Stat 8120 Final Project

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Introduction

In this project I attempted to generate a model for TNC fare from the publicly available Chicago TNC dataset for 2023+.[1] In my research, I work to improve the usage of pooled rideshare. Pooled rideshare is a service in which you share part of a rideshare trip with a stranged. Uber and Lyft offer such services, namely Uber Pool and Lyft Shared. In this project, led by Dr. Yunyi Jia and Dr. Johnelle Brooks, approached the topic of pooled rideshare from several different angles. Dr. Brooks lab focuses on the human factors of ridesharing and work with JD Power to construct national surveys designed to further the understanding of factors that impact people use of such services. Through two national surveys, we have learned that safety is the most important factor that prevents usage of pooled rideshare. More results from the analysis of the survey data can be viewed in[2] and.[3] This data was also utilized to create a choice model which helps predict whether a given rider will choose a pooled ride when presented with a choice between a pooled and solo ride.[4]

In addition to modeling and human factors work, we also tackle the ridership problem from the angle of transportation network company (TNC) operators, like Uber and Lyft. This section is my responsibility, and I attempt to address these issues through designing new fleet control algorithms that improve the service experienced by the riders. Given that TNC fleets are typically composed of contracted drivers utilizing their own vehicles, the best way to address level of service (LOS) issues like long waits or delays associated with pooled rides, is to control the fleets operations through fleet control algorithms. Fleet control can be divided into three primary categories as illustrated below in 1.

Algorithm	Explanation
Assignment	Control of which vehicles are matched to which request, including matching multiple requests to single vehicles
Repositioning	Moving vehicles that are not currently servicing requests to more optimal locations for servicing expected future demand
Routing	Controlling the turn by turn directions that vehicles use to navigate the traffic network

Table 1: Fleet control algorithms

My work thus far has been to design an assignment algorithm and to implement and test it in a traffic simulation application called POLARIS.[5] The assignment algorithm, detailed in my paper,[6] utilizes a willingness to pay formulation of the pooling choice model detailed in[4] to estimate the discount required to incentivize a rider to pool. The primary incentive for riders in pooled rideshare to pool is the cost savings over a solo ride. One important aspect to this study is to understand the base rate that riders should be charged. This is important because it helps us understand whether or not a system is likely to be profitable and provides a basis from which we can discount a trip. To estimate fares, a model is required.

I have previously generated a simple LM from,[1] but wanted to take this opportunity and the new skills learned in this class to rehash the model. Additionally, my original model was calibrated from the TNC data ending in Fall of 2022, and as inflation has heavily affected the US in the last several years, I felt it was necessary to recalibrate using the newest available data. Additionally, as several other factors are available in this dataset, and my original model only utilized the time and distance for its estimates, I wanted to use the feature selection techniques learned to determine whether my uninformed selection was satisfactory. To that end, the goal of this project is to calibrate a new fare model from the newest available TNC data and to utilize feature selection and advanced model generation techniques to find the best model for fare.

Outline of Analysis

To address this task, I will first draw a sample from the Chicago TNC dataset. I will then utilize some basic exploratory analysis including GG plots and summary statistics to understand which variables contribute to fare, and to identify any problem variable that should not be utilized in the model. I will start with a simple LM utilizing the significant variables. Since this dataset contains relative few predictors, especially relative to the number of samples, no dimension reduction should be necessary. However, I will utilize subset regression, stepwise selection with cross validation, and principal component analysis to help narrow in on the best model structure and most important variables. Finally, I will fit the final model and interpret its results.

Methodology

To calibrate a model, I first obtained a copy of the most recently available data through the City of Chicago's web data portal. I filtered the data for June only (the latest available date) to reduce the output size. Still, the dataset generated an over 2GB CSV containing 750,000 individual

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trips. The columns are illustrated in 2.

Next I utilized sqlite to convert the CSV into a sqlite database to pull a sample of rows small enough to work with. I used the "random" function in sqite to capture a random sample of trips accross the month. I pulled 2000 trips in total to use and split it into a test and train dataset with a 90/10 split. Prior to doing this, I used the sqldf package to query the 10 first rows to look at the data.

Next, I was curious whether the day of week had any affect on the fares, so I generated a day-of-week (DOW) column from the trip start timestamp column. Next, I removed any columns that I knew were not of interest, like the geographic columns and ID columns. Given that the total cost column was supposedly a sum of the three cost related variable columns, I decided to check if it matched the sum. In some cases it did not, and given its dependency on these columns anyways, I discarded it to remove colinearity. I then checked the rows within the sample for NA's in any of the remaining columns. Two had NAs so I removed these two rows.

Next, I began the work for model fitting by separating the dataframe into a train and test dataset in a 90/10 mix. I used the GGpairs function to inspect the relationship between the variables remaining in the training set. The GG pairs result is illustrated in 1.

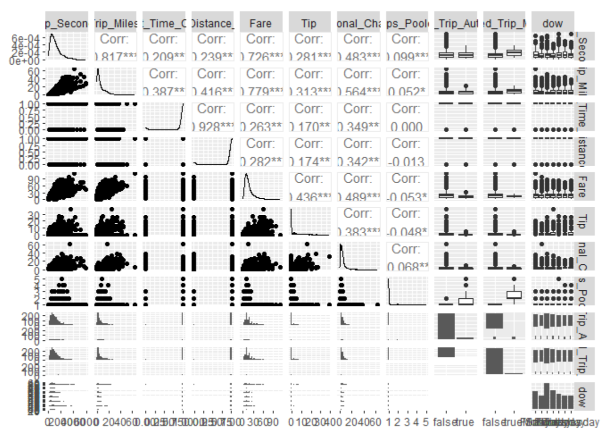

Figure 1: GGpairs results for training dataset.

While inspecting the GG pairs columns, I noticed that the distance and time in chicago columns were mostly 0, so I removed these from the dataframe also. They also would inhibit the models scalability to other regions. I removed them from the dataframe and reformed by test and train sets on the same test indices to ease the process. First, I used the LM function to inspect the significance of the remaining variables to predicting fare. I obtained the following output as illustrated in 3. The LM function automatically converted categorical variables to binary columns.

Analyzing the results, I found that trip-seconds, trip-miles, tip, and shared-trip-authorized were significant at a 0 level , and that dow sunday was significant at a 0.1 level. Since intuitively, tip was likely very colinear with fare, I formed a correlation matrix. Trip minutes and trip miles were highly

Variable	**Description**
PK-UID	Primary Index
Trip-ID	Coded trip identifier
Trip-Start-Timestamp	Time/Date pickup rounded to nearest 15 mins
Trip-End-Timestamp	time/Date dropoff rounded to nearest 15 mins
Trip-Seconds	trip time in seconds
Trip-Miles	trip distance in miles
Percent-Time-Chicago	percent time in Chicago city
Percent-Distance-Chicago	percent distance in Chicago
Pickup-Census-Tract	location reference to census data
Dropoff-Census-Tract	location reference to census data
Pickup-Community-Area	location reference to area name (encoded)
Dropoff-Community-Area	location reference to area name (encoded)
Fare	fare in dollars rounded to the nearest $2.50
Tip	Tip paid to driver rounded to the nearest $1
Additional-Charges	taxes, fees, other miscellaneous charges
Trip-Total	sum of tip, fare, and additional charges including rounding
Shared-Trip-Authorized	boolean for if a trip was accepted to be pooled regardless of whether a match was found
Shared-Trip-Match	boolean if match was found
Trips-Pooled	if a match was found, how many (including the base trip)
Pickup-Centroid-Latitude	geographic location of pickup tract centroid
Pickup-Centroid-Longitude	geographic location of pickup tract centroid
Pickup-Centroid-Location	geographic location of pickup tract centroid (stored in geo data form)
Dropoff-Centroid-Latitude	geographic location of pickup tract centroid
Dropoff-Centroid-Longitude	geographic location of pickup tract centroid
Dropoff-Centroid-Location	geographic location of pickup tract centroid (stored in geo data form)

Table 2: Columns in TNC Trip Dataset

correlated, and tip and additional charges were moderately correlated. I decided to remove tip knowing that it was likely a function of fare, and not useful predictor since it would not be know at the start of a trip anyways. I did the same with additional charges, match found, and trips pooled as they are also not likely to be known prior to a trip commencing. I reran the LM to check if any significances had been affected, and now dow Sunday was significant at the 0.05 level. The resulting LM, for minutes, miles, dow, and share trip authorized had an r^2 value of 0.6512 with an MSE when used to predict on the test dataset of 52.22.

Coefficient	Estimate	StdError	tvalue	Pr(>|t|)
(Intercept)	6.894924	1.621669	4.252	2.23e-05 ***
Trip Seconds	0.004439	0.000379	11.714	<2e-16 ***
Trip Miles	0.930867	0.045233	20.579	<2e-16 ***
Tip	0.798935	0.059870	13.344	<2e-16 ***
Additional Charges	-0.030049	0.053778	-0.559	0.5764
Trips Pooled	-0.792071	1.531302	-0.517	0.6050
Shared Trip Authorized true	-4.890068	1.067234	-4.582	4.92e-06 ***
Shared Trip Match true	-2.971141	2.640581	-1.125	0.2607
dow Monday	-0.085948	0.729787	-0.118	0.9063
dow Saturday	0.458279	0.623896	0.735	0.4627
dow Sunday	1.223020	0.671381	1.822	0.0687 .
dow Thursday	-0.705050	0.703864	-1.002	0.3166
dow Tuesday	-0.613870	0.728873	-0.842	0.3998
dow Wednesday	-0.520356	0.725991	-0.717	0.4736

Table 3: Coefficients and significances.

Next, I decided to continue my exploratory analysis by using subset regression. Of the 8 remaining variables, the subset of three variables illustrated the biggest transition across the evaluation metrics RSS, adjusted r^2, Cp and BIC. The charts for these at each subset are illustrated in 2.

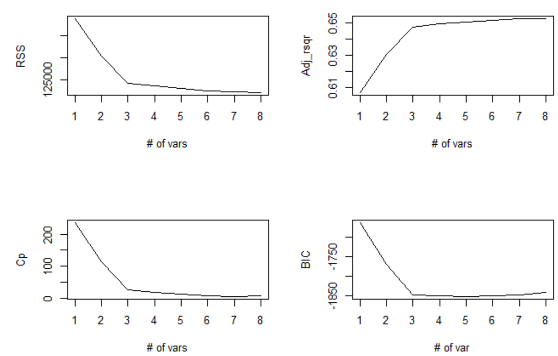

Figure 2: RSS, adjusted r^2, Cp and BIC for subset regression.

Although some of the higher order models showed improvement, it was apparent that the 3 variable model was the best fit due to its simplicity and transition point in the evaluative metrics. The 3 variable model utilized the trip seconds, trip miles, and shared trip authorized variables. Intuitively, this is what I was expecting, but, it was helpful to validate that DOW did not contribute significantly.

Please note, that set.seed does not appear to work properly in r markdown documents, and that these values may change in the final output r markdown document due to this fact. These results were written on a complete set of outputs, but if the workbook is reprocessed, they may change as the training sample will change.

Next, I utilized cross validation stepwise selection. The mean cv errors in this case yielded the lowest error in the 7 variable model, but, the 3 variable model look to be the best due to the spike in cv error at the 4 variable model. The mean cv error plot is illustrated in 3.

The model generated from the stepwise selection process yielded an MSE of 51.644 with and r^2 of 0.63. This is slightly worse than the r^2 from the LM but the MSE is slightly better.

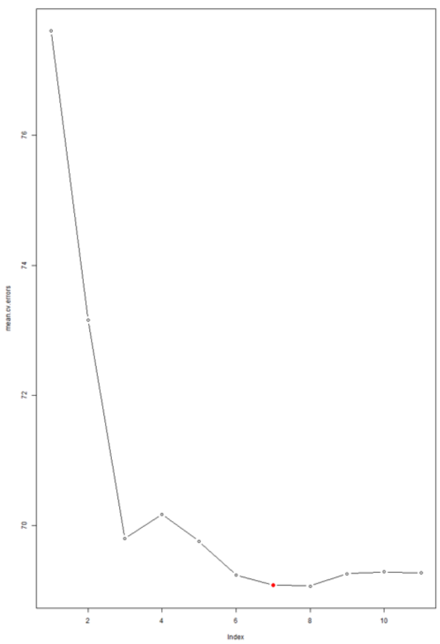

Figure 3: Mean CV Errors from Stepwise Selection

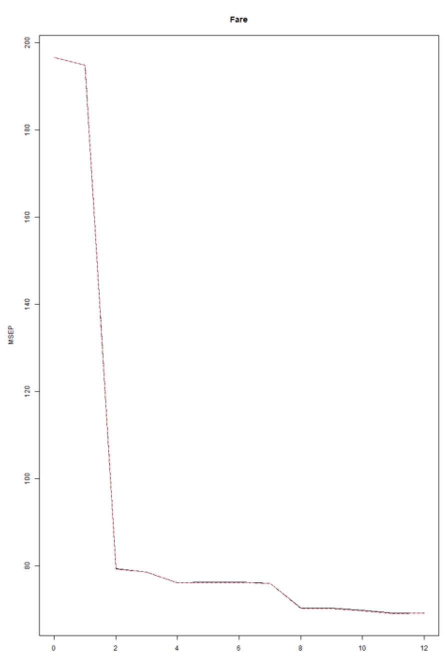

Figure 4: PLS Principal Components MSEP

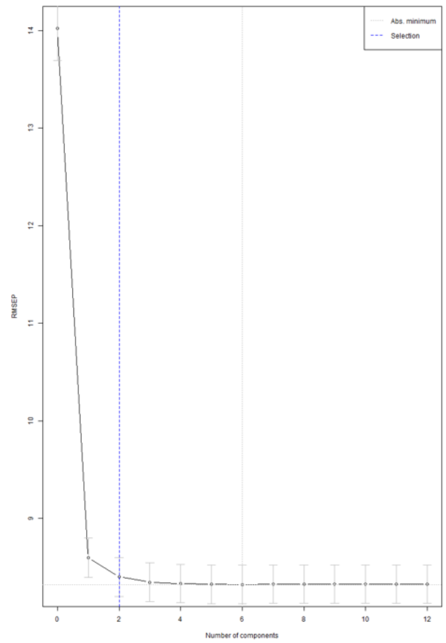

Figure 5: PLS automatic feature selection RMSEP.

Finally, principle component analysis was utilized. The model with 11 principal components had the best MSEP, but the 2 principal component model illustrated the largest drop, and therefore is the best selection. The PLS principal component MSEP errors are illustrated in 4 and the automatic feature selection function, "selectNcomp" was used to generate an additionaly chart with RMSEP as show in 5. The model generated from the PLS model yielded and MSE of 52.56, slightly higher than the LM.

Conclusions

Given the simplicity, interpretability, and predictive accuracy of the LM, I selected it as the final model. I selected the shared trip authorized, trip miles, and trip seconds variables as they were the most clearly significant. I fit a final model with just these three variables, and obtained the following coefficients as illustrated in 4.

Variable	**Value**
Intercept	\$6.60
Shared Trip Authorized (true = 1)	\$-7.80
Trip Miles	\$1.02 per mile
Trip Seconds	\$0.004737 (\$0.27 per minute)
MSE	51.30
r^2	0.648

Table 4: Final Fare Model

Removing the DOW improved the predictive accuracy slightly, making this the best performing model tested. The values obtained for each variable are reasonable and interpretable. To utilize the model for prediction, eqn. 1 illustrates the complete formulation.

$$f = 6.6 + -7.8 * s_a + 1.02 * t_m + 0.27 * t_d \qquad (1)$$

s_a is 1 if pooling is authorized, and zero otherwise, t_m is the trip distance in miles and t_d is the trip length in minutes.

through this study, a variety of exploratory and explanatory methods were utilized in pursuit of constructing an accurate TNC fare model for use in my ridesharing research. Although the initial LM was nearly the best model, the other methods utilized in this study helped illustrate and confirm that the simple LP was sufficient to capture the best model.

Appendix

Please see R Markdown below.

Setup

```r
library(data.table)
library(sqldf)
```

```
## Loading required package: gsubfn

## Loading required package: proto

## Loading required package: RSQLite
```

```r
library(ggplot2)
library(GGally)
```

```
## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2
```

```r
library(leaps)
library(MASS)
library(glmnet)
```

```
## Loading required package: Matrix

## Loaded glmnet 4.1-8
```

```r
library(pls)
```

```
##
## Attaching package: 'pls'

## The following object is masked from 'package:stats':
##
##     loadings
```

```r
library(boot)
library(gridExtra)
library(splines)
library(caret)
```

```
## Loading required package: lattice

##
## Attaching package: 'lattice'

## The following object is masked from 'package:boot':
##
##     melanoma

##
## Attaching package: 'caret'

## The following object is masked from 'package:pls':
##
##     R2
```

```r
library(alr4)
```

```
## Loading required package: car

## Loading required package: carData

##
## Attaching package: 'car'
```

```
## The following object is masked from 'package:boot':
##
##     logit

## Loading required package: effects

## Use the command
##     lattice::trellis.par.set(effectsTheme())
##   to customize lattice options for effects plots.
## See ?effectsTheme for details.
```

Read Data

This data csv is 2GB, way too big to read in on its own, so lets filter it down a bit.

```r
csv_pth = "C:\\Users\\jpaul4\\Downloads\\Transportation_Network_Providers_-_Trips__2023-__20240801.csv"

#Get coloumn names
top_10 = sqldf::read.csv.sql(csv_pth, sql= "select * from file limit 10")
```

Select a sample from this CSV to use as our training data

I selected a random set of 2000 rows using the SQL command "SELECT * FROM chic_trips ORDER BY RANDOM() LIMIT 2000;" for training and testing.

```r
csv_sample = "C:\\Users\\jpaul4\\Box\\Summer 2024\\S2405\\Projects\\Final Project\\result_set.csv"
trips = read.csv(csv_sample)
head(trips)
```

```
##    PK_UID                                  Trip_ID   Trip_Start_Timestamp
## 1 1078724 a45e404c67637a35ba8c68eb02abd0ef57a27851 06/26/2024 10:15:00 PM
## 2 5948098 9bd17c2ea621b7c1bba3725d89c18b45ac574971 06/07/2024 03:15:00 PM
## 3 1058729 92cc46f8531e33eee0e5a21cda3cb34d7997e0c8 06/27/2024 12:45:00 AM
## 4 2375826 4c4659ad8d22f0f0177e79e2140023a9ffea9ea2 06/21/2024 08:30:00 PM
## 5  559953 aceb9a135afb3a822bce97dbf5f80b31fa951c3d 06/28/2024 10:30:00 PM
## 6 7199958 8fd92610f23c8513b2618355ea3dbaf1ac734e37 06/02/2024 05:30:00 AM
##       Trip_End_Timestamp Trip_Seconds Trip_Miles Percent_Time_Chicago
## 1 06/26/2024 10:30:00 PM         1124        4.9                    1
## 2 06/07/2024 03:30:00 PM          896        3.0                    1
## 3 06/27/2024 01:30:00 AM         1994       27.8                    0
## 4 06/21/2024 09:15:00 PM         2963       26.9                    1
## 5 06/28/2024 10:45:00 PM          816        2.4                    1
## 6 06/02/2024 06:00:00 AM         2260       32.4                    1
##   Percent_Distance_Chicago Pickup_Census_Tract Dropoff_Census_Tract
## 1                        1                  NA                   NA
## 2                        1                  NA                   NA
## 3                        0         17031980000                   NA
## 4                        1                  NA                   NA
## 5                        1         17031081403          17031842200
## 6                        1         17031820901          17031980000
##   Pickup_Community_Area Dropoff_Community_Area Fare Tip Additional_Charges
## 1                    28                      6 32.5   0               1.23
## 2                    28                     24 17.5   0               5.68
## 3                    76                     NA 60.0  12              21.39
## 4                    NA                      6 22.5   0               6.95
## 5                     8                      8 10.0   0               1.23
## 6                    NA                     76 47.5  12              28.12
##   Trip_Total Shared_Trip_Authorized Shared_Trip_Match Trips_Pooled
## 1      33.73                  false             false            1
## 2      23.18                  false             false            1
## 3      93.39                  false             false            1
## 4      29.45                  false             false            1
```

```
## 5      11.23                 false             false             1
## 6      87.62                 false             false             1
##   Pickup_Centroid_Latitude Pickup_Centroid_Longitude
## 1                 41.87400                 -87.66352
## 2                 41.87400                 -87.66352
## 3                 41.97907                 -87.90304
## 4                       NA                        NA
## 5                 41.89092                 -87.61887
## 6                       NA                        NA
##               Pickup_Centroid_Location Dropoff_Centroid_Latitude
## 1  POINT (-87.6635175498 41.874005383)                  41.94423
## 2  POINT (-87.6635175498 41.874005383)                  41.90121
## 3 POINT (-87.9030396611 41.9790708201)                        NA
## 4                                                       41.94423
## 5 POINT (-87.6188683546 41.8909220259)                  41.90494
## 6                                                       41.97907
##   Dropoff_Centroid_Longitude           Dropoff_Centroid_Location
## 1                  -87.65600 POINT (-87.6559981815 41.9442266014)
## 2                  -87.67636 POINT (-87.6763559892 41.9012069941)
## 3                         NA
## 4                  -87.65600 POINT (-87.6559981815 41.9442266014)
## 5                  -87.64991 POINT (-87.6499072264 41.9049353016)
## 6                  -87.90304 POINT (-87.9030396611 41.9790708201)
```

```r
summary(trips)
```

```
##      PK_UID          Trip_ID          Trip_Start_Timestamp Trip_End_Timestamp
##  Min.   :   2180   Length:2000        Length:2000          Length:2000
##  1st Qu.:1857128   Class :character   Class :character     Class :character
##  Median :3728684   Mode  :character   Mode  :character     Mode  :character
##  Mean   :3749083
##  3rd Qu.:5638863
##  Max.   :7588816
##
##   Trip_Seconds      Trip_Miles     Percent_Time_Chicago
##  Min.   :  55.0   Min.   : 0.200   Min.   :0.0000
##  1st Qu.: 615.8   1st Qu.: 2.175   1st Qu.:1.0000
##  Median : 991.5   Median : 4.400   Median :1.0000
##  Mean   :1218.3   Mean   : 7.336   Mean   :0.9325
##  3rd Qu.:1583.0   3rd Qu.:10.000   3rd Qu.:1.0000
##  Max.   :5937.0   Max.   :63.900   Max.   :1.0000
##                                    NA's   :1
##  Percent_Distance_Chicago Pickup_Census_Tract Dropoff_Census_Tract
##  Min.   :0.0000           Min.   :1.703e+10   Min.   :1.703e+10
##  1st Qu.:1.0000           1st Qu.:1.703e+10   1st Qu.:1.703e+10
##  Median :1.0000           Median :1.703e+10   Median :1.703e+10
##  Mean   :0.9275           Mean   :1.703e+10   Mean   :1.703e+10
##  3rd Qu.:1.0000           3rd Qu.:1.703e+10   3rd Qu.:1.703e+10
##  Max.   :1.0000           Max.   :1.703e+10   Max.   :1.703e+10
##  NA's   :1                NA's   :775         NA's   :775
##  Pickup_Community_Area Dropoff_Community_Area      Fare              Tip
##  Min.   : 1.00         Min.   : 1.00          Min.   :  0.00   Min.   : 0.000
##  1st Qu.: 8.00         1st Qu.: 8.00          1st Qu.: 10.00   1st Qu.: 0.000
##  Median :25.00         Median :28.00          Median : 15.00   Median : 0.000
##  Mean   :28.14         Mean   :29.01          Mean   : 19.02   Mean   : 1.527
##  3rd Qu.:37.00         3rd Qu.:38.00          3rd Qu.: 22.50   3rd Qu.: 2.000
##  Max.   :77.00         Max.   :77.00          Max.   :110.00   Max.   :38.000
##  NA's   :189           NA's   :185            NA's   :1        NA's   :1
##  Additional_Charges   Trip_Total     Shared_Trip_Authorized Shared_Trip_Match
##  Min.   : 0.000     Min.   :   0.00   Length:2000           Length:2000
```

```
##  1st Qu.: 2.010     1st Qu.: 13.73   Class :character       Class :character  
##  Median : 3.700     Median : 19.43   Mode  :character       Mode  :character  
##  Mean   : 4.691     Mean   : 25.24                                            
##  3rd Qu.: 5.715     3rd Qu.: 29.69                                            
##  Max.   :62.680     Max.   :129.41                                            
##  NA's   :1          NA's   :1                                                 
##   Trips_Pooled   Pickup_Centroid_Latitude Pickup_Centroid_Longitude
##  Min.   :1.000   Min.   :41.66            Min.   :-87.91           
##  1st Qu.:1.000   1st Qu.:41.87            1st Qu.:-87.69           
##  Median :1.000   Median :41.89            Median :-87.65           
##  Mean   :1.042   Mean   :41.89            Mean   :-87.67           
##  3rd Qu.:1.000   3rd Qu.:41.94            3rd Qu.:-87.63           
##  Max.   :5.000   Max.   :42.02            Max.   :-87.53           
##                  NA's   :183              NA's   :183              
##  Pickup_Centroid_Location Dropoff_Centroid_Latitude Dropoff_Centroid_Longitude
##  Length:2000              Min.   :41.66             Min.   :-87.91            
##  Class :character         1st Qu.:41.87             1st Qu.:-87.70            
##  Mode  :character         Median :41.89             Median :-87.66            
##                           Mean   :41.89             Mean   :-87.67            
##                           3rd Qu.:41.94             3rd Qu.:-87.63            
##                           Max.   :42.02             Max.   :-87.55            
##                           NA's   :177               NA's   :177               
##  Dropoff_Centroid_Location
##  Length:2000              
##  Class :character         
##  Mode  :character         
##                           
##                           
##                           
## 
```

Add some calc columns

```r
trips$Trip_Start_Timestamp = as.Date(trips$Trip_Start_Timestamp, format="%m/%d/%Y")
trips$dow = weekdays(trips$Trip_Start_Timestamp)
head(trips)
```

```
##    PK_UID                                  Trip_ID Trip_Start_Timestamp
## 1 1078724 a45e404c67637a35ba8c68eb02abd0ef57a27851           2024-06-26
## 2 5948098 9bd17c2ea621b7c1bba3725d89c18b45ac574971           2024-06-07
## 3 1058729 92cc46f8531e33eee0e5a21cda3cb34d7997e0c8           2024-06-27
## 4 2375826 4c4659ad8d22f0f0177e79e2140023a9ffea9ea2           2024-06-21
## 5  559953 aceb9a135afb3a822bce97dbf5f80b31fa951c3d           2024-06-28
## 6 7199958 8fd92610f23c8513b2618355ea3dbaf1ac734e37           2024-06-02
##       Trip_End_Timestamp Trip_Seconds Trip_Miles Percent_Time_Chicago
## 1 06/26/2024 10:30:00 PM         1124        4.9                    1
## 2 06/07/2024 03:30:00 PM          896        3.0                    1
## 3 06/27/2024 01:30:00 AM         1994       27.8                    0
## 4 06/21/2024 09:15:00 PM         2963       26.9                    1
## 5 06/28/2024 10:45:00 PM          816        2.4                    1
## 6 06/02/2024 06:00:00 AM         2260       32.4                    1
##   Percent_Distance_Chicago Pickup_Census_Tract Dropoff_Census_Tract
## 1                        1                  NA                   NA
## 2                        1                  NA                   NA
## 3                        0         17031980000                   NA
## 4                        1                  NA                   NA
## 5                        1         17031081403          17031842200
## 6                        1         17031820901          17031980000
##   Pickup_Community_Area Dropoff_Community_Area Fare Tip Additional_Charges
```

```
## 1                    28                      6 32.5   0               1.23
## 2                    28                     24 17.5   0               5.68
## 3                    76                     NA 60.0  12              21.39
## 4                    NA                      6 22.5   0               6.95
## 5                     8                      8 10.0   0               1.23
## 6                    NA                     76 47.5  12              28.12
##   Trip_Total Shared_Trip_Authorized Shared_Trip_Match Trips_Pooled
## 1      33.73                  false             false            1
## 2      23.18                  false             false            1
## 3      93.39                  false             false            1
## 4      29.45                  false             false            1
## 5      11.23                  false             false            1
## 6      87.62                  false             false            1
##   Pickup_Centroid_Latitude Pickup_Centroid_Longitude
## 1                 41.87400                 -87.66352
## 2                 41.87400                 -87.66352
## 3                 41.97907                 -87.90304
## 4                       NA                        NA
## 5                 41.89092                 -87.61887
## 6                       NA                        NA
##                Pickup_Centroid_Location Dropoff_Centroid_Latitude
## 1  POINT (-87.6635175498 41.874005383)                  41.94423
## 2  POINT (-87.6635175498 41.874005383)                  41.90121
## 3 POINT (-87.9030396611 41.9790708201)                        NA
## 4                                                       41.94423
## 5 POINT (-87.6188683546 41.8909220259)                  41.90494
## 6                                                       41.97907
##   Dropoff_Centroid_Longitude            Dropoff_Centroid_Location       dow
## 1                  -87.65600 POINT (-87.6559981815 41.9442266014) Wednesday
## 2                  -87.67636 POINT (-87.6763559892 41.9012069941)    Friday
## 3                         NA                                       Thursday
## 4                  -87.65600 POINT (-87.6559981815 41.9442266014)    Friday
## 5                  -87.64991 POINT (-87.6499072264 41.9049353016)    Friday
## 6                  -87.90304 POINT (-87.9030396611 41.9790708201)    Sunday
```

```r
summary(trips)
```

```
##      PK_UID          Trip_ID          Trip_Start_Timestamp Trip_End_Timestamp
##  Min.   :   2180   Length:2000        Min.   :2024-06-01   Length:2000
##  1st Qu.:1857128   Class :character   1st Qu.:2024-06-08   Class :character
##  Median :3728684   Mode  :character   Median :2024-06-15   Mode  :character
##  Mean   :3749083                      Mean   :2024-06-15
##  3rd Qu.:5638863                      3rd Qu.:2024-06-23
##  Max.   :7588816                      Max.   :2024-06-30
##
##   Trip_Seconds      Trip_Miles     Percent_Time_Chicago
##  Min.   :  55.0   Min.   : 0.200   Min.   :0.0000
##  1st Qu.: 615.8   1st Qu.: 2.175   1st Qu.:1.0000
##  Median : 991.5   Median : 4.400   Median :1.0000
##  Mean   :1218.3   Mean   : 7.336   Mean   :0.9325
##  3rd Qu.:1583.0   3rd Qu.:10.000   3rd Qu.:1.0000
##  Max.   :5937.0   Max.   :63.900   Max.   :1.0000
##                                    NA's   :1
##  Percent_Distance_Chicago Pickup_Census_Tract Dropoff_Census_Tract
##  Min.   :0.0000           Min.   :1.703e+10   Min.   :1.703e+10
##  1st Qu.:1.0000           1st Qu.:1.703e+10   1st Qu.:1.703e+10
##  Median :1.0000           Median :1.703e+10   Median :1.703e+10
##  Mean   :0.9275           Mean   :1.703e+10   Mean   :1.703e+10
##  3rd Qu.:1.0000           3rd Qu.:1.703e+10   3rd Qu.:1.703e+10
##  Max.   :1.0000           Max.   :1.703e+10   Max.   :1.703e+10
```

```
##  NA's   :1                NA's   :775         NA's   :775
##  Pickup_Community_Area Dropoff_Community_Area      Fare             Tip
##  Min.   : 1.00         Min.   : 1.00          Min.   :  0.00   Min.   : 0.000
##  1st Qu.: 8.00         1st Qu.: 8.00          1st Qu.: 10.00   1st Qu.: 0.000
##  Median :25.00         Median :28.00          Median : 15.00   Median : 0.000
##  Mean   :28.14         Mean   :29.01          Mean   : 19.02   Mean   : 1.527
##  3rd Qu.:37.00         3rd Qu.:38.00          3rd Qu.: 22.50   3rd Qu.: 2.000
##  Max.   :77.00         Max.   :77.00          Max.   :110.00   Max.   :38.000
##  NA's   :189           NA's   :185            NA's   :1        NA's   :1
##  Additional_Charges   Trip_Total     Shared_Trip_Authorized Shared_Trip_Match
##  Min.   : 0.000     Min.   :  0.00   Length:2000            Length:2000
##  1st Qu.: 2.010     1st Qu.: 13.73   Class :character       Class :character
##  Median : 3.700     Median : 19.43   Mode  :character       Mode  :character
##  Mean   : 4.691     Mean   : 25.24
##  3rd Qu.: 5.715     3rd Qu.: 29.69
##  Max.   :62.680     Max.   :129.41
##  NA's   :1          NA's   :1
##   Trips_Pooled   Pickup_Centroid_Latitude Pickup_Centroid_Longitude
##  Min.   :1.000   Min.   :41.66            Min.   :-87.91
##  1st Qu.:1.000   1st Qu.:41.87            1st Qu.:-87.69
##  Median :1.000   Median :41.89            Median :-87.65
##  Mean   :1.042   Mean   :41.89            Mean   :-87.67
##  3rd Qu.:1.000   3rd Qu.:41.94            3rd Qu.:-87.63
##  Max.   :5.000   Max.   :42.02            Max.   :-87.53
##                  NA's   :183              NA's   :183
##  Pickup_Centroid_Location Dropoff_Centroid_Latitude Dropoff_Centroid_Longitude
##  Length:2000              Min.   :41.66             Min.   :-87.91
##  Class :character         1st Qu.:41.87             1st Qu.:-87.70
##  Mode  :character         Median :41.89             Median :-87.66
##                           Mean   :41.89             Mean   :-87.67
##                           3rd Qu.:41.94             3rd Qu.:-87.63
##                           Max.   :42.02             Max.   :-87.55
##                           NA's   :177               NA's   :177
##  Dropoff_Centroid_Location     dow
##  Length:2000               Length:2000
##  Class :character          Class :character
##  Mode  :character          Mode  :character
##
##
##
##
```

Get rid of some not useful columns that contain info like identifiers and coordinates

```r
trips_int = trips[,c("Trip_Seconds","Trip_Miles","Percent_Time_Chicago","Percent_Distance_Chicago","Fare","Tip","Ad
summary(trips_int)
```

```
##   Trip_Seconds      Trip_Miles     Percent_Time_Chicago
##  Min.   :  55.0   Min.   : 0.200   Min.   :0.0000
##  1st Qu.: 615.8   1st Qu.: 2.175   1st Qu.:1.0000
##  Median : 991.5   Median : 4.400   Median :1.0000
##  Mean   :1218.3   Mean   : 7.336   Mean   :0.9325
##  3rd Qu.:1583.0   3rd Qu.:10.000   3rd Qu.:1.0000
##  Max.   :5937.0   Max.   :63.900   Max.   :1.0000
##                                    NA's   :1
##  Percent_Distance_Chicago      Fare             Tip          Additional_Charges
##  Min.   :0.0000           Min.   :  0.00   Min.   : 0.000   Min.   : 0.000
##  1st Qu.:1.0000           1st Qu.: 10.00   1st Qu.: 0.000   1st Qu.: 2.010
##  Median :1.0000           Median : 15.00   Median : 0.000   Median : 3.700
```

```
##  Mean   :0.9275          Mean   : 19.02   Mean   : 1.527   Mean   : 4.691
##  3rd Qu.:1.0000          3rd Qu.: 22.50   3rd Qu.: 2.000   3rd Qu.: 5.715
##  Max.   :1.0000          Max.   :110.00   Max.   :38.000   Max.   :62.680
##  NA's   :1               NA's   :1        NA's   :1        NA's   :1
##    Trip_Total      Trips_Pooled   Shared_Trip_Authorized Shared_Trip_Match
##  Min.   :  0.00   Min.   :1.000   Length:2000            Length:2000
##  1st Qu.: 13.73   1st Qu.:1.000   Class :character       Class :character
##  Median : 19.43   Median :1.000   Mode  :character       Mode  :character
##  Mean   : 25.24   Mean   :1.042
##  3rd Qu.: 29.69   3rd Qu.:1.000
##  Max.   :129.41   Max.   :5.000
##  NA's   :1
##      dow
##  Length:2000
##  Class :character
##  Mode  :character
##
##
##
##
```

Check if the trip_total column is just the sum of the other three cost columns and get rid of it if so to not cause dependent columns

```r
trips_int$total_check = with(trips_int,trips_int$Fare + trips_int$Tip + trips_int$Tip + trips_int$Additional_Charge
summary(trips_int$total_check)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   0.000   0.000   0.000   1.527   2.000  38.000       1
```

Its inconsitent so we will clean by just dropping this column to be safe

```r
trips_int$total_check = NULL
trips_int$Trip_Total = NULL
```

Check for nulls

```r
head(trips_int)
```

```
##   Trip_Seconds Trip_Miles Percent_Time_Chicago Percent_Distance_Chicago Fare
## 1         1124        4.9                    1                        1 32.5
## 2          896        3.0                    1                        1 17.5
## 3         1994       27.8                    0                        0 60.0
## 4         2963       26.9                    1                        1 22.5
## 5          816        2.4                    1                        1 10.0
## 6         2260       32.4                    1                        1 47.5
##   Tip Additional_Charges Trips_Pooled Shared_Trip_Authorized Shared_Trip_Match
## 1   0               1.23            1                  false             false
## 2   0               5.68            1                  false             false
## 3  12              21.39            1                  false             false
## 4   0               6.95            1                  false             false
## 5   0               1.23            1                  false             false
## 6  12              28.12            1                  false             false
##         dow
## 1 Wednesday
## 2    Friday
## 3  Thursday
## 4    Friday
```

```
## 5    Friday
## 6    Sunday
```

```r
sum(is.na(trips_int))
```

```
## [1] 5
```

```r
trips_int=trips_int[complete.cases(trips_int),]
nrow(trips_int)
```

```
## [1] 1998
```

```r
set.seed(1)
train_ind = sample(1:nrow(trips_int),round(nrow(trips_int)*0.9))
train <- trips_int[train_ind,]
test <- trips_int[-train_ind,]
```

```r
ggpairs(train)
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
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## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```
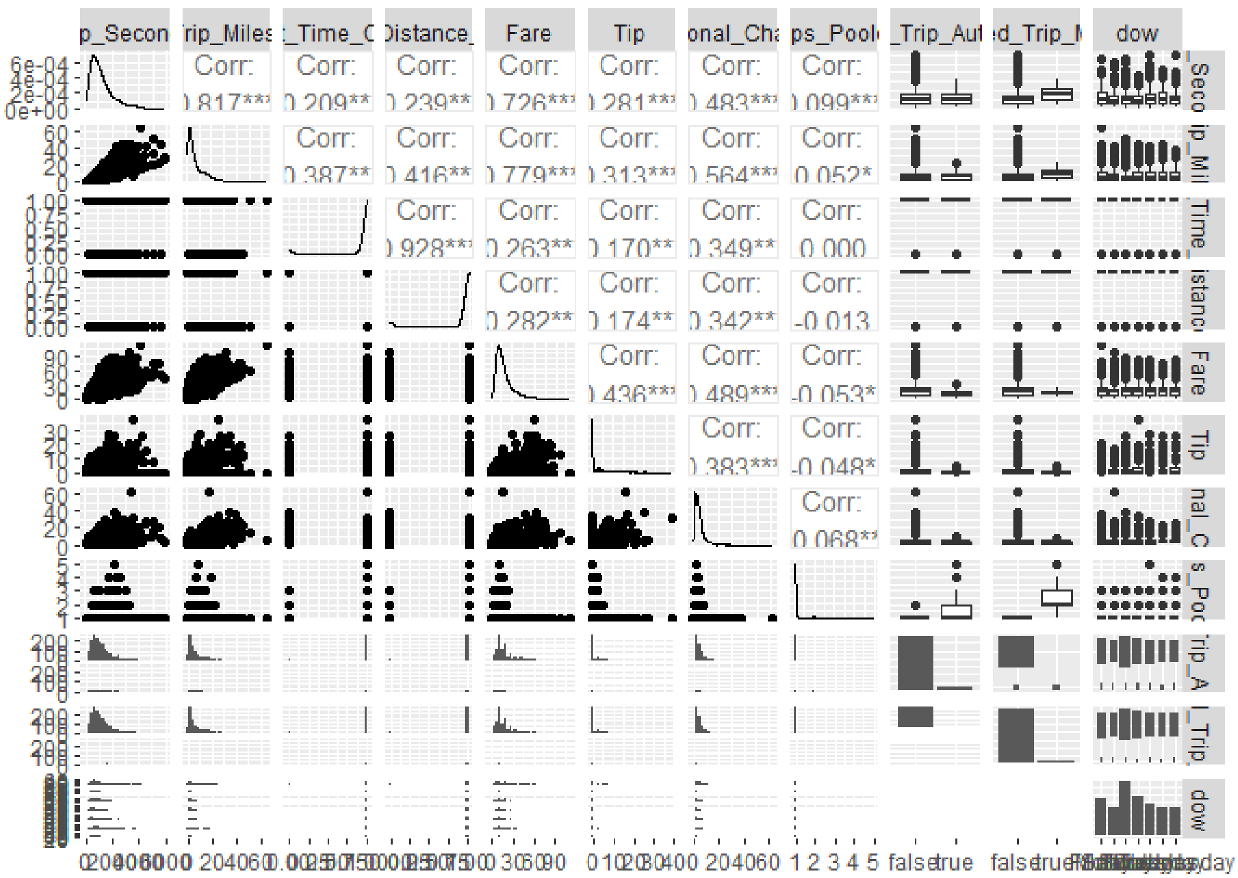



the two percent columns also do not seem useful so lets get rid of them too.

```
trips_int$Percent_Time_Chicago = NULL
trips_int$Percent_Distance_Chicago = NULL
train <- trips_int[train_ind,]
test <- trips_int[-train_ind,]
```

I want to create a fare model from this data to use in my research. Lets find out what variables are important to fare.

```
mod = lm(Fare~.,data = train)
summary(mod)
```

```
##
## Call:
## lm(formula = Fare ~ ., data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -31.136  -4.114  -1.440   2.645  52.441
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 6.894924   1.621669   4.252 2.23e-05 ***
## Trip_Seconds                0.004439   0.000379  11.714  < 2e-16 ***
## Trip_Miles                  0.930867   0.045233  20.579  < 2e-16 ***
## Tip                         0.798935   0.059870  13.344  < 2e-16 ***
```

```
## Additional_Charges         -0.030049   0.053778  -0.559   0.5764
## Trips_Pooled               -0.792071   1.531302  -0.517   0.6050
## Shared_Trip_Authorizedtrue -4.890068   1.067234  -4.582 4.92e-06 ***
## Shared_Trip_Matchtrue      -2.971141   2.640581  -1.125   0.2607
## dowMonday                  -0.085948   0.729787  -0.118   0.9063
## dowSaturday                 0.458279   0.623896   0.735   0.4627
## dowSunday                   1.223020   0.671381   1.822   0.0687 .
## dowThursday                -0.705050   0.703864  -1.002   0.3166
## dowTuesday                 -0.613870   0.728873  -0.842   0.3998
## dowWednesday               -0.520356   0.725991  -0.717   0.4736
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.886 on 1784 degrees of freedom
## Multiple R-squared:  0.6857, Adjusted R-squared:  0.6835
## F-statistic: 299.5 on 13 and 1784 DF,  p-value: < 2.2e-16
```

DOW doesn't appear to affect things but tip does, and thats of concern because there is an intuitive relationship between tip and fare. So we should drop this. But lets check correlation to be sure.

```r
train_num = subset(train, select = -c(dow,Shared_Trip_Authorized,Shared_Trip_Match))
test_num = subset(test, select = -c(dow,Shared_Trip_Authorized,Shared_Trip_Match))

cor_mat = cor(train_num)
cor_mat
```

```
##                    Trip_Seconds Trip_Miles        Fare         Tip
## Trip_Seconds         1.00000000  0.8167555  0.72560059  0.28135121
## Trip_Miles           0.81675553  1.0000000  0.77914316  0.31294200
## Fare                 0.72560059  0.7791432  1.00000000  0.43593463
## Tip                  0.28135121  0.3129420  0.43593463  1.00000000
## Additional_Charges   0.48296814  0.5638116  0.48942965  0.38281205
## Trips_Pooled         0.09920895  0.0524975 -0.05279474 -0.04785573
##                    Additional_Charges Trips_Pooled
## Trip_Seconds               0.48296814   0.09920895
## Trip_Miles                 0.56381163   0.05249750
## Fare                       0.48942965  -0.05279474
## Tip                        0.38281205  -0.04785573
## Additional_Charges         1.00000000  -0.06813661
## Trips_Pooled              -0.06813661   1.00000000
```

Trip miles and trip seconds are highly correlated but thats fine, most fare models use both so we will hold onto it for now.

```r
trips_int$Tip = NULL
train <- trips_int[train_ind,]
test <- trips_int[-train_ind,]
mod_lm = lm(Fare~.,data=train)
summary(mod_lm)
```

```
##
## Call:
## lm(formula = Fare ~ ., data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -31.048  -4.116  -1.617   2.567  53.791
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 6.5729591  1.7000144   3.866 0.000114 ***
## Trip_Seconds                0.0046652  0.0003969  11.754  < 2e-16 ***
## Trip_Miles                  0.9636633  0.0473538  20.350  < 2e-16 ***
```

```
## Additional_Charges          0.1529081  0.0545190   2.805 0.005091 **
## Trips_Pooled               -0.7980036  1.6054593  -0.497 0.619211
## Shared_Trip_Authorizedtrue -5.4702694  1.1179887  -4.893 1.08e-06 ***
## Shared_Trip_Matchtrue      -3.1061418  2.7684382  -1.122 0.262020
## dowMonday                   0.1151217  0.7649658   0.150 0.880393
## dowSaturday                 0.7886384  0.6535943   1.207 0.227739
## dowSunday                   1.6976677  0.7029062   2.415 0.015826 *
## dowThursday                -0.7321640  0.7379478  -0.992 0.321253
## dowTuesday                 -0.4810313  0.7640993  -0.630 0.529076
## dowWednesday               -0.2442809  0.7608396  -0.321 0.748197
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.268 on 1785 degrees of freedom
## Multiple R-squared:  0.6544, Adjusted R-squared:  0.6521
## F-statistic: 281.6 on 12 and 1785 DF,  p-value: < 2.2e-16
```

LM

Only Shared_Trip_Authorized, trip_miles, and trip_seconds were significant so lets use these only. Additional_Charges is significant but this is not a useful variable for our use case because this is not something we could know ahead of time or it would probably be fixed (taxes and fees). Sunday is now slightly significant so we will include that too.

```r
mod_lm = lm(Fare~dow+Shared_Trip_Authorized+Trip_Miles+Trip_Seconds,data=train)
summary(mod_lm)
```

```
##
## Call:
## lm(formula = Fare ~ dow + Shared_Trip_Authorized + Trip_Miles +
##     Trip_Seconds, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -27.049  -4.250  -1.698   2.665  54.253
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                6.2068590  0.5934005  10.460   <2e-16 ***
## dowMonday                  0.2200200  0.7669919   0.287    0.774
## dowSaturday                0.7154411  0.6557313   1.091    0.275
## dowSunday                  1.7009283  0.7052920   2.412    0.016 *
## dowThursday               -0.6983884  0.7400216  -0.944    0.345
## dowTuesday                -0.4207460  0.7658362  -0.549    0.583
## dowWednesday              -0.2132377  0.7631928  -0.279    0.780
## Shared_Trip_Authorizedtrue -7.7497278  0.8284607  -9.354   <2e-16 ***
## Trip_Miles                 1.0137258  0.0447858  22.635   <2e-16 ***
## Trip_Seconds               0.0046016  0.0003953  11.640   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.299 on 1788 degrees of freedom
## Multiple R-squared:  0.6512, Adjusted R-squared:  0.6495
## F-statistic: 370.9 on 9 and 1788 DF,  p-value: < 2.2e-16
```

Simple LM has r^2 of only 0.65, lets check its predictive accuracy.

```r
test$lm_preds = predict(mod_lm,newdata = test)
mse <- mean((test$Fare - test$lm_preds)^2)
paste("MSE=",mse)
```

```
## [1] "MSE= 52.2219365866465"
```

Lets use subsets to check and see if anything else is helpful

```r
regfit_full = regsubsets(Fare~.,train)
summary(regfit_full)
```

```
## Subset selection object
## Call: regsubsets.formula(Fare ~ ., train)
## 12 Variables  (and intercept)
##                             Forced in Forced out
## Trip_Seconds                    FALSE      FALSE
## Trip_Miles                      FALSE      FALSE
## Additional_Charges              FALSE      FALSE
## Trips_Pooled                    FALSE      FALSE
## Shared_Trip_Authorizedtrue      FALSE      FALSE
## Shared_Trip_Matchtrue           FALSE      FALSE
## dowMonday                       FALSE      FALSE
## dowSaturday                     FALSE      FALSE
## dowSunday                       FALSE      FALSE
## dowThursday                     FALSE      FALSE
## dowTuesday                      FALSE      FALSE
## dowWednesday                    FALSE      FALSE
## 1 subsets of each size up to 8
## Selection Algorithm: exhaustive
##          Trip_Seconds Trip_Miles Additional_Charges Trips_Pooled
## 1  ( 1 ) " "          "*"        " "                " "
## 2  ( 1 ) "*"          "*"        " "                " "
## 3  ( 1 ) "*"          "*"        " "                " "
## 4  ( 1 ) "*"          "*"        " "                " "
## 5  ( 1 ) "*"          "*"        "*"                " "
## 6  ( 1 ) "*"          "*"        "*"                " "
## 7  ( 1 ) "*"          "*"        "*"                " "
## 8  ( 1 ) "*"          "*"        "*"                " "
##          Shared_Trip_Authorizedtrue Shared_Trip_Matchtrue dowMonday dowSaturday
## 1  ( 1 ) " "                        " "                   " "       " "
## 2  ( 1 ) " "                        " "                   " "       " "
## 3  ( 1 ) "*"                        " "                   " "       " "
## 4  ( 1 ) "*"                        " "                   " "       " "
## 5  ( 1 ) "*"                        " "                   " "       " "
## 6  ( 1 ) "*"                        "*"                   " "       " "
## 7  ( 1 ) "*"                        "*"                   " "       "*"
## 8  ( 1 ) "*"                        "*"                   " "       "*"
##          dowSunday dowThursday dowTuesday dowWednesday
## 1  ( 1 ) " "       " "         " "        " "
## 2  ( 1 ) " "       " "         " "        " "
## 3  ( 1 ) " "       " "         " "        " "
## 4  ( 1 ) "*"       " "         " "        " "
## 5  ( 1 ) "*"       " "         " "        " "
## 6  ( 1 ) "*"       " "         " "        " "
## 7  ( 1 ) "*"       " "         " "        " "
## 8  ( 1 ) "*"       "*"         " "        " "
```

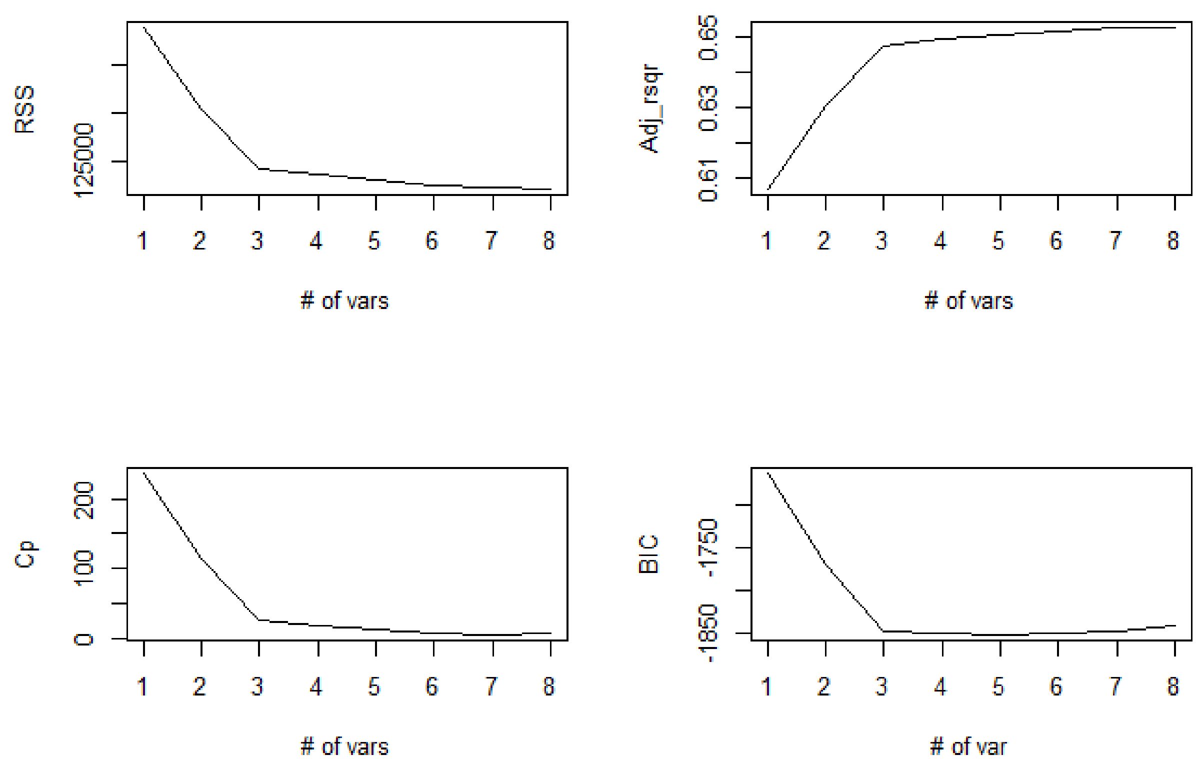
```r
regfit_full = regsubsets(Fare~.,data = train, nvmax=8)
reg_sum = summary(regfit_full)
names(reg_sum)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```r
reg_sum$rsq
```

```
## [1] 0.6070641 0.6309810 0.6482925 0.6501786 0.6517873 0.6531103 0.6540107
## [8] 0.6541979
```

```r
par(mfrow=c(2,2))
plot(reg_sum$rss,xlab = "# of vars",ylab="RSS",type="l")
plot(reg_sum$adjr2,xlab = "# of vars",ylab = "Adj_rsqr",type="l")
plot(reg_sum$cp,xlab="# of vars",ylab="Cp",type="l")
plot(reg_sum$bic, xlab="# of var",ylab="BIC",type="l")
```



These results are showing that some of the higher order models are better fits like 5 in BIC, 7 in Cp but the most obvious change is with the 3 variable model. Lets try stepwise selection.

```r
null <-lm(Fare ~ 1, data=train)
full <- lm(Fare ~ ., data=train)

stepAIC(full, scope = list(lower = null, upper= full),direction = "both", trace = FALSE)
```

```
##
## Call:
## lm(formula = Fare ~ Trip_Seconds + Trip_Miles + Additional_Charges +
##     Shared_Trip_Authorized + Shared_Trip_Match + dow, data = train)
##
## Coefficients:
##                (Intercept)                Trip_Seconds
##                   5.782927                    0.004662
##                 Trip_Miles          Additional_Charges
##                   0.963446                    0.153763
## Shared_Trip_Authorizedtrue       Shared_Trip_Matchtrue
##                  -5.476556                   -4.232899
##                  dowMonday                 dowSaturday
##                   0.119332                    0.784337
```

```
##                  dowSunday                 dowThursday
##                   1.689476                   -0.745963
##                 dowTuesday                dowWednesday
##                  -0.498965                   -0.255236
```

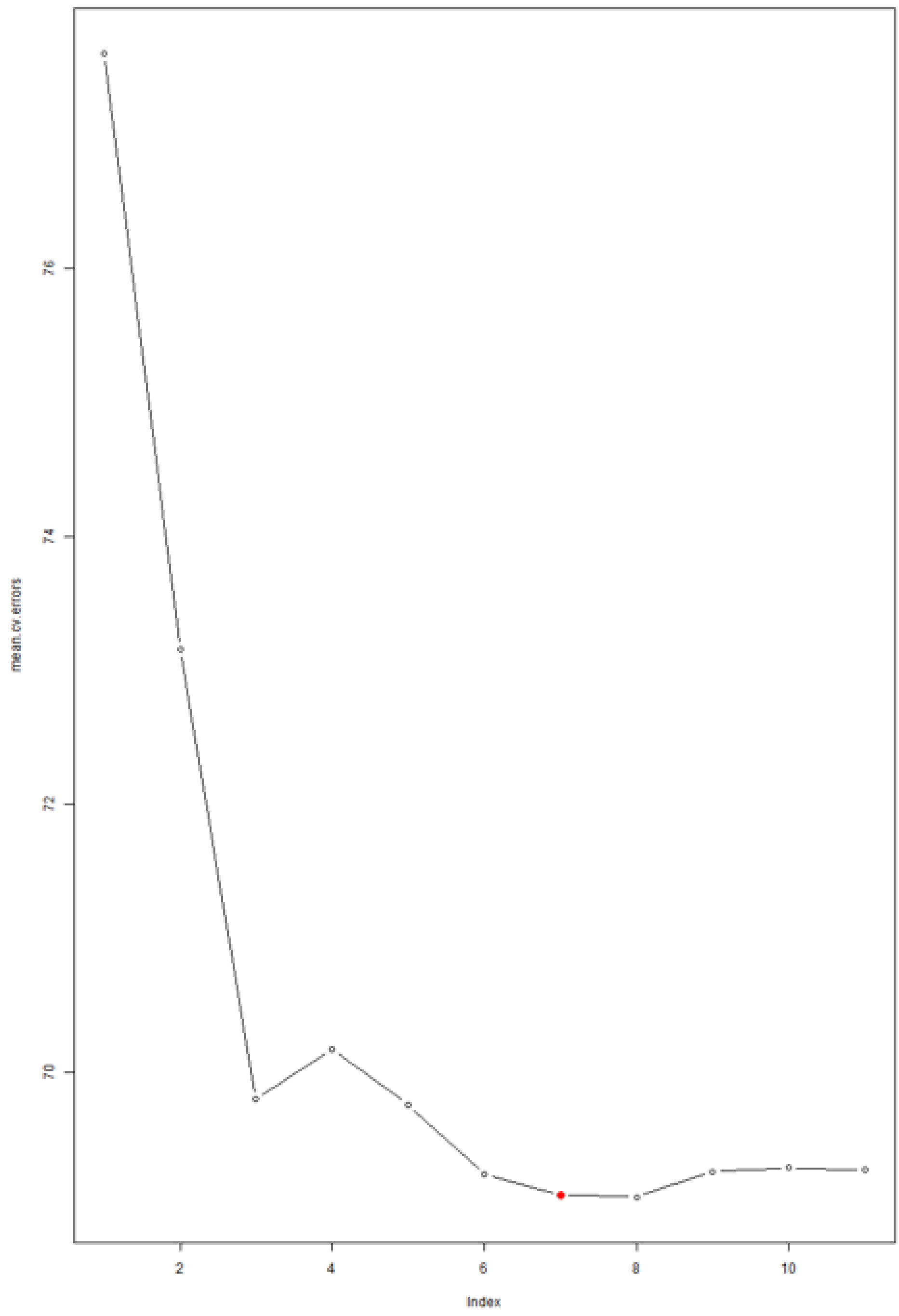
```
predict.regsubsets =function (object ,newdata ,id ,...){
form=as.formula (object$call [[2]])
mat=model.matrix (form ,newdata )
coefi =coef(object ,id=id)
xvars =names (coefi )
mat[,xvars ]%*% coefi
}


k= 10
folds=sample(1:k,nrow(train),replace = TRUE)
cv.errors=matrix(NA,k,11,dimnames=list(NULL,paste(1:11)))
for (j in 1:k){
best.fit=regsubsets(Fare~.,data=train[folds!=j,],nvmax=11)
for (i in 1:11){
pred=predict(best.fit,train[folds==j,],id=i)
cv.errors[j,i]=mean((train$Fare[folds==j]-pred)^2)
}
}
mean.cv.errors=apply(cv.errors,2,mean)
mean.cv.errors
```

```
##        1        2        3        4        5        6        7        8
## 77.23545 72.64004 69.28467 69.42865 69.30912 69.03773 68.52978 68.59183
##        9       10       11
## 68.73178 68.74530 68.73758
```

```
par(mfrow=c(1,1))
plot(mean.cv.errors,type="b")
which.min(mean.cv.errors)
```

```
## 7
## 7
```

```
points(7,mean.cv.errors[7],col="red",cex=2,pch=20)
```



The 8 variable model has the best mean.cv.errors.

```
reg.best = regsubsets(Fare~.,train,nvmax=11)
coef(reg.best,7)
```

```
##                (Intercept)              Trip_Seconds
##                5.521221404               0.004651536
##                 Trip_Miles        Additional_Charges
##                0.963793543               0.154063452
## Shared_Trip_Authorizedtrue      Shared_Trip_Matchtrue
```

```
##               -5.465101328               -4.217494625
##                dowSaturday                  dowSunday
##                1.053798586                1.958618473
```

```r
test$predicted_y_cv_subset <-predict.regsubsets(reg.best, test, 7)
mse <- mean((test$Fare - test$predicted_y_cv_subset)^2)
mse
```

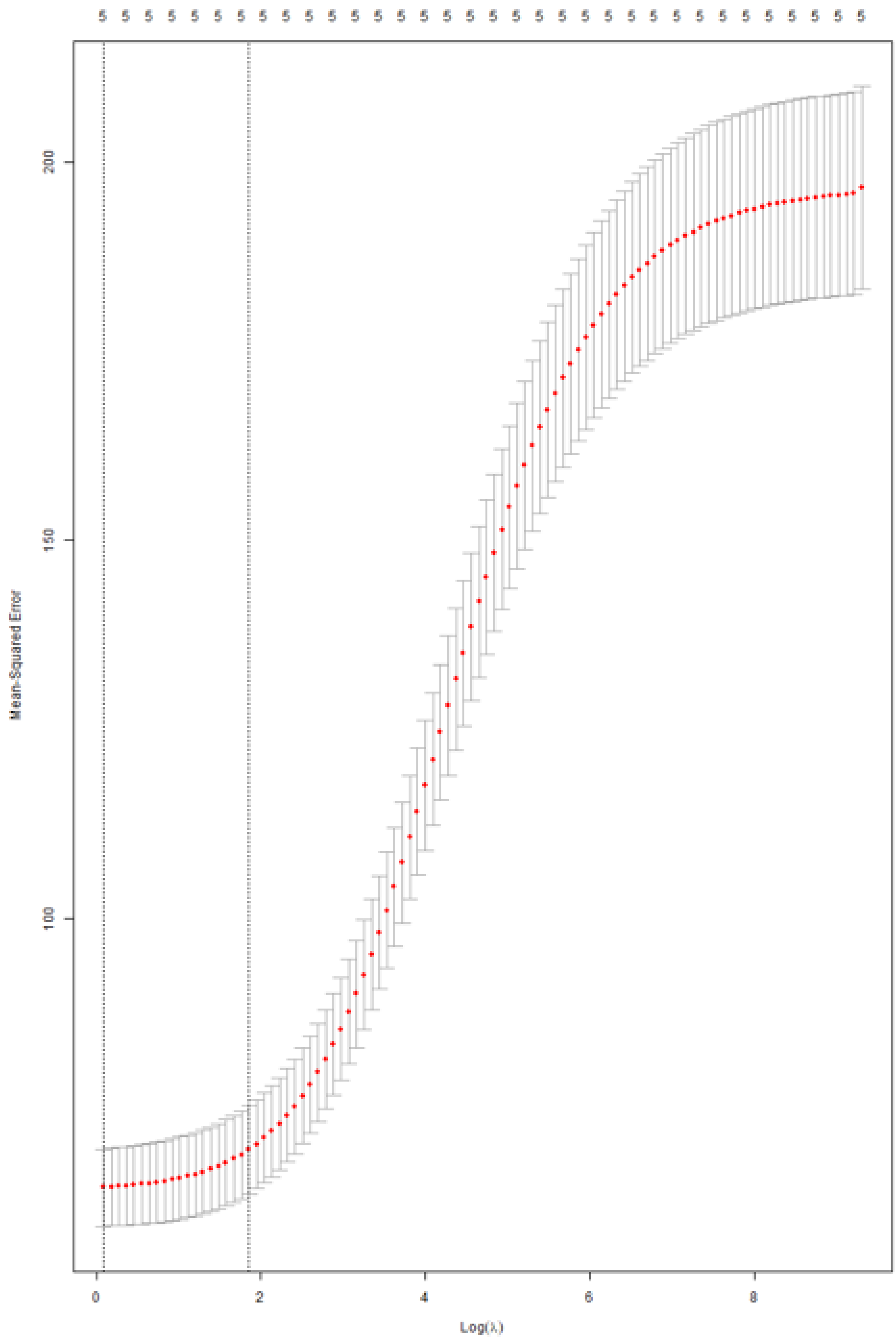
```
## [1] 51.64421
```

```r
ss_total <- sum((test$Fare - mean(test$Fare))^2)
ss_res <- sum((test$Fare - test$predicted_y)^2)
r_squared <- 1 - (ss_res / ss_total)
r_squared
```

```
## [1] 0.6314024
```

R^2 is still worse than LM, but MSE is slighly better. Less bias in the cv subset model.

```r
x=model.matrix(Fare~.,train_num)[,-1]
y=train_num$Fare
grid = 10^seq(10,-2,length=100)
ridge.mod = glmnet(x,y, alpha = 0,lambda=grid)
cv.out.ridge = cv.glmnet(x,y,alpha=0)
plot(cv.out.ridge)
```




```
bestlam = cv.out.ridge$lambda.min
bestlam
```

```
## [1] 1.091826
```

```
test_x =model.matrix(Fare~.,test_num)[,-1]
test_x
```

```
##      Trip_Seconds Trip_Miles Tip Additional_Charges Trips_Pooled
## 6            2260       32.4  12              28.12            1
```

```
## 10             421         1.3   0               1.23            1
## 24             908         3.6   2               1.18            2
## 25             592         1.4   0               2.94            1
## 30             541         1.8   0               1.23            1
## 32            1342         9.1   0               3.30            1
## 70             300         0.9   0               2.49            1
## 85            1379         8.1   0               7.02            1
## 123            980         2.2   3               4.46            1
## 154            919         6.6   0               5.35            1
## 155           2254         9.3   0               4.71            1
## 172           1024         5.1   3               3.45            1
## 178            482         4.1   0               3.89            1
## 188           2690        13.5   0               4.49            2
## 189            924         3.5   0               4.87            1
## 195           1072         6.0   6               7.90            1
## 200            444         0.7   3               4.89            1
## 211           1300         4.9   2               1.23            1
## 215            756         2.1   2               2.78            1
## 257           1273         8.2  10               2.98            1
## 263            783         2.5   2               1.23            1
## 283            943        10.6   0               6.83            1
## 288            908         4.7   0               1.23            1
## 295            366         1.1   3               3.77            1
## 297            309         1.3   0               1.23            1
## 301            459         1.5   3               2.01            1
## 331           2069        10.2   6              12.23            1
## 337            371         0.7   0               2.07            1
## 344           1868        13.0  14               1.23            1
## 362            697         2.3   0               2.52            1
## 367            731         4.2   0               3.29            1
## 370           1269        16.5   0              10.77            1
## 380           1421         5.6   0               2.98            1
## 385           1344         6.9   0               2.82            1
## 395            532         1.3   3               3.76            1
## 424            521         1.5   0               2.15            1
## 429           1652         7.2   0               6.00            1
## 433           1828        18.0   0               7.98            1
## 447           2204        13.2   0               4.57            1
## 475           1289        10.2   0               7.10            1
## 497           1973         9.0   0               1.23            1
## 523             97         0.4   0               2.68            1
## 527            527         1.3   3               4.35            1
## 531            759         3.0   0               1.23            1
## 542            492         2.0   0               4.27            1
## 545           1197         4.4   0               3.08            1
## 555            413         3.0   0               3.70            1
## 558           1814         8.6   0               5.89            1
## 602            681         3.2   0               3.93            1
## 603           1498        11.1   0               1.23            1
## 605            342         1.4   0               3.70            1
## 613            646         3.4   0               2.97            1
## 622            421         2.6   0               1.23            1
## 667            976         6.6   0               5.08            1
## 668            324         1.3   0               1.98            1
## 695           1625        17.0   9              11.23            1
## 697           1599         5.0   0               4.50            1
## 698           2512        14.4   5               6.23            1
## 700           1517        16.0   0               1.23            1
## 701            421         2.0   0               2.61            1
```

```
## 716           1154       9.8   0              1.23            1
## 734           1697       9.6   0              2.98            1
## 735           3107      16.4   0              5.55            1
## 742            283       1.1   0              1.88            1
## 755            288       0.8   3              2.16            1
## 772            755       6.7   3              3.08            1
## 803            353       1.2   0              2.82            1
## 806           1643      22.5   0              7.13            1
## 807           3205      14.8   0              9.98            1
## 814           2759      34.6   0              6.45            1
## 830            605       3.8   0              6.52            1
## 833           2454       9.9   0              4.52            2
## 834            788       3.4   0              3.10            1
## 870           1050       3.8   0              1.23            1
## 872           1911      16.5   0              7.06            1
## 884            459       2.8   0              3.32            1
## 888            671       2.0   1              4.46            1
## 893           1082      12.2  10             22.07            1
## 926            573       2.8   0              3.96            1
## 929            689       2.7   0              5.06            1
## 933            658       3.0   0              3.83            1
## 943            338       0.8   0              2.49            1
## 962            982       3.6   0              5.42            1
## 963           1171       9.4   0              4.81            1
## 964           1779       6.9   0              5.34            2
## 965            339       0.7   1              2.50            1
## 973           2650      13.7   0              5.56            1
## 982            476       1.8   1              2.73            1
## 1000          1836       5.6   0              6.14            1
## 1001           289       1.0   0              1.23            1
## 1003          3057      37.4   7             10.50            1
## 1005          1629      10.0   0              8.76            1
## 1034          1544      11.6   0              5.95            1
## 1044          1162       4.7   0              2.71            1
## 1058          3241      36.5   0              4.75            1
## 1063           778       2.4   0              3.45            1
## 1070           904       2.2   0              1.23            1
## 1071           319       1.0   0              8.10            1
## 1074           712       4.4   0              2.90            1
## 1077           370       0.8   5              1.23            1
## 1083           943       3.5   0              1.94            2
## 1086          1670       6.4   8              6.17            1
## 1097           357       1.6   0              1.84            1
## 1100          1070       7.1   0              5.48            1
## 1102          1768      12.9   0              6.11            1
## 1106          1779       8.4   0              4.17            1
## 1130          1089       5.5   0              7.08            1
## 1132          2254      13.4   7              5.46            1
## 1138          1007       8.2   4              1.23            1
## 1160          1148      13.9   0             19.64            1
## 1164           271       1.3   0              1.73            1
## 1173           771       2.1   0              4.23            1
## 1175           744       2.6   0              1.23            1
## 1185          1562      18.0   0              1.23            1
## 1193           804       7.4   0              3.34            1
## 1205          1702       9.4   0              5.06            1
## 1212           991       2.8   0              5.50            1
## 1223          1107       4.5   6              5.58            1
## 1227           292       1.3   0              2.78            1
```

```
## 1240          3985        14.5  20                6.23             1
## 1241          1985         8.3   0                6.75             1
## 1245           147         0.6   0                3.62             1
## 1248           641         1.8   2                1.23             1
## 1249           704         1.9   3                4.26             1
## 1263           870         2.3   0                2.98             1
## 1278           668         1.5   3                4.94             1
## 1283           510         1.4   0                2.98             1
## 1293          2251        19.2   0                6.23             1
## 1307           880         3.3   3                1.23             1
## 1311           704         2.2   0                1.23             1
## 1315           757         2.2   0                2.98             1
## 1321          1977        16.3   5                5.49             1
## 1322           671         1.4   0                3.82             1
## 1325           985         4.4   0                1.23             1
## 1335           908         7.2   0                5.70             1
## 1337           719         4.6   0                3.31             1
## 1339           995         5.1   0                1.23             1
## 1357          1815        17.2   7               22.26             1
## 1397           586         2.0   0                1.23             1
## 1409           426         1.5   2                1.23             1
## 1413           719         4.3   0                4.57             1
## 1415           484         1.0   3                2.65             1
## 1418          3608        33.3   0                8.47             1
## 1429          4337        40.4   5                7.23             1
## 1430          1549        14.8   0                6.15             1
## 1449          1286        11.7   0                1.23             1
## 1455          2164        31.9   8                5.72             1
## 1467           592         3.5   0                6.23             1
## 1476           814         4.8   0                1.23             1
## 1484           496         4.3   0                1.23             1
## 1489           632         3.7   0                4.11             1
## 1493          2087         9.0   0                8.04             1
## 1499          1679        12.4   0                3.93             2
## 1502           396         1.6   0                2.89             1
## 1505           734         1.1   1                4.24             1
## 1515          1216         3.3   0                5.14             1
## 1519           773         3.0   3                4.82             1
## 1520          1637        15.6   7               17.37             1
## 1548           729         3.7   0                2.98             1
## 1564          1008         5.6   0                2.73             1
## 1588           774         2.7   0                1.23             1
## 1613          1632        10.3   0                5.08             1
## 1623          1421        13.0   4                1.23             1
## 1644          1787         4.2   0                1.91             2
## 1651          1664        15.4   5                3.74             1
## 1674           831         7.4   0                2.66             1
## 1699          1390         7.7   4                5.36             1
## 1703          1315        16.8   0               16.98             1
## 1710          3173        21.3   9               13.99             1
## 1719           954         3.0   0                2.98             1
## 1726          2029         8.5   0                1.23             1
## 1729          1063         3.5   0                1.23             1
## 1743          2686         9.7  10                6.23             1
## 1766          2119        18.1   9                4.82             1
## 1767           316         1.5   0                9.24             1
## 1783          1274         2.3   0                2.98             1
## 1789           935         3.1   5                3.32             1
## 1790           757         2.3   0               14.67             1
```

```
## 1804         1745       13.0   0                1.96           3
## 1813         1054        4.9   0                1.54           2
## 1824         1309        9.7   4                1.23           1
## 1846          629        3.4   0                5.64           1
## 1859         1560       20.2   0                7.45           1
## 1863         2126       18.8   0                7.98           1
## 1869          690        4.7   0                4.60           1
## 1870         1175        6.7   0                7.99           1
## 1873         2083        5.2   3                2.98           1
## 1878          710        3.8   0                1.23           1
## 1902          455        1.3   3                2.89           1
## 1919         2631       13.9   7                5.24           1
## 1922         1027        3.2   3                5.80           1
## 1927          759        2.8   1                4.58           1
## 1928          660        2.6   3                4.12           1
## 1930          511        3.5   0                1.23           1
## 1935          436        1.4   0                2.98           1
## 1954          351        1.3   0                1.23           1
## 1985         1377        6.0   0                1.23           1
## 1992          912        4.9   0                1.23           1
## 1994          446        0.9   0                1.23           1
## 1996          375        1.2   5                2.27           1
```

```
ridge.pred=predict(ridge.mod,s=bestlam,newx=test_x)
mse_ridge <- mean((test_num$Fare - ridge.pred)^2)
paste("MSE=",mse_ridge)
```

```
## [1] "MSE= 44.5698834306074"
```

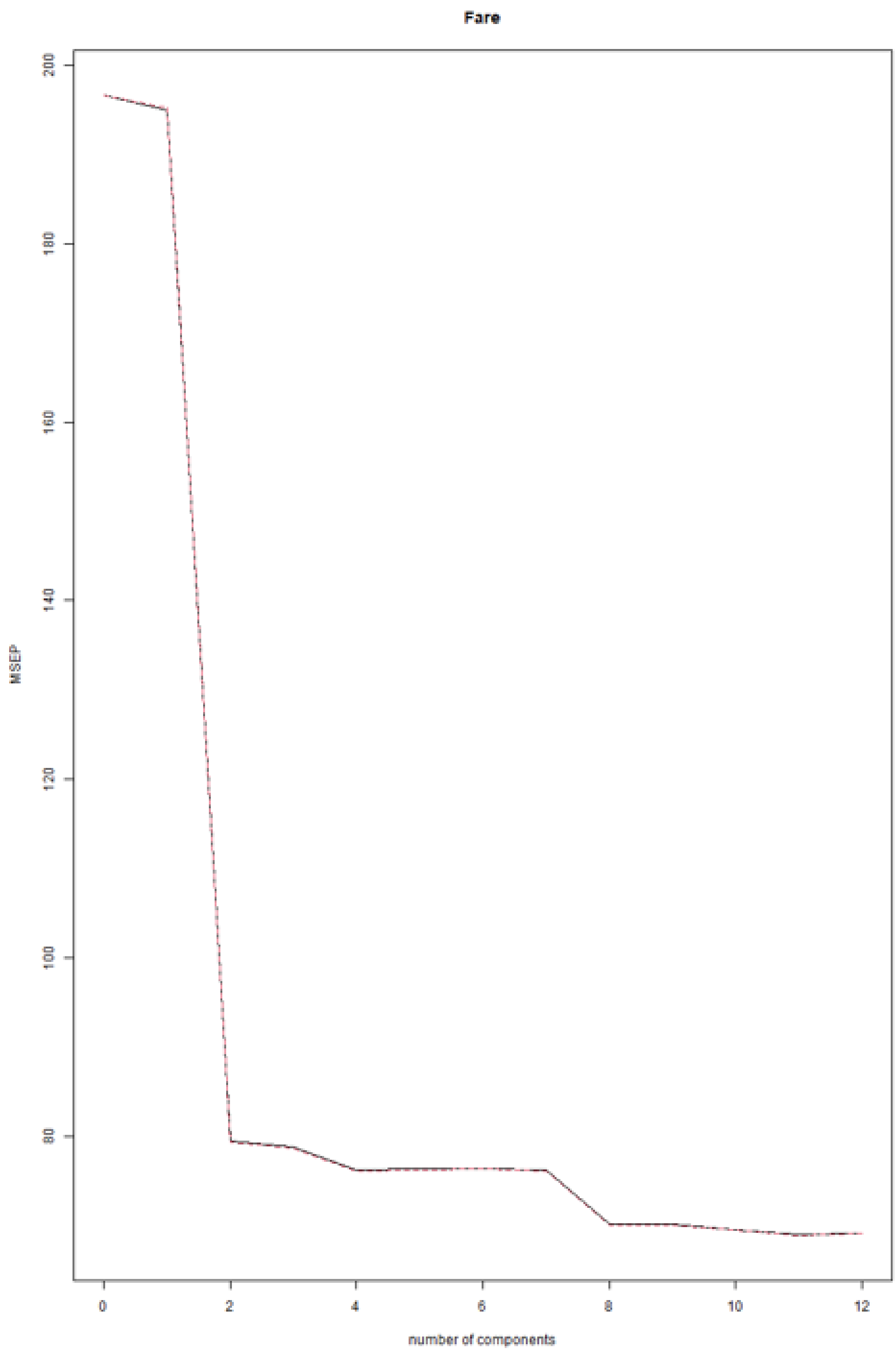
Very high MSE, not a lot of variables so do no really need ridge anyways.

PCR/pls

```
pcr.mod=pcr(Fare~.,data = train,scale=TRUE,validation="CV")
summary(pcr.mod)
```

```
## Data:    X dimension: 1798 12
##  Y dimension: 1798 1
## Fit method: svdpc
## Number of components considered: 12
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           14.02    13.93    8.920    8.877    8.746    8.749    8.749
## adjCV        14.02    13.94    8.914    8.871    8.731    8.740    8.745
##        7 comps  8 comps  9 comps  10 comps  11 comps  12 comps
## CV       8.745    8.387    8.387     8.367     8.336     8.337
## adjCV    8.740    8.382    8.383     8.363     8.330     8.332
##
## TRAINING: % variance explained
##       1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps  8 comps
## X     20.6891    39.56    49.89    59.60    69.12    78.54    87.95    92.52
## Fare   0.9291    59.90    60.32    61.65    61.66    61.67    61.79    64.81
##       9 comps  10 comps  11 comps  12 comps
## X       96.19     97.73     99.14    100.00
## Fare    64.81     65.14     65.44     65.44
```

```
validationplot(pcr.mod,val.type="MSEP")
```




```
model_pcr_mse = MSEP(pcr.mod,estimate="CV")
model_pcr_mse
```

```
## (Intercept)      1 comps      2 comps      3 comps      4 comps      5 comps
##      196.59       194.05        79.56        78.80        76.49        76.55
##     6 comps      7 comps      8 comps      9 comps     10 comps     11 comps
##       76.54        76.47        70.33        70.35        70.00        69.48
##    12 comps
##       69.51
```

```r
pcr.pred=predict(pcr.mod,test,ncomp=11)
mse_pcr <- mean((test$Fare - pcr.pred)^2)
paste("MSE=",mse_pcr)
```

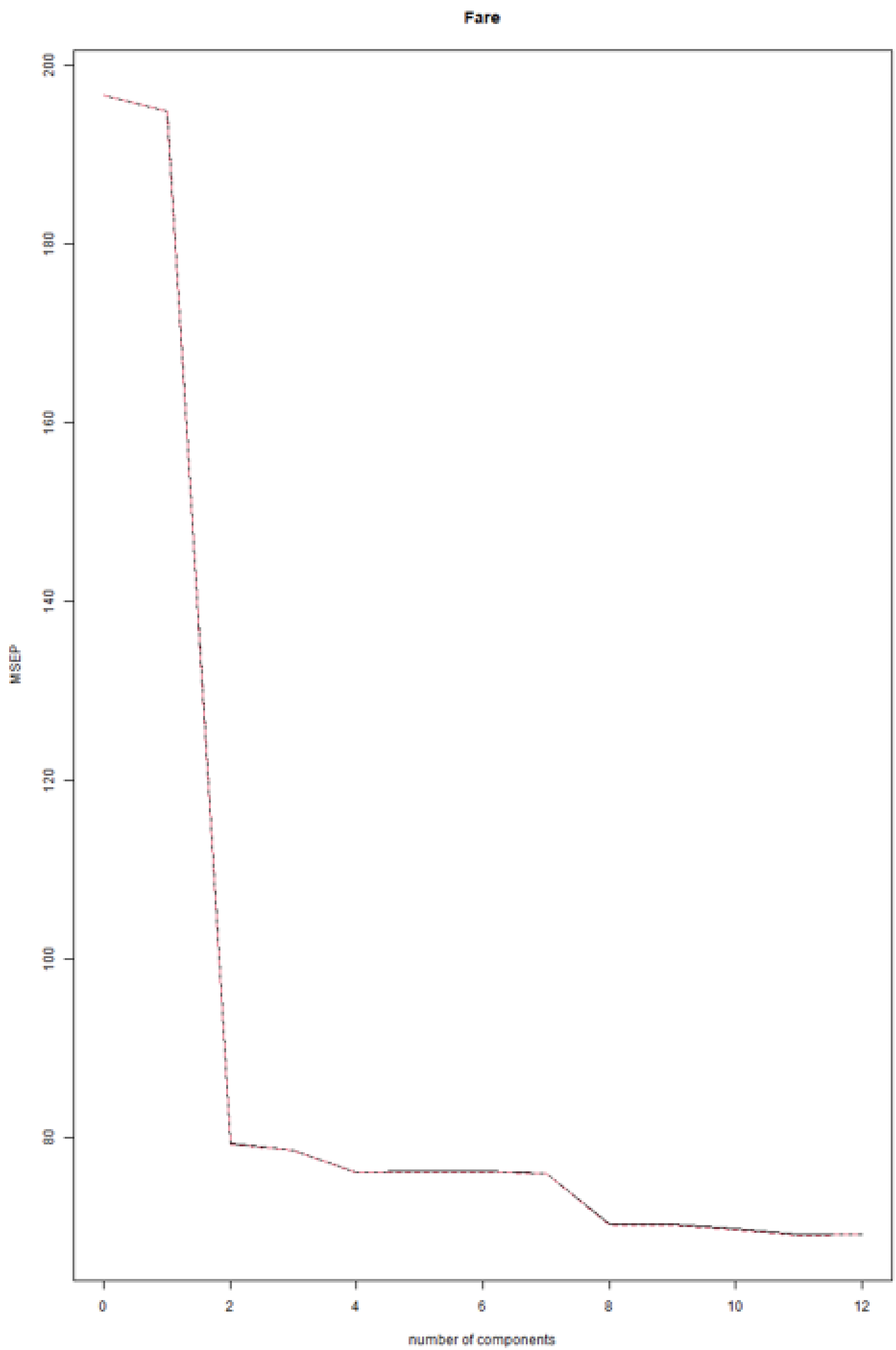
```
## [1] "MSE= 52.0691020843782"
```

The model with 11 principal components performs the best.

```r
pls.mod=plsr(Fare~.,data = train,scale=TRUE,validation="CV")
summary(pls.mod)
```

```
## Data:    X dimension: 1798 12
##  Y dimension: 1798 1
## Fit method: kernelpls
## Number of components considered: 12
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           14.02    8.609    8.412    8.352    8.322    8.323    8.323
## adjCV        14.02    8.606    8.404    8.348    8.320    8.318    8.318
##        7 comps  8 comps  9 comps  10 comps  11 comps  12 comps
## CV       8.324    8.324    8.324     8.324     8.324     8.324
## adjCV    8.319    8.319    8.319     8.320     8.320     8.320
##
## TRAINING: % variance explained
##       1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps  8 comps
## X       18.78    26.78    39.89    53.32    55.84    65.56    69.02    76.53
## Fare    62.74    64.82    65.18    65.31    65.43    65.44    65.44    65.44
##       9 comps  10 comps  11 comps  12 comps
## X       80.15     84.69     90.57    100.00
## Fare    65.44     65.44     65.44     65.44
```

```r
validationplot(pls.mod,val.type="MSEP")
```



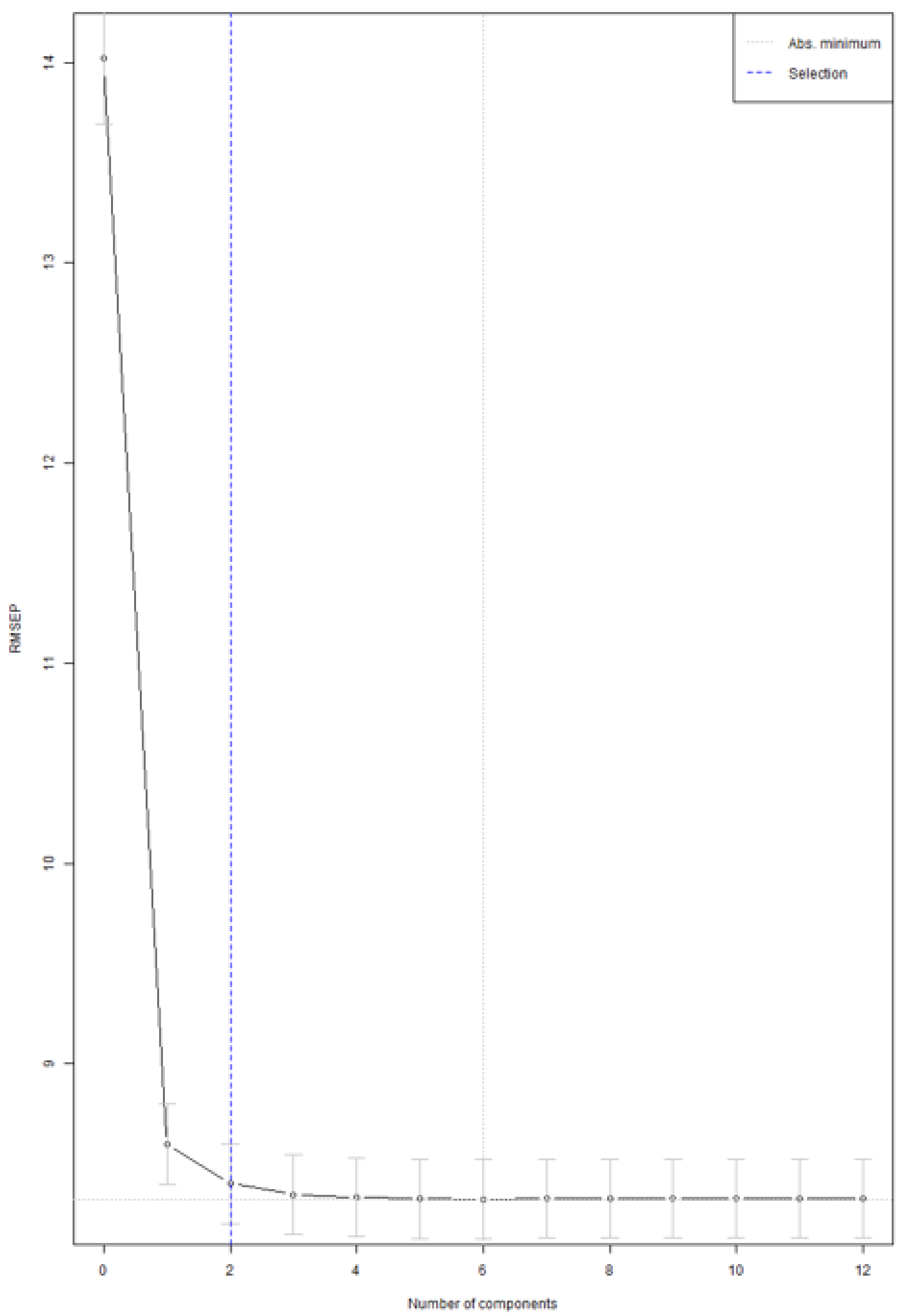

```
model_pls_mse = MSEP(pls.mod,estimate="CV")
model_pls_mse
```

```
## (Intercept)      1 comps      2 comps      3 comps      4 comps      5 comps
##      196.59        74.12        70.76        69.75        69.26        69.27
##     6 comps      7 comps      8 comps      9 comps     10 comps     11 comps
##       69.27        69.28        69.29        69.29        69.29        69.29
##    12 comps
##       69.29
```

```r
pls.pred=predict(pls.mod,test,ncomp=2)
mse_pls <- mean((test$Fare - pls.pred)^2)
paste("MSE=",mse_pls)
```

```
## [1] "MSE= 52.564886135774"
```

```r
ncomp.onesigma <- selectNcomp(pls.mod, method = "onesigma", plot = TRUE)
```



Analyzing the msep validation plot, 2 principal components appear to be enough.

Final model

The LM was sufficient for my purposes so lets summarize it and interpret its coefficients. Remove DOW also since its relatively insignificant.

```r
mod_lm_fin = lm(Fare~Shared_Trip_Authorized+Trip_Miles+Trip_Seconds,data=train)
summary(mod_lm_fin)
```

```
##
## Call:
## lm(formula = Fare ~ Shared_Trip_Authorized + Trip_Miles + Trip_Seconds,
##     data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -27.326  -4.232  -1.547   2.559  54.714
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                6.5967120  0.3491157  18.895   <2e-16 ***
## Shared_Trip_Authorizedtrue -7.7978116  0.8298213  -9.397   <2e-16 ***
## Trip_Miles                 1.0212039  0.0448049  22.792   <2e-16 ***
## Trip_Seconds               0.0044736  0.0003942  11.349   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.32 on 1794 degrees of freedom
## Multiple R-squared:  0.6483, Adjusted R-squared:  0.6477
## F-statistic:  1102 on 3 and 1794 DF,  p-value: < 2.2e-16
```

```r
test$lm_preds_fin = predict(mod_lm_fin,newdata = test)
mse <- mean((test$Fare - test$lm_preds_fin)^2)
paste("MSE=",mse)
```

```
## [1] "MSE= 51.3003840981791"
```

References

[1] Levy J. Transportation Network Providers-Trips (2018-2022)[supporting dataset]; 2023.

[2] Gangadharaiah R, Su H, Rosopa EB, Brooks JO, Kolodge K, Boor L, et al. A User-Centered Design Exploration of Factors That Influence the Rideshare Experience. Safety. 2023;9. Available from: https://www.mdpi.com/2313-576X/9/2/36.

[3] Gangadharaiah R, Brooks JO, Rosopa PJ, Su H, Boor L, Edgar A, et al. The Development of the Pooled Rideshare Acceptance Model (PRAM). Safety. 2023 9;9:61.

[4] Su H, Gangadharaiah R, Rosopa EB, Brooks JO, Boor L, Kolodge K, et al. Exploration of Factors That Influence Willingness to Consider Pooled Rideshare. Transportation Research Record: Journal of the Transportation Research Board. 2024 1.

[5] Auld J, Hope M, Ley H, Sokolov V, Xu B, Zhang K. POLARIS: Agent-based modeling framework development and implementation for integrated travel demand and network and operations simulations. Transportation Research Part C: Emerging Technologies. 2016;64:101-16. Available from: https://www.sciencedirect.com/science/article/pii/S0968090X15002703.

[6] Paul J, Gurumurthy KM, Cokyasar T, Su H, Auld J, Jia Y. Optimization of Dynamic Ride-Sharing by Considering User Preference Through Discount and Delay Tolerance. In: 2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC). IEEE; 2023. p. 2770-5.