Data types and encodings

Data types

We can classify data types into two broad categories

- Ordered
- Categorical

Ordered data types

> All ordered data has an *implicit* ordering

- Ordinal vs. quantitative
- Sequential and diverging
- Temporal

Ordinal data types

> There is a meaningful ordering, but we cannot do full-fledged arithmetic

- Shirt sizes (XS, S, M, L, XL)
- Rankings (1st, 2nd, 3rd, 4th, 5th)

Quantitative data

> There is a meaningful ordering, and arithmetic operations are supported

- Lengths, heights, etc…
- Counts
- Prices
- ….

Sequential and diverging data

> *sequential*: where there is a homogeneous range from a minimum to a maximum value

> *diverging*: can be deconstructed into two sequences pointing in opposite directions that meet at a *common zero* point

- Sequential: height of mountains, depth of seas
- Diverging: the elevation of points on earth surface; the PH scale (acid to alcaline, with middle point on 7.5)

This distinction will be useful mainly for defining meaningful scales

Temporal data

Time is a complex subject, so temporal data requires special care

- Does every year have 365 days?
- Does every day have 24 hours?
- Does every minute have 60 seconds?
- Leap years
- Daylight Saving Time
- Leap seconds

> Dates and times are hard because they have to reconcile two physical phenomena (the rotation of the Earth and its orbit around the sun) with a whole raft of geopolitical phenomena including months, time zones, and DST.

Lubridate

The `lubridate` package provides a series of facilities to deal with date and times.

It takes care for you of all the gory details of time handling on computers, including time zones, leap years/seconds, daylight saving times, etc…

```
renv::install("lubridate")
library(lubridate)
```

It provides three datatypes

- `date`
- `time`
- `datetime`

Creating dates and datetimes

Creating dates

```
ymd("2019-10-25")
```

```
[1] "2019-10-25"
```

```
mdy("October 25th, 2019")
```

```
[1] "2019-10-25"
```

```
dmy("25-Oct-2019")
```

```
[1] "2019-10-25"
```

```
# On dates that cannot be parsed will return NA
ymd("2019-4r-31")
```

```
[1] NA
```

Creating datetimes

```
ymd_hms("2019-10-25 08:10:03")
```

```
[1] "2019-10-25 08:10:03 UTC"
```

From components

```
make_date(2019, 10, 25)
```

```
[1] "2019-10-25"
```

```
make_datetime(2019, 10, 25, 8, 10, 25)
```

```
[1] "2019-10-25 08:10:25 UTC"
```

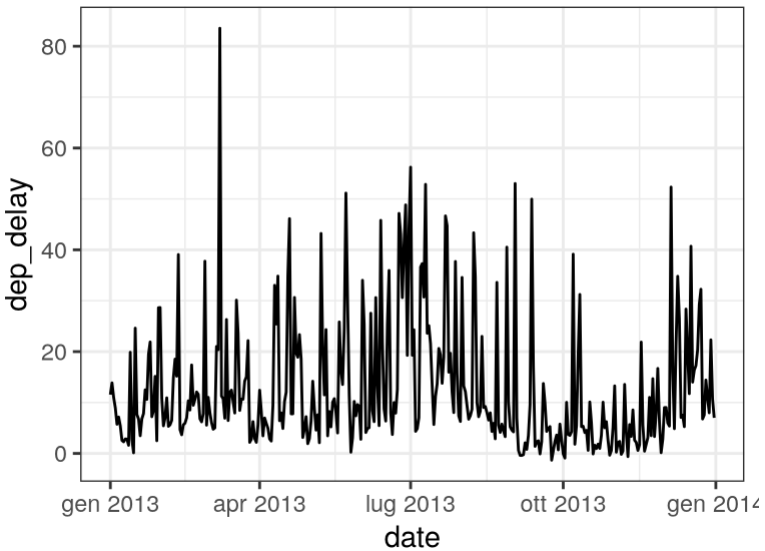
With vectorization

```
dates <- c(
  "October 25th, 2019",
  "October 26th, 2019",
  "Novembber 3rd, 2019",
  "November 4rd, 2019"
)
mdy(dates)
```

```
[1] "2019-10-25" "2019-10-26" NA
"2019-11-04"
```

Bringing proper dates to nycflights13

```
 1 library(nycflights13)
 2 library(tidyverse)
 3 library(lubridate)
 4
 5 flights |>
 6   drop_na(dep_delay) |>
 7   mutate(date = make_date(year, month, day)) |>
 8   group_by(date) |>
 9   summarise(dep_delay = mean(dep_delay)) |>
10   ggplot(aes(x=date, y=dep_delay)) +
11     geom_line()
```



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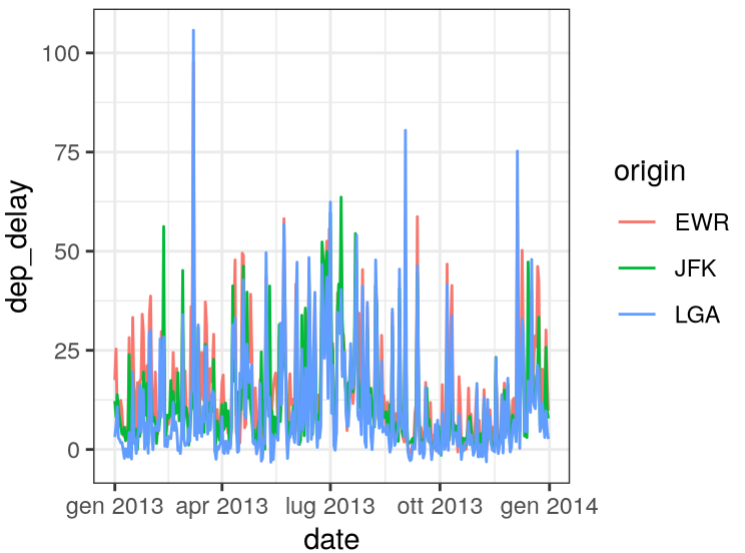
 7    mutate(date = make_date(year, month, day)) |>
 8    group_by(date, origin) |>
 9    summarise(dep_delay = mean(dep_delay)) |>
10    ggplot(aes(x=date, y=dep_delay, color=origin)) +
11      geom_line()
```



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 8    group_by(date, origin) |>
 9    summarise(dep_delay = mean(dep_delay)) |>
10    ggplot(aes(x=date, y=dep_delay, color=origin)) +
11      geom_line() +
12      facet_wrap(vars(origin))
```
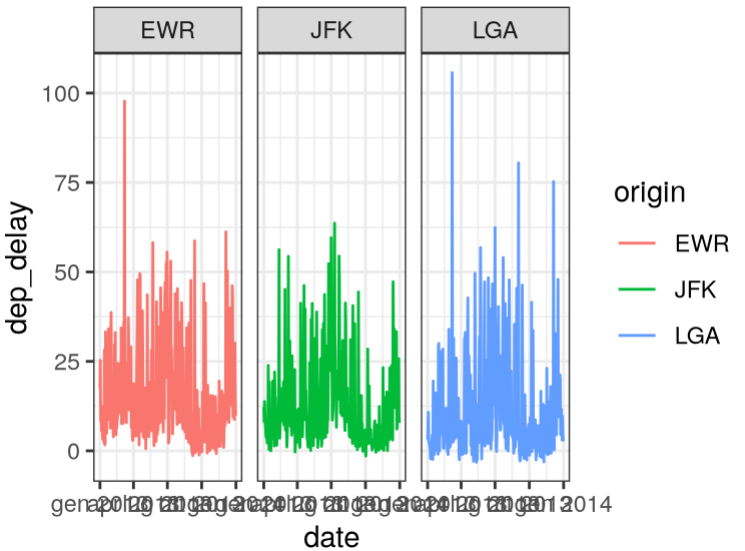
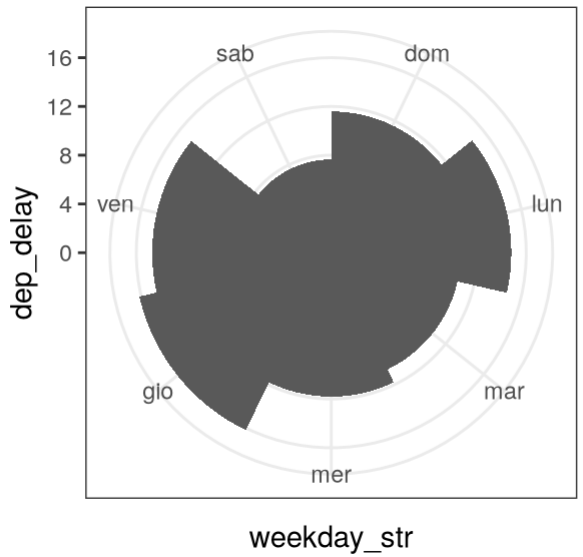



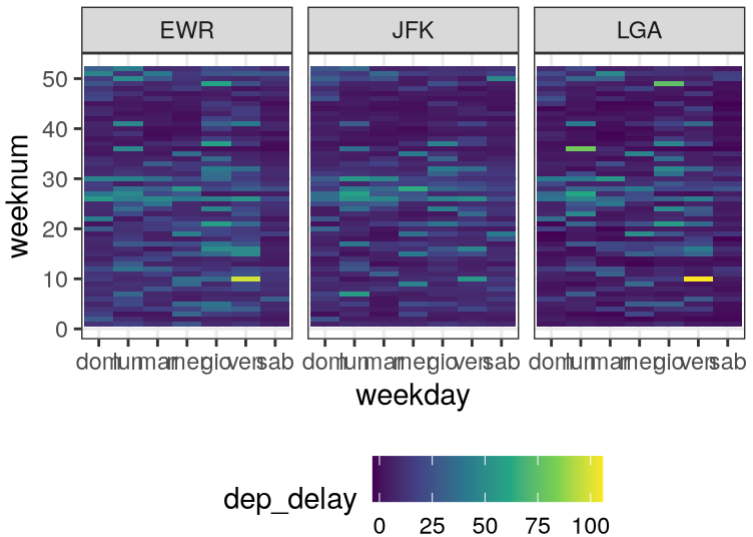
Bringing proper dates to nycflights13

```
flights |>
  drop_na(dep_delay) |>
  mutate(
    date = make_date(year, month, day),
    weekday = wday(date, label=FALSE), # Gets the d
    weekday_str = wday(date, label=TRUE)
  ) |>
  group_by(weekday, weekday_str) |>
  summarise(dep_delay = mean(dep_delay)) |>
  ggplot(aes(x=weekday_str, y=dep_delay)) +
    geom_col(width = 1) +
    coord_polar()
```



Bringing proper dates to nycflights13

```
flights |>
  drop_na(dep_delay) |>
  mutate(date = make_date(year, month, day)) |>
  group_by(date, origin) |>
  summarise(dep_delay = mean(dep_delay)) |>
  mutate(
    weekday = wday(date, label=TRUE),
    weeknum = isoweek(date))  |>
  ggplot(aes(x=weekday, y=weeknum,
             fill=dep_delay)) +
  geom_tile() +
  scale_fill_continuous(type="viridis") +
  facet_wrap(vars(origin)) +
  theme_bw() +
  theme(legend.position = 'bottom')
```



Bringing proper dates to nycflights13

```
flights |>
  drop_na(dep_delay) |>
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  group_by(date, origin) |>
  summarise(dep_delay = mean(dep_delay)) |>
  mutate(
    weekday = wday(date, label=TRUE),
    weeknum = isoweek(date))  |>
  ggplot(aes(x=weekday, y=weeknum,
             fill=dep_delay, color=dep_delay)) +
  geom_tile() +
  scale_fill_continuous(type="viridis", aesthetics=
  facet_wrap(vars(origin)) +
  coord_polar() +
  theme_void() +
  theme(axis.text.x = element_text(),
        strip.text = element_text(size=14),
        legend.position = 'bottom')
```
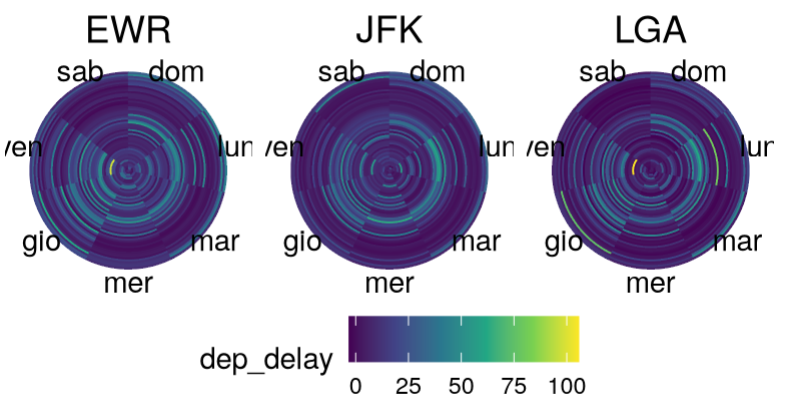



Categorical

> Categorical types do not have an implicit ordering.

With categories you can just compare for equality

- Apples, organes, bananas, grapes…

You can enforce an explicit ordering when needed

Forcats

This is a tidyverse library that helps with working with categorical data, which in R is called a `factor`

```
1 library(forcats)
```

Creating factors

You can use the `factor` function to create factors, which is vectorized

```
 1  library(gapminder)
 2
 3  mutate(gapminder,
 4         country = factor(country))
```

```
# A tibble: 1,704 × 6
   country     continent  year lifeExp      pop gdpPercap
   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
 1 Afghanistan Asia       1952    28.8  8425333      779.
 2 Afghanistan Asia       1957    30.3  9240934      821.
 3 Afghanistan Asia       1962    32.0 10267083      853.
 4 Afghanistan Asia       1967    34.0 11537966      836.
 5 Afghanistan Asia       1972    36.1 13079460      740.
 6 Afghanistan Asia       1977    38.4 14880372      786.
 7 Afghanistan Asia       1982    39.9 12881816      978.
 8 Afghanistan Asia       1987    40.8 13867957      852.
 9 Afghanistan Asia       1992    41.7 16317921      649.
10 Afghanistan Asia       1997    41.8 22227415      635.
# i 1,694 more rows
```

Factors and strings

What is the difference between factors and strings?

- Factors can take only a pre-specified number of values

```
x <- factor(c("a", "b", "c"))
x[4] <- "d"
x
```

```
[1] a    b    c    <NA>
Levels: a b c
```

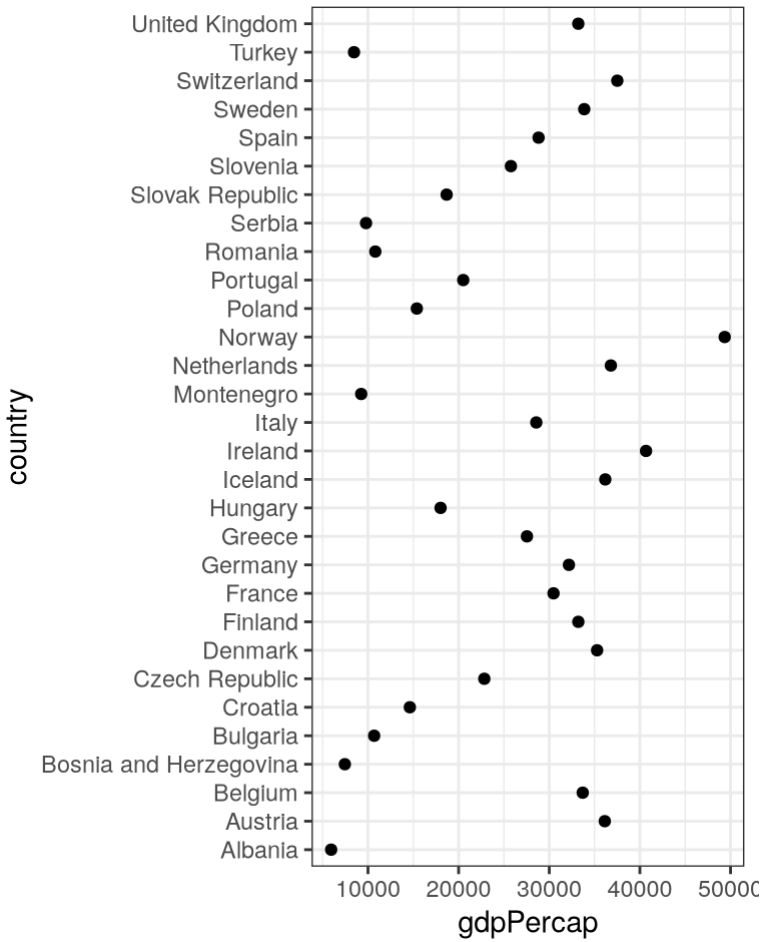
```
x <- factor(c("a", "b", "c"), levels = c("a", "b", "c", "d"))
x[4] <- "d"
x
```

```
[1] a b c d
Levels: a b c d
```

- You can impose an ordering different than alphabetical to factors.

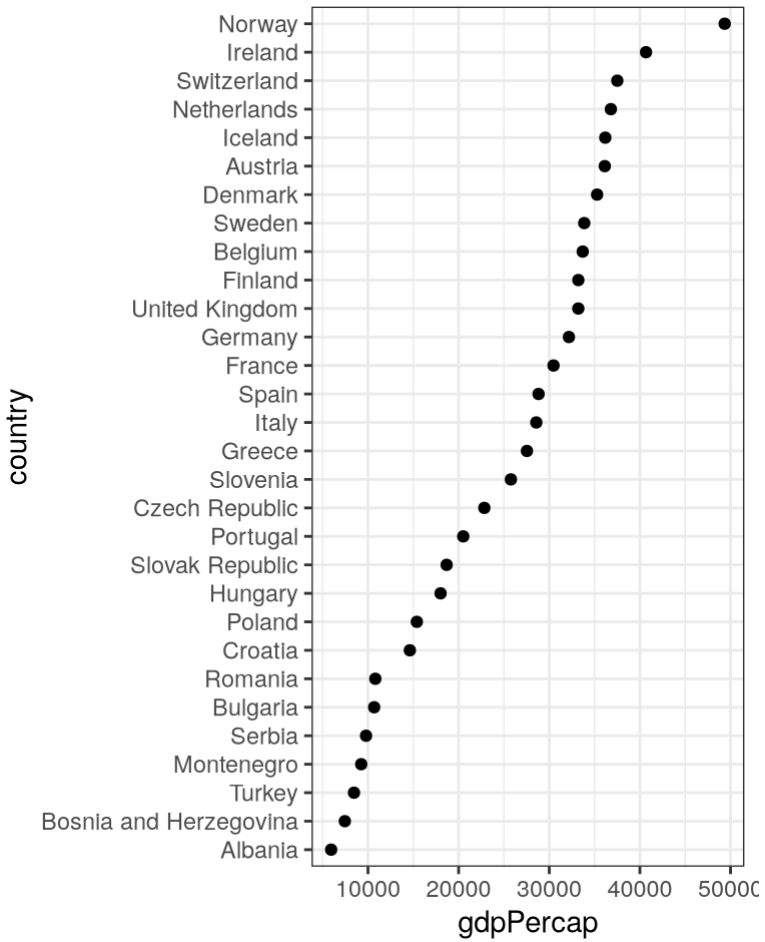
Reordering factors

```
gapminder |>
  filter(year==2007) |>
  filter(continent == 'Europe') |>
  ggplot(aes(x=country, y=gdpPercap)) +
    geom_point() +
    coord_flip()
```



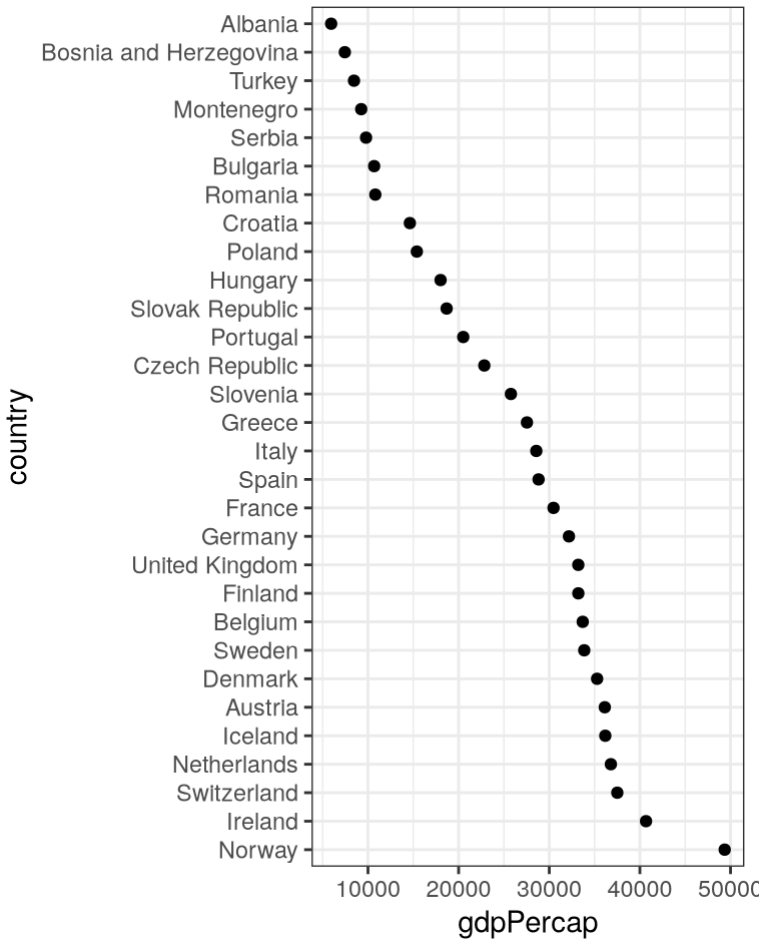
Reordering factors

```
gapminder |>
  filter(year==2007) |>
  filter(continent == 'Europe') |>
  mutate(
    country = fct_reorder(country, gdpPercap)
  ) |>
  ggplot(aes(x=country, y=gdpPercap)) +
    geom_point() +
    coord_flip()
```



Reordering factors

```
gapminder |>
  filter(year==2007) |>
  filter(continent == 'Europe') |>
  mutate(
    country = fct_reorder(country, desc(gdpPercap))
  ) |>
  ggplot(aes(x=country, y=gdpPercap)) +
    geom_point() +
    coord_flip()
```



Aesthetics, geoms, and data

Care must be used when selecting the mapping between attributes and aesthetics, as well as when choosing the geometric objects we use.

Aesthetic types

There are mainly two types of aesthetics

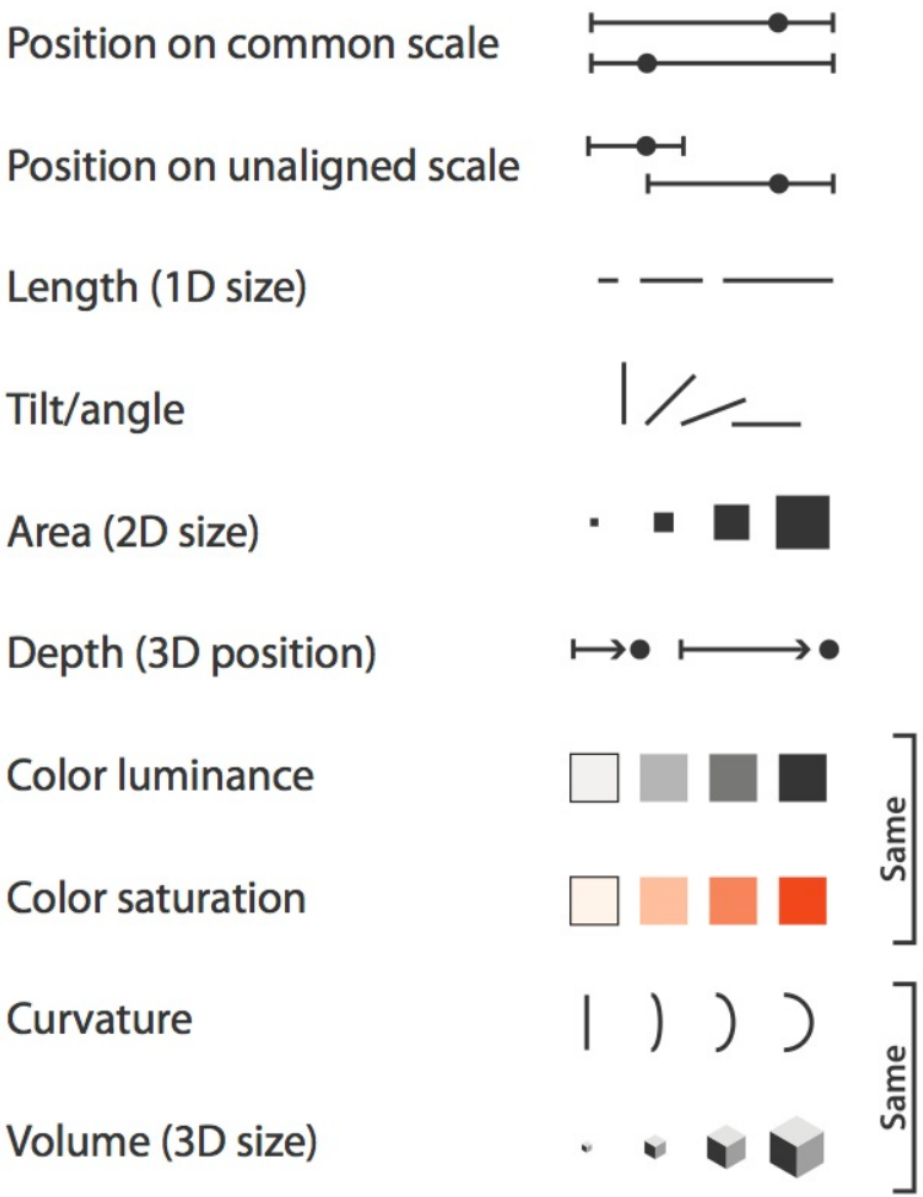
- Magnitude aesthetics
- Identity aesthetics

Aesthetic types

There are mainly two types of aesthetics

- Magnitude aesthetics: ordered data
- Identity aesthetics: categorical data

Magnitude Channels: Ordered Attributes



Identity Channels: Categorical Attributes

Spatial region

Color hue

Motion

Shape

Properties

- Expressivenes: what can be encoded by what
- Effectiveness: the importance should match the salience of the aesthetic, i.e. its noticeability

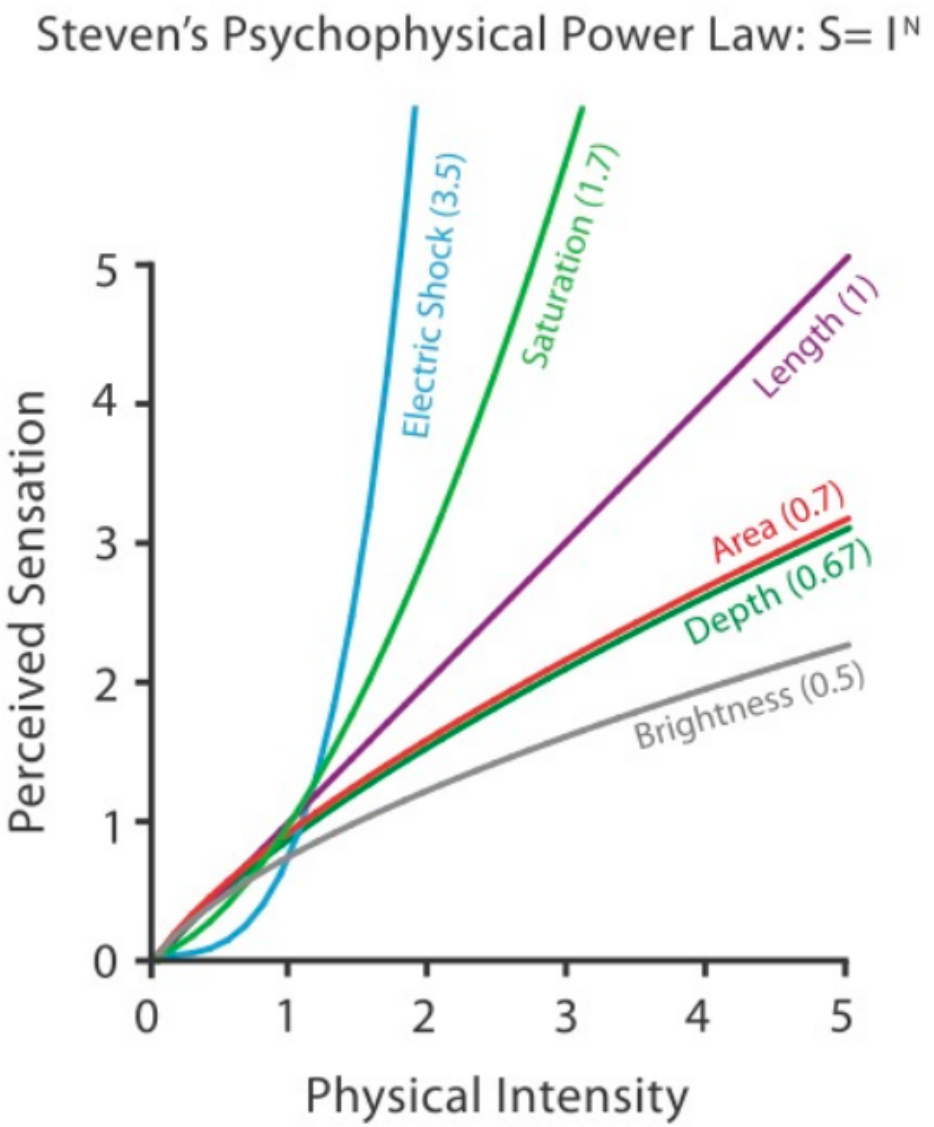
---

When choosing a mapping

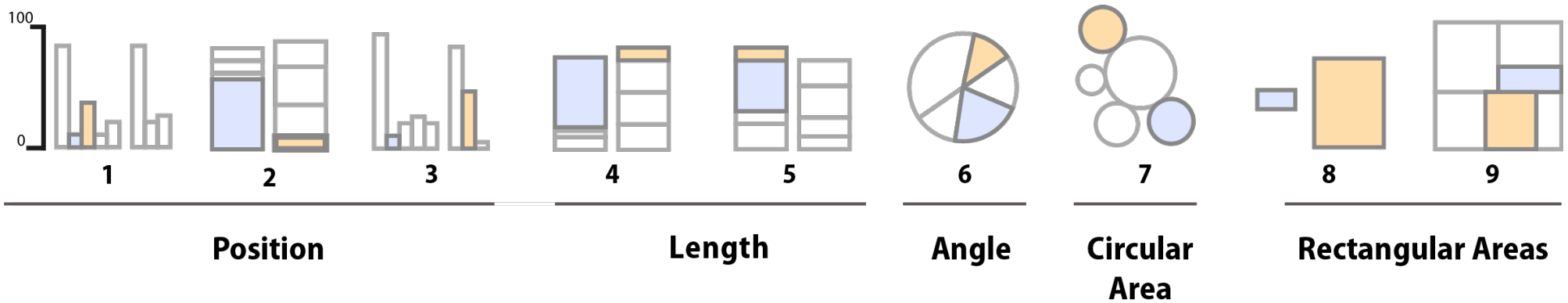
- Accuracy
- Discriminability
- Separability
- Popout

Accuracy

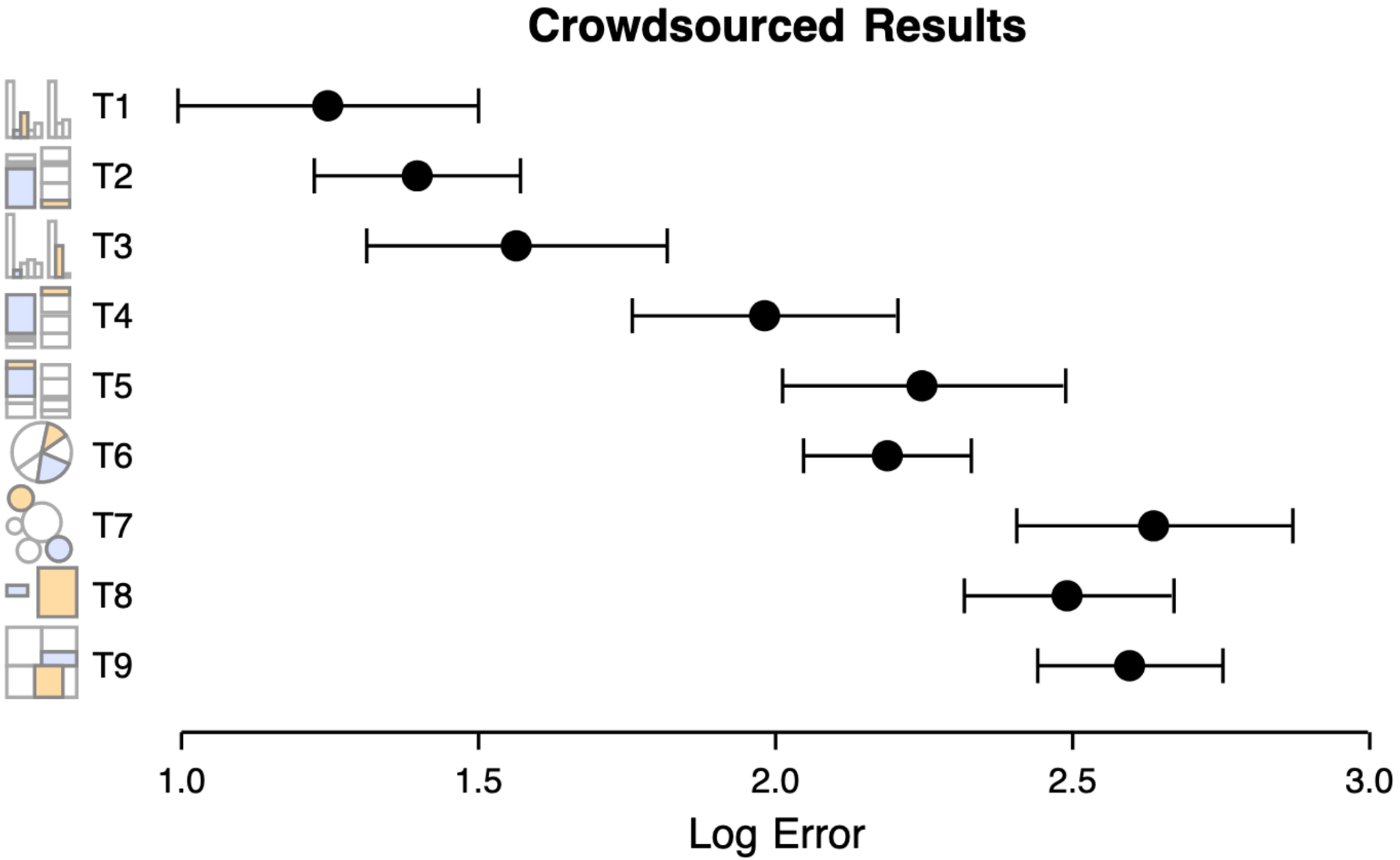
- Given a stimulus how close to the it measurement is the human perceptual judgement
- Stevens psychophysical power law [1975]
- Be careful with encoding linear information with a non perceptually-linear aesthetic



Accuracy

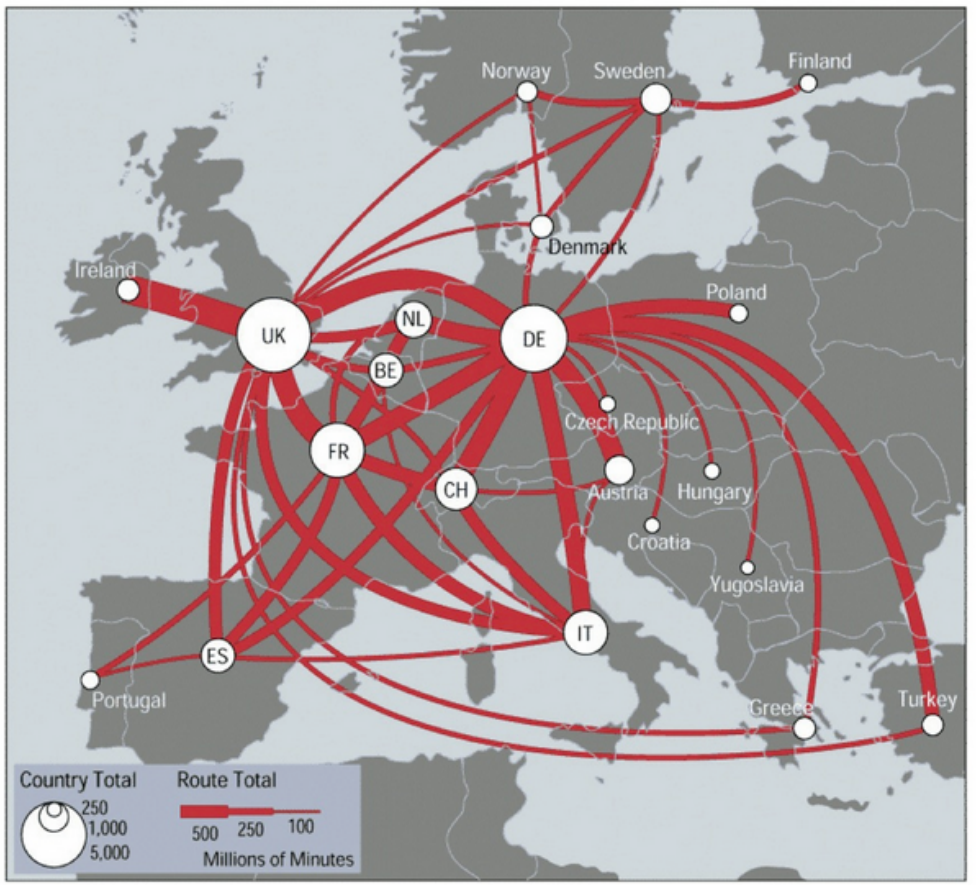


Heer et al. 2010: http://vis.stanford.edu/files/2010-MTurk-CHI.pdf


Crowdsourced Results
T1
T2
T3
T4
T5
T6
T7
T8
T9
1.0
1.5
2.0
2.5
3.0
Log Error

Discriminability

- If you encode data using a particular aesthetic, are the differences between items perceptible to the human as intended?
- How many levels can be distinguished?
- We should quantify the number of bins that are available in a visual channel



Separability

Popout

Table 1. Our sales grew to $600 million this year

	Q1	Q2	Q3	Q4
Bob	26	35	72	84
Ellie	22	15	61	35
Gerrie	19	20	71	55
Jack	22	95	13	64
Jon	83	62	46	48
Karen	30	65	98	82
Ken	38	28	45	71
Lauren	98	81	41	63
Steve	16	50	23	41
Valerie	46	24	30	57
Total	**$400**	**$475**	**$500**	**$600**

Popout

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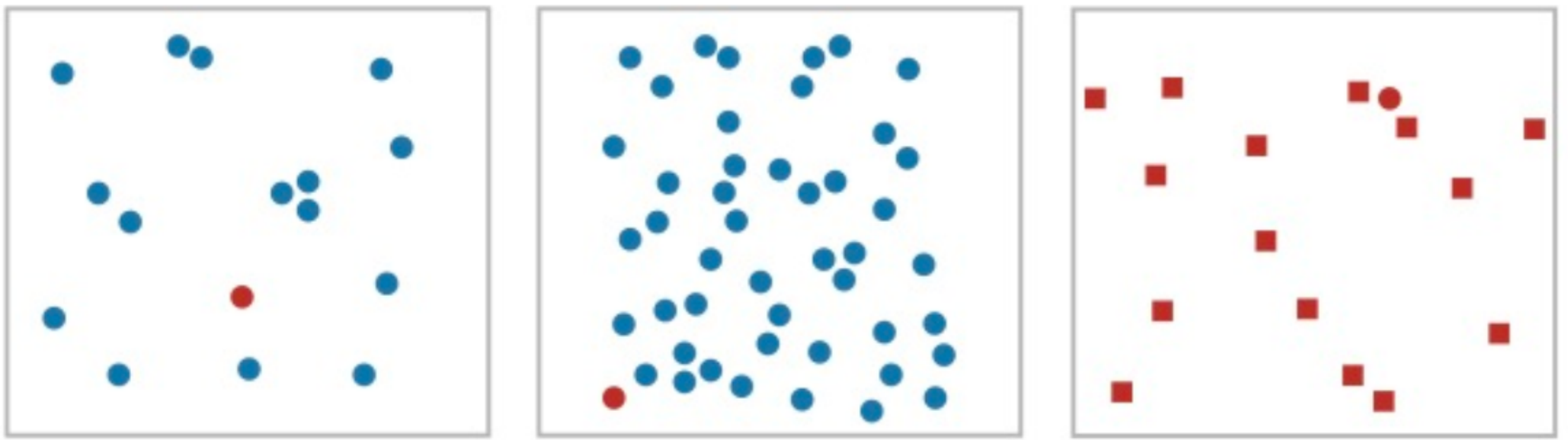
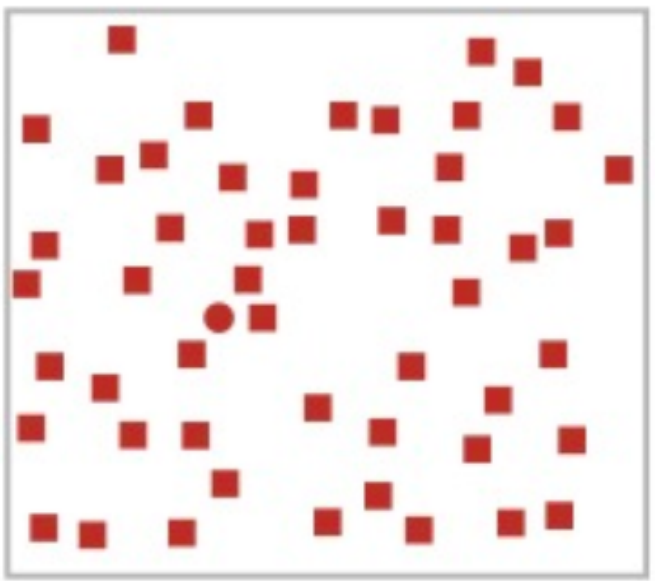
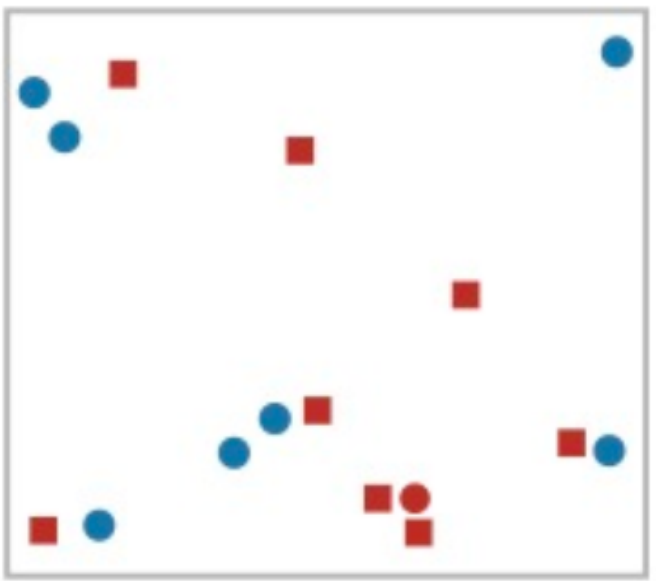
Popout, or preattentive processing



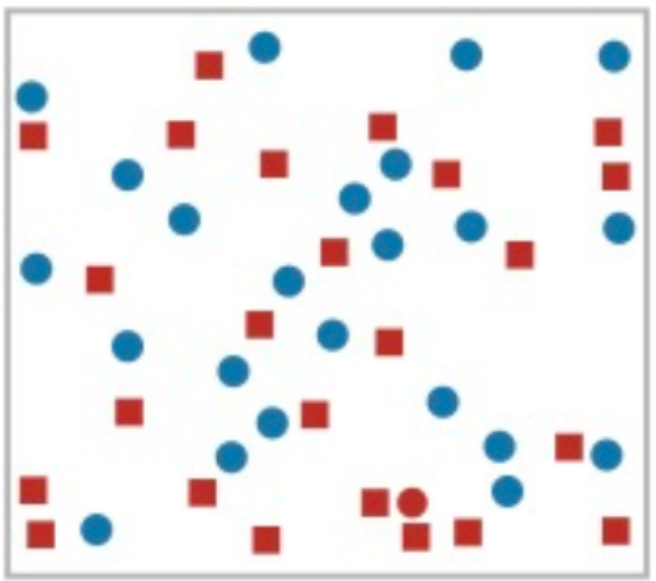
Popout, or preattentive processing



(d)

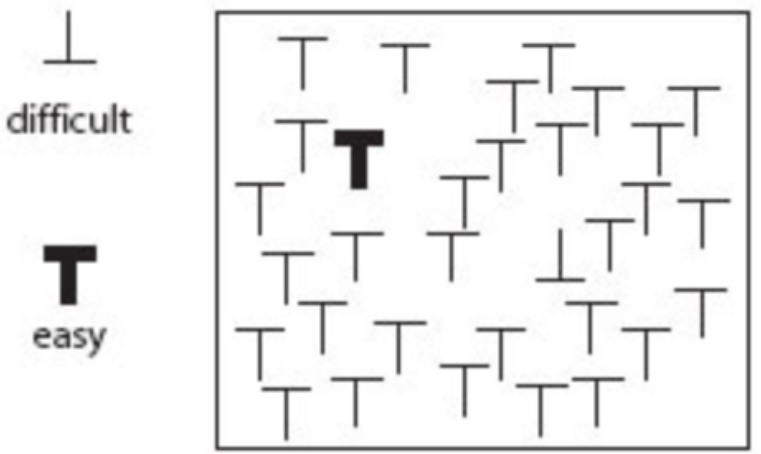


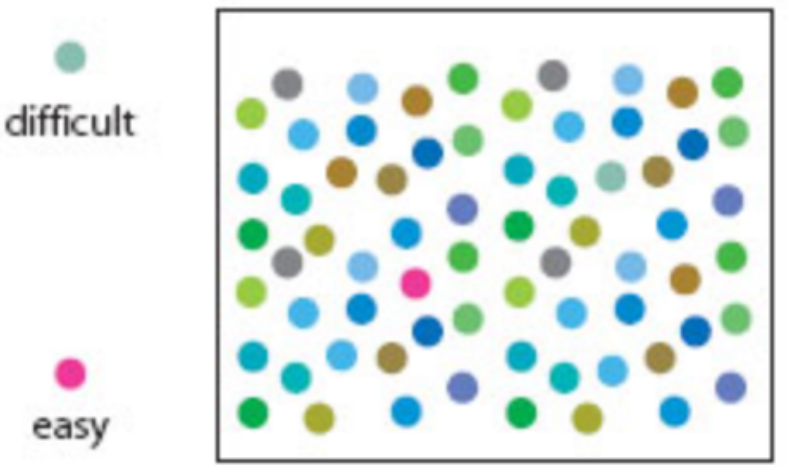
(e)

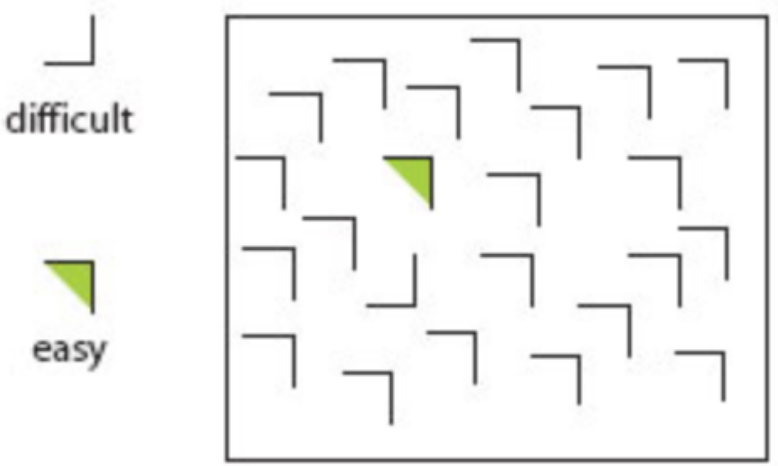


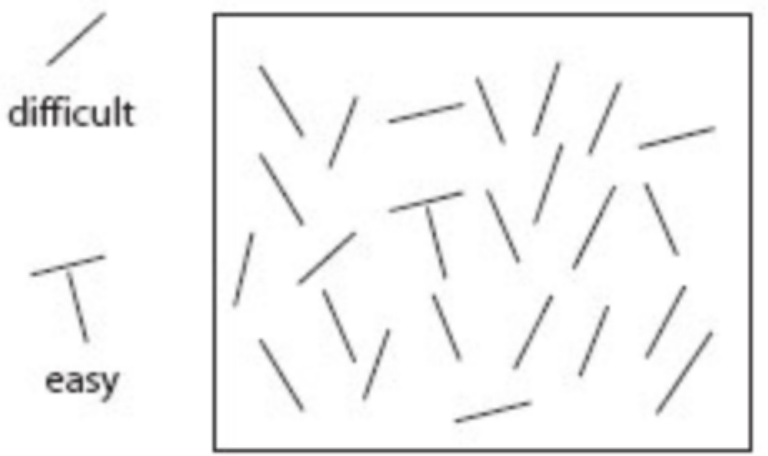
(f)

Popout, or preattentive processing





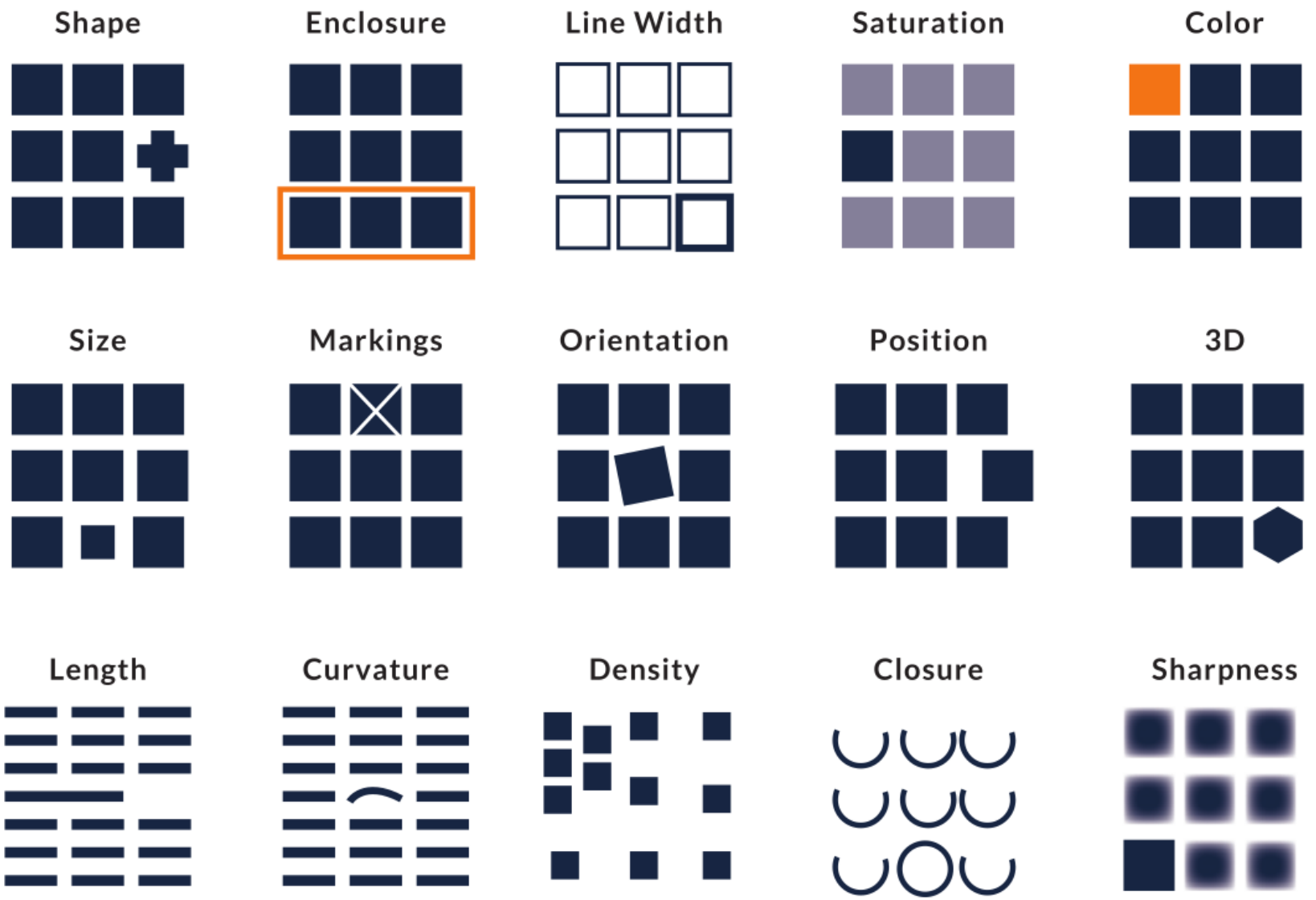




Popout, or preattentive processing

- The *popout* of the color aesthetic is stronger than the one of the shape aesthetic
- Using many aesthetics at the same time, for different encodings, might weaken the preattentive effect.
- Be very carfeul at representing several variables all at once using different channels: visual conjunctions are often difficult to see (cfr. separability property)
- In general, if you want something to stand out, make it different from everything else on prominent (possibly combined) visual channels (e.g. color and size)

Popout, or preattentive processing



Relative vs. absolute judgements

Weber's Law: our perceptual system is based on relative judgements, not absolute ones.
In other terms, our perception is contextual

Unframed
Unaligned

(a)

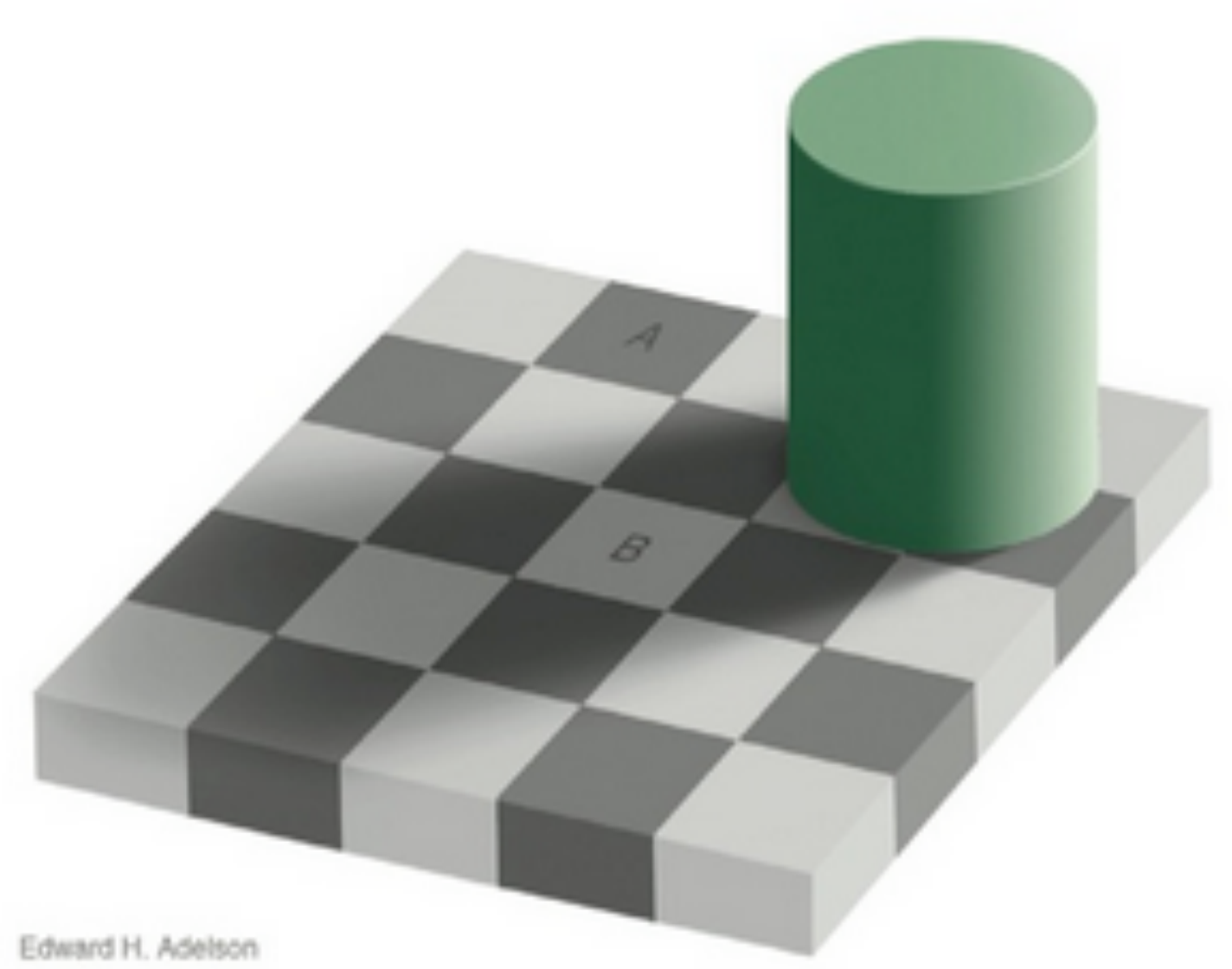
Framed
Unaligned

(b)

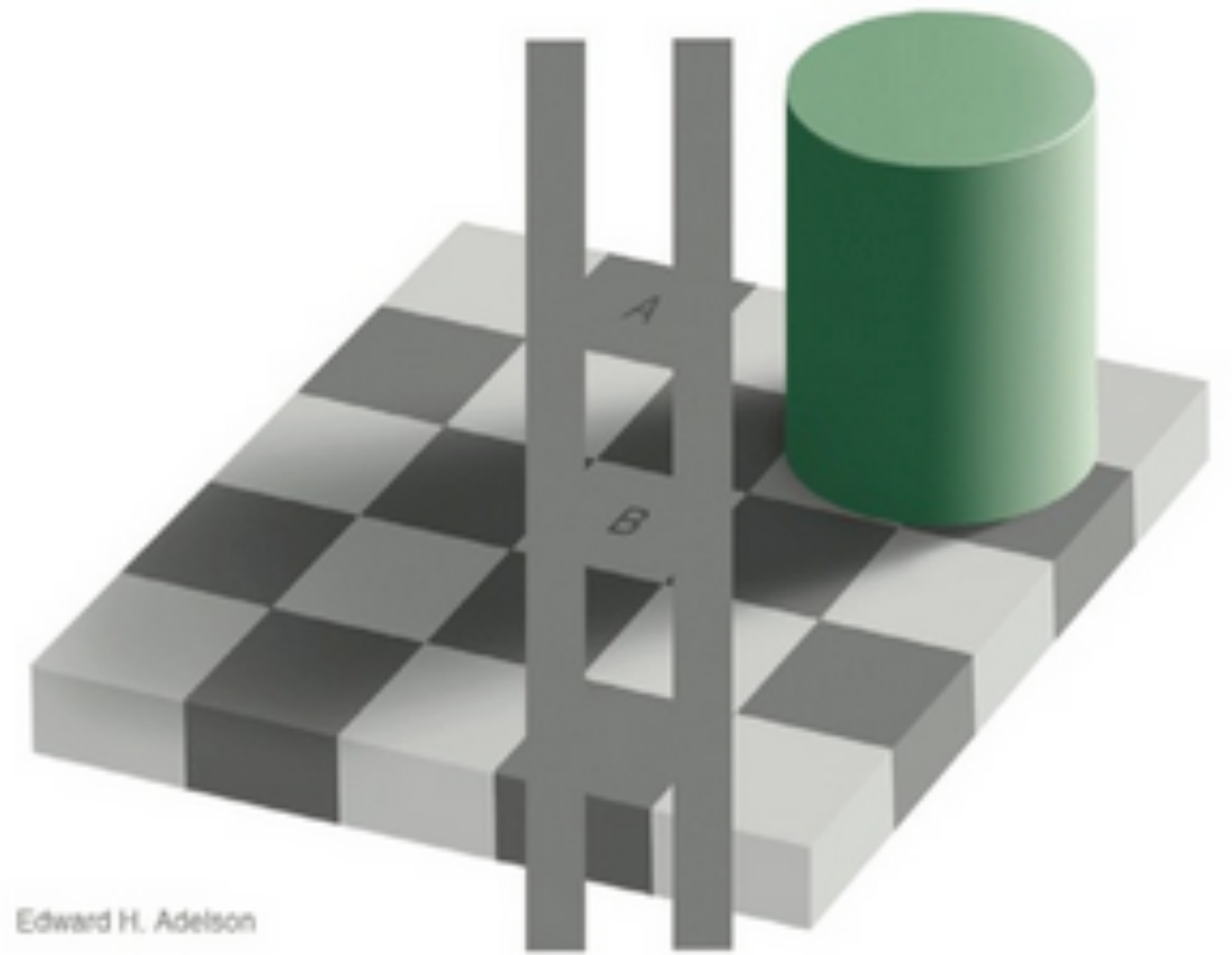
Unframed
Aligned

(c)

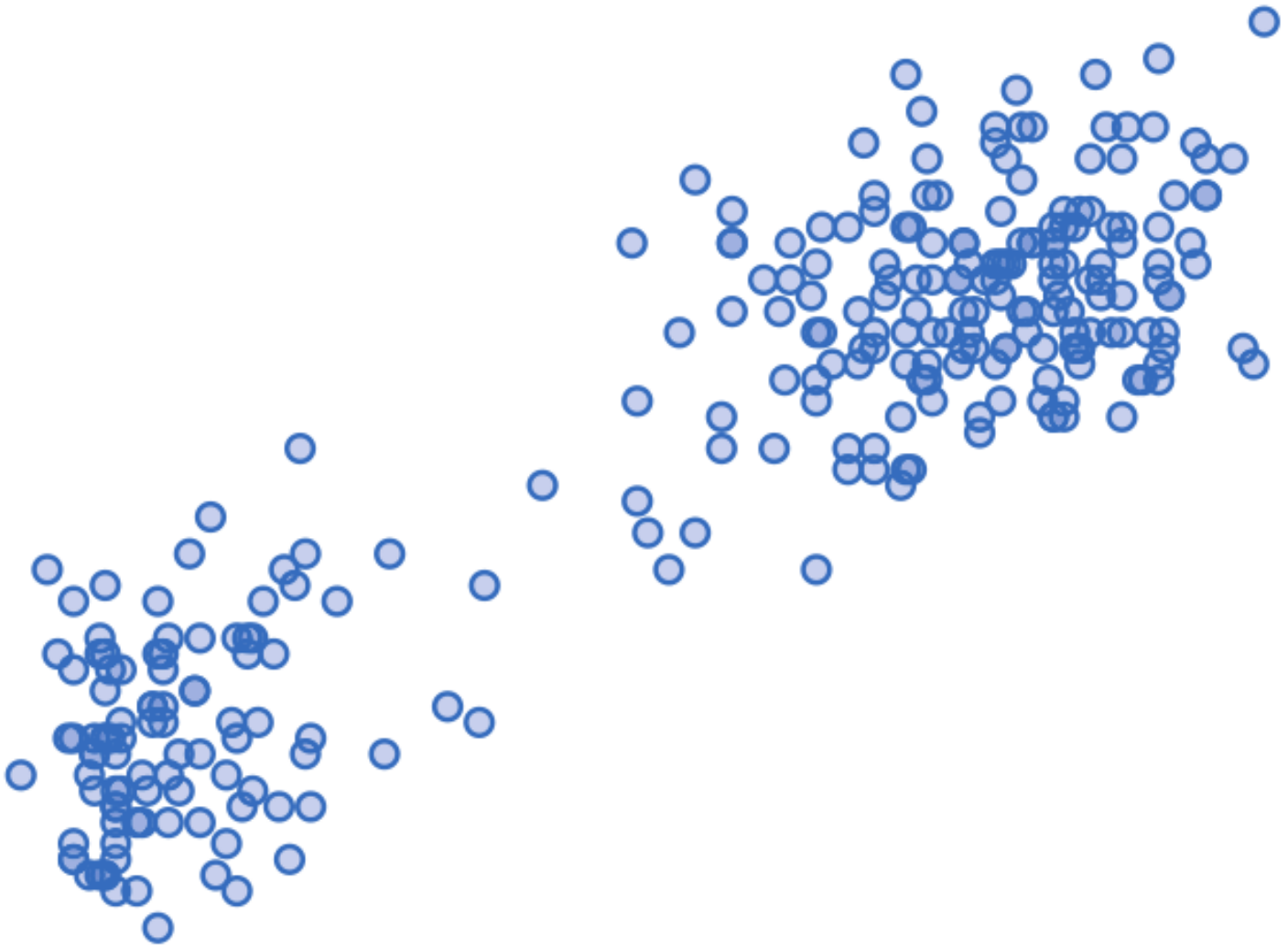
Relative vs. absolute judgements



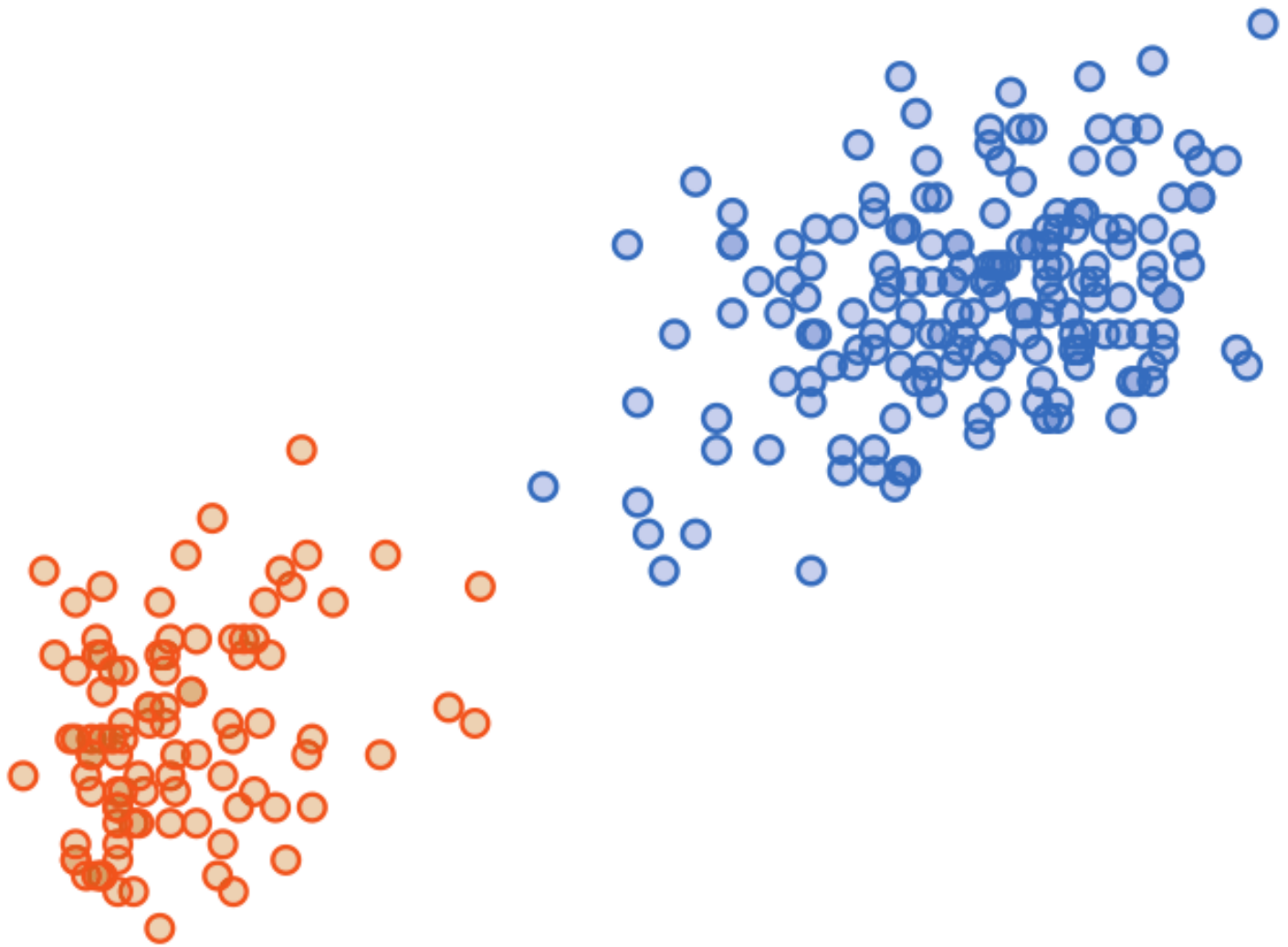
Relative vs. absolute judgements



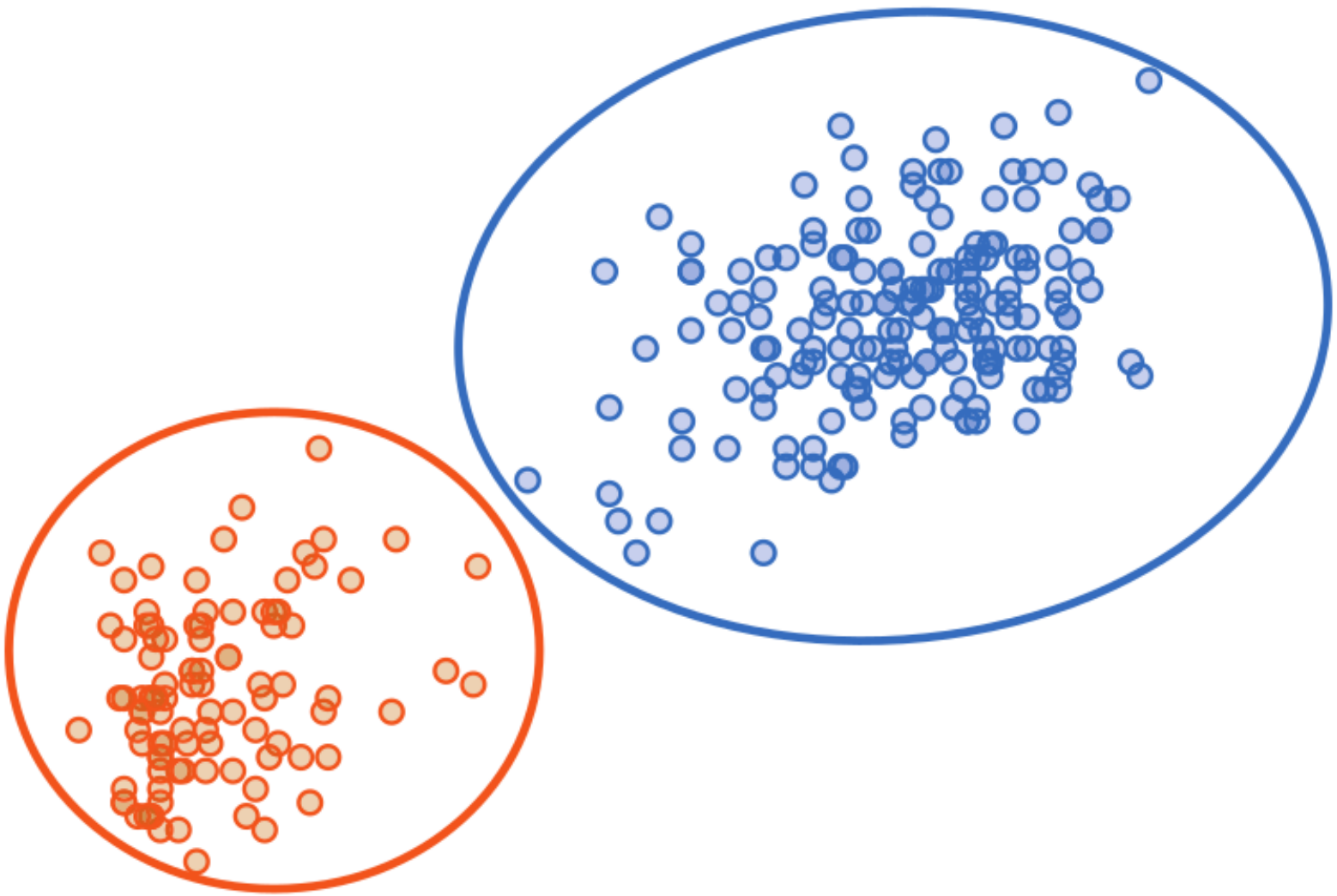
Gestalt: proximity



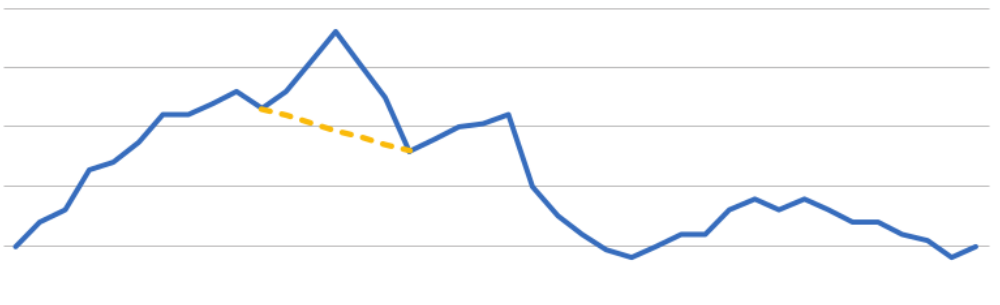
Gestalt: similarity



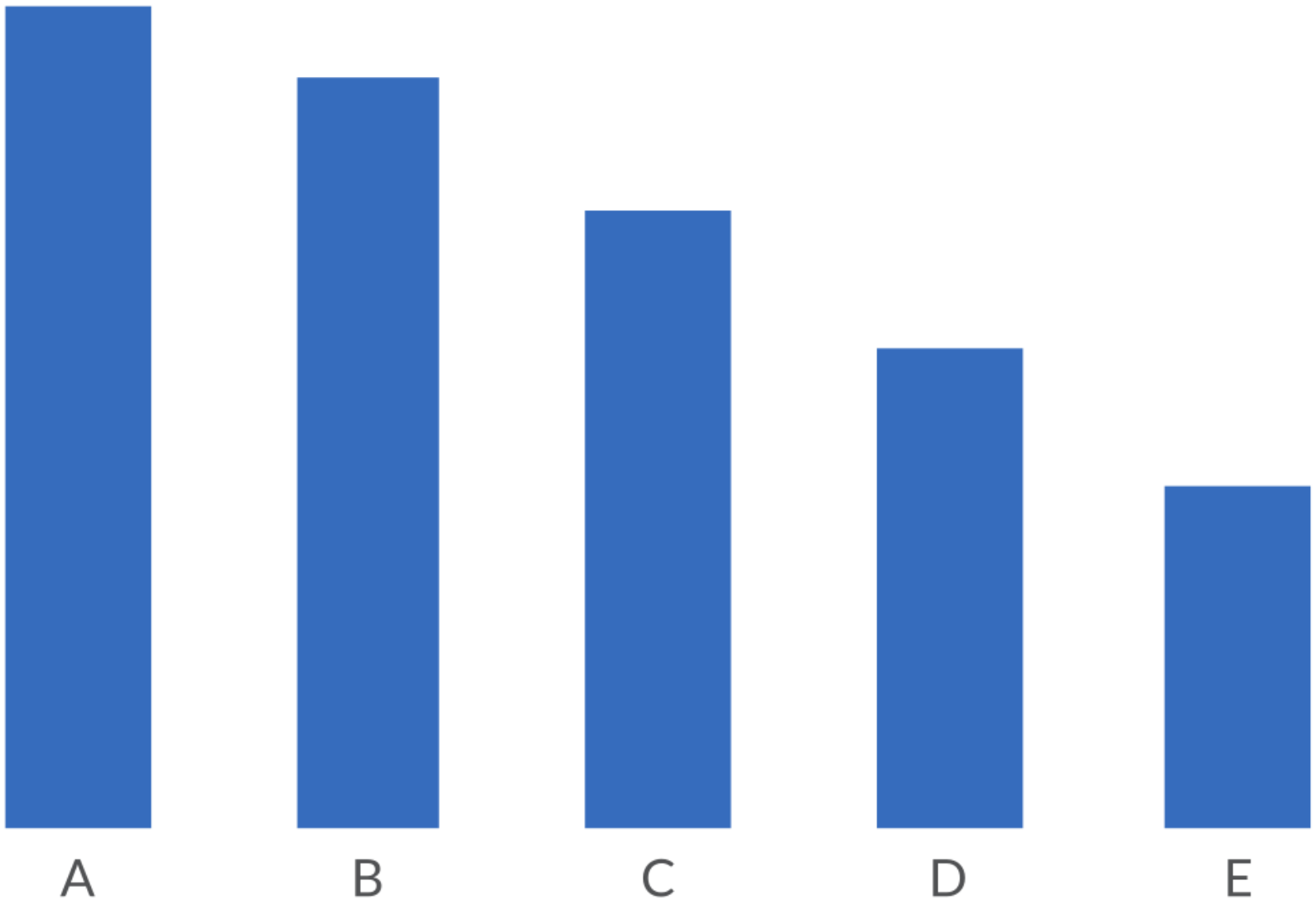
Gestalt: enclosure



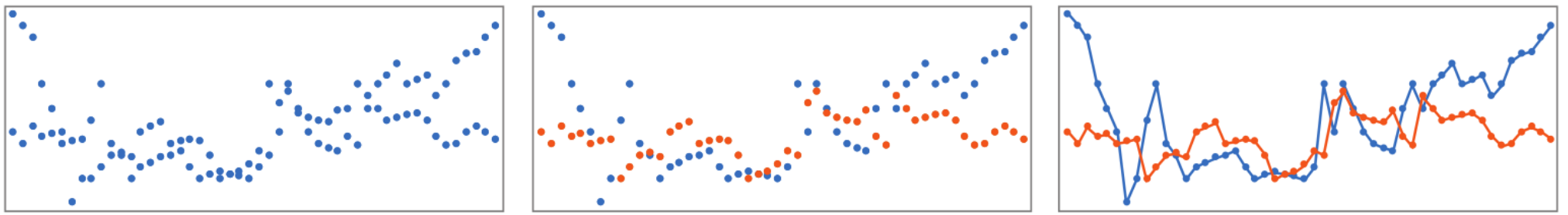
Gestalt: closure



Gestalt: continuity



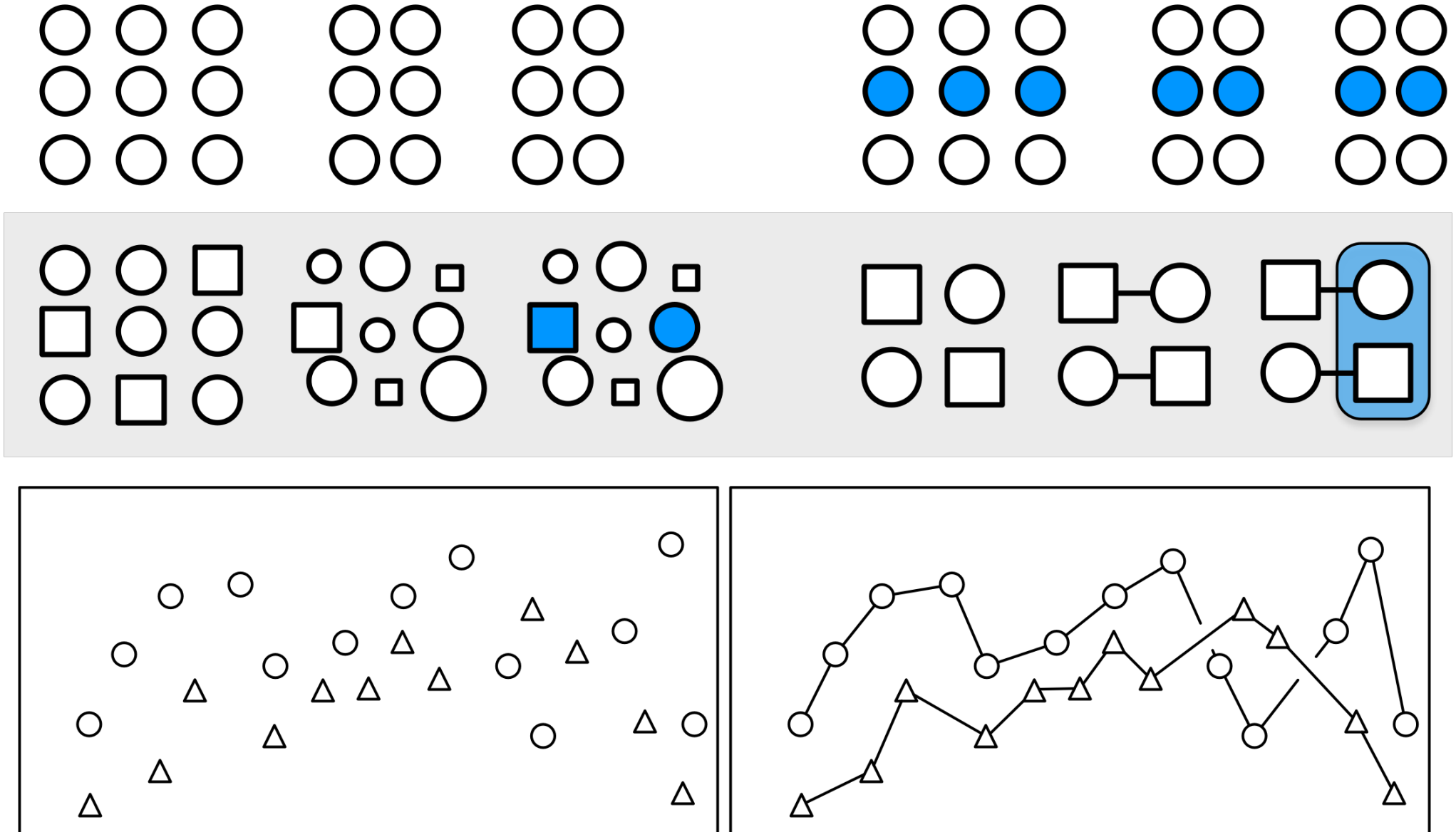
Gestalt: connection



Gestalt rules

We look for patterns in what we see:

- Proximity: Things that are spatially near to one another seem to be related.
- Similarity: Things that look alike seem to be related.
- Connection: Things that are visually tied to one another seem to be related.
- Continuity: Partially hidden objects are completed into familiar shapes.
- Closure: Incomplete shapes are perceived as complete.
- Figure and Ground: Visual elements are taken to be either in the foreground or the background.
- Common Fate: Elements sharing a direction of movement are perceived as a unit.



Reading list

- Munzner: *Visualization Analysis and Design*, chapters 2 and 5 (in the library)
- Ware: *Visual thinking for design*, chapter 2 (in the library)
- Hadley: *R for Data Science*, chapters 15 and 16