Visualization of Football Data

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1 Abstract

As data is being collected at a continuously increasing rate it has become a necessity to represent it in alternative manners for humans to make sense of it. One way of doing so is through visualization. Visualization is a powerful tool which augment human capabilities making it easier for us to interpreted data. However, there are many pitfalls and bad design decisions which may cause the visualizations to not perform as intended. For this paper, we have been working with football data and tried to create new forms of visualization whilst also answering some common questions regarding how you can statistically tell the difference between a good and a bad team, whilst also looking at what their play-style is like, both in single matches and seasonal. To aid in creating visualization we have been using technologies such as *R* and *D3.js* for preprocessing and visualizing, respectively. Throughout the the course of the project, we have also been using a variety of statistical methods to help finding patterns but also to prove some of the tendencies which were found along the way. We ended up with some visualizations, both new and common ones, which aided in finding patterns in the datasets. Some of the things which we found was that more shots are actually taken towards the end of a game. The number og shots will already from the beginning of the game progressively increase all the way until the end. Some other tendencies the visualizations showed was that teams usually makes more mistaken passes at the beginning of each half relative to the match, which may imply that some psychological factors affects the players and how they play. Another visualization which also undermined the idea of psychological affects on players was also made. The visualization showed us that when a good team faces a worse one and loses, one can actually see a difference in how many failed passes they do relative to when they win. It also indicated that more play would enroll around the middle of the field, which may indicate a rather frustrated play-style. Though these tendencies seemed clear in the visualization, the quantitative foundation was not there to confirm the hypothesis and thus allows for further investigation to either confirm or disprove the idea. All said, it turned out to be rather difficult to predict anything concrete about the differences between top- and bottom-tier teams, as the error margins were simply too high.

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2 Introduction

In modern day society, data is collected at a rapidly increasing rate in all fields and it has become a necessity to present data in different ways in order for humans to make sense of it. One way to do so is through data visualization. Visualization of data can help humans' understanding of large data sets, as the data can be summarized very effectively, and patterns can quickly be recognized. When making visualizations, there are several considerations the designer must make, including: What the semantics are of the data being visualized, what actions should be taken to reach the visualization, what is the target of the visualization and how the visualization is going to be created. It is also important to consider the human cognitive system when designing visualizations, such that the visualizations are designed to make it easier for humans to understand the data. Examples of this include limiting the amount of variables in the visualizations and highly contrasting colours. Given that visualizations are created to simplify large and complex data sets, sacrifices must be made to get the knowledge parsed to humans. Too complex visualizations will not accomplish the task of presenting the data in an easily understandable manner, as humans won't be able to process all of the information. In order to design good visualizations, we will apply principles from the field of visualization to present football data. We will use tools such as the programming language R to process data and plot static visualizations, and use the JavaScript library D3.js to make interactive and dynamic visualizations. Specifically, we will do this both by making visualizations that can help explore the questions that we present below, and by doing exploratory analysis such that new patterns can be discovered. The specific questions that we will be investigating are:

- How does a team evolve throughout a season in terms of goals, points, etc.?
- How does a team's playing style change throughout a match?
- How does a winning team differ from a losing team?

During the visualization process we will consider different visualization techniques and choose a suitable one based on principles and analysis tools given by Tamara Munzner in "Visualization Analysis and Design" to make sure that the data is presented in an accurate and easily understandable manner. This includes understanding the type of data that is to be visualized, considering how to filter the data to get the relevant data for the individual visualizations and how to create the visualization. We will discuss the results of the visualizations, specifically what we can and can't learn from them, and reflect on how these visualizations could be used in other fields.

3 Theory

3.1 Design Process

This section describes the typical workflow of a data scientist. We will focus on the following four phases: *Preparation*, *Analysis*, *Reflection* and *Dissemination*.

The process of getting the data, understanding the data and producing results is an iterative process. The process can be seen in Figure 1.

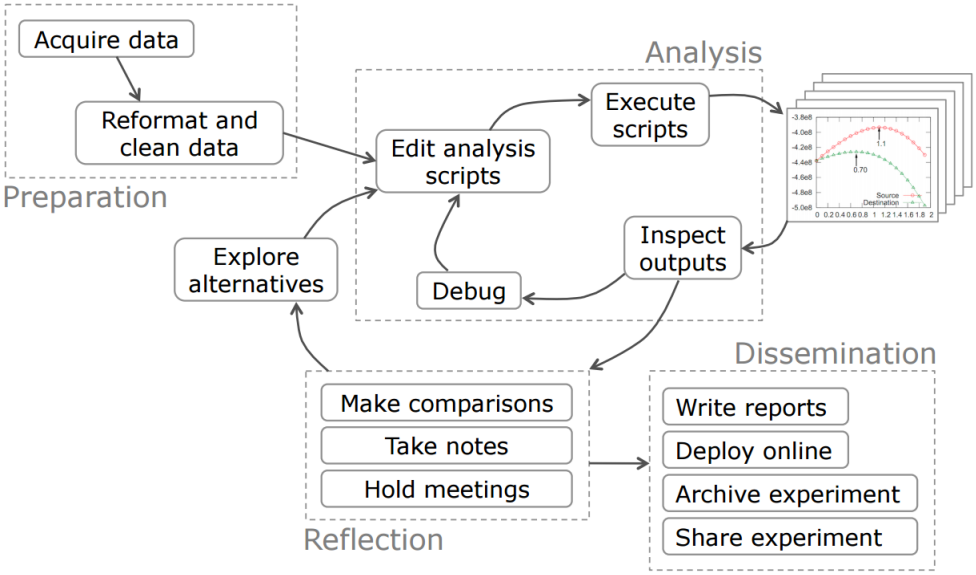


Figure 1: The model showing the iterative process [Guo(2012), Chapter 2]

- The first phase is the *preparation* phase. Here the data is acquired, which could be from hard disk, server, through an API etc. Where to store and how to organize the data files should also be considered, to allow easy replacement of the right files should the data be updated. Hereafter the data should be cleaned, which includes removing tuples with missing values, changing the formatting, sorting the data etc.

- The second phase is the *analysis phase*. Here the data is analysed to get more information. This is an iterative process, where you create and run scripts, look at the output, correct eventual errors, debug these and run it again.

- The third phase is the *reflection phase*. Here the output results are discussed, for example by making comparisons between outputs, and exploring alternatives.

- The fourth and last phase is the *dissemination phase*. Here the results are reported and possibly published in a report. [Guo(2012), Chapter 2]

3.2 Design

The following section explains the process of designing visualizations. The process follows the "What-Why-How"-structure. In the end of this section is a brief explanation of the considerations a designer makes during the process.

The first question a designer has to answer is: What. What are the semantics of the data, what type of data is provided, what dataset is the data presented in. This is important, as understanding the specifics of the provided data is necessary for designing the most efficient visualization for this data. An efficient visualization illustrates the data as simple and understandable as possible. The efficient visualization designs for geometry are drastically different from those of tables. An example of geometry is the location on a football field where a given action has taken place, like a successful tackle. Here, a smart visualization could be illustrating where on the football field the most successful tackles are made, using a football field as a coordinate system. The data type would be positions and items, describing what happened, and where. In a table, similar information could be

stored. However, instead of positions, it would contain attributes. For instance, an item could be a specific player, and an attribute could be how many successful tackles he had during a game. A clever design would be a bar chart, illustrating the player's efficiency (amount of successful tackles in games) compared to other players at his position. This would help a coach figure out who is the best player for certain situations where defending is key.
After the data has been identified by the designer, the next question that needs to be answered is: "Why?". What are the ideas behind the specific visualization? What is the target of this visualization? Is the goal of the visualization to consume existing data or to produce new information to visualize? This phase can be split in two: actions and targets. Actions are mainly comprised of analyzing, searching and querying. Analyzing depends on whether the goal is to consume or produce data. Search describes finding the data that answers the questions that are being asked. Searching is dependent on whether the location of the data is known or unknown, and whether the target is known or unknown. There are four kinds of searching; lookup, where location and target is known; browse, where location is known and target is unknown; locate, where the target is known but location is unknown; and explore, where neither target nor location is known. After the search, the goal is to query the targets at one of three scopes: identify, compare or summarize. Identify refers to a single target, compare refers to multiple targets and summarize refers to the full set of possible targets.

The other part of the "Why?" phase is Targets. Here, the designer identifies what the goal of the visualization is. To locate trends or outliers in datasets, identify correlations, the shape of objects, etc.

The final question is "How?". How is this visualization going to be designed, what design choices should be made to accomplish the goal of the visualization? Here, the designer should also decide the specifics of the visualization. In short, this is where the designer maps out how to arrive at the final visualization. How to encode the data, how to map it in the visualization, how to manipulate the visualizations for better visual efficiency, how to facet the data and how to reduce the data. We will go into further detail in this later in the report.

3.3 Data Types and Data Sets

As Tamara Munzner describes, data semantics and data types are important. In short, these are vital for humans' ability to understand the data. The semantics of the data is what the data represent in the real world. A table with a row containing 5 different numeric values is useless unless the person working on it knows what these numbers represent. The type of the data is equally important, as this is vital in understanding how to work with the given data. If it is a number, is it a quantity or an ID? This information is key, as adding two numeric values together makes sense for quantities, but would be useless for ID or code.
There are five basic data types: Items, attributes, links, positions and grids. An item is an individual entity, like a row in a table, since a single row in a table only describes one unique item in the given table. An attribute is a measurable property, such as the base salary in different professions, a person's height and so on. A link is the relationship between items in networks, an example being the relationships between people in a city, such that a link describes the relationship between the citizens (Neighbours, family, acquaintances, friends...). A position is spatial data, describing a location in two-dimensional or three-dimensional space. Here, a great example is the earth, which is divided into latitude and longitude coordinates, such that every point on earth has positional data, or a coordinate.

Finally, a grid describes the strategy for sampling continuous data in geometric and topological relationship between its cells.
The four basic dataset types are tables, networks, fields and geometry. Other possibilities include clusters, sets and lists. However, it is common for these basic types to be combined in real-world situations. Following will be a short description of each dataset type. In a table, each row represents an item of data, and each column is an attribute of the dataset. Each individual cell contains a value of the pair of the item and the attribute.

Networks and Trees specify the relationship between two or more items. An item in a network is commonly referred to as a node, and a link is the relation between two nodes. A network with a hierarchical structure is called a Tree. Unlike general networks, trees don't have cycles, as every child has only one node pointing to it, referred to as its parent node.

The field dataset type consists of cells. It is similar to tables, as it is build by keys and attributes. The main difference between fields and tables is that fields are used for continuos data. Each cell contains measurements from a continuous domain. In a way, there is an infinite amount of values to measure. Examples of this in the real world would be measuring the temperature. Finally, the geometry dataset type describes information about the shape of items. The items can range from one-dimensional lines to three-dimensional reconstructions of buildings and landmarks.

3.4 Idioms

In the world of data visualization, there are many different ways to present data. In fact, there are so many ways, or idioms, that it is impossible to comprehend the (dis)advantages of every single one. These idioms range from simple static ones, such as bar charts, scatter plots and line charts, to more complex ones, such as static idioms linked together by interaction and thus converted to dynamic idioms, such as the comparison of success rates, described later.

When selecting an idiom to represent a dataset, it is important to know the strengths and weaknesses associated with that idiom. Different data sets require different idioms, and in order to choose the right one, it is paramount to know about marks and channels.

3.4.1 Marks and Channels

Marks are basic graphic elements in a picture, while channels control the appearance of the marks [Munzner and Maguire(2015), Chapter 5, p. 95-96]. Marks can be anything from small points in a scatter plot, to lines in a line chart, or even areas. Channels can be the position of the mark, the shape, tilt, length or color of the mark, or anything else that alters the appearance of the mark. In a bar chart, the mark is typically a line with the channels being the length of that line, as well as horizontal categorical information. Color can also be used as a channel, making it possible to encode more information in a chart, for example by plotting different variables in a group, each variable having its own color.

Not all channels can be used with all marks. If a two-dimensional mark is used, it is not practical to use a shape-based visual channel, as it makes it harder to compare the different marks with one another. Therefore, if one runs out of channels to encode information with, it might be wise to contemplate using other kinds of marks, or even other visual channels, if the usage of one channel means that other channels can't be used. An example of this is trying to compare the area of triangles and rectangles.

The most effective channels should be matched with the most important attributes, in order to increase perception of the visualization, and therefore efficiency of the idiom. When the most important attributes are the easiest to compare, it strengthens the visualization as a whole. There a two main types of channels. Magnitude channels are channels that describe quantity, while identity channels describe categories. The most effective magnitude channel is aligned spatial position, with unaligned spatial position channels being second best. After these comes length, angle and area, length being more effective than area to convey quantitative data. The most effective identity channels are spatial regions, followed by color hue[Munzner and Maguire(2015), Chapter 5, p. 101].

3.4.2 Graphs

- **Scatter Plots**
  Scatter plots are effective when visualizing few (typically two) variables of a large dataset[Iliinsky and Steele(2011), Chapter 5, p. 54]. Visual channels typically used in scatter plots include horizontal and vertical spatial position, color hue, area, as well as shape. However, if area is used on the marks, one should not use shape as an identity channel, but instead color hue. Scatter plots can be used to quickly gain an overview of the data set, since it is possible to plot large quantities of observations.

- **Line charts**
  Line charts are good for displaying continuous data or trends, and they can be much cleaner to look at, than bar charts. They usually have independent data on the x-axis, such as time or matches played, and dependent data on the y-axis, such as points in the league.

- **Bar charts** Bar charts are widely used for comparing variables, either across, or within categories. Grouped or stacked bar charts are useful when comparing different variables between different categories. Groups are better than stacked bars, since stacked bars don't share the same baseline on the top bars.

- **Radar Chart** Radar charts are useful for comparing independent variables, such as the different success rates between teams. They can be used to show up to seven variables simultaneously and efficiently, thus quickly creating an overview of the differences in observations. For comparing dependent variables, such as a distribution, a histogram or a pie chart should be considered instead, as well as other idioms.

3.5 Visualization validation

This section briefly summarizes some of the considerations and steps that should be taken when validating that visualizations show what is intended.

3.5.1 Four levels of visualization design

Visualization design consist of four nested levels [Munzner and Maguire(2015), 68]:

1. Domain situation, where it is considered whether or not a problem could be solved or even partially solved by visualization

2. Data/task abstraction, where the data that contain the (partial) solution is found, and abstracted from the domain.

3. The third level, where visualization idioms and interaction methods are chosen.

4. The algorithm level, where the algorithms behind the visualization idioms are constructed.

Splitting visualizations up in four parts like this will make things easier when analysing, and if something doesn't work, finding the root of the problem will be easier as well. There are two ways of going through this model, first being down-stream, where the designer try to solve a visualization problem that exist for a target group. In this case, there are usually already visualizations that will suit the problem. The other is up-stream, where the objective is usually to create some new visualization, starting at the algorithm, or idiom step, working up to test practical use of the visualization.

3.5.2 Visualization validation

When a visualization is made, it is time to validate it. There are several threats to a visualization's validity, neatly summarized in "Visualization analysis and Design" [Munzner and Maguire(2015), 75]

- Wrong problem: You misunderstood their needs.
- Wrong abstraction: You're showing them the wrong thing.
- Wrong idiom: The way you show them doesn't work.
- Wrong algorithm: Your code is too slow.

Wrong problem: this is most likely to happen with a down-stream design, where there is some sort of miscommunication between the designer and the people who need the visualization. This will almost guaranteed cause problems in the data abstraction step as well, so if something seems to be wrong there, it would be a good idea to check the problem step as well.
To solve this, one should first contact and interview the target group if possible, however if the target group is too broad, or very general they might not know what they need themselves, in which case validating everything else first, and then looking at adoption rates, checking if people actually start using the visualization.
Wrong abstraction: This occurs if the data selected simply does not have what is needed to solve the given problem. A common way to validate the correctness of the abstraction, is getting target users to use the visualization system, and see if the user base find it useful.
Wrong idiom: This happens if the visualization technique isn't suitable for the given dataset or simply doesn't lower the cognitive load for the user compared to looking at the raw data. If something is wrong at this level, using a different visualization technique should be considered, if the designer is working down-stream. Otherwise double-checking the visual encoding/interaction is recommended, followed by getting people to test the visualization for different purposes, and adjusting based on their feedback.
Wrong algorithm: The major problem here is, if visualization would take seconds, minutes or even more, where a user would expect a result in less than a second.
A good first step, is to analyse the complexity of the algorithm, and see if any apparent improvements can be made. After that, it is worth taking a look at the input data to check if it can be pre-processed, to improve the visualization loading times and responsiveness even further. Then there are other cases, where the problem is the memory usage. In these cases it should be considered to reduce memory usage where possible, even if it will reduce performance.

3.6 Facets and View Manipulation

When creating visualizations it is not always enough with one idiom to present the data in an understandable way. One way to cram more information into the idiom, but still keeping the number of variables low is, to either manipulate the view of the idiom or to facet into multiple idioms.

3.6.1 View Manipulation

By creating multiple views in an idiom, the idiom can contain more information, without introducing clutter. The different views can include changes like switching between different idioms, changing the viewpoint, changing the order of the data, changing the number of items shown and so on. For example one can change the way the data is ordered by sorting the data by different variables. This is very powerful because of spatial position being the highest ranked visual channel. Many view manipulations are based on animation. Animating has a trade off, the cognitive load can be very high if too many elements change. This means that we get low cognitive load if either some elements are static and others are moving, or some groups of elements are static and others are moving. If few elements change by a graduate transition, the viewer can keep the context between the two views. [Munzner and Maguire(2015), Chapter 11]

Selecting one or more elements is common in many interactive visualizations. The result of selecting an element is then some change in the view. It has to be considered which elements the user can select, and how many. Choosing how to select items is also a subject which has to be considered, clicking to select, hovering over some element with the cursor or something else. Changing the view by highlighting some element and creating pop out could be done by changing the channel, for example the color, the size, the outline or the shape of the element. This change should of course be so dramatic that the element clearly stands out from the rest. Look at Figure 2 for an example of highlighting. [Munzner and Maguire(2015), Chapter 11]

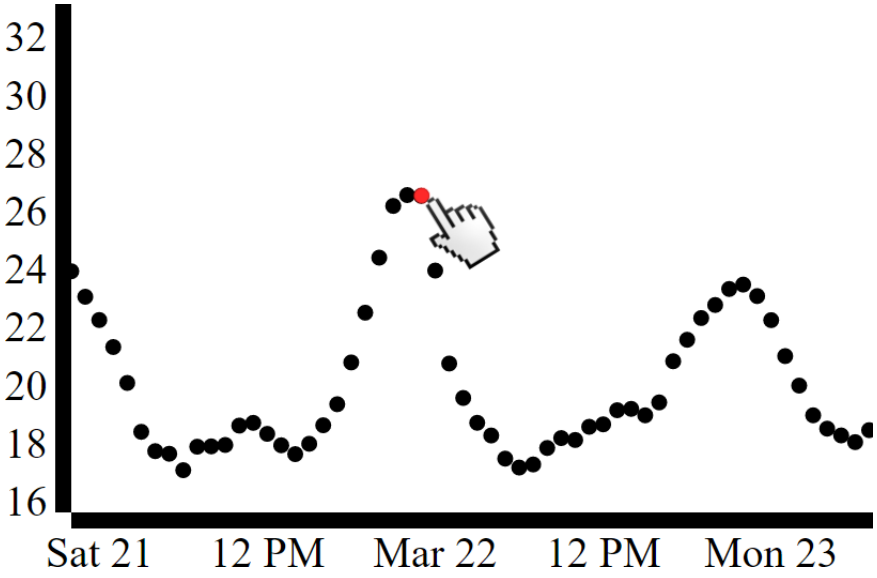


Figure 2: Highlighting the selected element

Another option for an interactive idiom is the ability to navigate the view by changing the viewpoint. Here we think as if we have a camera pointed at the view. We can then

change the view by zooming, panning or rotating the the camera around its own axis. There are two kinds of zooming, geometric zooming and semantic zooming. Geometric zooming is straight forward making some elements appear closer to the camera. With semantic zooming not only the size of the elements change, but the semantics too. Semantic zooming changes what is shown, and possibly the representation of it. For example zooming semantically could reveal more detail about some element showing new information about it. Navigation could also be changed through reduction of attributes, by slicing, cutting or projecting. These are all dimension reduction techniques. To slice, a specific value at a dimension is chosen, and only elements matching this value is shown. A cut is made by placing a plane in front of the camera, all elements in front of the plane is not shown, in this way it is possible to explore elements behind other elements, or look inside 3D objects. Projection is done by eliminating some dimension while still showing all the data. This is similar to what the humans do when looking at a 3D object.

3.6.2 Facet

Faceting is splitting the view up into multiple views or into multiple layers. One of the main reasons to facet is to compare views. This is much easier than comparing two views in a changing view, because we do not have to remember the prior view, but just move our eyes to compare them. Another reason to facet is to gain more information about the data through a multiform design, where data is shown using different encodings. By having multiple views, more attributes can also be shown. Of course when one has multiple views shown beside each other, each view has less space, which is one of the trade-offs and why having multiple layers on top of each other, and switching between them sometimes is better. When having juxtaposed views it might be interesting to link the views. This could be done by sharing the data, sharing the visual encoding, synchronizing the navigation or highlighting.

Each view could show different subsets of the data, or having different viewpoints like the classic overview in one view combined with detail in another view. Multiple views sharing encoding but showing different parts of the data, is called *small multiples* and is often structured in a matrix. This could be an alternative to animations, where we lay out all the frames. The cognitive load is smaller with small multiples, and it is easy to go one frame back or forth. An example of small multiples is seen in Figure 3.

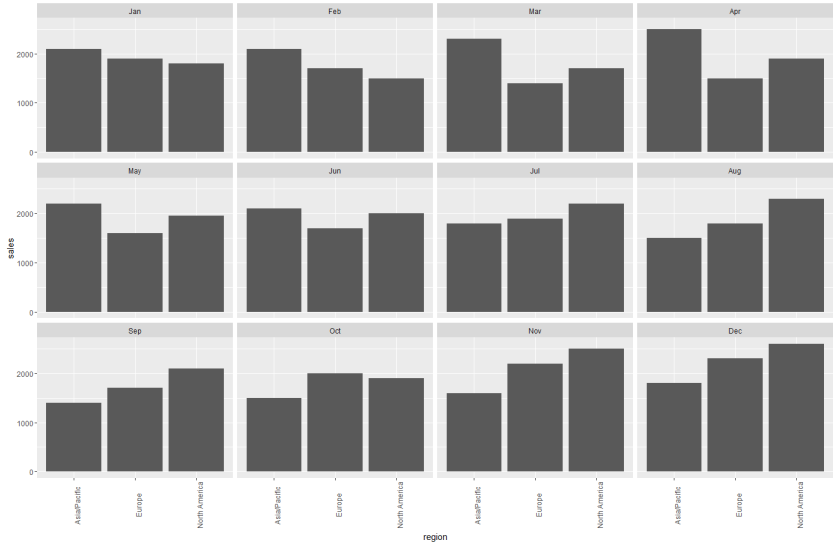


Figure 3: An example of small multiples

Instead of juxtaposing the views, it is an option to stack them into a single frame. The views should have the same horizontal and vertical extend and blend together as one frame, by being transparent where there are no marks. The problem with stacking is distinguishing between the layers. This is easy with only a few layers, especially if the layers use different visual channels. But distinguishing between more than three layers, can be a real challenge. [Munzner and Maguire(2015), Chapter 12]

3.7 Exploratory Data Analysis

Exploratory data analysis, EDA, is a philosophy about how one can approach the analysis of a data set. It is not a fixed collection of tools that one can use to analyze a data set, but it is a general approach which promotes looking at data in different ways without having any assumptions. It is usually used when one receives a new data set, and wishes to learn something about the underlying structure of it, or wishes to discover outliers or trends in the data. Both visual and non-visual methods are used in EDA. Examples of non-visual methods are simply to calculate the mean, median, variance, quartiles etc. of the data, while visual methods could be a boxplot, scatterplot or even a simple bar chart. The boxplot is a quick way to present some of the calculated properties mentioned above, such as the median and the quartiles. The boxplot was invented by John Tukey[Weimer(2016)], who is widely regarded as one of the big promoters of EDA, and it was presented in his book "Exploratory Data Analysis", as a method one could use while doing EDA.

Specifically a boxplot[Seltman(2016)] presents the following to the viewer, see figure 4.

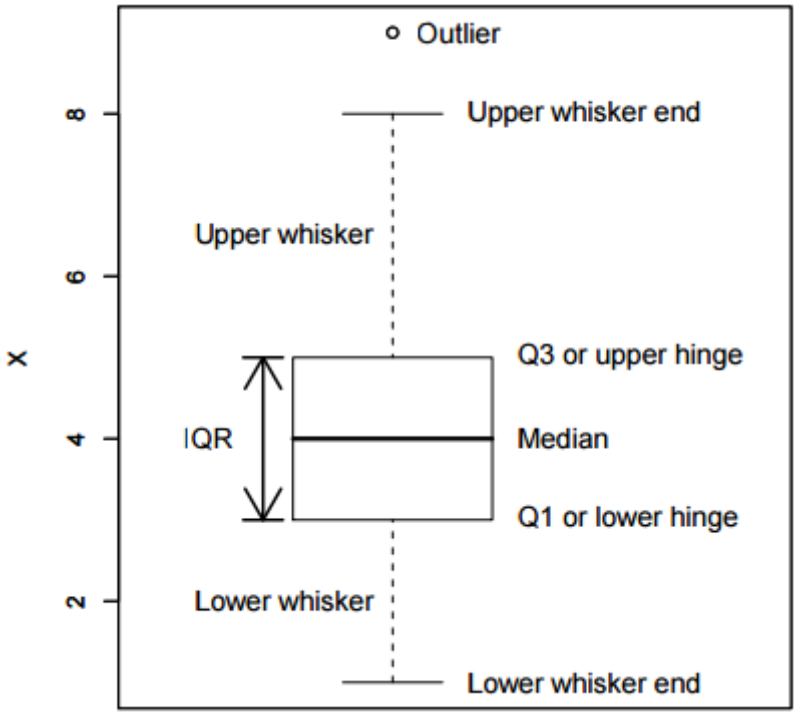


Figure 4: A boxplot[Seltman(2016)]

Where a quarter of the data lies below Q1, a quarter is above Q3, and a half is between Q1 and Q3, where the median is centered between the Q1 and Q3. The area between Q1 and Q3 is often referred to as the interquartile range, IQR, which is calculated as Q3 minus Q1. The strength of this visualization is that one can quickly see the spread of the data. The bigger the relative value of IQR, the more the data is spread, and the smaller the relative value of IQR, the less the data is spread. The boxplot also shows the extremes of the data set and the outliers. The lower whisker encodes the minimum value that is within 1.5 times the IQR subtracted from the Q1. Any value that is smaller than this will be represented as an outlier, which is a mark that is placed below the whisker. The same goes for the upper whisker. Boxplots are especially useful when you have multiple data sets that you want to compare, as you can place multiple boxplots next to eachother, and very quickly be able to recognize the differences between the data sets, as data has now been encoded into something visual which is easier for the human cognitive system to process subconsciously.

Another approach one can use within EDA is principal component analysis, PCA, which is described in a later section.

When doing EDA, one will often be able to use the acquired knowledge to formulate new hypotheses about the data, which can then be used to make more specific visualizations or calculate more specific properties of the data set, but it is not a guaranteed outcome. EDA will not always produce new knowledge, which is not a flaw in the approach, but rather a natural consequence.

When doing EDA, one is not limited to the "known" idioms/methods to visualize or look at the data. One can easily produce new kinds of visualizations which can be used to learn about the data.

3.7.1 Principal Component Analysis

Principal Component Analysis, or in short PCA, is a way to take high dimensional data and reduce it without losing much information. It is difficult to find clusters, similarities and differences in high dimensional data, but by doing PCA it becomes much easier because of the dimensions reduction. [Smith(2002)]

With multidimensional data plotted in a coordinate system, PCA finds the vectors which describes the most variance in the data. These are called the *eigenvectors*. The eigenvector describing the most variance is the first *principal component* (PC in short), the eigenvector describing the second most variance is the second PC and so on. The PCs are perpendicular. Figure 5 shows a scatter plot with the first and second PC drawn as the red and green line.

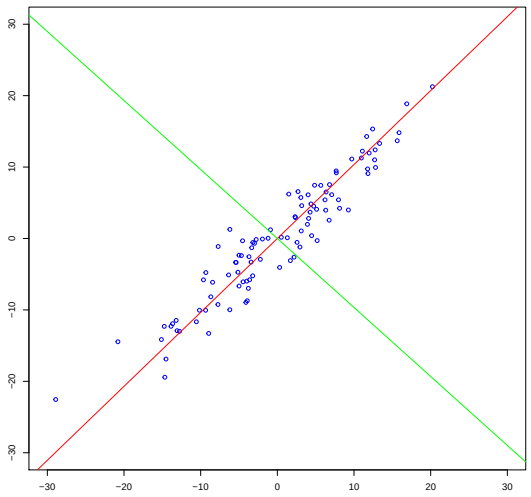


Figure 5: Some data set plotted, red line is PC1, green is PC2

To find out which variables have the most influence on a PC, we can look at the coefficients of the PC, meaning the coefficients of the eigenvector, the higher the coefficient, the higher the influence. When the principal components have been found, it is time to find out which to keep. This can be done by looking at a *scree plot*. This is a bar chart showing the variance for each of the PCs. Typically it is interesting to look at the first two PCs. We then look at the data expressed in terms of the principal components we have chosen. If we plot the derived data as a scatter plot, with for example the first PC on the x-axis and the second PC on the y-axis, we can easily point out the clusters of the data if there are any. This way we can look at the data in fewer dimensions but without much loss of information. In section 5.1.2 we do principal components analysis on some of our own data.

3.8 Tools and Technologies

3.8.1 R

R is an open-source programming language and is often the go-to in fields such as statistics, visualization and other branches concerned with huge amounts of data. The language is heavily inspired by *S* developed at Bell Laboratories and thus one may find them to be

quite similar. Being an open-source project under *GNU*, *R* is free to use both personally and commercially.

Even though *R* is often used as a tool to explore data, *R* is in fact a true programming language allowing the user to write and reuse procedures. Doing so eases the work flow when working on datasets with a reappearing structure in the sense that once a procedure is defined, it can easily be reused. Due to the fact that it combines the best of both worlds in statistics and programming it is a good candidate for areas such as machine learning too. Other than being a strong environment in itself, offering many standard operations, one of the true strength in *R* is its extensive range of packages. Being open-source, developers are constantly adding new packages to the environment extending the functionality of *R* whereof most of them are also free to use. The packages are what makes *R* really shine, as it adds some crucial functionality which has undoubtedly contributed to its mass popularity. Some of the packages such as *knitr* allows the user to write full reports alongside their results and convert them to various formats. Other packages makes some procedures less complicated by wrapping them into single methods, making *R* feel slightly more like a high-level programming language than it already is and allows the user to get results faster. Another strengths of *R* which aided it in gaining mass popularity amongst the scientific community is its outstanding possibilities to visually display data. Other than having an array of different options in regards of how to visualize the data, being a programming language, one can alter how the specific visualization will look, making it highly customizable and almost limitless to the advanced user. Once again, packages extend the integrated functionalities and some mentionable ones would be *ggplot2* which makes it easier to plot data and takes care of the more complicated aspects such as drawing legends or making multi-layers. Another one would be *Shiny*, which also allows the user to make dynamic visualizations and add components to alter the plotted view.

Before visualizing data, one has to clean and reformat it in respect to the preparation phase described earlier. *R* offers a range of different options when reformatting and supports a various number of data types to store and alter the data within. Other than supporting some basic data types such as arrays and lists, it also supports *vectors*. A vector is, simply put, a sequence of elements in an array-like structure. Vectors can be accessed through indices like an array but the size of it will grow and shrink according to how much data it contains. Vectors have multiple purposes and may be used to describe a sequence of values along an axis in a coordinate system or may just be used as a middle-ground to construct some other rather sophisticated data structures such as the *data frame*. Data frames are commonly used as the go-to input type in different methods and thus, the user will often need the data converted into this format at some point. Data frames are very much like a matrix structure-wise but they are slightly more general purpose in the sense that each column does not need to have the same data type. Having this property makes it a very good candidate for storing large datasets, as it is more flexible in terms of what each cell actually contains. Often R will have a built-in method to import a data set into the environment and convert it into a data frame but sometimes a package will need to do the trick. However, as some datasets may have a more complicated structure than a data frame, for instance by having multiple in-going layers, a direct conversion is not always an option and some manual work must be done to built the data frame. When a data frame is constructed, the user often want to restructure it. Unfortunately, *R* does not offer an easy and intuitive way itself to get such a job done. Luckily however the packages *tidyr* and *dplyr* comes in handy when facing such issues. *Tidyr* helps in obtaining a tidy

data set, meaning that each column represents only one variable and each row contains a single record. To obtain a tidy dataset, the package allow operations on a data frame to reshape the structure which may be to split a column into two or converting a row into columns. *Dplyr* on the other hand allows the user to do operations on the data frame like selecting single columns, add new ones and much more. Combined, these two make up for an excellent framework to sanitize data before visualizing.

However, even though R is an excellent choice in some cases it also has its limitations where other technologies may be better suited. The way *R* is built makes it very prone to heavy memory costs partly because it allows the user to do single line execution and thus have to save all assignments of variables. Single line execution is indeed a neat feature whilst developing code but may not always be desirable. In terms of speed it is very often criticized for being really slow. In a test done by Jacob Simmering [Simmering(2013)] he found that *R* performed 270 times slower than *C* when looking for prime numbers. Some factors such as the fact that `C` is compiled at runtime may have an impact on the result. However, another language which is also not compiled is Python, which turned out to have 17 times faster performance relative to *R*. Some tricks can however be done to boost the performance of *R*, as Simmering proposes a *byte code compiler* which can increase the speed of *R* tremendously. In regards to competitors, some users tend towards technologies with a more "What-You-See-Is-What-You-Get" focused approach such as *Excel*. Whilst R is really good at exploring data once the method to get there is defined, it takes a while to wind up the configuration. Spreadsheets like *Excel* are rather fast at getting smaller tasks done and are arguably visually prettier for presentation purposes which makes it a viable option in some scenarios. However, Excel may fall short if the tasks become more complex, for instance if the data has to be formatted before being visualized or has to be presented in some highly customizable way where the bounds of *R* are almost limitless. *Python* is another viable option when doing statistics and is a more programming focused solution. Both solutions are indeed viable options and it is a matter of taste to which one might prefer. As argued earlier, Python may win when it comes to speed and due to the fact that it is a more programmer oriented language, small tasks which no one has done before may be accomplished more easily, where *R* tends to be slightly more reliant on packages which is a doubled-edged sword.

3.8.2 D3.js

D3, short for Data-Driven Documents, is an open-source JavaScript library that allows Document Object Model (DOM) manipulation based on data.
It is designed to work on most "modern" internet browsers, *which generally means everything except IE8 and older versions.* [Bostock et al.(2016), Browser / Platform Support]

Like R, the code written using D3 will provide high code reusability, as different visualizations will likely include similar elements. Once a visualization is made, it can be kept up to date simply by updating the data files, or not necessary at all if data is gathered through an API.
D3 assists with binding arbitrary data to selected DOM elements.
This is done through creating a selection, on which the `.data()` function is called. This function joins the selection with the array provided as parameter, returning a new selection. On this selection the `.enter()` and `.exit()` selection functions can be called, `.enter()` returning a selection placeholder nodes for the data that had no DOM elements in the selection, and `.exit()`, the selection of existing DOM elements, which had no data points

in the selection. DOM elements can then be added or removed based on these selections. Although D3 can be used to create HTML tables etc. the most common use of D3 for visualization purposes, is through Scalable Vector Graphics (SVG). SVG is based on XML, and can be modified / styled on the go through JavaScript for editing the SVG elements, and CSS for styling them. The CSS styling can be set and/or modified at runtime through JavaScript as well. Because of this, the programmer have the possibility to create visualizations that react to what the user is doing in interesting ways, or create dynamic visualizations.
Another reason to use SVG over raster image formats, is that it will look as intended no matter how much it is scaled, where raster images like png or jpeg become pixelated when scaled. One of the core features in d3 is the Scales sub-library, which provides functionality that can transform all data given to fit inside the given range, while still maintaining the relative position / size between elements. This is especially useful when designing responsive web pages, where dimensions of the SVG element may differ.
D3's SVG sub-library brings generators for several non-standard shapes in SVG. These generators can generate SVG paths which resemble the shapes. Some of these shapes are lines, arcs and chords. These shapes can be modified with options such as interpolation, which can be used to smoothen lines in a line chart, while they are still styleable through CSS.

While this way of doing visualizations is preferred in a lot of cases due to reusability, and user interactivity, working with large datasets can give unwanted results. If the user has to load more than a few megabytes of data in order to create the visualization, it is going to take some time, and if that data result in a large amount of SVG elements, a dynamic or interactive visualization could become unresponsive, which is undesired, as it will lower user experience.

4 Data and API

The data that we use in our visualizations come from two different places. The first place is from an Excel sheet with data about the football teams in the "Superliga" (now referred to as the league), which we were sent by Prozone (the company that is giving us access to their football data). That data is already somewhat processed and it is convenient to work with it in R, as one doesn't have to do any API calls. The second place that we get our data from is through an API that Prozone has given us access to. The API works in this way: one goes to their website and browses the different things one can request. When one have found what one needs, one receives a URL where one can append arguments, for example specify a team id or the encoding format (XML or JSON). When that is done, one needs to generate a signature, which is the current unix time plus a shared key and an API key which we have been provided by Prozone. That string is then hashed using SHA-256, and appended onto the request URL along with the shared key unhashed. Then one simply sends a HTTP GET-request, and one receives the data in the response. The request link is only valid for a short period of time, meaning that generally, if anything interesting has to be done, the requests have to be generated automatically. For this purpose, a function has been implemented in R which automatically generates the request URL and returns a data frame, when given the first part of the URL which describes what data is desired. The function is especially useful when one has to retrieve large amounts of data from the API, as some of the data can be very tedious to get from the API.

The data that we have access to through the API is things such as a list of all football

teams in the league, their rankings and so on as well as data from specific matches. An example of what one has to do to get all of the goal attempts throughout the season is: First get a list of all football teams in the league. For each football team get a list of the matches that they have participated in. For each match retrieve the events in that match, and put all of those events into one big data frame, and then filter the events such that only goal attempts are left. What is important to note about the API is that one cannot simply say for example "give me all matches where there is at least 5 goal attempts within 10 minutes". One has to programmatically make multiple calls to the API and based on the responses, decide what other calls should be made.

A short list of some of the data we can get through the API:

- Football teams in the league
- Statistics about a football team (goal attempts, points, number of players, city of origin etc.)
- Players on a team
- Information about a player (height, weight, age etc.)
- Matches a team has participated in
- Statistics about a match (outcome, injuries, event data etc.)

5 Results

5.1 Exploratory Data Analysis

5.1.1 Goal Attempts Box Plot

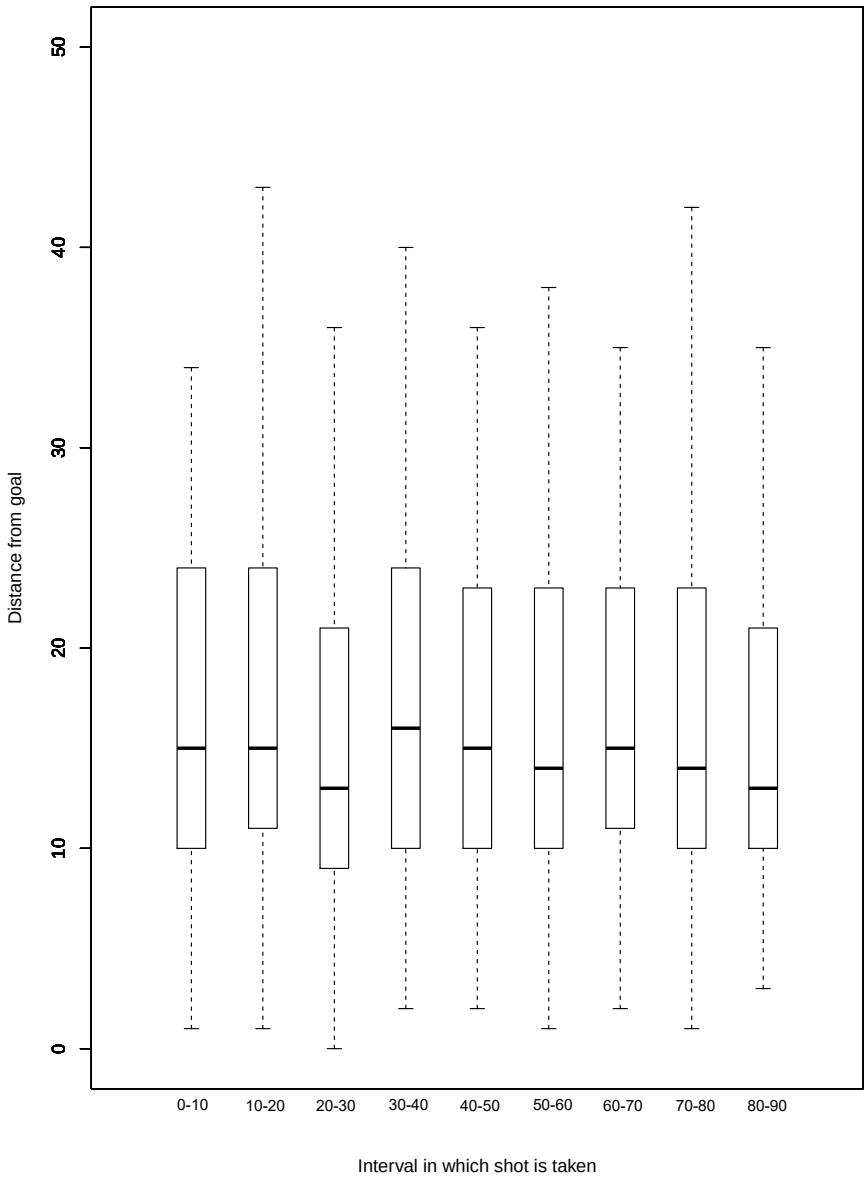


Figure 6: Box plot of goal attempts in the first 10 minutes, the next 20 minutes and so on. The distance is the distance from the goal on the x-axis on the football field

To easily see how the goal attempts change throughout a match, the goal attempts of an entire season has been aggregated and then split into intervals such that it is possible to see the distance from the goal a goal attempt is made during the first 10 minutes, the next 10 minutes and so on. This information has been visualized using a box plot (Figure 6).

As described in the theory section, a box plot quickly allows a user to see different things about a data set, and therefore functions as a quick way to propose hypotheses about the data.

5.1.2 Principal Component Analysis

In this section we do Principal Component Analysis for one season of aggregated football data. The data includes observations like the number of goals, the number of shots, the number of passings and so on. The full list of variables can be seen in the appendix. The data is collected for each player, but we have summed it to each team. We would like to find any clusters by using PCA in R.

The resulting scree plot from doing the PCA is seen in Figure 7.

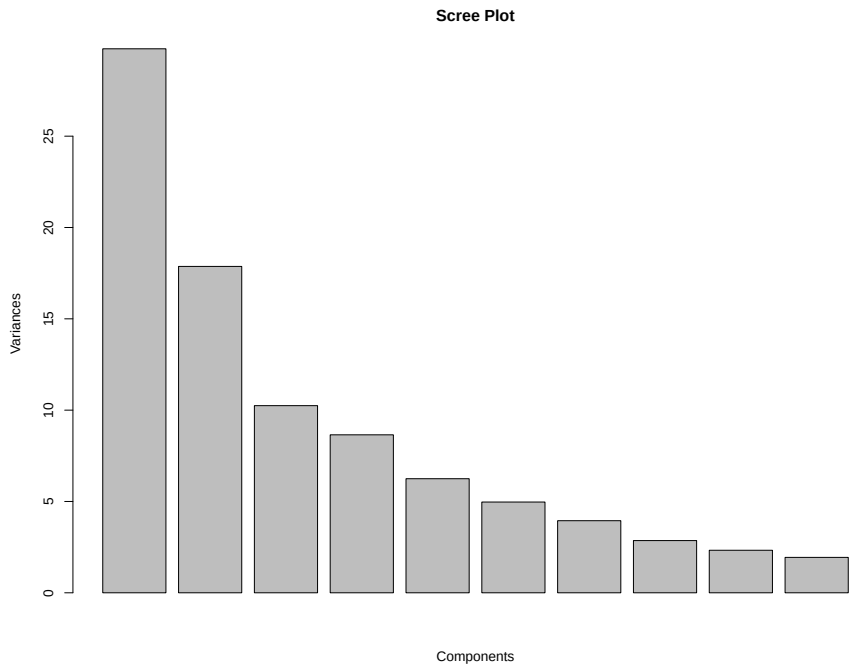


Figure 7: The resulting scree plot

The scree plot tells us which eigenvectors have the highest eigenvalue, meaning which principal components describe the most of the data. In our case we find that the first two components describe a lot of the variance in the data, to some extend also component 3.

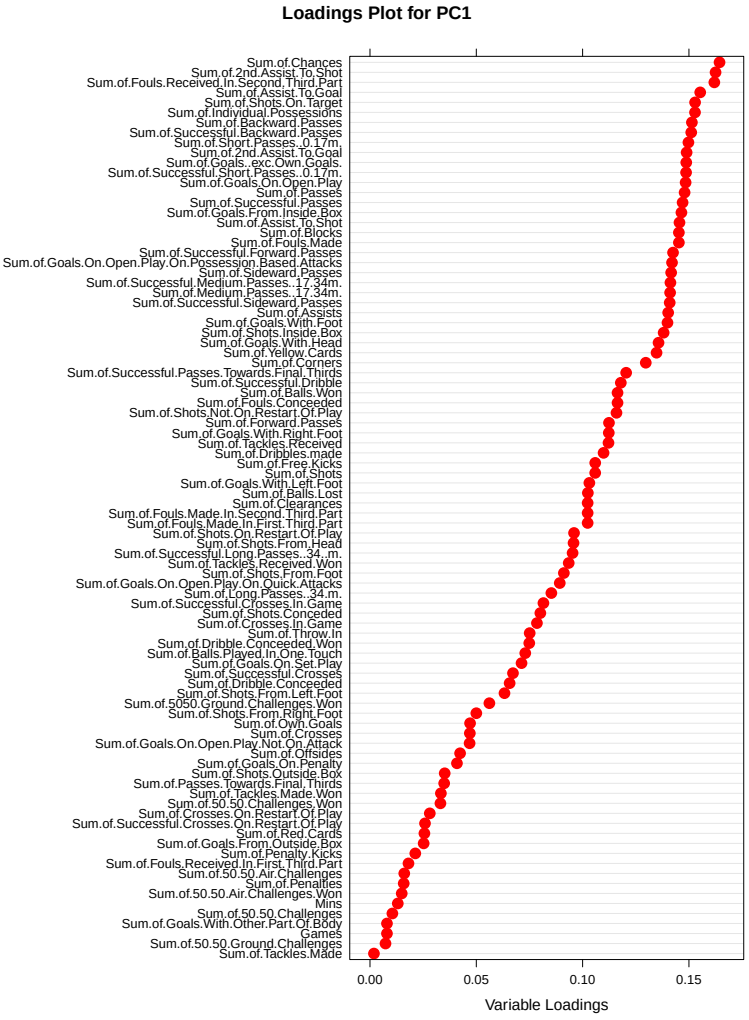


Figure 8: Loadings for PC1

We now look at the loadings of each of the components that we choose to keep. The loadings describe the importance of the different variables in relation to the chosen component. In Figure 8 we see the loadings for PC1. Being that PC1 is the component describing most of the variance in the data, the most important variables of PC1 is also the most important variables for the entire data set. The three most important variables in regards to PC1 is the `Sum.of.Chances`, `Sum.of.2nd.Assist.To.Shot` and `Sum.of.Fouls.Received.In.Second.Third.Part`.

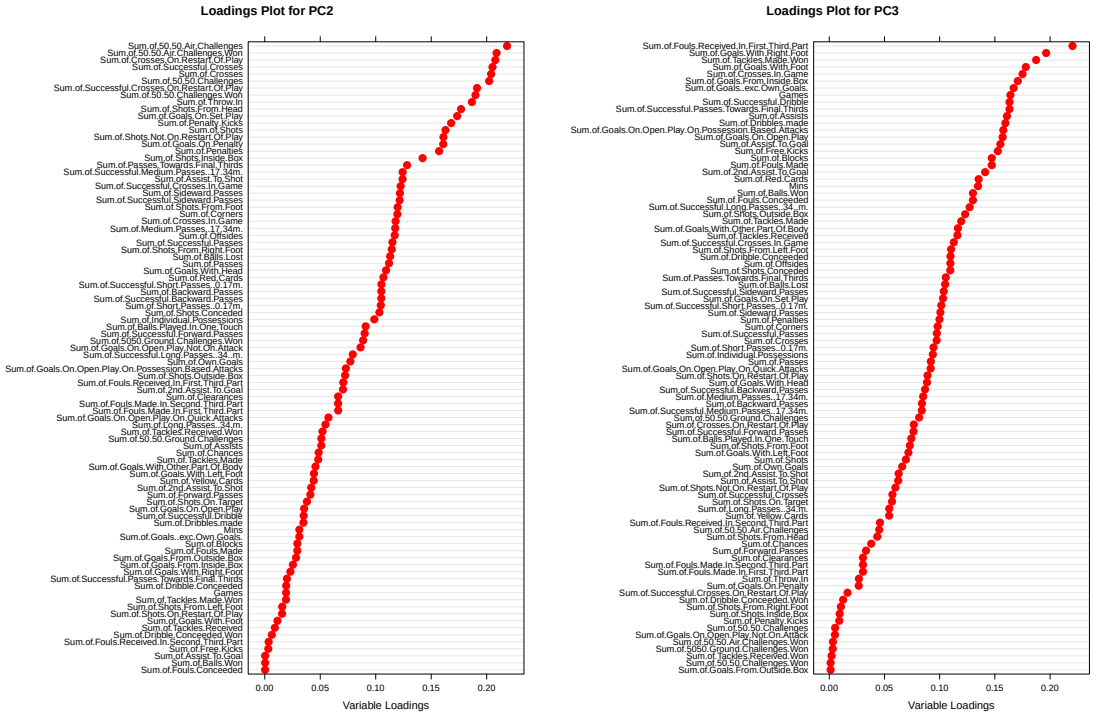
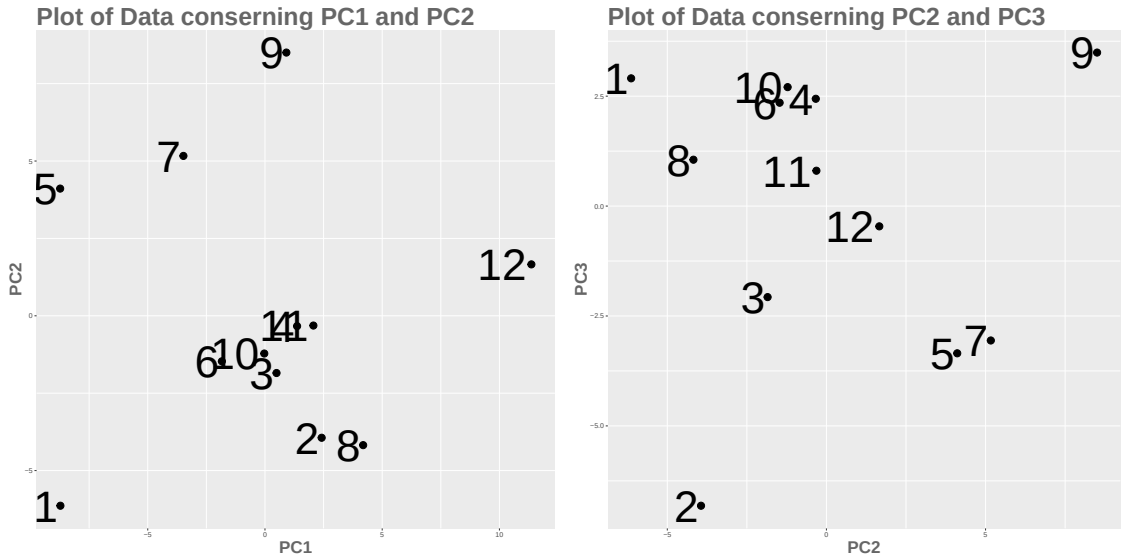


Figure 9: Loadings for PC2 and PC3

We can do the same with PC2 and PC3. These are seen at Figure 9. From the loadings in regard to PC2 we conclude that the three most important variables are the `Sum.of.50.50.Air.Challenges`, `Sum.of.50.50.Air.Challenges.Won` and `Sum.of.Crosses.On.Restart.Of.Play`. For PC3 the three most important variables are the `Sum.of.Fouls.Received.In.First.Third.Part`, `Sum.of.Goals.With.Right.Foot` and `Sum.of.Tackles.Made.Won`.

We can now plot the data points in regards to the principal components to find clusters. The data is labelled in regards to current position of the teams in the table. This means that we can easily find out if the top/bottom teams cluster. In Figure 10a the data is plotted in regard to PC1 and PC2. We do not have any clear clusterings, some teams are clustered in the middle. There is no correlation between the standings and the teams clustering.



(a) The data plotted in regard to PC1 and PC2 (b) The data plotted in regard to PC2 and PC3

Figure 10: Data plotted in regards to principal components 1-3

In Figure 10b the data is plotted in regard to PC2 and PC3. Once again we have a little cluster. There is no relation to the standings, but the cluster may arise from something else.

The PCA has not given any clusters, but it has giving us some of the most important variables of the dataset. Further analysis on these variables did not reveal any interesting aspects.

5.2 Source of Goals

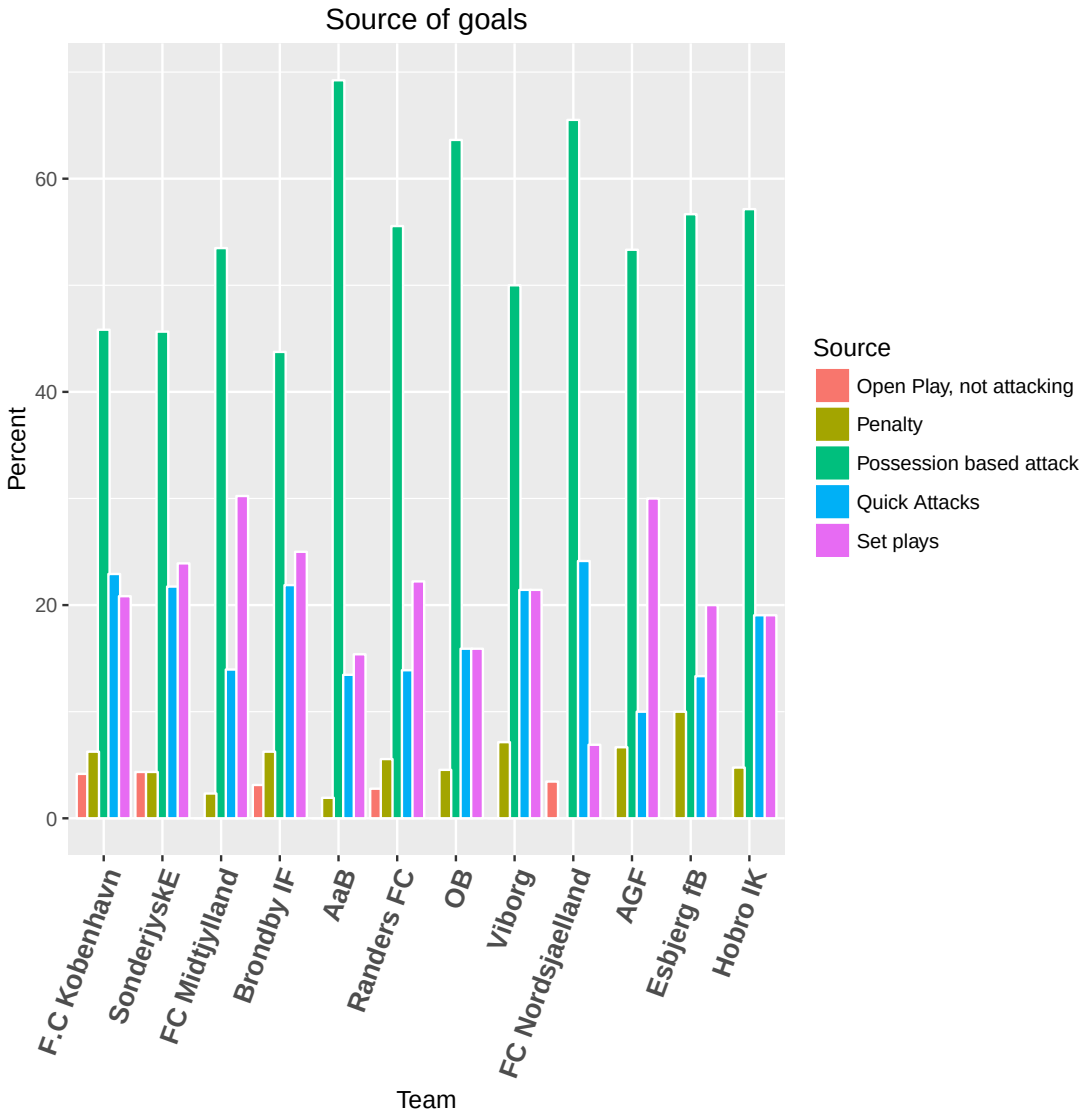


Figure 11: Grouped bar chart showing the kinds of attack leading to goals

5.2.1 What-why-how

11 shows the average sources of goals for every team in the league. Goals are divided into five categories - Goals from not attacking open plays, penalties, goals from possession based attacks, goals from quick attacks, and goals from set plays. A grouped bar chart is utilized to clearly show the differences between the teams. Color hue determines the source of goal, and all values are percentages. A team's percentages add up to 100, and the bar groups are ordered, based on the team's rank in the league. The purpose of this idiom is to see if there are any noticable correlations between a team's position in the league, and how they score their goals on average.

5.2.2 Code

R was used to prepare the data from the excel sheet. The variables in the bar chart were selected from the dataset, then summed for each team. After this, the variables were divided with the total number of goals per team, to get the average distribution of goal sources. This was done in a loop, adding variables, variable names and a team's ranking to predefined lists, and then creating a data frame from these lists. It is more efficient to create a data frame this way, instead of growing a predefined data frame inside the loop. The order of the groups in the bar chart is determined by the order of the levels inside the data frame, so these levels had to be reordered based on the team's ranking. The chart was then made with ggplot2, with teamnames on the x-axis, the percentages on the y-axis, and with the different variables as fill (Set plays etc.)

5.3 Passes -Direction

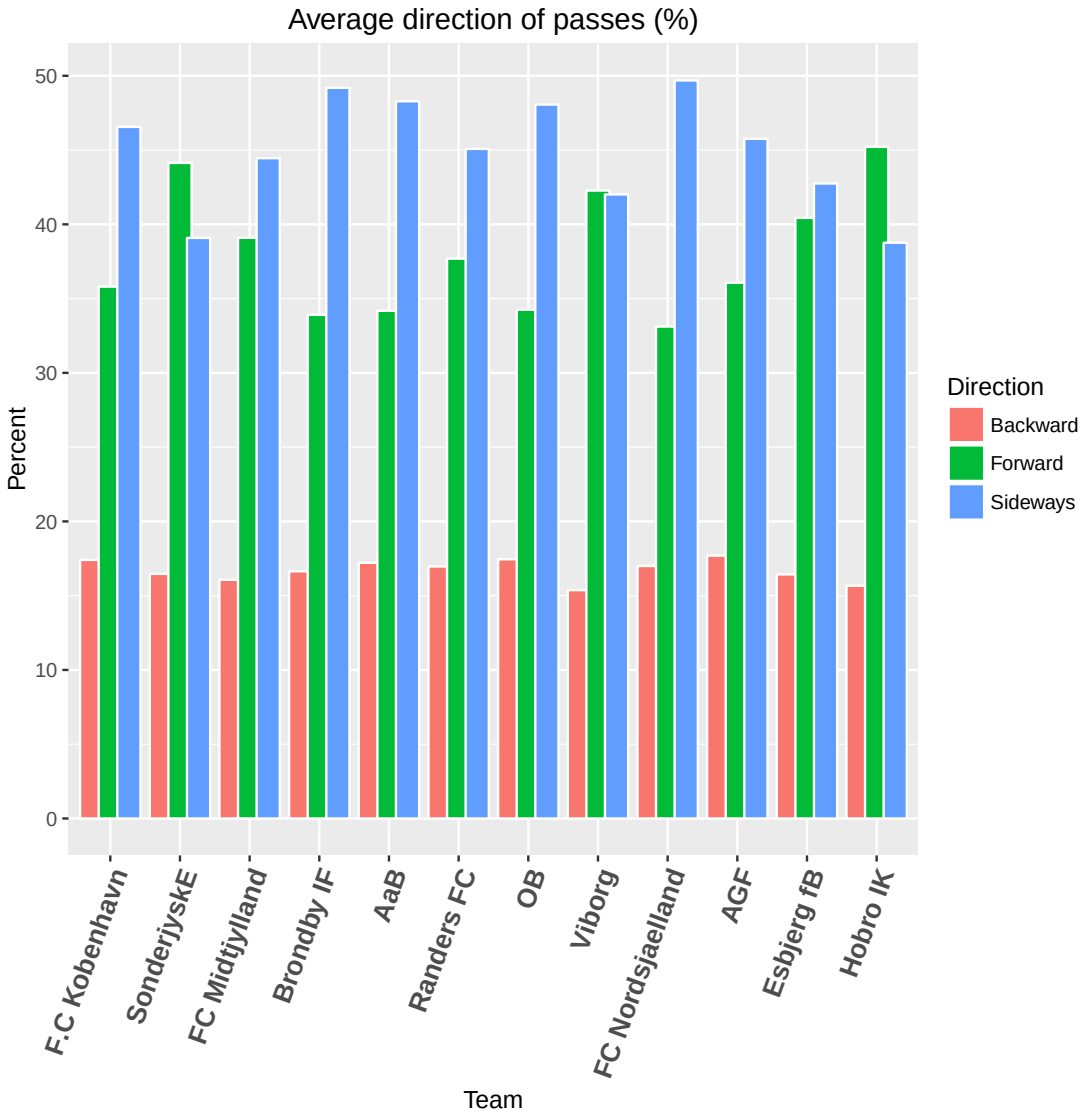


Figure 12: Grouped bar chart showing average pass directions per team

5.3.1 What-why-how

The purpose of this idiom (Figure 12) is to see if there is a correlation between the direction of a team's passes on average, and their ranking in the league. This is done by creating a grouped bar chart, with a group per team. The bar chart is ordered by the ranking of the team, with the highest ranking team as the first group from the left.

5.3.2 Code

The bar chart, as well as the data processing for the chart, was created in R. This was done by first selecting the variables in question from the Excel sheet, then splitting it into 12 tables (one per team). The variables were then summed, and each summed variable divided by total number of passes, to get the percentages of short, medium and long passes. This was done by creating variable and value lists, adding elements to these lists in a loop, and then creating a data frame. ggplot2 was then used to create the bar chart, in much the same was as the other grouped bar charts.

5.4 Passes -Length

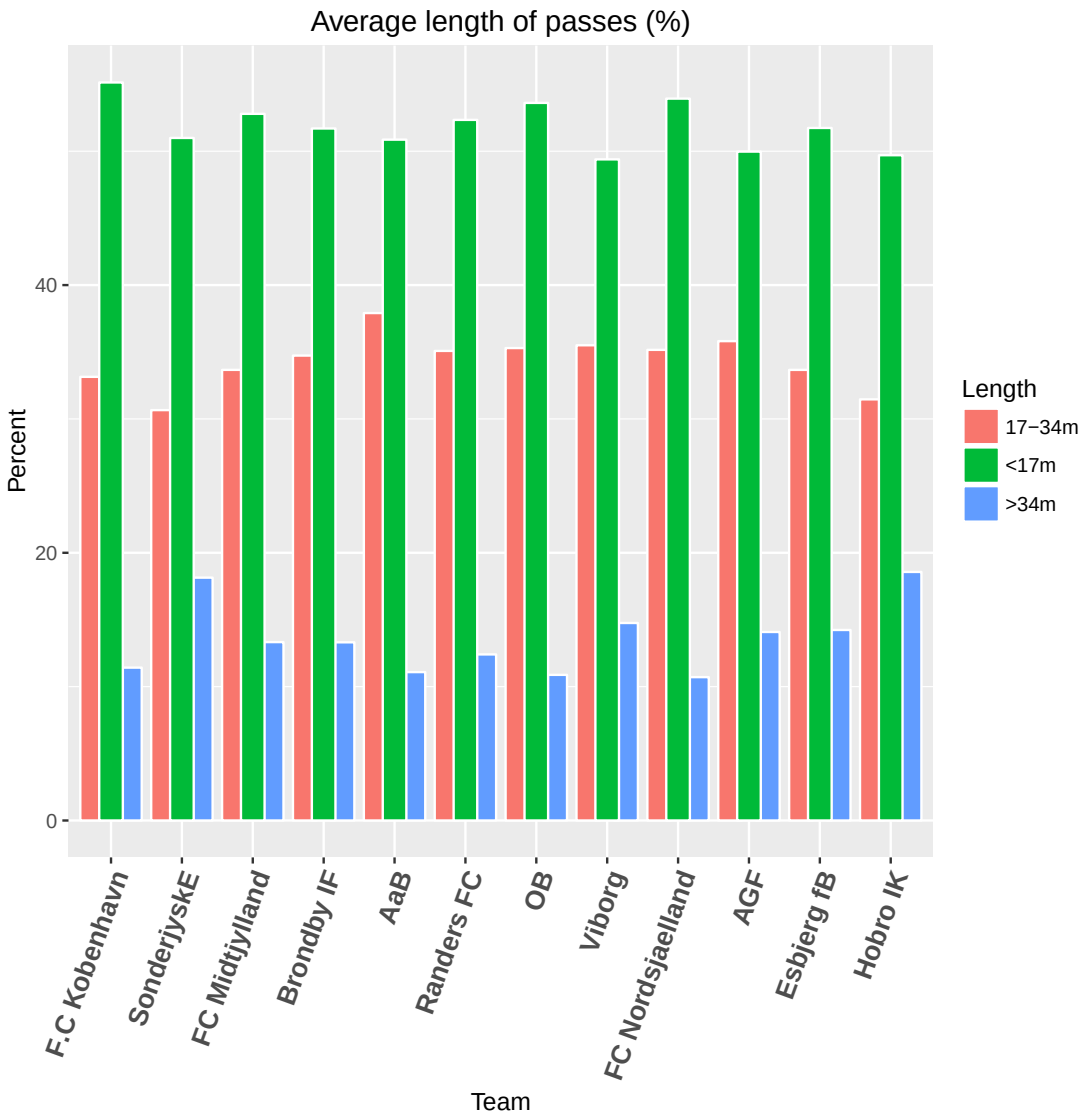


Figure 13: Grouped bar chart showing average pass length per team

5.4.1 What-why-how

Figure 13 represents a grouped bar chart that shows the length of passes of a team, on average, divided into three categories - less than 17 meters, between 17 and 34 meters, and passes greater than 34 meters. These three variables are grouped by teams, and the groups are sorted, based on the team's ranking in the league. The purpose of this idiom is to see if there is a correlation between the length of a team's passes, and their rank in the league. Summing the average passing lengths of a team results in 100%.

5.4.2 Code

This chart was made completely in R, by first selecting the desired variables from the Excel sheet, then splitting this data into 12 sets, one per team. The columns were then summed, then divided with the total number of passes, to get the different percentages. This was

done in a loop, by adding variables and values to predefined lists, instead of iteratively adding data to a data frame. By creating a data frame of the lists after iterating, a new data frame is not created after every iteration, thus increasing efficiency. The order of the groups is decided on the levels of the data frame, and thus these are reordered, based on the ranking of the team in question.

5.5 Shots -Head vs Foot

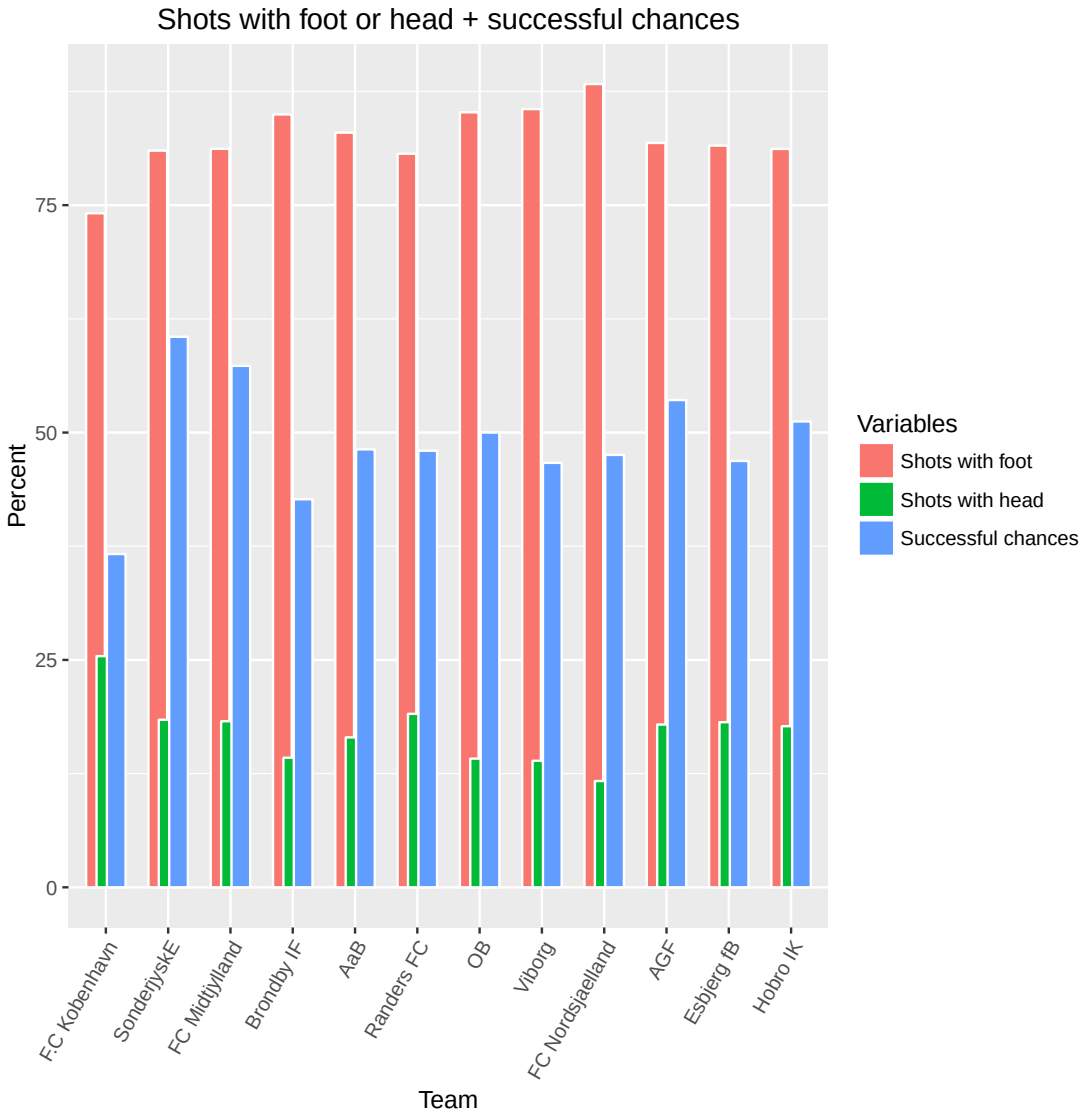


Figure 14: Grouped bar chart showing the ratio of headers and shots with foot as a percentage of total shots, together with the percentage of chances that results in goal

5.5.1 What-why-how

This idiom (Figure 14) shows the number of shots taken with the players' feet, versus their head, as well as the ratio of goals per chance ('successful chances'). The groups (teams) are ordered based on their ranking in the league, with the highest ranking team as the first group. This visualization was created to see if there is a correlation between a team's

ranking, and how many shots were headers, as well as how many of their chances were successful.

5.5.2 Code

As with the other grouped bar charts, R was used exclusively, with the Excel sheet as input data. The variables in question were selected, then split into different tables for each team. Then the variables were summed, and shots from head and foot were divided by total shots. The successful chances were calculated by dividing the total number of goals with the total number of chances. ggplot2 was utilized to create the grouped bar chart, ordering the groups by the ranking of the team, with the highest ranked team as the first group.

5.6 Shots -Inside box vs Outside box

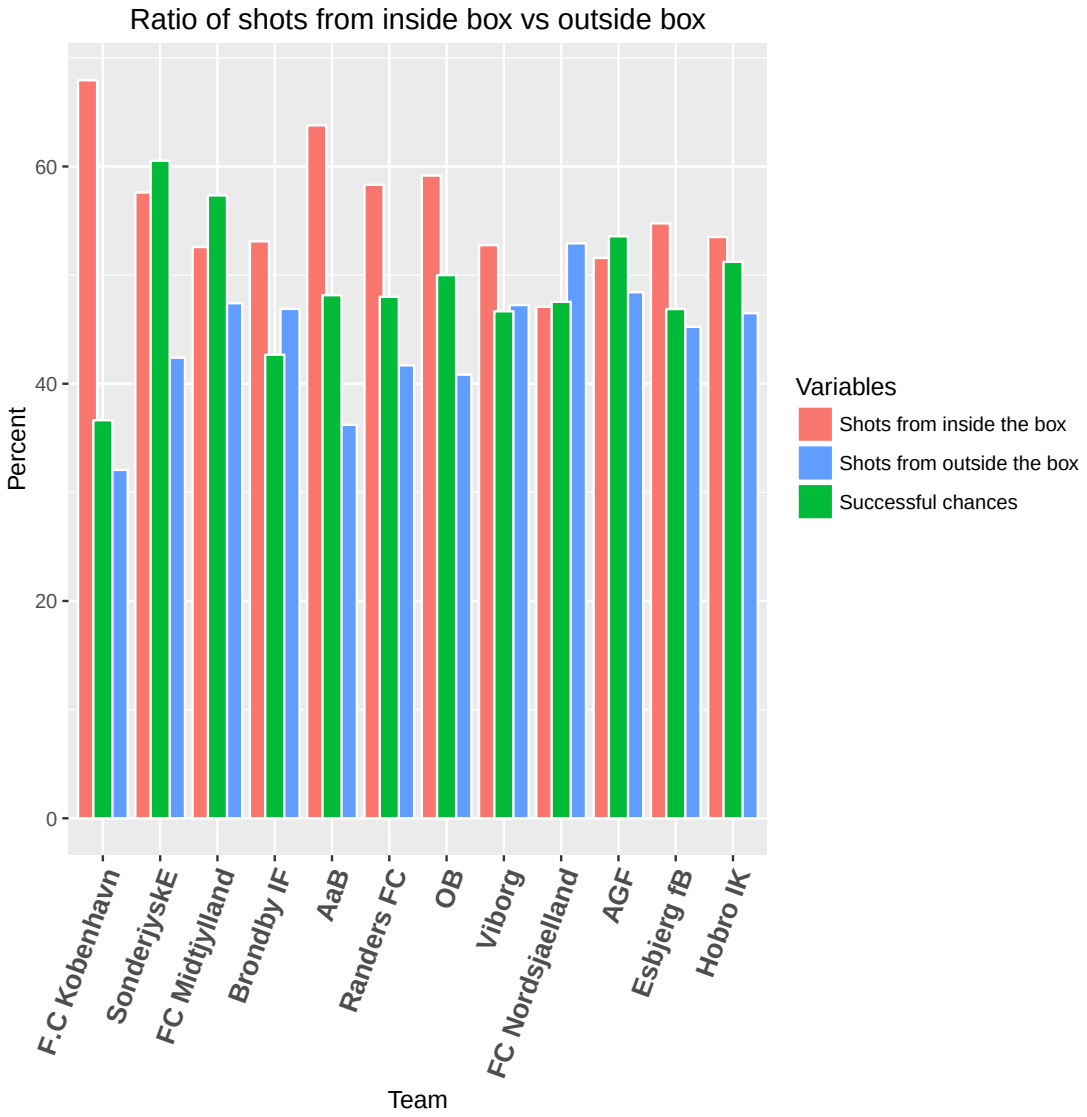


Figure 15: Grouped bar chart showing how many shots were taken from inside the box and outside the box, as percentages of total shots, as well as the percentage of chances that result in goal.

5.6.1 What-why-how

This visualization (Figure 15 shows how many of a team's shots are taken from inside the box and outside the box, as well as the percentage of chances that are successful. It was created to explore possible correlations between a team's ranking, and where the shots originate from. The bar charts are grouped, based on a team's ranking, with the highest ranking team as the first group.

5.6.2 Code

The bar chart was created in almost the same way as the other grouped bar charts, utilizing R for both data processing, and creating the graph (with ggplot2.) Data was selected from

the Excel sheet, and then split into the different teams, before summing the variables. The shots from inside/outside the box were then divided by total number of shots to get the percentages. Successful chances were calculated by dividing total number of chances with total number of goals. As with the other bar charts, the data was processed in a loop, processing one team at a time, appending the values to a list, and then creating a data frame outside the loop, with data from all the teams. ggplot2 was then used on this data frame to create the chart.

5.7 Success Rates

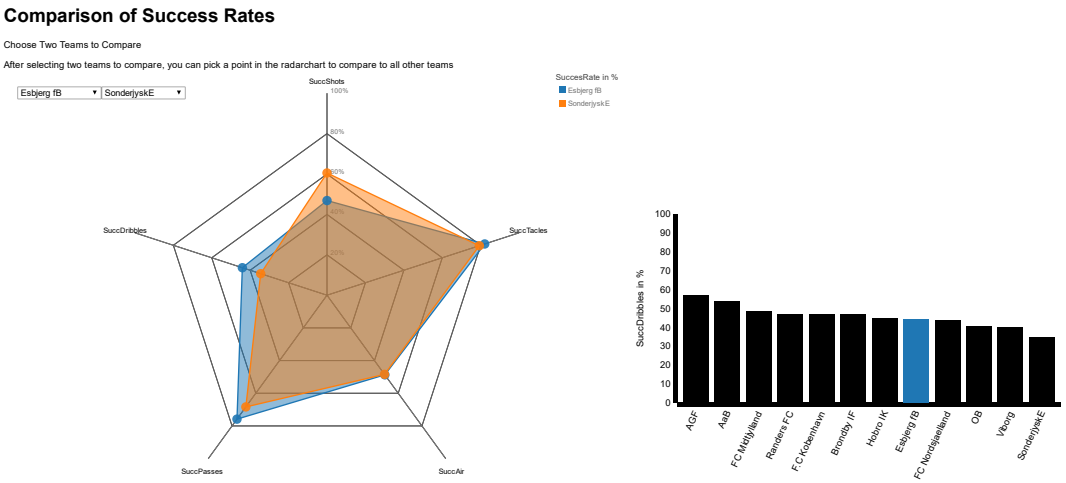


Figure 16: Idiom showing the comparison of the success rates using a radar chart for comparing two teams and bar chart for comparing with all other teams in the league `http://footviz.copus.dk/radarchart1/`

5.7.1 What-why-how

The visualisation shows the comparison of two teams' success rates on several points of measure in a radar chart combined with a bar chart. This is shown in Figure 16. Concerning magnitude channels we position the marks on a common scale and also use the area of the radar chart for comparison. For categorising we use color hue.

The action of the idiom is to compare two teams to find differences/similarities, maybe in relation to the placement in the league table, and to analyse where the teams differ. The target is to find extremes and outliers.

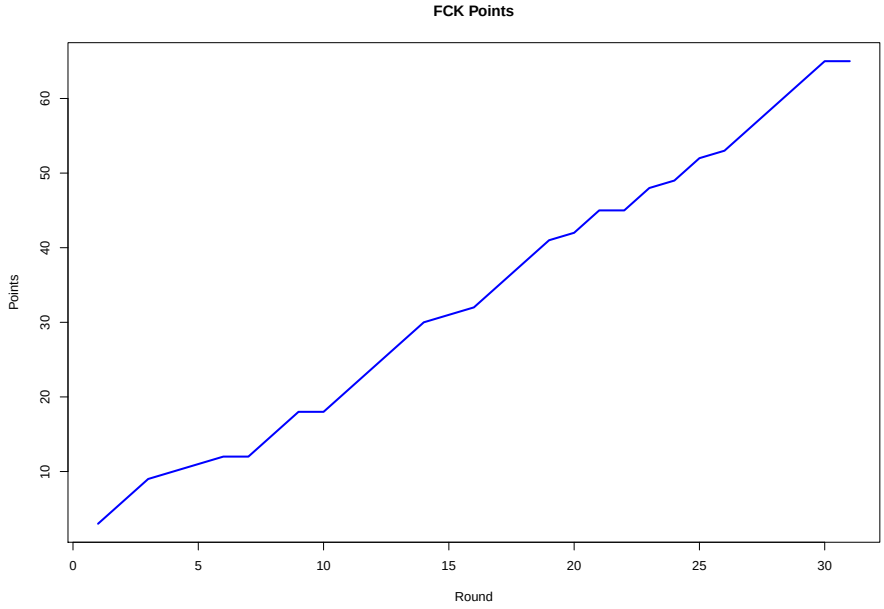
This is done by faceting into two views. In the left view we have a radar chart and in the right view we have a bar chart. The user can select two teams to compare in the radar chart. The teams' success rates in relation to shots, tackles, air challenges, passes and dribbles, is shown on the radar chart. When clicking one of the teams' values in one of the measurement points the bar chart comparing all teams in this measurement is shown. The views are linked together by synchronizing the highlighting. The team chosen in the radar chart gets highlighted in the bar chart. The highlight in the bar chart creates pop out by having this bar coloured and all others black. The raw data is reduced by filtering and by aggregating. Only some variables are chosen and the values for each team is calculated

from the individual players' values. The radar chart is manipulated first by selecting two teams to compare. If the user hovers over a value, all the team's values together with the area of the chart is highlighted, by changing the opacity of the other team.

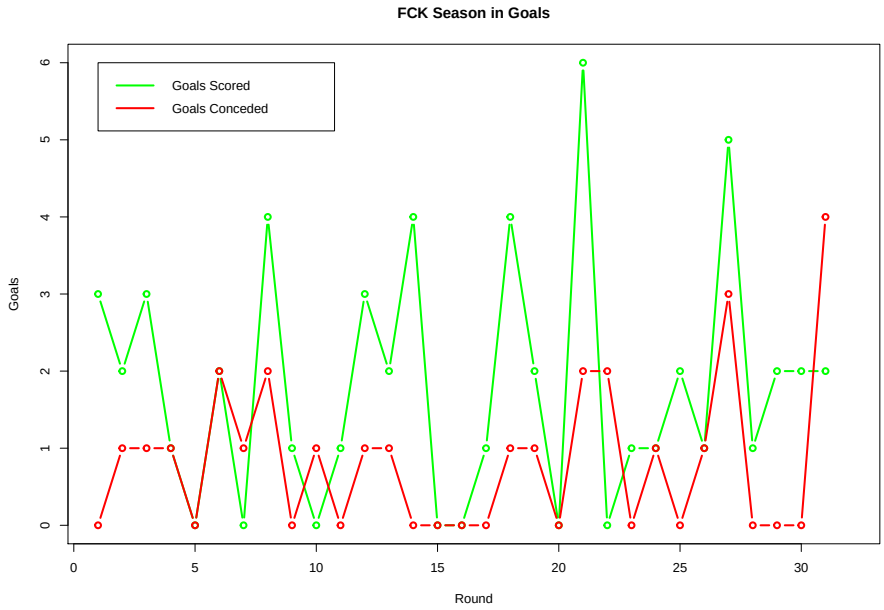
The R code is quite simple. In broad strokes it does the following: Read the data file, convert columns to be numeric, sum the player data by team, add and calculate the success columns, remove the unnecessary columns, restructure the data to a format that fits the radar chart and write three files, one containing the names of the teams, one containing the data in one format and one containing it in another format. The data is exported in two files to suit both the radar chart and the bar chart.

In JavaScript we create the selectors, where the user chooses the teams. If two teams are chosen the radar chart is drawn. The radar chart is based on [d3noob(2013)] and modified to our needs. One of the modifications is that we draw a bar chart if the user presses a value, represented by a circle. The function which draws the chart takes the data variable to visualise as an argument together with the selected team. The data is then loaded and drawn making sure that the data is sorted for better comparison, and that the right team is highlighted.

5.8 Season Review FCK



(a) A line chart illustrating the amount of points FCK has after each round



(b) A line chart illustrating how many goals FCK scores and concedes in every round

Figure 17: some text

5.8.1 What-why-how

This visualization (Figure 17) is a combination of two line graphs. It visualizes the amount of points the Danish football team F.C. Copenhagen has accumulated throughout the season and the amount of goals scored and conceded throughout the season. Why this visualization? For this particular visualization the goal is to illustrate a team's overall

evolution throughout a season. Each of these visualizations take a table as an input. The reason these visualizations are being made is to discover a trend or certain outliers. For the points graph, the data is ordered. It shows the progression of the team's point total throughout the season. For the goals graph, the two different lines are separated to illustrate the success of the team offense and defence. The colours in this graph are chosen based on human perception, as green is perceived as a positive colour, hence representing the positive event of scoring a goal, and red is perceived as a negative colour. The raw data is also reduced, as the visualization only shows the data from F.C. Copenhagen's season.

5.8.2 Code

These charts are created using only R. First, the data file is loaded into R. Second, we use the functions in R to create a plot, and to create a line in the plot.

5.9 Fouls Committed over season

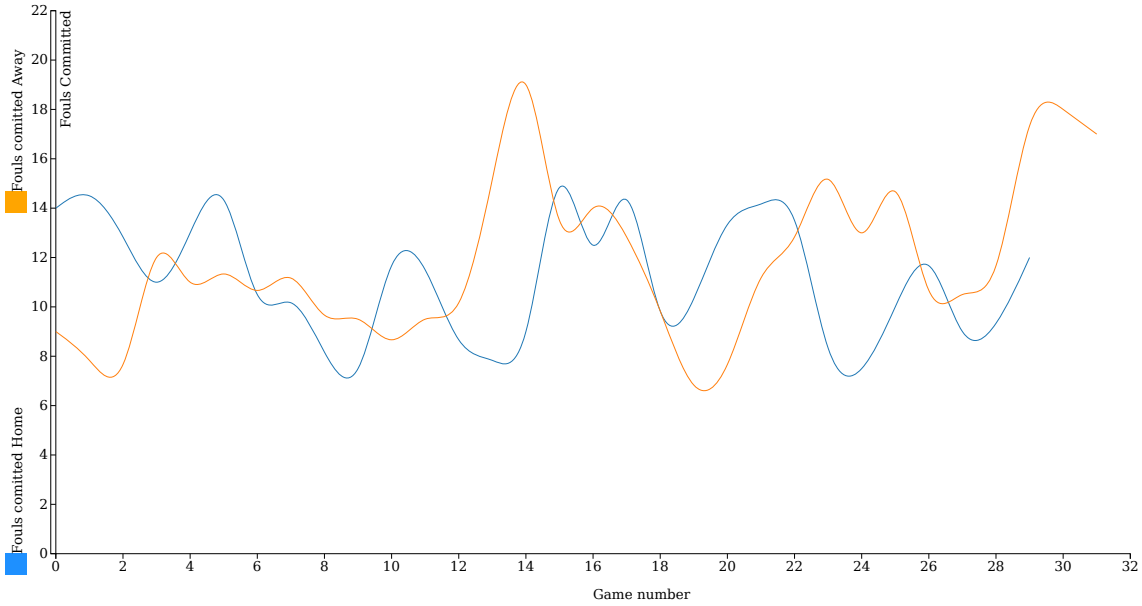


Figure 18: A line chart showing fouls committed throughout a season, split up in those committed home, and those away.

5.9.1 What-why-how

18 is the result of Exploratory Data Analysis. The hypothesis behind it, was that the closer to the end of a season, teams would get more aggressive. The idea behind splitting home and away matches up, is that a team might be more comfortable when playing home than away, which could influence the results.
The idea was to plot the fouls committed throughout a season and see some sort of trend, one of the things line charts are especially useful for. However, it turned out that no apparent trend could be found from the data available. However, what could be seen, is that the spikes of fouls committed is consistently higher when away. One thing to mention, is that in the dataset plotted, the season is not complete yet, as seen on the chart, a few matches are missing on the home variable.

5.9.2 Code

The code behind this chart lies in gathering and processing statistics for a team over multiple rounds, then filtering it for everything else than the foul statistics, while still preserving the right order of the matches. After that is done, it is put in D3, with some relatively simple code for a line chart.

5.10 Comparison viz

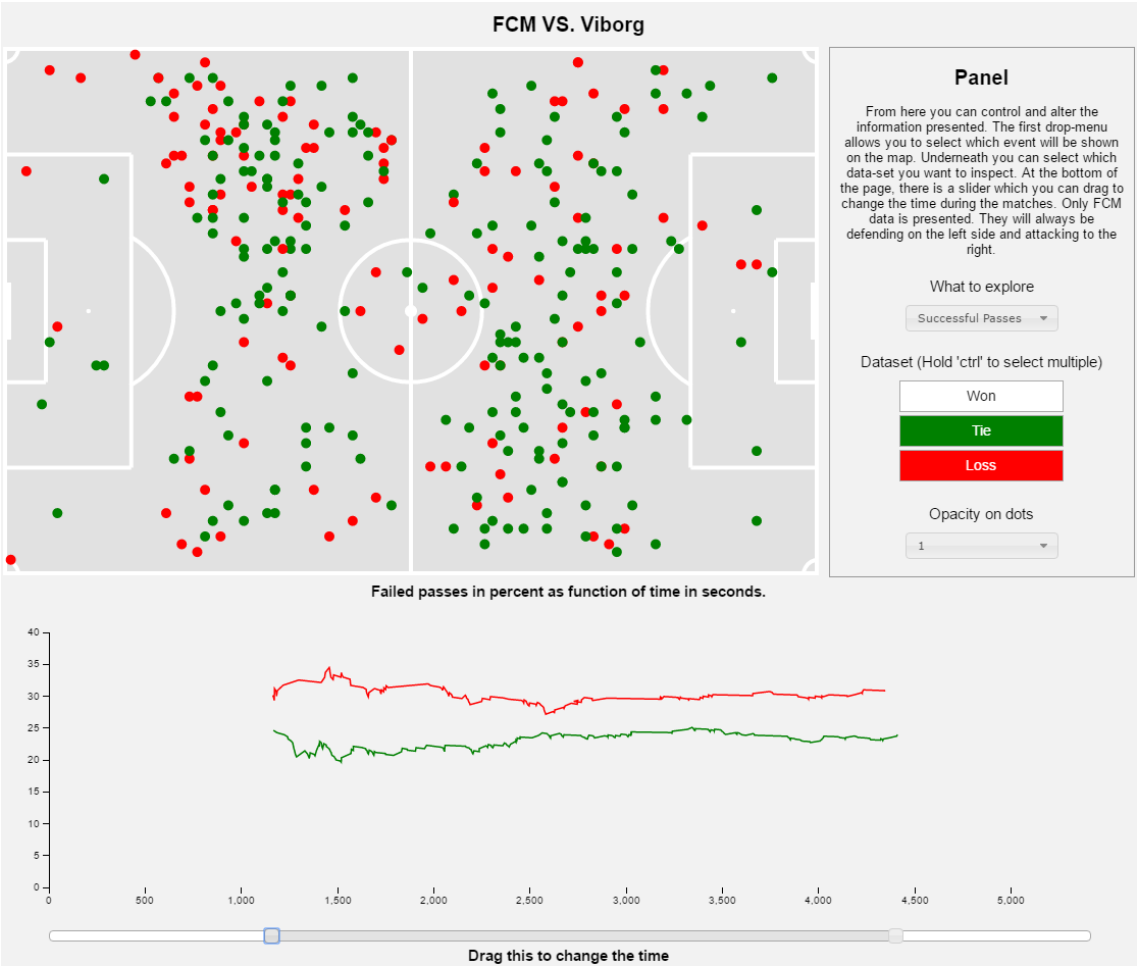


Figure 19: The successful passes on the map and the relationship between failed and successful ones in the line chart. Notice how a lot of passes happen over the middle while losing or tying. Interact with it live here.`http://footviz.copus.dk/gameView/`

5.10.1 What-why-how

The visualization at figure 19 attempts to give an overview of the three matches played between FCM and Viborg this season from FCM's point of view. The visualization presents various information regarding where touch-related data has taken place and also keeps track of the rate which different types of errors has occurred in percent.

The purpose is to allow the user to explore how a top-tier team such as FCM, deducted by the fact that they won the league in 2014/2015 and at the moment of writing is number three, can play against a new-coming underdog team from first division and in some cases

win, tie or lose. The hypothesis is that their play-style will change when being behind, partly because they are not playing well in the first place, but also due to the pressure of losing to an on paper worse team.

To investigate the notion, the visualization gives two different views where information can be deducted to find differences. The first one is a map which displays where certain events have taken place. The type of event is determined by the user in the selection-menu in the panel to the right. Six options are available and can be categorized into three overall themes which are: Aerial duals, shots and passes where for each the user can also select whether he wants to inspect the "successful" ones or those which went wrong. By mapping the events, the user can look for clusters in the data and may find patterns to where certain events happen. To aid in finding such clusters, two more options are available in the panel. The first one allows the user to select which matches should be inspected as the dots on the map may at times be so overwhelming that nothing can be concluded at all. Each match is represented by its own color with high variety in hue and brightness so they are easier to differentiate as well the background is very neutral to avoid interference with the inspected elements. The background also have the lines of a real football field to give a better feel of where on the field the events have happened. The last option in the panel allows the user to select an opacity of the dots. As all the coordinates have been altered in such a way that it looks like FCM is always playing on the left side of the field, many dots may at times overlap and thus making them slightly more transparent enables the user to spot overlaps. The altering of the coordinates serves the purpose of creating a more intuitive view to spot clusters and thus the opacity serves an important part in the exploration. The second view is a line-chart which illustrates the relation between two variables in percent on the y-axis and the time which has passed in seconds on the x-axis. The relation which is shown depends on the selection in the panel, so it may be how many percent of the passes failed, shots were missed or aerial duels lost. The number lines in the line chart will also toggle to the selection of matches in the panel. However, the opacity can not be changed here as it would merely serve as mere distraction in that context. Lastly at the very bottom is a slider which determines the point in time the user intends to inspect in the three matches. The slider also contains ranges so snapshots of the match can be inspected in further detail.

5.10.2 Code

As the visualization required information about the relationship between different variables, it was a necessity to pre-process the data to avoid computing too much in D3 and keeping it responsive, R was used to do the task. Firstly, the required columns were selected from the data-sheets from the API, more specifically all touches and shots in all three matches. The shots were then filtered to only be of the type necessary for the visualization, each time a successful event or an unsuccessful one occurred, a counter was incremented and the relationship between them were noted at each row, thus making it easier to plot in a line chart. Also, each row was noted with its field coordinate to allow map-plotting in d3. However, instead of setting the literal coordinates for each event, everything was firstly mirrored so it looked like FCM was always playing from the left side and attack the right to make it easier to find patterns. All the data was exported into three csv-files each representing a match. At load time, the D3 scripts would load each dataset and store it in a variable to avoid further I/O-operations in terms of loading sheets, as it affects the responsivity in a negative way.

5.11 Nationality of players

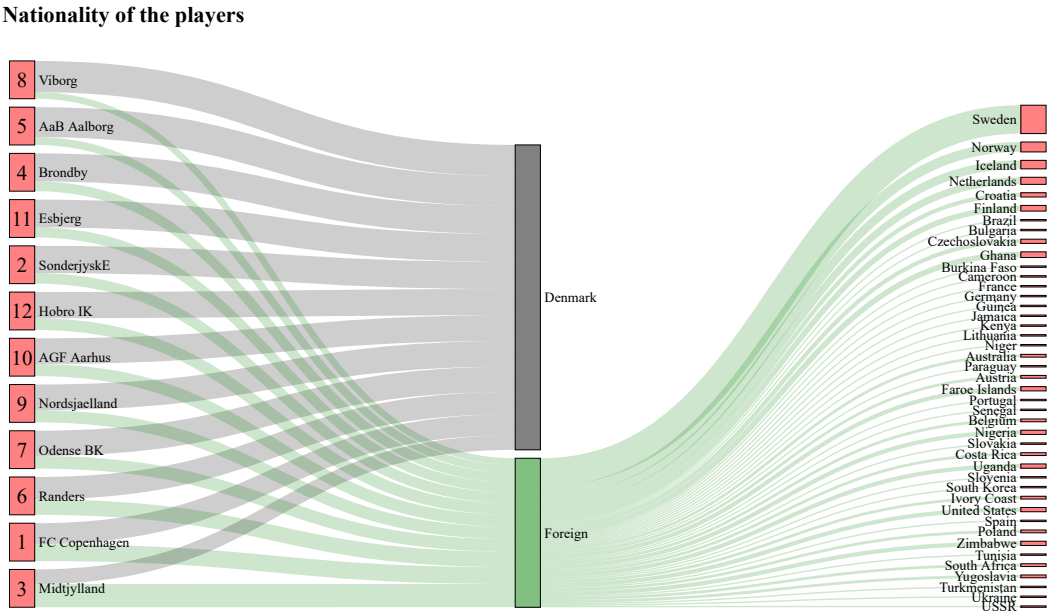


Figure 20: Sankey-Chart showing the distribution of Danish vs. foreign players on the different teams `http://footviz.copus.dk/nationality/`

5.11.1 What-why-how

This visualization shows the nationality of the players on the different teams in the league. It also shows the distribution of the foreign players among the other countries. This is done by a sankey chart, where the teams are sources, the target is either Denmark or Foreign. On the second level the source is Foreign and the target is the other countries. The idiom is shown in Figure 20.

The actions of this idiom is to summarise the players' nationality, to explore and compare the different teams to find similarities/differences between the teams in comparison to the standing in the table.

The view is manipulated by highlighting when hovering over a link, where we also get the percentage of players in this connection in the form of a text box. The raw data is reduced by filtering by only focusing on the nationality of the players. The players are categorised into the different bins by using hue and region.

In R we load in the data file, which now is a .json file. We then find the data we want to look at in the .json file, and convert it into a data frame. The nationalities of each club is summed. A copy of the data frame is created. In the original frame we set all the sources to be foreign where the target is not Denmark. In the second frame we set the targets to be Foreign where the target is not Denmark, and then remove all rows where the target is Denmark. In both frames we sum the values for each source-target pair. We then combine the two frames and exchange the value being the number of players, to now being the percentage of players. Finally we write the data to a .csv file.

The sankey chart itself is based on [Bremer(2016)] and modified to our use. We modify the placement of the nodes to have multiple levels, and clearer color scheme with clear differences between the links.

5.12 Success Rates Animated

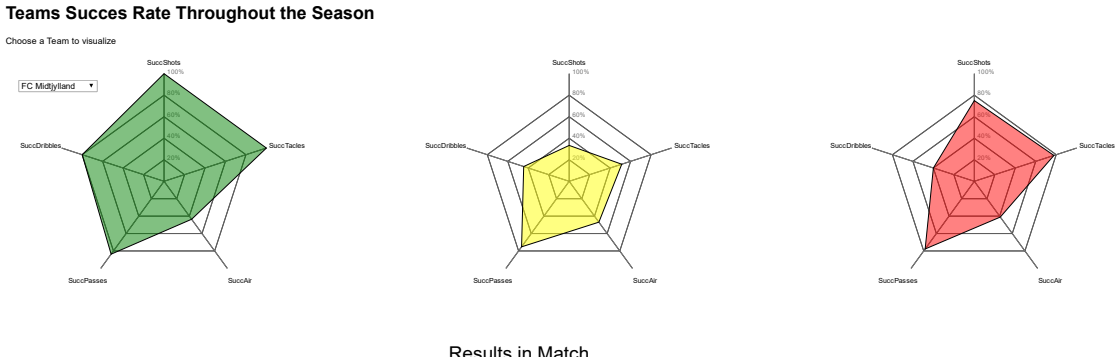


Figure 21: Comparison of a Teams success rates throughout the season, split in wins, draws and losses `http://footviz.copus.dk/radarchart2/`

5.12.1 What-why-how

Figure 21 shows the multi-view Radar Chart comparing a team's success rates. Concerning the marks and channels, we use position on a common scale in terms of the different axis of measure together with area, as the combined area of all the scores on each axis. The result of the match is categorised by color hue, in easy separable colours.

The action of the idiom is to compare a team's success rates throughout the season in wins, losses and draws. It summarises the team's success throughout the season. The target is to find similarities between the different matches in each of the match results, and maybe find some common shapes for the different teams.

This is done by an idiom faceted into three views. The views are linked by having the same data variables shown, but on different data. The view is manipulated by animation, looping over the different matches for the selected team. It is a smooth transition between the matches, to create context. The raw data is reduced through aggregation by calculating new attributes.

In R we load the data file, convert columns to be numerics, aggregate by team, calculate the success rates, transforming the data to a format suited for the radar chart, select the columns we are interested in, and write it to csv.

The D3 radar chart is based on [d3noob(2013)], and modified to become animated. We create an update function which is called continuously with different data matches to be drawn.

5.13 Custom bubble chart

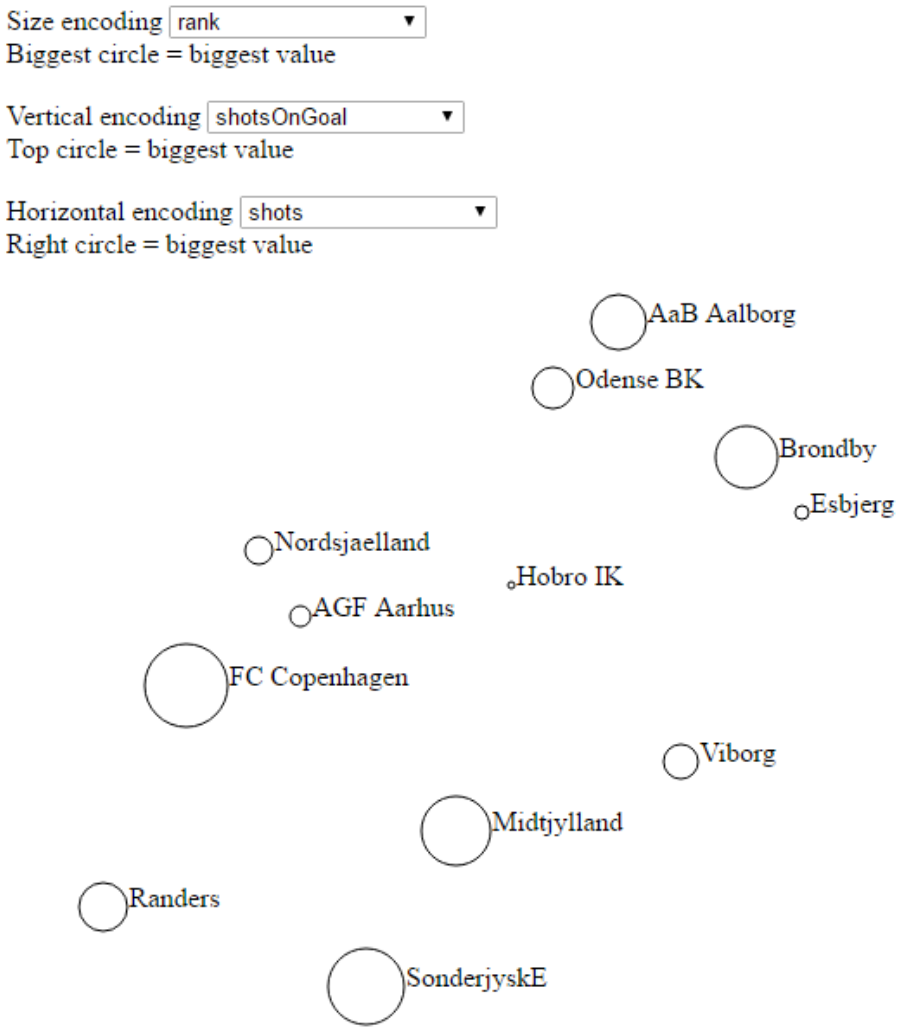


Figure 22: "Custom bubble chart". Visualization of statistics of teams from the current season. Encodes rank, shots and shots on goal

5.13.1 What-why-how

What The data being presented in this visualization (Figure 22) is the statistics of the teams from the current season. This includes parameters such as their current ranking in the league and the total shots on goal, number of yellow cards etc.

Why. As a user is able to choose what is encoded in the different dimensions, the user can easily test hypotheses about correlations between different parameters, for example how rank, shots and shots on goal affect each other. The user can also discover new correlations by simply browsing through the different parameters and trying different combinations. The visualization offers a platform where the user can play with the different parameters. The transition when the user has changed the options is animated such that the user can easily follow the circles with their eyes, and in that way see how a change in an option changes the order between the circles.

How In the beginning of the iterative design process, the visualization started out by only having a vertical axis and size encoding. This provided meaningful information to the user, but based on feedback another axis was added such that three different parameters could be encoded in the graph. However, as the last axis was added, it turns out that the "bubble chart" had been reinvented. The only minor difference between this visualization and the traditional bubble chart is that this visualization allows the user to interact with the visualization and change the parameters. The time complexity of this specific implementation is O(nlgn) where n is the amount of different parameters available to choose from. The reason being that when a user has selected the options, the coordinates and sizes of the circles are calculated in the following way: First the circles are sorted based on the first parameter, and then the radius of the circle is assigned in the order that they are now in. Then they are sorted based on the second parameter, and the y-coordinate is assigned based on the radius and the order they are in (we have to base it on the radius as well such that there is equal distance between them and no overlaps). Finally they are sorted based on the third parameter, and the x-coordinate is assigned. Since we sort 3 times, the complexity is going to be O(nlgn), as we can sort in O(nlgn) time. While there might be smarter implementations than this straightforward approach, it is not of any concern at the moment as the different number of parameters a user can choose from in football data is very limited. The smart thing about this implementation is that it is very flexible. All of the data that a user is being presented with is based on the data that is in the data file that the visualization is based on. The data file that is supplied should be encoded in JSON as a list of objects, where all of the objects have the same attributes and all of the values are numerical except for the "name" attribute which is excluded from the drop down list, and is used as a label on the circles. This means that the implementation can be used to visualize many different things. It automatically extracts the attributes that must go in the drop down list, and assigns the names to the circles. The mark chosen in this visualization is a point, and the visual channel chosen to encode data into the mark is size and position. Color could have been chosen aswell, and a fourth parameter could be encoded within that, but this was not the intention with the visualization. The data that the visualization uses is preproccessed in R and exported in the format that was described above.

5.13.2 Code

This is the pseudocode for the way that the x, y and size dimensions are calculated for each circle. Since we receive the data as a list of objects, we can append/change the x, y and radius of each circle directly on the object as each circle represents an object. The updateDimensions function takes as arguments the list of objects, the parameters that it should encode the circles by and the distance between each circle. Note that when calculating the y-coordinate of the circles, we sort the objects in reverse order as coordinates in graphical spaces usually have the origin in the upper left corner, meaning that it is counter intuitive for users compared to how they normally view graphs, meaning that we have to inverse the y-coordinates. After the dimensions have been updated, the circles will transition into their new dimensions (i.e. grow or shrink and move along the axes).

```
updateDimensions(objects, sizePar, xPar, yPar, distance) {
  sortByParameter(objects, sizePar)

  currentRadius = 1

  for(object in objects)
    object.radius = currentRadius
    currentRadius++

  sortByParameterReverse(objects, yPar)

  prevRadius = 0
  prevY = 0

  for(object in objects)
    object.y = prevY + prevRadius + distance + object.radius
    prevY = object.y
    prevRadius = object.radius

  sortByParameter(objects, xPar)

  prevRadius = 0
  prevX = 0

  for(object in objects)
    object.x = prevX + prevRadius + distance + object.radius
    prevX = object.x
    prevRadius = object.radius
}
```

Figure 23: Pseudocode for updating the circles' parameters

5.14 Field events in intervals

(a) Goal attempts during the 70 to 80 minutes.

(b) Goal attempts during the 80 to 90 minutes.

Figure 24: Visualization of event data in intervals during a match. Goal attempts during the 70 to 80 minutes compared to goal attempts during the 80 to 90 minutes.

5.14.1 What-why-how

What The data being presented in this visualization (Figure 24) is event data from a football season split into intervals. Event data is things such as a good pass to another player or a goal attempt. From the API we can request events from a match. The event data include the type of event, the time stamp and the coordinates. What is being shown in the visualization is then all of the event data from an entire football season aggregated such that when a user selects good passes and the time interval 0 to 10 minutes, the user will be presented with all of the good passes that has happened in the season during the first 10 minutes.

Why This visualization could be categorized as being in the exploratory data analysis category, as it allows a user to browse through the data in a very intuitive way, such that the user can get a feeling of how common each event is, and where on the field it often occurs. But the visualization can also be used if the user has a specific hypothesis that they want to test. The visualization was first build because we had a hypothesis about the goal attempts, where the hypothesis was about how football players might take more risky attempts at goals during the late part of a game, as they perhaps are more desperate to score. To test this specific hypothesis, a user can select goal attempts and then use the slider to see how the goal attempts change throughout a match. The result of the hypothesis test is described later in the report in the discussion section.

How As the data to be shown is spatial and discrete data, it is being presented in a field. The type of mark being used is a point and the visual channel used to encode the mark is spatial position in both vertical and horizontal directions. To control what kind of event a point represents, the user is presented with a drop down menu, where the user can select the type of event. An alternative to this option could be to use the visual channel color, such that goal attempts was blue, good passes was yellow and so on. However, it was decided that only one type of event should be shown at once, as multiple types of events at once become noisy. Alternatively, a user could select two types and choose the color of them.

Because the resolution of the coordinates is not very high (coordinates are seperated by 1 meter), a lot of points are going to overlap because a lot of events happen at the same coordinates. To prevent this from disturbing the meaning of the data, two things have been done. The first thing is that the opacity of each point is lowered slightly, meaning that points are actually a bit transparent. This means that if two points are on top of eachother, the resulting point will appear more opaque. The other thing that is done is that there is added or subtracted a small random amount from each point's x- and y-coordinates. This approach is called "jittering" and is often used when overlapping data are to be visually presented without appearing to be overlapping. However, there might still be overlaps, as it is actually not checked whether or not the new x and y coordinates of a point collides with another point. One could make an implementation where this is checked, but even if a collision check is done by an array look-up in O(1) time, a naive implementation could easily result in a worst case time complexity of O(n) where n is the number of events, if the events are laid out in an unfortunate way (for example if they all have the same x and y coordinates, and they are centered around those coordinates, and the algorithm checks for a place to place a point in a circular fashion centered around the original coordinates). The time complexity of the algorithm behind the visualization is O(n), where n is the amount of data points, as the data is read from disk, then the data is bound to the points, and the points' coordinates are updated. Finally, the old data points

are removed. This time complexity assumes that the D3 library data binding operation is done in O(n) time. Note that this is not that good of a time complexity for a dynamic visualization, and sometimes it can be slow depending on how fast the data is loaded from disk and whether it is cached or not. Alternatively the different events and periods could be preprocessed even further and saved as images that is displayed instead, but this would still require loading the images from the disk, but would make each change of visualization O(1) instead of O(n). This approach would however limit the options of what can be done with the data in D3, if one wishes to develop the visualization further.

The data is prepared in R before it is used by D3. The pseudocode for the R code can be seen in the code section below. The API that we get our data from can only serve event data from one match at a time. This means that we have to automatically query the API for the event data from all of the different matches that is in a season, and then aggregate all of the data into one data frame. From that data frame, the data is sorted into different data frames depending on their event type. The data frames are then each split into 9 different data frames depending on the minute attribute of each event. The events during minute 0 to 10 are split into one data frame, the events during 10 to 20 are split into another and so on. These data frames are then saved to seperate files on the disk, where the name of the file is (type of event) + (period in the game) + (.json). 171 different files are produced from this process, which shows that it is important to automate processes as this. These files are then placed in a directory where the javascript of the visualization can read them. Because we label the event types the same way as the API does, we have a global naming scheme, meaning that the javascript can simply reconstruct the file names and request them from the OS. Another benefit of doing this automatically is that the visualization can quickly be adopted to different kinds of data, and show different seasons etc.

5.14.2 Code

The visualization is made using the D3 javascript library, but the visualization itself is coded entirely from scratch, and is not just a modified example (except for the slider).

The pseudocode for the data processing in R is as follows. Where eventID is the id of a match and touch means an event within the game, for example a good pass.

```
getTouchesAndWriteToFiles() {
  teams = getDataFrame(teams)

  eventIDs = new DataFrame()

  for(teamID in teams.teamID)
    events = getDataFrame(events + teamID)
    eventIDs = combine(eventIDs, events)

  eventIDs = distinct(eventIDs)

  allTouches = new DataFrame()

  for(eventID in eventIDs.IDs)
    touches = getDataFrame(touches + eventID)
    allTouches = combine(allTouches, touches)

  splittedTouches = split(allTouches, touchID)

  for(touchDataFrame in splittedTouches)
    for(i = 0 to 8)
      currentTouches = select(touchDataFrame, minutes >= i*10 AND minutes < (i +
          1)*10)
      toWrite = toJSON(currentTouches)
      write(toWrite, touchDataFrame.name + i + ".json")
}
```

Figure 25: Processing event data in R for the Field events visualization

6 Discussion

Our visualizations allowed us to find certain patterns in the data and partly prove or disprove some of our hypotheses. One of the things we intended to look into was how the playing style of a team changed throughout a match and to this end we saw some tendencies which seemed to apply. The first one was the fact that late in a match, it seemed as a general tendency that teams had more goal attempts than early on in the match. We actually found a direct correlation between time passed and how many goal attempts were taken which may imply that the players either become more desperate and shoot more, or the defense-line simply perform worse as the game progresses. Also, it seemed that teams would actually fail more passes at the very beginning of a match and at the start of the second half, which may be due to the fact they have to get "warmed up" and thus make some mistakes at the beginning of each half. These theories are based on the results of summing up all touch-related data throughout an entire season and thus there is a large amount of data to back up the notion. By looking at leagues from other countries as well as multiple seasons, it would be possible to either confirm or deny the hypothesis. Another thing which was found, though more based on single instances, was that a winning team would play more horizontally along the sides of a football field, whilst when losing they would play vertically and close to the middle instead. This was deducted by analyzing three matches between FCM and Viborg which indicated that when a top-tier team as FCM played against a supposedly on paper worse team like Viborg, they would in their supposed state of winning play more along the sides whilst when losing would put more

focus in the center. Also, the rate at which FCM failed their passes when losing seemed to be rather high, when comparing with winning or tying. By cross checking with a lost match against another top-tier team, namely FCK we found that this rate actually dropped dramatically, even though the outcome of the matches were much alike. Thus, it seems that when a team, or at least FCM, are losing to a much worse team, they make more mistakes when passing. The cause can indeed be discussed, a possible explanation could be that they are stressing more to get ahead as they are supposed to win the match. However, it may as well simply be due to the fact that they are playing way under their normal level on the given day in the first place. In regards to finding key differences between top-tier and low-tier teams, it turned out rather complicated to find any consistently different attributes. Some of the factors that we focused on, were based on summing some general player stats for all teams and compare them. Possibly counterintuitively, we were not able to find any direct correlation between how the best teams played nor the worse in opposition to each other, which lead to the notion that there may not be a single player attribute which leads to a winning team but rather a combination which is far more complicated. Another thing which was investigated was the distribution of players in terms of their nationality. We were not able to find any correlation between how many foreign players were on a team and their ranking, but we saw small tendencies of teams having more foreigners depending on their establishment, meaning teams that have been in the league for a while and thus have a larger budget, tended to have more foreigners which may simply be due to the fact that they have the money and thus the option to purchase players from other countries. With regards to a team's evolution throughout a season, we were hoping, among other things, to find some correlation between how far in the season a game was, and how many fouls a team committed. This was with the mindset that a team would get more aggressive as the end of the season came closer. However, how far into the season a match was, didn't seem to affect how many fouls were committed, instead, it kept jumping up and down throughout the season. This could indicate that the aggressiveness of a team's playing style is more dependent on their opponent, than the position and/or time in the league. There was however a small spike towards the last couple of matches, but nothing bigger than some of the spikes from mid-season. Something else that 18 did show, was that the spikes in fouls committed in a match was consistently higher when away. This could indicate that a team tend to be more aggressive when away, than home. Another possibility could be that the referees tend to go easier on a home team. However, to validate that even in the slightest, significantly more in-depth analysis would have to take place.

We dove further into investigating how a team evolves throughout a season by looking at FCK. Here, the biggest takeaway comes when looking at the amount of points FCK has after each round. This visualization helped illustrate the highs and lows of the team's season, and it showed how the team got off to a relatively slow start, only to get going and never looking back. We assumed that by looking at goal scoring and conceding in the first 10 games and comparing them to the remaining games, we could illustrate the evolution in the team. However, the results are simply far too inconsistent to reach any conclusions of note.

Despite using PCA and manually testing different variables that would make sense to change throughout a season, there simply weren't enough season-wide data to draw any substantial conclusions regarding how a team evolves throughout a season.

In order to try and establish which variables determine the differences between winning teams and losing teams, a series of grouped bar charts were created, see figures 11-15. 11 shows different types of attacks that lead to a goal, in percentages, grouped in teams by

ranking order. For instance, Viborg scores as often from set plays as on quick attacks. On this chart, it is hard to notice any obvious tendencies between the higher ranked teams to the lowest, but there are a couple of interesting things to point out. FC Midtjylland, which is one of the top-tier teams in the league, is the team that scores most goals on set plays, compared to total goals scored, closely followed by AGF, which is currently the third-worst performing team this season. It seems as such, that instead of finding a grouping of these variables, we see them spread out across the teams, disregarding the ranking somewhat. FC Midtjylland scores more on quick attacks than AGF, so one is left to wonder if it is the combination of set plays and quick attacks that is more effective, or if other variables come into play, which is probably the most likely.

It does seem like there is a slight tendency towards better teams scoring less from possession based attacks, although there are some strong outliers, namely AaB, OB and FC Nordsjaelland, who all score more than 60 % of their goals from possession based attacks, but these outliers all lie somewhat in the middle of the league, with FC Nordsjaelland scoring much less on set plays compared to the other two teams.

Goals from open play, not attacking, are somewhat rare, as it is not often a team scores suddenly, without being the attackers. The same goes for penalties, although they are less rare than the aforementioned. For penalties, there does seem to be a slight tendency for lower ranked teams to score more on these, and this does make sense, as one could expect a lower ranked team to struggle with scoring enough goals, and so penalties account for a larger share of their goals. There are of course outliers, again FC Nordsjaelland, who didn't receive any goals from penalties, but instead a few goals from non-attacking open play.

12 shows which direction the 12 different teams prefer to pass in, divided between backward, sideways and forward passes. For the 2nd to the 4th team, it seems like there is a local negative linear correlation between forward and sideways passes, with forward passes being less for the 4th team, who pass sideways much more frequently compared to team 2 and 3. The same is seen for the last 4 teams, but in reverse order - teams pass less sideways and somewhat less backwards, but more frequently forward.

13 shows how far the teams pass on average, divided into three categories - $<$17m, 17-34m, and $>$34m. On this chart, it is clear that FC Copenhagen less frequently passes the ball long than the other top-tier teams, in fact there are only 3 other teams in the league that pass less long balls than FC Copenhagen, and none of these are top-tier teams. It is interesting then, to see that SonderjyskE is one of the teams that pass long balls most frequently, being the team in 2nd place. When you take into account that SonderjyskE was also among the teams passing the ball forward most frequently, this makes good sense - it is better to pass short balls backwards and long balls forward - a long ball backward would cost the team momentum. Hobro is the other team that looks like SonderjyskE in respect to both length and direction of passes.

14 shows how many shots are taken with the foot versus head, as percentages out of 100, as well as successful chances, which is calculated as the total number of goals divided by the total number of chances, and selected to indicate how successful a team is when trying to score. It clearly shows, counterintuitively, that the top ranking team, FC Copenhagen, actually has the worst goal to chance ratio, which indicates that they are maximizing the number of chances, and not necessarily the quality of these. This team is also the most heading team in the league, leading by a relatively large margin.

SonderjyskE and FC Midtjylland stand out in terms of successful chances, indicating they take the opposite approach to quantity vs quality, compared to FC Copenhagen. Apart from these two teams, it looks like there is a slight correlation between lower ranked

teams having a higher ratio of successful chances, with a bit of variance. This is well within reason, since lower ranked teams create less chances, so they want to create the best possible chances in general. It also seems as though lower ranked teams shoot more with their feet than with their heads, but this is less clear, since the lowest 3 teams head about as much as the 2nd and 3rd teams.

15 shows where shots are taken from, divided into shots from inside the box, and shots from outside the box. Successful chances is based on the same data as in 14, and calculated the same way.

From 15 it is clear that the highest ranking team is also the team that shoots from inside the box most frequently. Based on the earlier charts, one can speculate that FC Copenhagen concentrates on passing the ball forward with short passes, getting it inside the box, and then getting the ball into the goal, instead of trying to create chances by lurking outside the box.

As with the other charts, it looks - apart from SonderjyskE and FC Midtjylland - as if there is somewhat of a linear correlation between different variables and the ranking of teams. Here, it seems as if lower ranked teams tend to shoot more often from outside the box, but again the correlation is too weak to conclude anything meaningful.

7 Conclusion

It turned out to be rather difficult to make any assured conclusion in regards to how a team evolves throughout a season as there turned out to be a lot of inconsistencies in most patterns we investigated, which lead to a high margin of error in the results. These inconsistencies seemed to be rather volatile, due to the fact that only 12 teams were compared, if a single team was not fitting the pattern our hypothesis had at proposal it lead to a high divagation. The issue also applied whilst looking for differences between the top-tier and bottom-tier teams. Some tendencies were arguably found but were simply not supported well enough with evidence to actually conclude something concretely. However, some of the patterns which were found, seemed to indicate a tendencies for bottom-tier team's to generally speaking shoot more, especially from outside of the box. Whilst looking at how a teams play-style changed throughout a match, we found a relatively clear indication that teams tend to shoot more frequently as the game progresses. The root of cause was not clear but one could suggest that either teams become more desperate as the game progresses, or maybe the defense line cuts a bit more slack later into the game and make more pressure based errors. It also seemed like teams were at higher risk of making unsuccessful passes at the beginning of each half, indicating that some factors must apply that causes players to perform slightly worse, which may be attributed to factors such as pressure or uncertainty of the opponent. Though these conclusions were supported by a substantial amount of quantitative records, some other tendencies were also found which were slightly less supported. The top-tier teams seemed to change their play-style in matches against bottom-tier teams but it depended heavily on what the outcome was. Especially factors such as failed passes seemed to truly change depending on whom the opponent was, as it would often be higher if the opponent was worse on paper, in respect to playing against an on paper even opponent. Another tendency which was found, was that a losing team may start playing more towards the middle of the field when being behind, as opposed to being ahead in the match. Although this theory is very poorly supported, it may very well lay grounds for a new hypothesis which is yet to be proven.

8 Perspectivation

The visualization techniques and idioms we have presented in this report can be applied in many different settings. Some of the visualizations are very specific to football, for example the ones with a football field, but these can easily be adapted to visualize data from other branches of sports. The more generic ones we have made such as the variation of a bubble chart and the radar plots can easily be used to present other kinds of data which is not necessarily from sport. This could be financial data, biological data etc. The visualizations we have made can specifically be used by a team to analyze how other teams play and adopt their strategy when they meet those teams, or to analyze in general how teams play throughout a match, and then see if they can learn something which can improve their own strategy. The visualizations can also be used on websites where normal football fans can view them and see if they can produce any interesting hypotheses, which they can try to test the next time they watch a game on tv. The visualizations can be used by betting companies such that they can give their users tools such that the users can find out how they want to place their bets. The visualizations can also be used during live transmissions of football games, for example by showing statistics about the match during the intermission. In the academic setting, some of the visualizations can be used by psychologists for example, to learn something about the mentality of players during a game, for example by using the field representation of shots, to see where a player is likely to shoot from under certain conditions.

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Process Evaluation

At our first meeting in the group we made the group contract. We discussed how we would like to distribute our work and what we should do to cooperate in the most successful way. Early in our process we also met with the company Prozone, which is the company providing us with data. Here we got information about their data, current tools, what they could be interested in and what they could offer us. It seemed very promising but unfortunately the process of getting the data was a longer than expected. It took around a month to get access to the API, which of course was a challenge, because we did not know exactly what data we could get access to. We got some data from the beginning, but this was of very scarce quantity. Because of that most of our visualizations are based on this test data, and scaled up when we finally got access to more.

Because of the lack of data, we focused on the theory the first few weeks. We explored theoretical materials on our own, and later on discussed them in the group. This has generally been the process of our work. Also when getting access to the API we could start to share knowledge about the data we could get. We have programmed our visualizations individually and helped each other to understand the programming languages. If one had problems we tried to solve these together. During the design process we also gave each other feedback on the specific visualizations.

At the midway seminar we had some ideas about what we would like to visualise, and had some basic visualizations to show. There was a general structural feedback on our presentations, like missing slide numbers, slide titles and conclusion slide. We needed a greater theoretical knowledge too, making us able to answer any questions, and explain every topic we mention. Lastly our supervisor emphasised the importance of using original and innovative graphics, which not all members did.

At one of our meetings we talked about which theoretical topics we would like to include in our report. Afterwards we delegated the different sections between us. In the end we read each others sections to check for spelling mistakes, typos but more importantly to agree on the content. Each member has written their own results section, and contributed to the discussion and conclusion section from this. We agreed on when to finish with the theory sections, but this deadline was not met by most of the group members. This meant that the last week has been somewhat stressful for some group members.

Generally the group has met a couple of times a week, to discuss progress and theory. We evaluated how long we had come, and what the next step was. We met once a week with our supervisor to get feedback on our work. The group meetings have typically been placed before and after each meeting with our supervisor, to discuss what our agenda to the supervisor meeting would be, and what we should do next based on the feedback from our supervisor. At almost every group meeting every member was present, and most of the time arriving on time. We have generally given members who was late a few minutes before we started the meeting. After each meeting we have posted entries to the journal concerning what we have accomplished, and what we would do next.

We have been using Github to share all our materials. We have uploaded most of the sources, together with all our visualizations and documents. It has made the work much easier because we could get updates on each others work and get inspired just by looking at the uploaded materials. Also when writing the report it has been very helpful, especially combined with a LaTeX document for each section, meaning that each member could write in their own document, and just link it to the final document.

We have had no major conflicts, only minor disagreements with our supervisor about what we thought the project should be about, and which topics we should include. Our

supervisor suggested to include some machine learning, which we thought was a bit off topic. In the end we decided not to include it. The group has worked together in mutual respect for each other, no conflicts have risen.

From slides on e-learn we got a time line over the project but have had big problems following this, because of the late data arrival. A lot of time has also been wasted on email correspondence with Prozone concerning the data. This also means that the process has been somewhat even more compressed and pushed to the end.

Concerning the mandatory LaTeX and library courses we have the following comments. The library course was informative, and gave us some knowledge of where to find materials and what to use. We already had plenty of materials, so we have not used the knowledge much. The LaTeX courses were not so informative, because we were already used to writing in LaTeX, only few informations were valuable for us. The course about poster creation in LaTeX was not useful at all. A few examples was explained, and we could begin to make our posters, and the instructor could help us. The structure would be great if the course had been later in the process, we did not begin creation of the poster because we were not ready for it.

When having to evaluate the process it is our opinion that we should have been working even more together in the same room, discussing our temporary results and discoveries. In the last couple of weeks we worked more intensively together, which yielded great results, and which showed new opportunities which we could have followed if we had the time. It worked out nicely to study the theory individually and then talk about it, if we had any doubts, but once again it could have been a great idea, maybe to study different parts of theory and then explain it to the others. In this way we could have covered a larger field without having to individually read it all by our self. This would also be a great way to practise explaining the theory for others. In relation to the deadlines not being respected, we should have been more honest with each other, and talked about why this was the case. Earlier in the project, we should have made deadlines for bringing concrete visualizations, such that we would be more on the same level in the process and could have improved our visualizations even further.