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Deceptive visualizations for time series datasets: an experiment on y-axis manipulation

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Sila Ezgi Biber

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Department of Information and Service Economy
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School of Business

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Sila Ezgi Biber
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Abstract

The importance of understanding the power of visualizations is increasing with their growing popularity in many fields. Deceptive visualizations are visualizations that distort the message in data with or without the intentions of the designer. This study aims to investigate the impact of truncated y-axis usage, a commonly used deception method, in visualizations that represent time series data sets.

The study starts with an in-depth analysis of the existing literature in the visualization field. The theoretical part provides a summary of the existing literature for deceptive visualizations, with topics such as the goals and types of visualizations, visual perception process, the design principles for visualizations, and the types of deceptive visualizations for time series data sets.

In this paper, an empirical analysis of truncated y-axis usage is presented. Also, not-connected axes usage is empirically tested as a solution to prevent the deceptiveness of truncated y-axis usage. An experiment is designed to measure the perceived message from visualizations. In total, six visualizations are created for the experiment. The experiment data is collected with two online questionnaires. In total, over 200 people participated in the study.

The findings suggest that truncated y-axis usage is deceptive for the visualizations that represent time series data sets. Also, not-connected axis usage does not prevent the deceptiveness of truncated y-axis usage in these charts. Moreover, the results of the experiment shows that individual differences (gender, age, and education level) do not change the deceptiveness of truncated y-axis usage.

Keywords visualizations, truncated y-axis, time series data, experiment, visual perception

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1 Introduction

"The assumption that seeing is believing makes us susceptible to visual deceptions."

- Kathleen Hall Jamieson, 2010

Our eyes are trained to see visualizations as evidence, and words as arguments (Zer-Aviv, 2014). A recent study showed that a written claim gets more persuasive when it is accompanied by a graph (Tal & Wansink, 2016). In addition to being persuasive, visualizations motivate people, present new perspectives, and focus the attention of the viewer (Burkhard, 2004). The power of visualizations is not recently noticed. Communicating through visualizations is not a new trend. Visualizations were used to communicate information and convince people already 200 years ago (Kosera, 2012). However, a noteworthy increase in the adoption of visualization as a communication tool, has been witnessed in recent years (Pandey, Manivannan, Nov, Satterthwaite, & Bertini, 2014). It is now possible to design a very insightful and good looking chart in a few seconds by using common software tools (e.g. Microsoft Excel).

The popular use of visualizations as a communication tool, makes it important to understand the dynamics of visual perception. Visual perception rules and the design principles of visualizations are closely related (Ware, 2012). The design of a visualization affects how we perceived the information (Tufte & Graves-Morris, 1983), and it is very easy to create a visualization that deceives the message in the data. Deceptive visualizations may result from a lack of expert knowledge or from the incentive to manipulate the viewers (Pandey, Rall, Satterthwaite, Nov, & Bertini, 2015). Regardless of the intention behind, deceptive visualizations that disrupt the information are not uncommon. Frownfelter-Lohrke & Fulkerson (2001) report that inappropriately designed visualizations appear in 26% to 52% of the annual reports.

There is more than one way to create a deceptive visualization, and deception methods are visualization type specific (Pandey et al., 2015). A design element may be deceptive in one type of visualization, while it does not affect another type. The type of dataset at hand and the goal of the visualization determine the type of visualization (Heer, Bostock, & Ogievetsky, 2010). For narrowing down the scope of the study, this paper will focus on the visualizations that communicate the trends of time series datasets. Time series data is one of the most common forms

of recorded data and approximately 75% of all business graphs display time series data (Few & Principal, 2005). Therefore, studying the visualizations that are used to represent time series datasets is beneficial. In this paper, line charts and column charts will be studied, because they are the most appropriate chart types for representing time series datasets (Few, 2004).

Arunachalam, Pei, & Steinbart (2002) compared the impacts of commonly used deception methods. They found that manipulating the axes of a chart causes the strongest deceptions for time series data. Truncated y-axis means that the y-axis of the chart does not start from zero. Not starting the y-axis from zero is a method for exaggerating the change in data. Truncated y-axis is a very commonly used in charts representing time series data. A study that analyzed 207 annual reports found that 17% of the charts had a truncated y-axis (Frownfelter-Lohrke & Fulkerson, 2001).

In this paper, the ways of representing time series dataset and the design principles will be researched. The aim of the paper is to understand the impact of truncated y-axis usage in line charts and column charts on the perceived message.

1.1 Research Objective and Methods

As mentioned earlier, this study aims to investigate the visual deception method that is commonly used to exaggerate the change in time series data, namely truncated y-axis. The main research question of this study is: ***How does using a truncated y-axis affect the perceived message from the visualizations representing time series data, and how can the deceptiveness of truncated y-axis be prevented?***

To answer this question, an extensive literature review is conducted. The visualization types that are suitable to represent time series datasets are determined, based on the literature review. Moreover, the visual perception process is studied to understand how we perceive information from visualizations. Also, the design principles for the visualizations representing time series data are listed. Finally, deceptive visualizations and the truncated y-axis method are analyzed. At this step, not-connected axes is determined as a design method that may prevent the deceptiveness of truncated y-axis.

In light of the literature review, an experiment is designed to understand the effects of truncated y-axis in line and column charts and to investigate not-connected axes as a way to prevent the deception that is caused from truncated y-axis usage. Data for the experiment is collected

through an online questionnaire. The experiment data is analyzed in two main topics: the impact of truncated y-axis and the impact of not-connected axes. Quantitative analysis methods are used to answer the research questions below:

The impact of truncated y-axis:

1. Does truncated y-axis usage in column charts have an impact on the perceived message?
2. Does truncated y-axis usage in line charts have an impact on the perceived message?

The impact of not-connected axes:

3. Does not-connected axes usage prevent truncated y-axis usage from being deceptive in column charts?
4. Does not-connected axes usage prevent truncated y-axis usage from being deceptive in line charts?

1.2 Structure of the Study

This study has nine sections. The first introductory section introduces the visualization topic, and discusses the objective of the thesis. The following three sections review the existing literature on visualizations and visual deceptions for time series data. The second section gives an overview of the definition, goals, and types of visualizations. The third section covers the visual perception rules by explaining preattentive and attentive processing of information. Design principles for visualizations are also investigated in this section. The fourth section identifies the deceptive visualizations and the types of deceptions in the charts representing time series datasets. Truncated y-axis is also introduced in this section. In addition, the not-connected axes method is reviewed. In the fifth section, the theory of experiment design is introduced.

In the sixth section, the experiment of the study is designed and explained. Also, the structure of the questionnaire and the data collection process are covered. The seventh section presents the empirical findings of the experiment. The eighth section discusses the empirical findings of the study, and investigates the validity and reliability of the results. In addition, suggestions for future studies are shared. Finally, in the last section, a short conclusion is provided to the reader.

2 Visualization Basics

It is important to understand the basics before making a detailed analysis of a subject. This section will introduced the main concepts related to the visualization field. Section 2.1 introduces the definition and a brief history of visualizations. The goals of visualizations are summarized in Section 2.2. In Section 2.3, types of visualizations that are used to represent time series data are introduced. The aim of this chapter is to familiarize the reader with the visualization field.

2.1 Visualization Definition

Gershon, Eick, & Card (1998) defines visualization as "the process of transforming data, information, and knowledge into visual form making use of humans' natural visual capabilities." Another definition of visualization is "the computer assisted use of visual processing to gain understanding" (Card & Mackinlay, 1997). The practice of creating visual displays of abstract data is 200 years old (Tufte & Graves-Morris, 1983). Tufte states that Playfair (1786) introduced the methods to represent economic data with a chart (1983). Figure 1 shows one of the first charts that represent economic data, and this chart was published in Playfair's book in 1786.

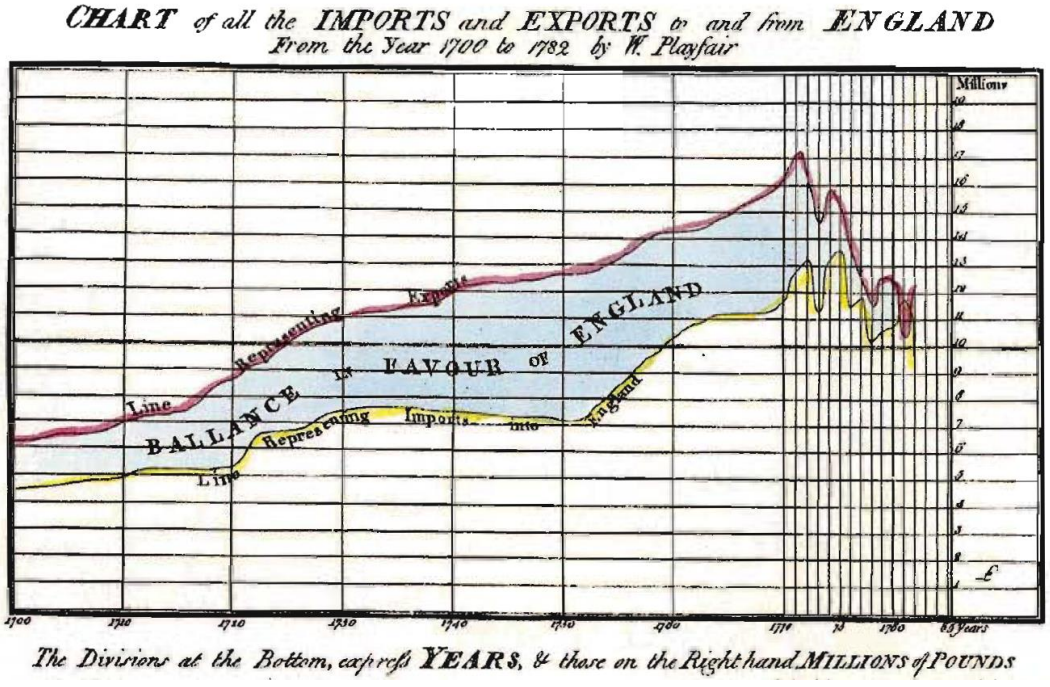


Figure 1. Chart of all the imports and exports to and from England (Playfair, 1786).

The practice of creating visual displays of data had various names other than visualization: graphs (Anscombe, 1973), graphing data (Cleveland, 1985), visual displays (Tufte & Graves-Morris, 1983), data displays (Friendly & Kwan, 2003), and data visualization (Post, Nielson, & Bonneau, 2012). In this paper, the visualization term will be used. The reason for this decision is that the visualization term has been popular and widely used in many recent papers (Burkhard, 2004; Card & Mackinlay, 1997; Card, Mackinlay, & Shneiderman, 1999; Gershon et al., 1998; Plaisant, 2004; Shneiderman & Plaisant, 2006; Ware, 2012).

Information visualization is a broad subject, which brings many different topics together. Figure 2 shows the concept map of the information visualization field. The width of the connections between bubbles shows the strength of the relation between the concepts. As it can be seen from the concept map, Information Visualization is strongly connected to perception, applications, data, graphs, and computer graphics. Applications and computer graphics concepts play a role in the recent improvements in the quality of the visualizations. Also, improvements in these concepts made it very easy to design visualizations. However, the focus will be on data, graph and perception concepts. These areas influence the perceived message from the visualizations.

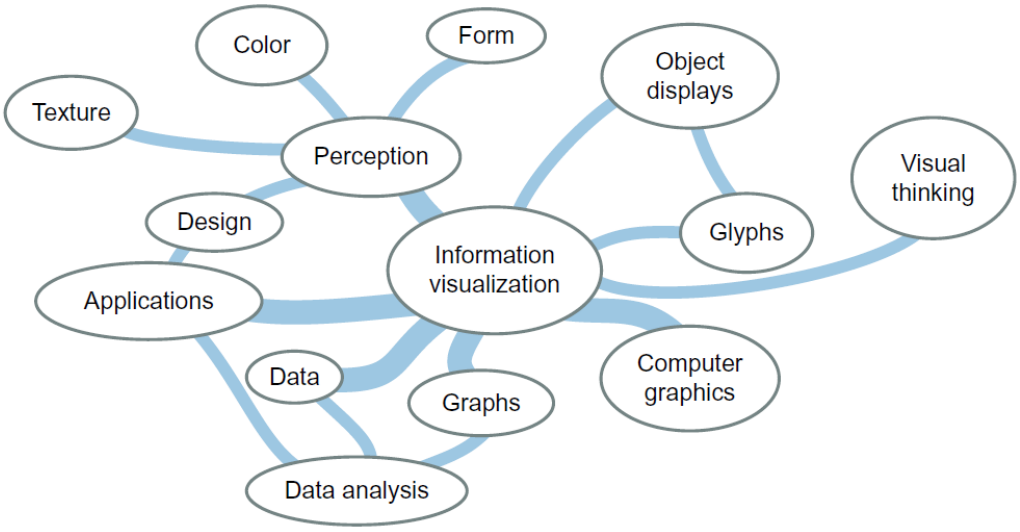


Figure 2. Concept map of Information Visualization (Ware, 2012)

2.2 Visualizations Goals

Defining the goals of the visualizations is needed to evaluate the visualizations. Heer, Bostock, & Ogievetsky (2010, pg. 59) define the goal of visualizations as "to aid our understanding of data by leveraging the human visual system's highly tuned ability to see patterns, spot trends, and identify outliers". This definition is focused on the process of making sense of data by visualizing it. However, there is another important goal of visualizations: communicating the information gathered from the data. Most studies divide the goals of visualizations into two: visual thinking and visual communication (DiBiase, MacEachren, Krygier, & Reeves, 1992), analysis and presentation (Friendly, 2000), analysis and communication (Evergreen & Metzner, 2013), discovery and communication (Gelman & Unwin, 2013). There is a consensus on the main division for goals of visualizations.

Following the classification done by Gelman & Unwin (2013), the visualizations goals will be divided into two, as discovery and communication. In this paper, the focus will be on visualizations with communication goals. However, before focusing on the visualizations with communication goals, visualizations with discovery goals will be introduced. Understanding the differences between the two groups, namely visualizations with communication goals and visualizations with discovery goals, will help to determine the design needs for visualizations according to their goals.

2.2.1 Visualizations with Discovery Goals

Using visualizations to discover the patterns of data is a recent data analysis method. Only in the 1960-70s, statisticians like Tukey started to create visualizations to understand the data better (Kosera, 2012). Anscombe (1973) stated that the attempts to use visualizations for statistical analysis were criticized by many statistics textbooks. This was because the statisticians thought that graphs only showed rough values whereas tables gave exact numbers. To explain the usefulness of graphs Anscombe (1973) introduced four datasets that have the same statistical summary. The datasets and their statistical summary can be seen in Figure 3. For all four datasets, the mean of the *x* values is 9.0, the mean of *y* values is 7.5, and they have almost identical variances, correlations, and regression lines (Anscombe, 1973). These four datasets are now called Anscombe's Quartet (Kosara, 2011).

I		II		III		IV	
X	Y	X	Y	X	Y	X	Y
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

$N = 11$
mean of X's $= 9.0$
mean of Y's $= 7.5$
equation of regression line: $Y = 3 + 0.5X$
standard error of estimate of slope $= 0.118$
$t = 4.24$
sum of squares $X - \overline{X} = 110.0$
regression sum of squares $= 27.50$
residual sum of squares of $Y = 13.75$
correlation coefficient $= .82$
$r^2 = .67$

Figure 3. Anscombe's Quartet (Tufte & Graves-Morris, 1983)

In Figure 4, scatter plots of Anscombe's Quartet can be seen. Even though, they have the same statistical summary, it is very easy to spot the different patterns in each dataset.

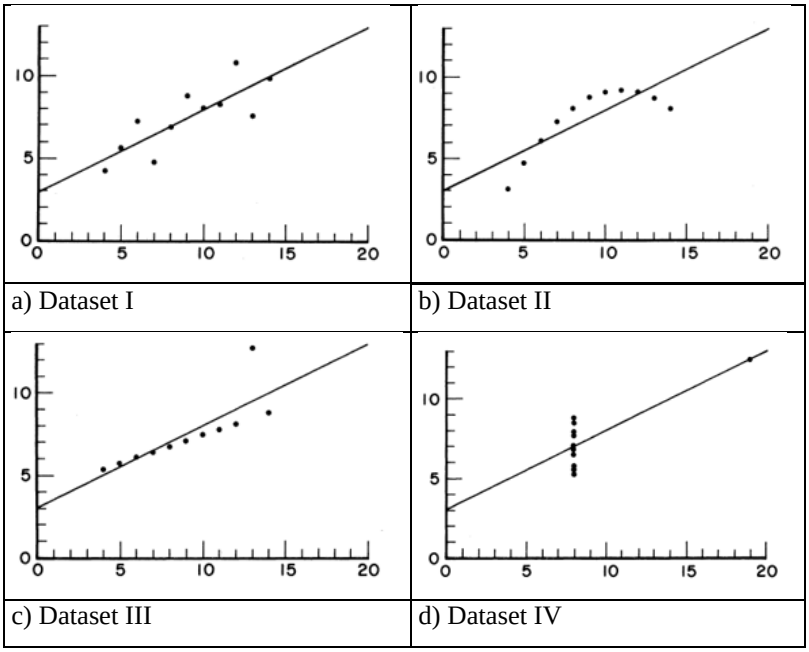


Figure 4. Graphical Display of Anscombe's Quartet (Anscombe, 1973)

Visualizations with discovery goals are designed to get insights about the data. Whether the visualizations are good at communicating the information has not been an important aspect for the designers (Kosera, 2012). However, some discovery visualizations, like the scatter plots in Figure 4, can serve also as a communication tool. Gelman & Ulwin (2013) point out what is important for discovery visualizations as:

> "With presentation graphics you prepare some small number of graphs, which may be viewed by thousands, and with exploratory graphics you prepare thousands of graphs, which are viewed by one person, yourself. Exploratory graphics is all about speed and flexibility and alternative views." (pg. 4)

As Gelman & Ulwin (2013) stated, discovery visualizations are usually seen by and designed for the people who work on the data. The viewers of these visualizations have knowledge about the represented data in the visualization. Also, the viewers are familiar with the visualizations. In addition, these visualizations do not carry a message. Therefore, discovery visualizations will not be the focus of this study.

2.2.2 Visualizations with Communication Goals

Oxford English Dictionary defines communication as "the imparting or exchanging of information by speaking, writing, or using some other medium." (2004). Visualization of data is one of the mediums used to communicate. In fact, communicating the information was the motivation behind the first visualizations in the 1800s (Kosera, 2012).

In his pioneering book, *Commercial and Political Atlas*, William Playfair (1786) used visualizations to illustrate the situation of England's imports compared to exports with different countries. An example of his work can be seen in Figure 5. With this graph, Playfair (1786) successfully communicates the export and import trends of England. It is also very easy to spot that England started to export more than it imported between 1750 and 1760. The goal of this graph is not to find out whether the import to England from Denmark and Norway was higher than the export to Denmark and Norway from England. The goal is to communicate the changes in import and export amounts of England and to show the period in which import/export ratio is in favor of England.

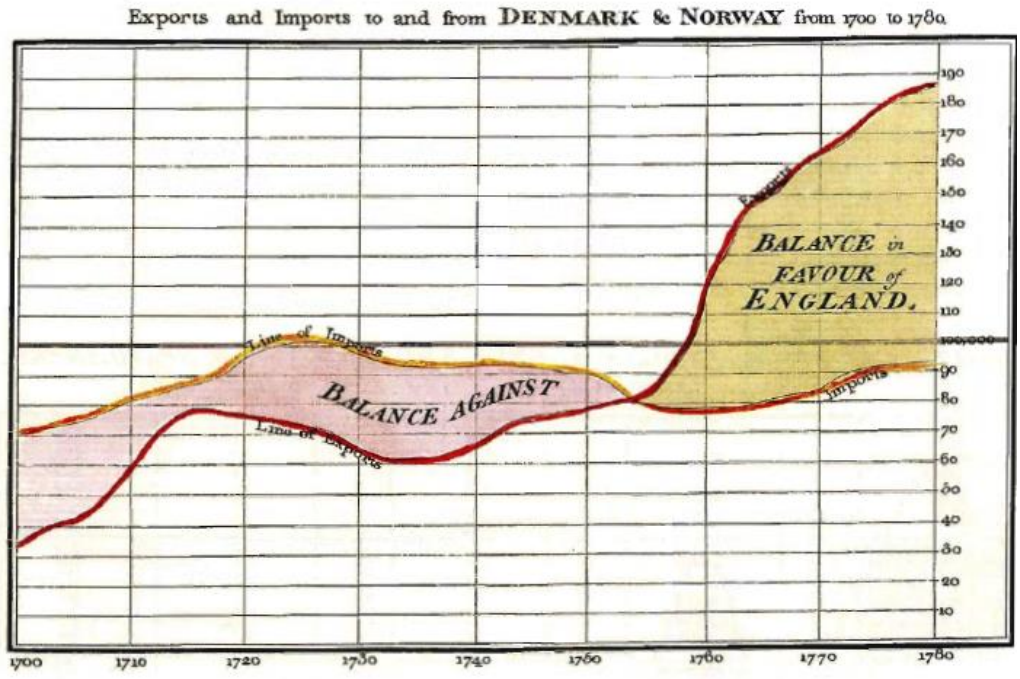


Figure 5. Graph of all the imports and exports between England and Denmark & Norway (Tufte & Graves-Morris, 1983).

Visualizations with communication goals are designed to deliver a message, which is already known by the designer, to the viewers. Visualization are widely used for communication, because visualizations can make messages more accessible, understandable and persuasive (Pandey et al., 2015). These skills are, without any doubt, very important for a communication tool. However, this power also brings the issue that visualizations can be easily used to mislead the audience. Tufte (1983) argues that the visual displays are no different than words in communication, in regard to being manipulative, and they are vulnerable to exploitation by liars.

Visualizations with communication goals are also used to share information with the viewers. For example, visualizations used in business presentations, TV news, newspapers or magazines aim to give a message to their audience. In these situations, the viewers do not always have information about the dataset represented. Also, the viewers are not always familiar with the visualization types. Therefore, these visualizations can be easily manipulated and used to deliver a deceptive message to the audience. To prevent the manipulation, there are basic design principles for visualizations and those will be explained later in the Visual Perception Rules and Design Principles for Visualizations section.

2.3 Types of Visualizations for Time Series Datasets

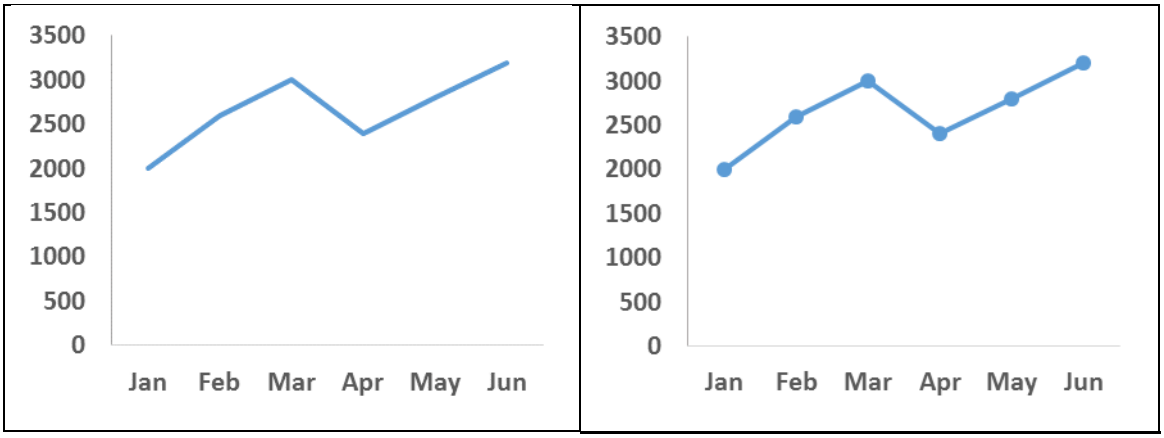
There are many methods for visualizing the data. Moreover, there is a consensus on the importance of the type of visualization for giving correct insights about the data (Friendly, 2000; Heer et al., 2010; Khan & Khan, 2011). Defining the data types and the visualizations techniques for each data type is an important step for understanding the visualization choice. In their article Heer et al. (2010) divide the visualization techniques to groups according to data type, such as time series data, statistical distributions data, map data, hierarchical data, and network data. Few (2004) divides the data types into seven groups as nominal comparison data, time series data, ranking data, part-to-whole data, deviation data, frequency distribution data, and correlation data. In this paper, the focus will be on the visualizations techniques that are used for time series datasets.

Time series data is a set of values changing over time (Heer et al., 2010). Time series data is chosen for this study, because it is one of the most common forms of recorded data (Heer et al., 2010). In addition, many visualizations in the business world are created with time series data. It is estimated that approximately 75% of all business graphs display time series data (Few & Principal, 2005).

Few (2004) recommends three visualization techniques for displaying time series data:

- Line chart
- Point and line chart
- Column chart.

Line charts and column charts are recommended to display time series data by other researchers as well (Jarvenpaa & Dickson, 1988; Robertson, Fernandez, Fisher, Lee, & Stasko, 2008; Steinbart, 1989). The difference between a line chart and a point and line chart is the emphasis on single data points. In Figure 6, a line chart and a point and line chart for the same dataset can be seen. A point and line chart should be used when the single data points are important in addition to the trend in time (Few, 2004). The focus of this study is on displaying the trend in a time series dataset. Therefore, line charts and column charts will be the chosen types of visualizations.



a) Line chart b) Point and line chart

Figure 6. Line Chart and Point and Line Chart comparison

2.3.1 Line Chart

Line chart is a graphical representation of data, which connects the data points over time to illustrate the shape of the data. Line charts are suitable for a series of measurements taken across equal intervals of time (Few & Principal, 2005). Horizontal x-axis should have the time scale and vertical y-axis should have the variable that is measured over time. In Figure 6.a, an example of a line chart can be seen.

> "Lines alone display the overall shape of data as it changes through time more clearly than any other encoding method. Nothing distracts from the pure movement of the data up and down from one value to the next. Lines excel in their ability to show trends and patterns of change." (Few & Principal, 2005, pg. 4)

2.3.2 Column Chart

In column charts, vertical bars are used to display data. The length of a bar displays the value of the data point. Column charts are the most common chart type in business reports (Beattie & Jones, 2002b; Robertson et al., 2008). Column chart is the visualization type that have the most accurate results for evaluating data (Cleveland & McGill, 1984). A column chart is a good way to represent time series data, and it also makes it easy to compare individual data points (Few & Principal, 2005). When we look at the example column chart in Figure 7, it is easy to see the up and down trend of the data as well as the individual value for each month.

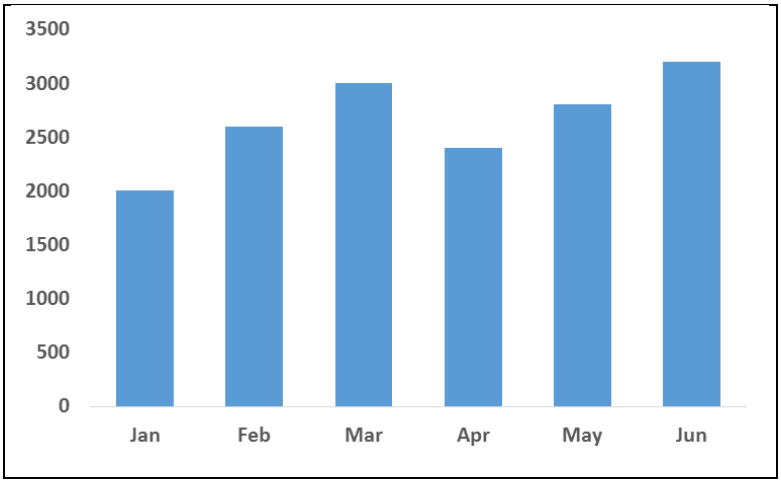
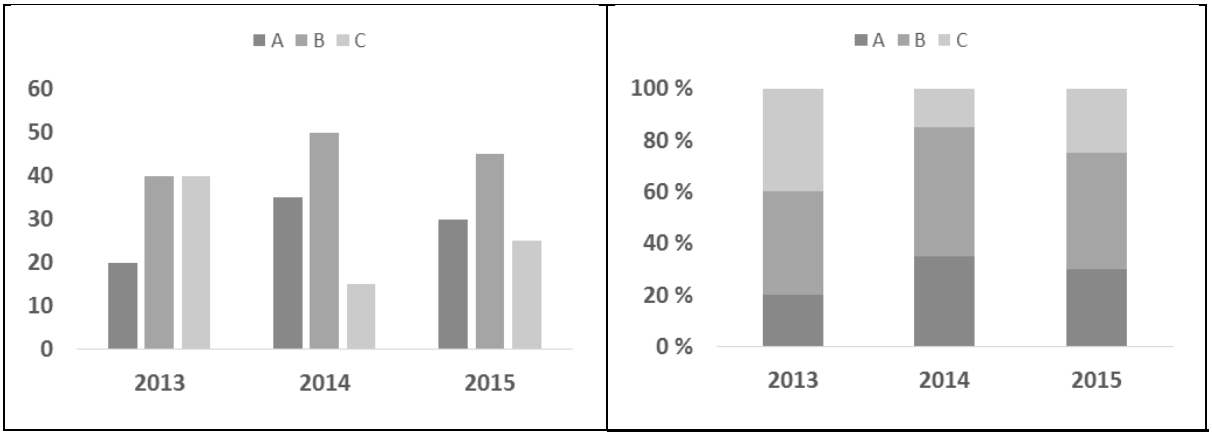


Figure 7. A Column Chart

Column charts are not only used to display time series data, but also various other data types such as nominal comparison data, ranking data and part-to-whole data. For different data types, variations of column charts exist. For instance, stacked column charts are used to show the relationship of individual items to the whole, and clustered column charts are used to compare values across categories. Figure 8 shows a clustered column chart and a stacked column chart, both representing the same dataset. As it can be seen in in Figure 8, these types of column charts are not suitable for time series dataset.



a) Clustered Column Chart b) Stacked Column Chart

Figure 8. Clustered Column Chart and Stacked Column Chart comparision

Column charts are also referred as bar charts in some papers (Heer et al., 2010; Jarvenpaa & Dickson, 1988; Steinbart, 1989). However, there is a difference between a bar chart and a column chart. The difference between two chart types is the rotation of the bars. Bar charts are created with horizontal bars, whereas column charts are created with vertical bars. A bar chart example

can be seen in Figure 9. Bar charts with horizontal bars are ideal to compare the values for different categories or to show ranking, but they are not used to display time series data (Few & Principal, 2005). Bar charts will not be included to the scope of this paper since they are not used for time series datasets.

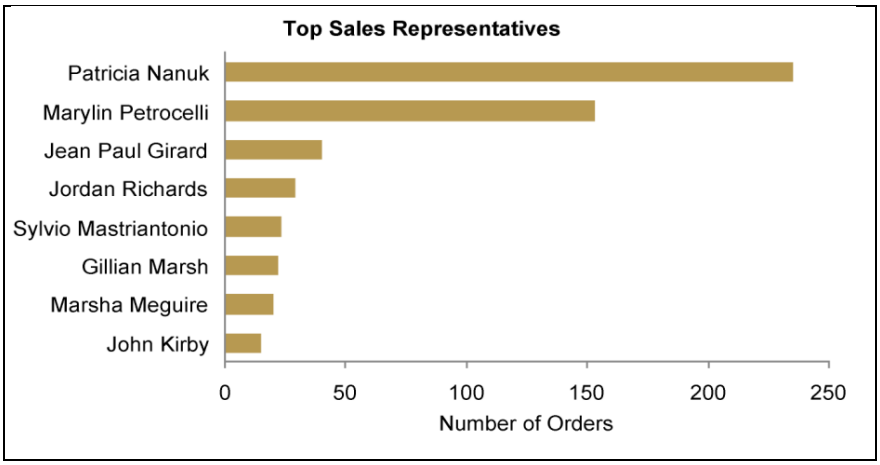


Figure 9. Bar Chart (Few & Principal, 2005)

3 Visual Perception Rules and Design Principles for Visualizations

Design principles for visualizations and visual perception rules are strongly related. The goal of this section is to provide insights into the visual perception process and the design principles for visualizations. We will start with introducing visual perception rules in Section 3.1. That will be followed by design principles for visualizations in Section 3.2.

3.1 Visual Perception Rules

Visualizations have an easy to understand form. However, it is necessary to know how we perceive information from visualizations, to be able to use visualizations effectively. Ware (2012) beautifully explains the importance of visual perception rules:

> "We can easily see patterns presented in certain ways, but if they are presented in other ways they become invisible…The more general point is that when data is presented in certain ways the patterns can be readily perceived. If we can understand how perception works, our knowledge can be translated into guidelines for displaying information. Following perception-based rules, we can present our data in such a way that the important and informative patterns stand out. If we disobey these rules, our data will be incomprehensible or misleading."

There are two main concepts that are necessary to know in order to understand visual perception: preattentive processing and preattentive attributes. Firstly, preattentive processing will be introduced. After that, preattentive attributes will be explained briefly.

3.1.1 Preattentive Processing

Few (2006b) defines preattentive processing as "the early stage of visual perception that rapidly occurs below the level of consciousness, is tuned to detect a specific set of visual attributes". Attentive processing occurs after the preattentive processing, and it is slower than the preattentive processing. It is easy to demonstrate the difference between two processing types with an example. In Figure 10, there is a list of numbers. Try to find the number of times the number 2 appears in the list as quick as possible.

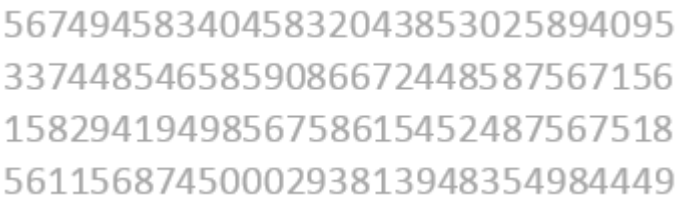


Figure 10. Preattentive processing first task

The correct answer is six. The process of finding the number 2 in the list takes a while, because you have to go through each number. There is not any preattentive attribute to distinguish the number 2 from the other numbers in the list. This is attentive processing. Now, try the same task with the numbers in Figure 11.

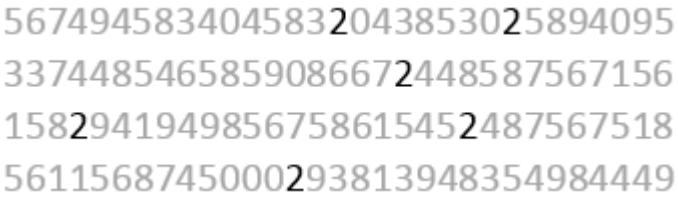


Figure 11. Preattentive processing second task

The cognitive task of finding number 2 in the list is a lot easier when the number list is represented as in Figure 11. The twos are black and the other numbers are gray, which makes the number twos stand out. Noticing the twos in the list is very quick and easy. When the numbers are represented like this, we use preattentive processing instead of attentive processing. To make the visual task preattentive, preattentive attributes are needed. In this example, color intensity is used. Preattentive attributes will be introduced in the next section.

3.1.2 Preattentive Attributes

Ware (2012) states that preattentive attributes can be grouped into four categories as form, color, position, and motion. Under these categories, he lists seventeen preattentive attributes. Few (2006b) selects eleven of those preattentive attributes that are used to visualize information. Since the focus of this paper is on information visualizations, we will follow Few's (2006b) selection of preattentive attributes. Preattentive attributes are illustrated in Figure 12.

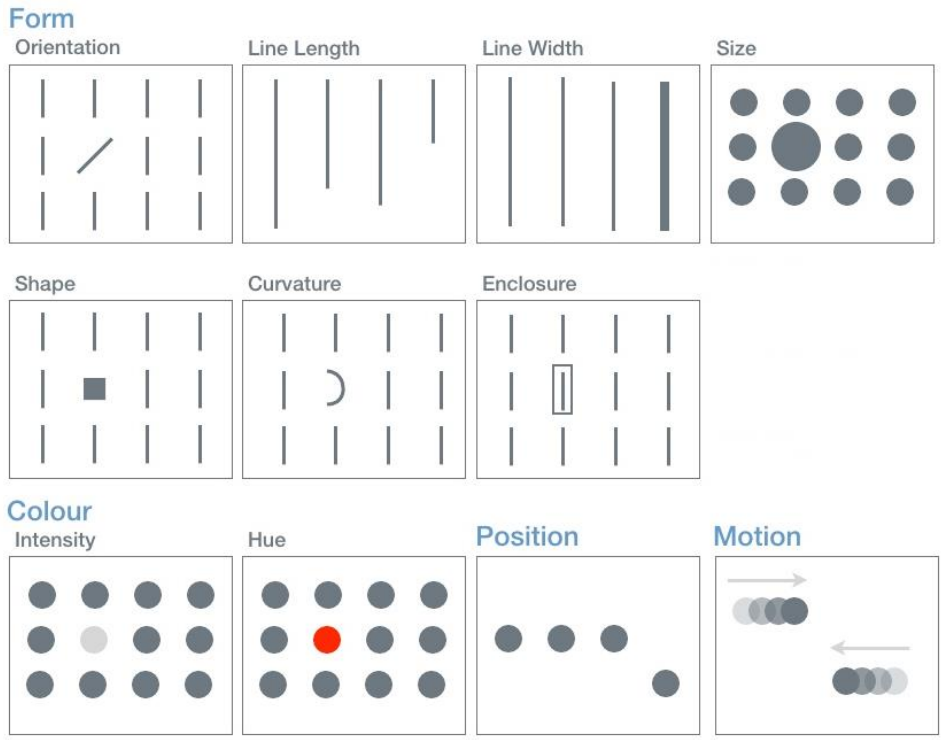


Figure 12. Preattentive attributes (Flink Labs, 2011)

Few (2006b) states that all the attributes presented in Figure 12 can be used to group or highlight information. Some of the attributes are also used to encode quantitative information. The attributes that allow us to perceive one thing greater than others in some way (bigger, taller) can be used to represent the quantitative information. Rest of the attributes can only be used to distinct different categories or to emphasize importance (Few, 2006b). For example, we can compare the size of two squares in a display and conclude that the bigger square represents the bigger amount. However, we cannot make a quantitative comparison between a square and a triangle. If a square and a triangle have the same area size, we would consider them equally big. Few (2006b) points out that line length and position are the best attributes for encoding quantitative data. He adds that size, line width, color intensity, and motion (based on speed) can also be used for quantitative comparisons, but their ability to show the difference is limited. In their extensive research, Cleveland & McGill (1984) conclude that position allows people to make the most accurate comparison of different values. They also state that length is the second most effective way to compare values. These findings explain why line charts and column charts are used to display time series data. Line charts make us compare the position of different data points, and column charts make us compare the length of different data points.

3.2 Design Principles for Visualizations

Design principles for visualizations are studied by many researchers (Bertin, 1983; Few, 2006a; Henry, 1995; Kosslyn, 1994; Tufte & Graves-Morris, 1983; Ware, 2012). The principles introduced by Tufte (1983), in his classical book The Visual Display of Quantitative Information, are widely accepted. His main principles for visualizations are clarity, precision, and efficiency. Based on the prior work in the field, and especially on Tufte's (1983) principles, three specific criteria for graphs of quantitative data are proposed:

1. The numerical values in graphs must match the numbers in the data.
2. The portrayed magnitude of change must match the numerical magnitude of change.
3. Formatting choices should not obscure changes in the data (Steinbart, 1989).

These three principles will be the guidelines used in this thesis, as this study's focus is on quantitative data. This paper will go through each principle and explain their relation to the focus of this study.

3.2.1 The numerical values in graphs must match the numbers in the data.

If a visualization is prepared with different numerical values than the original values in the data, it is not possible to call that visualization accurate. Even the people who do not know much about the design principles or visual perception system expect the correct data from the designers. Steinbart (1989) checked these criteria across the financial statements of Fortune 500 companies, and he did not find any graph that was created with wrong numerical values. Even though this criteria is the most important one in order to have an accurate visual display of any given data, it is not sufficient to ensure that a graph accurately represents data (Steinbart, 1989). Tufte (1983) claims that having the correct data is often used as an excuse for not following other two criteria of visual design.

3.2.2 The portrayed magnitude of change must match the numerical magnitude of change.

Tufte (1983) defines this principle as follows: "the representation of numbers, as physically measured on the surface of the graphic itself, should be directly proportional to the numerical quantities represented." After introducing this principle, Tufte (1983) also developed a formula to

measure the accuracy of the graphs, which is called lie factor. The formula for the lie factor is below:

$$Lie\ Factor = \frac{size\ of\ effect\ shown\ in\ the\ graph}{size\ of\ effect\ in\ data} \quad 1.$$

Size of effect in the formula is measured with the formula below:

$$size\ of\ effect = \frac{|second\ value - first\ value|}{first\ value} \quad 2.$$

It is easier to explain the formula by an example. In Figure 13, a graph from a TV channel can be seen. The graph compares two tax percentages: the first value is 35% and the second value is 39.6%. To be able to calculate the Lie Factor in this graph, we first need to calculate the size of effect in data. If we use equation 2, the size of effect in data is 0.13 ((39.6-35)/35).

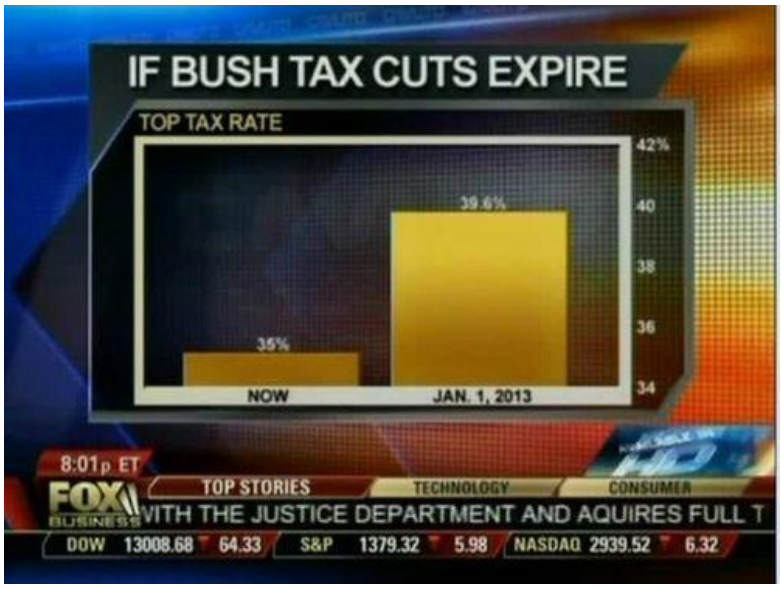


Figure 13. Lie Factor Example

The second step for calculating the Lie Factor of the graph is to calculate the size of effect shown in the graph. When physically measured as suggested, the first data point with the value of 35% is represented with an 18 millimeter long column in the graph. The second data point with the value of 39.6% is represented with 88 millimeter long column in the graph. With these values at hand, we can calculate the size of effect shown in the graph as 3.89 ((88-18)/18) by using equation 2.

For the graph in Figure 13, size of effect in data is 0.13 and size of effect shown in the graph is 3.89. If we use these values in equation 1, we can calculate the Lie Factor for the graph as 29.59 (3.89/0.13). This means that the graph represents the change in data almost thirty times more than it is in reality. Tufte (1983) suggests that Lie Factor for any proper graph should be between 0.95 and 1.05. Beattie, & Jones (2002b) tested this limitation and they found that up to 1.10 lie factor displays do not change the perception of the viewers. In the light of their empirical study, we can conclude that visualizations with a lie factor between 0.90 and 1.10 meet this criteria.

3.2.3 Formatting choices should not obscure changes in the data.

Meeting the first two criteria is not enough to design a visualization properly. Formatting choices of the visualization can also make a difference in the message that the visualization gives. Steinbart (1989) states that one of the common ways of masking the change in data is to combine two datasets with very different scales into one graph. An example can be seen in Figure 14. Net income and revenue of a company is given in a clustered column chart. The scale of the revenue data is much bigger than the scale of net income data. Even though we can observe the increase in the revenue data, the change in net income data is not clear.

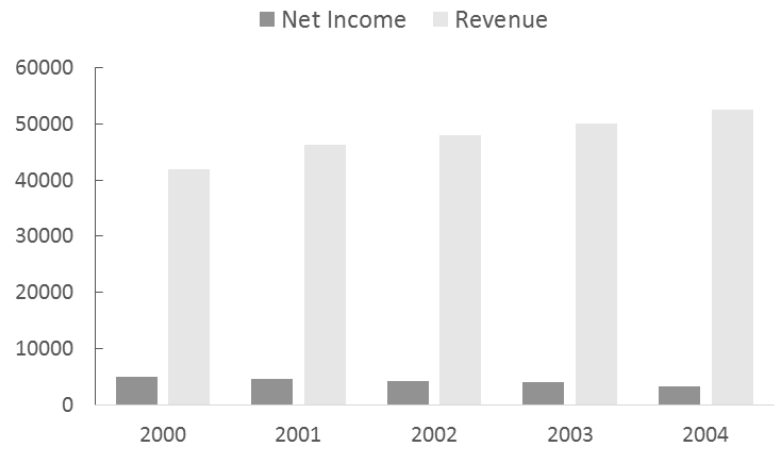


Figure 14. Net Income and Revenue combined graph

In Figure 15, the same net income data is represented in a column chart. This time the scale of the y-axis is ten times smaller than the scale in Figure 14. With this column chart, it is very easy to notice the decrease in the net income data in the given period.

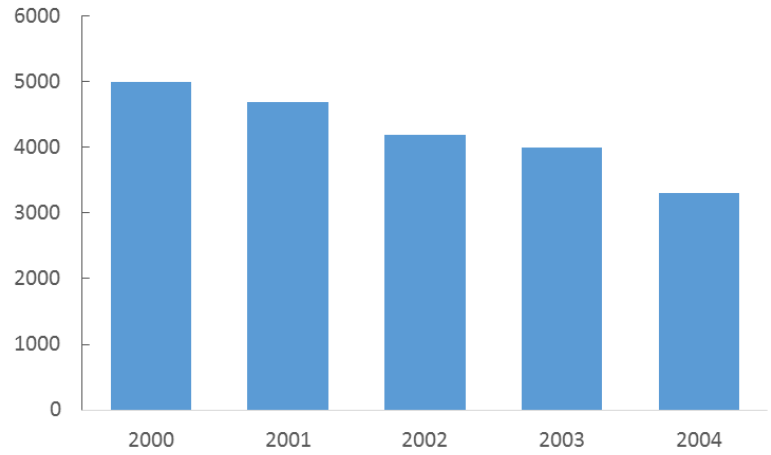
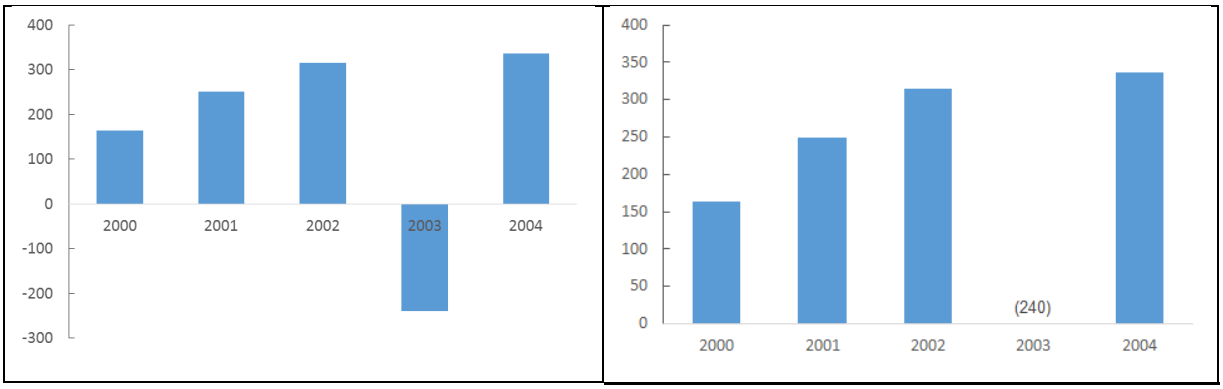


Figure 15. Net income data alone

Omitting negative values in charts is another formatting choice that masks the change in data (Steinbart, 1989). In Figure 16.a, time series data with a negative value is represented properly. In Figure 16.b, the negative value in the same dataset is omitted and only shown numerically. This prevents the viewers from comparing the magnitude of the negative value with other values in the dataset.



a) Column chart with a negative value

b) Column chart negative value omitted

Figure 16. Column charts with negative values

Examples of formatting choices can be increased, however the point of this section is to introduce the criteria of properly designed visualizations.

4 Deceptive Visualizations and Truncated Y-Axis

In previous sections, visualization goals and design principles for visualizations are introduced. In this section, deceptive visualizations and truncated y-axis, a commonly used method in deceptive visualizations, will be introduced. The goal of this section is to explain the consequences of not following design principles for visualizations. Firstly, the definition of deceptive visualizations will be discussed in Section 4.1. That will be followed by message deceptions in visualizations in Section 4.2. Finally, truncated y-axis definition and usage area will be explained in Section 4.3.

4.1 Deceptive Visualizations

Pandey et al. (2015) define deceptive visualizations as "a graphical depiction of information, designed with or without an intent to deceive, that may create a belief about the message and/or its components, which varies from the actual message." According to this definition, deceptive visualizations can be created with or without an intention. The focus of this study is on the deceptive visualizations and their impact on the perceived message. Therefore, we will look into deceptive visualizations by analyzing distortion techniques, rather than searching for the intent of the designer of the visualizations.

Pandey et al. (2015) claim that deception can occur at two different levels in a visualization: the chart level, and the message level. They state that chart level deceptions occur in visual encoding process and are related to the viewer's personal ability or inability to read the chart correctly. They define message level deceptions as incorrect interpretations of the message that the visualization delivers, and they claim that a message level deception is the result of the deceptive visualization design (Pandey et al., 2015). This classification is useful to separate the deceptions that are caused by the viewer's inability to read the chart correctly from the deceptions that are caused by the poor design of the visualizations. We will follow this classification of deceptions and focus on the deceptions that occur on the message level.

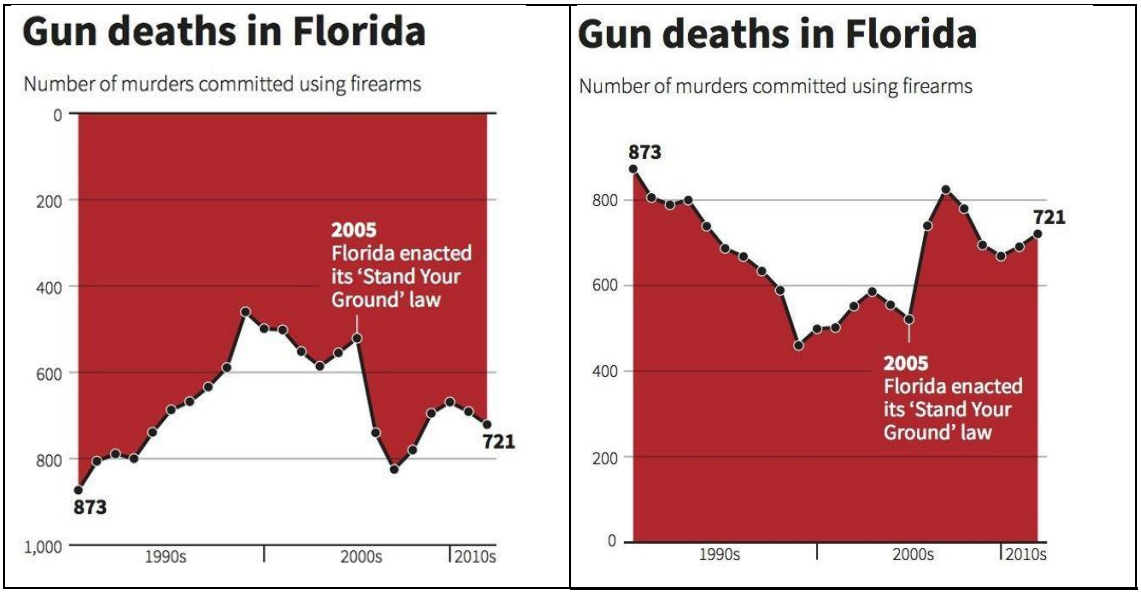
4.2 Message Level Deceptions in Visualizations

Deceptions on the message level are caused by designs that do not follow the design principles for visualizations, which are introduced in the previous section. Pandey et al. (2015)

divide the deceptions on the message level into two broad groups, as message reversal and message exaggeration. These two groups will be introduced.

4.2.1 Message Reversal Deceptions

Message reversal deceptions occur when the visualizations lead the viewers to conclude an incorrect message (Pandey et al., 2015). For example, if a chart shows the change in data over time, where the quantity of X increased over time, and the viewers perceive the message as the quantity of X decreased over time. This kind of deception is usually caused by not following the third design principle for visualizations, which is that formatting choices should not obscure the changes in data. A popular example of these deceptive visualizations can be seen in Figure 17.a. The y-axis of the chart is inverted, which makes the sharp increase in the data after the "Stand Your Ground" law seem like a decrease. After receiving criticism, the author added a corrected version of the chart with a normal y-axis that starts from zero and increases while going up (Engel, 2014). Corrected version of the chart can be seen in Figure 17.b. Another way for message reversal is to show the change in data in a reversed chronological order by flipping the x-axis of the chart. In the western world where the language proceeds from left-to-right, it is expected that the time will increase from left-to-right (Burgess, Dilla, Steinbart, & Shank, 2008). Therefore, when the most recent date is on the most left point, it reverses the message in data.



a) Original chart from Reuters with an inverted y-axis

b) Corrected version with a normal y-axis

Figure 17. Charts showing the Gun Deaths in Florida (Engel, 2014)

4.2.2 Message Exaggeration Deceptions

Message exaggeration deceptions happen when the fact is represented correctly, while the extent of the presented fact is tweaked (Pandey et al., 2015). For example, if a chart shows the change in data over time, where the quantity of X increased over time, and the viewers perceive the message that the quantity of X increased over time correctly. However, the chart can represent this fact with an exaggeration. As a result, the viewers perceive an incorrect message about the level of change in data. Therefore, this type of visualizations do not obey the second design principle of visualizations, which is that the portrayed magnitude of change must match the numerical magnitude of change.

Message exaggeration deceptions will be the focus of this study. The first reason is their common use in especially business world (Heer et al., 2010; Jarvenpaa & Dickson, 1988; Steinbart, 1989). The second reason is that time series datasets are very vulnerable to message exaggeration deception methods. Time series datasets show how the quantity of a variable changed over time and it is important that a visualization gives the same message as the data about the magnitude of change (Tufte & Graves-Morris, 1983).

Message exaggeration deceptions are very common and less obvious compared to message reversal deceptions. For instance, a study showed that the graphs that represented sales, profits and dividends of 319 U.S. companies exaggerated the magnitude of change by about 11% on average (Steinbart, 1989). Another study that investigated 207 annual reports from 12 countries (U.S., U.K., Australia/New Zealand, Spain, Netherlands, Philippines, Italy, Israel, South Africa, Denmark, Mexico, and Hong Kong) found that 17% of all charts had designs that result in message exaggeration deceptions, whereas only 1% of the charts had designs that result in message reversal deceptions (Frownfelter-Lohrke & Fulkerson, 2001).

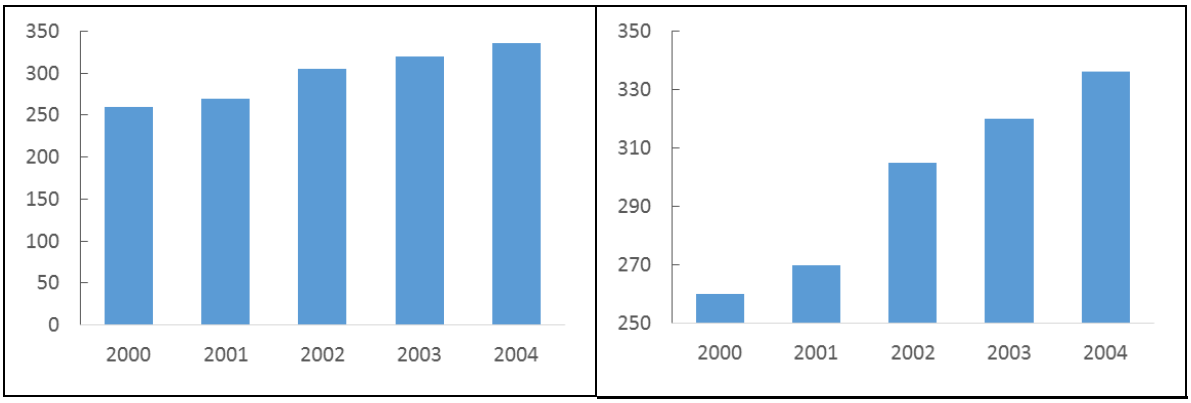
There are many ways to deliver an exaggerated message with a visualization. Some of these ways are as following: using area as quantity (Pandey et al., 2015; Tufte & Graves-Morris, 1983), using altered aspect ratio (Beattie & Jones, 2002b; Pandey et al., 2015; Tufte & Graves-Morris, 1983), and using a truncated y-axis (Arunachalam et al., 2002; Frownfelter-Lohrke & Fulkerson, 2001; Pandey et al., 2015; Tufte & Graves-Morris, 1983). Many more deception methods for message exaggeration can be named. However, deception methods should be investigated with a consideration of the visualization type, because visual deception techniques are visualization specific (Pandey et al., 2015). A design choice can result in creating a deceptive visualization with one chart type, while the same design choice does not impact the message of another chart type. Therefore, we will focus on the deception method that is the most common in our chosen chart types for this study, which are line charts and column charts.

Arunachalam et al. (2002) investigated a few deception methods for time series data, and found the strongest deceptions in charts with a manipulated x-axis or y-axis. Among the scale manipulations, Steinbart (1989) found that truncated y-axis usage is the most common deception method that is used in annual reports.

4.3 Truncated Y-Axis

Truncated y-axis means that the y-axis of the graph does not start from zero. Starting the y-axis from a number above zero exaggerates the change in data. In Figure 18, there are two column charts representing the same time series dataset. In Figure 18.a, the column chart has a normal y-axis that has zero as the starting point, and the other chart in Figure 18.b has a truncated y-axis that

starts from two hundred fifty. It is possible to see the increase in data in both charts. However, in Figure 18.b, the increase in data is exaggerated due to the truncated y-axis.



a) Column chart with a normal y-axis b) Column chart with a truncated y-axis

Figure 18. Column charts with and without truncated y-axis

This paper will look into the impact of truncated y-axis on line charts and column charts. It is important to investigate the two chart types separately, because deceptions are visualization specific (Pandey et al., 2015). After going through the impacts of truncated y-axis for both of the chart types, a recommended design element for the charts will be introduced.

4.3.1 Truncated Y-Axis in Line Charts

Truncated y-axis can be seen in many line charts, because truncated y-axis usage in line charts is considered to be an unproblematic visual design (Few, 2006a; Fung, 2014). Few (2006a) states that viewers use position (See 3.1.2 Preattentive Attributes) to encode information from a line chart. He adds that it is safe to use a truncated y-axis in a line chart, because the scale does not change the delivered message when the information is encoded with the position preattentive attribute. Tufte (1983), a well-respected authority in the visualization community, also recommends using truncated y-axis to decrease the empty space in the chart for line charts.

There are also charts for which using truncated y-axis is considered necessary, such as charts that represent stock price data (Yanofsky, 2015). Stock charts are used to show the tiniest fluctuations in stock prices, and exaggerating the change in data is, therefore, not considered deceptive for those charts. In Figure 19, Google's stock price in March, 2016 is represented. The y-axis of the chart starts from zero. It is not possible to see how the prices of the stock changed during this period, except the slight decrease trend during the first ten days.

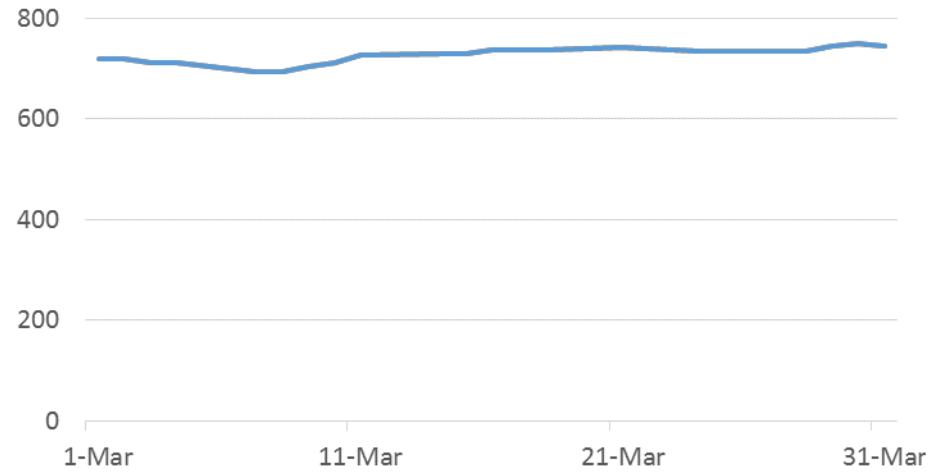


Figure 19. Stock data with a Y-axis starting at 0

In Figure 20, the same stock price dataset as in Figure 19 is represented with a line chart that has a truncated y-axis. With the help of a truncated y-axis, this chart shows the trends in data clearly. The truncated y-axis enables viewers to see that the price started increasing steadily, after it saw its lowest value for the month, and also that the stock price reached its highest value for the month at the end of the month.

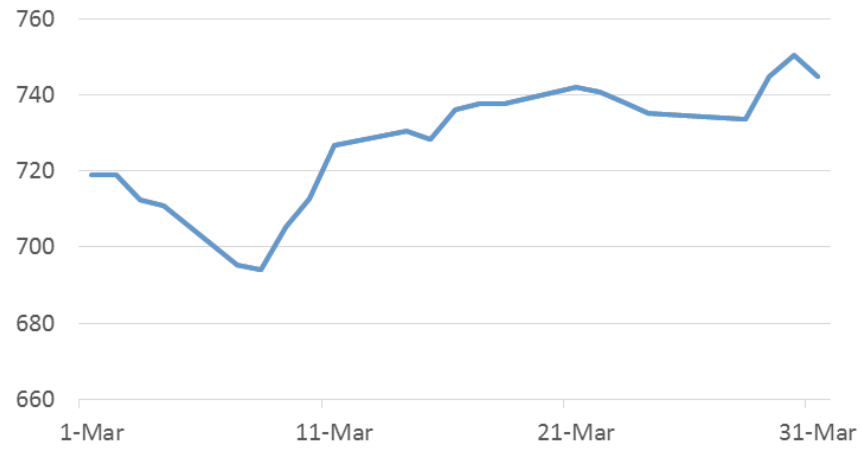


Figure 20. Stock data with a truncated Y-axis

In conclusion, truncated y-axis usage is not always criticized for line charts. On the contrary, line charts with a truncated y-axis is recommended in case there is a need to show small changes in data (Few, 2006a). However, there is an agreement on the need of the awareness of the viewers (Evergreen, 2014; Yanofsky, 2015). This means that the viewers should be aware of the fact that

the chart exaggerate the change in data. For datasets, like stock price data, where the viewers are used to look at the charts with an exaggeration of the change in data, truncated y-axis is not seen as a problem in line charts.

4.3.2 Truncated Y-Axis in Column Charts

An example of truncated y-axis in column charts can be found in Figure 19.b. In the visualization community, truncated y-axis usage in column charts is heavily criticized (Pandey et al., 2015). Few (2006a) explains the reason why truncated y-axis should not be used in column charts with preattentive attributes. When we look at a column chart, there are two preattentive attributes that play role in encoding the visual information: position and length (Cleveland & McGill, 1984; Few, 2006a). When the y-axis is truncated in a column chart, the length of the bars becomes deceptive for the viewers, because we compare the length of the bars in a column chart. So, if a bar is two times taller than the bar next to it, we expect that the value represented with the taller bar is also two times bigger than the value of the shorter bar.

In conclusion, truncated y-axis usage for column charts are considered to be deceptive, while it is considered to be not problematic for line charts, and even recommended in some cases. The difference between line and column charts is the preattentive attributes that are used to encode information from these charts. With line charts, position preattentive attribute is used to compare data points (Few, 2006a), whereas with column charts both position and length preattentive attributes are used (Cleveland & McGill, 1984; Few, 2006a).

4.3.3 Truncated Y-Axis with Not-connected Axes

Truncated y-axis should only be used in line charts and when the viewers are aware of the emphasis in the graph (Evergreen, 2014; Yanofsky, 2015). However, it is a challenge to find a method to alarm the viewers about the truncated y-axis. As in stock price charts, the awareness usually is gained by getting used to the exaggerated charts over time with seeing many of them. The author of this paper is not aware of any study that studied the methods for alarming the viewer about the truncated y-axis. A possible solution for alarming the viewers about the y-axis could be not connecting the axes of charts. Tufte (1983) does not connect the x-axis and y-axis in his charts. He also recommends using the baseline as the start point instead of zero. An example chart with not-connected axes can be seen in Figure 21. Tufte (1983) also states that erasing the corner of the

frame increases the data representing power of the graph, because the graph has less elements that do not show data after erasing.

Figure 21. Not connected x-axis and y-axis (Tufte & Graves-Morris, 1983)

In conclusion, a design method that alarms the viewers successfully about the deceptive emphasis in the data could be very beneficial for both the viewers of the charts and the designers. Not-connected axes is a possible design method to alarm the viewers, and it is very easy to apply. Unfortunately, there is no empirical study that tests whether it is possible to make a difference in the viewer's awareness by using not-connected axes.

5 Research Design and Methodology

Existing literature on visualizations, visual perception process and truncated y-axis was reviewed in the previous sections. In this section, research design and methodology will be discussed. First, research method selection basis will be explained in Section 5.1. In the following section, the basic principles of experiment design will be introduced. Finally, the steps of an experiment design will be defined. The aim of this section is to provide the guideline for the experiment design of the study.

5.1 Research Method

According to Rugg, & Petre (2006, pg. 61), research design is "finding things out systematically, -map making as opposed to treasure hunting". With the foundation provided from the literature review, the empirical part of this study aims to understand the impact of truncated y-axis usage on the perceived message in line charts and column charts for time series datasets. Yin (2013) states that research method selection should be done with consideration of three conditions. He illustrates these three conditions and their relations to five different research methods in a table. This table can be seen in Figure 22. Considering the fact that this study aims to understand how truncated y-axis usage affects the perceived message from line and column charts for time series datasets, experiment is chosen as the research method. For the experiment, an online questionnaire is chosen as the data collection method, which allows the collection of a big amount of data from a sizeable population at a very low cost (Saunders, Lewis, & Thornhill, 2009). Even though questionnaires are commonly used for the survey research method, they can be also used in experiments as a data collection method (Saunders et al., 2009).

METHOD	Form of Research Question	Requires Control of Behavioral Events?	Focuses on Contemporary Events?
Experiment	how, why?	yes	yes
Survey	who, what, where, how many, how much?	no	yes
Archival Analysis	who, what, where, how many, how much?	no	yes/no
History	how, why?	no	no
Case Study	how, why?	no	yes

Figure 22. Relevant Situations for Different Research Methods (Yin, 2013)

5.2 Experiment Design Principles

Montgomery (2008, pg. 1) defines an experiment as "a test or series of runs in which purposeful changes are made to the input variables of a process or system so that we may observe and identify the reasons for changes that may be observed in the output response". To be able to perform an experiment efficiently, a scientific approach to the experiment design is necessary. A well-designed experiment is necessary to draw correct conclusions, because the results of the study depend on the manner in which the data was collected (Montgomery, 2008). There are three basic principles for design of experiments: randomization, replication, and blocking (Hinkelmann, 2015; Montgomery, 2008). Each principle will be introduced shortly.

5.2.1 Randomization

Randomization is the first principle of an experiment design. Randomization means that each experimental unit is randomly assigned to a treatment (Montgomery, 2008). Treatment is the measured experimental condition and experimental unit is the studied object. The aim of randomization is to prevent the accidental bias from entering the study (Boundless, 2015). For example, time of the day may have an impact on the experiment result. By allocating the experimental units randomly to treatments, the impacts of the uncontrollable variables on the experiment results can be brought to a minimum.

5.2.2 Replication

Replication is an independent repetition of the basic experiment (Montgomery, 2008). With more replications, researchers can estimate the effect of the explanatory variable on the response (Boundless, 2015). Montgomery (2008) states that replication has two important properties. First, replication enables the researcher to obtain an estimate of the experimental error. Second, replication allows the researcher to obtain a more precise estimate of the sample mean, in cases where the sample mean is used to estimate the true mean response for one of the factor levels. For example, in a medical experiment, experimental units will have genetic differences. If two individual, who are randomly chosen, are taken as the experimental units for a medical study, the results are likely to be affected by their genetics. On the other hand, when the experiment is replicated with more experimental units, the impact of individual differences will decrease.

5.2.3 Blocking

Montgomery (2008, pg. 13) defines blocking as "a design technique used to improve the precision with which comparisons among the factors of interest are made". Blocking is a powerful technique for isolating a source of variability in experimental material to prevent the source variability from interfering with the results of the study (Morgan, 2015). For instance, the gender of the participants is often an important factor for human studies. By using gender as a block, the biases that are likely to occur due to the gender can be avoided.

5.3 Experiment Design Process

A well-designed experiment is necessary to draw right conclusions from the study (Montgomery, 2008). Besides the principles introduced in the previous section, there are steps to follow while designing an experiment. Montgomery (2008) defines seven steps to follow for the experimental design process. These steps are:

1. Recognition of and statement of the problem
2. Selection of the response variable
3. Choice of factors, levels, and ranges
4. Choice of experimental design
5. Performing the experiment
6. Statistical analysis of the data

7. Conclusions and recommendations.

Montgomery (2008) states that the first three steps are part of the pre-experimental design process, and they are usually done simultaneously. These steps will be followed for the experiment design of the study.

6 Design of the Experiment

Design process of this study's experiment will be explained in this section. The theory of experiment design was introduced in the previous section. First, pre-experimental design process of the study will be introduced in Section 6.1. Further, the design of the experiment and how the experiment meets the design principles will be discussed in Section 6.2. How the experiment is performed will be explained in Section 6.3, and Section 6.4. Finally, quantitative analysis methods will be mentioned in Section 6.5. The purpose of this section is to explain the empirical study of the paper.

6.1 Pre-Experimental Design

The first three steps of an experiment design is called pre-experimental design (Montgomery, 2008). These steps were introduced in 5.3 Experiment Design Process section of the paper. Now, the process will be explained for this study.

6.1.1 Recognition and Statement of the Problem

Recognition and statement of the problem step of this study was completed during the literature review. According to the literature review and previous experiments, truncated y-axis usage is expected to have a deceptive impact on the perceived message. One of the objectives of this study is to confirm this claim by measuring the impact of truncated y-axis usage. As explained previously, there are different approaches for line chart and column charts. Truncated y-axis usage in column charts is considered to be wrong under any circumstances, whereas it is considered to be acceptable in line charts. Therefore, the author aims to see whether there is a difference between the impact of truncated y-axis usage in line charts and in column charts.

In addition, a design technique that may prevent truncated y-axis usage from being deceptive was discovered during the literature review, which is not-connected axes usage. The study also aims to find out whether this technique will have an impact on the perceived message when used together with a truncated y-axis.

In conclusion, there are four questions that this experiment aims to answer. The questions are as below:

1. Does truncated y-axis usage in column charts have an impact on the perceived message?
2. Does truncated y-axis usage in line charts have an impact on the perceived message?
3. Does not-connected axes usage prevent truncated y-axis usage from being deceptive in line charts?
4. Does not-connected axes usage prevent truncated y-axis usage from being deceptive in column charts?

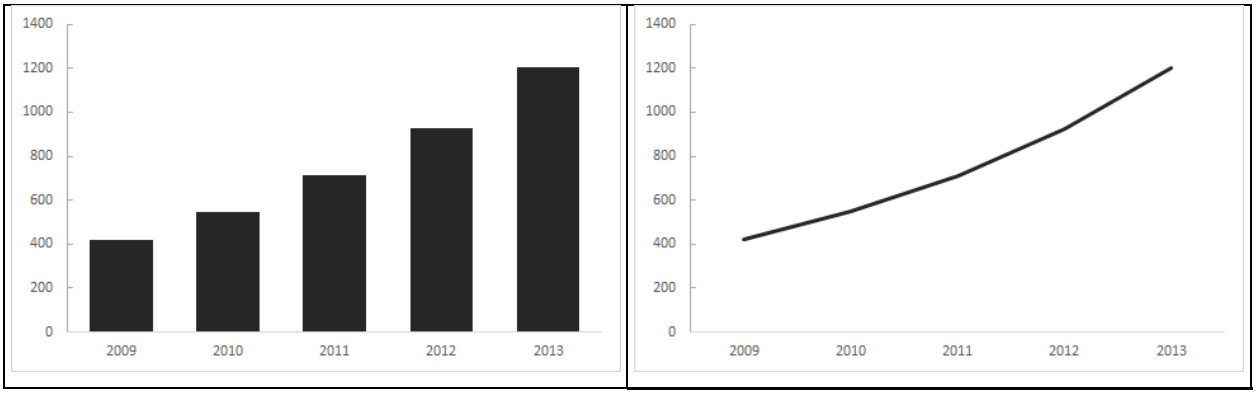
6.1.2 Selection of the Response Variable

The response variable of this study is the perceived message about the data. According to Montgomery (2008), it is important to be certain that the response variable provides useful information. Perceived message is a rather obvious response variable, therefore defining the response variable is easy for this experiment. However, measuring the perceived message requires attention. In previous studies, perceived message about the data is measured with verbal statements by using a five item Likert scale (Beattie & Jones, 2002a; Pandey et al., 2015). Verbal statements are ideal to measure perceived message from a chart, because we do not store precise quantitative information when reading graphs, instead we summarize the information from a chart with a linguistic label, such as slightly increasing (Beattie & Jones, 2002a). Therefore, perceived message will be measured according to the verbal statement selection of the participants. Similar to the studies stated before, these five categories will be used: very slightly increased, slightly increased, moderately increased, sharply increased, and very sharply increased. So, the response variable will be the mean of the perceived increase level in the data.

6.1.3 Choice of Factors, Levels, and Ranges

Montgomery (2008) classifies factors into two main groups: potential design factors and nuance factors. He later divides potential design factors into these three groups: design factors, held-constant factors, and allowed-to-vary factors. Each factor group will be shortly introduced and factors of this study will be explained.

Design factors. The design factors are the factors that are selected for the study (Montgomery, 2008). For this experiment, visual design factors of the charts are in this category. Example designs of the column charts and the line charts for the experiment can be seen in Figure 23. Colors used in the charts and grids are the design factors of the experiment.



a) Column chart example b) Line chart example

Figure 23. Column charts with and without truncated y-axis

Color is one of these factors. Both charts are designed only with black color over a white ground to avoid the distraction that different colors might have caused (Beattie & Jones, 2002a; Tufte & Graves-Morris, 1983). In addition, a darker shade of black is used to represent the data compared to axes and scales of the charts. This design decision was also made to keep the focus on the data during pre-attentive processing (Tufte & Graves-Morris, 1983).

Grid usage is also a design factor. Grids are omitted from the charts in the experiment to keep the focus on the represented data. Grids may make it challenging to focus on the data and distract the viewers (Tufte & Graves-Morris, 1983).

Held-constant factors. Held-constant factors are variables that may have an impact on the response variable, but these factors are not in the scope of the experiment, so they are held at a specific level for the experiment (Montgomery, 2008). Shape parameter, the width of the bars, lie factor, data increase level, and time period are the variables that are held-constant in the experiment.

Shape parameter, the width of a chart divided by the length of it, is an important variable for the experiment, because the shape parameter has an impact on the slope of the data. Since truncated y-axis usage changes the slope of the data as well, the other variable needs to be held constant. Held-constant factor needs to be held at a specific level that does not harm the experiment. Tufte (1983) proposes that an ideal chart should be wider than taller and the shape parameter should be between 1.4 and 1.8, ideally closed to 1.60. The shape parameter of the charts in the experiment are identical and equal to 1.74.

The width of the bars for the column charts in the experiment are equal to 0.5 cm. The width of the bars is a held-constant factor to prevent the viewers from getting confused about the represented data (Tufte & Graves-Morris, 1983).

Lie Factor of the charts with a truncated y-axis is also a held-constant factor. Lie factor shows the difference level between the actual magnitude of change in the data and the represented magnitude of change in the chart. Deceptiveness of a chart increases with a higher lie factor (Beattie & Jones, 2002a; Beattie & Jones, 2002b; Tufte & Graves-Morris, 1983). A recent study measured the impact of the truncated y-axis in a column chart on the perceived message by using a lie factor as high as 82 (Pandey et al., 2015). However, Beattie, & Jones (Beattie & Jones, 2002b) show that charts start being deceptive with a lie factor higher than 1.2. Therefore, the author avoided using a very high lie factor for the charts. The lie factor in the experiment is held-constant at 6.76 for the charts with a truncated y-axis. The lie factor of the charts without a truncated y-axis is held constant at 0.97. The lie factor of the charts is calculated by measuring the physical length of the bars for column charts, and by measuring the distance from the x-axis of data points for line charts. The measurements are done with a ruler, and the lie factor is calculated with the formula introduced in the Design Principles for Visualizations section.

The level of increase in the data is another variable that is held constant in the experiment. It is important that all datasets have the same increase level in the given time period. Beattie, & Jones (2002a) show that different increases in the time series data have different verbal coding for participants. For example, fifty percent increase in the given time period is evaluated as slightly increasing, whereas hundred percent increase is evaluated as moderately increasing. Since the response variable is the perceived increase in the data, the actual increase in the datasets is held constant. Each data point had a ten percent increase compared to the previous data point, resulting in a forty-six percent increase in the whole five year period. This data increase level is chosen because it is coded as a slightly increase in previous studies by the participants (Beattie & Jones, 2002a). Having the slight increase level as the baseline is suitable for the testing the impact of a message exaggeration method, namely truncated y-axis. Too high and too low increases in data may be coded with the same wording despite the exaggeration. For instance, three hundred percent increase in data is likely to be coded as a sharp increase with and without an exaggeration, or one percent increase in data is likely to be coded as a slight increase with and without an exaggeration.

Time period of the datasets is a held-constant factor as well. A fifty percent increase may be perceived differently by the participants according to the given time period. For instance, it may be perceived as a bigger increase if it happens in five days compared to if it happens in five years. Therefore, the time period of the datasets is held constant in the experiment as 5 years.

Allowed-to-vary factors. Allowed-to-vary factors are factors that have unit-to-unit variability and rely on randomization to balance out any experimental unit effect (Montgomery, 2008). In this experiment, there is no variable that is allowed to vary among the units. Charts in the experiment are created before the experiment with many held-constant factors.

Nuisance factors. Montgomery (2008) claims that a controllable nuisance factor is one whose levels may be set by the researcher. For instance, the researcher can select different days of the week, when conducting the experiment. The blocking principle, mentioned in the previous section, is useful in dealing with nuisance factors. Online questionnaires are used for the data collection for this experiment. To be able to reach a big enough sample size, links of two treatments are shared through different channels. For blocking the domination of a certain social circle in one the treatment groups, links are edited and changed every day in every channel.

6.2 Experiment Design

After completing the pre-experimental design, the experiment structure was designed. There were three different designs of which the impact on the perceived message was studied.

1. A chart without a truncated y-axis and with connected axes (baseline)
2. A chart with a truncated y-axis and with connect axes
3. A chart with a truncated y-axis and with not-connected axes

These three designs were design for two chart types: a line chart and a column chart. Showing a chart for every measurement to each participant could cause biased answers due to repetition, and it was necessary to measure the perceived message for the three conditions for each participants. So, the experiment is designed in a way that each treatment group was shown each design but with a different chart type. Every participant was shown three charts. The first chart shown the participants, was designed without a truncated and with connected-axes. The second chart was designed with a truncated y-axis to measure the impact of a truncated y-axis. Finally, the third chart was with a truncated y-axis and not-connected axes, which was shown in the last

question. The design features of the charts for two treatment groups can be seen in Table 1. As stated before, each question was identical for both treatment groups except the chart type.

Table 1: Designs of the Charts of the Experiment

	Treatment group	Chart type	Y-Axis Design	Axes Design
Chart 1	Treatment 1	Column	Not-truncated	Connected
	Treatment 2	Line	Not-truncated	Connected
Chart 2	Treatment 1	Column	Truncated	Connected
	Treatment 2	Line	Truncated	Connected
Chart 3	Treatment 1	Column	Truncated	Not-connected
	Treatment 2	Line	Truncated	Not-connected

Each chart that is shown to the participants had a specific purpose. Chart 1 aims to build a baseline for the perceived message for the given increase in the data, when represented with usual features (y-axis starts at zero, and x-axis and y-axis are connected). Chart 2 aims to measure the perceived message for the given increase in the data, when represented with a truncated y-axis and connected axes. Chart 3 aims to measure the perceived message for the given increase in the data, when represented with a truncated y-axis and not-connected axes.

In addition, it was important for the purpose of the study that the participants did not get familiar with the presented datasets and did not understand the aim of the study. So, a different dataset with the same increase level was used for every chart. The datasets were imaginary business data from an imaginary company X. Pandey et al. (2015) state that they found no difference between the results of real and artificial datasets, regarding deceptiveness of the visualizations. With this information at hand, artificial datasets were preferred for the survey, because it was important that all datasets had the same amount of increase, and it was easier to provide control over the increase level in the data.

6.3 Questionnaire Design and Structure

Self-administered online questionnaire was chosen as the data collection method for the experiment. Online questionnaire was chosen, because it is very easy to use. Collecting data with an online questionnaire enables the researchers to reach a large sample at a very low cost. Secondly, visualizations are created and shared with software programs. So, an online questionnaire provides a setting very close to a real life situation for the participant, by showing the visualizations on a device instead of a paper. Finally, recent studies in the visualization field

used online questionnaires as their data collection method for the experiments (Haroz, Kosara, & Franconeri, 2015; Pandey et al., 2015; Talbot, Setlur, & Anand, 2014).

The design of the questionnaire is very important, because it affects the response rate and the reliability and validity of the collected data (Saunders et al., 2009). For a high response rate, it is necessary to ensure that the questionnaire seems appealing to the respondents. Explaining the aim of the study clearly and concisely at the beginning of the questionnaire increases the response rate for self-administered questionnaires (Dillman, 2007; Saunders et al., 2009). Therefore, the questionnaire started with an introduction page about the study. The participants were told that the aim of the study was to measure the effectiveness of different charts for delivering a message. This was done to prevent the participants from guessing the real purpose of the study. The wording of the aim of the study was taken from a similar study for deceptive visualizations (Beattie & Jones, 2002a).

After the introduction page, the participants were asked three demographic questions: gender, birth year and the number of years of university education. All questions were asked in one page and all questions were required to be answered, before moving on to the next page. The page with demographic questions can be seen in Figure 24. Demographic information questions were the same for both of the treatment groups. It was shown in previous studies that gender, age, or education level do not have an impact on perceiving a message from deceptive visualizations (Pandey et al., 2015). However, it was important to collect the demographic information form the participants to make sure the two treatment groups had similar demographics.

Figure 24. Demographic Information Questions

After the demographic questions were answered, an informative page was shown to the participants, where examples for line chart and column chart were introduced. The example charts shown on this page can be seen in Figure 23. Participants were told that they were expected to evaluate the change in data presented in the chart. Introducing the chart types before asking questions about the charts is a common method in the studies with visualizations (Pandey et al., 2015). In addition, explaining the upcoming questions when introducing a new topic is considered useful (Saunders et al., 2009). Following the informative page, experiment questions with charts were asked. The structure of both questionnaires can be seen in Figure 25.

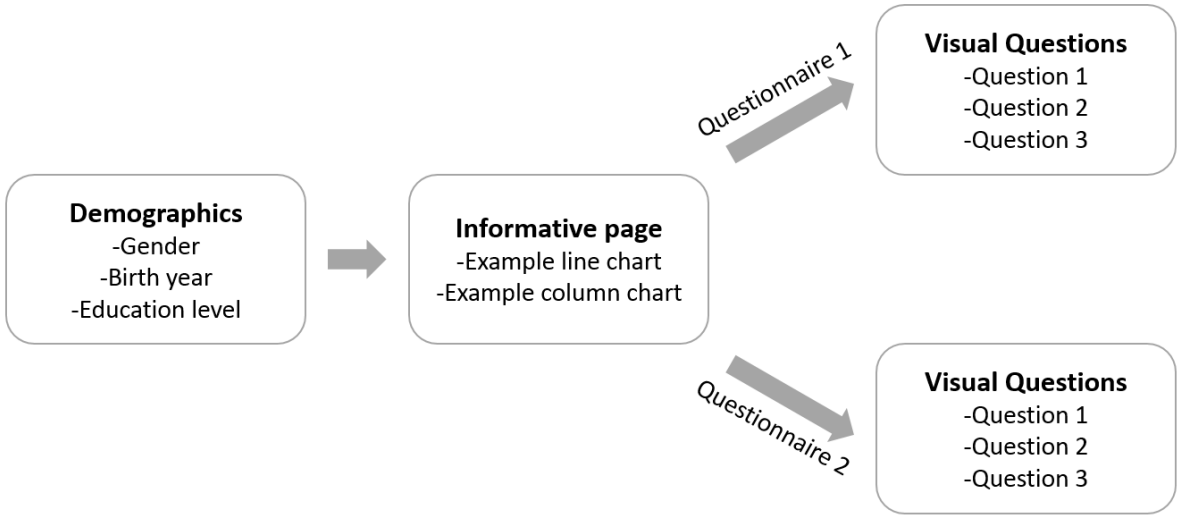


Figure 25. The structure of Questionnaire 1 and Questionnaire 2

The design and wording of questions should be decided with consideration of the type of data that will be collected (Saunders et al., 2009). In this experiment, opinion data will be collected with the visual questions. Opinion data shows how participants feel about something or what they think is true or false (Saunders et al., 2009). When opinion data is collected, it needs to be told the participants that they are expected to provide their personal opinions on the given subject. There are three ways of designing individual questions:

1. Adopt questions from other questionnaires
2. Adapt questions used in other questionnaires
3. Develop new questions (Bourque & Clark, 1994).

Adopting or adapting questions from other questionnaires is more efficient than developing new questions, because using similar questions allows the researcher to compare the finding of the study with other studies (Saunders et al., 2009). Questions in this experiment were adapted from questions used in another questionnaire. Wording of the questions were adapted from a recent study that aimed to measure the impact of deceptive visualizations on perceived message (Pandey et al., 2015). The wording of the questions with visualizations was as follows: "How much do you think [Quantity A] has increased in the given time period?"

The response variable of the experiment is determined during pre-experimental design and explained previously (See 5.3.2 Selection of the Response Variable) Questions had the five

response categories: very slightly increased, slightly increased, moderately increased, sharply increased, and very sharply increased. The questions that offer the participant a list of responses are defined as list questions and they are beneficial when it is needed to ensure that the participant considered all possible responses (Saunders et al., 2009). For this experiment, it was crucial that the participants were aware of all the response categories. So, visual questions were designed as a list question. Making all the response categories visible to the respondents is considered helpful for list questions (Saunders et al., 2009). Therefore, all response categories were visible on the question page. An example question page can be seen in Figure 26.

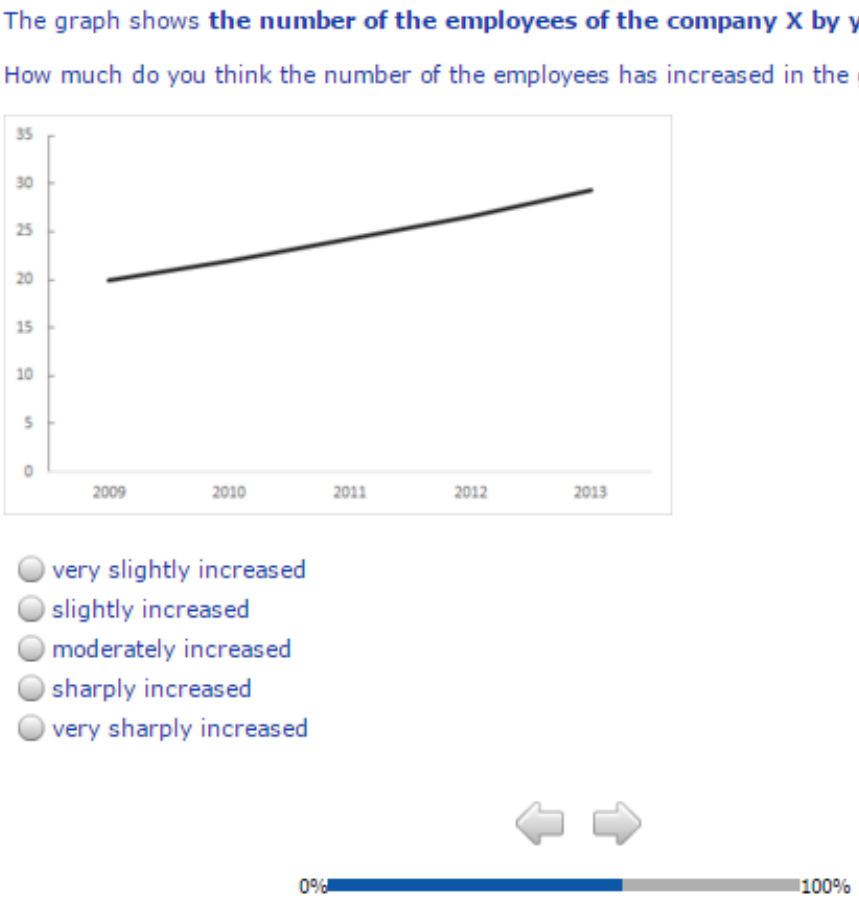


Figure 26. An example question with a visualization from the questionnaire

6.4 Data Collection

The online questionnaires were created by using Sawtooth Software. The choice for the software was made on the basis of availability to the author and ease of use. The language of the questionnaire was chosen as English to reach as many respondents as possible. Difficult wording and complicated sentences were avoided to make the questionnaire clear and easily understandable for everyone.

Two treatments were designed as two separate questionnaires that could be reached by two different links. Both links were circulated at the same time period through same channels: Facebook, Twitter, LinkedIn, and e-mail. Most of the respondents were reached through Facebook. Online social network sites were used in the study because they offer new ways to researchers to get respondents quickly and cheaply (Bhutta, 2012). Sampling through one's social connections is called snowball sampling and it is likely to cause sampling bias, because the technique itself increases the possibility of the sample not being representative of the whole population (Saunders et al., 2009). To avoid this affect as much as possible self-selection sampling was also applied. For this type sampling, the need for participants is announced through a communication channel (for this study, Facebook and LinkedIn group pages) and the data is collected from those who respond (Saunders et al., 2009). The link in all posts were edited on a regular basis to collect data for both links from all channels. It is not possible to obtain response rate, however Sawtooth Software provides information on completion rate. The first questionnaire was started 181 times and 127 respondents completed it, resulting in 70% completion rate. The second questionnaire was started 148 times and 121 respondents completed it, resulting in 82% completion rate. In total, the questionnaires were started 329 times and 248 respondents completed the survey, giving 75% completion rate. The responses were gathered within two weeks from 31st March 2016 till 15th April 2016.

6.5 Quantitative Analysis Methods

Montgomery (2008) states that statistical methods are needed to analyze the data to get findings that are objective rather than subjective in nature. In this section, statistical methods and the software that were used in this study, will be introduced.

Research questions of many experiments can be turned into an hypothesis-testing framework (Montgomery, 2008). For the analysis part of this experiment, hypothesis-testing framework will be used. The response variable, perceived increased level from charts, will be tested using t-tests. Two-sample t-test is used to compare the means of a numerical variable that can be divided into two distinct groups using a descriptive variable (Saunders et al., 2009). This is the case for comparing the perceived increase level from the baseline charts and the charts with a truncated y-axis. Two sample t-tests are used for this comparison because the perceived increase level is evaluated by different participants. Paired t-test compares the results from the same participants (Saunders et al., 2009). In this experiment, the increase level for the baseline chart and the chart with not-connected axes are evaluated by the same participants. Therefore, paired t-test will be used to analyze their results.

The response variable of this experiment is the perceived increased level, which the participants chose among 5-Likert scale categories. To be able to do a statistical analysis, numerical values are needed. Therefore, the response variable is coded with numerical values. The coding of the variable can be seen in Table 2. The variable is coded in a way that the lowest increase category, very slightly increased, has the minimum value, and the highest increase category, very sharply increased, has the maximum value.

Table 2: Coding of the response variable

Response variables	Numerical value
Very slightly increased	1
Slightly increased	2
Moderately increased	3
Sharply increased	4
Very sharply increased	5

With the coding, the average value for the questions gives the perceived increase level from the chart. To compare perceived message from two charts, we need to compare the mean of the response variable between two treatment groups. Therefore, two-sample t-test is a selected as the testing method for the analysis. Variances of two groups are also important for evaluating the results of two-sample t-test. If two groups have equal variances, Pooled method is used. However, if two groups have unequal variances, Satterthwaite method is used. All t-tests are two-sided. SAS Enterprise Guide is used for the statistical tests.

7 Findings

In this section, findings of the experiment will be introduced. The response variable, perceived increase level from charts, will be analyzed to answer the research questions of the study. The analysis will be done in three main parts. Firstly, the baseline value will be introduced for both charts. Secondly, the impact of truncated y-axis usage on the perceived message will be analyzed. Finally, the impact of not-connected axes design on the perceived message will be analyzed. All the analysis will be done for different demograhpic groups to see whether individual differences affect the results.

7.1 Demographics

Two questionnaires are designed and used to collect the data. Gender, age and the duration of university studies are collected as demographic information. Demographic groups of the respondents can be seen in Table 3. It can be seen that sample sizes of two groups are almost equal. The first treatment group has 127 respondents, and the second treatment group has 121 respondents.

Table 3: Demographic Characteristics of Respondents

	Questionnaire 1		Questionnaire 2		Total	
Demographics	**Number of respondent (N=127)**	**Percentage (%)**	**Number of respondent (N=121)**	**Percentage (%)**	**Number of respondent (N=248)**	**Percentage (%)**
Gender						
Male	73	57	63	52	112	45
Female	54	43	58	48	136	55
Age						
18 – 25	55	43	42	35	97	39
26 – 30	42	33	65	54	107	43
31 – 35	19	15	8	7	27	11
36 – 40	8	6	4	3	12	5
40+	3	2	2	2	5	2
Years at a university						
0	2	2	2	2	4	2
1	9	7	2	2	11	4
2	14	11	4	3	18	7
3	10	8	4	3	14	6
4	34	27	27	22	61	25
5+	58	46	82	68	140	56

Almost half (45%) of all the respondents are female. In both groups, there are slightly more male participants compared to female participants. The proportion of females is 43% in the first group and 48% in the second group. Both treatment groups are mostly populated with young participants. 76% of treatment 1 and 89% of treatment 2 are 30 years old or younger. The average age of two treatment groups are the same and equal to 27.2. Since the size of older age groups are very small, the treatment groups will be divided into two groups as "30 years old or younger" and "older than 30". Size of age groups for treatments after the new age classification can be seen in Table 4.

Table 4: Age classification for analysis

	Treatment 1	**Treatment 2**
30 years old or younger	97	107
Older than 30 years old	30	14
Total	**127**	**121**

Almost all the participants has a university education at some level. Only four participants did not study at a university. Also, most participants has been studying or studied at university for four or more years. A new classification is also needed for the education level, since the number of participants with lower education is very small for an analysis. 73% of treatment 1 and 90% of

treatment 2 have studied at a university for four or more years. Treatment groups will be classified into two groups regarding the education level as "four or more years" and "less than four years". Size of education level groups for treatment groups can be seen in Table 5.

Table 5: Education classification for analysis

	Treatment 1	Treatment 2
Four or more years	92	109
Less than four years	35	12
Total	**127**	**121**

In age and education level, the impact of snowball sampling is visible. Majority of the respondents are educated young people. 82% of the participants is younger than 30 years old and 81% of the participants have four or more years of education in a university. Therefore, the results of the study will not be representative of the whole population. On the other hand, it has been found in previous studies that individual differences do not cause any difference in message perception from visualizations (Pandey et al., 2015). So, the sample is considered sufficient for the experiment.

7.2 Baseline Value for the Perceived Message

Baseline value for the perceived message is necessary to understand the impact of the truncated y-axis usage and the not-connected axes usage on the perceived message. The first chart in both questionnaires were designed to get a value that can be used a baseline for the analysis. The participants in treatment 1 saw a column chart, and the participants in treatment 2 saw a line chart. Y-axis of these charts started at zero, and their axes were connected. Baseline for both charts will be introduced. Also, demographics will be tested to see whether the perceived message from charts is different for different demographic groups.

7.2.1 Column Chart Baseline

The participants in the first treatment group evaluated a column chart for their first visual question in the questionnaire. Frequency of their answers and the percentage of these answers can be seen in Table 6. As it can be seen in the table, the most common answers are slightly increased and moderately increased. 81% of the participants chose one of these two categories as the increase level.

Table 6: Column chart baseline answers

	Frequency	Percentage
Very slightly increased	11	9%
Slightly increased	55	43%
Moderately increased	48	38%
Sharply increased	12	9%
Very sharply increased	1	1%

The mean of the response variable for the baseline column chart is 2.50. The mean and the standard deviation of the response variable are calculated for all the demographic groups. The values are given in Table 7. None of the demographic groups have a much higher or a much lower value than the overall mean of the group. No significant difference has been found between the mean of the responses of the demographic groups. Gender, education level, and age did not affect the perceived increase level from the baseline column chart.

Table 7: Demographic Characteristics of Respondents for column chart baseline

	Perceived Increase Level	
Demographics	**Mean**	**Std Dev**
Total	2.50	0.82
Gender		
Male	2.47	0.75
Female	2.53	0.91
Age		
30 years old or younger	2.49	0.84
Older than 30 years old	2.57	0.73
Years at a university		
Less than four years	2.71	0.75
Four or more years	2.42	0.83

To sum up, the baseline value for the column chart is equal to 2.50, and none of the demographic groups have a different value for the perceived increase level (See Appendix C for the test results). This value is between the slightly increased and moderately increased answer categories.

7.2.2 Line Chart Baseline

The participants in treatment 2 evaluated a line chart for their first visual question in the questionnaire. The frequency and the proportion of their answers can be seen in Table 8. As it can

be seen in the table, the most common answers are slightly increased and moderately increased. 80% of the participants chose one of these two categories as the increase level.

Table 8: Line chart baseline answers

	Frequency	Percentage
Very slightly increased	4	3%
Slightly increased	43	36%
Moderately increased	53	44%
Sharply increased	20	17%
Very sharply increased	1	1%

The mean of the response variable for the line chart is 2.76. The means and the standard deviations of the response variable are calculated for all the demographic groups. The values can be found in Table 9. Demographics of the participants did not affect the perceived increase level from the baseline line chart. No statistically significant difference has been found, when the means of the response variable is tested for the demographic groups (See Appendix D for the test results).

Table 9: Demographic Characteristics of Respondents for line chart baseline

	Perceived Increase Level	
Demographics	**Mean**	**Std Dev**
Total	2.76	0.80
Gender		
Male	2.73	0.87
Female	2.79	0.71
Age		
30 years old or younger	2.80	0.79
Older than 30 years old	2.43	0.76
Years at a university		
Less than four years	2.92	0.67
Four or more years	2.74	0.81

7.3 Truncated Y-Axis Analysis

Both treatment groups were shown a chart with a truncated y-axis on the second question. Treatment 1 evaluated a line chart, whereas treatment 2 evaluated a column chart. The perceived message from a chart with a truncated y-axis is calculated according to the answers of the participants for the second question in their questionnaires. To understand the impact of the truncated y-axis usage, it is necessary to compare the mean of the perceived increased level from the baseline chart to the perceived message from the charts with a truncated y-axis. First the impact

of truncated y-axis in column charts will be analyzed. Later, the impact of the truncated y-axis usage will be analyzed in line charts.

7.3.1 Impact of Truncated Y-Axis in Column Charts

The participants in the second treatment group evaluated a column chart with a truncated y-axis. The frequency of the responses and their percentage among the responses can be seen in Table 10. The most popular answers were moderately increased and sharply increased. A little more than half of the participants (52%) perceived the increase level as a moderate increase. Only 7% of the participants chose the slightly increased option, which was the most popular answer for the baseline question.

Table 10: Answers for the column chart with a truncated y-axis

	Frequency	Percentage
Very slightly increased	1	1%
Slightly increased	8	7%
Moderately increased	63	52%
Sharply increased	40	33%
Very sharply increased	9	7%

The means and standard deviations of the response variable for the baseline column chart and the column chart with a truncated y-axis can be seen in Table 11. The mean of the response variable for the column chart with a truncated y-axis is 3.40, whereas the baseline value for column charts is 2.50. The difference between the means of two samples is found statistically significant ($t(246) = -8.92$, $p<0.0001$, equal variances).

Table 11: The mean and standard variation comparison for the column chart: baseline vs. truncated y-axis

	Mean	Std Dev
Baseline	2.50	0.82
With a truncated y-axis	3.40	0.76

The mean and standard variation of the response variable for different demographic groups can be seen in Table 12. For all the groups, the mean of perceived increase level is higher than the baseline for the column chart with a truncated y-axis. All the demographic groups had similar results to the general sample. The perceived increase level from the column chart with a truncated y-axis was significantly different from the perceived increase level from the baseline column chart (See Appendix E for the test results).

Table 12: The comparison of baseline and truncated y-axis in column charts for demographic groups

	Baseline		Truncated Y-axis	
Demographics	***Mean***	***Std Dev***	***Mean***	***Std Dev***
Gender				
Male	2.48	0.75	3.38	0.81
Female	2.54	0.91	3.41	0.70
Age				
30 years old or younger	2.48	0.84	3.43	0.78
Older than 30 years old	2.57	0.73	3.14	0.53
Years at a university				
Less than four years	2.71	0.75	3.67	0.78
Four or more years	2.42	0.83	3.37	0.75

7.3.2 Impact of Truncated Y-Axis in Line Charts

The participants in the first treatment group evaluated a line chart with a truncated y-axis. The frequency and the proportion of the responses can be seen in Table 13. The most popular answers were moderately increased and sharply increased.

Table 13: Answers for the line chart with a truncated y-axis

	Frequency	Percentage
Very slightly increased	1	1%
Slightly increased	16	13%
Moderately increased	59	46%
Sharply increased	45	35%
Very sharply increased	6	5%

In Table 14, the means and the standard deviations of the response variable can be seen. The mean of the perceived increase level for the line chart with a truncated y-axis is 3.31, whereas the baseline value for line charts is 2.76. The difference between the means is found statistically significant ($t(246) = -5.46$, $p<0.0001$, equal variances).

Table 14: The mean and standard variation comparison for the line chart: baseline vs. truncated y-axis

	Mean	Std Dev
Baseline	2.76	0.80
With a truncated y-axis	3.31	0.78

The mean and the standard variation of the response variable for the demographic groups can be seen in Table 15. For all the groups, the mean of perceived increase level is higher for the line chart with a truncated y-axis compared to the baseline value. There was not any demographic

group that behaved differently than the whole sample. The differences between the means were statistically significant for all the groups (See Appendix F for the test results)

Table 15: The comparison of baseline and truncated y-axis in line charts for demographic groups

	Baseline		Truncated Y-axis	
Demographics	***Mean***	***Std Dev***	***Mean***	***Std Dev***
Gender				
Male	2.73	0.87	3.23	0.77
Female	2.79	0.72	3.41	0.79
Age				
30 years old or younger	2.80	0.79	3.30	0.78
Older than 30 years old	2.43	0.76	3.33	0.80
Years at a university				
Less than four years	2.92	0.67	3.31	0.76
Four or more years	2.74	0.81	3.30	0.79

7.4 Not-Connected Axes

Not-connected axes was used with a truncated y-axis to understand whether it prevents the truncated y-axis usage from being deceptive. To be able to measure this, the mean of the perceived increase level from a chart with not-connected axes will be compared to the baseline values for the perceived increase level. The analysis of not-connected axes will be done in two parts. First, the impact of not-connected axes will be analyzed in column charts. Then, the impact of not-connected axes will be analyzed in line charts.

7.4.1 Impact of Not-Connected Axes in Column Charts

The participants in the first treatment group evaluated a column chart with not-connected axes. The column chart also had a truncated y-axis. The frequency and the proportion of the responses can be seen in Table 18. The most popular answers were moderately increased and sharply increased. These two categories are 74% of all the answers in total.

Table 16: Answers for the column chart with not-connected axes

	Frequency	Percentage
Very slightly increased	4	3%
Slightly increased	18	14%
Moderately increased	61	48%
Sharply increased	33	26%
Very sharply increased	11	9%

The perceived increase level from the chart with not-connected axes was compared to the baseline value with a paired t-test. The participants in the first treatment group evaluated the both charts. The mean and the standard deviation of the difference between two variables can be seen in Table 19. The mean of the difference is equal to 0.72. The difference between the perceived increased level is statistically significant ($t(126) = 7.55$, $p<0.0001$).

Table 17: The mean and standard variation of the difference between the baseline column chart and the column chart with not-connected axes

	Mean	Std Dev
Not-connected axes – Baseline	0.72	1.08

It was also analyzed whether not-connected axes is able to prevent deception for any of the demographic groups. The means and the standard variations of the differences between two charts for the demographic groups can be seen in Table 20. For all the groups, the mean of the differen is positive, which means that the perceived increase level is higher than the baseline for the column charts with not-connected axes. The differences between the perceived increased level means were statistically significant for all the demographic groups. (See Appendix G for the test results)

Table 18: The comparison of baseline and not-connected axes in column charts for demographic groups

	Not-connected axes – Baseline	
Demographics	***Mean***	***Std Dev***
Gender		
Male	0.74	1.08
Female	0.70	1.09
Age		
30 years old or younger	0.75	1.14
Older than 30 years old	0.63	0.89
Years at a university		
Less than four years	0.51	1.17
Four or more years	0.80	1.04

7.4.2 Impact of Not-connected Axes in Line Charts

The participants in the second treatment group evaluated a line chart with not-connected axes. The frequency and the proportion of the responses can be seen in Table 21. The most popular answers were moderately increased and sharply increased. In total 81% of the respondents selected these two categories.

Table 19: Answers for the line chart with not-connected axes

	Frequency	Percentage
Very slightly increased	3	2%
Slightly increased	7	6%
Moderately increased	47	39%
Sharply increased	51	42%
Very sharply increased	13	11%

The second treatment group evaluated the increased level for the baseline line chart and the line chart with not-connected axes. Therefore, the difference between the perceived increase levels for the two charts was compared with a paired t-test. The mean and the standard deviation of the difference can be seen in Table 22. The mean of the difference is equal to 0.77. The difference between the means is statistically significant ($t(120) = 8.54$, $p<0.0001$).

Table 20: The mean and standard variation of the difference between the baseline line chart and the line chart with not-connected axes

	Mean	Std Dev
Not-connected axes – Baseline	0.77	0.99

The means and the standard variations of the differences in the perceived increase level for two charts for the demographic groups can be seen in Table 23. For all the groups, the mean of difference is positive, and the differences between the two charts were statistically significant. (See Appendix H for the test results)

Table 21: The comparison of baseline and not-connected axes in line charts for demographic groups

	Not-connected axes – Baseline	
Demographics	***Mean***	***Std Dev***
Gender		
Male	0.57	1.01
Female	0.98	0.93
Age		
30 years old or younger	0.76	1.03
Older than 30 years old	0.86	0.66
Years at a university		
Less than four years	0.75	1.22
Four or more years	0.77	0.97

8 Discussion

In this section, the research questions will be answered by analyzing the key findings of the experiment with the help of previous studies in the literature. This paper investigated two design technique: truncated y-axis and not-connected axes. First, the impact of truncated y-axis will be discussed. Later, the impact of not-connected axes will be discussed. The research questions will be answered in the same order and structure.

8.1 Impact of Truncated Y-Axis Usage

Truncated y-axis is seen as a deception method in the literature (Beattie, & Jones 2002a; Beattie, & Jones, 2002b; Pandey et al, 2015). In this study, we studied its effects on the charts that represent time series data. Time series data is represented often with a line chart or a column chart (Few, 2004). This study aims to answer two question related to truncated y-axis impact on the charts. These questions will be discussed in this section.

8.1.1 Does truncated axis usage in column charts have an impact on the perceived message?

In the experiment, the perceived increase level from a column chart with a y-axis starting at zero is measured as the baseline value for column charts. The baseline value for the perceived increase level was 2.50. This value means that the increase level in data was perceived as between the slightly increased and moderately increased categories. This finding is in line with the claims from previous studies. Beattie, & Jones (2002a) showed that fifty percent increase in data is evaluated as slightly increasing, when the data is represented by a column chart with a proper design. The perceived increase level from a column chart with a truncated y-axis is also measured in the experiment. The mean of the responses for the column chart with a truncated y-axis was 3.40. This value falls somewhere between the moderately increased and sharply increased categories. Also, the proportion of the "slightly increased" option falls from 43% to 7%, when the data is represented by a column chart with a truncated y-axis instead of a baseline column chart. The difference between the perceived increase level from the baseline chart and the chart with a truncated y-axis is statistically significant.

With the finding of the experiment, we can conclude that the truncated y-axis usage in a column chart has a deceptive effect on the perceived message. This result is in line with the literature in the field. Many researchers state that truncated y-axis usage should be avoided while designing column charts (Few, 2006a; Pandey et al., 2015). This experiment provides evidence for the deceptive effects of truncating the y-axis in column charts.

8.1.2 Does truncated axis usage in line charts have an impact on the perceived message?

In the experiment, participants were shown a line chart with a y-axis starting from zero. The perceived increase level from this chart is taken as the baseline value for line charts. The baseline value for the line charts was 2.76. This numeric value is between the slightly increased and the moderately increased categories. In the experiment, there was also a line chart with a truncated y-axis. The mean of the perceived increase level from the line chart with a truncated y-axis was 3.31. The difference between the means of response variable for the baseline chart (2.71) and for the chart with a truncated y-axis (3.31), is statistically significant. Thus, the experiment shows that truncated y-axis usage has a deceptive impact on the perceived increase level in line charts.

This finding is contradicting to some studies in the literature, which state that using truncated y-axis in a line chart is not problematic (Few, 2006a; Fung, 2014). Few (2006a) claims that the viewers will not get manipulated by a line chart with a truncated y-axis, because only position attribute is used to process information from a line chart. However, there are also claims that a line chart with a truncated y-axis is not problematic, only if the viewer is aware of the emphasis in the chart (Evergreen, 2014; Yanofsky, 2015). In the experiment of this paper, no warning is given to the participants for the purpose of the study. Also, the participants were not selected from the members of any special community, which has certain way of representing the data. For example, it may be possible to get different results from the same experiment, if the participants are working in stock market. Additional research is needed to investigate the case where the viewers are aware of the manipulation in the chart. The aim of this research is to understand the impact of the truncated y-axis usage, when no additional information is given to the viewer. In this case, truncated y-axis usage affects the perceived increased level from a line chart.

8.2 Impact of Not-Connected Axes

During the literature review, the need for a method to alarm the viewers about the truncated y-axis was discovered (Evergreen, 2014; Yanofsky, 2015). Not-connected axes is a design method that is recommended in line charts (Tufte, & Graves-Morris, 1983). Since having not-connected axes may draw the attention of the viewer to the data (Tufte, & Graves-Morris, 1983), it is considered as a way to avoid deception that is caused by the truncated y-axis usage. First, the effectiveness of not-connected axes will be analyzed for column charts. Then, a similar analysis will be done for line charts.

8.2.1 Does not-connected axes usage prevent truncated y-axis from being deceptive in column charts?

The experiment of this study showed that truncated y-axis usage in a column chart causes a deception in the perceived increase level. Another aim of the study is to understand whether the not-connected axes can prevent truncated y-axis usage from being deceptive. For this purpose, a chart with not-connected axes is used in the experiment. The mean of the perceived increase level from this column chart with not-connected axes is 3.23, whereas the baseline value for the perceived increase level is 2.50. The difference in the means is significantly different.

Having not-connected axes was expected to prevent the deception in the perceived message. However, the experiment showed that the perceived increase level is different than the baseline value, when the axes of the charts are not connected. Therefore, we can conclude that the not-connected axes usage cannot be seen as a solution for the column charts. Truncated y-axis usage in a column chart is always considered wrong, because the length attribute is used to retrieve information from a column chart (Few, 2006a; Fung, 2014; Evergreen, 2014; Yanofsky, 2015). The length attribute is still in play when the axes of the chart are not connected. Not-connected axes were considered as a solution for the column chart because of its alarming capability. In conclusion, truncated y-axis usage is still deceptive for a column chart, when the axes of the chart are not-connected.

8.2.2 Does not-connected axes usage prevent truncated y-axis from being deceptive in line charts?

As discussed earlier, the experiment showed that using a truncated y-axis in a line chart affects the perceived increase level. There are some studies that claim that having a truncated y-axis in a line chart is not deceptive (Few, 2006a; Fung, 2014; Evergreen, 2014; Yanofsky, 2015), however the importance of the awareness of the viewers is emphasized (Fung, 2014; Evergreen, 2014). Not-connected axes method is considered as a way to alarm the viewers about the truncated y-axis of the chart. To measure the effectiveness of the not-connected axes method in line charts, a line chart with a truncated y-axis and with connected axes was shown to the participants in the experiment. The mean of the perceived increase level for this line chart is 2.76, and the baseline value of the perceived increase is 3.53. The difference between the means of the perceived increase level is statistically significant.

Not-connected axes method is recommended to keep the focus on the data (Tufte, & Graves-Morris, 1983). It was hoped to work as an alarming method as well, however the experiment showed that not-connected axes is not an effective alarming method in line charts.

8.3 Validity and Reliability

In this section, validity and reliability of the study will be discussed. Validity means that the method actually measures what it is intended to measure (Greener, 2008). In other words, the validity of a study gives some indication of how well an experiment measures a given area, under the given circumstances, and with a given group (Burns & Dobson, 2012). On the other hand, reliability refers to consistency or repeatability of the study over time (Greener, 2008). The synonyms for reliability are: dependability, stability, predictability, and accuracy (Burns, & Dobson, 2012). Validity is an essential part of any study. If the method is valid for measuring what it aims to measure, it does not help that the method is reliable. Also, an unreliable measure cannot be valid because it would not be possible to distinguish the systematic error from the random error (Sarstedt & Mooi, 2014).

The experiment of this study had one response variable for the questions with visualizations. The aim of the experiment was to measure and compare the perceived increase level from the charts with different designs. It is recommended to use established indicators in the field to ensure

the validity of the study (De Vaus, 2013). The wording of the question and the response variable are adopted from another studies in the field (Beattie, & Jones, 2002a; Pandey et al., 2015). The participants were asked to choose among the options with a 5-Item Likert scale. The response options and the numerical values assigned to the options can be seen in Table 22. During the analysis of a Likert scale question, it is assumed that the distance between each category is equal (Alphen, Halfens, Hasman, & Imbos, 1994). For this experiment, the distance between the very slightly increased and slightly increased categories and the distance between the slightly increased and moderately increased categories are assumed to be the same. However, this is not necessarily true. Therefore, evaluating the response options with an interval scale, instead of evaluating each response as a different category may have an impact on the results.

Table 22: Response options and assigned numerical values

Response variables	Numerical value
Very slightly increased	1
Slightly increased	2
Moderately increased	3
Sharply increased	4
Very sharply increased	5

Multiple-item indicator are recommended to increase the reliability of the study (De Vaus, 2013). However, due to the nature of the experiment in this study, using multiple-item indicators would harm the results. Since showing similar charts more than once to a participant could reveal the purpose of the study to the participants.

Furthermore, comparison between the baseline column chart and the column chart with a truncated y-axis is done during the analysis. However, the evaluation of these charts are done by two different groups. Having the same person evaluating the two charts would make it possible to execute a paired test. This could improve the reliability of the results. Showing both the baseline and the manipulated chart to the same person was avoided to not reveal the purpose of the study. The questionnaires and the charts were designed carefully to enable the comparison of responses collected from two different sample. Also the analysis showed that none of the demographic groups had a different result. So, it is considered to be fine to compare the results from two samples.

8.4 Limitations and Suggestions for Future Research

The limitations of the study and the suggestions for future research in the field will be discussed in this section. First, the limitations and their effects will be explained. Further, suggestions for future research will be given by asking questions that are emerged as a result of this study.

Firstly, the sample of the experiment was not representing the whole population. The participants were mostly young and highly educated people. Therefore, the finding of the study may not be true for age or education classes. However, earlier studies that investigated message deceptions with visualizations found that individual differences did not affect the results (Pandey et. al, 2015).

Secondly, the order of the questions were not randomized and not tested for the ordering effects. All the participants saw the baseline chart as their first chart, the chart with a truncated y-axis as their second chart, and the chart with a truncated y-axis and not-connected axes as their last charts. A software tool for preparing a questionnaire that can randomly assign visualizations and the design conditions was not available to the author.

Furthermore, the study showed the impact of truncated y-axis usage in line and column charts on the perceived message. The results indicate that truncated y-axis usage results in deception in both chart types. Truncated y-axis usage in line charts is considered to be acceptable, as long as the viewers are aware of the deception (Evergreen, 2014; Yanofsky, 2015). It would be conduct a similar experiment to test whether the awareness of the viewers actually prevents the deception in the message.

In this study, visualizations were investigated as a communication tool. Therefore, the participants were not asked to make a decision with the perceived message from the charts. Testing the perceived message for the situation where the participants need to make a decision with the perceived information, can also be interesting.

9 Conclusions

The importance of understanding the power of visualizations is increasing with their common use in many fields. This paper investigated the deceptive visualizations for time series datasets. The selection of the topic was due to lack of empirical studies in the field of deceptive visualizations (Pandey et al., 2015). Many important reports are accompanied by graphs both in academic ad

business worlds. Approximately 75% of all business graphs display time series data (Few & Principal, 2005). Therefore, it carry a great importance to study the deceptiveness of the common design methods. For this purpose, the types of visualizations and the design principals for these visualization types are reviewed in this paper. Also, a basic understanding of visual perception rules are provided in the literature review part. In the light of the literature review, an experiment was designed to measure the impact of y-axis manipulation on the perceived message. The experiment showed that the perceived message is affected by the y-axis manipulation. This effect is seen both in line charts and column charts. The study provided an empirical evidence of the effect of deceptive visualizations.

10 References

Alphen, A., Halfens, R., Hasman, A., & Imbos, T. (1994). Likert or rasch? Nothing is more applicable than good theory. *Journal of Advanced Nursing, 20*(1), 196-201.

Anscombe, F. J. (1973). Graphs in statistical analysis. *The American Statistician, 27*(1), 17-21.

Arunachalam, V., Pei, B. K., & Steinbart, P. J. (2002). Impression management with graphs: Effects on choices. *Journal of Information Systems, 16*(2), 183-202.

Beattie, V., & Jones, M. J. (2002a). The impact of graph slope on rate of change judgments in corporate reports. *Abacus, 38*(2), 177-199.

Beattie, V., & Jones, M. J. (2002b). Measurement distortion of graphs in corporate reports: An experimental study. *Accounting, Auditing & Accountability Journal, 15*(4), 546-564.

Bertin, J. (1983). Semiology of graphics: Diagrams, networks, maps.

Bhutta, C. B. (2012). Not by the book: Facebook as a sampling frame. *Sociological Methods & Research*.

Boundless. (2015). OpenIntro statistics. Retrieved from https://www.boundless.com/users/233402/textbooks/openintro-statistics/introduction-to-data-1/experiments-15/principles-of-experimental-design-79-13692/

Bourque, L. B., & Clark, V. (1994). Processing data: The survey example (quantitative applications in the social sciences).

Burgess, D. O., Dilla, W. N., Steinbart, P. J., & Shank, T. M. (2008). Does graph design matter to CPAs and financial statement readers? *Journal of Business & Economics Research (JBER), 6*(5)

Burkhard, R. A. (2004). Learning from architects: The difference between knowledge visualization and information visualization. *Information Visualisation, 2004. IV 2004. Proceedings. Eighth International Conference On*, 519-524.

Burns, R. B., & Dobson, C. B. (2012). *Experimental psychology: Research methods and statistics* Springer Science & Business Media.

Card, S. K., & Mackinlay, J. (1997). The structure of the information visualization design space. *Information Visualization, 1997. Proceedings, IEEE Symposium On*, 92-99.

Card, S. K., Mackinlay, J. D., & Shneiderman, B. (1999). *Readings in information visualization: Using vision to think* Morgan Kaufmann.

Cleveland, W. S. (1985). *The elements of graphing data* Wadsworth Advanced Books and Software Monterey, CA.

Cleveland, W. S., & McGill, R. (1984). Graphical perception: Theory, experimentation, and application to the development of graphical methods. *Journal of the American Statistical Association, 79*(387), 531-554.

De Vaus, D. (2013). *Surveys in social research* Routledge.

DiBiase, D., MacEachren, A. M., Krygier, J. B., & Reeves, C. (1992). Animation and the role of map design in scientific visualization. *Cartography and Geographic Information Systems, 19*(4), 201-214.

Dictionary, O. E. (2004). Oxford English dictionary online. *Mount Royal College Lib., Calgary, 14*

Dillman, D. A. (2007). Mail and internet surveys: The tailored design method.

Engel, P. (2014). This chart shows an alarming rise in Florida gun deaths after 'stand your ground' was enacted. *Business Insider*.

Evergreen, S. (2014). When it's OK to not start your axis at zero. Retrieved from http://stephanieevergreen.com/non-zero-axis-rules/

Evergreen, S., & Metzner, C. (2013). Design principles for data visualization in evaluation. *New Directions for Evaluation, 140*, 5-20.

Few, S. (2004). Enie, meenie, minie, moe: Selecting the right graph for your message. *Intelligent Enterprise*.

Few, S. (2006a). Data visualization: Rules for encoding values in graph. Retrieved from https://www.perceptualedge.com/articles/b-eye/encoding_values_in_graph.pdf

Few, S. (2006b). *Information dashboard design* O'Reilly.

Few, S., & Principal, P. E. (2005). Effectively communicating numbers. *Principal Perceptual Edge.* Retrieved from https://www.perceptualedge.com/articles/Whitepapers/Communicating_Numbers.pdf

Flink Labs. (2011). Data Visualisation Workshop. Retrieved from http://www.slideshare.net/Flinklabs/visualizing-marathon-data-visualisation-workshop-introduction

Friendly, M. (2000). *Visualizing categorical data.* SAS Institute Cary, NC.

Friendly, M., & Kwan, E. (2003). Effect ordering for data displays. *Computational Statistics & Data Analysis, 43*(4), 509-539.

Frownfelter-Lohrke, C., & Fulkerson, C. L. (2001). The incidence and quality of graphics in annual reports: An international comparison. *Journal of Business Communication, 38*(3), 337-357.

Fung, K. (2014). When to use start-at-zero rule. Retrieved from http://junkcharts.typepad.com/junk_charts/2014/04/when-to-use-the-start-at-zero-rule-.html

Gelman, A., & Unwin, A. (2013). Infovis and statistical graphics: Different goals, different looks. *Journal of Computational and Graphical Statistics, 22*(1), 2-28.

Gershon, N., Eick, S. G., & Card, S. (1998). Information visualization. *Interactions, 5*(2), 9-15.

Greener, S. (2008). *Business research methods* BookBoon.

Heer, J., Bostock, M., & Ogievetsky, V. (2010). A tour through the visualization zoo. *Commun.Acm, 53*(6), 59-67.

Henry, G. T. (1995). *Graphing data: Techniques for display and analysis* Sage Publications, Inc.

Hinkelmann, K. (2015). History and overview of design and analysis of experiments. In A. Dean, M. Morris, J. Stufken & D. Bingham (Eds.), *Handbook of design and analysis of experiments* (pp. 3-63) CRC Press.

Jarvenpaa, S., & Dickson, G. W. (1988). Graphics and managerial decision making: Research-based guidelines. *Communications of the ACM, 31*(6), 764-774.

Khan, M., & Khan, S. S. (2011). Data and information visualization methods, and interactive mechanisms: A survey. *International Journal of Computer Applications, 34*(1), 1-14.

Kosara, R. (2011). Ancombe's quartet. Retrieved from https://eagereyes.org/criticism/anscombes-quartet

Kosera, R. (2012). The changing goals of visualization. Retrieved from https://eagereyes.org/criticism/changing-goals-data-visualization

Kosslyn, S. M. (1994). *Elements of graph design.* WH Freeman New York.

Montgomery, D. C. (2008). *Design and analysis of experiments.* John Wiley & Sons.

Morgan, J. P. (2015). Blocking with indepent responses. In A. Dean, M. Morris, J. Stufken & D. Bingham (Eds.), *Handbook of design and analysis of experiments*.

Pandey, A. V., Manivannan, A., Nov, O., Satterthwaite, M., & Bertini, E. (2014). The persuasive power of data visualization. *Visualization and Computer Graphics, IEEE Transactions On, 20*(12), 2211-2220.

Pandey, A. V., Rall, K., Satterthwaite, M. L., Nov, O., & Bertini, E. (2015). How deceptive are deceptive visualizations?: An empirical analysis of common distortion techniques. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems,* 1469-1478.

Plaisant, C. (2004). The challenge of information visualization evaluation. *Proceedings of the Working Conference on Advanced Visual Interfaces,* 109-116.

Playfair, W. (1786). The commercial and political atlas (London).

Post, F. H., Nielson, G., & Bonneau, G. (2012). *Data visualization: The state of the art* Springer Science & Business Media.

Robertson, G., Fernandez, R., Fisher, D., Lee, B., & Stasko, J. (2008). Effectiveness of animation in trend visualization. *Visualization and Computer Graphics, IEEE Transactions On, 14*(6), 1325-1332.

Rugg, G., & Petre, M. (2006). *A gentle guide to research methods* McGraw-Hill Education (UK).

Sarstedt, M., & Mooi, E. (2014). A concise guide to market research.

Saunders, M., Lewis, P., & Thornhill, A. (2009). Research methods for business students. *Financial Times Prentice Hall Inc., London.*

Shneiderman, B., & Plaisant, C. (2006). Strategies for evaluating information visualization tools: Multi-dimensional in-depth long-term case studies. *Proceedings of the 2006 AVI Workshop on Beyond Time and Errors: Novel Evaluation Methods for Information Visualization*, 1-7.

Steinbart, P. J. (1989). The auditor's responsibility for the accuracy of graphs in annual reports: Some evidence of the need for additional guidance. *Accounting Horizons, 3*(3), 60-70.

Tal, A., & Wansink, B. (2016). Blinded with science: Trivial graphs and formulas increase ad persuasiveness and belief in product efficacy. *Public Understanding of Science (Bristol, England), 25*(1), 117-125.

Tufte, E. R., & Graves-Morris, P. (1983). *The visual display of quantitative information* Graphics press Cheshire, CT.

Ware, C. (2012). *Information visualization: Perception for design* Elsevier.

Yanofsky, D. (2015). It's OK not to start your y-axis at zero. Retrieved from http://qz.com/418083/its-ok-not-to-start-your-y-axis-at-zero/

Yin, R. K. (2013). *Case study research: Design and methods* Sage publications.

Zer-Aviv, M. (2014). Disinformation visualization: How to lie with datavis. Retrieved from https://visualisingadvocacy.org/blog/disinformation-visualization-how-lie-datavis

Appendix A: Questionnaire 1

Welcome!

This survey is prepared to gather data for my Master's Thesis at Aalto University School of Business.

The aim of this survey is to measure the effectiveness of different graphs for delivering a message.

The survey will take less than 5 minutes of your time.

Thank you for your participation!

Sila Ezgi Biber
silaezgibiber@gmail.com

First, there will be three short questions about yourself.

Please select your gender

- female
- male

What year were you born? (e.g. 1989)

How many years have you studied at a university?

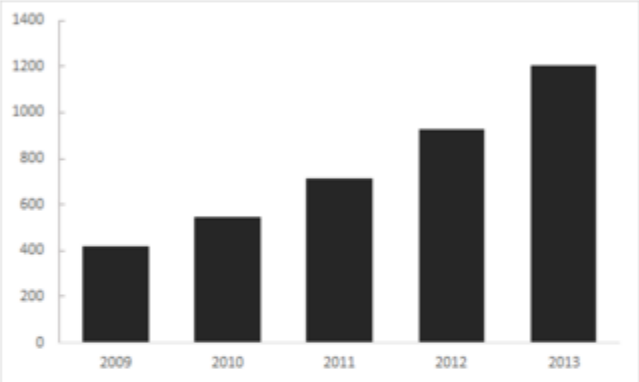
- 0
- 1
- 2
- 3
- 4
- 5+

Next, there will be three questions with different charts.

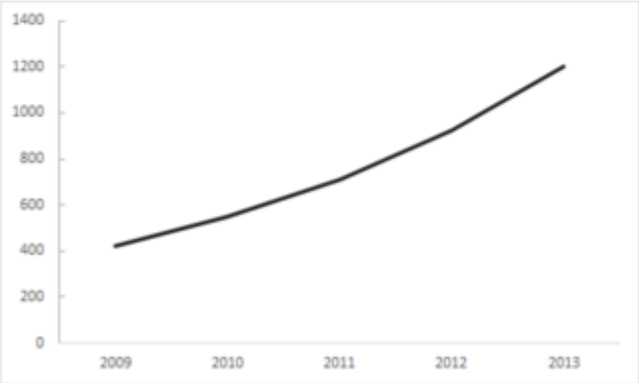
For each question, you will be presented either with a column chart or a line chart. An example of each chart type can be seen below.

After looking at the chart, you are asked to choose the verbal description that - you feel - describes best the change in the given data.

Column Chart Example

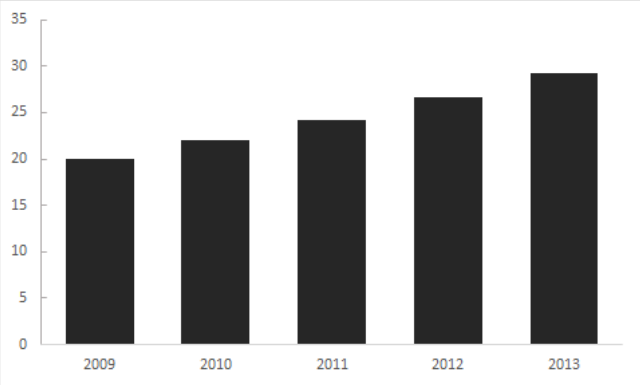


Line Chart Example



The graph shows **the number of the employees of the company X by year**.

How much do you think the number of the employees has increased in the given time period?

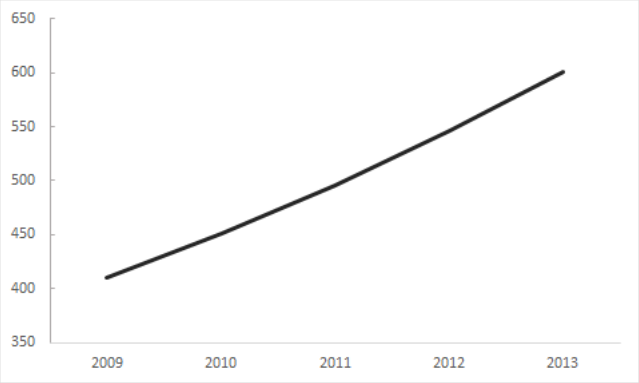


- very slightly increased
- slighty increased
- moderately increased
- sharply increased
- very sharply increased

0% 100%

The graph shows **the total spending of the company X by year.**

How much do you think the total spending of the company X has increased in the given time period?

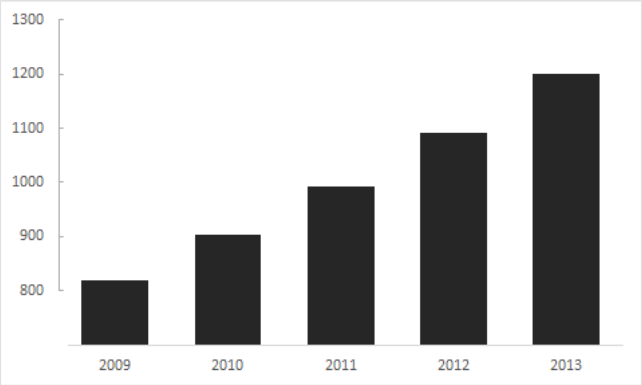


- very slightly increased
- slighty increased
- moderately increased
- sharply increased
- very sharply increased

0% 100%

The graph shows **the revenue of the company X by year.**

How much do you think the revenue of the company X has increased in the given time period?



- very slightly increased
- slighty increased
- moderately increased
- sharply increased
- very sharply increased

0% 100%

Thank you for your participation!

Sila Ezgi Biber
silaezgibiber@gmail.com

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0% 100%

Appendix B: Questionnaire 2

Welcome!

This survey is prepared to gather data for my Master's Thesis at Aalto University School of Business.

The aim of this survey is to measure the effectiveness of different graphs for delivering a message.

The survey will take less than 5 minutes of your time.

Thank you for your participation!

Sila Ezgi Biber
silaezgibiber@gmail.com

First, there will be three short questions about yourself.

Please select your gender

- female
- male

What year were you born? (e.g. 1989)

How many years have you studied at a university?

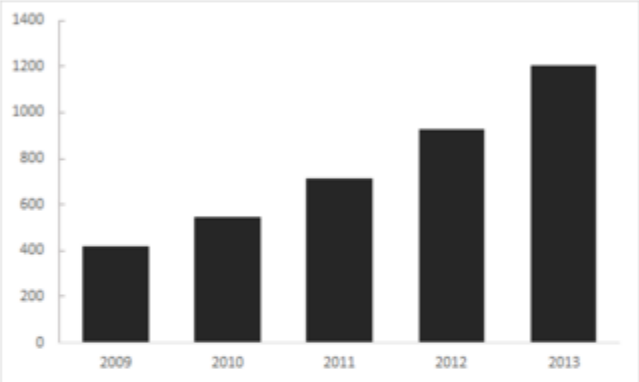
- 0
- 1
- 2
- 3
- 4
- 5+

Next, there will be three questions with different charts.

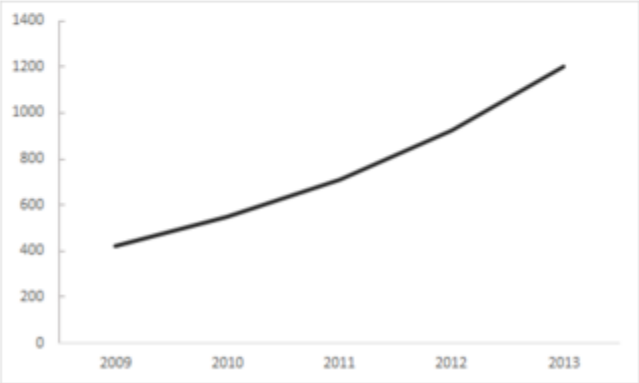
For each question, you will be presented either with a column chart or a line chart. An example of each chart type can be seen below.

After looking at the chart, you are asked to choose the verbal description that - you feel - describes best the change in the given data.

Column Chart Example

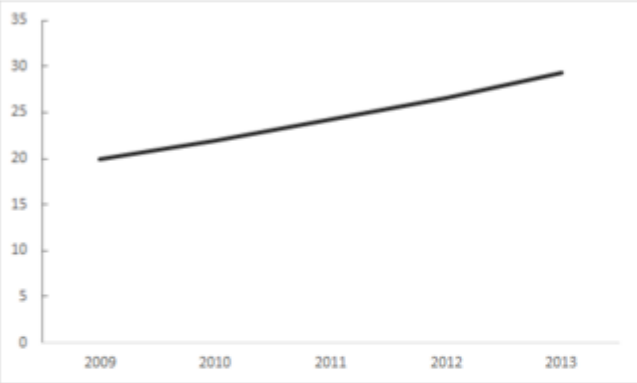


Line Chart Example



The graph shows **the number of the employees of the company X by year.**

How much do you think the number of the employees has increased in the given time period?

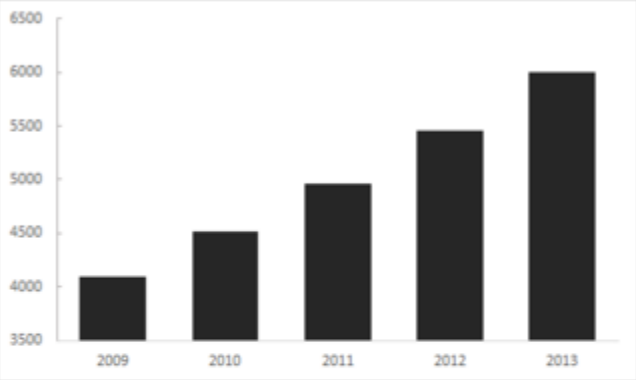


- very slightly increased
- slightly increased
- moderately increased
- sharply increased
- very sharply increased

0% 100%

The graph shows **the total sales of the company X by year.**

How much do you think the total sales of the company X has increased in the given time period?

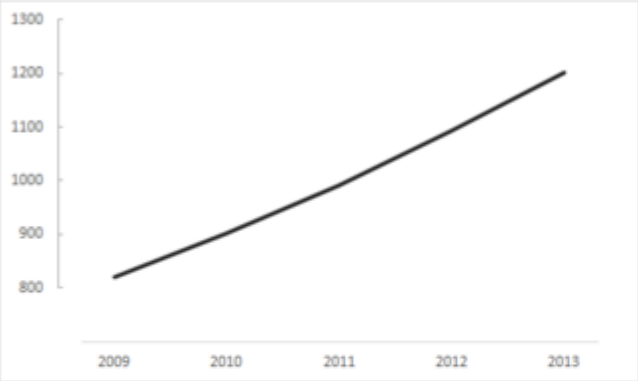


- very slightly increased
- slightly increased
- moderately increased
- sharply increased
- very sharply increased

0% 100%

The graph shows **the total spending of the company X by year.**

How much do you think the total spending of the company X has increased in the given time period?



- very slightly increased
- slightly increased
- moderately increased
- sharply increased
- very sharply increased

0% 100%

Thank you for your participation!

Sila Ezgi Biber
silaezgibiber@gmail.com

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0% 100%

Appendix C: T-test Results for Column Chart Baseline

Gender comparison

t Test

The TTEST Procedure

Variable: Perceived Increase

Treatment=1 Question=1

Gender	N	Mean	Std Dev	Std Err	Minimum	Maximum
female	54	2.5370	0.9052	0.1232	1.0000	5.0000
male	73	2.4795	0.7474	0.0875	1.0000	4.0000
Diff (1-2)		0.0576	0.8180	0.1468		

Gender	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
female		2.5370	2.2900	2.7841	0.9052	0.7609	1.1175
male		2.4795	2.3051	2.6538	0.7474	0.6427	0.8931
Diff (1-2)	Pooled	0.0576	-0.2330	0.3482	0.8180	0.7280	0.9337
Diff (1-2)	Satterthwaite	0.0576	-0.2421	0.3573			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	125	0.39	0.6956
Satterthwaite	Unequal	101.02	0.38	0.7039

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	53	72	1.47	0.1301

Age group comparison

t Test

The TTEST Procedure

Variable: Perceived Increase

Question=1 Treatment=1

AgeGroup	N	Mean	Std Dev	Std Err	Minimum	Maximum
1	97	2.4845	0.8430	0.0856	1.0000	5.0000
2	30	2.5667	0.7279	0.1329	1.0000	4.0000
Diff (1-2)		-0.0821	0.8178	0.1708		

AgeGroup	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
1		2.4845	2.3146	2.6544	0.8430	0.7388	0.9818
2		2.5667	2.2949	2.8385	0.7279	0.5797	0.9786
Diff (1-2)	Pooled	-0.0821	-0.4202	0.2560	0.8178	0.7277	0.9334
Diff (1-2)	Satterthwaite	-0.0821	-0.3989	0.2346			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	125	-0.48	0.6315
Satterthwaite	Unequal	55.181	-0.52	0.6055

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	96	29	1.34	0.3706

Education group comparison

t Test

The TTEST Procedure

Variable: Perceived Increase

Question=1 Treatment=1

EducationGroup	N	Mean	Std Dev	Std Err	Minimum	Maximum
1	35	2.7143	0.7504	0.1268	1.0000	4.0000
2	92	2.4239	0.8285	0.0864	1.0000	5.0000
Diff (1-2)		0.2904	0.8080	0.1605		

EducationGroup	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
1		2.7143	2.4565	2.9720	0.7504	0.6069	0.9831
2		2.4239	2.2523	2.5955	0.8285	0.7237	0.9692
Diff (1-2)	Pooled	0.2904	-0.0272	0.6080	0.8080	0.7191	0.9223
Diff (1-2)	Satterthwaite	0.2904	-0.0159	0.5966			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	125	1.81	0.0728
Satterthwaite	Unequal	67.435	1.89	0.0628

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	91	34	1.22	0.5221

Appendix D: T-test Results for Line Chart Baseline

Gender comparison

t Test

The TTEST Procedure

Variable: Perceived Increase

Treatment=2 Question=1

Gender	N	Mean	Std Dev	Std Err	Minimum	Maximum
female	58	2.7931	0.7196	0.0945	1.0000	4.0000
male	63	2.7302	0.8652	0.1090	1.0000	5.0000
Diff (1-2)		0.0629	0.7988	0.1454		

Gender	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
female		2.7931	2.6039	2.9823	0.7196	0.6084	0.8810
male		2.7302	2.5123	2.9481	0.8652	0.7361	1.0496
Diff (1-2)	Pooled	0.0629	-0.2249	0.3508	0.7988	0.7089	0.9150
Diff (1-2)	Satterthwaite	0.0629	-0.2227	0.3486			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	119	0.43	0.6658
Satterthwaite	Unequal	117.82	0.44	0.6634

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	62	57	1.45	0.1606

Appendix E: T-test Results for Column Chart Baseline vs. Truncated Y-axis

Baseline vs. Truncated y-axis column chart comparison

t Test

The TTEST Procedure

Variable: Perceived Increase

Chart type=Column chart

Truncated y-axis	N	Mean	Std Dev	Std Err	Minimum	Maximum
No	127	2.5039	0.8153	0.0723	1.0000	5.0000
Yes	121	3.3967	0.7581	0.0689	1.0000	5.0000
Diff (1-2)		-0.8928	0.7879	0.1001		

Truncated y-axis	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
No		2.5039	2.3608	2.6471	0.8153	0.7258	0.9300
Yes		3.3967	3.2602	3.5331	0.7581	0.6731	0.8678
Diff (1-2)	Pooled	-0.8928	-1.0899	-0.6956	0.7879	0.7240	0.8642
Diff (1-2)	Satterthwaite	-0.8928	-1.0896	-0.6960			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	246	-8.92	<.0001
Satterthwaite	Unequal	245.86	-8.94	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	126	120	1.16	0.4221

Baseline vs. Truncated y-axis column chart comparison for females

t Test

The TTEST Procedure

Variable: Perceived Increase

Chart type=Column chart Gender=female

Truncated y-axis	N	Mean	Std Dev	Std Err	Minimum	Maximum
No	54	2.5370	0.9052	0.1232	1.0000	5.0000
Yes	58	3.4138	0.7017	0.0921	1.0000	5.0000
Diff (1-2)		-0.8768	0.8062	0.1525		

Truncated y-axis	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
No		2.5370	2.2900	2.7841	0.9052	0.7609	1.1175
Yes		3.4138	3.2293	3.5983	0.7017	0.5933	0.8591
Diff (1-2)	Pooled	-0.8768	-1.1789	-0.5746	0.8062	0.7123	0.9289
Diff (1-2)	Satterthwaite	-0.8768	-1.1820	-0.5716			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	110	-5.75	<.0001
Satterthwaite	Unequal	99.841	-5.70	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	53	57	1.66	0.0605

Baseline vs. Truncated y-axis column chart comparison for males

The TTEST Procedure

Variable: Perceived Increase

Chart type=Column chart Gender=male

Truncated y-axis	N	Mean	Std Dev	Std Err	Minimum	Maximum
No	73	2.4795	0.7474	0.0875	1.0000	4.0000
Yes	63	3.3810	0.8118	0.1023	2.0000	5.0000
Diff (1-2)		-0.9015	0.7778	0.1338		

Truncated y-axis	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
No		2.4795	2.3051	2.6538	0.7474	0.6427	0.8931
Yes		3.3810	3.1765	3.5854	0.8118	0.6907	0.9848
Diff (1-2)	Pooled	-0.9015	-1.1661	-0.6369	0.7778	0.6948	0.8836
Diff (1-2)	Satterthwaite	-0.9015	-1.1678	-0.6352			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	134	-6.74	<.0001
Satterthwaite	Unequal	127.25	-6.70	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	62	72	1.18	0.4971

Baseline vs. Truncated y-axis column chart comparison for younger than 30 years old age group

t Test

The TTEST Procedure

Variable: Perceived Increase

Chart type=Column chart AgeGroup=1

Truncated y-axis	N	Mean	Std Dev	Std Err	Minimum	Maximum
No	97	2.4845	0.8430	0.0856	1.0000	5.0000
Yes	107	3.4299	0.7784	0.0752	1.0000	5.0000
Diff (1-2)		-0.9454	0.8098	0.1135		

Truncated y-axis	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
No		2.4845	2.3146	2.6544	0.8430	0.7388	0.9818
Yes		3.4299	3.2807	3.5791	0.7784	0.6862	0.8994
Diff (1-2)	Pooled	-0.9454	-1.1692	-0.7215	0.8098	0.7379	0.8972
Diff (1-2)	Satterthwaite	-0.9454	-1.1701	-0.7206			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	202	-8.33	<.0001
Satterthwaite	Unequal	195.81	-8.29	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	96	106	1.17	0.4222

Baseline vs. Truncated y-axis column chart comparison for educated more than 4 years at a university

t Test

The TTEST Procedure

Variable: Perceived Increase

Chart type=Column chart EducationGroup=2

Truncated y-axis	N	Mean	Std Dev	Std Err	Minimum	Maximum
No	92	2.4239	0.8285	0.0864	1.0000	5.0000
Yes	109	3.3670	0.7535	0.0722	1.0000	5.0000
Diff (1-2)		-0.9431	0.7887	0.1117		

Truncated y-axis	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
No		2.4239	2.2523	2.5955	0.8285	0.7237	0.9692
Yes		3.3670	3.2239	3.5100	0.7535	0.6650	0.8694
Diff (1-2)	Pooled	-0.9431	-1.1633	-0.7229	0.7887	0.7182	0.8746
Diff (1-2)	Satterthwaite	-0.9431	-1.1651	-0.7210			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	199	-8.45	<.0001
Satterthwaite	Unequal	186.02	-8.38	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	91	108	1.21	0.3430

Appendix F: T-test Results for Line Chart Baseline vs. Truncated Y-axis

Baseline vs. Truncated y-axis line chart comparison

Chart type=Line chart

Truncated y-axis	N	Mean	Std Dev	Std Err	Minimum	Maximum
No	121	2.7603	0.7961	0.0724	1.0000	5.0000
Yes	127	3.3071	0.7819	0.0694	1.0000	5.0000
Diff (1-2)		-0.5468	0.7888	0.1002		

Truncated y-axis	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
No		2.7603	2.6170	2.9036	0.7961	0.7068	0.9113
Yes		3.3071	3.1698	3.4444	0.7819	0.6961	0.8919
Diff (1-2)	Pooled	-0.5468	-0.7441	-0.3494	0.7888	0.7249	0.8653
Diff (1-2)	Satterthwaite	-0.5468	-0.7442	-0.3493			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	246	-5.46	<.0001
Satterthwaite	Unequal	244.91	-5.45	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	120	126	1.04	0.8407

Baseline vs. Truncated y-axis line chart comparison for males

t Test

The TTEST Procedure

Variable: Perceived Increase

Chart type=Line chart Gender=male

Truncated y-axis	N	Mean	Std Dev	Std Err	Minimum	Maximum
No	63	2.7302	0.8652	0.1090	1.0000	5.0000
Yes	73	3.2329	0.7732	0.0905	2.0000	5.0000
Diff (1-2)		-0.5027	0.8170	0.1405		

Truncated y-axis	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
No		2.7302	2.5123	2.9481	0.8652	0.7361	1.0496
Yes		3.2329	3.0525	3.4133	0.7732	0.6649	0.9239
Diff (1-2)	Pooled	-0.5027	-0.7806	-0.2248	0.8170	0.7298	0.9281
Diff (1-2)	Satterthwaite	-0.5027	-0.7831	-0.2223			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	134	-3.58	0.0005
Satterthwaite	Unequal	125.55	-3.55	0.0005

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	62	72	1.25	0.3563

Baseline vs. Truncated y-axis column chart comparison for females

The TTEST Procedure

Variable: Perceived Increase

Chart type=Line chart Gender=female

Truncated y-axis	N	Mean	Std Dev	Std Err	Minimum	Maximum
No	58	2.7931	0.7196	0.0945	1.0000	4.0000
Yes	54	3.4074	0.7895	0.1074	1.0000	5.0000
Diff (1-2)		-0.6143	0.7541	0.1426		

Truncated y-axis	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
No		2.7931	2.6039	2.9823	0.7196	0.6084	0.8810
Yes		3.4074	3.1919	3.6229	0.7895	0.6637	0.9747
Diff (1-2)	Pooled	-0.6143	-0.8969	-0.3317	0.7541	0.6663	0.8688
Diff (1-2)	Satterthwaite	-0.6143	-0.8979	-0.3307			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	110	-4.31	<.0001
Satterthwaite	Unequal	107.11	-4.29	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	53	57	1.20	0.4918

Baseline vs. Truncated y-axis line chart comparison for younger than 30 years old age group

t Test

The TTEST Procedure

Variable: Perceived Increase

Chart type=Line chart AgeGroup=1

Truncated y-axis	N	Mean	Std Dev	Std Err	Minimum	Maximum
No	107	2.8037	0.7943	0.0768	1.0000	5.0000
Yes	97	3.2990	0.7795	0.0791	1.0000	5.0000
Diff (1-2)		-0.4952	0.7873	0.1104		

Truncated y-axis	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
No		2.8037	2.6515	2.9560	0.7943	0.7003	0.9178
Yes		3.2990	3.1419	3.4561	0.7795	0.6831	0.9078
Diff (1-2)	Pooled	-0.4952	-0.7129	-0.2776	0.7873	0.7174	0.8724
Diff (1-2)	Satterthwaite	-0.4952	-0.7127	-0.2778			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	202	-4.49	<.0001
Satterthwaite	Unequal	200.72	-4.49	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	106	96	1.04	0.8530

Baseline vs. Truncated y-axis line chart comparison for educated more than 4 years at a university

t Test

The TTEST Procedure

Variable: Perceived Increase

Chart type=Line chart EducationGroup=2

Truncated y-axis	N	Mean	Std Dev	Std Err	Minimum	Maximum
No	109	2.7431	0.8097	0.0776	1.0000	5.0000
Yes	92	3.3043	0.7948	0.0829	1.0000	5.0000
Diff (1-2)		-0.5612	0.8029	0.1137		

Truncated y-axis	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
No		2.7431	2.5894	2.8968	0.8097	0.7146	0.9342
Yes		3.3043	3.1398	3.4689	0.7948	0.6942	0.9297
Diff (1-2)	Pooled	-0.5612	-0.7854	-0.3371	0.8029	0.7312	0.8904
Diff (1-2)	Satterthwaite	-0.5612	-0.7851	-0.3374			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	199	-4.94	<.0001
Satterthwaite	Unequal	194.5	-4.95	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	108	91	1.04	0.8580

Appendix G: T-test Results for Column Chart Baseline vs. Not-connected axes

Baseline vs. not-connected axes column chart comparison

t Test

The TTEST Procedure

Difference: question3 - question1

Treatment=Treatment1

N	Mean	Std Dev	Std Err	Minimum	Maximum
127	0.7244	1.0814	0.0960	-2.0000	3.0000

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.7244	0.5345	0.9143	1.0814	0.9628	1.2337

DF	t Value	Pr > |t|
126	7.55	<.0001

Baseline vs. not-connected axes column chart comparison for males

t Test

The TTEST Procedure

Difference: question3 - question1

gender=male Treatment=Treatment1

N	Mean	Std Dev	Std Err	Minimum	Maximum
73	0.7397	1.0805	0.1265	-2.0000	3.0000

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.7397	0.4876	0.9918	1.0805	0.9292	1.2911

DF	t Value	Pr > |t|
72	5.85	<.0001

Baseline vs. not-connected axes column chart comparison for females

t Test

The TTEST Procedure

Difference: question3 - question1

gender=female Treatment=Treatment1

N	Mean	Std Dev	Std Err	Minimum	Maximum
54	0.7037	1.0925	0.1487	-2.0000	3.0000

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.7037	0.4055	1.0019	1.0925	0.9184	1.3487

DF	t Value	Pr > |t|
53	4.73	<.0001

Baseline vs. not-connected axes column chart comparison for younger than 30 years old age group

t Test

The TTEST Procedure

Difference: question3 - question1

AgeGroup=1 Treatment=Treatment1

N	Mean	Std Dev	Std Err	Minimum	Maximum
97	0.7526	1.1368	0.1154	-2.0000	3.0000

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.7526	0.5235	0.9817	1.1368	0.9962	1.3239

DF	t Value	Pr > |t|
96	6.52	<.0001

Baseline vs. not-connected axes column chart comparison for older than 30 years old age group

t Test

The TTEST Procedure

Difference: question3 - question1

AgeGroup=2 Treatment=Treatment1

N	Mean	Std Dev	Std Err	Minimum	Maximum
30	0.6333	0.8899	0.1625	-1.0000	2.0000

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.6333	0.3010	0.9656	0.8899	0.7087	1.1963

DF	t Value	Pr > |t|
29	3.90	0.0005

Baseline vs. not-connected axes column chart comparison for educated less than 4 years at a university

t Test

The TTEST Procedure

Difference: question3 - question1

EducationGroup=1 Treatment=Treatment1

N	Mean	Std Dev	Std Err	Minimum	Maximum
35	0.5143	1.1725	0.1982	-2.0000	3.0000

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.5143	0.1115	0.9171	1.1725	0.9484	1.5362

DF	t Value	Pr > |t|
34	2.59	0.0139

Baseline vs. not-connected axes column chart comparison for educated more than 4 years at a university

t Test

The TTEST Procedure

Difference: question3 - question1

EducationGroup=2 Treatment=Treatment1

N	Mean	Std Dev	Std Err	Minimum	Maximum
92	0.8043	1.0403	0.1085	-2.0000	3.0000

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.8043	0.5889	1.0198	1.0403	0.9086	1.2169

DF	t Value	Pr > |t|
91	7.42	<.0001

Appendix H: T-test Results for Line Chart Baseline vs. Not-connected axes

Baseline vs. not-connected axes line chart comparison

t Test

The TTEST Procedure

Difference: question3 - question1

Treatment=Treatment2

N	Mean	Std Dev	Std Err	Minimum	Maximum
121	0.7686	0.9896	0.0900	-2.0000	3.0000

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.7686	0.5905	0.9467	0.9896	0.8787	1.1329

DF	t Value	Pr > |t|
120	8.54	<.0001

Baseline vs. not-connected axes line chart comparison for males

t Test

The TTEST Procedure

Difference: question3 - question1

gender=male Treatment=Treatment2

N	Mean	Std Dev	Std Err	Minimum	Maximum
63	0.5714	1.0115	0.1274	-2.0000	2.0000

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.5714	0.3167	0.8262	1.0115	0.8605	1.2271

DF	t Value	Pr > |t|
62	4.48	<.0001

Baseline vs. not-connected axes line chart comparison for females

t Test

The TTEST Procedure

Difference: question3 - question1

gender=female Treatment=Treatment2

N	Mean	Std Dev	Std Err	Minimum	Maximum
58	0.9828	0.9270	0.1217	-1.0000	3.0000

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.9828	0.7390	1.2265	0.9270	0.7837	1.1350

DF	t Value	Pr > |t|
57	8.07	<.0001

Baseline vs. not-connected axes line chart comparison for younger than 30 years old age group

Page Break

t Test

The TTEST Procedure

Difference: question3 - question1

AgeGroup=1 Treatment=Treatment2

N	Mean	Std Dev	Std Err	Minimum	Maximum
107	0.7570	1.0265	0.0992	-2.0000	3.0000

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.7570	0.5603	0.9537	1.0265	0.9049	1.1860

DF	t Value	Pr > |t|
106	7.63	<.0001

Baseline vs. not-connected axes line chart comparison for younger than 30 years old age group

Page Break

t Test

The TTEST Procedure

Difference: question3 - question1

AgeGroup=2 Treatment=Treatment2

N	Mean	Std Dev	Std Err	Minimum	Maximum
14	0.8571	0.6630	0.1772	0	2.0000

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.8571	0.4743	1.2399	0.6630	0.4806	1.0681

DF	t Value	Pr > |t|
13	4.84	0.0003

Baseline vs. not-connected axes line chart comparison for educated less than 4 years at a university

Page Break

t Test

The TTEST Procedure

Difference: question3 - question1

EducationGroup=1 Treatment=Treatment2

N	Mean	Std Dev	Std Err	Minimum	Maximum
12	0.7500	1.2154	0.3509	-1.0000	3.0000

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.7500	-0.0222	1.5222	1.2154	0.8610	2.0637

DF	t Value	Pr > |t|
11	2.14	0.0558

Baseline vs. not-connected axes line chart comparison for educated more than 4 years at a university

t Test

The TTEST Procedure

Difference: question3 - question1

EducationGroup=2 Treatment=Treatment2

N	Mean	Std Dev	Std Err	Minimum	Maximum
109	0.7706	0.9683	0.0927	-2.0000	3.0000

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.7706	0.5868	0.9545	0.9683	0.8546	1.1172

DF	t Value	Pr > |t|
108	8.31	<.0001