Introduction to "R"
Data and model visualization

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Data visualization I

Plotting in R

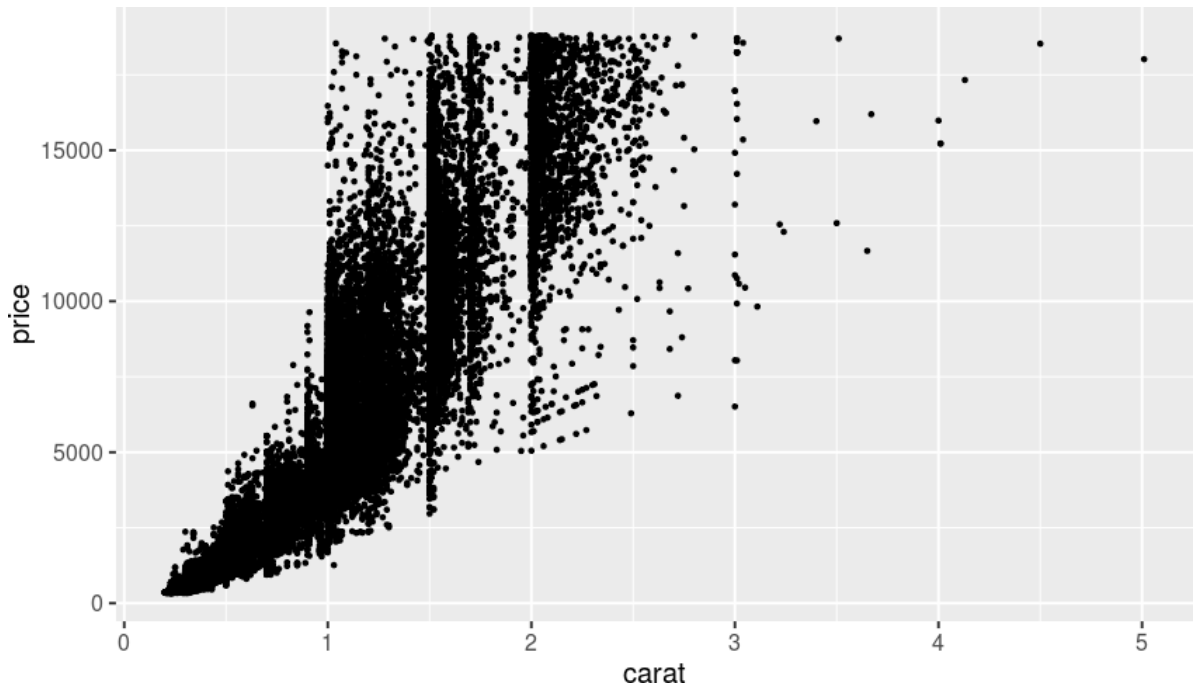
R has exceptional graphing facitilies. There is the base `plot` package and additional packages such as `lattice` and `ggplot2`. We will use `ggplot2` because it is easy and intuitive to use.

```
library(ggplot2)
```

A first glimpse at ggplot2

- We'll use the dataset `diamonds` included in `ggplot2`
- Here's a scatter plot of the price of diamonds against carat.

```
data(diamonds)
# a standard scatter plot
ggplot(diamonds, aes(x = carat, y = price)) + geom_point()
```



The grammar of graphics

A plot consists of

1. `data`
2. `mappings` describing how variables in the data are mapped to aesthetic attributes
3. `geoms` geometric objects
4. `stats` statistical transformations
5. `scales` map values in data to values in aesthetic space
6. `coord` coordinate system, most of the cases cartesian
7. `facet` facetting breaks up plot in several group-specific subplots

ggplot2

```
ggplot(diamonds, aes(x = carat, y = price)) + geom_point()
```

- `ggplot()` is the main function and takes the `data` and a `mapping` (`aes()`) as arguments
  - `aes()` sets the aesthetics, `x` and `y` variables but also other variables depending on the plot
- `+` adds a new layer on top of the plot
- `geom_point()` is a geometric object, it draws dots at the x-y-coordinates
- there are no statistical transformations
- `scales` are given on the axis
- `coord` is cartesian
- no facetting

Data

```
ggplot(diamonds, aes(x = carat, y = price)) + geom_point()
```

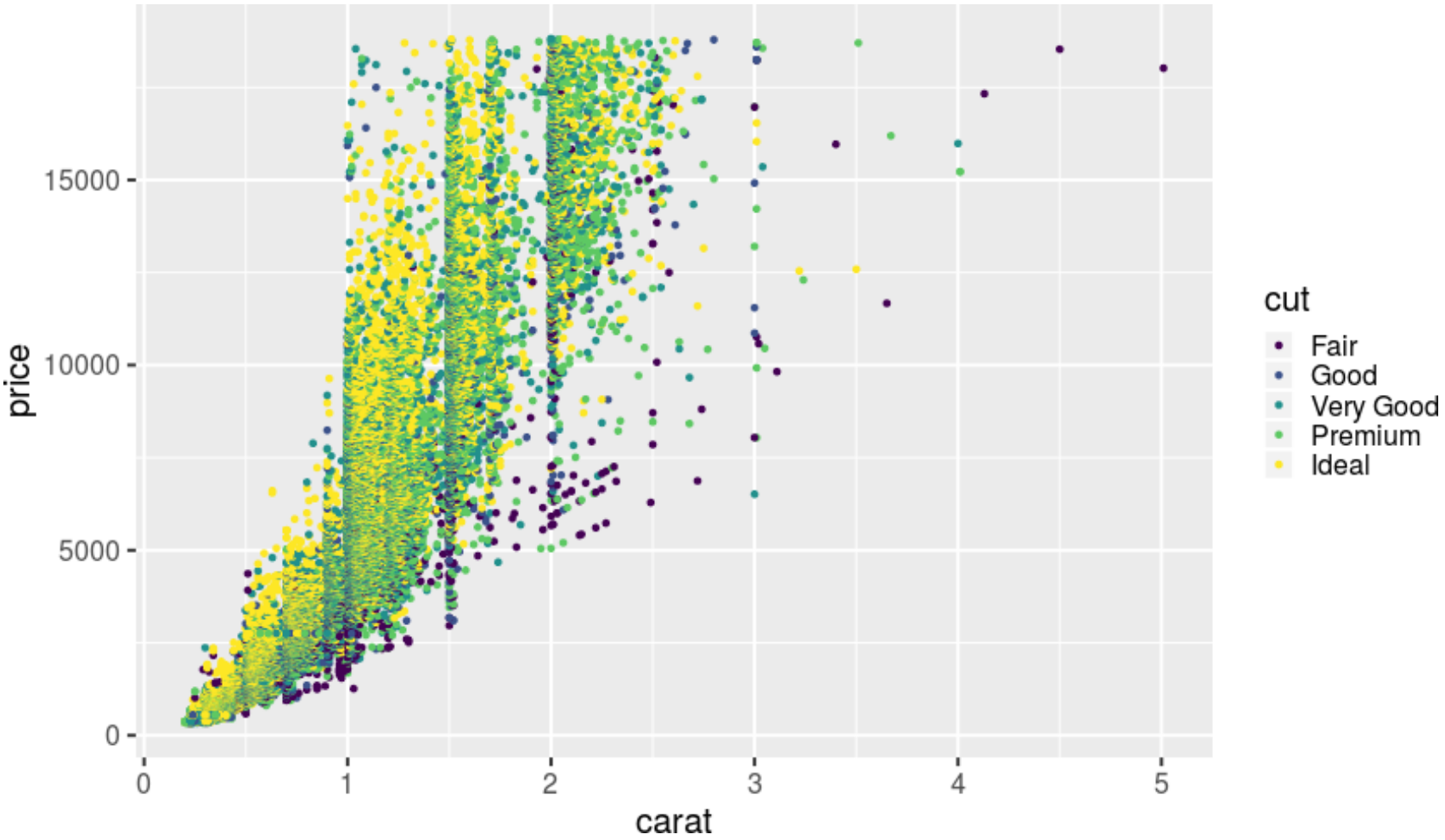
- `data` is the first argument in `ggplot()`
- the input needs to be a `data.frame`
- `geom_...()` can also take a `data.frame` as second argument

Mapping

- `aes()` knows the following arguments:
  - `x` and `y` (also `xmin`, `xmax`, `xend`, `ymin`, `ymax`, `yend`)
  - `group` seperates the data into groups for separate geoms
  - `fill` for filling geometric objects with color
  - `color` for coloring dots and outlines of other objects
  - `shape` to determine the shape of e.g. `geom_point()`
  - `size` to determine the size of points or width of lines

Adding color

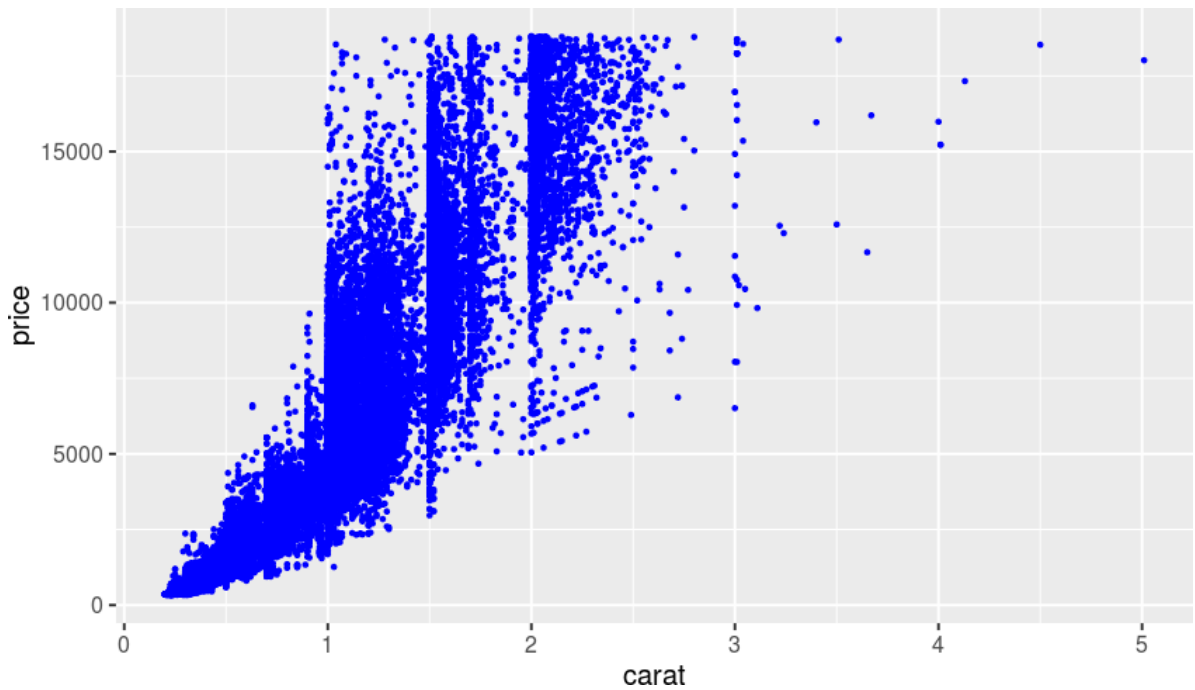
```
ggplot(diamonds, aes(x = carat, y = price, color = cut)) +
    geom_point()
```



Aesthetics vs. settings

- Aesthetics represent mappings of variables from the data to aesthetics
- settings specify the aesthetics without relying on data

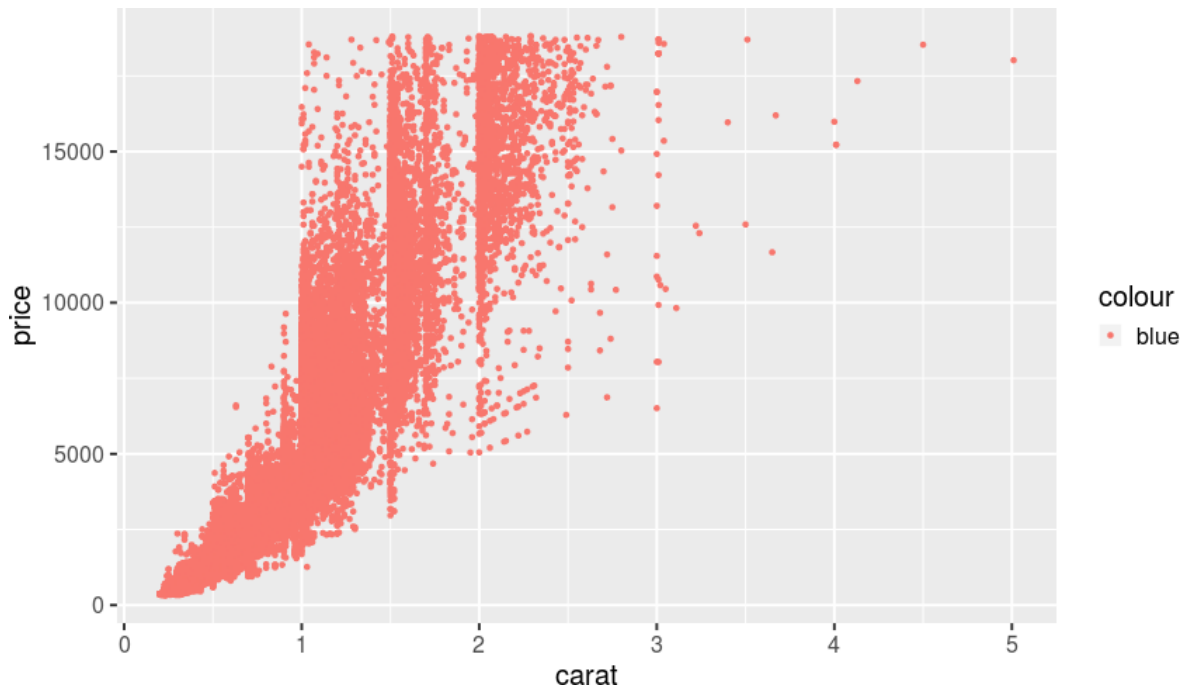
```
ggplot(diamonds, aes(x = carat, y = price)) +
  geom_point(color = 'blue')
```



Aesthetics vs. settings

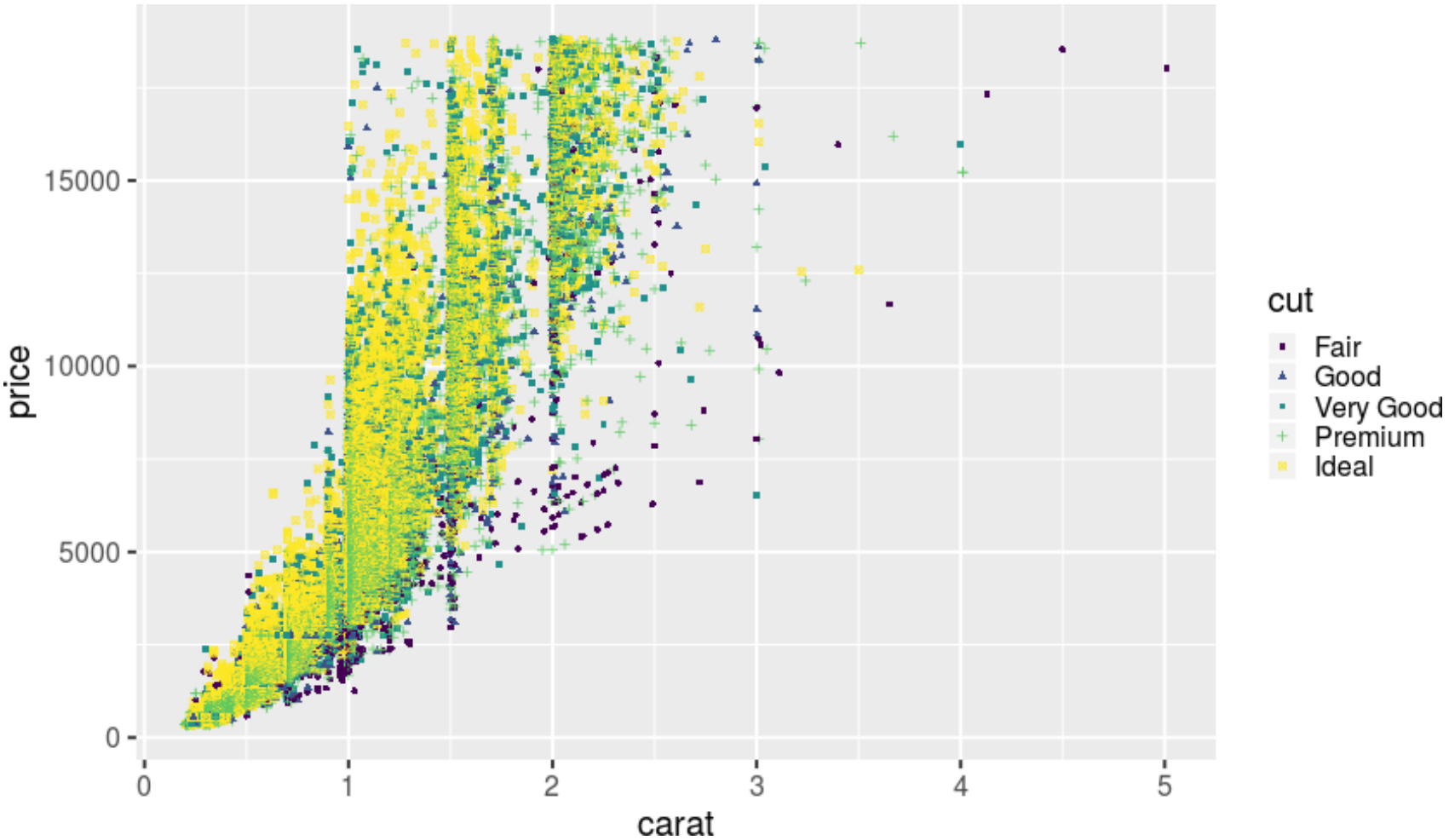
- Aesthetics represent mappings of variables from the data to aesthetics
- settings specify the aesthetics without relying on data

```
ggplot(diamonds, aes(x = carat, y = price, color = "blue")) +
    geom_point()
```



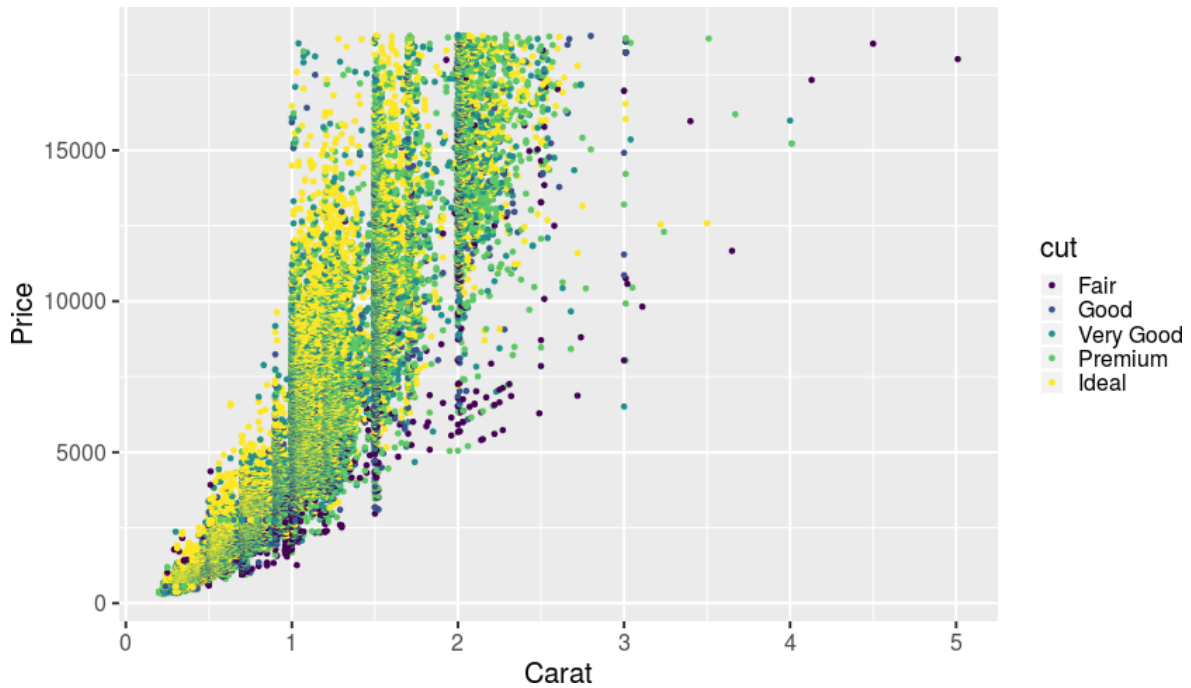
Modifying shapes

```
ggplot(diamonds, aes(x = carat, y = price, color = cut,
    shape = cut)) + geom_point()
```



Axis labels

```
# Let's make our plot look nicer
ggplot(diamonds, aes(x = carat, y = price, color = cut)) +
    geom_point() + xlab("Carat") + ylab("Price")
```

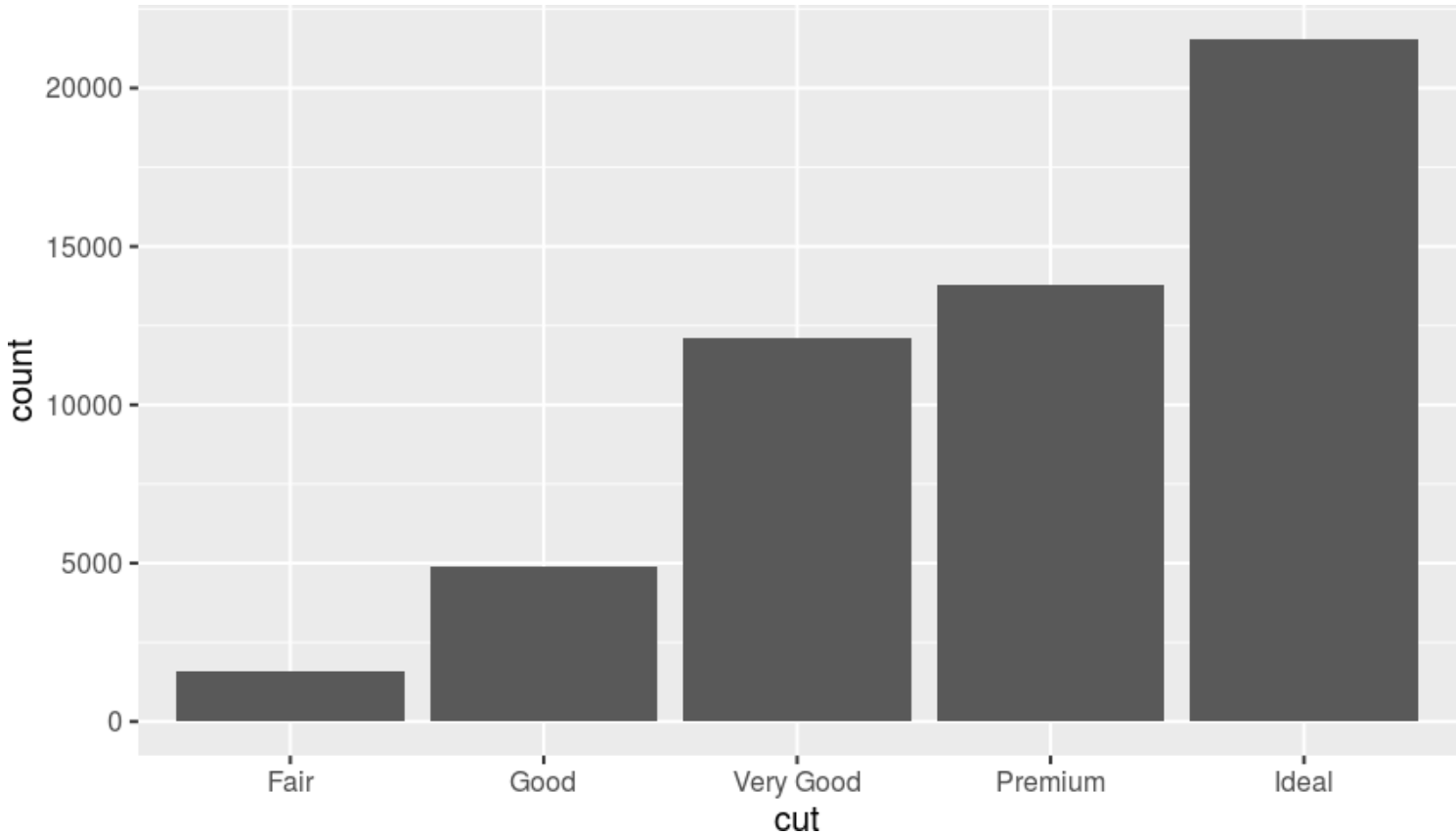


Geoms

- scatter plot: `geom_point()`
- bar chart: `geom_bar()`
- line plot: `geom_line` draws a line through the x-y-coordinates
- `geom_ribbon()` useful for confidence intervals around lines
- `geom_segment()` for simple lines
- `geom_smooth()` for smoother functions such as LOESS
- there are many more `geom` functions
- stats, scales, coord and facetting later

Bar chart

```
ggplot(diamonds, aes(x = cut)) + geom_bar()
```

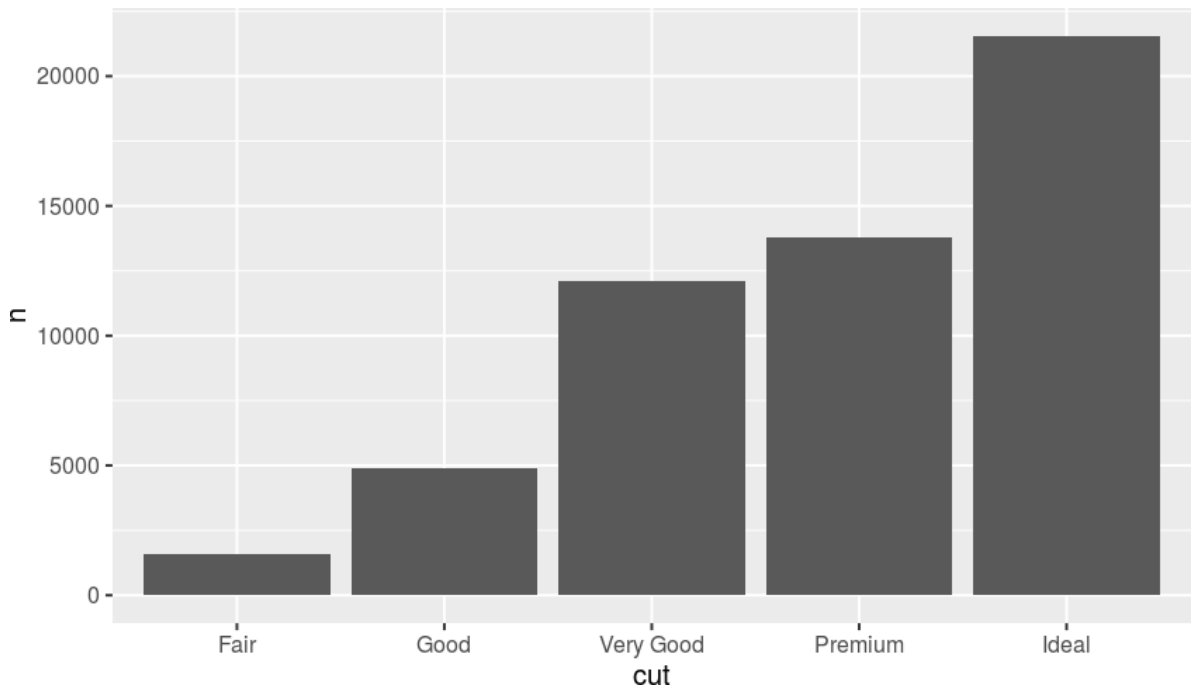


- `geom_bar()` does not need a `y`, `y` is defined by statistical transformation of `x`, simply the count of `x`

Bar chart

- you can also explicitly define a `y` defining the height and bars
- for this you need to the set the `statistical` transformation to 'identity' (the default for most geoms)

```
library(dplyr)
df <- diamonds %>% group_by(cut) %>% summarise(n = n())
ggplot(df, aes(x = cut, y = n)) + geom_bar(stat = "identity")
```



Line chart

- line charts are very helpful for plotting temporal developments

```
t <- read.csv("data/BundestagForecastReplicationData.csv",
    stringsAsFactors = F)
ggplot(t, aes(x = year, y = outgovshare)) + geom_line()
```

Line chart

- scaling of the axis or of the group, color, . . . ‘dimension’ can be done with the requisite functions

```
ggplot(t, aes(x = year, y = outgovshare)) + geom_line() +
    scale_y_continuous(limits = c(0, 100))
```

Further modifications

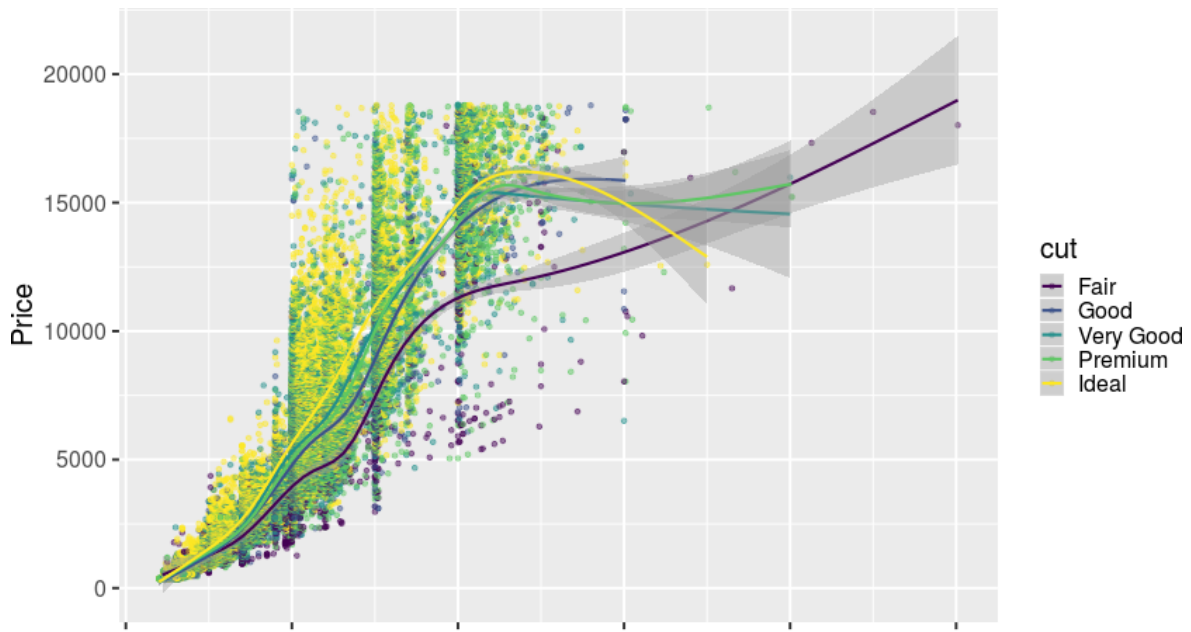
```
ggplot(t, aes(x = year, y = outgovshare)) + geom_line() +
    scale_y_continuous(limits = c(0, 100))
```

Layers

- We can overlay lots of plots one on top of one another.
- We just add a new function and precede it with a +.
- We add a loess curve with `geom_smooth()`

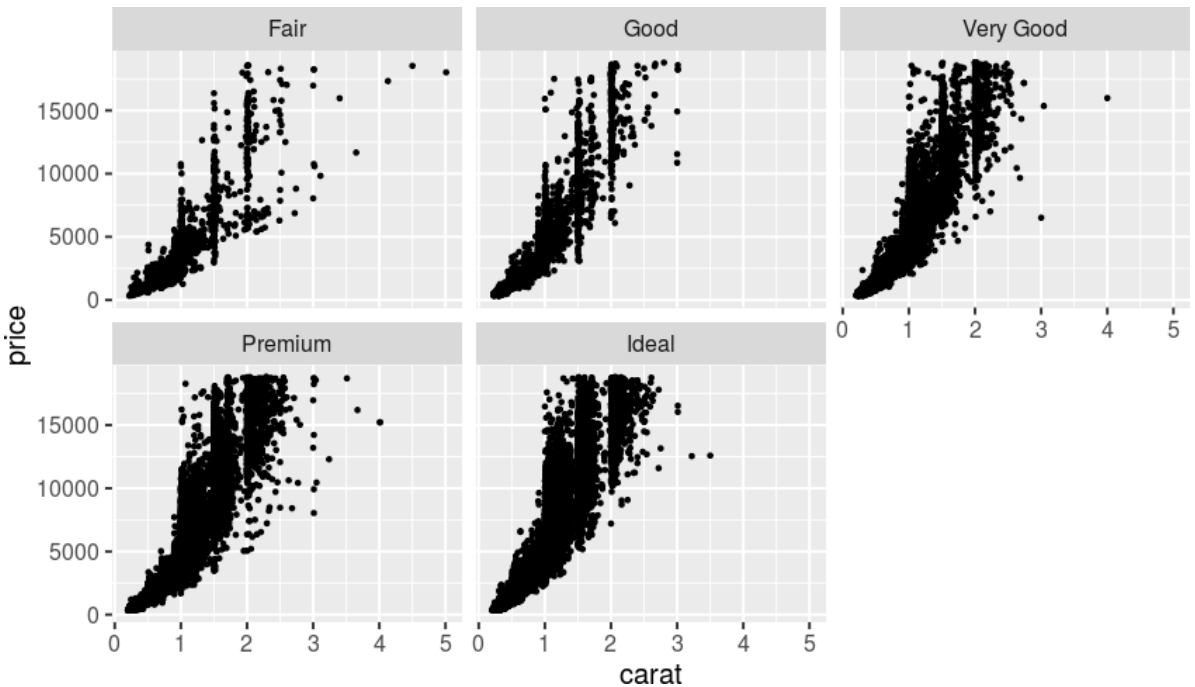
```
ggplot(diamonds, aes(x = carat, y = price, color = cut)) +
    geom_point(alpha = 0.5) + geom_smooth() + xlab("Carat") +
    ylab("Price")
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs
```



Facetting

```
ggplot(diamonds, aes(x = carat, y = price)) + geom_point() +
    facet_wrap(~cut)
```

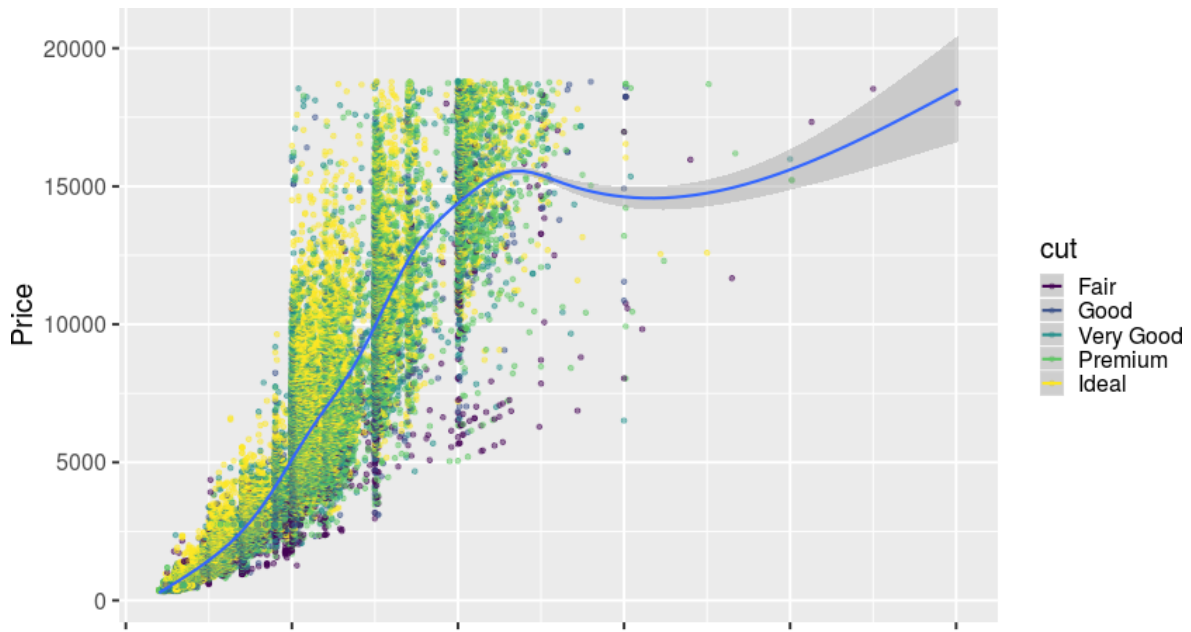


Aesthetics

- What if we only want to have one loess curve based on the whole data?
- Simply override the aesthetic in `geom_smooth()`

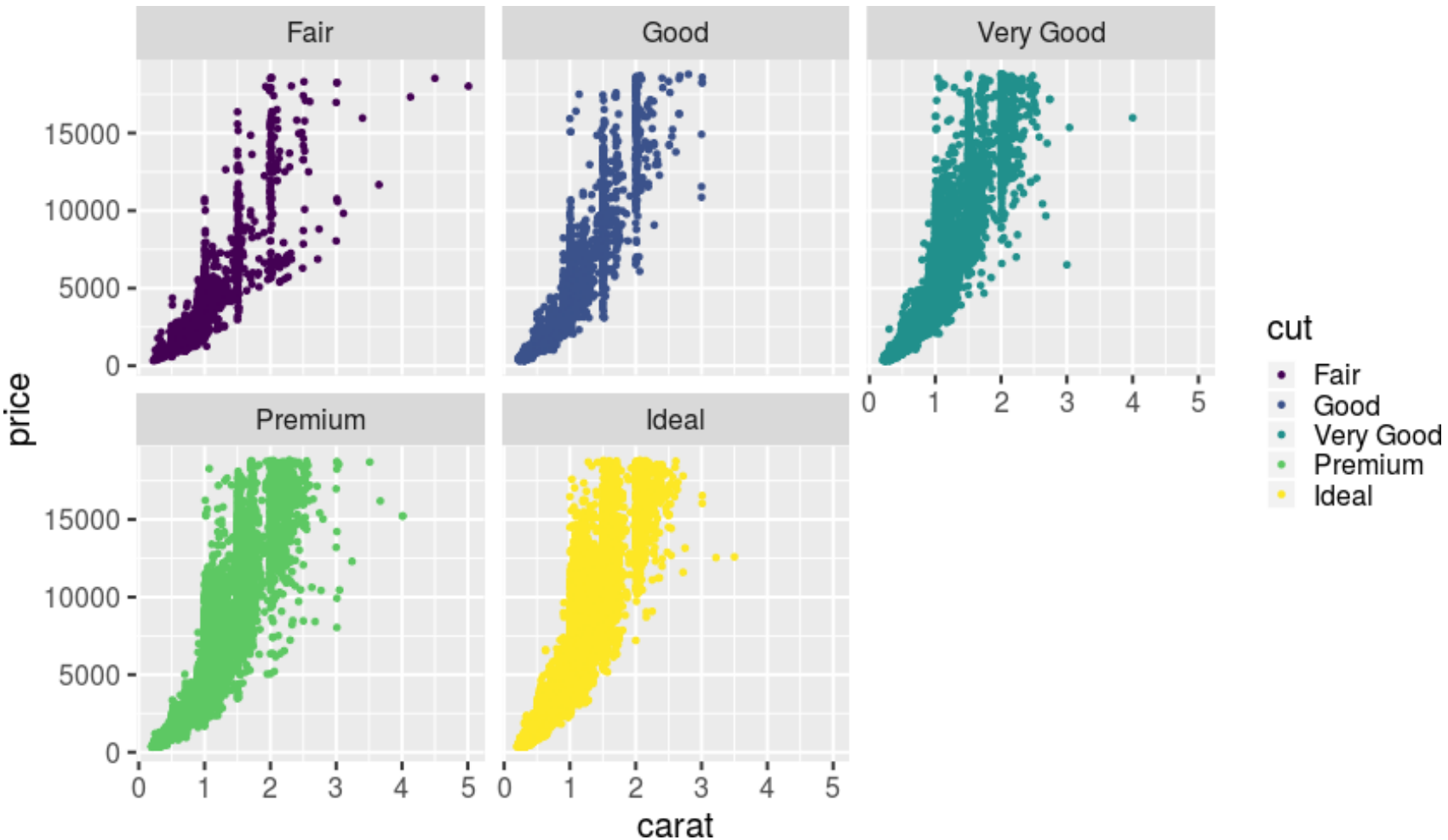
```
ggplot(diamonds, aes(x = carat, y = price, color = cut)) +
    geom_point(alpha = 0.5) + geom_smooth(aes(color = NULL)) +
    xlab("Carat") + ylab("Price")
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs
```



Facetting

```
ggplot(diamonds, aes(x = carat, y = price, color = cut)) +
    geom_point() + facet_wrap(~cut)
```



Hands-on I

Hands-on I

`hands-on/05_visualization/hands-on1.R`

Data visualization II

Figures as objects

- ggplot figures can be saved as objects

```
f <- ggplot(diamonds, aes(x = cut)) + geom_bar()
```

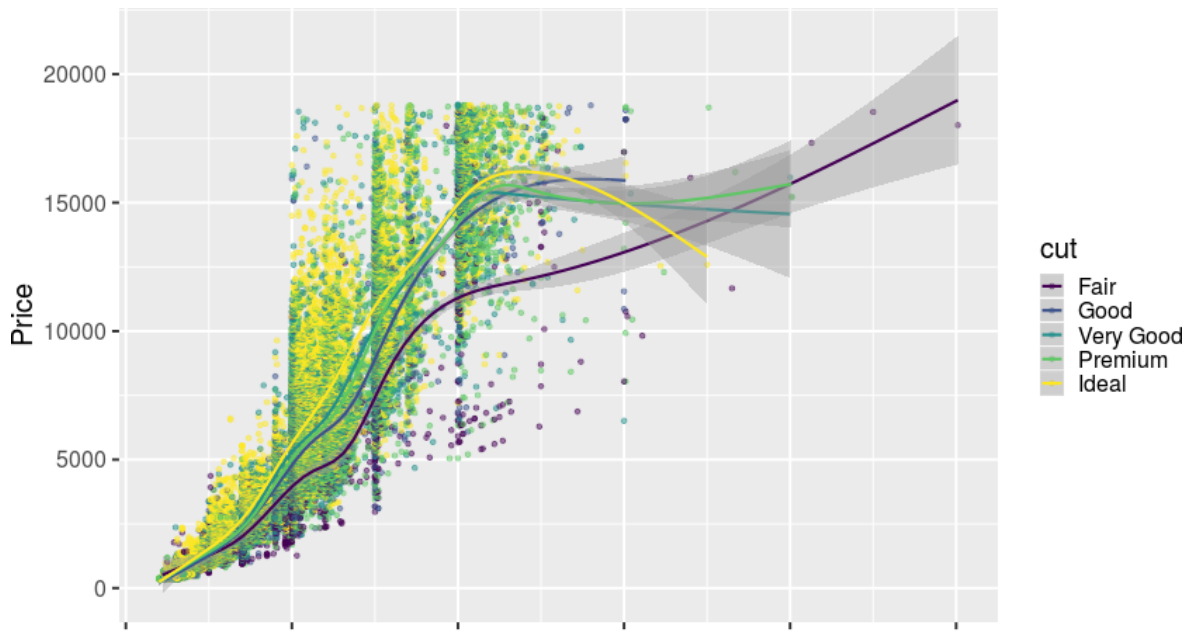
- These objects are self-contained. They are a list object containing:
  - the data
  - aesthetics
  - stats
  - scales
- If you chage the original data and redraw the plot object, the plot will not change

Layers

- We can overlay lots of plots one on top of one another.
- We just add a new function and precede it with a +.
- We add a loess curve with `geom_smooth()`

```
ggplot(diamonds, aes(x = carat, y = price, color = cut)) +
    geom_point(alpha = 0.5) + geom_smooth() + xlab("Carat") +
    ylab("Price")
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs
```

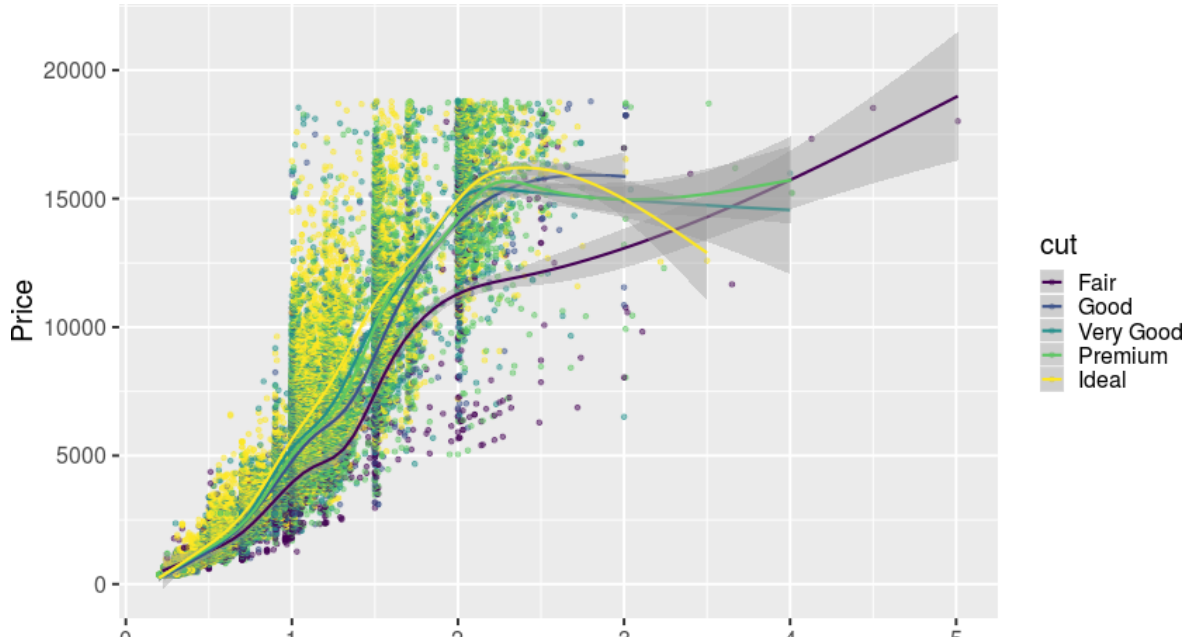


Layers

- You can also save a figure and build on it by adding further ggplot2 functions

```
f <- ggplot(diamonds, aes(x = carat, y = price, color = cut)) +
    geom_point(alpha = 0.5)

f + geom_smooth() + xlab("Carat") + ylab("Price")
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs
```



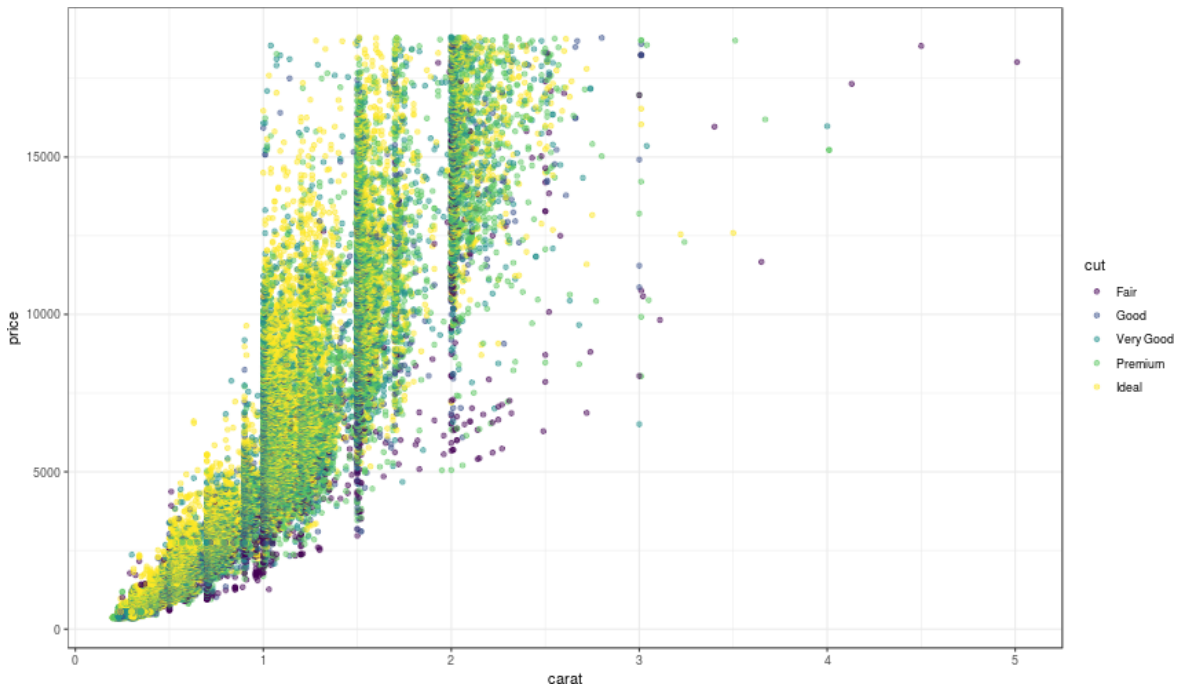
Themes

- Various themes are available.
- For instance:
  - `theme_bw()`
  - `theme_minimal()`
- Further themes are available in the package `ggthemes`:
  - `theme_tufte` is minimal and elegant
  - there is also an Excel theme (`theme_excel`)

```
install.packages("ggthemes")
```

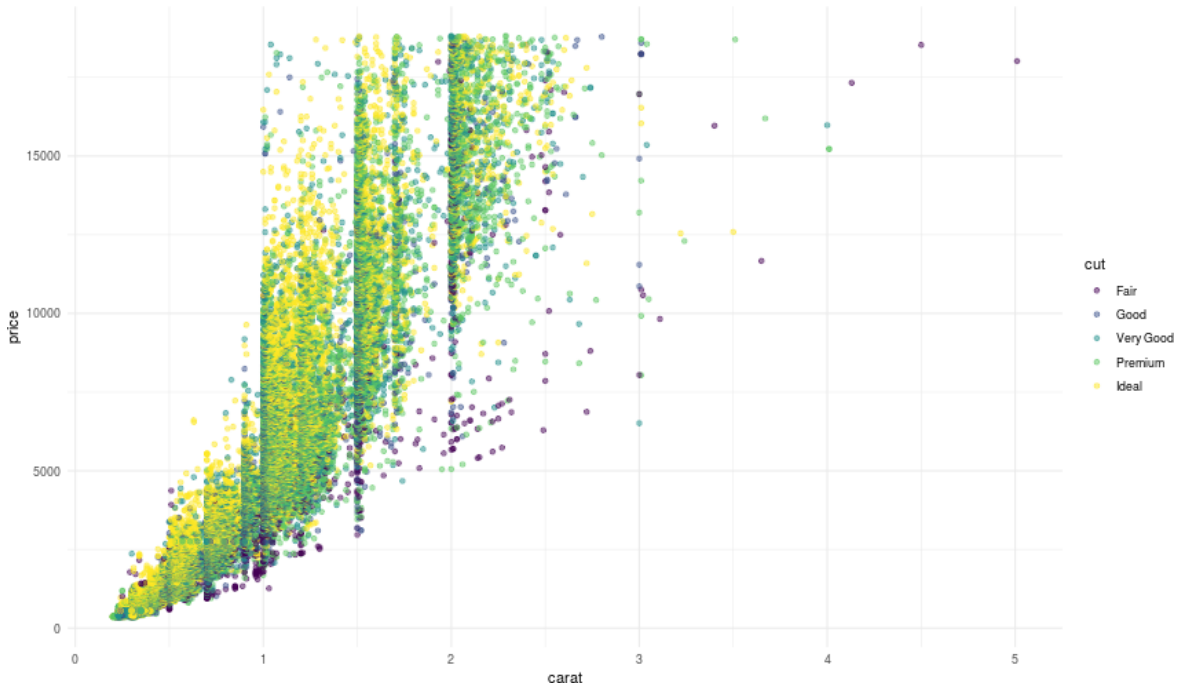
Themes

```
library(ggthemes)

f + theme_bw()
```



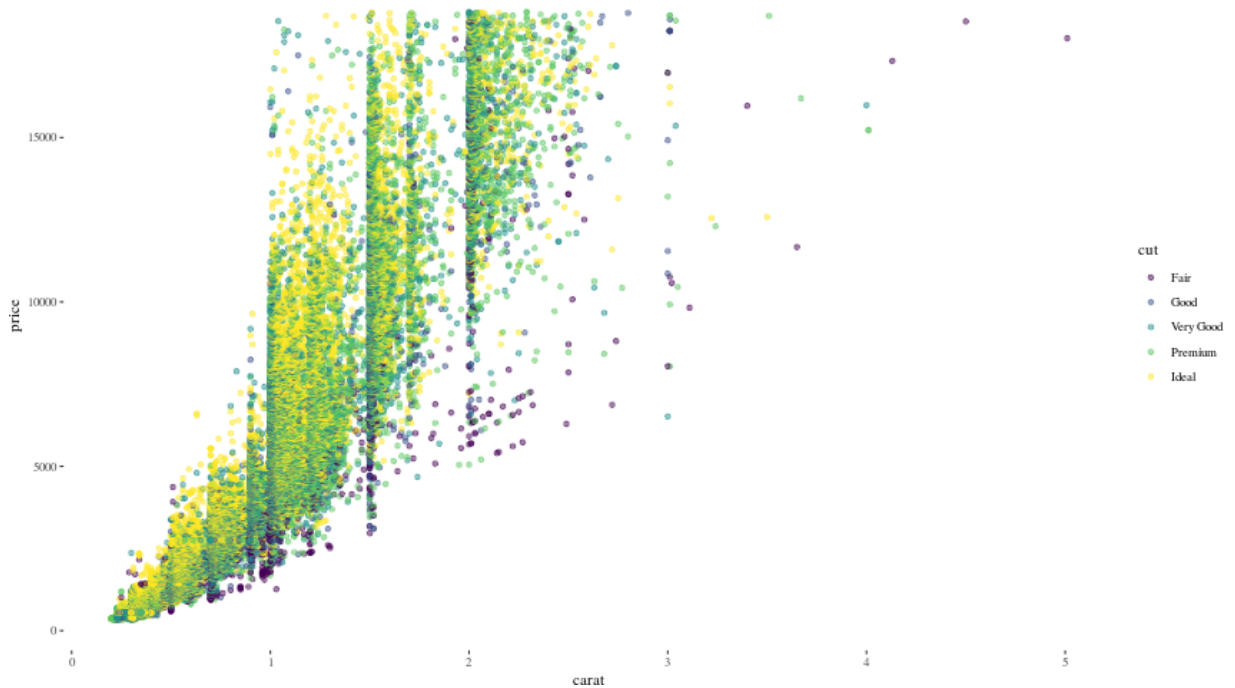
Themes

```
f + theme_minimal()
```



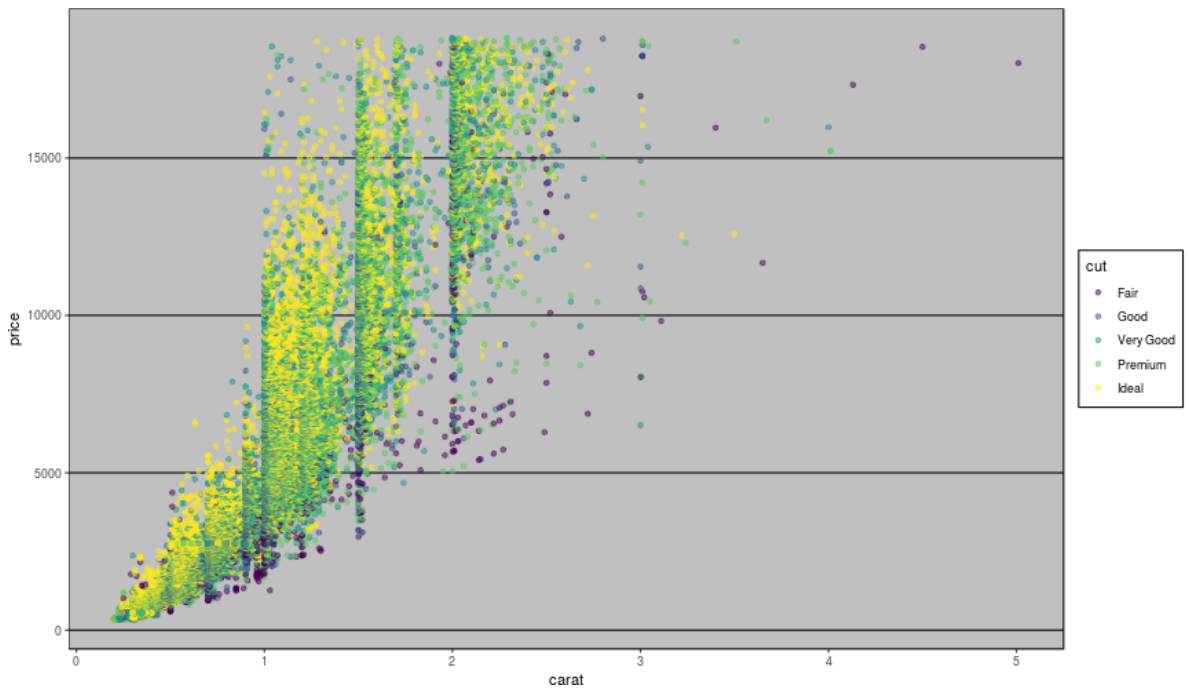
Themes

```
f + theme_tufte()
```



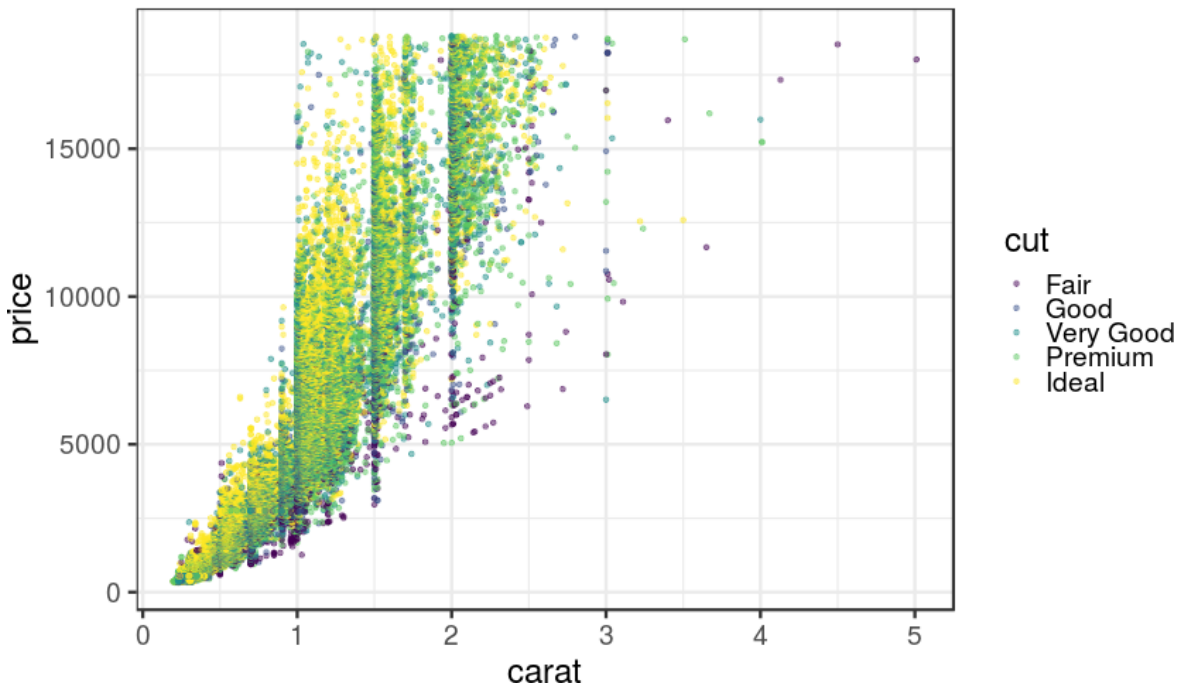
Themes

```
f + theme_excel()
```



Font size

```
f + theme_bw(base_size = 24)
```



Saving graphics

Of course plots can be saved to objects as well as to the hard drive.

```
fig <- ggplot(diamonds, aes(x = price, y = carat)) +
  geom_point() +   xlab('Price') + ylab('Carat') +
  theme_bw()
pdf('figures/fig.pdf')
fig
dev.off()
```

- or `png()`, `jpeg()`, `tiff()` followed by plot function or object and dev.off()
- or `ggsave()`

```
ggsave(filename = "figures/fig.pdf", plot = fig)
```

Saving graphics

```
# set dimensions in inches for pdf
pdf('figures/fig.pdf', width = 5, height = 4)
fig
dev.off()
# and in pixels for png
png('figures/fig.png', width = 500, height = 400)
fig
dev.off()
```

Hands-on II

Hands-on II

`hands-on/05_visualization/hands-on2.R`

Turning a table into a figure

Table 1. Party candidates' positions on the use of referendums: Percentage responding that referendums are 'good things'

	% responding that referendums are 'good things'
Australia 2001[1]	
Liberals	65
Nationals	65
Australian public	**66**
Labour	71
Democrats	84
Greens	86
One Nation Party	89
Canada 1999/2000[2]	
New Democratic Party	15
Liberal	37
Canadian public	**57**
Progressive Conservatives	61
Reform Alliance	100
New Zealand 1999[3]	
Labour	28
Alliance	48
National	51
ACT	53
Green	54
New Zealand public	**74**
New Zealand First	81

Figure 1: Bowler, S., Denemark, D., Donovan, T., McDONNELL, D., 2016. Right-wing populist party supporters: Dissatisfied but not direct-

Turning a table into a figure

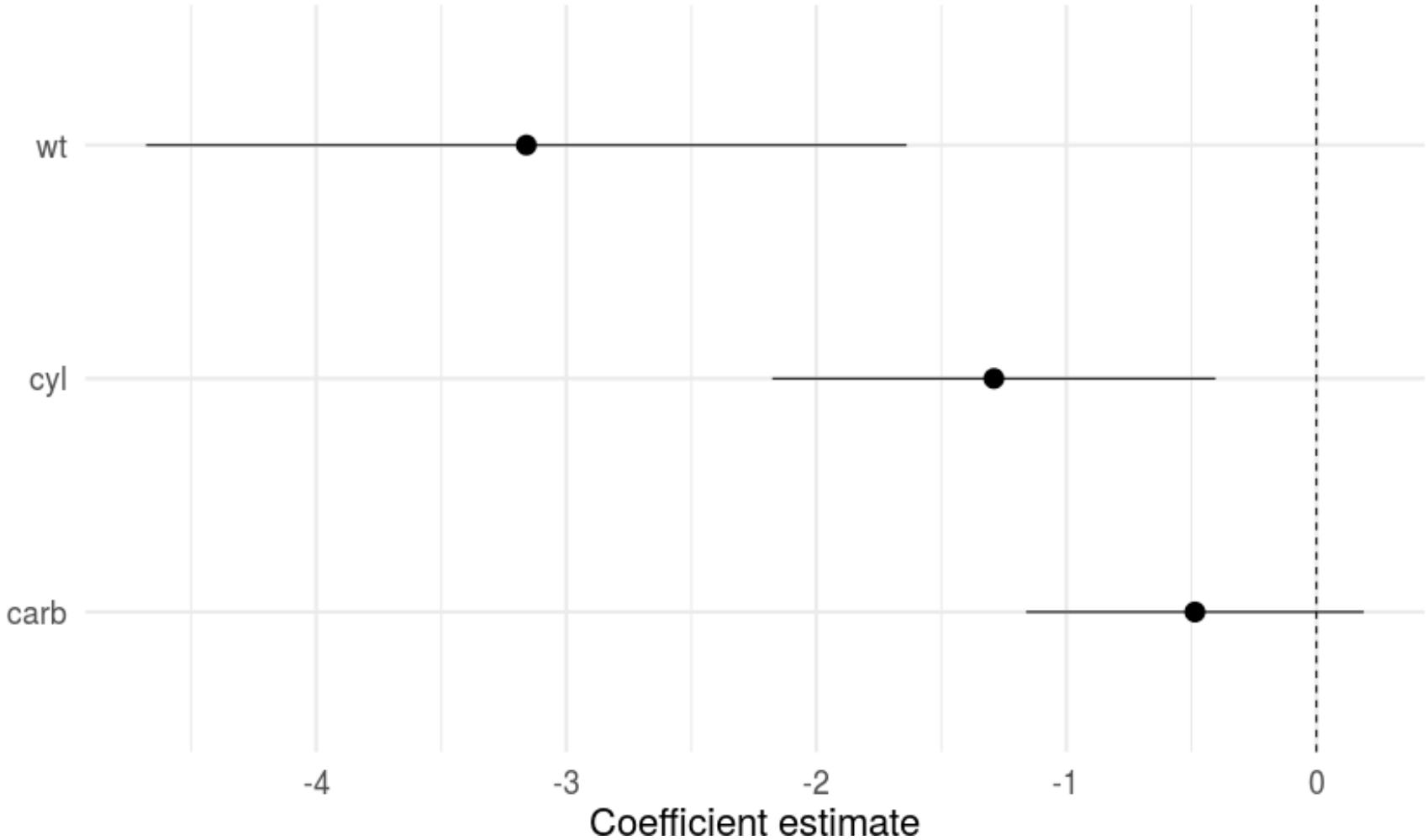
- Turn this table into a figure which provides the same or more information as the table
- The data reported in the table are found in `table1.csv`

Model visualization

Coefficient plot

```r
# Create a model to plot
m1 <- lm(mpg ~ wt + cyl + carb, data=mtcars)

coefs <- data.frame(names(coef(m1)), coef(m1), confint(m1))
names(coefs) <- c('var', 'coef', 'lwr', 'upr')
coefs <- coefs[-1,]

ggplot(coefs, aes(var, coef)) +
  geom_hline(yintercept = 0, linetype = 'dashed') +
  geom_point(size = 5) +
  geom_errorbar(aes(ymin = lwr, ymax = upr), width = 0) +
  xlab('') + ylab('Coefficient estimate') +
    coord_flip() + theme_minimal(base_size = 22)
```

Coefficient plot

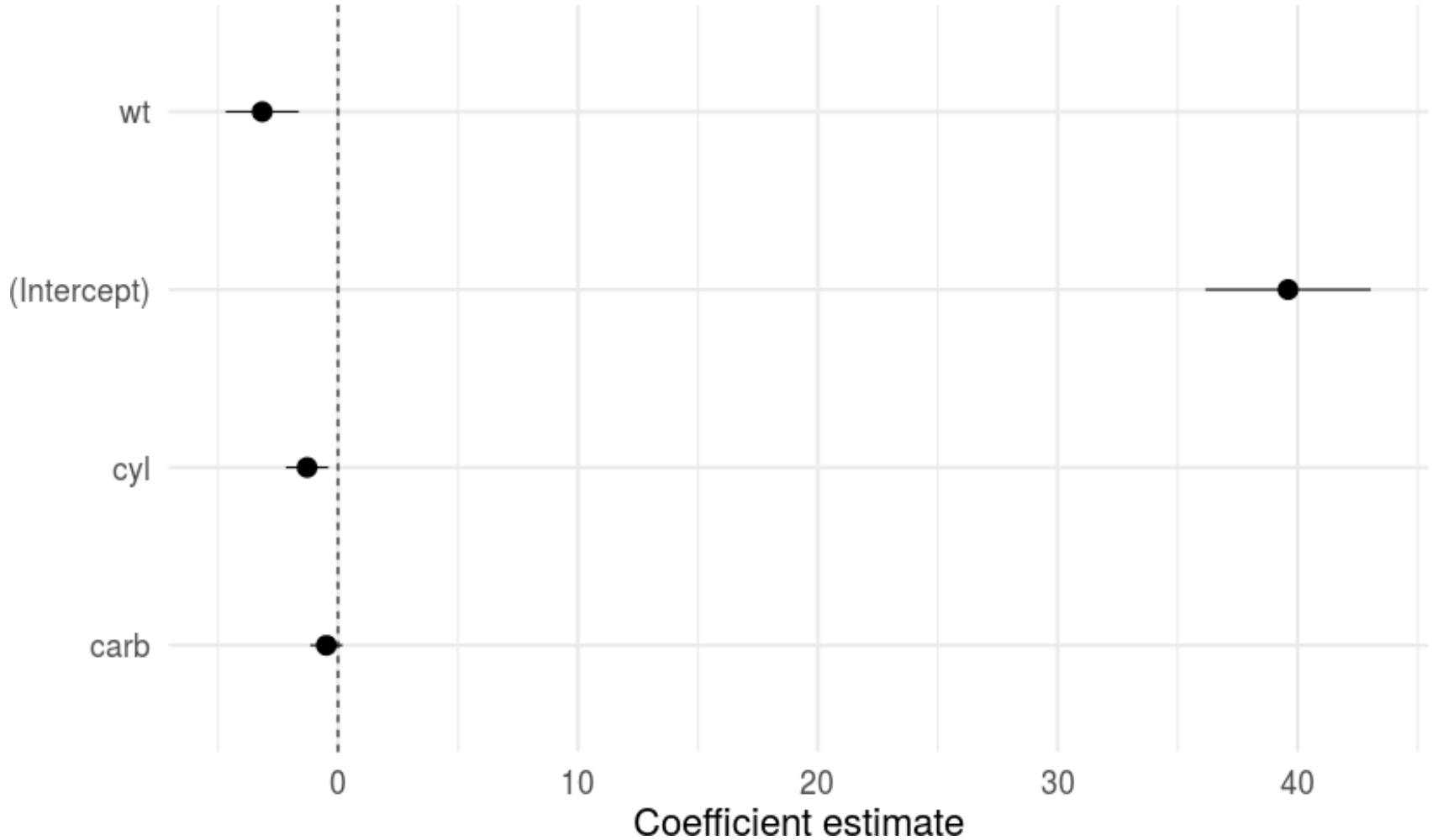


Coefficient plot with broom

```
library(broom)

coefs <- tidy(m1)
coefs <- cbind(coefs,
               lwr = confint(m1)[,1],
               upr = confint(m1)[,2])
coefs
```

```
##                    term   estimate std.error statistic
## (Intercept) (Intercept) 39.6021403 1.6822639 23.540979
## wt                   wt -3.1594517 0.7423463 -4.256035
## cyl                 cyl -1.2897877 0.4325975 -2.981496
## carb               carb -0.4857629 0.3294704 -1.474375
##                    p.value       lwr        upr
## (Intercept) 5.418679e-20 36.156179 43.0481018
## wt          2.107662e-04 -4.680079 -1.6388243
## cyl         5.880227e-03 -2.175923 -0.4036518
## carb        1.515365e-01 -1.160652  0.1891267
```

Coefficient plot with `broom`



Hands-on III

Hands-on III

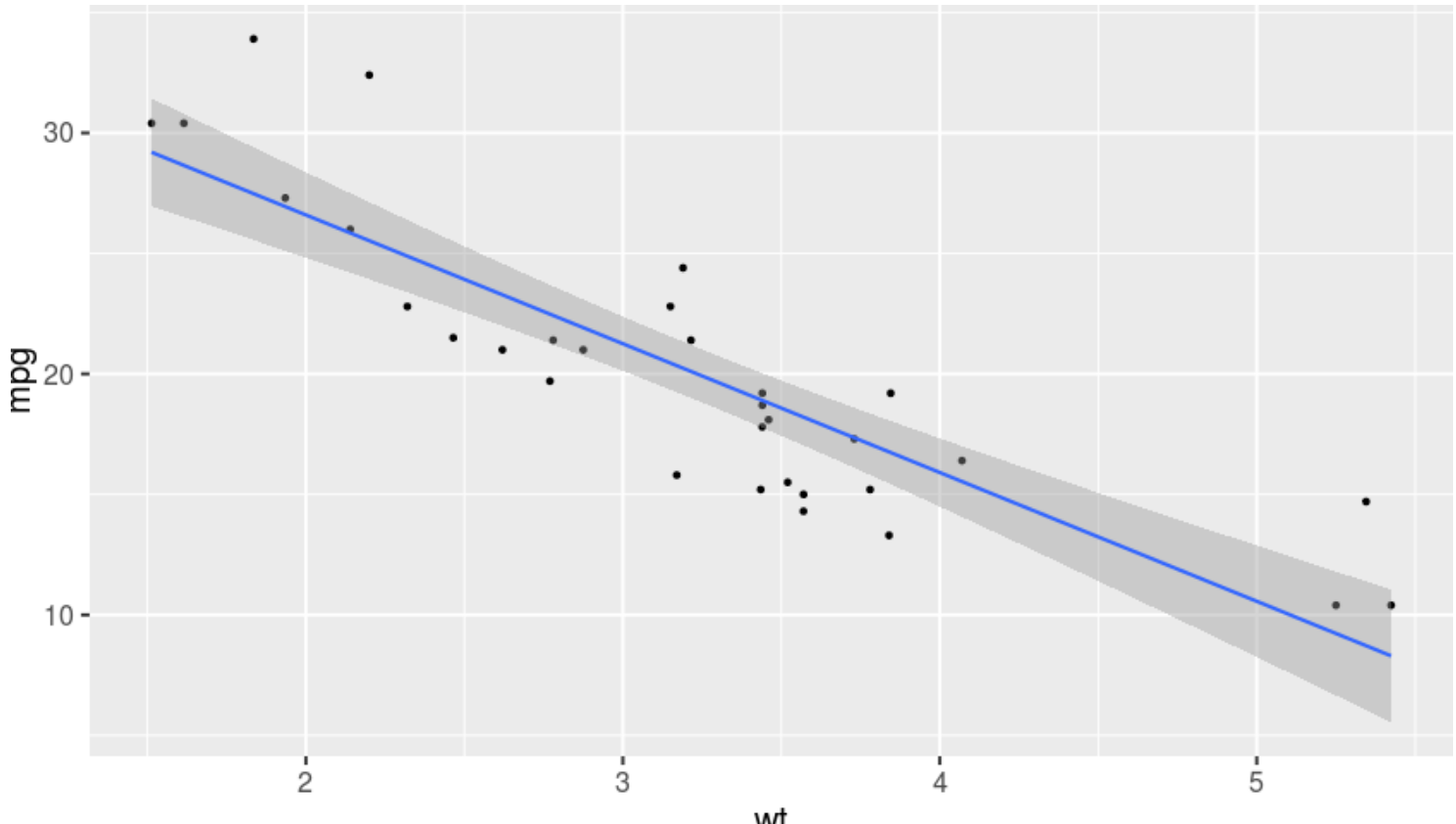
`hands-on/05_visualization/hands-on3.R`

Appendix

Predicted values: `lm()`

- For a bivariate model it's simple
- Just use `geom_smooth(method = 'lm')`

```
ggplot(mtcars, aes(x = wt, y = mpg)) +
  geom_point() +
  geom_smooth(method = 'lm')
```

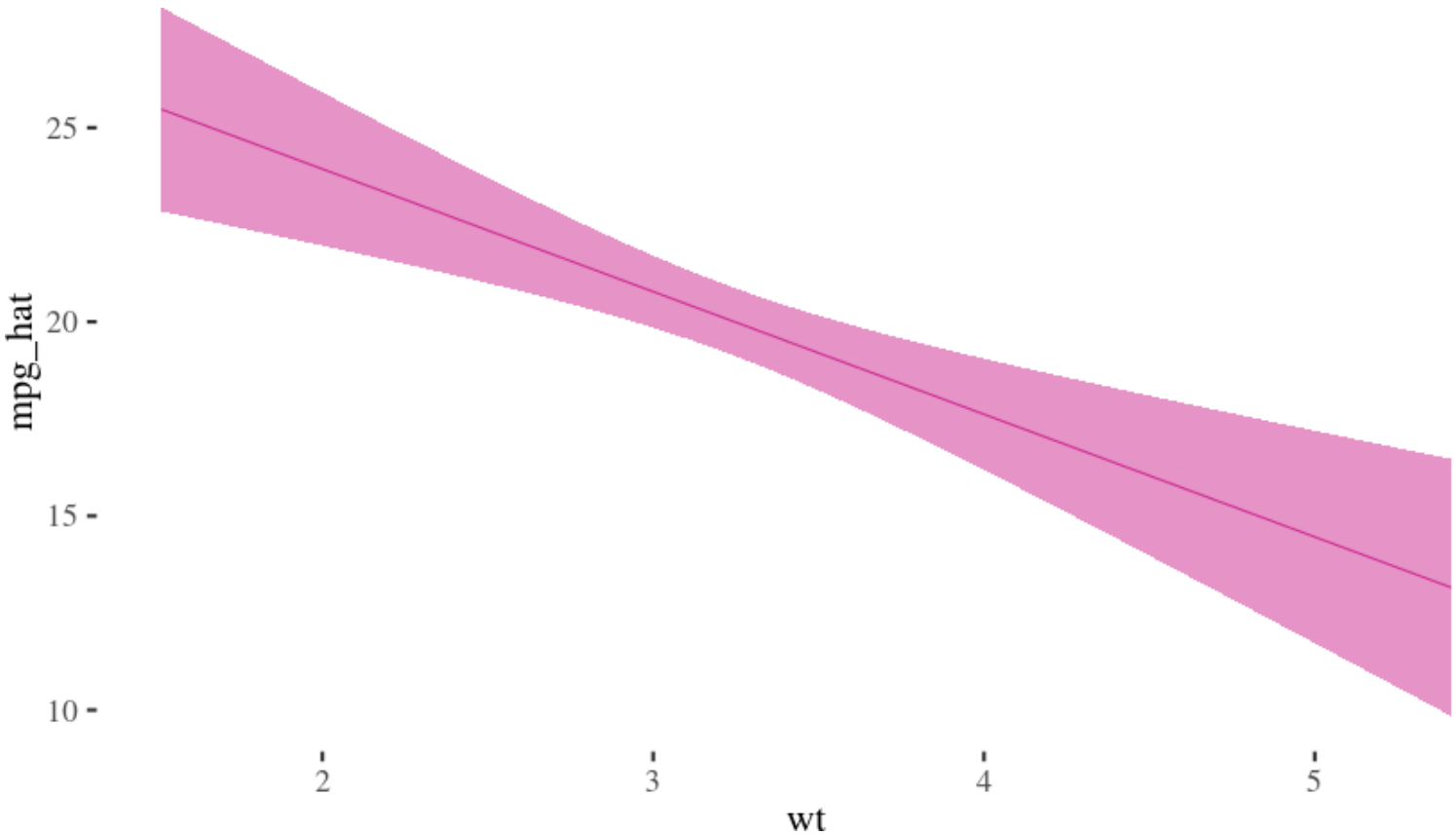


Predicted values: `lm()`

```r
# Recall m1
m1 <- lm(mpg ~ wt + cyl + carb, data=mtcars)

tmp <- data.frame(wt = seq(min(mtcars$wt),
                           max(mtcars$wt), .1),
                  cyl = mean(mtcars$cyl),
                  carb = mean(mtcars$carb))

tmp$mpg_hat <- predict(m1, newdata = tmp)
tmp$lwr <- tmp$mpg_hat - 1.96 *
  predict(m1, newdata = tmp, se.fit = T)$se.fit
tmp$upr <- tmp$mpg_hat + 1.96 *
  predict(m1, newdata = tmp, se.fit = T)$se.fit
```

Predicted values: `lm()`

```
ggplot(tmp, aes(x = wt, y = mpg_hat)) +
  geom_ribbon(aes(ymin = lwr, ymax = upr),
              fill = 'maroon3', alpha = .5) +
  geom_line(color = 'maroon3') +
  theme_tufte(base_size = 22)
```



Predicted values: `glm()`

```
library(foreign)

d <- read.dta("data/anes.dta", convert.factors = F)

glm1 <- glm(vote ~ age + gender + black + education + income +
    attendance + lib_con, d, family = binomial(link = logit))
```

Predicted values: `glm()`

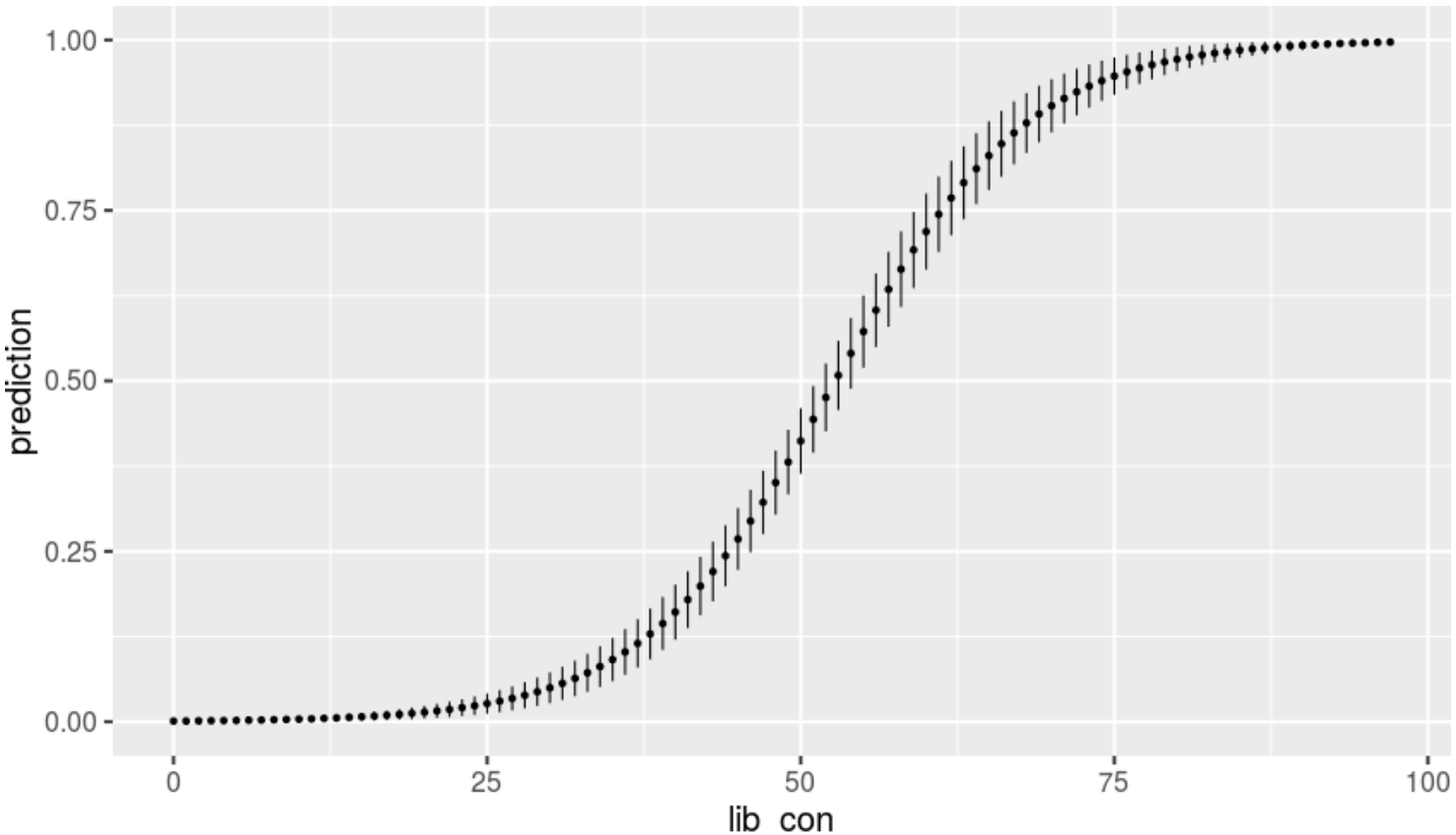
```
# The effect of lib/conservative placement
df <- data.frame(age = mean(d$age, na.rm = T),
                 gender = mean(d$gender, na.rm = T),
                 black = mean(d$black, na.rm = T),
                 education = mean(d$education, na.rm = T),
                 income = mean(d$income, na.rm = T),
                 attendance = mean(d$attendance, na.rm = T),
                 lib_con = min(d$lib_con,
                               na.rm = T):max(d$lib_con,
                                              na.rm = T)
)

df$prediction <- predict(glm1, newdat = df, type = 'response')
```

Predicted values: `glm()`

```
# have predict produce standard errors
se <- predict(glm1, newdata = df, type = 'response',
              se.fit = T)
df$se <- se$se.fit # save standard error
df$lwr <- df$prediction - 1.96 * df$se
df$upr <- df$prediction + 1.96 * df$se
```

Predicted values: `glm()`

```
ggplot(df, aes(x = lib_con, y = prediction, ymin = lwr,
    ymax = upr)) + geom_errorbar(width = 0) + geom_point()
```



Plotting an interaction (nominal × continuous)

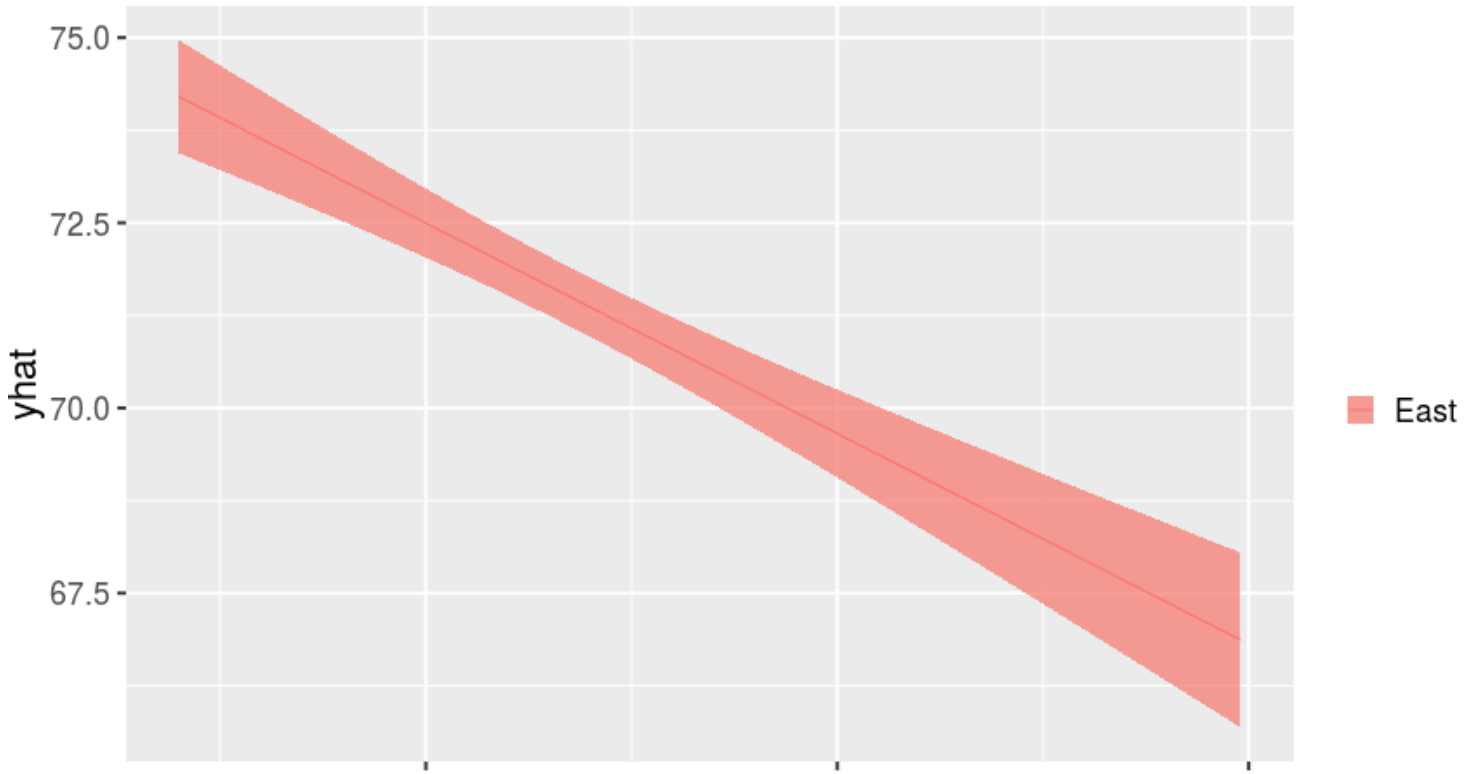
```r
d <- read.csv("data/btw2013.csv", stringsAsFactors = F)
# We want to code distrcits from East Germany, that is
# disctricts in Mecklenburg-Vorpommern, Brandenburg,
# Berlin,
east <- c("Mecklenburg-Vorpommern", "Brandenburg", "Berlin",
    "Saxony-Anhalt", "Saxony", "Thuringia")

d$land <- d$land.x
d$land.x <- d$land.y <- NULL

d$east <- d$land %in% east
# d$east is TRUE for all states in East Germany

m1 <- lm(turnout ~ east * unemployment, d)
# the * operator defines the interaction including
# constituent terms
```

Plotting an interaction (nominal × continuous)

```
# let's create a new data.frame to hold the predicted values
# + CI and independent variables
df <- data_frame(yhat = predict(m1, newdata = d),
# if I didn't set set newdata = d no NAs would be output
# (the vector of predicted values would be shorter
# than columns in the data.frame)
                 se.fit = predict(m1, newdata = d,
                                  se.fit = T)$se.fit,
                 upr = yhat + 1.96 * se.fit,
                 lwr = yhat - 1.96 * se.fit,
                 east = d$east,
                 unemployment = d$unemployment)
# when you use data_frame (rather than data.frame) v
# ariable definitions can
# depend on prior variable definitions
# It is included in the dplyr package
```

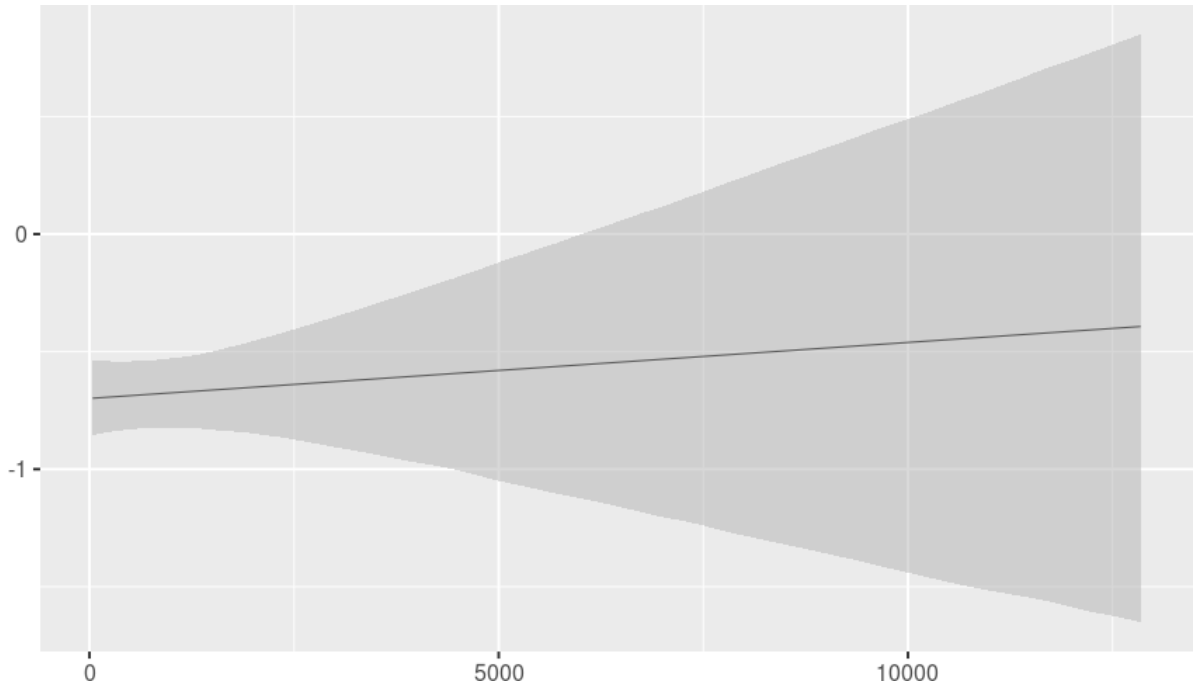
Plotting an interaction (nominal × continuous)

```
ggplot(df, aes(x = unemployment, y = yhat,
               ymin = lwr, ymax = upr)) +
  geom_ribbon(alpha = .7, aes(fill = east)) +  # CI
  geom_line(aes(color = east)) +  # fit line
  scale_color_discrete(name = '', labels = c('East', 'West')) +
  scale_fill_discrete(name = '', labels = c('East', 'West')) +
  theme(text = element_text(size = 22))
```



Plotting marginal effects

```
m3 <- lm(turnout ~ unemployment * popdensity, d)

library(interplot)
interplot(m3, var1 = "unemployment", var2 = "popdensity")
```



- Check out https://cran.r-project.org/web/packages/interplot/vignettes/interplot-vignette.html