# Team Presentation 2: Predicting NYC Taxi Fares

Christopher Carlevato, Kate Luo, David Tabert, Ian Wesley McDaniel

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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)
```

```
##      key             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    dropoff_longitude
##  Min.   :-3426.61   Min.   :-3488.08   Min.   :-3408.43
##  1st Qu.:  -73.99   1st Qu.:   40.73   1st Qu.:  -73.99
##  Median :  -73.98   Median :   40.75   Median :  -73.98
##  Mean   :  -72.51   Mean   :   39.92   Mean   :  -72.51
##  3rd Qu.:  -73.97   3rd Qu.:   40.77   3rd Qu.:  -73.96
##  Max.   : 3439.43   Max.   : 2912.47   Max.   : 3457.62
##                                        NA's   :23
##  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)
```

```
##                          key                         pickup_datetime
##  2009-01-01 11:04:24.0000001:   1   2011-12-13 22:00:00 UTC: 270
##  2009-01-01 11:04:24.0000002:   1   2013-09-25 22:00:00 UTC: 251
##  2009-01-01 11:04:24.0000003:   1   2012-11-20 21:54:00 UTC: 246
##  2009-01-02 17:45:40.0000001:   1   2014-07-21 18:19:00 UTC: 243
##  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
##  (Other)                    :9908   (Other)                :8442
##  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:

Pulled some code from this notebook: https://www.kaggle.com/obrienmitch94/nyc-taxi-fare-prediction

```
#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))
```

```
## [1] 46
```

```
NY_Train <- na.omit(NY_Train)
#Filter out unreasonable price data:
NY_Train<- filter(NY_Train, fare_amount > 0, fare_amount < 700)
#Filter our unreaonable 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)
```

# Feature egineering:

```
#Use package lubridate to extract various time components:
combined<-data.frame(rbind(NY_Train, NY_Test))

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 >= 3 & hour < 9,
                                 "Morning", ifelse(hour >= 9 & hour < 14, "Mid-Day",
                                                  ifelse(hour >= 14 & hour < 18, "Evening", "Night"))))
  )%>%
  select(-pickup_datetime)

#Picking out distance to exact locations:
#jfk
jfk_lat<-40.6413
jfk_long<--73.7781
jfk<-c(jfk_long, jfk_lat)
#newark
nwk_lat<-40.6895
nwk_long<--74.1745
nwk<-c(nwk_long, nwk_lat)
#laguardia
lag_lat<-40.779
lag_long<--73.8740
lag<-c(lag_long, lag_lat)
```

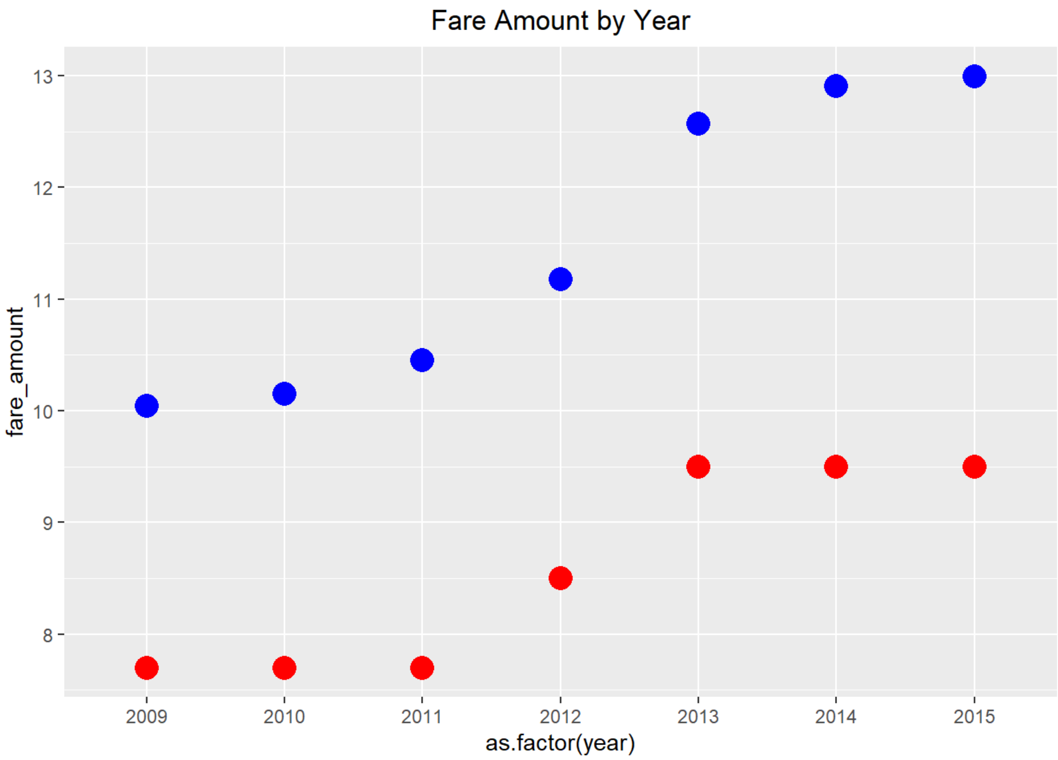
```
#MSG
msg_lat<-40.7505
msg_long<--73.9934
msg<-c(msg_long, msg_lat)
#times square
ts_lat<-40.7589
ts_long<--73.9851
ts<-c(ts_long, ts_lat)
#freedom tower
freedom_lat<-40.7127
freedom_long<--74.0134
freedom<-c(freedom_long, freedom_lat)
#empire state building
esb_lat<-40.7484
esb_long<--73.9857
esb<-c(esb_long, esb_lat)
#grand central
grand_lat<-40.7527
grand_long<--73.9772
grand<-c(grand_long, grand_lat)
#bronx
bronx_lat <- (40.837048 * pi)/180
bronx_long <- (-73.865433 * pi)/180
bronx<-c(bronx_long, bronx_lat)
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), 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), msg, r = 6371) + distHaversine(cbind(dr
opoff_longitude, dropoff_latitude), msg, r = 6371),
    to_ts = distHaversine(cbind(pickup_longitude, pickup_latitude), ts, r = 6371) + distHaversine(cbind(drop
off_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(dr
opoff_longitude, dropoff_latitude), nyc, r = 6371)
  )

#Now resplit train and test:
NY_Test <- combined[is.na(combined$fare_amount), ]
NY_Train <- combined[!is.na(combined$fare_amount), ]
```

# Further Explore and Visualize Data:

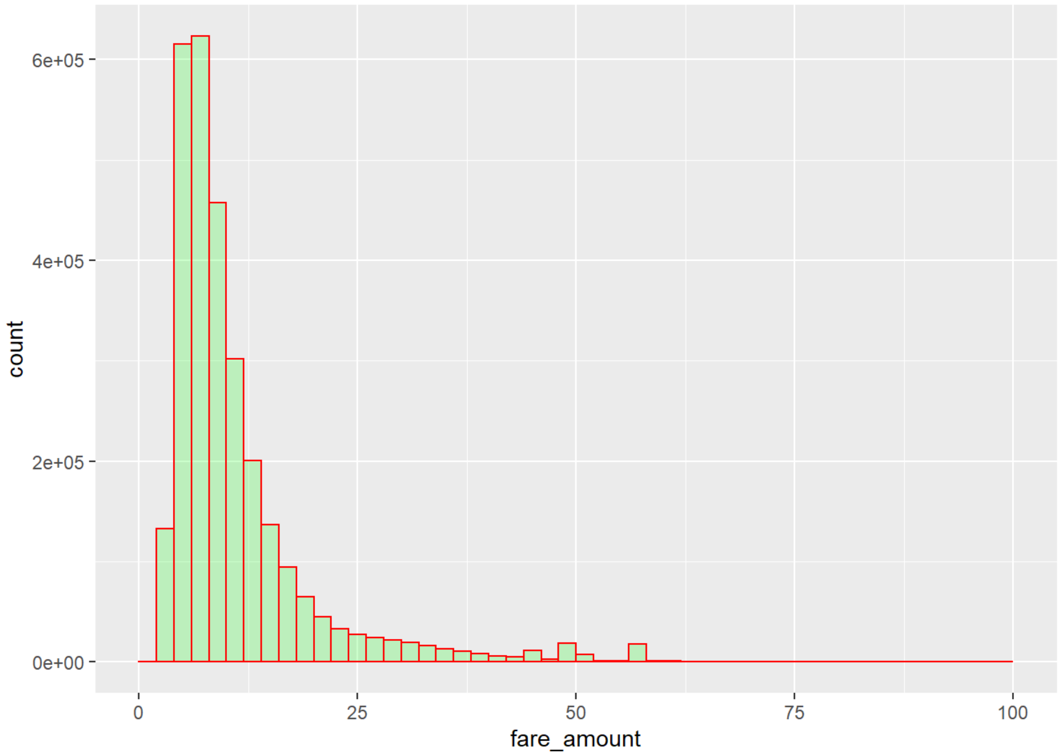
```
print(paste("The mean fair price in the training data set is $", round(mean(NY_Train$fare_amount),2), ".", s
ep=""))
```

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

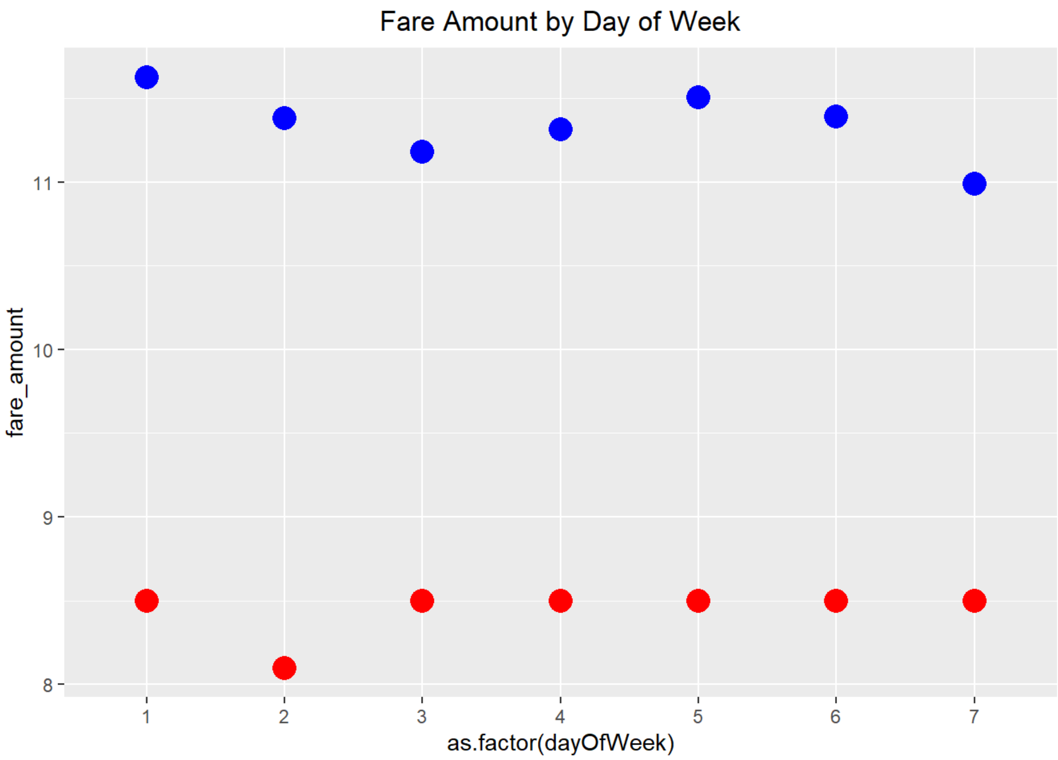
```
#ggplot variables:
m<-geom_point(stat = "summary", fun.y = "mean", col = "blue", size = 5)
med<-geom_point(stat = "summary", fun.y = "median", col = "red", size = 5)
manLegend<-scale_color_manual(name = "Summary Stat", values = c("mean"="blue", "median"="red"))

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



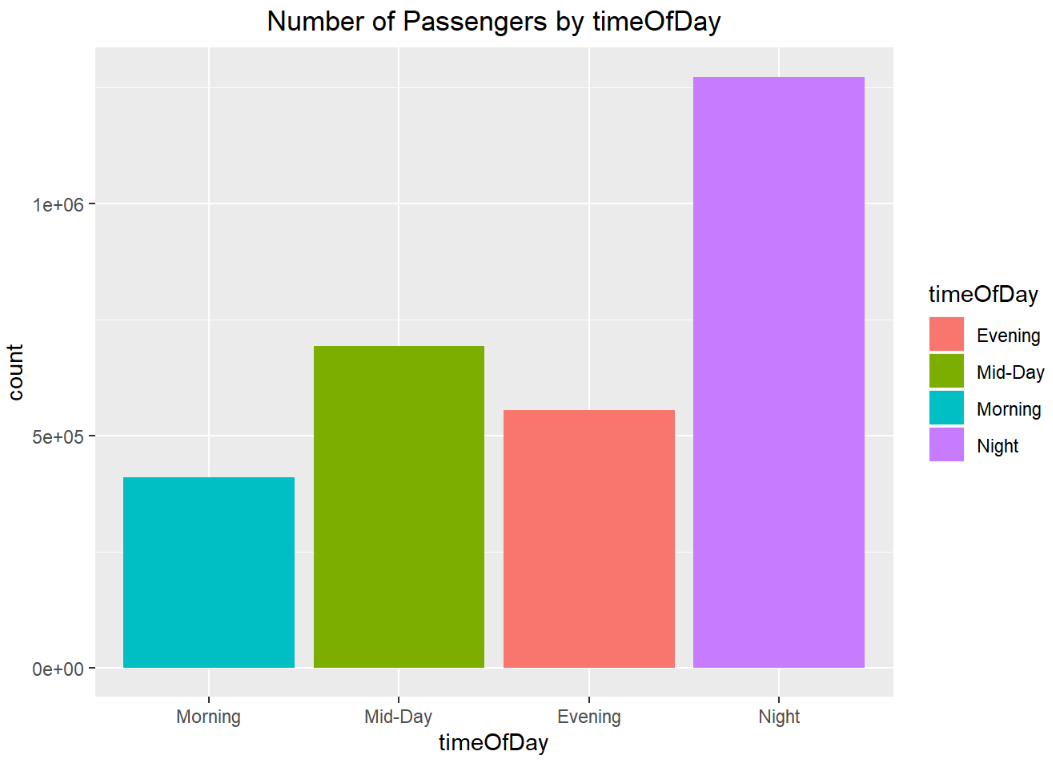

```
#Distribution of prices:
ggplot(NY_Train, aes(fare_amount)) +
  geom_histogram(breaks=seq(0, 100, by=2),
                 col="red",
                 fill="green",
                 alpha=.2)
```




```
#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")
```




```
#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))
```




# XGBoost Model:

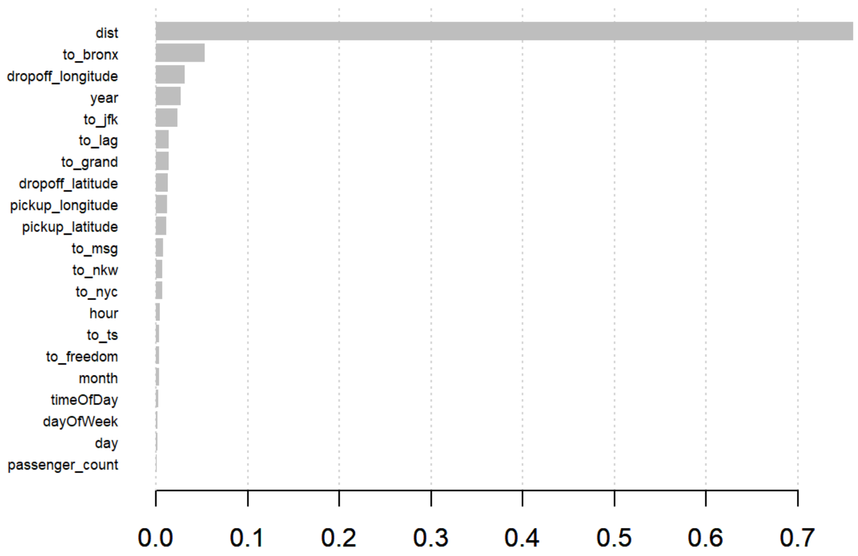
```
#Create a validation set:
size = floor(.8*nrow(NY_Train))

xx <-sample(1:nrow(NY_Train), size)
NY_Valid<-NY_Train[-xx,]
NY_Train<-NY_Train[xx,]

#Convert to matrices for XGBoost algorithm to work:
dvalid <- xgb.DMatrix(data = data.matrix(NY_Valid[,-1]), label = NY_Valid[,1])
dtrain <- xgb.DMatrix(data = data.matrix(NY_Train[,-1]), label = NY_Train[,1])
dtest<-xgb.DMatrix(data = data.matrix(NY_Test[,-1]))


p <- list(objective = "reg:linear",
          eval_metric = "rmse",
          max_depth = 8 ,
          eta = .05,
          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)
```

```
## [1]  val-rmse:13.876215
## Will train until val_rmse hasn't improved in 10 rounds.
##
## [11] val-rmse:8.932336
## [21] val-rmse:6.223444
## [31] val-rmse:4.862237
## [41] val-rmse:4.229647
## [51] val-rmse:3.953760
## [61] val-rmse:3.826144
## [71] val-rmse:3.762820
## [81] val-rmse:3.723959
## [91] val-rmse:3.699872
## [101]    val-rmse:3.687511
## [111]    val-rmse:3.675316
## [121]    val-rmse:3.668603
## [131]    val-rmse:3.659486
## [141]    val-rmse:3.654562
## [151]    val-rmse:3.648380
## [161]    val-rmse:3.642535
## [171]    val-rmse:3.636734
## [181]    val-rmse:3.630234
## [191]    val-rmse:3.625056
## [201]    val-rmse:3.619195
## [211]    val-rmse:3.614953
## [221]    val-rmse:3.610587
## [231]    val-rmse:3.608291
## [241]    val-rmse:3.603860
## [251]    val-rmse:3.600462
## [261]    val-rmse:3.597854
## [271]    val-rmse:3.594986
## [281]    val-rmse:3.591316
## [291]    val-rmse:3.588857
## [301]    val-rmse:3.587003
## [311]    val-rmse:3.582674
## [321]    val-rmse:3.581218
## [331]    val-rmse:3.578719
## [341]    val-rmse:3.576914
## [351]    val-rmse:3.575416
## [361]    val-rmse:3.574199
## [371]    val-rmse:3.572995
## [381]    val-rmse:3.571548
## [391]    val-rmse:3.569588
## [401]    val-rmse:3.568532
## [411]    val-rmse:3.567861
## [421]    val-rmse:3.566636
## [431]    val-rmse:3.564747
## [441]    val-rmse:3.563703
## [451]    val-rmse:3.562382
## [461]    val-rmse:3.561083
## [471]    val-rmse:3.560673
## [481]    val-rmse:3.558550
## [491]    val-rmse:3.557608
## [500]    val-rmse:3.556207
```

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

```
##                Feature         Gain       Cover  Frequency
##  1:               dist 0.7602974483 0.115247263 0.09554723
##  2:           to_bronx 0.0529260760 0.067105997 0.05373046
##  3: dropoff_longitude 0.0309330850 0.091710745 0.09073182
##  4:               year 0.0267047952 0.035413365 0.03659711
##  5:             to_jfk 0.0232334331 0.089344476 0.07961477
##  6:             to_lag 0.0141169298 0.045384459 0.05079365
##  7:           to_grand 0.0135515169 0.033321574 0.02065276
##  8:  dropoff_latitude 0.0133162638 0.080587330 0.07571488
##  9:  pickup_longitude 0.0118748399 0.087313979 0.11272814
## 10:   pickup_latitude 0.0112031681 0.054213107 0.08790203
## 11:             to_msg 0.0076397724 0.025722171 0.03131800
## 12:             to_nkw 0.0069639439 0.049318999 0.04200702
## 13:             to_nyc 0.0064901098 0.020157884 0.02084299
## 14:               hour 0.0045420516 0.055643094 0.04355270
## 15:              to_ts 0.0035594715 0.026820858 0.02798882
## 16:         to_freedom 0.0029924773 0.019007658 0.02486178
## 17:              month 0.0029900473 0.034436065 0.02753701
## 18:          timeOfDay 0.0026438153 0.006315184 0.01407764
## 19:          dayOfWeek 0.0018682536 0.030189047 0.02305452
## 20:                day 0.0016039032 0.014542212 0.03002200
## 21:   passenger_count 0.0005485977 0.018204533 0.01072469
##                Feature         Gain       Cover  Frequency
```

```
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 <- 3.07516
print(paste("The RMSE for our model is $", round(RMSE,2), ".", sep=""))
```

```
## [1] "The RMSE for our model is $3.08."
```

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

```
## [1] "This means that, on average, the model misestimated the fare price by $3.08."
```