Team Presentation 2: Predicting NYC Taxi Fares

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Read in and inspect data:

Fread is fast and convenient way to read in large CSV files.

Data Source: https://www.kaggle.com/c/new-york-city-taxi-fare-prediction/data

```
set.seed(1)
NY_Train <- fread("train.csv", nrows = 3000000) #Read 3M rows of the trainig data
NY_Test <- read.csv("test.csv")
summary(NY_Train)</pre>
```

```
kev
                   fare_amount pickup_datetime
## Length:3000000 Min. : -62.00 Length:3000000
## Class:character 1st Qu.: 6.00 Class:character
## Mode :character Median : 8.50 Mode :character
##
                  Mean : 11.34
\# \#
                   3rd Qu.: 12.50
##
                   Max. :1273.31
##
## pickup_longitude pickup_latitude
## Min. :-3426.61 Min. :-3488.08
                                    dropoff longitude
                                    Min. :-3408.43
                   1st Qu.: 40.73
##
   1st Qu.: -73.99
                                    1st Qu.: -73.99
                                    Median : -73.98
## Median : -73.98 Median :
                            40.75
                                    Mean : -72.51
## Mean : -72.51 Mean :
                            39.92
## 3rd Qu.: -73.97 3rd Qu.: 40.77 3rd Qu.: -73.96
## Max. : 3439.43 Max. : 2912.47 Max. : 3457.62
## dropoff_latitude passenger_count
## Min. :-3488.08 Min. : 0.000
## 1st Qu.: 40.73 1st Qu.: 1.000
## Median: 40.75 Median: 1.000
## Mean : 39.92 Mean : 1.685
##
   3rd Qu.: 40.77
                    3rd Qu.: 2.000
   Max. : 3345.92
                  Max. :208.000
   NA's
        :23
```

```
summary(NY_Test)
```

```
##
                                                  pickup_datetime
                         key
## 2009-01-01 11:04:24.0000001: 1 2011-12-13 22:00:00 UTC: 270
   2009-01-01 11:04:24.0000002: 1
2009-01-01 11:04:24.0000003: 1
                                   2013-09-25 22:00:00 UTC: 251
                                   2012-11-20 21:54:00 UTC: 246
   2009-01-02 17:45:40.0000001:
                                   2014-07-21 18:19:00 UTC: 243
                                1
## 2009-01-02 17:45:40.0000002: 1 2010-08-27 18:45:00 UTC: 235
## 2009-01-02 17:45:40.0000003: 1 2011-06-01 07:37:00 UTC: 227
                          :9908 (Other)
## (Other)
## pickup_longitude pickup_latitude dropoff_longitude dropoff_latitude
## Min. :-74.25 Min. :40.57 Min. :-74.26 Min. :40.57
## 1st Qu.:-73.99 1st Qu.:40.74 1st Qu.:-73.99 1st Qu.:40.74
## Median :-73.98 Median :40.75 Median :-73.98 Median :40.75
## Mean :-73.97 Mean :40.75 Mean :-73.97 Mean :40.75
## 3rd Qu.:-73.97 3rd Qu.:40.77 3rd Qu.:-73.96 3rd Qu.:40.77
## Max. :-72.99 Max. :41.71 Max. :-72.99
                                                  Max. :41.70
##
## passenger_count
## Min. :1.000
## 1st Qu.:1.000
## Median :1.000
## Mean :1.671
## 3rd Qu.:2.000
## Max. :6.000
##
```

Data cleansing:

```
#Remove key column:
NY_Train <- NY_Train %>% select(-key)
NY_Test <- NY_Test %>% select(-key)

#Create place holder column in NY_test for fare_amount:
NY_Test$fare_amount <- NA

#Drop NAs in train data:
sum(is.na(NY_Train))</pre>
```

```
## [1] 46

NY Train <- na.omit(NY Train)
```

```
NY_Train <- na.omit(NY_Train)
#Filter out unreasonable price data:
NY_Train<- filter(NY_Train, fare_amount > 0, fare_amount < 700)
#Filter our unreasonable passenger data:
NY_Train%>%
filter(passenger_count==0)%>%
nrow()
```

```
## [1] 10610
```

```
NY_Train <- filter(NY_Train, passenger_count >0, passenger_count <= 10)

#Filter out geo data that is not in NYC boroughs:
NY_Train<-NY_Train%>%
  filter(pickup_longitude > -80 & pickup_longitude < -70) %>%
  filter(pickup_latitude > 35 & pickup_latitude < 45) %>%
  filter(dropoff_longitude > -80 & dropoff_longitude < -70) %>%
  filter(dropoff_latitude > 35 & dropoff_latitude < 45)</pre>
```

Feature engineering:

```
#Use package lubridate to extract various time components:
combined<-data.frame(rbind(NY_Train, NY_Test))</pre>
combined<-combined%>%
 mutate(
   pickup_datetime = ymd_hms(pickup_datetime),
    year = as.factor(year(pickup_datetime)),
    month = as.factor(month(pickup datetime)),
    day = as.numeric(day(pickup_datetime)),
    dayOfWeek = as.factor(wday(pickup_datetime)),
    hour = as.numeric(hour(pickup_datetime)),
    timeOfDay = as.factor(ifelse(hour \geq 3 & hour < 9,
                                  "Morning", ifelse(hour >= 9 & hour < 14, "Mid-Day",
                                                     ifelse(hour >= 14 & hour < 18, "Evening", "Night"))))</pre>
  select(-pickup_datetime)
#Picking out distance to exact locations:
#jfk
jfk_lat<-40.6413
jfk long<--73.7781
jfk<-c(jfk_long, jfk_lat)</pre>
nwk_lat<-40.6895
nwk_long<--74.1745
nwk<-c(nwk_long, nwk_lat)</pre>
#laguardia
lag lat<-40.779
lag_long<--73.8740
lag<-c(lag_long, lag_lat)</pre>
# #MSG
# msg_lat<-40.7505
```

```
# msg_long<--73.9934
# msg<-c(msg_long, msg_lat)</pre>
# #times square
# ts lat<-40.7589
# ts_long<--73.9851
# ts<-c(ts long, ts lat)
# #freedom tower
# freedom lat<-40.7127
# freedom long<--74.0134
# freedom<-c(freedom long, freedom lat)</pre>
# #empire state building
# esb_lat<-40.7484
# esb long<--73.9857
# esb<-c(esb_long, esb_lat)</pre>
#grand central
grand lat<-40.7527
grand long<--73.9772
grand<-c(grand long, grand lat)</pre>
#bronx
bronx lat <- (40.837048 * pi)/180
bronx long <- (-73.865433 * pi)/180
bronx<-c(bronx_long, bronx_lat)</pre>
nyc<-c(-74.0063889, 40.7141667)
combined <- combined %>%
 mutate(
   dist = distHaversine(cbind(pickup_longitude, pickup_latitude), cbind(dropoff_longitude, dropoff_latitude
), r = 6371),
   to jfk = distHaversine(cbind(pickup_longitude, pickup_latitude), jfk, r = 6371) + distHaversine(cbind(dr
opoff longitude, dropoff latitude), jfk, r = 6371),
    to nkw = distHaversine(cbind(pickup longitude, pickup latitude), <math>nwk, r = 6371) + distHaversine(cbind(dr
opoff_longitude, dropoff_latitude), nwk, r = 6371),
    to lag = distHaversine(cbind(pickup longitude, pickup latitude), lag, r = 6371) + distHaversine(cbind(dr
opoff_longitude, dropoff_latitude), lag, r = 6371),
    \#to msg = distHaversine(cbind(pickup longitude, pickup latitude), <math>msg, r = 6371) + distHaversine(cbind(distribution))
ropoff longitude, dropoff latitude), msg, r = 6371),
    \#to ts = distHaversine(cbind(pickup longitude, pickup latitude), <math>ts, r = 6371) + distHaversine(cbind(dro
poff longitude, dropoff latitude), ts, r = 6371),
    \#to freedom = distHaversine(cbind(pickup longitude, pickup latitude), freedom, r = 6371) + distHaversine
(cbind(dropoff\ longitude,\ dropoff\ latitude),\ freedom,\ r=6371),
    to_grand = distHaversine(cbind(pickup longitude, pickup_latitude), grand, r = 6371) + distHaversine(cbin
d(dropoff_longitude, dropoff_latitude), grand, r = 6371),
    to bronx = distHaversine(cbind(pickup longitude, pickup latitude), bronx, r = 6371) + distHaversine(cbin
d(dropoff longitude, dropoff latitude), bronx, r = 6371)
    \#to nyc = distHaversine(cbind(pickup longitude, pickup latitude), nyc, r = 6371) + distHaversine(cbind(d
ropoff longitude, dropoff latitude), nyc, r = 6371)
#Now resplit train and test:
NY Test <- combined[is.na(combined$fare amount), ]</pre>
NY Train <- combined[!is.na(combined$fare amount), ]</pre>
```

Further Explore and Visualize Data:

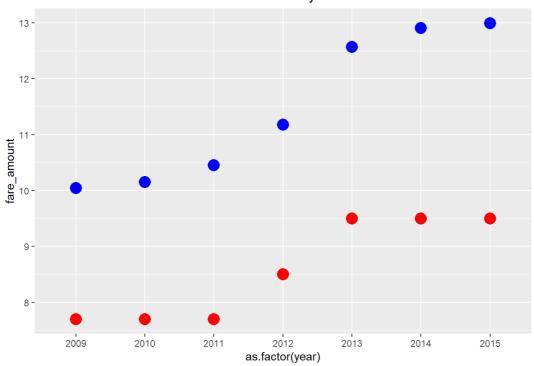
```
print(paste("The mean fair price in the training data set is $", round(mean(NY_Train$fare_amount),2), ".", s
ep=""))
```

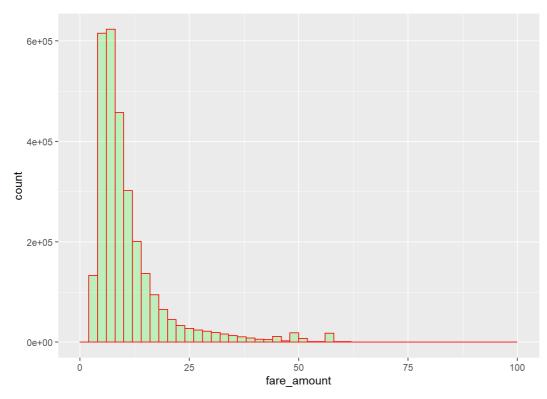
```
## [1] "The mean fair price in the training data set is $11.34."
```

```
#ggplot variables:
m<-geom_point(stat = "summary", fun.y = "mean", col = "blue", size = 5)
med<-geom_point(stat = "summary", fun.y = "median", col = "red", size = 5)
manLegend<-scale_color_manual(name = "Summary Stat", values = c("mean"="blue", "median"="red"))

#Year and price:
ggplot(NY_Train, aes(as.factor(year), fare_amount))+
m+
med+
med+
manLegend+
ggtitle("Fare Amount by Year")+
theme(plot.title = element_text(hjust = .5), legend.position = "bottom")</pre>
```

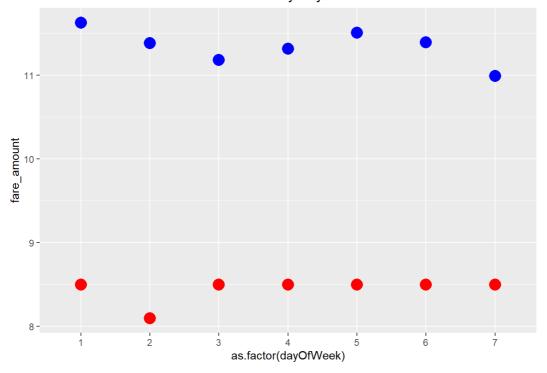
Fare Amount by Year





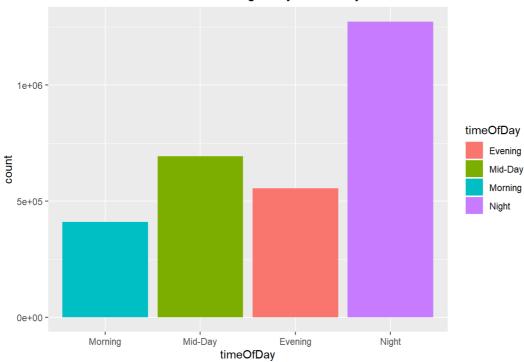
```
#Fare amount by day of week:
ggplot(NY_Train, aes(as.factor(dayOfWeek), fare_amount))+
   m+
   med+
   manLegend+
   ggtitle("Fare Amount by Day of Week")+
   theme(plot.title = element_text(hjust = .5), legend.position = "bottom")
```

Fare Amount by Day of Week



```
#Passengers by time of day:
ggplot(NY_Train, aes(timeOfDay, fill = timeOfDay))+
  geom_bar(stat = "count", aes(y = ..count..))+
  scale_x_discrete(limits=c("Morning", "Mid-Day", "Evening", "Night"))+
  ggtitle("Number of Passengers by timeOfDay")+
  theme(plot.title = element_text(hjust = .5))
```

Number of Passengers by timeOfDay



XGBoost Model:

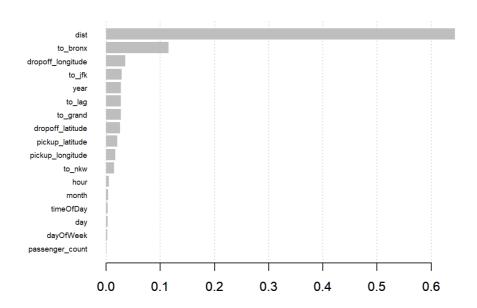
```
#Create a validation set:
size = floor(.8*nrow(NY_Train))
xx <-sample(1:nrow(NY_Train), size)</pre>
NY_Valid<-NY_Train[-xx,]</pre>
NY_Train<-NY_Train[xx,]</pre>
#Convert to matrices for XGBoost algorithm to work:
dvalid <- xgb.DMatrix(data = data.matrix(NY_Valid[,-1]), label = NY_Valid[,1])</pre>
dtrain <- xgb.DMatrix(data = data.matrix(NY_Train[,-1]), label = NY_Train[,1])</pre>
dtest<-xgb.DMatrix(data = data.matrix(NY_Test[,-1]))</pre>
p <- list(objective = "reg:linear",</pre>
          eval_metric = "rmse",
          max_depth = 10,
          eta = .02,
          subsample=1,
          colsample_bytree=0.8,
          num boost round=250,
          nrounds = 500)
#Train the model:
set.seed(1)
m_xgb <- xgb.train(p, dtrain, p$nrounds, list(val=dvalid), print_every_n = 10, early_stopping_rounds = 10)</pre>
```

```
## [1] val-rmse:14.272313
## Will train until val rmse hasn't improved in 10 rounds.
\# \#
## [11] val-rmse:11.897102
## [21] val-rmse:10.014572
## [31] val-rmse:8.529146
## [41] val-rmse:7.323254
## [51] val-rmse:6.387753
## [61] val-rmse:5.671983
## [71] val-rmse:5.128957
## [81] val-rmse:4.726066
## [91] val-rmse:4.431731
## [101]
         val-rmse:4.214577
## [111]
           val-rmse:4.060880
## [121]
           val-rmse:3.948243
## [131]
           val-rmse:3.866209
## [141]
           val-rmse:3.806600
## [151]
          val-rmse:3.760950
## [161]
         val-rmse:3.728875
## [171]
         val-rmse:3.703937
## [181]
         val-rmse:3.684858
## [191]
        val-rmse:3.668841
## [201] val-rmse:3.656088
## [211] val-rmse:3.645313
## [221] val-rmse:3.635564
## [231]
          val-rmse:3.627590
## [241]
           val-rmse:3.620423
## [251]
           val-rmse:3.614422
## [261]
           val-rmse:3.609952
## [271]
           val-rmse:3.606364
## [281]
          val-rmse:3.602234
## [291]
         val-rmse:3.598963
## [301]
         val-rmse:3.595448
## [311]
        val-rmse:3.592509
## [321] val-rmse:3.589816
## [331] val-rmse:3.587926
## [341]
         val-rmse:3.585603
           val-rmse:3.583902
## [351]
## [361]
           val-rmse:3.581295
## [371]
           val-rmse:3.579829
## [381]
           val-rmse:3.577835
## [391]
           val-rmse:3.576200
## [401]
           val-rmse:3.574358
## [411]
           val-rmse:3.571254
## [421]
           val-rmse:3.570027
## [431]
         val-rmse:3.568401
## [441]
         val-rmse:3.566739
## [451]
         val-rmse:3.564548
## [461]
         val-rmse:3.562817
## [471]
         val-rmse:3.561215
## [481] val-rmse:3.558859
## [491] val-rmse:3.558043
## [500]
           val-rmse:3.556642
```

```
#Feature importance:
(impt_matrix <- xgb.importance(colnames(dtrain), model = m_xgb))</pre>
```

```
##
                                Gain
                                          Cover Frequency
##
   1:
                   dist 0.6438705640 0.20147209 0.08438685
##
   2:
                to_bronx 0.1153522954 0.06509696 0.05877893
   3: dropoff_longitude 0.0354258208 0.07717865 0.08995730
##
                 to_jfk 0.0284823425 0.09076591 0.08376058
## 4:
## 5:
                   year 0.0275103059 0.06460437 0.03521163
## 6:
                 to lag 0.0273045825 0.03412743 0.05801783
## 7:
               to_grand 0.0270446162 0.03699437 0.04613979
## 8: dropoff_latitude 0.0256484103 0.06541405 0.08771593
## 9: pickup_latitude 0.0204772809 0.04436401 0.09842235
## 10: pickup_longitude 0.0167353853 0.06843292 0.12761405
## 11:
                 to nkw 0.0148450739 0.03728096 0.05194397
## 12:
                   hour 0.0051391290 0.07044823 0.05218069
## 13:
                  month 0.0038145099 0.04992147 0.03543936
## 14:
              timeOfDay 0.0027381620 0.01177675 0.01624991
## 15:
                    day 0.0025599695 0.01555296 0.03447449
              dayOfWeek 0.0022509792 0.04456362 0.02780733
## 16:
       passenger_count 0.0008005726 0.02200526 0.01189902
## 17:
```

```
xgb.plot.importance(impt matrix)
```



```
#Make predictions:
preds <- predict(m_xgb, dtest)

#Create CSV file with predictions to submit to Kaggle to obtain RMSE:
read.csv("sample_submission.csv")%>%
    mutate(fare_amount = preds)%>%
    write.csv("team12_sub.csv", row.names = F)

#Test RMSE: Obtained by submitting to Kaggle
RMSE <- 3.04896
print(paste("The RMSE for our model is $", round(RMSE,2), ".", sep=""))

### [1] "The RMSE for our model is $3.05."</pre>

print(paste("This means that, on average, the model misestimated the fare price by $" ,round(RMSE,2), ".", sep=""))
```

[1] "This means that, on average, the model misestimated the fare price by \$3.05."