HORIZON-MSCA-2023-DN-01-01 ID-101168344
MSCA Doctoral Networks 2023
TUAI Project

Deep Visual Analytics

Session 2 · Good visualizations

Why one chart beats another, and how to make better figures

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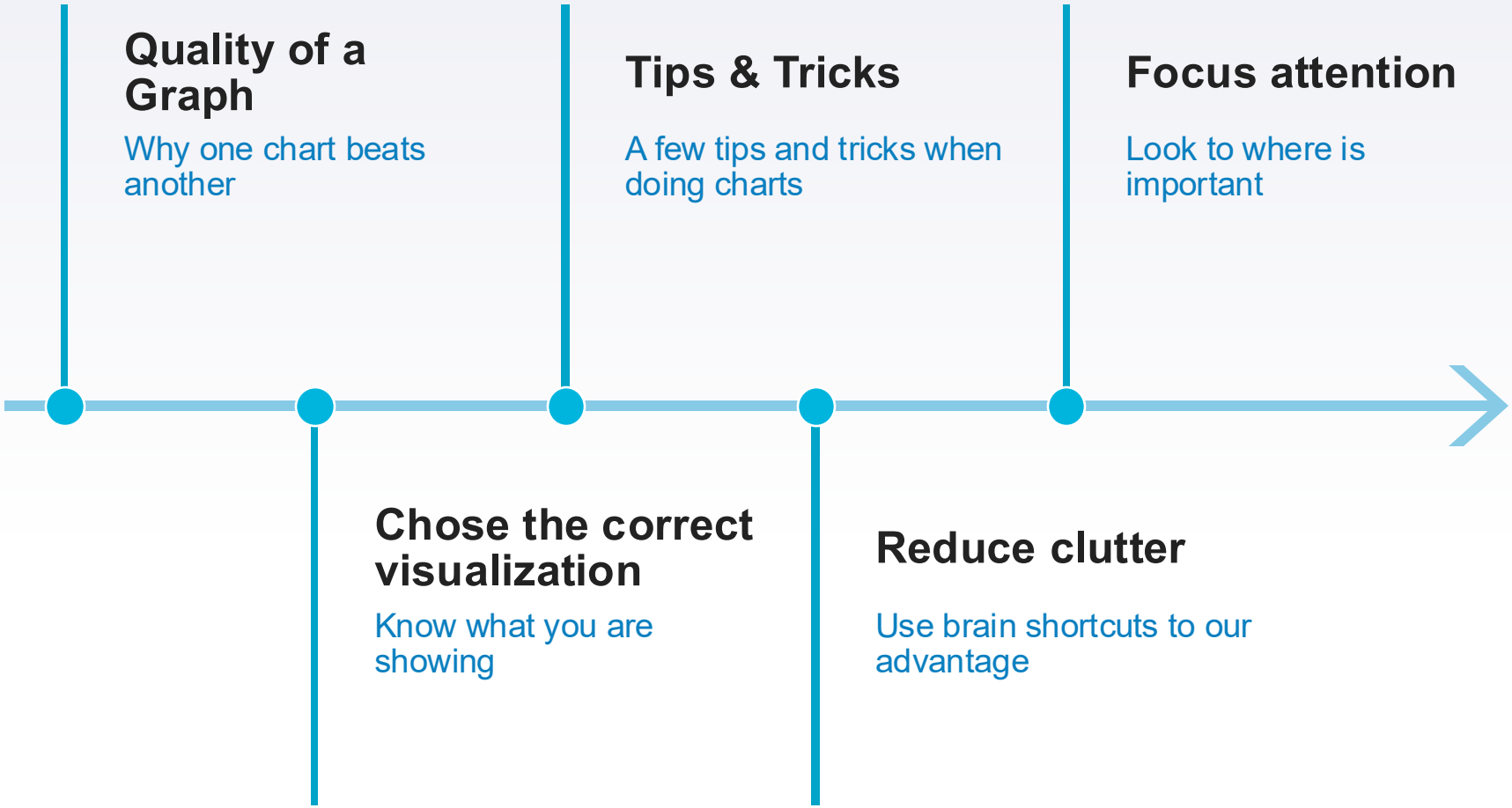
TUAI - D2.1

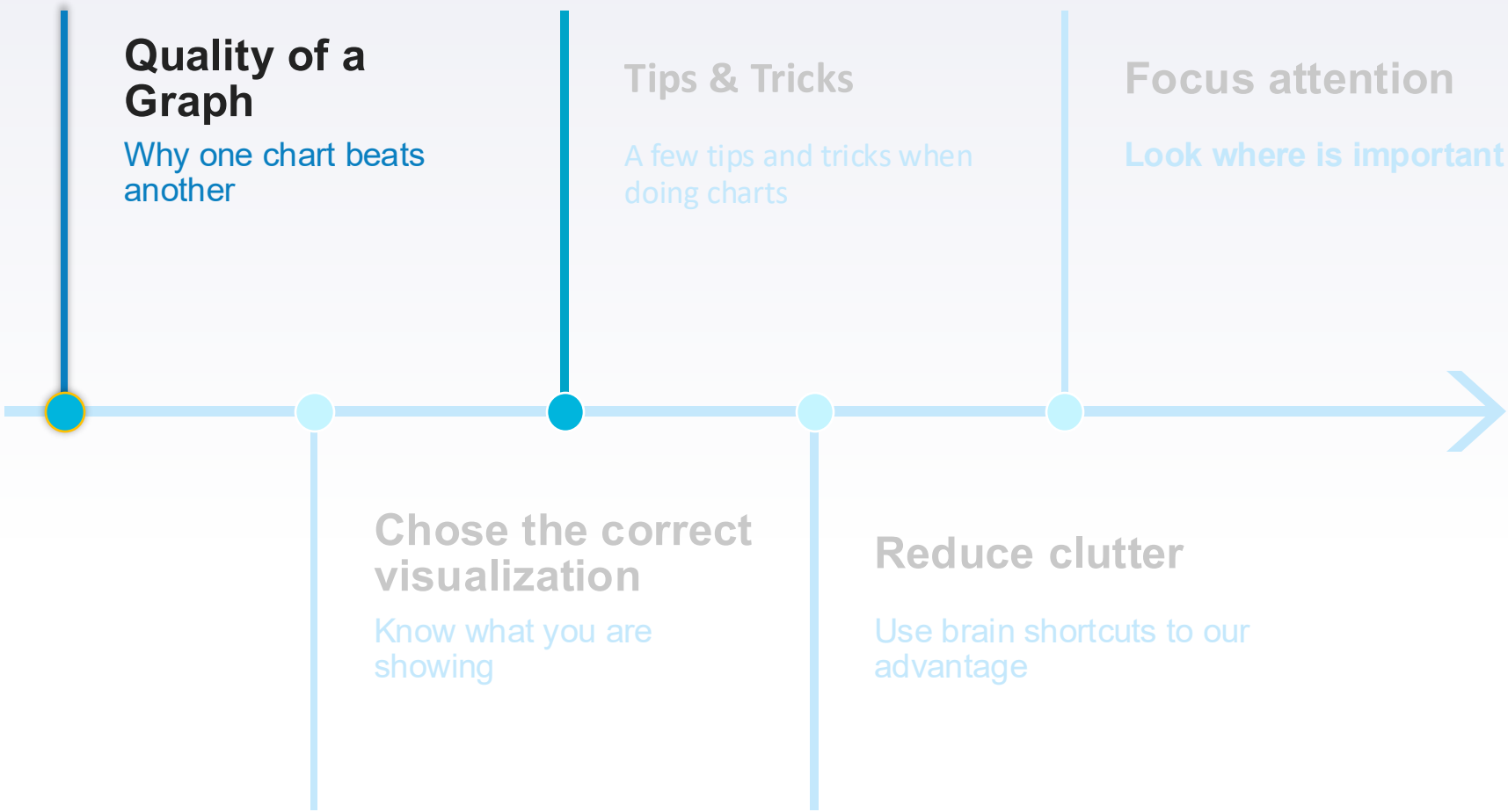
Workshop progression

6 Nov Fri · 2026	1 · PRESENTATION	**Workshop introduction + Masterclass: What is DVA?** Organisation, phases and expectations of the workshop. 10:00 CET (Madrid, UTC+1) · Zoom: upm.zoom.us/j/86107545468
23 Nov Mon · 2026	1 · PRESENTATION	**Masterclass: Making quality visualizations** By this date, DCs should have formed their groups. 14:00 CET (Madrid, UTC+1) · Zoom: upm.zoom.us/j/84615234389
24 Nov Tue · 2026	2 · GROUPS	**Group proposals: SOTA to be studied (5 min per group)** Each group presents which part of the DVA state of the art it will explore. A UPM supervisor is assigned to each group. 14:00 CET (Madrid, UTC+1) · Zoom: upm.zoom.us/j/85690380040
≈ 11 Dec Fri · 2026	3 · SOTA	**Check-up session with UPM supervisors** Review of each group's progress. Key decision: is a publication feasible or desirable?
17–18 Dec Thu–Fri · 2026	3 · SOTA	**DCs' masterclass: SOTA presentations by the groups** Each group teaches its SOTA to the other DCs (one or two days). Groups aiming for a publication keep working on it.
≈ 15 Jan Fri · 2027	4 · APPLIED	**Individual DVA proposal for your thesis** Check-up with UPM supervisors on how DVA will be used in each thesis. Publication-related topics can also be discussed.
28–29 Jan Thu–Fri · 2027	4 · APPLIED	**DCs' masterclass: final individual presentations** Each DC presents how they use DVA in their thesis, followed by discussion and feedback from colleagues (two days).

Today


Quality of a Graph
Why one chart beats another
Chose the correct visualization
Know what you are showing
Tips & Tricks
A few tips and tricks when doing charts
Reduce clutter
Use brain shortcuts to our advantage
Focus attention
Look to where is important

Today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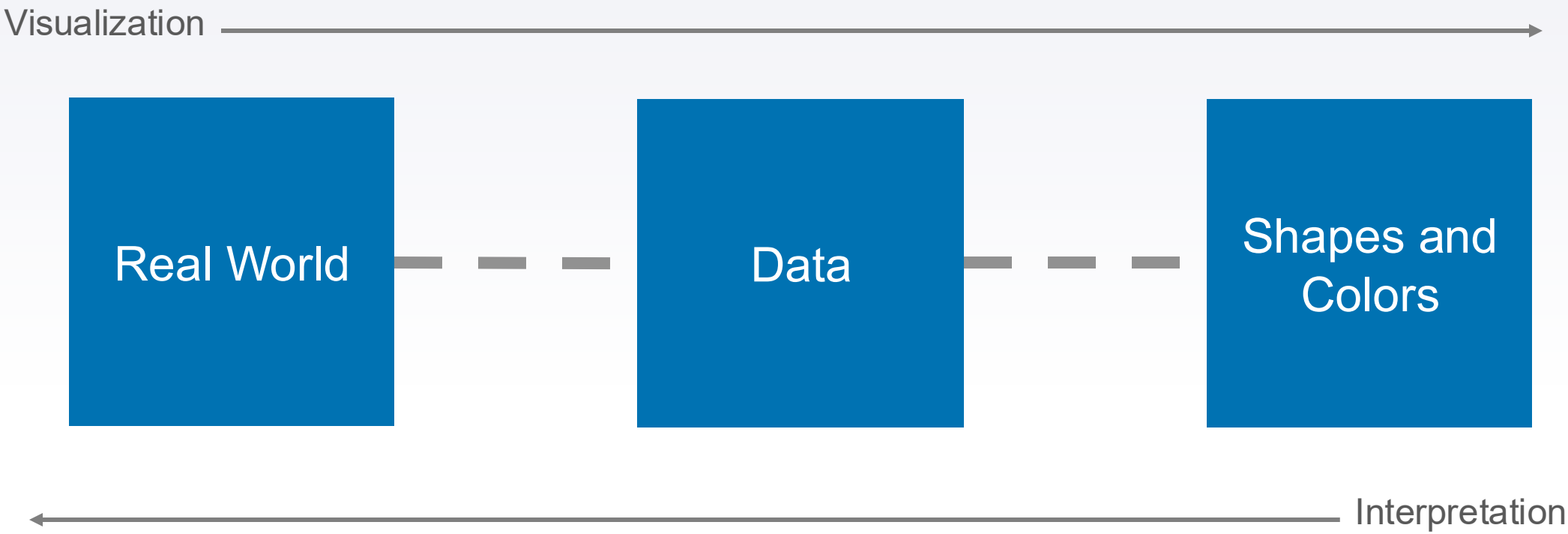
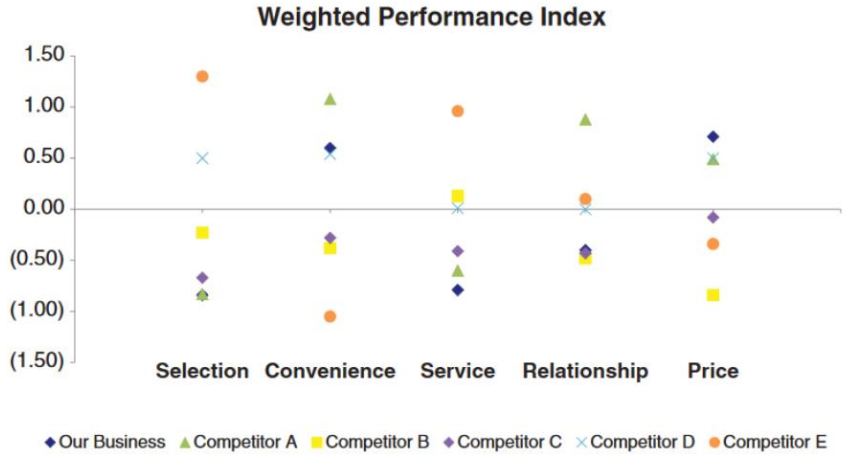
Process of visualization



Yau, N. (2013). Data Points: Visualization That Means Something. Wiley.

Graph examples

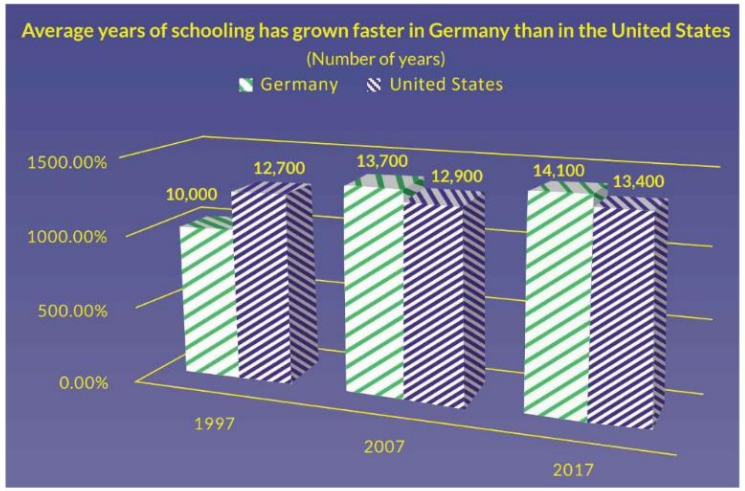
A



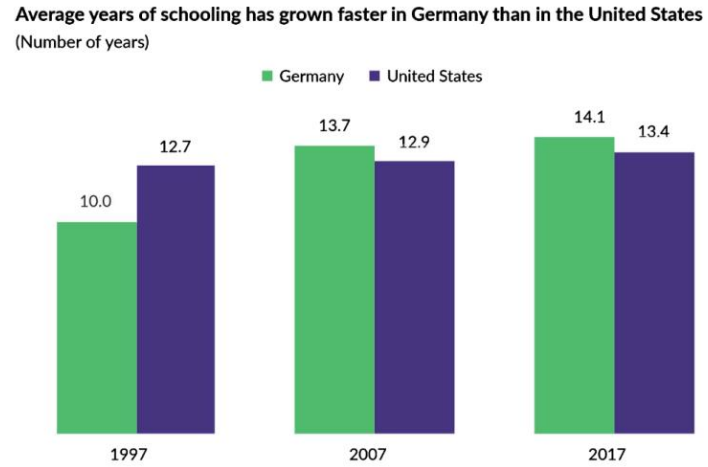
B



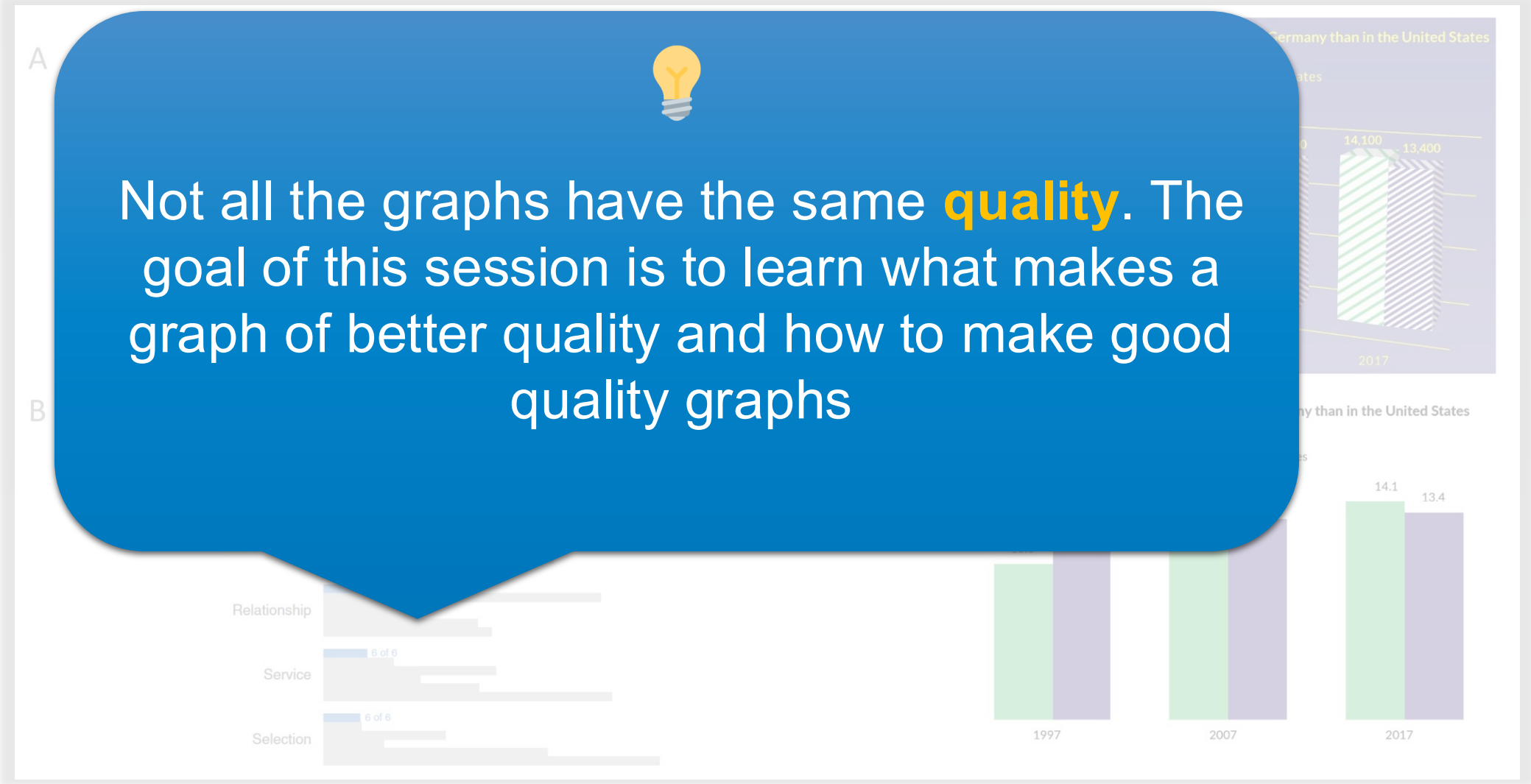
A



B



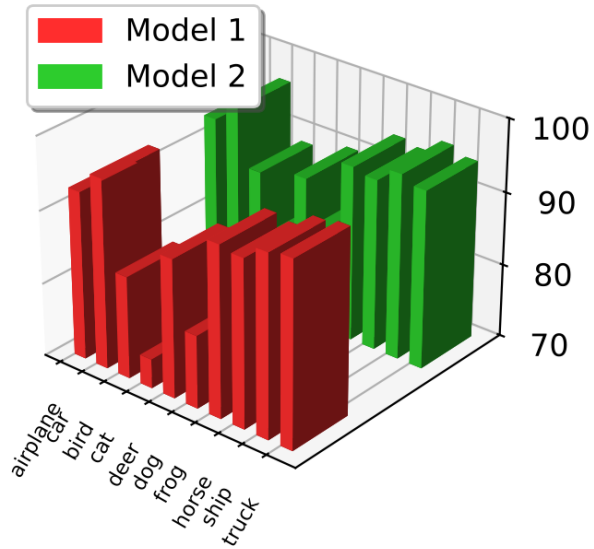
Graph examples



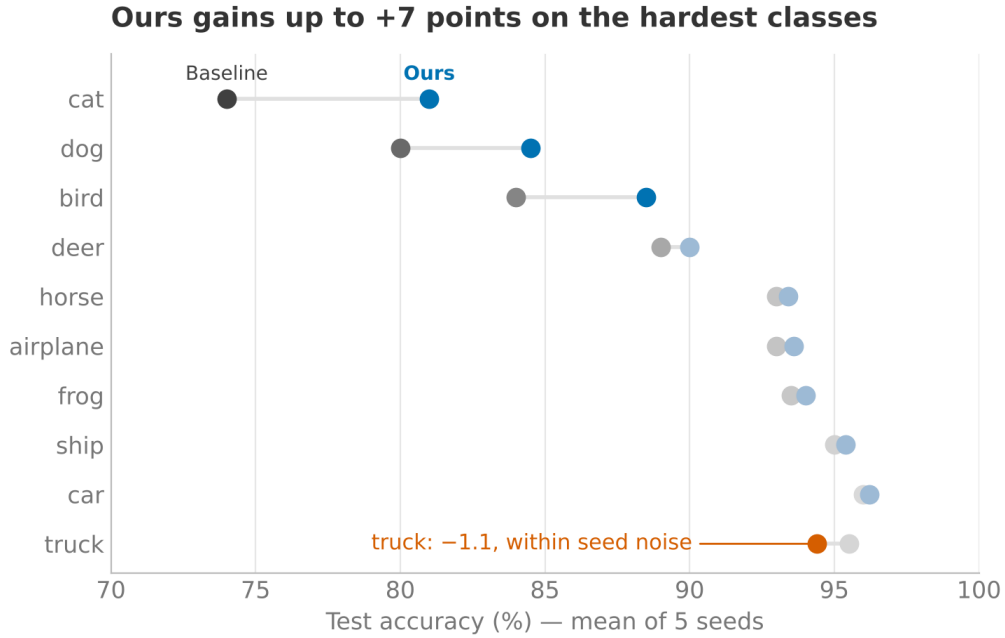
Not all the graphs have the same **quality**. The goal of this session is to learn what makes a graph of better quality and how to make good quality graphs



RESULTS

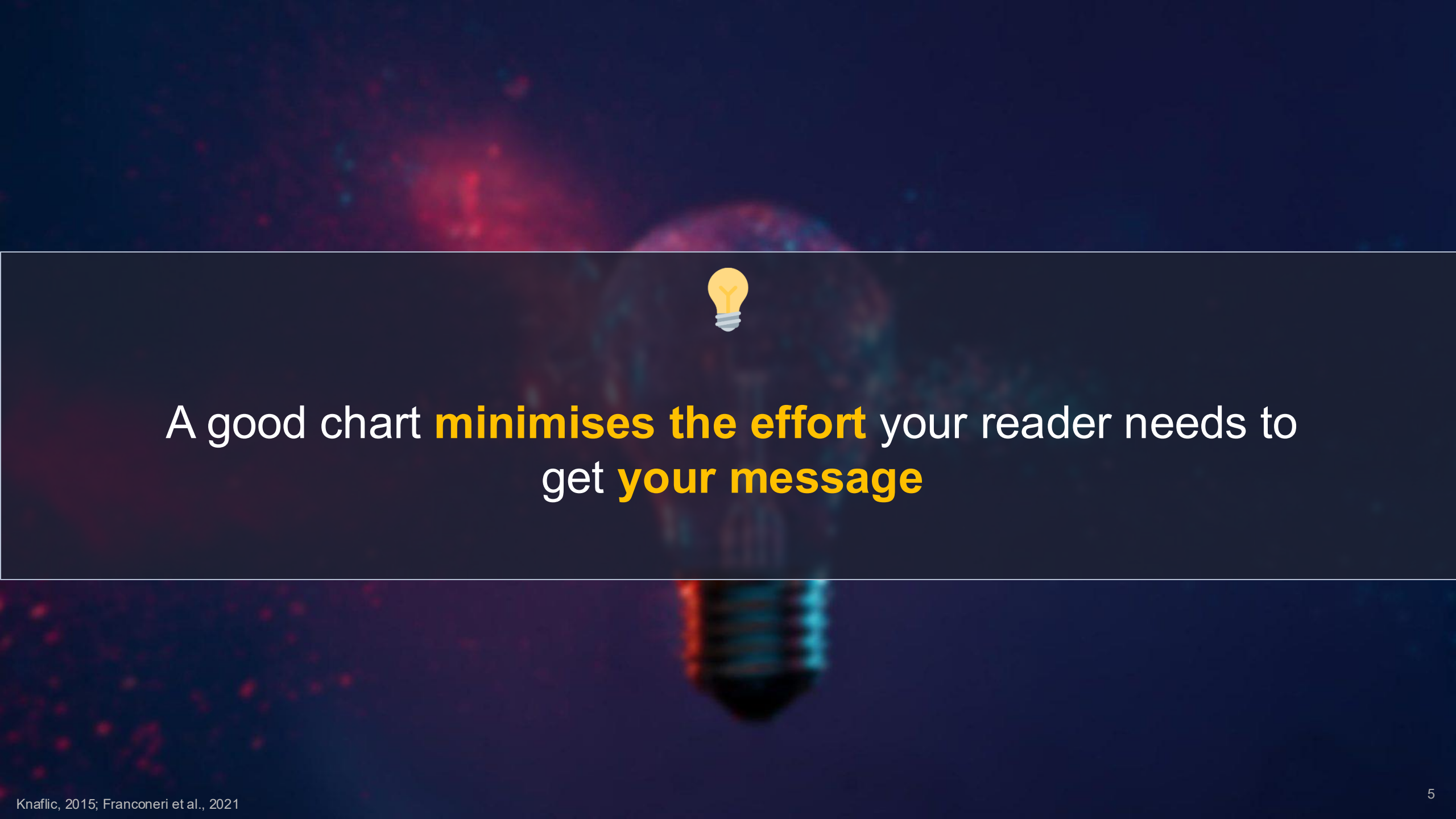

Model 1
Model 2
100
90
80
70
airplane
car
bird
cat
deer
dog
frog
horse
ship
truck




Ours gains up to +7 points on the hardest classes
Baseline
Ours
cat
dog
bird
deer
horse
airplane
frog
ship
car
truck
truck: −1.1, within seed noise
70
75
80
85
90
95
100
Test accuracy (%) — mean of 5 seeds



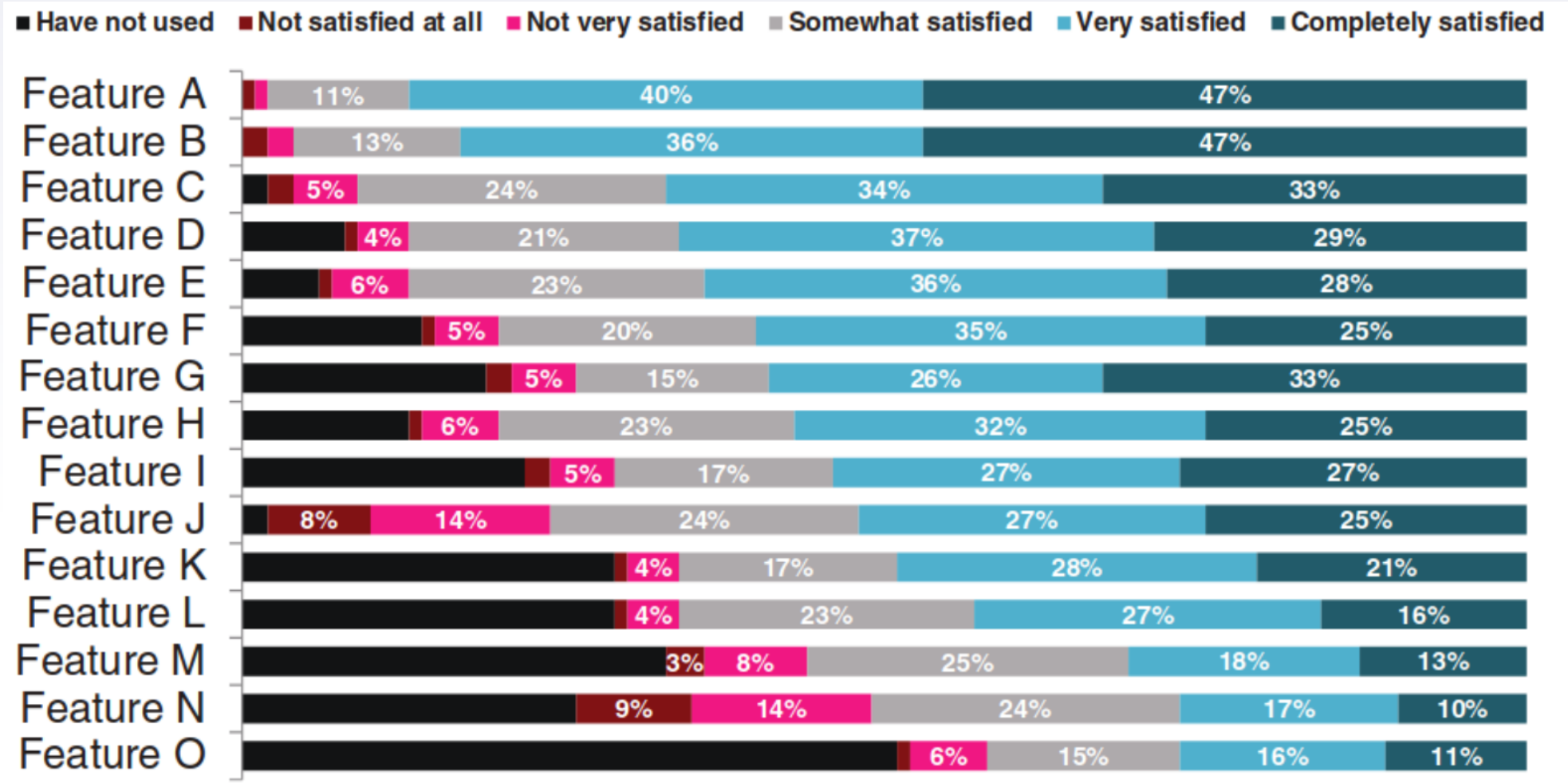
WHY IS A CHART BETTER THAN OTHER?



A good chart **minimises the effort** your reader needs to get **your message**

Knaflic, 2015; Franconeri et al., 2021

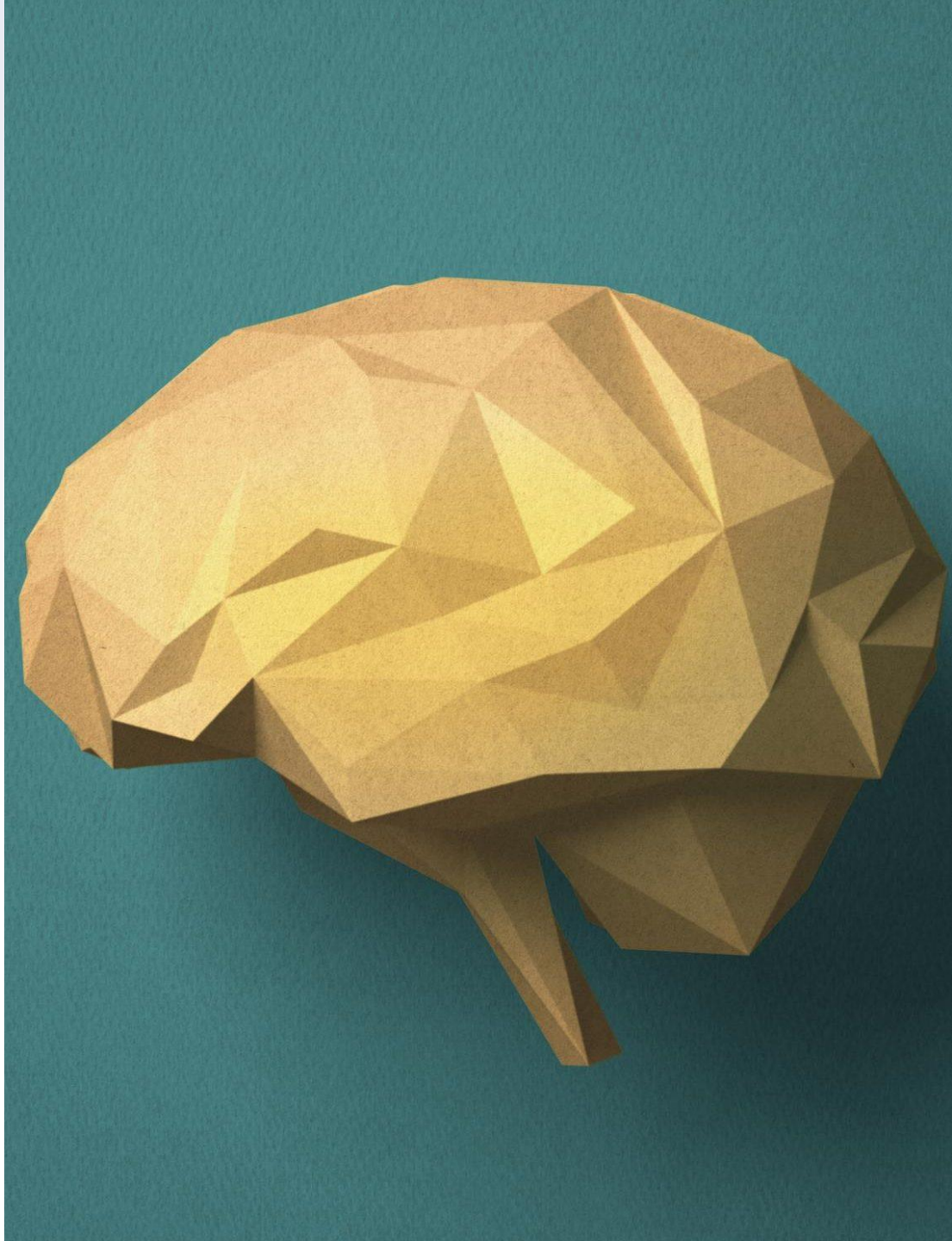
How are the features ordered?



Knaflic, C.N. (2015). Storytelling with Data: A data visualization guide for business professionals. John Wiley & Son.

Cognitive load

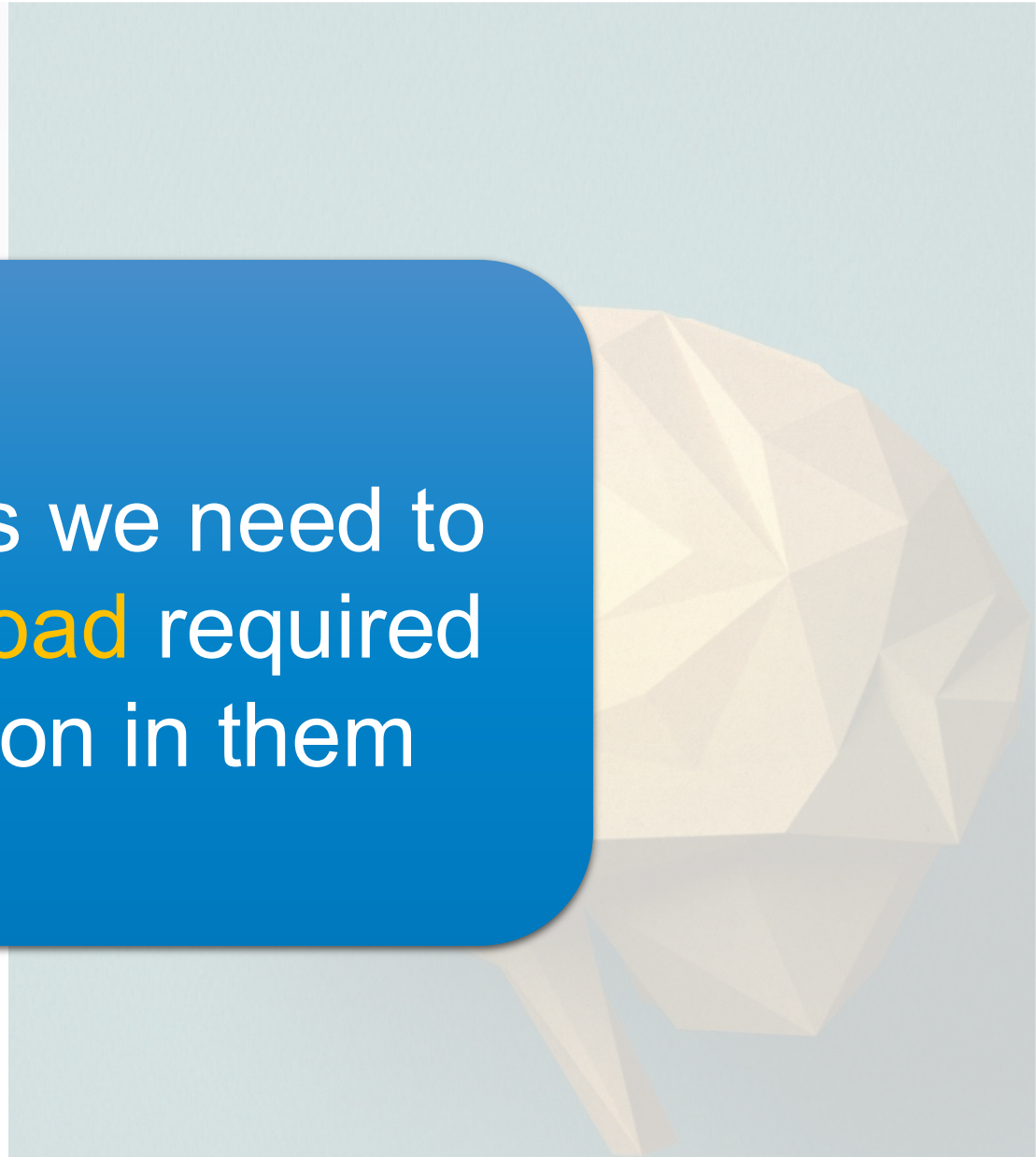
- The **mental effort** needed to absorb new information
- Our working memory is **finite**
- A hard-to-read chart is one that needs a lot of **cognitive load**



Sweller, J. (1988). Cognitive load during problem solving. Cognitive Science 12(2)

Cognitive load

- The
new
- Our
- A ha
lot of

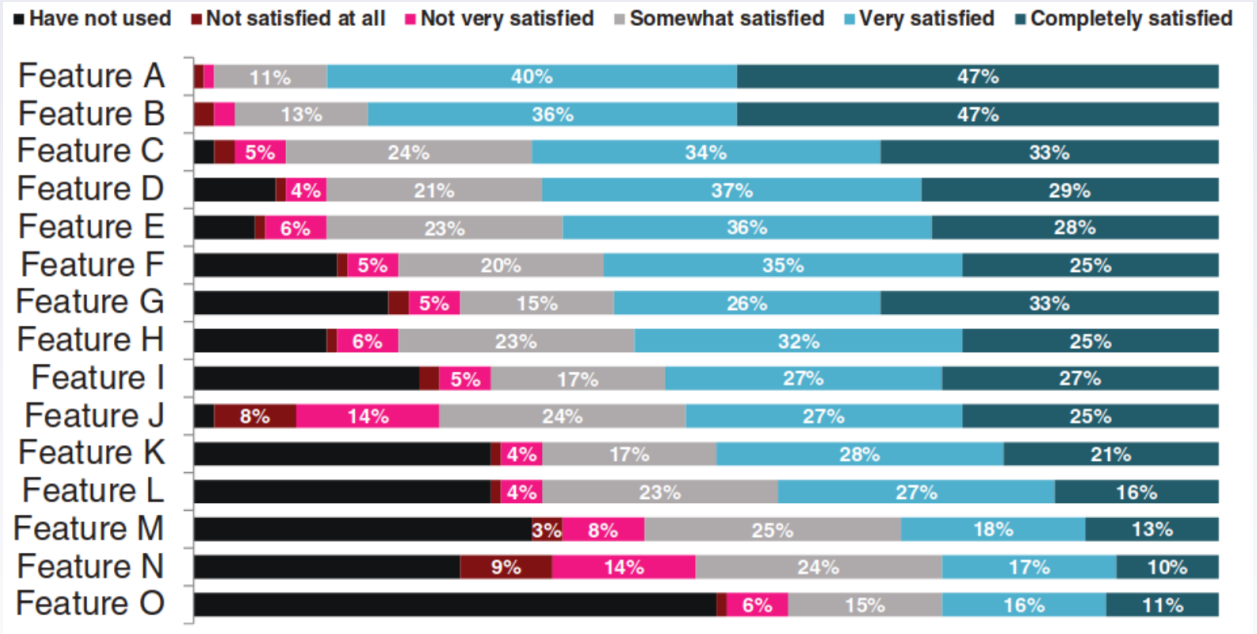




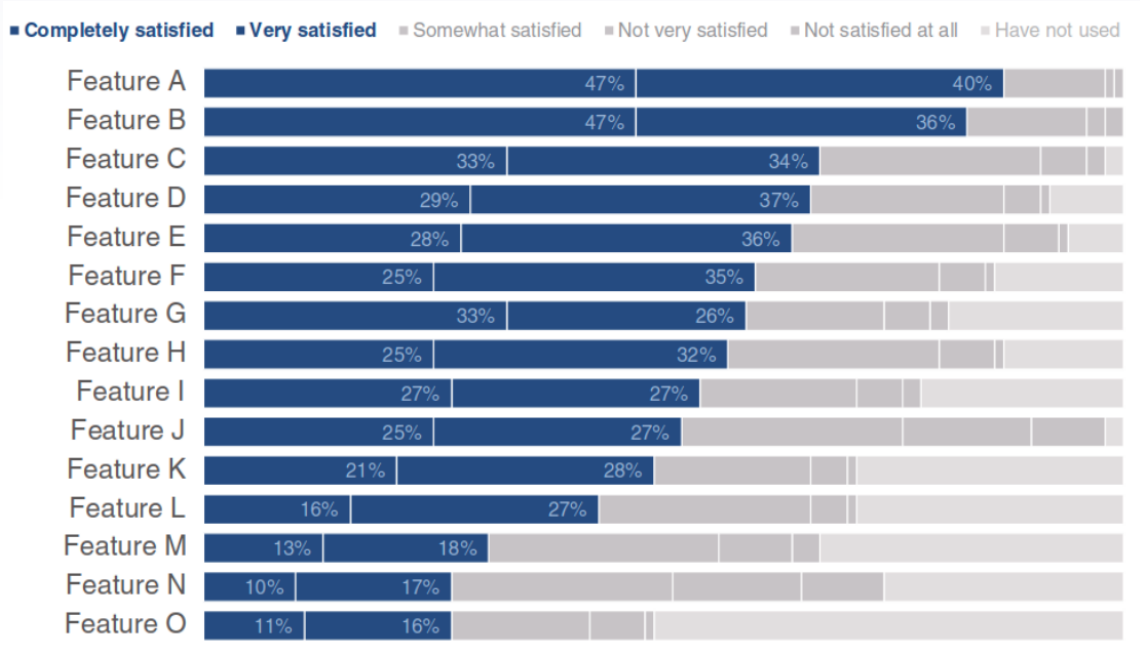
To make quality charts we need to reduce the cognitive load required to read the information in them

Sweller, J. (1988). Cognitive load during problem solving. Cognitive Science 12(2)









Knaflic, C.N. (2015). Storytelling with Data: A data visualization guide for business professionals. John Wiley & Son.



WHAT CAN I CHANGE IN A CHART?

Dimensions of a chart



Visual cues

How values are **encoded**: position, length, angle, area, colour…



Coordinates

Cartesian, **polar** or **geographic** space where marks live



Scale

Linear, **log**, categorical, ordinal, time…



Context

Titles, **annotations**, ordering, reference lines, highlights

Yau, N. (2013). Data Points: Visualization That Means Something. Wiley.

👀 Visual cues

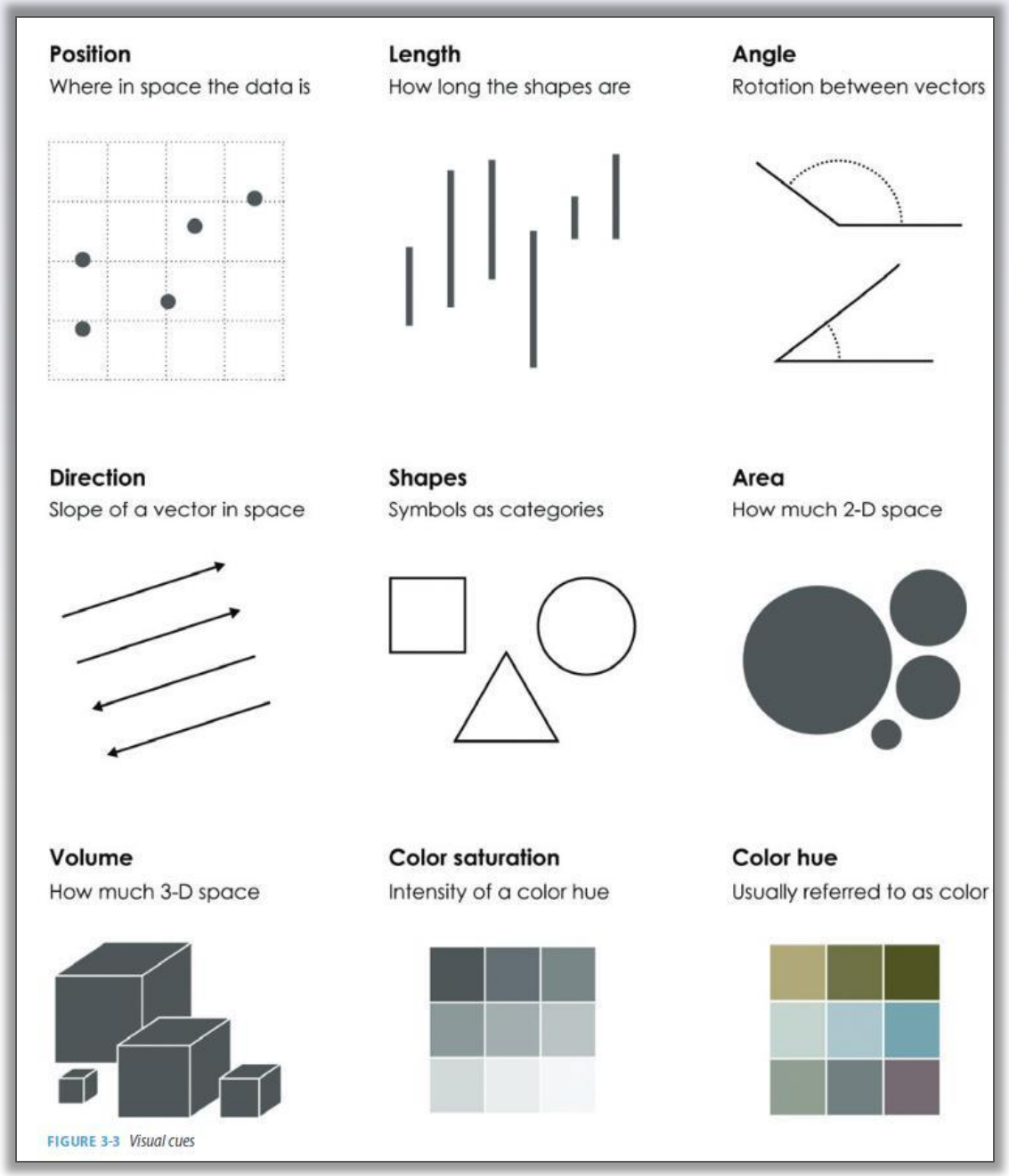
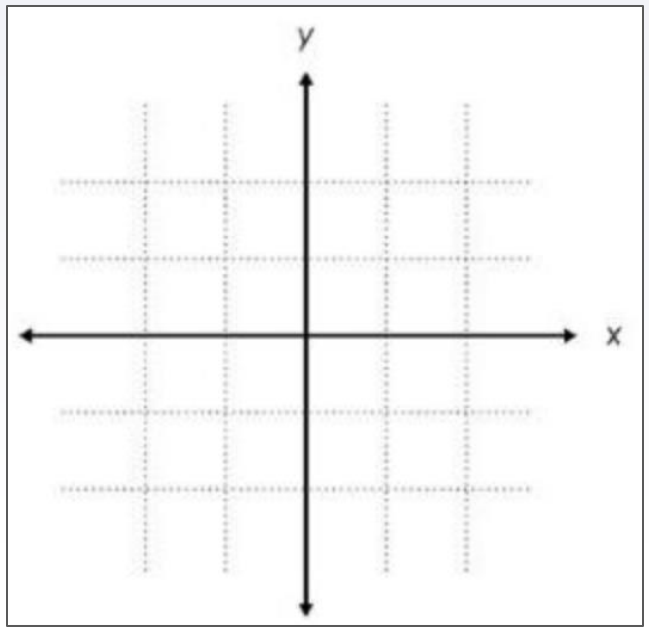


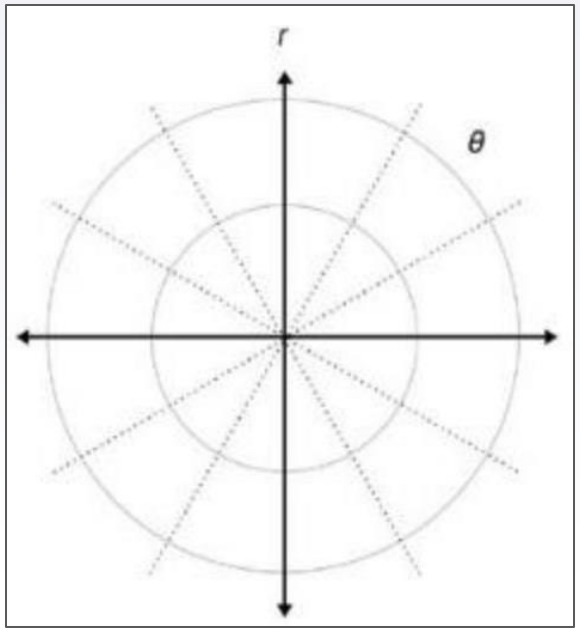
FIGURE 3-3 *Visual cues*

Yau, N. (2013). Data Points: Visualization That Means Something. Wiley.

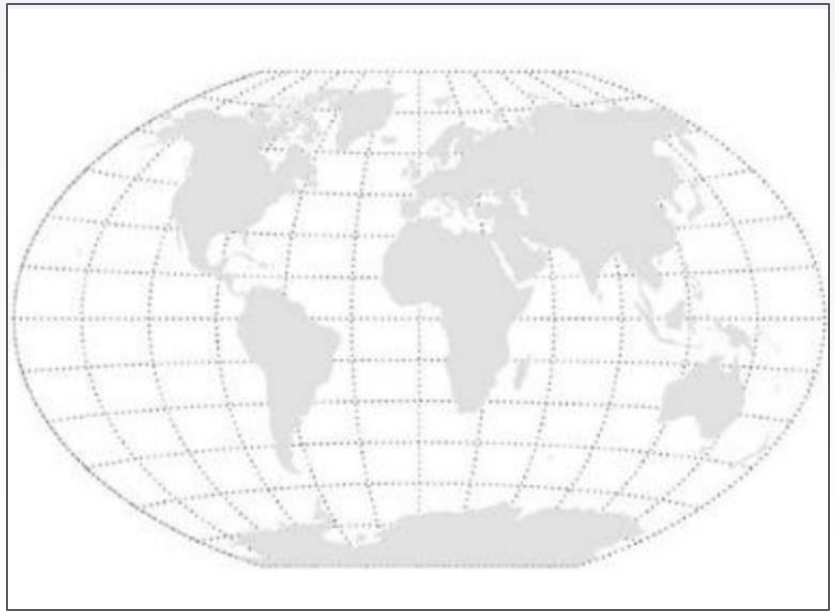
🤓 Coordinates



Cartesian



Polar

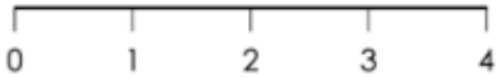


Geographic

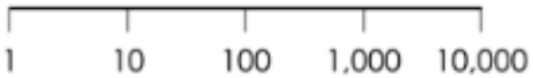
Yau, N. (2013). Data Points: Visualization That Means Something. Wiley.

💡 Scales

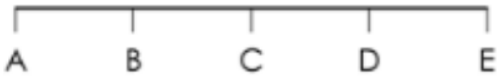
Linear
Values are evenly spaced



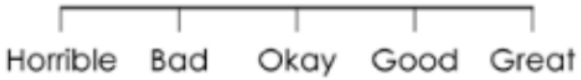
Logarithmic
Focus on percent change



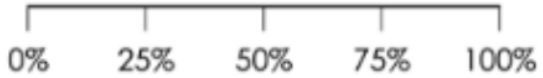
Categorical
Discrete placement in bins



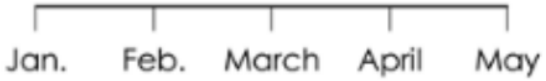
Ordinal
Categories where order matters

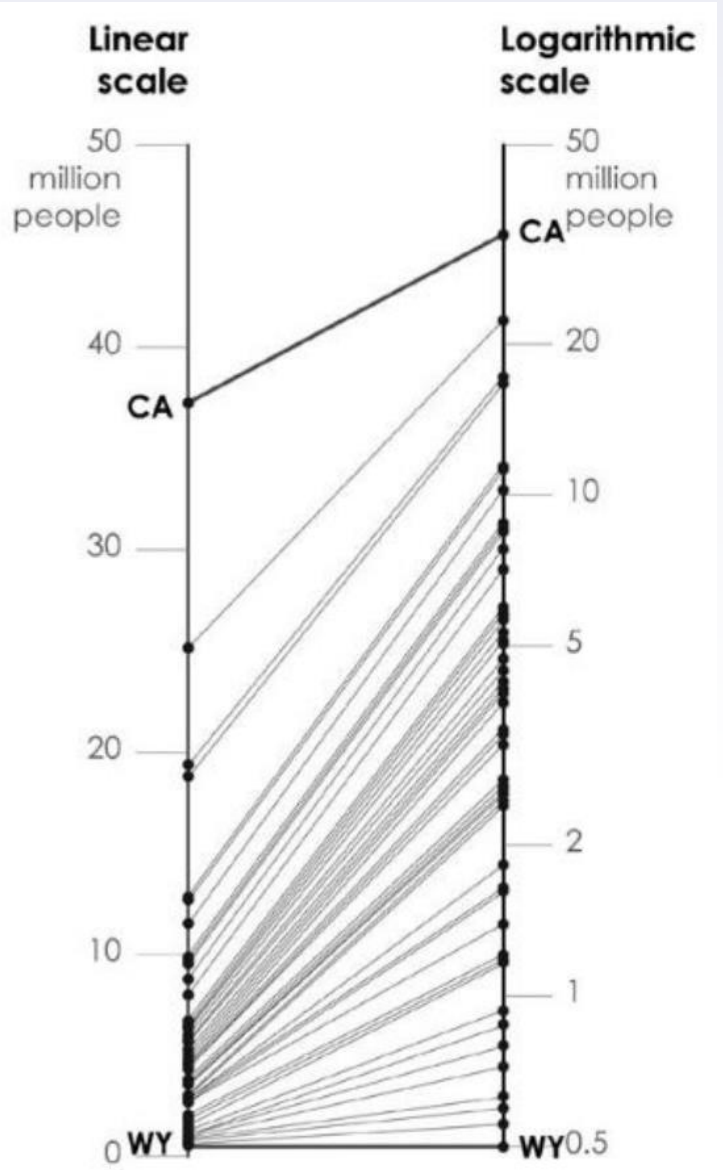


Percent
Representing parts of a whole



Time
Units of months, days, or hours





Context

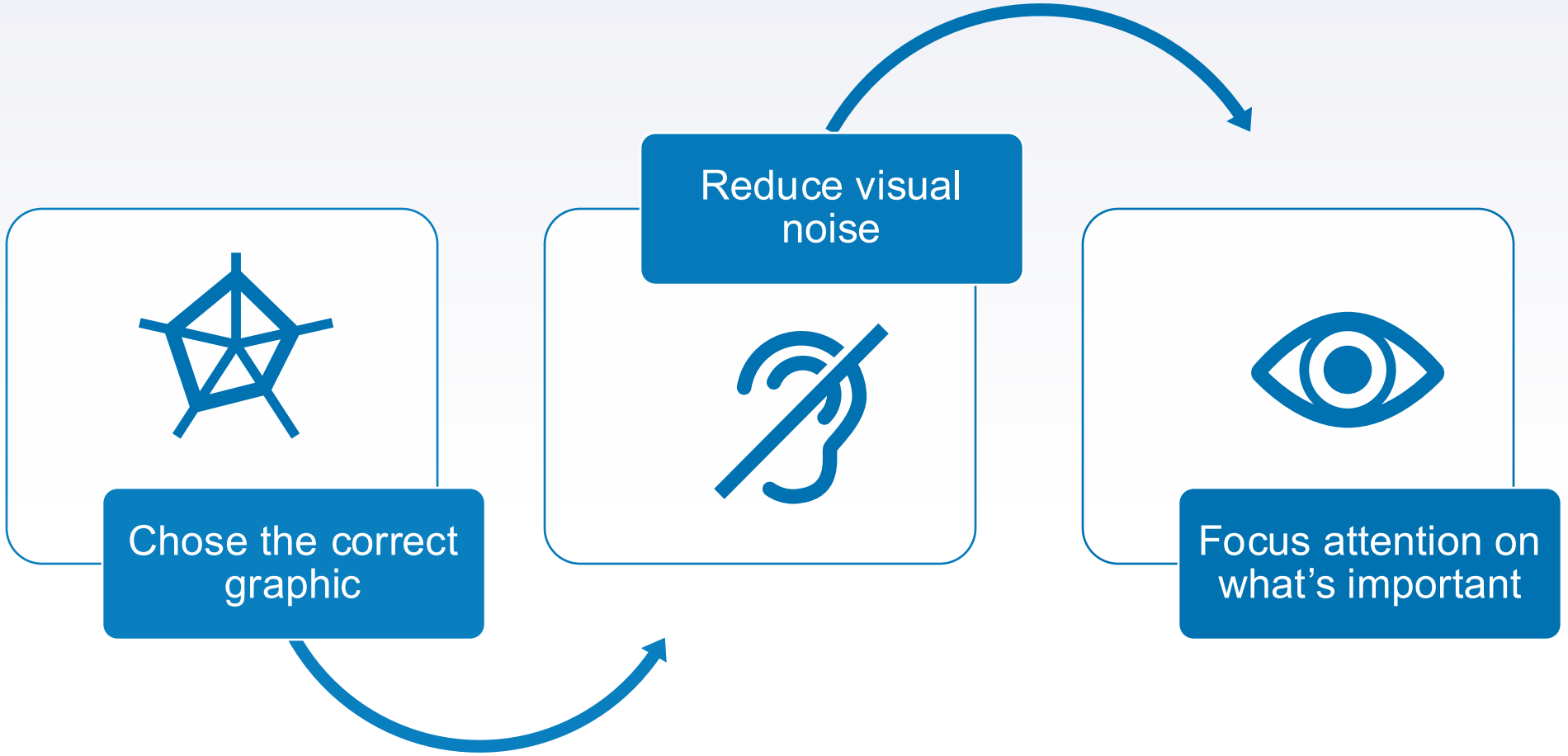
- Information that **helps us read** a chart
  - Order the elements
  - Lines that helps us reading an axis
  - Highlights
  - Textual annotations
  - … etc.



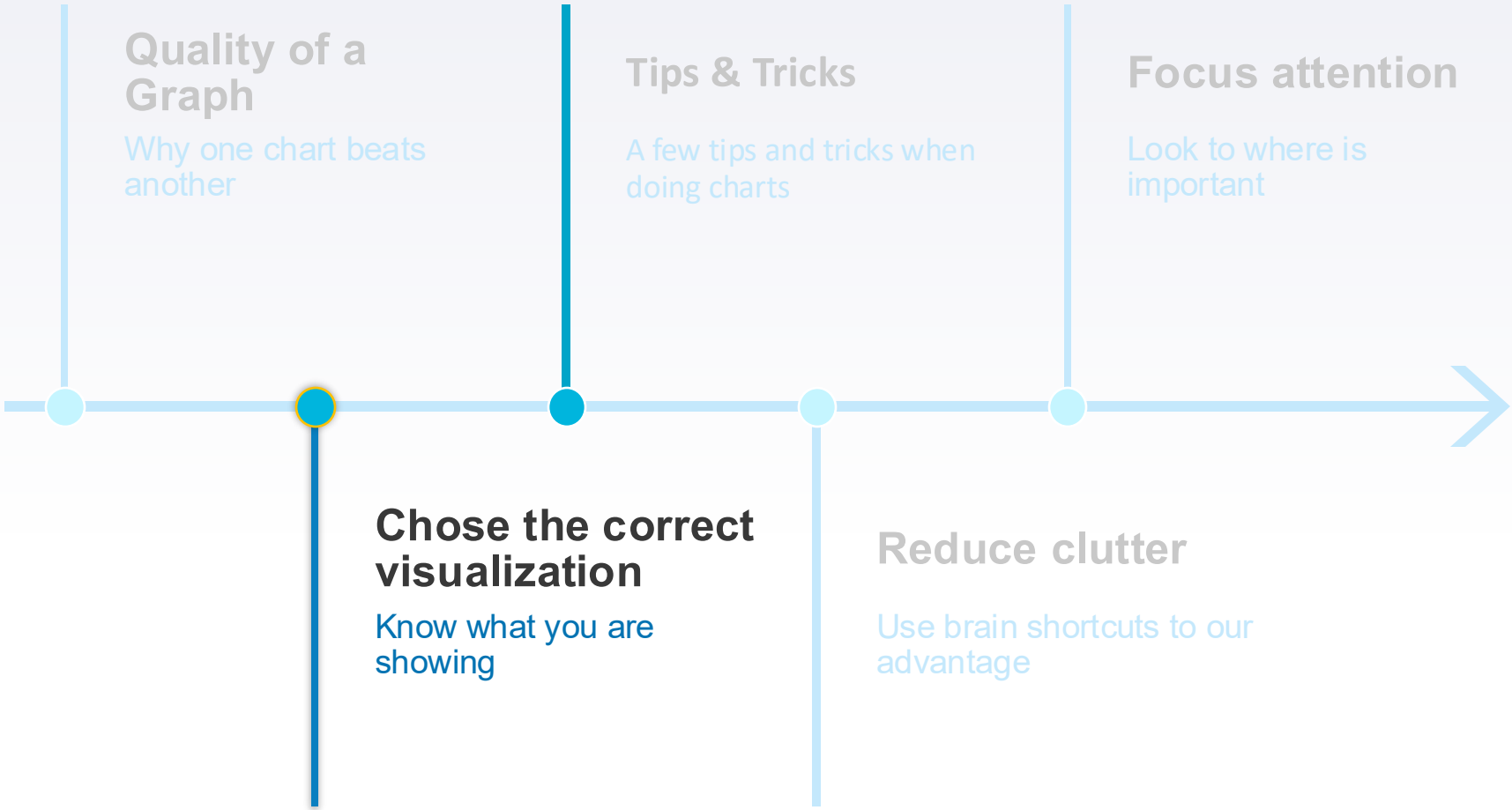


HOW DO I DO IT?

Steps to make a good chart



Today


Quality of a Graph
Why one chart beats another
Tips & Tricks
A few tips and tricks when doing charts
Focus attention
Look to where is important
Chose the correct visualization
Know what you are showing
Reduce clutter
Use brain shortcuts to our advantage



WHAT TYPE OF CHART DO I SELECT?

Diagram zoon

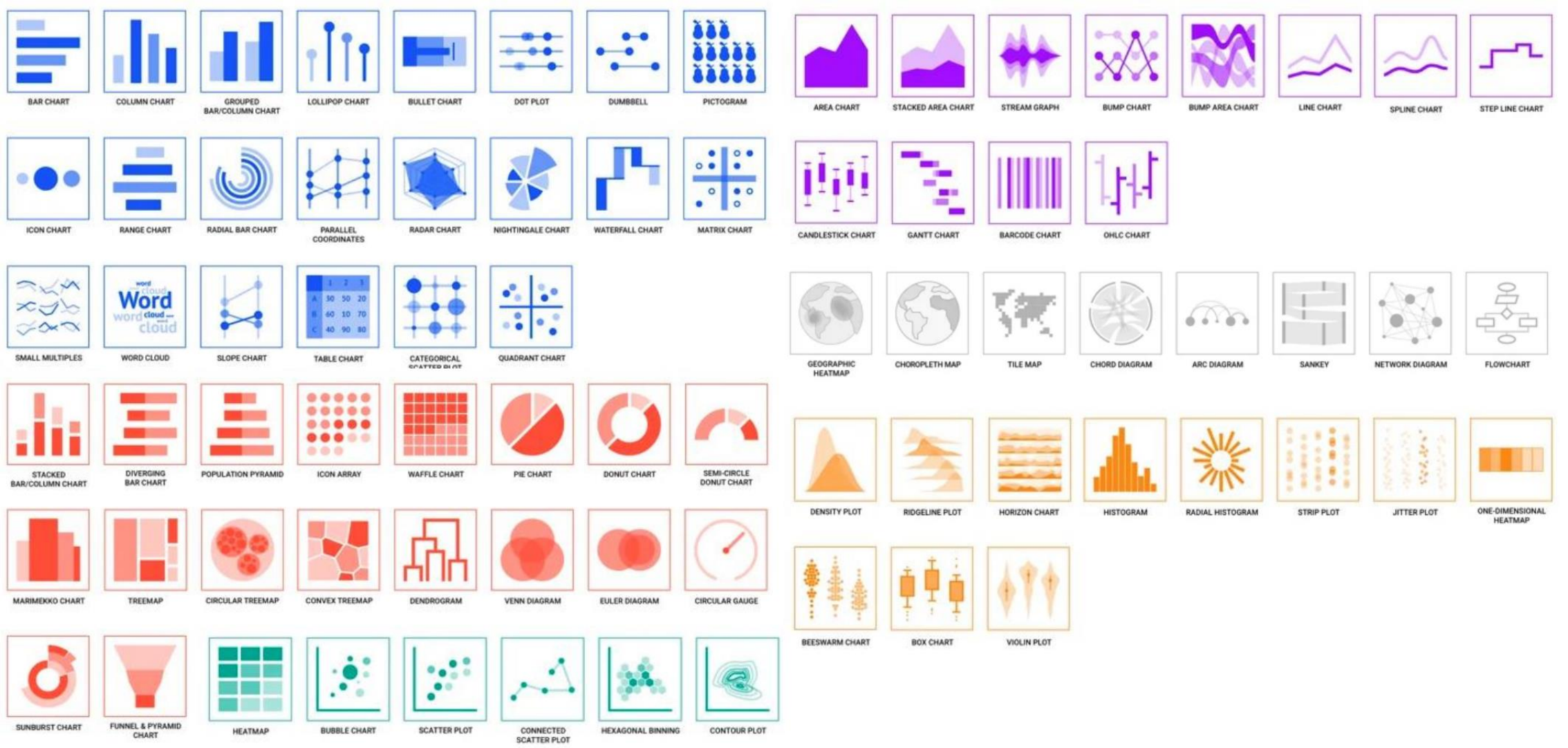
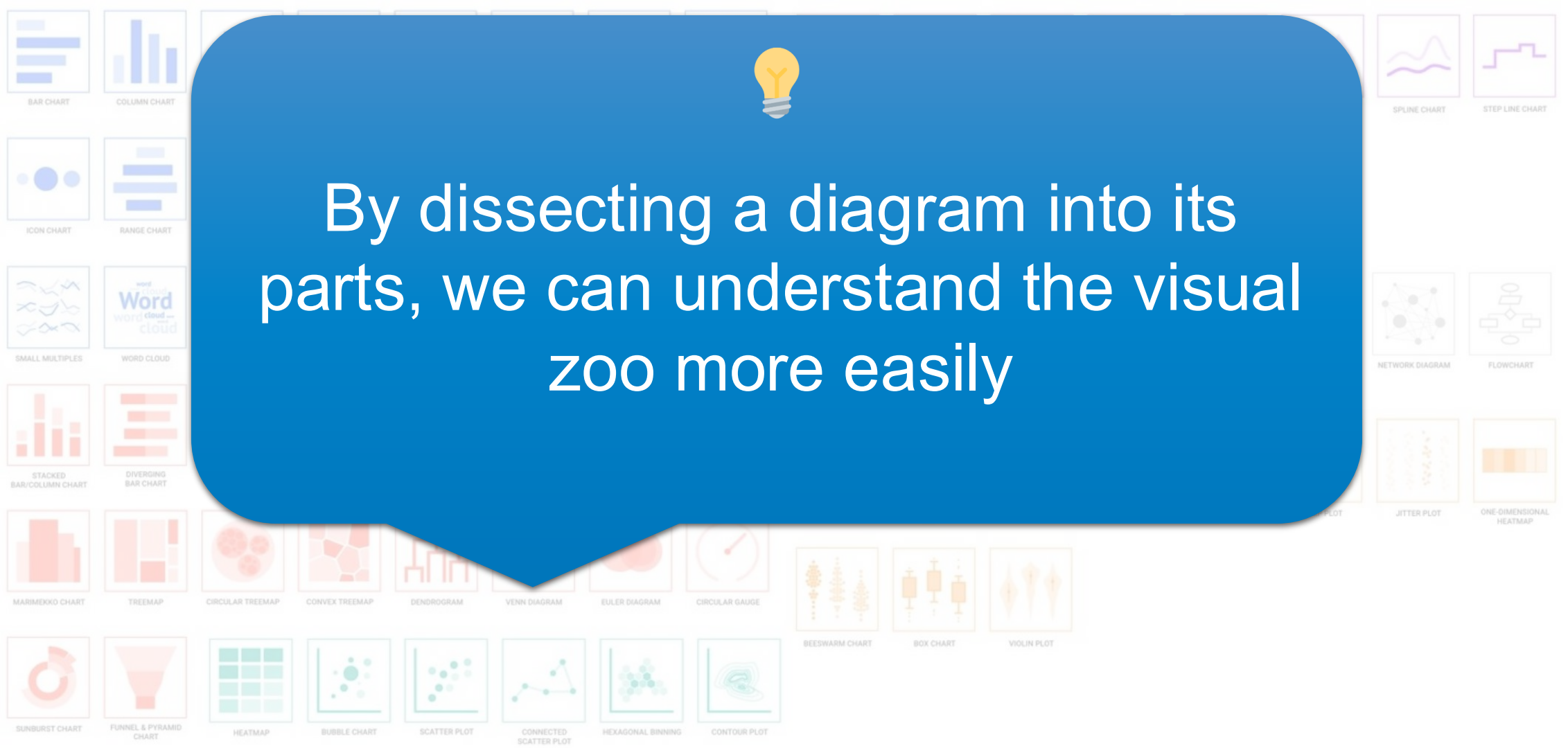
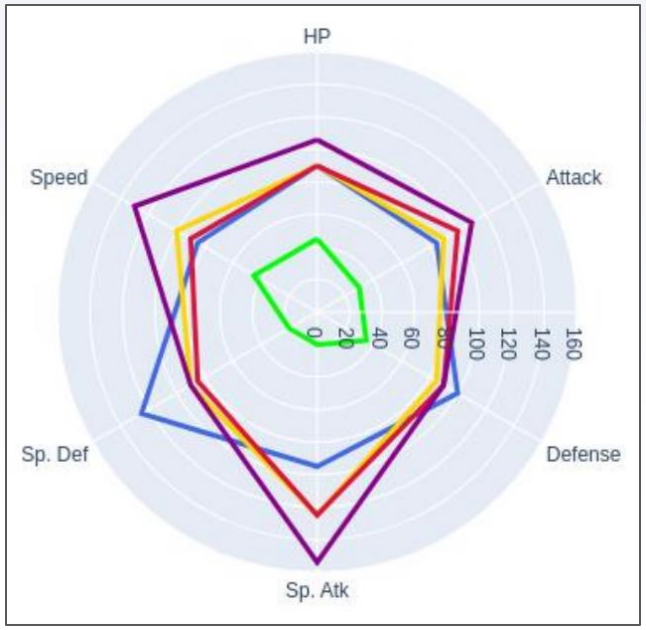


Diagram zoon

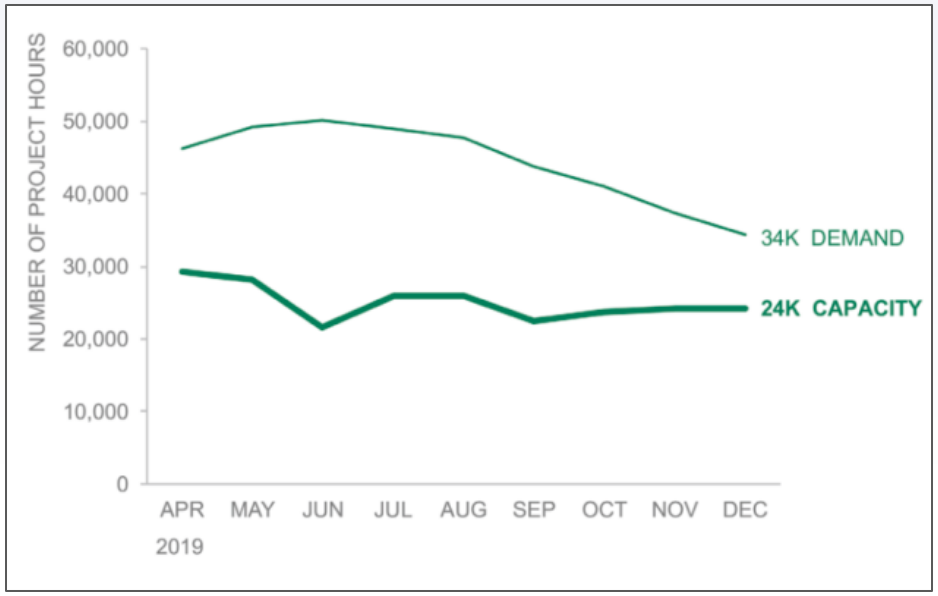


Graph analysis



Visual cues
Position
Direction

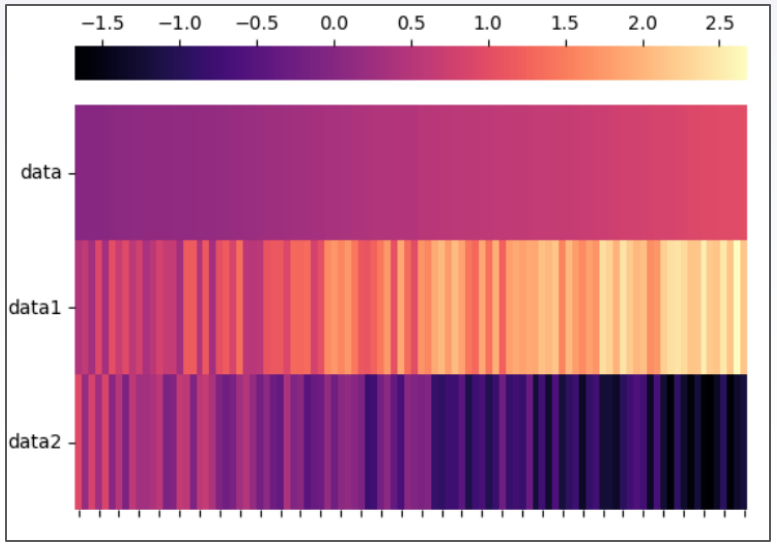
Coordinates
Polar



Visual cues
Position
Direction

Coordinates
Cartesian

Graph analysis



Visual cues
Position
Saturation

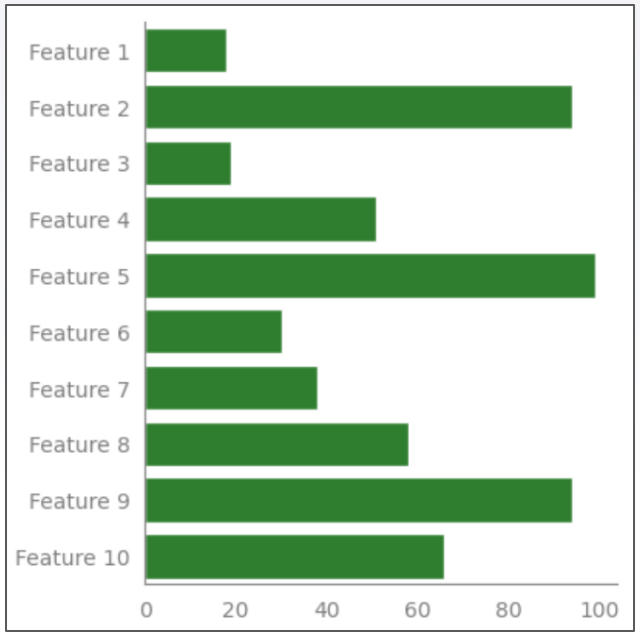
Coordinates
Cartesian



Visual cues
Position
Saturation

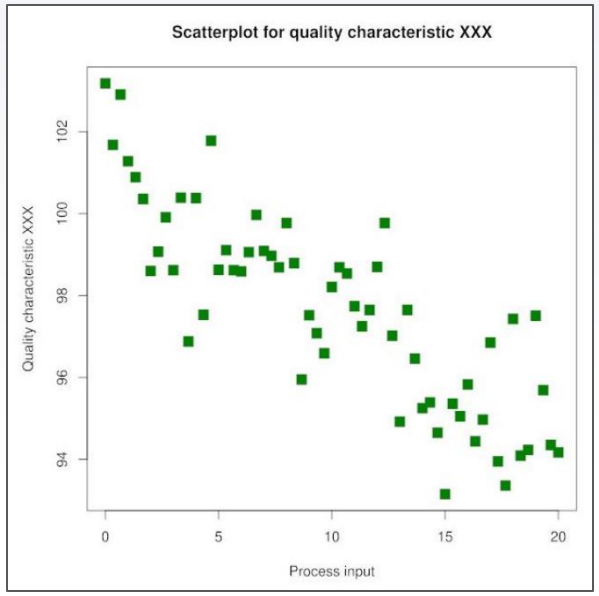
Coordinates
Geographic

Graph analysis



Visual cues
Position
Saturation

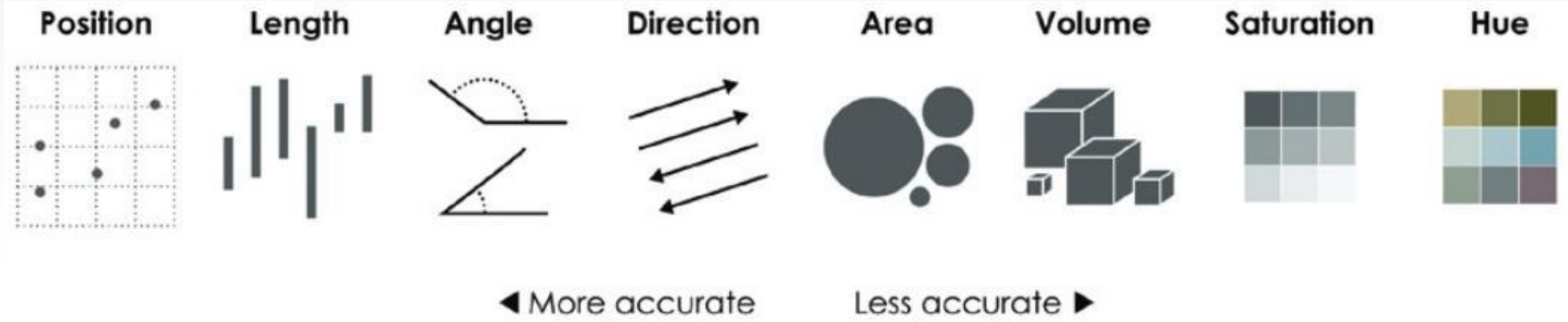
Coordinates
Cartesian



Visual cues
Position
Saturation

Coordinates
Geographic

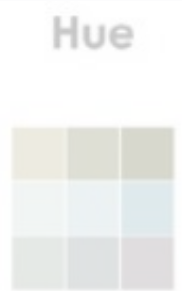
Ranking of visual cues



Cleveland & McGill (1984), JASA 79(387); Heer & Bostock (2010), CHI; figure: Schwabish (2021), Better Data Visualizations

Ranking of visual cues



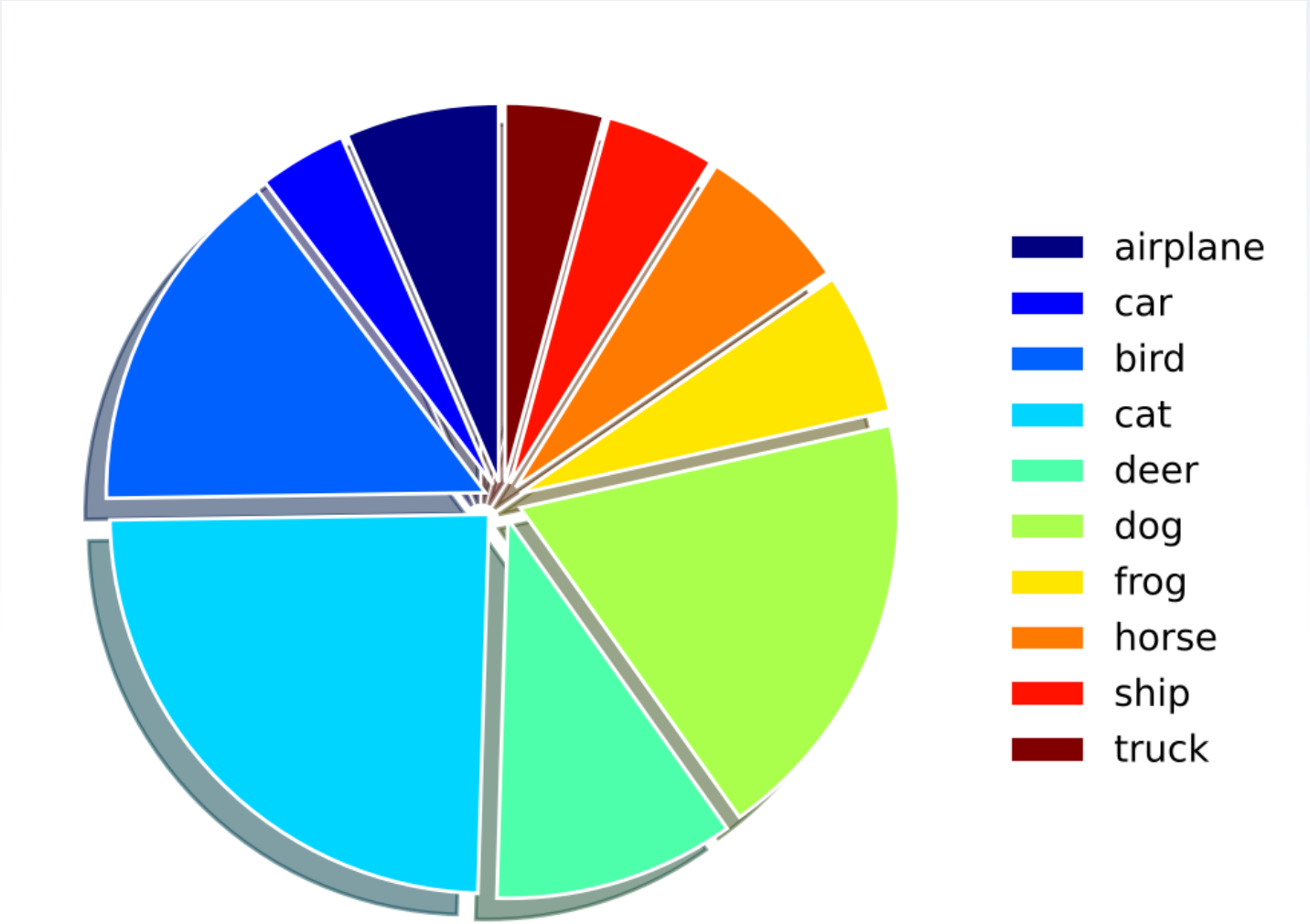




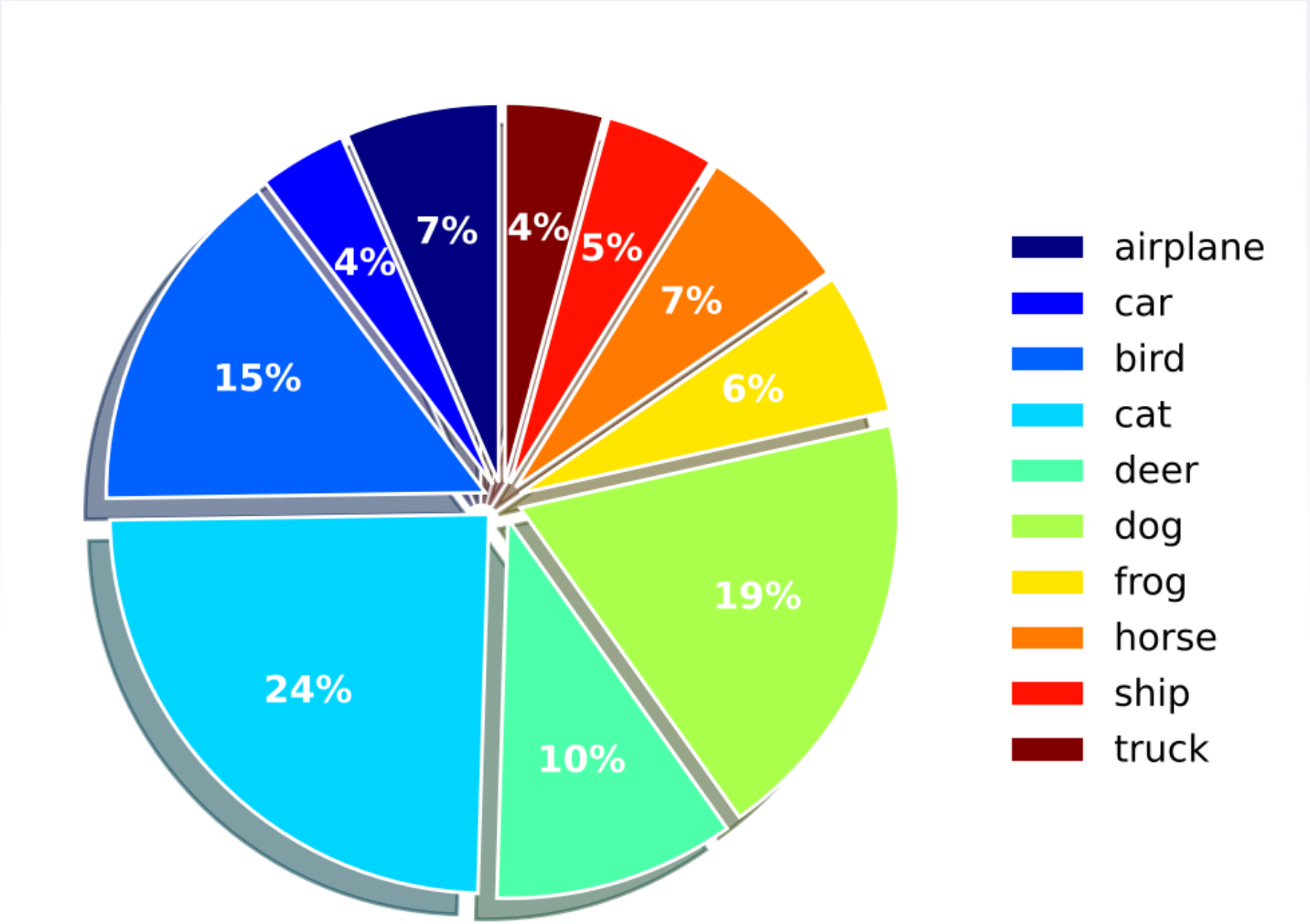
This is not taste: it was **measured**. Cleveland & McGill ran perception experiments in 1984; Heer & Bostock **replicated** them with crowdsourcing in 2010.

Cleveland & McGill (1984), JASA 79(387); Heer & Bostock (2010), CHI; figure: Schwabish (2021), Better Data Visualizations

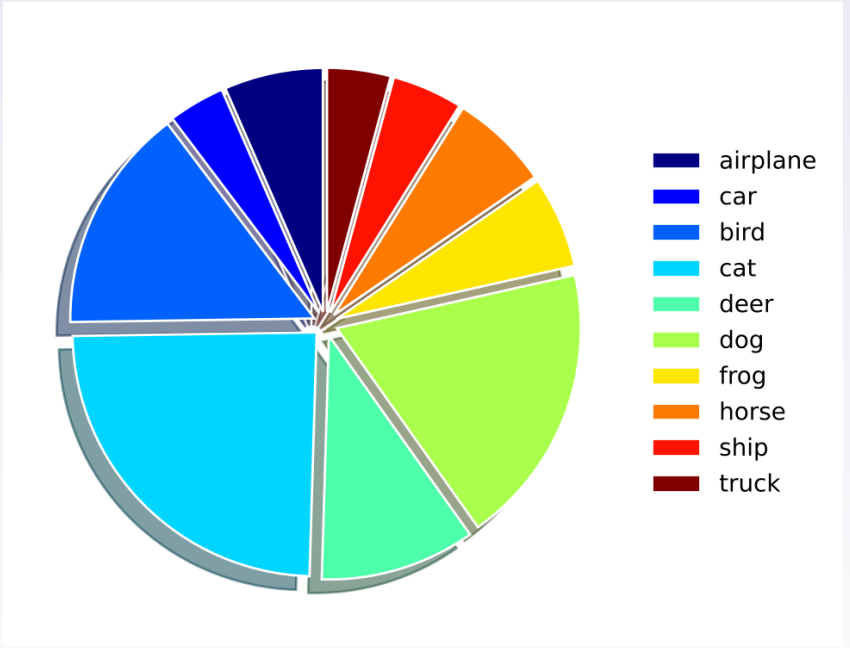
Which class causes most Baseline errors?



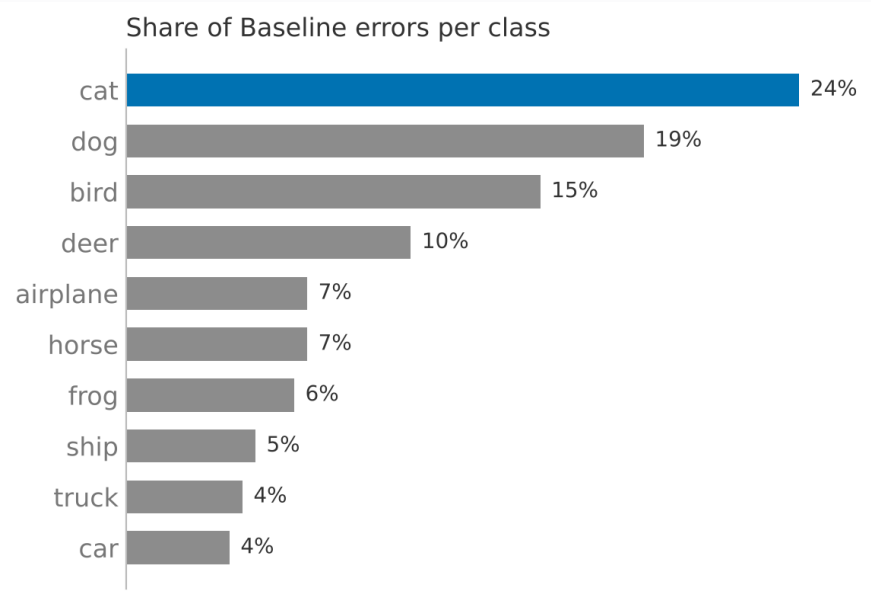
Which class causes most Baseline errors?



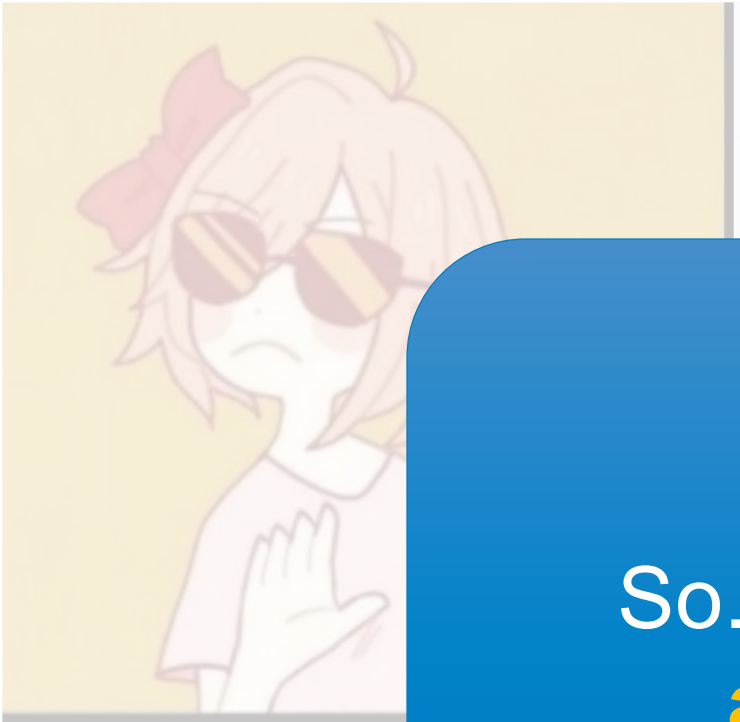




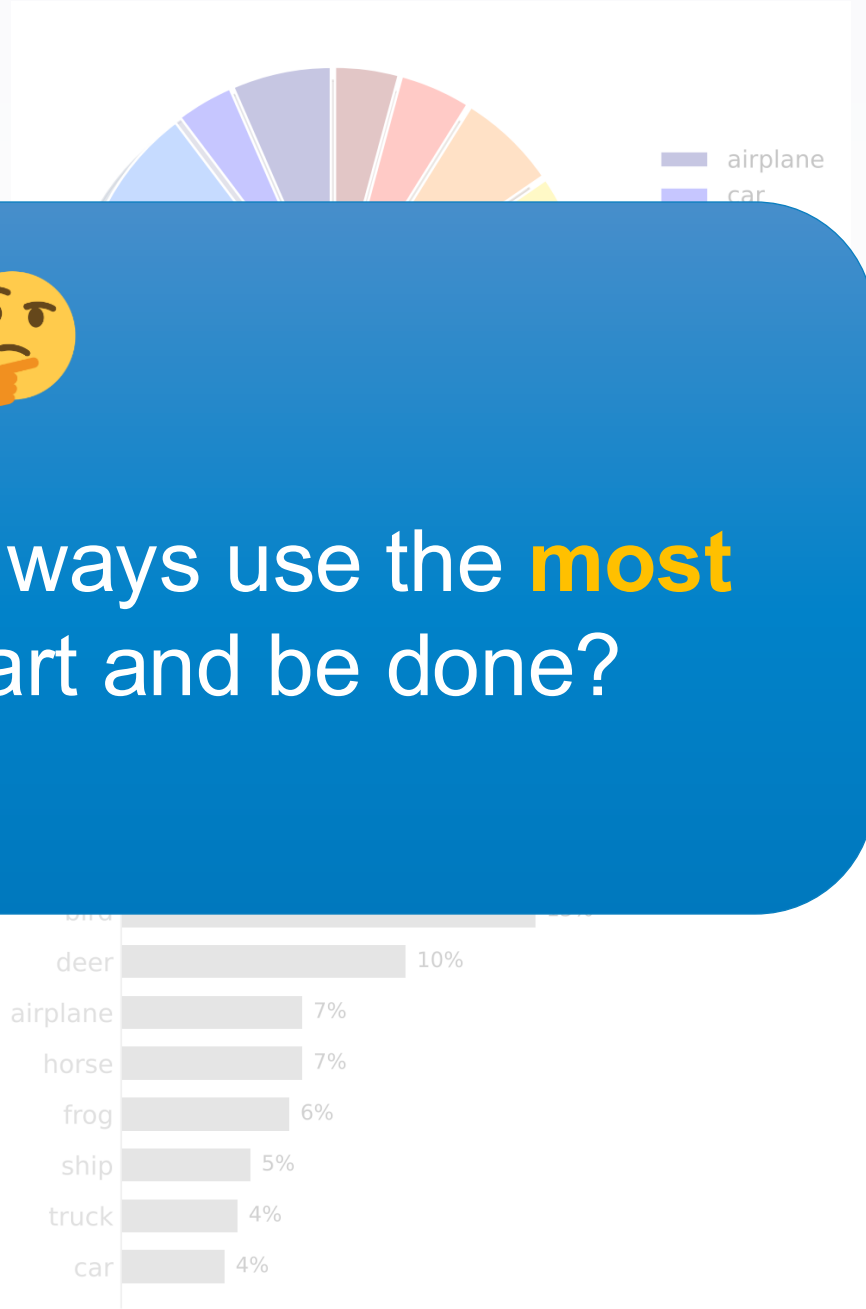




Skau & Kosara (2016), Computer Graphics Forum 35(3)







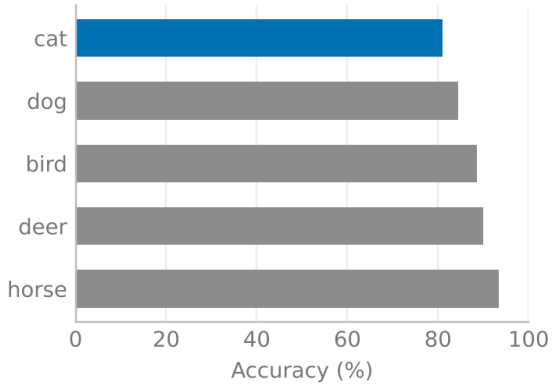
🤔

So… should I always use the **most accurate** chart and be done?

Which chart for which data?

Categories

Bars



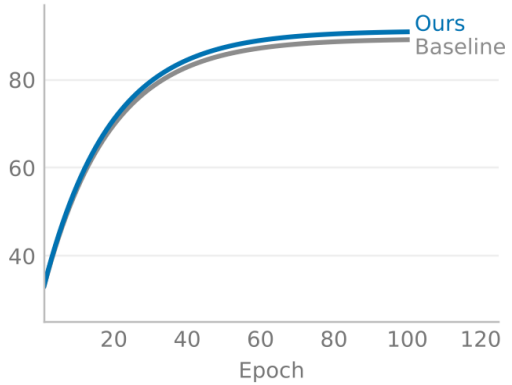
Compare a **quantity** across **categories**.

Start at **zero**; horizontal if the labels are long.

e.g. per-class accuracy

Ordered / continuous variable

Lines



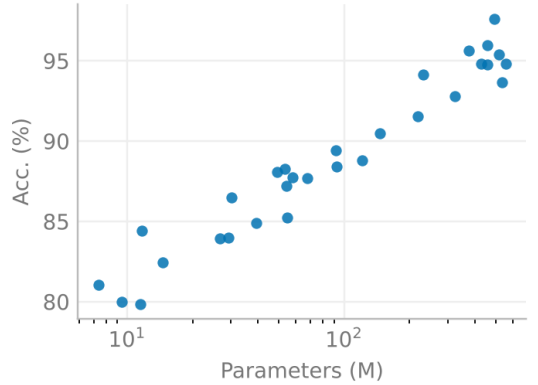
Show how a value **evolves** along an **ordered** variable (time, epochs, threshold).

A line implies continuity: **never** join unordered categories.

e.g. training curves

Two numeric variables

Scatter



Show the **relationship** between two variables: trend, clusters, outliers.

A 3rd variable with colour or size, **sparingly**.

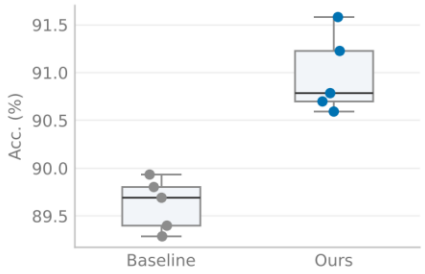
e.g. parameters vs accuracy

Yau, N. (2013). Data Points. Wiley · Knaflic, C. N. (2015). Storytelling with Data. Wiley · Schwabish, J. (2021). Better Data Visualizations. Columbia UP

Beyond the big three

Distribution

Box / strip plot



Show the **spread**, not only the mean. Violins for many points.

e.g. results over seeds or folds

Part of a whole

100% stacked bar



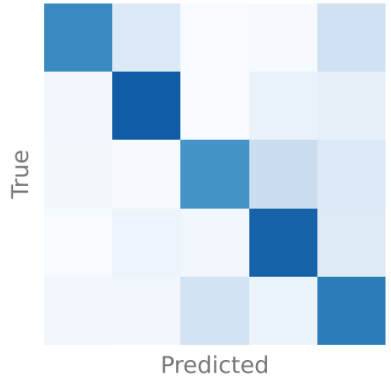
Proportions that add up to **100 %**.

Better than a **pie** to compare groups.

e.g. error types per model

Two categorical variables

Heatmap

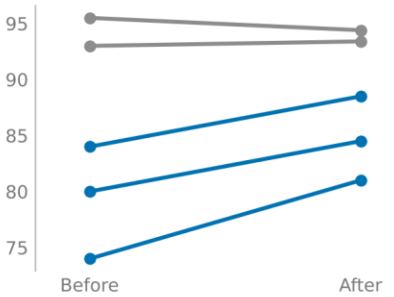


A value for each **pair** of categories.

e.g. confusion matrix, correlations

Before vs after

Slopegraph



Before vs after for each item; the slope is the change.

e.g. Baseline vs Ours, before vs after fine-tuning

Knaflic, C. N. (2015). Storytelling with Data. Wiley · Weissgerber et al. (2015), PLOS Biology 13(4) · Schwabish, J. (2021). Better Data Visualizations



Case study – Baseline vs Ours

- CIFAR-10-style benchmark: **10 classes**
- **2 models**: Baseline and Ours
- **5 seeds** per model
- Metric: per-class **test accuracy**
- Numbers are **synthetic**

*Questions: Is Ours better? **Where**? Is it **robust**?*

Attempt 0 – A table

Class	Baseline (%)	Ours (%)
airplane	93.0	93.6
car	96.0	96.2
bird	84.0	88.5
cat	74.0	81.0
deer	89.0	90.0
dog	80.0	84.5
frog	93.5	94.0
horse	93.0	93.4
ship	95.0	95.4
truck	95.5	94.4

Answers…

*What is the **exact** value of each model on each class?*

👍 Precise; good for an appendix or paper

👎 No pattern visible at a glance, bad for presentation or poster

Attempt 0 – A table

Class	Baseline (%)	Ours (%)
airplane		
car		
bird		
cat		
deer		
dog		
frog		
horse	93.0	93.4
ship	95.0	95.4
truck	95.5	94.4

Answers…

of each model

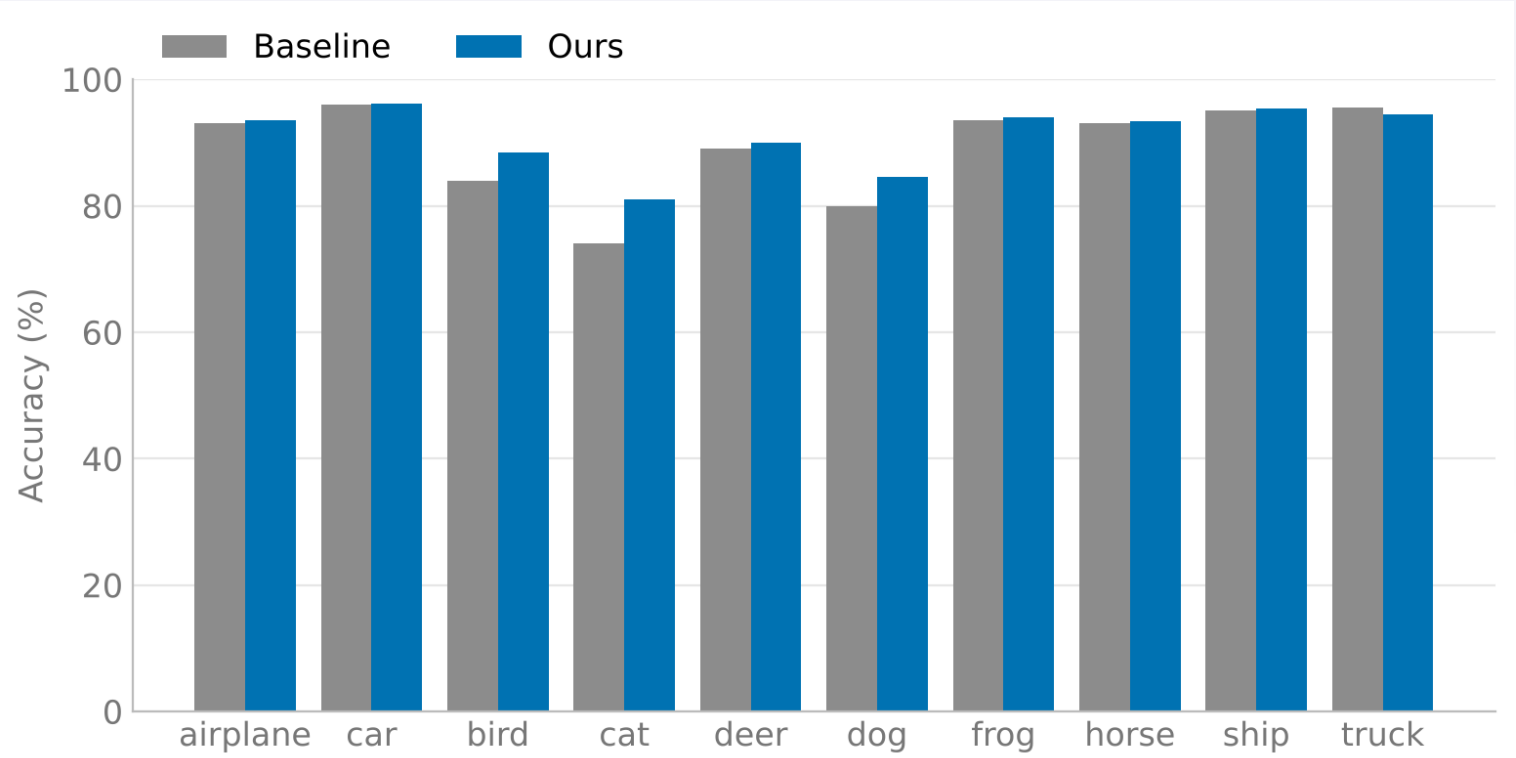
ppendix

glance



Tables give **exact values**, but the reader has to **compute** the pattern in their head.

Attempt 1 – Bar chart



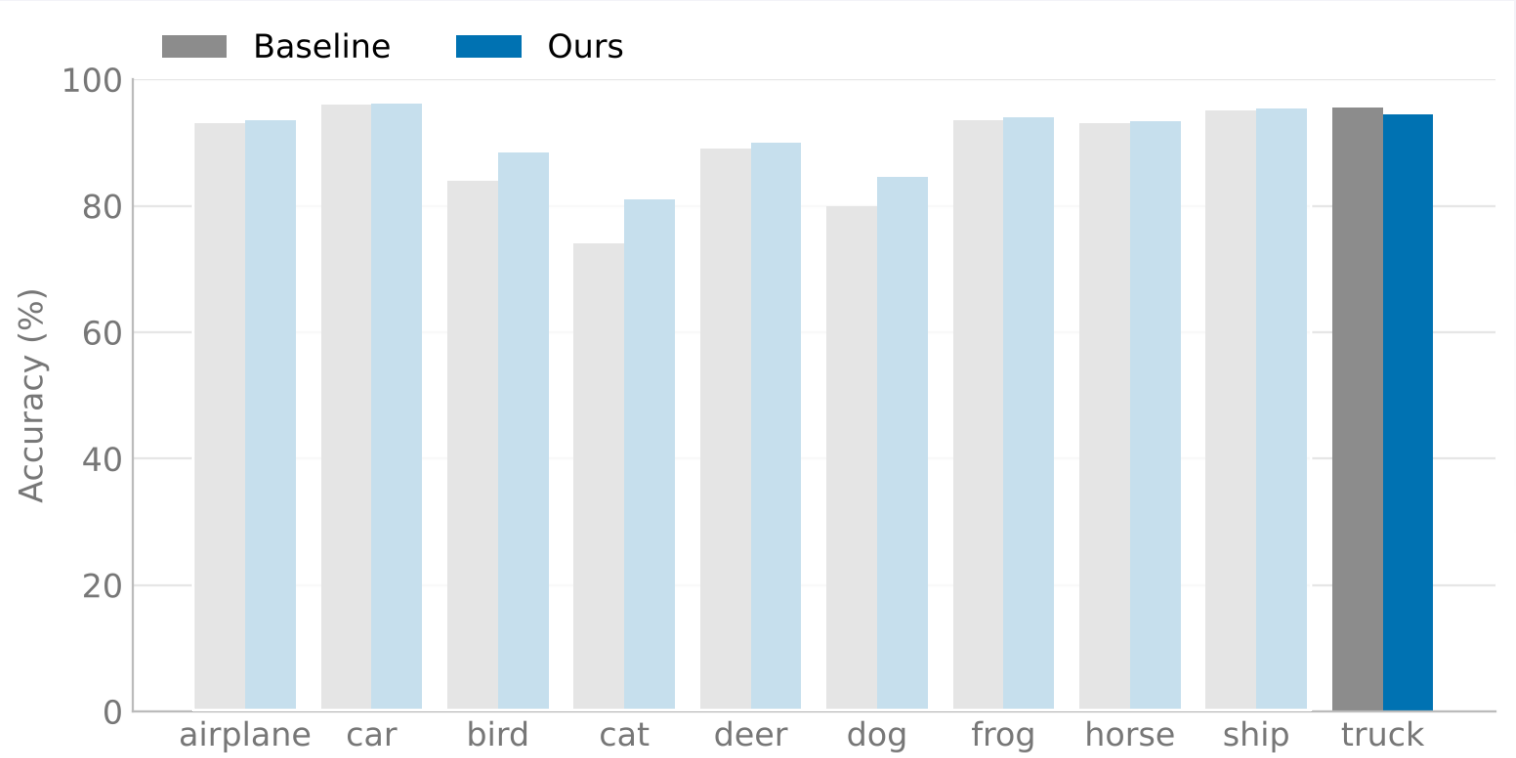
Answers…

How does each model do on each class?

👍 Requires less cognitive load than the table

👎 Differences easy to see, however when ours win or loss is not so clear.

Attempt 1 – Bar chart



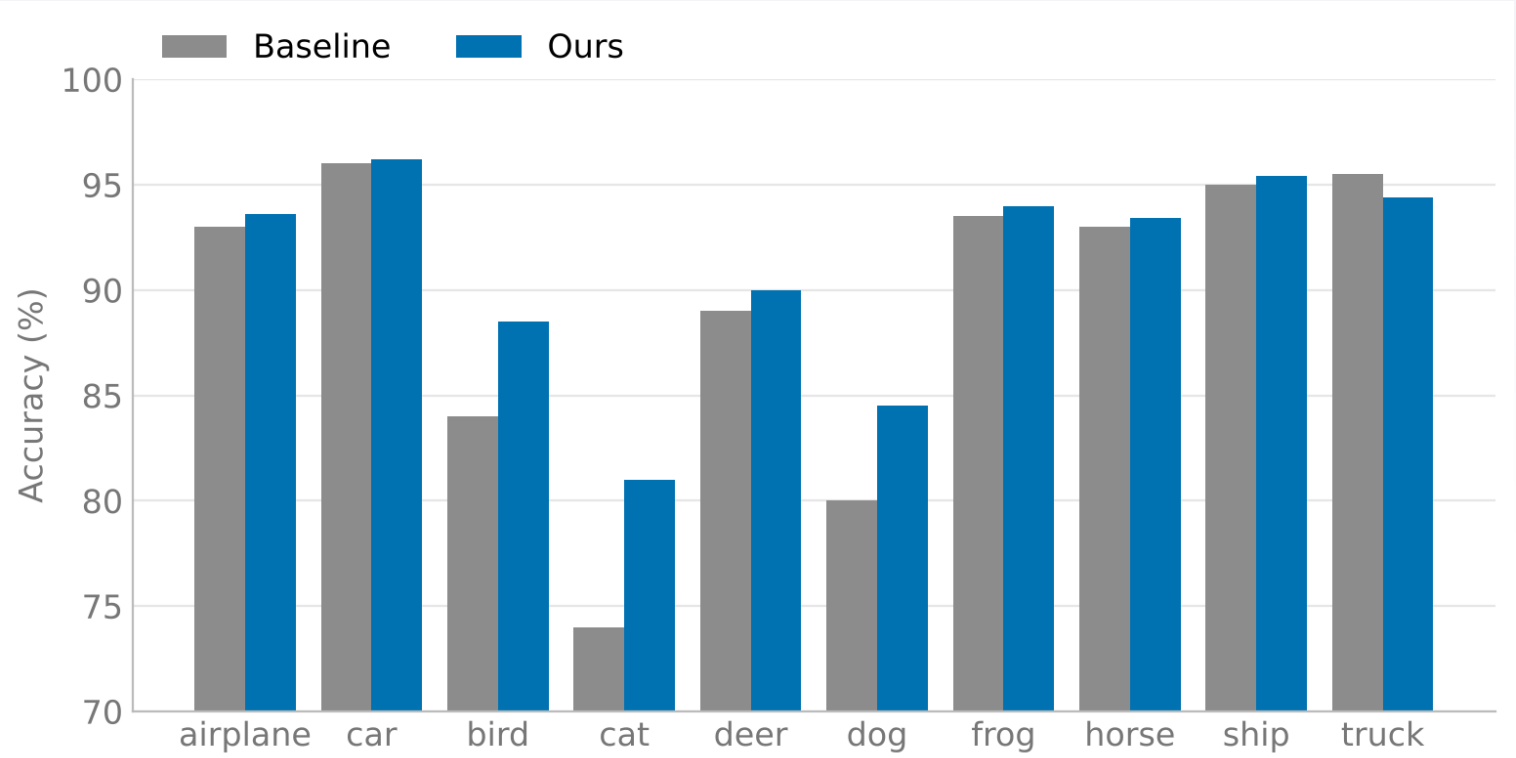
Answers…

How does each model do on each class?

👍 Requires less cognitive load than the table

👎 **Differences easy to see, however when ours win or loss is not so clear.**

Attempt 2 – Bar chart zoom



Answers…

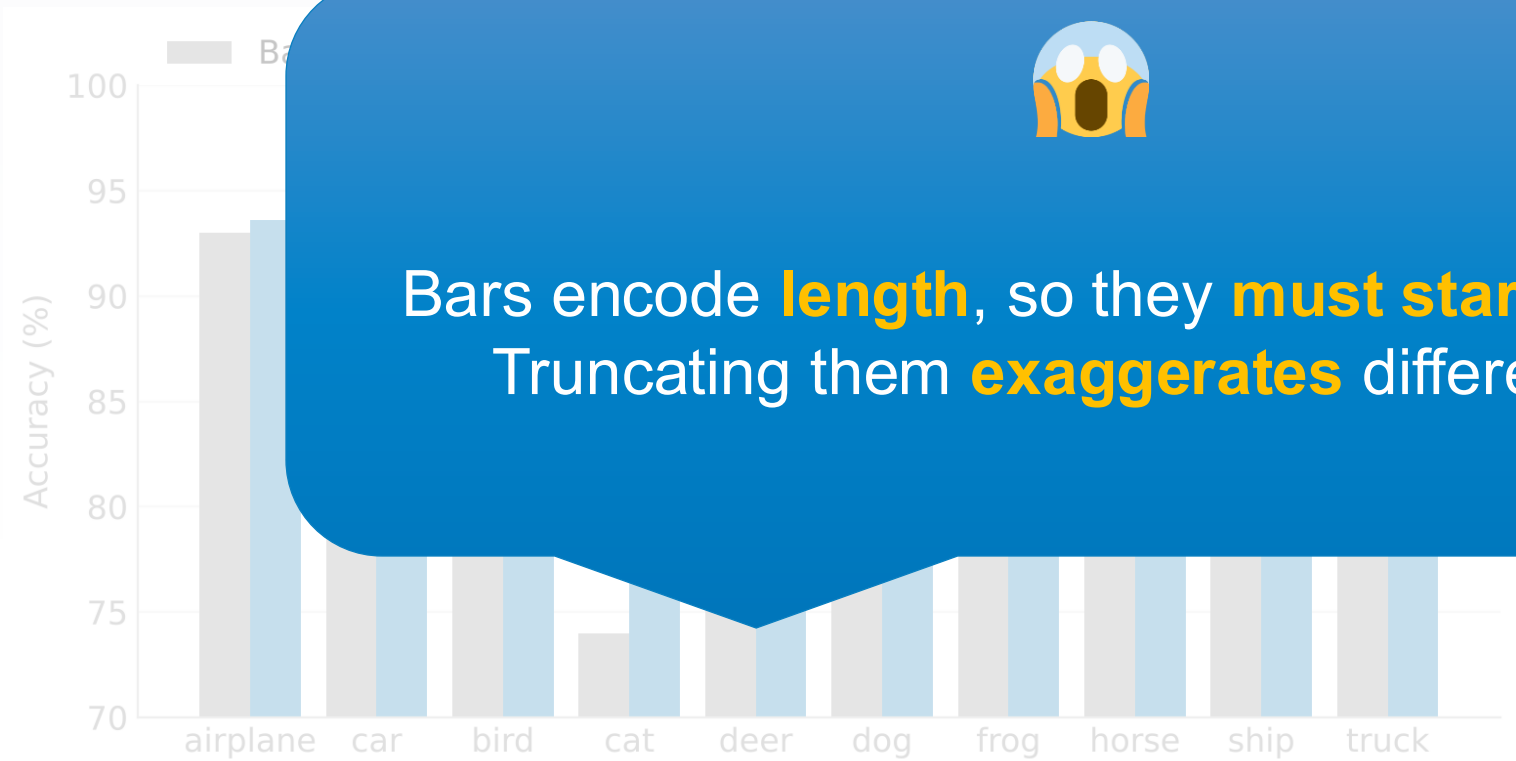
How does each model do on each class?

👍 Differences are easier to see

👎 Differences are too exaggerate easy to miss understand

Yau, N. (2013). Data Points. Wiley.

Attempt 2 – Zoomed bars



Bars encode **length**, so they **must start at zero**.
Truncating them **exaggerates** differences.

Answers…

…on, zoomed in

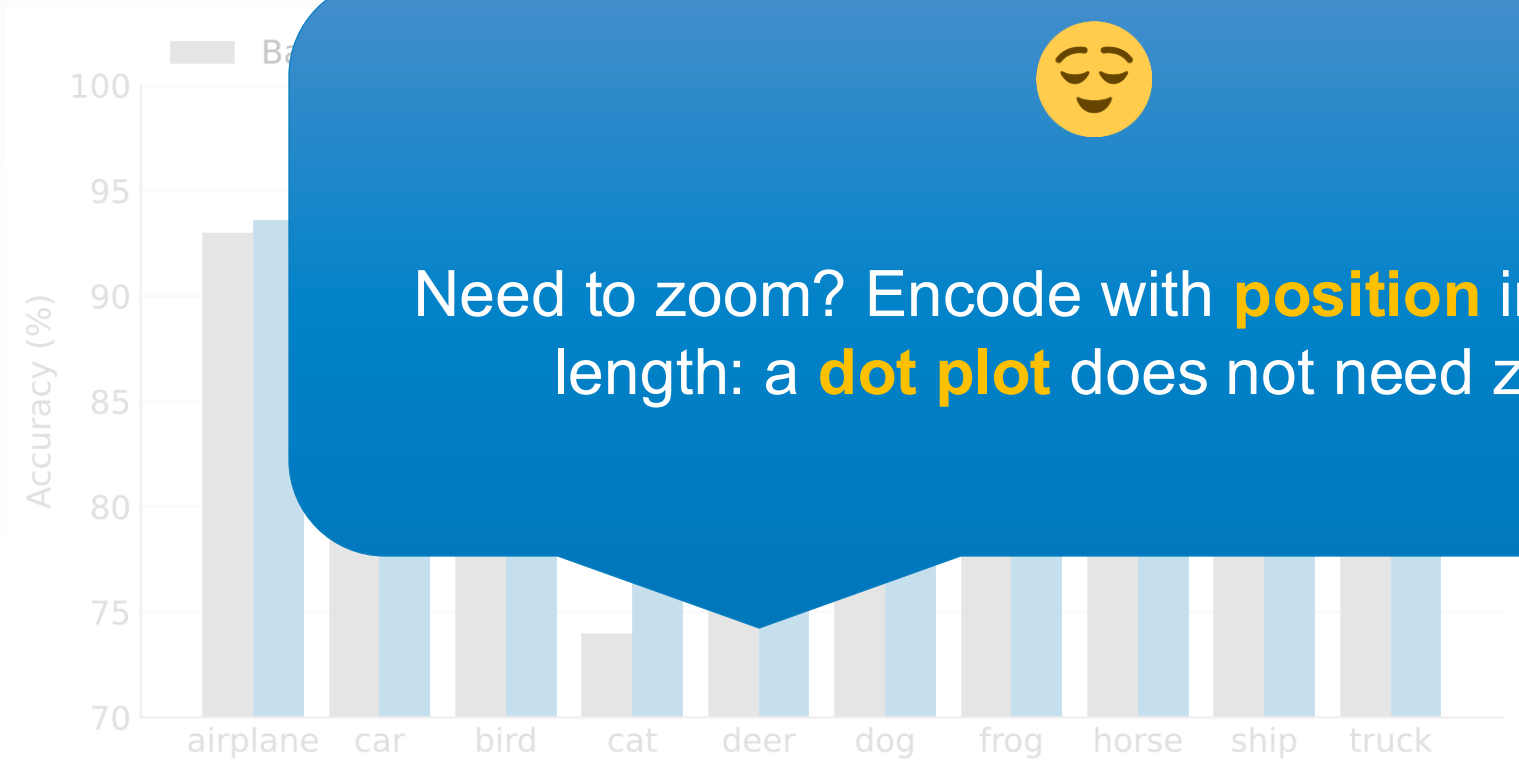
now **visible**

…lies: cat looks 3×

Easy to exaggerate on purpose

Yau, N. (2013). Data Points. Wiley.

Attempt 2 – Zoomed bars



Answers…

…on, zoomed in

now **visible**

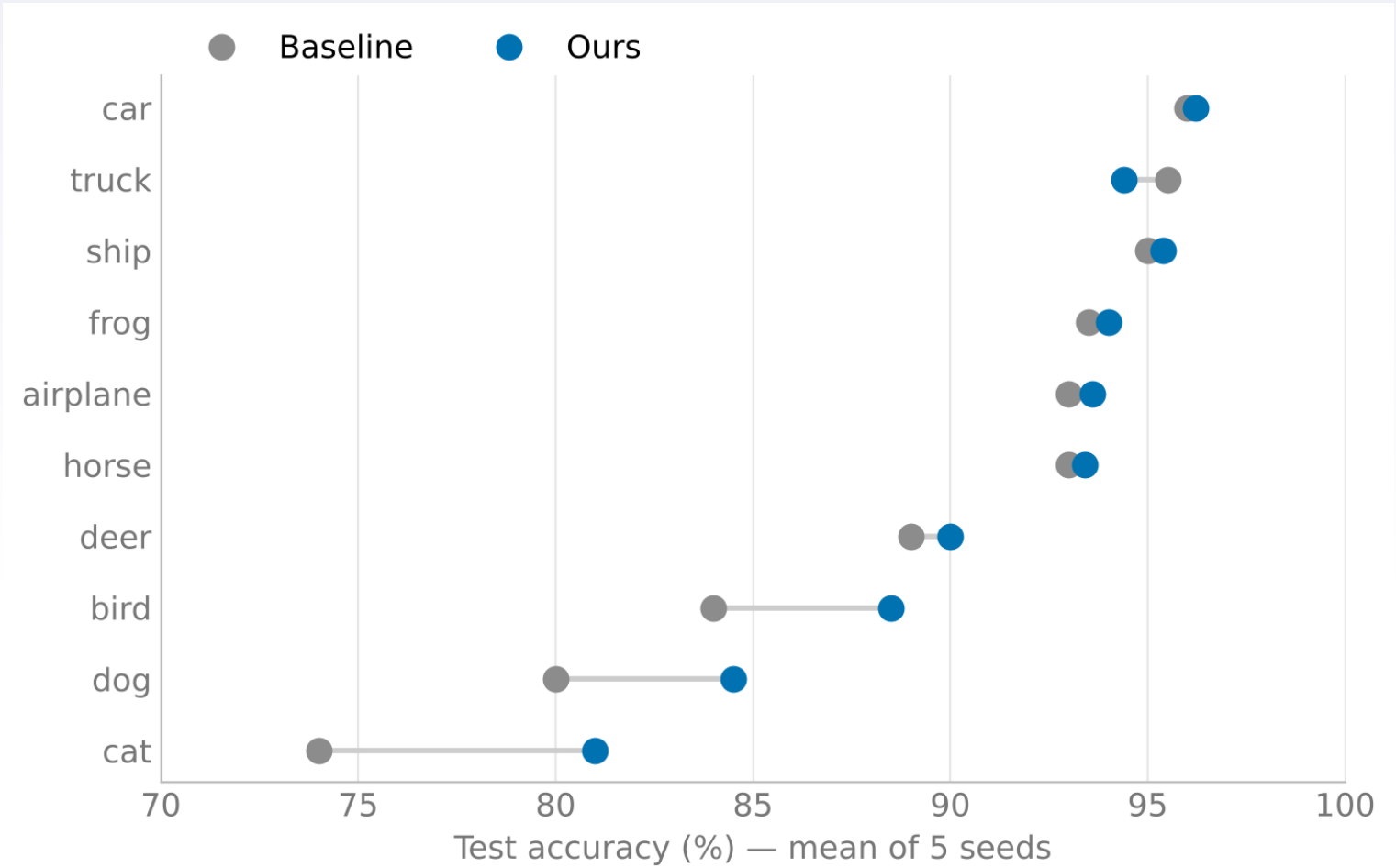
lies: cat looks 3×

Easy to exaggerate on purpose

Need to zoom? Encode with **position** instead of length: a **dot plot** does not need zero.

Yau, N. (2013). Data Points. Wiley.

Attempt 3 – Dot plot



Answers…

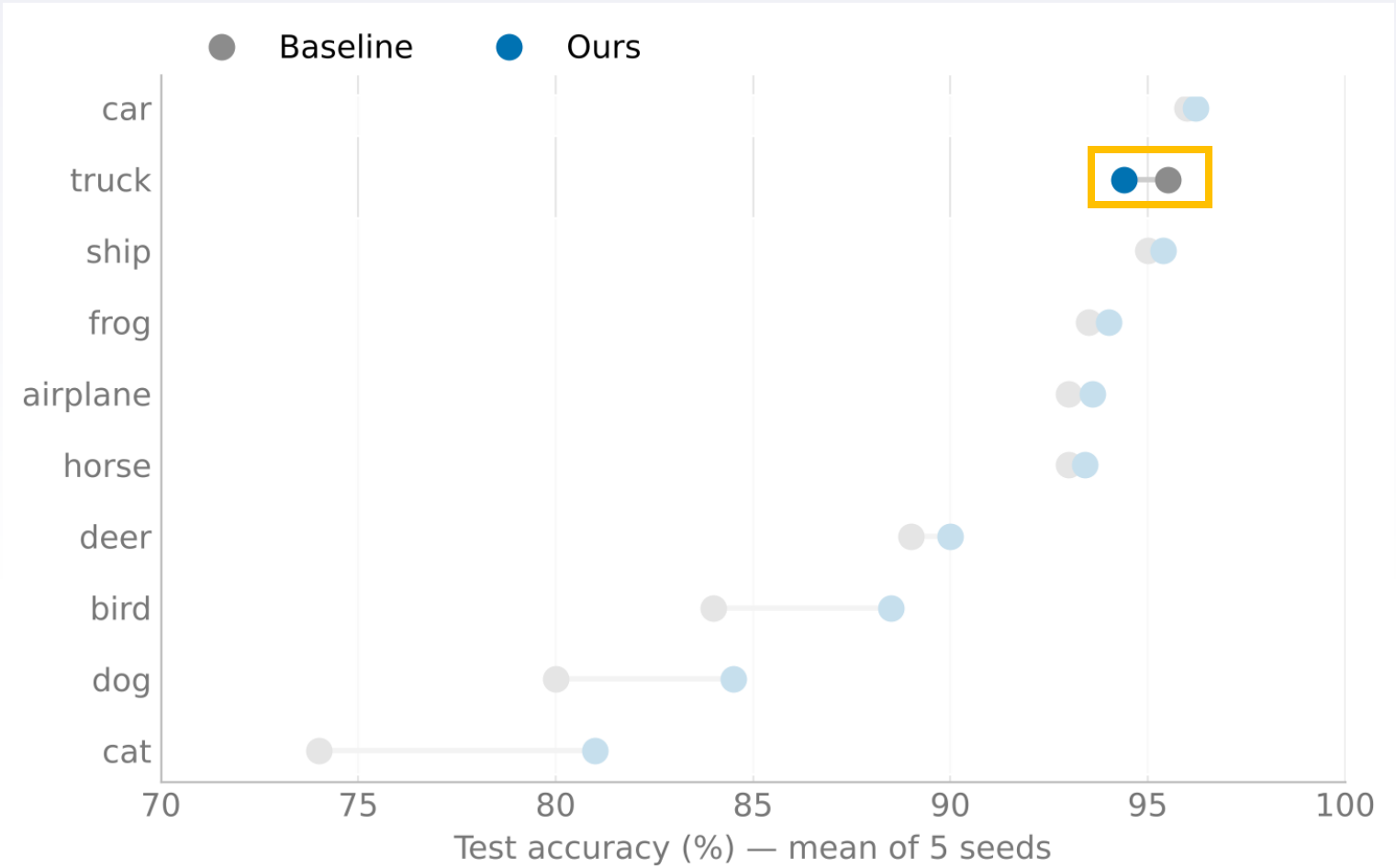
*What is the accuracy of **each model** on each class?*

👍 **Position**: zoom allowed, and easier to see differences

👎 Still difficult to see in which cases I do worse

Cleveland & McGill (1984), JASA 79(387)

Attempt 3 – Dot plot



Answers…

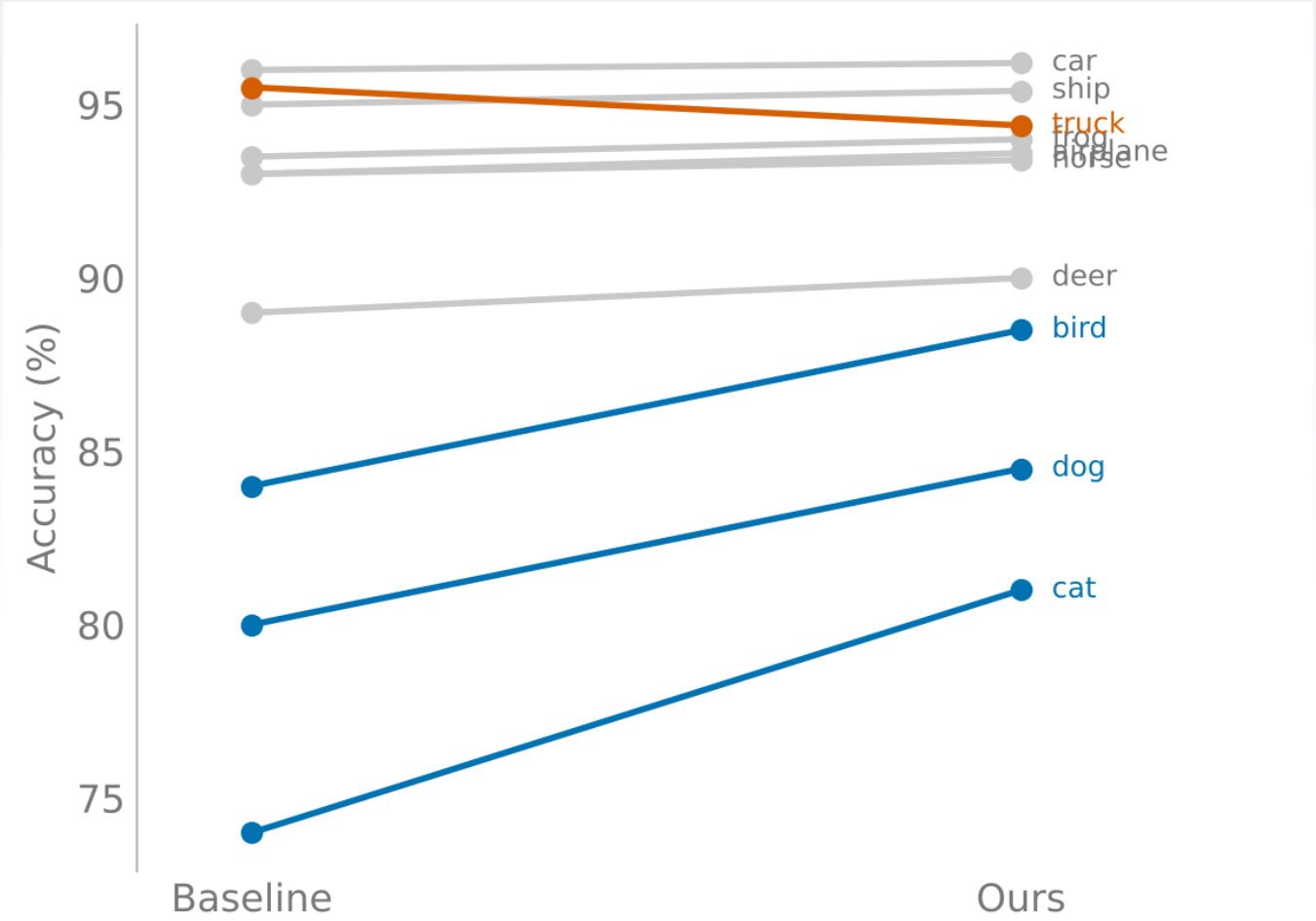
*What is the accuracy of **each model** on each class?*

👍 **Position**: zoom allowed, and easier to see differences

👎 Still difficult to see in which cases I do worse

Cleveland & McGill (1984), JASA 79(387)

Attempt 4 – Slopegraph



Answers…

*Which classes go **up** and which go **down**?*

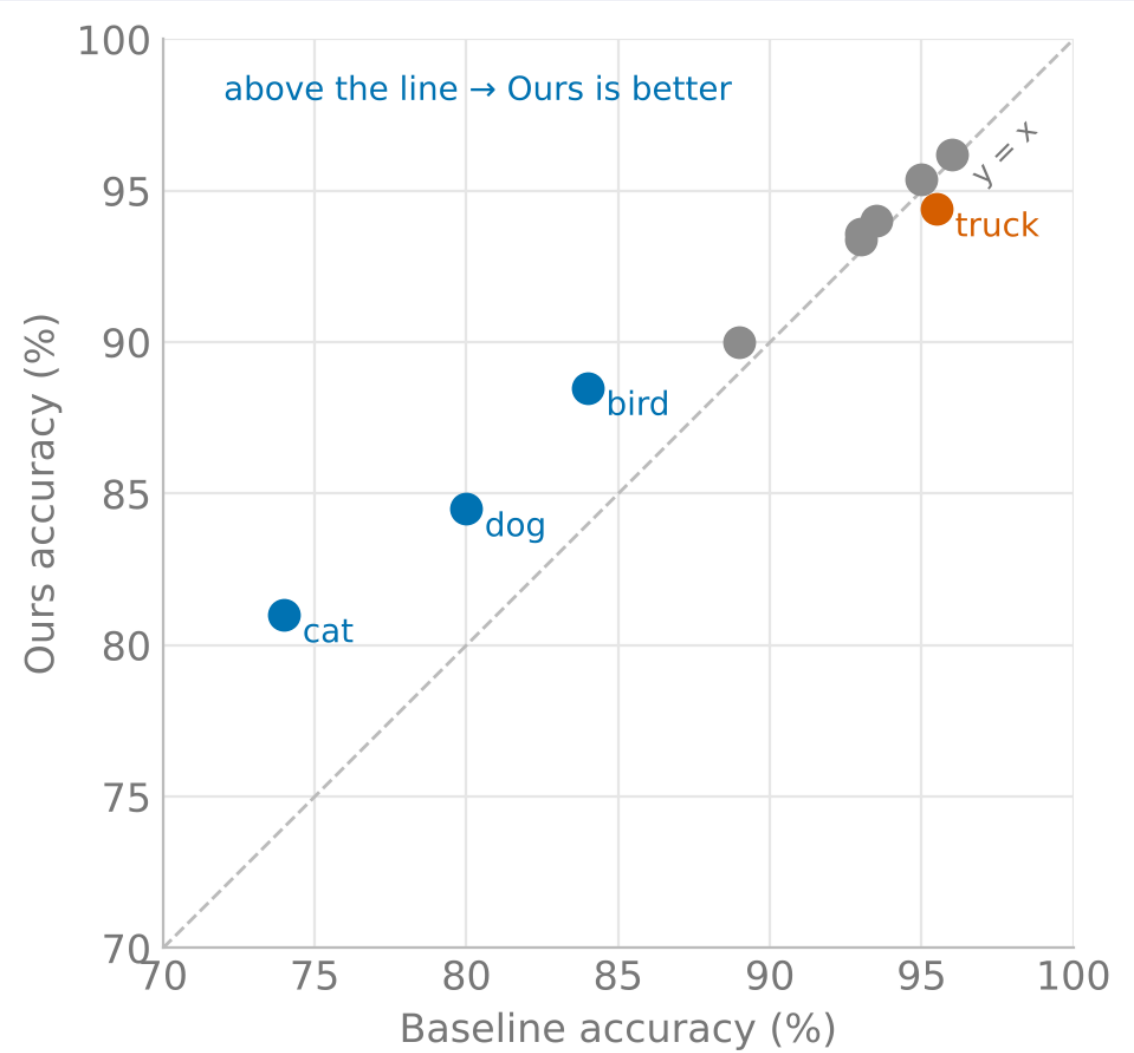
👍 **Change** pops out

👍 Winners and losers coloured

👎 Labels collide in dense regions

Knaflic, C. N. (2015). Storytelling with Data. Wiley.

Attempt 5 – Scatter against y = x



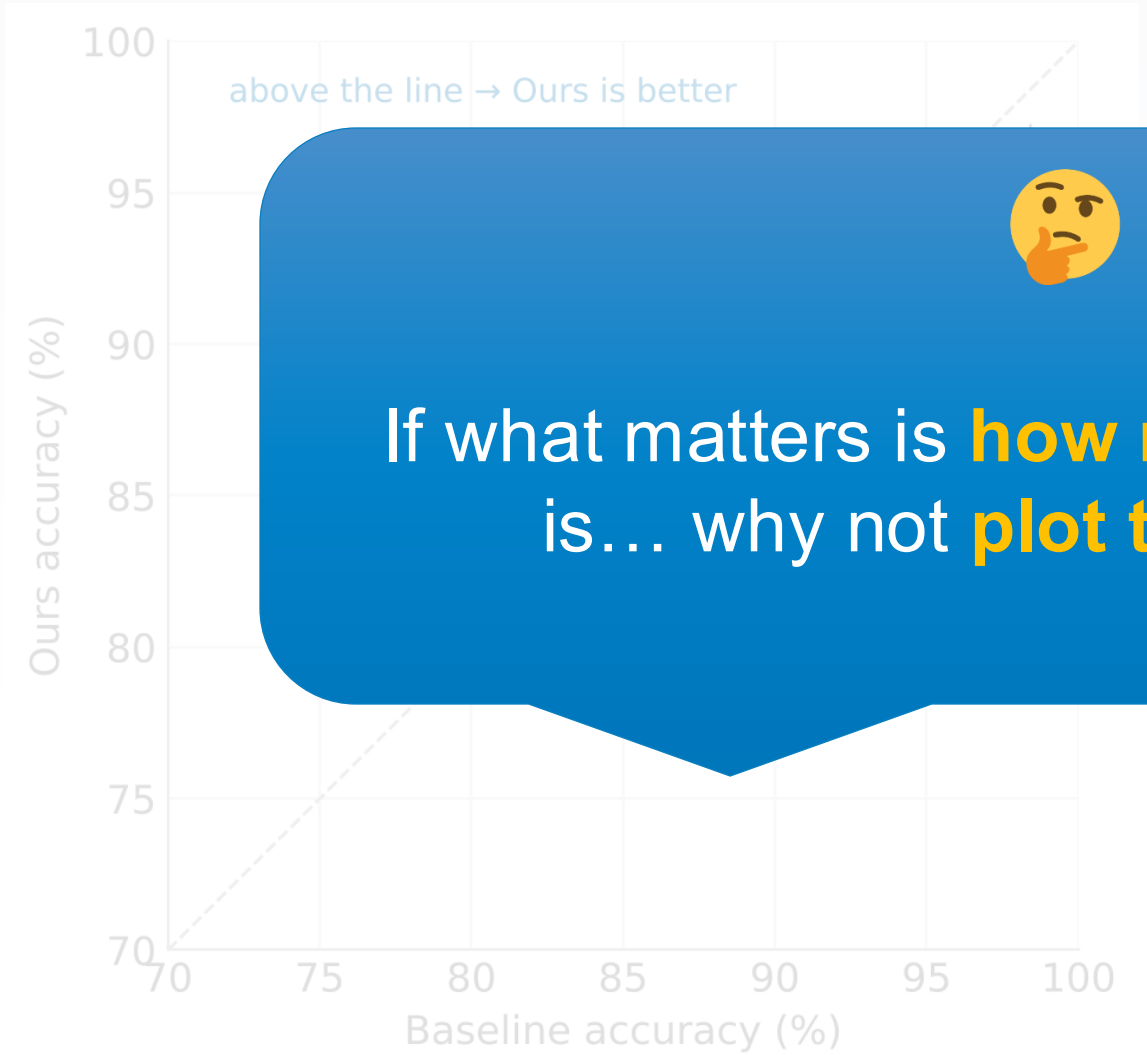
Answers…

*Does Ours help **more** where Baseline **struggles**?*

👍 Reveals a **relationship**: the harder the class, the bigger the gain

👎 Reader must understand the **diagonal**

Attempt 5 – Scatter against y = x



Answers…

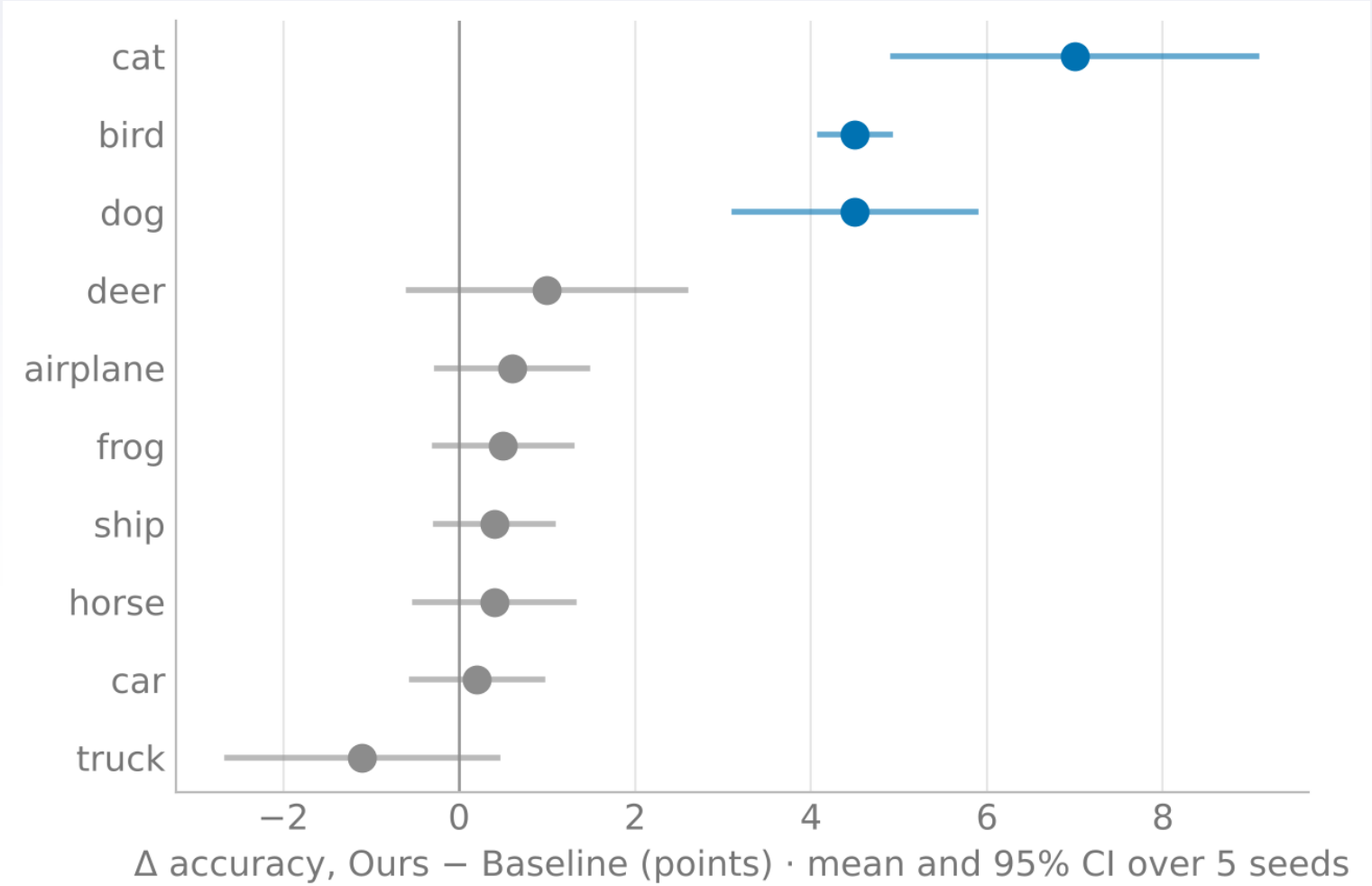
elp **more** where
ggles?

relationship: the
class, the bigger the

st understand the

If what matters is **how much better** Ours is… why not **plot that** variable?

Attempt 6 – Plot the difference



Answers…

***Where** does Ours improve, and is it **beyond noise**?*

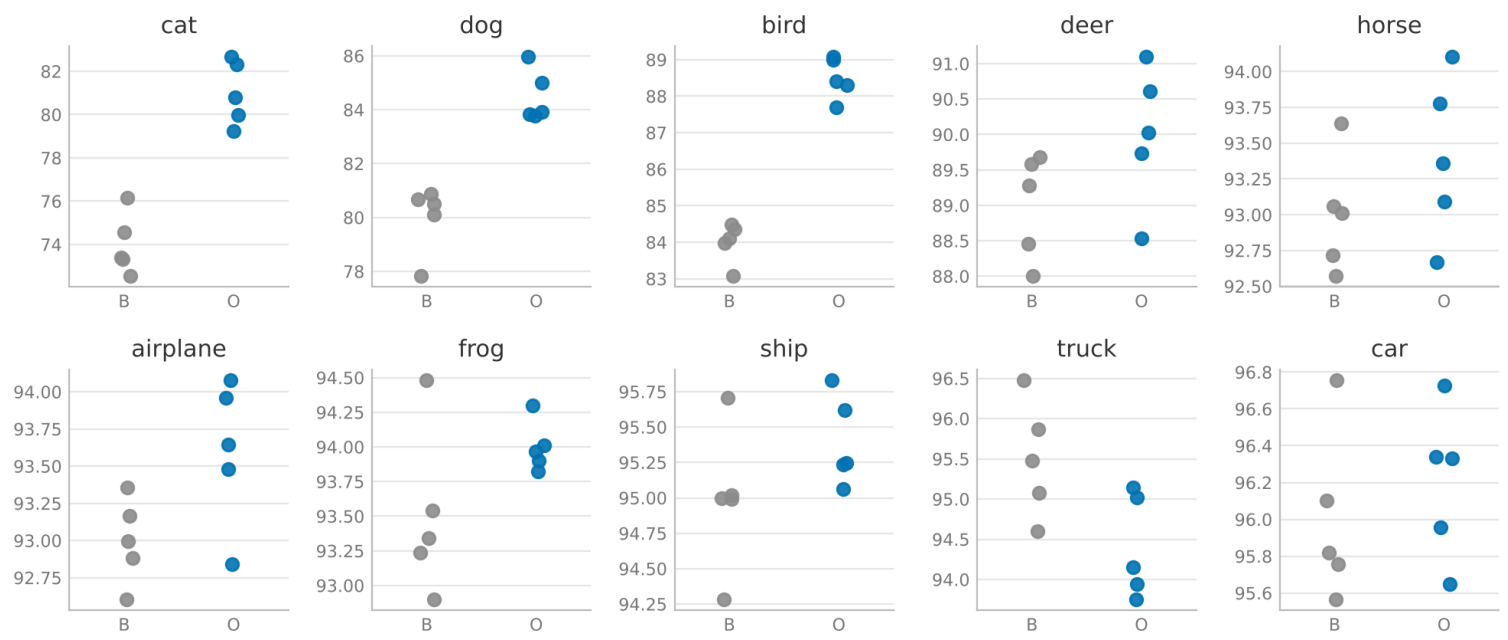
👍 The message **is** the chart

👍 CI shows the truck loss is **within noise**

👎 Absolute accuracies are lost

Knaflic, C. N. (2019). Storytelling with Data: Let's Practice! Wiley.

Attempt 7 – Show the seeds



Answers…

*How **robust** is each result across seeds?*

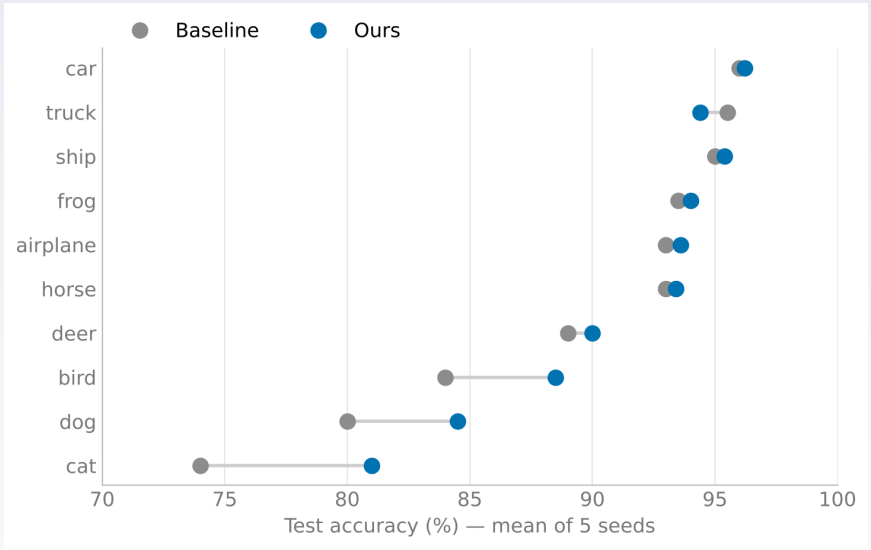
👍 Shows the **raw** variability

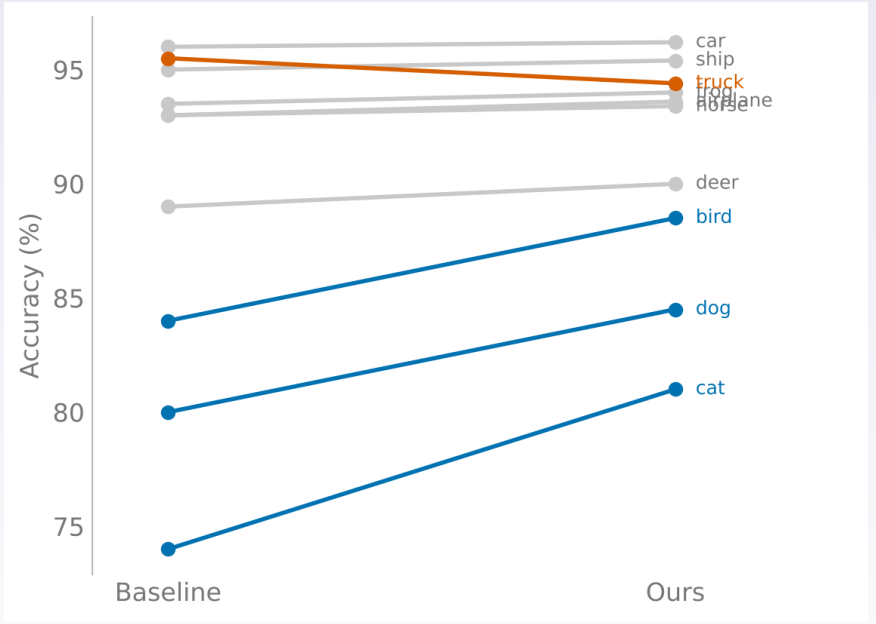
👎 Busy: better for the **appendix**

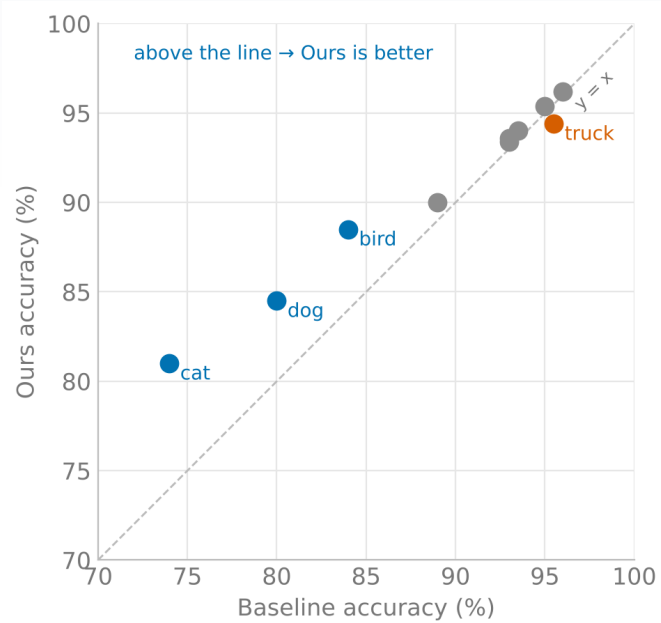
Weissgerber et al. (2015), PLOS Biology 13(4)

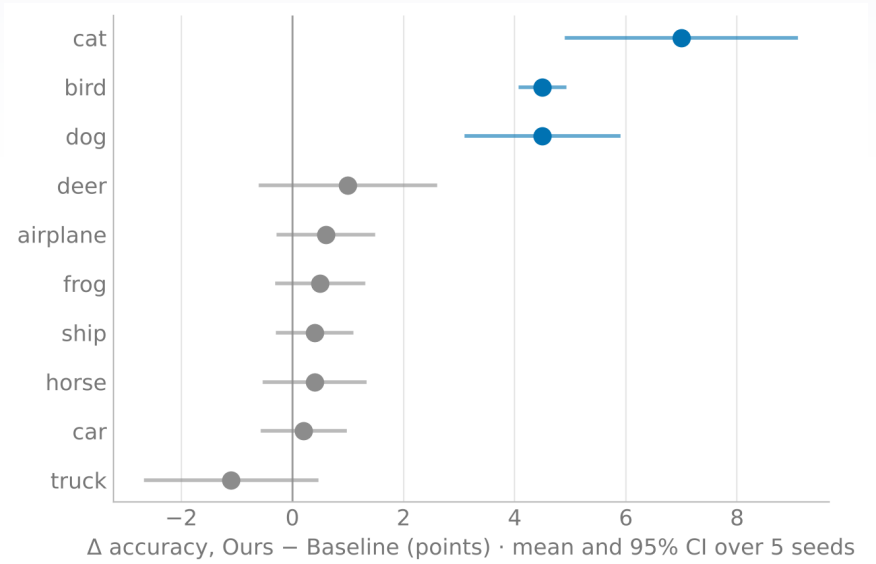


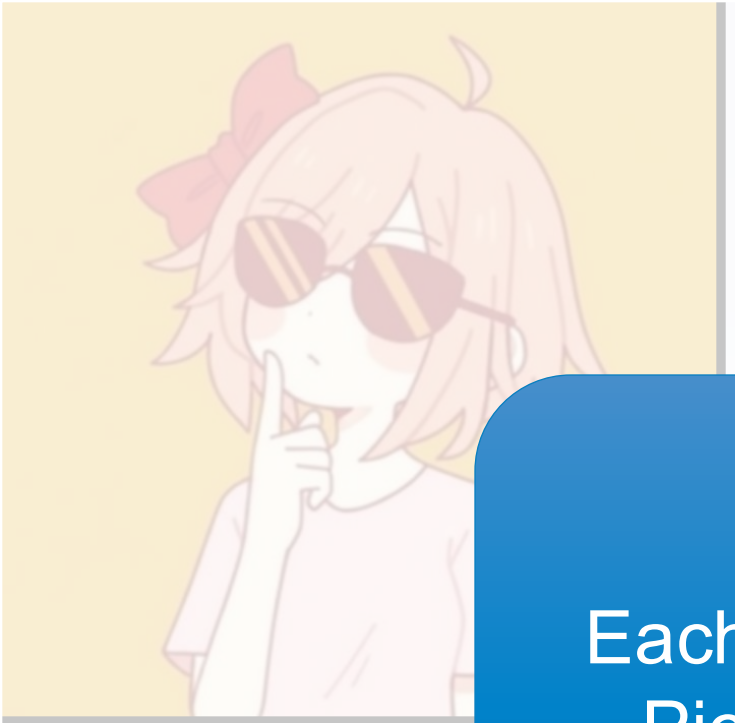


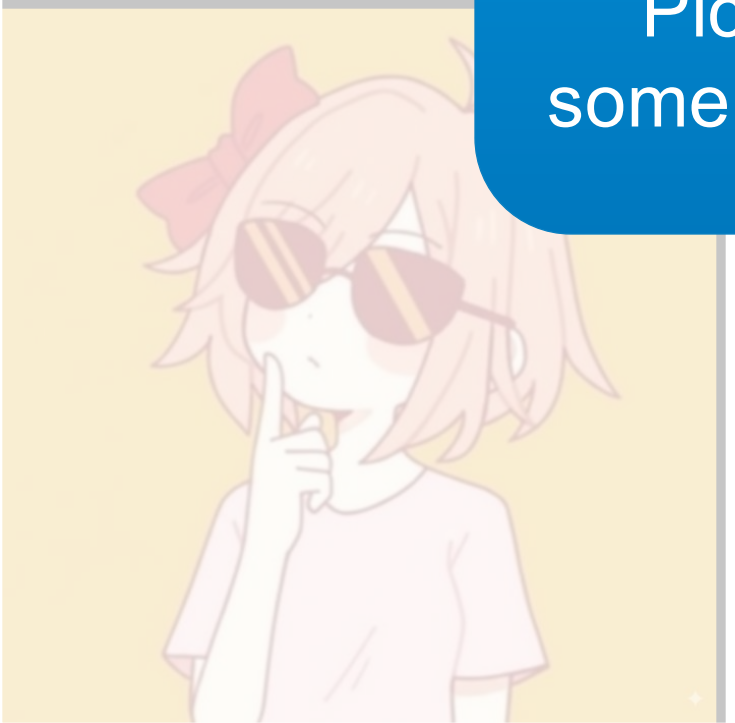

Baseline
Ours
car
truck
ship
frog
airplane
horse
deer
bird
dog
cat
70
75
80
85
90
95
100
Test accuracy (%) — mean of 5 seeds

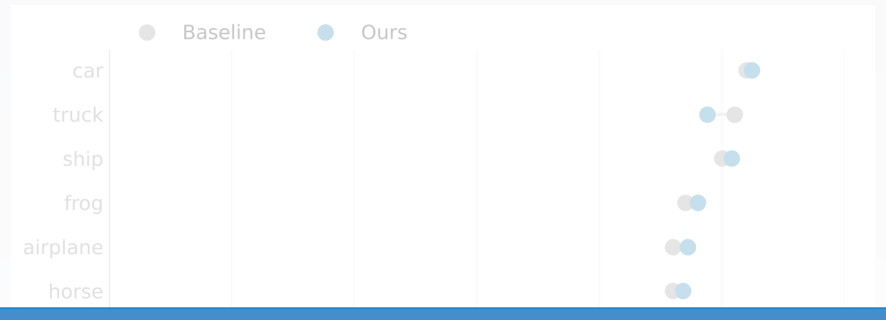

95
90
85
80
75
Accuracy (%)
car
ship
truck
frog
airplane
horse
deer
bird
dog
cat
Baseline
Ours

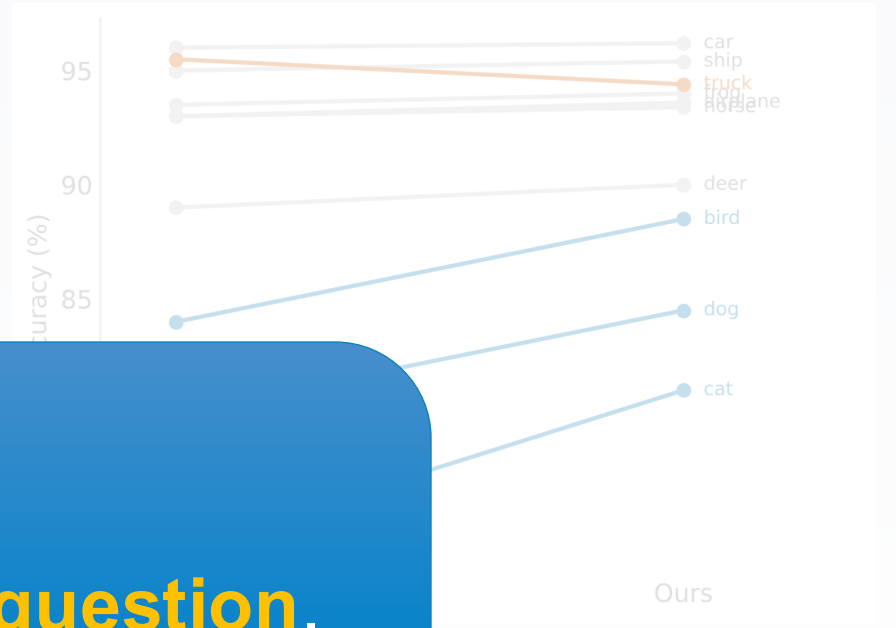

above the line → Ours is better
y = x
truck
bird
dog
cat
100
95
90
85
80
75
70
Ours accuracy (%)
70
75
80
85
90
95
100
Baseline accuracy (%)

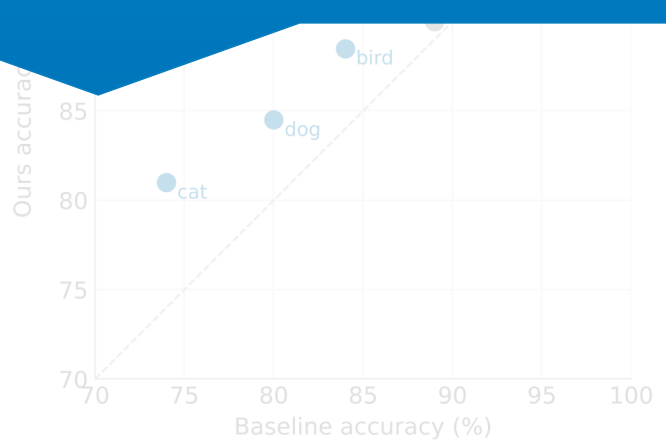

cat
bird
dog
deer
airplane
frog
ship
horse
car
truck
−2
0
2
4
6
8
Δ accuracy, Ours − Baseline (points) · mean and 95% CI over 5 seeds

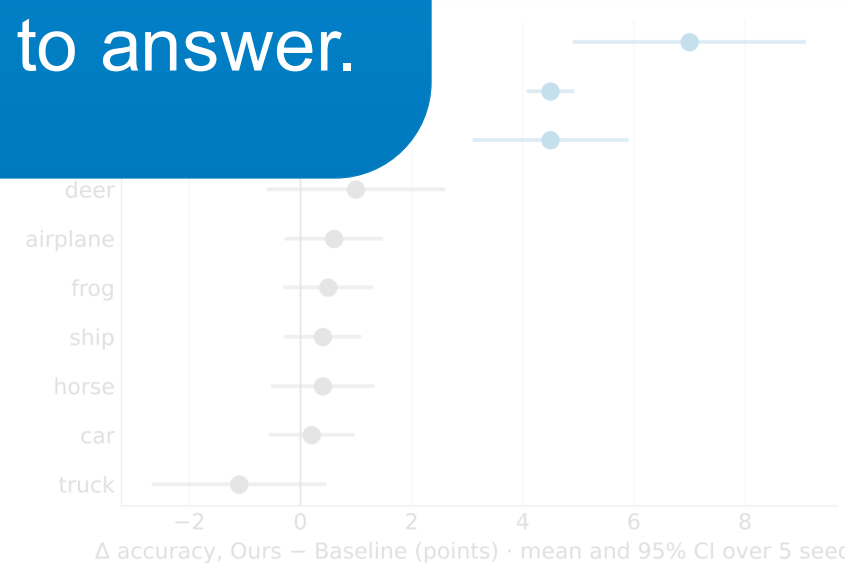






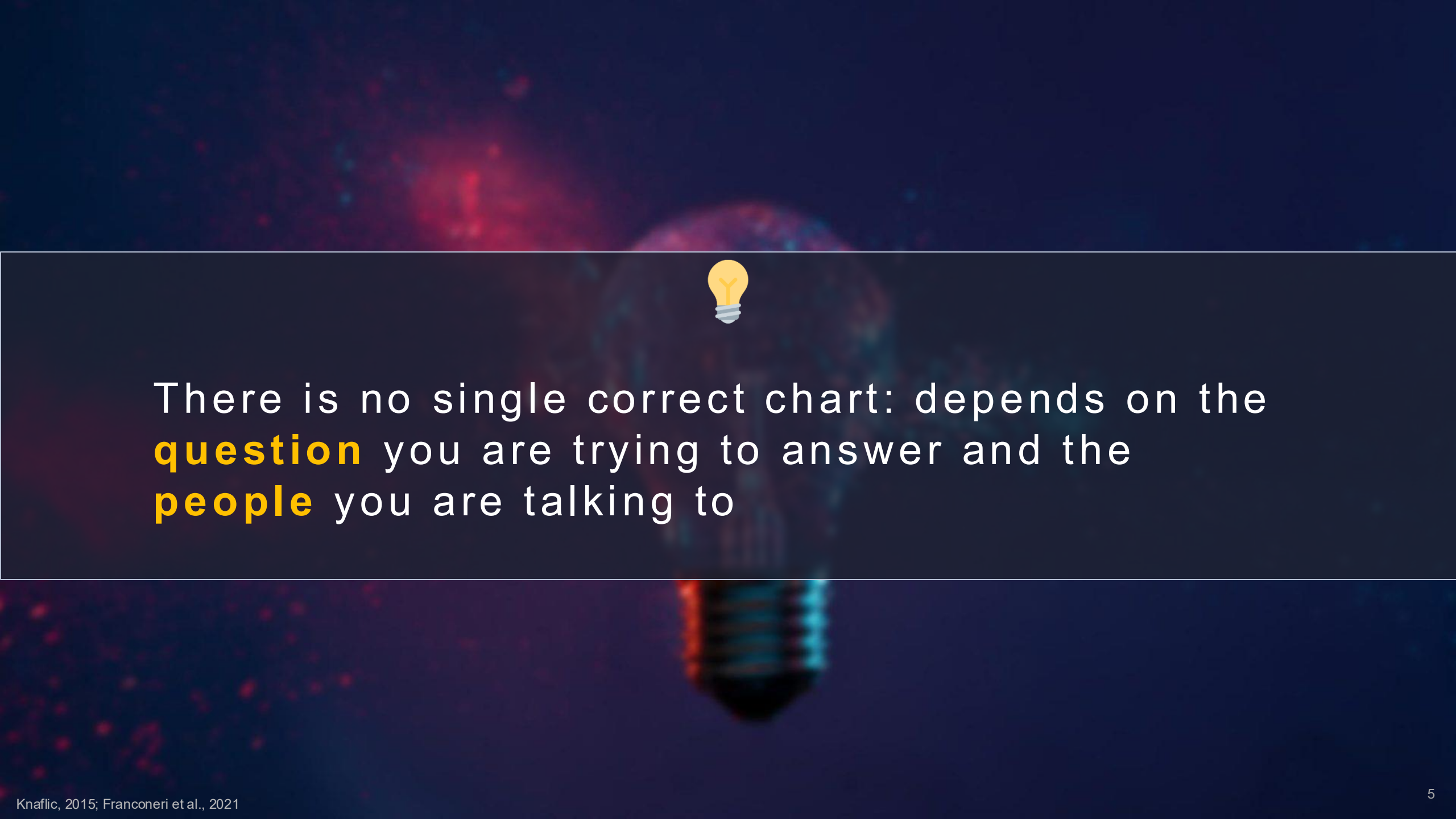








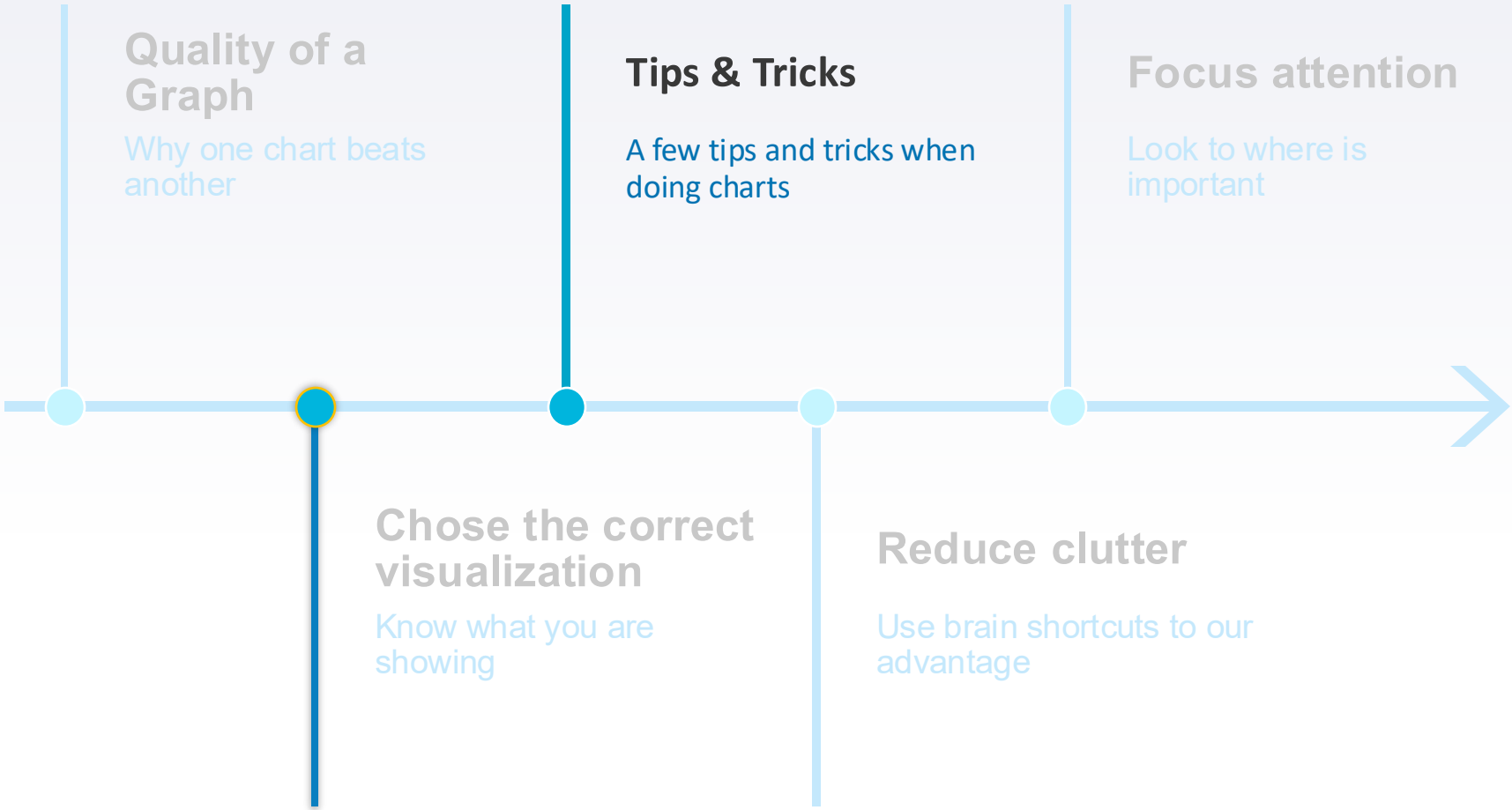
Each chart answers a **different question**. Pick the one that answers **yours**. Take some time to think what you want to answer.



There is no single correct chart: depends on the **question** you are trying to answer and the **people** you are talking to

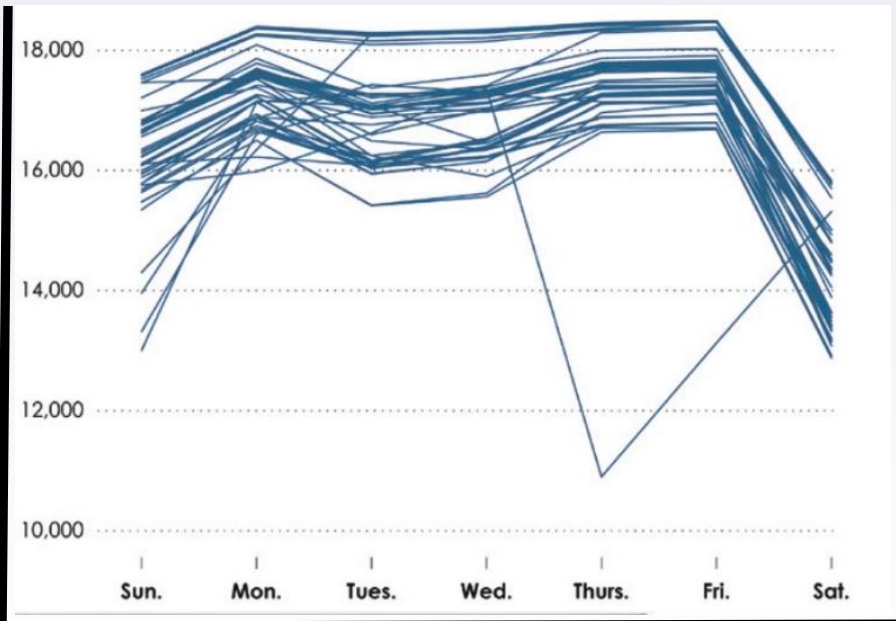
Knaflic, 2015; Franconeri et al., 2021

Today

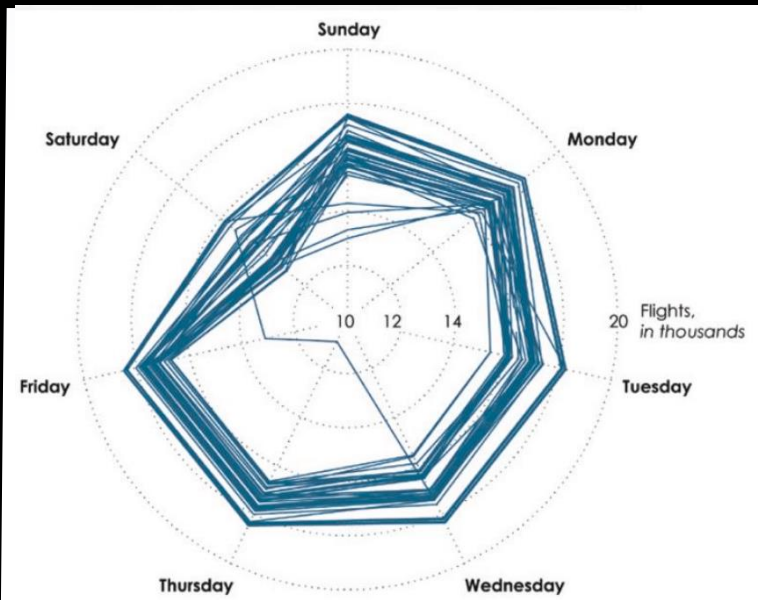

Quality of a Graph
Why one chart beats another
Tips & Tricks
A few tips and tricks when doing charts
Focus attention
Look to where is important
Chose the correct visualization
Know what you are showing
Reduce clutter
Use brain shortcuts to our advantage

Periodic Data



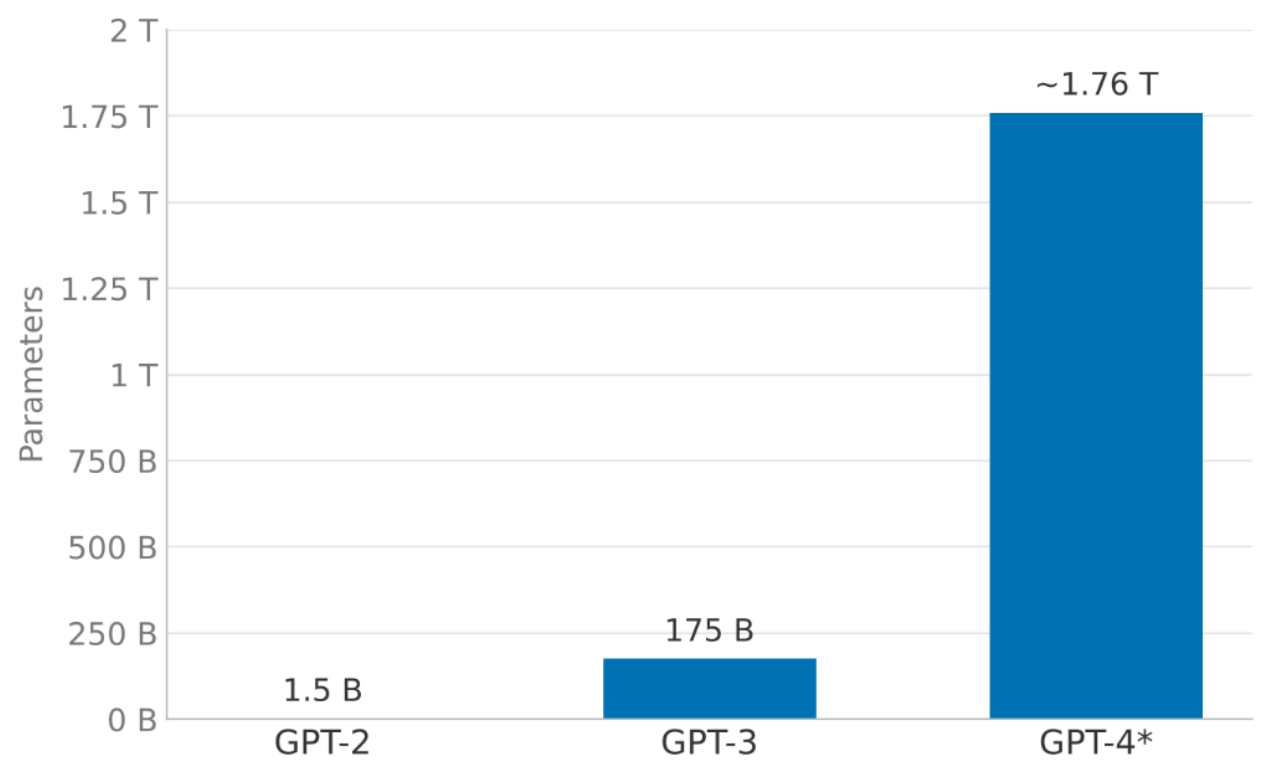






For **periodic** data better use **polar** coordinates

Comparing data with huge differences in scale



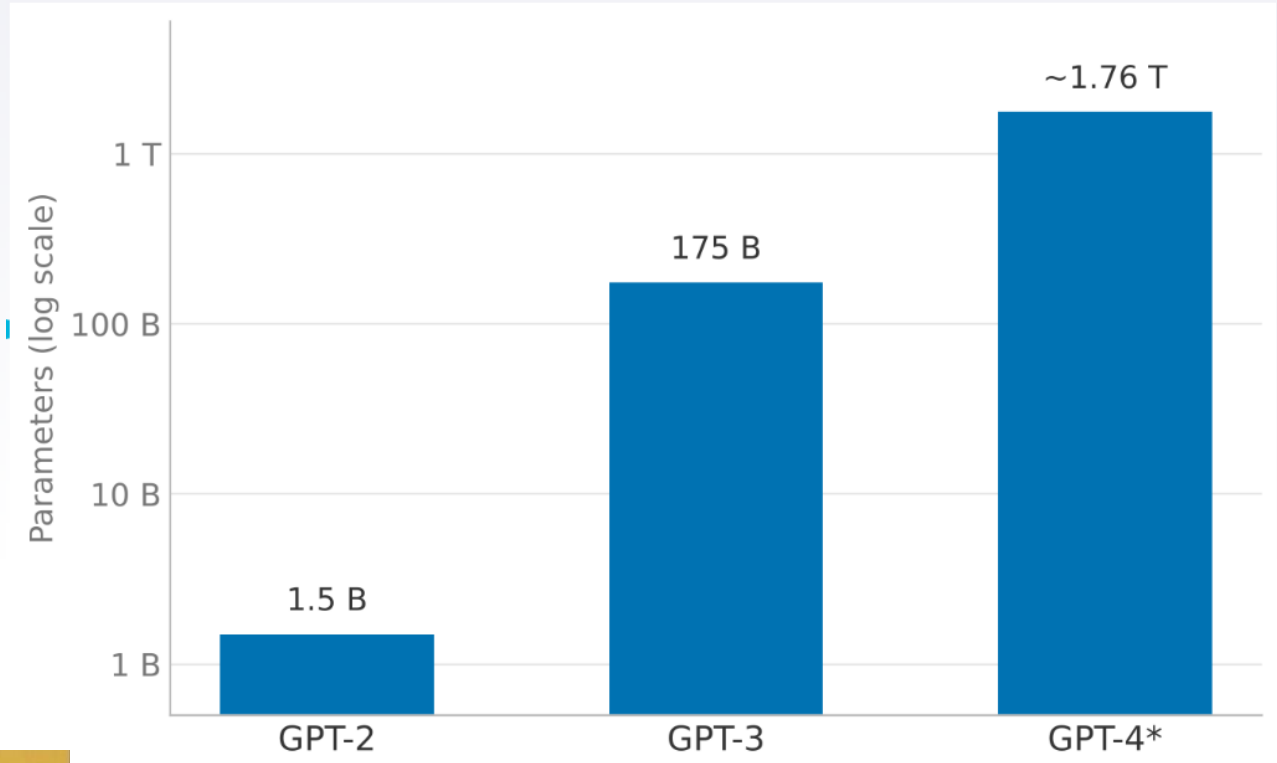
Answers…

How big is each model?

👍 Honest to read: length proportional to size

👎 GPT-2 is not visible: ~0.1 % of GPT-4

Comparing data with huge differences in scale: log-scale





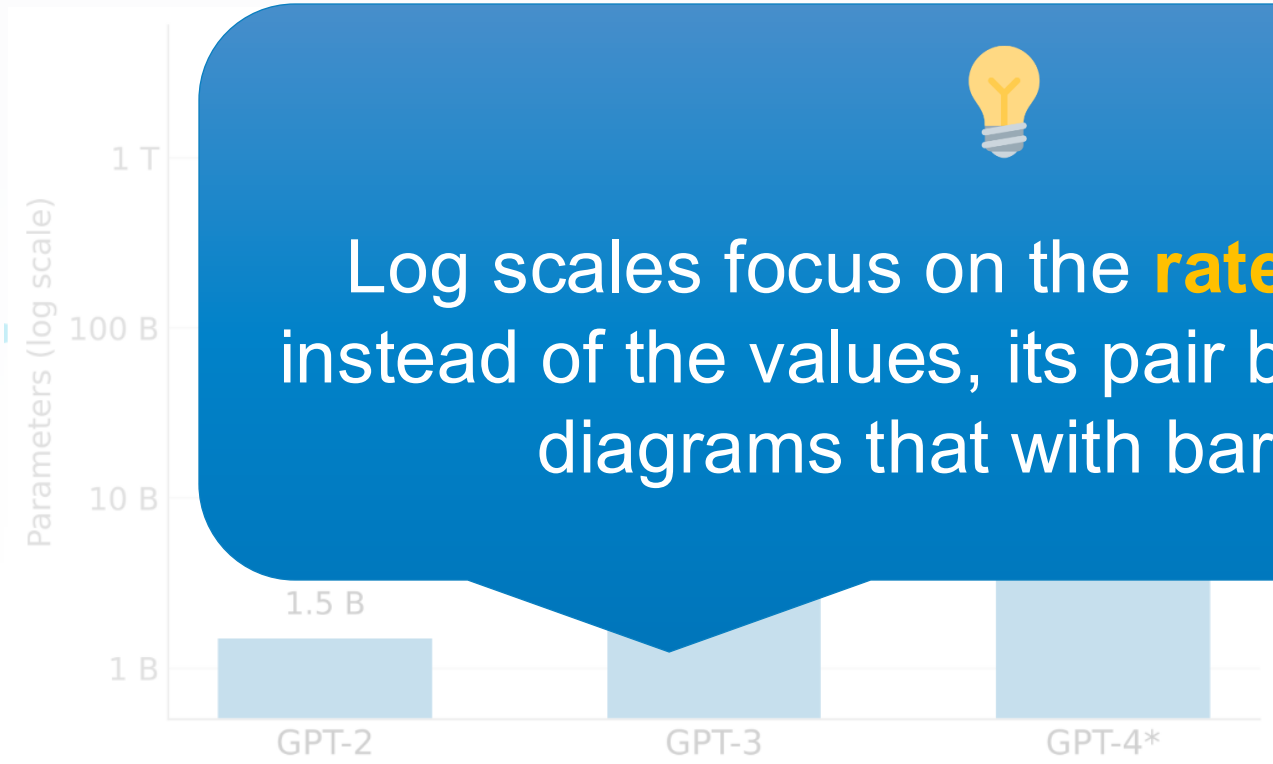
Answers…

How big is each model?

👍 With linear scale, now GPT-2 is visible

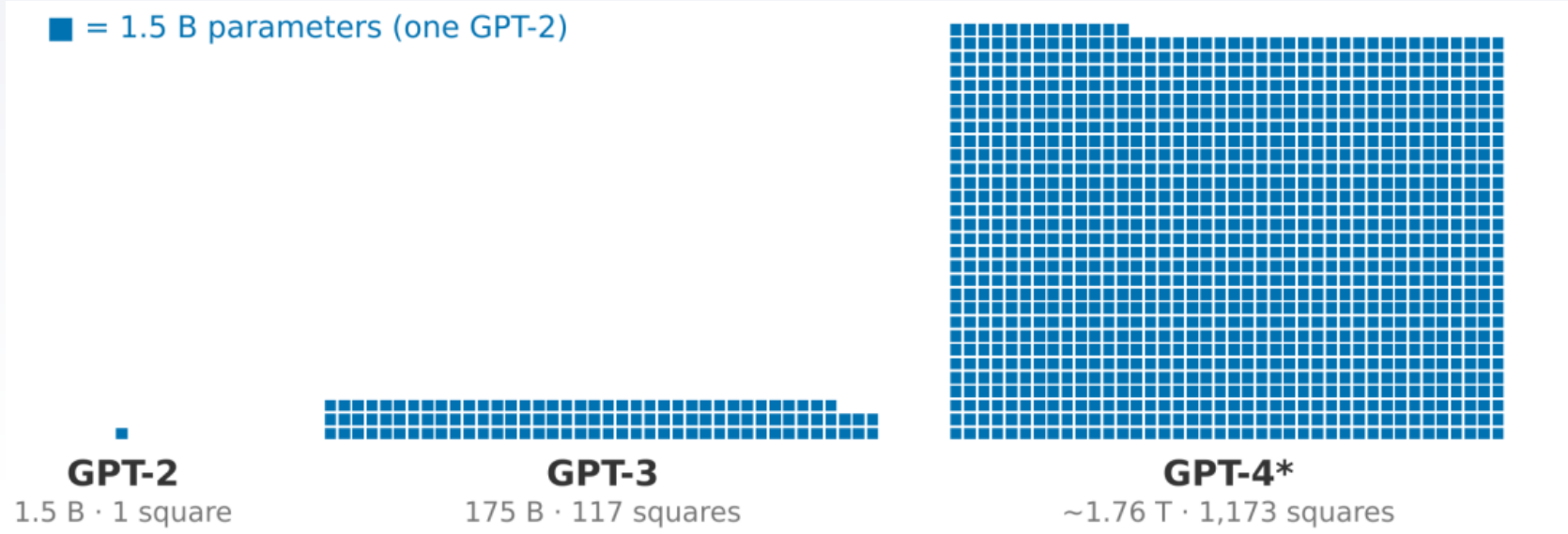
👎 Bar lenghts mean nothing here. The graphic could be deceptive.

Comparing data with huge differences in scale



Log scales focus on the **rate of change** instead of the values, its pair better with line diagrams that with bar plots.

Comparing data with huge differences in scale



Answers…

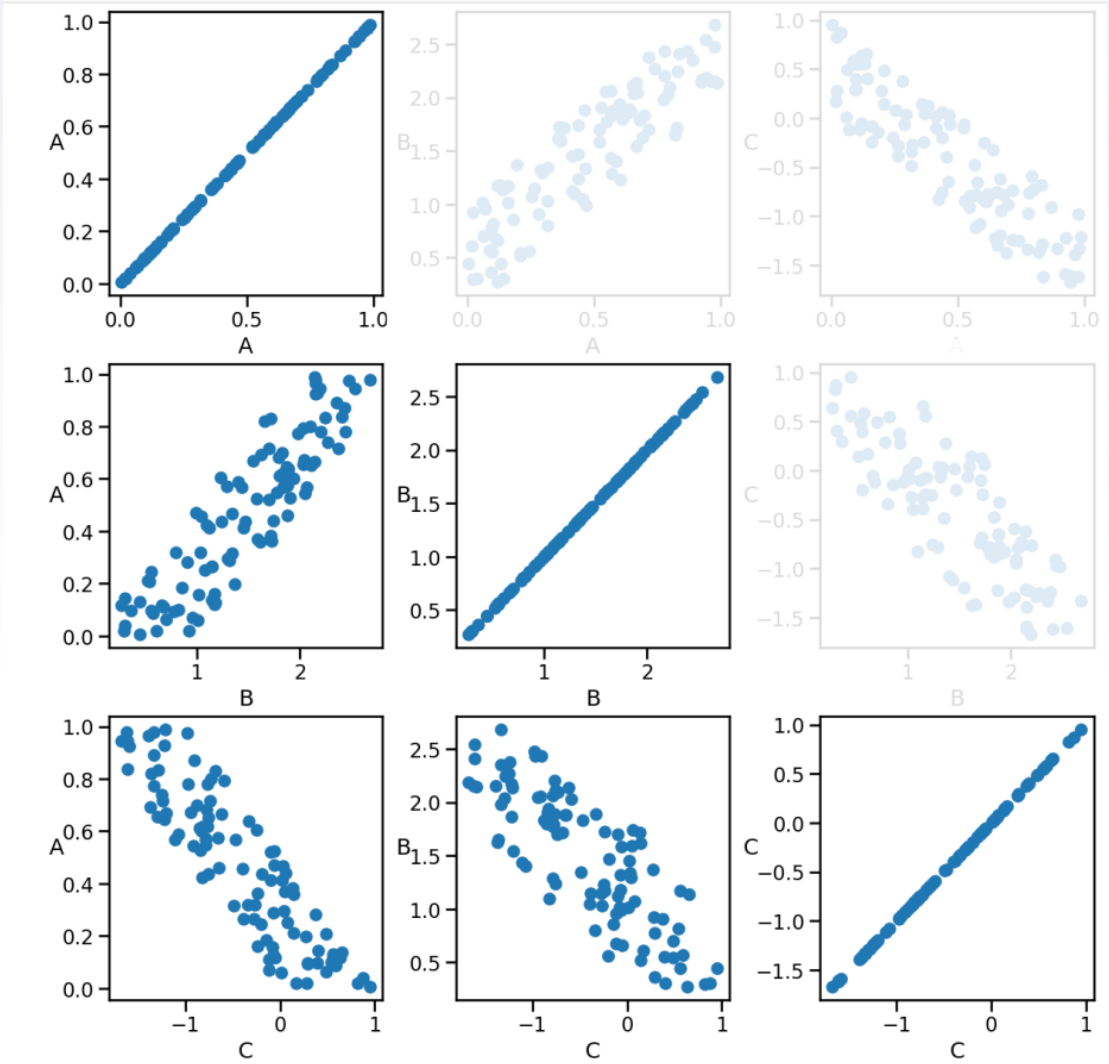
How big is each model?

👍 The difference is size is felt at a glance.

👎 Area is less accurate. Include specific values as annotations



Relation between variables



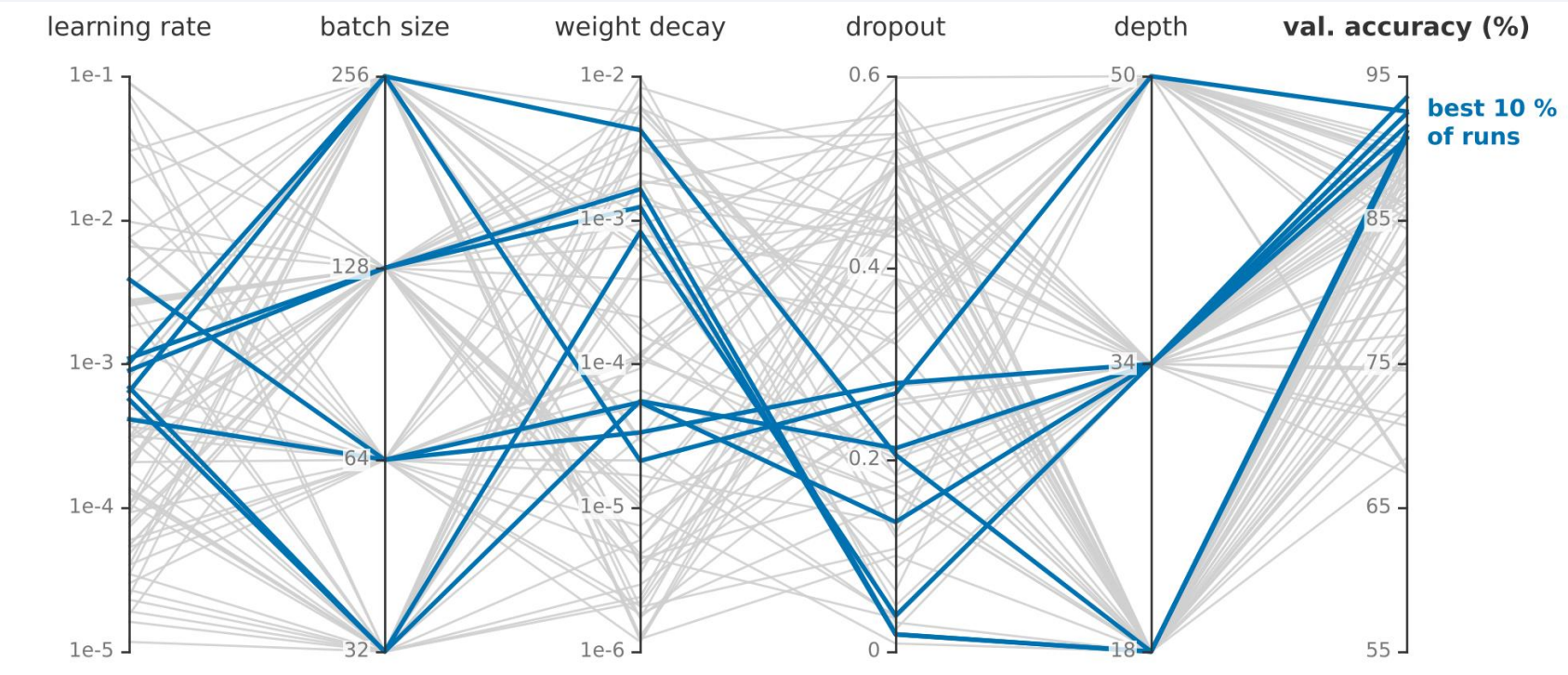
Answers…

Are variables correlated?

👍 Each plot is easy to read

👎 Scales poorly if there are many variables

Relation between variables: Parallel plots



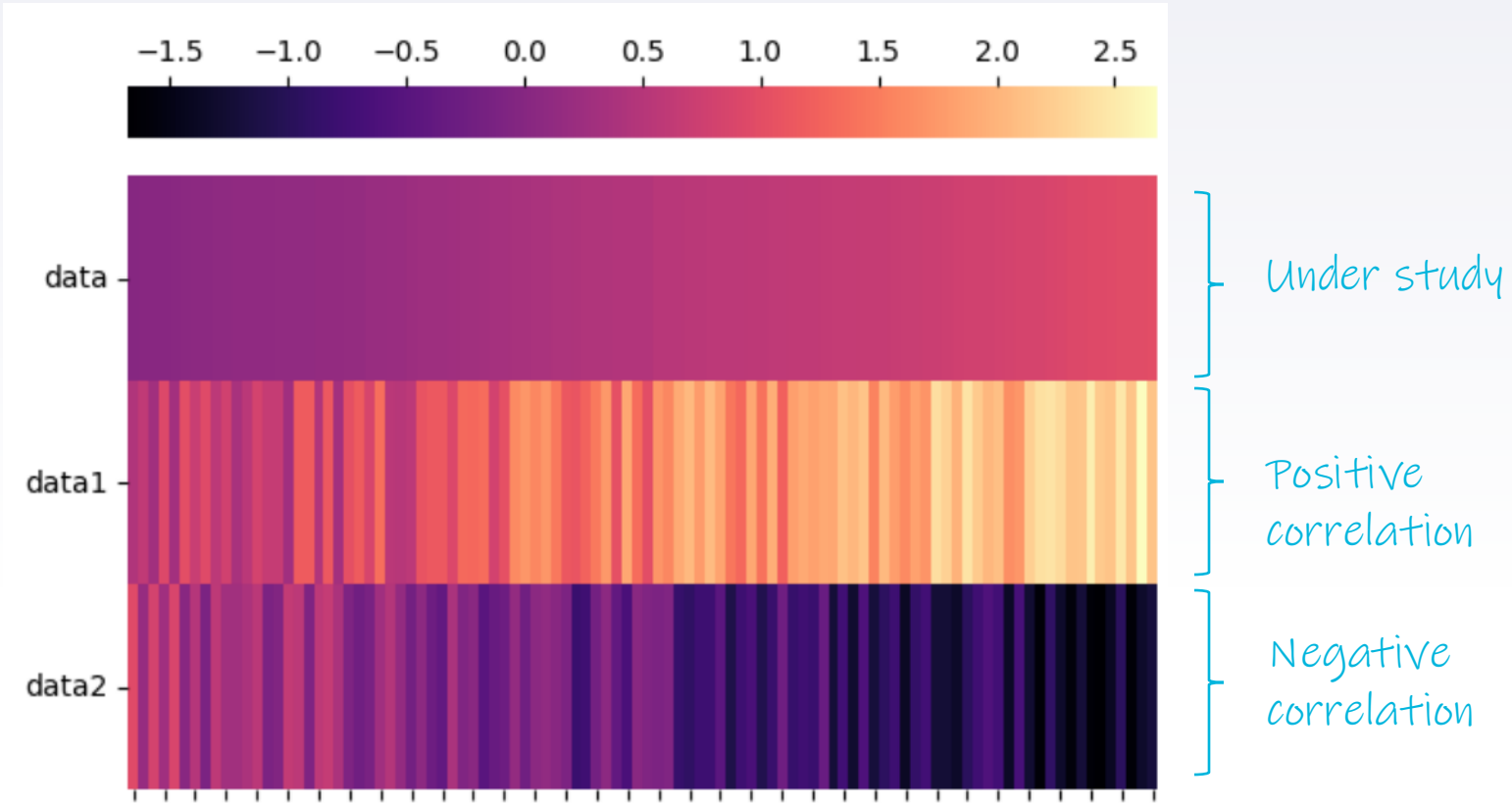
Answers…

Are variables correlated?

👍 Scales to a lot of variables

👎 Highlight and mutter to avoid spaguetti

Correlation 1xN variables



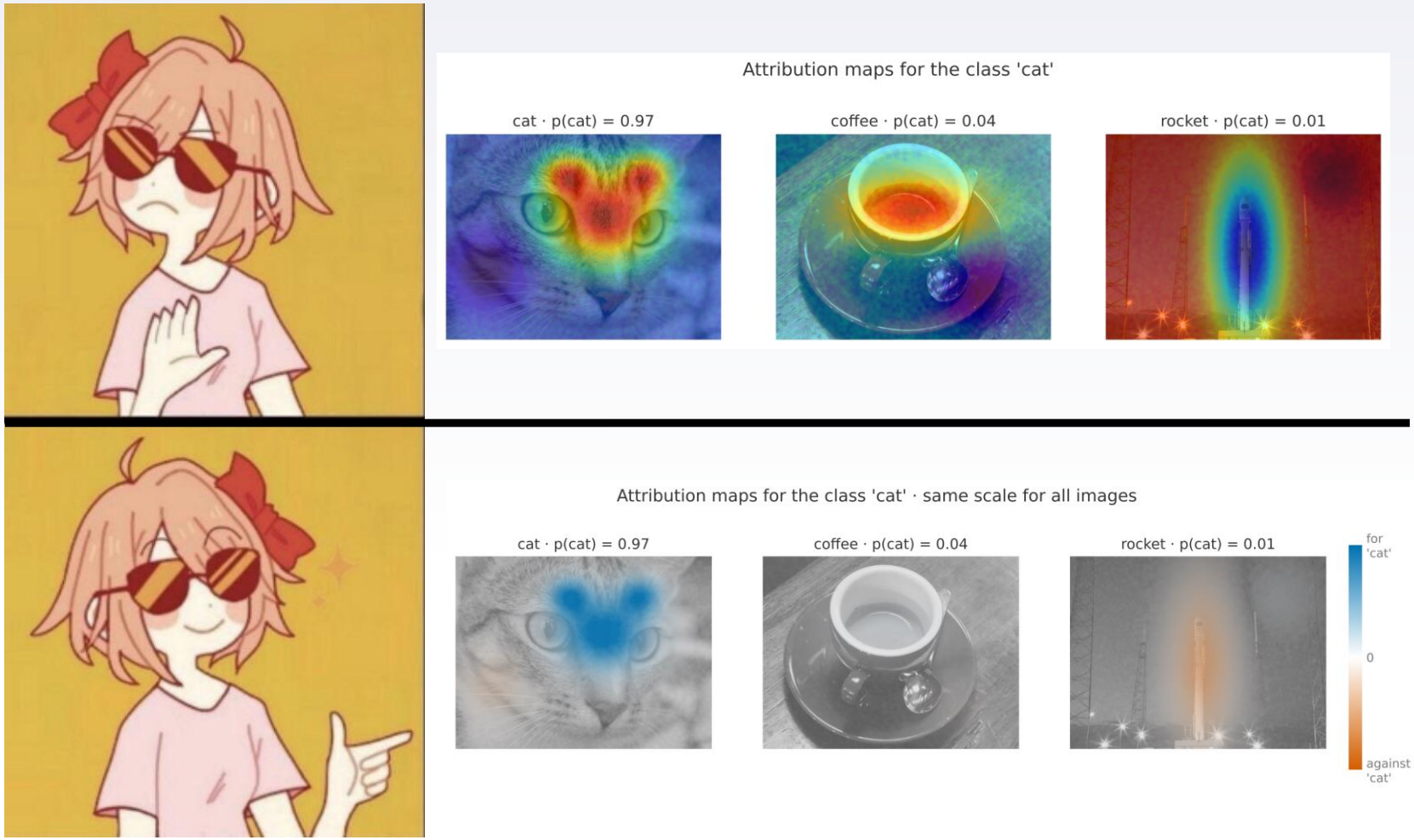
Answers…

Are variables correlated?

👍 Easy to scale to a lot of variables

👎 Less accurate to read and only 1xN

Comparing heatmaps



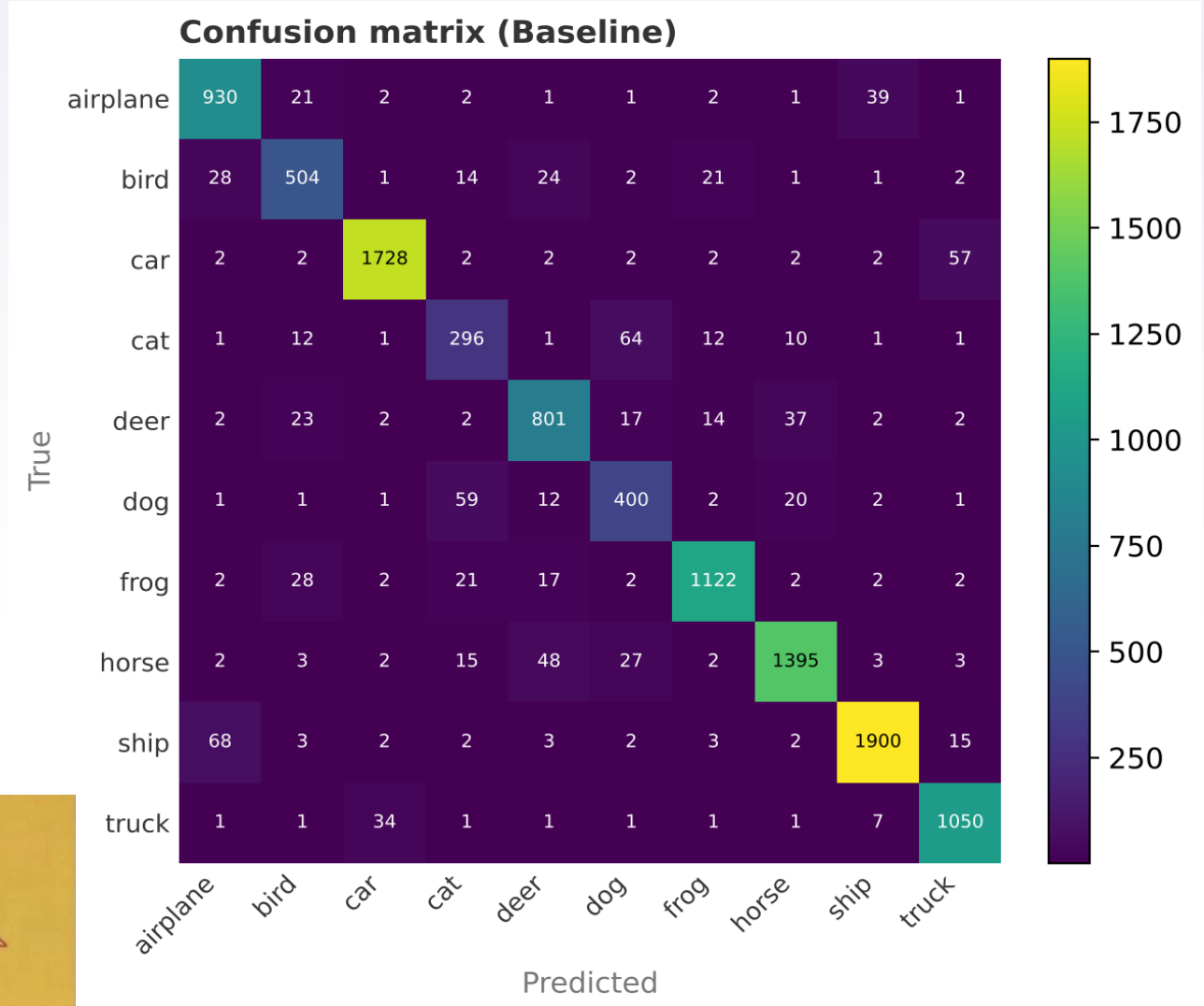
Answers…

Where does the model look for class cat

👍 When heatmaps are compared the scale must be shared

👎 If there are big outliers you cannot see anything

Confusion matrices





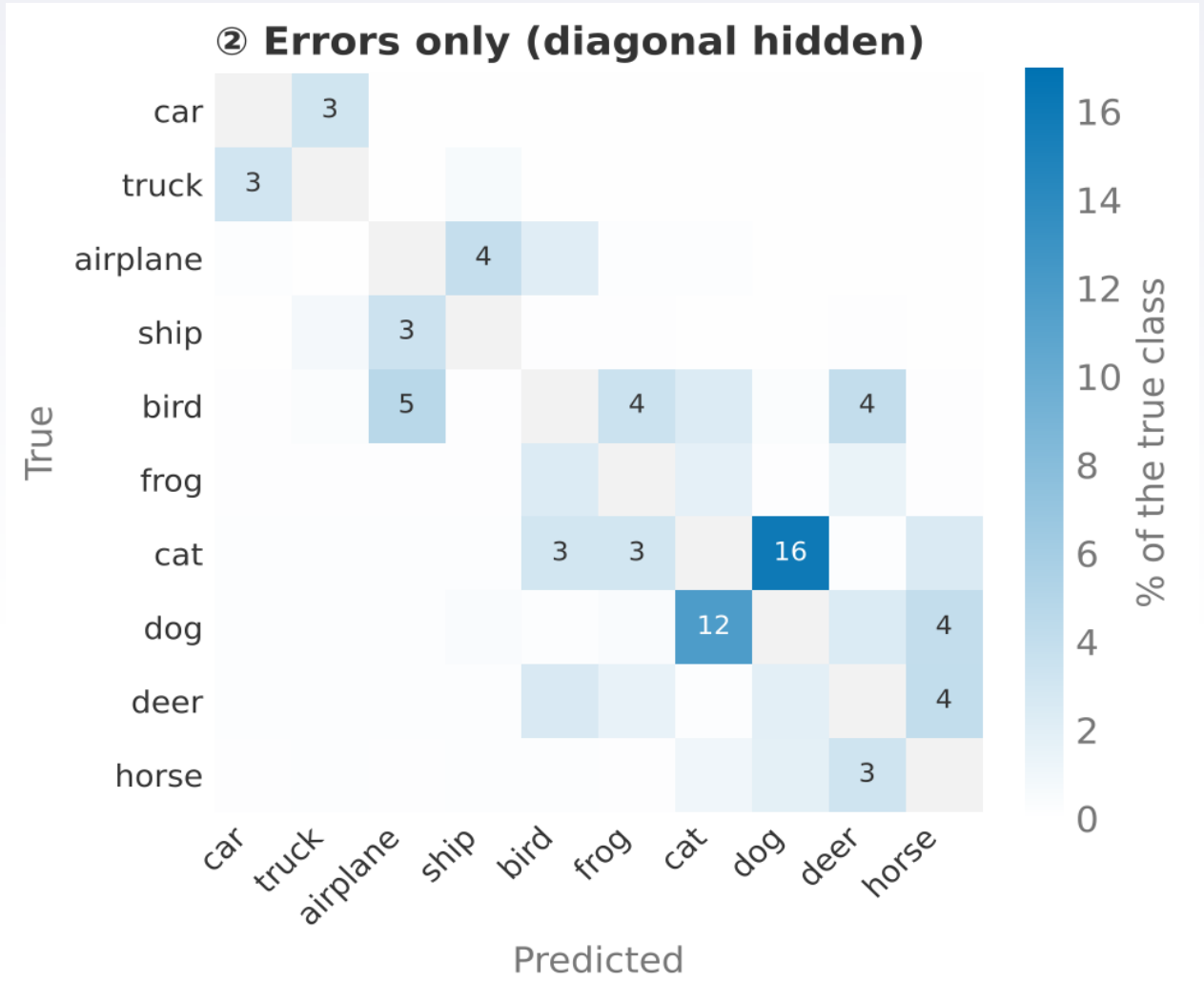
Answers…

On which class my model fails

👎 Hard to read, you follow the numbers

👎 Errors are not highlighted; your eyes move to the diagonal (correct values)

Confusion matrices: plot only errors



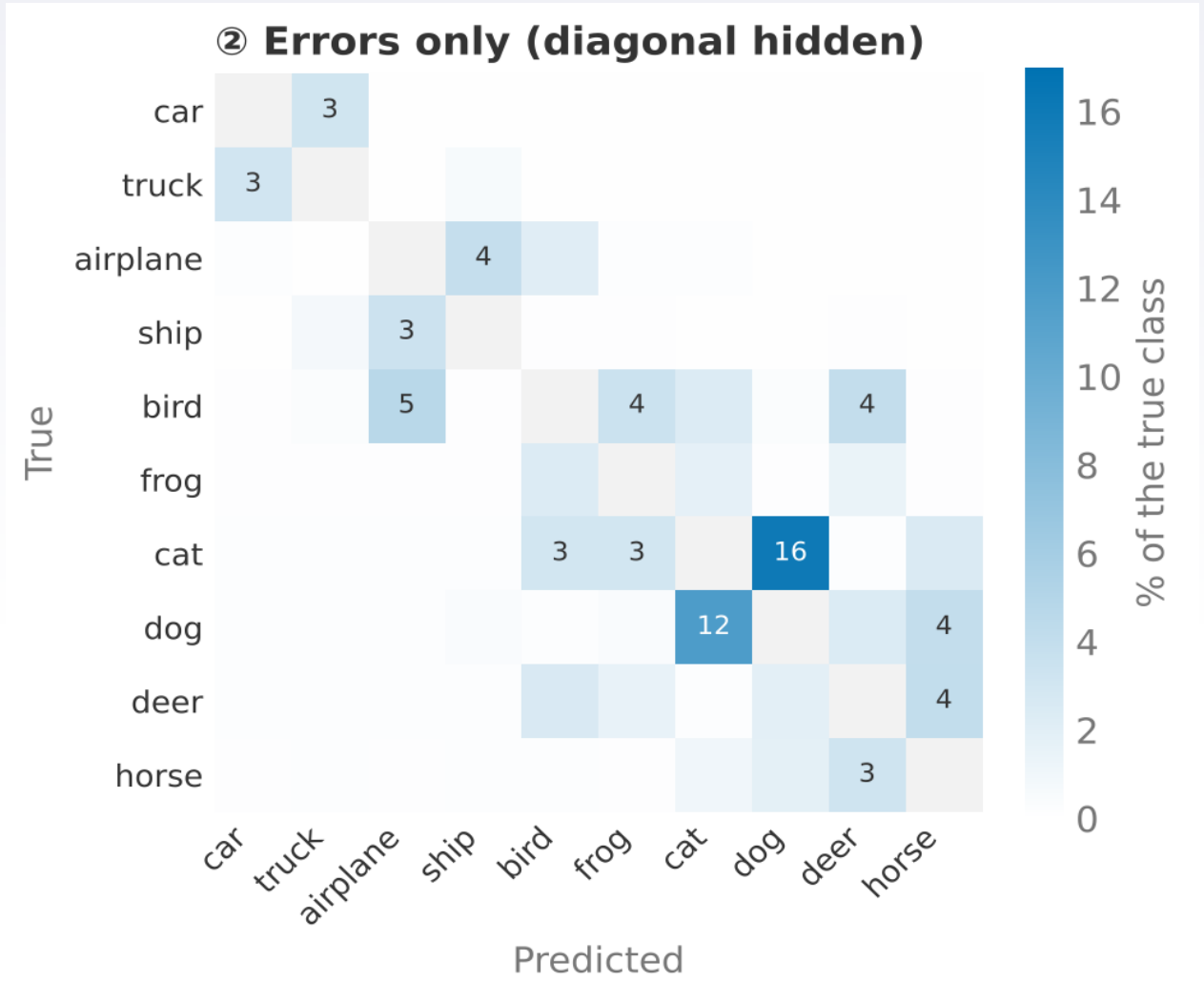
Answers…

On which class my model fails

👍 Your eyes move errors directly.
Easier to read



Confusion matrices: plot only errors



Answers…

On which class my model fails

👍 Your eyes move errors directly.
Easier to read



Confusion matrices: plot differences



Answers…

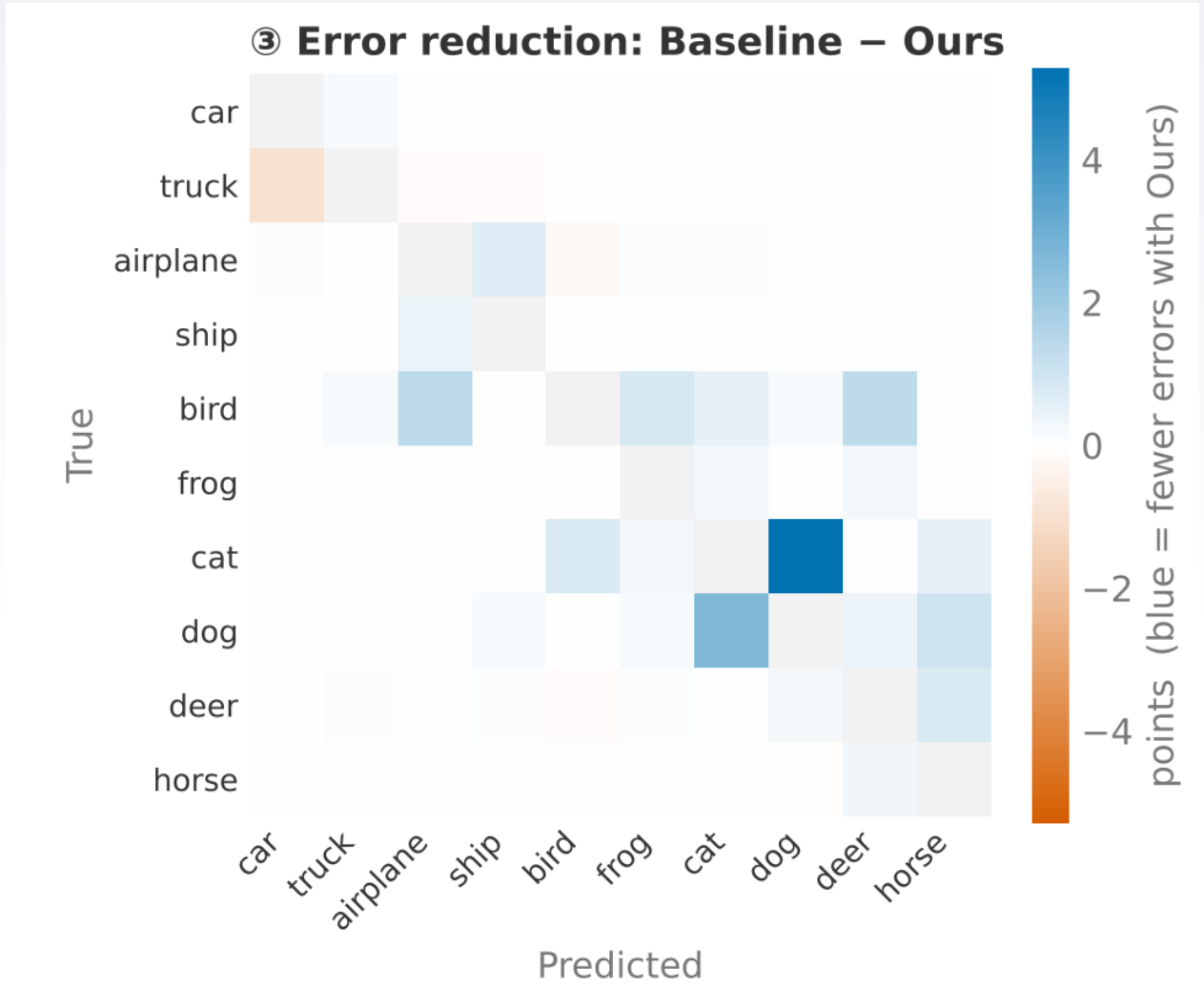
ss my model fails

e where you win and
underperform

💡

When you compare against a baseline, plot the differences with a divergent palette

Confusion matrices: plot differences



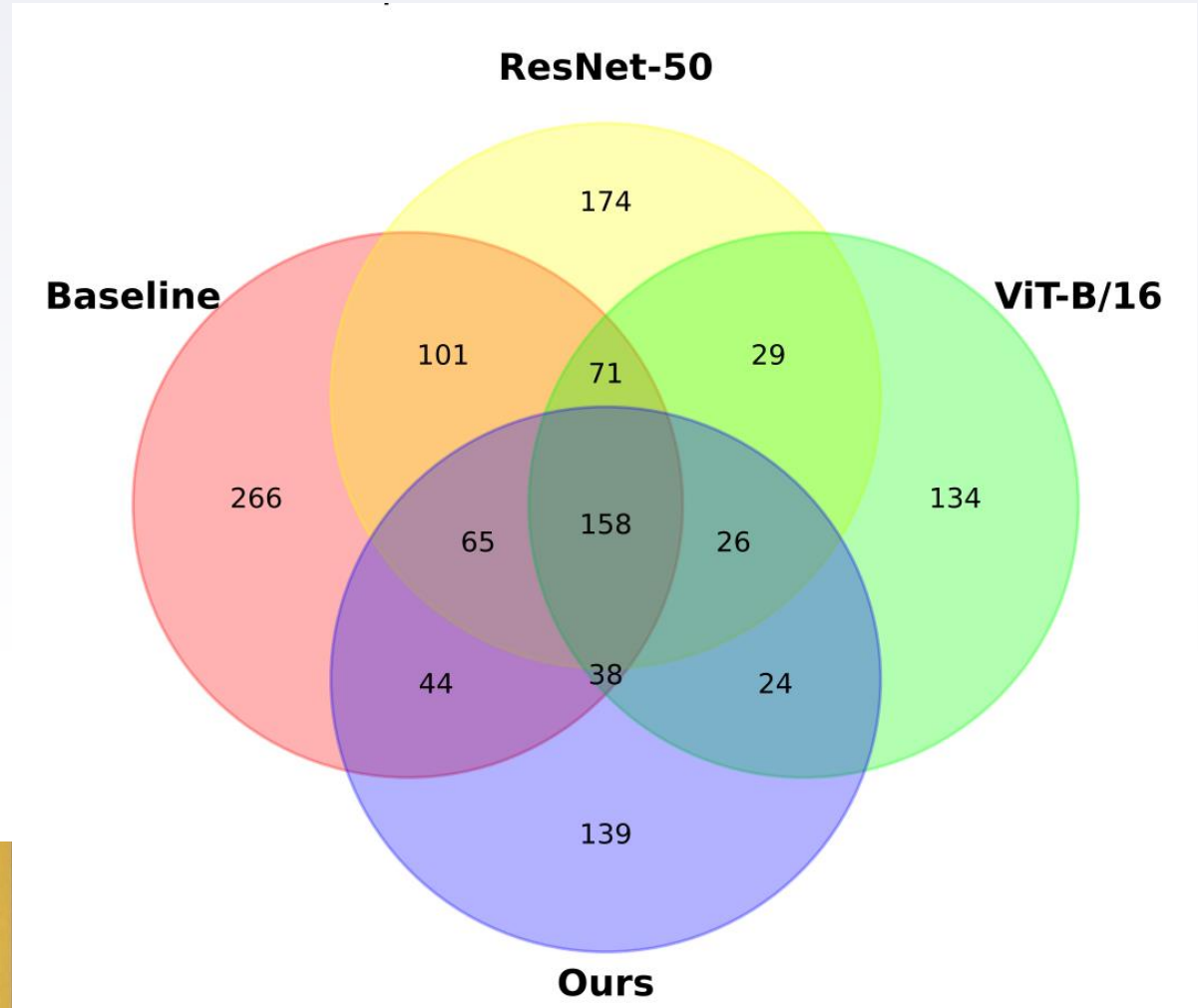


Answers…

On which class my model fails

👍 Easy to see where you win and where you underperform

Intersection and differences



Answers…

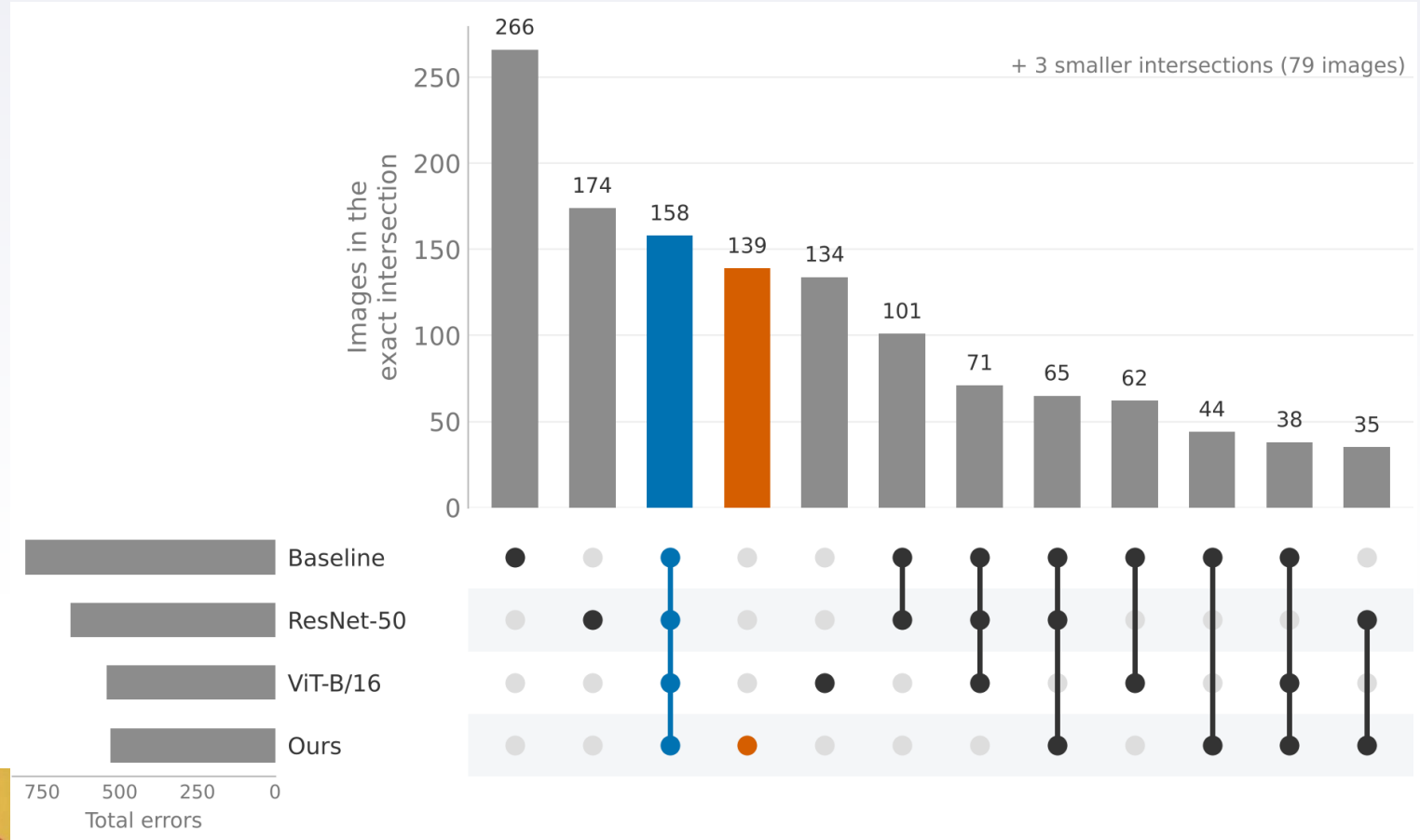
Which unique and common erros has each model?

👎 Some options are missing

👎 Are does not mean anything, you need to read the numbers



Intersection and differences



Answers…

Which unique and common erros has each model?

👍 All combinations are present

👍 Area has meaning and can be compared visually.



Lex et al. (2014), “UpSet: Visualization of Intersecting Sets”, *IEEE TVCG* 20(12)

Compare many datasets and models: Table

Dataset	Ours	ViT-B/16	ResNet-50	ConvNeXt-T	Baseline
D01	81.9 (2)	**82.8 (1)**	81.7 (3)	80.7 (5)	80.8 (4)
D02	**80.7 (1)**	78.2 (3)	78.9 (2)	77.7 (4)	77.6 (5)
D03	84.2 (3)	**85.1 (1)**	84.5 (2)	83.7 (4)	82.2 (5)
D04	**88.3 (1)**	87.4 (3)	86.7 (4)	87.5 (2)	85.5 (5)
D05	**93.3 (1)**	92.6 (2)	89.7 (4)	91.1 (3)	89.1 (5)
D06	**87.2 (1)**	86.9 (2)	84.6 (5)	85.5 (3)	84.7 (4)
D07	**84.7 (1)**	82.5 (3)	83.7 (2)	81.4 (4)	81.3 (5)
D08	81.9 (4)	**83.7 (1)**	82.4 (3)	83.5 (2)	81.1 (5)
D09	**91.1 (1)**	90.8 (2)	89.0 (4)	88.9 (5)	89.4 (3)
D10	94.4 (2)	**94.6 (1)**	94.0 (3)	93.9 (4)	92.2 (5)
D11	87.8 (2)	**87.9 (1)**	87.3 (3)	85.8 (5)	86.6 (4)
D12	79.3 (2)	79.1 (3)	78.5 (4)	**79.9 (1)**	77.9 (5)
D13	80.9 (2)	80.5 (3)	**81.4 (1)**	79.5 (4)	78.5 (5)
D14	**95.2 (1)**	93.2 (3)	93.5 (2)	93.2 (4)	92.0 (5)
D15	87.6 (2)	**88.5 (1)**	86.3 (3)	85.1 (4)	83.8 (5)
D16	**77.8 (1)**	77.3 (3)	77.4 (2)	76.1 (4)	75.3 (5)
D17	**85.5 (1)**	85.4 (3)	85.5 (2)	84.4 (4)	84.1 (5)
D18	**82.5 (1)**	80.9 (3)	78.6 (5)	80.9 (2)	78.9 (4)
D19	82.6 (3)	**84.0 (1)**	82.7 (2)	81.5 (4)	80.7 (5)
D20	83.3 (3)	83.9 (2)	**84.3 (1)**	82.5 (4)	82.3 (5)
Average rank	**1.75**	**2.10**	**2.85**	**3.60**	**4.70**

Test accuracy (%) and rank on each dataset (1 = best, in blue). Synthetic data. Friedman p ≈ 4e-9; Nemenyi CD = 1.36.

Answers…

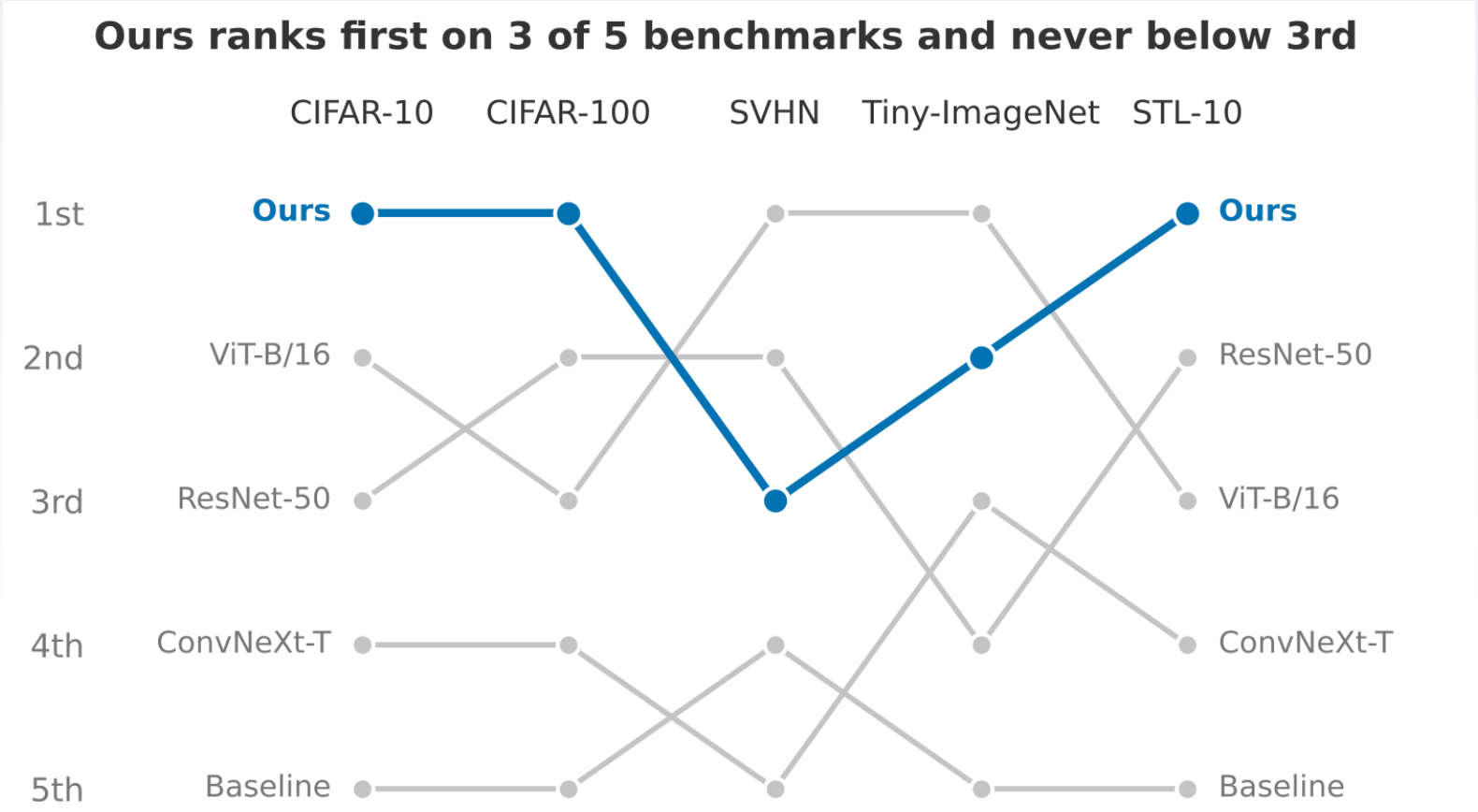
Which model wins on each dataset?

👍 Good for a paper, very complete.

👎 Bad for presentations and posters not enough time to read and listen



Compare many datasets and models: bumb chart



Answers…

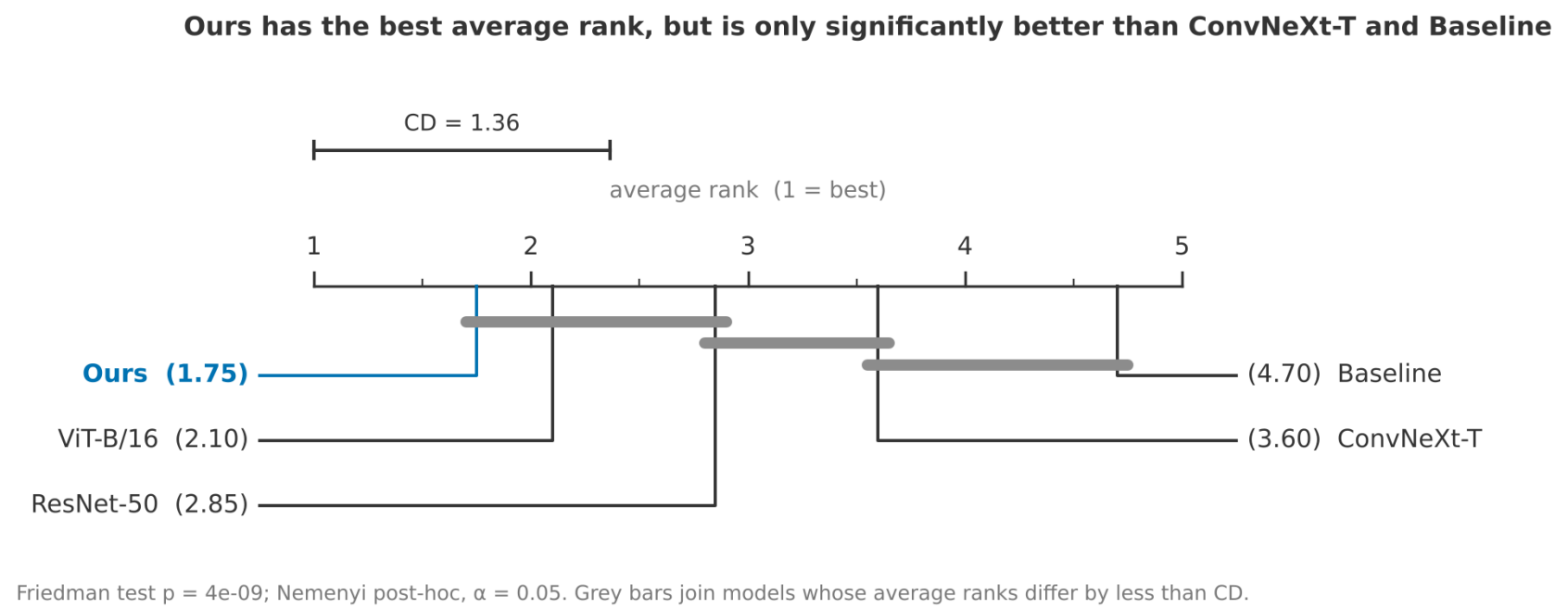
Which model wins on each dataset?

👍 Good for presentation

👎 Only ranking, you miss buy how much



Compare many datasets and models: bumb chart



Answers…

Which model wins on each dataset?

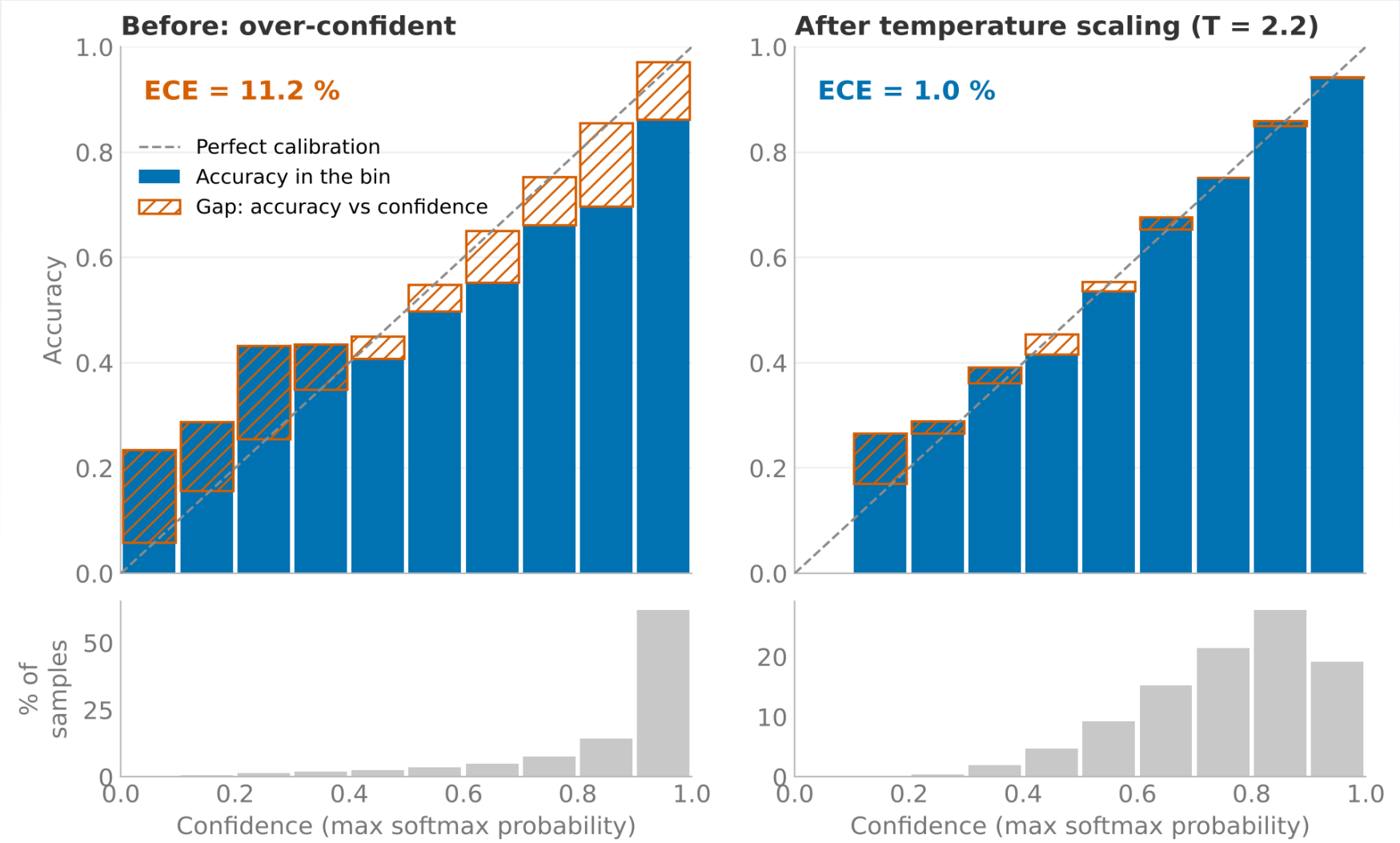
👍 Ranking, and by how much

👎 You loss fine grain information of the datasets



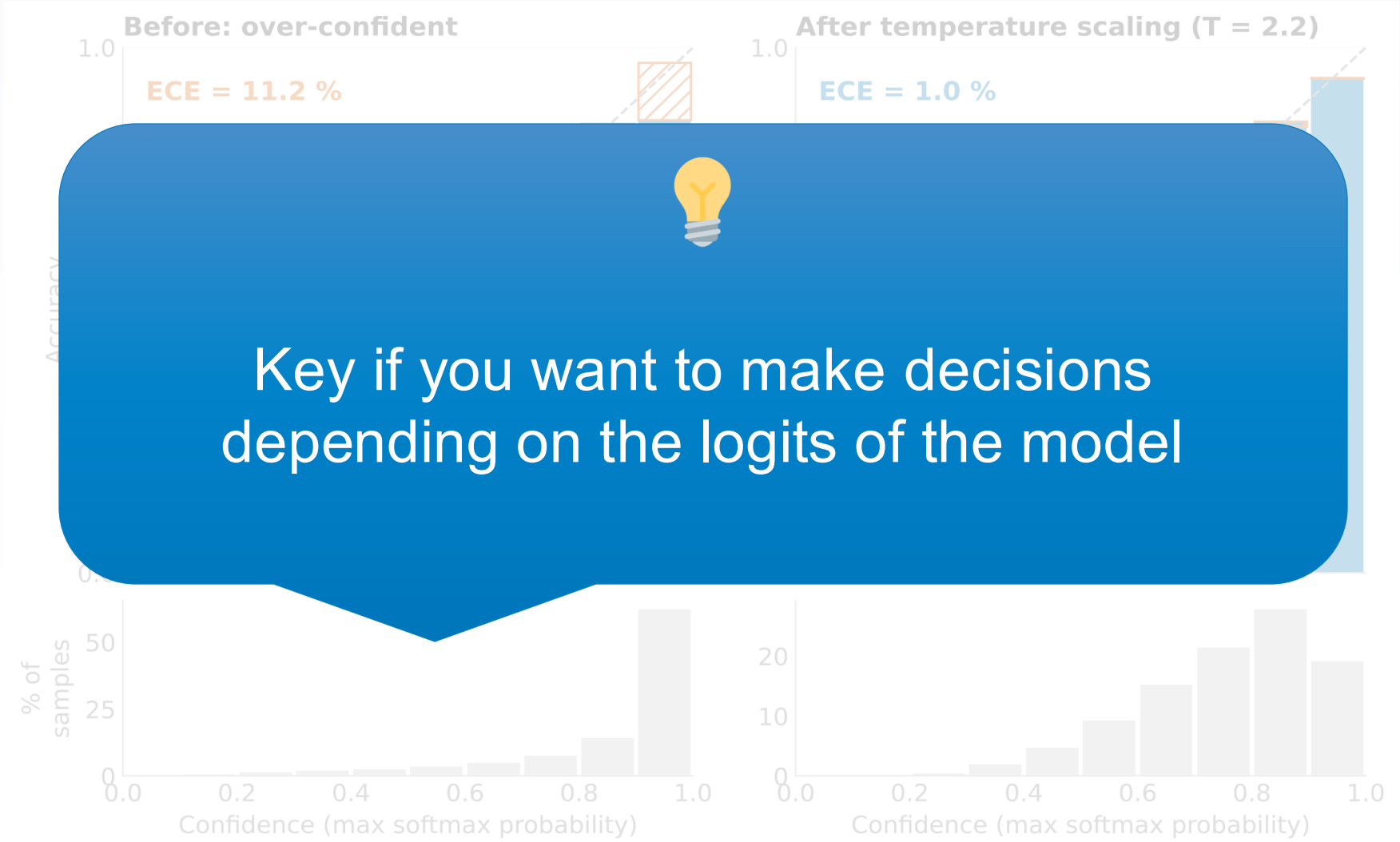
Demšar, J. (2006). Statistical comparisons of classifiers over multiple data sets. *Journal of Machine Learning Research, 7*, 1–30

Show calibration of the model when working with confidence



Guo, C., Pleiss, G., Sun, Y., & Weinberger, K. Q. (2017). On calibration of modern neural networks. In Proceedings of the 34th International Conference on Machine Learning, PMLR 70, 1321–1330.Guo, C., Pleiss, G., Sun, Y., & Weinberger, K. Q. (2017). On calibration of modern neural networks. In Proceedings of the 34th International Conference on Machine Learning, PMLR 70, 1321–1330.

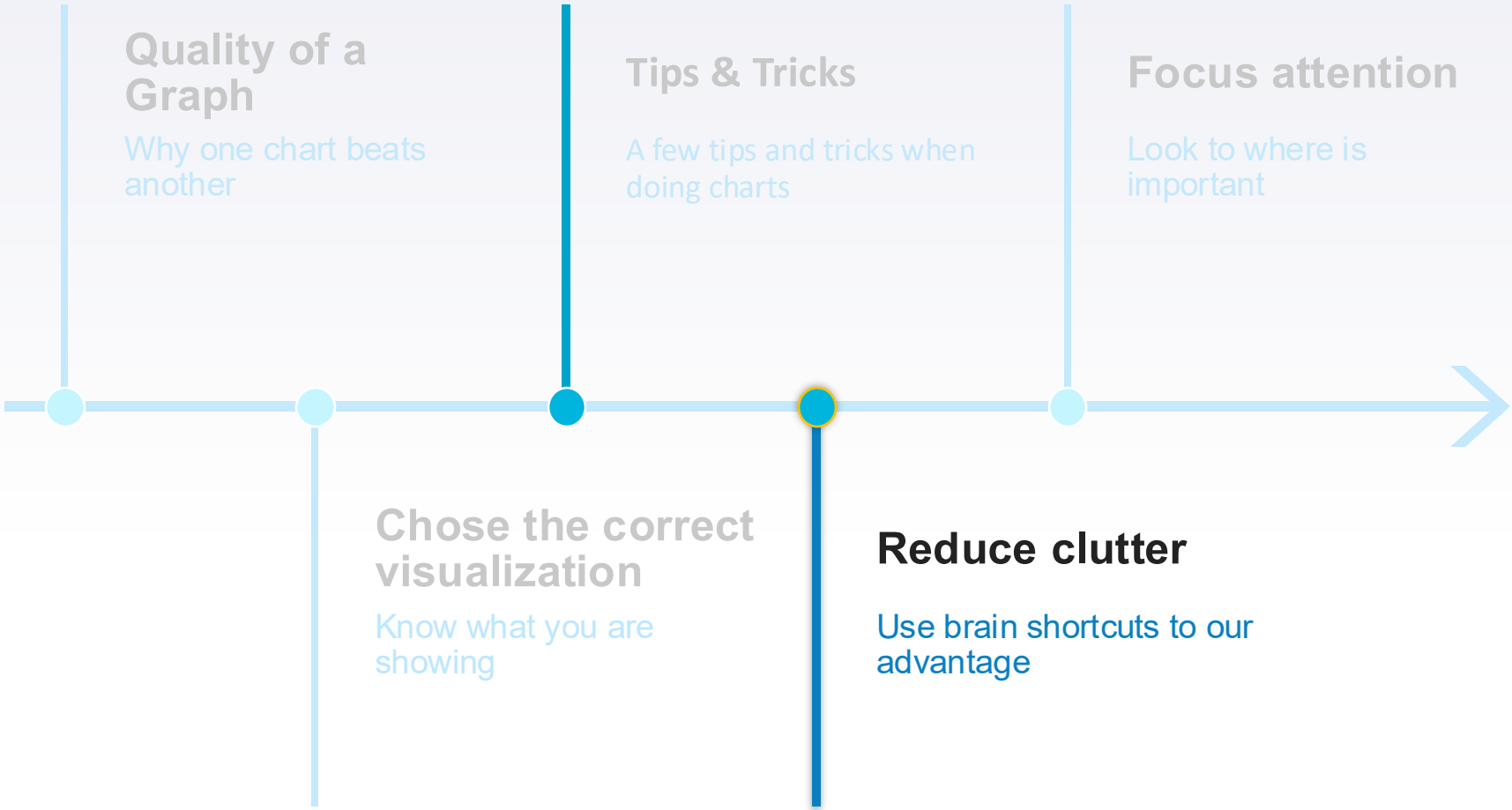
Show calibration of the model when working with confidence

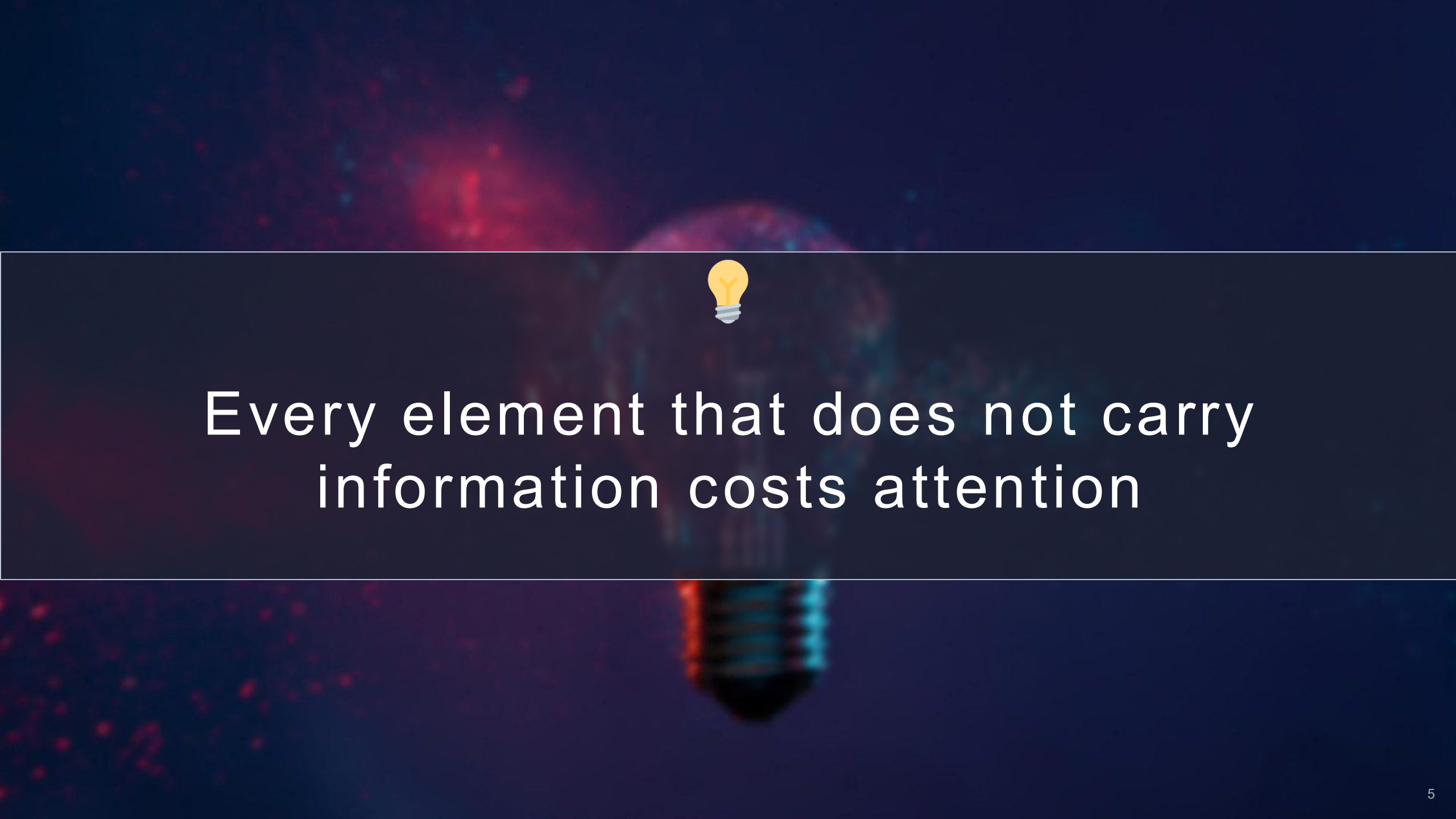


Key if you want to make decisions depending on the logits of the model

Guo, C., Pleiss, G., Sun, Y., & Weinberger, K. Q. (2017). On calibration of modern neural networks. In Proceedings of the 34th International Conference on Machine Learning, PMLR 70, 1321–1330.Guo, C., Pleiss, G., Sun, Y., & Weinberger, K. Q. (2017). On calibration of modern neural networks. In Proceedings of the 34th International Conference on Machine Learning, PMLR 70, 1321–1330.

Today


Quality of a Graph
Why one chart beats another
Tips & Tricks
A few tips and tricks when doing charts
Focus attention
Look to where is important
Chose the correct visualization
Know what you are showing
Reduce clutter
Use brain shortcuts to our advantage



Every element that does not carry information costs attention

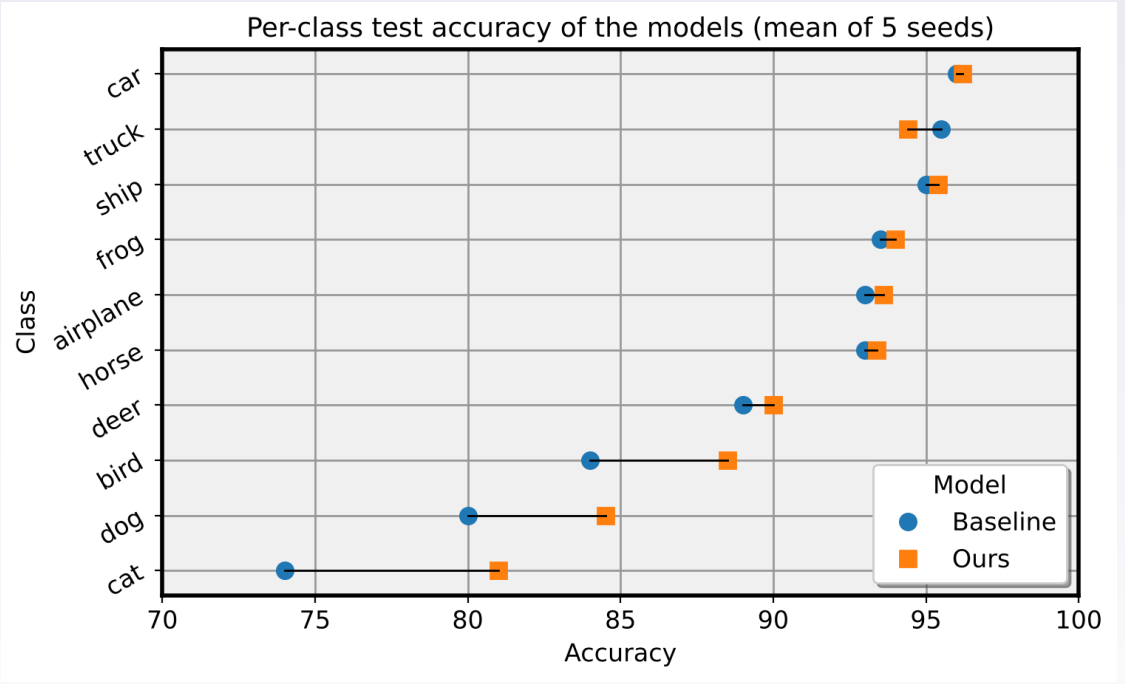
Visual noise

- Elements that take space but add **no clarity**
- Shadows, gradients, **3D**
- Heavy gridlines, frames, boxed legends
- Too many series, **rotated text**, misalignment

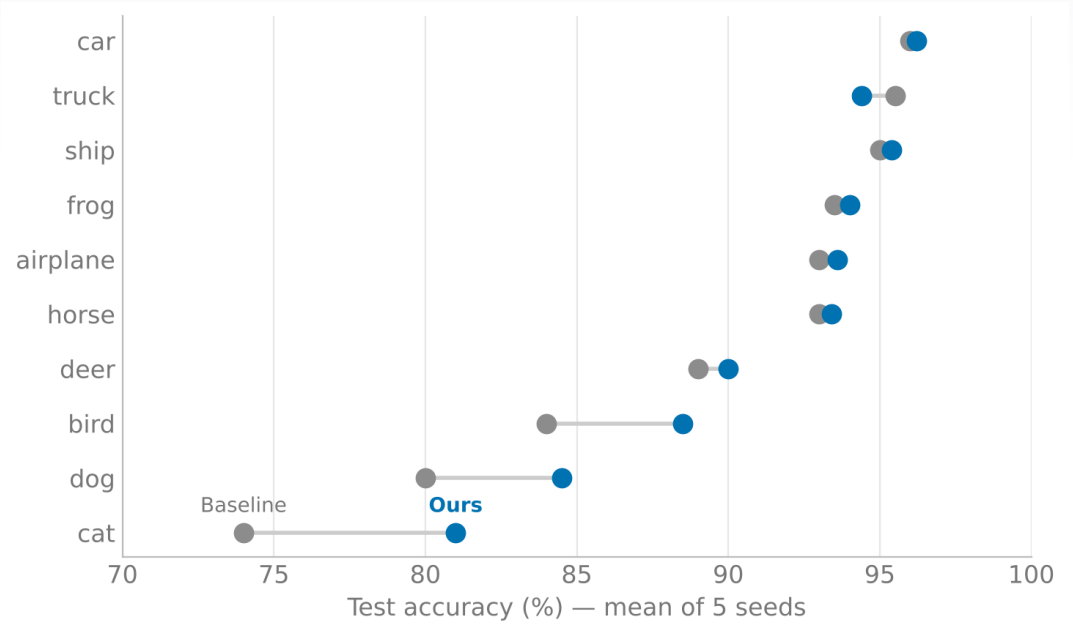


Tufte, E. R. (1983). The Visual Display of Quantitative Information. Graphics Press.

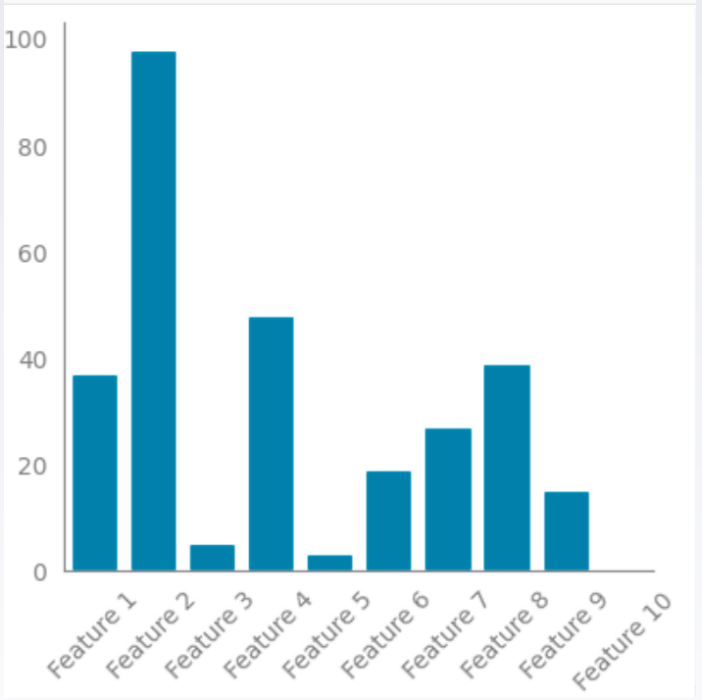



Per-class test accuracy of the models (mean of 5 seeds)
Class
car
truck
ship
frog
airplane
horse
deer
bird
dog
cat
70
75
80
85
90
95
100
Accuracy
Model
Baseline
Ours

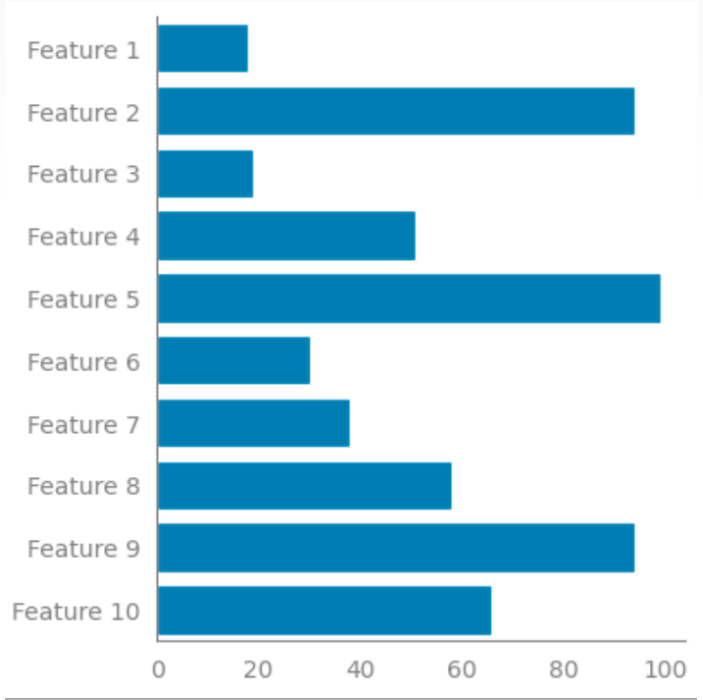



car
truck
ship
frog
airplane
horse
deer
bird
dog
Baseline
Ours
cat
70
75
80
85
90
95
100
Test accuracy (%) — mean of 5 seeds



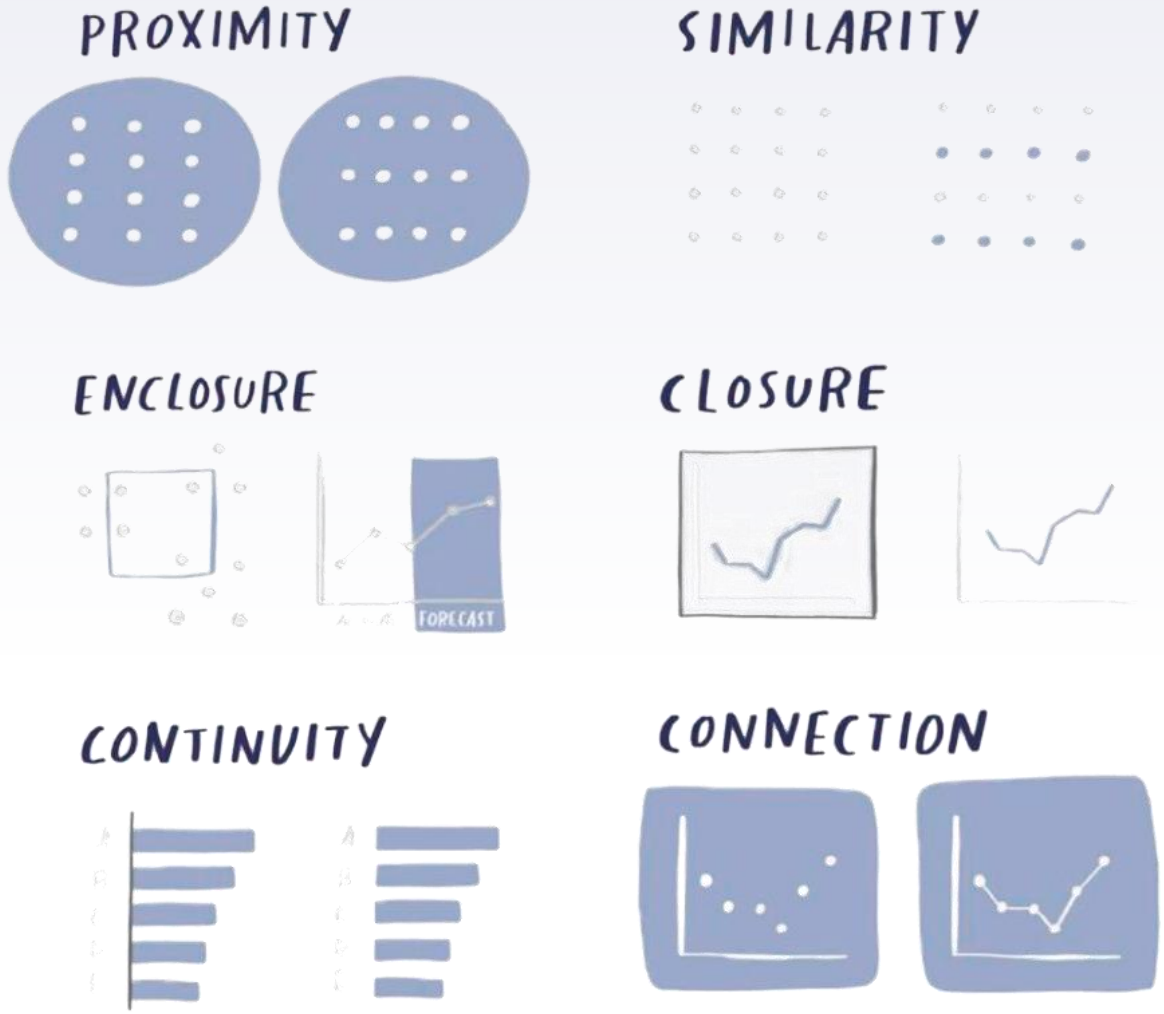

100
80
60
40
20
0
Feature 1
Feature 2
Feature 3
Feature 4
Feature 5
Feature 6
Feature 7
Feature 8
Feature 9
Feature 10




Feature 1
Feature 2
Feature 3
Feature 4
Feature 5
Feature 6
Feature 7
Feature 8
Feature 9
Feature 10
0
20
40
60
80
100

Gestalt principles

- How the brain **groups** visual elements into patterns
- **Proximity**, **similarity**, **enclosure**
- Closure, continuity, connection



Knaflic, C. N. (2019). Storytelling with Data: Let's Practice! Wiley.

Gestalt principles

- How the brain **groups** visual elements into patterns
- **Proximity**
- Closure, c



If I know how the brain **groups** things, I can **delete** elements **without losing information**.

Knaflic, C. N. (2019). Storytelling with Data: Let's Practice! Wiley.

How to use the Gestalt principles



Simplify the layout

Group related data and **separate** what is unrelated, removing unnecessary elements



Be consistent

Consistent **colours**, **shapes** and **alignments** make the chart tidier and easier to read

Keep the focus on the data

Remove unnecessary **background** elements; use **preattentive attributes** to mute what you cannot remove

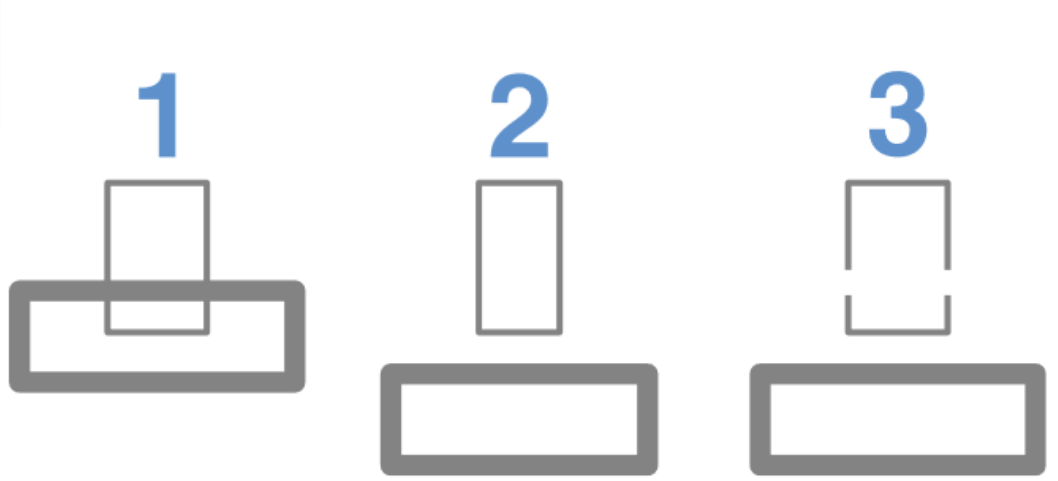
Knaflic, C. N. (2015). Storytelling with Data. Wiley.

Continuity and closure

Elements aligned along a straight or curved line are perceived as **related**.

The brain tends to **complete** incomplete shapes to see them as a whole, **even when data are missing**.





Knaflic, C. N. (2015). Storytelling with Data. Wiley.

Continuity and closure

Elements aligned along a straight or curved line are perceived as **related**.

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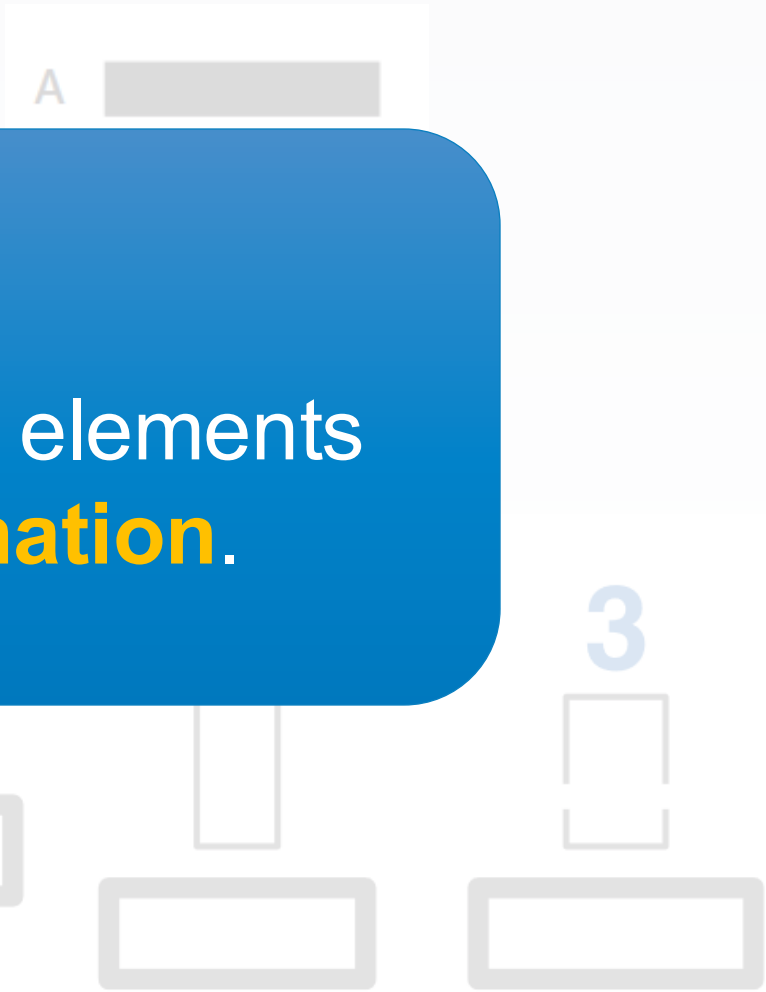
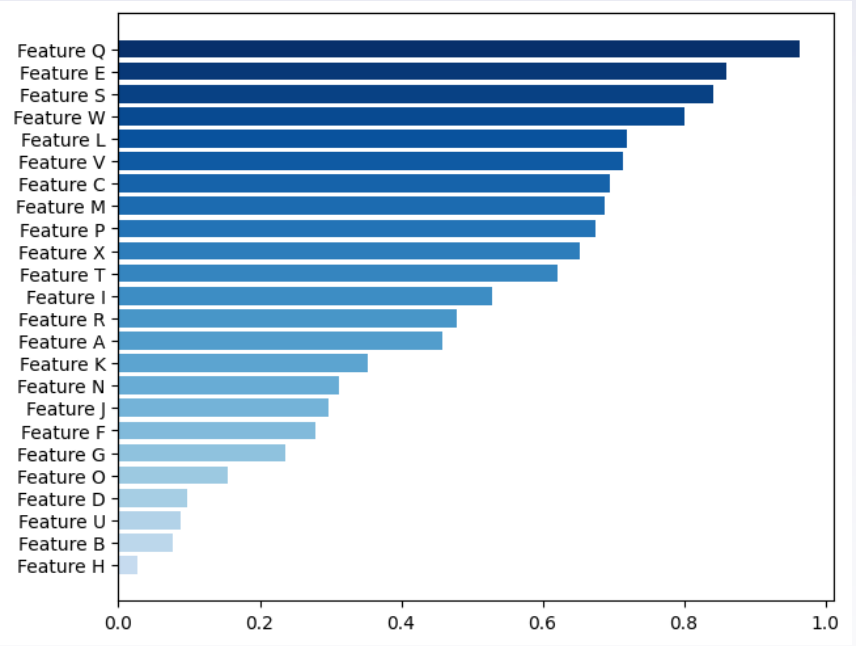
to see them a
missing.



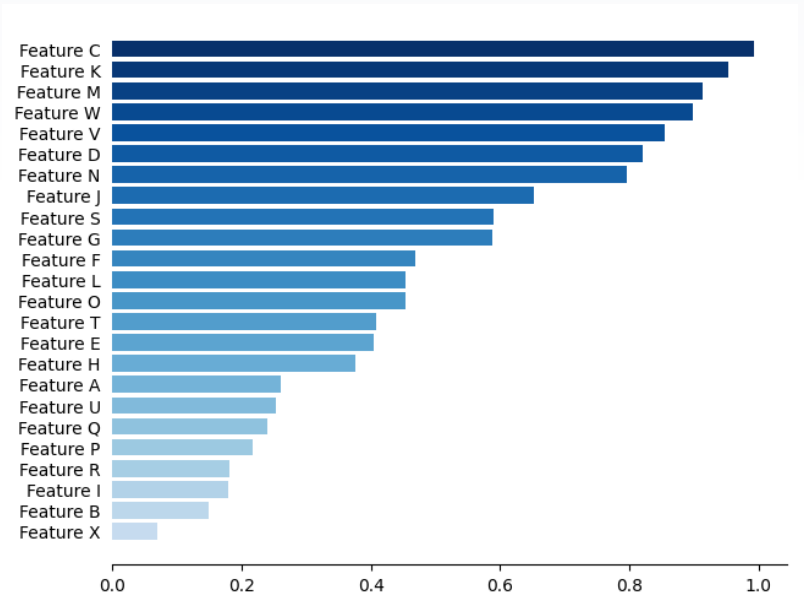
Use this to **remove** visual elements **without losing information**.

Knaflic, C. N. (2015). Storytelling with Data. Wiley.




Feature Q
Feature E
Feature S
Feature W
Feature L
Feature V
Feature C
Feature M
Feature P
Feature X
Feature T
Feature I
Feature R
Feature A
Feature K
Feature N
Feature J
Feature F
Feature G
Feature O
Feature D
Feature U
Feature B
Feature H
0.0
0.2
0.4
0.6
0.8
1.0

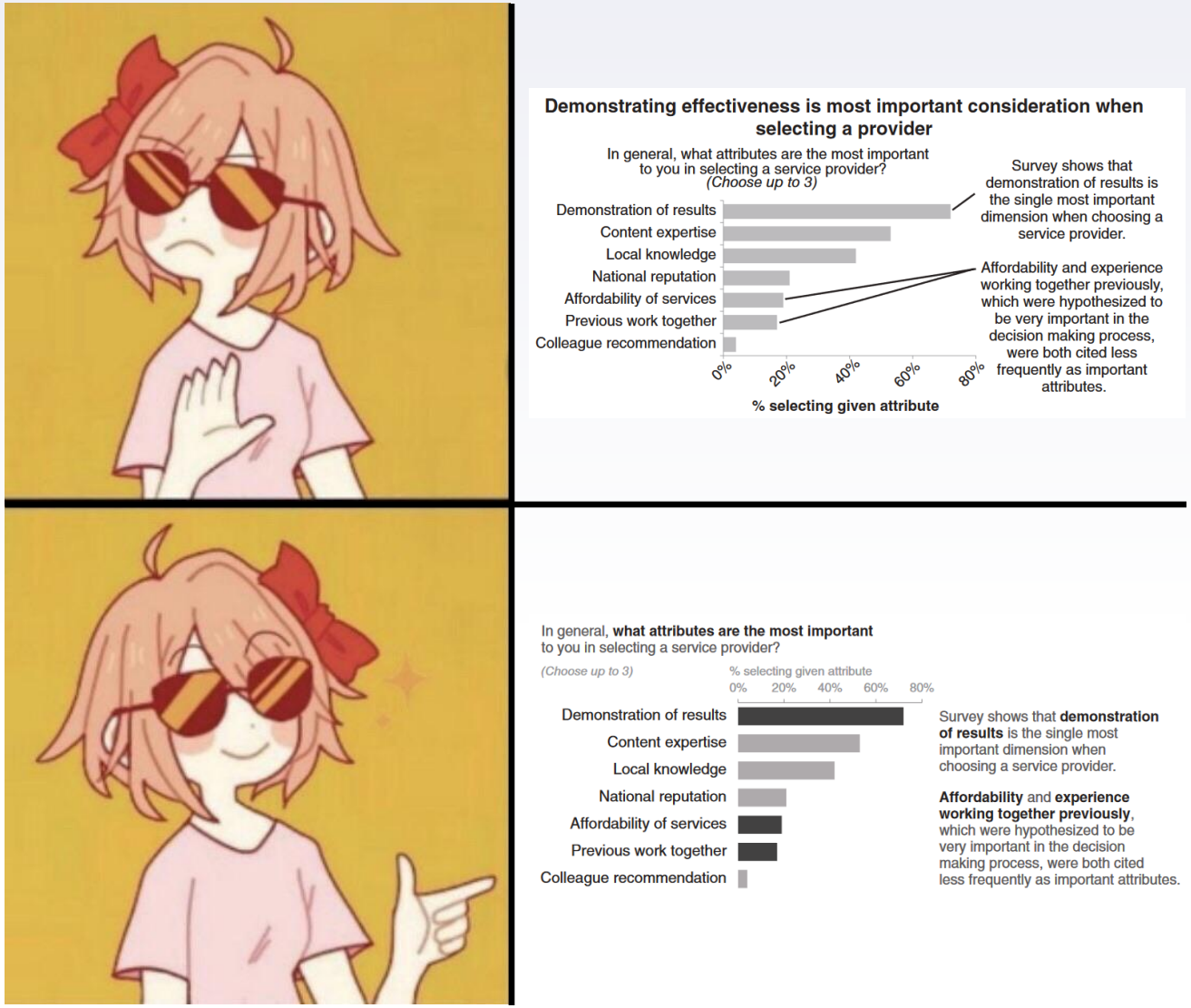



Feature C
Feature K
Feature M
Feature W
Feature V
Feature D
Feature N
Feature J
Feature S
Feature G
Feature F
Feature L
Feature O
Feature T
Feature E
Feature H
Feature A
Feature U
Feature Q
Feature P
Feature R
Feature I
Feature B
Feature X
0.0
0.2
0.4
0.6
0.8
1.0

Similarity

Elements **similar** in colour, shape or size are perceived as part of the **same group**.

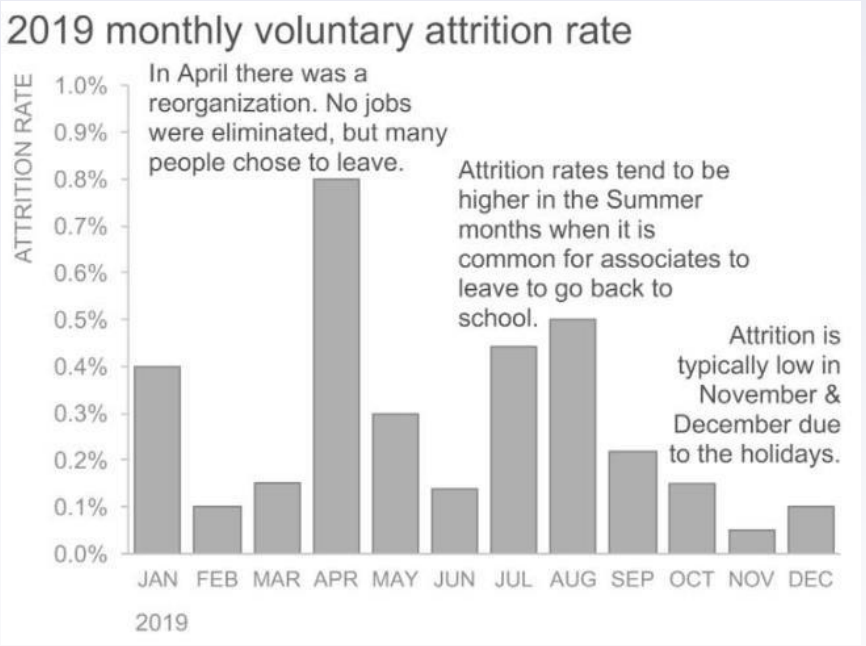
Use **consistent** colours or shapes to **group** similar data and tell categories apart.

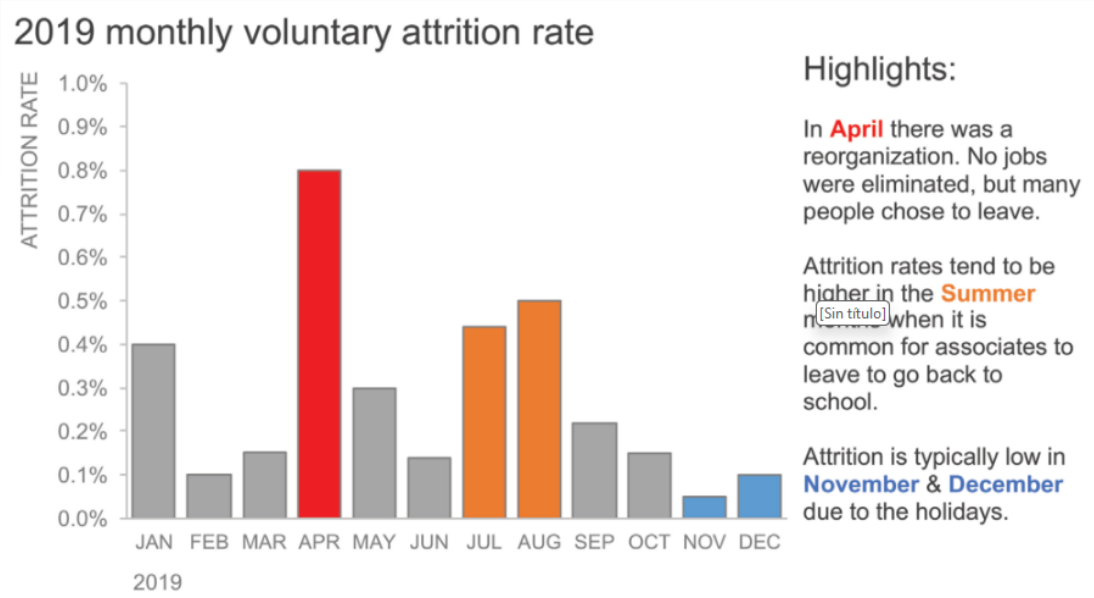


Knaflic, C. N. (2015). Storytelling with Data. Wiley.









Knaflic, C. N. (2019). Storytelling with Data: Let's Practice! Wiley.

Colour has meaning

- Red usually reads as **bad**, blue/green as **good**
- Use it: a loss in red, a gain in blue
- Careful: these conventions **change across cultures**. Know your audience



Knaflic, C. N. (2015). Storytelling with Data. Wiley.

A bit of colour theory

- Need **two** highlight colours? Pick **complementary** ones: opposite on the wheel
- Need **more**? Pick **equidistant** ones on the wheel
- Then **check** them for colour blindness



Colour blindness

~8 %

of men

~0.5 %

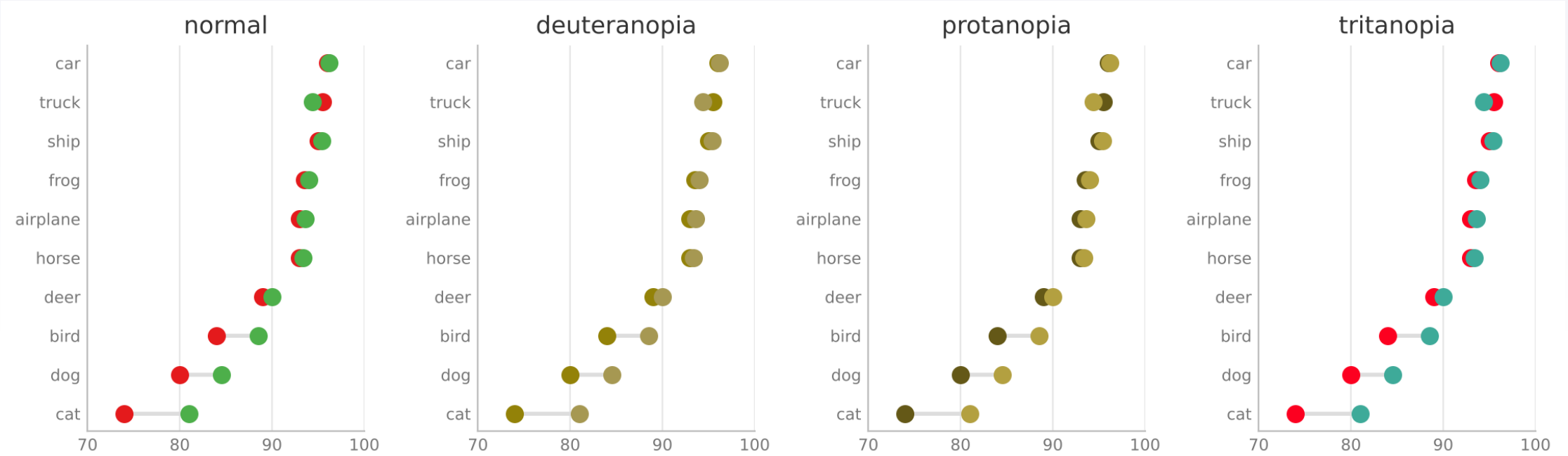
of women

- **Deutan** (green cones): the most common, mostly deuteranomaly
- **Protan** (red cones)
- **Tritan** (blue cones): rare
- In a room of 25 men, statistically **about 2** see your figure differently



Wong, B. (2011). Points of view: Color blindness. Nature Methods 8, 441 · Nuñez et al. (2018), PLOS ONE 13(7)

Example: red vs green



Simulation: Machado, Oliveira & Fernandes (2009), IEEE TVCG 15(6)

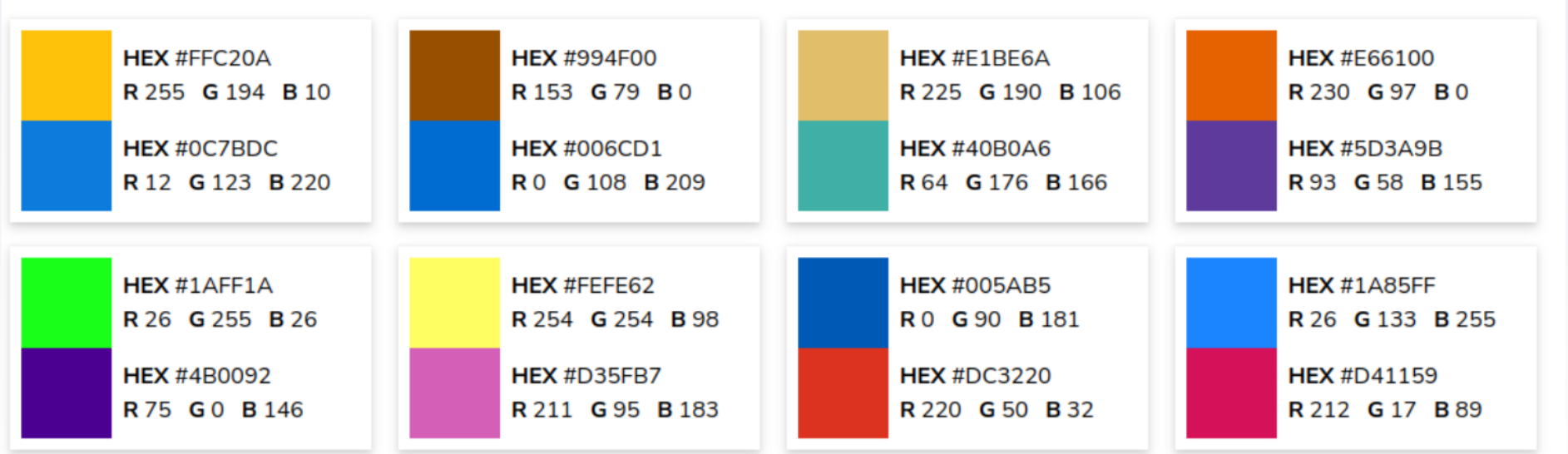
Our case study in red vs green

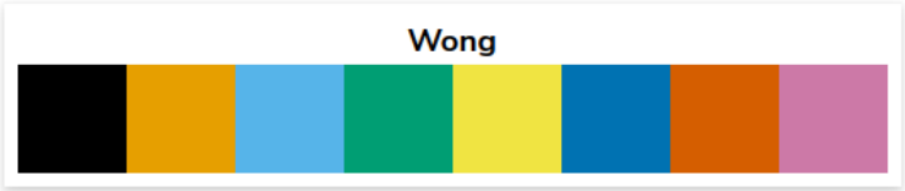


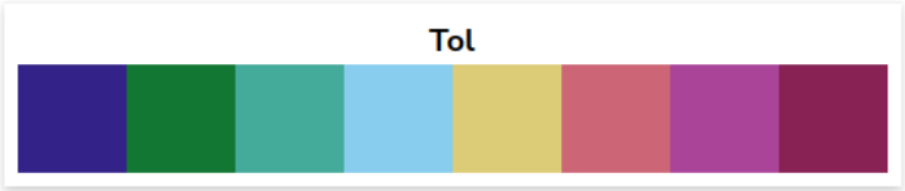
Red vs green, perhaps the most common pair in papers, is exactly the pair most colour-blind readers **cannot** separate.

Simulation: Machado, Oliveira & Fernandes (2009), IEEE TVCG 15(6)

Colour-blind-safe palettes



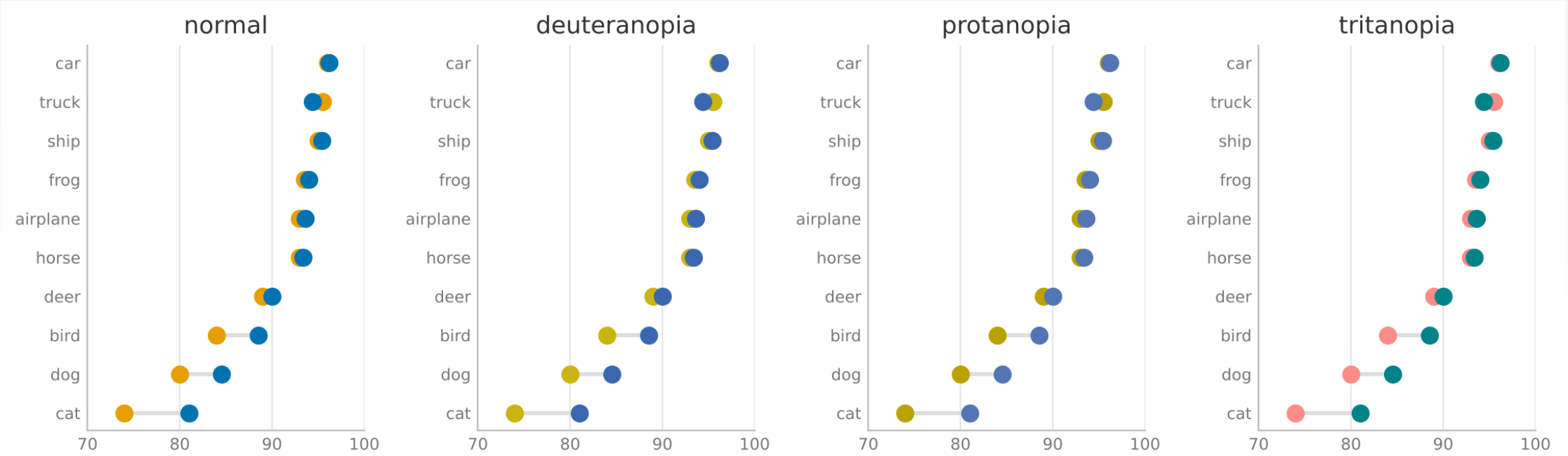






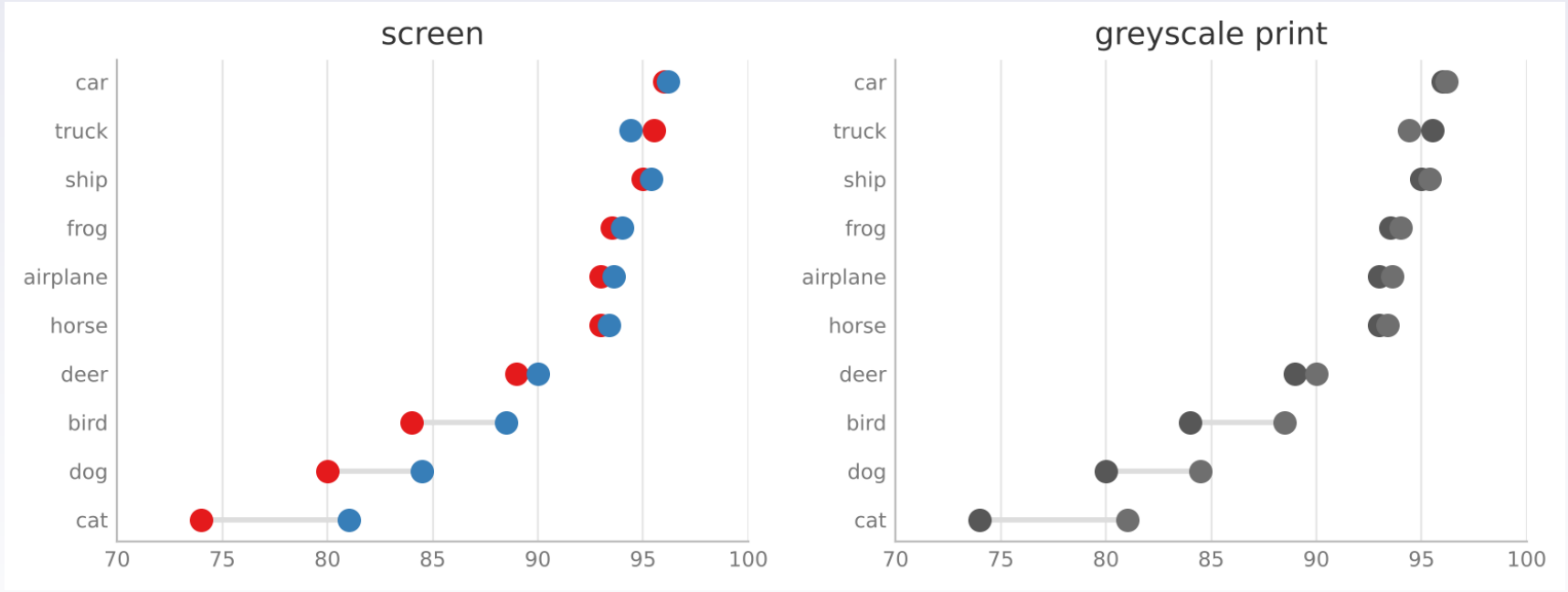
https://davidmathlogic.com/colorblind

Example: orange vs blue



Simulation: Machado, Oliveira & Fernandes (2009), IEEE TVCG 15(6)




screen
car
truck
ship
frog
airplane
horse
deer
bird
dog
cat
70
75
80
85
90
95
100
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90
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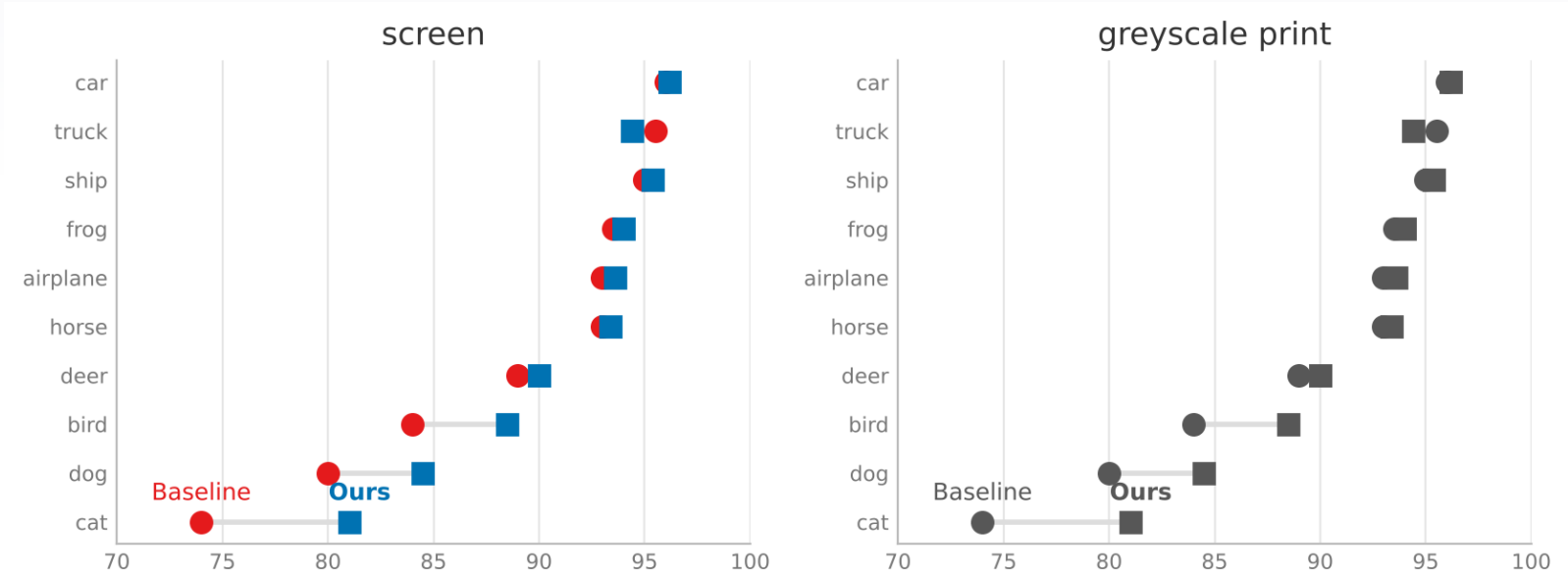
100




screen
car
truck
ship
frog
airplane
horse
deer
bird
dog
cat
Baseline
Ours
70
75
80
85
90
95
100
greyscale print
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dog
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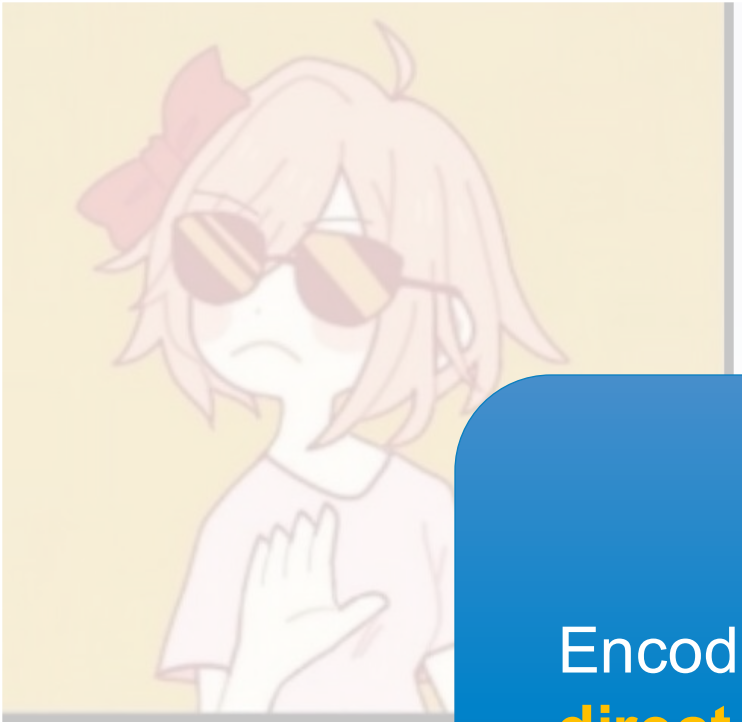
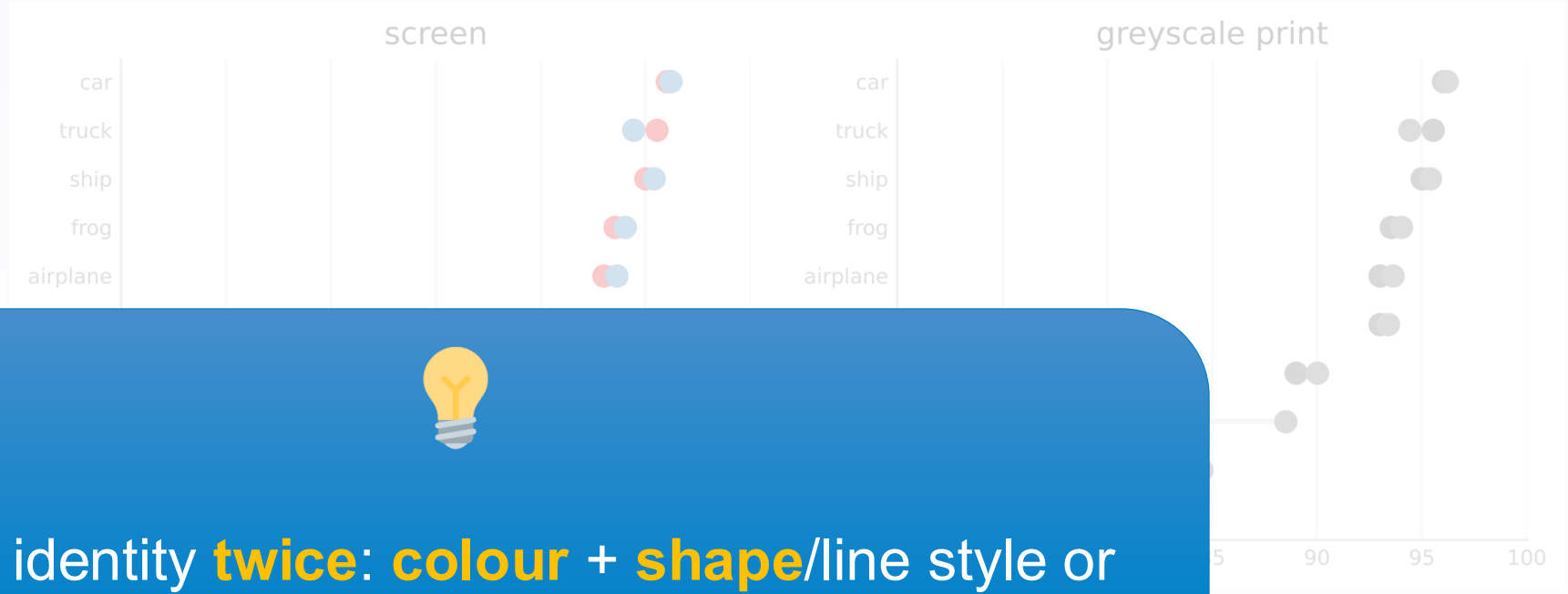
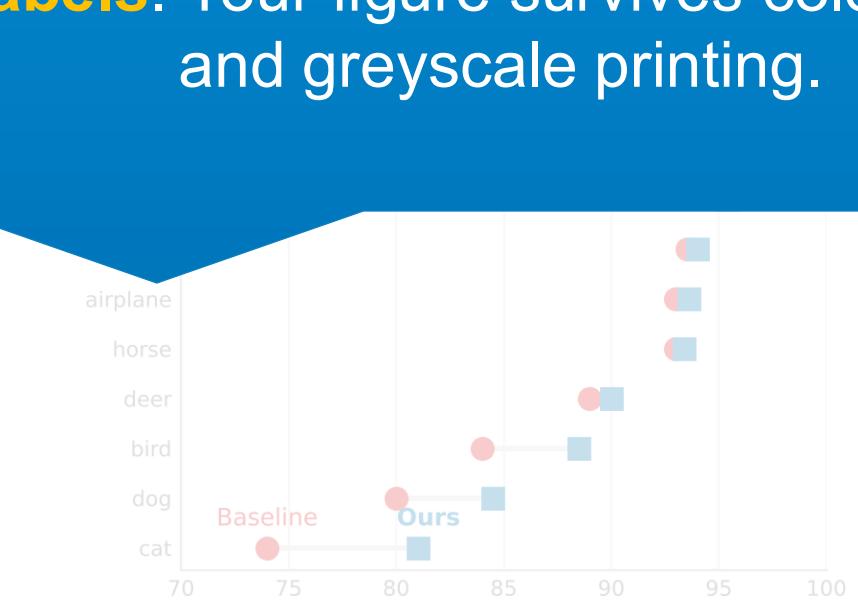
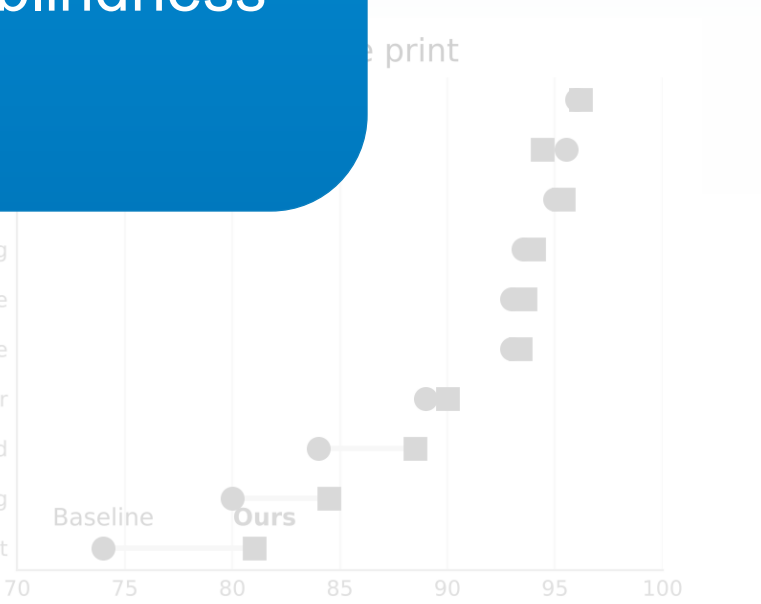








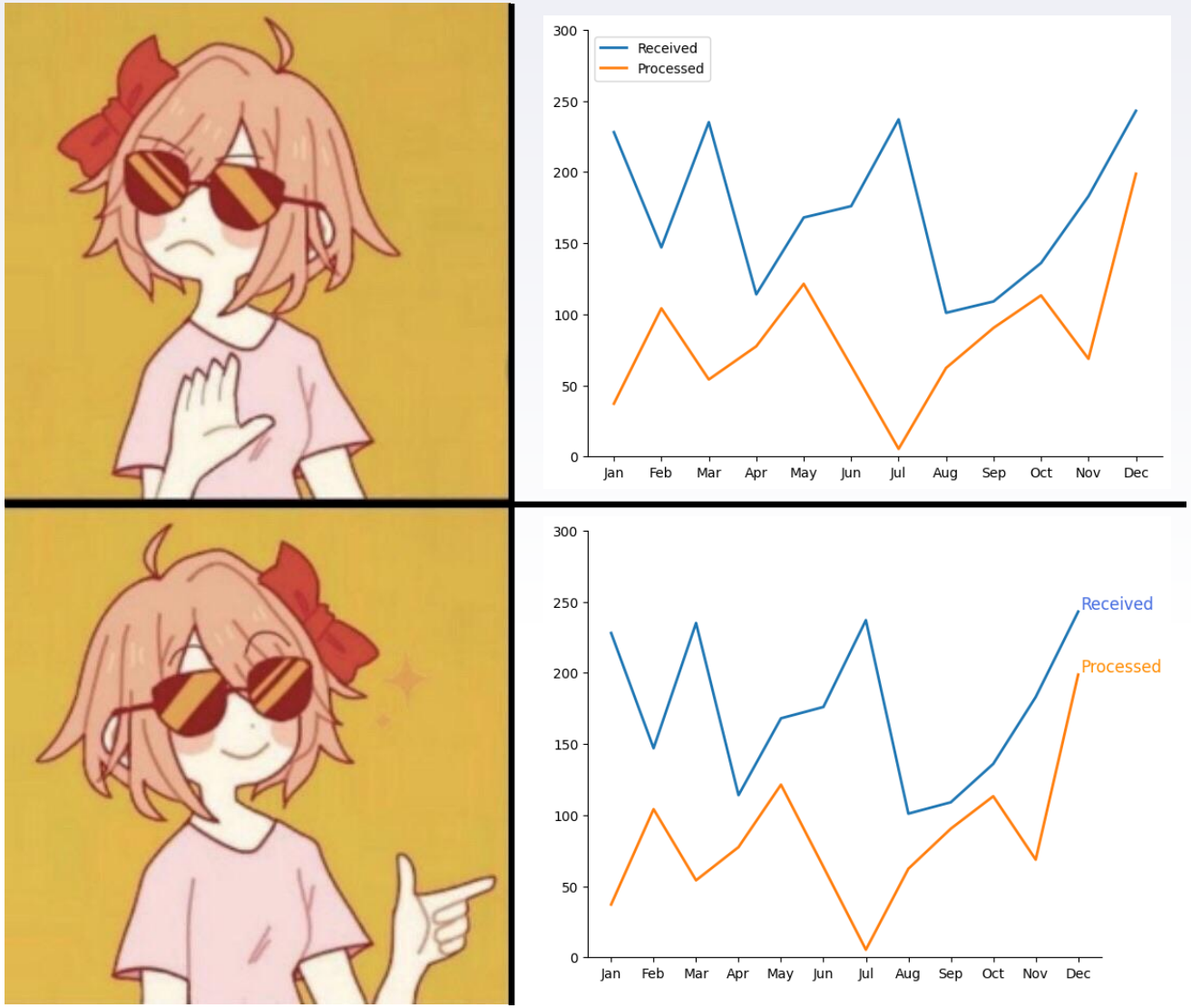


Encode identity **twice**: **colour** + **shape**/line style or **direct labels**. Your figure survives colour blindness and greyscale printing.

Proximity

Group related data close together to show they are **connected**.

Separate unrelated data with white space to avoid **misreadings**.



Knaflic, C. N. (2015). Storytelling with Data. Wiley.

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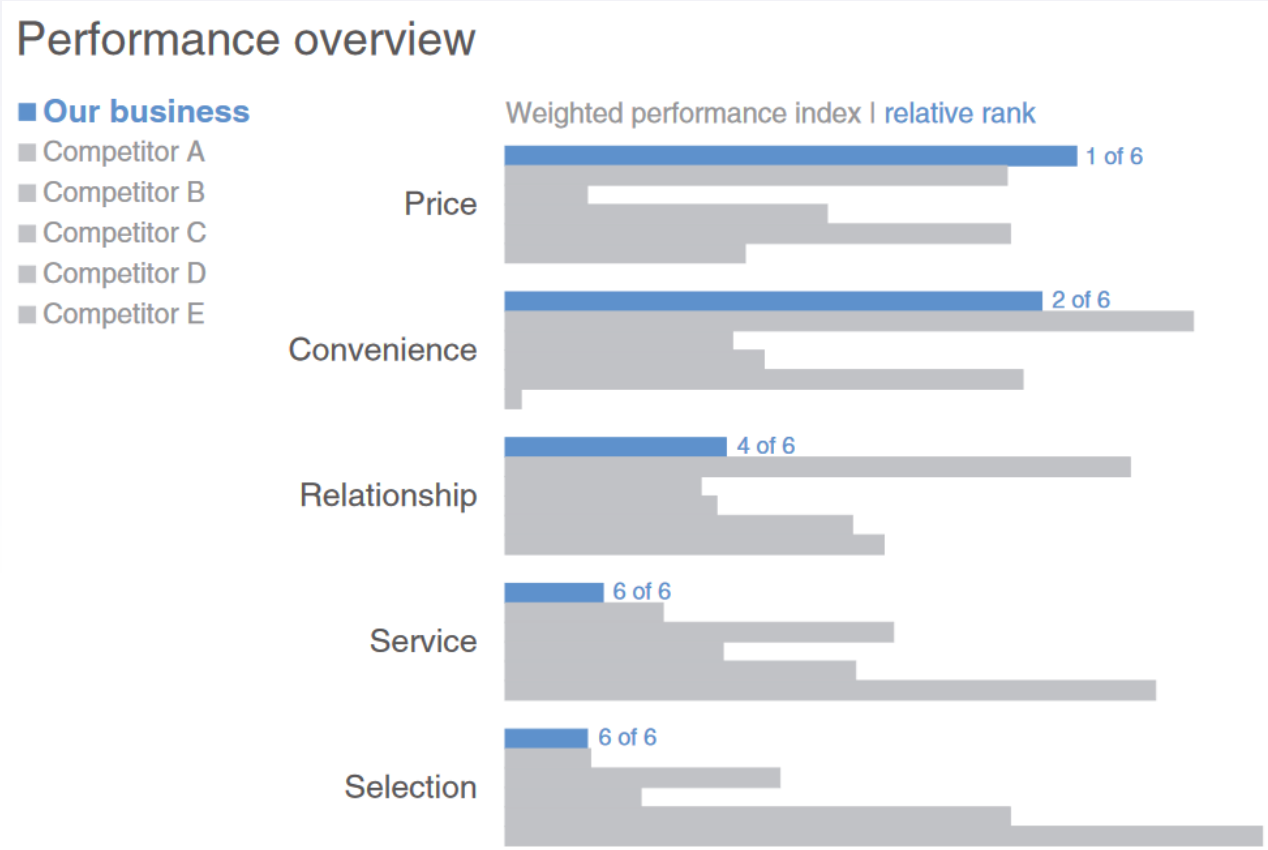


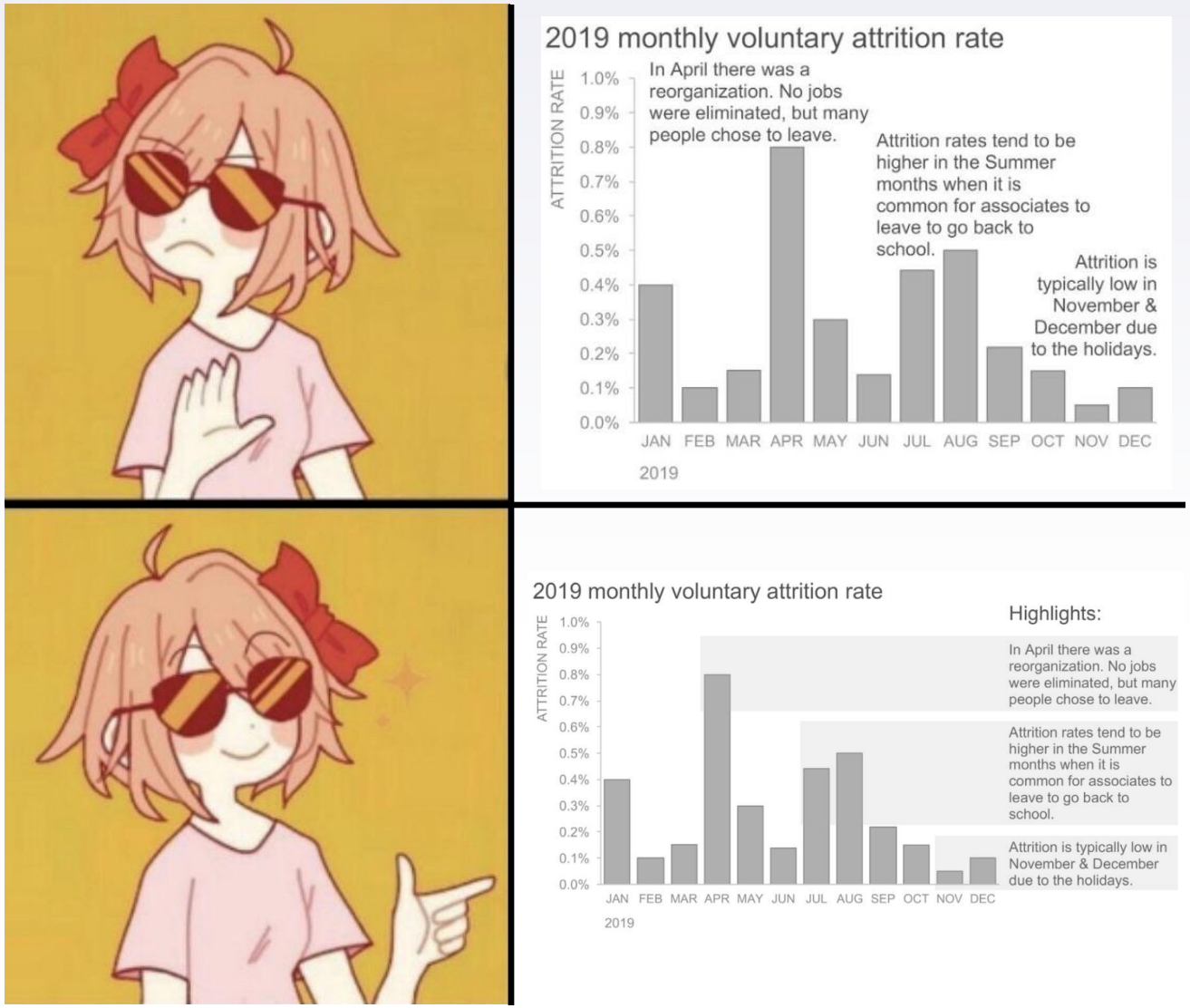
Knaflic, C. N. (2015). Storytelling with Data. Wiley.

Enclosure

Elements inside a common **boundary** are **perceived** as a **group**.

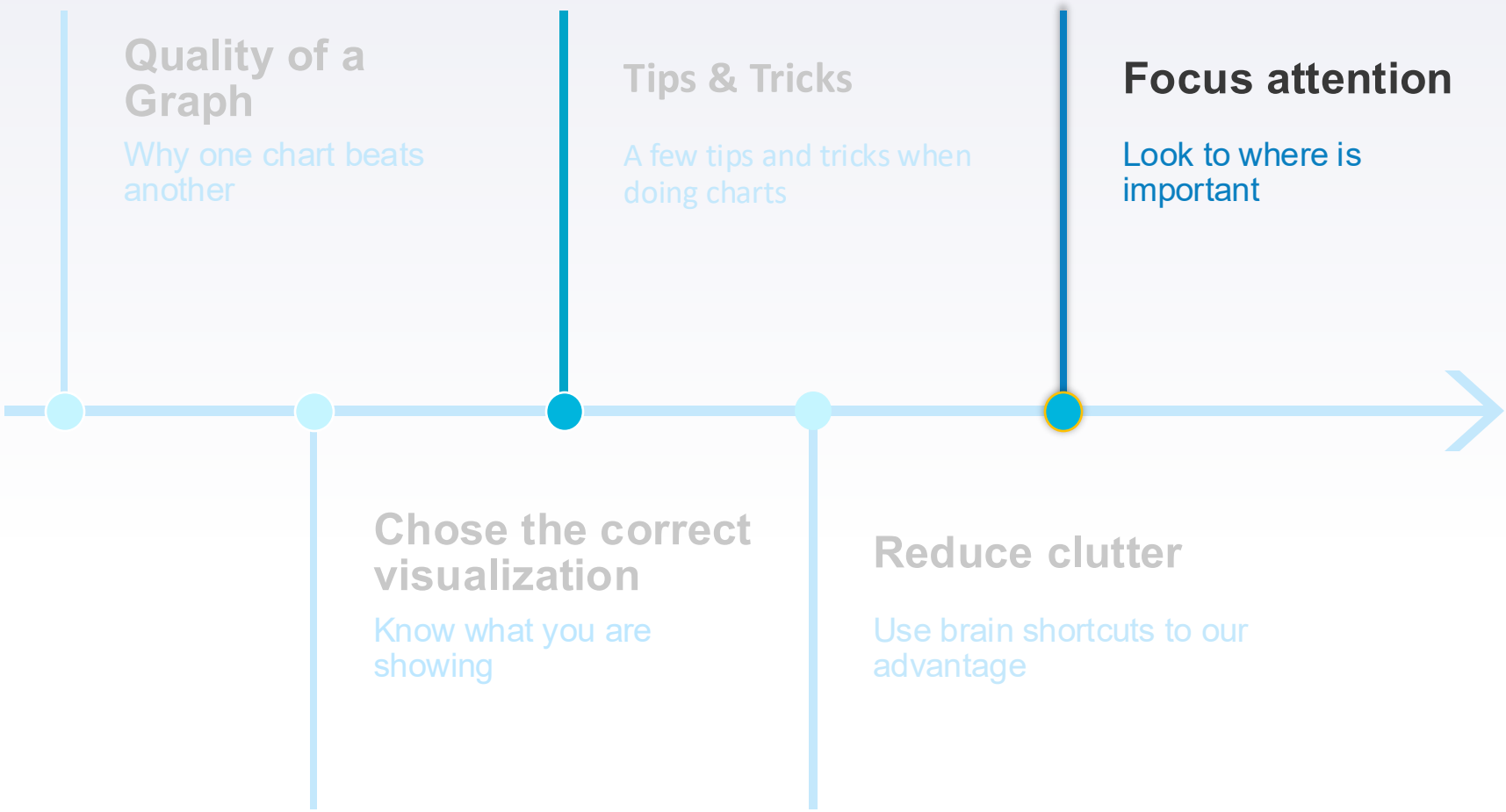
Use boxes or **shaded areas** to group related data.

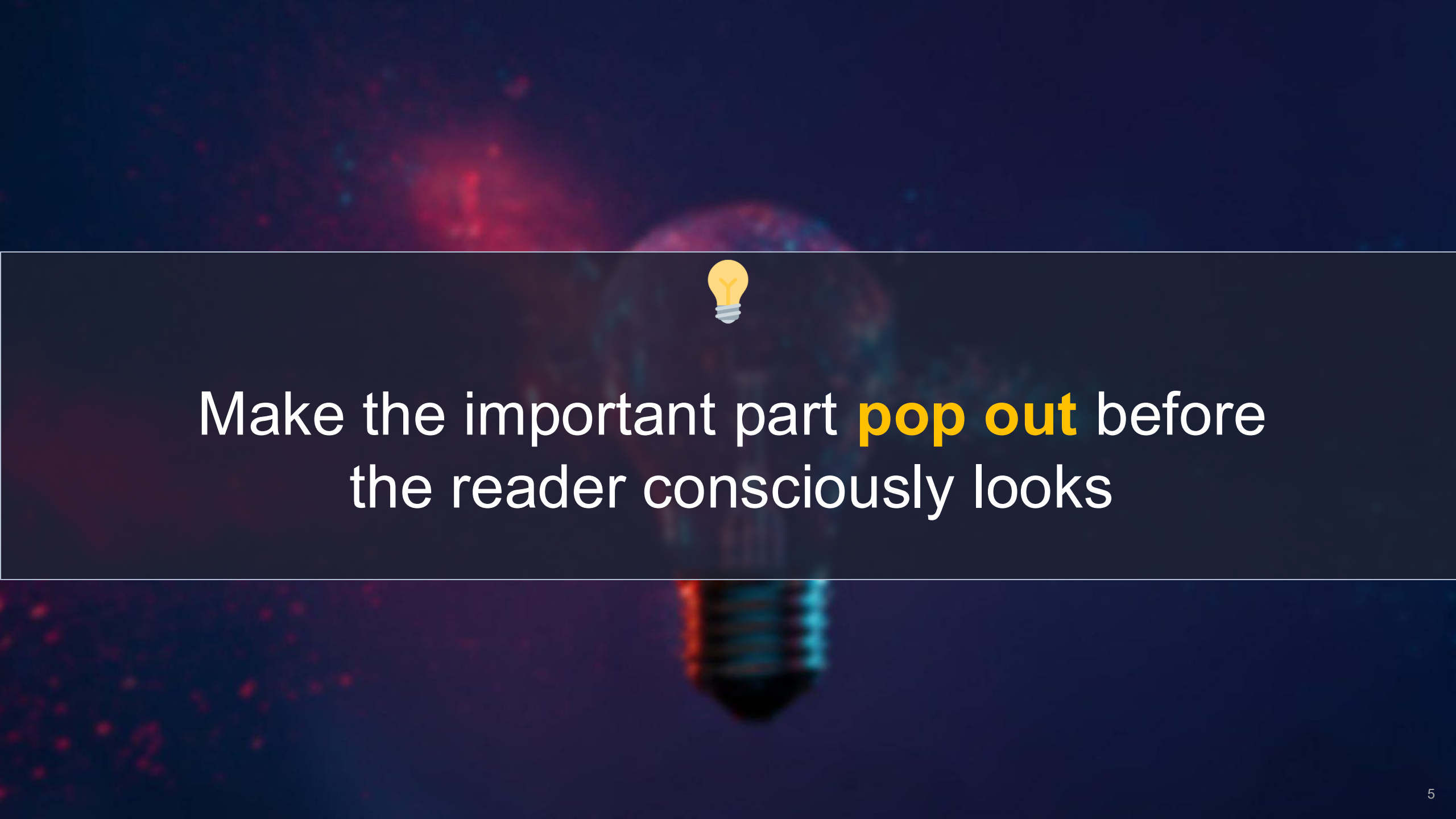
Use light lines or **subtle** borders that do not dominate the visualization.



Knaflic, C. N. (2019). Storytelling with Data: Let's Practice! Wiley.

Today

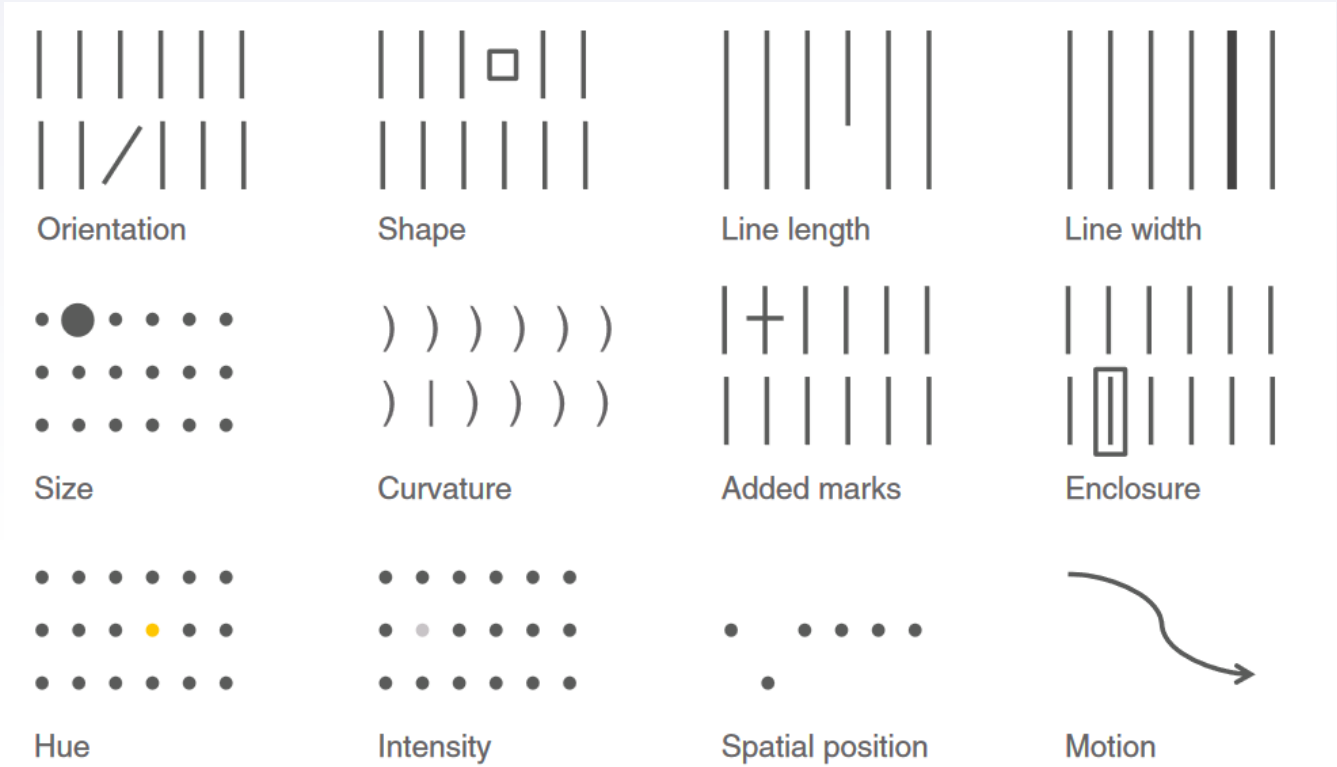

Quality of a Graph
Why one chart beats another
Chose the correct visualization
Know what you are showing
Tips & Tricks
A few tips and tricks when doing charts
Reduce clutter
Use brain shortcuts to our advantage
Focus attention
Look to where is important



Make the important part **pop out** before the reader consciously looks

Preattentive attributes

- Visual features the brain processes **almost instantly**
- Without **conscious** effort
- Orientation, shape, size, **colour hue**, **intensity**, enclosure, position…



Healey & Enns (2012), IEEE TVCG 18(7); figure: Knaflic (2015)

Count the 3s

75639506847 3

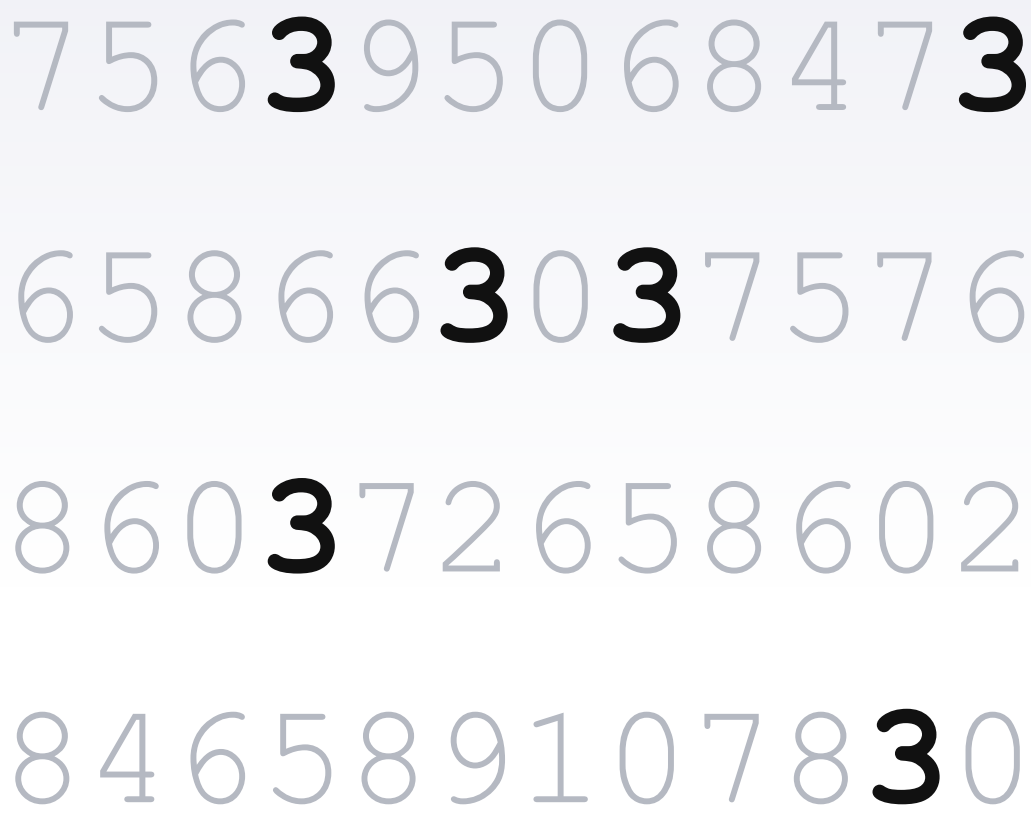
6586630375 76

8603726586 02

8465891078 30

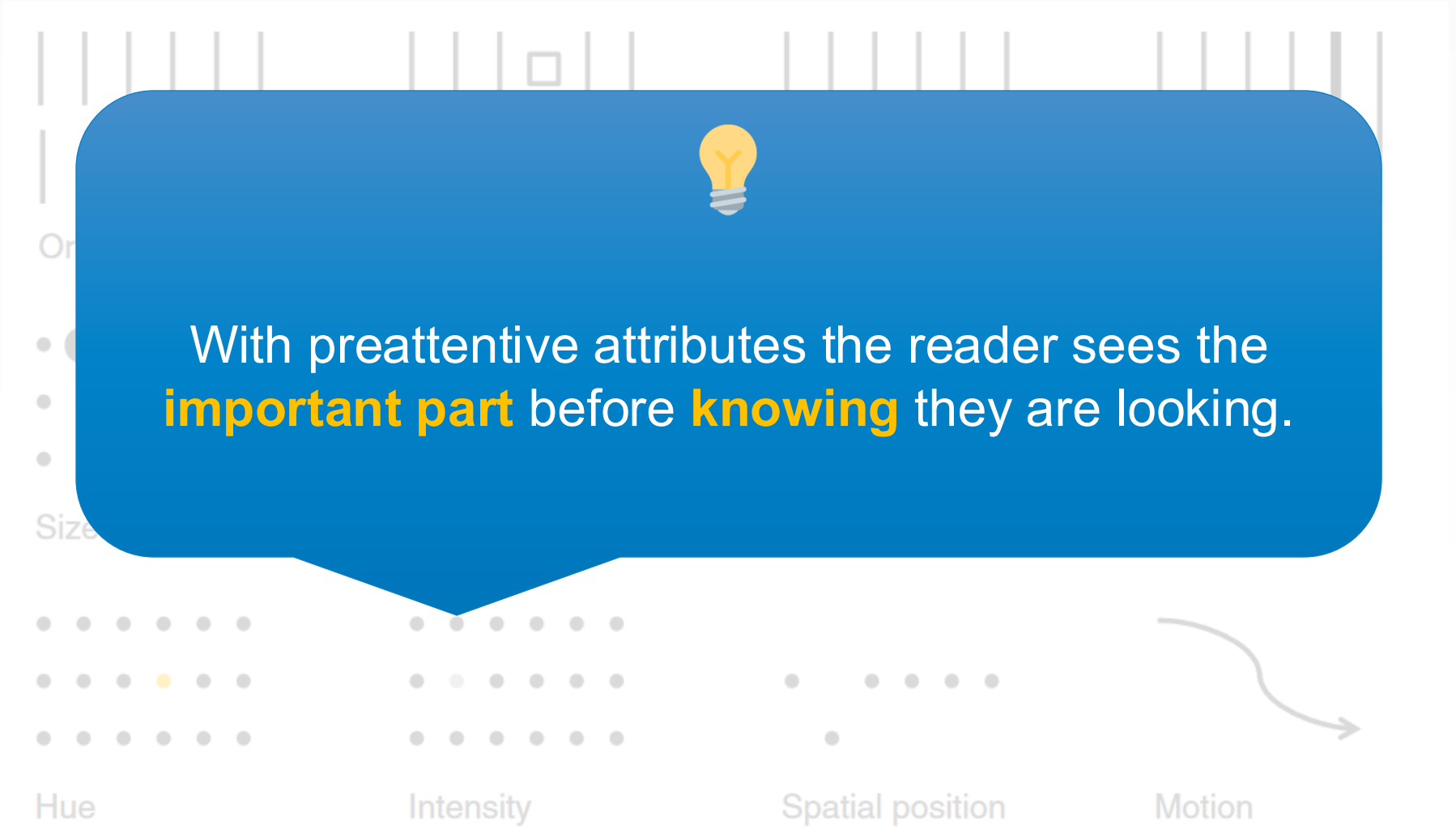
Knaflic, C. N. (2015). Storytelling with Data. Wiley.

Count the 3s



Knaflic, C. N. (2015). Storytelling with Data. Wiley.

Preattentive attributes



With preattentive attributes the reader sees the **important part** before **knowing** they are looking.

Visual hierarchy

- Use size, **weight**, **colour** and **intensity** to highlight what matters and mute the rest
- Place the key elements in **high-impact** areas
- The hierarchy guides the eye **in order of importance**



Knaflic, C. N. (2015). Storytelling with Data. Wiley.



Rainbow distribution in color indicates sales rank in given country from #1 (red) to #10 or higher (dark purple)

Country	A	B	C	D	E
AUS	1	2	3	6	7
BRA	1	3	4	5	6
CAN	2	3	6	12	8
CHI	1	2	8	4	7
FRA	3	2	4	8	10
GER	3	1	6	5	4
IND	4	1	8	10	5
ITA	2	4	10	9	8
MEX	1	5	4	6	3
RUS	4	3	7	9	12
SPA	2	3	4	5	11
TUR	7	2	3	4	8
UK	1	2	3	6	7
US	1	2	4	3	5

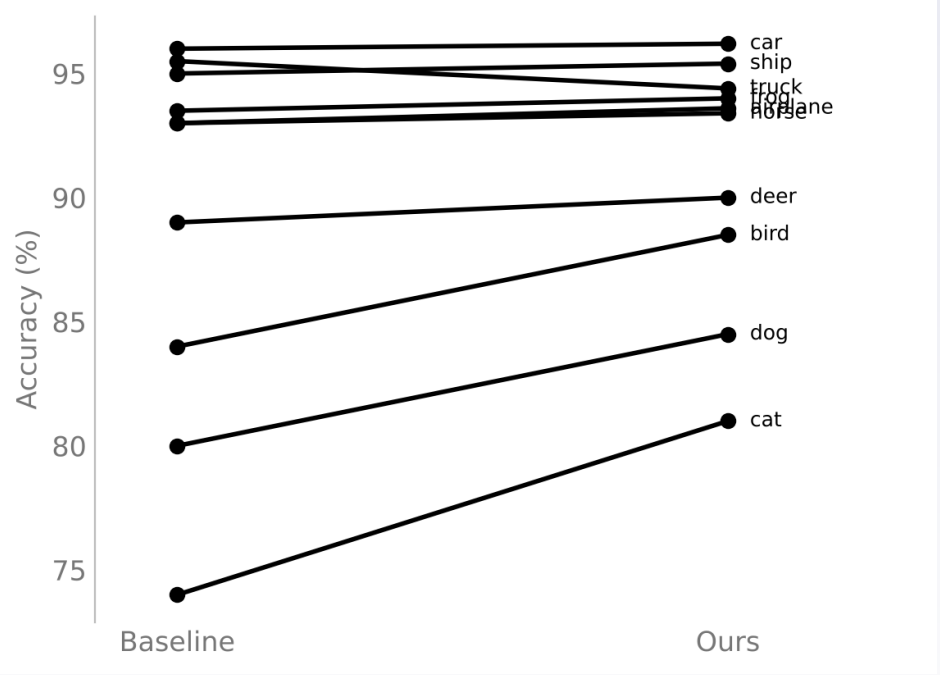


RANK 1 2 3 4 5+

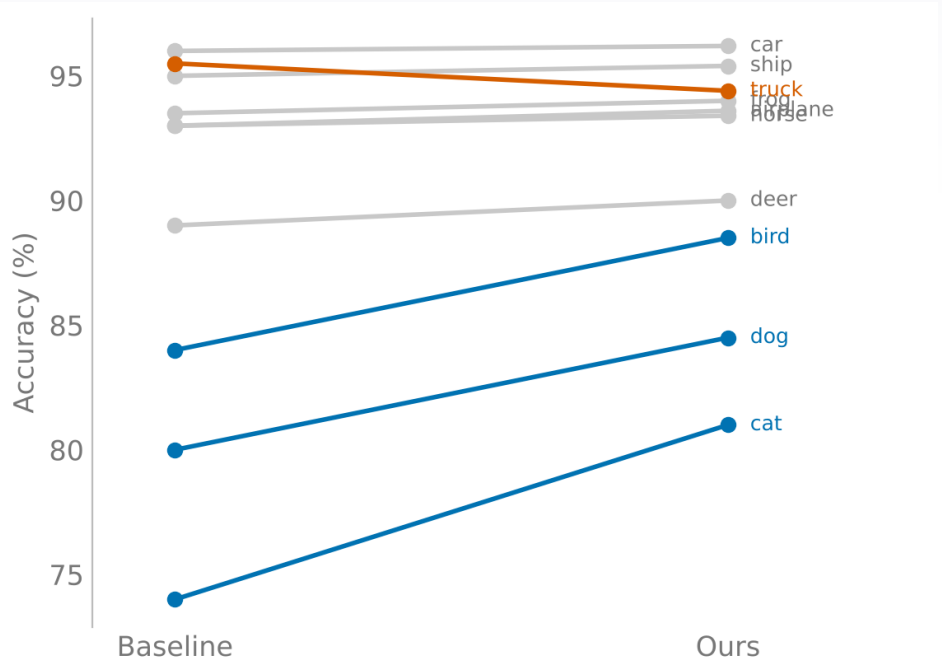
COUNTRY I DRUG

	A	B	C	D	E
Australia	1	2	3	6	7
Brazil	1	3	4	5	6
Canada	2	3	6	12	8
China	1	2	8	4	7
France	3	2	4	8	10
Germany	3	1	6	5	4
India	4	1	8	10	5
Italy	2	4	10	9	8
Mexico	1	5	4	6	3
Russia	4	3	7	9	12
Spain	2	3	4	5	11
Turkey	7	2	3	4	8
United Kingdom	1	2	3	6	7
United States	1	2	4	3	5




95
90
85
80
75
Accuracy (%)
car
ship
truck
frog
airplane
horse
deer
bird
dog
cat
Baseline
Ours




95
90
85
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75
Accuracy (%)
car
ship
truck
frog
airplane
horse
deer
bird
dog
cat
Baseline
Ours

Visual hierarchy

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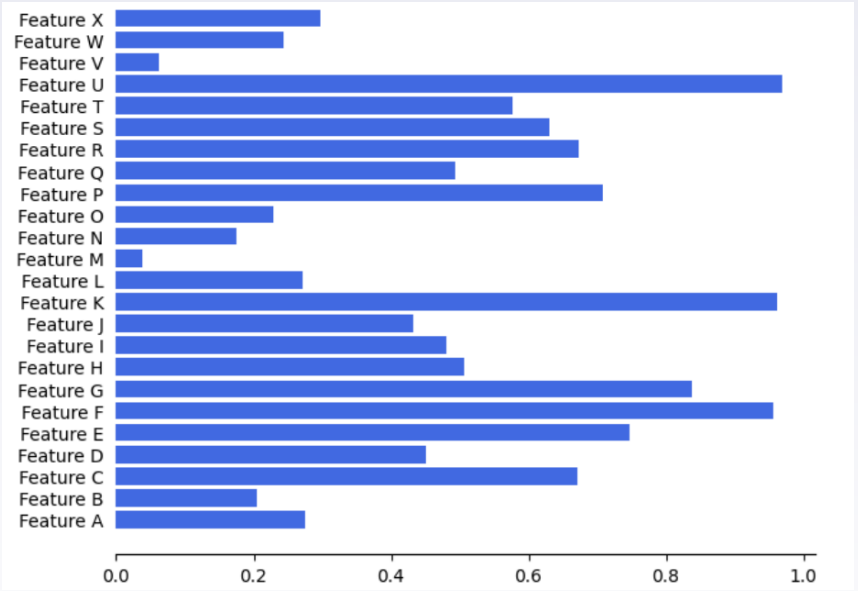
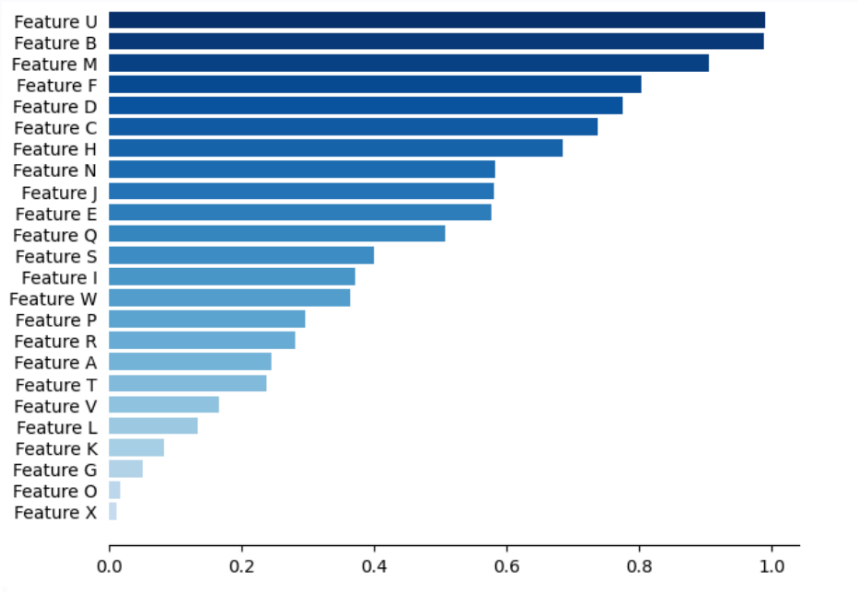
Knaflic, C. N. (2015). Storytelling with Data. Wiley.




Feature X
Feature W
Feature V
Feature U
Feature T
Feature S
Feature R
Feature Q
Feature P
Feature O
Feature N
Feature M
Feature L
Feature K
Feature J
Feature I
Feature H
Feature G
Feature F
Feature E
Feature D
Feature C
Feature B
Feature A
0.0
0.2
0.4
0.6
0.8
1.0




Feature U
Feature B
Feature M
Feature F
Feature D
Feature C
Feature H
Feature N
Feature J
Feature E
Feature Q
Feature S
Feature I
Feature W
Feature P
Feature R
Feature A
Feature T
Feature V
Feature L
Feature K
Feature G
Feature O
Feature X
0.0
0.2
0.4
0.6
0.8
1.0



WHERE DO I FOCUS THE ATTENTION?

Exploratory vs explanatory

👀 Exploratory

The goal is to find patterns. You try to answer a question reading the data

💡 Explanatory

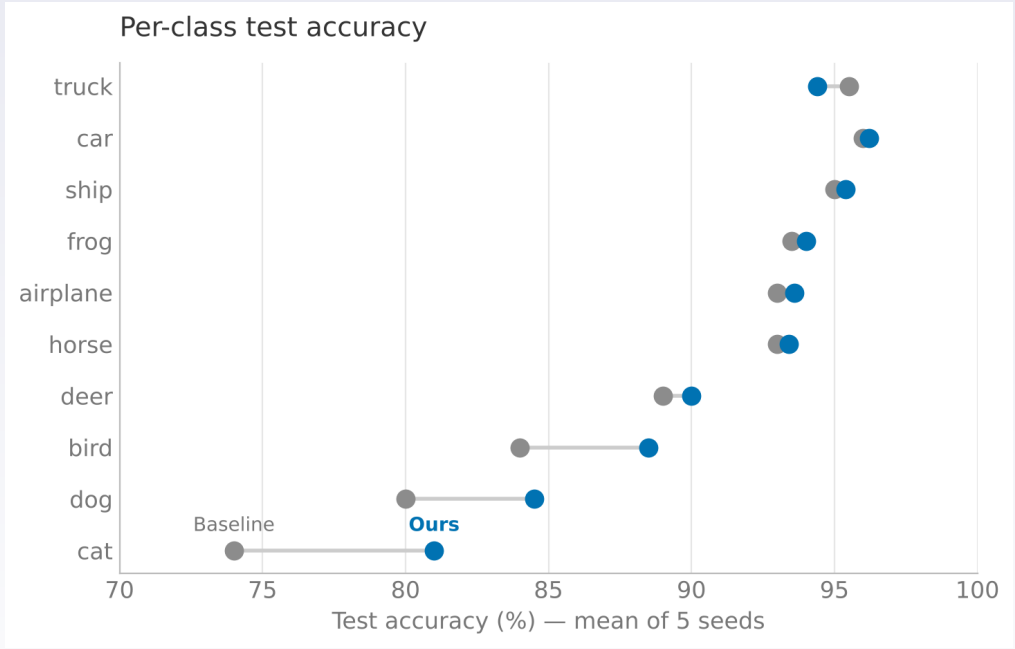
The goal is to explain a pattern to an audience. You have already answered a question.



Knaflic, C. N. (2015). Storytelling with Data. Wiley.

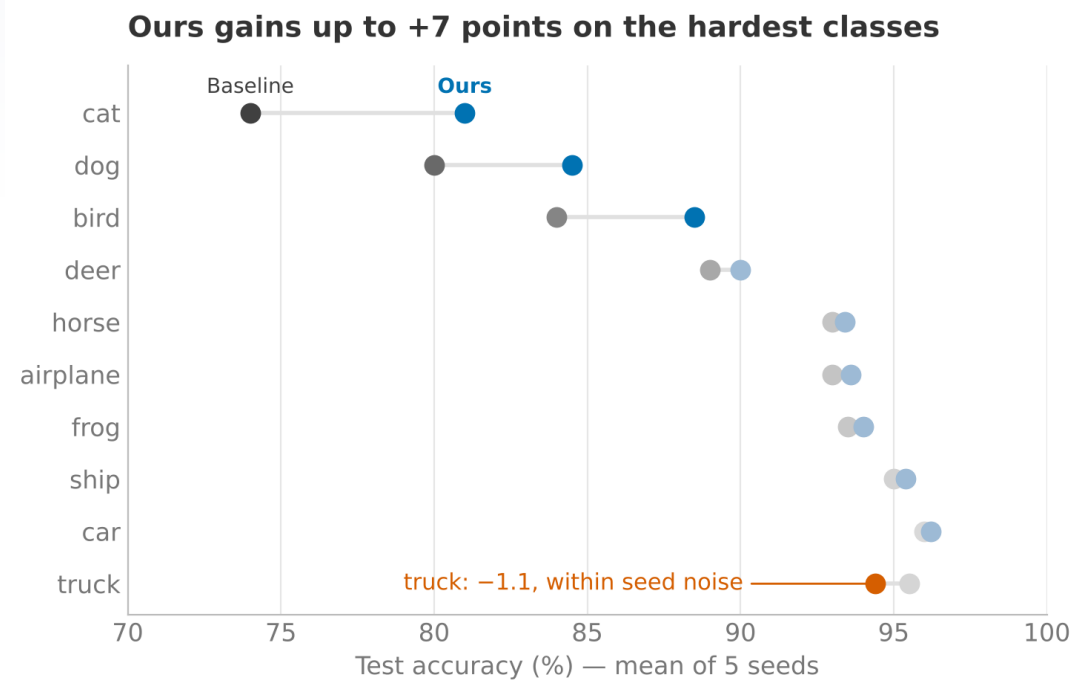


Exploratory





Explicatory



Exploratory vs explanatory



The go rn to an
answe



Explorative charts are suitable for **papers** and **thesis** where you plot the data and try no to bias too much the reader. However, in **presentations**, **posters** and **deliverables** we need to communicate information quickly and **explanatory** charts are more suitable



Knaflic, C. N. (2015). Storytelling with Data. Wiley.



In explicative charts where to focus your audience attention is key

Clear message

- Before doing the chart **think what is the message** you want to tell.
- This message decides where to focus the attention.



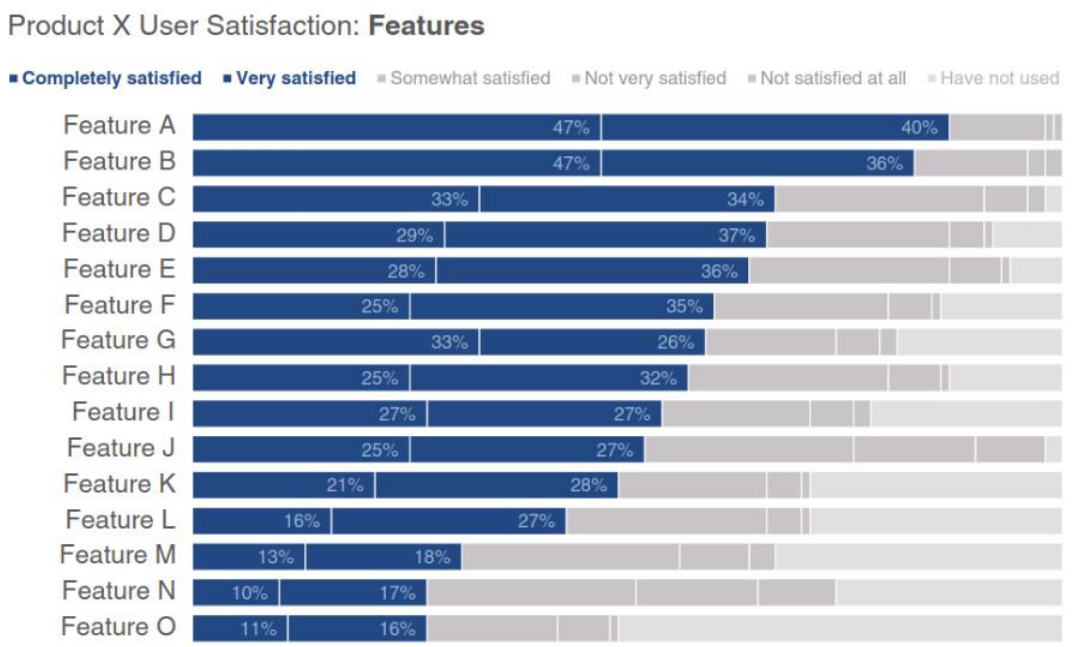
Knaflic, C. N. (2015). Storytelling with Data. Wiley.

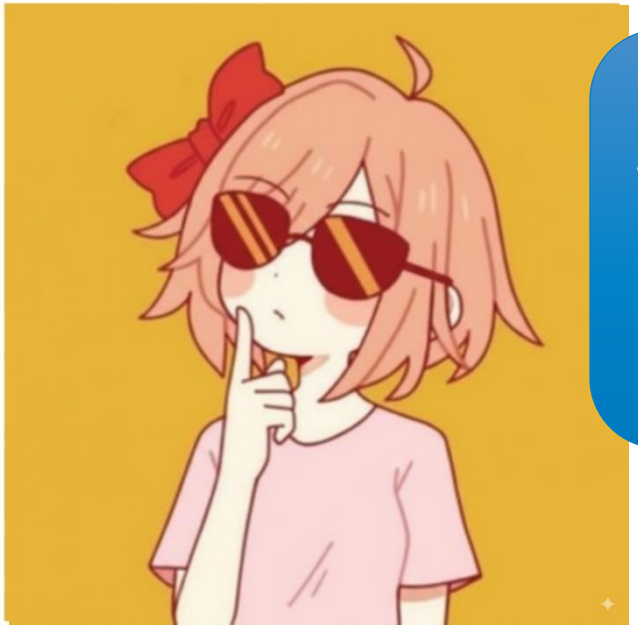
One chart, one message

- Centre each chart on **one** thing
- If there are several series, **one** should stand out
- Highlight colour for it, **grey** for the rest
- More than **3** highlights → split the chart

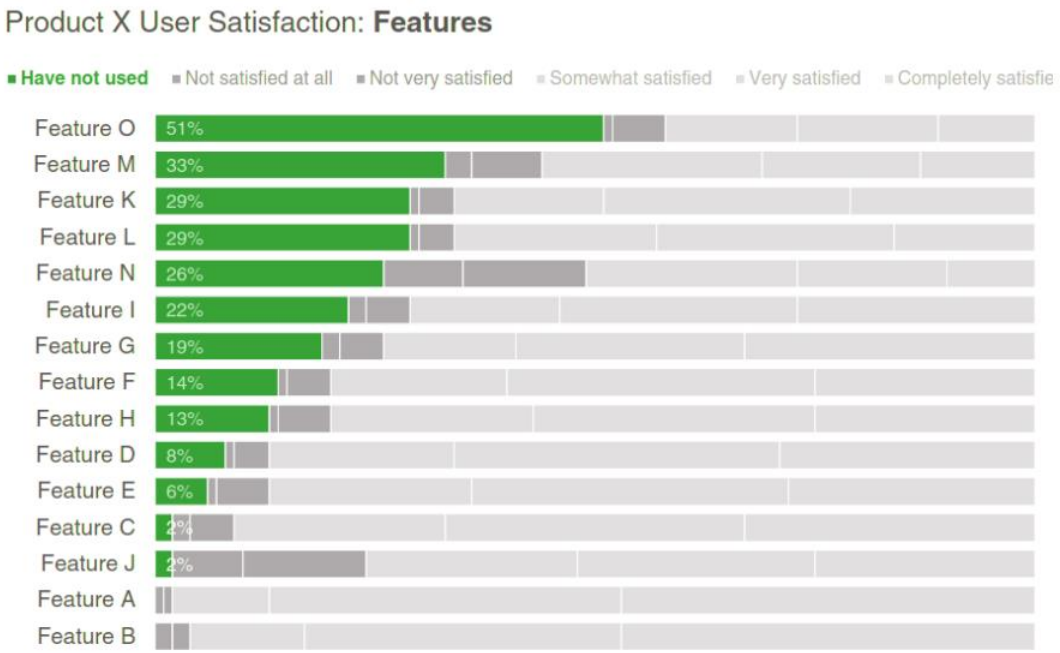


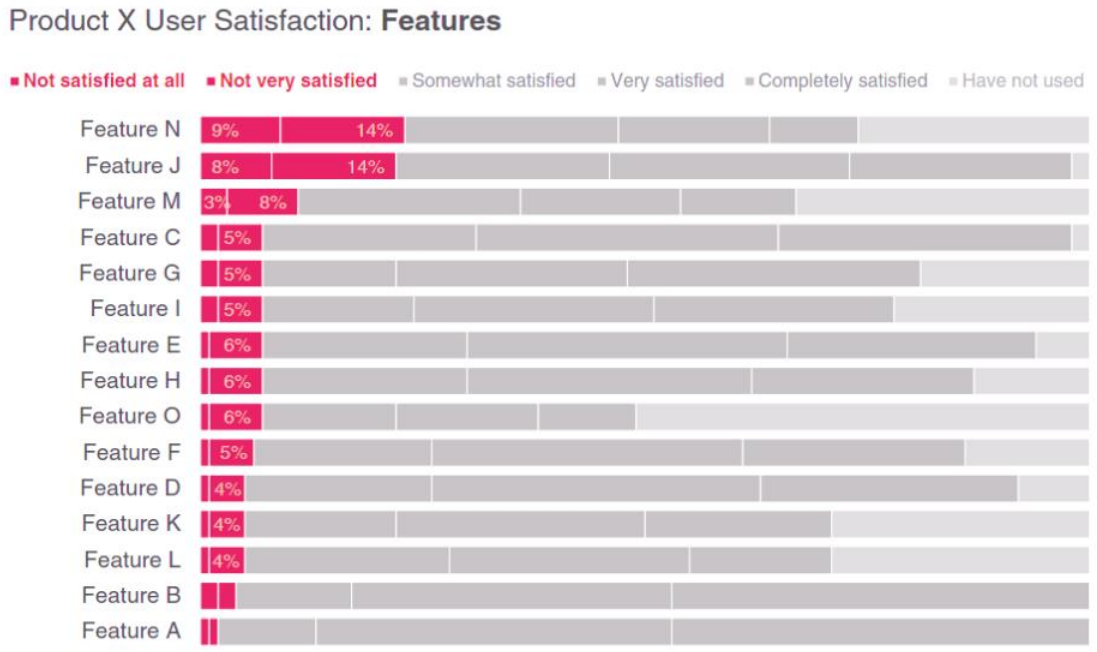
Knaflic, C. N. (2015). Storytelling with Data. Wiley.





What do i want to tell ?





Knaflic, C. N. (2015). *Storytelling with data: A data visualization guide for business professionals*. John Wiley & Sons.

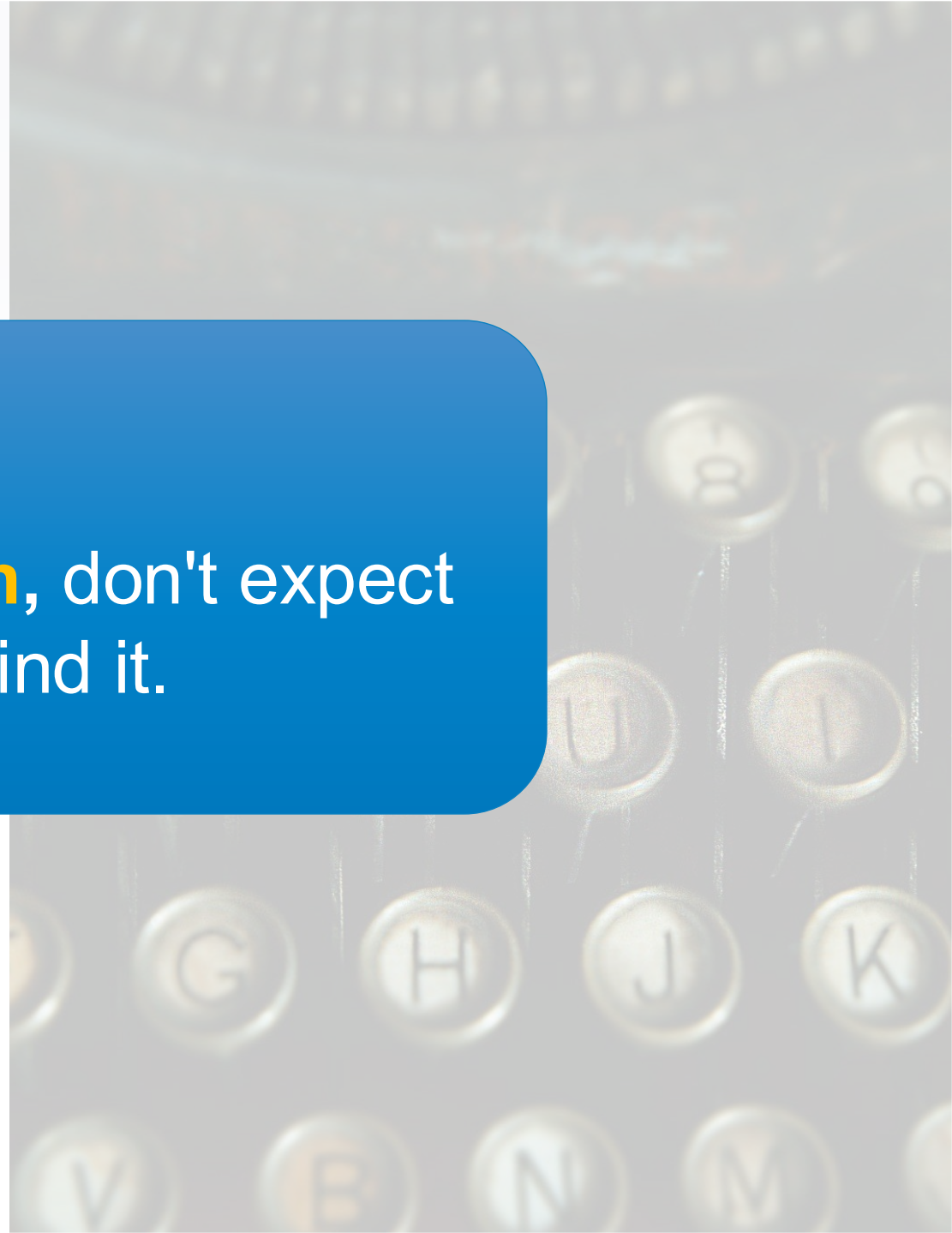
Text is your friend

- **Action title**: the message, not the variable names
- **Annotate** the key point, where it happens
- **Self-contained caption**: what is shown, what to look at, n seeds, SD or CI



Text is your friend

- **Action title**: the message, not the variable na
- **Annotate** happens
- **Self-cont** what to lo

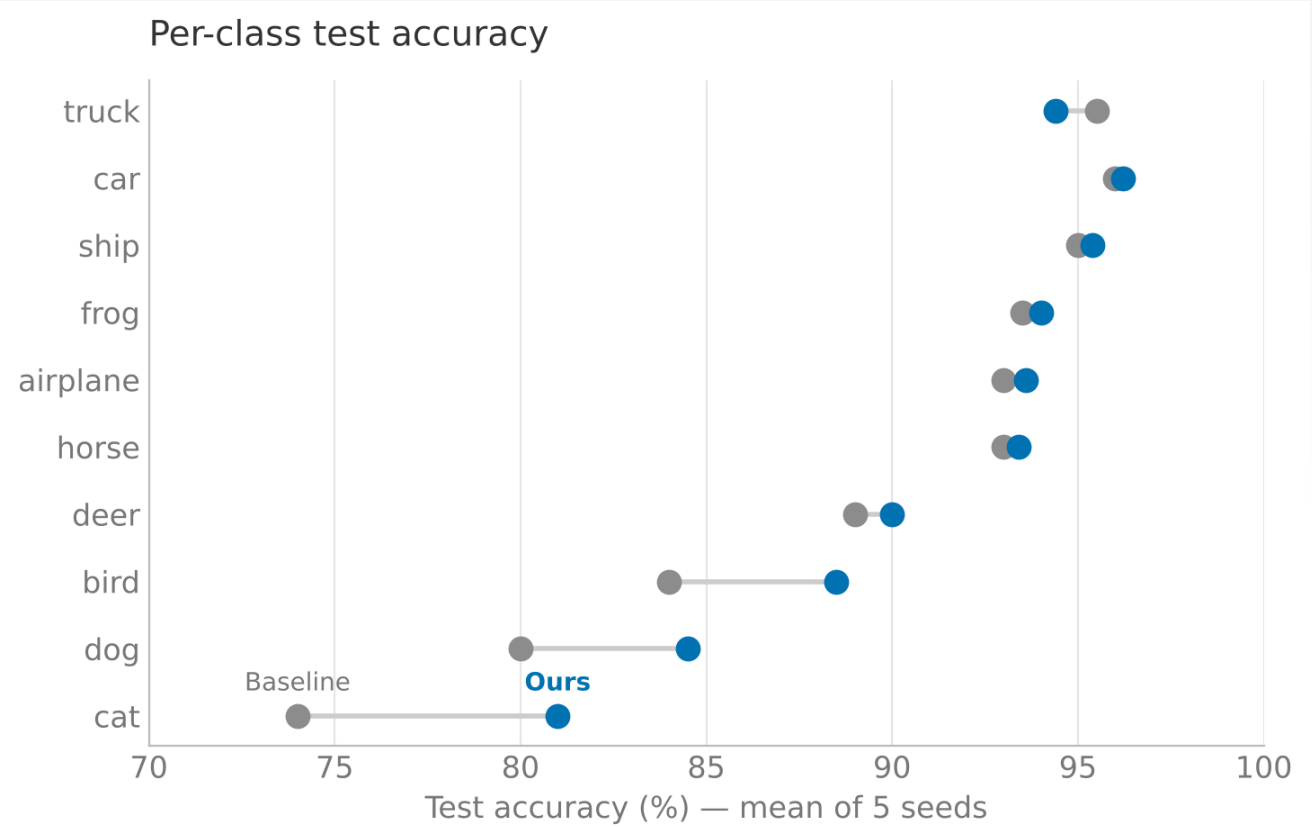


State your conclusion, don't expect the reader to find it.

Makeover : 1º The message

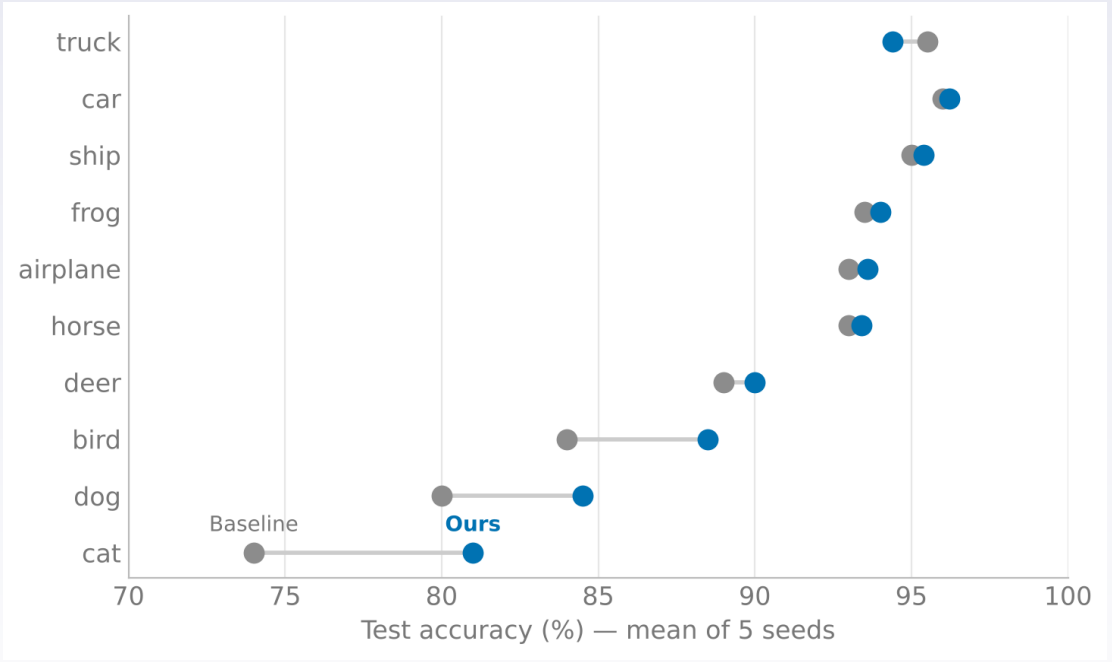
Think what do you want to tell here:

1. Our model improves in the classes where the baseline works bad.
2. Our model losses performance on the truck class, however it is within noise



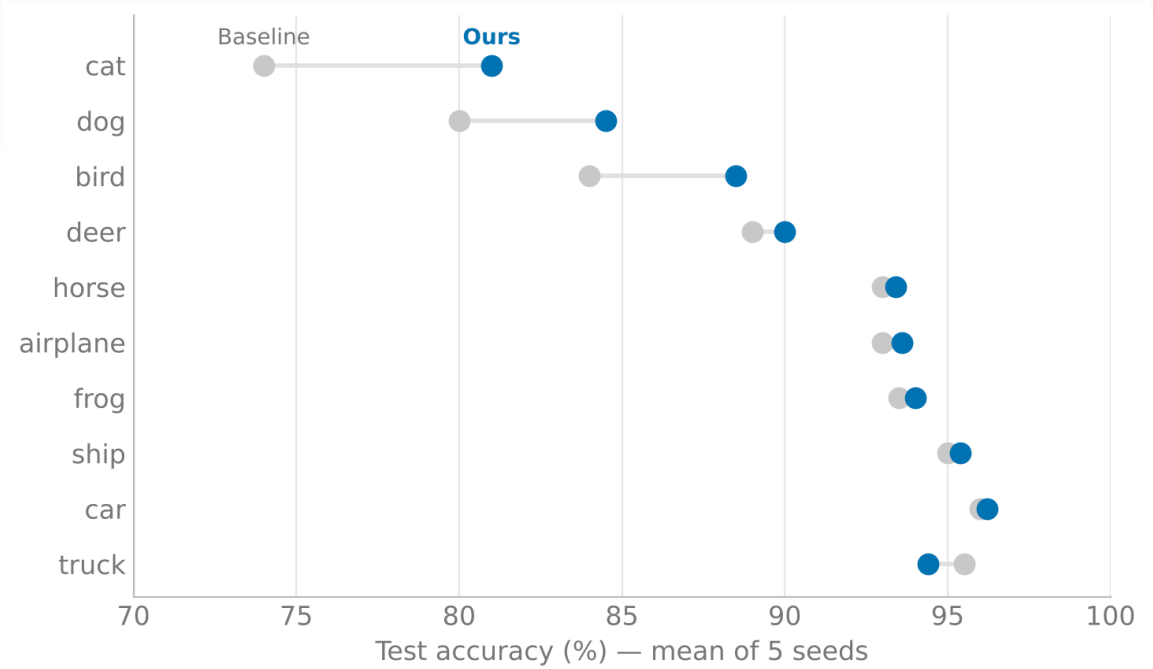


Focus losses





Focus gains



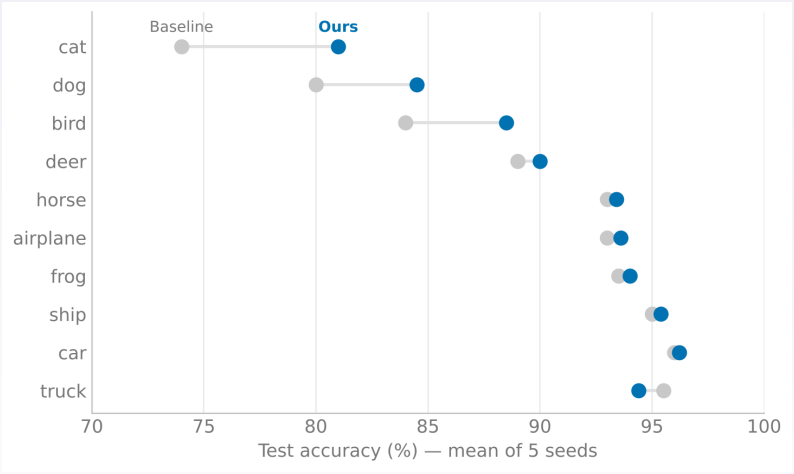
Makeover : Focus on gains

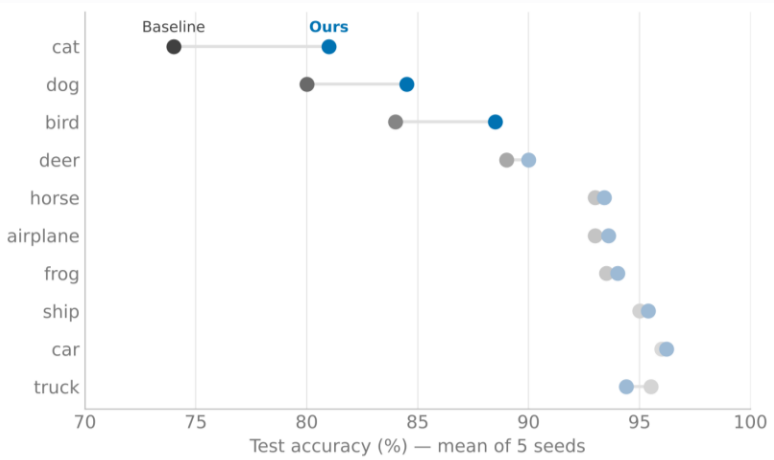
We want to focus the attention to the gains of the model.

Highlight our model the top 3 clases with more gain.

Mute the classes where the base model works good.





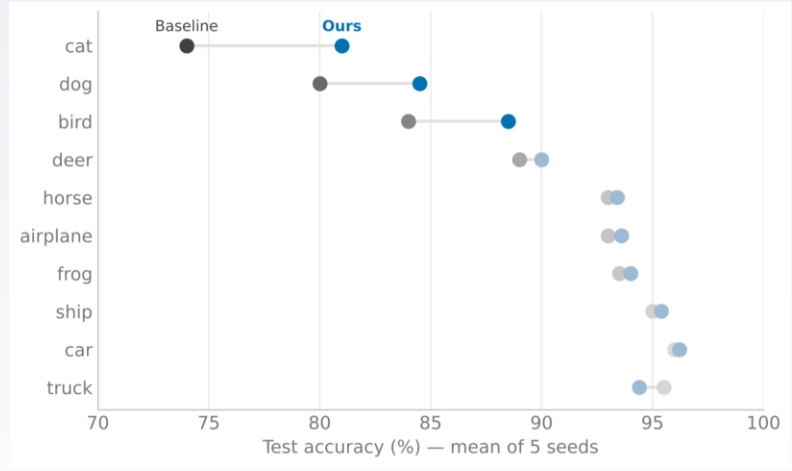


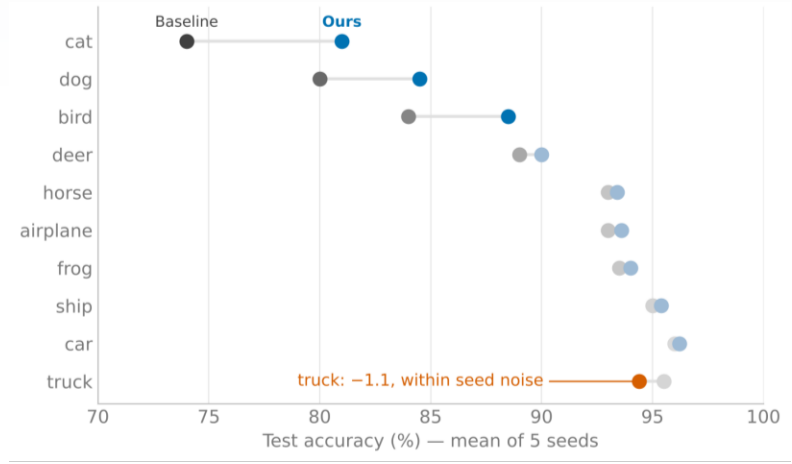
Makeover : Include the limits

Our model works worse than the baseline in the truck class. However, is within noise.

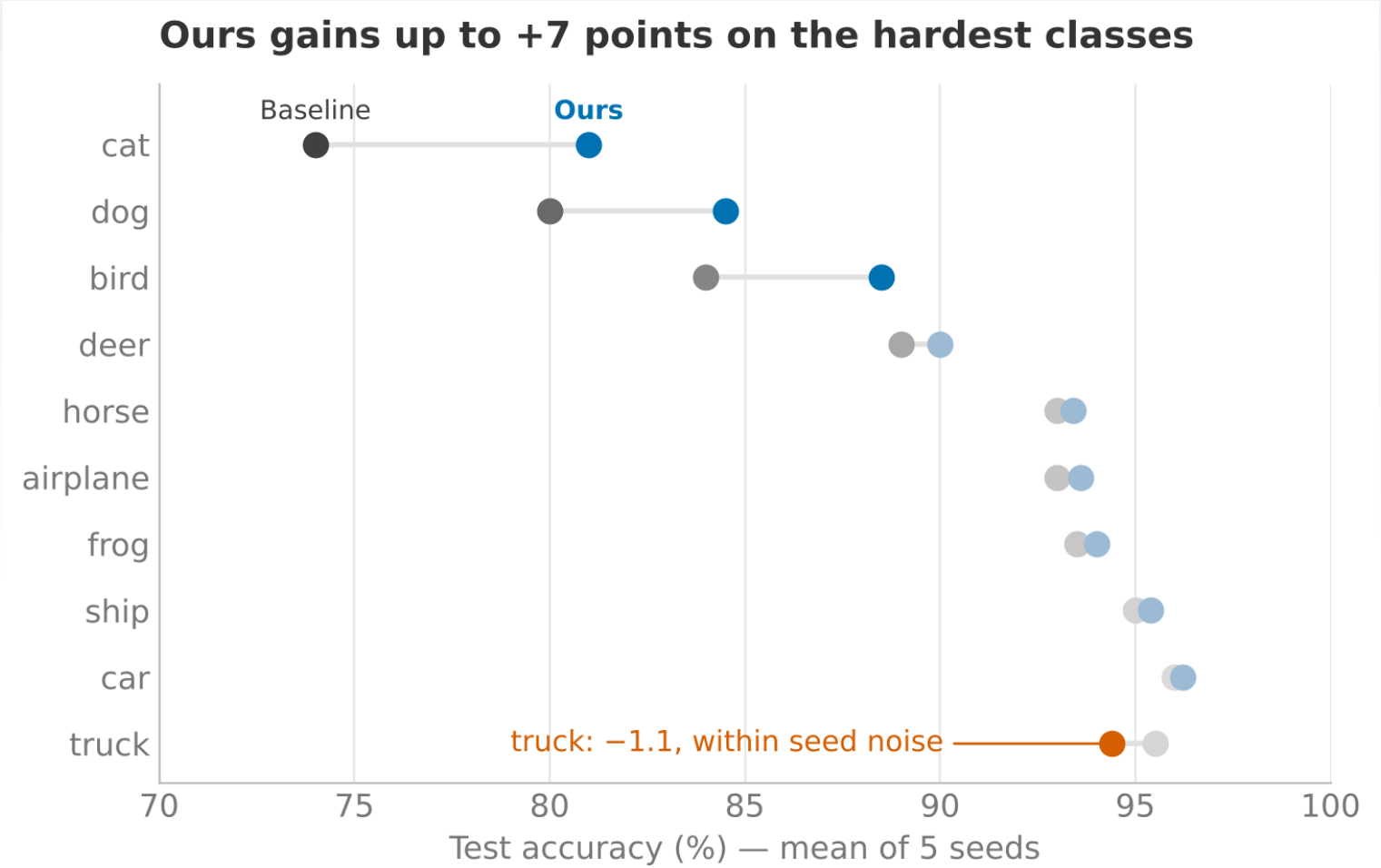
Highlight the case with a different color and use text to indicate the noise.







Makeover – step 3: say it



Answers…

*What is the **message**?*

👍 Action title states the finding

👍 Annotation answers the obvious **objection**

Kong, Liu & Karahalios (2018), CHI