New Tools for Data Analysis

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Some New Tools for Working with Data

There are two new tools we will use in working with data for this lab:

Getting fancy with the pipe operator (%>%)

With the tidyverse, we often use the "pipe" operator `%>%` to send the output from one function into the input of another function. In most cases, this works very simply and it uses the output from the function on the left as the first argument of the function on the right.

For instance, the `filter` function selects certain rows in a data frame or tibble. I will work here with examples from the built-in `storms` data frame that lists a subset of hurricanes from the National Oceanic and Atmospheric Administration's Atlantic hurricane database. The data includes the positions and attributes of 198 tropical storms, measured every six hours during the lifetime of the storm.

Let's select Hurricane Katrina from 2005 (I specify the year because there were two earlier Katrinas in 1981 and 1999; storm names are re-used periodically unless they are retired because a storm with that name becomes historically important).

```
data(storms)
katrina <- filter(storms, name == "Katrina", year == 2005)
```

and we can also do the same thing using the pipe operator like this:

```
storms %>% filter(name == "Katrina", year == 2005)
```

What the pipe operator `%>%` does behind the scenes is take that output of whatever is on the left (the data frame `storms`) and stick it in front of the arguemnts for the function on the right so the two examples given above are equivalent.

We have been usuing the pipe operator throughout the semester to combine functions. Suppose we want to `mutate` the `storms` data frame to add a new column `ts_area` that is equal to `pi * (ts_diameter / 2)^2`, where `ts_diameter` is a column in `storms` that corresponds to the diameter (in nautical miles) of the area in which winds are tropical storm strength or greater (36 knots), and then we want to select only the data where the tropical storm area is greater than 10,000 square nautical miles, and finally sort the data so the rows of the data frame go from largest to smallest tropical storm area. We can do that as follows:

```r
# First way
df1 = arrange(filter(mutate(storms, ts_area = pi * (ts_diameter / 2.0)^2),
      ts_area > 10000), desc(ts_area))

# Second way, using a temporary variable
df2 = mutate(storms, ts_area = pi * (ts_diameter / 2.0)^2)
df2 = filter(df2, ts_area > 10000)
df2 = arrange(df2, desc(ts_area))

# Third way, using the pipe operator
df3 = storms %>% mutate(storms, ts_area = pi * (ts_diameter / 2.0)^2) %>%
      filter(ts_area > 10000) %>% arrange(desc(ts_area))
```

We use pipes because often they are simpler to understand. If we use the first way in the example above, if we are combining many functions, nesting functions inside other functions becomes very difficult to read and understand. The second way, of using temporary variables is fine, but it can get confusing to have lots of variable names that we use only one time to pass data from one function to another. The third way, using the pipe operator makes it easier to understand how the data is moving through the processing pipeline.

But the way pipe operators work can sometimes get in the way of things we want to do.

First, suppose that I want to send the results of a function into the second or third argument of a subsequent function instead of the first argument? We use the `lm` function to calculate the slope and intercept of a trend line that best fits some data. The lm function expects the formula for the line to fit to be the first argument and the data to be the second.

Suppose I want to examine hurricanes from the year 2005 and look for a relationship between the air pressure in the eye and the wind speed, but only during the time when they are classified as hurricanes.

I can do this as follows:

```r
hurricanes_2005 = storms %>% filter(status == "hurricane", year == 2005)
lin_fit = lm(wind ~ pressure, data = hurricanes_2005)
```

The `lm` function looks at the data given by the `data` argument and then finds the best line that characterizes the linear relationship `wind ~ pressure`, which means that the wind is a linear function of the pressure (this would be the slope of a graph where `wind` is on the y-axis and `pressure` is on the x-axis).

Suppose that I would like to pipe data from the `filter` function to the `lm` function. I have a problem because the pipe operator would put the output from `filter` as the first argument of the `lm` function, but in `lm` the first argument is the formula and `data` is the second. I can do this as follows:

```r
lin_fit2 = storms %>% filter(status == "hurricane", year == 2005) %>%
           lm(wind ~ pressure, data = .)
```

The pipe operator creates a new variable `.` (the period), which gets the value of whatever is on the left of the operator. If I don't use the `.` in the function on the right, the pipe operator invisibly puts `.` in the first argument so `foo(x) %>% bar(y, z)` is re-written behind the scenes to become

```
. = foo(x)
bar(., y, z)
```

However, if I want to use the `.` somewhere else, I can do that explicitly and when the pipe operator looks at the function on its right, it knows not to stick the `.` in the first argument if I use `.` in the function call. This, I could write `foo(y) %>% bar(x, ., z)` if I want to substitute the output of `foo(y)` for the second argument of `bar`.

Extracting columns from a data frame in a pipeline

If I just want to look at the names of the hurricanes from the `storms` data frame, I can use the `$` operator:

```
names = storms$name
```

But suppose that I want to filter the storms and then extract the names. What are the names of category 5 hurricanes?

```
cat_5 = storms %>% filter(category == 5)
names = cat_5$name
```

Suppose I want to do this without creating a variable `cat_5`? I could try

```
# This will give an error
names = storms %>% filter(category == 5)$name
```

but it turns out that this doesn't work because of the way the pipe operators work. To do this, I need to load the `magrittr` library and use the `%$%` operator instead of `$`:

```
# This will work
names = storms %>% filter(category == 5) %$% name
```

The `%$%` operator works like the pipe operator, but instead of calling a function, it extracts the specified column (in this case, `name`).

This will be useful for what comes next.

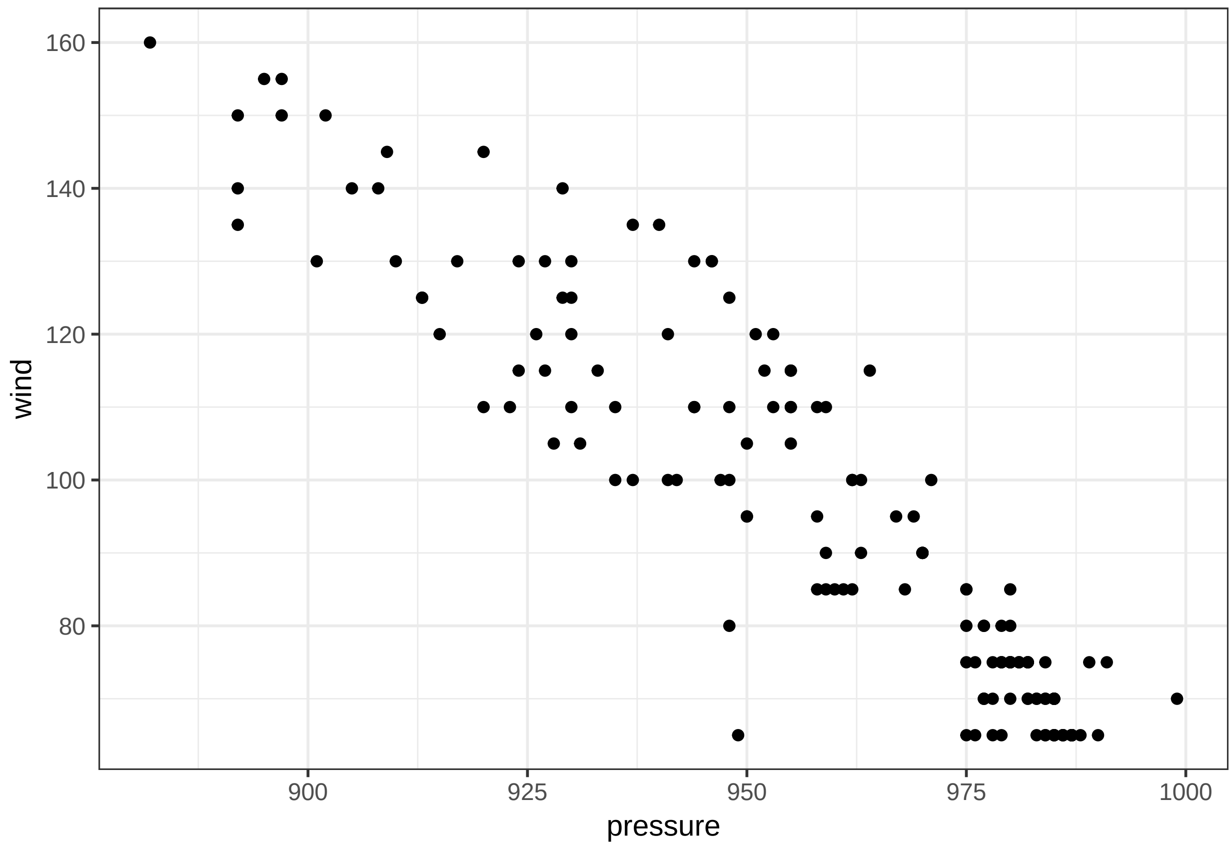
Tidying up results of statistical modeling

`lm` is one example of a lot of powerful functions in R that let you analyze data by fitting models. A statistical model is an idealized functional relationship between different attributes of the data (attributes are represented by columns in a data frame). For instance, a linear model idealizes two columns in the data frame in terms of a linear relationship. For instance `y~x` represents a model in which $y = a + bx$. In fact, the data rarely lie exactly along a line, but the `lm` function will find the values for `a` and `b` that define the line that best relates y to x (specifically this will be the line such that the minimizes the sum of the square of the errors between the actual y and the line: $\sum_i (y_i - (a + bx_i))^2$.

We will be using `lm` in this lab to find the rates of change of different parameters in the Kaya identity. For that we want to examine the slopes of the lines identified by `lm`. We can do that as follows for the slope that relates wind speed to pressure for a hurricane.

First, let's plot the two variables to see wether there's an apparent relationship. Let's look at hurricanes from 2005:

```
storms %>% filter(status == "hurricane", year == 2005) %>%
  ggplot(aes(x = pressure, y = wind)) + geom_point(na.rm = T)
```



The data clearly doesn't lie on a straight line, but there is a clear relationship that lower pressures tend to go along with higher wind speeds and higher pressures with lower wind speeds.

First, let's review how we can fit a relationship between wind speed and pressure for hurricanes from 2005:

```
lin_fit = storms %>% filter(status == "hurricane", year == 2005) %>%
          lm(wind ~ pressure, data = .)
```

But how can we get the slope out of the variable `lin_fit`? Here we use the `broom` package, which gives us a `tidy` function that will tidy up the results of statistical models and put them into a nice data frame:

```
lin_fit = storms %>% filter(status == "hurricane", year == 2005) %>%
           lm(wind ~ pressure, data = .)
tidy(lin_fit)
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)  947.       25.3        37.4 5.07e-86
## 2 pressure      -0.890     0.0263    -33.8 3.43e-79
```

Here, `term` tells us the parameter: `(Intercept)` is the intercept (a in the formula above), and `pressure` is the slope with respect to the pressure (b in the formula above). `estimate` is the estimate of the parameter (intercept or slope), `std.error` is the uncertainty about the estimate of the parameter, `statistic` and `p.value` are used for statistical hypothesis testing and we will not use them so you can ignore them.

If I just want the slope, I can get that as follows:

```
lin_fit = storms %>% filter(status == "hurricane", year == 2005) %>%
           lm(wind ~ pressure, data = .)
slope = tidy(lin_fit) %>% filter(term == "pressure") %$% estimate
slope
```

```
## [1] -0.8896546
```

Here, `filter` selects the row where term equals "pressure" and `%$% estimate` then selects the `estimate` column.

We can write this more compactly as follows:

```
slope = storms %>%
           filter(status == "hurricane", year == 2005) %>%
           lm(wind ~ pressure, data = .) %>%
           tidy() %>%
           filter(term == "pressure") %$% estimate
slope
```

```
## [1] -0.8896546
```

Writing functions

If you are going to do the same calculation many times in R it is often useful to define a function that performs that calculation and then you can simply call the function whenever you want to do the calculation with new values.

For instance, in the "Growth Rates and Trends" section of the assignment for the bottom-up decarbonization lab, we see that if we have a quantity q that is growing at a steady percentage rate r_q each year and we know the value in one year y_0 and want to predict what the value will be at a future year y, we can calculate this as follows:

$$q(y) = q(y_0) \times \exp(r_q \times (y - y_0)).$$

We can write this as an R function that we can call for different quantities and years:

```
growth = function(q_0, rate, start_year, end_year) {
  q_0 * exp(rate * (end_year - start_year))
}
```

A function definition has three parts: First we have the name of the function (`growth`), then we have the word `function`, followed by the arguments that the user must supply to the function `(q_0, rate, start_year, end_year)`, and then the body of the function, between curly braces `{ ... }`. When you call the function, it executes all of the code between the curly braces and returns the last value calculated before the closing brace. Thus, we can call the function like this to estimate the world population in 2050

```
P_2017 = 7.53 # world population was 7.53 billion
r_P = 0.0141  # growth rate is 1.41% per yer
P_2050 = growth(q_0 = P_2017, rate = r_P, start_year = 2017, end_year = 2050)
P_2050
```

```
## [1] 11.99146
```

If you don't specify the name of the parameter, the function fills them out in order, so we could also write

```
P_2017 = 7.53 # world population was 7.53 billion
r_P = 0.0141  # growth rate is 1.41% per yer
P_2050 = growth(P_2017, r_P, 2017, 2050)
P_2050
```

```
## [1] 11.99146
```

`kayadata`: an R package for analyzing Kaya-identity data

You can install the `kayadata` package as follows:

```
library(devtools)
install_github("jonathan-g/kayadata")
```

or

```r
library(pacman)
p_load_current_gh("jonathan-g/kayadata")
```

Once you have installed the `kayadata` package, you load it as follows:

```r
library(kayadata)
```

This package has several useful functions:

- `get_kaya_data(region_name)`: Get Kaya-identity data for a country or region.
  - **Argument:** `region_name` is the name of the country or region you want data for (e.g., "United States", "World", "China", etc.).
    You can inspect a list of countries and regions by running `kaya_region_list()`.
  - **Results:** The function returns a data frame with the following columns:
    - `region`: The country or region.
    - `year`: The year.
    - `P`: The population (in billions).
    - `G`: The gross domestic product (in trillions).
    - `E`: The primary energy consumption (in quads).
    - `F`: The energy-related CO_2 emissions (in millions of metric tons of CO_2).
    - `g`: Per-capita GDP (in thousands of dollars per person).
    - `e`: The energy intensity of the economy (in quads per trillion dollars of GDP).
    - `f`: The emissions intensity of the energy supply (in millions of metric tons of CO_2 per quad).
    - `ef`: The emissions intensity of the economy (in millions of metric tons of CO_2 per trillion dollars of GDP).
- `get_top_down_values(region_name)`: Get projections of the future values of Kaya-identity variables for a country, from the top-down International Energy Outlook analysis by the U.S. Energy Information Administration.
  - **Argument:** `region_name` is the name of the country or region you want data for (e.g., "United States", "World", "China", etc.).
  - **Results:** The function returns a data frame with the following columns:
    - `region`: The country or region.
    - `year`: The year (five-year intervals from 2015–2050).
    - `P`: The population (in billions).
    - `G`: The gross domestic product (in trillions).
    - `E`: The primary energy consumption (in quads).
    - `F`: The energy-related CO_2 emissions (in millions of metric tons of CO_2).
    - `g`: Per-capita GDP (in thousands of dollars per person).
    - `e`: The energy intensity of the economy (in quads per trillion dollars of GDP).
    - `f`: The emissions intensity of the energy supply (in millions of metric tons of CO_2 per quad).
    - `ef`: The emissions intensity of the economy (in millions of metric tons of CO_2 per trillion dollars of GDP).
- `get_top_down_trends(region_name)`: Get the trends for Kaya-identity variables for a country, from the top-down International Energy OUtlook analysis by the U.S. Energy

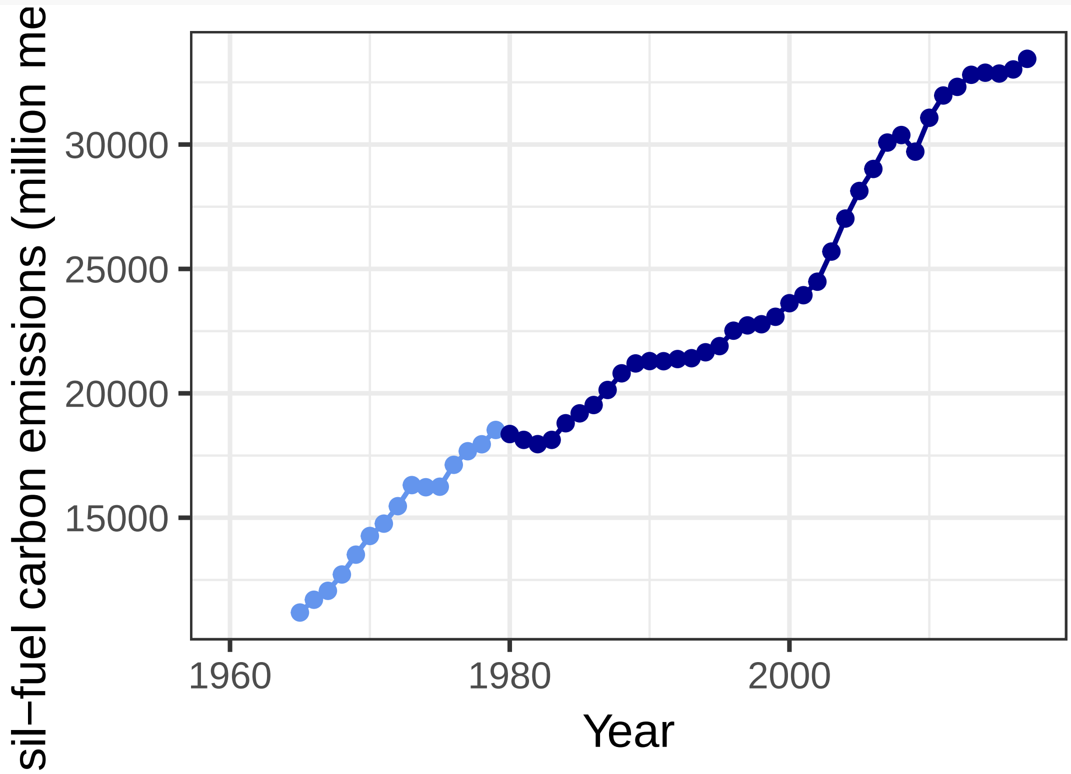
Information Administration.

- **Argument:** `region_name` is the name of the country or region you want data for (e.g., "United States", "World", "China", etc.).
- **Results:** The function returns a data frame with the following columns:
  * `region`: The country or region
  * `P`: The rate of change of the population (multiply by 100 to get the rate in percent per year).
  * `G`: The rate of change of GDP.
  * `E`: The rate of change of primary energy consumption.
  * `F`: The rate of change of CO_2 emissions.
  * `g`: The rate of change of per-capita GDP.
  * `e`: The rate of change of the energy intensity of the economy.
  * `f`: The rate of change of the emissions intensity of the energy supply.
  * `ef`: The rate of change of the emissions intensity of the economy.

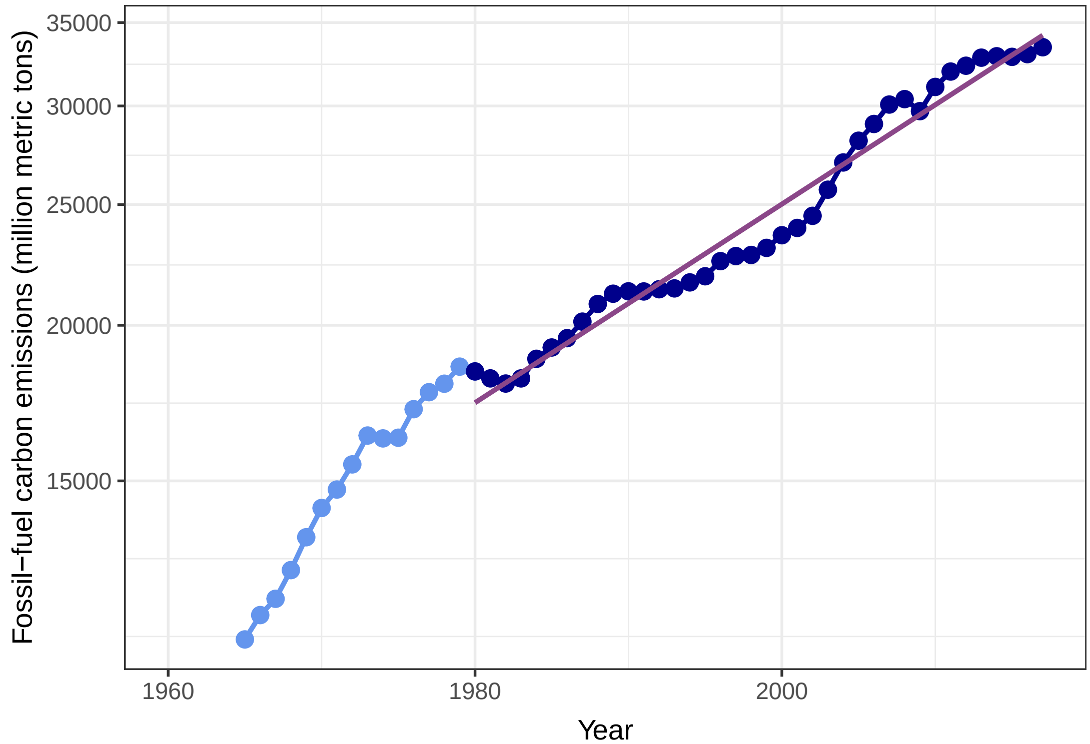
- `get_fuel_mix(region_name)`: Get the mixture of primary energy sources used by a country or region. * **Argument:** `region_name` is the name of the country or region you want data for (e.g., "United States", "World", "China", etc.).
  - **Results:** The function returns a data frame with the following columns:
    * `region`: The country or region
    * `region_code`: A three-letter code for the country or region.
    * `geography`: The kind of region ("nation", "region", or "world").
    * `year`: The year the data represents.
    * `fuel`: The kind of energy source ("Oil", "Natural Gas", "Coal", "Nuclear", "Hydro", or "Renewables")
    * `quads`: The number of quads of that kind of energy consumed in that year.
    * `pct`: The percent of total primary energy consumption that came from that kind of energy source.
- `plot_kaya(kaya_data, variable, start_year, stop_year, y_lab, log_scale, trend_line, points, font_size)`: Plot a time series showing trends in a Kaya variable.
  - **Arguments:**
    * `kaya_data`: A data frame, like those returned by `get_kaya_data`.
    * `variable`: A quoted Kaya variable name ("P", "G", "E", "F", "g", "e", "f", or "ef").
    * `start_year` (optional): If you want to do trend analysis, you can specify the year to start calculating the trend. The graph will color the years from `start_year` to `stop_year` in a darker color.
      If you don't specify `start_year`, the default value is 1980. You can eliminate the special coloring and trend analysis by setting `start_year = NULL`.
    * `stop_year` (optional): The year to stop the trend analysis. If you don't specify `stop_year`, it defaults to the last year in the data frame.
    * `y_lab` (optional): The label for the y-axis. If you don't specify this, R will pick an appropriate label based on which variable you choose.
    * `log_scale` (optional): Set this to `TRUE` or `FALSE` to specify whether to plot the y-axis on a logarithmic scale. The default is to set `log_scale = FALSE` if you don't specify a value.

    * `trend_line` (optional): Set this to `TRUE` or `FALSE` to specify whether to plot a trend line. The default is to set `trend_line = FALSE` if you don't specify a value.
    * `points` (optional): Set this to `TRUE` or `FALSE` to specify whether to plot points on the line. If you are making a small graph, the points may make the graph too busy. The default is to set `points = TRUE` if you don't specify a value.
    * `font_size` (optional): This lets you adjust the size of the fonts used in labeling the axes on the graph. If you are making small plots and the y-axis label won't fit on the side of the graph, you might want to use a smaller font size. The default is to set `font_size = 20` if you don't specify a value.
- **Result:** This function returns a plot object.
- **Example:**

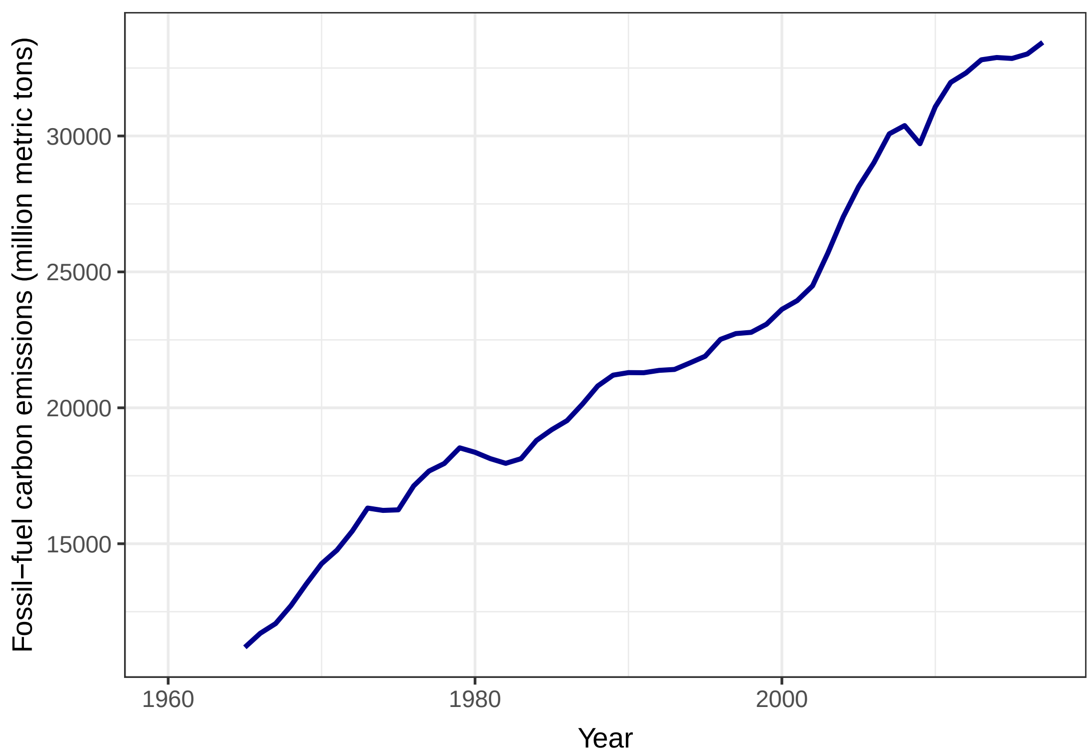
```
kd <- get_kaya_data("World")
plot_kaya(kd, "F")
```




```
plot_kaya(kd, "F", log_scale = TRUE, font_size = 12, trend_line = TRUE)
```



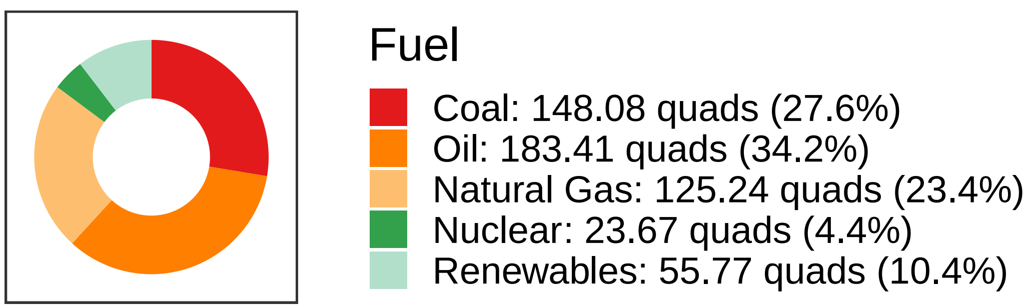

```r
plot_kaya(kd, "F", points = FALSE, start_year = NULL, font_size = 12)
```



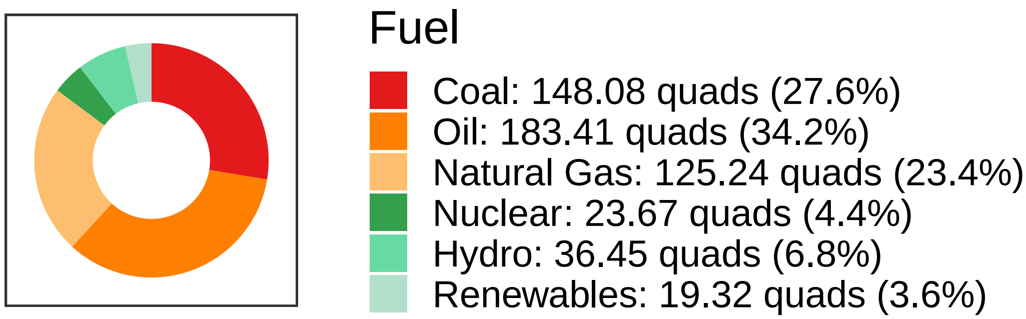
- `plot_fuel_mix(fuel_mix, collapse_renewables)`: Make a "donut" chart showing the amount of energy the country got from different energy sources.
  - **Arguments:**

    * `fuel_mix`: A data frame with the fuel mix for the country, like the ones returned by `get_fuel_mix()`
    * `collapse_renewables` (optional): Set this to `TRUE` or `FALSE` to specify whether to combine "Hydro" with other renewables to make one "Renewables" category (`TRUE`), or plot "Hydro" separately from the other renewables (`FALSE`).
      If you don't specify `collapse_renewables`, the default is to set `collapse_renewables = TRUE`.
- **Results:** A plot object with a donut chart.
- **Example:**

```
fm <- get_fuel_mix("World")
plot_fuel_mix(fm)
```




```
plot_fuel_mix(fm, collapse_renewables = FALSE)
```


Fuel
Coal: 148.08 quads (27.6%)
Oil: 183.41 quads (34.2%)
Natural Gas: 125.24 quads (23.4%)
Nuclear: 23.67 quads (4.4%)
Hydro: 36.45 quads (6.8%)
Renewables: 19.32 quads (3.6%)