Predicting Bike Rental Counts

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Contents

Chapter 1

Problem Definition & Data Distributions

1.1 Problem Statement

The problem is how to predict the daily total count (casual + registered) of bikes that will be rented taking into consideration the historical data, day of week, weather and temperature on the particular day. We can ask several questions in this problem definition as under:

1. Do we have a pattern in past historical data that can be used to predict the total count of bike rentals?
2. Does count of bike rentals depend on the day of week?
3. Does holiday have any effect on the count of bike rentals?
4. Does season have any effect on the count of bike rentals?
5. Does weather have any effect on the count of bike rentals?
6. Does temperature have any effect on the count of bike rentals?
7. Does humidity have any effect on the count of bike rentals?
8. Does wind speed have any effect on the count of bike rentals?

1.2 Data

The data given has 15 variables (not considering instant). A sample is shown below:

dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp
1/1/2011	1	0	1	0	6	0	2	0.344167	0.363625
1/2/2011	1	0	1	0	0	0	2	0.363478	0.353739
1/3/2011	1	0	1	0	1	1	1	0.196364	0.189405
1/4/2011	1	0	1	0	2	1	1	0.2	0.212122
1/5/2011	1	0	1	0	3	1	1	0.226957	0.22927

hum	windspeed	casual	registered	cnt
0.805833	0.160446	331	654	985
0.696087	0.248539	131	670	801
0.437273	0.248309	120	1229	1349
0.590435	0.160296	108	1454	1562
0.436957	0.1869	82	1518	1600

Variable description is as under:

1. **dteday**: Date
2. **season**: Season (1:springer, 2:summer, 3:fall, 4:winter)
3. **yr**: Year (0: 2011, 1:2012)
4. **mnth**: Month (1 to 12)
5. **holiday**: whether day is holiday or not (extracted from Holiday Schedule)
6. **weekday**: Day of the week
7. **workingday**: If day is neither weekend nor holiday is 1, otherwise is 0.
8. **weathersit**: (extracted from Freemeteo)
   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
9. **temp**: Normalized temperature in Celsius
10. **atemp**: Normalized feeling temperature in Celsius
11. **hum**: Normalized humidity
12. **windspeed**: Normalized wind speed
13. **casual**: count of casual users
14. **registered**: count of registered users
15. **cnt**: count of total rental bikes including both casual and registered

There are 3 dependent variables here – casual, registered and cnt. Casual and registered variables will be dropped since cnt is present which can be used as dependent variable.

All other variables are independent variables.

This is a regression problem since dependent variable is continuous.

We will use these machine learning algorithms to see which algorithm performs best out of these for regression in this problem:

1. Linear Regression
2. Decision Tree
3. Random Forest
4. K Nearest Neighbors
5. Gradient Boosted Trees

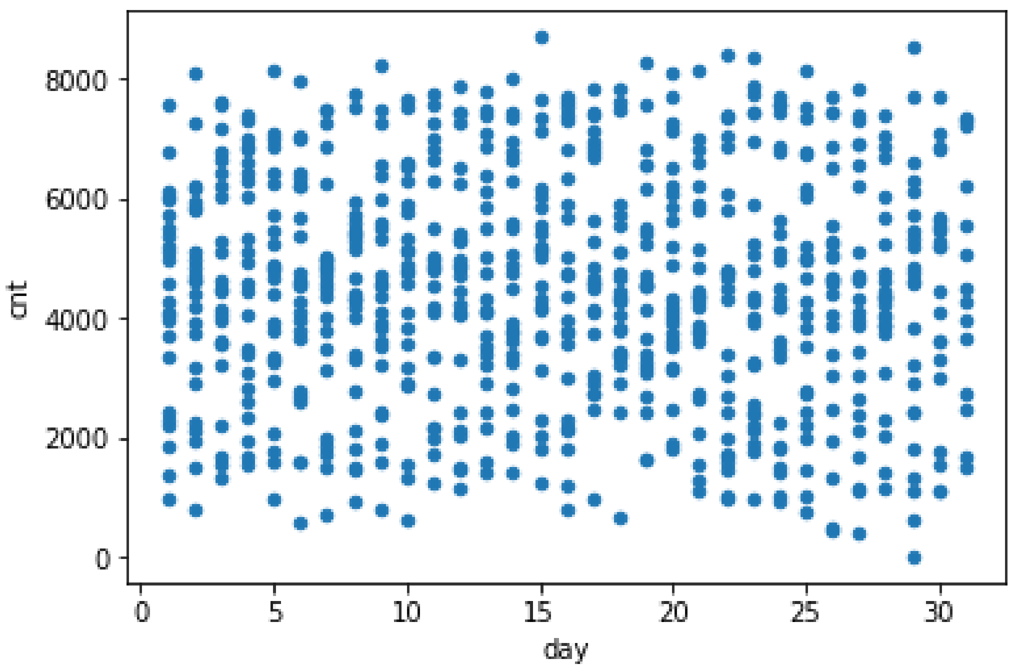
Modelling in Python

Chapter 2

Exploratory Data Analysis

Day Relationship with cnt

Day was extracted from dteday variable to check if day has any relationship with cnt. But it was found that no relationship exists between day and cnt as shown by scatter plot of day vs cnt.



So, we are dropping instant, dteday (mnth and yr are present), day, casual & registered from the dataframe df (data has been read as df).

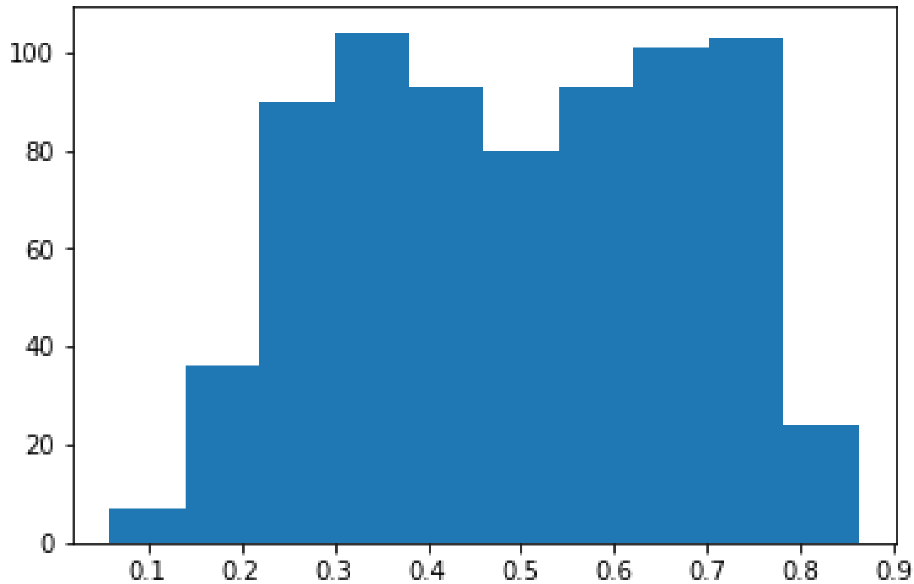
Now df has 12 variables.

	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	cnt
0	1	0	1	0	6	0	2	0.344167	0.363625	0.805833	0.160446	985
1	1	0	1	0	0	0	2	0.363478	0.353739	0.696087	0.248539	801
2	1	0	1	0	1	1	1	0.196364	0.189405	0.437273	0.248309	1349
3	1	0	1	0	2	1	1	0.200000	0.212122	0.590435	0.160296	1562
4	1	0	1	0	3	1	1	0.226957	0.229270	0.436957	0.186900	1600

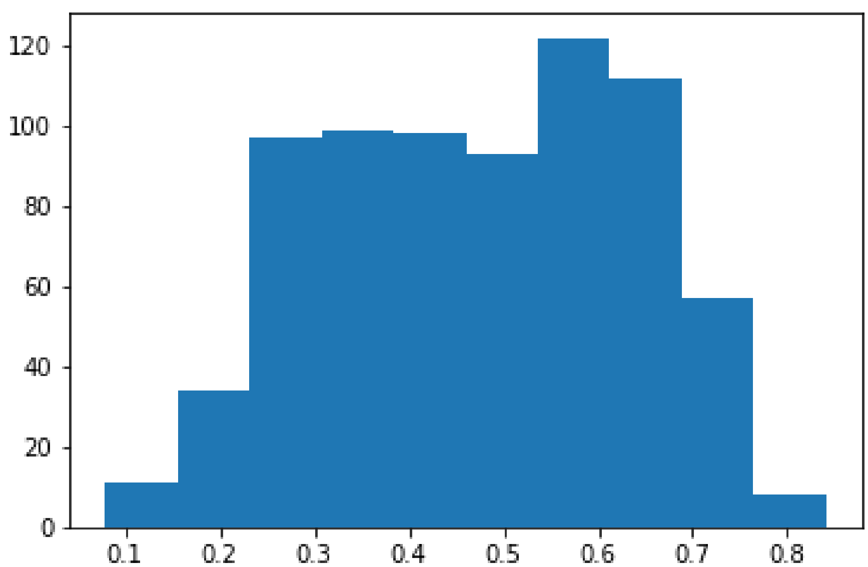
2.1 Variables distributions

Variables - season, yr, mnth, holiday, weekday, workingday, weathersit - are categorical so there is no need of distribution visualization.

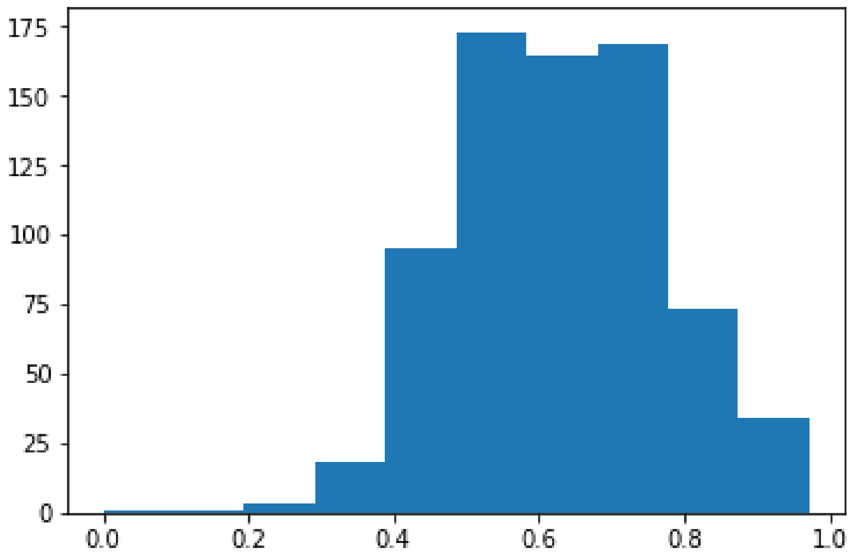
1. Variable temp distribution



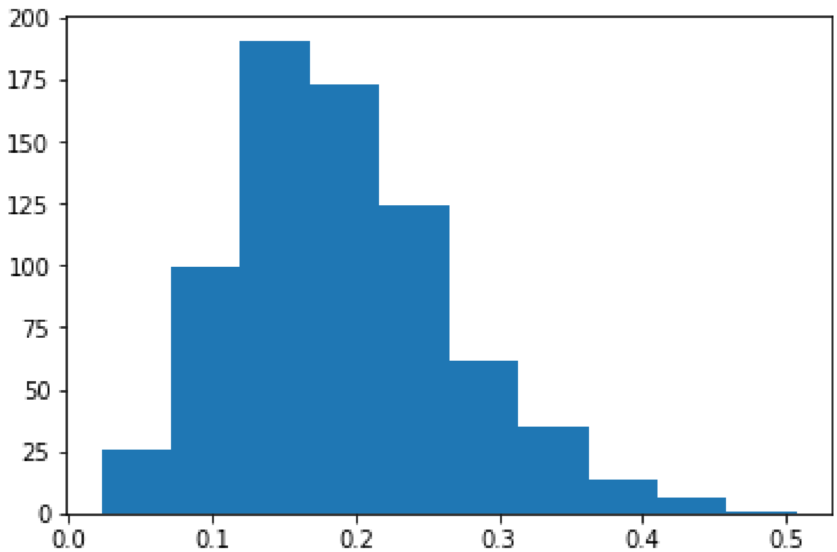
2. Variable atemp distribution



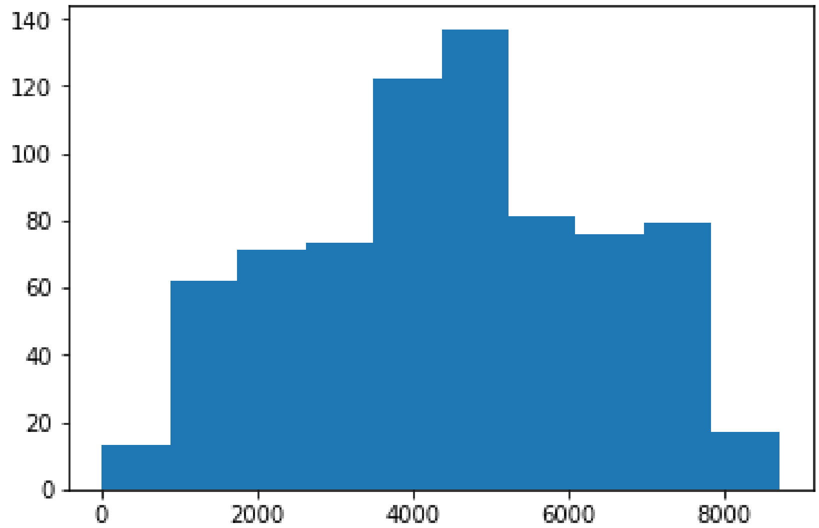
3. Variable hum distribution



4. Variable windspeed distribution



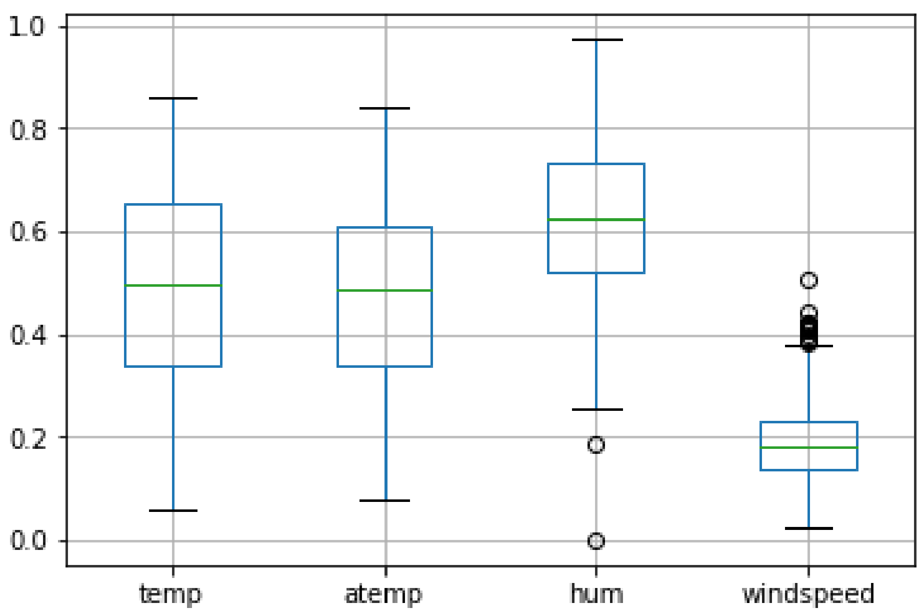
5. Variable cnt distribution



Variables registered & cnt are close to normal. All other continuous variables are skewed.

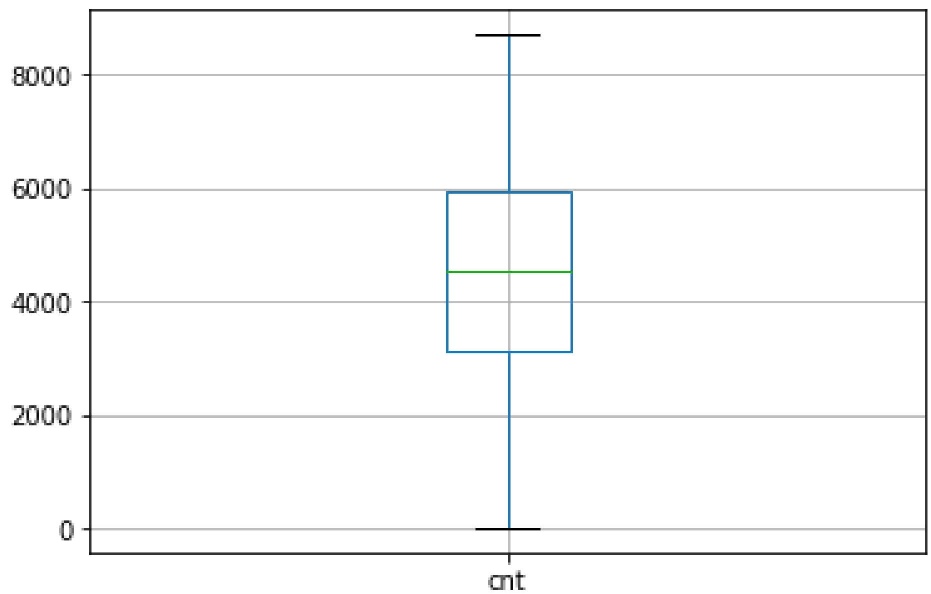
2.2 Outliers Analysis

Boxplots for variables – temp, atemp, hum, windspeed



Variables hum & windspeed have outliers. These outliers will be replaced with NaNs.

Boxplot for variable cnt



Variable cnt has no outliers.

Variable hum has got 2 null values and variable windspeed has got 13 null values after outliers replacement with NaNs.

2.3 Missing Values Analysis

There are several methods for missing values replacement as under:

1. Mean Substitution – Missing values for a variable column are replaced by the mean of all values in the column.
2. Median Substitution – Missing values are replaced by the median of all values in the column.
3. KNN imputation – Missing values are imputed by K Nearest Neighbours algorithm. This algorithm finds the K nearest observations to the observation having missing value and takes the mean of K nearest observations for the column having missing values to find the missing value replacement.

   We apply the 3 methods above to find the replacement for the missing value. We take one observation with non-missing values and put the value equal to np.nan for the column (whose missing values have to be replaced).

The method which gives the replacement closest to original value of the column in the observation is taken as the best method for missing values replacement.
Median substitution has been found to the best method for imputing missing values in the variables hum & windspeed.

2.4 Correlation Analysis

Variables - season, yr, mnth, holiday, weekday, workingday, weathersit have been converted to category type.

Chi-square test was done for correlation between categorical variables:

	season	yr	mnth	holiday	weekday	workingday	weathersit
season	0.000000	0.999929	0.000000	6.831687e-01	1.000000e+00	8.865568e-01	0.021179
yr	0.999929	0.000000	1.000000	9.949247e-01	9.999996e-01	9.799434e-01	0.127379
mnth	0.000000	1.000000	0.000000	5.593083e-01	1.000000e+00	9.933495e-01	0.014637
holiday	0.683169	0.994925	0.559308	0.000000e+00	8.567055e-11	4.033371e-11	0.600857
weekday	1.000000	1.000000	1.000000	8.567055e-11	0.000000e+00	6.775031e-136	0.278459
workingday	0.886557	0.979943	0.993350	4.033371e-11	6.775031e-136	0.000000e+00	0.253764
weathersit	0.021179	0.127379	0.014637	6.008572e-01	2.784593e-01	2.537640e-01	0.000000

workingday vs weekday and holiday vs weekday have p-value < 0.01 so we can drop workingday and holiday but we will keep holiday and drop workingday.

Correlation test was done for continuous independent variables:

	temp	atemp	hum	windspeed
temp	1.000000	0.991702	0.123723	-0.138937
atemp	0.991702	1.000000	0.137312	-0.164157
hum	0.123723	0.137312	1.000000	-0.200237
windspeed	-0.138937	-0.164157	-0.200237	1.000000

temp and atemp have coeff. of correlation 0.99 so we will drop atemp.

Chapter 3

Modelling

Categorical variables have been converted to dummy variables for modelling.

After dummy variables conversion, dataframe df has 33 independent variables and one dependent variable.

Dataframe df has been split into train & test sets in the ratio of 80:20.

3.1 Linear Regression

Ordinary Least Squares Regression has been applied to the data to build a model.

Model Summary is:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.852
Model:	OLS	**Adj. R-squared:**	0.845
Method:	Least Squares	**F-statistic:**	118.7
Date:	Wed, 08 Aug 2018	**Prob (F-statistic):**	6.12e-211
Time:	11:27:22	**Log-Likelihood:**	-4689.8
No. Observations:	584	**AIC:**	9436.
Df Residuals:	556	**BIC:**	9558.
Df Model:	27		
Covariance Type:	nonrobust		

R-squared is 0.852 which means that the model is good. R-squared of 0.852 means that 85% of variance in dependent variable may be explained by variance in independent variables.

temp and windspeed are the variables having most effect on bike counts. temp has positive effect and windspeed has negative effect.

Prediction was done for test set. Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE) was calculated.

MAPE was 139 % and MAE was 598.19

3.2 Decision Tree

A decision tree was fit to the train data with maximum depth of tree equal to 4.

MAPE was 159% and MAE was 739.63

3.3 Random Forest

A random forest of 570 trees was fit to train data with max. depth of tree equal to 9.

MAPE was 159% and MAE was 565.61

3.4 K Nearest Neighbors

KNN was fit to train data with no. of nearest neighbors to be considered as 8.

MAPE was 132% and MAE was 665.80

3.5 Gradient Boosted Trees

140 GBT were fit to train data with max. depth of trees equal to 4.

MAPE was 112% and MAE was 520.76

So, Gradient Boosted Trees algorithm has given us the best result for this problem.

Feature importance is as under:

	feature	score
0	temp	0.255050
1	hum	0.234613
2	windspeed	0.161937
7	yr_0	0.043693
29	weekday_6	0.024917
8	yr_1	0.024777
23	weekday_0	0.021230
3	season_1	0.017868

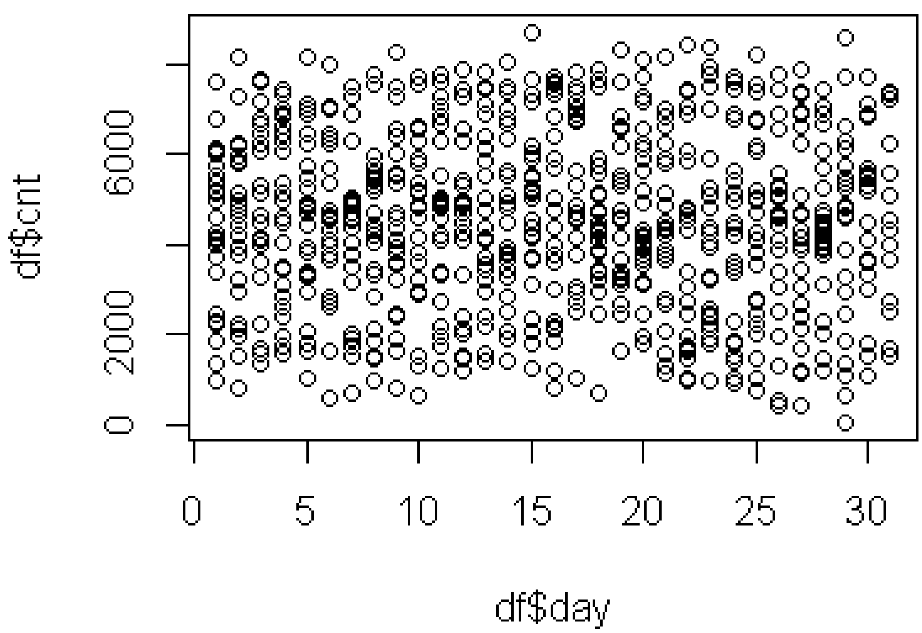
temp, hum and windspeed are the three most important features.

Chapter 4

Exploratory Data Analysis

4.1 Day Relationship with cnt

First, dteday was converted to date type and then day was extracted from dteday variable to check if day has any relationship with cnt. But it was found that no relationship exists between day and cnt as shown by scatter plot of day vs cnt.



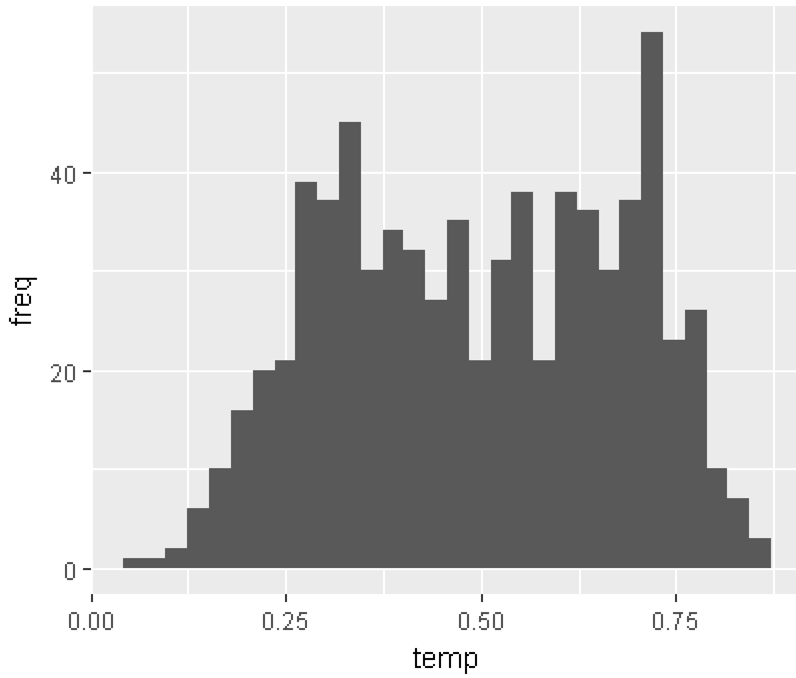
We are dropping instant, dteday (mnth and yr are present), day, casual & registered. Now, data has 12 variables only.

	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	cnt
1	1	0	1	0	6	0	2	0.344167	0.363625	0.805833	0.1604460	985
2	1	0	1	0	0	0	2	0.363478	0.353739	0.696087	0.2485390	801
3	1	0	1	0	1	1	1	0.196364	0.189405	0.437273	0.2483090	1349
4	1	0	1	0	2	1	1	0.200000	0.212122	0.590435	0.1602960	1562
5	1	0	1	0	3	1	1	0.226957	0.229270	0.436957	0.1869000	1600
6	1	0	1	0	4	1	1	0.204348	0.233209	0.518261	0.0895652	1606

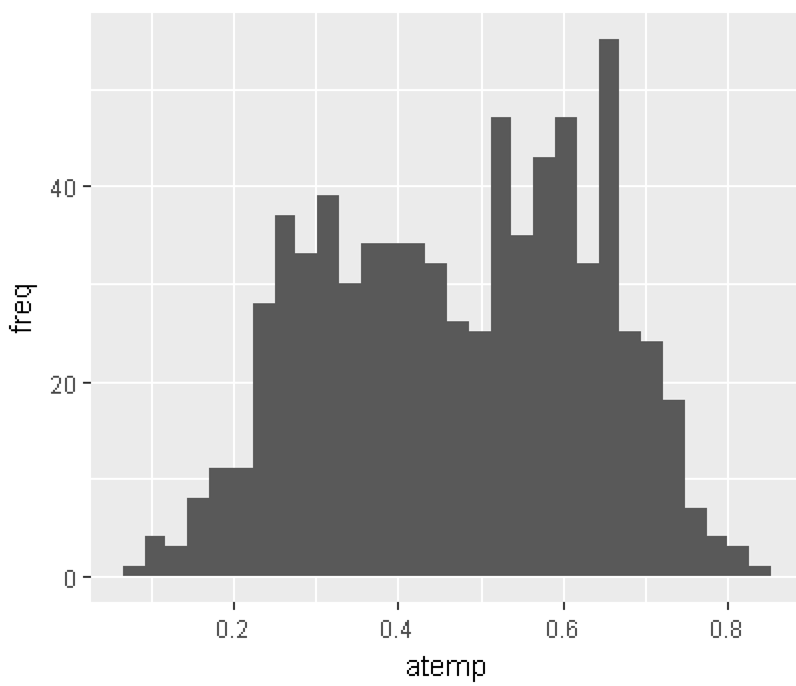
4.2 Variables distributions

Variables - season, yr, mnth, holiday, weekday, workingday, weathersit - are categorical so there is no need of distribution visualization.

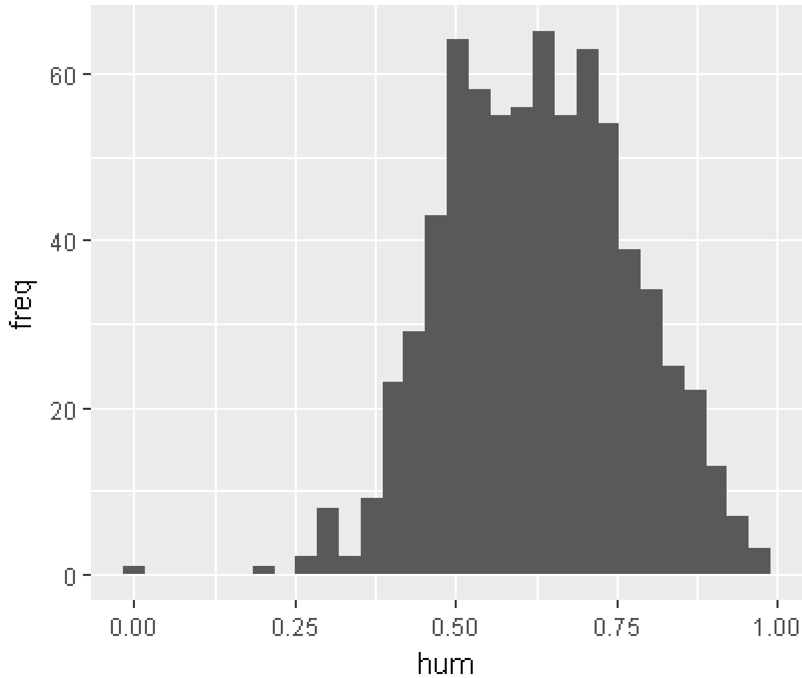
1. Variable temp distribution



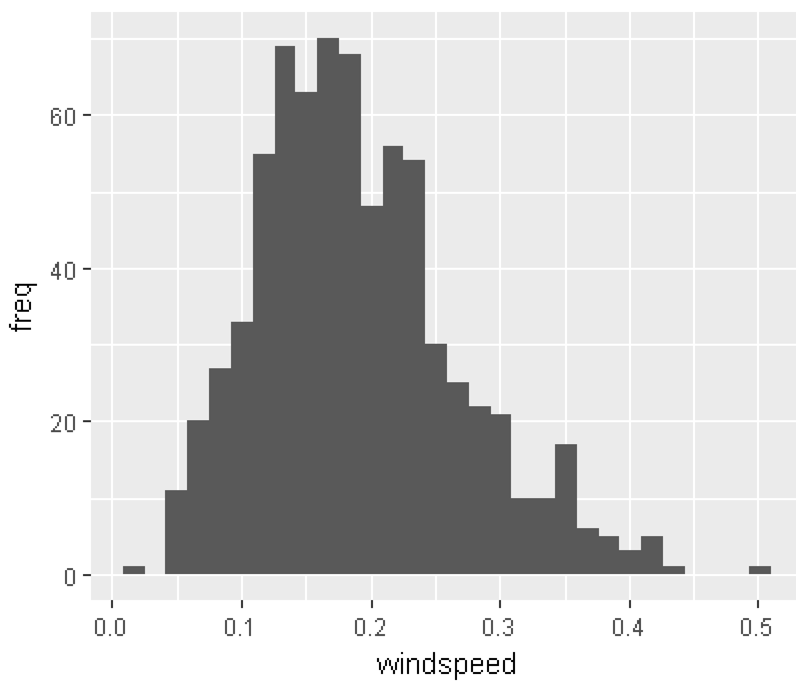
2. Variable atemp distribution



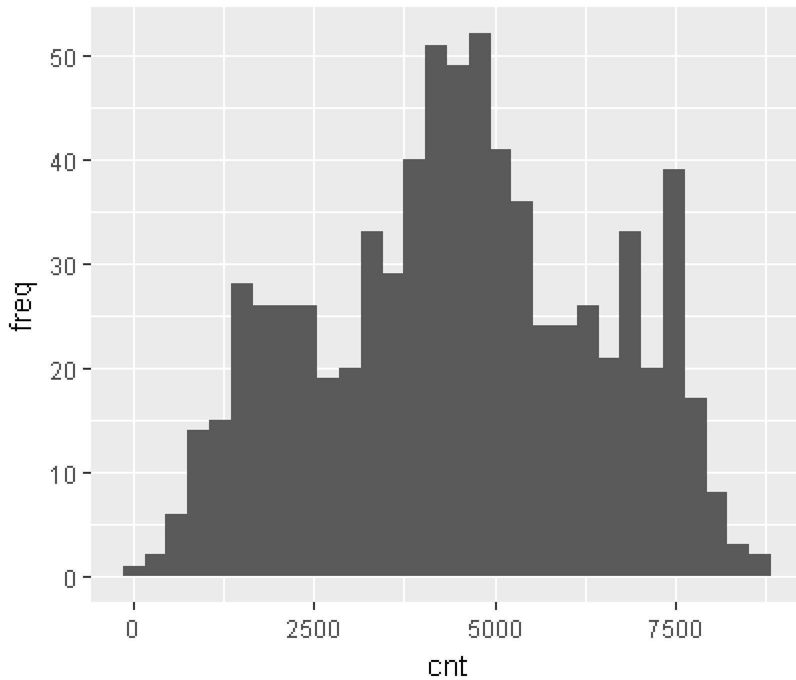
3. Variable hum distribution



4. Variable windspeed distribution



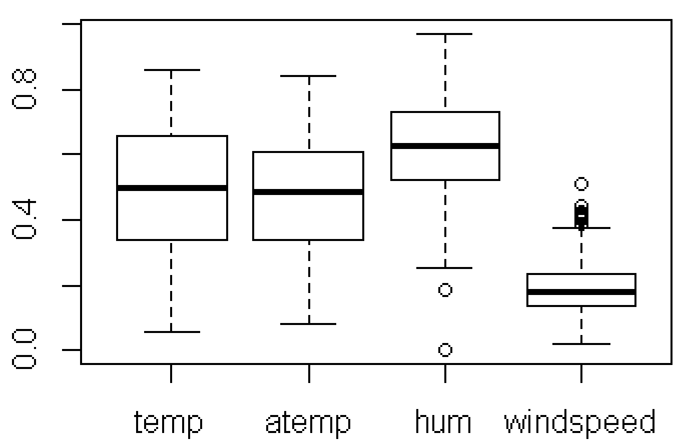
5. Variable cnt distribution



Variables hum & cnt are close to normal. All other continuous variables are skewed.

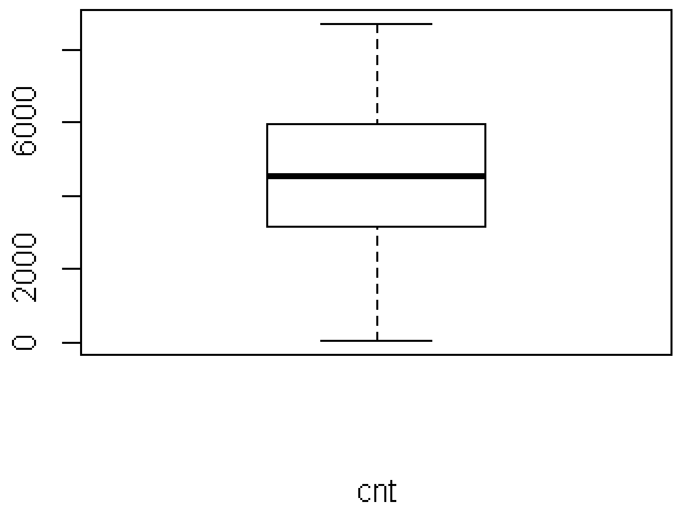
4.2 Outliers Analysis

Boxplots for variables – temp, atemp, hum, windspeed



hum & windspeed have outliers. These outliers will be replaced with NAs.

Boxplot for cnt



cnt has no outliers.

Variable hum has 2 missing values and windspeed has 13 missing values after outliers replacement with NAs.

4.3 Missing Values Analysis

Knn Imputation has been found to the best method for imputing missing values in the variables hum & windspeed.

4.4 Correlation Analysis

Variables - season, yr, mnth, holiday, weekday, workingday, weathersit have been converted to factor.

Chi-square test has been done for finding correlation between factors:

	season	yr	mnth	holiday	weekday	workingday	weathersit
season	0.0000000	9.999288e-01	0.00000000	6.831687e-01	1.000000e+00	8.865568e-01	2.117930e-02
yr	0.9999288	4.011854e-160	1.00000000	1.000000e+00	9.999996e-01	1.000000e+00	1.273794e-01
mnth	0.0000000	1.000000e+00	0.00000000	5.593083e-01	1.000000e+00	9.933495e-01	1.463711e-02
holiday	0.6831687	1.000000e+00	0.55930831	2.706945e-153	8.567055e-11	4.033371e-11	6.008572e-01
weekday	1.0000000	9.999996e-01	1.00000000	8.567055e-11	0.000000e+00	6.775031e-136	2.784593e-01
workingday	0.8865568	1.000000e+00	0.99334952	4.033371e-11	6.775031e-136	5.484935e-160	2.537640e-01
weathersit	0.0211793	1.273794e-01	0.01463711	6.008572e-01	2.784593e-01	2.537640e-01	2.484533e-315

workingday vs weekday and holiday vs weekday have p-value < 0.01 so we can drop workingday and holiday.

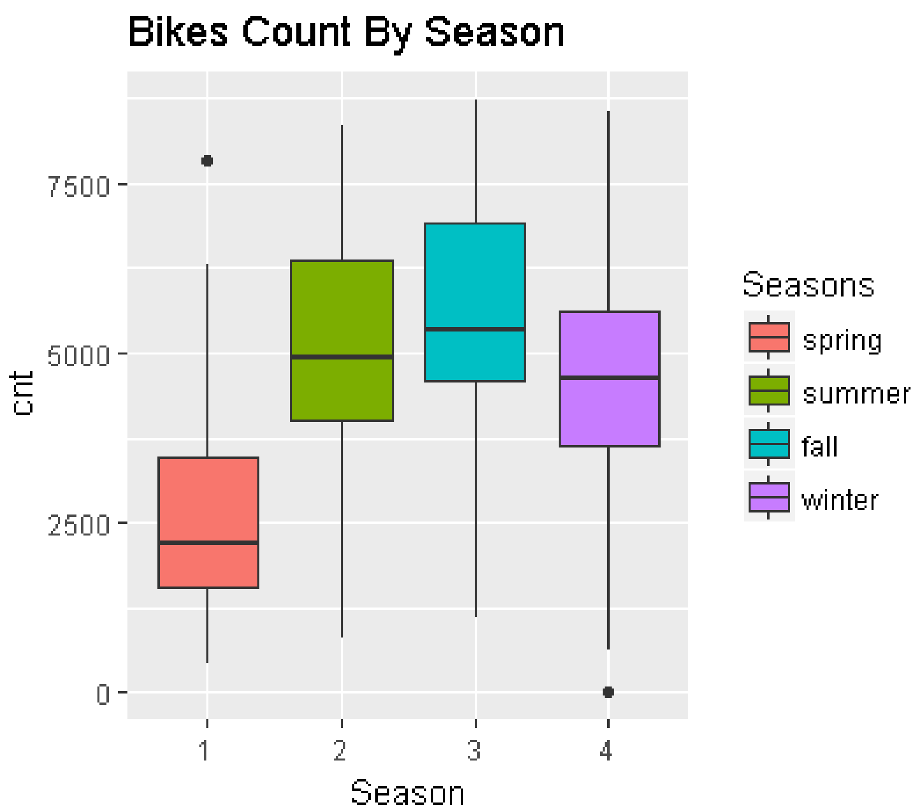
Correlation between continuous independent variables

	temp	atemp	hum	windspeed
temp	1.0000000	0.9917016	0.1228026	-0.1442859
atemp	0.9917016	1.0000000	0.1364223	-0.1700440
hum	0.1228026	0.1364223	1.0000000	-0.2025662
windspeed	-0.1442859	-0.1700440	-0.2025662	1.0000000

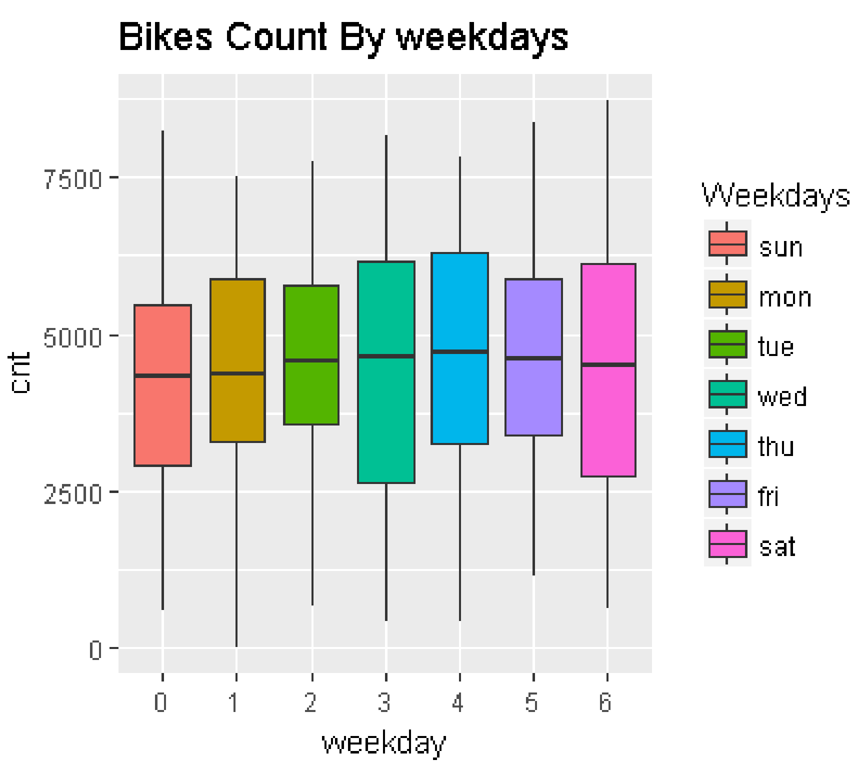
temp and atemp have correlation coeff. of 0.99 so we will drop atemp.

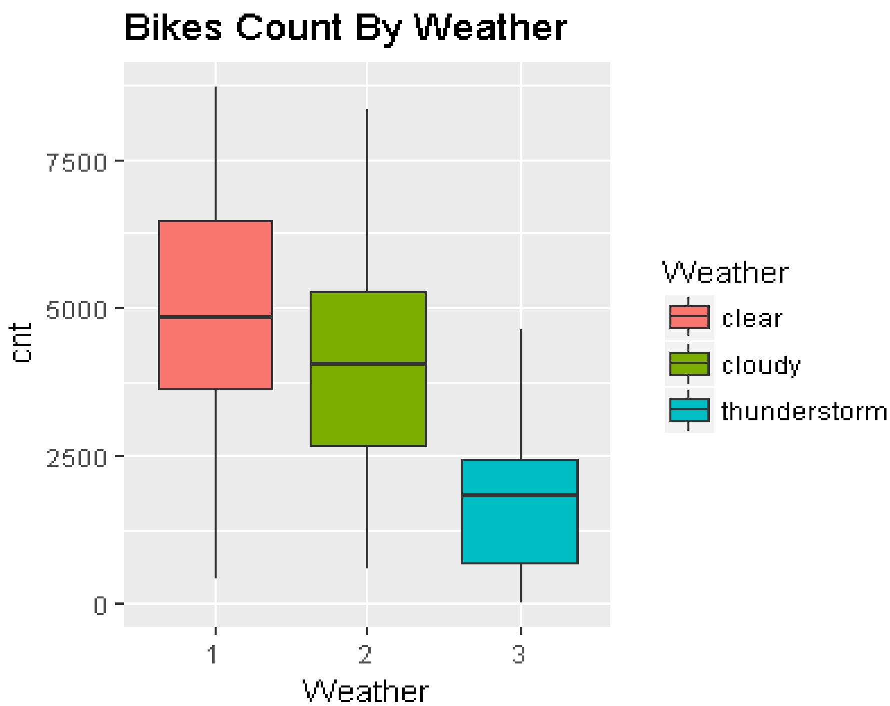
Now, df has 9 variables.

	season	yr	mnth	weekday	weathersit	temp	hum	windspeed	cnt
1	1	0	1	6	2	0.344167	0.805833	0.1604460	985
2	1	0	1	0	2	0.363478	0.696087	0.2485390	801
3	1	0	1	1	1	0.196364	0.437273	0.2483090	1349
4	1	0	1	2	1	0.200000	0.590435	0.1602960	1562
5	1	0	1	3	1	0.226957	0.436957	0.1869000	1600
6	1	0	1	4	1	0.204348	0.518261	0.0895652	1606

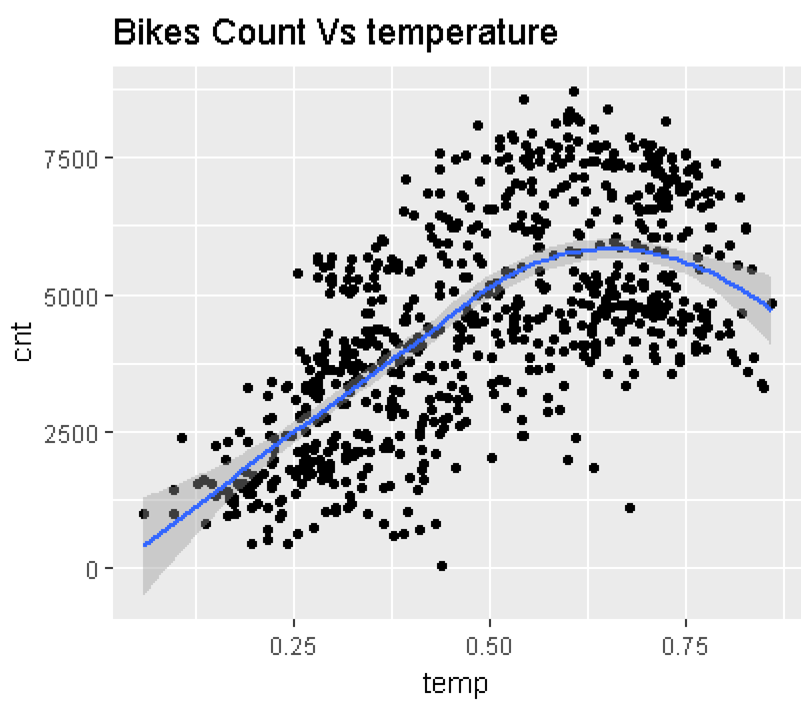


Most bike rentals occur in Fall followed by Summer.

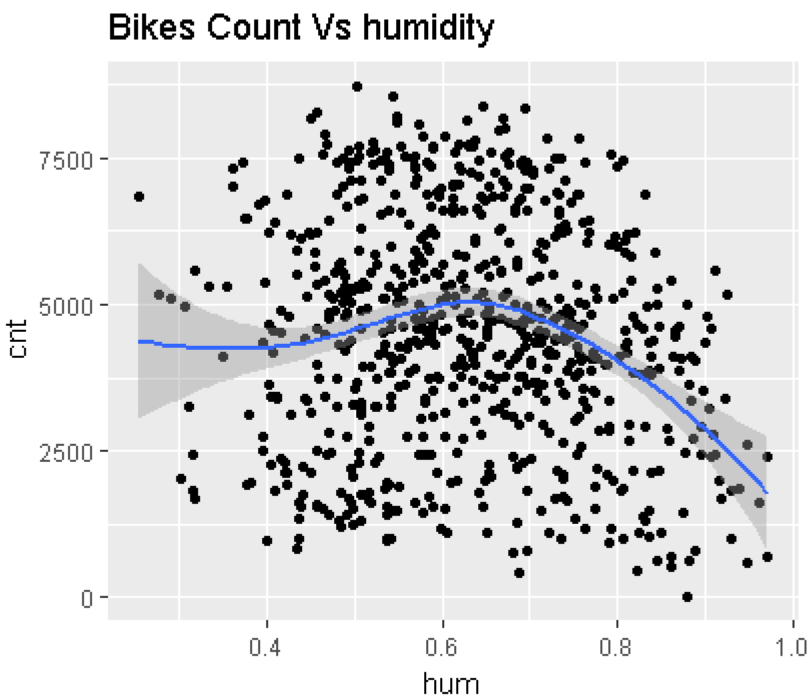




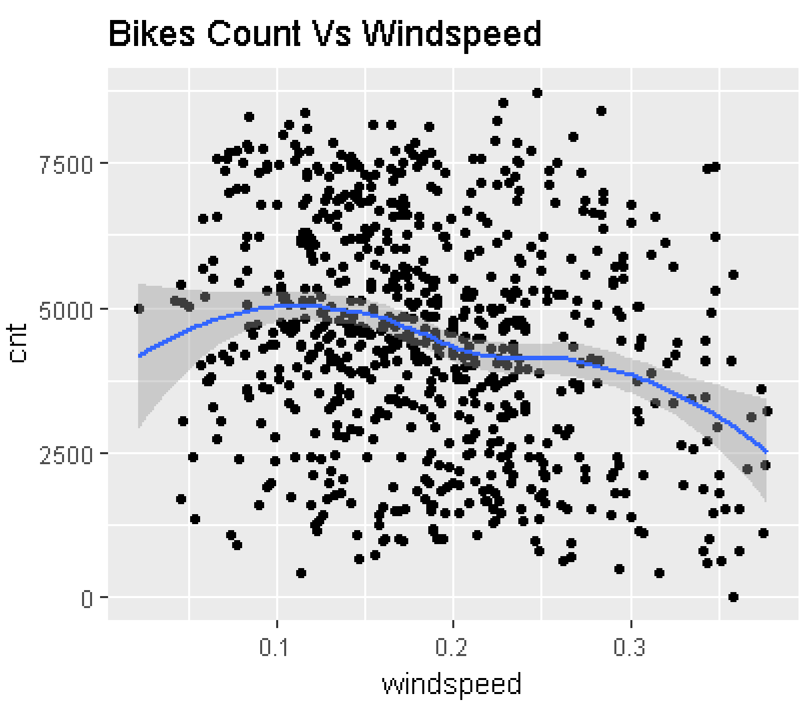
Most bikes are rented during clear weather



As temp. increases, bikes count increases initially then decreases.



As humidity increases, bike count decreases.



As windspeed increases, bike count decreases.

Chapter 5

Modelling

Dataframe df has 8 independent variables and one dependent variable.

Dataframe df has been split into train & test sets in the ratio of 80:20.

5.1 Linear Regression

lm function has been applied to the data to build a model.

Model summary:

```
Residuals:
    Min      1Q  Median      3Q     Max 
-3992.2  -352.7    63.0   462.5  2207.6 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1356.56     274.87   4.935 1.06e-06 ***
season2       958.08     209.12   4.581 5.70e-06 ***
season3       753.00     246.48   3.055 0.002358 ** 
season4      1719.00     202.45   8.491  < 2e-16 ***
yr1          2051.86      64.40  31.859  < 2e-16 ***
mnth2         240.34     160.00   1.502 0.133642    
mnth3         586.55     192.15   3.053 0.002377 ** 
mnth4         473.05     278.03   1.701 0.089421 .  
mnth5         775.60     298.92   2.595 0.009718 ** 
mnth6         730.50     314.11   2.326 0.020396 *  
mnth7         296.89     349.51   0.849 0.395998    
mnth8         757.21     336.07   2.253 0.024640 *  
mnth9        1235.58     296.59   4.166 3.59e-05 ***
mnth10        511.47     264.25   1.936 0.053429 .  
mnth11       -103.16     255.08  -0.404 0.686062    
mnth12        -79.52     199.53  -0.399 0.690394    
weekday1       94.49     117.96   0.801 0.423447    
weekday2      270.91     117.81   2.300 0.021840 *  
weekday3      293.50     120.15   2.443 0.014880 *  
weekday4      388.10     117.24   3.310 0.000992 ***
weekday5      440.77     121.24   3.636 0.000303 ***
weekday6      393.51     116.60   3.375 0.000790 ***
weathersit2  -561.56      87.10  -6.448 2.47e-10 ***
weathersit3 -1889.02     235.89  -8.008 6.83e-15 ***
temp         4196.15     452.74   9.268  < 2e-16 ***
hum         -1361.91     342.93  -3.971 8.08e-05 ***
windspeed   -2211.15     483.82  -4.570 6.01e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 756.7 on 557 degrees of freedom
Multiple R-squared:  0.854,	Adjusted R-squared:  0.8472 
F-statistic: 125.3 on 26 and 557 DF,  p-value: < 2.2e-16
```

R-squared is 0.854 which means that about 85% of variance in dependent variable can be explained by variance in independent variables.

temp has coeff. of 4196.15 which means that temp is having the most(positive) effect on cnt.

windspeed has coeff. of -2211.15 which means that windspeed is having the second most effect(negative) on cnt.

MAPE was 133 % and MAE was 602.36

5.2 Decision Tree

Rpart package was used to fit a decision tree to the train data.

MAPE was 196 % and MAE was 678.02

5.3 Random Forest

randomForest package was used to fit 500 trees.

MAPE was 140 % and MAE was 554.63

5.4 K Nearest Neighbors

Knn.reg from FNN was used to fit to train data.

MAPE was 171 % and MAE was 738.44

5.5 Gradient Boosted Trees

50000 Gradient Boosted Trees from gbm library was used to fit to train data.

MAPE was 99 % and MAE was 506

Variables relative influence:

Variable	**Rel. Influence**
temp	35.419354
yr	25.271824
mnth	11.605649
hum	8.668744
season	6.797198
windspeed	4.612378
weekday	4.406589
weathersit	3.218264

Gradient Boosted Trees have the lowest MAPE and lowest MAE so GBT is the best algorithm for this problem.

Chapter 6

Conclusion

We have applied following algorithms to the problem in both R and Python:

1. Linear Regression
2. Decision Tree
3. Random Forest Regression
4. K Nearest Neighbors
5. Gradient Boosted Trees

Gradient Boosted Trees have been found to be the best algorithm for this problem in both R and Python.

140 Gradient Boosted Trees with maximum depth of tree as 4 were fit to training data in Python. Then, prediction for test data was done. Mean Absolute Percent Error (MAPE) was 1.12(112%) and Mean Absolute Error (MAE) was 520.76

50000 Gradient Boosted Trees with maximum depth of tree as 4 were fit to training data in R. Then, prediction for test data was done. Mean Absolute Percent Error (MAPE) was 0.99(99%) and Mean Absolute Error (MAE) was 506.48

Gradient Boosted trees model in Python is similar to that in R.

Gradient Boosted Trees model in Python gives temp(temperature), hum(humidity) and windspeed as top three influencers of dependent variable cnt.

Temperature has a positive influence on cnt whereas humidity and windspeed have negative influence on cnt.

We can also quantify their effects if we consider Linear Regression models in both Python and R as under:

Variable	Coefficient in Python	Coefficient in R
temp	4265.5183	4196.15
hum	-1232.0776	-1361.91
windspeed	-1589.6639	-2211.15

Regression Coefficients of temp(temperature) and hum(humidity) are almost similar in both Python & R.