First, let's read in two of the datasets for this week.

```
library(tidyverse)

key_crop_yields <- read_csv("https://raw.githubusercontent.com/rfordatascience/tidytuesday/master/data/2020/2020-09-01/key_crop_yields.csv")
land_use <- read_csv("https://raw.githubusercontent.com/rfordatascience/tidytuesday/master/data/2020/2020-09-01/land_use_vs_yield_change_in_cereal_production.csv")
```

I'm going to use the `land_use` dataset only to find the top population countries. Let's create a vector of their names.

```
top_countries <- land_use %>%
  janitor::clean_names() %>%
  filter(!is.na(code), entity != "World") %>%
  group_by(entity) %>%
  filter(year == max(year)) %>%
  ungroup() %>%
  slice_max(total_population_gapminder, n = 30) %>%
  pull(entity)

top_countries
```

```
##  [1] "China"                 "India"
##  [3] "United States"         "Indonesia"
##  [5] "Pakistan"              "Brazil"
##  [7] "Nigeria"               "Bangladesh"
##  [9] "Russia"                "Mexico"
## [11] "Japan"                 "Ethiopia"
## [13] "Philippines"           "Egypt"
## [15] "Vietnam"               "Democratic Republic of Congo"
## [17] "Germany"               "Turkey"
## [19] "Iran"                  "Thailand"
## [21] "United Kingdom"        "France"
## [23] "Italy"                 "South Africa"
## [25] "Tanzania"              "Myanmar"
## [27] "Kenya"                 "South Korea"
## [29] "Colombia"              "Spain"
```

Now let's create a tidy version of the crop yields data, for the countries and crops I am interested in.

```
tidy_yields <- key_crop_yields %>%
  janitor::clean_names() %>%
  pivot_longer(wheat_tonnes_per_hectare:bananas_tonnes_per_hectare,
    names_to = "crop", values_to = "yield"
  ) %>%
  mutate(crop = str_remove(crop, "_tonnes_per_hectare")) %>%
  filter(
    crop %in% c("wheat", "rice", "maize", "barley"),
    entity %in% top_countries,
    !is.na(yield)
  )

tidy_yields
```

```
## # A tibble: 6,032 x 5
##    entity      code    year crop    yield
```

```
##
##  1 Bangladesh BGD    1961 wheat  0.574
##  2 Bangladesh BGD    1961 rice   1.70
##  3 Bangladesh BGD    1961 maize  0.799
##  4 Bangladesh BGD    1961 barley 0.577
##  5 Bangladesh BGD    1962 wheat  0.675
##  6 Bangladesh BGD    1962 rice   1.53
##  7 Bangladesh BGD    1962 maize  0.738
##  8 Bangladesh BGD    1962 barley 0.544
##  9 Bangladesh BGD    1963 wheat  0.607
## 10 Bangladesh BGD    1963 rice   1.77
## # … with 6,022 more rows
```

This data structure is just right for plotting **crop yield over time**!

```
tidy_yields %>%
  ggplot(aes(year, yield, color = crop)) +
  geom_line(alpha = 0.7, size = 1.5) +
  geom_point() +
  facet_wrap(~entity, ncol = 5) +
  scale_x_continuous(guide = guide_axis(angle = 90)) +
  labs(x = NULL, y = "yield (tons per hectare)")
```

Notice that not all countries produce all crops, but that overall crop yields are *increasing*.

Many models

Now let's fit a linear model to each country-crop combination.

```
library(tidymodels)

tidy_lm <- tidy_yields %>%
  nest(yields = c(year, yield)) %>%
  mutate(model = map(yields, ~ lm(yield ~ year, data = .x)))

tidy_lm
```

```
## # A tibble: 111 x 5
##    entity     code  crop   yields             model
##
##  1 Bangladesh BGD   wheat
##  2 Bangladesh BGD   rice
```

```
##   3 Bangladesh BGD   maize
##   4 Bangladesh BGD   barley
##   5 Brazil     BRA   wheat
##   6 Brazil     BRA   rice
##   7 Brazil     BRA   maize
##   8 Brazil     BRA   barley
##   9 China      CHN   wheat
##  10 China      CHN   rice
## # … with 101 more rows
```

Next, let's `tidy()` those models to get out the coefficients, and adjust the p-values for multiple comparisons while we're at it.

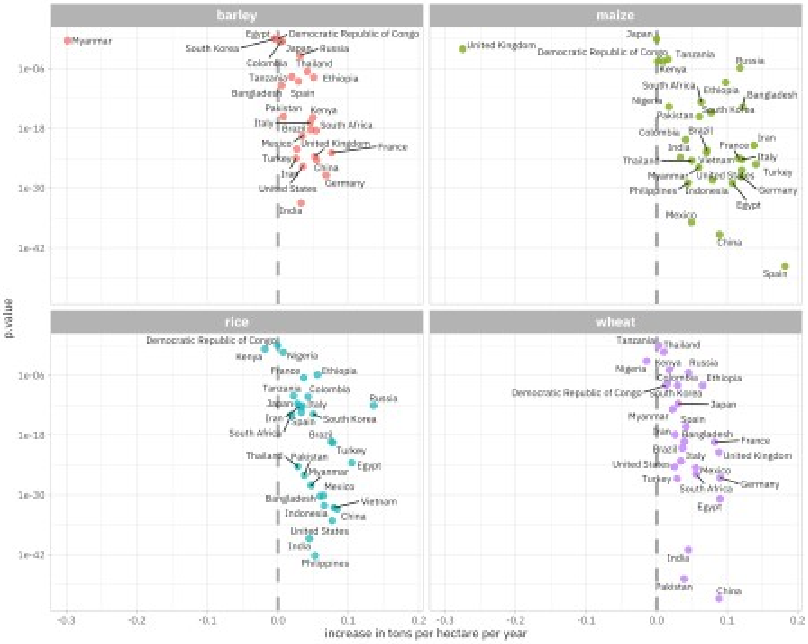
```
slopes <- tidy_lm %>%
  mutate(coefs = map(model, tidy)) %>%
  unnest(coefs) %>%
  filter(term == "year") %>%
  mutate(p.value = p.adjust(p.value))

slopes
```

```
## # A tibble: 111 x 10
##    entity  code  crop  yields  model term  estimate std.error statistic
p.value
##
##  1 Bangla… BGD   wheat   year   0.0389   0.00253      15.4  5.11e-20
##  2 Bangla… BGD   rice    year   0.0600   0.00231      26.0  6.05e-31
##  3 Bangla… BGD   maize   year   0.122    0.0107       11.3  1.82e-14
##  4 Bangla… BGD   barl…   year   0.00505  0.000596      8.47 4.34e-10
##  5 Brazil  BRA   wheat   year   0.0366   0.00222      16.5  2.55e-21
##  6 Brazil  BRA   rice    year   0.0755   0.00490      15.4  4.96e-20
##  7 Brazil  BRA   maize   year   0.0709   0.00395      18.0  4.37e-23
##  8 Brazil  BRA   barl…   year   0.0466   0.00319      14.6  5.05e-19
##  9 China   CHN   wheat   year   0.0880   0.00141      62.6  1.72e-51
## 10 China   CHN   rice    year   0.0843   0.00289      29.2  1.47e-33
## # … with 101 more rows
```

Explore results

Now we can visualize the results of this modeling, which is estimating how crop yields are changing around the world.

```
library(ggrepel)
slopes %>%
  ggplot(aes(estimate, p.value, label = entity)) +
  geom_vline(
    xintercept = 0, lty = 2,
    size = 1.5, alpha = 0.7, color = "gray50"
  ) +
  geom_point(aes(color = crop), alpha = 0.8, size = 2.5, show.legend = FALSE) +
  scale_y_log10() +
  facet_wrap(~crop) +
  geom_text_repel(size = 3, family = "IBMPlexSans") +
  theme_light(base_family = "IBMPlexSans") +
  theme(strip.text = element_text(family = "IBMPlexSans-Bold", size = 12)) +
  labs(x = "increase in tons per hectare per year")
```



- On the x-axis is the slope of these models. Notice that most countries are on the positive side, with increasing crop yields. The further to the right a country is, the larger the increase in crop yield over this time period. Corn yields have increased the most.
- On the y-axis is the p-value, a measure of how surprising the effect we see is under the assumption of no relationship (no change with time). Countries lower in the plots have smaller p-values; we are more certain those are real relationships.

We can extend this to check out how well these models fit the data with `glance()`. This approach for using statistical models to estimate changes in many subgroups at once has been so helpful to me in many situations!