Lesson notes | Lines, scales, and labels

Created by the GRAPH Courses team

November 2023

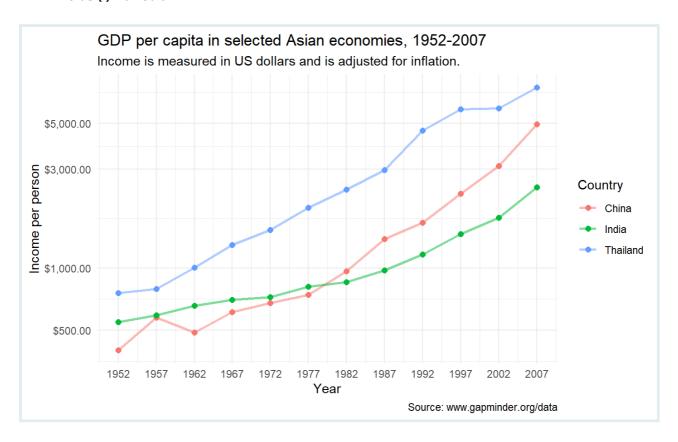
This document serves as an accompaniment for a lesson found on https://thegraphcourses.org.

The GRAPH Courses is a project of the Global Research and Analyses for Public Health (GRAPH) Network, a non-profit headquartered at the University of Geneva Global Health Institute, and supported by the World Health Organization (WHO) and other partners

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Learning Objectives

- 1. You can create **line graphs** to visualize relationships between two numerical variables with **geom line()**.
- 2. You can **add points** to a line graph with geom_point().
- 3. You can use aesthetics like color, **size**, **color**, and **linetype** to modify line graphs.
- 4. You can **manipulate axis scales** for continuous data with **scale_*_continuous()** and scale_*_log10().
- 5. You can **add labels** to a plot such as a **title**, **subtitle**, or **caption** with the **labs()** function.



Introduction

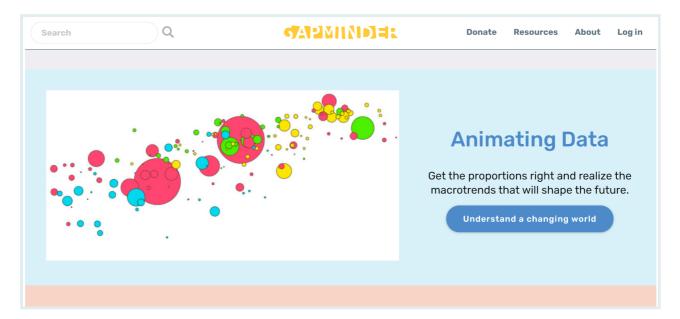
Line graphs are used to show **relationships** between two **numerical variables**, just like scatterplots. They are especially useful when the variable on the x-axis, also called the *explanatory* variable, is of a **sequential** nature. In other words, there is an inherent ordering to the variable.

The most common examples of line graphs have some notion of **time on the x-axis**: hours, days, weeks, years, etc. Since time is sequential, we connect consecutive observations of the variable on the y-axis with a line. Line graphs that have some notion of time on the x-axis are also called **time series plots**.

Packages

The gapminder data frame

In February 2006, a Swedish physician and data advocate named Hans Rosling gave a famous TED talk titled "The best stats you've ever seen" where he presented global economic, health, and development data complied by the Gapminder Foundation.



We can access a clean subset of this data with the R package {**gapminder**}, which we just loaded.

```
# Load gapminder data frame from the gapminder package
data(gapminder, package="gapminder")

# Print dataframe
gapminder
```

Each row in this table corresponds to a country-year combination. For each row, we have 6 columns:

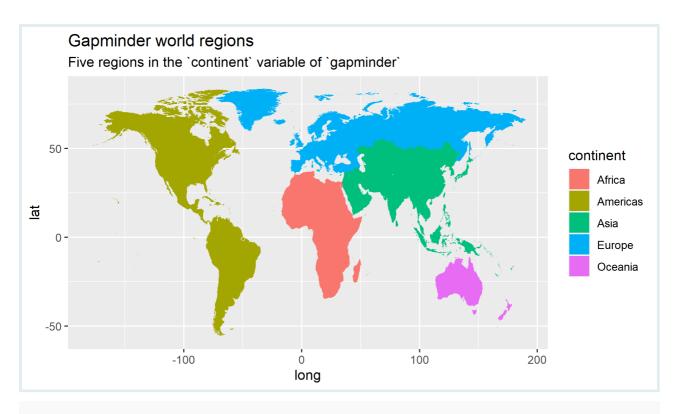
1. country: Country name

- 2. continent: Geographic region of the world
- 3. **year**: Calendar year
- 4. **lifeExp**: Average number of years a newborn child would live if current mortality patterns were to stay the same
- 5. **pop**: Total population
- 6. **gdpPercap**: Gross domestic product per person (inflation-adjusted US dollars)

The str() function can tell us more about these variables.

```
# Data structure
str(gapminder)
```

This version of the **gapminder** dataset contains information for **142 countries**, divided in to **5 continents**.



Data summary
summary(gapminder)

```
year
##
           country
                          continent
##
    Afghanistan:
                       Africa :624
                  12
                                       Min.
                                              :1952
##
    Albania
                  12
                       Americas:300
                                       1st Qu.:1966
                  12
##
    Algeria
                       Asia
                               :396
                                       Median:1980
##
    Angola
                  12
                       Europe :360
                                       Mean
                                             :1980
    Argentina :
                  12
                       Oceania: 24
                                       3rd Qu.:1993
##
                                              :2007
##
    Australia
                 12
                                       Max.
##
    (Other)
               :1632
##
       lifeExp
                          pop
                                           gdpPercap
## Min.
                           :6.001e+04
                                                    241.2
           :23.60
                    Min.
                                         Min.
    1st Qu.:48.20
                    1st Qu.:2.794e+06
                                         1st Qu.:
                                                   1202.1
    Median :60.71
##
                    Median :7.024e+06
                                         Median:
                                                   3531.8
##
    Mean
          :59.47
                    Mean
                           :2.960e+07
                                         Mean
                                                   7215.3
    3rd Qu.:70.85
                    3rd Qu.:1.959e+07
                                         3rd Qu.:
                                                   9325.5
##
##
   Max.
           :82.60
                    Max.
                           :1.319e+09
                                         Max.
                                                :113523.1
##
```

Data are recorded every 5 years from 1952 to 2007 (a total of 12 years).

Let's say we want to visualize the relationship between time (year) and life expectancy (lifeExp).

For now let's just focus on one country - United States. First, we need to create a new data frame with only the data from this country.

REMINDER

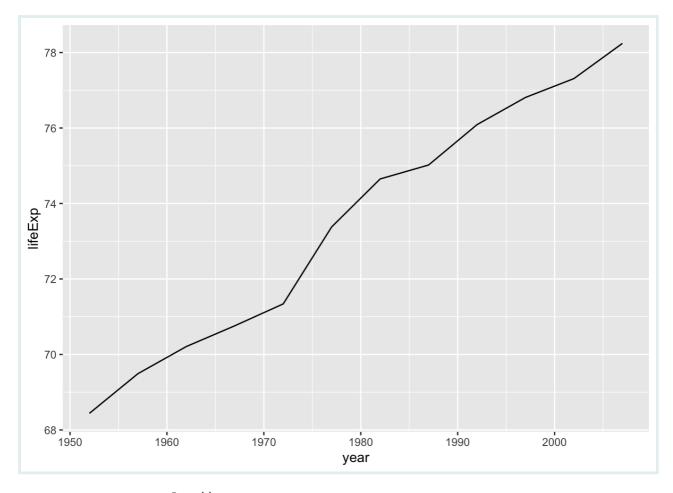


The code above is a covered in our course on Data Wrangling using the {dplyr} package. Data wrangling is the process of transforming and modifying existing data with the intent of making it more appropriate for analysis purposes. For example, this code segments used the filter() function to create a new data frame (gap_US) by choosing only a subset of rows of original gapminder data frame (only those that have "United States" in the country column).

Line graphs via geom_line()

Now we're ready to feed the gap_US data frame to ggplot(), mapping **time** in years on the horizontal x axis and **life expectancy** on the vertical y axis.

We can visualize this time series data by using geom_line() to create a line graph, instead of using geom_point() like we used previously to create scatterplots:



Much as with the ggplot() code that created the scatterplot of age and viral load with geom_point(), let's break down this code piece-by-piece in terms of the grammar of graphics:

Within the ggplot() function call, we specify two of the components of the grammar of graphics as arguments:

- 1. The data to be the gap_US data frame by setting data = gap_US.
- 2. The aesthetic mapping by setting mapping = aes(x = year, y = lifeExp). Specifically, the variable year maps to the x position aesthetic, while the variable lifeExp maps to the y position aesthetic.

After telling R which data and aesthetic mappings we wanted to plot we then added the third essential component, the geometric object using the + sign, In this case, the geometric object was set to lines using geom_line().



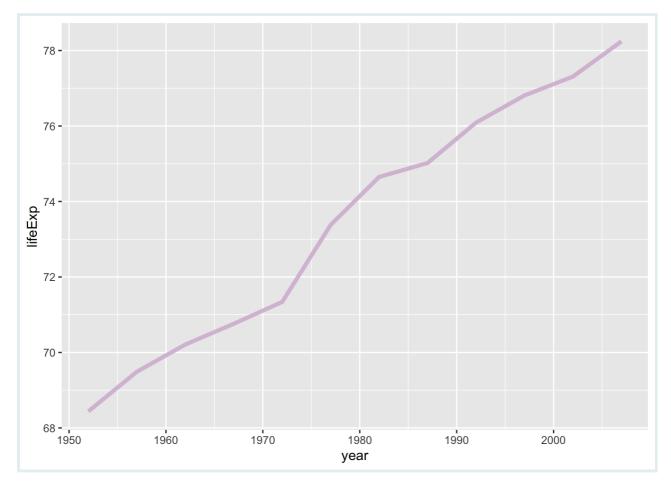
Create a time series plot of the GPD per capita (gdpPercap) recorded in the gap_US data frame by using geom_line() to create a line graph.

Fixed aesthetics in geom_line()

The color, line width and line type of the line graph can be customized making use of color, size and linetype arguments, respectively.

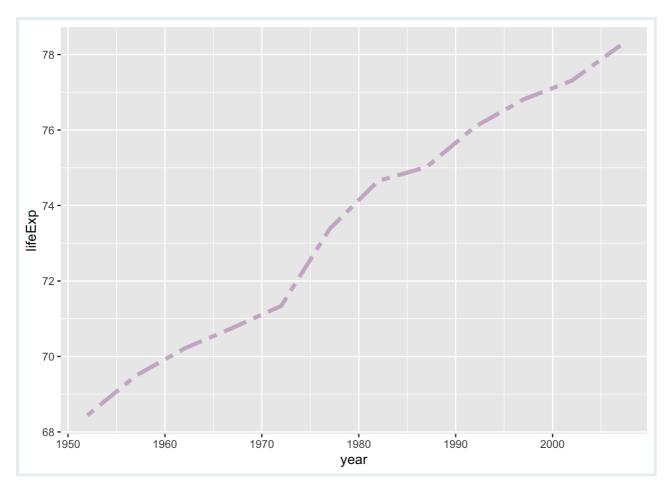
We've changed the color and size of geoms in previous lessons.

Here we will add these as fixed aesthetics:



In this lesson we introduce a new fixed aesthetic that is specific to line graphs: linetype (or lty for short).

Line type can be specified using a name or with an integer. Valid line types can be set using a human readable character string: "blank", "solid", "dashed", "dotted", "dotdash", "longdash", and "twodash" are all understood by linetype or lty.

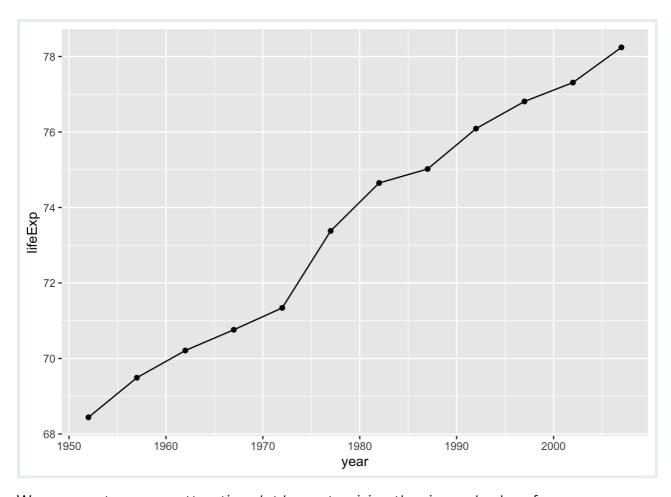


In these line graphs, it can be hard to tell where exactly there data points are. In the next plot, we'll add points to make this clearer.

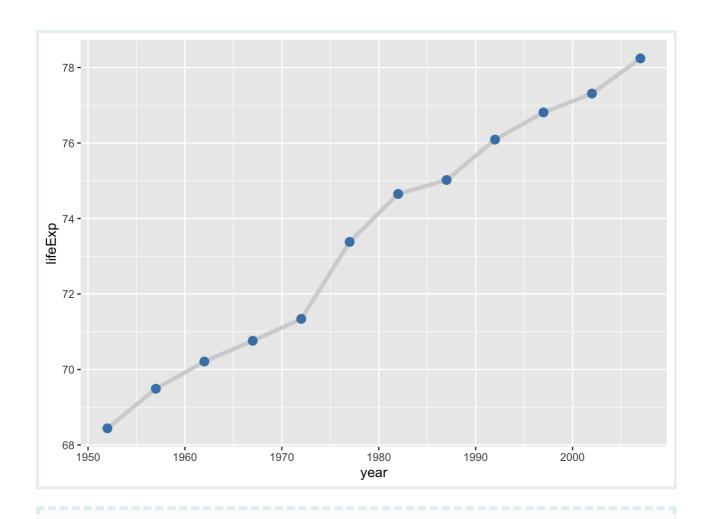
Combining compatible geoms

As long as the geoms are compatible, we can layer them on top of one another to further customize a graph.

For example, we can add points to our line graph using the + sign to add a second geom layer with geom_point():



We can create a more attractive plot by customizing the size and color of our geoms.





Building on the code above, visualize the relationship between time and **GPD per capita** from the gap_US data frame.

Use both points and lines to represent the data.

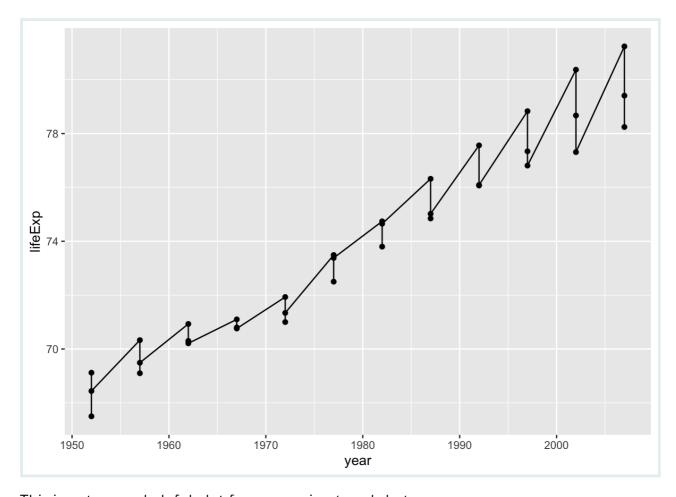
Change the line type of the line and the color of the points to any valid values of your choice.

Mapping data to multiple lines

In the previous section, we only looked at data from one country, but what if we want to plot data for multiple countries and compare?

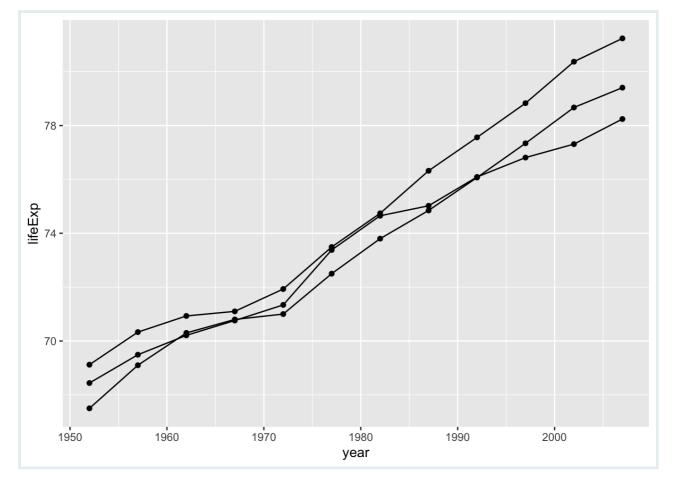
First let's add two more countries to our data subset:

If we simply enter it using the same code and change the data layer, the lines are not automatically separated by country:



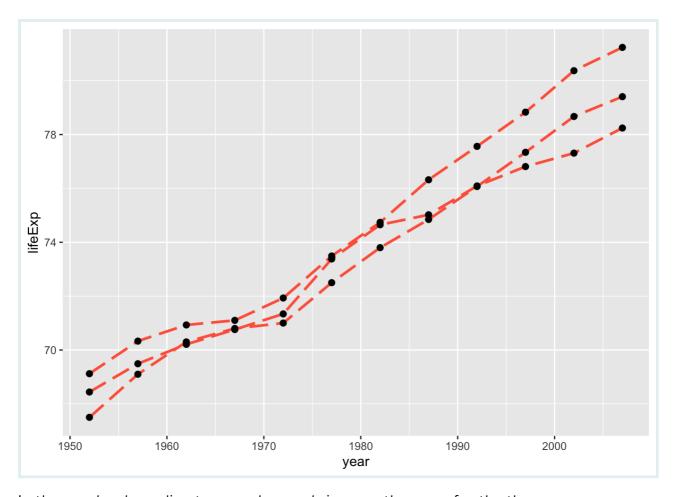
This is not a very helpful plot for comparing trends between groups.

To tell ggplot() to map the data from each country separately, we can the group argument as an as aesthetic mapping:



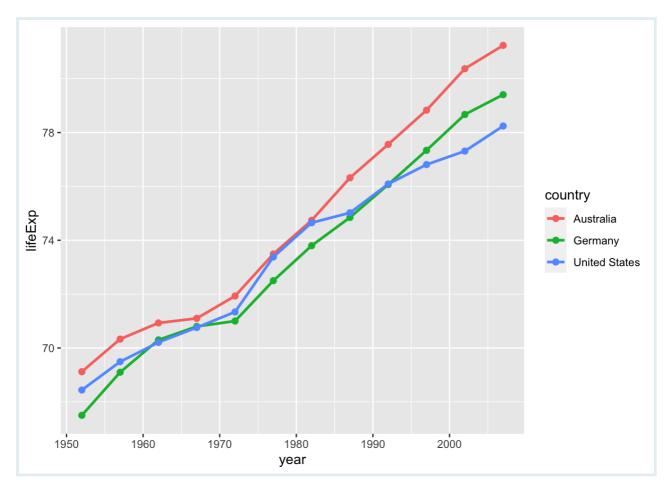
Now that the data is grouped by country, we have 3 separate lines - one for each level of the country variable.

We can also apply fixed aesthetics to the geometric layers.



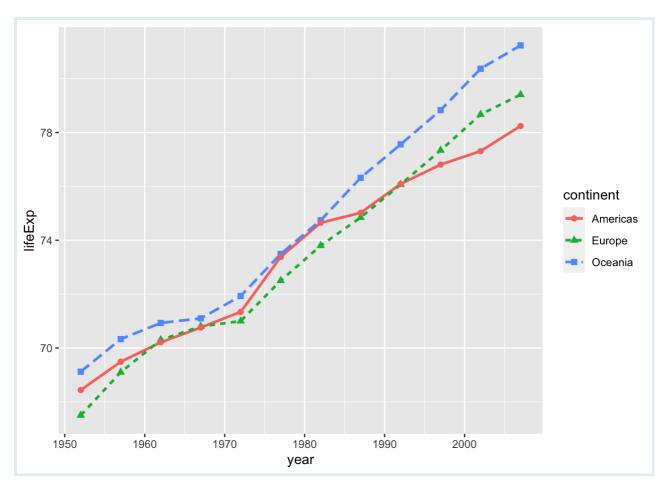
In the graphs above, line types, colors and sizes are the same for the three groups.

This doesn't tell us which is which though. We should add an aesthetic mapping that can help us identify which line belongs to which country, like color or line type.



Aesthetic mappings specified within ggplot() function call are passed down to subsequent layers.

Instead of grouping by country, we can also group by continent:



When given multiple mappings and geoms, {ggplot2} can discern which mappings apply to which geoms.

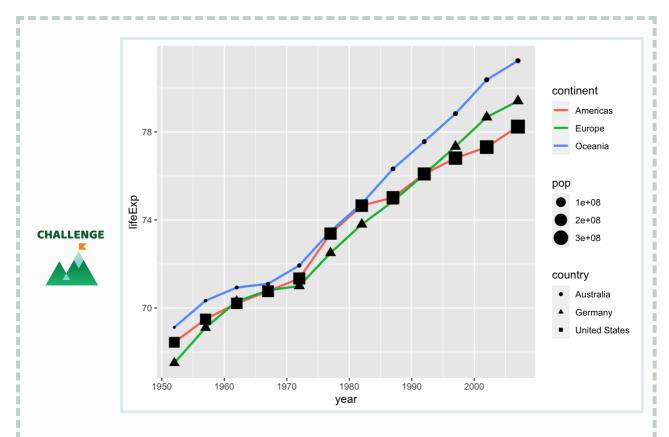
Here color was inherited by both points and lines, but lty was ignored by geom_point() and shape was ignored by geom_line(), since they don't apply.

Challenge

Mappings can either go in the ggplot() function or in geom_*() layer.

For example, aesthetic mappings can go in geom_line() and will only be applied to that layer:

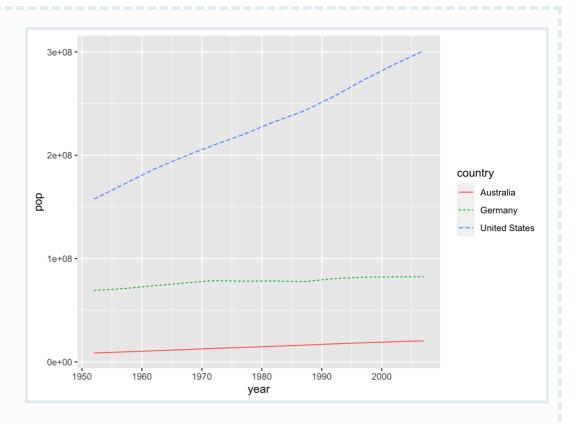




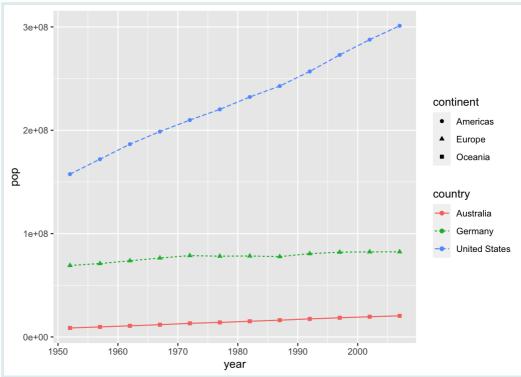
Try adding mapping = aes() in geom_point() and map continent to any valid aesthetic!



Using the gap_mini data frame, create a **population** growth chart with these aesthetic mappings:



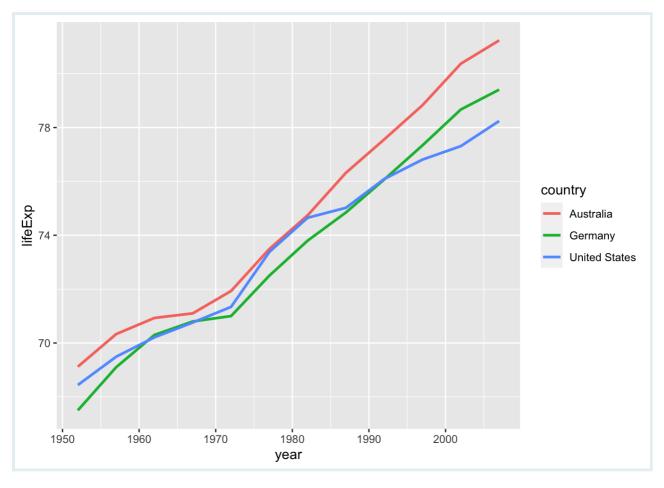
Next, add a layer of points to the previous plot, and add the required aesthetic mappings to produce a plot that looks like this:



Don't worry about any fixed aesthetics, just make sure the mapping of data variables is the same.

Modifying continuous x & y scales

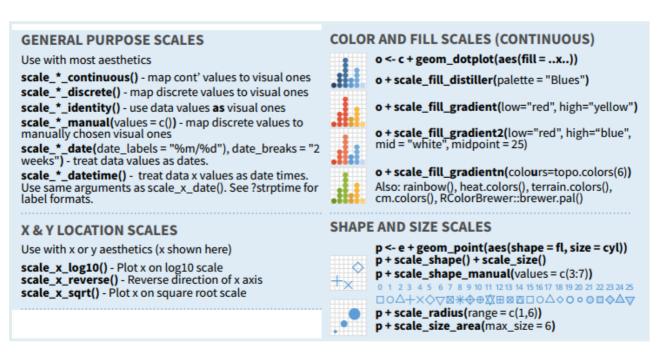
{ggplot2} automatically scales variables to an aesthetic mapping according to type of variable it's given.



In some cases the we might want to transform the axis scaling for better visualization. We can customize these scales with the $scale_*()$ family of functions.

```
ggplot(data = <DATAFRAME>,
    mapping = aes(<VARS TO MAP>) +
    <GEOM_FUNCTION>() +
    stat = <STAT>, position = <POSITION>) +
    <COORDINATE_FUNCTION> +
    <SCALE_FUNCTION> +
    <THEME_FUNCTION>
```

scale_x_continuous() and **scale_y_continuous()** are the default scale functions for continuous x and y aesthetics.

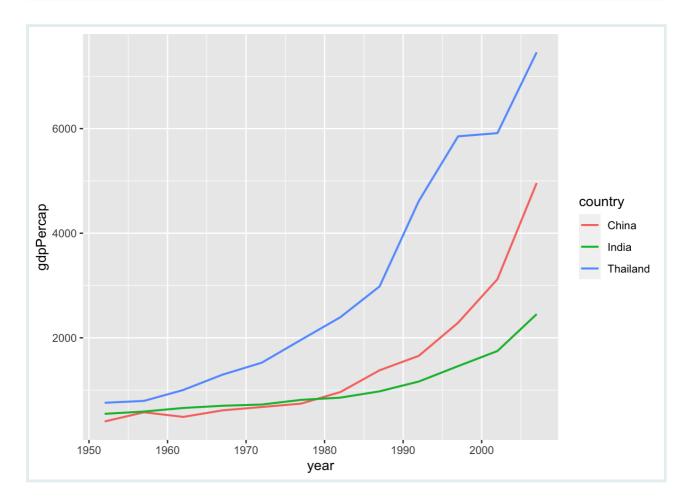


Scale breaks

Let's create a new subset of countries from gapminder, and this time we will plot changes in GDP over time.

```
"China",
"Thailand")) gap_mini2
```

Here we will change the y-axis mapping from lifeExp to gdpPercap:



The x-axis labels for year in don't match up with the dataset.

```
gap_mini2$year %>% unique()

## [1] 1952 1957 1962 1967 1972 1977 1982 1987 1992 1997 2002
## [12] 2007
```

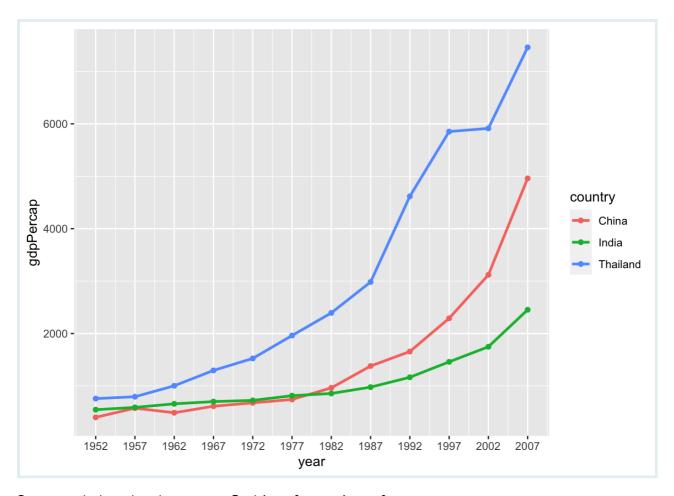
We can specify exactly where to label the axis by providing a numeric vector.

```
# You can manually enter scale breaks (don't do this)
c(1952, 1957, 1962, 1967, 1972, 1977, 1982, 1987, 1992, 1997, 2002,
2007)

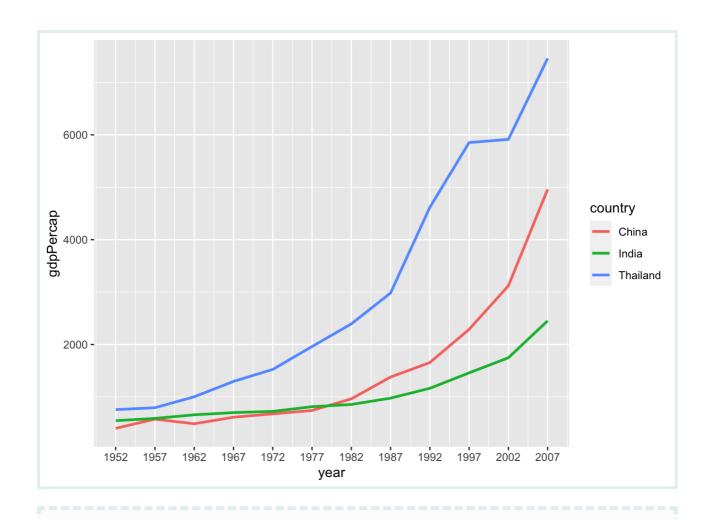
## [1] 1952 1957 1962 1967 1972 1977 1982 1987 1992 1997 2002
## [12] 2007

## [1] 1952 1957 1962 1967 1972 1977 1982 1987 1992 1997 2002
## [1] 1952 1957 1962 1967 1972 1977 1982 1987 1992 1997 2002
## [1] 2007
```

Use scale_x_continuous to make the axis breaks match up with the dataset:



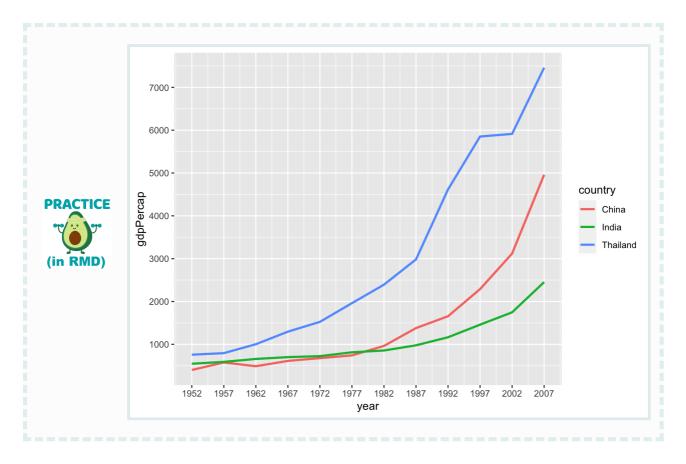
Store scale break values as an R object for easier reference:





We can customize scale breaks on a continuous **y**-axis values with **scale_y_continuous()**.

Copy the code from the last example, and add scale_y_continuous() to add the following y-axis breaks:



Logarithmic scaling

In the last two mini sets, I chose three countries that had similar range of GDP or life expectancy for good scaling and readability so that we can make out these changes.

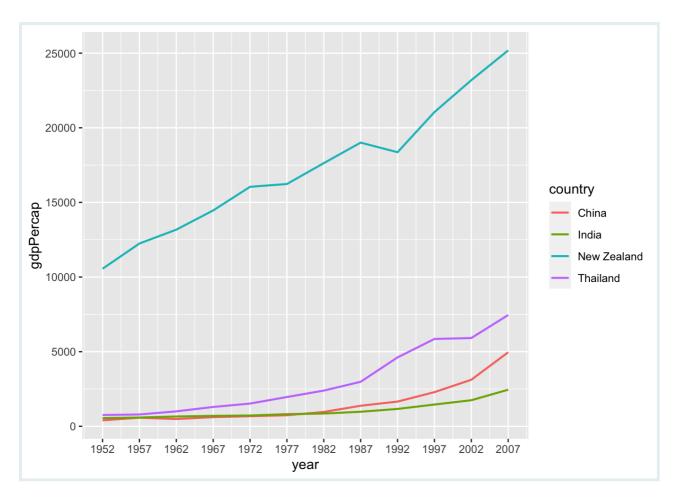
But if we add a country to the group that significantly differs, default scaling is not so great.

We'll look at an example plot where you may want to rescale the axes from linear to a log scale.

Let's add New Zealand to the previous set of countries and create gap_mini3:

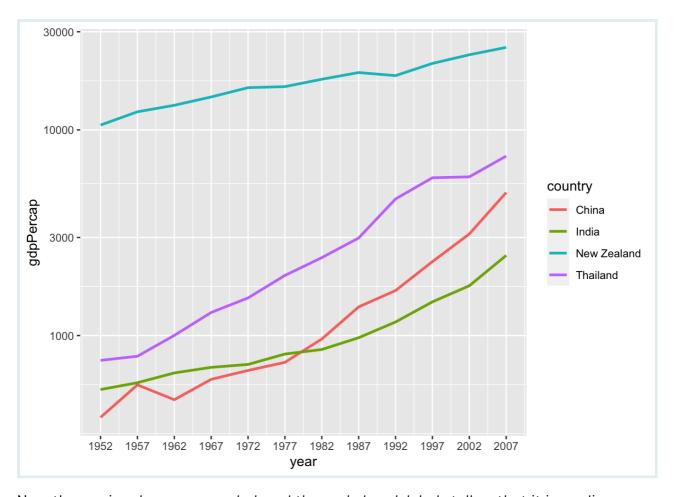
Now we will recreate the plot of GDP over time with the new data subset:

```
color = country)) + geom_line(size =
0.75) + scale_x_continuous(breaks = gap_years)
```



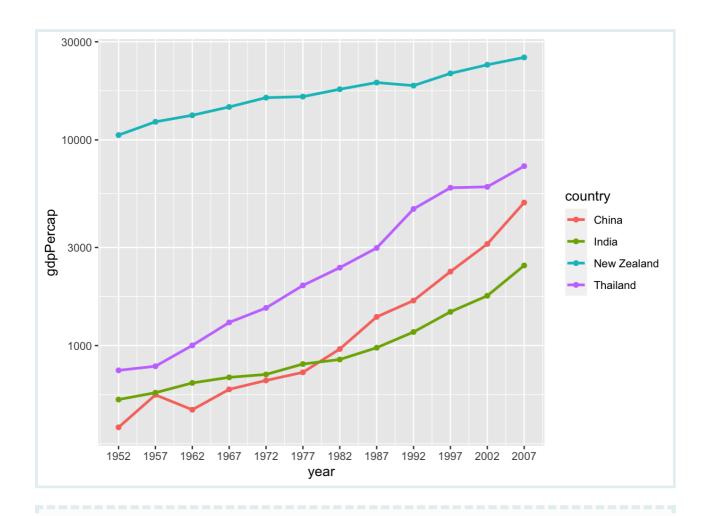
The curves for India and China show an exponential increase in GDP per capita. However, the y-axes values for these two countries are much lower than that of New Zealand, so the lines are a bit squashed together. This makes the data hard to read. Additionally, the large empty area in the middle is not a great use of plot space.

We can address this by log-transforming the y-axis using scale_y_log10(), which log-scales the y-axis (as the name suggests). We will add this function as a new layer after a + sign, as usual:



Now the y-axis values are rescaled, and the scale break labels tell us that it is nonlinear.

We can add a layer of points to make this clearer:



PRACTICE

(in RMD)

First subset gapminder to only the rows containing data for **Uganda:**

Now, use **gap_Uganda** to create a time series plot of population (**pop**) over time (**year**). Transform the y axis to a log scale, edit the scale breaks to **gap_years**, change the line color to forestgreen and the size to 1mm.

Next, we can change the text of the axis labels to be more descriptive, as well as add titles, subtitles, and other informative text to the plot.

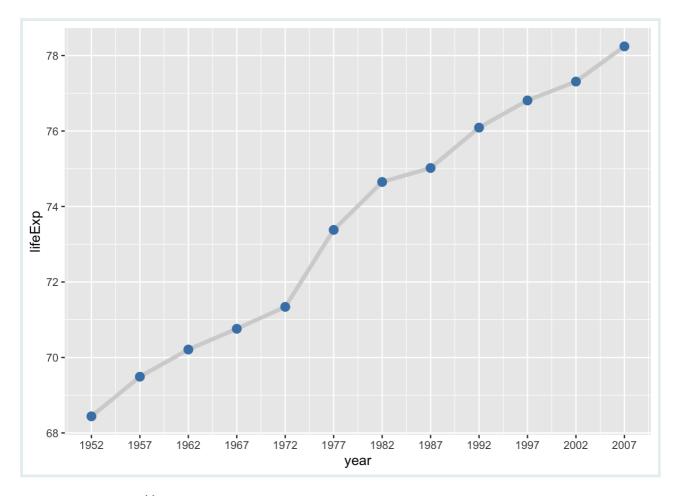
Labeling with labs()

You can add labels to a plot with the labs() function. Arguments we can specify with the labs() function include:

• title: Change or add a title

- subtitle: Add subtitle below the title
- x: Rename x-axis
- y: Rename y-axis
- caption: Add caption below the graph

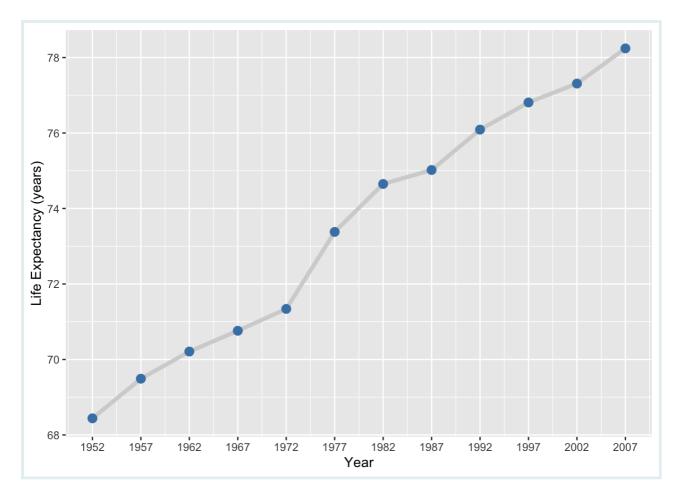
Let's start with this plot and start adding labels to it:



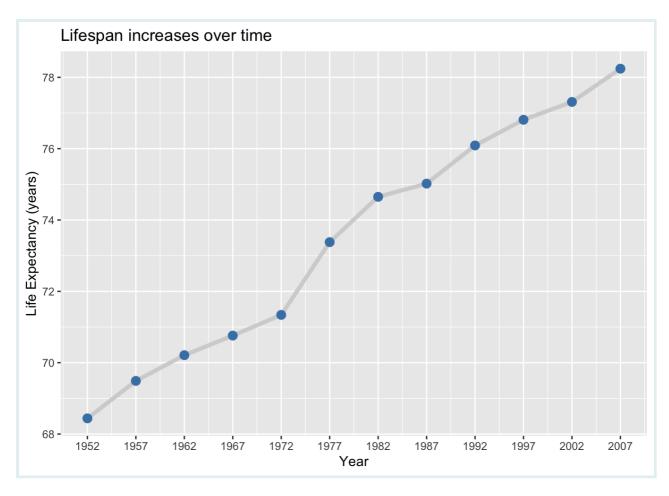
We add the labs() to our code using a + sign.

First we will add the x and y arguments to labs(), and change the axis titles from the default (variable name) to something more informative.

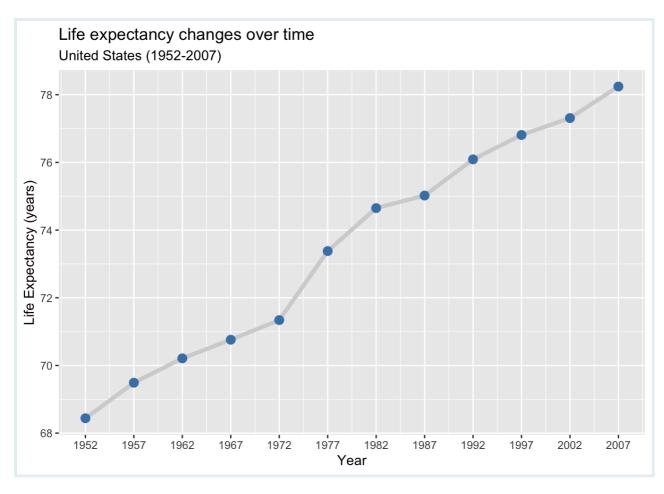
```
# Rename axis titles
ggplot(data = gap_US,
```



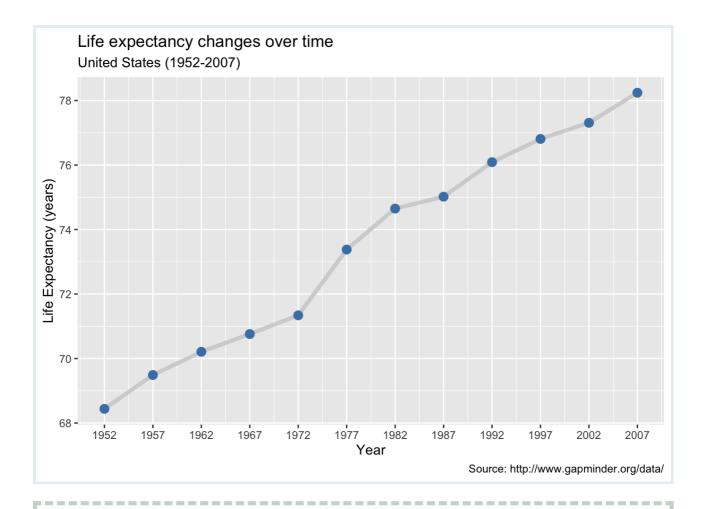
Next we supply a character string to the title argument to add large text above the plot.



The subtitle argument adds smaller text below the main title.



Finally, we can supply the caption argument to add small text to the bottom-right corner below the plot.

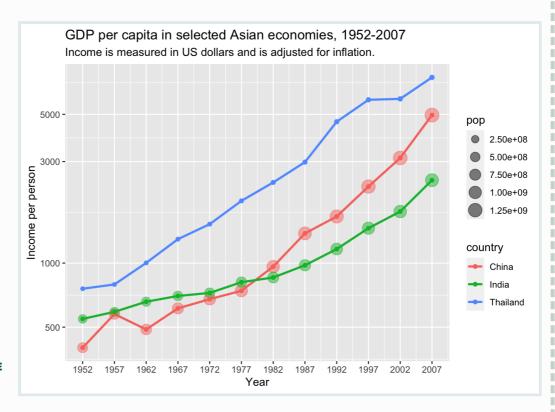


When you use an aesthetic mapping (e.g., color, size), {ggplot2} automatically scales the given aesthetic to match the data and adds a legend.

Here is an updated version of the gap_mini3 plot we made before. We are changing the of points and lines by setting aes(color = country) in ggplot(). Then the size of points is scaled to the pop variable. See that labs() is used to change the title, subtitle, and axis labels.

CHALLENGE

```
title = "GDP per capita in selected Asian economies, 1952-2007", subtitle = "Income is measured in US dollars and is adjusted for inflation.")
```



CHALLENGE

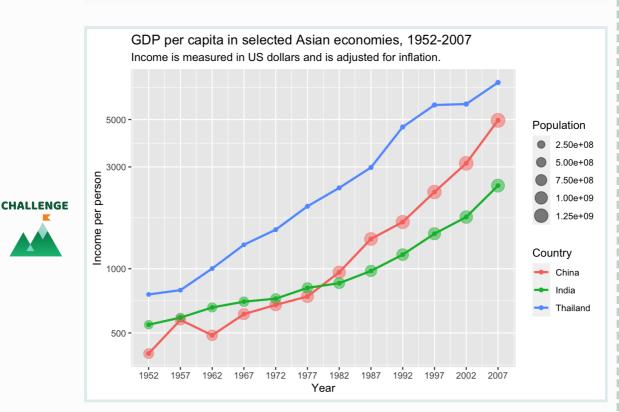


The default title of a legend or key is the name of the data variable it corresponds to. Here the color lengend is titled country, and the size legend is titled pop.

We can also edit these in labs() by setting AES_NAME = "CUSTOM_TITLE".

```
ggplot(data = gap_mini2,
               mapping = aes(x = year,
                              y = gdpPercap,
                              color = country)) +
          geom_line(size = 1) +
          geom_point(mapping = aes(size = pop),
                                    alpha = 0.5) +
          geom_point() +
          scale_x_continuous(breaks = gap_years) +
          scale_y_log10() +
          labs(x = "Year",
               y = "Income per person",
               title = "GDP per capita in selected Asian
economies, 1952-2007",
               subtitle = "Income is measured in US dollars
and is adjusted for inflation.",
```





The same syntax can be used to edit legend titles for other aesthetic mappings. A common mistake is to use the variable name instead of the aesthetic name in labs(), so watch out for that!

Create a time series plot comparing the trends in GDP per capita from 1952-2007 for **three countries** in the gapminder data frame.

First, subset the data to three countries of your choice:



Use my_gap_mini to create a plot with the following attributes:

- Add points to the line graph
- Color the lines and points by country
- Increase the width of lines to 1mm and the size of points to 2mm
- Make the lines 50% transparent

• Change the x-axis scale breaks to match years in dataset

Finally, add the following labels to your plot:



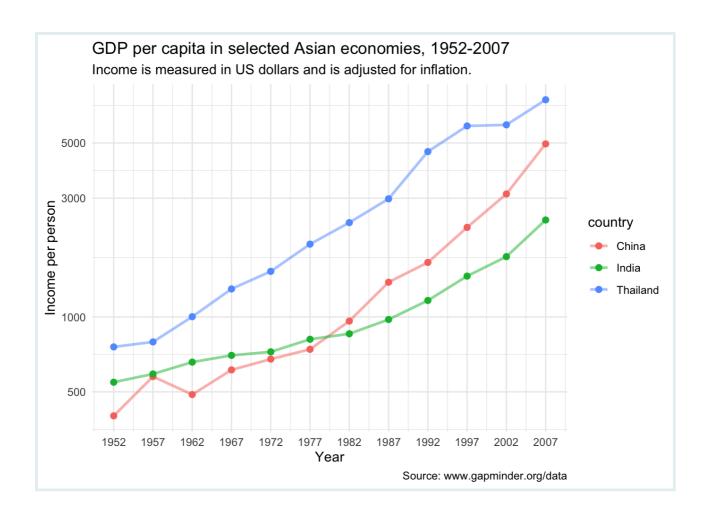
- Title: "Health & wealth of nations"
- Axis titles: "Longevity" and "Year"
- Capitalize legend title

(Note: subtitle requirement has been removed.)

Preview: Themes

In the next lesson, you will learn how to use theme functions.

```
# Use theme_minimal()
        ggplot(data = gap_mini2,
               mapping = aes(x = year,
                             y = gdpPercap,
                             color = country)) +
          geom_line(size = 1, alpha = 0.5) +
          geom_point(size = 2) +
          scale_x_continuous(breaks = gap_years) +
          scale_y_log10() +
          labs(x = "Year",
               y = "Income per person",
               title = "GDP per capita in selected Asian economies, 1952-
2007",
               subtitle = "Income is measured in US dollars and is adjusted
for inflation.",
               caption = "Source: www.gapminder.org/data") +
          theme_minimal()
```



Wrap up

Line graphs, just like scatterplots, display the relationship between two numerical variables. When one of the two variables represents time, a line graph can be a more effective method of displaying relationship. Therefore, it is preferred to use line graphs over scatterplots when the variable on the x-axis (i.e., the explanatory variable) has an inherent ordering, such as some notion of time, like the year variable of gapminder.

We can change scale breaks and transform scales to make plots easier to read, and label them to add more information.

Hope you found this lesson helpful!

Contributors

The following team members contributed to this lesson:



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R Developer and Instructor, the GRAPH Network Loves doing science and teaching science



ADMIN TEAM

GRAPH Courses Administration Team

The GRAPH Courses team is building epidemiological training courses to enhance disease surveillance and data science for public health across the globe

References

Some material in this lesson was adapted from the following sources:

- Ismay, Chester, and Albert Y. Kim. 2022. *A ModernDive into R and the Tidyverse*. https://moderndive.com/.
- Kabacoff, Rob. 2020. Data Visualization with R. https://rkabacoff.github.io/datavis/.
- https://www.rebeccabarter.com/blog/2017-11-17-ggplot2_tutorial/

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