3: Basic Theory and Practice of Data Visualization

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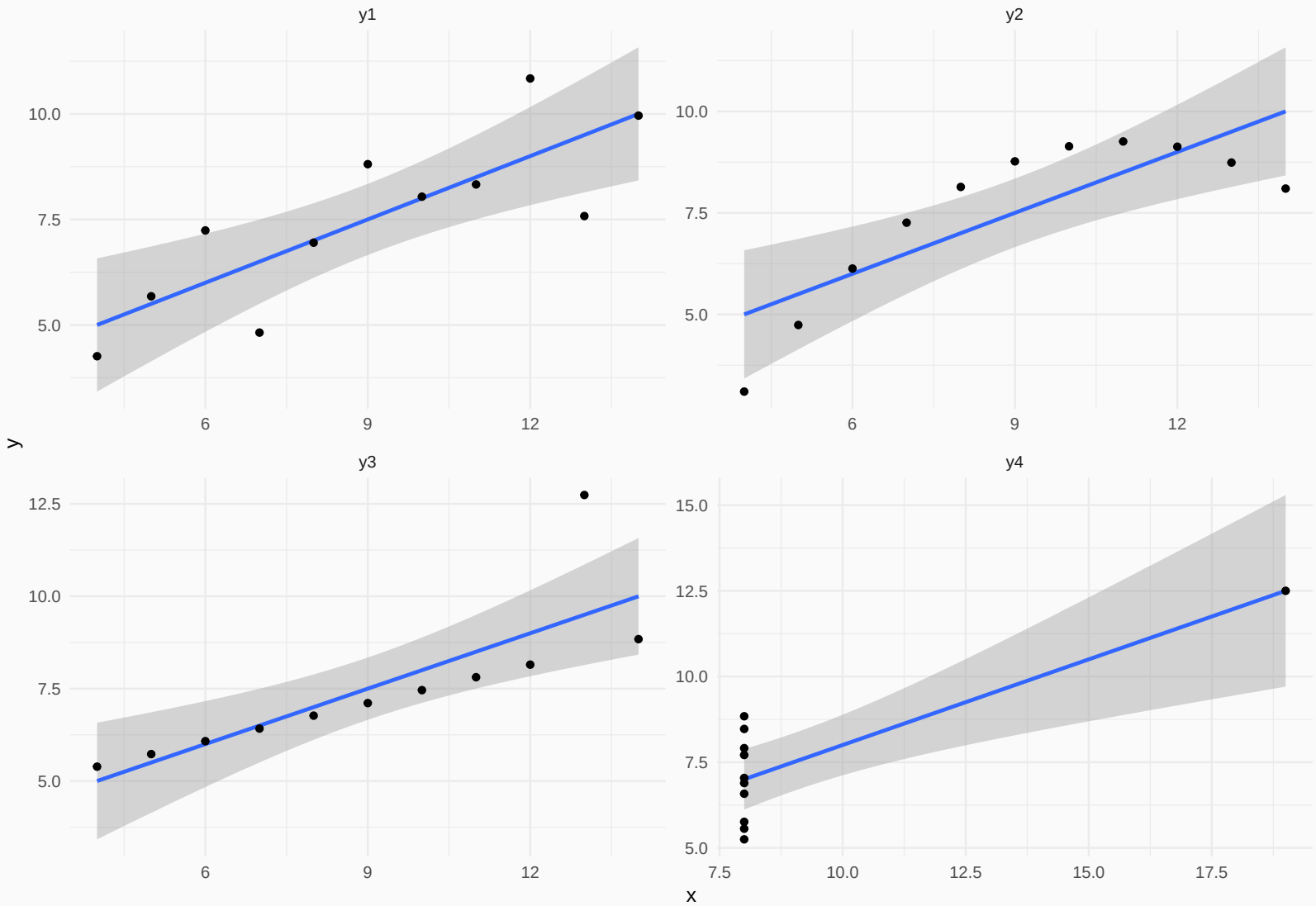
Data visualization

- What makes a good visual?
- Why visualize?
- How to use ggplot to make visuals in R

Why do we visualize data?

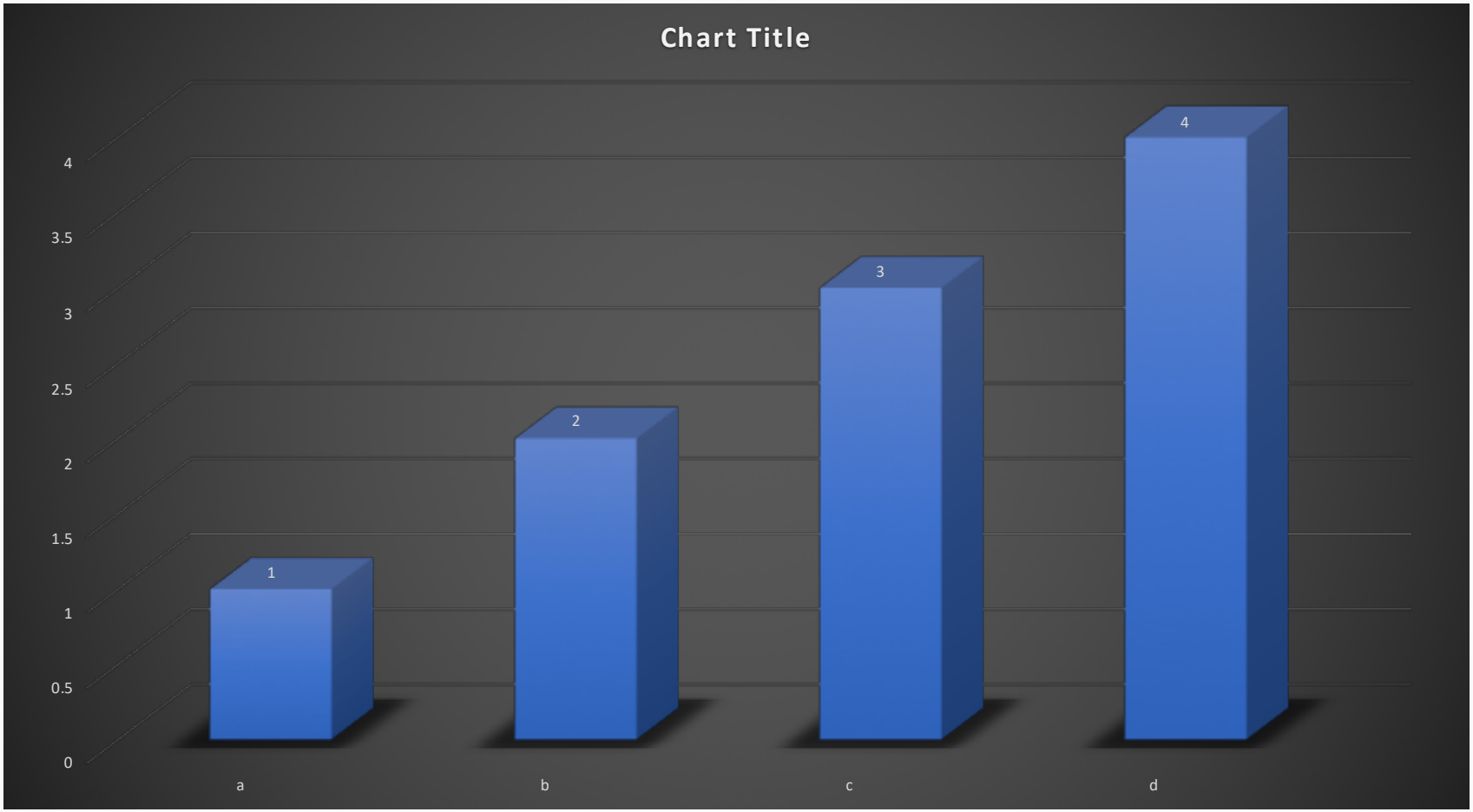


Principles of good data visuals

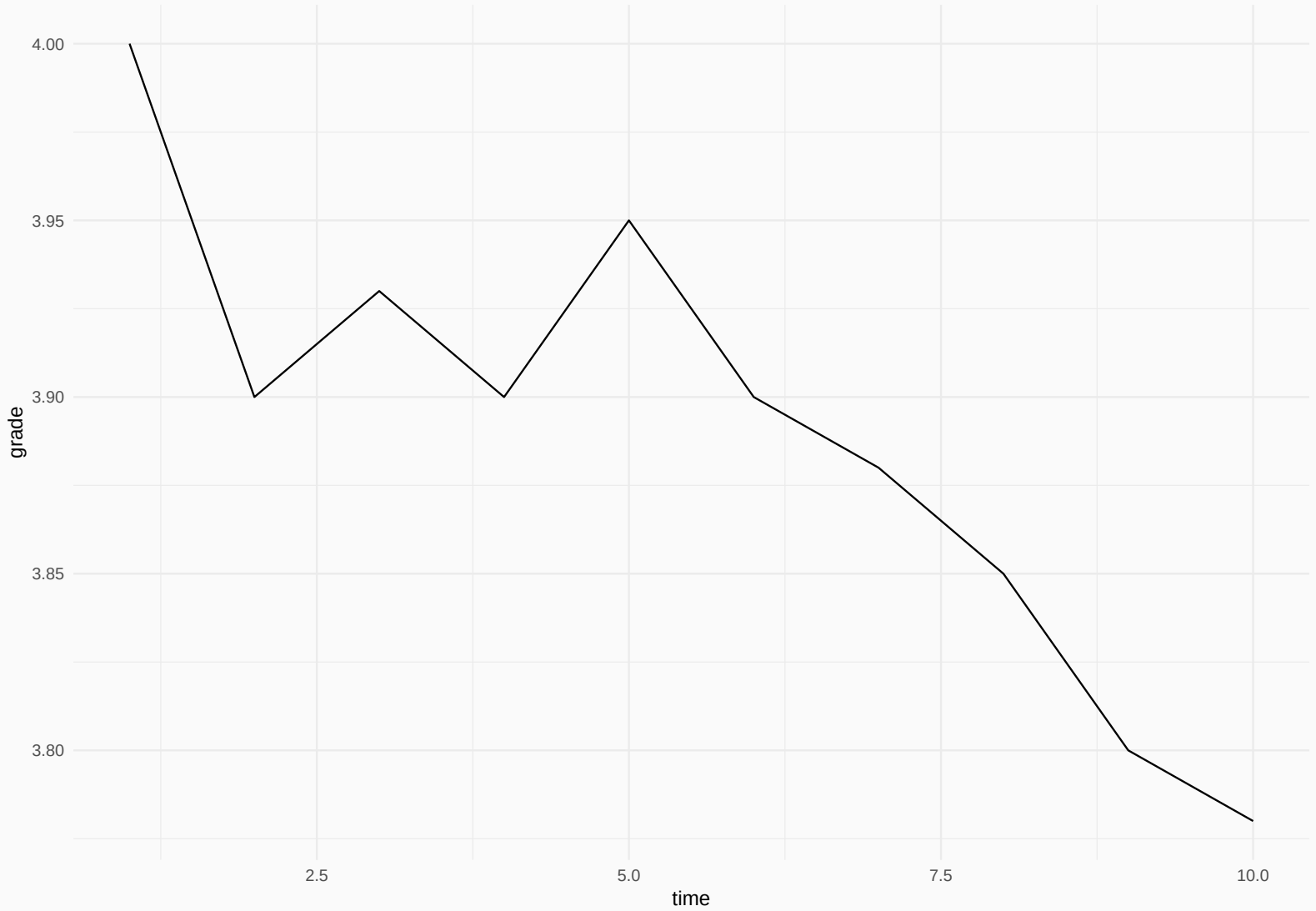
Good data visuals

- Are clearly labeled
- Avoid deception
- Use repetition to invite comparisons
- Minimize ‘chartjunk’

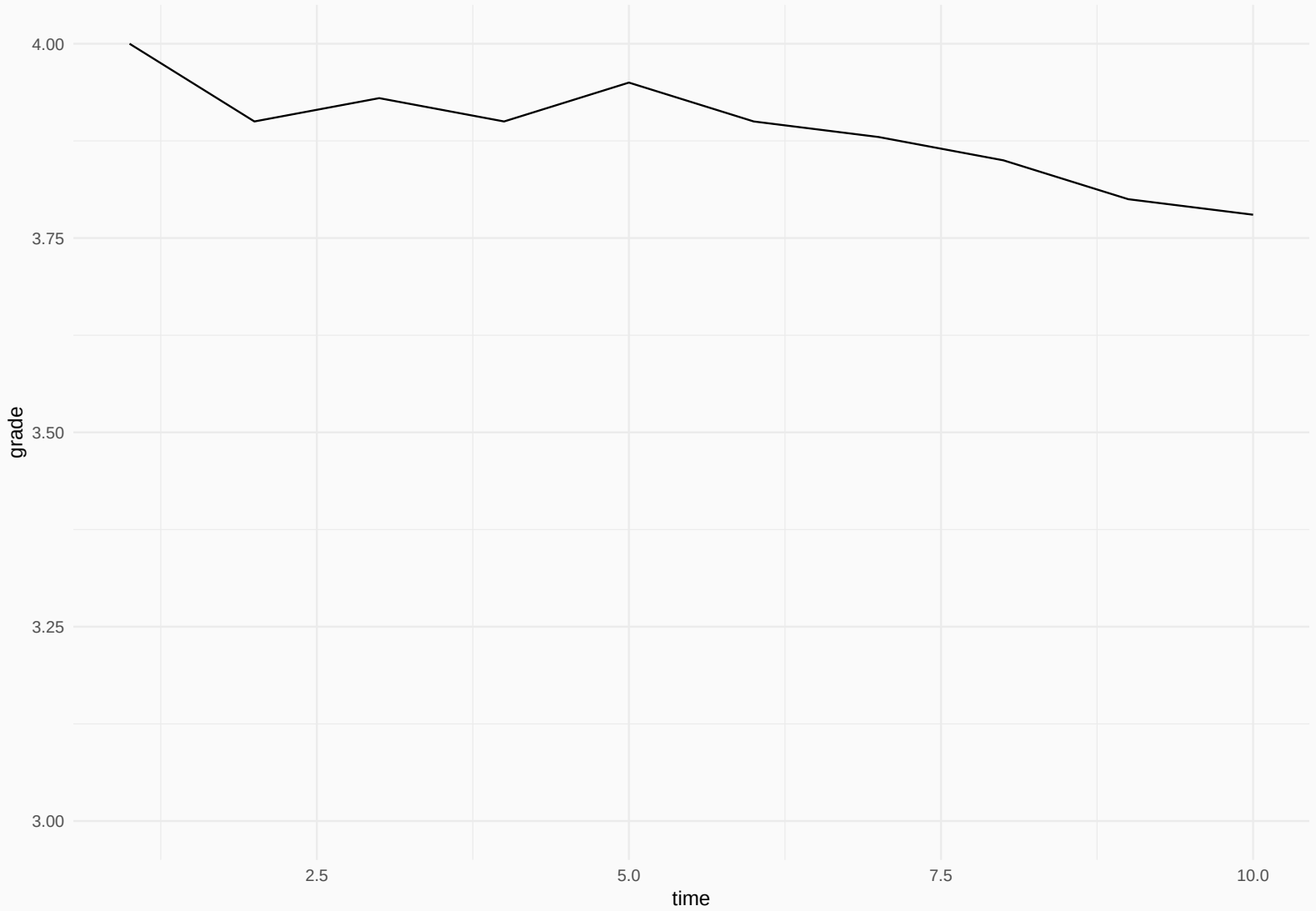
Find the chartjunk



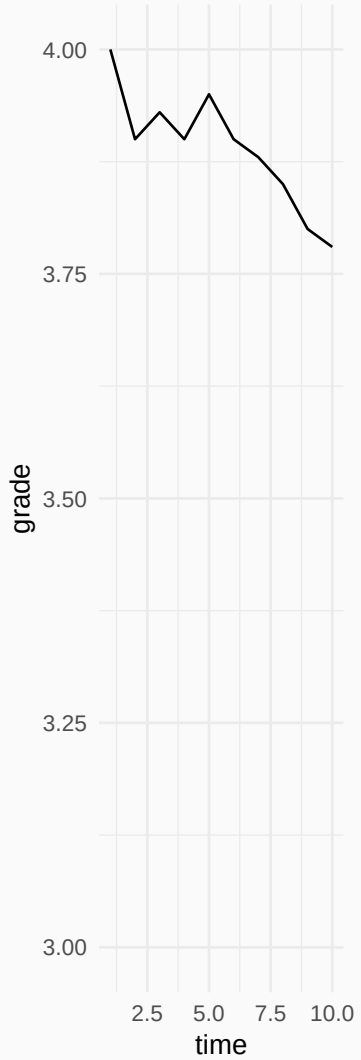
The importance of axes



The importance of axes



The importance of aspect ratio



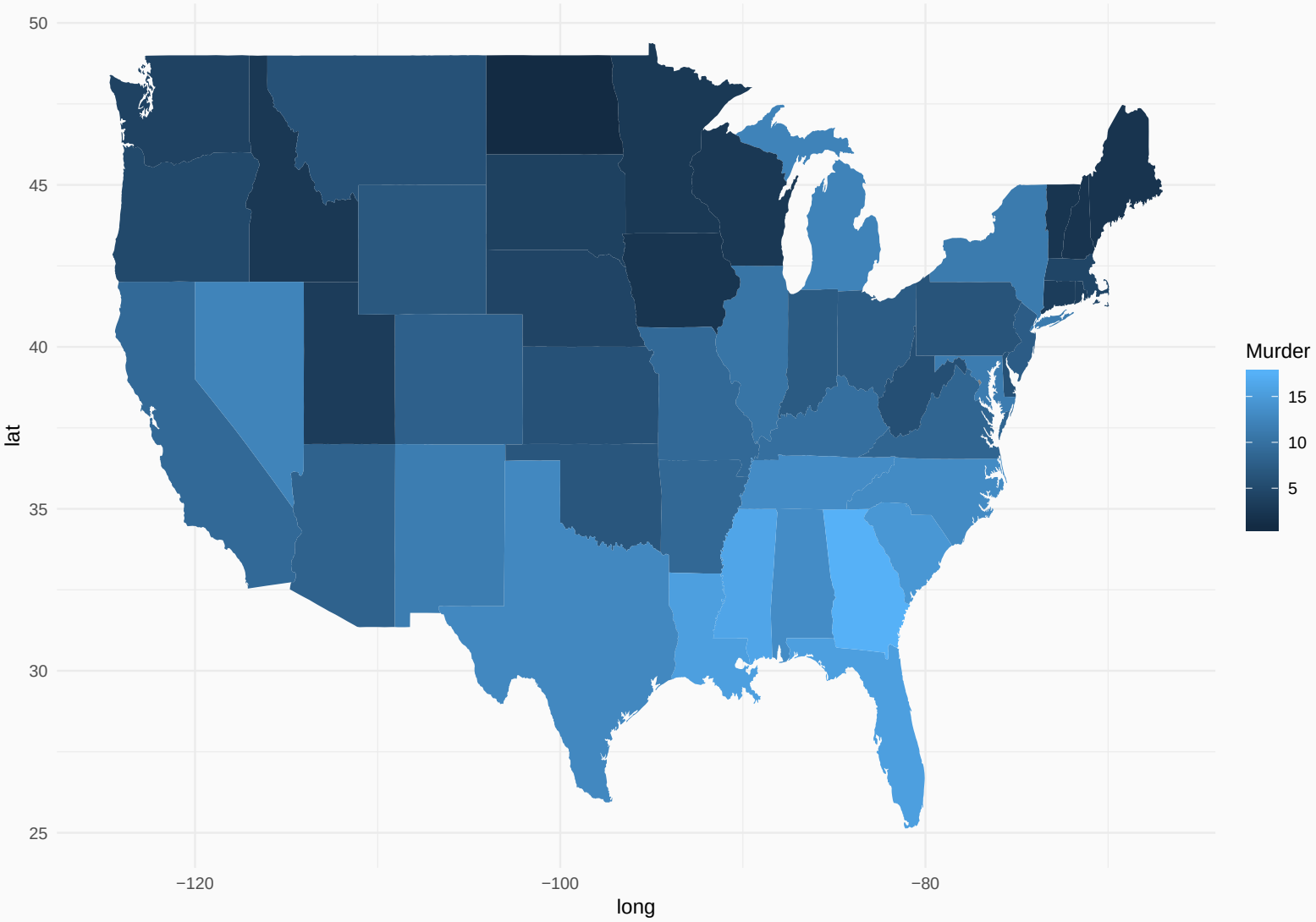
Why Visualize Data?

Why do we visualize data?

- Visuals can quickly reveal patterns in data
- Visuals are a (more) effective way to communicate quantitative information

Geographic Data

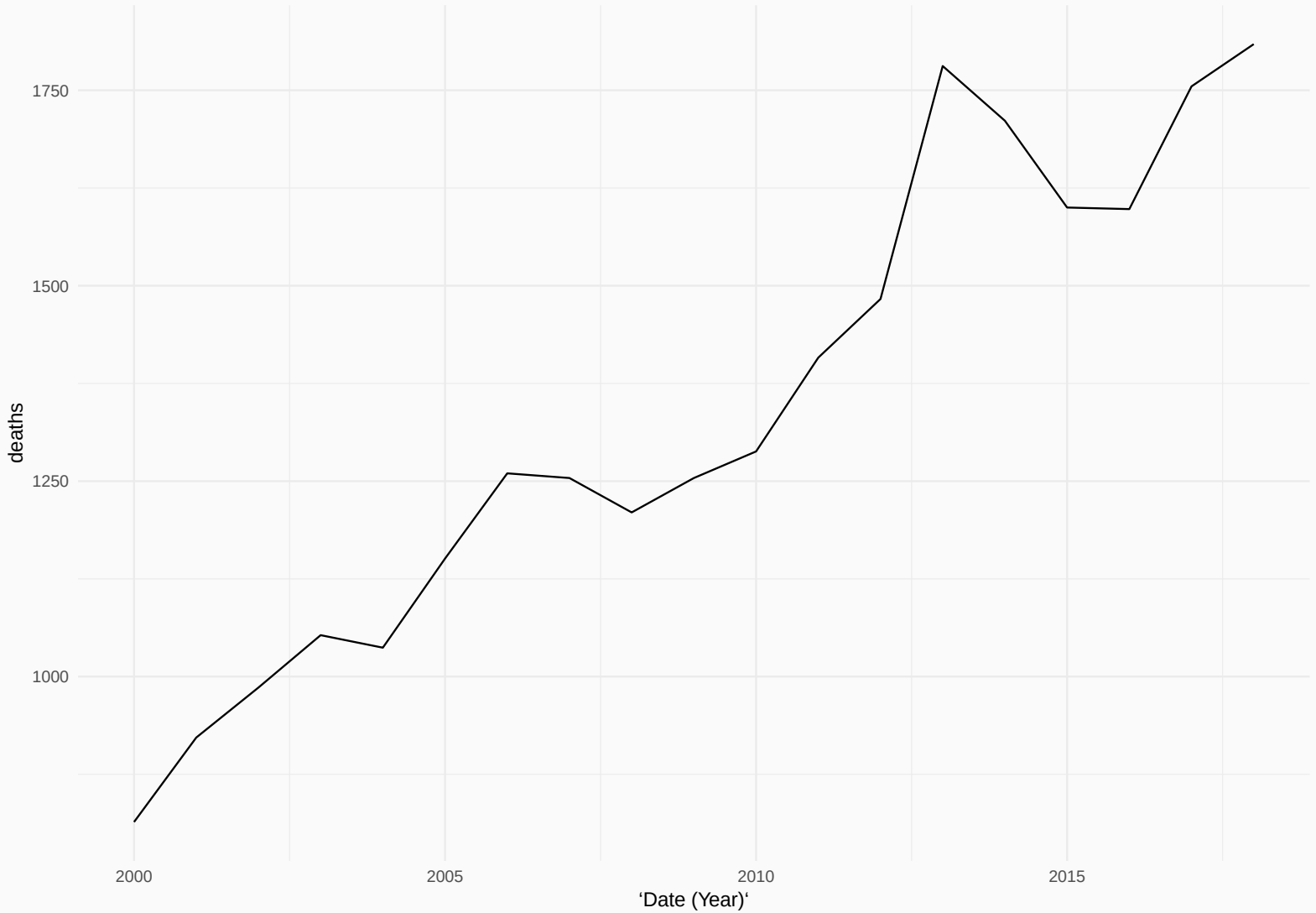
	V1	V2
1	Alabama	13.2
2	Alaska	10
3	Arizona	8.1
4	Arkansas	8.8
5	California	9
6	Colorado	7.9
7	Connecticut	3.3
8	Delaware	5.9
9	Florida	15.4
10	Georgia	17.4
11	Hawaii	5.3
12	Idaho	2.6
13	Illinois	10.4
14	Indiana	7.2
15	Iowa	2.2
16	Kansas	6
17	Kentucky	9.7
18	Louisiana	15.4
19	Maine	2.1
20	Maryland	11.3
21	Massachusetts	4.4
22	Michigan	12.1
23	Minnesota	2.7
24	Mississippi	16.1
25	Missouri	9
26	Montana	6
27	Nebraska	4.3
28	Nevada	12.2
29	New Hampshire	2.1
30	New Jersey	7.4
31	New Mexico	11.4
32	New York	11.1


50
45
40
35
30
25
lat
−120
−100
−80
long
Murder
15
10
5

Which is most effective? Why?

Time Series

	Date (Year)	deaths
1	2000	814
2	2001	922
3	2002	986
4	2003	1053
5	2004	1037
6	2005	1151
7	2006	1260
8	2007	1254
9	2008	1210
10	2009	1254
11	2010	1288
12	2011	1408
13	2012	1483
14	2013	1781
15	2014	1711
16	2015	1600
17	2016	1598
18	2017	1755
19	2018	1809


1750
1500
1250
1000
deaths
2000
2005
2010
2015
‘Date (Year)‘

Which is most effective? Why?

Model results

Investigated police child maltreatment reports, parameter estimates and standard errors for multilevel poisson regression. Results combined across multiple imputations

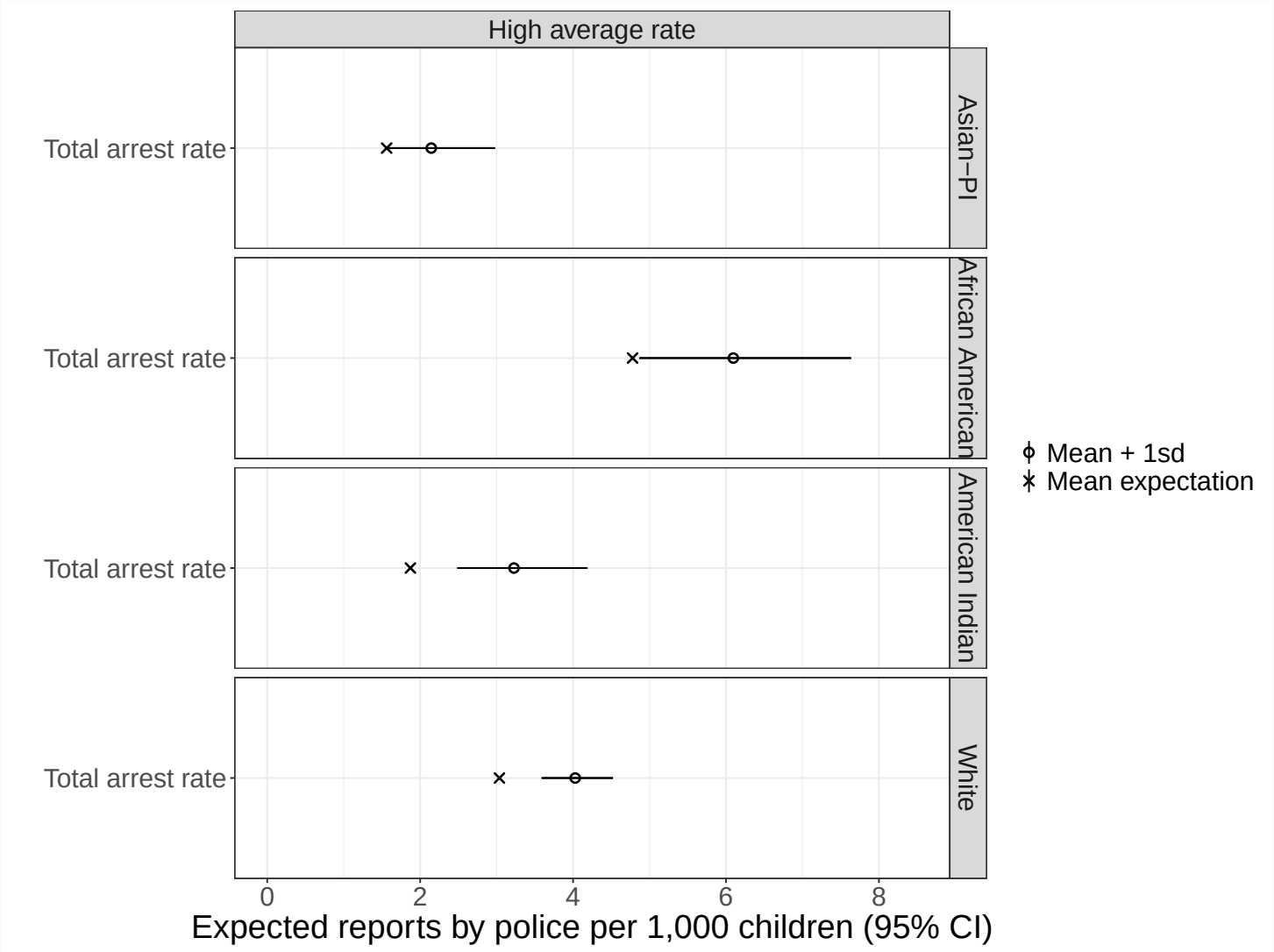
	All arrests	**Violent arrests**	**Drug arrests**	**QoL arrests**
Intercept	-5.80***	-5.74***	-5.77***	-5.61***
	(0.04)	(0.04)	(0.04)	(0.04)
Asian Am/PI	-0.66***	-0.83***	-0.79***	-0.94***
	(0.06)	(0.07)	(0.06)	(0.07)
Native Am	-0.48***	-0.56***	-0.26***	-0.79***
	(0.05)	(0.06)	(0.05)	(0.06)
African Am	0.45***	0.42***	0.43***	0.36***
	(0.04)	(0.04)	(0.04)	(0.04)
Mean arrest	0.28***	0.29***	0.25***	0.15***
	(0.02)	(0.02)	(0.02)	(0.01)
Change in arrest	0.03***	0.01***	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Mean child pov	0.30***	0.30***	0.31***	0.34***
	(0.02)	(0.02)	(0.02)	(0.02)
Change in child pov	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Year	0.09***	0.08***	0.08***	0.09***
	(0.00)	(0.00)	(0.01)	(0.00)
No. of police depts	0.05***	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
UR	0.07	0.11	0.09	0.07
	(0.04)	(0.04)	(0.05)	(0.04)
UR1	-0.04	-0.09	-0.07	-0.09
	(0.04)	(0.04)	(0.04)	(0.04)
UR2	0.01	0.01	-0.01	0.02
	(0.03)	(0.03)	(0.03)	(0.03)
UR3	-0.03	-0.07	-0.03	-0.06
	(0.03)	(0.03)	(0.03)	(0.03)
UR4	0.02	0.03	0.03	0.03
	(0.02)	(0.03)	(0.03)	(0.03)
Officers per cap	-0.03*	-0.02*	-0.02*	-0.01*
	(0.01)	(0.01)	(0.01)	(0.01)
Pct pop	0.40***	0.34***	0.35***	0.20***
	(0.04)	(0.04)	(0.04)	(0.04)
Asian Am/PI x Mean arrest	0.03	-0.04	-0.00	0.09
	(0.04)	(0.03)	(0.04)	(0.03)
Native Am x Mean arrest	0.26***	0.27***	0.35***	0.23***
	(0.02)	(0.02)	(0.02)	(0.02)
African Am x Mean arrest	-0.04*	-0.11*	-0.03*	0.06*
	(0.02)	(0.02)	(0.02)	(0.02)
Asian Am/PI x change in arrest	0.03	0.02	0.00	0.02
	(0.02)	(0.03)	(0.02)	(0.02)
Native Am x change in arrest	0.01	0.02	0.00	0.01
	(0.02)	(0.02)	(0.02)	(0.01)
African Am x change in arrest	-0.01	0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Asian Am/PI x Mean child pov	-0.27***	-0.26***	-0.28***	-0.30***
	(0.03)	(0.03)	(0.03)	(0.02)
Native Am x Mean child pov	-0.18***	-0.13***	-0.16***	-0.15***
	(0.03)	(0.03)	(0.03)	(0.03)
African Am x Mean child pov	-0.22***	-0.22***	-0.23***	-0.26***
	(0.02)	(0.02)	(0.02)	(0.02)
Asian Am/PI x Change in child pov	-0.01	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Native Am x Change in child pov	-0.01	0.00	-0.01	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)
African Am x Change in child pov	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Asian Am/PI x Pct pop	-0.60***	-0.56***	-0.56***	-0.36***
	(0.07)	(0.07)	(0.07)	(0.07)
Native Am x Pct pop	-0.57***	-0.51***	-0.38***	-0.37***
	(0.05)	(0.05)	(0.05)	(0.05)
African Am x Pct pop	-0.95***	-0.93***	-0.89***	-0.72***
	(0.05)	(0.05)	(0.05)	(0.05)
Residual variance	0.36	0.36	0.36	0.36
County intercept variance	0.19	0.19	0.20	0.20

***p < 0.001, **p < 0.01, *p < 0.05

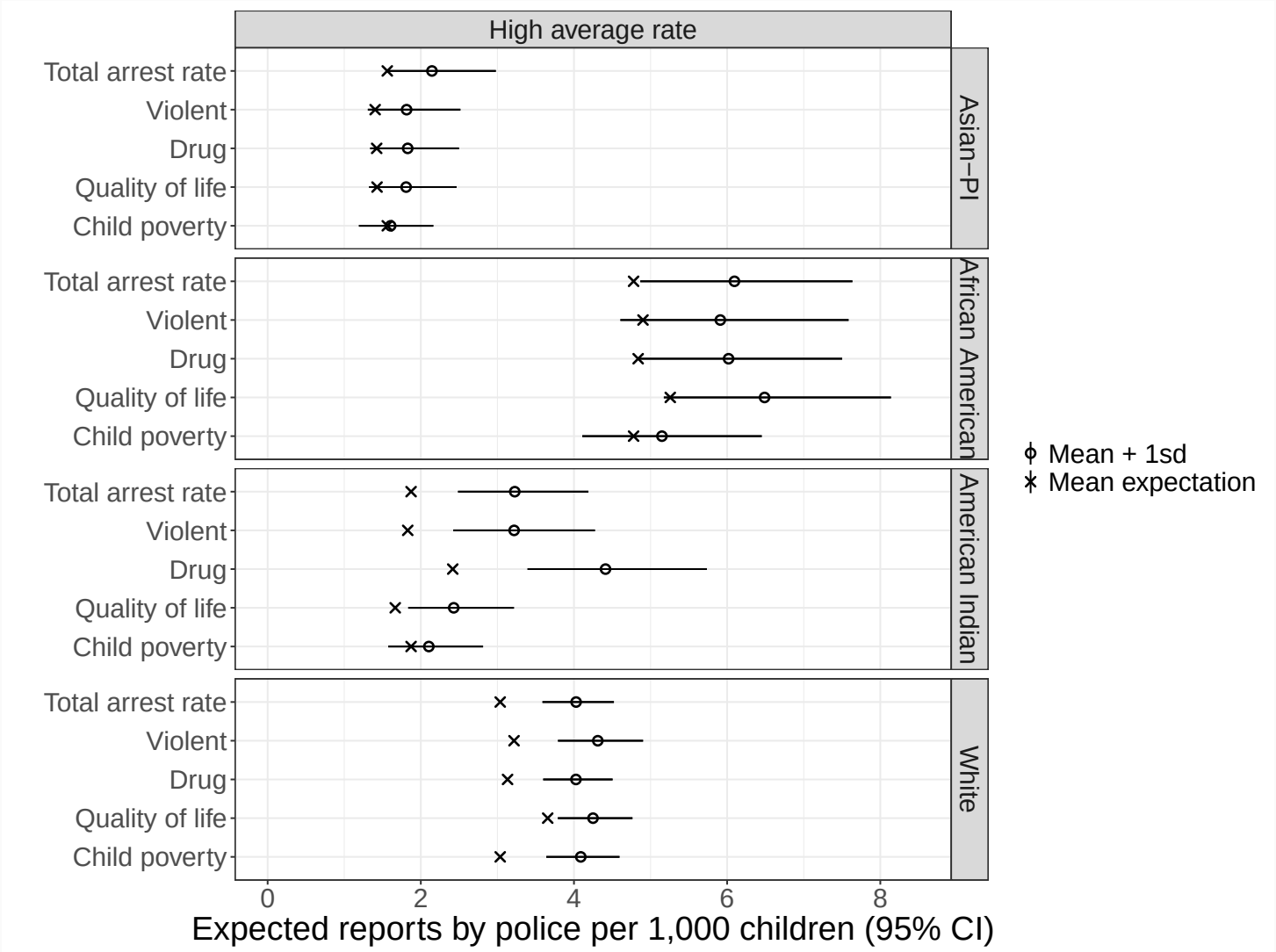
Reduced format: focal variable sign and significance

	Parameter	All	Violent	Drug	Quality of life
Total	Between counties	+	+	+	+
	Within county	+	+	+	+
African American	Between counties	+	+	+	+
	Within county	+	+	+	+
Asian-Pacific Islander	Between counties	+	+	+	+
	Within county	+	+		+
American Indian / Alaska Native	Between counties	+	+	+	+
	Within county	+	+	+	+
White	Between counties	+	+	+	+
	Within county	+	+	+	+

Plot summary



Plot summary



Which is most effective? Why?

Break

Using ggplot2 to visualize data in R

The importance of tidy (long) data for ggplot

Data is generally either wide or long

- In wide format, column position may indicate a variables value
- In long format, each variable has its own column

Example of long data: each column is a variable

```
head(iris)
```

```
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1          5.1         3.5          1.4         0.2  setosa
## 2          4.9         3.0          1.4         0.2  setosa
## 3          4.7         3.2          1.3         0.2  setosa
## 4          4.6         3.1          1.5         0.2  setosa
## 5          5.0         3.6          1.4         0.2  setosa
## 6          5.4         3.9          1.7         0.4  setosa
```

Example of the same data in wide format

```
##   setosa.Sepal.Length setosa.Sepal.Width setosa.Petal.Length
## 1                 5.1                3.5                 1.4
## 2                 4.9                3.0                 1.4
## 3                 4.7                3.2                 1.3
## 4                 4.6                3.1                 1.5
## 5                 5.0                3.6                 1.4
## 6                 5.4                3.9                 1.7
##   setosa.Petal.Width versicolor.Sepal.Length versicolor.Sepal.Width
## 1                0.2                    7.0                   3.2
## 2                0.2                    6.4                   3.2
## 3                0.2                    6.9                   3.1
## 4                0.2                    5.5                   2.3
## 5                0.2                    6.5                   2.8
## 6                0.4                    5.7                   2.8
##   versicolor.Petal.Length versicolor.Petal.Width virginica.Sepal.Length
## 1                     4.7                   1.4                    6.3
## 2                     4.5                   1.5                    5.8
## 3                     4.9                   1.5                    7.1
## 4                     4.0                   1.3                    6.3
## 5                     4.6                   1.5                    6.5
## 6                     4.5                   1.3                    7.6
##   virginica.Sepal.Width virginica.Petal.Length virginica.Petal.Width
## 1                   3.3                    6.0                   2.5
## 2                   2.7                    5.1                   1.9
## 3                   3.0                    5.9                   2.1
## 4                   2.9                    5.6                   1.8
## 5                   3.0                    5.8                   2.2
## 6                   3.0                    6.6                   2.1
```

Tidy data lets us efficiently feed aesthetic parameters to ggplot.

- Tidy data is harder for humans to read in a spreadsheet, but much easier to program with. Tidyverse packages are built around making and keeping our R objects in tidy (long data.frame) format
- Try to keep your data tidy - all variables should be variables, not embedded in column names.

Frequent untidy variables:

- Time (i.e. year)
- Group

Basic anatomy of a ggplot command

Give it data

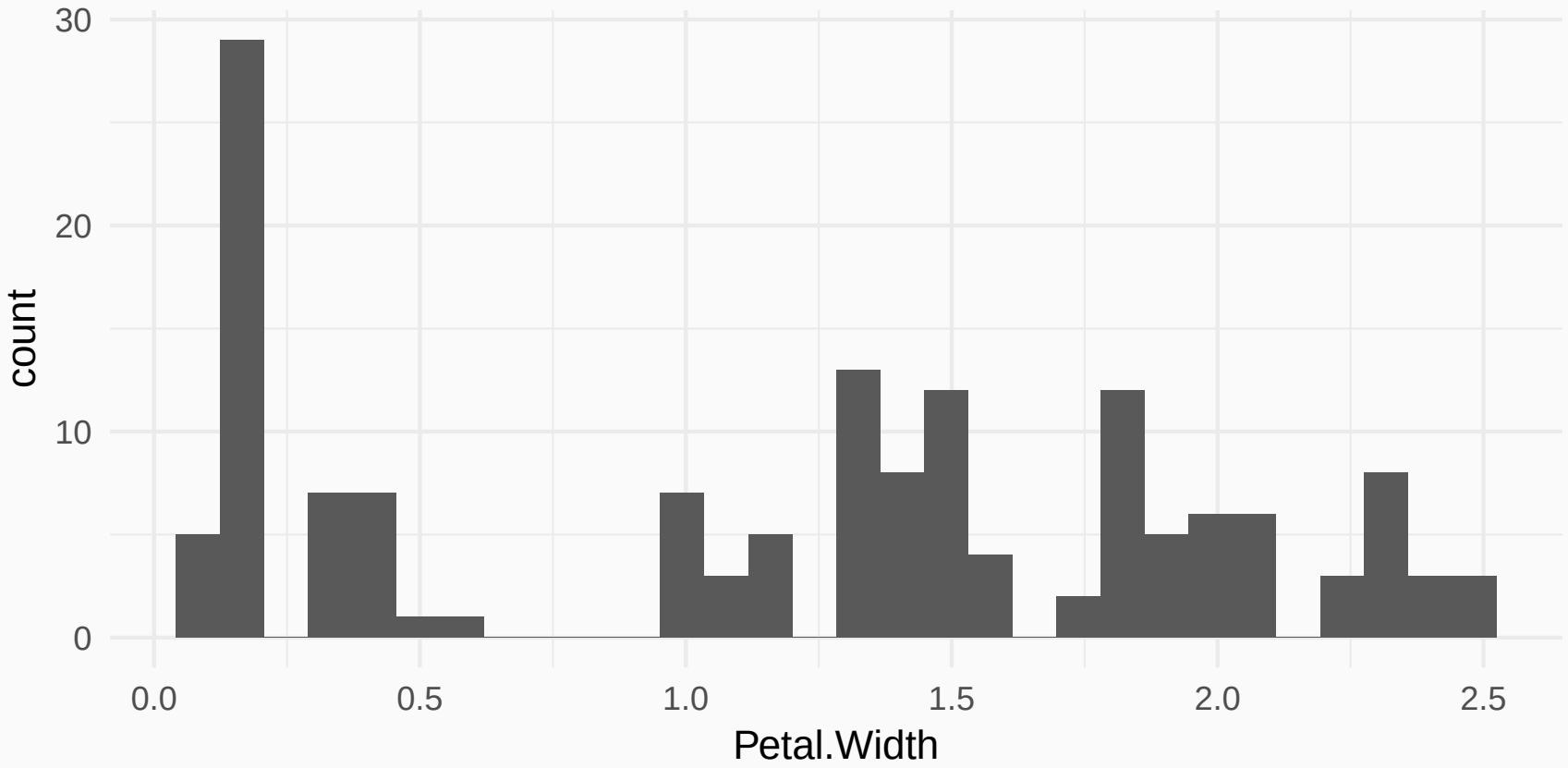
```r
data("iris")
my_plot <- ggplot(data = iris)
```

Add a single aesthetic parameter

```
ggplot(data = iris, aes(x = Petal.Width))
```

Add a geom

```
ggplot(data = iris, aes(x = Petal.Width)) + geom_histogram()
```

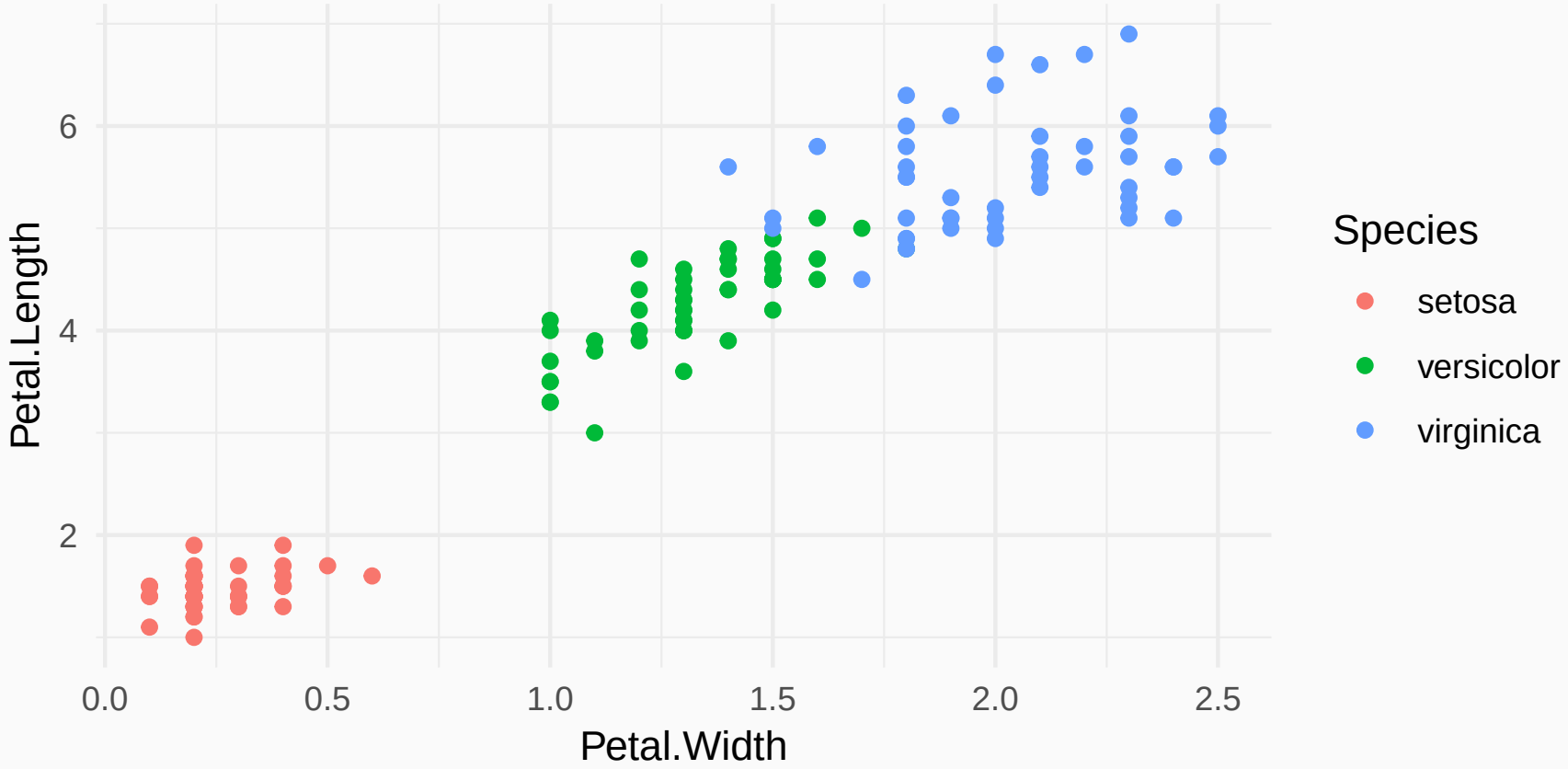


Add two aesthetic parameters and a geom

```
ggplot(data = iris, aes(x = Petal.Width, y = Petal.Length)) + geom_point()
```

Three variables: two continuous, one categorical

```
ggplot(data = iris, aes(x = Petal.Width, y = Petal.Length, color = Species)) +
    geom_point()
```

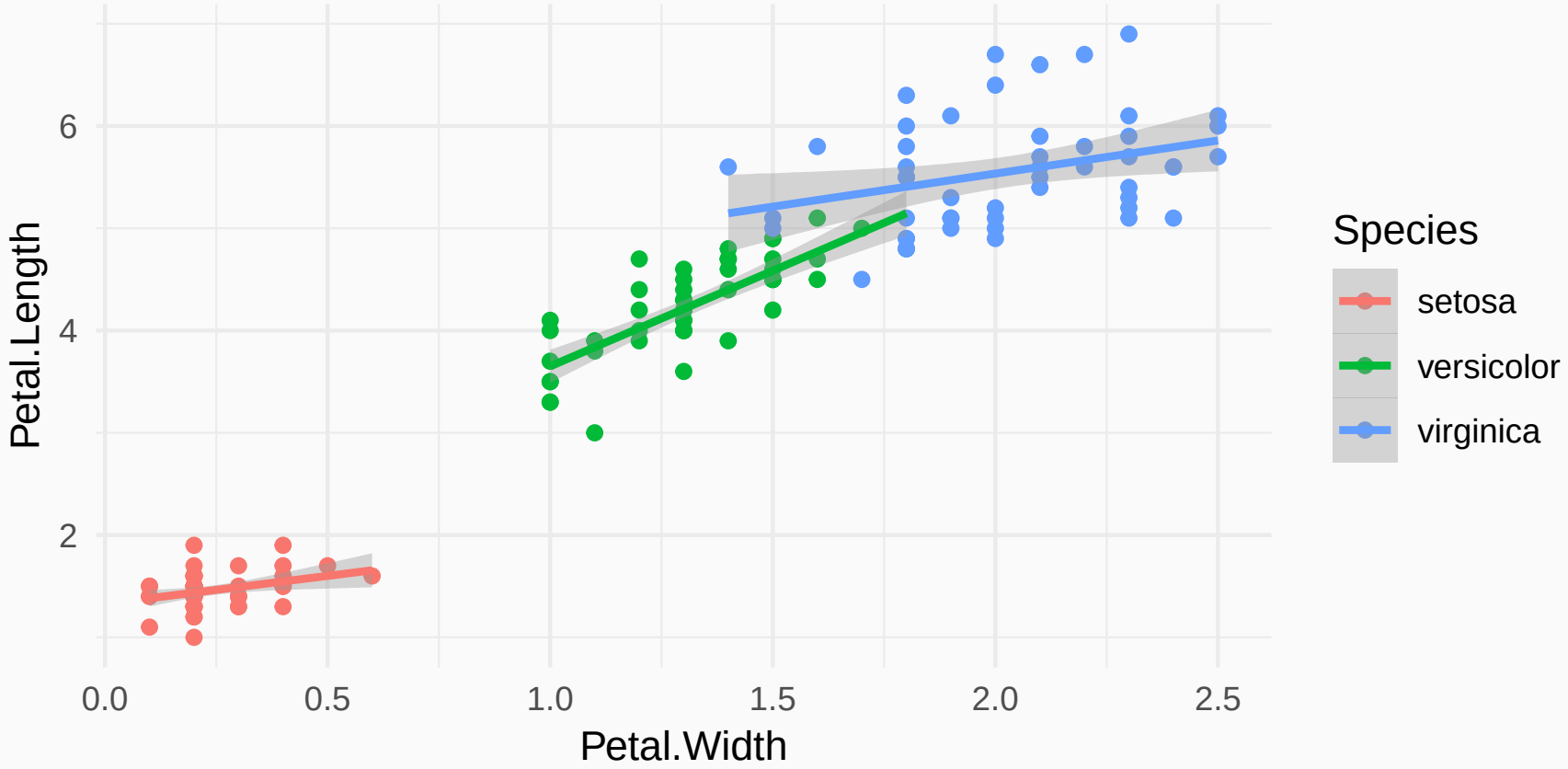


Three variables: two continuous, one categorical

```
ggplot(data = iris, aes(x = Petal.Width, y = Petal.Length, shape = Species)) +
    geom_point()
```

Multiple geoms

```
ggplot(data = iris, aes(x = Petal.Width, y = Petal.Length, color = Species)) +
    geom_point() + geom_smooth(method = "lm")
```



To review

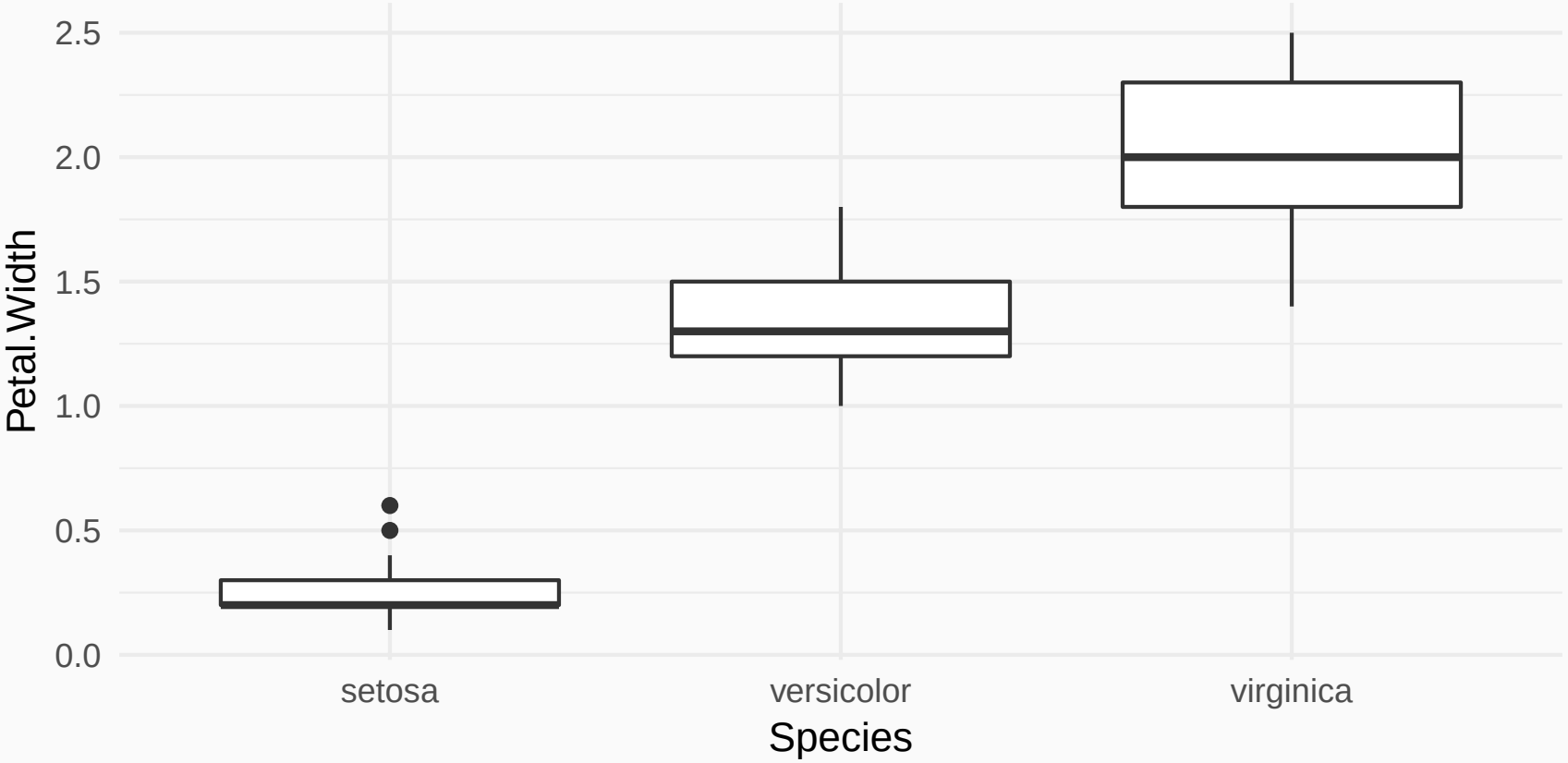
ggplot needs three things to make a graphic

1. Data
2. Aesthetic paramaters
3. Geoms

More advanced plots

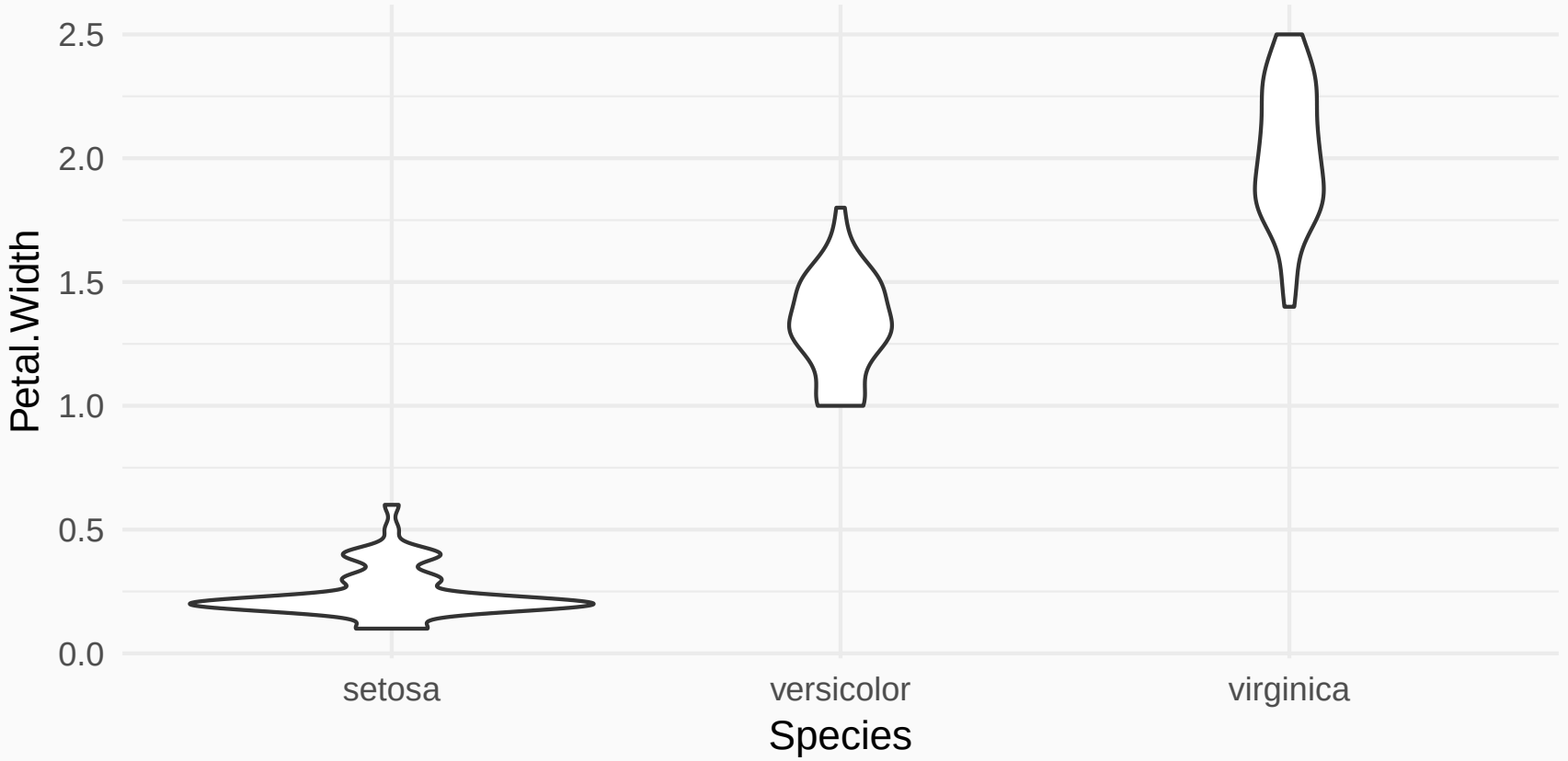
Boxplots (one continuous, one categorical)

```
ggplot(data = iris, aes(y = Petal.Width, x = Species)) + geom_boxplot()
```



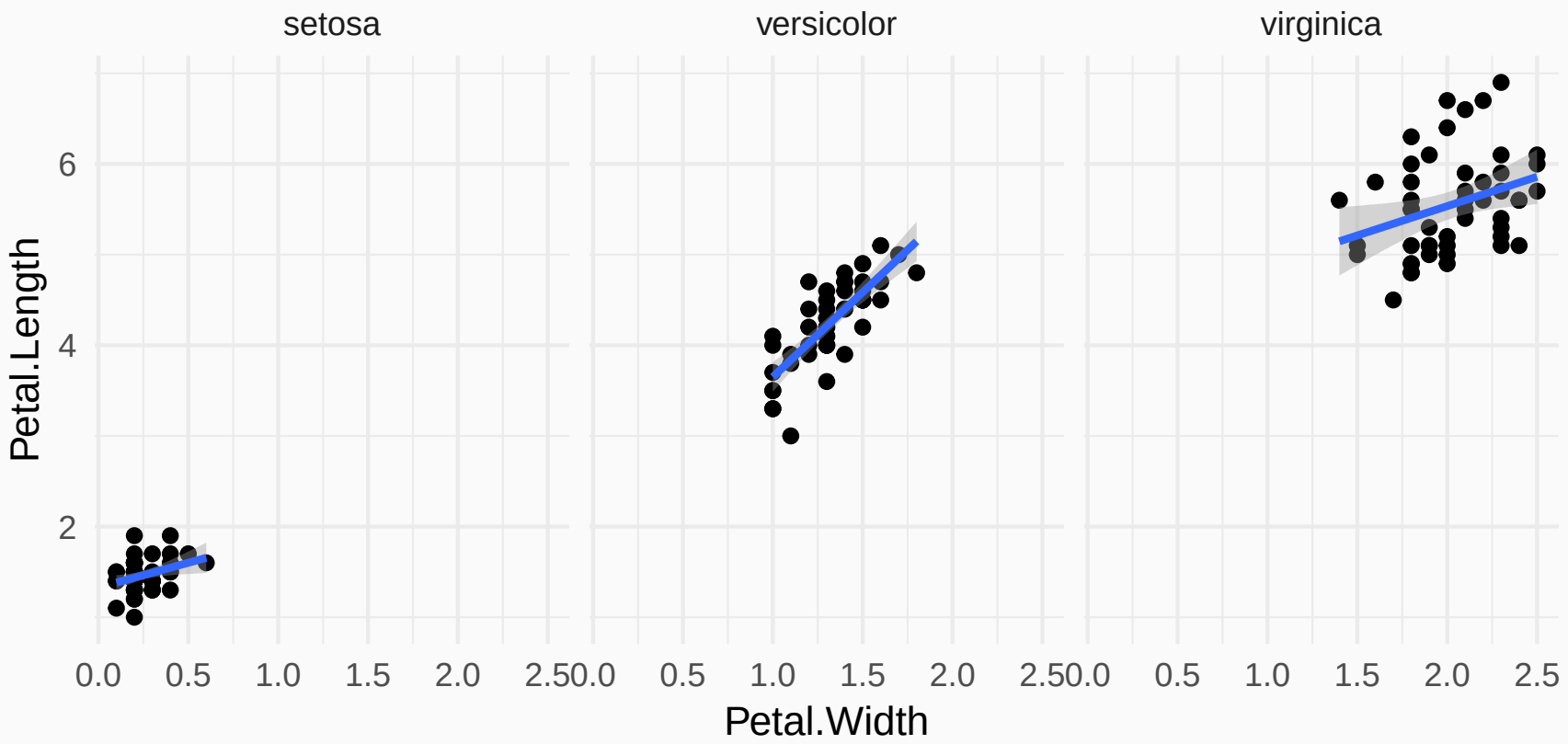
Violin plot

```
ggplot(data = iris, aes(y = Petal.Width, x = Species)) + geom_violin()
```

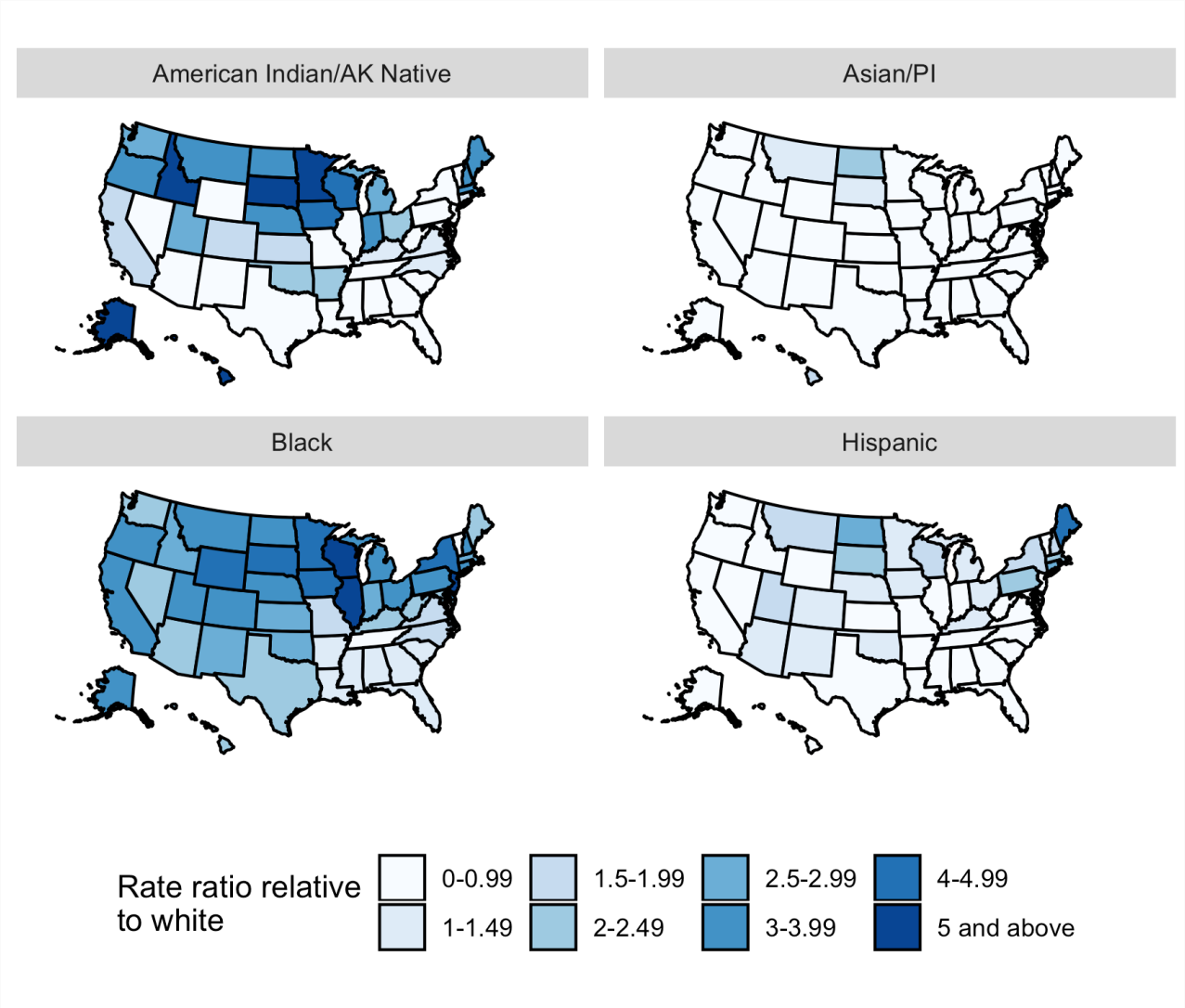


Small multiples (facets)

```
ggplot(data = iris, aes(x = Petal.Width, y = Petal.Length)) + geom_point() +
    geom_smooth(method = "lm") + facet_wrap(~Species)
```



Small multiples are very powerful



Maps

```
data <- data.frame(murder = USArrests$Murder, state = tolower(rownames(USArrests)))
map <- map_data("state")
ggplot(data, aes(fill = murder)) + geom_map(aes(map_id = state), map = map) +
    expand_limits(x = map$long, y = map$lat)
```