

Reproducible Research: Peer Assessment 1

Jim Callahan

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This report analyzes the number of steps taken by an anonymous individual user of a personal fitness armband device similar to the Nike “Fit” armband. The number of steps were measured over five minute intervals, 24 hours a day during the months of October and November 2012.

The 2012 steps per five minute interval data is for the months of October (30 days) and November (31 days) for a total of 61 days. In each hour there are 12 “five minute” intervals ($60/5 = 12$ intervals per hour). Thus, there are 288 five minute intervals in a 24 hour day ($288 = 24 \text{ hours} * 12 \text{ intervals per hour}$). Therefore, with 288 measurements per day for 61 days (24 hour days) one would **expect 17,568 observations** ($17,568 = 61 \text{ days} * 288 \text{ per 24 hour day}$).

Loading and preprocessing the data

The dataset is stored in a comma-separated-value (CSV) file in the main directory of a **GitHub** repository. So, we can load the data with an R “read.csv()” function. In this case name the **R** dataframe “**activity**”, the same name as the input filename. Finally, the initial struture of the **R** dataframe is shown with the R `str()` function:

```
#### Set directory to the local GitHub project of this assignment.
setwd("~/GitHub/RepData_PeerAssessment1")

activity <- read.csv("activity.csv",
                     na.strings = "NA", stringsAsFactors = FALSE )

str(activity)
```

```
## 'data.frame':   17568 obs. of  3 variables:
## $ steps      : int   NA NA NA NA NA NA NA NA NA NA NA ...
## $ date       : chr   "2012-10-01" "2012-10-01" "2012-10-01" "2012-10-01" ...
## $ interval   : int    0  5 10 15 20 25 30 35 40 45 ...
```

As expected, for 61 days, the “**activity**” data frame has **17,568 observations**. The “**activity**” data frame has three variables: “**steps**”, “**date**” and “**interval**”. The initial values for the “**steps**” variable are missing and are marked as “NA”. The “**date**” variable is a character string we will want to convert to an **R** date type using the **R** “`as.Date()`” function. The “**interval**” variable is an integer that initially appears to be incremented by 5 for each observation, this first impression will be modified on closer observation.

So, let’s convert “**date**” to an R date type and take a closer look at “**steps**” and “**interval**”. We want to know if all of the “**steps**” are missing? or if not all are missing, how many are missing? and what percentage of the dataset is that? For the “**interval**” variable, we want to know how often the pattern restarts at zero (or does it increase all the way through the data set?). We will print 289 observations of “**interval**”, one more than the 288 observations per day.

```
activity$date <- as.Date(activity$date) # coerce "date" to date data type
sum(is.na(activity$steps))             # How many missing values?
```

```
## [1] 2304
```

```
mean(is.na(activity$steps))           # What percent are missing values?
```

```
## [1] 0.1311475
```

Over 2,300 observations of the “**steps**” variable are missing, while this is a lot; it is still only 13.1% of the 17,568 observations. So, for our initial analysis, we can simply ignore the missing values, by removing them and only work with complete cases. Later, we can try to guess (technically, “impute”) the missing values in a process called “imputation” and see whether that changes the analysis. Not shown, but there are no missing values for “**date**” and “**interval**”.

As for “**interval**”, What does a full daily cycle look like?

```
head(activity$interval, 289)         # What does a full daily cycle look like?
```

```
## [1] 0 5 10 15 20 25 30 35 40 45 50 55 100 105
## [15] 110 115 120 125 130 135 140 145 150 155 200 205 210 215
## [29] 220 225 230 235 240 245 250 255 300 305 310 315 320 325
## [43] 330 335 340 345 350 355 400 405 410 415 420 425 430 435
## [57] 440 445 450 455 500 505 510 515 520 525 530 535 540 545
## [71] 550 555 600 605 610 615 620 625 630 635 640 645 650 655
## [85] 700 705 710 715 720 725 730 735 740 745 750 755 800 805
## [99] 810 815 820 825 830 835 840 845 850 855 900 905 910 915
## [113] 920 925 930 935 940 945 950 955 1000 1005 1010 1015 1020 1025
## [127] 1030 1035 1040 1045 1050 1055 1100 1105 1110 1115 1120 1125 1130 1135
## [141] 1140 1145 1150 1155 1200 1205 1210 1215 1220 1225 1230 1235 1240 1245
## [155] 1250 1255 1300 1305 1310 1315 1320 1325 1330 1335 1340 1345 1350 1355
## [169] 1400 1405 1410 1415 1420 1425 1430 1435 1440 1445 1450 1455 1500 1505
## [183] 1510 1515 1520 1525 1530 1535 1540 1545 1550 1555 1600 1605 1610 1615
## [197] 1620 1625 1630 1635 1640 1645 1650 1655 1700 1705 1710 1715 1720 1725
## [211] 1730 1735 1740 1745 1750 1755 1800 1805 1810 1815 1820 1825 1830 1835
## [225] 1840 1845 1850 1855 1900 1905 1910 1915 1920 1925 1930 1935 1940 1945
## [239] 1950 1955 2000 2005 2010 2015 2020 2025 2030 2035 2040 2045 2050 2055
## [253] 2100 2105 2110 2115 2120 2125 2130 2135 2140 2145 2150 2155 2200 2205
## [267] 2210 2215 2220 2225 2230 2235 2240 2245 2250 2255 2300 2305 2310 2315
## [281] 2320 2325 2330 2335 2340 2345 2350 2355 0
```

The “**interval**” variable does not make sense as an integer.

Although, the “**interval**” variable does reset to zero at observation 289, as expected (recall there are 288 observations per 24 hour day); the 288th observation is 2,355 rather than the 1,435 one would expect if one multiplied the intervals 0 (zero) through 287 by 5 ($1,435 = 287 \times 5$). That is a big gap between 2,355 and 1,435 so something different is going on.

If we examine the first dozen observations we see the “**interval**” variable jumps from 55 to 100. It is 100 when it should be 60. But, wait, if the “1” in “100” represents “one hour” and the “23” in “2355” represents “23 hours” then it is clear that the “**interval**” variable is actually hours and minutes with the leading zeros removed. That is, “100” should be understood as “01:00” and “2355” should be understood as “23:55” and so on.

We can fix the integer representation by using the R “**sprintf()**” function to restore the leading zeros to the time and store the result in a variable named “**HHMM**” which in turn, can be combined with the date to build a POSIX standard date time string in a variable named, “**datetime**”.

```

# Convert the interval to HHMM by formatting with leading zero
activity$HHMM <- sprintf("%04d", as.integer(activity$interval))
# Now we can combine date and time as a string
# and format the resulting string as a POSIX datetime string
datetimestring <- paste(activity$date, activity$HHMM)
activity$datetime <- strptime(datetimestring,
                              "%Y-%m-%d %H%M", tz = "")

# Use the weekday() function to interrogate the POSIX datetime string
# to obtain a day of week abbreviation ("Sun", "Mon", "Tue", etc) for each date
activity$dayofweek <- weekdays(activity$datetime, abbreviate=TRUE)

# Create a weekday/weekend factor by first assigning all data to "weekday"
# and then check for "Sat" or "Sun" and reassign to "weekend".
activity$daytype = "weekday"
activity$daytype[activity$dayofweek == "Sat" | activity$dayofweek == "Sun"] <- "weekend"

# Convert to R "factor" data type
activity$dayofweek = factor(activity$dayofweek)
activity$daytype = factor(activity$daytype)

```

With these changes, the “**activity**” data set is ready for the first stage of our analysis where we simply ignore (remove) the missing values. But, for cosmetic reasons, we might want to reorder the “**activity**” data frame variables in a more logical order:

```

activity <- subset( activity, select = c(datetime, date, dayofweek, daytype, HHMM, interval, steps))
str(activity)

```

```

## 'data.frame':   17568 obs. of  7 variables:
## $ datetime : POSIXlt, format: "2012-10-01 00:00:00" "2012-10-01 00:05:00" ...
## $ date      : Date, format: "2012-10-01" "2012-10-01" ...
## $ dayofweek : Factor w/ 7 levels "Fri","Mon","Sat",...: 2 2 2 2 2 2 2 2 2 ...
## $ daytype   : Factor w/ 2 levels "weekday","weekend": 1 1 1 1 1 1 1 1 1 ...
## $ HHMM      : chr "0000" "0005" "0010" "0015" ...
## $ interval  : int  0 5 10 15 20 25 30 35 40 45 ...
## $ steps     : int  NA NA NA NA NA NA NA NA NA NA ...

```

What is mean total number of steps taken per day?

If we sum the steps for all of the intervals for a given date, we have a daily total. This use of the **R** `aggregate()` function follows an example in Jared Lander’s book “*R for Everyone*” page 121 where he uses the “**diamonds**” data frame which comes with the **ggplot2** package.

Once we have a daily total for each of the days; we can calculate a value for the average (mean) and median by removing the NAs, that would otherwise cause an NA result. We round the steps to zero because users expect a whole number of steps and we already have five significant digits of precision.

```

PerDay <- aggregate(steps ~ date, data=activity, sum)
meanstepsperday <- round(mean(PerDay$steps, na.rm = TRUE), digits = 0)
meanstepsperday

```

```
## [1] 10766
```

```
medianstepsperday <- median(PerDay$steps, na.rm = TRUE)
medianstepsperday
```

```
## [1] 10765
```

The **average (mean) number of steps per day** is **10,766** ; and the **median number of steps per day** is very close at **10,765**.

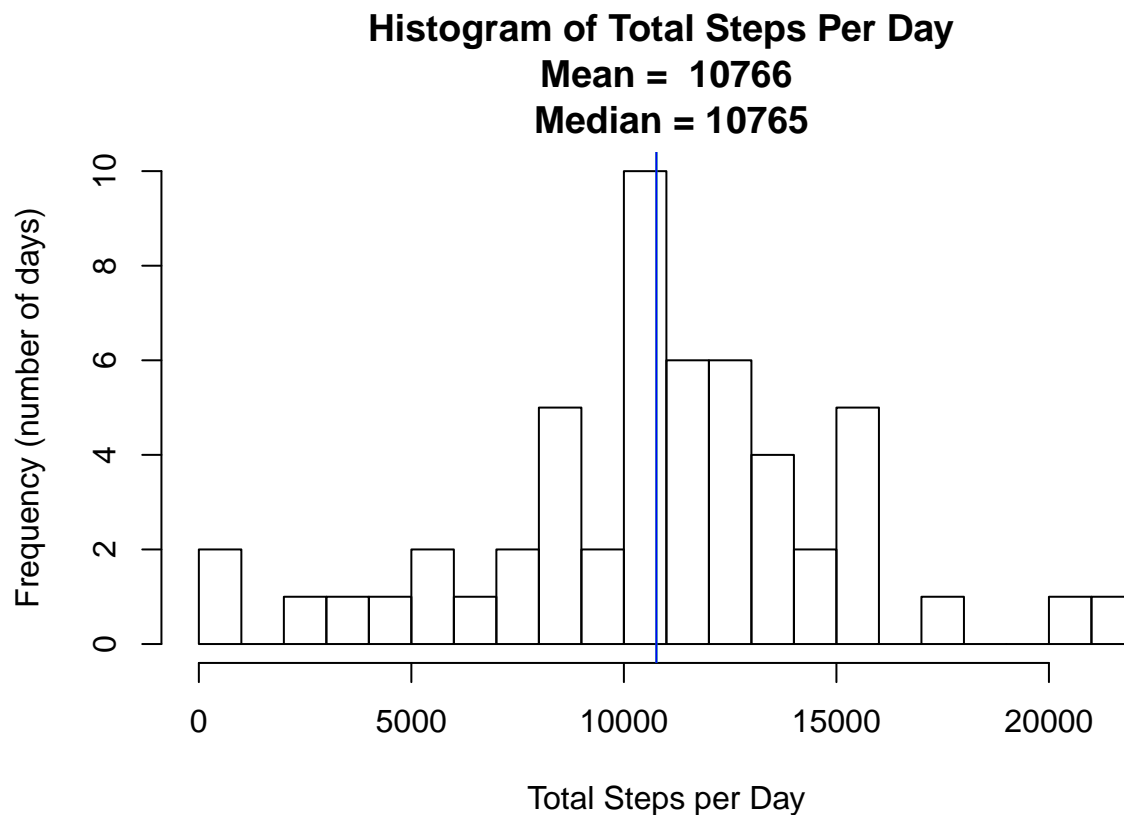
What is the average daily activity pattern?

As a “sanity check”, the 10,000+ average steps per day seems plausible for an active person with a 10,000 steps a day goal, which seems to be a popular goal:

“The origins of the 10,000-steps recommendation aren’t exactly scientific. Pedometers sold in Japan in the 1960s were marketed under the name “manpo-kei,” which translates to “10,000 steps meter” ... studies conducted since then suggest that people who increased their walking to 10,000 steps daily experience health benefits.”

Rachael Rettner, “*The Truth About ‘10,000 Steps’ a Day*” LiveScience.org, March 2014
retrieved from **LiveScience.org** during September 2015

<http://www.livescience.com/43956-walking-10000-steps-healthy.html>



While a central value (mean or median) near 10,000 seems plausible for an active person with a 10,000 steps per day goal; the extremes of near zero steps per day and a maximum over 20,000 steps per day may require further inquiry. For example, did the person spend a sick day in bed (with near zero steps)? and did the

person participate in a 10,000 step walk in addition to their normal 10,000 steps (resulting in over 20,000 steps per day)?

What interval contains the maximum number of steps? and how does the number of steps vary over the course of an average day?

```
# Calculate steps per five minute interval
# (in 24 hour cycle)
PerIntervalMean <- aggregate(steps ~ factor(HHMM), activity, mean)
PerIntervalMedian <- aggregate(steps ~ factor(HHMM), activity, median)
ColumnNames <- c("HHMM", "steps")
# colnames(PerIntervalSum) <- ColumnNames
colnames(PerIntervalMean) <- ColumnNames
colnames(PerIntervalMedian) <- ColumnNames

PerIntervalMean$timeofday <- strptime(PerIntervalMean$HHMM, "%H%M", tz = "")
PerIntervalMedian$timeofday <- strptime(PerIntervalMedian$HHMM, "%H%M", tz = "")

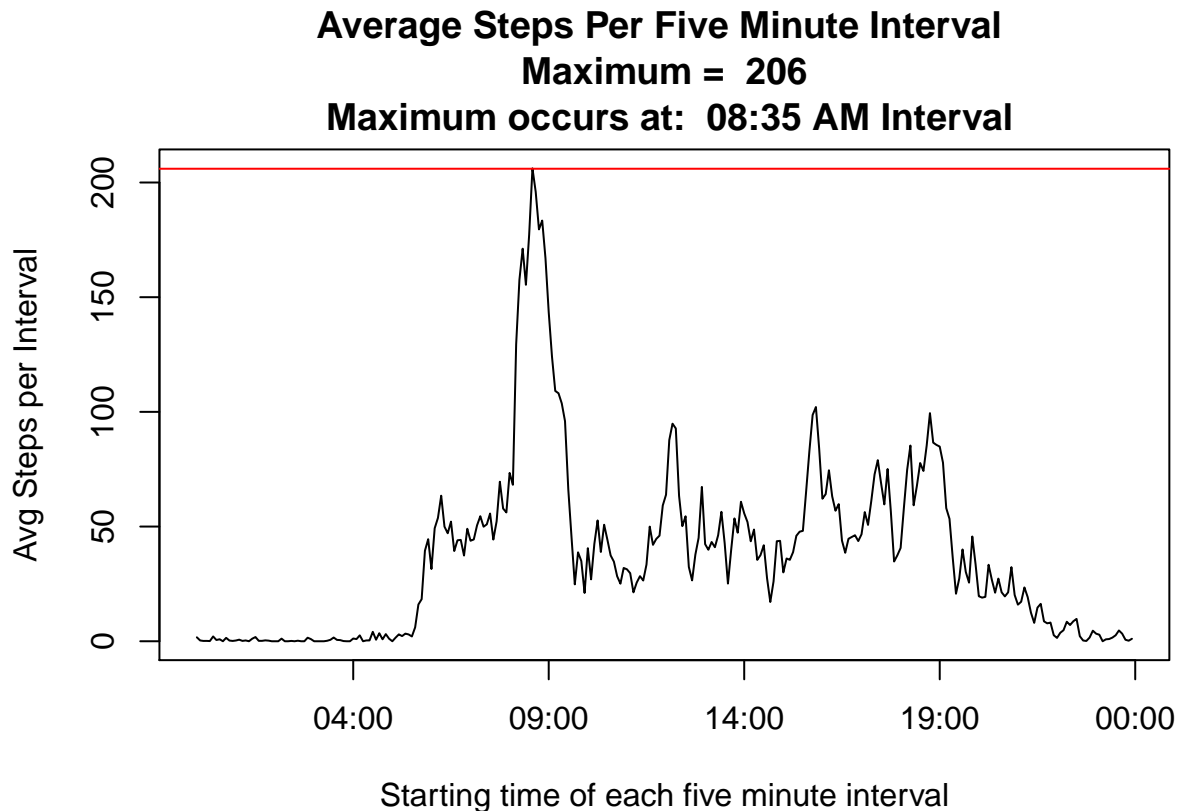
Max5MinuteSteps <- PerIntervalMean[PerIntervalMean$steps == max(PerIntervalMean$steps), ]
Max5MinuteSteps

##      HHMM      steps      timeofday
## 104 0835 206.1698 2015-09-20 08:35:00
```

The interval beginning at 8:35 AM on average has the most steps with 206 steps.

```
plot(PerIntervalMean$timeofday, PerIntervalMean$steps, type = "l",
     xlab = "Starting time of each five minute interval",
     ylab = "Avg Steps per Interval",
     main = paste("Average Steps Per Five Minute Interval",
                  "\n Maximum = ", round(max(PerIntervalMean$steps), digits=0),
                  "\n Maximum occurs at: ", format(Max5MinuteSteps$timeofday, "%H:%M AM"),
                  "Interval"
     )
)

abline(h = round(max(PerIntervalMean$steps), digits=0), col = "red")
```



The number of steps in the graph could be interpreted as the person sleeps between midnight and 5 AM, gets up around 5 or 6 AM and commutes to work by 9 AM, has a lunch hour and returns home between 5 PM and 7 PM. Such a pattern would be consistent with the peaks, but is conjecture and the reality may be different.

Imputing missing values

So far, we have ignored (omitted) the missing values, and as noted earlier, over 2,300 observations of the “steps” variable are missing, while this is a lot; it is still only 13.1% of the 17,568 observations.

```
sum(is.na(activity$steps))      # How many missing values?
```

```
## [1] 2304
```

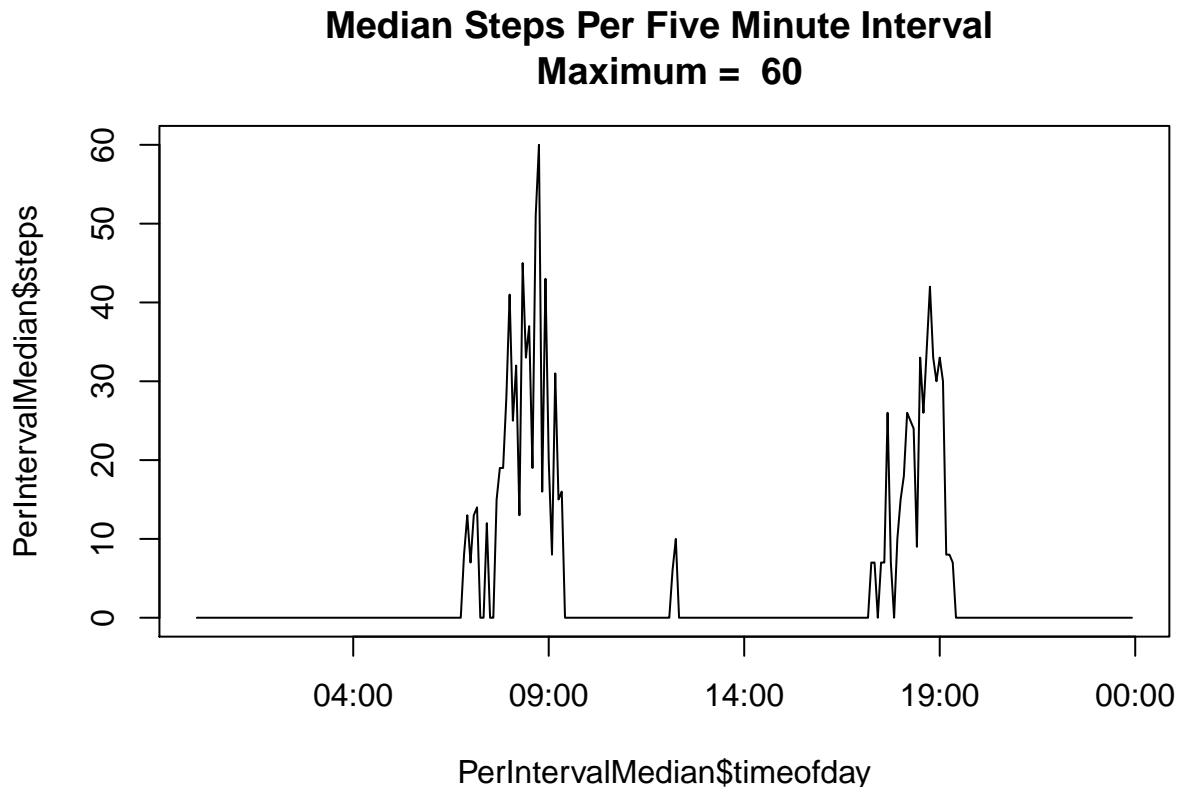
```
mean(is.na(activity$steps))     # What percent missing values?
```

```
## [1] 0.1311475
```

There seems to be a regular pattern for time of day, but we still have to decided whether we should impute with 5 minute interval **averages** or **medians**.

We have already made a graph of the **five minute means (averages)**, and for comparison here is a graph of **median steps per five minutes**, it peaks at 60 steps and often takes on a zero value.

```
plot(PerIntervalMedian$timeofday, PerIntervalMedian$steps, type = "l",
     main = paste("Median Steps Per Five Minute Interval",
                  "\n Maximum = " , round(max(PerIntervalMedian$steps), digits=0)
     )
)
```



Overall, the median graph shows a much sharper, commute to work, lunch hour and return from work and sleep pattern. It is much less noisy and extreme. So, let's use the “steps” variable in the “PerIntervalMedian” data frame to create a variable we can use to **impute (fill-in) the missing values** of the “steps” variable in the “activity” data frame. We need to expand the “PerIntervalMedian” version of “steps” from just one day to all **61 days** (17,568 observations). We can do this in **R** by repeating the variable **61 times** using the **R rep()** function:

```
# Expand PerIntervalMedian from one day to 61 days by repeating the daily values
activity$fill1 <- rep(PerIntervalMedian$steps, 61)
str(activity$fill1)
```

```
## int [1:17568] 0 0 0 0 0 0 0 0 0 0 ...
```

We now have a prediction variable “fill” that we can use to “fill-in” (replace) the missing values (NA) of the “steps” variable.

The strategy for replacement is to “zero-out” the unwanted values in “steps” and “fill” using **R**’s subsetting (square brackets) and the is.na() function. This way we can zero out the NA’s in a copy of “steps” (we

want to get rid of) and zero out the opposite values in a copy of “fill” that correspond to non-NA values in “steps” (we want to keep). Once we have the zeros in the correct places we can simply add the variables together into a third variable.

```
# Keep the non-NA values; zero-out the NA observations.
stepsNA2Zero <- activity$steps
stepsNA2Zero[is.na(activity$steps)] <- 0

# Keep the values needed to fill NAs; but zero-out the others.
# NOTE: this subset is for "not-NA"
filltheNAs <- activity$fill
filltheNAs[!is.na(activity$steps)] <- 0

# Now we can add the values
activity$stepsNoNA <- stepsNA2Zero + filltheNAs
activity$stepsNoNA <- round(activity$stepsNoNA, digits = 0)
```

We confirm our NA fill worked, and the number of NAs in “activity\$stepsNoNA” is zero.

```
sum(is.na(activity$stepsNoNA)) # How many missing values in "NoNA" version?
```

```
## [1] 0
```

Are there differences in activity patterns between weekdays and weekends?

Using our newly filled in “stepsNoNA” variable we can look to see if there is any difference between weekdays and weekends.

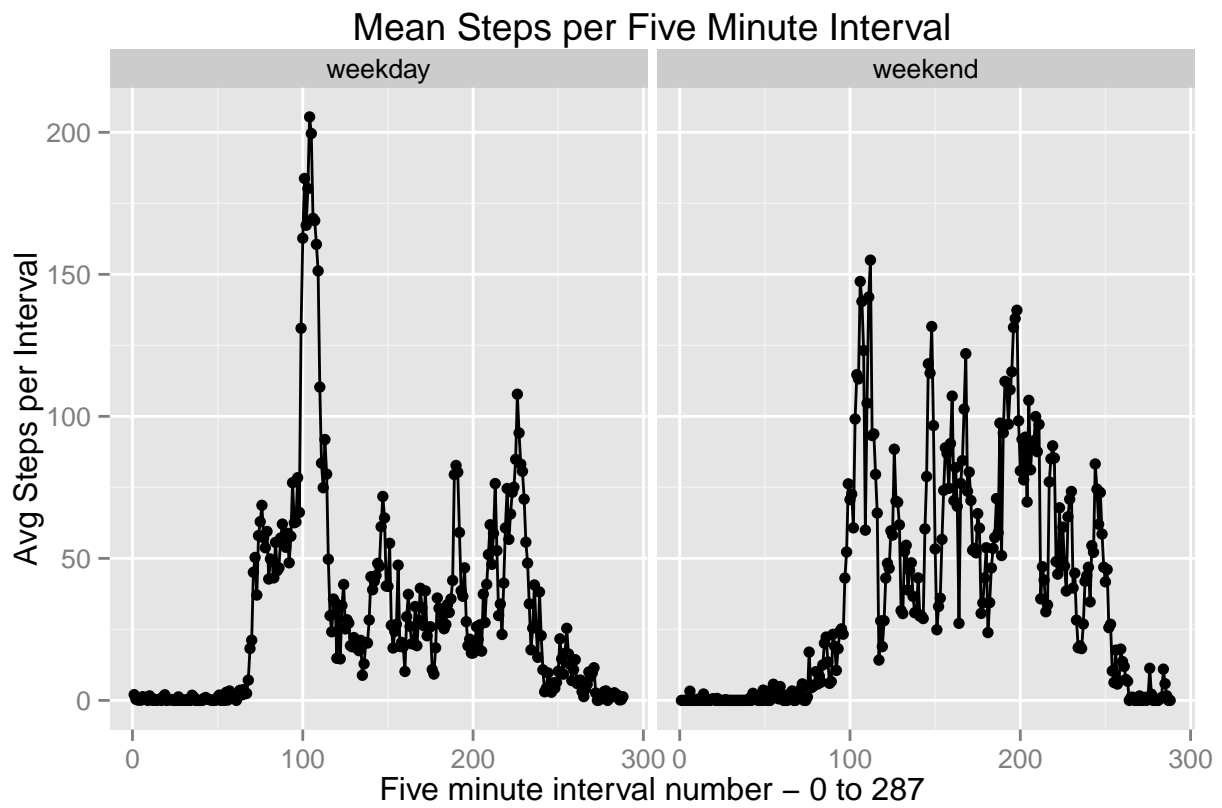
```
ColumnNames <- c("HHMM", "daytype", "stepsNoNA")
DayTypePerIntervalMean <- aggregate(stepsNoNA ~ factor(HHMM)+daytype, data=activity, mean)
colnames(DayTypePerIntervalMean) <- ColumnNames
DayTypePerIntervalMean$timeofday <- strptime(DayTypePerIntervalMean$HHMM, "%H%M", tz = "")
DayTypePerIntervalMean$interval <- as.integer(DayTypePerIntervalMean$HHMM)

WeekdayPerIntervalMean <- DayTypePerIntervalMean[DayTypePerIntervalMean$daytype == "weekday", ]
WeekendPerIntervalMean <- DayTypePerIntervalMean[DayTypePerIntervalMean$daytype == "weekend", ]

require(ggplot2)
```

```
## Loading required package: ggplot2
```

```
# use facets to display type.
# HONOR CODE: "R Graphics Cookbook" by Winston Chang page 163 and 208
par(mar = c(4, 4, 4, 1) )
line2 <- qplot( data = DayTypePerIntervalMean, x = interval, y = stepsNoNA) +
  geom_line() + facet_grid(. ~daytype) +
  ggtitle("Mean Steps per Five Minute Interval") +
  xlab("Five minute interval number - 0 to 287") +
  ylab("Avg Steps per Interval")
line2
```

The weekend has activity throughout the day and is less peaked at typical commuter hours.