

Visualisation Week 2

2.1 Introduction

Session two it's about how you conceive visualisations. You will learn about the difference between perception and cognition, in general, and how to perceive colours. We're also going to discuss visual marks and channels, which are the basic building blocks of any visualisation you could create.

And throughout the session, you will also do some exercises using public visualisations that you can pick from the internet. And in the end of the session, we will also look at some design principles that you can follow to create better visualisations.

Learning objectives

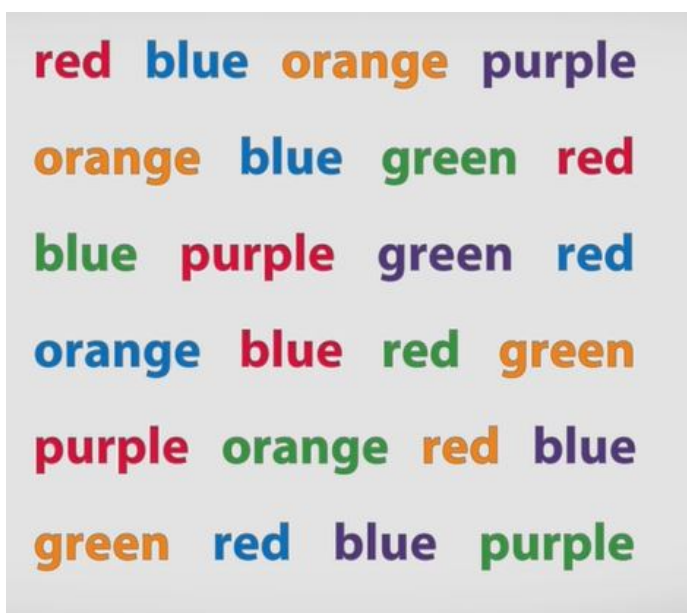
By the end of this session, you should be able to:

- Understand, in general terms, how the human visual system works
- Select the appropriate colour scale for a particular visualisation
- Identify the visual marks and channels of a given visualisation
- Apply Tufte's design principles to visualisations
- Critique and improve a given visualisation.

2.2 The human visual system

You should know from our previous session that visualisation is a powerful tool to analyse and discover patterns in our data. When designing effective visualisations we should take into account our end users, and a part of this involves understanding the particularities of the human visual system. In my next presentation, I will examine the difference between perception and cognition.

First, we need to differentiate between two fundamental concepts, perception and cognition. Let's start with an example that demonstrates the difference. How many words are written in the colour green? Well, we can estimate this very quickly, right?



Estimating the number of objects is a perceptual task. But if I ask you, how many of the words are the actual words green, then you need to read all the words, which also takes much more time.

Reading the words is a cognitive process that requires us to think. So perception, on the one hand, deals with the identification and interpretation of sensory information. It is the first processing of low level features, such as edges and planes that we see with our eyes. And it happens in the visual cortex. It's a reflex, which we cannot control consciously. Cognition, on the other hand, is the processing of information for which we need to apply our pre-existing knowledge and also problem solving strategies. Another example of perception is when we hear someone speak, but understanding the language and the words is a cognitive task.

Perception vs. Cognition

■ Perception

- Identification and interpretation of sensory information
- First processing (edges, planes) in visual cortex
- From the physical stimulus to recognising information
- Reflexes, not conscious

■ Cognition

- Processing of information, applying knowledge, conclusion drawing, problem solving, learning, relations between objects

Let's look at this photo. It shows a painting of a lady on the floor. Looks like a perfectly fine leg that the lady holds up, right? But the first interpretation is not always right. This is the same painting from a different perspective, and it looks completely different.



The take home message here for visualisation is that we heavily rely on priors, which also means that we can be manipulated and make false assumptions, based on what we expect and what we have learned. Humans don't have a general purpose vision. What we see always depends on our goals and expectations. Our brain is trained to relative judgments, but we are bad at doing absolute judgments. An excellent example is the Ames Room that can be found its installations in many science museums around the world.

As we have seen, cognition requires more mental resources and is therefore a longer process, whilst perception is immediate and involuntary. Our visual system relies heavily on prior experiences, which means it can sometimes be manipulated.

Apart from being manipulated as in the example above, our visual perception sometimes misses important stimuli, either by being briefly interrupted, or by being entirely focused on something else. This causes the phenomena of change blindness and inattention blindness. Let me explain why it is important to take them into account when creating animations.

Change blindness is where details of an image cannot be remembered across separate scenes. Exceptions are areas with focused attention, interruptions, amplify the effect. An example of interruption would be a blink of an eye or a blank screen, like in the example before. Change blindness is not a failure of our visual system but a failure caused by inappropriate attentional guidance. In the context of visualisation, the effect is relevant for comparison tasks where animation is used to encode changes in the data, such as in the time series dataset. Inattention blindness, also known as exceptional blindness, is another effect. It happens when a person fails to notice some stimulus that is in plain sight. This stimulus is usually unexpected but fully visible. This typically happens because humans are overloaded with inputs. It's impossible to pay attention to every single input that we see.

Change blindness

- Details of an image cannot be remembered across separate scenes – except in areas with focused attention
- Interruption amplifies this effect (e.g., a blink, eye saccade, or blank screen)
- No failure of vision system, failure based on inappropriate attentional guidance
- Relevant for visualisation when using animation to encode time-dependent data

I hope these examples of change blindness and inattention blindness helped illustrate how our perception is not always perfect and can miss some important details. If we want to ensure that this doesn't happen in our visualisation, there are some techniques we can make use of. **Understanding preattentive features**, for instance, can help us draw the user's attention to certain information of interest.

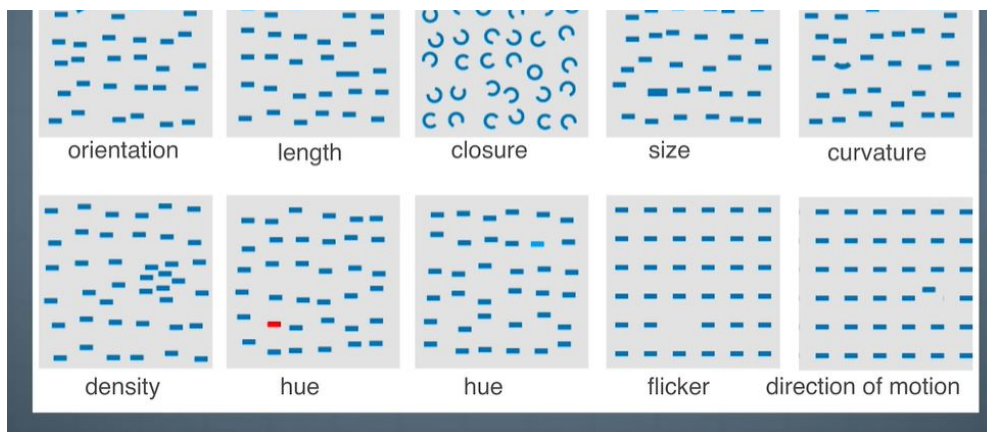
Next, I want to tell you about preattentive features that are also detected by a low level visual system. Preattentive features are visual properties that cause a pop-out effect, which means that we can recognise a change immediately.

Preattentive features are orientation, length, closure, size, curvature, density, hue, flicker, and the direction of motion. Notice that flicker is actually rarely used in visualisation because it's highly distracting and can also be annoying.

Preattentive features

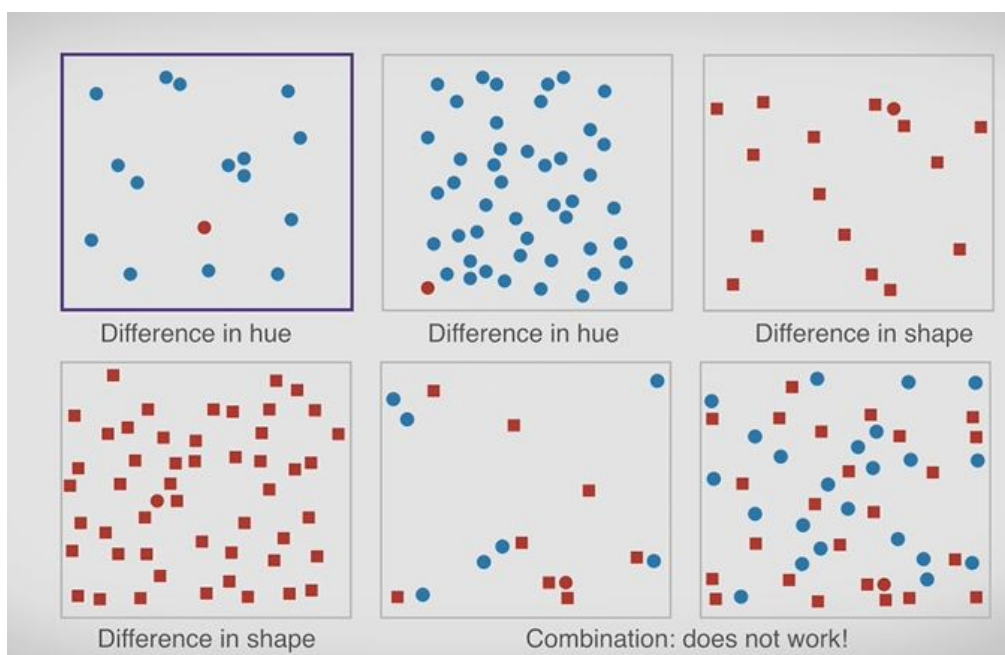
Visual popout





Let's look at some examples of preattentive features. You see six examples here. If you start with the first one, you immediately recognise that the red dot is different from the blue dots. You also can see that in the second one, where you have many more blue dots, which means that it still works even if you have a lot of distracting dots.

And then it also works with shape, not just hue. That's what you see in the third image. And it still works even if you increase the number of objects you have in your image. But if you start to mix them, then it gets problematic. So it might work with a few elements--that's what you see in the fifth example-- but you are going to have problems if you mix shape and hue as the pop-out effect in one visualisation, as you can see in the last image.



So preattentive processing is handled by our low level visual system, as I said before. It is very rapid, very accurate, and the information is processed in parallel. It also happens before focused attention. That's why it's called preattentive.

Attention can be used to draw the attention of the user to areas in your visualisation. And you can, for instance, change the colour of items to highlight them. Let's conclude with a couple of take-home messages that you should remember.

Our low level visual system is driven by object features. And to find meaning in what we see, we have to selectively pay attention to what is important. And our attention is always driven by pre-existing knowledge, expectations, and goals stored in our long term memory.

Now that you are more familiar with how our visual system works in general, move on to the next activity, where we will discuss the topic of colour.

2.3 Colour theory

We have just seen that colour can help draw the viewer's attention if used properly. In this activity we will learn about how to use it best.

Individual exercise

Drag and drop: order colour blocks by colour and brightness

Order the blocks by colour.



Order the blocks by brightness.

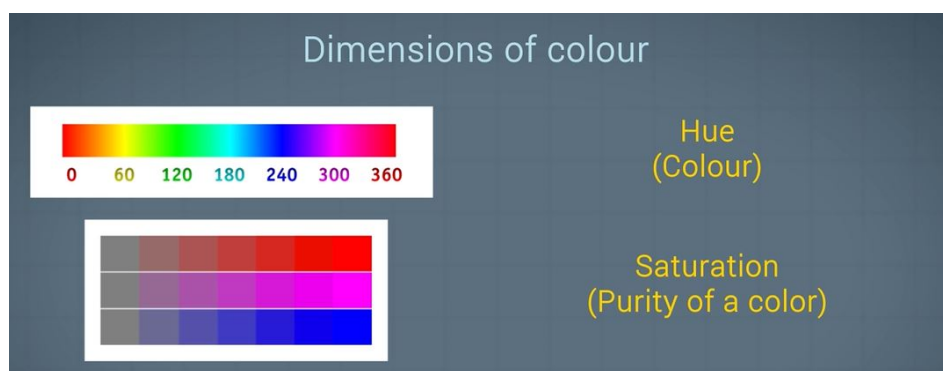


I can imagine that most of you found the second set easier to order. But why is that? In order to find the answer to that questions let's explore some colour basics. And I'm sure many of you have heard about those before.

So light can be split up by a prism into different wavelength, and the visible part of the electromagnetic spectrum is between 390 and 750 nanometers. Spectral colours are colours that are evoked by a single wavelength.

Other colours are just a mixture of multiple wavelength, such as the colour magenta.

Colour has three dimensions, hue, saturation, and luminance.





Knowing the three dimensions is very important when you want to encode data by using colour. The first dimension is hue. Hue is what most people colloquially refer to as colour.

The second dimension is set duration, which is the purity of a colour. And the third dimension is its brightness, which is also called value or luminance. Colour has special properties that are very relevant for visualisation. As you have seen in the previous exercise, ordering these colours is not easy. Some people might start with yellow, then pink orange, red, and so on.

But then they are not sure how to continue. And other people, again, might start with red, then pick orange, and continue somehow. So ordering colours is highly subjective.

That's why hue doesn't work well for encoding ordered attributes. When we remove the hue and trust vary the brightness of the blocks, this ordering task becomes much easier. That's what you've seen also in your exercise.

And as we've seen before, this is still an easy task even after adding a single hue, like in this case, red. It still works. To sum up here, again, those are the three dimensions of colour, hue, saturation, and brightness. So what this exercise tells us about colour is, when you try to encode colour data attributes, stick to brightness and saturation, but avoid using hue.



Another fact you should know about colour is that it's highly relative to its surrounding. Colour blindness is yet another reason why we should be cautious when using colour for encoding data. About 8% of the male population and 1% of the female population are colour blind or have at least a colour blindness. The most common weakness is the red-green weakness. In this colour table, the rightmost columns show how colour blind people see the colours from the first column.

It turns out that around 300 million people in the world have some type of colour blindness, and as I

have mentioned, we should take this into account when using colour to encode information. The following optional resource explains more about the different types of colour blindness that exist, as well as their causes, prevalence and myths. It also contains a link to a famous colour blindness test, the Ishihara test.

Let's move on to colormaps Here is a summary of which colormaps you should use for the different attribute types. If you have categorical data, you should use a so-called qualitative colormap, where each is reserved for each of the categories.

The goal of a qualitative colormap is that the colours used are as different as possible. If you have ordered data that starts at zero, you should use a sequential scale. For data attributes that are zero based, like positive and negative numbers, you should use a diverging colormap. Diverging colormaps have a neutral colour in the centre, like white, grey, or yellow. And then use two different hue values, which decrease in brightness towards the extreme values.

This is an example of a visualisation that uses a categorical colormap with two colours. This is each population chart from the UK in 2017. Blue stands for male and red stands for female. This is nice, but let's look at the next six sample. That's a visualisation that tries to visualise the servers of the internet in 2002. Visualising the internet, by the way, is a bad idea. Don't do that.

But here, there are 20 different types of servers which are encoded using 20 different colours. The problem is that when we have too many hues, we start to sort them, But in categorical data, there is no order. The green server is not better than the ones that have a slightly different shading of green. And at some point, it's also hard to distinguish between the colours that become very similar.

So a nice rule of thumb, you should not use more than seven to 10 colours for encoding categorical data. This is a colormap Visualising the unemployment rate in the US using the sequential colormap, going from light blue to dark blue.

So this is the proper use of a sequential colormap. But many people like rainbow colormaps, because they make a visualisation very colourful. What do you think about the effectiveness of a rainbow colormap?

Rainbow colormaps have major problems. This brings us back to the ordering problem of colour. The colormap applied here includes different hues. Without the legend, it would be impossible to interpret the temperature of values, right? So when we removed the hue, we see that the brightness actually varies along the colormap. And this is a main reason why we cannot intuitively interpret the colour versions shown in this image.

Besides the ordering problem, the rainbow colormap also has perceptual problems. If you look at the contrast sensitivity images, you see that many of the patterns cannot be seen when using the rainbow colormap. Another problem is that the perception is not linear. Some colours like green are more dominant, even though but we can see is a perfect interpolation of the colours along the colormap. Let's look at these examples now the green is much more dominant in the rainbow colormap, as you've seen before, compared to the blue/yellow colormap that you see before.

Also, in the blue/yellow colormap, you see many, many more details that are really not visible in the rainbow colormap version. What you see here is the map of the Brexit referendum from 2016 that you've seen also in session one already. It's a good example of a diverging colormap. Grey is mapped to zero. And then you have blue for remain, and red for leave, with decreasing brightness the bigger the percentages get. And finally, this is a collection of all diverging, sequential, and qualitative colormaps that are available in the Colour Brewer online tool.

2.4 The alphabet of visualisation: Visual marks and channels

In the next presentation, I explore different types of visual marks and channels, which are very useful elements when breaking down visual encodings.


Now we will come to the basic building blocks of visualisations, marks, and channels. Some people also call it the alphabet of visualisation. Marks are basic geometric primitives or elements that you find in visualisations.

The three types of marks are points, lines, and areas. Channels are then the different ways, how to change the appearance of those marks based on the attributes you have in your data.


Marks

Basic geometric elements in visualizations


➔ Points



➔ Lines



➔ Areas



3D mark: volume, but rarely used

Channels

Change appearance of marks based on attribute

Channels are also called visual variables. And the channels we know are position, shape, colour, tilt, and size. Size works in 1D, where it's a line, in 2D, where it's an area, and in 3D, where it becomes volume. And the theory of marks and channels goes back to Jacques Bertin, a French cartographer who lived from 1918 to 2010. And he wrote a very influential book that has the title *The Semiology of Graphics*. And it was first published in 1967. But later on it was translated to other languages as well.

Channels (visual variables)


Ways to **control appearance of marks** proportional to or based on attributes

➔ Position


➔ Horizontal

➔ Vertical


➔ Both




➔ Color



➔ Shape



➔ Tilt



➔ Size

➔ Length

➔ Area

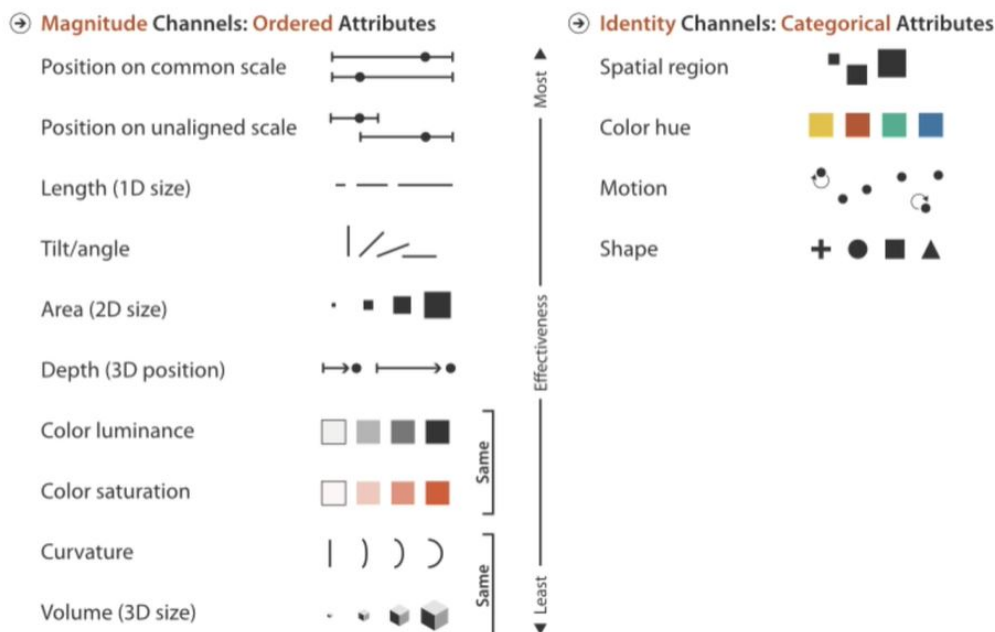
➔ Volume



And the cool thing is that the theoretical principles for visual encodings are still valid nowadays. In Tamara's textbook, she differentiates between magnitude and identity channels. Magnitude channels answer the question, how much you have of something. And magnitude channels are used to encode ordered attributes. And then you have identity channels. They answer the question what and where. And identity channels are to encode categorical attributes. Here is the overview table from Tamara's book that shows how effective the different channels are for encoding the attributes-- very effective at the top and the least effective ones at the bottom.

The magnitude channels for ordered attributes are shown on the left. Always your best choice is position, on a common scale, but also on an unaligned scale. Then you have length, tilt, area, depth in 3D and after that you have colour luminous saturation. So they're actually quite bad if you compare it to others. And it ends with curvature and volume. They are the worst. And on the right hand side you see the different identity channels for encoding categorical attributes. You could use the spatial region. You could use colour hue, motion, and shape. Now, after this presentation, let's do a little spot challenge, where you are supposed to interpret the visualisation, the channel that you see, and get back to the original data. And you will see sometimes it's more difficult, and sometimes it's easier depending on the channel you use.

Channels: Expressiveness Types and Effectiveness Ranks



NOTE: Tamara Munzner Visualization Analysis and Design. Please read Chapter 5. In the next activity, you will complete a short quiz assessing your understanding of visual marks and channels. After that, I will show an example of how to use them to deconstruct a visualisation.

2.5 Assessed Quiz

2.6 Deconstruction of existing visualisations

As you now know what channels are and which ones exist, we can now talk about their characteristics. Depending on what you want to achieve, you need to think about the following five characteristics.

The first one is, is a channel selective? So can you tell the difference between two marks? The second one is, is it associative? So does it support grouping? The third one is about, is it quantitative? So can we quantify the difference between two marks? Then we have the order. Can we see a change in the order? Can we order the elements in this channel? And the last one is, what is the length of this channel? And this is not the length of an actual line. It means that, how many unique marks can we see? And this then the length of a channel. And we will now go through the different characteristics for each of the channels.

Characteristics of Channels

Selective
Is a mark distinct from other marks?
Can we make out the difference between two marks?

Associative
Does it support grouping?

Quantitative
Can we quantify the difference between two marks?

Order
Can we see a change in order?

Length
How many unique marks can we see?

Let's start with position. Position is always the strongest channel. So if you remember the table, it was at the very top of the table for the magnitude channels. But problems are, position is not available on a map, for instance, because you can't move a city to a different place. You have to find a different attribute, a different channel, to encode the attribute.

Then if we go through the five characteristics, position is selective. It's associative. It's quantitative. You can order the elements. And the length is fairly big. The only problem you have is, if you, for instance, have a scatter plot where the points get very close to each other, you run into a cluttering problem. It's called visual clutter, which will be discussed later on in an upcoming session. Position, as I said, is the strongest visual channel for the two-dimensional space. But what about 3D?

Position

Strongest channel!

Problems:
Not available for maps
Cluttering

Selective: yes
Associative: yes
Quantitative: yes
Order: yes
Length: fairly big

www.nytimes.com/interactive/2009/03/01/business/20090301_WageGap.html

And we're going to discuss this also later on in the session. Moving on to the next channel, it's length

And we're going to discuss this also later on in the session. Moving on to the next channel, it's length and area. Length is good for 1D case where it's aligned. It's OK for 2D where element gets an area. And it doesn't work too well for 3D. But length and area, they're selective. They're associative. They're quantitative. You can order them. And you have a high length. So this is actually a pretty good channel that you have.

Length (1D) & Area (2D)

Good for 1D, OK for 2D, Bad for 3D
 Easy to see which one is bigger
 Aligned bars use position redundantly


Selective: yes

Associative: yes

Quantitative: yes

Order: yes

Length: high



The next one is brightness and saturation. Brightness and saturation are OK for quantitative data if length and area are used. The problem is that you have not very many shades that you can recognise. But if we go to the five characteristics, brightness and saturation, they're selective, associative. They're somewhat quantitative. You can order them. But the length is quite limited.

Brightness & Saturation

OK for quantitative data when length & area are used
 Not very many shades recognisable


Selective: yes

Associative: yes

Quantitative: somewhat (with problems)

Order: yes

Length: limited



We already talked about colour quite a bit. We talked about colour theory. Colour, again, is good for categorical data. But you only have a limited number of categories that you should use, different colours, usually seven, but not more than 10. And colour does not work for quantitative data. So if you go to rainbow colourmaps, then we discussed the problems before. So in Colour, you have lots of pitfalls. And you should be careful. The rule of thumb here is minimise colour for encoding data. But you can use it for highlighting, for instance. So if we go through the different characteristics, colour is selective. It's associative. It's not quantitative, not too well. You can't really order it. And the length is limited. So you can see position and also other channels are actually more appropriate for some of your data.

your data.

Colour


Good for categorical data
 Limited number of categories/length (~7-10!)

Does not work well for quantitative data!




Lots of pitfalls! Be careful!

Rules of thumb:

- Minimise color use for encoding data
- Use for highlighting



Selective: yes
 Associative: yes
 Quantitative: no
 Order: no
 Length: limited


?????
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Then we have shape. If we look at shape, shape is nice, because you can use it to recognise many classes, many more classes compared to what you have using colour. But the problem is you have no grouping and no ordering in shape. The order of shapes doesn't really make sense, right? So shape is selective. It's associative but only to a limited degree. It's not quantitative. You cannot order it. But the length is pretty good.


Shape

Great to recognise many classes

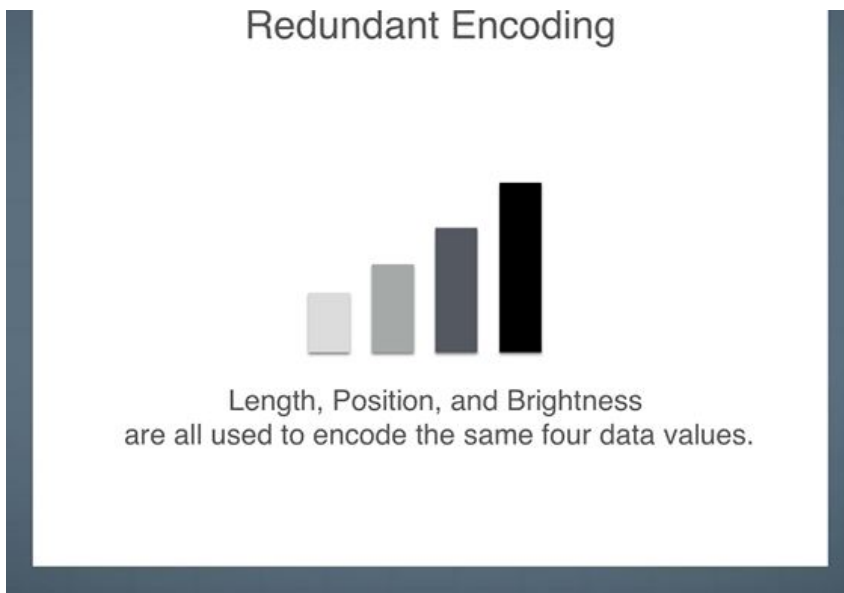
No grouping, no ordering



Selective: yes
 Associative: limited
 Quantitative: no
 Order: no
 Length: vast



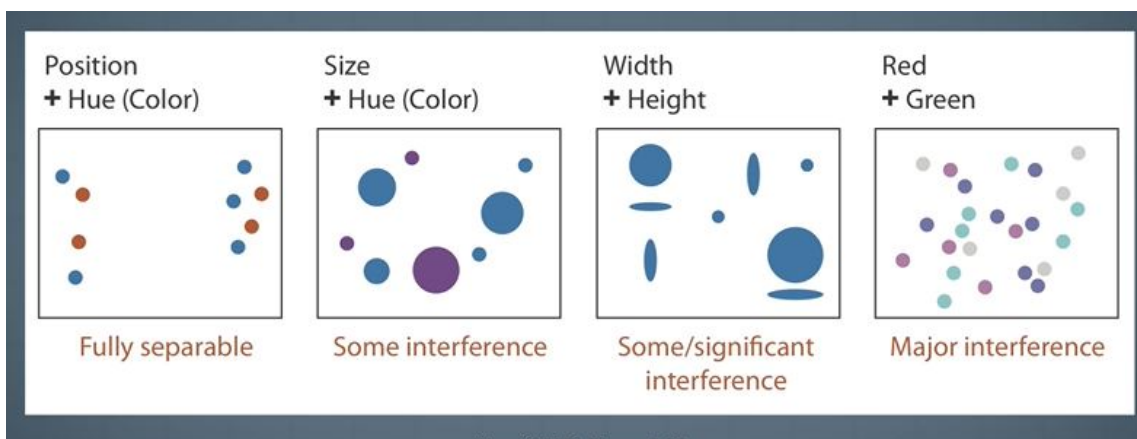
Now after discussing all the different characteristics that you have for the channels, I want to tell you about an interesting concept, which is called redundant encoding. It's also a very powerful concept in visualisation. The idea here is that you use different channels to encode the same attribute in your dataset. In this little example that you can see here, you have length, position, and brightness. And they all encode the same four data values. And you can make use of that in visualisation. If you really want to stress an attribute in your data set, you can just assign two channels to the same information. We are almost at the end. But before summarising this part, I want to talk about the separability of attributes. So if you look at those examples here, position and hue, they can be well separated, right?



So you can use hue and position in the same visualisation without any problems. If you use size and hue, you already have some kind of inference, because your bigger elements will just have a bigger footprint in your visualisation, which makes this column more dominant than the hue. But if you then start, for instance, to mix other visual channels, like the width and the height, then we, for instance, start to classify this as three different objects, although this is not a categorical data set.

And it even gets worse if we use the different aspects of colour, like red and green, and we start to mix them for different attributes. That doesn't make sense, because there is lots of interference. And you can't separate the data anymore.

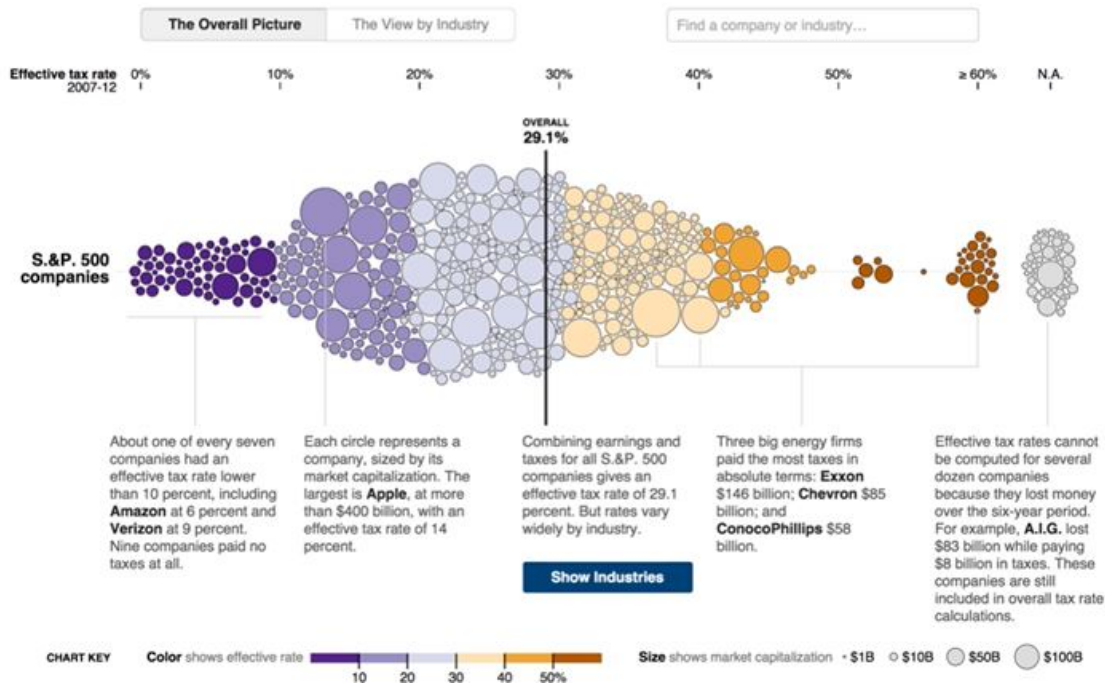
Before we are moving on to an example, I want to quickly summarise marks and channels. So we talked about marks. Those are the geometric primitives-- points, lines, and areas. And then we talked about the different channels, which are the ways, how to manipulate the appearance of those marks. And we talked about colour, position, shape, tilt, and so on and so forth.



And now let's move on to an example.

What are the marks and channels used in this visualisation? So we want to deconstruct the visualisation based on what we've learned. The visualisation that you can see here is from The New York Times. And it shows how much tax US companies listed in the S&P 500 Index pay. The basic visual mark that you can see here is a point. And the point corresponds to a single company. Then we have the size of the point that encodes the market capitalisation, one of the attributes in the dataset.

The position on the x-axis encodes the tax rate, ranging from 0 to over 60%. So some companies really pay 0%, which is not a good thing. But what about the vertical position? And if you think about it, the vertical position, it doesn't really encode something in your data.

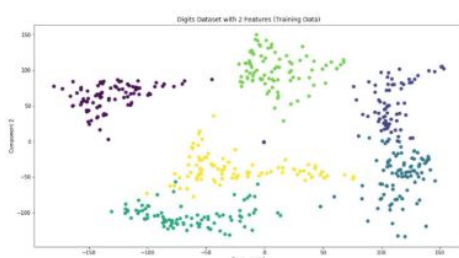


It was just chosen to avoid overlap. So you don't want to have one company drawn over another company. In the followup exercise, you're supposed to do that on your own. Just take what you've learned, the marks and the channels, and try to deconstruct a visualisation you will find on the internet. And tell me and tell your colleagues, what are the visual marks and channels that are used in the visualisation?

Image Tile Exercise



Faiz W Mohamad
Fablillah



Comments

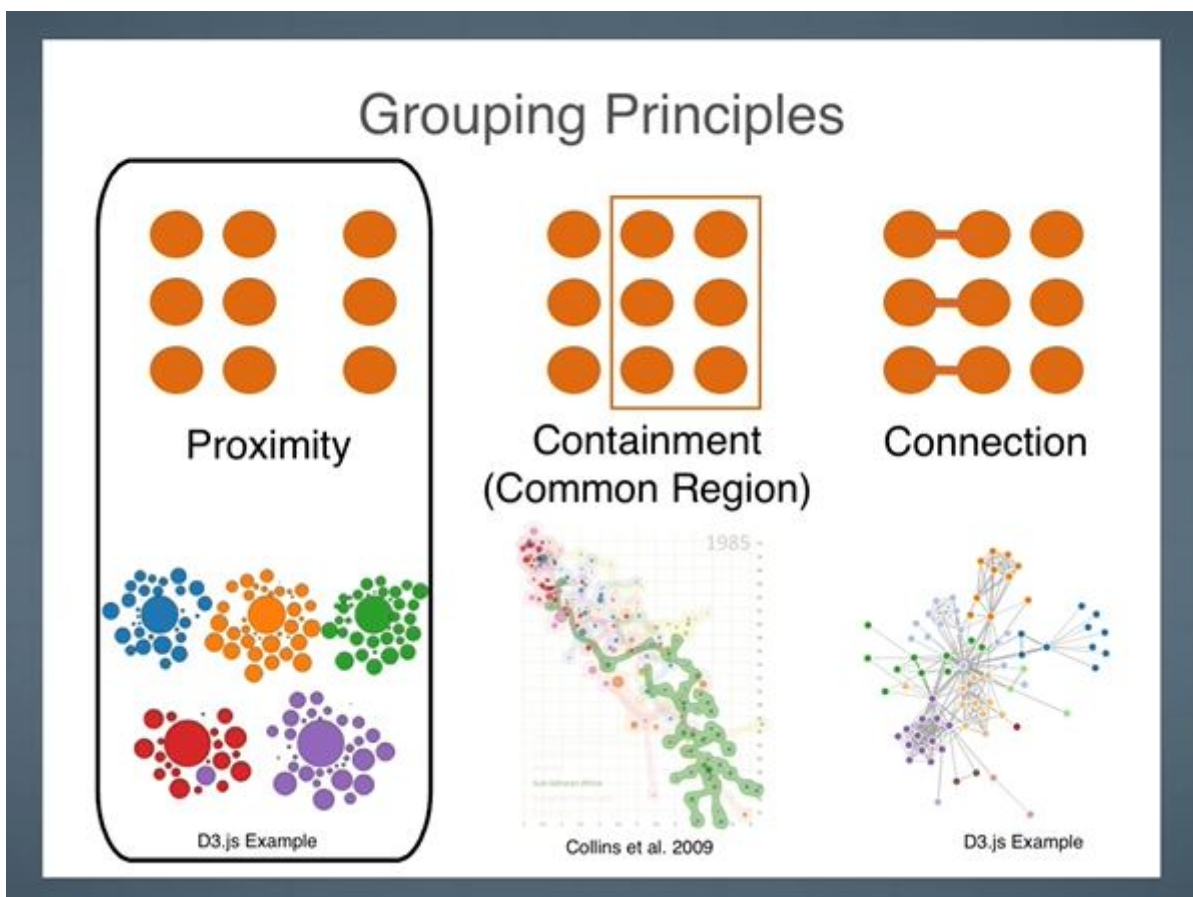
We are visualising data of digits dataset which we got after transformation through Isomap. It has digits dataset with 1083 samples with 2 features. The dataset has been

divided into train and test sets (50% each). Below we are visualising Train dataset to show digits. Visual marks and channels used are points and colours.

2.7 Gestalt laws

Many tasks in visualisation rely on our ability to group data items that we see in a graph. An example is a scatterplot where the proximity of items tells us something about how similar they are. Items that are close to each other form clusters, for instance. I want to take the opportunity now to explain the Gestalt principles of grouping in more detail.

Our visual system is very powerful. I have shown you this image with a well hidden Dalmatian before. And once you've seen it, you can't un-see it. So now you should immediately recognise the dog in the picture. And this effect is called perceptual hysteresis. And why we are able to make sense of such images and find patterns was described in 1912 by Westheimer, Koffka, and Kohler. And they belong to the gestalt school of psychology. And they wanted to better understand how we perceive and understand images. And the rules we are going to discuss are known as the laws of groupings, principles of grouping, or gestalt laws. And what is interesting here is that they actually, in 1912, made the correct observations, but they gave the wrong reasons at that time. So here are the first three grouping principles.

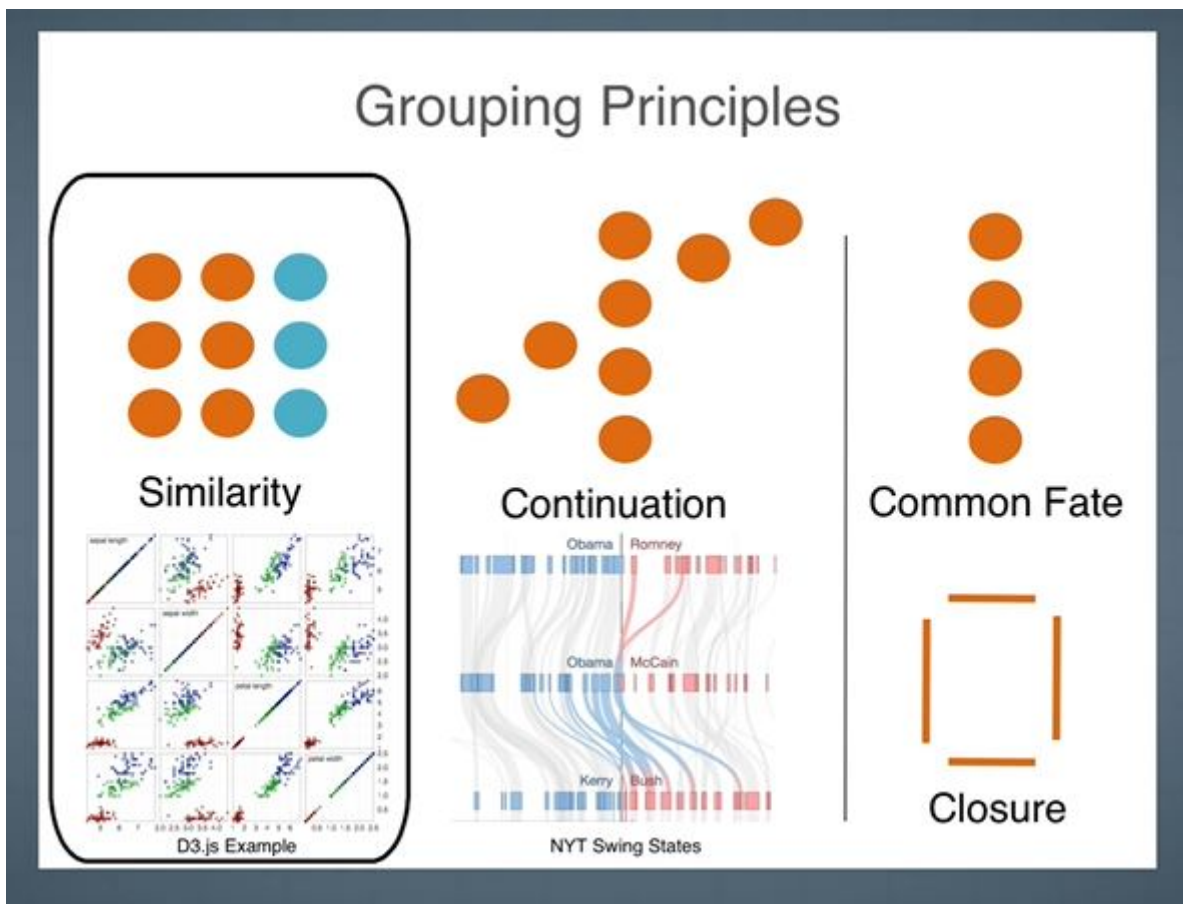


The first one is proximity. And you might perceive the six dots on the left hand side as a group. And in

visualisation, we use this, for instance, in a scatter plot or a the bubble chart. Dots that are closer to each other are more similar or related to each other. The next grouping's principle is containment. So if you draw an outline around objects, they will be perceived as a group. It's also called common region.

We can also make use of this in visualisation by just drawing a region around elements. Then we have connection, which is a very strong grouping principle. If we connect those dots, they will be perceived as a group. We will just make use of this very often in visualisation if you look at graphs and networks. Nodes that are connected will be perceived as related to each other.

Then we have similarity. For instance, if you use the same colour for objects, they will be perceived as a group. We make use of this in visualisation, for instance, in scatter plots, like in the scatter blood matrix. We are going to discuss this later on-- what the scatter plot matrix is. But you will see that, for instance, here, you have three different types of elements-- each of them having a different colour. Then we have continuation as a grouping principle. For instance, this is used in this New York Times swing states example, because with our eyes, we just follow the lines along. And then you also have additional grouping principles that were described, like common fate. It's like a flock of birds. If the birds fly in the same direction, we perceive them as a group and closure. Like those four lines here that you will see-- we humans will just auto complete the corners and will perceive this as one group.



Very interesting is also the fact that these grouping principles stand in a hierarchical relationship, meaning that some of them overwrite others. They are stronger than others. And here you can see grouping examples for proximity, colour, size, and shape. And you will immediately recognise the groups.

