Chapter 4

Bivariate Graphs

Bivariate graphs display the relationship between two variables. The type of graph will depend on the measurement level of the variables (categorical or quantitative).

4.1 Categorical vs. Categorical

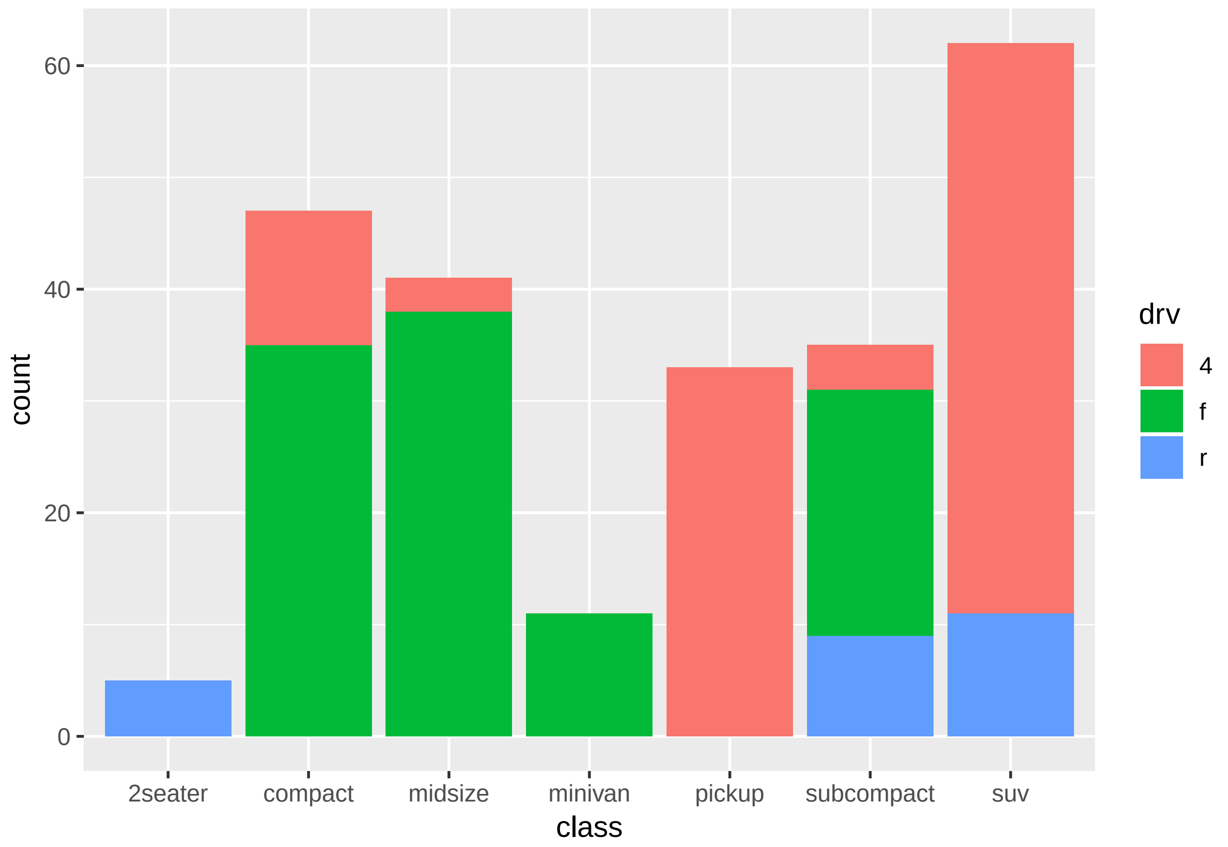
When plotting the relationship between two categorical variables, stacked, grouped, or segmented bar charts are typically used. A less common approach is the mosaic chart.

✓ Bar chart = categorical vs count/percentage

4.1.1 Stacked bar chart

Let's plot the relationship between automobile class and drive type (front-wheel, rear-wheel, or 4-wheel drive) for the automobiles in the Fuel economy dataset.

```r
library(ggplot2)

# stacked bar chart
ggplot(mpg,
       aes(x = class,
           fill = drv)) +
  geom_bar(position = "stack")
```



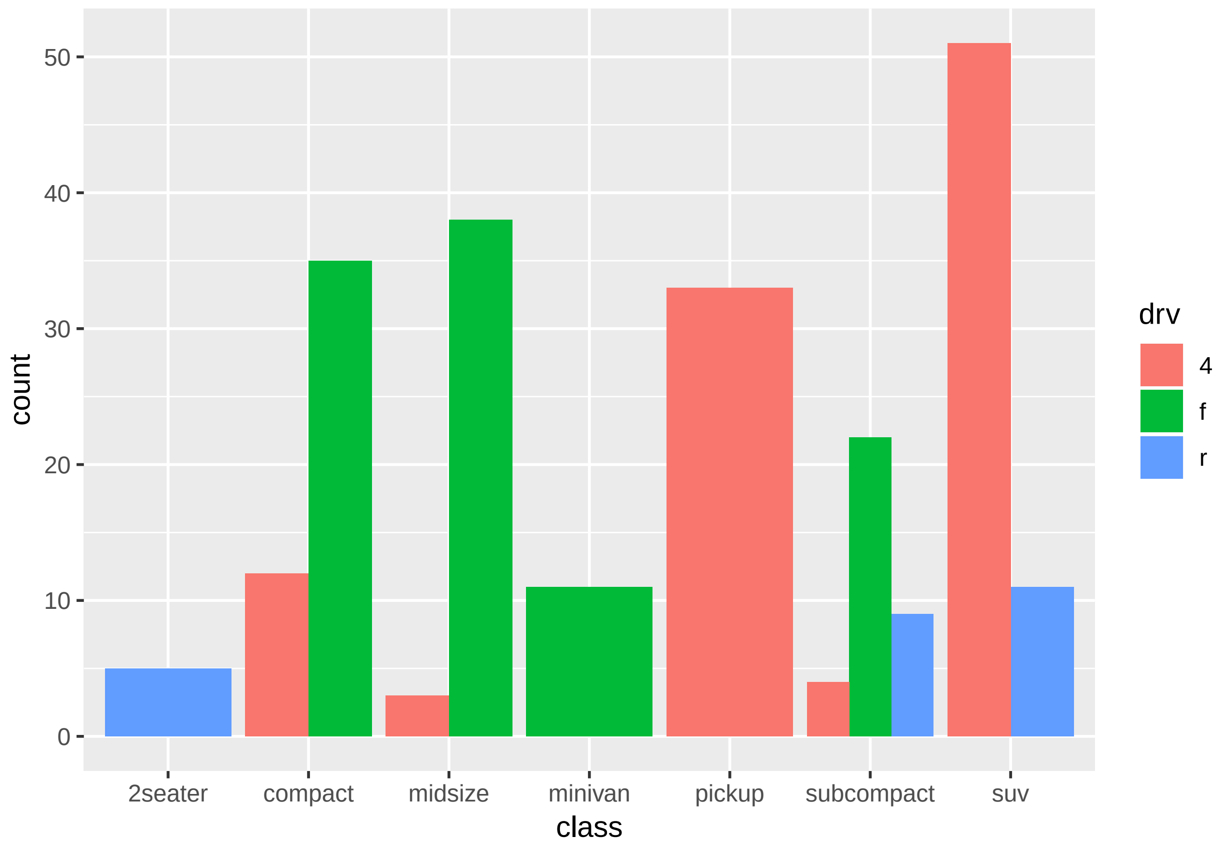
From the chart, we can see for example, that the most common vehicle is the SUV. All 2seater cars are rear wheel drive, while most, but not all SUVs are 4-wheel drive.

Stacked is the default, so the last line could have also been written as `geom_bar()`.

4.1.2 Grouped bar chart

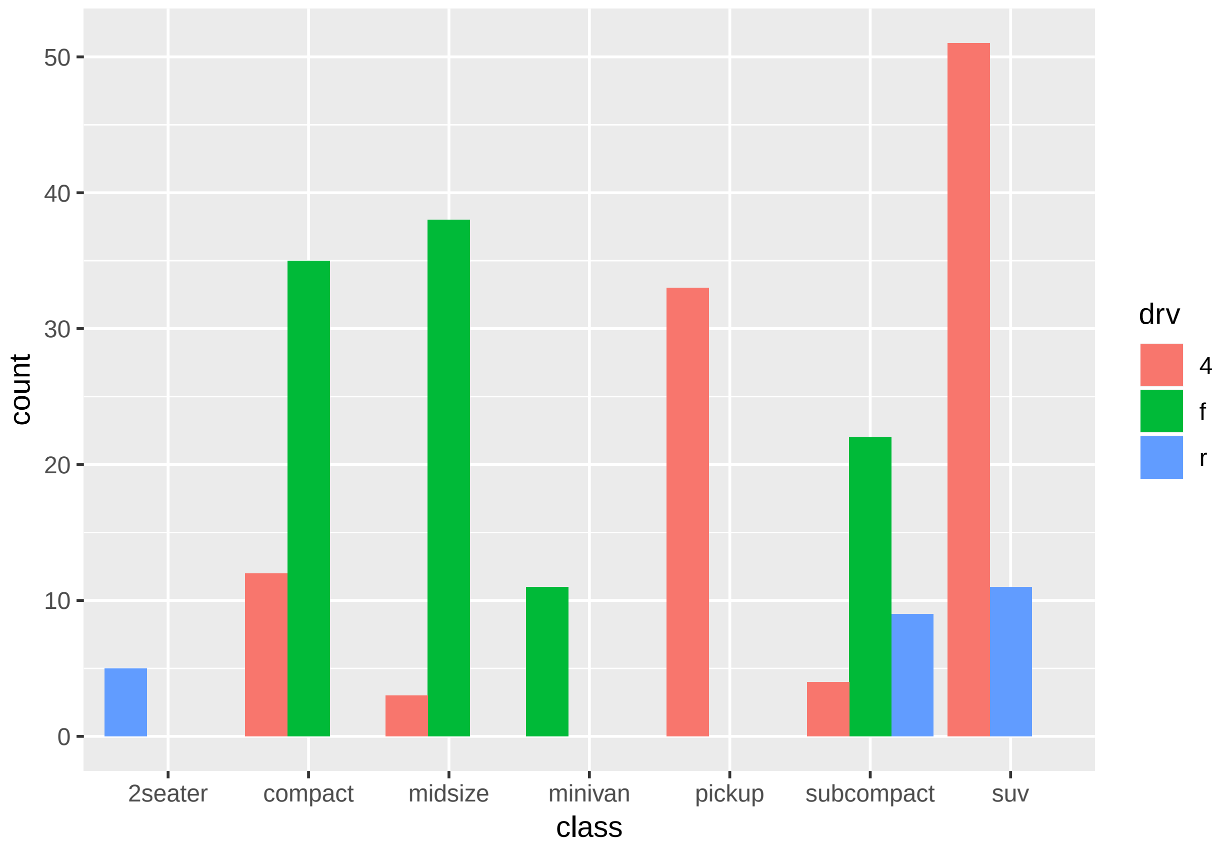
Grouped bar charts place bars for the second categorical variable side-by-side. To create a grouped bar plot use the `position = "dodge"` option.

```
library(ggplot2)

# grouped bar plot
ggplot(mpg,
       aes(x = class,
           fill = drv)) +
  geom_bar(position = "dodge")
```



Notice that all Minivans are front-wheel drive. By default, zero count bars are dropped and the remaining bars are made wider. This may not be the behavior you want. You can modify this using the `position = position_dodge(preserve = "single")"` option.

```
library(ggplot2)

# grouped bar plot preserving zero count bars
ggplot(mpg,
       aes(x = class,
           fill = drv)) +
  geom_bar(position = position_dodge(preserve = "single"))
```



Note that this option is only available in the latest development version of `ggplot2`, but should should be generally available shortly.

4.1.3 Segmented bar chart

A segmented bar plot is a stacked bar plot where each bar represents 100 percent. You can create a segmented bar chart using the `position = "filled"` option.

```
library(ggplot2)

# bar plot, with each bar representing 100%
ggplot(mpg,
       aes(x = class,
           fill = drv)) +
  geom_bar(position = "fill") +
  labs(y = "Proportion")
```

This type of plot is particularly useful if the goal is to compare the percentage of a category in one variable across each level of another variable. For example, the proportion of front-wheel drive cars go up as you move from compact, to midsize, to minivan.

4.1.4 Improving the color and labeling

You can use additional options to improve color and labeling. In the graph below

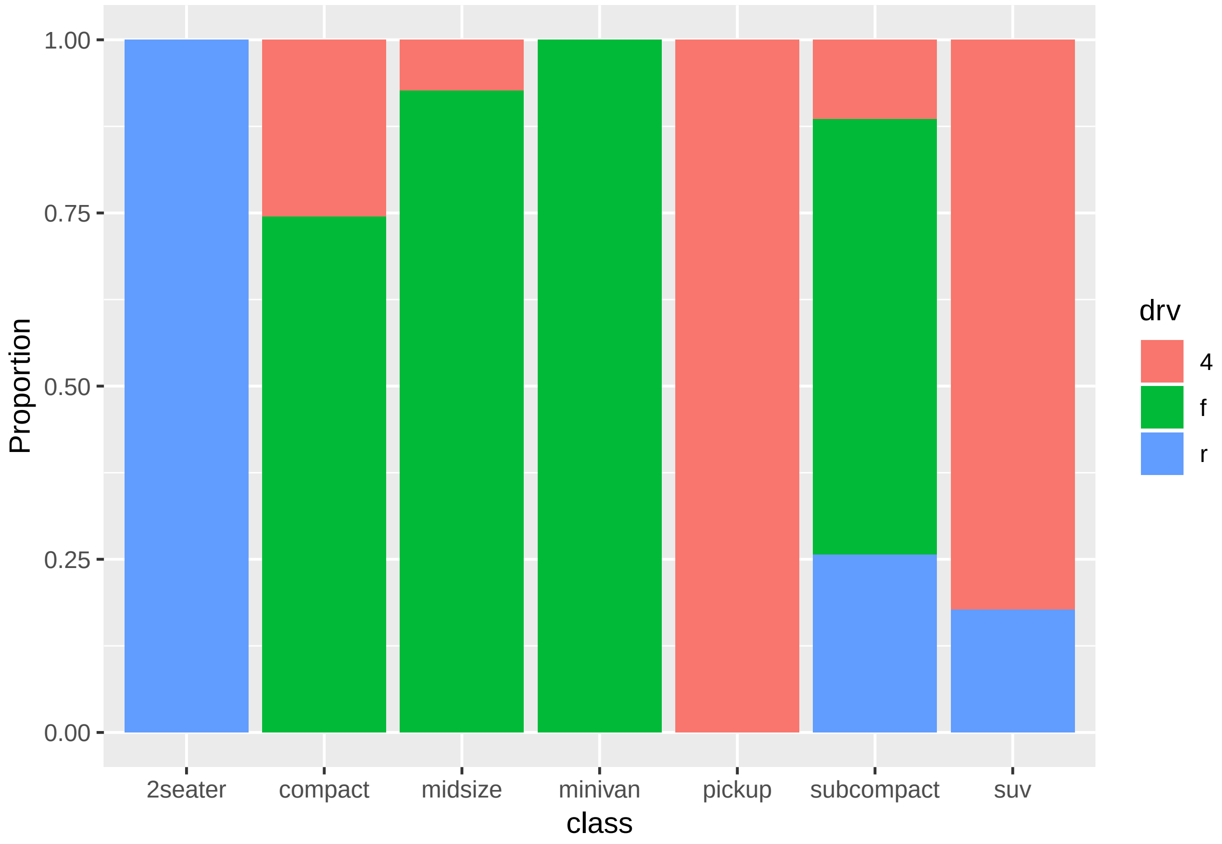


Figure 4.1: Segmented bar chart

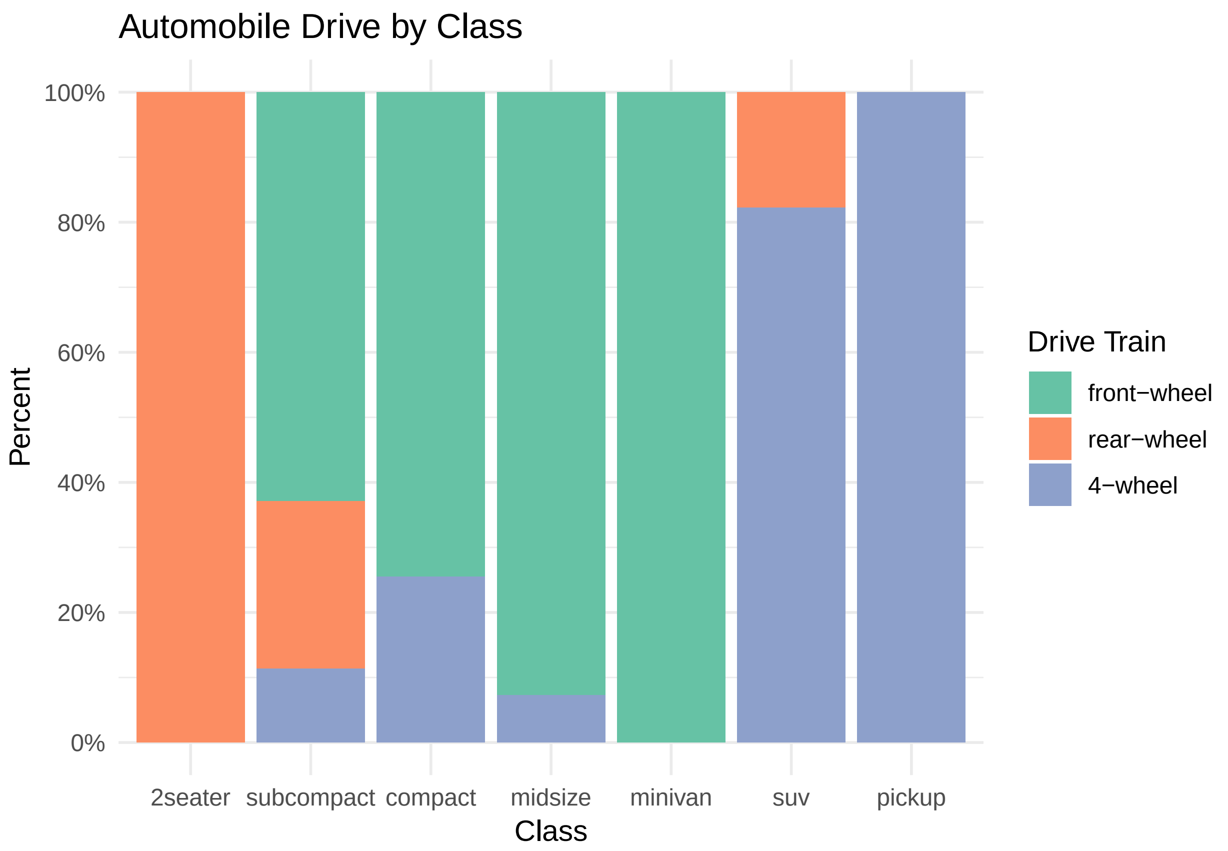
- `factor` modifies the order of the categories for the class variable and both the order and the labels for the drive variable

- `scale_y_continuous` modifies the y-axis tick mark labels

- `labs` provides a title and changed the labels for the x and y axes and the legend
- `scale_fill_brewer` changes the fill color scheme

- `theme_minimal` removes the grey background and changed the grid color

```r
library(ggplot2)

# bar plot, with each bar representing 100%,
# reordered bars, and better labels and colors
library(scales)
ggplot(mpg,
       aes(x = factor(class,
                      levels = c("2seater", "subcompact",
                                "compact", "midsize",
                                "minivan", "suv", "pickup")),
           fill = factor(drv,
                         levels = c("f", "r", "4"),
                         labels = c("front-wheel",
                                    "rear-wheel",
                                    "4-wheel")))) +
  geom_bar(position = "fill") +
  scale_y_continuous(breaks = seq(0, 1, .2),
                     label = percent) +
  scale_fill_brewer(palette = "Set2") +
  labs(y = "Percent",
       fill = "Drive Train",
       x = "Class",
       title = "Automobile Drive by Class") +
  theme_minimal()
```



In the graph above, the `factor` function was used to reorder and/or rename the levels of a categorical variable. You could also apply this to the original dataset, making these changes permanent. It would then apply to all future graphs using that dataset. For example:

```
# change the order the levels for the categorical variable "class"
mpg$class = factor(mpg$class,
                   levels = c("2seater", "subcompact",
                              "compact", "midsize",
                              "minivan", "suv", "pickup")
```

I placed the `factor` function within the `ggplot` function to demonstrate that, if desired, you can change the order of the categories and labels for the categories for a single graph.

The other functions are discussed more fully in the section on Customizing graphs.

Next, let's add percent labels to each segment. First, we'll create a summary dataset that has the necessary labels.

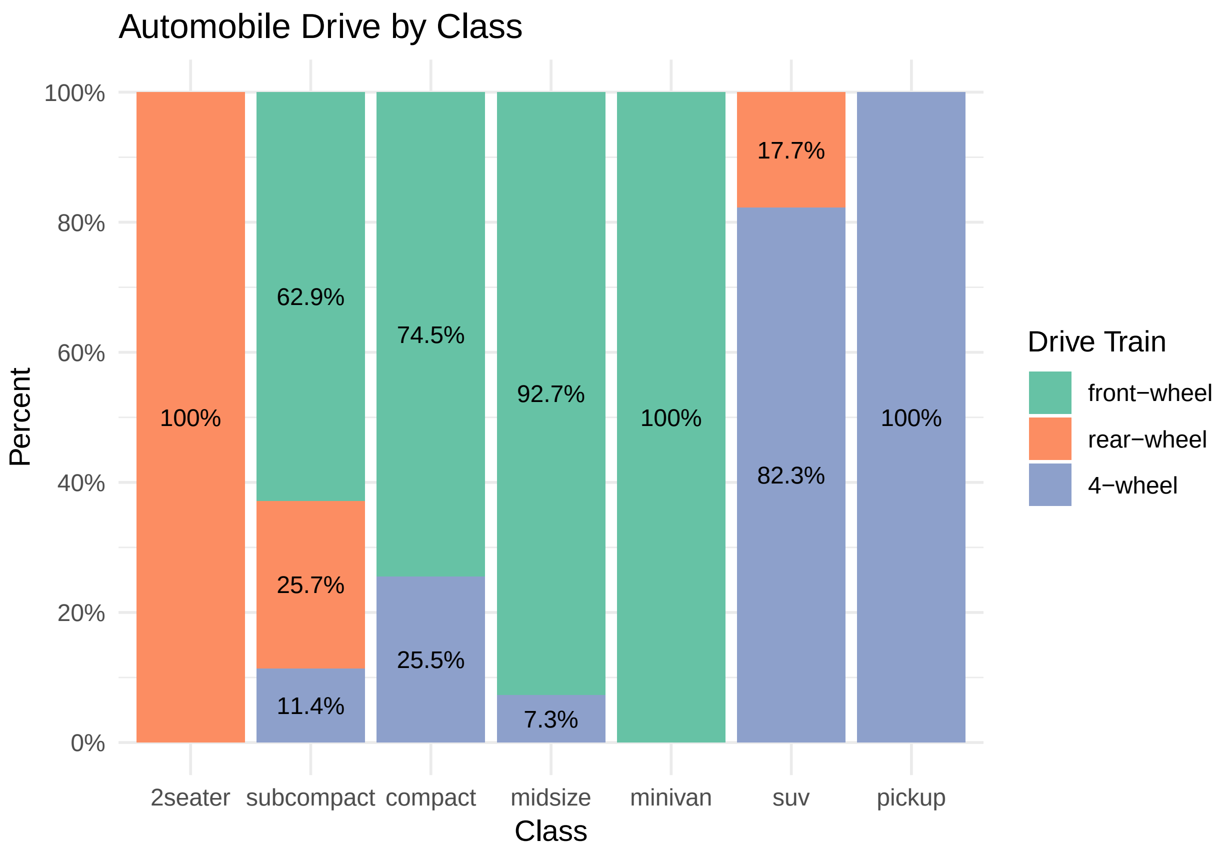
```
# create a summary dataset
library(dplyr)
plotdata <- mpg %>%
  group_by(class, drv) %>%
  summarize(n = n()) %>%
  mutate(pct = n/sum(n),
         lbl = scales::percent(pct))
plotdata
```

```
## # A tibble: 12 x 5
## # Groups:   class [7]
##    class      drv       n    pct lbl
##    <chr>      <chr> <int>  <dbl> <chr>
##  1 2seater    r         5 1.00   100%
##  2 compact    4        12 0.255  25.5%
##  3 compact    f        35 0.745  74.5%
##  4 midsize    4         3 0.0732 7.3%
##  5 midsize    f        38 0.927  92.7%
##  6 minivan    f        11 1.00   100%
##  7 pickup     4        33 1.00   100%
##  8 subcompact 4         4 0.114  11.4%
##  9 subcompact f        22 0.629  62.9%
## 10 subcompact r         9 0.257  25.7%
## 11 suv        4        51 0.823  82.3%
## 12 suv        r        11 0.177  17.7%
```

Next, we'll use this dataset and the `geom_text` function to add labels to each bar segment.

```r
# create segmented bar chart
# adding labels to each segment

ggplot(plotdata,
       aes(x = factor(class,
                      levels = c("2seater", "subcompact",
                                 "compact", "midsize",
                                 "minivan", "suv", "pickup")),
           y = pct,
           fill = factor(drv,
                         levels = c("f", "r", "4"),
                         labels = c("front-wheel",
                                    "rear-wheel",
                                    "4-wheel")))) +
  geom_bar(stat = "identity",
           position = "fill") +
  scale_y_continuous(breaks = seq(0, 1, .2),
                     label = percent) +
  geom_text(aes(label = lbl),
            size = 3,
            position = position_stack(vjust = 0.5)) +
  scale_fill_brewer(palette = "Set2") +
  labs(y = "Percent",
       fill = "Drive Train",
       x = "Class",
       title = "Automobile Drive by Class") +
  theme_minimal()
```

This will change the labels from f,r,4 to front-wheel ,rea



Now we have a graph that is easy to read and interpret.

4.1.5 Other plots

Mosaic plots provide an alternative to stacked bar charts for displaying the relationship between categorical variables. They can also provide more sophisticated statistical information.

4.2 Quantitative vs. Quantitative

The relationship between two quantitative variables is typically displayed using scatterplots and line graphs.

4.2.1 Scatterplot

The simplest display of two quantitative variables is a scatterplot, with each variable represented on an axis. For example, using the Salaries dataset, we can plot experience (*yrs.since.phd*) vs. academic salary (*salary*) for college professors.

```
library(ggplot2)
data(Salaries, package="carData")

# simple scatterplot
ggplot(Salaries,
       aes(x = yrs.since.phd,
```

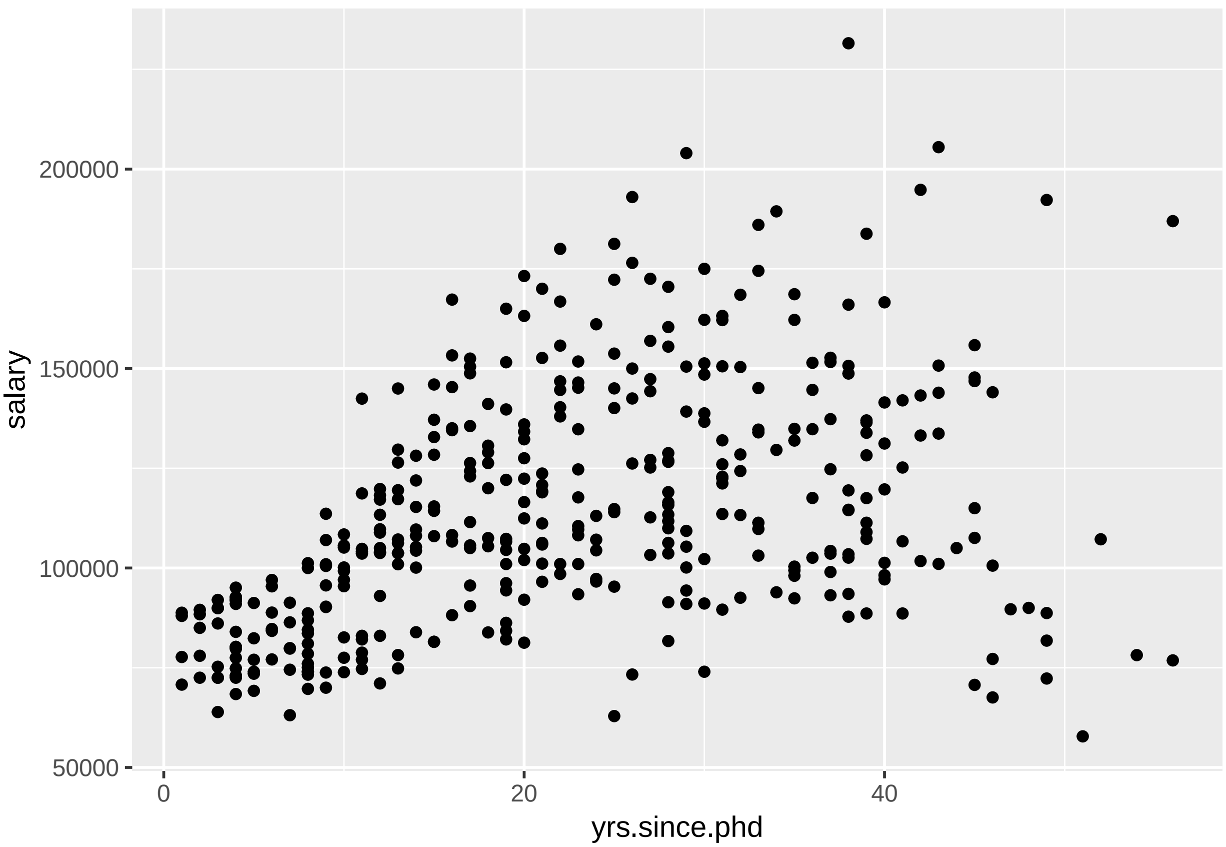


Figure 4.2: Simple scatterplot

```
           y = salary)) +
  geom_point()
```

`geom_point` options can be used to change the

- `color` - point color
- `size` - point size
- `shape` - point shape
- `alpha` - point transparency. Transparency ranges from 0 (transparent) to 1 (opaque), and is a useful parameter when points overlap.

The functions `scale_x_continuous` and `scale_y_continuous` control the scaling on x and y axes respectively.

See Customizing graphs for details.

We can use these options and functions to create a more attractive scatterplot.

```
# enhanced scatter plot
ggplot(Salaries,
       aes(x = yrs.since.phd,
           y = salary)) +
  geom_point(color="cornflowerblue",
```

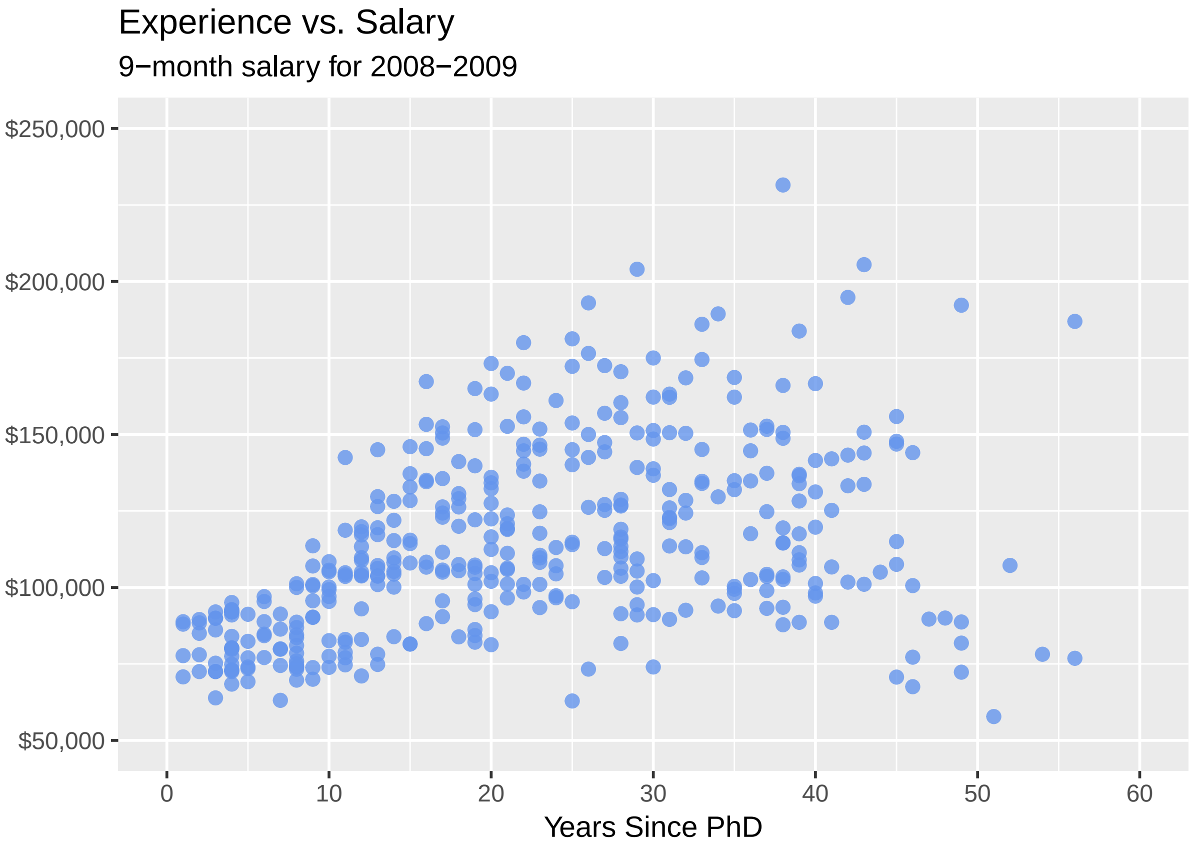


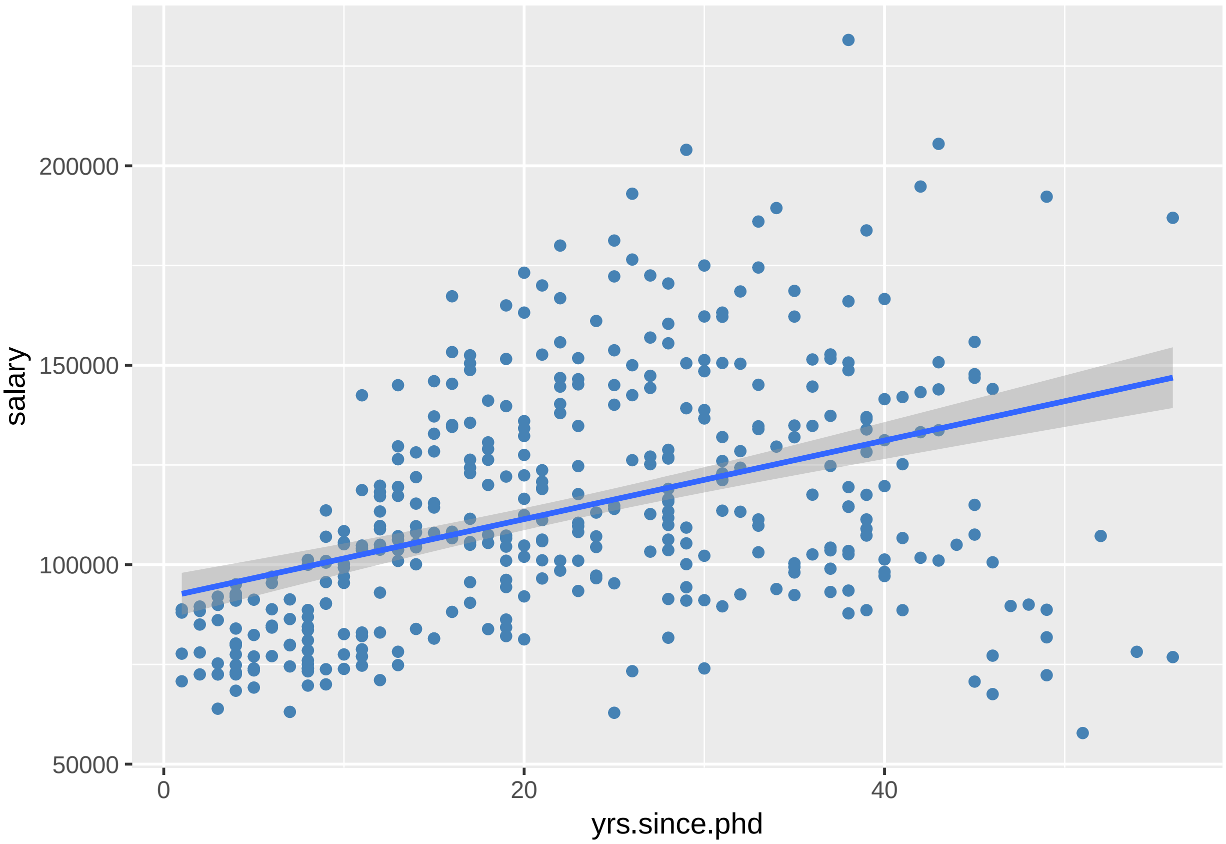
Figure 4.3: Scatterplot with color, transparency, and axis scaling

```
             size = 2,
             alpha=.8) +
  scale_y_continuous(label = scales::dollar,
                     limits = c(50000, 250000)) +
  scale_x_continuous(breaks = seq(0, 60, 10),
                     limits=c(0, 60)) +
  labs(x = "Years Since PhD",
       y = "",
       title = "Experience vs. Salary",
       subtitle = "9-month salary for 2008-2009")
```

4.2.1.1 Adding best fit lines

It is often useful to summarize the relationship displayed in the scatterplot, using a best fit line. Many types of lines are supported, including linear, polynomial, and nonparametric (loess). By default, 95% confidence limits for these lines are displayed.

```
# scatterplot with linear fit line
ggplot(Salaries,
       aes(x = yrs.since.phd,
           y = salary)) +
  geom_point(color= "steelblue") +
  geom_smooth(method = "lm")
```



Clearly, salary increases with experience. However, there seems to be a dip at the right end - professors with significant experience, earning lower salaries. A straight line does not capture this non-linear effect. A line with a bend will fit better here.

A polynomial regression line provides a fit line of the form

$$\hat{y} = \beta_0 + \beta_1 x + \beta 2x^2 + \beta 3x^3 + \beta 4x^4 + \dots$$

Typically either a quadratic (one bend), or cubic (two bends) line is used. It is rarely necessary to use a higher order(>3) polynomials. Applying a quadratic fit to the salary dataset produces the following result.

```
# scatterplot with quadratic line of best fit
ggplot(Salaries,
       aes(x = yrs.since.phd,
           y = salary)) +
  geom_point(color= "steelblue") +
  geom_smooth(method = "lm",
              formula = y ~ poly(x, 2),
              color = "indianred3")
```

Finally, a smoothed nonparametric fit line can often provide a good picture of the relationship. The default in `ggplot2` is a loess line which stands for for **l**ocally **w**eighted **s**catterplot **s**moothing.

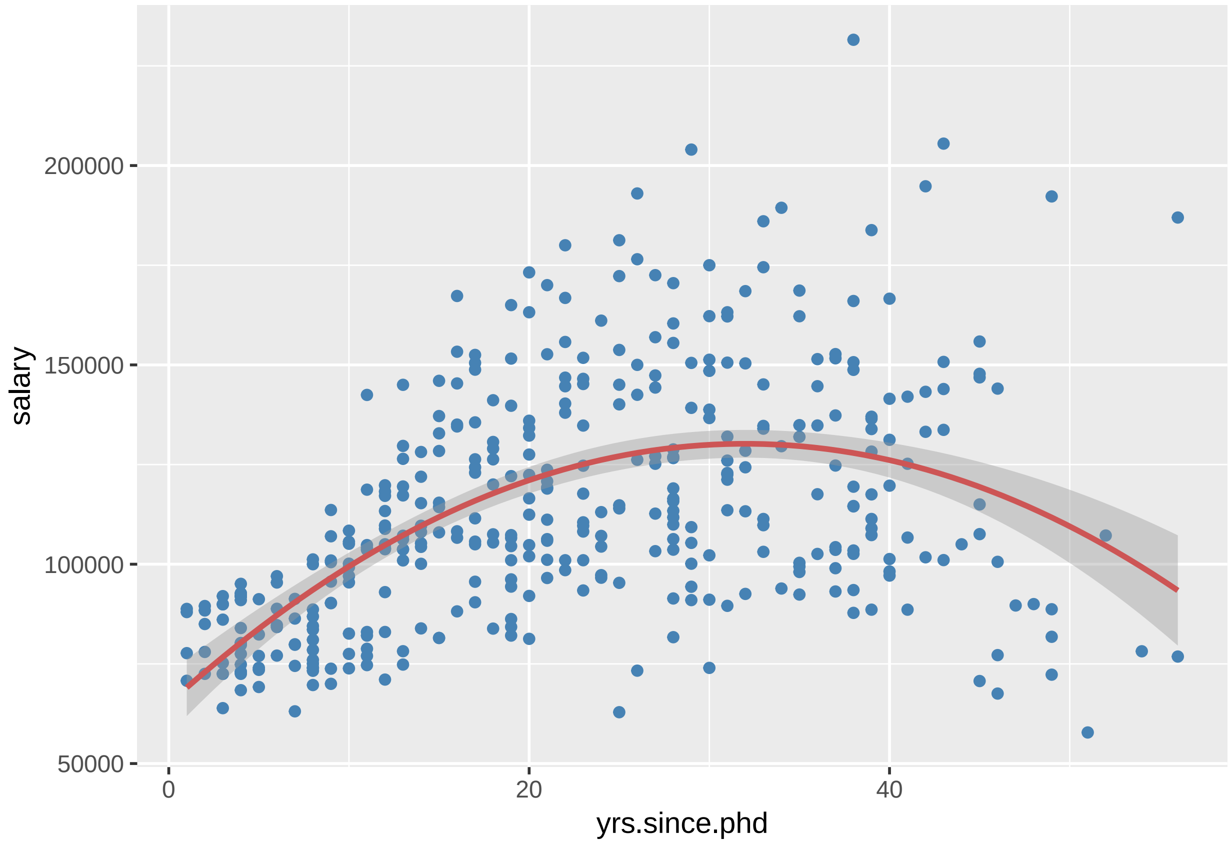


Figure 4.4: Scatterplot with quadratic fit line

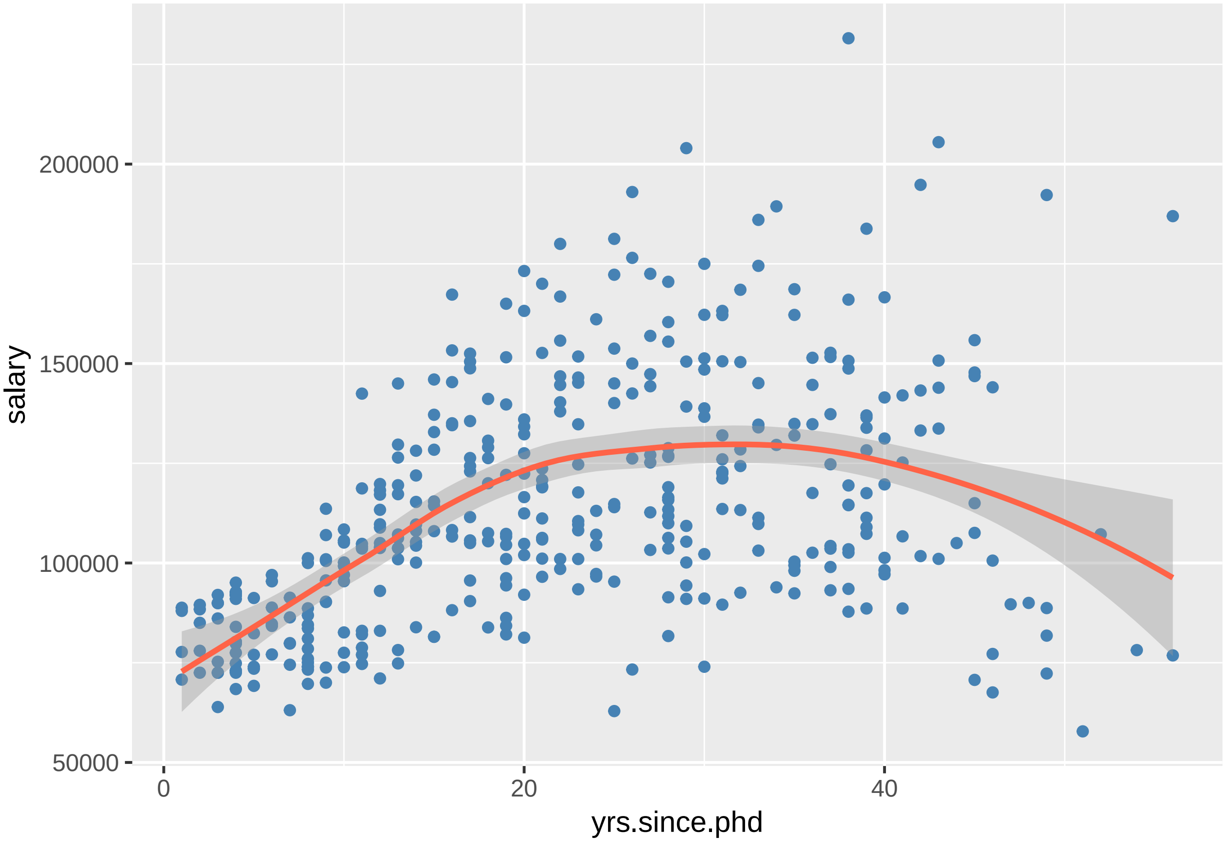


Figure 4.5: Scatterplot with nonparametric fit line

```r
# scatterplot with loess smoothed line
ggplot(Salaries,
       aes(x = yrs.since.phd,
           y = salary)) +
  geom_point(color= "steelblue") +
  geom_smooth(color = "tomato")
```

You can suppress the confidence bands by including the option `se = FALSE`.

Here is a complete (and more attractive) plot.

```r
# scatterplot with loess smoothed line
# and better labeling and color
ggplot(Salaries,
       aes(x = yrs.since.phd,
           y = salary)) +
  geom_point(color="cornflowerblue",
             size = 2,
             alpha = .6) +
  geom_smooth(size = 1.5,
              color = "darkgrey") +
  scale_y_continuous(label = scales::dollar,
                     limits = c(50000, 250000)) +
```

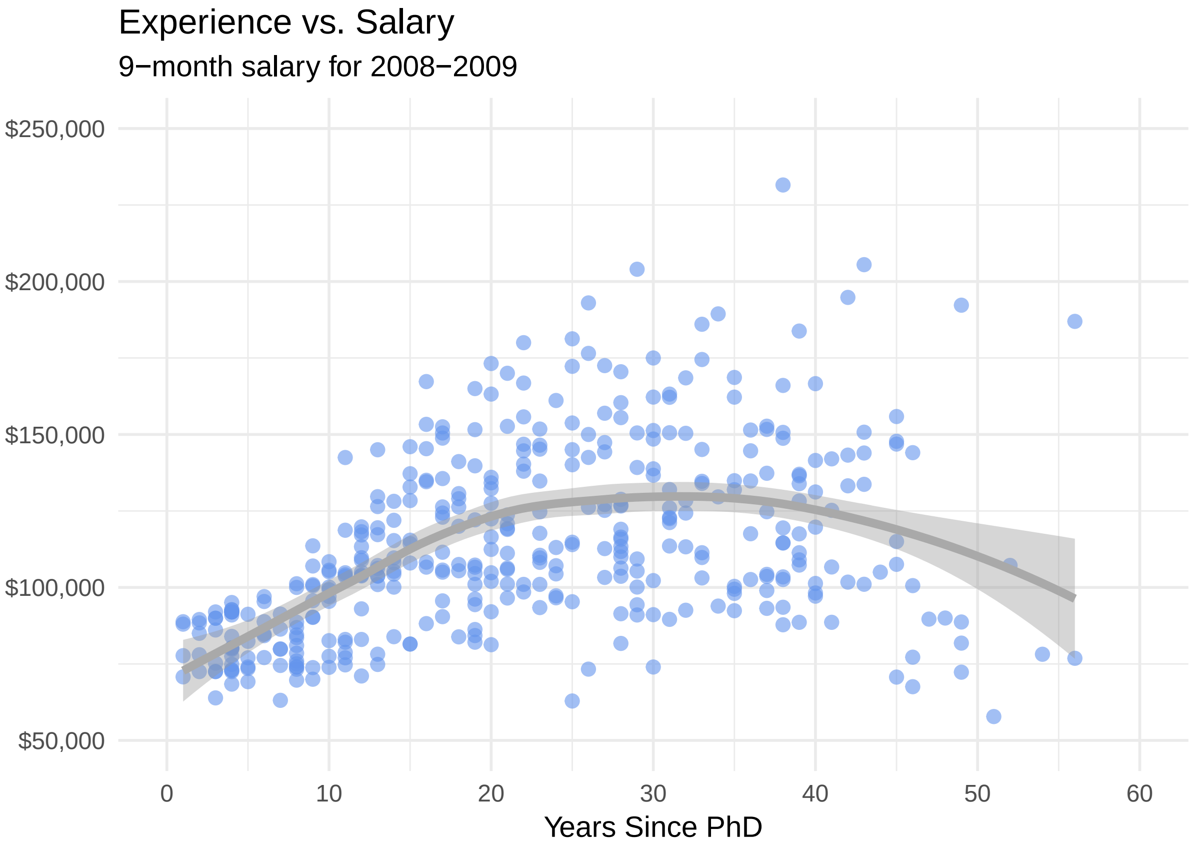


Figure 4.6: Scatterplot with nonparametric fit line

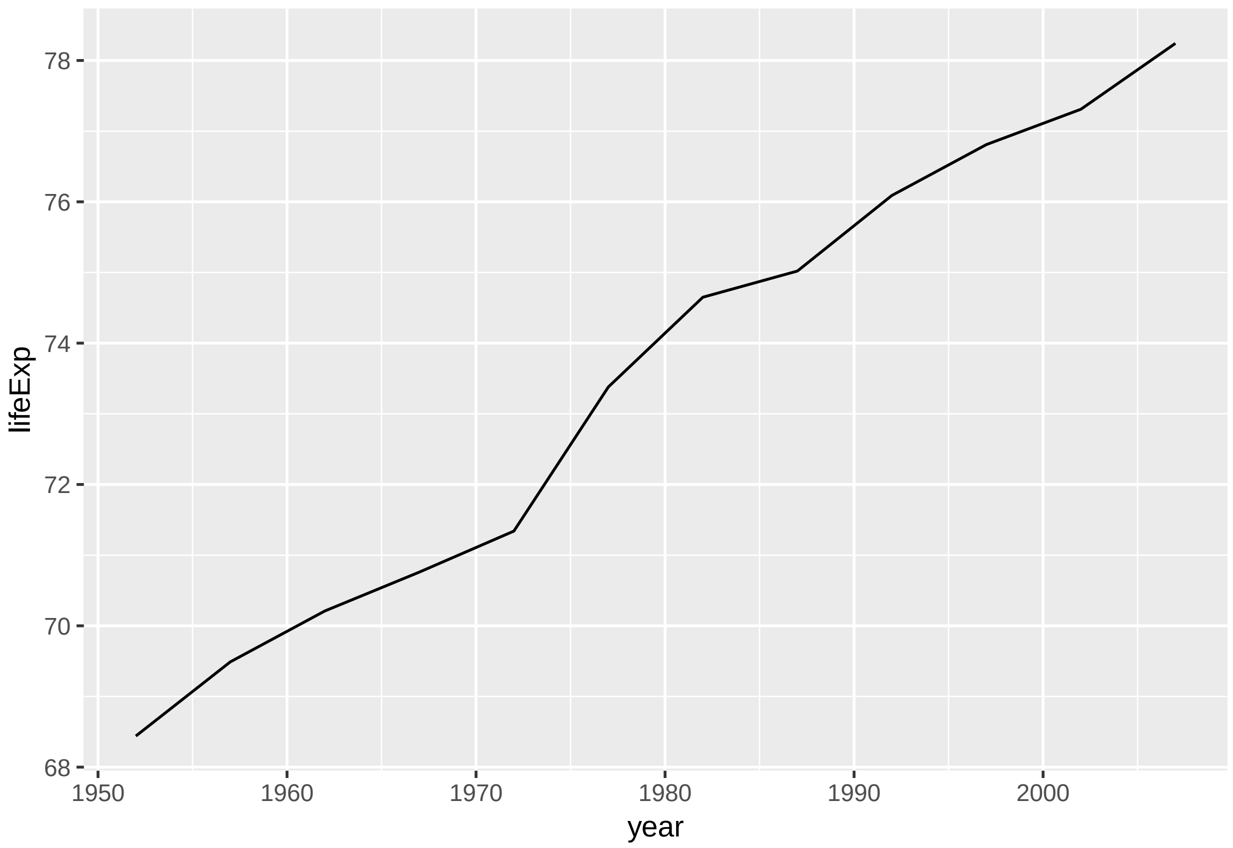
```
  scale_x_continuous(breaks = seq(0, 60, 10),
                     limits = c(0, 60)) +
  labs(x = "Years Since PhD",
       y = "",
       title = "Experience vs. Salary",
       subtitle = "9-month salary for 2008-2009") +
  theme_minimal()
```

4.2.2 Line plot

When one of the two variables represents time, a line plot can be an effective method of displaying relationship. For example, the code below displays the relationship between time (*year*) and life expectancy (*lifeExp*) in the United States between 1952 and 2007. The data comes from the gapminder dataset.

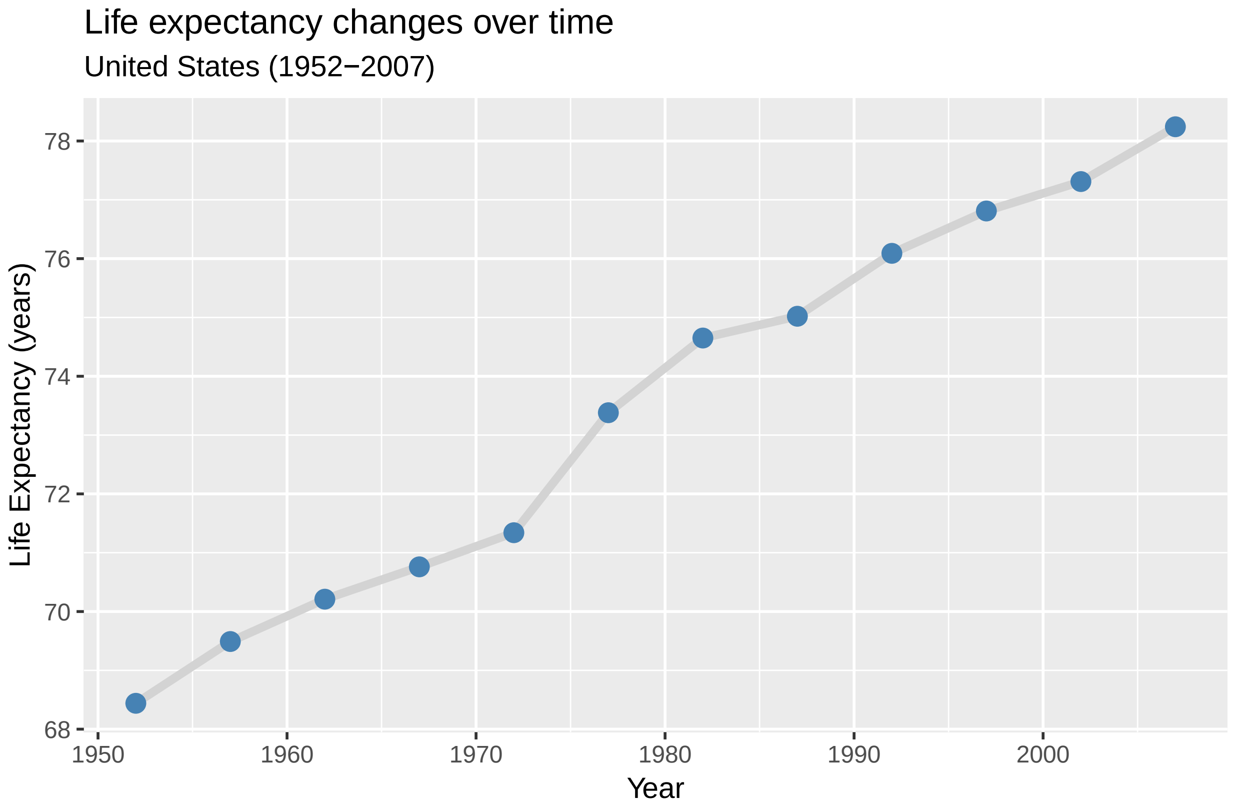
```
data(gapminder, package="gapminder")

# Select US cases
library(dplyr)
plotdata <- filter(gapminder,
                   country == "United States")
```

```r
# simple line plot
ggplot(plotdata,
       aes(x = year,
           y = lifeExp)) +
  geom_line()
```



It is hard to read individual values in the graph above. In the next plot, we'll add points as well.

```r
# line plot with points
# and improved labeling
ggplot(plotdata,
       aes(x = year,
           y = lifeExp)) +
  geom_line(size = 1.5,
            color = "lightgrey") +
  geom_point(size = 3,
             color = "steelblue") +
  labs(y = "Life Expectancy (years)",
       x = "Year",
       title = "Life expectancy changes over time",
       subtitle = "United States (1952-2007)",
       caption = "Source: http://www.gapminder.org/data/")
```



Source: http://www.gapminder.org/data/

Time dependent data is covered in more detail under Time series. Customizing line graphs is covered in the Customizing graphs section.

4.3 Categorical vs. Quantitative

When plotting the relationship between a categorical variable and a quantitative variable, a large number of graph types are available. These include bar charts using summary statistics, grouped kernel density plots, side-by-side box plots, side-by-side violin plots, mean/sem plots, ridgeline plots, and Cleveland plots.

4.3.1 Bar chart (on summary statistics)

In previous sections, bar charts were used to display the number of cases by category for a single variable or for two variables. You can also use bar charts to display other summary statistics (e.g., means or medians) on a quantitative variable for each level of a categorical variable.

For example, the following graph displays the mean salary for a sample of university professors by their academic rank.

```r
data(Salaries, package="carData")

# calculate mean salary for each rank
library(dplyr)
plotdata <- Salaries %>%
  group_by(rank) %>%
  summarize(mean_salary = mean(salary))
```

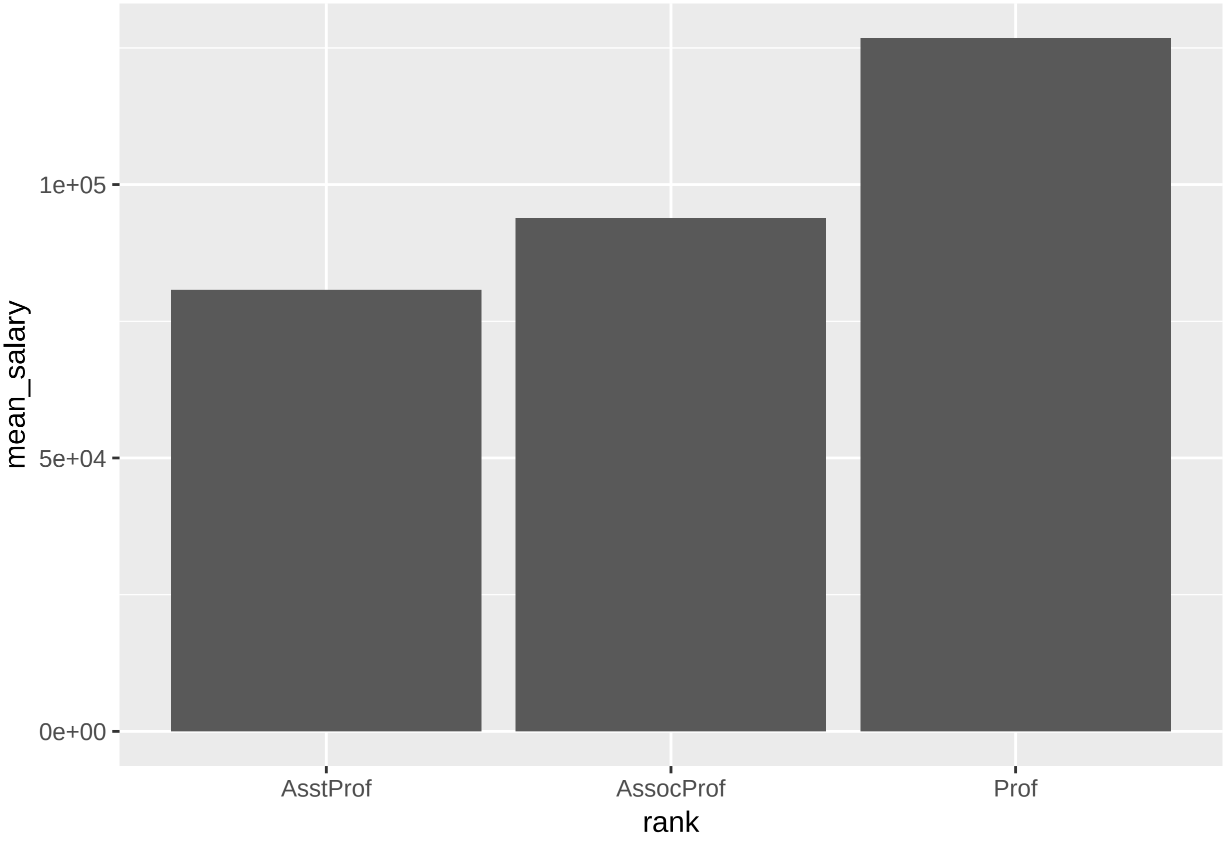
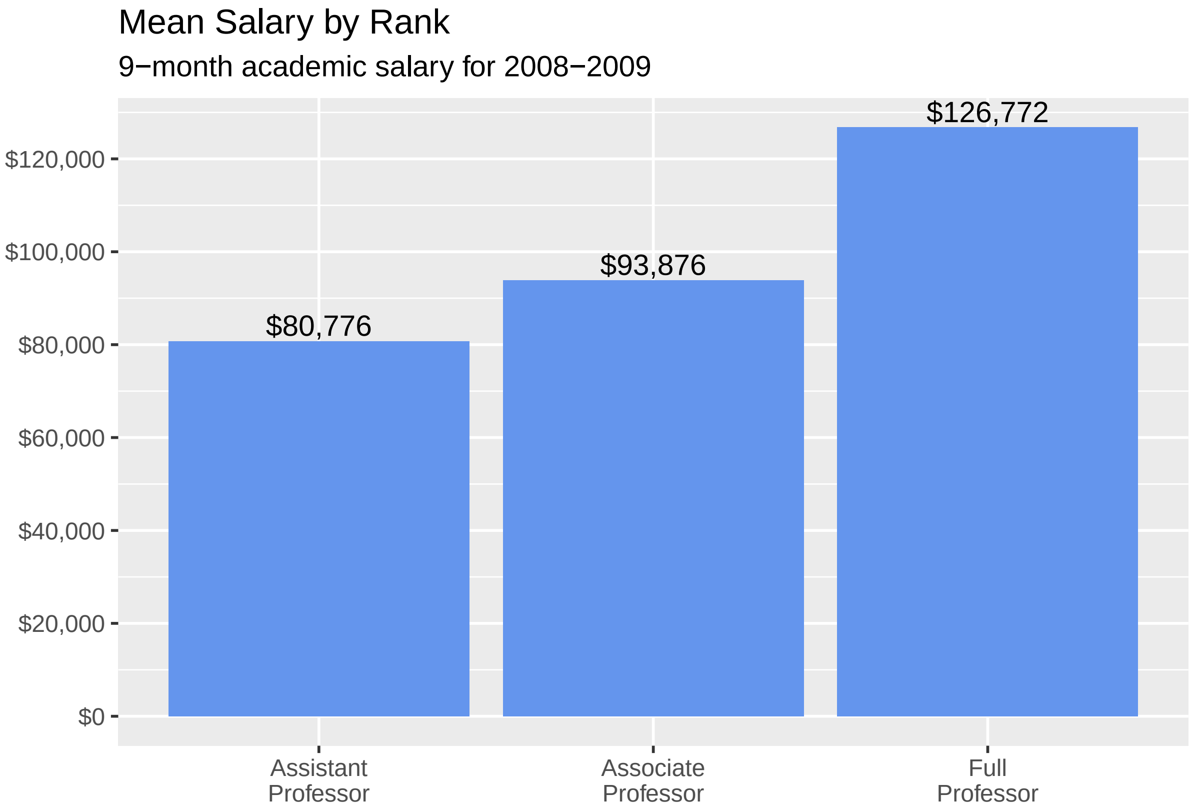


Figure 4.7: Bar chart displaying means

```r
# plot mean salaries
ggplot(plotdata,
       aes(x = rank,
           y = mean_salary)) +
  geom_bar(stat = "identity")
```

We can make it more attractive with some options.

```r
# plot mean salaries in a more attractive fashion
library(scales)
ggplot(plotdata,
       aes(x = factor(rank,
                      labels = c("Assistant\nProfessor",
                                 "Associate\nProfessor",
                                 "Full\nProfessor")),
                      y = mean_salary)) +
  geom_bar(stat = "identity",
           fill = "cornflowerblue") +
  geom_text(aes(label = dollar(mean_salary)),
            vjust = -0.25) +
  scale_y_continuous(breaks = seq(0, 130000, 20000),
                     label = dollar) +
  labs(title = "Mean Salary by Rank",
       subtitle = "9-month academic salary for 2008-2009",
       x = "",
       y = "")
```

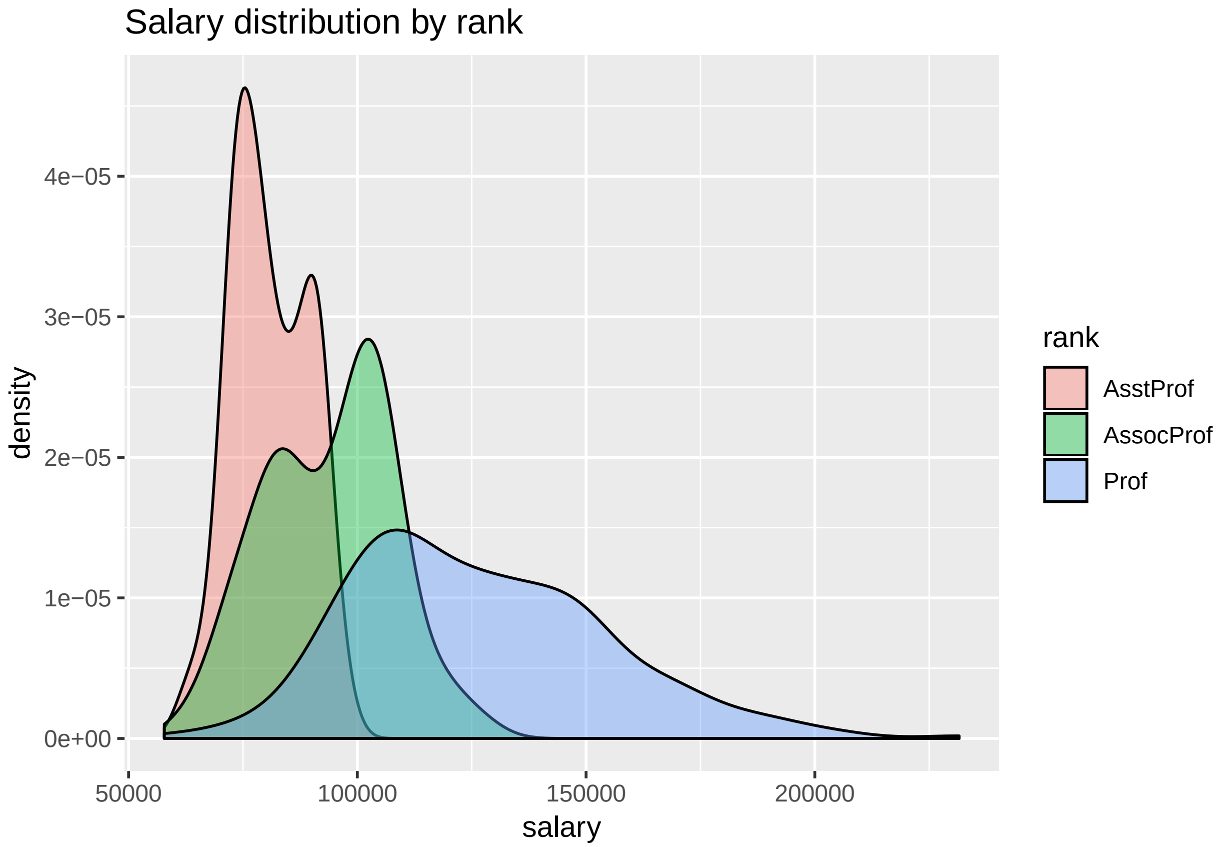


One limitation of such plots is that they do not display the distribution of the data - only the summary statistic for each group. The plots below correct this limitation to some extent.

4.3.2 Grouped kernel density plots

One can compare groups on a numeric variable by superimposing kernel density plots in a single graph.

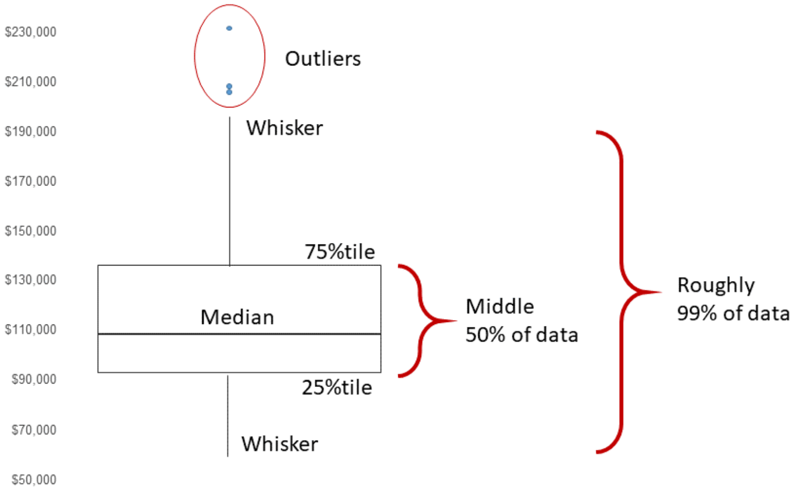
```
# plot the distribution of salaries
# by rank using kernel density plots
ggplot(Salaries,
       aes(x = salary,
           fill = rank)) +
  geom_density(alpha = 0.4) +
  labs(title = "Salary distribution by rank")
```



The `alpha` option makes the density plots partially transparent, so that we can see what is happening under the overlaps. Alpha values range from 0 (transparent) to 1 (opaque). The graph makes clear that, in general, salary goes up with rank. However, the salary range for full professors is *very* wide.

4.3.3 Box plots

A boxplot displays the 25th percentile, median, and 75th percentile of a distribution. The whiskers (vertical lines) capture roughly 99% of a normal distribution, and observations outside this range are plotted as points representing outliers (see the figure below).



Side-by-side box plots are very useful for comparing groups (i.e., the levels of a categorical variable) on a numerical variable.

```
# plot the distribution of salaries by rank using boxplots
ggplot(Salaries,
       aes(x = rank,
           y = salary)) +
  geom_boxplot() +
  labs(title = "Salary distribution by rank")
```

Notched boxplots provide an approximate method for visualizing whether groups differ. Although not a formal test, if the notches of two boxplots do not overlap, there is strong evidence (95% confidence) that the medians of the two groups differ.

```
# plot the distribution of salaries by rank using boxplots
ggplot(Salaries, aes(x = rank,
                     y = salary)) +
  geom_boxplot(notch = TRUE,
               fill = "cornflowerblue",
               alpha = .7) +
  labs(title = "Salary distribution by rank")
```

In the example above, all three groups appear to differ.

One of the advantages of boxplots is that their widths are not usually meaningful. This allows you to compare the distribution of many groups in a single graph.

4.3.4 Violin plots

Violin plots are similar to kernel density plots, but are mirrored and rotated 90°.

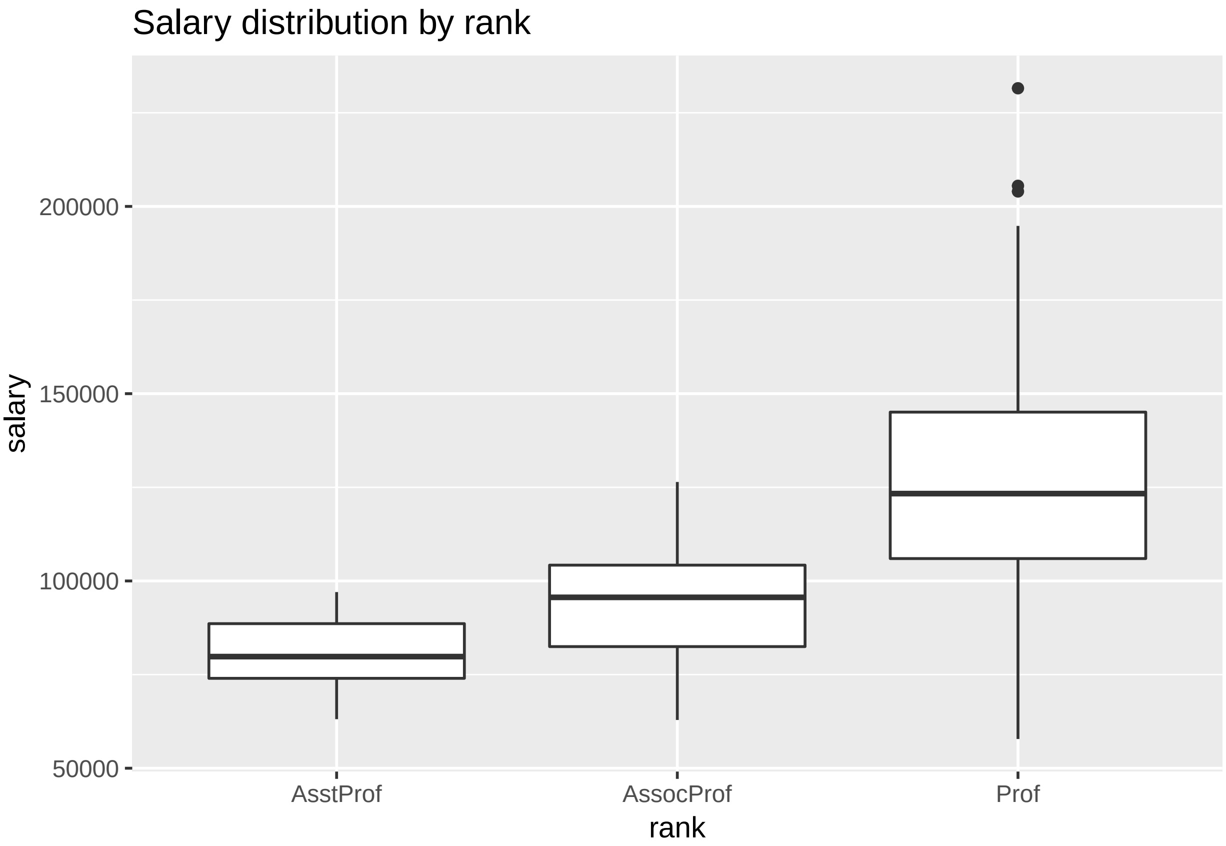


Figure 4.8: Side-by-side boxplots

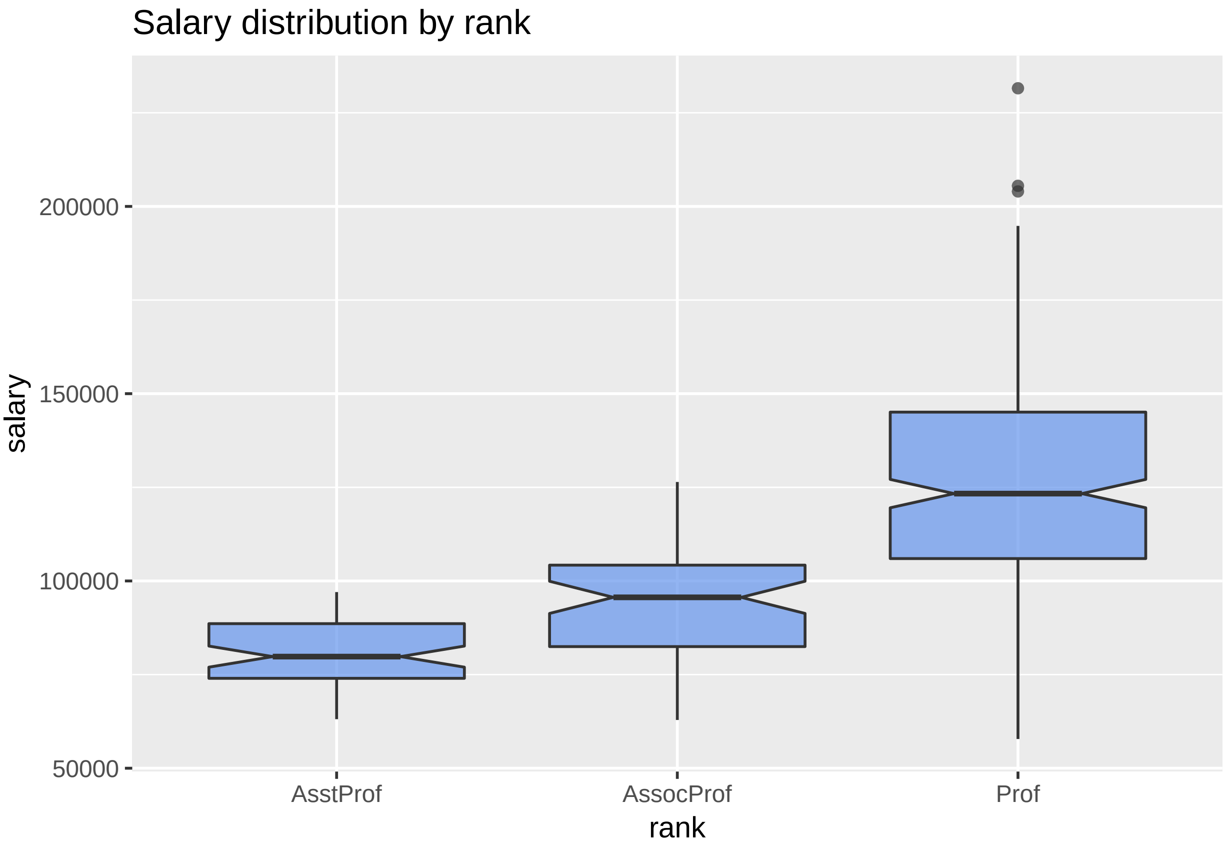
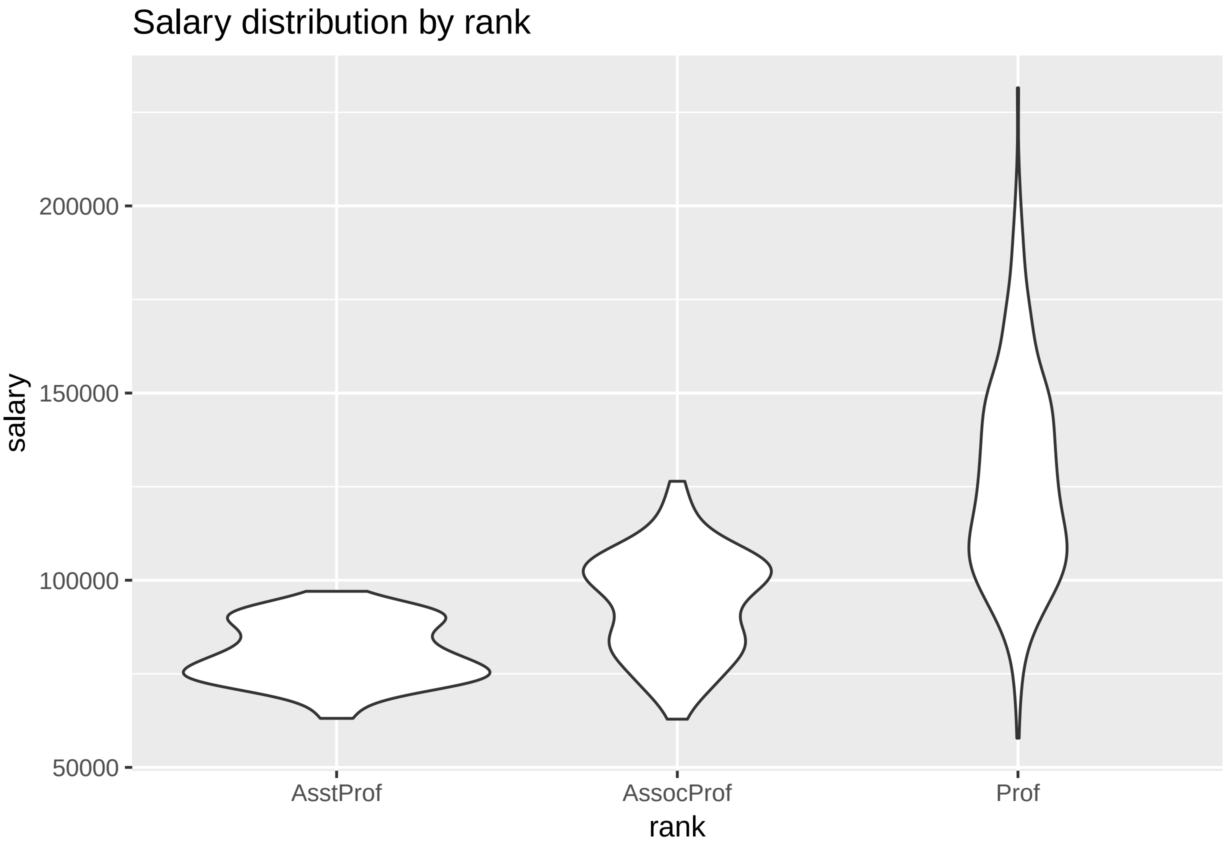


Figure 4.9: Side-by-side notched boxplots

```
# plot the distribution of salaries
# by rank using violin plots
ggplot(Salaries,
       aes(x = rank,
           y = salary)) +
  geom_violin() +
  labs(title = "Salary distribution by rank")
```



A useful variation is to superimpose boxplots on violin plots.

```
# plot the distribution using violin and boxplots
ggplot(Salaries,
       aes(x = rank,
           y = salary)) +
  geom_violin(fill = "cornflowerblue") +
  geom_boxplot(width = .2,
               fill = "orange",
               outlier.color = "orange",
               outlier.size = 2) +
  labs(title = "Salary distribution by rank")
```

4.3.5 Ridgeline plots

A ridgeline plot (also called a joyplot) displays the distribution of a quantitative variable for several groups. They're similar to kernel density plots with vertical faceting, but take up less room. Ridgeline plots are

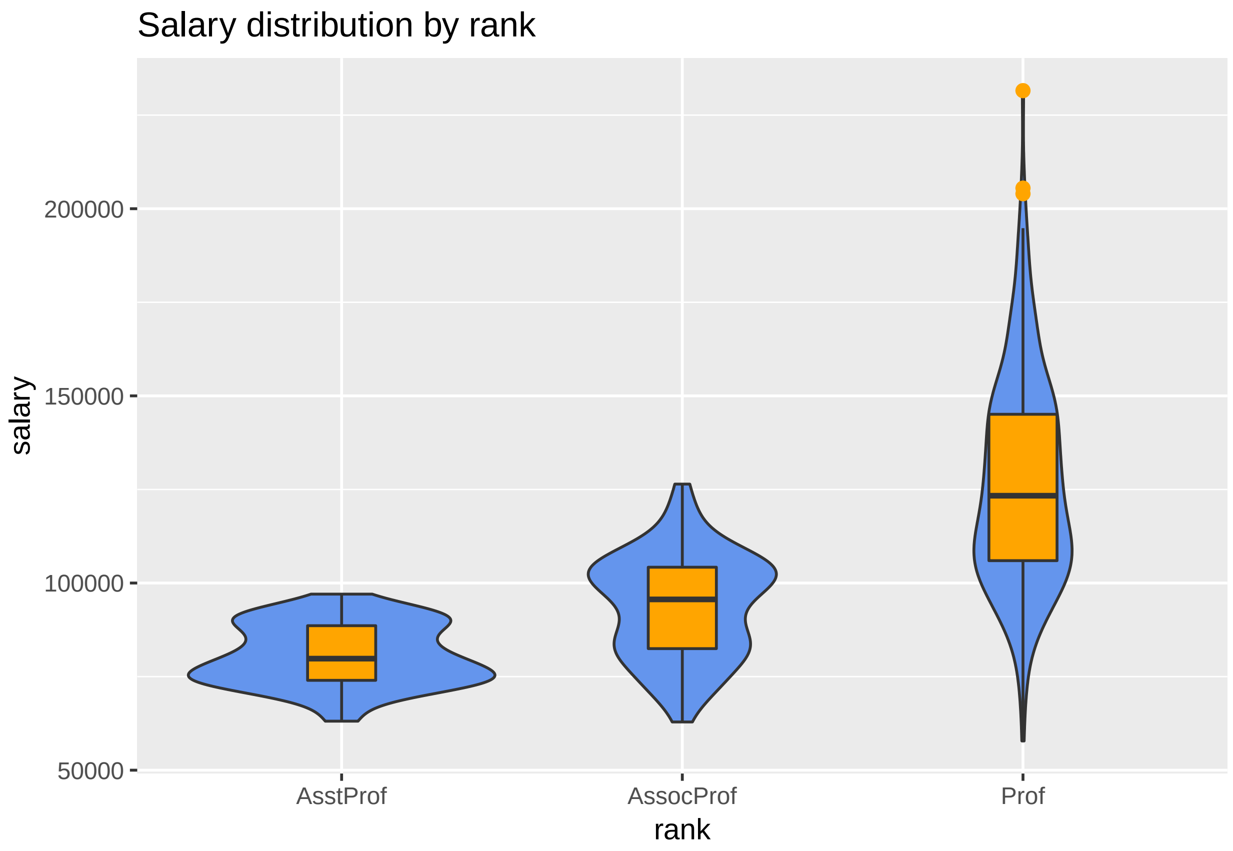


Figure 4.10: Side-by-side violin/box plots

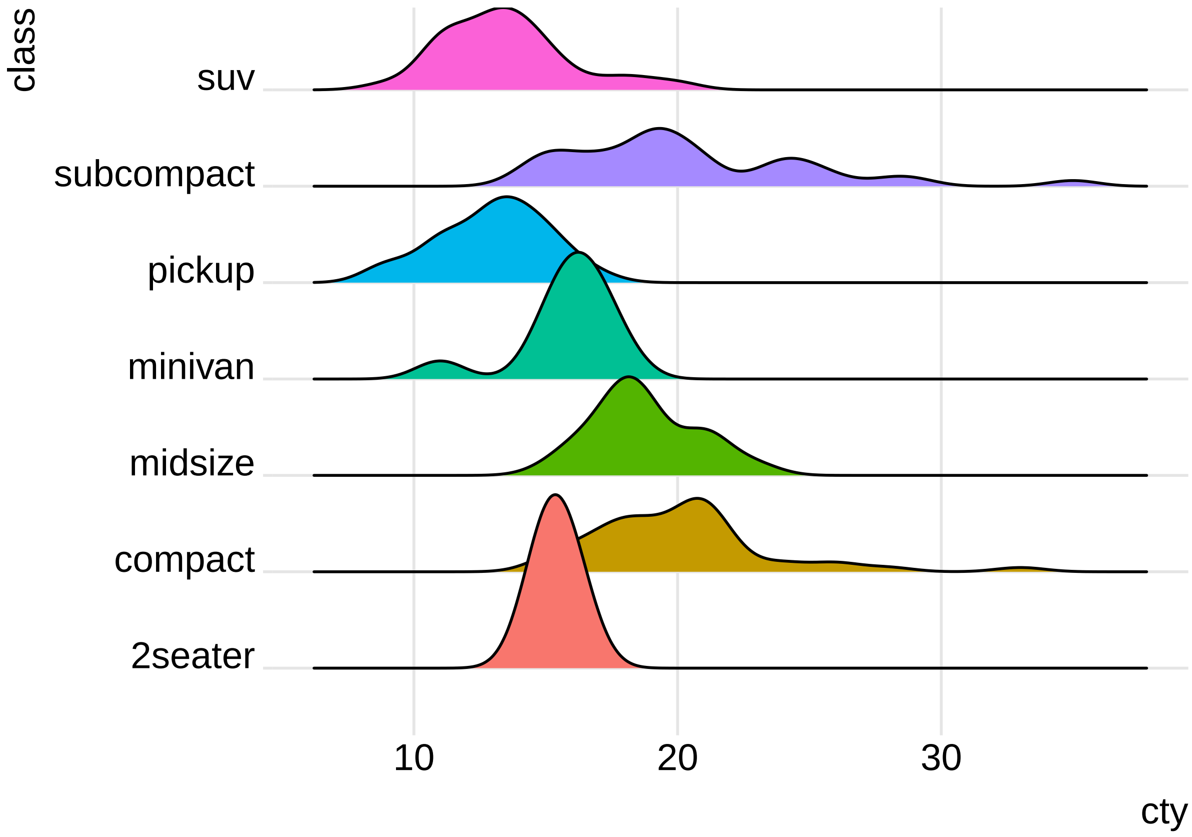


Figure 4.11: Ridgeline graph with color fill

created with the `ggridges` package.

Using the Fuel economy dataset, let's plot the distribution of city driving miles per gallon by car class.

```
# create ridgeline graph
library(ggplot2)
library(ggridges)

ggplot(mpg,
       aes(x = cty,
           y = class,
           fill = class)) +
  geom_density_ridges() +
  theme_ridges() +
  labs("Highway mileage by auto class") +
  theme(legend.position = "none")
```

I've suppressed the legend here because it's redundant (the distributions are already labeled on the y-axis). Unsurprisingly, pickup trucks have the poorest mileage, while subcompacts and compact cars tend to achieve ratings. However, there is a very wide range of gas mileage scores for these smaller cars.

Note the the possible overlap of distributions is the trade-off for a more compact graph. You can add transparency if the the overlap is severe using `geom_density_ridges(alpha = n)`, where n ranges from 0 (transparent) to 1 (opaque). See the package vignette for more details.

Table 4.1: Plot data

rank	n	mean	sd	se	ci
AsstProf	67	80775.99	8174.113	998.6268	1993.823
AssocProf	64	93876.44	13831.700	1728.9625	3455.056
Prof	266	126772.11	27718.675	1699.5410	3346.322

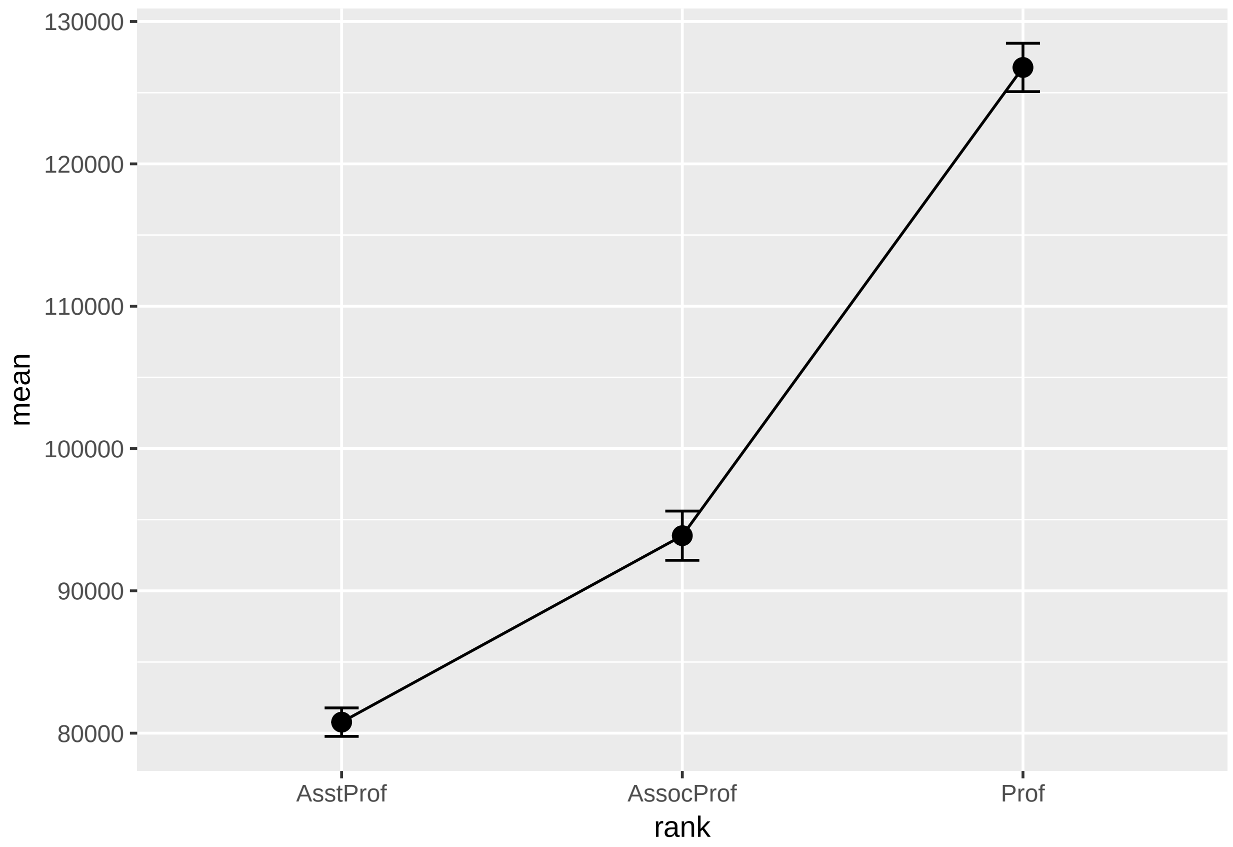
4.3.6 Mean/SEM plots

A popular method for comparing groups on a numeric variable is the mean plot with error bars. Error bars can represent standard deviations, standard error of the mean, or confidence intervals. In this section, we'll plot means and standard errors.

```r
# calculate means, standard deviations,
# standard errors, and 95% confidence
# intervals by rank
library(dplyr)
plotdata <- Salaries %>%
  group_by(rank) %>%
  summarize(n = n(),
         mean = mean(salary),
         sd = sd(salary),
         se = sd / sqrt(n),
         ci = qt(0.975, df = n - 1) * sd / sqrt(n))
```

The resulting dataset is given below.

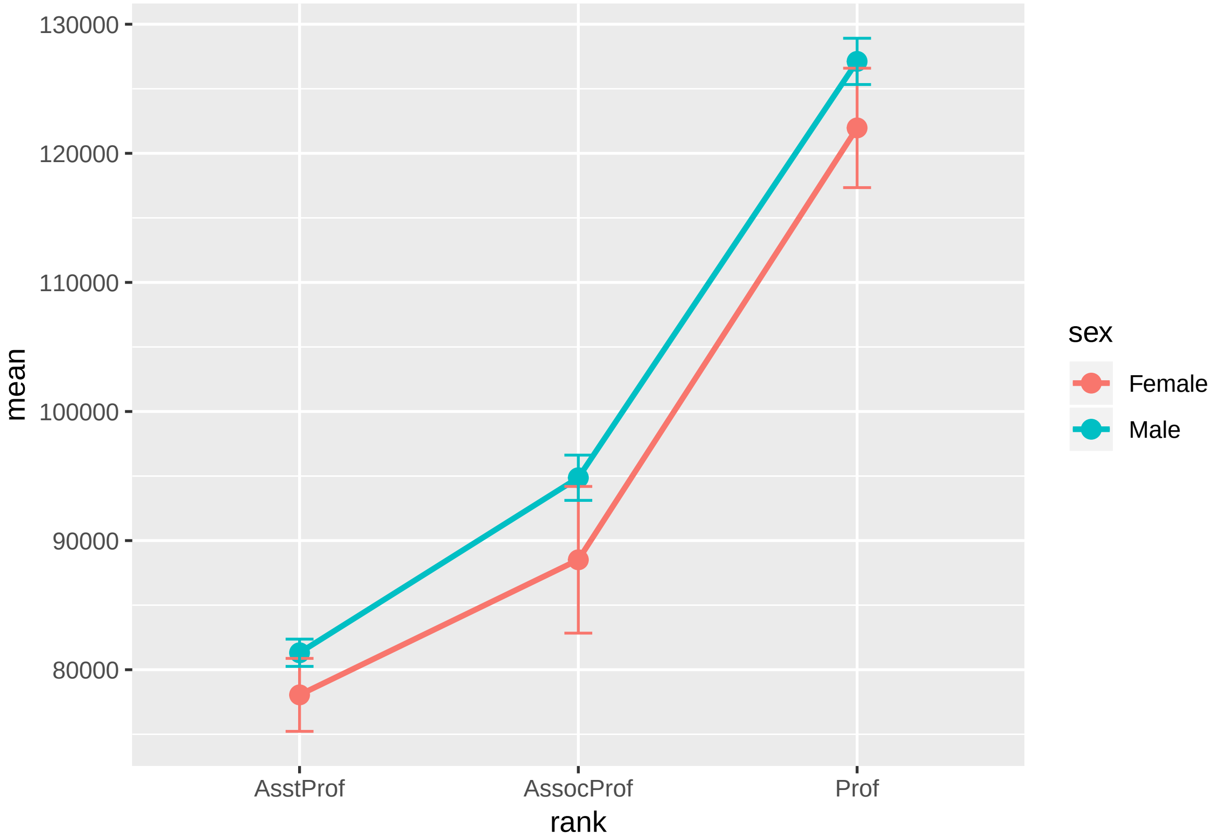
```r
# plot the means and standard errors
ggplot(plotdata,
       aes(x = rank,
           y = mean,
           group = 1)) +
  geom_point(size = 3) +
  geom_line() +
  geom_errorbar(aes(ymin = mean - se,
                    ymax = mean + se),
                width = .1)
```



Although we plotted error bars representing the standard error, we could have plotted standard deviations or 95% confidence intervals. Simply replace `se` with `sd` or `error` in the `aes` option.

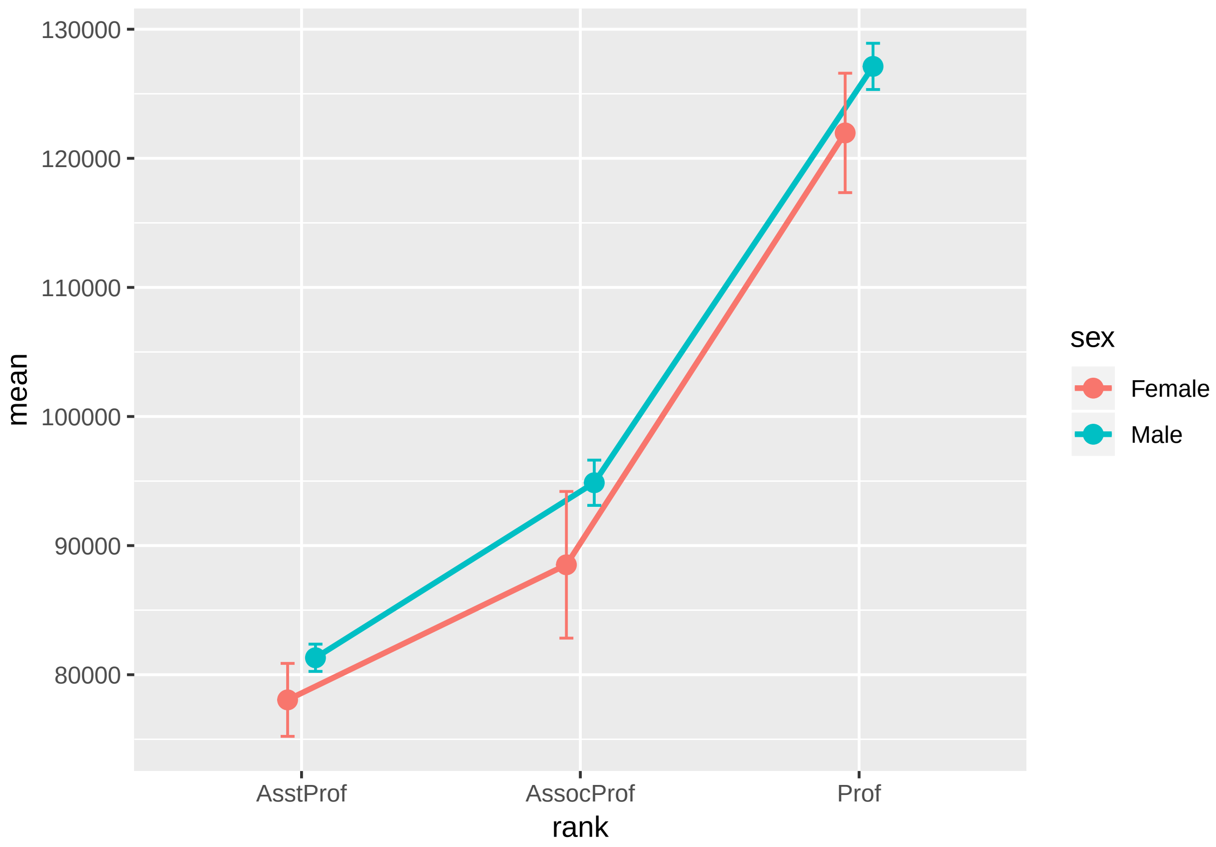
We can use the same technique to compare salary across rank and sex. (Technically, this is not bivariate since we're plotting rank, sex, and salary, but it seems to fit here)

```
# calculate means and standard errors by rank and sex
plotdata <- Salaries %>%
  group_by(rank, sex) %>%
  summarize(n = n(),
            mean = mean(salary),
            sd = sd(salary),
            se = sd/sqrt(n))

# plot the means and standard errors by sex
ggplot(plotdata, aes(x = rank,
                     y = mean,
                     group=sex,
                     color=sex)) +
  geom_point(size = 3) +
  geom_line(size = 1) +
  geom_errorbar(aes(ymin  =mean - se,
                    ymax = mean+se),
                width = .1)
```



Unfortunately, the error bars overlap. We can dodge the horizontal positions a bit to overcome this.

```
# plot the means and standard errors by sex (dodged)
pd <- position_dodge(0.2)
ggplot(plotdata,
       aes(x = rank,
           y = mean,
           group=sex,
           color=sex)) +
  geom_point(position = pd,
             size = 3) +
  geom_line(position = pd,
            size = 1) +
  geom_errorbar(aes(ymin = mean - se,
                    ymax = mean + se),
                width = .1,
                position= pd)
```



Finally, lets add some options to make the graph more attractive.

```
# improved means/standard error plot
pd <- position_dodge(0.2)
ggplot(plotdata,
       aes(x = factor(rank,
                      labels = c("Assistant\nProfessor",
                                 "Associate\nProfessor",
                                 "Full\nProfessor")),
           y = mean,
           group=sex,
           color=sex)) +
  geom_point(position=pd,
             size = 3) +
  geom_line(position = pd,
            size = 1) +
  geom_errorbar(aes(ymin = mean - se,
                    ymax = mean + se),
                width = .1,
                position = pd,
                size = 1) +
  scale_y_continuous(label = scales::dollar) +
  scale_color_brewer(palette="Set1") +
  theme_minimal() +
  labs(title = "Mean salary by rank and sex",
       subtitle = "(mean +/- standard error)",
       x = "",
```

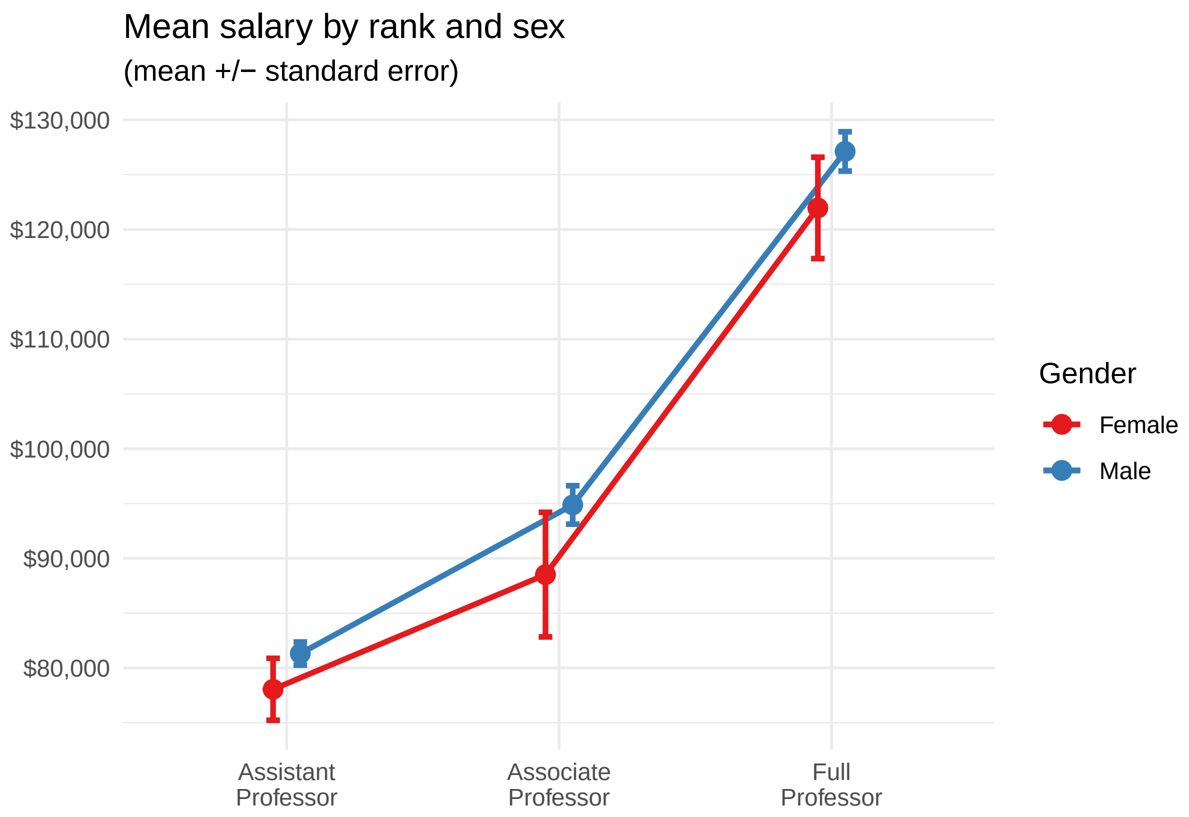


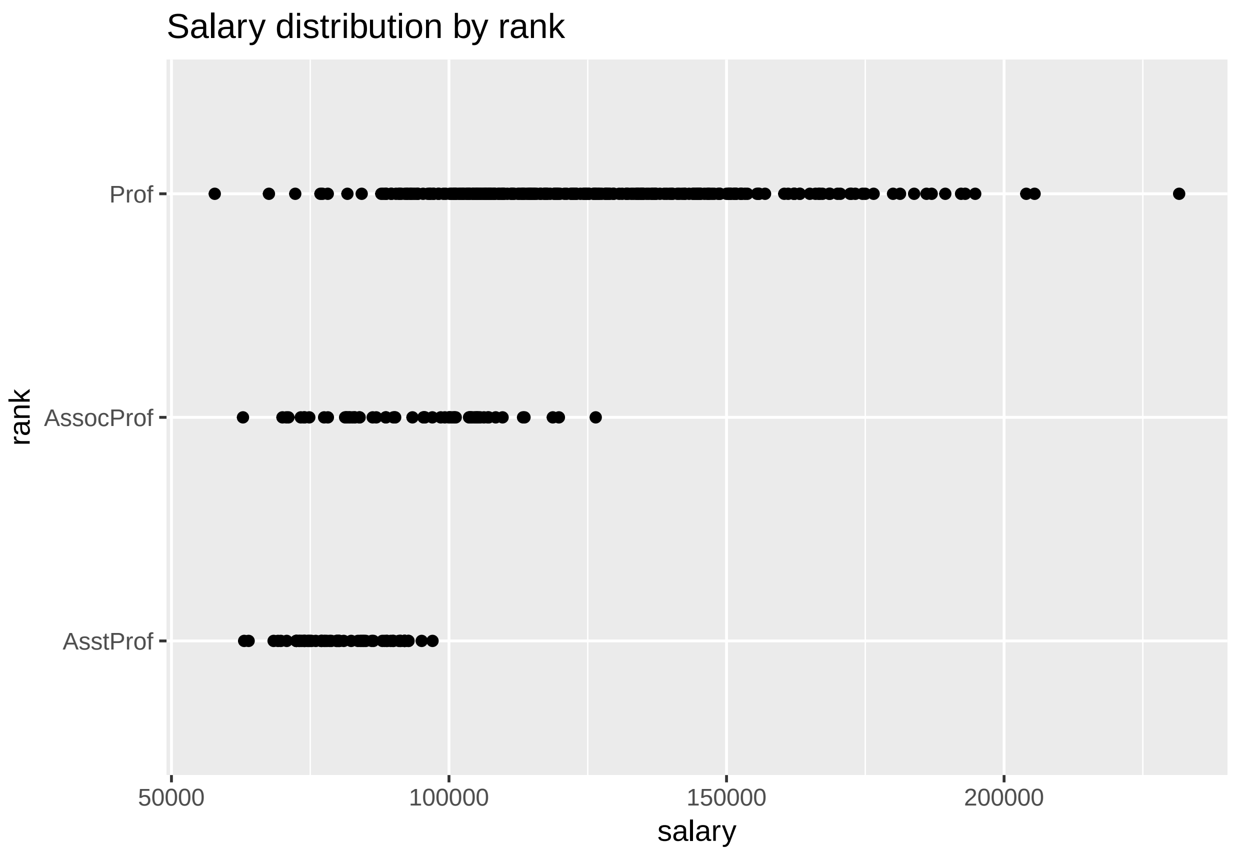
Figure 4.12: Mean/se plot with better labels and colors

```
       y = "",
       color = "Gender")
```

4.3.7 Strip plots

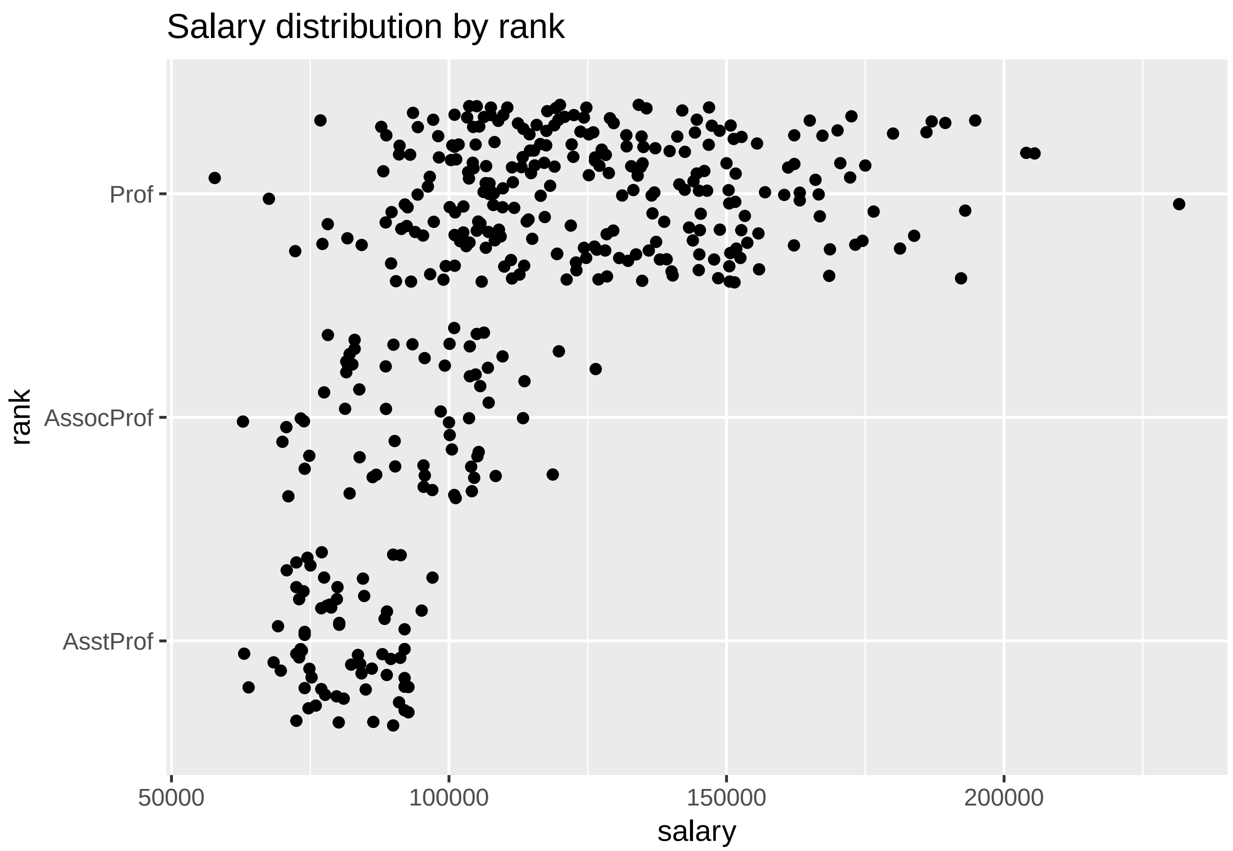
The relationship between a grouping variable and a numeric variable can be displayed with a scatter plot. For example

```
# plot the distribution of salaries
# by rank using strip plots
ggplot(Salaries,
       aes(y = rank,
           x = salary)) +
  geom_point() +
  labs(title = "Salary distribution by rank")
```



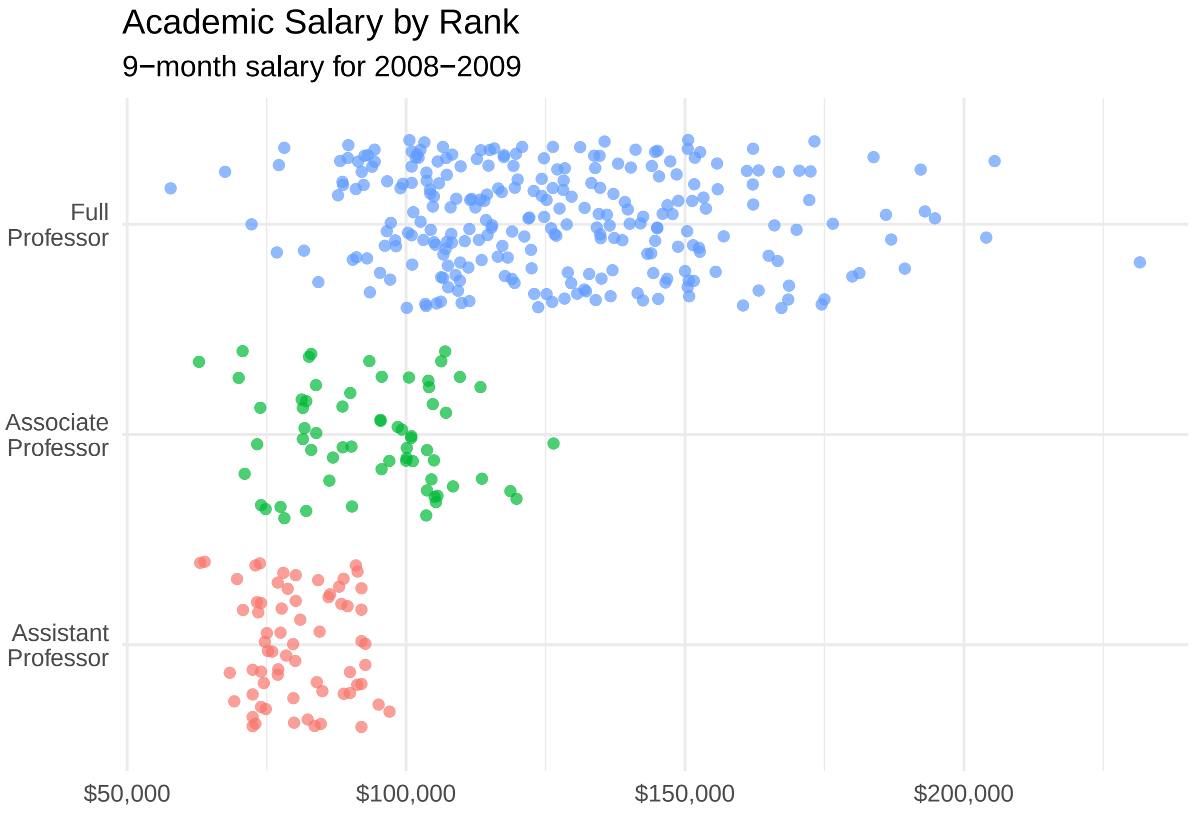
These one-dimensional scatterplots are called strip plots. Unfortunately, overprinting of points makes interpretation difficult. The relationship is easier to see if the the points are jittered. Basically a small random number is added to each y-coordinate.

```r
# plot the distribution of salaries
# by rank using jittering
ggplot(Salaries,
       aes(y = rank,
           x = salary)) +
  geom_jitter() +
  labs(title = "Salary distribution by rank")
```



It is easier to compare groups if we use color.

```
# plot the distribution of salaries
# by rank using jittering
library(scales)
ggplot(Salaries,
       aes(y = factor(rank,
                      labels = c("Assistant\nProfessor",
                                 "Associate\nProfessor",
                                 "Full\nProfessor")),
           x = salary,
           color = rank)) +
  geom_jitter(alpha = 0.7,
              size = 1.5) +
  scale_x_continuous(label = dollar) +
  labs(title = "Academic Salary by Rank",
       subtitle = "9-month salary for 2008-2009",
       x = "",
       y = "") +
  theme_minimal() +
  theme(legend.position = "none")
```

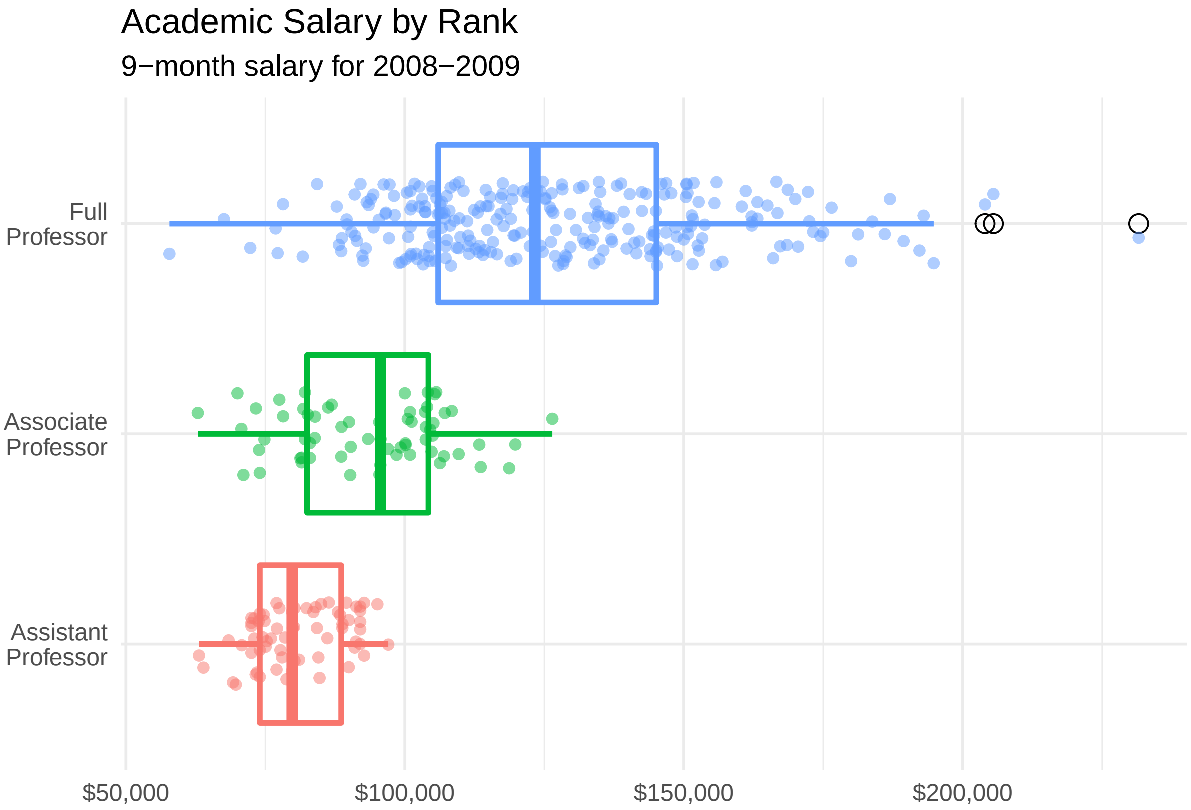


The option `legend.position = "none"` is used to suppress the legend (which is not needed here). Jittered plots work well when the number of points in not overly large.

4.3.7.1 Combining jitter and boxplots

It may be easier to visualize distributions if we add boxplots to the jitter plots.

```
# plot the distribution of salaries
# by rank using jittering
library(scales)
ggplot(Salaries,
       aes(x = factor(rank,
                      labels = c("Assistant\nProfessor",
                                 "Associate\nProfessor",
                                 "Full\nProfessor")),
           y = salary,
           color = rank)) +
  geom_boxplot(size=1,
               outlier.shape = 1,
               outlier.color = "black",
               outlier.size  = 3) +
  geom_jitter(alpha = 0.5,
              width=.2) +
  scale_y_continuous(label = dollar) +
  labs(title = "Academic Salary by Rank",
       subtitle = "9-month salary for 2008-2009",
       x = "",
       y = "") +
  theme_minimal() +
  theme(legend.position = "none") +
  coord_flip()
```



Several options were added to create this plot.

For the boxplot

- `size = 1` makes the lines thicker

- `outlier.color = "black"` makes outliers black
- `outlier.shape = 1` specifies circles for outliers
- `outlier.size = 3` increases the size of the outlier symbol

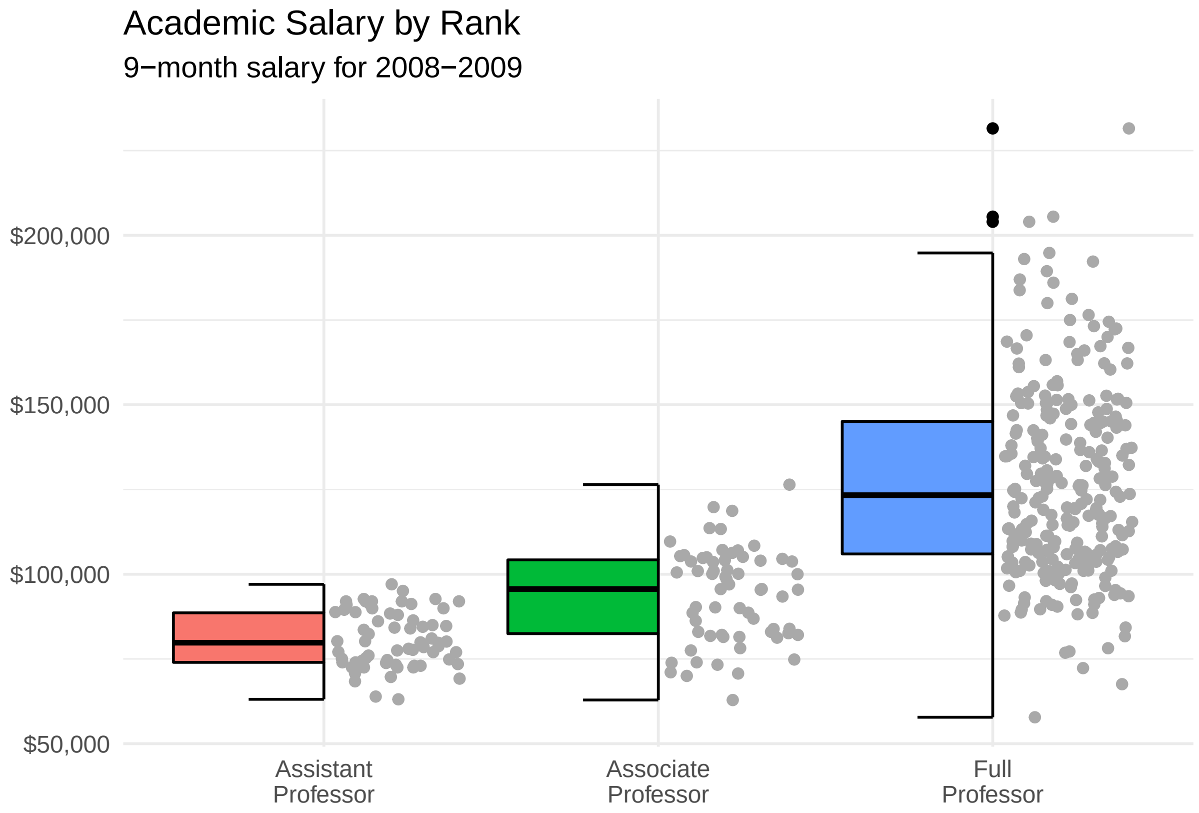
For the jitter

- `alpha = 0.5` makes the points more transparent
- `width = .2` decreases the amount of jitter (.4 is the default)

Finally, the x and y axes are revered using the `coord_flip` function (i.e., the graph is turned on its side).

Before moving on, it is worth mentioning the `geom_boxjitter` function provided in the `ggpol` package. It creates a hybrid boxplot - half boxplot, half scatterplot.

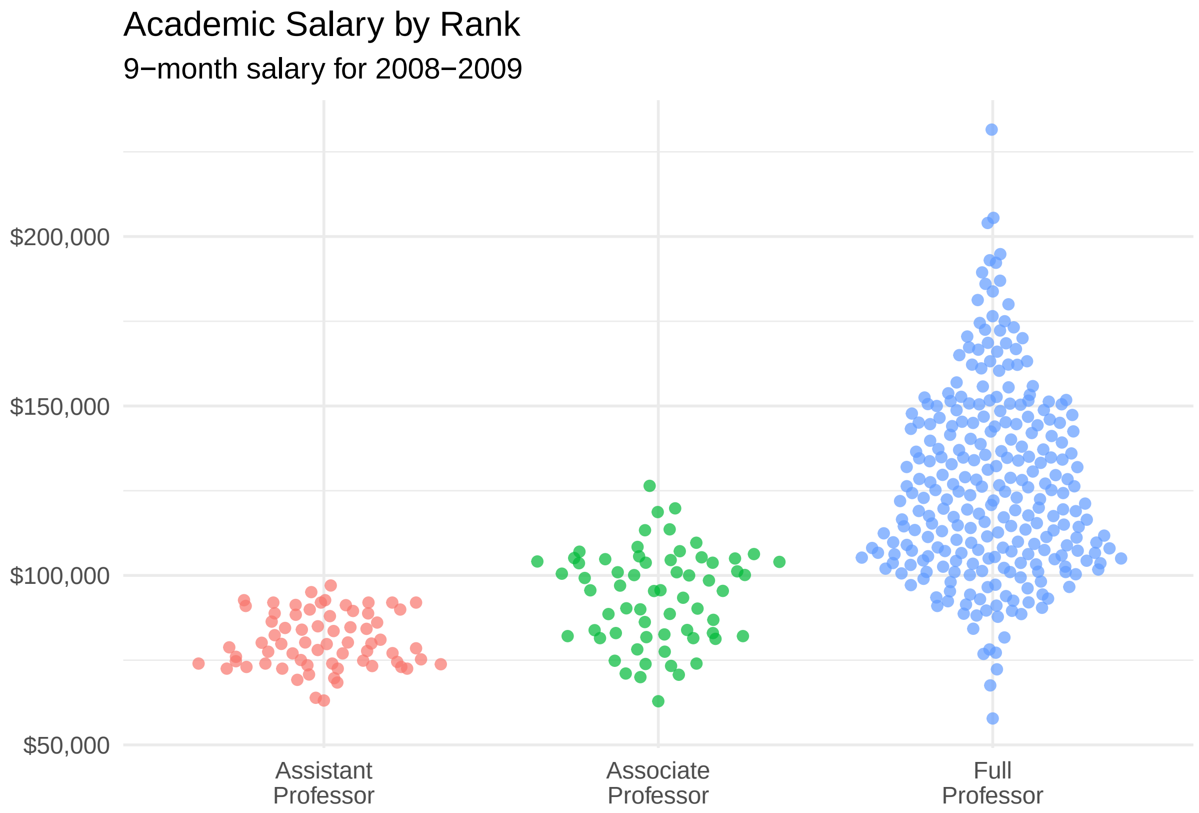
```
# plot the distribution of salaries
# by rank using jittering
library(ggpol)
library(scales)
ggplot(Salaries,
       aes(x = factor(rank,
                      labels = c("Assistant\nProfessor",
                                 "Associate\nProfessor",
                                 "Full\nProfessor")),
           y = salary,
           fill=rank)) +
  geom_boxjitter(color="black",
                 jitter.color = "darkgrey",
                 errorbar.draw = TRUE) +
  scale_y_continuous(label = dollar) +
  labs(title = "Academic Salary by Rank",
       subtitle = "9-month salary for 2008-2009",
       x = "",
       y = "") +
  theme_minimal() +
  theme(legend.position = "none")
```



### Beeswarm Plots

Beeswarm plots (also called violin scatter plots) are similar to jittered scatterplots, in that they display the distribution of a quantitative variable by plotting points in way that reduces overlap. In addition, they also help display the density of the data at each point (in a manner that is similar to a violin plot). Continuing the previous example

```
# plot the distribution of salaries
# by rank using bewarm-syle plots
library(ggbeeswarm)
library(scales)
ggplot(Salaries,
       aes(x = factor(rank,
                      labels = c("Assistant\nProfessor",
                                 "Associate\nProfessor",
                                 "Full\nProfessor")),
           y = salary,
           color = rank)) +
  geom_quasirandom(alpha = 0.7,
                   size = 1.5) +
  scale_y_continuous(label = dollar) +
  labs(title = "Academic Salary by Rank",
       subtitle = "9-month salary for 2008-2009",
       x = "",
       y = "") +
  theme_minimal() +
  theme(legend.position = "none")
```



The plots are create using the `geom_quasirandom` function. These plots can be easier to read than simple jittered strip plots. To learn more about these plots, see Beeswarm-style plots with ggplot2.

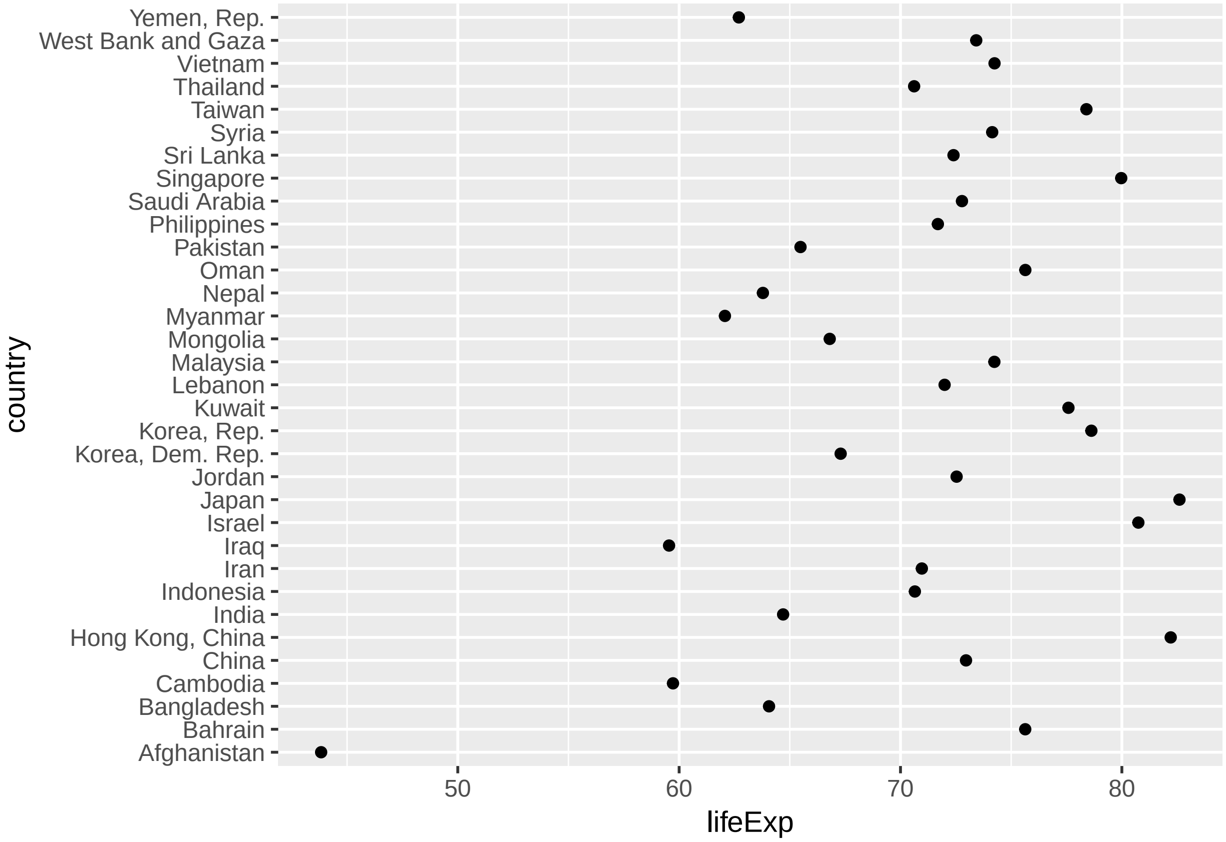


Figure 4.13: Basic Cleveland dot plot

4.3.8 Cleveland Dot Charts

Cleveland plots are useful when you want to compare a numeric statistic for a large number of groups. For example, say that you want to compare the 2007 life expectancy for Asian country using the gapminder dataset.

```
data(gapminder, package="gapminder")

# subset Asian countries in 2007
library(dplyr)
plotdata <- gapminder %>%
  filter(continent == "Asia" &
         year == 2007)

# basic Cleveland plot of life expectancy by country
ggplot(plotdata,
       aes(x= lifeExp, y = country)) +
  geom_point()
```

Comparisons are usually easier if the y-axis is sorted.

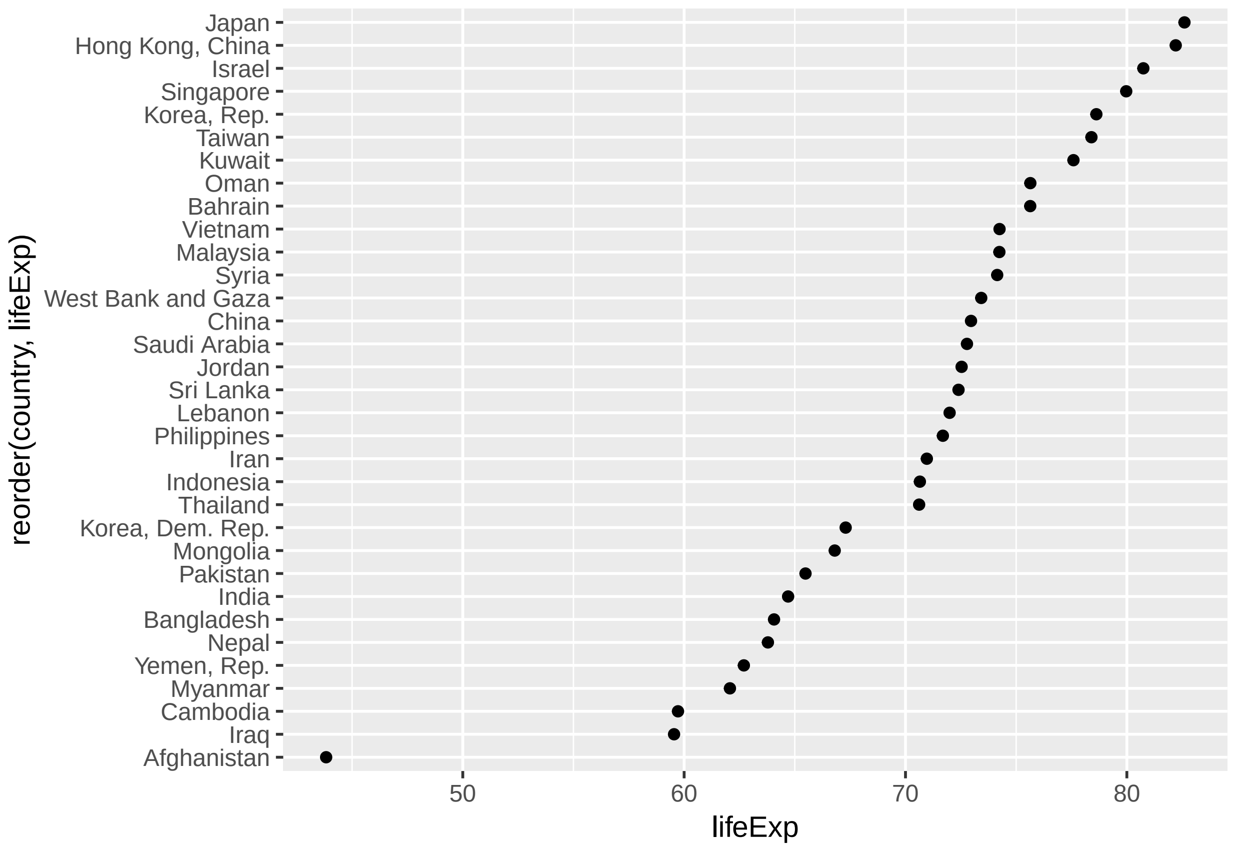


Figure 4.14: Sorted Cleveland dot plot

```
# Sorted Cleveland plot
ggplot(plotdata,
       aes(x=lifeExp,
           y=reorder(country, lifeExp))) +
  geom_point()
```

Finally, we can use options to make the graph more attractive.

```
# Fancy Cleveland plot
ggplot(plotdata,
       aes(x=lifeExp,
           y=reorder(country, lifeExp))) +
  geom_point(color="blue",
             size = 2) +
  geom_segment(aes(x = 40,
               xend = lifeExp,
               y = reorder(country, lifeExp),
               yend = reorder(country, lifeExp)),
               color = "lightgrey") +
  labs (x = "Life Expectancy (years)",
        y = "",
        title = "Life Expectancy by Country",
        subtitle = "GapMinder data for Asia - 2007") +
```

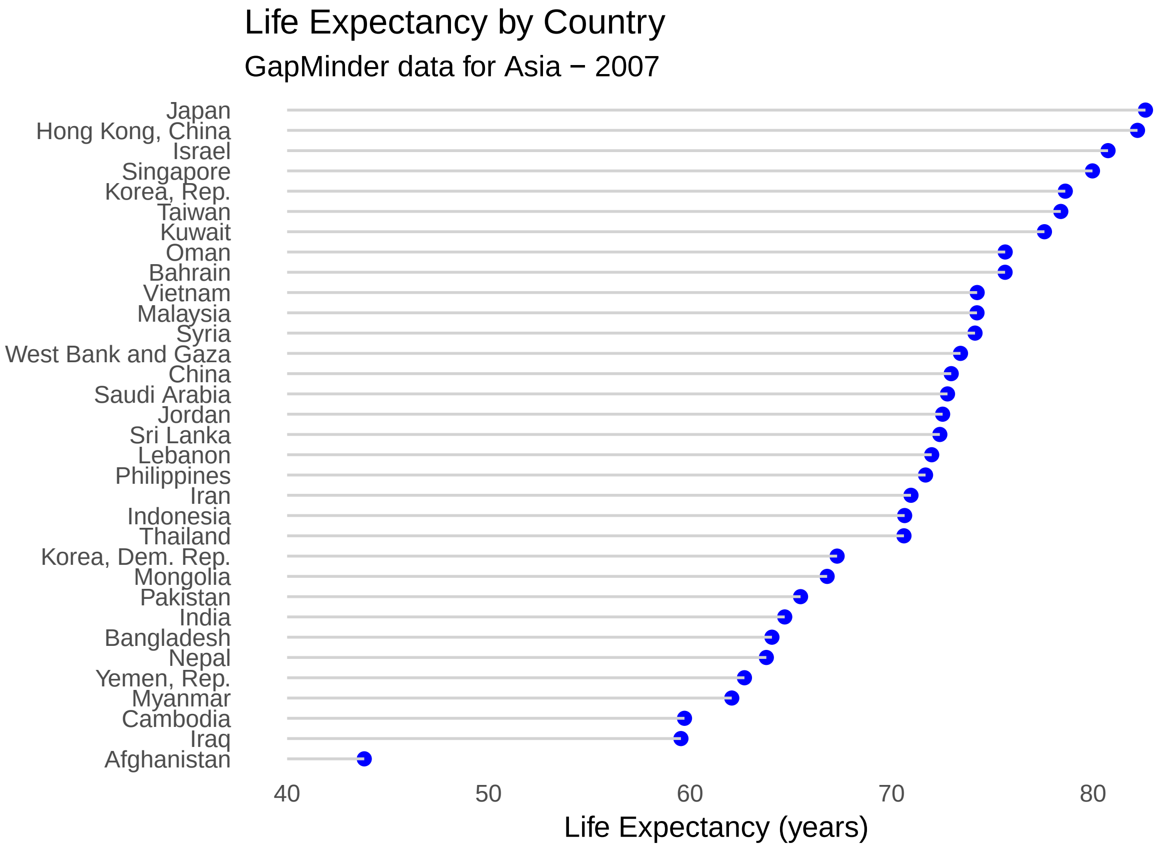


Figure 4.15: Fancy Cleveland plot

```
  theme_minimal() +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank())
```

Japan clearly has the highest life expectancy, while Afghanistan has the lowest by far. This last plot is also called a lollipop graph (you can see why).