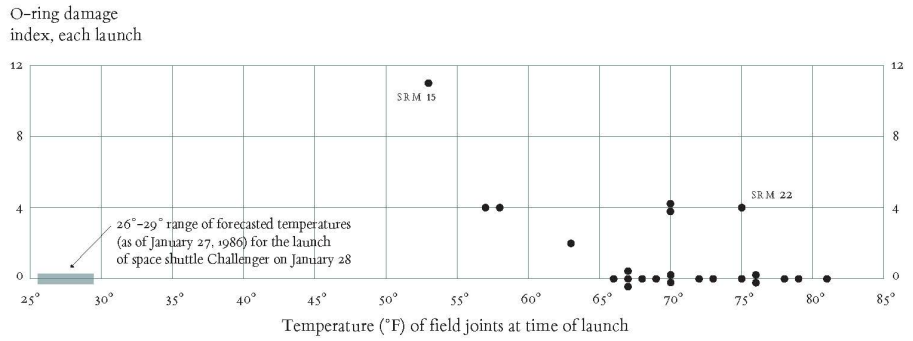


Figure 1.3: Snow's map shows cholera cases in London during the 1854 epidemic. Taken from https://commons.wikimedia.org/wiki/File:Snow-cholera-map-1.jpg (John Snow, Public domain, via Wikimedia Commons)

1.0.3 Visualization Example: Space Shuttle Challenger Disaster

On January 28, 1986 the Space Shuttle Challenger broke apart shortly after the launch and all seven crew members were killed. Tufte (Tufte, 1997) argues that based on the data provided informed decision making was impossible. Even though, engineers sent 13 charts to the NASA to stop the launch, the provided evidence was inconclusive. They had the correct theory but were not able to display this theory in an understandable way, thus, the correlation between temperature and O-ring distress was not clearly communicated. Instead of analyzing and showing the data of all previous shuttle launches, they considered only selected data. Tufte highlights that instead of focusing on selected data the full range should be considered, especially in cases where the database is rather

limited (24 launches prior to Challenger). In their 13 charts, the engineers were not able to convey the existing evidence. It seemed an understanding of the basic principles for effectively communicating data using visualization was missing and this missing understanding led to an incorrect decision. Tufte shows his proposal for an alternative visualization by a graph shown in Figure XX. It is obvious from the data that a launch at 29 degree F is very risky.

In summary, Tufte calls for both the reasoning about statistical evidence and for the design of visualizations and defines six requirements "(1) *documenting* the sources and characteristics of the data, (2) insistently enforcing appropriate *comparisons*, (3) demonstrating mechanisms of *cause and effect*, (4) expressing those mechanisms *quantitatively*, (5) recognizing the inherently *multivariate* nature of analytic problems, and (6) inspecting and evaluating *alternative explanations*." (Tufte, 1997). Visualizations should be "documentary, comparative, causal and explanatory, quantified, multivariate, exploratory, skeptical."(Tufte, 1997).

1.1 Human-Centered Data Visualization

Human-Centered Design (HCD) is an approach to systems design and development that aims to make interactive systems more usable by focusing on the use of the system and applying usability knowledge and techniques (for Standardization, 2010). We use the term "human-centered design" rather than "user-centered design" in order to emphasize that system design can also impact "indirect" stakeholders, not just users as "direct" stakeholders. However, in practice, these terms are often used synonymously.

The norm provides requirements and recommendations for human-centered design principles and activities throughout the life cycle of computer-based interactive systems, i.e., interactive visualization systems. There are a number of key principles that are defined by a norm of the international standard organization (for Standardization, 2010). The design is based upon an explicit understanding of stakeholders, tasks and environments, thus, the design addresses the whole user experience, i.e., considers the whole context. These stakeholders are, therefore, involved throughout design and development. The iterative design process is driven and refined by human-centered evaluation. The design team includes multidisciplinary skills and perspectives.

HCD comprises a number of dimensions (Kling and Star, 1998) that can be used for designing data visualizations: (1) Who does the usage of visualization affect? (*stakeholder*); (2) whose purposes are served in the design process and whose not? (*purpose*); and (3) how will the design of the visualization impact people's experience? What unintended consequences might result from the design and the deployment of the visualization? (*context*).

These dimensions can be translated into a process that consists of seven phases.

Chapter 2

The Process of Visualizing Data

In Chapter 1, we have learned that visualization have helped people from the beginning to make sense of their environment. Before we dive deeper into data visualization, we need to build the necessary methodological foundation. For this, we already introduced human-centered design (see Section 1); however, in this chapter, I want to focus specifically on the process of visualizing data. In general, we can differentiate two motivations for visualization design: a problem-driven and a technique driven design (Munzner, 2014). In the former case, a visualization designer tackles a real-world problem of specific users and attempt to design a solution that helps them work more effectively. Such problem can often be solved based on existing visual encoding and interaction idioms (see Section 1.1, thus, the main challenge is to understand the problem and translate it into an effective visualization design. In the latter case, a visualization designer has an idea for a new visual encoding, an interaction idiom, or a new algorithm. Sometimes, such ideas emerges during problem-driven visualization design.

2.1 The Process of Visualizing Data

When preparing a data visualization project, we are often wondering where to begin with in the first place? From data collection, cleaning, exploration, analysis and visualization, there is a lot that needs to be done in order to derive an insight from data. As you can imagine, there are many proposed data visualization pipelines (e.g., (Fry, 2008), (Kirk, 2016)). However, I would like to focus on one proposition - the four levels nested model of visualization design (Munzner, 2014). Munzner proposed to divide the problem of visualization design into four cascading levels: (1) the situation level, which contains details

of a specific application domain; (2) the data/task abstraction level, where the domain-specific problems and data are separated from context; (3) the visual encoding/interaction idiom level, where the data are visualized and interaction is added; (4) the algorithmic level, where the algorithm is realized to computationally instantiate these idioms. These levels are nested, which means that if you make a bad choice in the abstraction phase, then even perfect choices at the idiom and algorithm levels will not result in a visualization solution that solves the intended problem. For example, you misunderstand the context, and thus, the needs of your stakeholders, because of that you are focusing on the wrong data that are being visualized with a insufficient idiom. Finally, it could happen that your code is too slow. Visualization design is usually a highly iterative refinement process, in other words, visualization design follows the principle of design as redesign. In the following, I detail each of these levels.

The question arises, how you can tackle these challenges properly. Munzner proposes here an immediate validation and downstream validation, in other words, she recommends to properly reflect on each stage on your design decisions before your enter the next level. Taking this very validation-centered perspective on vis design and if you consider that the design of visualizations follows the principle of design as redesign, then your see the parallels to the human-centered design process. You can easily map the Munzner's levels on the HCD process, which makes it easier to position all the methods you already know in Munzner's model.

2.1.1 The situation level

The **Domain Situation** contains the details of a specific application domain. This level focuses on a specific domain situation, which encompasses a group of target users, their domain of interest, their questions, and their data. A domain relates to a particular field of interest of the target users of a vis tool, for example open access, microbiology, or health care. Each domain usually has its own vocabulary for describing its data and problems, and there is usually some existing workflow of how the data is used to solve their problems. A group of target users can be narrowly defined as a handful of people working at a specific company, or broadly defined as anybody who does research.

Domain Validation Primary threat is the mischaracterizing of the the problem An immediate form of validation is to interview and observe the target audience to verify the characterization. Contextual inquiry is typically better suited for vis designers than silent observation because of the complex cognitive tasks that are targeted. One downstream form of validation is to report the rate at which the tool has been adopted by the target audience. A tool that is actually used by its intended users has reached a different level of success than one that has only been used by its designers.

2.1.2 The data/task abstraction level

The _Data/Task Abstraction___ (What-why-level) separates the domain-specific problems and data from the context. Your goal is to determine which data type would support a visual representation that addresses the user's problem. Abstracting specific domain questions and data into a domain-independent vocabulary. It allows you to identify situations that are similar, even though there are using a very different language. Questions from very different domain situations can map to the same abstract vis tasks. We talked about abstract tasks such as browsing, comparing, and summarizing. The data abstraction level requires you to consider whether and how the same dataset provided by a user should be transformed into another form.

Abstraction Validation The main thread is that the identified task and designed data abstraction do not solve the characterized problems. A immediate validation is that the system must be tested by target users, rather than doing an abstract task specified by the vis system developers. A common downstream form of validation is to have a member of the target user community try the tool in controlled user studies. A more rigorous validation approach for this level is to conduct a field study. Other evaluation methods for visualizations focus on data insight (types of insight visualizations provide and the time it takes to acquire it).

2.1.3 The visual encoding/interaction idiom level

The **Visual Encoding/Interaction Idiom** maps the data and task on a visual coding and adds interaction capabilities. Decision on a specific way to create and manipulate the visual representation of the abstract data, guided by the abstract tasks that you also identified. There are two major concerns at play with idiom design: (1) How to create a single picture of the data? It defines the visual encoding idiom controls exactly what users see. (2) How to manipulate that representation dynamically? The interaction idiom controls how users change what they see.

Idiom Validation Threat is that the chosen idioms are not effective at communicating the desired abstraction to the person using the system. One immediate validation approach is to justify the design of the idiom with respect to known perceptual and cognitive principles by using heuristic evaluation or expert reviews. Downstream validation approaches are * a controlled experiment in a laboratory setting: Evaluating the impact of specific idiom design choices by measuring human performance on abstract tasks or getting qualitative feedback; * presentation of and qualitative discussion of results in the form of still images or videos as usage scenarios; and * quantitative measurement of result images (e.g., number of edge crossings in networks.

2.1.4 The algorithmic level

The **Algorithm** translates the idioms in a concrete programming language. The level involves all of the design choices involved in creating an algorithm. The goal is to efficiently handle the visual encoding and interaction idioms. The nested model emphasizes separating algorithm design, where your primary concerns are about computational issues, from idiom design, where your primary concerns are about human perceptual issues. There is an interplay between these levels. For example, a design that requires something to change dynamically when the user moves the mouse may not be feasible if computing that would take minutes or hours instead of a fraction of a second.

Algorithm Validation The primary threat is that the algorithm is suboptimal in terms of time or memory performance, either to a theoretical minimum or in comparison with previously proposed algorithms. An immediate form of validation is to analyze the computational complexity of the algorithm. The downstream forms of validation: * Measure the wall-clock time and memory performance of the implemented algorithm * Determine what data you should use to test the algorithm (use benchmarks) * Verify the correctness of the algorithm whether through careful testing or formal methods.

2.1.5 Validity of Your Vis Design

We differentiate three types of validity: construct validity, internal validity, and external validity.

For example, if a hypothesis states that ''self-esteem" increases with age, research tracking self-esteem over time from social media must ask whether its assessment of self-esteem from text is actually measuring ''self-esteem" versus other related or unrelated constructs. In other words, are the observed behaviors (such as words used or frequency of posting) driven primarily by self-esteem as opposed to community norms, variations in system functionality, or other individual aspects.

Internal validity or does our analysis correctly lead from the measurements to the conclusions of the study? For example, an analysis of whether self-esteem increases with age may not be internally valid if data cleaning accidentally removes messages expressing confidence; or if machine learned classifiers were inadvertently trained to recognize self-esteem only in younger people. Of course, while we do not dwell on them, researchers should also be aware of more blatant logical errors—e.g., comparing the self-esteem of today's younger population to the self-esteem of today's older population would be consistent with but would not actually prove that self-esteem increases with age.

For example, effects observed on one social media platform may manifest differently on another platform due to platform differences, differing community or cultural norms. This concept includes what is sometimes called ecological validity, which captures the extent to which an artificial situation (constrained

social media platform) properly reflect a broader real-world phenomenon. For example, even after we conclude a successful study of self-esteem in a longitudinal social media dataset, its findings may not generalize to a broader setting because of worries that the kinds of people who self-select into a particular platform are not representative of the broader setting; or that the behaviors they express online may not be representative of their behaviors in other settings.

Each type of Validity has a tradeoff depending on the method applied (see Figure XX).

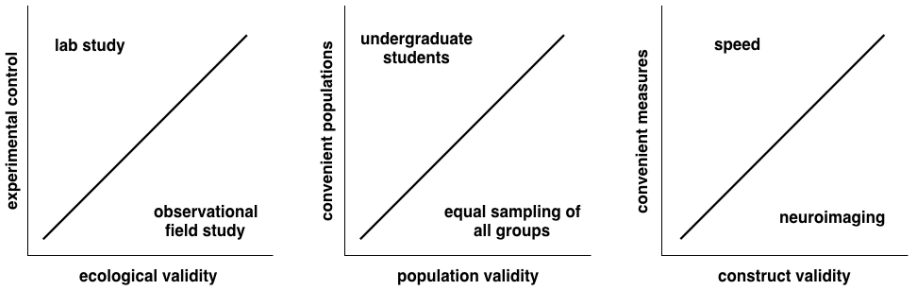


Figure 2.1: Types of Validity and Tradeoff. Taken from (Padilla, 2018)

2.2 Mapping the Human-Centered Design Process and the Nested Model

In Section 1.1, we introduced the human-centered design process; how can we bring the nested model and the human-centered design approach together? We can map the analysis step onto the domain situation level, the idea/concept step onto the data/task abstraction level, the design prototype step onto visual encoding/interaction idiom level and the algorithmic level. What is the advantage of this mapping? We can apply all methods, we know from human-centered design for designing our visualizations.

In her visualization design work, Munzner realized that different ways to get a visualization design wrong (Munzner, 2014). You might identify the wrong problem, by misunderstanding user's needs. You might focus on the wrong data and tasks, thus, you're showing them the wrong thing. You might decide for the wrong idiom, thus, the way you show the data doesn't work. Finally, you might implement the visualization correctly, thus your code is too slow.

2.3 Major Elements of Visualization Design

In the following, we want to focus on the major elements of visualization design the what–why–how questions which translate into a data–task–idiom trio. By focusing on this trio, we need to answer the following questions: * What data

is shown in the views? * Why is the task being performed? * How is the vis idiom constructed in terms of design choices?

In the following, we look into each question in more detail.

2.3.1 Reflecting on Data

Back in 2017, the newspaper ''The Economist" published a story titled, "The world's most valuable resource is no longer oil, but data." Since its publication, the topic has generated a great deal of discussion, and "Data is the new oil" has become a common refrain. How could this happen?

Already in 2008, the Wired magazine editor Chris Anderson titled in an article "The End of Theory," (https://www.wired.com/2008/06/pb-theory/).

> This is a world where massive amounts of data and applied mathematics replace every other tool that might be brought to bear. Out with every theory of human behavior, from linguistics to sociology. […] Who knows why people do what they do? The point is they do it, and we > can track and measure it with unprecedented fidelity. With enough data, the numbers speak for themselves.
>
> — Chris Anderson, WIRED, 2008

Anderson made the claim that "with enough data, the numbers speak for themselves." The article explains several examples of how the abundance of data helps people and companies take decision without even having to understand the meaning of the data itself. His assertion was that the age of Big Data will soon permit data scientists to do analysis at the scale of the population. Statistics is based on the idea that you can infer things about a population by taking a random and representative sample.At the point when we have data collected about an entire population, theory is no longer necessary. We also, he wrote, don't need models and theories to understand why something is happening, just to be able to see that one thing is correlated with another: "Correlation is enough."

As D'Ignazio and Klein (D'ignazio and Klein, 2020) point out, there is a misconception when saying that ''numbers speak for themselves". The assumption is that data are a raw input rather than seeing them as artifacts that have emerged "fully cooked" into the world, birthed out of a complex set of social and political circumstances already existing in the data setting. But data is an output first. After that, it can become an input into a new process, but only with understanding of what the limitations of the collection environment were. "Raw Data" is an Oxymoron. Many data-driven projects aiming towards producing new, future insights forget to interrogate how the data got collected and cooked in the first place.

What is the difference between data, information, and knowledge?

The following three points summarize the essential differences between the three concepts (Aamodt and Nygård, 1995): Data are syntactic entities, i.e., data are patterns with no meaning; they are input to an interpretation process, i.e. to the initial step of decision making. Information is interpreted data, i.e., information is data with meaning; it is the output from data interpretation as well as the input to, and output from, the knowledge-based process of decision making. Knowledge is learned information, i.e., knowledge is information incorporated in an agent's reasoning resources, and made ready for active use within a decision process; it is the output of a learning process. The role of knowledge, in general, is therefore to play the active part in the processes of transforming data into information, deriving other information, and acquiring new knowledge, i.e., to learn. This leads to the following summary of knowledge roles: knowledge is needed to transform data into information; knowledge is needed to derive new information from existing; knowledge is needed to acquire new knowledge, thus is referred to as data interpretation, to as elaboration, and to as learning.

As Donna Harraway emphazised all knowledge is ''situated." (Haraway, 1988) It means that context matters. When we want to create new knowledge based on a given dataset, we have to reflect about the social, cultural, historical and material conditions in which that data was produced, as well as the people who created that data.Rather defining data as objective, that can be taken as it is, we need to connect data back to their context, to better understand existing limitations, but also for example, ethical obligations, or existing privacy concerns. However, we also need to think about our own role when analyzing the data. What is our perspective we bring in and how we decide which part of the data are valuable and which don't. To come back to Chris Anderson. His post was possible also a provocation but when working with data, we need *more* theory, context, and scientific methods, not less. Why? Because data is often created by humans or by software that was designed by humans. Thus, it makes sense to add qualitative data to a dataset.

Thick Data or qualitative data is data brought to light using qualitative, ethnographic research methods that uncover people's emotions, stories, and models of their world (Tricia Wang, 2016). It's the sticky stuff that's difficult to quantify. It comes to us in the form of a small sample size and in return we get an incredible depth of meanings and stories. Thick Data is the opposite of Big Data (or thin data), which is quantitative data at a large scale that involves new technologies around capturing, storing, and analyzing. For Big Data to be analyzable, it must use normalizing, standardizing, defining, clustering, all processes that strips the the data set of context, meaning, and stories. Thick Data can rescue Big Data from the context-loss that comes with the processes of making it usable.

Big Data requires a humongous N to uncover patterns at a large scale while Thick Data requires a small N to see human-centered patterns in depth. Both types of Thick Data relies on human learning, while Big Data relies on machine learning. Thick Data reveals the social context of connections between data

points while Big Data reveals insights with a particular range of quantified data points. Thick Data techniques accepts irreducible complexity, while Big Data techniques isolates variables to identify patterns. Thick Data loses scale while Big Data loses resolution.

Thus it makes sense to take a human-centered design approach. You should think about the audience, the purpose and the context of your research. * Audience: Who are you publishing your research for? * Purpose: How do you want them to use your research? * Context: What factors (under your control) will impact whether/how they use it?

Publishing your research openly shows that you take responsibility for your research. Including the possibility that you might be wrong. It provides transparency around your values, motivations, and assumptions. Having a public audience in mind when designing and publishing your projects encourages you to reflect on your values, motivations, assumptions, and thought process—and how that might influence your project. Thinking in terms of HCD can also help you think of trade-offs in open research. For example, it can help you decide when/what NOT to publish openly!

2.3.1.1 Data Set

What kind of data are you given? What information can you figure out from the data, versus the meanings that you must be told explicitly? What high-level concepts will allow you to split datasets apart into general and useful pieces? To move beyond guesses, you need to know two crosscutting pieces of information about these terms: their semantics and their types. The semantics of the data is its real-world meaning.

A dataset is any collection of data. There are four basic dataset types: tables, networks/trees, spatial (fields, geometry). In real-world situations, complex combinations of these basic types are common.

Consider the concept of a table as a type of record that is independent of any particular visual representation. In (simple flat) tables, each row represents an item of data, and each column is an attribute of the dataset. Each cell in the table is fully specified by the combination of a row and a column and contains a value for that pair. A multidimensional table has a more complex structure since each cell is indexed by multiple keys. It can be a table in a table, which is called a tensor.

Networks are well suited for specifying some kind of relationship between two or more items. An item in a network is often called a node (or vertex). A link (or edge) is a relation between two items. Nodes can have associated attributes, just like items in a table.Links could also have attributes associated with them; these may be partly or wholly disjoint from the node attributes. Networks can also be represented by two tables. Networks with hierarchical structure are more specifically called trees. In contrast to a general network, trees do not

have cycles: each child node has only one parent node pointing to it.

The field dataset type also contains attribute values associated with cells. Each cell in a field contains measurements or calculations from a continuous domain. Continuous phenomena include temperature, pressure, speed, force, and density (or mathematical functions). Continuous data requires careful treatment that takes into account the mathematical questions of sampling, how frequently to take the measurements, and interpolation, how to show values in between the sampled points in a way that does not mislead.

The geometry dataset type specifies information about the shape of items with explicit spatial positions. The items could be points, or one-dimensional lines or curves, or 2D surfaces or regions, or 3D volumes. Spatial data often includes hierarchical structure at multiple scales.

2.3.1.2 What Data Types Should be Differentiated?

An attribute is some specific property that can be measured, observed, or logged. For example, attributes could be salary, price, or protein expression levels. An item is an individual entity that is discrete, such as a row in a simple table. For example, items may be people, stocks, or genes. A link is a relationship between items, typically within a network.
A position is spatial data, providing a location in two-dimensional (2D) or three-dimensional (3D) space. A grid specifies the strategy for sampling continuous data in terms of both geometric and topological relationships between its cells.

2.3.1.3 What Attribute Types Do you Know?

What kind of data are you given? What information can you figure out from the data, versus the meanings that you must be told explicitly? What high-level concepts will allow you to split datasets apart into general and useful pieces?

To move beyond guesses, you need to know two crosscutting pieces of information about these terms: their semantics and their types. The semantics of the data is its real-world meaning.

2.3.2 Reflecting on Tasks

Why Analyze Tasks Abstractly? You need to consider tasks in an abstract form, rather than the domain-specific way that users typically think about them. Transforming task descriptions from domain-specific language into abstract form allows you to reason about similarities and differences between them.

Munzner (Munzner, 2014) differentiated a small set of carefully chosen words to describe why people are using visualization, designed to help you crisply and concisely distinguish between different goals. We differentiate a set has verbs describing actions, and nouns describing targets.

Type of attribute	Examples	Appropriate scale	Description
quantitative/ numerical continuous	1.3, 5.7, 83, $1.5x10^{-2}$	continuous	Arbitrary numerical values. These can be integers, rational numbers, or real numbers.
quantitative/ numerical discrete	1, 2, 3, 4	discrete	Numbers in discrete units. These are most commonly but not necessarily integers. For example, the numbers 0.5, 1.0, 1.5 could also be treated as discrete if intermediate values cannot exist in the given dataset.
qualitative/categorical unordered	dog, cat, fish	discrete	Categories without order. These are discrete and unique categories that have no inherent order. These variables are also called factors.
qualitative/categorical ordered	good, fair, poor	discrete	Categories with order. These are discrete and unique categories with an order. For example, "fair" always lies between "good" and "poor". These variables are also called ordered factors.
date or time	Jan. 5 2018, 8:03am	continuous or discrete	Specific days and/or times. Also generic dates, such as July 4 or Dec. 25 (without year).
text	The quick brown fox jumps over the lazy dog.	none, or discrete	Free-form text. Can be treated as categorical if needed.

Figure 2.2: Types of variables encountered in typical data visualization scenarios. Taken from (https://clauswilke.com/dataviz/aesthetic-mapping.html)

2.3.2.1 User Goals are Defined by Actions

We can define three levels of action. The high-level choices describe how the visualisation is being used to analyze, either to consume existing data or to also produce additional data. The mid-level choices cover what kind of search is involved, in terms of whether the target and location are known or not. The low-level choices pertain to the kind of query: does the user need to identify one target, compare some targets, or summarize all of the targets? Decisions at each of these three levels are independent, and it is usually useful to describe actions at all three levels.

Action: Analyze for Consumption or Production In contrast to the use of vis only for the consumption of existing information, in the production case the intention of the user is to generate new material. Often, the goal in production is to produce output that is immediately used as input for a next instance. Sometimes the user intends to use this new material for some other vision-related task, such as discovery or presentation. Sometimes the intended use of the new material is for another purpose that does not require a vis, such as downstream analysis with non-visual tools. There are three types of production goals: Annotate, Record, and Derive.

Action: Search and their Classification All high-level analysis cases require the user to search for items of interest within the vis as a middle-level target. The classification of search into four alternatives is broken down according to whether the identity and location of the search target is already known or not. If users already know both what they're looking for and where it is, then the search type is simply lookup. If users want to find a known target at an unknown location, the search type is locate, that is, find out where the specific object is. If users don't know exactly what they're looking for, but they do have a location in mind of where to look for it, the search type is browse. If users are not even sure of the location, the search type is explore.

Action: Query A low-level user goal is to query targets at one of three scopes. Once a target or set of targets for a search has been found, a low- level user goal is to query these targets at one of three scopes: identify, compare, or summarize. The progression of these three corresponds to an increase in the amount of search targets under consideration: one, some, or all. That is, identify refers to a single target, compare refers to multiple targets, and summarize refers to the full set of possible targets.

Actions Refer to Targets All actions refer to a target, i.e. an aspect of the data that is of interest to the user. The idea of a goal is explicit in search and query actions. It is more implicitly related to the usage actions, but still relevant: for example, what the user presents or discovers.

Tasks are defined by a {action, target} pairs, for example, discover distribution, compare trends, locate outliers, browse topology.

2.3.3 The How of Visualization Design - At A Glance

Coming Soon

Chapter 3

Understanding your Data

By building on the Nested odel of Munzner (Munzner, 2014), we have realized how important it is to understand the context of the data origin and the data at hand. In this chapter, we focus on the data, because many data viz project start with so-called ''found data". These are data sets that are openly available on the internet, data sets in which creating you were not involved. The increasing use of data everywhere requires to think about data literacy, inclusion, and fairness to ensure that data creates value (Koesten and Simperl, 2021). However, data is often reused, thus, we need to reflect on where data has been created. Koesten & Simperl (Koesten and Simperl, 2021) differentiate three main activities to interact with data: inspecting, engaging with the data, and placing data in context.

Thus, in order to understand, whether data are valuable for your research question and which questions you can really tackle with these data, you need an understanding of its origin (the context of creation) and an understanding of its structure.

3.1 Understanding the Data Context

People's perception of what constitutes good-quality data changed as they engaged with the data. Koesten & Simperl (Koesten and Simperl, 2021) highlight the importance of engagement around datasets, including discussions, feedback, reviews, ratings, and means to contact data creators. User communities and peer support can complement documentation efforts and make dataset maintenance sustainable. They, furthermore, propose the three activities:

1. Explore the environment of the dataset's creation (e.g., a study setup or the conditions surrounding data collection, with timeframes, geospatial boundaries, or configurations of collection devices).

2. Explore the norms of the discipline in which the data was collected, including methods of analysis and validation, as well as limitations (e.g., common margins of error).
3. Connect data with the world, gauging how representative it is and reflecting on assumptions about how much it mirrors reality (includes also the question of what might be missing from the data.

Gebru et al. (Gebru et al., 2018) propose ''datasheets" inspired by more robust documentation standards in the electronics industry. Datasheets are meant to improve transparency and accountability of datasets and to be useful to both dataset creators and dataset consumers. For consumer of datasets, datasheets should encourage reflection on the process of creating, distributing, and maintaining a dataset (including benefits and harms). For dataset creators it helps also to reflect on the data and to make more informed decisions about its use. The authors offer guiding questions towards creating datasheets for datasets:

- Motivations: Describe the motivations for creating the dataset, including funding, any specific tasks the authors had in mind, and who the authors are.
- Composition: Describe the composition of the dataset, like what kinds of data are in it, how it was collected, whether labels are associated with the data, and whether the dataset contains sensitive information.
- Collection Process: Describe the data collection process, like how the data was collected, where or who is was collected from, who was involved in the collection process, and, if people are involved, if consent was given for the data to be collected.
- Processing: Whether the data was process or labelled and how it was done.
- Uses: The tasks the dataset is intended to be used for, how it has already been used, and limitations of use. Distribution: How the dataset will be distributed and to who, and any restrictions on distribution.
- Maintenance: Who and how the dataset will be maintained, and if and how others will be able to build on it.

Building on this idea Holland et al. (Holland et al., 2018) proposed the dataset nutrion label. An example is given in Fugure

3.2 Understanding the Data Structure

In this section, we focus on understanding the structure of our data by employing the Exploratory Data Analysis (EDA). EDA is an approach of analyzing data sets to summarize their main characteristics by using data visualizations. In 1970 John Tukey (Tukey, 1977) introduced EDA with this seminal book on this topic. He was an extraordinary scientist who had a profound impact on

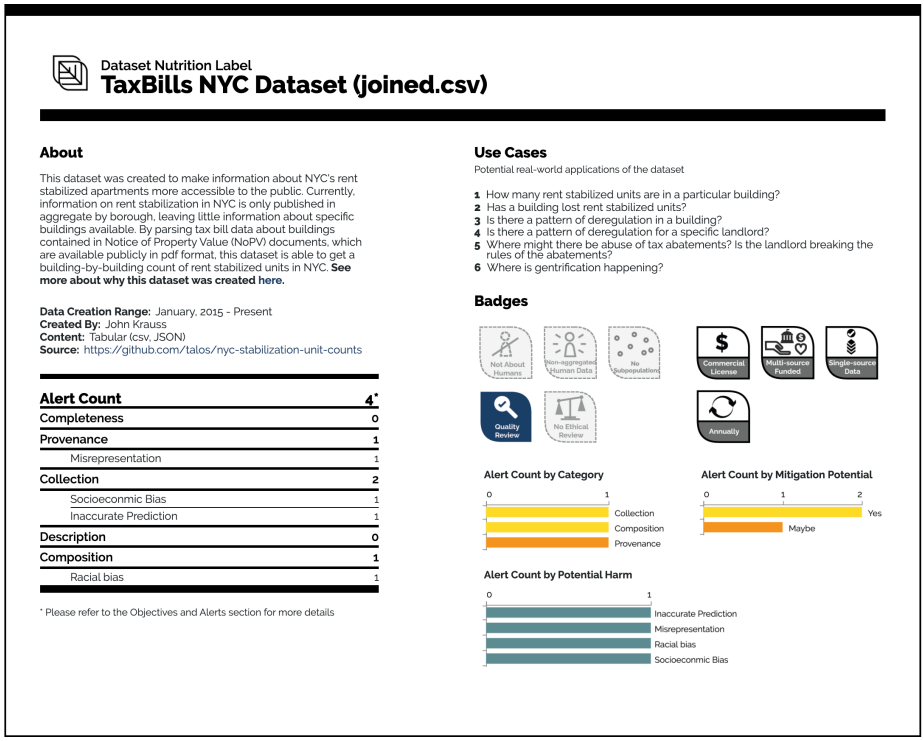


Figure 3.1: Example of the Dataset Nutrion Label (first generation). Taken from https://datanutrition.org/

statistics and computer science[1]. Much of what we cover in EDA today is based on his work. Part of EDA is the so-called initial data analysis (IDA) (https://towardsdatascience.com/a-basic-guide-to-initial-and-exploratory-data-analysis-6d2577dfc242). IDA focuses on identifying data inconsistencies (e.g., missing values) and the description of the data properties; thus, EDA encompasses IDA.

EDA allows the data analysts to achieve a richer qualitative understanding by ''looking at data to see what it seems to say". Explorative Data Analysis should be understood as an iterative process that supports: * the search for answers by visualizing, transforming, and modeling your data, * the generation of hypotheses about what might be happening in a data set, and * the refining of your analysis goals or the generation of additional goals.

This step should not be underestimated since data analysts spend much of their time (sometimes 80% or more) cleaning and formatting data to make it suitable for analysis, then actually carrying out the analysis.

EDA is based on three principles: (1) Continuous openness and re-expression, (2) Initial skepticism, and (3) Exploratory versus confirmatory. Rather than immediately imposing a model on the data that may obscure important details, EDA analysts try to find patterns in the data and describe them with simple summary statistics (descriptive statistics). It may take several iterations for the analyst to reach a satisfactory summary or ''smoothing" of the data[2] Re-expressions or transformations of the data are essential for smoothing because they help the analyst identify new patterns. Because EDA analysts assume that there is no uniquely correct numerical summary of a data set, they are very skeptical of initial numerical summaries. Numerical summaries and smoothings are constantly tested against the raw data to ensure that they adequately represent the data. To identify patterns and look for data points that do not fit the smooth part (outliers), EDA analysts rely heavily on visualization. By supporting data exploration, EDA helps researchers generate hypotheses. These hypotheses can later be tested with formal confirmatory procedures using inferential statistics.

In summary, your goal during the EDA is to develop an understanding of your data. The easiest way to accomplish this is to use questions to guide your investigation. When you ask a question, the question focuses your attention on a particular part of your data set and helps you decide which graphs, models, or transformations to make.

EDA is a creative process (Wickham and Grolemund, 2017), thus the key to asking meaningful questions is to generate a large number of questions. Of course, it is very challenging to generate these questions at the beginning because you are not familiar with the dataset. On the other hand, each new question

[1] I highly recommend reading more about him, for example in https://www.stat.berkeley.edu/~brill/Papers/life.pdf .

[2] The so-called "smooth part of a data set" is the variability that the analyst has accounted for so far, while the "rough" part is the variability that remains unexplained.

you ask will expose you to a new aspect of your data and increase your chance of discovery. You can quickly break down the most interesting parts of your data - and develop a thought-provoking set of questions - if you follow each question with a new question based on your findings. This challenge has been already formulated by Tukey:

> Far better an approximate answer to the right question, which is often vague, than an exact answer to the wrong question, which can always be made precise. — John Tukey (The future of data analysis. Annals of Mathematical Statistics 33 (1), (1962), page 13)

There is no rule about what questions you should ask to guide your research. However, two types of questions will always be useful for making discoveries in your data. You can phrase these questions loosely as (1) What kind of variation occurs within my variables? and (2) What kind of co-variation occurs between my variables?

3.2.1 Using R for Data Exploration

In the following, we address these two questions based on the example of Héctor Corrada Bravo from the EDA chapter of his course on ''Introduction to Data Science" from the Center for Bioinformatics and Computational Biology from the Univ. of Maryland.

We employ the GNU R which is a widespread tool for statistical analysis. However, you can follow these steps with any programming language at hand. I would like to provide you an methodological understanding of how to explore data, rather than provide an introduction into R (http://www.r-project.org/) which is a GNU project, thus, R is Free Software under the terms of GPL. There are over 2,000 user-contributed packages available at R CRAN (https://cran.r-project.org/) with packages for specific functions or specific areas of study. It has an excellent integration with DBs (MySQL, SQLite) and automation based on scripts is easy. Furthermore, the graphical user interface RStudio (https://www.rstudio.com/) makes its usage very convenient. R is an interpreted language. It supports procedural programming with functions and, for some functions, object-oriented programming with generic functions. A generic function acts differently depending on the type of arguments passed to it, for example, R has a generic print() function that can print almost every type of object in R with a simple ''print(objectname)" syntax. A Base R Cheat Sheet can be found here.

3.2.2 Visualizing Data

In the following, we use the on-time data for all flights that departed NYC, i.e., JFK, LGA or EWR, in 2013. The Bureau of transportation statistics has released these data, and it was included into R. Let's get an overview about this dataset.

```
library(nycflights13)
library(skimr)

# Show the internal structure of the R object (= flights)
str(flights)
```

```
## tibble [336,776 x 19] (S3: tbl_df/tbl/data.frame)
##  $ year          : int [1:336776] 2013 2013 2013 2013 2013 2013 2013 2013 2013 2013
##  $ month         : int [1:336776] 1 1 1 1 1 1 1 1 1 ...
##  $ day           : int [1:336776] 1 1 1 1 1 1 1 1 1 ...
##  $ dep_time      : int [1:336776] 517 533 542 544 554 554 555 557 557 558 ...
##  $ sched_dep_time: int [1:336776] 515 529 540 545 600 558 600 600 600 600 ...
##  $ dep_delay     : num [1:336776] 2 4 2 -1 -6 -4 -5 -3 -3 -2 ...
##  $ arr_time      : int [1:336776] 830 850 923 1004 812 740 913 709 838 753 ...
##  $ sched_arr_time: int [1:336776] 819 830 850 1022 837 728 854 723 846 745 ...
##  $ arr_delay     : num [1:336776] 11 20 33 -18 -25 12 19 -14 -8 8 ...
##  $ carrier       : chr [1:336776] "UA" "UA" "AA" "B6" ...
##  $ flight        : int [1:336776] 1545 1714 1141 725 461 1696 507 5708 79 301 ...
##  $ tailnum       : chr [1:336776] "N14228" "N24211" "N619AA" "N804JB" ...
##  $ origin        : chr [1:336776] "EWR" "LGA" "JFK" "JFK" ...
##  $ dest          : chr [1:336776] "IAH" "IAH" "MIA" "BQN" ...
##  $ air_time      : num [1:336776] 227 227 160 183 116 150 158 53 140 138 ...
##  $ distance      : num [1:336776] 1400 1416 1089 1576 762 ...
##  $ hour          : num [1:336776] 5 5 5 5 6 5 6 6 6 6 ...
##  $ minute        : num [1:336776] 15 29 40 45 0 58 0 0 0 0 ...
##  $ time_hour     : POSIXct[1:336776], format: "2013-01-01 05:00:00" "2013-01-01 05:0
```

The first line shows the dimension of your data frame[3], and then each of the columns (attributes) and show with their respective datatype.

Understanding the structure of the dataset is quite useful, since it allows you to get an overview on the available data types. A good understanding of the different data types is an important prerequisite for EDA, because you can use certain statistical measurements only for certain data types. You also need to know which data type you are dealing with in order to choose the right visualization method. Think of data types as a way to categorize different types of variables. We already discussed different types of variables in Section 2.3.1.3.

For setting up the pipeline it makes sense to work with a subset only, thus, we sample from the available data 10 percent. Furthermore, I decided to include only those observations that are complete. However, this decision should not be made carelessly.

[3]A dataframe is a list, with each component of that list being a equal length vector. Thus, intuitively, a dataframe is like a matrix with a rows-and-comlumns-structure. However, it differs from a matrix, since each column can having different mode (data type) (Matloff, 2011).

```
library(dplyr)

# Select a sample from the whole data set
fly.sample <- sample_frac(flights, .1) # takes a sample of 10 per cent

# dimensions of the data set
dim(fly.sample)
```

```
## [1] 33678    19
```

```
fly.sample <- fly.sample[complete.cases(fly.sample), ]
dim(fly.sample)
```

```
## [1] 32702    19
```

3.2.3 Scatterplot

The next step is to get a first overview about the data, and for this, we can use a visualization already. For this I use a simple scatterplot.

```
library(ggplot2)
library(tibble)

# Visualize Data 1 - Scatterplot
fly.viz1 <- rowid_to_column(fly.sample)
ggplot(fly.viz1, aes(x=rowid, y=dep_delay)) + geom_point() +
  xlab("Flight ID") + ylab("Departure delay (in min)")
```

This is not very informative because this plot is not structured. However, let us reflect about the visualization for a moment. A scatterplot encodes two quantitative variables using both the vertical and horizontal spatial position channels., and the mark type is necessarily a point. They are highly effective for judging the correlation between two attributes. Scatterplots are often augmented with color coding to show an additional attribute. We talk about these characteristics in detail again.

Table: Characteristics of a scatterplot (Munzner, 2014)

Idiom

Scatterplot	
What: Data	Table: two quantitative value attributes.
How: Encode	Express values with horizontal and vertical spatial position and point marks
Why: Task	Find trends, outliers, distribution, correlation; locate clusters.
Scale	Items: hundreds

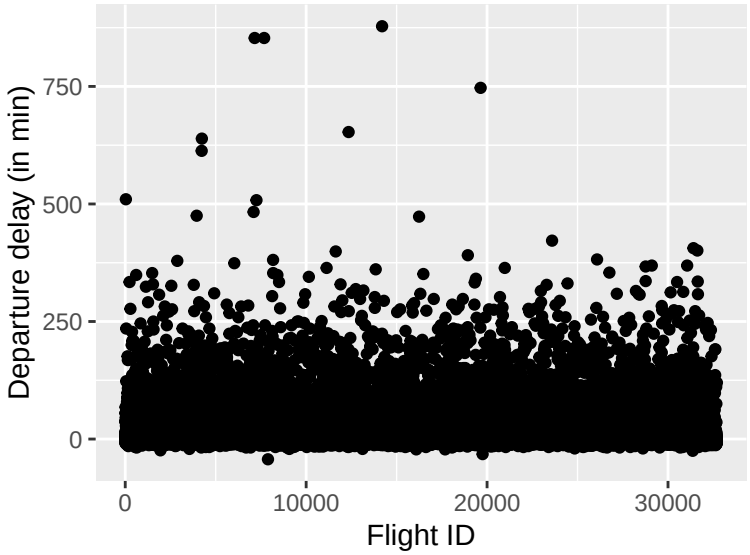


Figure 3.2: Scatterplot of delay times.

Let's sort the values and change the graphical representation to make it easier to see.

```
# Visualize Data - Scatterplot with ordered values

# 'arrange' sorts a variable, here dep_delay, in descending order
fly.viz2 <- arrange(fly.sample, fly.sample$dep_delay)

# create new column with row numbers
fly.viz2 <- rowid_to_column(fly.viz2)

ggplot(fly.viz2, aes(x=rowid, y=dep_delay)) + geom_point() + xlab("Ordered Flight ID")
```

What do you think of this chart? What can you say about flight delay times now? In the following, we focus on the delays only, since many flights seems to be one time.

```
# Remove all flights with no delay
dim(fly.sample)
```

```
## [1] 32702    19
```

```
fly.sample <- subset(fly.sample, dep_delay>0)

dim(fly.sample)
```

```
## [1] 12571    19
```

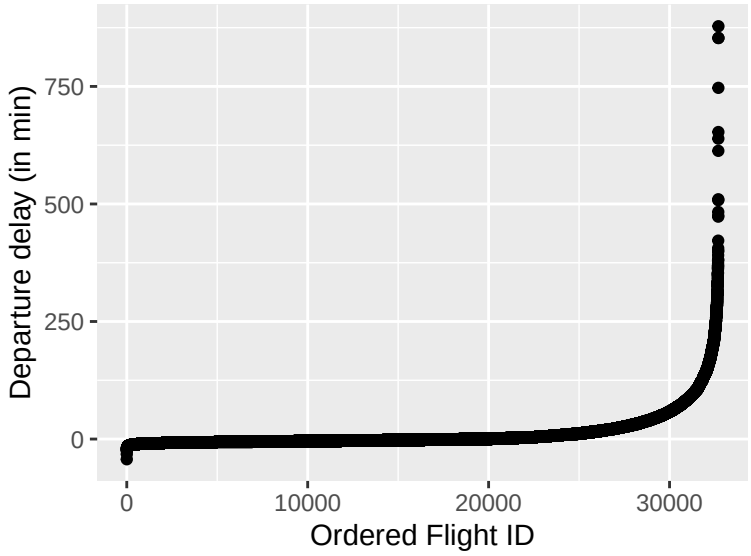


Figure 3.3: Second scatterplot of delay times.

3.2.4 Histogram

Let's now create a graphical summary of these variables. Let's start with a histogram. It divides the range of the dep_delay attribute into equal-sized bins and then plots the number of observations within each bin. What additional information does this new visualization give us about this variable?

The idiom of histograms shows the distribution of elements within an attribute. In the example, you can see a histogram of the weight distribution for all cats in a neighborhood, binned into 5-pound ranges.

The visual coding of a histogram is very similar to bar charts, with a line marker. One difference is that histograms are sometimes displayed with no space between bars to visually imply continuity, while bar charts conversely have spaces between bars to imply discretization. Despite their visual similarity, histograms are very different from bar charts. They do not show the original data but aggregate it.

The number of bins in the histogram can be chosen independently of the number of elements in the data set. The choice of bin size is crucial and tricky: a histogram can look very different depending on the discretization chosen. One possible solution to the problem is to calculate the number of bins based on the features of the data set; another is to provide controls for the user to interactively change the number of bins and see how the histogram changes.

Table 3.2: Characteristics of a histogram (Munzner, 2014)

Idiom	Histogram
What: Data	Table: one quantitative value attribute.
What: Derived	Derived table: one derived ordered key attribute (bin), one derived quantitative value attribute (item count per bin).
How: Encode	Rectilinear Layout. Line mark with aligned position to express derived value attribute. Position: key attribute.

```
# Visualize Data - Histogram
ggplot(fly.sample, aes(x=dep_delay)) + geom_histogram() +
  xlab("Departure delay (in min)") + ylab("Number of Flights")
```

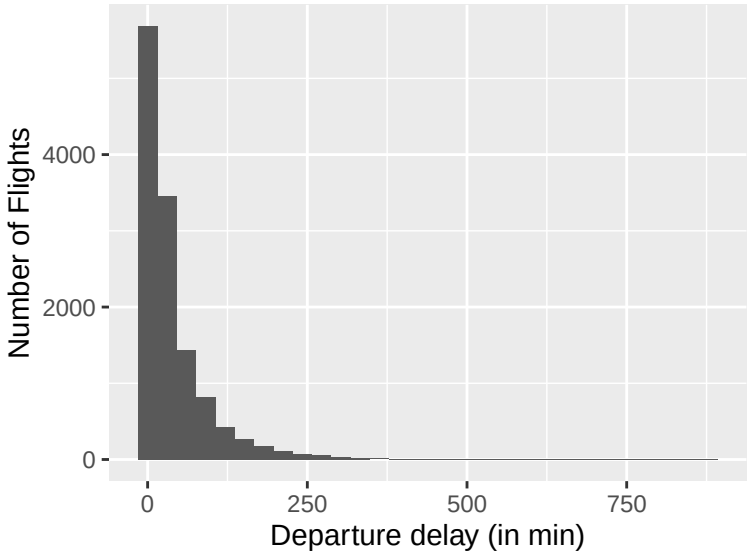
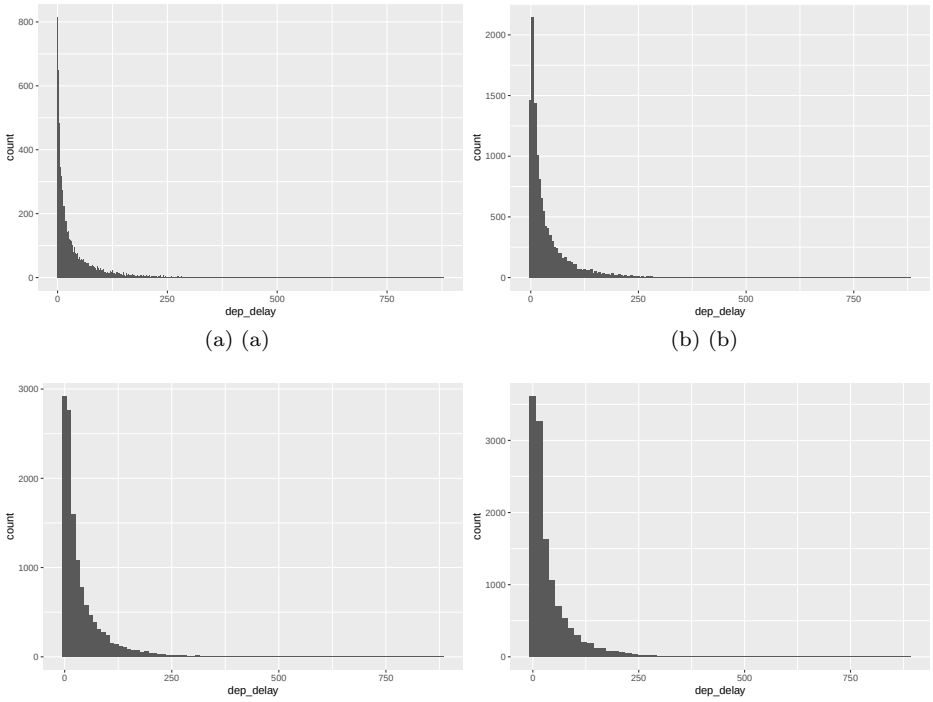


Figure 3.4: Histogram of Delay Times.

In the standard function the number of bins are 30, but of course, you can change them easily. The choice of binwidth significantly affects the resulting plot. Smaller binwidths can make the plot cluttered, but larger binwidths may obscure nuances in the data.

```
#Change the size of the bins
ggplot(fly.sample, aes(x=dep_delay)) + geom_histogram(binwidth = 1)
ggplot(fly.sample, aes(x=dep_delay)) + geom_histogram(binwidth = 5)
ggplot(fly.sample, aes(x=dep_delay)) + geom_histogram(binwidth = 10)
ggplot(fly.sample, aes(x=dep_delay)) + geom_histogram(binwidth = 15)
```



(a) (a) (b) (b)

(c) (c) (d) (d)

Figure 3.5: Histogram of Delay Times.

3.3 Density Plot

A Density Plot is a smoothed, continuous version of a histogram that visualizes the underlying probability distribution of the data by a continuous curve[4]. The peaks of a Density Plot help display where values are concentrated over the interval. The most common form of estimation is known as kernel density estimation. In this method, a continuous curve (the kernel) is drawn at every individual data point and all of these curves are then added together to make a single smooth density estimation. The kernel most often used is a Gaussian (which produces a Gaussian bell curve at each data point). A good explanation, how the density estimation works in general is given on Wikipedia.

Just as is the case with histograms, the exact visual appearance of a density plot depends on the kernel and bandwidth choices. In addition, the choice of the kernel affects the shape of the density curve.

```
# Visualize Data - Density Plot
ggplot(fly.viz2, aes(x=dep_delay)) + geom_density(color="darkblue", fill="lightblue")
```

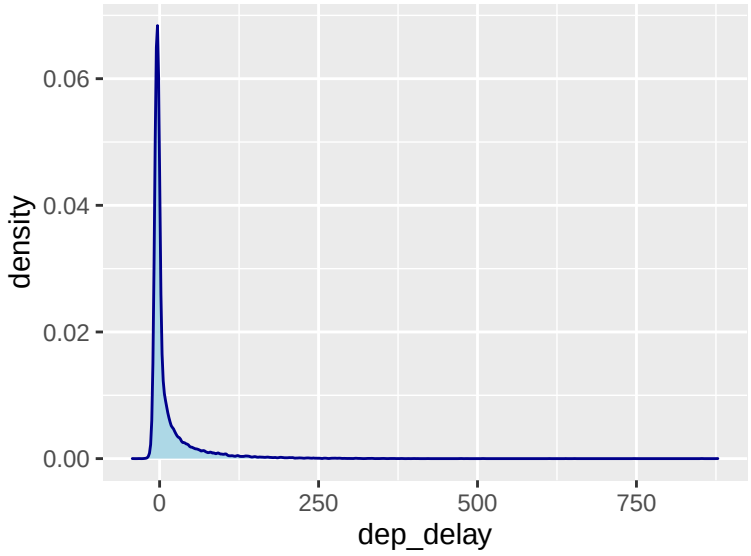


Figure 3.6: Density Plot of Delay Times.

3.4 Box Plots

Another alternative to display the distribution of a continuous variable broken down by a categorical variable is the boxplot. The boxplot is an idiom presenting

[4] An excellent introdcution in the usefulness of this method is given in https://clauswilke.com/dataviz/histograms-density-plots.html

summary statistics for the distribution of a quantitative attribute, using five derived values.

A box that extends from the *25th percentile* (lower quartile, Q1) of the distribution to the *75th percentile* (higher quartile, Q3), a distance called the *interquartile range* (IQR). In the center of the box is a line indicating the *median*, or 50th percentile, of the distribution. These three lines give you an idea of the spread of the distribution and whether the distribution is symmetrical about the median or skewed to one side. Furthermore, a line (or whisker) extending from each end of the box to the furthest non-outlier point (Q1-1.5 x IRQ and Q3+1.5 x IRQ) in the distribution which indicates the *range*. Visual points indicating observations that fall more than 1.5 times the IQR from each edge of the box. These outer points are unusual, so they are plotted individually.

Boxplots are useful when we want to visualize many distributions at once and/or if we are primarily interested in overall shifts among the distributions.

Table 3.3: Characteristics of a boxplot (Munzner, 2014)

Idiom	Boxplot
What: Data	Table: many quantitative value attributes.
What:Derived	Five quantitative attributes for each original attribute, representing its distribution.
Why: Task	Characterize distribution; find others, extremes, averages; identify skew.
How: Encode	One glyph per original attribute expressing derived attribute values using vertical spatial position, with 1D list alignment of glyphs into separated with horizontal spatial position.
How: Reduce	Item aggregation.
Scale	Items: unlimited. Attributes: dozens.

```
# Visualize Data - Box Plot
ggplot(fly.viz2, aes(x='',y=dep_delay)) + geom_boxplot()
```

```
# Visualize Data - Box Plot with log scale
# the function mutate() adds new variables and preserves existing ones
fly.viz2 <- mutate(fly.viz2, min_delay=min(fly.viz2$dep_delay, na.rm=TRUE))
fly.viz2 <- mutate(fly.viz2, log_dep_delay = log(fly.viz2$dep_delay - fly.viz2$min_delay))
ggplot(fly.viz2, aes(x='', y=log_dep_delay)) + geom_boxplot()
```

Now we can start looking at the relationship between pairs of attributes. That is, how are each of the distributional properties we care about (central trend,

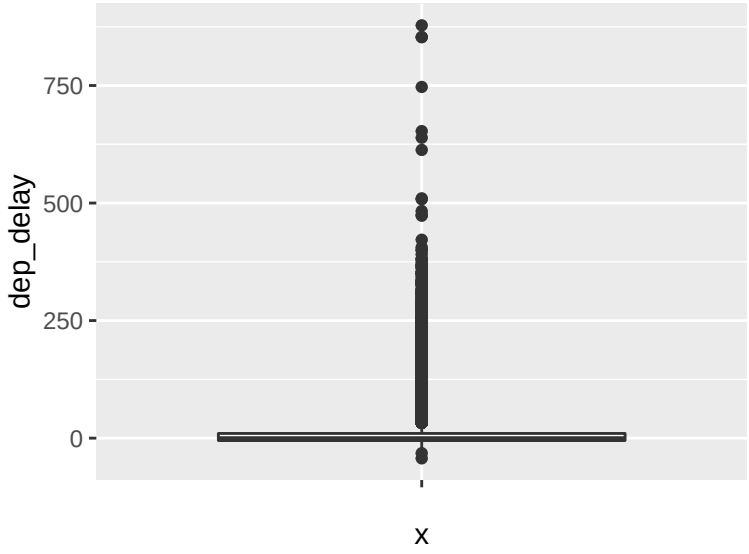


Figure 3.7: Boxplot of Delay Times.

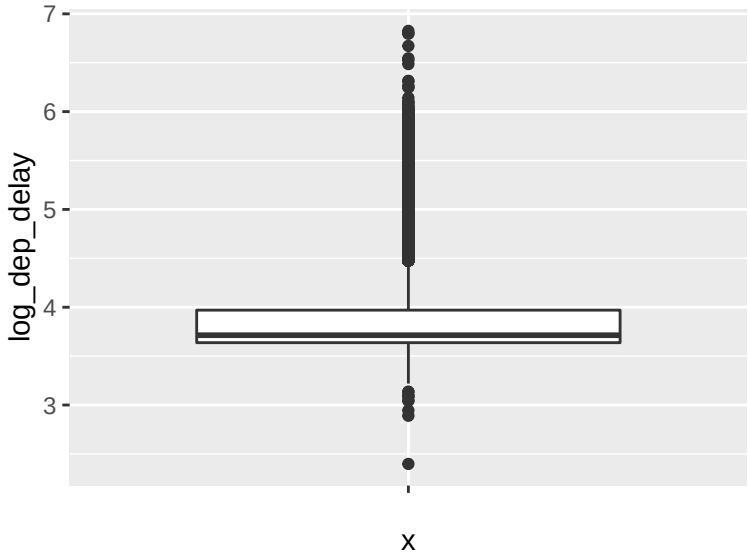


Figure 3.8: Boxplot of Delay Times (log scale).

spread and skew) of the values of an attribute changing based on the value of a different attribute. Suppose we want to see the relationship between departure delay time (a numeric variable), and the airport origin (a categorical variable).

```
# Visualize Data - Box Plot in groups
ggplot(fly.viz2, aes(x=origin, y=log_dep_delay)) + geom_boxplot()
```

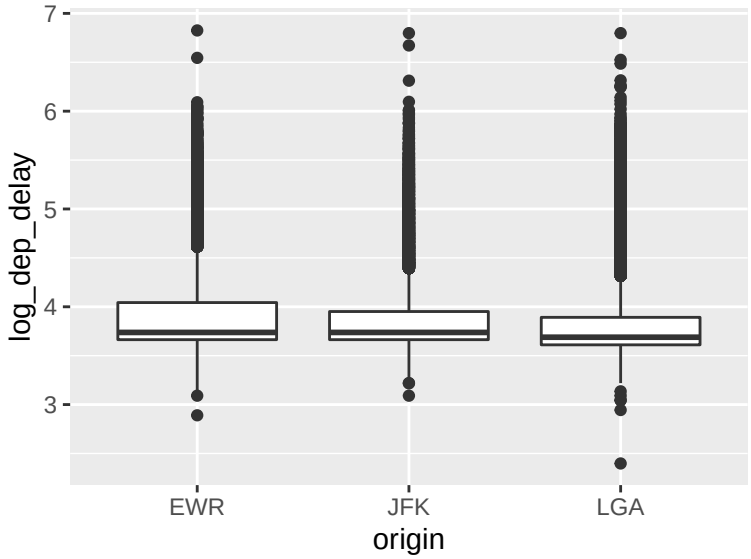


Figure 3.9: Multiple Boxplots of Delay Times depending on airport origine.

For pairs of continuous variables, the most useful visualization is the scatter plot. This gives an idea of how a variable varies (in terms of central trend, variance and skewness) depending on another variable. A scatter plot can be used to show relationship between `dep_delay` and `arr_delay`.

```
# Visualize Data - Scatterplot
ggplot(fly.viz2, aes(x=dep_delay, y=arr_delay)) + geom_point()
```

3.5 Summary Statistics

Let's continue our discussion of exploratory data analysis. In the previous section, we saw ways to visualize attributes (variables) using graphs to begin understanding the properties of the data distribution, an essential and preliminary step in data analysis. In this section, we begin discussing statistical or numerical summaries of data to quantify properties we have observed using visual summaries and plots. Remember that one purpose of EDA is to identify problems in data and understand variable properties. We also want to use EDA to understand the relationship between pairs of variables, such as their correlation or covariance.

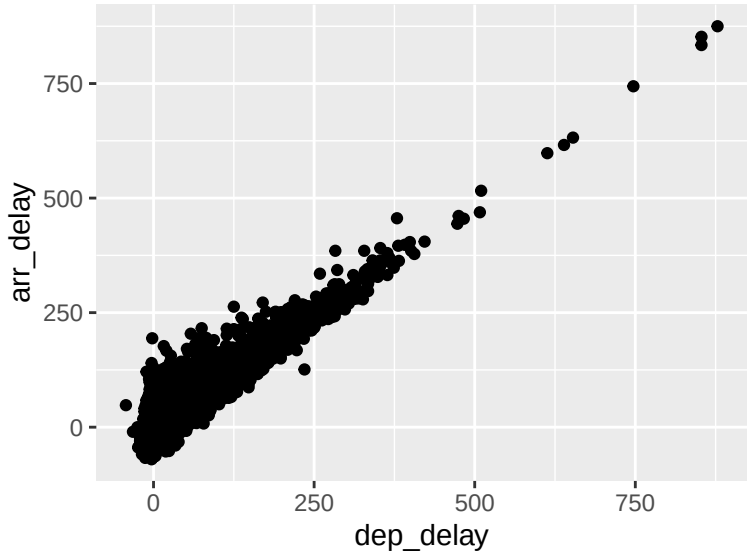


Figure 3.10: Scatterplot of Departure Delay Depending On Arrival Delay.

We differentiate measures of central tendency, i.e., measures of location that describe a tendency of data to center about certain numerical value. Here we have mode, median, and mean. Then we have measures of variability, i.e., dispersion that describe the spread of the data across possible values. To this group the range, interquartile range, variance, and standard deviation belong to. Finally we have measures of shape that relate to the form of the distribution, its skewness.

In this chapter, we use the diamond data set, that contains the prices, carat, color and other attributes of almost 54,000 diamonds.

```
#library(skimr)

# load dataset and show structure
data(diamonds)
#skim(diamonds)

#show attributes only
names(diamonds)
```

```
##  [1] "carat"   "cut"     "color"   "clarity" "depth"   "table"   "price"
##  [8] "x"       "y"       "z"
```

3.5.1 Explore the Distribution

Part of our goal is to understand how the variables are distributed in a given data set. Again, note that we are not using distribution in a formal mathematical (or probabilistic) sense. All the statements we make here are based on the data at hand, so we might call this an empirical distribution of data. Empirical is used here in the sense that it is data resulting from an experiment. Let's take a data set on the properties of diamonds as an example.

```
# dimensions of the data set
ggplot(diamonds, aes(x=depth)) + geom_histogram(bins=100)
```

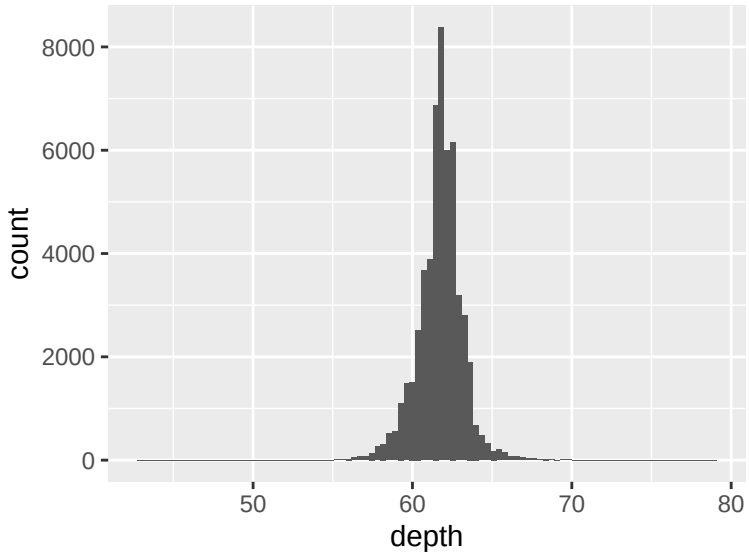


Figure 3.11: Distribution of Depth in the Diamonds Data Set.

3.5.2 Central Tendency

Now that we know the area over which the data is distributed, we can figure out an initial summary of the data over that area. Let's start with the center of the data:

The median is a statistic defined such that half of the data has a smaller value. We can use the notation `x(n/2)` (a rank statistic) to represent the median.

Note that we can use an algorithm based on the quicksort partition scheme to compute the median in linear time (on average).

$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$.

```
# determine median
ggplot(diamonds, aes(x=depth)) + geom_histogram(bins=100) + geom_vline(aes(xintercept=median(dept
```

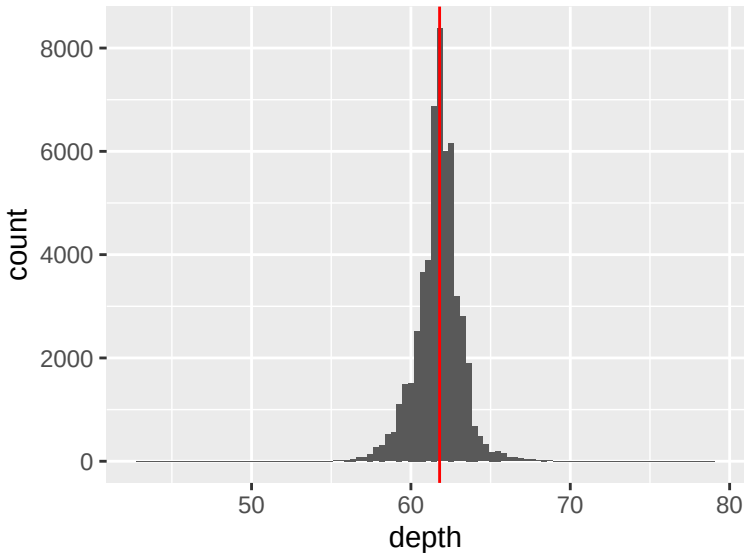


Figure 3.12: Show Mean in Distribution of Depth in the Diamonds Data Set.

Now that we have a measure of the center, we can now discuss how the data is distributed around that center.

3.5.3 Median, and IQR

Median is better measure of central tendency than the mean when we have outliers or/and skewed distribution, e.g., income, housing prices, waiting time. It is the middle observation when data is sorted in the order of magnitude. Thus (about) 50 % of observations are smaller and (about) 50 % are larger than the median. In our dataset:

```
# min and max value
summarize(diamonds, min_depth = min(diamonds$depth), max_depth = max(diamonds$depth))
```

```
## # A tibble: 1 x 2
##   min_depth max_depth
##       <dbl>     <dbl>
## 1        43        79
```

```
# mean vs. median
summarize(diamonds, mean_depth = mean(diamonds$depth), median_depth = median(diamonds$d
```

```
## # A tibble: 1 x 2
##   mean_depth median_depth
##        <dbl>        <dbl>
## 1       61.7         61.8
```

For the mean, we have a convenient way to describe this: the average distance (using the squared difference) from the mean. We call this the variance of the data. vhe Variance is a commonly used statistic for dispersion, but it has the disadvantage that its units are not easily conceptualized (e.g., squared diamond depth). $sd(x) = \frac{1}{n}\sum_{i-1}^{n}(x_i - \bar{x})^2$

A scatter statistic that is in the same units as the data is the standard deviation, which is just the square root of the variance: $var(x) = \sqrt{\frac{1}{n}\sum_{i-1}^{n}(x_i - \bar{x})^2}$

We can also use standard deviations as an interpretable unit for how far a particular data point is from the mean. This is often use in tables.

Just like we saw how the median is a rank statistic used to describe central tendency, we can also use rank statistics to describe spread. For this we use two more rank statistics: the first and third quartiles, x(n/4) and x(3n/4) respectively. We know this already, it is the interquartile range. Also called midspread and is the difference between third and first quartiles (spread in the middle 50%). It is not affected by extreme values.

```
# Summary statistics
range(diamonds$depth)
```

```
## [1] 43 79
```

3.5.4 Outliers

There is no precise way to define and identify outliers. Instead, a subject matter expert must interpret the raw observations and decide whether or not a value is an outlier.

However, we can use estimates of dispersion to identify outlier values in a data set. If we make an estimate of dispersion based on the techniques we have just seen, we can identify values that are unusually far from the center of the distribution. Although this method works relatively well in practice, it presents a fundamental problem. Severe outliers can significantly affect standard deviation-based spread estimates. In particular, the spread estimates are inflated in the presence of severe outliers. To circumvent this problem, we use rank-based spread estimates to identify outliers as such: $outliers_{sd}(x) = \{x_i | |x_j| > \bar{x} + k \times sd(x)\}$

To mitigate the effect of severe outliers you can use rank-based estimates of spread to identify outliers as:

$\text{outliers}_{IQR}(x) = \{x_j | x_j < x_{(1/4)} - k \times IQR(x) \text{ or } x_j > x_{(3/4)} + k \times IQR(x)\}$

This is usually referred to as the Tukey outlier rule, where the multiplier k plays the same role as before. We use IQR here because it is less prone to inflating due to severe outliers in the data set. It also works better for skewed data than the standard deviation based method.

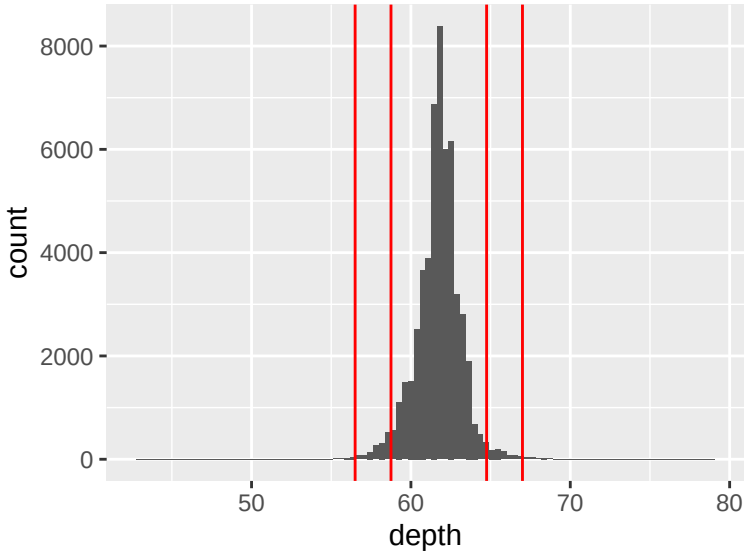


Figure 3.13: Spread of Depth in the Diamonds Data Set.

When does it make sense to remove outliers?

Well, it depends. As you can see in this visualization, removing outliers can distort your analyses by removing important information from the dataset. However, you have to make an informed decision what to do with them because removing outliers is legitimate only for specific reasons. Outliers can provide very interesting information about the subject-area and data collection process. It's essential to understand how outliers occur and whether they might happen again as a normal part of the process or study area. You might be tempted to simply remove outliers to decrease the variability in your data and therefore the increases statistical power, which makes your results to become statistically significant. These temptation might be a reason for the reproducibility crisis in psychology and other disciplines.

3.5.5 Skewness

One final thought. Although there are formal ways to define this precisely, the five-number summary can be used to understand if data are biased. How?

If one of these differences is larger than the other, then it suggests that this data set may be skewed, meaning that the range of data on one side of the median is longer (or shorter) than the range of data on the other side of the median. Do you think our diamond depth data set is biased?

```
# Summary statistics
summary(diamonds$depth)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   43.00   61.00   61.80   61.75   62.50   79.00
```

```
# Count frequencies
table(diamonds$cut)
```

```
##
##      Fair      Good Very Good   Premium     Ideal
##      1610      4906     12082     13791     21551
```

```
# Counts proportions
prop.table(table(diamonds$cut))
```

```
##
##       Fair       Good  Very Good    Premium      Ideal
## 0.02984798 0.09095291 0.22398962 0.25567297 0.39953652
```

3.5.6 Covariance and Correlation

As you have learned, the scatterplot is a visual method for observing relationships between pairs of variables.

```
# Covariance and correlation
diamonds %>%
  ggplot(aes(x=carat, y=price)) +
  geom_point() +
  geom_hline(aes(yintercept = mean(price)), color="blue", lty=2) +
  geom_vline(aes(xintercept = mean(carat)), color="blue", lty=2)
```

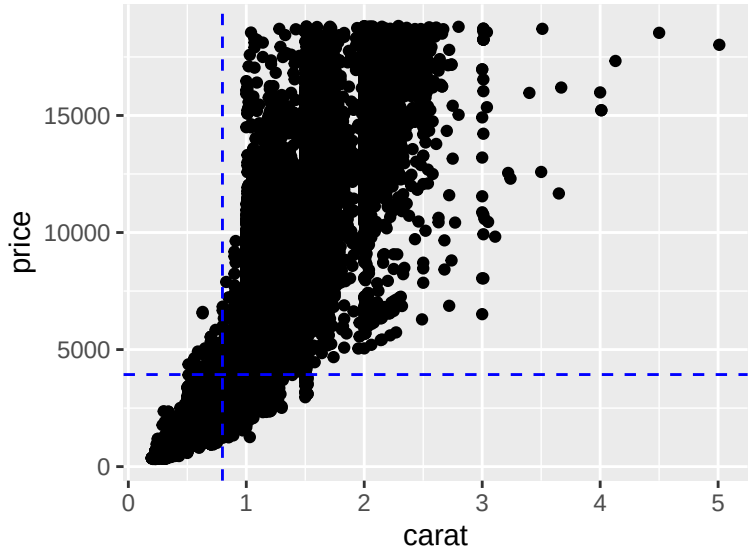


Figure 3.14: Covariance and correlation.

However, how do we quantitatively summarize the relationship between two variables. We need to extend our notion of scatter (or variation of data around the mean) to the notion of covariation: do pairs of variables vary around the mean in the same way or more precisely, does x~i vary in the same direction and on the same scale away from its mean as y~i?

This leads to covariance: $cov(x, y = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})$

Correlation (formally, Pearson's correlation coefficient) summarizes the same relationship in a unit-less way:

$r(x, y) = \frac{con(x,y)}{sd(x)sd(y)}$

Correlation evaluates the direction as well as strength of a relationship between continuous variables. The correlation coefficient can range from -1 to +1, which signifies strong negative to strong positive relation between the variables.

You can think of the correlation as the covariance between x and y after transforming each to the unitless scale of z-scores. Just to recall, a z-score of a sample x is defined as the mean-centered, scale normalized observations: $z_i(x) = \frac{x_i - \bar{x}}{sd(x)}$, thus $r(x, y) = Cov(z(x), z(y))$.

3.5.7 Correlation Matrix

The covariance is a simple summary of association between two variables, but it certainly may not capture the whole "story" when dealing with more than two variables. The most common summary of multivariate relation, is the covariance matrix, but we warn that only the simplest multivariate relations are fully summarized by this matrix.

```
# Correlation Matrix (less meaningful example - just a showcase)

diamonds_corr <- cor(diamonds[,c(1,5,6)])

# Print mcor and round to 2 digits
round(diamonds_corr, digits=2)
```

```
##       carat depth table
## carat  1.00  0.03  0.18
## depth  0.03  1.00 -0.30
## table  0.18 -0.30  1.00
```

```
# Load visualization from package
library(corrplot)
corrplot(diamonds_corr)
```

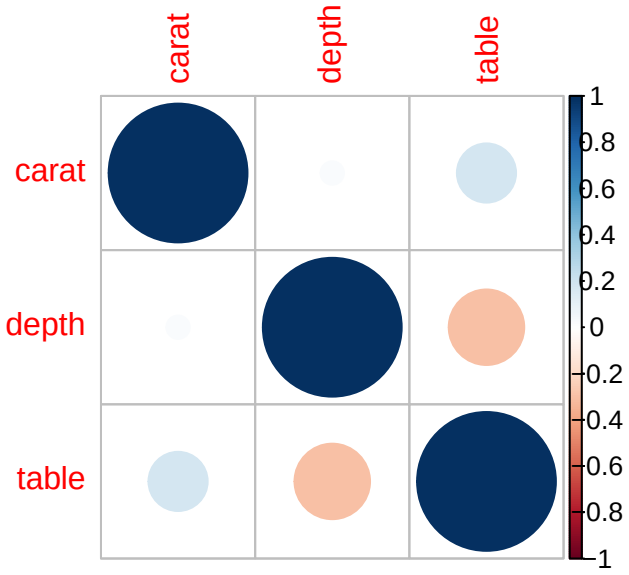


Figure 3.15: Correlation Matrix.

3.6 General Guidelines for EDA

It is difficult to say, what the best practice is in EDA. You find various answer for this, if provide you one: - Begin with a discussion of the "center" of the data, generally based on mean. - Describes how data are distributed. - Follow with a discussion of variability (and of skew if appropriate). - End with a summary evaluation which may have a subjective component (numbers must be interpreted, they don't speak for themselves). - Make sure to use numbers in a description wisely – not too few or too many.

However, each dataset is very special, thus, as often it stays to be an indivdualized process. Therefore, reproducibility is very important during EDA. Computational notebooks such as R Markdown (used here), but also Jupyter notebooks (used in our exercise), Observable (google product) support readability and understandability of your exploration process. This supports Knuth's vision of literate programming.

3.7 Tools and Libraries for Data Exploration

Wrangler provides data-transformation scripts within a visual, direct manipulation interface augmented by predictive models (Kandel et al., 2011). Wrangler is an interactive system for creating data transformations. It uses semantic data types, such as geographic locations, dates, classification codes to support the validation of data and the type conversion. Interactive histories support review, refinement, and annotation of transformation scripts. The researchers provide

a WebApp but also a commercial product.

A similar approach is realized by Open Refine. This tool was formerly developed by Google but it is now maintained by the open source community. It allows you to clean data, transform it from one format into another, or extend you data by additional data from an API.

Besides DataWrangler, I would like to mention the tool Voyager (Wongsuphasawat et al., 2015). The Voyager system is specifically suitable for exploratory visual analysis. You can again test it via a WebApp and the source code is available on Github. And for the sake of completeness, there is also a commercial software Tableau, which can be freely used in the educational context.

Both, Data Wrangler and Voyager are using a formal language - the Vega-Lite visualization grammar. Vega-Lite is a high-level grammar of interactive graphics that provides a concise, declarative JSON syntax to create diagrams for data analysis and presentation. Vega-Lite specifications describe visualizations as "encoding mappings'' from data to properties of graphical marks (e.g., points or bars).

The Vega-Lite compiler automatically produces visualization components including axes, legends, and scales. Vega-Lite supports both data transformations (e.g., aggregation, binning, filtering, sorting) and visual transformations (e.g., stacking and faceting). Moreover, Vega-Lite specifications can be composed into layered and multi-view displays, and made interactive with selections as you can see in the example.

Vega-Lite is being used in another interesting library. On top of the Vega-Lite JSON specification a simple API was built: Altair. It is a declarative statistical visualization library for Python. Source code and a comprehensive documentation as well as Tutorial Notebooks are available on Github.

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