TEXAS
The University of Texas at Austin

Why you Bikein'?

TEAM

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Agenda

Problem Statement

Predict the demand of bike users based on the number of rides w.r.t casual and registered users.

Data Explanation

A normalized set of 17580 rows having number of casual and registered rides based on day of the week, month, years season and multiple weather variables.

Exploratory Data Analysis

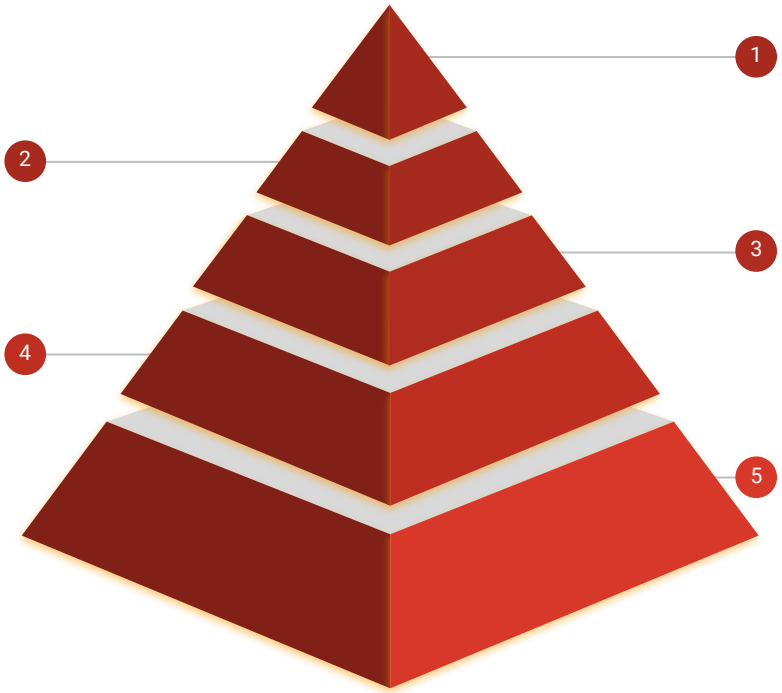
Analyzing the number of rides based on categorical variables (day of the week, season and weather variables)

Data Preprocessing

One Hot encoding - data transmitted into 0 and 1 to turn categorical variables to numerical variables

Model Selection

Non-parametric and parametric model selection : Multiple regression, Trees and Knn



Problem Statement

Bike sharing is one of the most accessible way to commute for employees and students. Lime and Bird were the commonly used bikes in Austin especially for student commute and it is interesting to see how the membership, payment and trips have become more automatic.

Inspired by these observations, we took the trips data from Capital Bikeshare[1] to predict the demand of bike users based on the number of rides pertaining to registered and casual users.

[1] Capital Bikeshare – State owned bike sharing system in counties around Washington D.C and Virginia

Data Explanation

Data set : 17380 rows

Processing : One hot encoding to convert data from categorical to numerical as we are predicting a quantitative factor. Also removed highly correlated variables to reduce the RMSE.

Training 50% | Testing 25% | Validation 25%

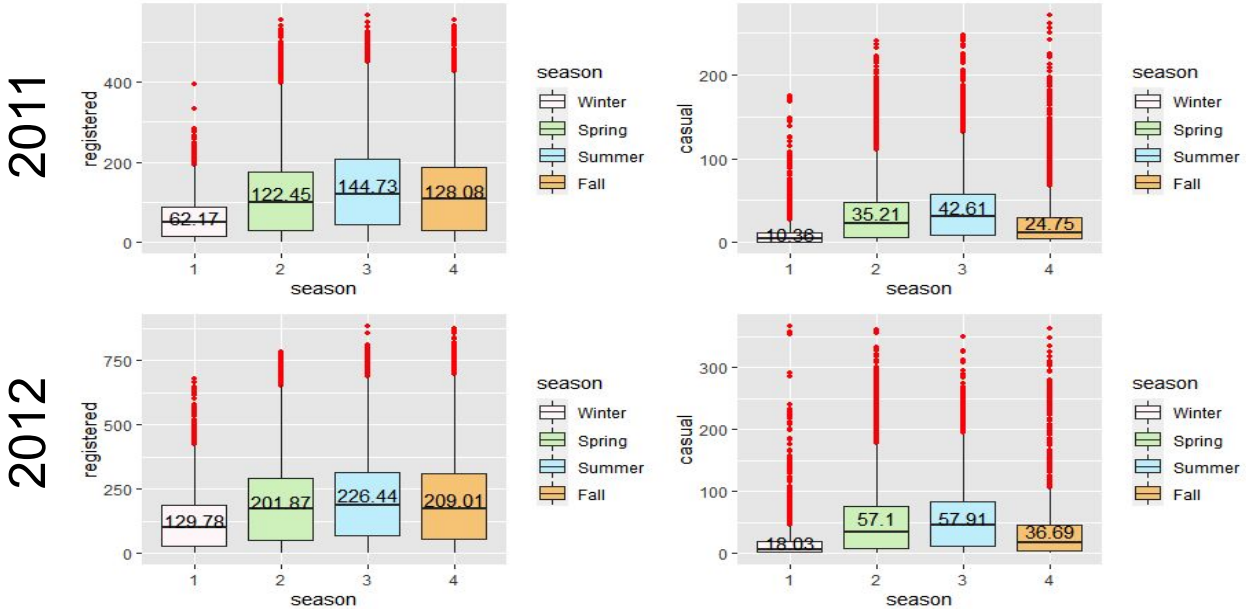
- instant: record index
- dteday : date
- season : season (1:winter, 2:spring, 3:summer, 4:fall)
- yr : year (0: 2011, 1:2012)
- mnth : month (1 to 12)
- hr : hour (0 to 23)
- holiday : weather day is holiday or not (extracted from [Web Link])
- weekday : day of the week
- workingday : if day is neither weekend nor holiday is 1, otherwise is 0.

+ weathersit :

- 1: Clear, Few clouds, Partly cloudy, Partly cloudy
- 2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
- 3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds
- 4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog
- temp : Normalized temperature in Celsius. The values are derived via (t-t_min)/(t_max-t_min), t_min=-8, t_max=+39 (only in hourly scale)
- atemp: Normalized feeling temperature in Celsius. The values are derived via (t-t_min)/(t_max-t_min), t_min=-16, t_max=+50 (only in hourly scale)
- hum: Normalized humidity. The values are divided to 100 (max)
- windspeed: Normalized wind speed. The values are divided to 67 (max)
- casual: count of casual users
- registered: count of registered users
- cnt: count of total rental bikes including both casual and registered

Dataset obtained from University of California, Irvine archive (2nd hand) - https://archive.ics.uci.edu/ml/datasets/Bike+Sharing+Dataset
Original data (1st hand) sourced from Capital Bikeshare system data archive - https://ride.capitalbikeshare.com/system-data

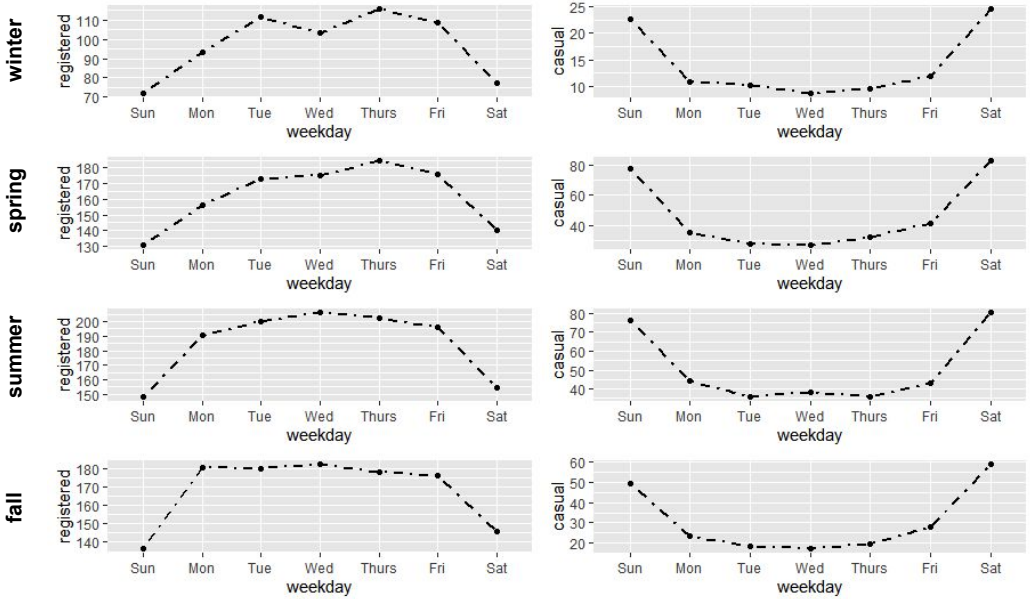
Exploratory Data Analysis



Season wise registered and casual rides per hr

- Both registered and casual users had increased number of rides in Summer and Spring
- Large range of outliers for casual users while the registered users have a small range with higher magnitude

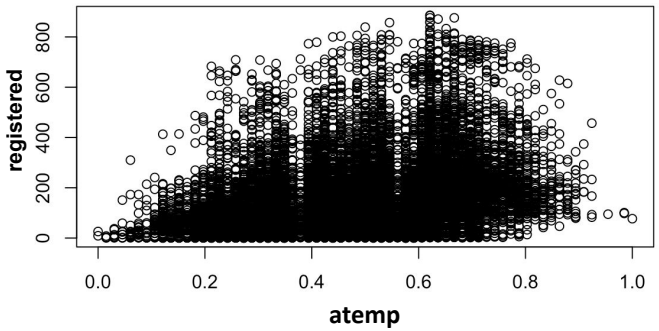
Exploratory Data Analysis

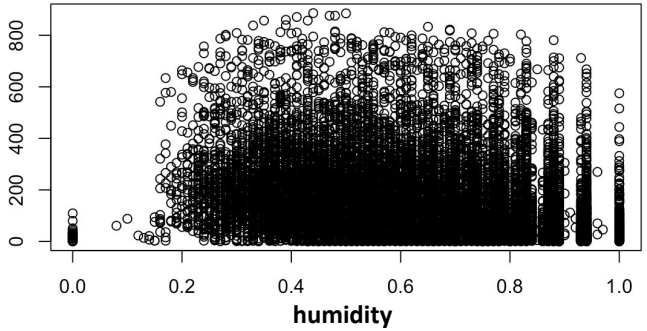


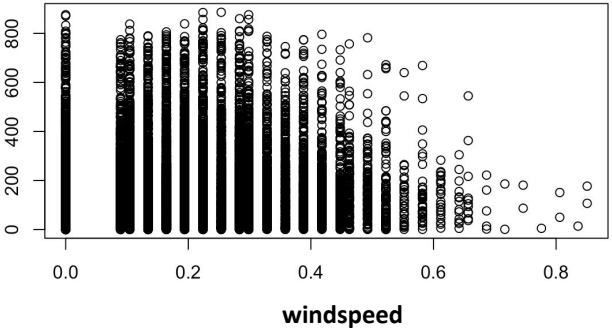
No. of rides for registered and casual across the week w.r.t seasons

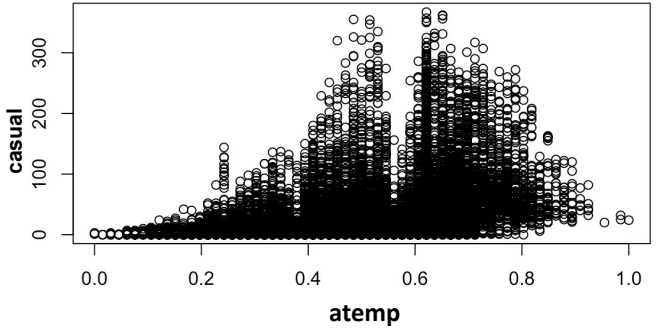
- A contrasting pattern in the number of rides observed for both registered and casual riders
- Increased number of rides over the week and decreased number of rides over the weekends for registered users
- Decreased number of rides in weekdays and increased number of rides over the weekends for casual users

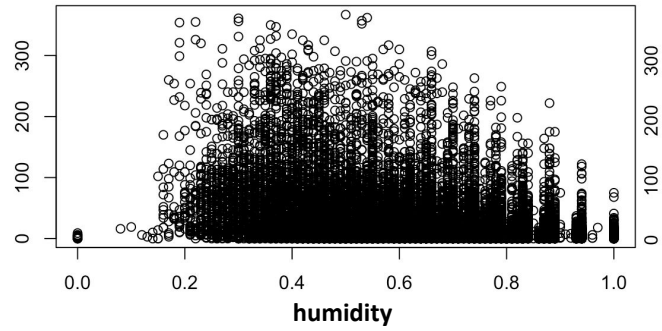
Exploratory Data Analysis

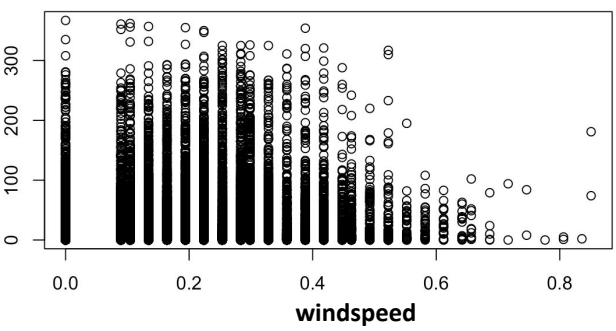










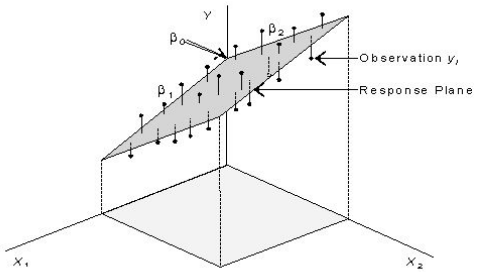


Approach

- Build separate models for *registered* users and *casual* users

3 approaches to consider – Regression, K Nearest Neighbours, Trees

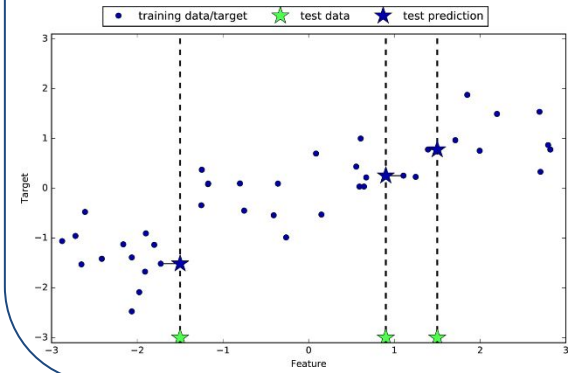
Parametric

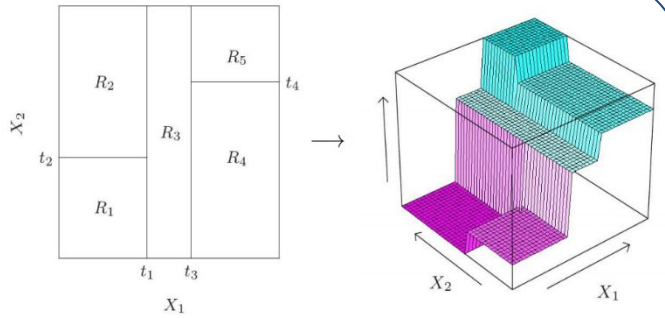


Multilinear Regression
+
(Ridge and Lasso)

Non - Parametric

K Nearest Neighbours





Tree Regression

Multilinear Regression

Data Pre-Processing

1) Encoding Categorical Variables
(converting factors to integer inputs)
Two methods –
Ordinal Encoding and OneHot Encoding

season = {1, 2, 3, 4} ->

season_1 = {0, 1}
season_2 = {0, 1}
season_3 = {0, 1}
season_4 = {0, 1}

e.g.

season	s_1	s_2	s_3	s_4
1	0	0	1	0

2) Removing unnecessary variables

- instant (serial no.), dte (date), yr (year), cnt (total rides per hour)

A) For 'registered' users
- casual (no. of casual rides per hour)

B) For 'casual' users
- registered (no. of registered rides per hour)

Standard 80-20 split for training and test/validation sets

Multilinear Regression

Registered Users

- Simple model with all predictors - `reg_mlr <- lm(registered~., data=newdata_tr)`

Coefficients: (6 not defined because of singularities)

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	78.7416	66.4693	1.185	0.236182	
season_1	-64.8434	4.7986	-13.513	< 2e-16	***
season_2	-35.1019	5.6315	-6.233	4.69e-10	***
season_3	-36.5785	5.0584	-7.231	5.02e-13	***
season_4	NA	NA	NA	NA	
mnth_1	8.9759	4.8776	1.840	0.065754	.
mnth_2	11.5552	4.8883	2.364	0.018099	*
mnth_3	6.6308	4.8516	1.367	0.171736	
mnth_4	-2.1317	6.2980	-0.338	0.735017	
mnth_5	8.7006	6.6484	1.309	0.190667	
mnth_6	-6.2026	6.5767	-0.943	0.345634	
mnth_7	-26.5935	7.0080	-3.795	0.000148	***
mnth_8	-4.7479	6.8233	-0.696	0.486548	
mnth_9	16.9256	5.6348	3.004	0.002671	**
mnth_10	2.7937	4.2928	0.651	0.515195	
mnth_11	-12.2396	4.0997	-2.985	0.002836	**
mnth_12	NA	NA	NA	NA	
hr_0	-27.8180	5.2579	-5.291	1.24e-07	***
hr_1	-41.9033	5.2408	-7.996	1.38e-15	***
hr_2	-48.5245	5.3152	-9.129	< 2e-16	***
hr_3	-57.7344	5.3240	-10.844	< 2e-16	***
hr_4	-57.6386	5.3528	-10.768	< 2e-16	***
hr_5	-42.8105	5.2923	-8.089	6.46e-16	***
hr_6	12.0549	5.2765	2.285	0.022349	*
hr_7	138.2743	5.2635	26.270	< 2e-16	***
hr_8	272.1059	5.2433	51.895	< 2e-16	***
hr_9	115.1939	5.2509	21.938	< 2e-16	***
hr_10	42.3958	5.2585	8.062	8.05e-16	***
hr_11	56.8320	5.3169	10.689	< 2e-16	***
hr_12	88.7857	5.3331	16.648	< 2e-16	***
hr_13	81.1071	5.3573	15.139	< 2e-16	***
hr_14	60.2285	5.3883	11.178	< 2e-16	***
hr_15	73.7507	5.4346	13.570	< 2e-16	***
hr_16	139.3247	5.4032	25.786	< 2e-16	***
hr_17	289.5501	5.3563	54.058	< 2e-16	***
hr_18	274.4671	5.3457	51.344	< 2e-16	***
hr_19	173.6713	5.3159	32.670	< 2e-16	***
hr_20	105.7933	5.2519	20.144	< 2e-16	***
hr_21	64.2633	5.2572	12.224	< 2e-16	***
hr_22	32.4652	5.2611	6.171	6.97e-10	***
hr_23	NA	NA	NA	NA	
holiday_0	9.4176	4.7327	1.990	0.046621	*
holiday_1	NA	NA	NA	NA	
workingday_0	-39.1123	1.7000	-23.008	< 2e-16	***
workingday_1	NA	NA	NA	NA	
weathersit_1	2.8262	65.8346	0.043	0.965759	
weathersit_2	0.4817	65.8311	0.007	0.994161	
weathersit_3	-48.0169	65.8609	-0.729	0.465974	
weathersit_4	NA	NA	NA	NA	
temp	126.1760	28.3600	4.449	8.69e-06	***
atemp	71.8406	29.3688	2.446	0.014450	*
hum	-81.2101	5.4268	-14.965	< 2e-16	***
windspeed	-26.0292	6.9204	-3.761	0.000170	***

Standard 80-20 split for training and test/validation sets

Multilinear Regression

Registered Users

What are singularities ?

- Singularity is the extreme form of multicollinearity - when a perfect linear relationship exists between variables or, in other terms, when the correlation coefficient is equal to 1.0 or -1.0

$$X_1 = a*X_2 + b*X_3 + c$$

- Usually happens when encoding dummy variables during data preprocessing

- Leads to incorrect calculations of coefficients with the OLS method

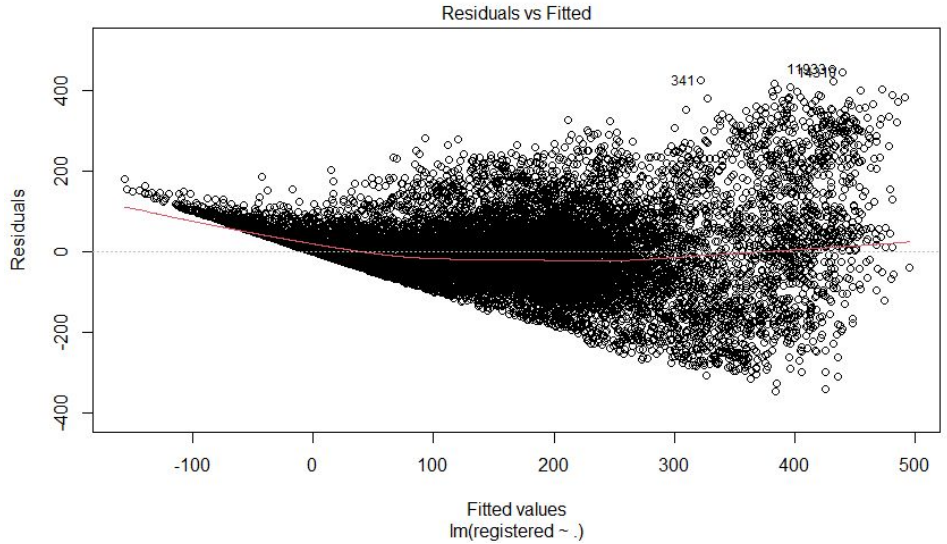
Multilinear Regression

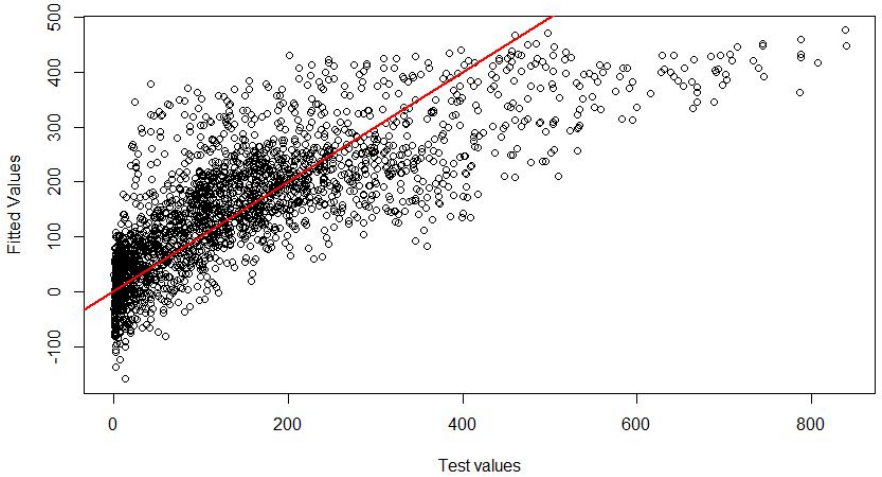
Registered Users

```
Residual standard error: 92.92 on 14953 degrees of freedom
Multiple R-squared:  0.6278,    Adjusted R-squared:  0.6267
F-statistic: 548.3 on 46 and 14953 DF,  p-value: < 2.2e-16
```

```
[1] "Root mean square error -"
> round(rmse.mlr,2)
[1] 92.92

[1] "R-squared value for test set -"
> round(r2.mlr,4)
[1] 0.599
```





Multilinear Regression

Registered Users

Other model building techniques to consider -

- Nth root model with all predictors – `reg_mlr_root <- lm(registered^(1/n)~., data=newdata_tr)`
- Log model with all predictors – `reg_mlr_log <- lm(log(registered+1)~., data=newdata_tr)`

  (Note we added a value of 1 to registered no. of riders per hour because we log(0) is not defined)

Standard 80-20 split for training and test/validation sets

Multilinear Regression

Registered Users

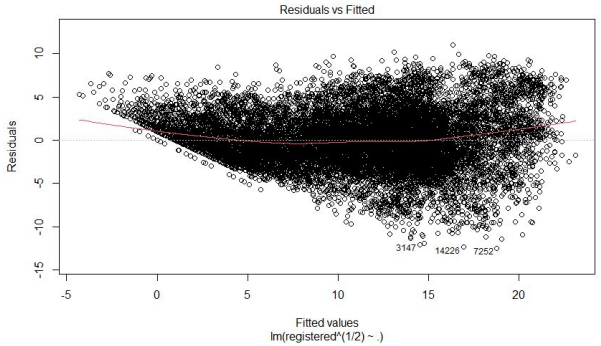
- Nth root model with all predictors - `reg_mlr_root <- lm(registered^(1/n)~., data=newdata_tr)`

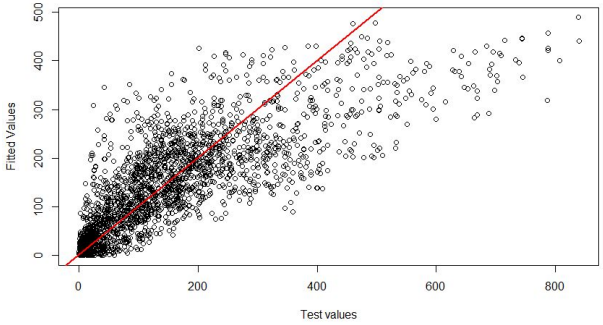
  N = 2

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   9.2507104  2.2594427   4.094 4.26e-05 ***
season_1     -2.8241070  0.1631162 -17.313  < 2e-16 ***
season_2     -1.5211135  0.1914268  -7.946 2.06e-15 ***
season_3     -1.3776772  0.1719479  -8.012 1.21e-15 ***
mnth_1        0.3961497  0.1658008   2.389  0.01689 *
mnth_2        0.6695769  0.1661642   4.030 5.61e-05 ***
mnth_3        0.3717264  0.1649185   2.254  0.02421 *
mnth_4       -0.0062021  0.2140834  -0.029  0.97689
mnth_5        0.4967974  0.2259958   2.198  0.02795 *
mnth_6       -0.1336239  0.2235561  -0.598  0.55004
mnth_7       -0.9911199  0.2382167  -4.161 3.19e-05 ***
mnth_8       -0.2868708  0.2319411  -1.237  0.21617
mnth_9        0.4191153  0.1915409   2.188  0.02868 *
mnth_10      -0.0006239  0.1459219  -0.004  0.99659
mnth_11      -0.4122169  0.1393585  -2.958  0.00310 **
hr_0         -1.9880028  0.1787270 -11.123  < 2e-16 ***
hr_1         -3.4349847  0.1781474 -19.282  < 2e-16 ***
hr_2         -4.3414905  0.1806751 -24.029  < 2e-16 ***
hr_3         -5.3698346  0.1809738 -29.672  < 2e-16 ***
hr_4         -5.7047536  0.1819527 -31.353  < 2e-16 ***
hr_5         -3.7953653  0.1798960 -21.098  < 2e-16 ***
hr_6         -0.0080504  0.1793618  -0.045  0.96420
hr_7          4.9269826  0.1789183  27.538  < 2e-16 ***
hr_8          9.0629513  0.1782335  50.849  < 2e-16 ***
hr_9          5.1011442  0.1784900  28.579  < 2e-16 ***
hr_10         2.2436935  0.1787501  12.552  < 2e-16 ***
hr_11         2.8478759  0.1807344  15.757  < 2e-16 ***
hr_12         4.1110491  0.1812826  22.678  < 2e-16 ***
hr_13         3.8317203  0.1821086  21.041  < 2e-16 ***
hr_14         3.0323100  0.1831592  16.556  < 2e-16 ***
hr_15         3.5645933  0.1847358  19.296  < 2e-16 ***
hr_16         5.8082196  0.1836669  31.624  < 2e-16 ***
hr_17         9.6926891  0.1820740  53.235  < 2e-16 ***
hr_18         9.3604225  0.1817125  51.512  < 2e-16 ***
hr_19         6.7713659  0.1806999  37.473  < 2e-16 ***
hr_20         4.6199200  0.1785247  25.878  < 2e-16 ***
hr_21         3.0905888  0.1787046  17.294  < 2e-16 ***
hr_22         1.7510740  0.1788365   9.791  < 2e-16 ***
holiday_0     0.6481452  0.1608760   4.029 5.63e-05 ***
workingday_0 -1.1266033  0.0577858 -19.496  < 2e-16 ***
weathersit_1 -1.2757949  2.2378693  -0.570  0.56862
weathersit_2 -1.3349891  2.2377501  -0.597  0.55080
weathersit_3 -3.5412173  2.2387635  -1.582  0.11372
temp          4.7789876  0.9640217   4.957 7.22e-07 ***
atemp         3.0449611  0.9983134   3.050  0.00229 **
hum          -2.8543112  0.1844680 -15.473  < 2e-16 ***
windspeed    -1.0694743  0.2352411  -4.546 5.50e-06 ***
---
```

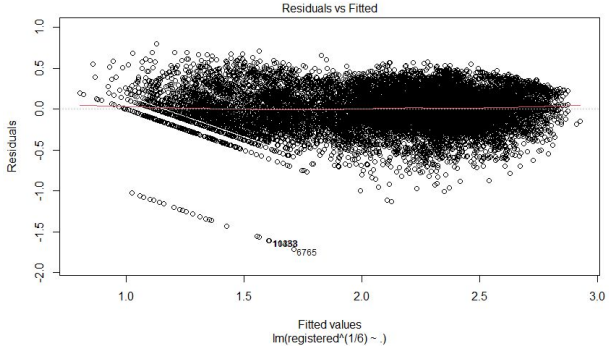
Standard 80-20 split for training and test/validation sets

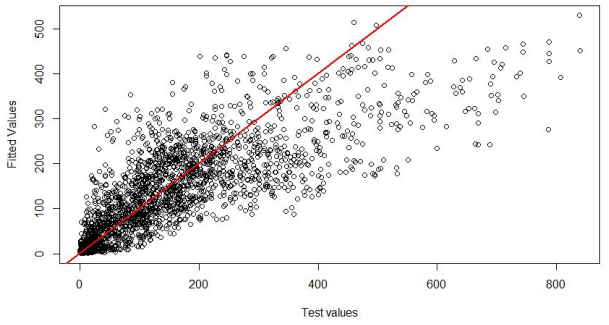
N = 2



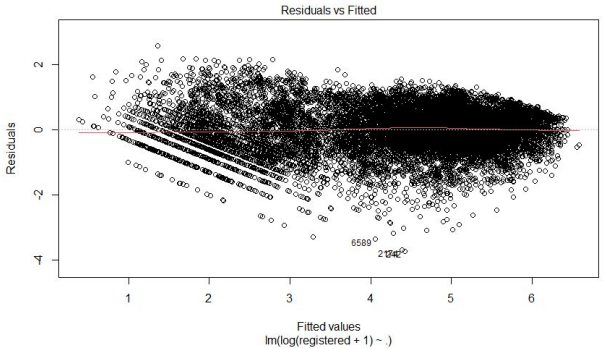


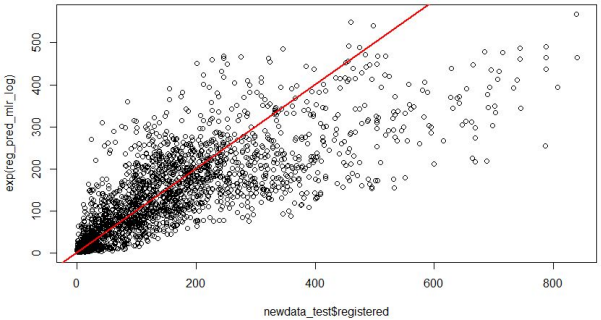
N = 6





Log Model





Multilinear Regression

Registered Users

Model (Regression)	RMSE (training)	RMSE (test)	R-square (training)	R-square (test)
Simple	92.921	92.92	0.6267	0.599
2nd Root	NA	88.99	0.729	0.632
6th Root	NA	90.62	0.7731	0.617
Log Model	NA	92.72	0.786	0.6008

Multilinear Regression

Casual Users

- Root (N=6) model with all predictors - `cas_mlr_root <- lm(casual^(1/6)~., data=newdata_tr)`

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	1.133118	0.224205	5.054	4.38e-07	***
season_1	-0.119222	0.016186	-7.366	1.85e-13	***
season_2	0.004937	0.018995	0.260	0.794935	
season_3	-0.021124	0.017062	-1.238	0.215712	
mnth_1	-0.065257	0.016452	-3.966	7.33e-05	***
mnth_2	-0.001874	0.016488	-0.114	0.909525	
mnth_3	0.145727	0.016365	8.905	< 2e-16	***
mnth_4	0.121930	0.021244	5.740	9.67e-09	***
mnth_5	0.149956	0.022426	6.687	2.36e-11	***
mnth_6	0.076181	0.022183	3.434	0.000596	***
mnth_7	0.036126	0.023638	1.528	0.126463	
mnth_8	0.080506	0.023016	3.498	0.000470	***
mnth_9	0.126893	0.019007	6.676	2.54e-11	***
mnth_10	0.154256	0.014480	10.653	< 2e-16	***
mnth_11	0.078886	0.013829	5.705	1.19e-08	***
hr_0	-0.134661	0.017735	-7.593	3.31e-14	***
hr_1	-0.314302	0.017678	-17.780	< 2e-16	***
hr_2	-0.465062	0.017928	-25.940	< 2e-16	***
hr_3	-0.681903	0.017958	-37.972	< 2e-16	***
hr_4	-0.808220	0.018055	-44.764	< 2e-16	***
hr_5	-0.691850	0.017851	-38.757	< 2e-16	***
hr_6	-0.316069	0.017798	-17.759	< 2e-16	***
hr_7	-0.013345	0.017754	-0.752	0.452273	
hr_8	0.192759	0.017686	10.899	< 2e-16	***
hr_9	0.248392	0.017712	14.024	< 2e-16	***
hr_10	0.301961	0.017737	17.024	< 2e-16	***
hr_11	0.360564	0.017934	20.105	< 2e-16	***
hr_12	0.389066	0.017989	21.628	< 2e-16	***
hr_13	0.379683	0.018071	21.011	< 2e-16	***
hr_14	0.381031	0.018175	20.965	< 2e-16	***
hr_15	0.391224	0.018331	21.342	< 2e-16	***
hr_16	0.391985	0.018225	21.508	< 2e-16	***
hr_17	0.418805	0.018067	23.180	< 2e-16	***
hr_18	0.357717	0.018031	19.839	< 2e-16	***
hr_19	0.292608	0.017931	16.319	< 2e-16	***
hr_20	0.207832	0.017715	11.732	< 2e-16	***
hr_21	0.151586	0.017733	8.548	< 2e-16	***
hr_22	0.098353	0.017746	5.542	3.04e-08	***
holiday_0	0.070149	0.015964	4.394	1.12e-05	***
workingday_0	0.258768	0.005734	45.128	< 2e-16	***
weathersit_1	-0.198020	0.222064	-0.892	0.372555	
weathersit_2	-0.214215	0.222052	-0.965	0.334708	
weathersit_3	-0.442147	0.222153	-1.990	0.046578	*
temp	0.488980	0.095660	5.112	3.23e-07	***
atemp	0.512748	0.099063	5.176	2.30e-07	***
hum	-0.174239	0.018305	-9.519	< 2e-16	***
windspeed	-0.157970	0.023343	-6.767	1.36e-11	***

Standard 80-20 split for training and test/validation sets

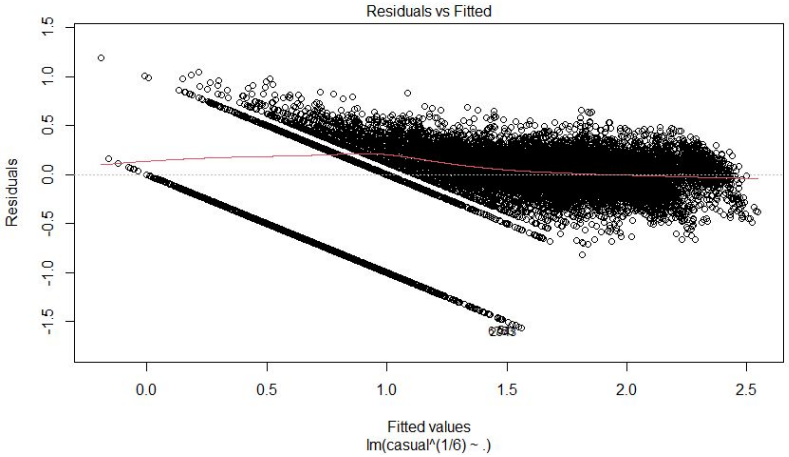
Multilinear Regression

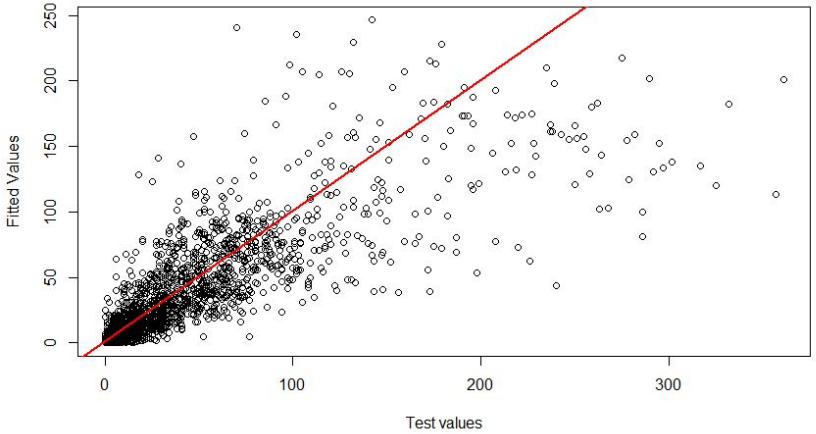
Casual Users

```
Residual standard error: 0.3134 on 14953 degrees of freedom
Multiple R-squared:  0.7246,    Adjusted R-squared:  0.7238
F-statistic: 855.3 on 46 and 14953 DF,  p-value: < 2.2e-16
```

```
[1] "Root mean square error -"
> round(rmse_lm_root_cas,2)
[1] 28.14

[1] "R-square value for test set -"
> round(rsq_lm_root_cas,4)
[1] 0.6847
```





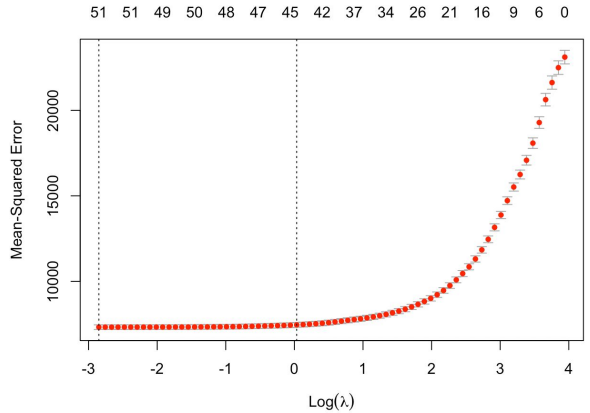
Lasso and Ridge Regression

We tried to predict the registered users using regularization models - Lasso and Ridge regression

Lasso Regression

Training data	Test data
- **R square_test** - 0.68	- **R square_test** - 0.66
- **RMSE_test** - 85.29	- **RMSE_test** - 85.55

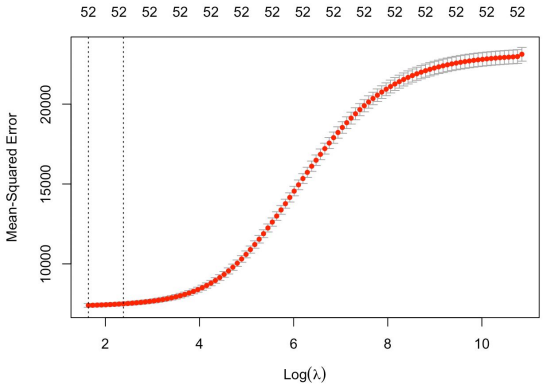
Lasso regression removes the predictors -
mnth_4 and weathersit_2



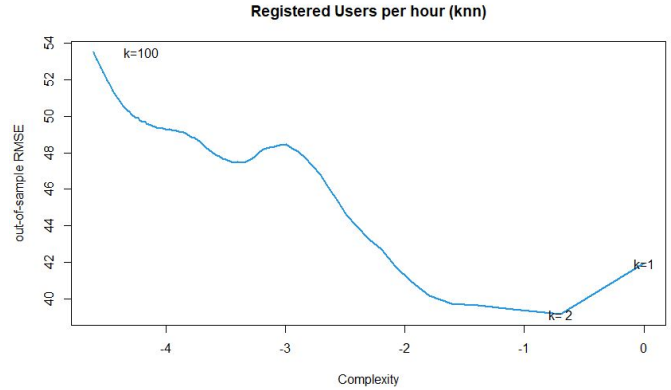
Ridge Regression

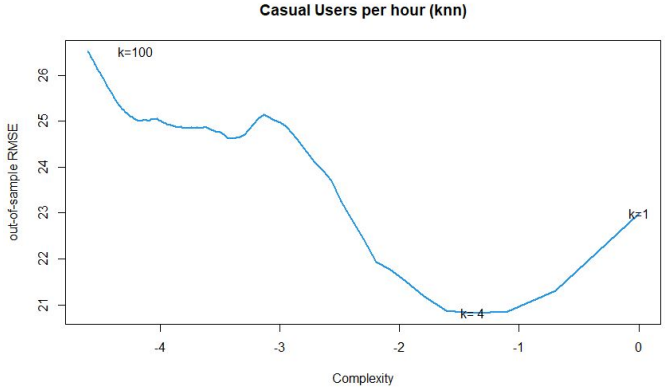
Training data	Test data
- **R square_test** - 0.68	- **R square_test** - 0.65
- **RMSE_test** - 85.71	- **RMSE_test** - 90.20

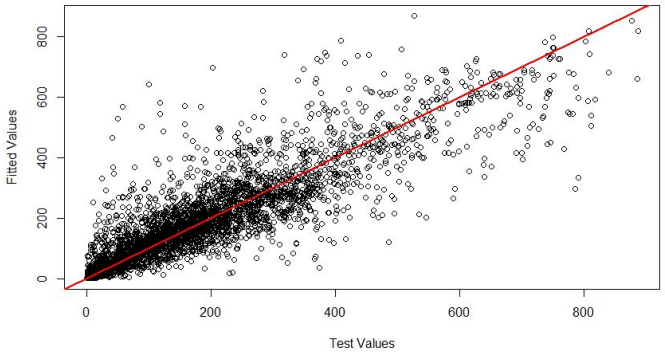
Ridge regression shrinks the following predictors to 0 -
mnth_3 and hr_22

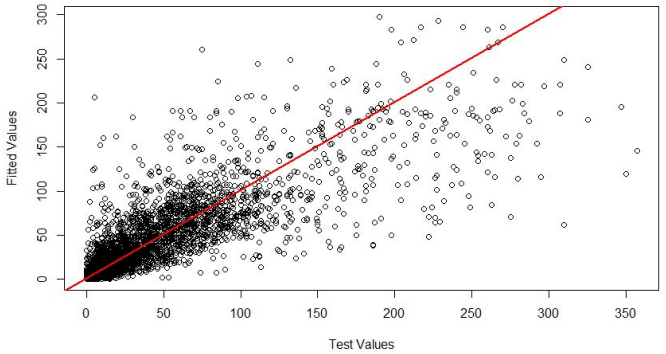


K Nearest Neighbours







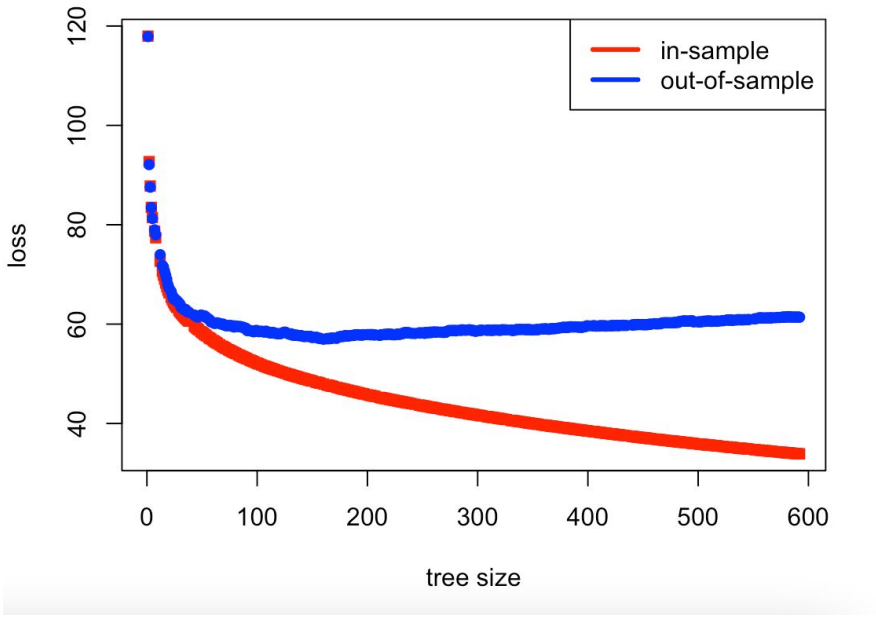


Trees

Fit a big tree using rpart

For Registered Users:

```
size of big tree:  592
```

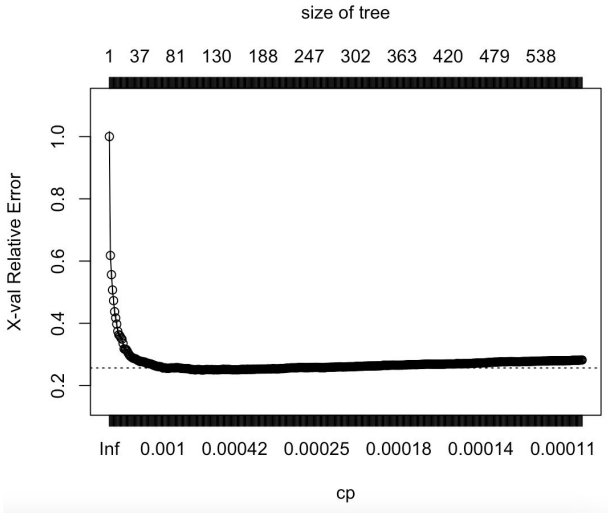



```
> mean(oltree)
[1] 60.08772
> mean(iltree)
[1] 44.58782
```

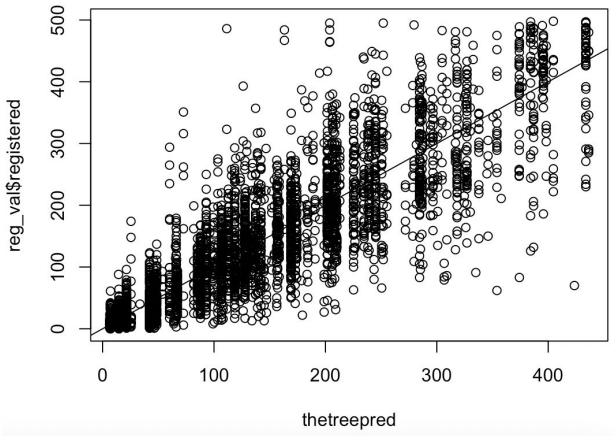
- We first fit a big tree to the training set through a very small CP value.
- Then we fit on the training set and predict on the validation set.
- Mean in sample loss came to be 44.58, but mean out of sample loss is **60.08!**

Trees

Pruning the tree



Pruned Tree RMSE for validation set : 56.9648



For Registered Users:

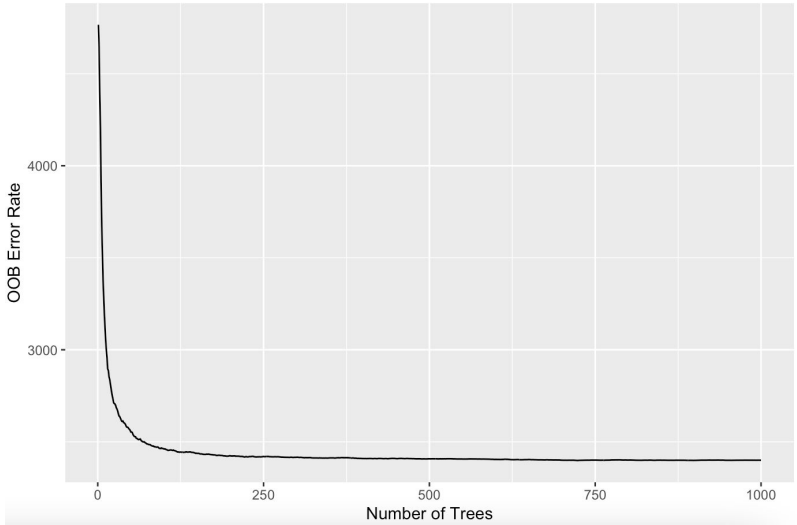
- Let's look at the cross validation results from plotcp.
- Prune the tree using the CP value that gave us the lowest out of sample loss

76.64% Variance Explained

56.96 RMSE

Random Forests

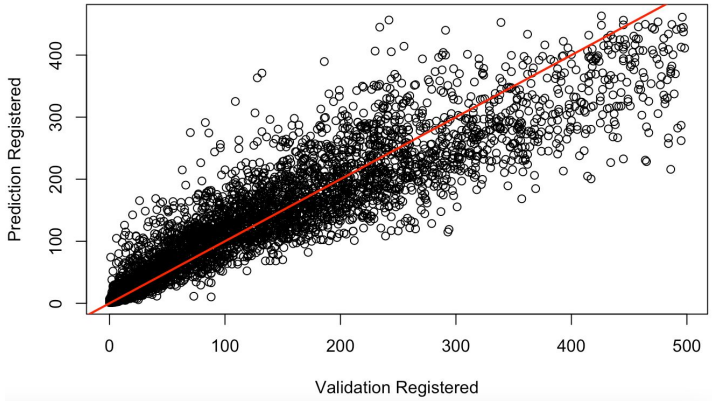
mtry	ntree	olrf	ilrf
11	200	49.488	49.697
3	200	53.757	53.736
11	500	49.449	49.583
3	500	53.661	53.683

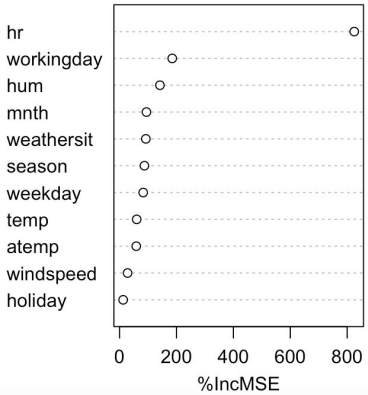


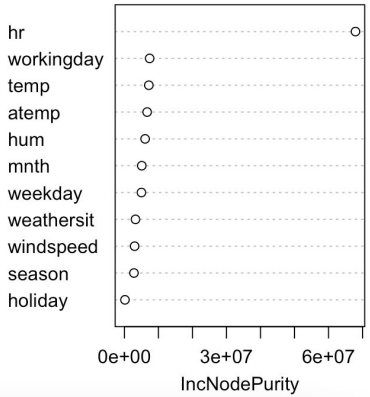
For Registered Users:

- Using random forests, we first tried 11 predictors (bagging) and 3 predictors with 200 and 500 trees.
- Minimum out of sample loss of **49.50** is much better than pruned tree
- Clearly, out of sample loss is lesser when we use the entire predictor set

Random Forests (Bagging)





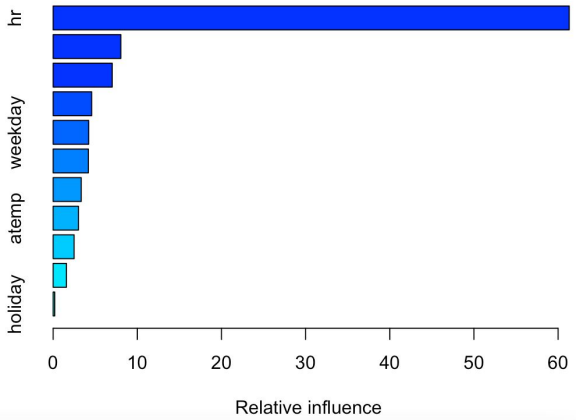


For Registered Users:

- Thus, we wanted to see if we can get better results by exploring more with bagging
- In fact we can! 1000 trees and 100 trees both gave us very similar OOB **RMSE of ~48.8** and **~82.8% Variance Explained**
- Hr is clearly the most impactful variable

Boosting

tdepth	ntree	lam	olb	ilb
5	500	0.05	49.760	44.758
10	500	0.05	48.797	39.301
20	500	0.05	48.399	32.547
5	1000	0.05	49.386	40.935
10	1000	0.05	49.042	33.714
20	1000	0.05	48.878	25.338
5	2000	0.05	49.274	36.204
10	2000	0.05	49.113	27.062
20	2000	0.05	49.703	17.473
5	500	0.20	50.695	37.554
10	500	0.20	51.796	29.241
20	500	0.20	52.737	19.703
5	1000	0.20	51.979	33.069
10	1000	0.20	53.642	21.946
20	1000	0.20	53.162	11.817
5	2000	0.20	52.772	27.245
10	2000	0.20	54.334	14.450
20	2000	0.20	53.719	5.463



For Registered Users:

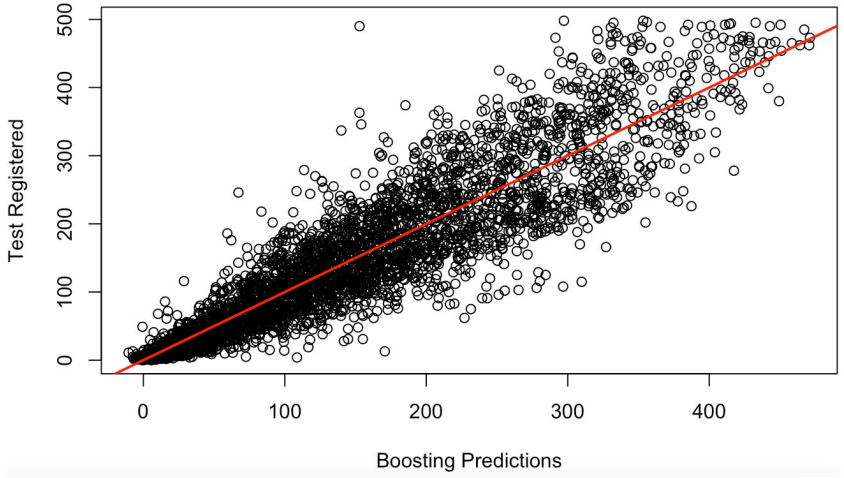
- We wanted to see if we could improve the results by tuning the parameters through boosting

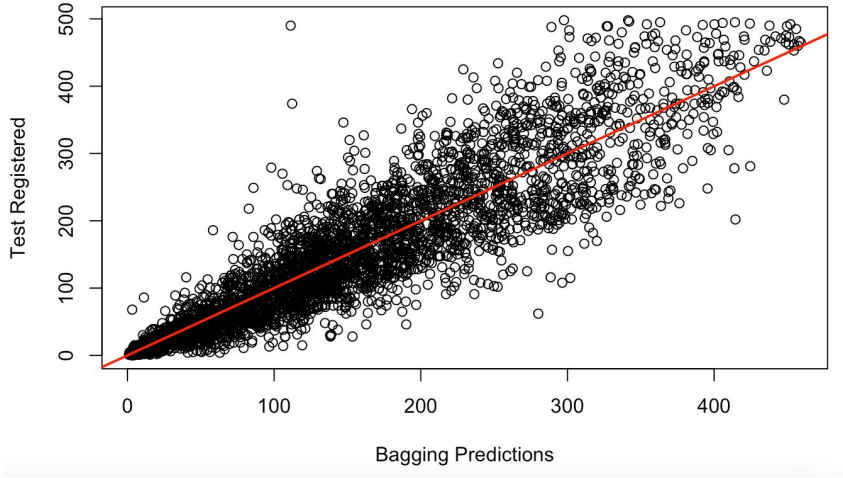
Best in sample loss: **5.463**

Best out of sample loss: **48.399**

- Again, hr is the most important variable

Fit on Testing Set

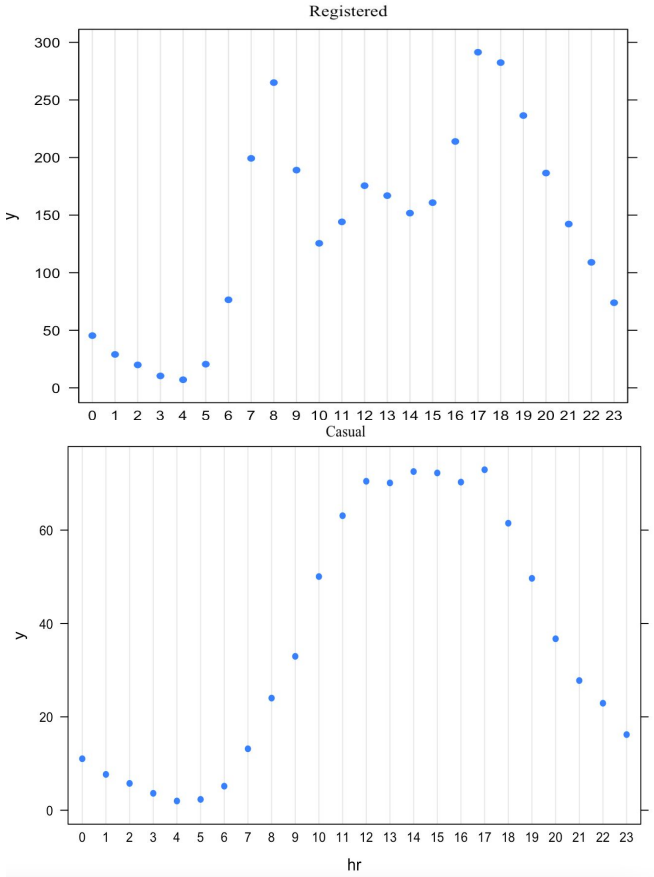




Fit on Testing Set

Registered Users	RMSE (Validation)	RMSE (Test)	R-square (Validation)	R-square (Test)
Pruned Tree	56.9	NA	76.6%	NA
Random Forest(Bagging)	48.8	46.2	82.2%	83.5%
Boosting	48.3	45.6	84.8%	84.4%

Casual User Predictions

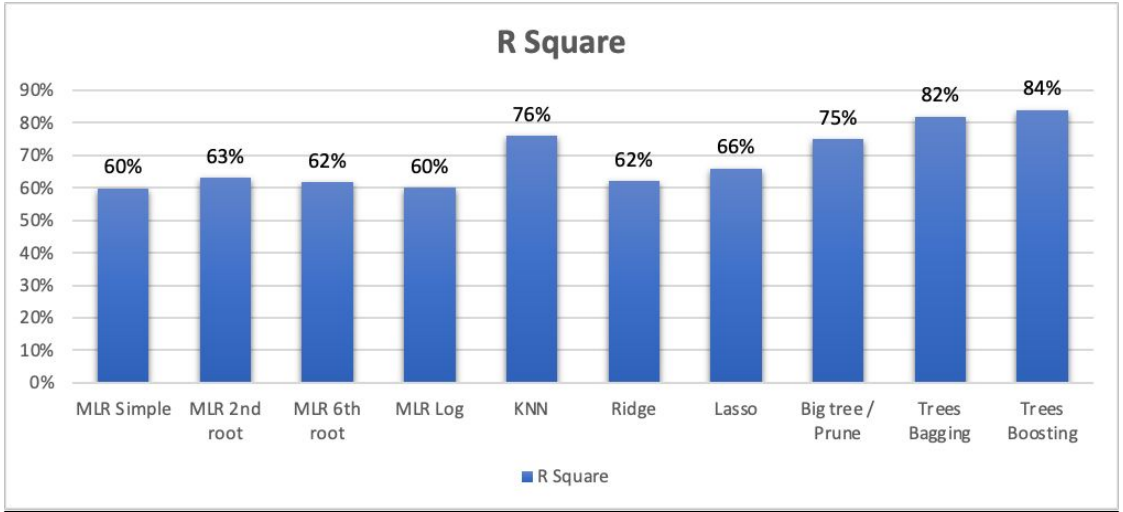


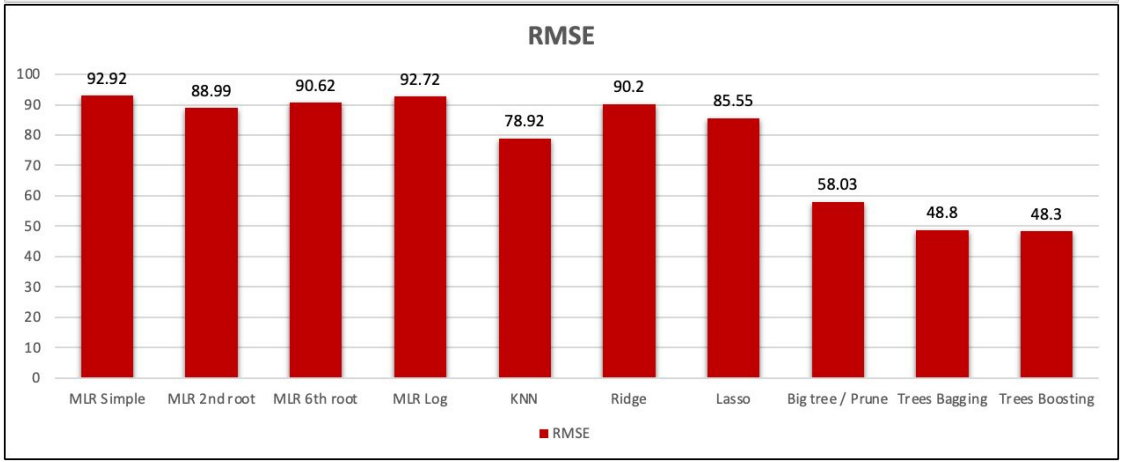
var	rel.inf
hr	36.4039009
temp	18.0786968
workingday	13.0298824
weekday	9.8553259
atemp	8.1963716
mnth	6.8000714
hum	4.4867479
windspeed	1.1222483
weathersit	0.8801604
season	0.7659165
holiday	0.3806780

For Casual Users:

- We used the same approach in predicting the registered users and found that boosting & bagging produced very similar results in the test set

Casual Users	RMSE (Test)	R Squared (Test)
Random Forest (Bagging)	17.01	87.8%
Boosting	17.13	88.7


R Square
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
60%
63%
62%
60%
76%
62%
66%
75%
82%
84%
MLR Simple
MLR 2nd root
MLR 6th root
MLR Log
KNN
Ridge
Lasso
Big tree / Prune
Trees Bagging
Trees Boosting
R Square


RMSE
100
90
80
70
60
50
40
30
20
10
0
92.92
88.99
90.62
92.72
78.92
90.2
85.55
58.03
48.8
48.3
MLR Simple
MLR 2nd root
MLR 6th root
MLR Log
KNN
Ridge
Lasso
Big tree / Prune
Trees Bagging
Trees Boosting
RMSE

Conclusion

- On running multiple linear regression, we found that the best fit was the square root model. So this implied that at least a square relationship existed.
- The coefficients in our Square Root MLR model seemed to agree with the initial Exploratory Data Analysis for both registered and casual users.
- As expected, a non parametric model like trees worked best for our dataset which had multiple nominal categorical variables (without an inherent order).
- So, the major factor influencing registered users was **Hour of the Day**, while the temporal/weather factors were not as important.
- On the other hand, while the **Hour of the Day** was still the most important variable influencing the casual riders, the **Temperature** too was of considerable importance.

Next Steps

- For casual users, we can try introducing a weekend pass model to take advantage of the positive correlation between no. of casual users and weekend days.
- Price surging/dynamic pricing can be based on weather conditions (temperature) for casual users. E.g. if it is a hot, sunny day and a weekend, our model says that there should be a higher number of casual users. It can be a good opportunity to raise prices.
- Using our model, Capital Bikeshare can perform demand and supply planning with reasonable accuracy.
- Finally, Capital Bikeshare should hire us for a model with even better accuracy!!

THANK YOU!!