Assignment R Bootcamp

Tu Tran and Andy Gubser

/today

Contents

Clarify question

get data: d1 <- read_csv(relative path)

data prep: saveRDS(d1, "file.RDS")

data visualisation: set.seed(19)

fit models

interpretation

Abstract

Purpose / Research question

The purpose of this project is to analyse the hourly demand of using bike sharing in New York City in 2016. In particular, we would like to explore the provided bike sharing, weather data and then create different models to predict the hourly demand for sharing bikes. These models will be compared to find one best model with a least prediction error rate.

Methodology

The analysis bases on the bike sharing data sets for New York City in 2016 from Kaggle [^1 https://www.kaggle.com/samratp/bikeshare-analysis#NYC-CitiBike-2016.csv]. The weather data is retrieved from the Weather.com API [^2 https://api.weather.com/v1/location/KLGA:9:US/observations/historical.json]. After the data preparation step, we provide an graphical analysis to approach the research question on the usage of shared bikes. Then, we fit a poisson model, high level polynomial linear model followed by a random forest model to deepen our analysis.

Analysis

R and knitr Setup

```
# remove all objects loaded and clear memory
rm(list = ls(all.names = TRUE))
gc()
```

```
##           used (Mb) gc trigger (Mb) max used (Mb)
## Ncells  532917 28.5    1211954 64.8   621331 33.2
## Vcells 1005622  7.7    8388608 64.0  1600107 12.3
```

```r
library(checkpoint)
```

```
##
## checkpoint: Part of the Reproducible R Toolkit from Microsoft
## https://mran.microsoft.com/documents/rro/reproducibility/
```

```r
#checkpoint(snapshotDate = "2099-12-29")

knitr::opts_knit$set(root.dir = rprojroot::find_rstudio_root_file())
knitr::opts_chunk$set(echo=TRUE)
set.seed(19)
```

Library Import

User Defined Functions and Constants

```r
## user defined functions and constants ##

## holidays in New York City in 2016
public_holidays <- c("2016-01-01", "2016-01-18", "2016-02-12", "2016-02-15",
                     "2016-05-30", "2016-07-04", "2016-09-05", "2016-10-10",
                     "2016-11-11", "2016-11-24", "2016-12-26")

## plot bike rental count over 24 hours for different category groups
## @param d.data: expects properties: category, hour, rental
## @param title: the title of the plot
## @param category_name: the category group name used as the legend's name in the plot
show_24h_category_statistics_plot <- function (d.data, title, category_name) {
  ggplot(d.data, aes(x=hour, y=rental, color=category)) +
    geom_point(data=d.data, aes(group=category)) +
    geom_line(data=d.data, aes(group=category)) +
    ggtitle(title) + ylab("rentals / hour") +
    scale_color_hue(category_name, breaks=levels(d.data$category))
}
```

Process bike sharing data

The bike data set consists of 276'798 observation and 15 variables. These variables include the two categories user type and gender as well as the numeric birth year. User type defines if the user is a registered subscriber of the bike sharing service or a casual user. Gender says if the user is female, male or unknown. The continous variable age is calculated from the birth year. Further, the categorical variable age_cor is created, where users over 70 are put into a single bin in order to reduce potential bias of these observations. Further, the data set include start and stop time stamps as well as trip duration of individual trips, station names, ids and its coordinates. By checking for outliers, one observation was detected to have meaningless coordinates. These observations are excluded from further analysis. The prepared data set includes 242'746 observations and 21 variables.

Process weather data

The weather data set includes 366 observations and the 7 variables maximum, minimum and average temperature, precipitation, snow fall and snow depth on specific dates. In order to merge the two data sets on the date variable, this variable is created in the bike sharing data set by extracting the date from the start timestamps. The merged data set consists of 242'746 observations and 15 variables.

Read bike and weather dataset and merge for the analysis

```
## read bike and weather data sets
d.bike <- readRDS("./data/d.bike.rds")
d.weather <- readRDS("./data/d.weather.rds")

## merge both bike and weather data for analysis
d.total <- merge(d.bike, d.weather, all.x=TRUE)
# order by data and hour
d.total <- d.total[with(d.total, order(date, hour)),]
d.total$weekday <- factor(d.total$weekday,
                          levels = c("Montag", "Dienstag", "Mittwoch",
                                     "Donnerstag", "Freitag", "Samstag", "Sonntag"))
# reset row index to normal
rownames(d.total) <- NULL
```

Public holiday data analysis

```
## public holiday analysis ##

## rental statistics in weekdays
rentweekday <- d.total %>%
  group_by(weekday) %>%
  summarise(rental=round(sum(rental_count)/52),
            tripduration=round(sum(tripduration)/52)) %>% # 52 weeks of a year
  arrange(weekday)
rentweekday
```

```
## # A tibble: 7 x 3
##   weekday    rental tripduration
##   <fct>       <dbl>        <dbl>
## 1 Montag        756        10773
## 2 Dienstag      815        11250
## 3 Mittwoch      858        11892
## 4 Donnerstag    852        11769
## 5 Freitag       796        11086
## 6 Samstag       641        11132
## 7 Sonntag       603        10475
```

```
## rentals statistics in public holidays
rentholiday <- d.total %>%
  filter(as.character(date) %in% public_holidays) %>%
  group_by(date) %>%
  summarise(rental=sum(rental_count),
            tripduration=sum(tripduration)) %>%
  arrange(date)
rentholiday
```

```
## # A tibble: 11 x 3
##    date       rental tripduration
```

```
##     <date>      <int>        <dbl>
##   1 2016-01-01    205         3780
##   2 2016-01-18    249         2730
##   3 2016-02-12    321         3671
##   4 2016-02-15    117         1129
##   5 2016-05-30    600        10715
##   6 2016-07-04    689        13326
##   7 2016-09-05    910        15916
##   8 2016-10-10   1017        16348
##   9 2016-11-11    956        13598
##  10 2016-11-24    249         3641
##  11 2016-12-26    214         2520
```

```
## As we can see, the rental in public holidays are different among and the weekdays.
## Public holiday data can be used for the model fitting if we would like to predict
## for a different year.
## However, only data from 2016 are available for both the analysis and model testing.
## Droping the public holiday data would reduce the variance in the model.

## remove public holiday dataset
d.total <- filter(d.total, !as.character(date) %in% public_holidays)
```

No more data processing and wrangling, make a copy of the analysis data in a file

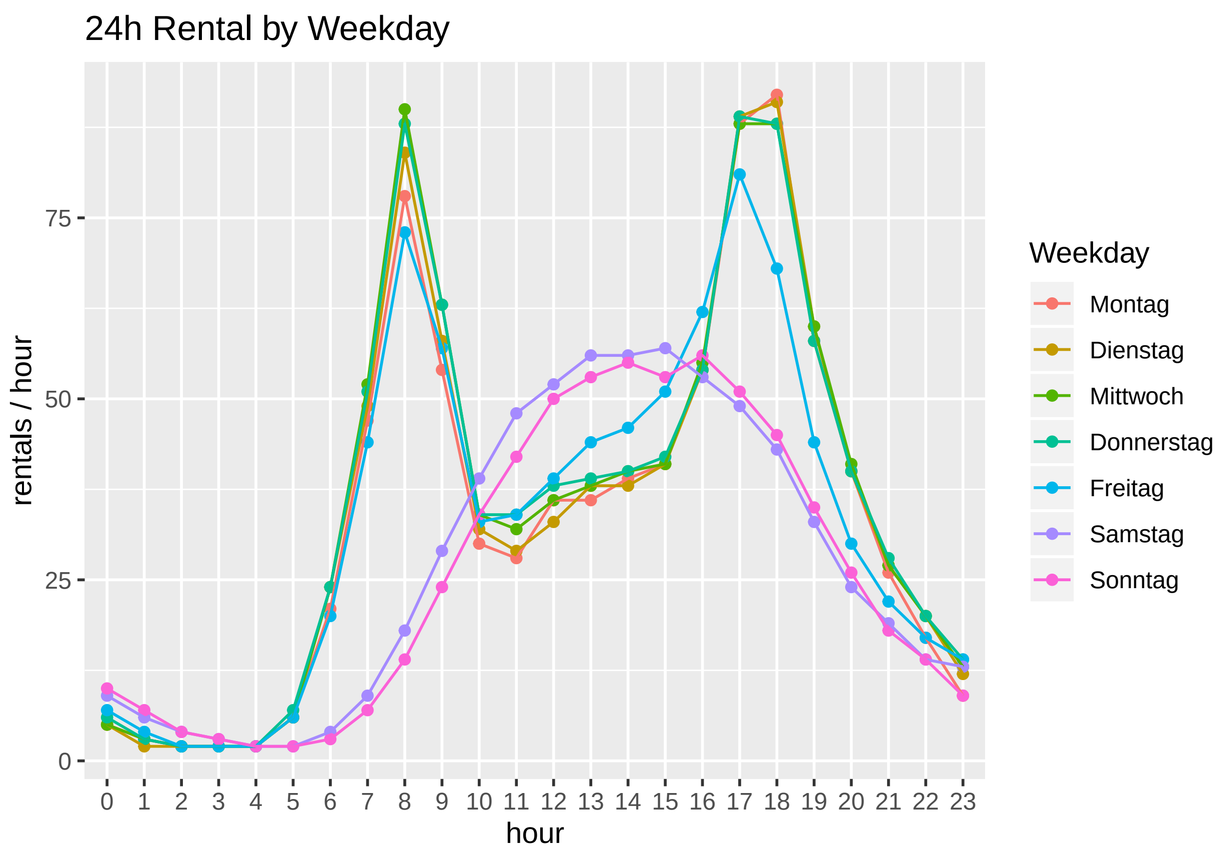
```
## save processed data to file
saveRDS(d.total, file = "./data/d.total.rds")
```

Exploratory Data Analysis, Graphical Analysis

ggplot rentals over 24h for different weekdays

The plot shows the usage pattern of shared bikes in New York City. It is clear that there are two different usage patterns for working days and weekend. In the working days, we can see two peaks at the rush hours. One is at about 8:00 AM when people go to work and another is between 5:00 PM and 6:00 PM when finish working and going home. In the weekend, people are more relaxing and may take longer sleep. The number of bikes goes slow up hill, reach its top at around 2:00 PM and get smoothly down hill to the end of the day. The least bike usage period are at round 1:00 AM to 5:00 AM, with its mininum at 4:00 AM.

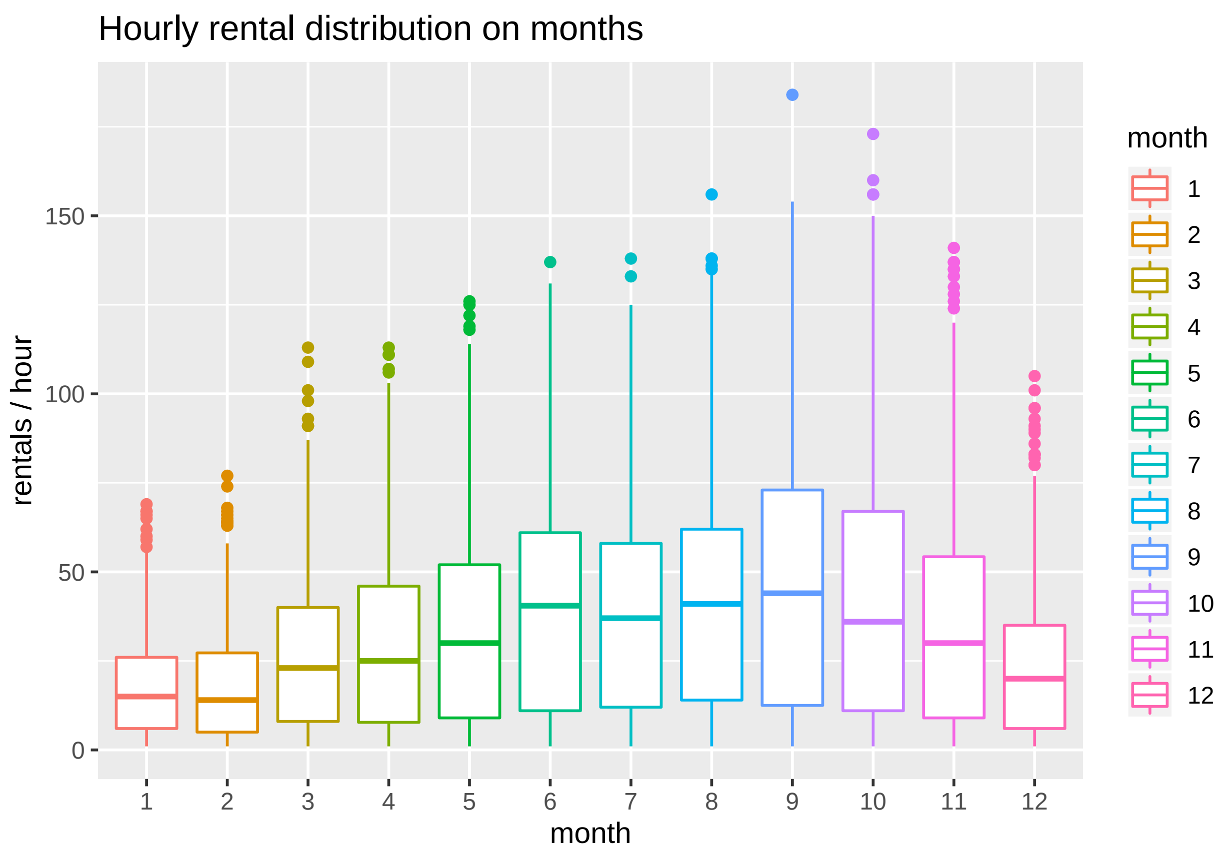
```
# ggplot 24h by weekday
d.weekday <- d.total %>% group_by(weekday, hour) %>%
  summarise(rental = round(mean(rental_count))) %>%
  rename(category = weekday)
show_24h_category_statistics_plot(d.weekday, "24h Rental by Weekday", "Weekday")
```



ggplot rentals over 24h for different months

As illustrated on the box plot, overall the rental low season is in winter and high season in autumn. The lowest months are January and February with a median rental per hour for only about 15. From March to Juni, there is an increasing trend in the rental. July witnesses a small drop, but then going upward to reach its peak in September. At its peak, the trend drops about 10% to 15% over months still January. The rental trend could possibly be explained with the temperature and klimate over the months. When it is colder, there are less rentals. When it is getting warmer, the trend increases. When it is much hotter, e.g. mid-sommer, there is a drop in trend. And people enjoy biking at cool and fair weather the most.

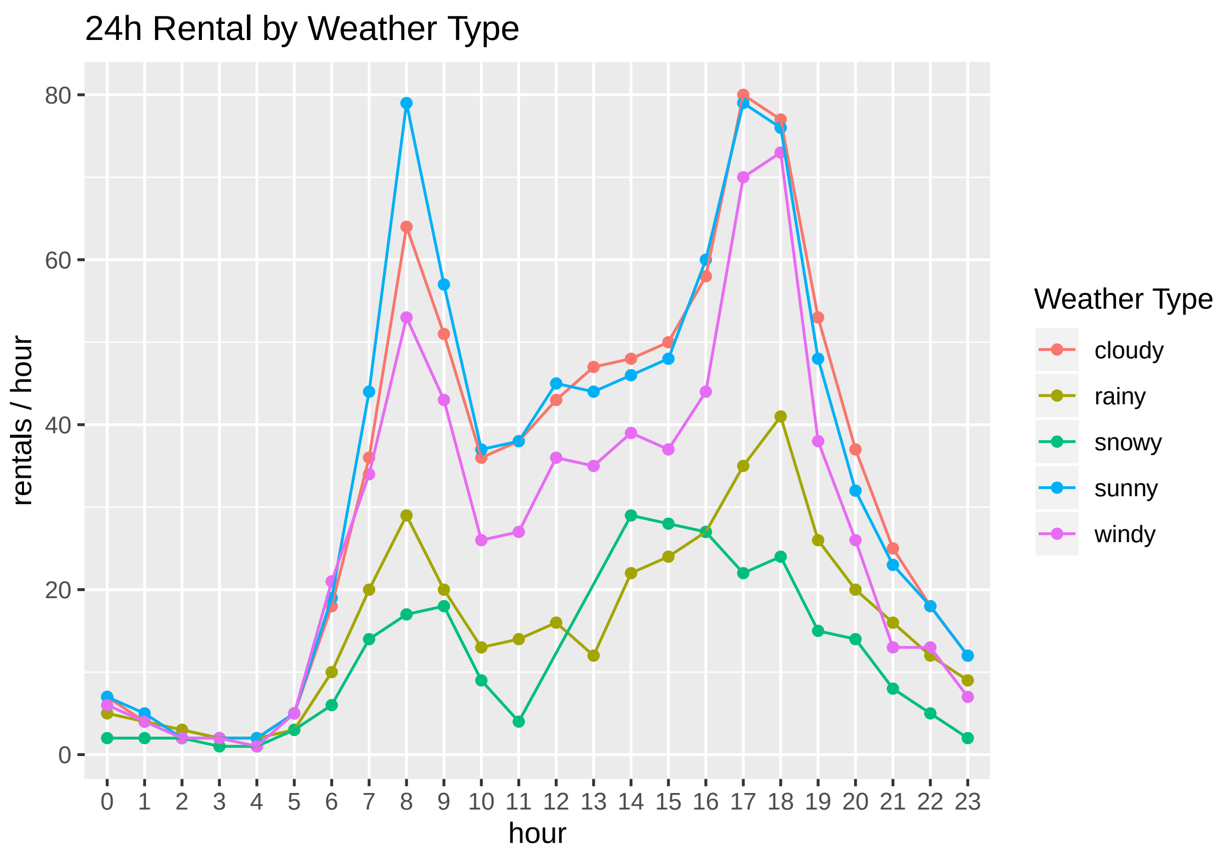
```
ggplot(d.total, aes(x=month, y=rental_count, color=month)) +
  geom_boxplot(data=d.total, aes(group=month)) +
  ggtitle("Hourly rental distribution on months") + ylab("rentals / hour")
```



ggplot rentals over 24h for different months

With this figure, we can see the highest demands on sunny and cloudy days with its peak at 80 rental at 5:00 PM. There is a drop about 10% to 20% in demand when it is windy. The need for bike is dramatically drop more than a half for rainy and snowy weather as compared to a sunny day. Here, we could easily recognize the usage pattern during rush hours as described in the first plot.

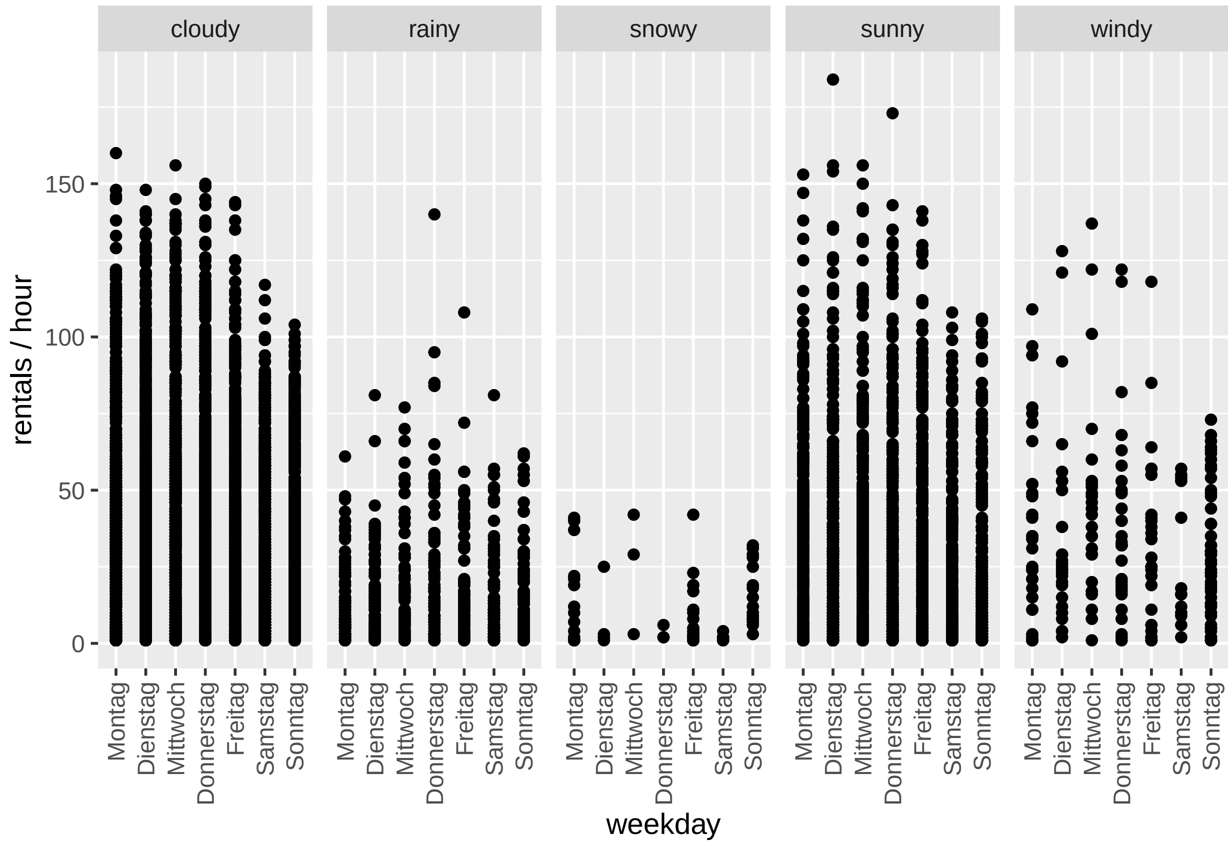
```
# ggplot 24h by weather types
d.wtype <- d.total %>% group_by(type, hour) %>%
  summarise(rental = round(mean(rental_count))) %>%
  rename(category = type)
show_24h_category_statistics_plot(d.wtype, "24h Rental by Weather Type", "Weather Type")
```



ggplot for the rental of the weekdays with an influence of the weather factor

In general, the usage pattern of the weekdays are stable, but then be strongly influenced and changed by the different weather conditions. The cloudy and sunny days has similar pattern. However, snowy, rainy and windy weather have strong impact and affect to change its usage pattern differently.

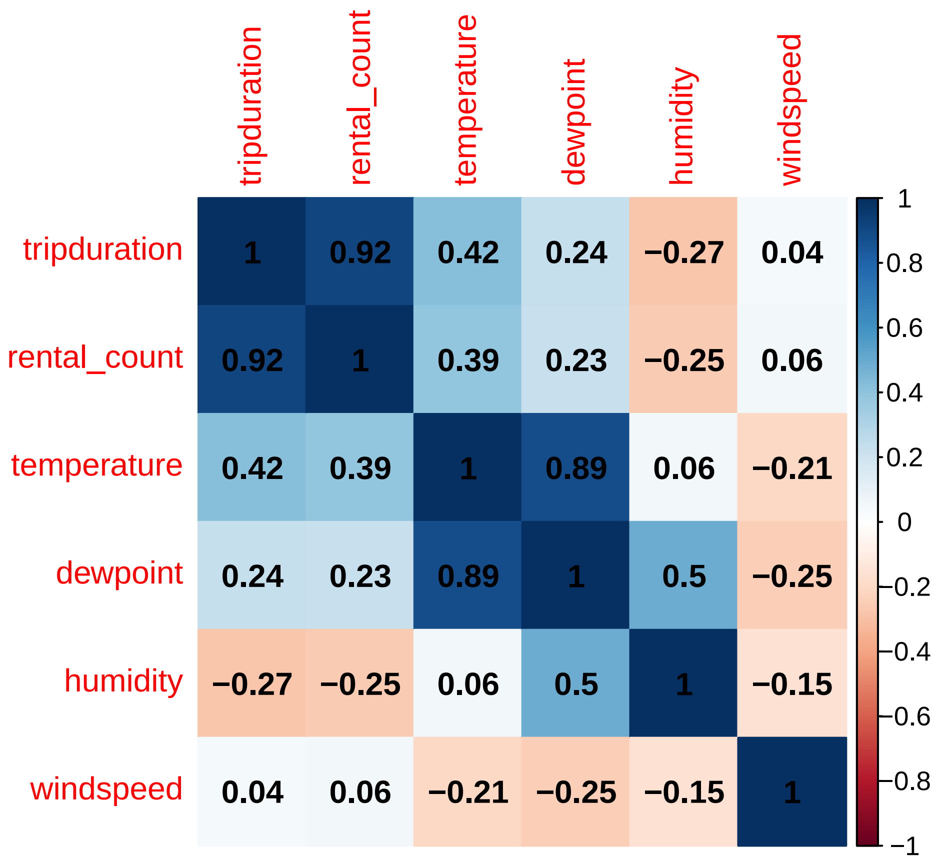
```
## the rental of the weekdays with an influence of the weather
ggplot(d.total, aes(x=weekday, y=rental_count)) +
  geom_point() +
  geom_smooth(method="lm") +
  ylab("rentals / hour") +
  facet_grid(. ~ type) +
  ggpubr::rotate_x_text()
```



ggplot heatmap for correlation analysis between numeric predictors

The below heatmap shows some strong correlation between several predictors. High correlations can be seen for the pairs of dew point and the temperature, the dew point and the humidity, tripduration and rental_count. Interestingly, there is a moderate correlation between temperature and tripduration, but not for temperature and rental count, even though, tripduration and rental_count are highly correlated. These information are used to decide which predictors will be considered for the model fitting. Predictors for a model should not have high correlation.

```
## correlation plot
d.total[,5:10] %>% cor() %>% corrplot(method = 'color', addCoef.col="black")
```



Fitting models

We would like to fit different models for predicting the hourly bike rental demand in New York City. In this section, we will apply different machine learning regression models on the data sets. Furthermore, we compare the performances of these different model based on the mean squared error and comment on the outcomes.

A simple Poisson model

As the amount of bike rental the prediction a count data, we will use the Poisson model for this task.

```
## split a train and a test set
set.seed(1)
d.split <- sample.split(d.total, SplitRatio = 0.7)
d.train <- subset(d.total, subset = d.split)
d.test <- subset(d.total, subset = !d.split)

# Poisson model with all possible predictors
pm.fit <- glm(rental_count ~ . - rental_count - tripduration - date,
              family="poisson", data=d.train)

#pm.err <- cv.glm(d.train, pm.fit, K=10)$delta[1]
#cat("10 K cross-validation error rate on Poisson model: ", pm.err)

# predict model on test data
pm.pred <- predict(pm.fit, newdata = d.test, type="response")
# compute MSE
```

```
pm.mse <- mean((d.test$rental_count - pm.pred)^2)
cat("Complex Poisson model MSE: ", pm.mse)
```

```
## Complex Poisson model MSE:  181.9057
```

Residual Analysis

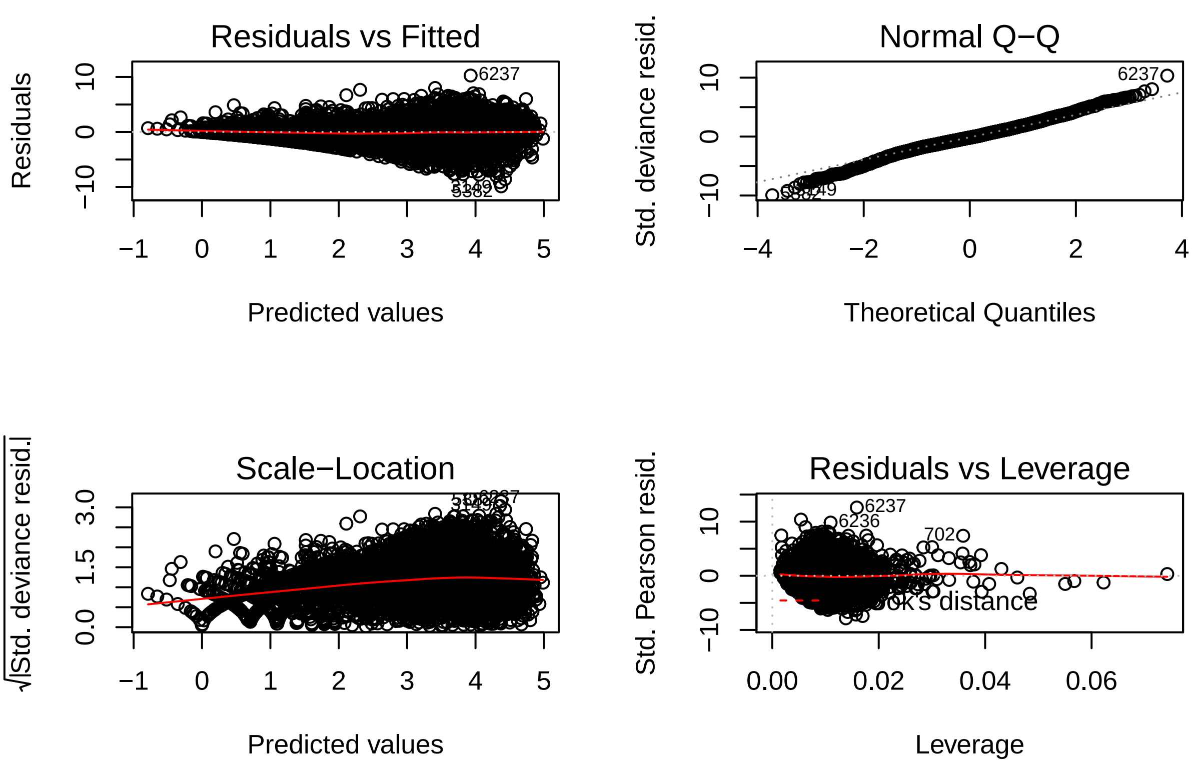
```
# residual
resid_values <- resid(pm.fit)
cat("Residual legnth: ", length(resid_values))
```

```
## Residual legnth:  5082
```

```
cat("Residual header: ", head(resid_values))
```

```
## Residual header:  -0.7866357 -0.8484774 0.603783 -0.8796609 2.460592 1.344774
```

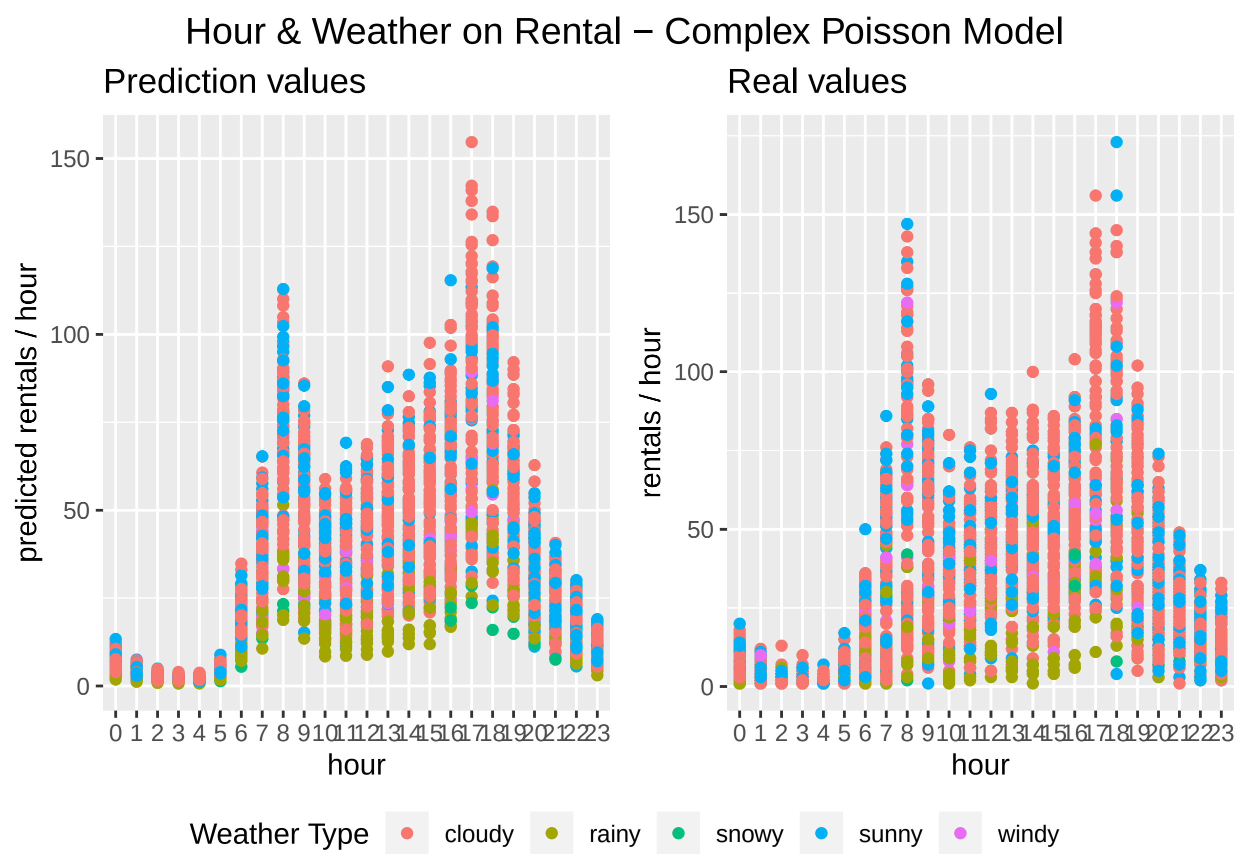
```
# residual analysis plots
par(mfrow=c(2,2))
plot(pm.fit)
```



Plotting predicted values with GGPlot

```
# ggplot predicted values of hourly rental for different weather types
p1 <- ggplot(d.test, aes(x=hour, y=pm.pred, color=type)) +
  geom_point(data=d.test, aes(group=type)) +
  ggtitle("Prediction values") + ylab("predicted rentals / hour") +
  scale_color_hue("Weather Type", breaks=levels(d.test$type))
```

```r
# ggplot true values of hourly rental for different weather types
p2 <- ggplot(d.test, aes(x=hour, y=rental_count, color=type)) +
  geom_point(data=d.test, aes(group=type)) +
  ggtitle("Real values") + ylab("rentals / hour") +
  scale_color_hue("Weather Type", breaks=levels(d.test$type))

figure <- ggarrange(p1, p2, ncol=2, common.legend = TRUE, legend="bottom")
annotate_figure(figure, top=text_grob("Hour & Weather on Rental - Complex Poisson Model",
                                      size = 14))
```

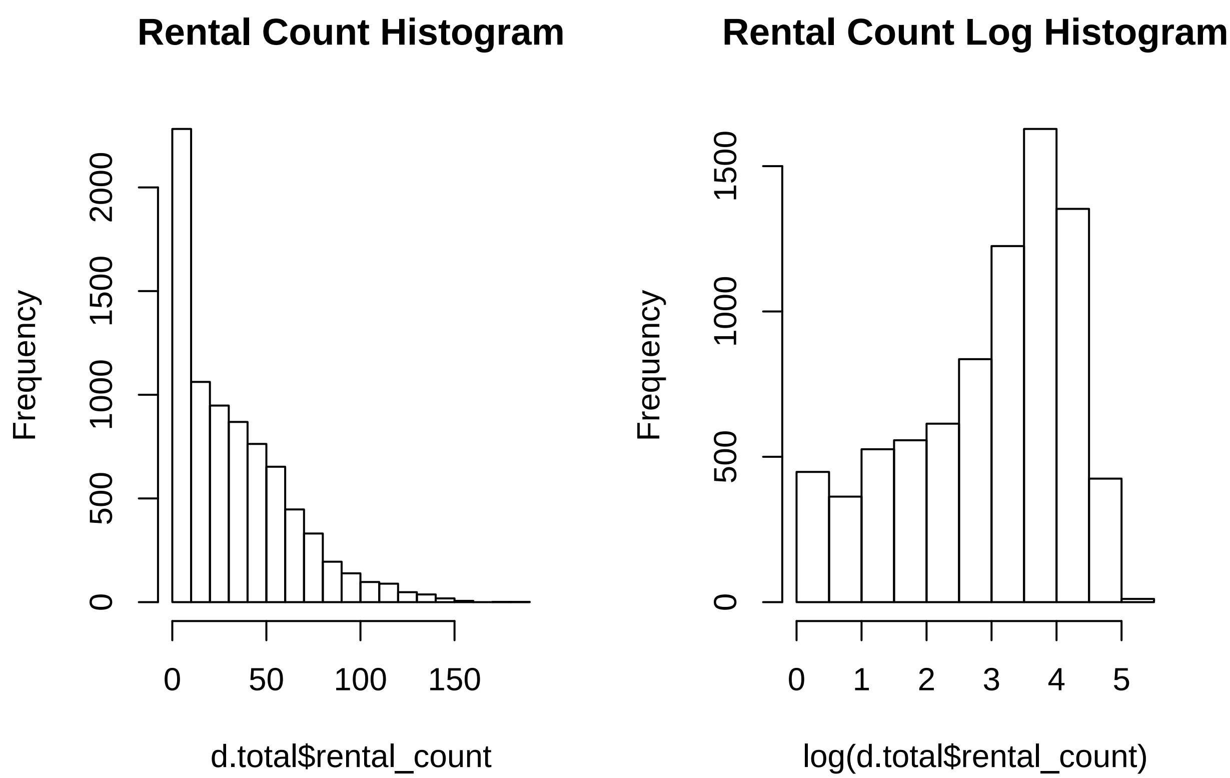


More complex model: Linear model with different polynomial levels

In this section, we apply cross validation in order to run a list of complex models with increasing polynomial levels of the temperature predictor. Besides, these models have many predictors and an interaction between humidity and dewpoint.

The histograms below show that the distribution of rental_count is not normal distribution. We have to use log transformation for fitting a linear model.

```r
## check normal distribution for linear model fitting
par(mfrow=c(1, 2))
hist(d.total$rental_count, main = "Rental Count Histogram")
hist(log(d.total$rental_count), main = "Rental Count Log Histogram")
```



Fitting the linear model

```
set.seed(1)

cv.error.10 <- rep(0, 10)
for (i in 1:10) {
  glm.fit <- glm(log(rental_count) ~ type + month + weekday + hour + humidity * dewpoint +
                   poly(windspeed, degree=i) + poly(temperature, degree=i), data=d.train)
  cv.error.10[i] <- cv.glm(d.train, glm.fit, K=10)$delta[1]
}

best.level <- which.min(cv.error.10)
cat("Index of model with least error rate: ", best.level)
```

```
## Index of model with least error rate:  4
```

```
cat("Cross validation error of 10 different polynominal linear models:\n", cv.error.10)
```

```
## Cross validation error of 10 different polynominal linear models:
##  0.3013236 0.2976461 0.2962701 0.294151 0.2954633 0.2966329 0.3022395 0.3036237 0.3408784 0.3650716
```

```
glm.fit.best <- glm(log(rental_count) ~ type + month + weekday + hour +
                      humidity * dewpoint +
                      poly(windspeed, degree = best.level) +
                      poly(temperature, degree = best.level),
                    data=d.train)

# predict model on test data
```

```r
glm.pred <- predict(glm.fit.best, newdata = d.test)
# convert log value to normal value via exponential
glm.pred <- exp(glm.pred)

# compute MSE
glm.mse <- mean((d.test$rental_count - glm.pred)^2)
cat("GLM polynomial model MSE: ", glm.mse)
```

```
## GLM polynomial model MSE:  199.2743
```

Residual Analysis

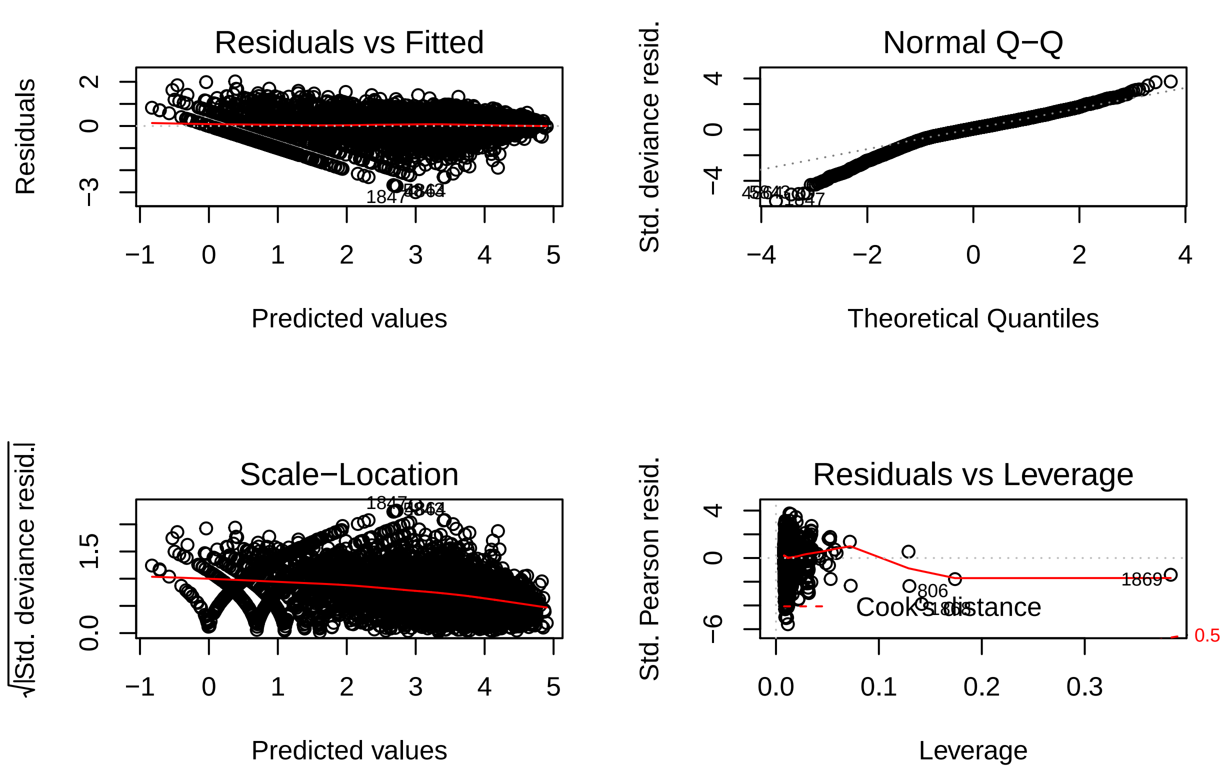
```r
# residual
resid_values <- resid(glm.fit.best)
cat("Residual length: ", length(resid_values))
```

```
## Residual length:  5082
```

```r
cat("Residual header: ", head(resid_values))
```

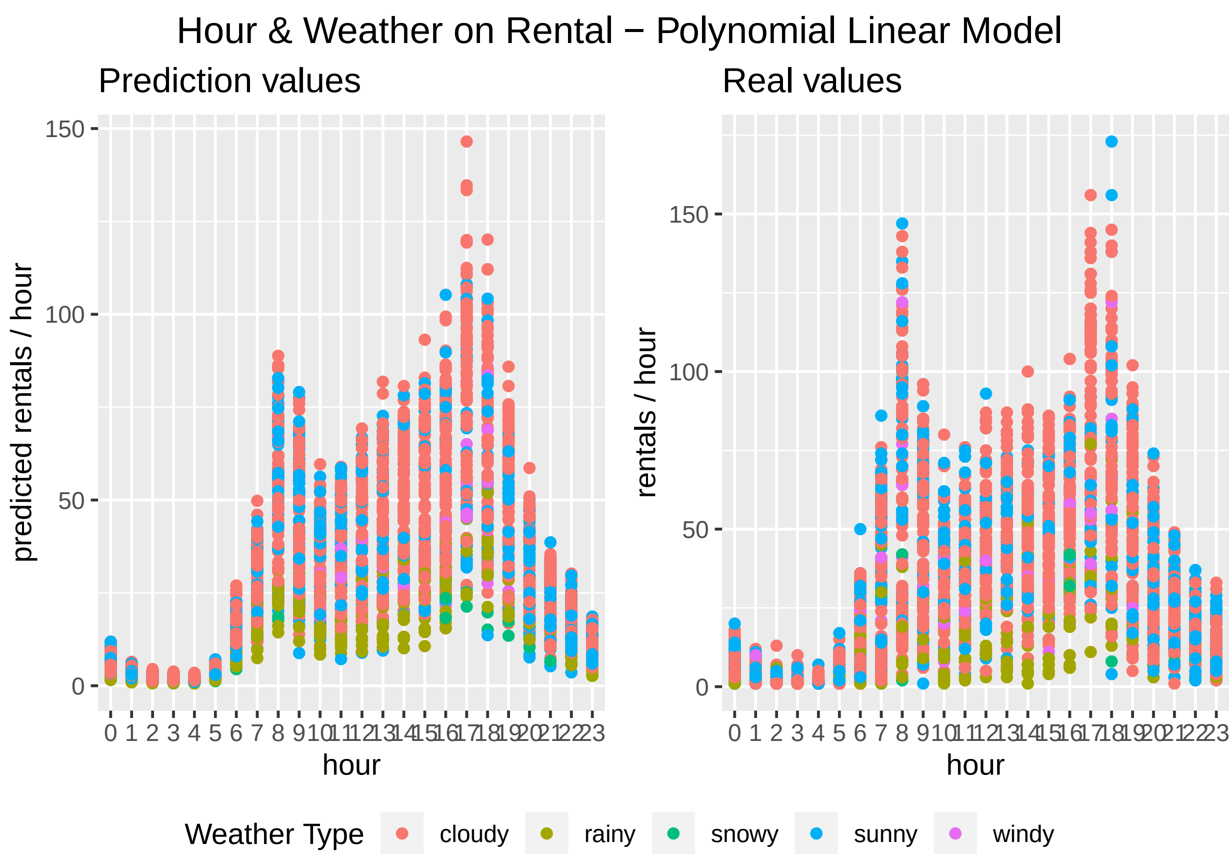
```
## Residual header:  -0.3650641 -0.5091433 0.5738417 -0.5843946 0.5253908 0.3276906
```

```r
# plot
par(mfrow=c(2,2))
plot(glm.fit.best)
```



Plotting predicted values with GGPlot

```r
# ggplot predicted values of hourly rental for different weather types
p1 <- ggplot(d.test, aes(x=hour, y=glm.pred, color=type)) +
  geom_point(data=d.test, aes(group=type)) +
  ggtitle("Prediction values") + ylab("predicted rentals / hour") +
  scale_color_hue("Weather Type", breaks=levels(d.test$type))

# ggplot true values of hourly rental for different weather types
p2 <- ggplot(d.test, aes(x=hour, y=rental_count, color=type)) +
  geom_point(data=d.test, aes(group=type)) +
  ggtitle("Real values") + ylab("rentals / hour") +
  scale_color_hue("Weather Type", breaks=levels(d.test$type))

figure <- ggarrange(p1, p2, ncol=2, common.legend = TRUE, legend="bottom")
annotate_figure(figure, top = text_grob("Hour & Weather on Rental - Polynomial Linear Model",
                                        size = 14))
```



Fitting with Regression Tree - Randomforest

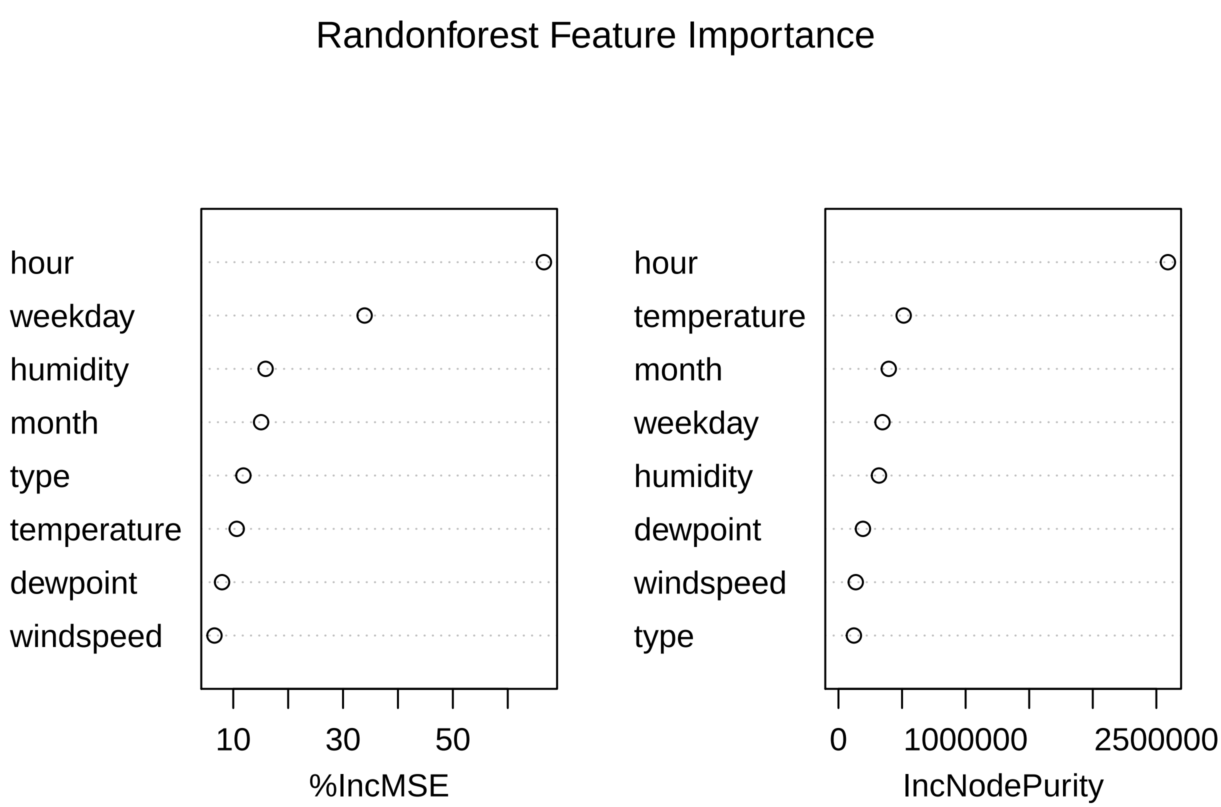
```r
set.seed(1)
rf.fit <- randomForest(rental_count ~ . - rental_count - tripduration - date,
                       data = d.train, mtry=3, ntree=50, importance=TRUE)
rf.pred <- predict(rf.fit, d.test)
rf.mse <- mean((rf.pred - d.test$rental_count)^2)
cat("Randomforest mode MSE: ", rf.mse)
```

```
## Randomforest mode MSE:  101.0408
```

```r
importance(rf.fit)
```

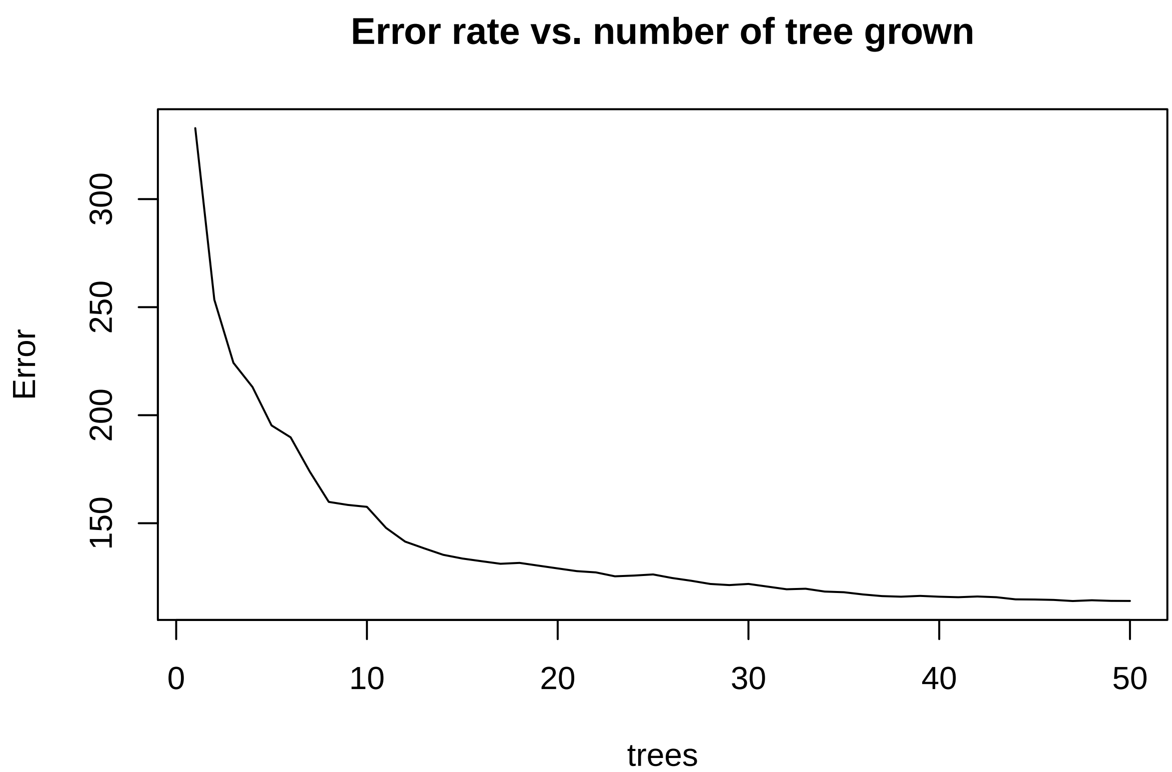
```
##               %IncMSE IncNodePurity
## hour        66.583721     2590888.8
## month       15.076734      395430.4
## weekday     33.926246      346111.6
## temperature 10.635035      512802.7
## dewpoint     7.960879      192456.9
## humidity    15.888705      318434.0
## windspeed    6.579759      135717.1
## type        11.851720      121317.7
```

```r
varImpPlot(rf.fit, main = "Randonforest Feature Importance")
```

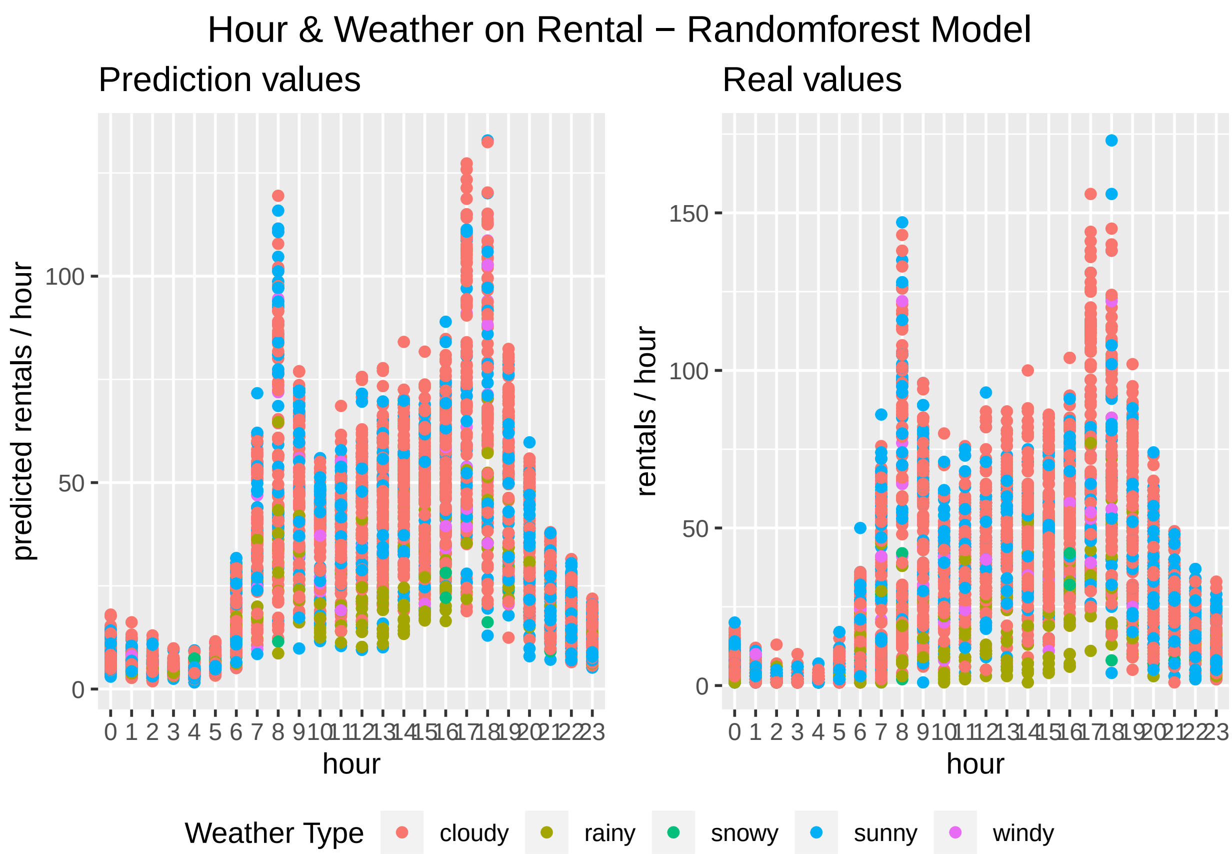



```r
# plot randomforest model fit
plot(rf.fit, main="Error rate vs. number of tree grown")

# ggplot predicted values of hourly rental for different weather types
p1 <- ggplot(d.test, aes(x=hour, y=rf.pred, color=type)) +
  geom_point(data=d.test, aes(group=type)) +
  ggtitle("Prediction values") + ylab("predicted rentals / hour") +
  scale_color_hue("Weather Type", breaks=levels(d.test$type))

# ggplot true values of hourly rental for different weather types
p2 <- ggplot(d.test, aes(x=hour, y=rental_count, color=type)) +
  geom_point(data=d.test, aes(group=type)) +
  ggtitle("Real values") + ylab("rentals / hour") +
```

```
  scale_color_hue("Weather Type", breaks=levels(d.test$type))

figure <- ggarrange(p1, p2, ncol=2, common.legend = TRUE, legend="bottom")
```




```
annotate_figure(figure, top = text_grob("Hour & Weather on Rental - Randomforest Model",
                                        size = 14))
```



A chapter of your choice: Regression Tree Randonforest

TODO:

Conclusion

```
cat("Poisson model MSE: ", pm.mse)
```

```
## Poisson model MSE:  181.9057
```

```
cat("Linear Polynomial model MSE: ", glm.mse)
```

```
## Linear Polynomial model MSE:  199.2743
```

```
cat("Randomforest model MSE: ", rf.mse)
```

```
## Randomforest model MSE:  101.0408
```