Bike Share Demand Forecast

November 19, 2019

[ ]:
```
# ----------- Step 1a: Define and categorize the problem statement␣
↪--------------

# The problem statement is to "Predict the daily bike rental count based on the␣
↪environmental and seasonal settings"
# This is clearly a 'Supervised machine learning regression problem' to predict␣
↪a number based on the input features.

# ----------- Step 1a ends here -----------------
```

[1]:
```
# ----------Step 1b: Import all the required libraries ----------

#---- for data transformations----
    #install.packages("lubridate")
    library(lubridate)

#---- for EDA Visualizations ------
    #install.packages("corrplot")
    library(corrplot)
    #install.packages("ggplot2")
    library(ggplot2)
    #install.packages("GGally")
    library("GGally")
    #install.packages("ggExtra")
    library(ggExtra)

#---- for model building----
    library(caret)
    #install.packages("Metrics")
    library(Metrics)
    #install.packages("randomForest")
    library(randomForest)

# ------------------- Step 1b ends here --------------------------
```

```
Attaching package: lubridate
```

```
The following object is masked from package:base:

    date

corrplot 0.84 loaded
Registered S3 method overwritten by 'GGally':
  method from
  +.gg   ggplot2
Loading required package: lattice

Attaching package: Metrics

The following objects are masked from package:caret:

    precision, recall

randomForest 4.6-14
Type rfNews() to see new features/changes/bug fixes.

Attaching package: randomForest

The following object is masked from package:ggplot2:

    margin
```

[3]:
```
# ------------------- Step 2: Gather the data -----------------

  # Data is provided as .csv file and already split into Test and Train.
  # The training set is comprised of the first 19 days of each month, while the␣
↪test set is the 20th to the end of the month.
  # Let's import the data
    bike= read.csv("/Users/snehashrungarpawar/Documents/Master in Data Science/
↪DPA/Project/Data/train.csv", header=TRUE)
    bike_test = read.csv("/Users/snehashrungarpawar/Documents/Master in Data␣
↪Science/DPA/Project/Data/test.csv", header=TRUE)
# ------------------- Step 2 ends here -------------------------
```

[ ]:
```
# ------------------- Step 3: Data Preparation ---------------------
  # 3a. Analyze Attributes: Check properties of data
  # 3b. Complete Data Perform missing value analysis and Impute if needed
  # 3c. Correct Data: Check for any invalid data points
  # 3d. Create Derived Attributes - Feature Extraction
  # 3e. Convert - Converting data to proper formats
```

[4]:
```
# 3a. Analyze Attributes: Check properties of data
    dim(bike)
```

```
    str(bike)
    head(bike, 10)
# 3a -> Inference:
        #i. The dataset has 10,886 observations (n=10886) and 12 columns of␣
↪type int, num and factor.
        #ii. Season, Holiday, Working day and weather are categorical variables.
        #ii. temp, atemp, humidity, windspeed, casual, registered and count are␣
↪continuous numerical variables.
```

1. 10886 2. 12

```
'data.frame':   10886 obs. of  12 variables:
 $ datetime  : Factor w/ 10886 levels "2011-01-01 00:00:00",..: 1 2 3 4 5 6 7 8
9 10 ...
 $ season    : int  1 1 1 1 1 1 1 1 1 1 ...
 $ holiday   : int  0 0 0 0 0 0 0 0 0 0 ...
 $ workingday: int  0 0 0 0 0 0 0 0 0 0 ...
 $ weather   : int  1 1 1 1 1 2 1 1 1 1 ...
 $ temp      : num  9.84 9.02 9.02 9.84 9.84 ...
 $ atemp     : num  14.4 13.6 13.6 14.4 14.4 ...
 $ humidity  : int  81 80 80 75 75 75 80 86 75 76 ...
 $ windspeed : num  0 0 0 0 0 ...
 $ casual    : int  3 8 5 3 0 0 2 1 1 8 ...
 $ registered: int  13 32 27 10 1 1 0 2 7 6 ...
 $ count     : int  16 40 32 13 1 1 2 3 8 14 ...
```

datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed
2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0000
2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0000
2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0000
2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0000
2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0000
2011-01-01 05:00:00	1	0	0	2	9.84	12.880	75	6.0032
2011-01-01 06:00:00	1	0	0	1	9.02	13.635	80	0.0000
2011-01-01 07:00:00	1	0	0	1	8.20	12.880	86	0.0000
2011-01-01 08:00:00	1	0	0	1	9.84	14.395	75	0.0000
2011-01-01 09:00:00	1	0	0	1	13.12	17.425	76	0.0000

[5]:
```
# 3b. Complete Data Perform missing value analysis and Impute if needed
    table(is.na(bike))
# 3b -> Inference: There are no null values in the dataset. If it had, then␣
↪either the rows/columns had to be
    # dropped or the null values be imputed based on the % of null values
```

```
 FALSE
130632
```

[ ]:
```
# 3c. Correct Data: Check for any invalid data points
    # From above observations data doesnot seem to have any invalid datatypes␣
↪to be handled.
    # Let's check for the outliers in EDA step
```

[6]:
```
# 3d. Create Derived Attributes - Feature Extraction
      # Lets extract 'date','month','weekday' and 'year' from 'datetime' column␣
↪as we will be needing it for analysis
      bike$date=as.Date(substr(bike$datetime,1,10))
      bike$year = as.factor(year(bike$datetime))
      bike$month = as.factor(month(bike$datetime))
      bike$hour = as.factor(hour(bike$datetime))
      bike$wkday = as.factor(wday(bike$datetime))

      bike_test$date=as.Date(substr(bike_test$datetime,1,10))
      bike_test$year = as.factor(year(bike_test$datetime))
      bike_test$month = as.factor(month(bike_test$datetime))
      bike_test$hour = as.factor(hour(bike_test$datetime))
      bike_test$wkday = as.factor(wday(bike_test$datetime))

      # Drop datetime as we have extracted all the above needed information␣
↪from it
      bike = bike[-c(1)]
      bike_test = bike_test[-c(1)]

      head(bike, 5)
      head(bike_test, 5)

  # 3d -> Inference: There are no null values in the dataset. If it had, then␣
↪either the rows/columns had to be
                    #dropped or the null values be imputed based on the % of␣
↪null values.
```

season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered
1	0	0	1	9.84	14.395	81	0	3	13
1	0	0	1	9.02	13.635	80	0	8	32
1	0	0	1	9.02	13.635	80	0	5	27
1	0	0	1	9.84	14.395	75	0	3	10
1	0	0	1	9.84	14.395	75	0	0	1

season	holiday	workingday	weather	temp	atemp	humidity	windspeed	date	year
1	0	1	1	10.66	11.365	56	26.0027	2011-01-20	2011
1	0	1	1	10.66	13.635	56	0.0000	2011-01-20	2011
1	0	1	1	10.66	13.635	56	0.0000	2011-01-20	2011
1	0	1	1	10.66	12.880	56	11.0014	2011-01-20	2011
1	0	1	1	10.66	12.880	56	11.0014	2011-01-20	2011

[7]:
```
# 3e. Convert - Converting data to proper formats
```

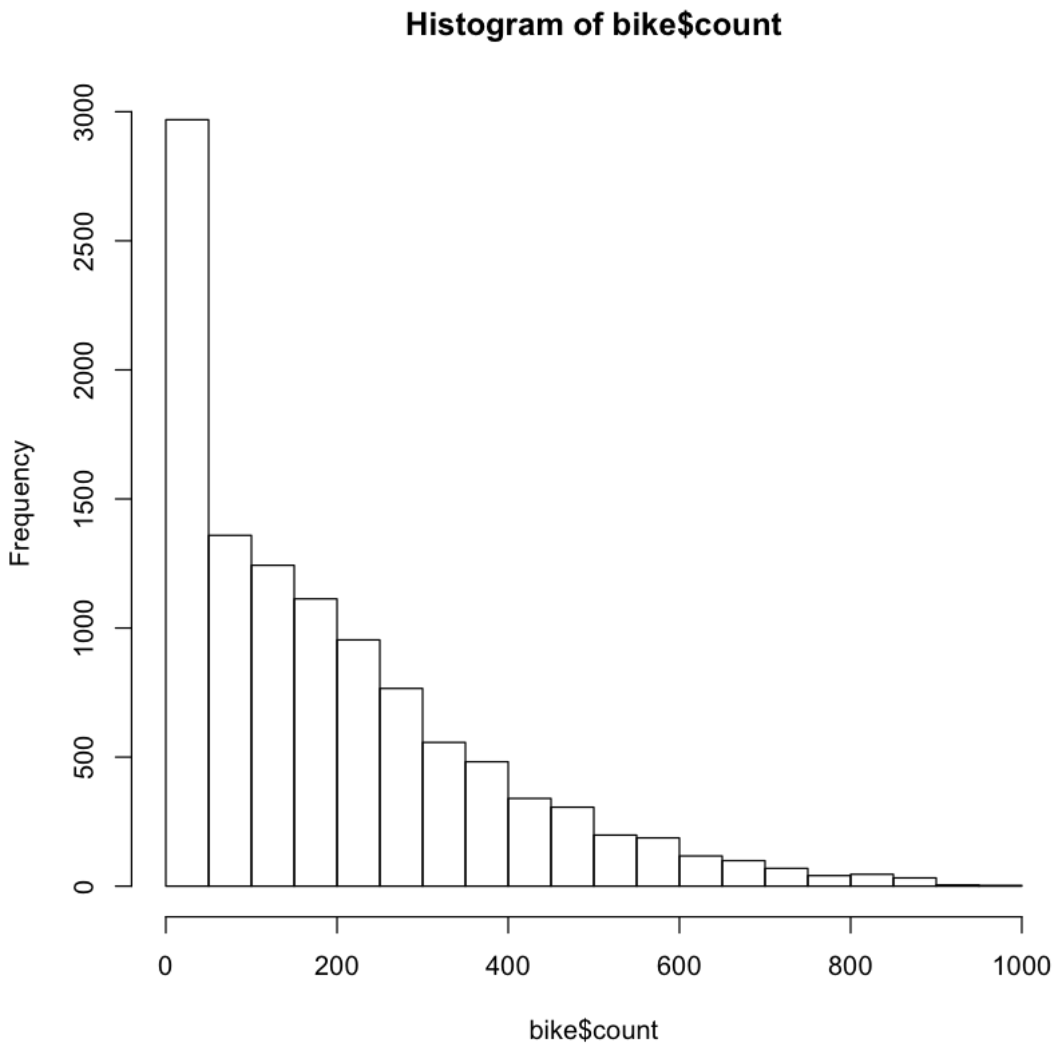
```
    # We can clearly see that "season",␣
↪"yr","mnth","holiday","weekday","workingday","weather","date" are␣
↪categories,rather than continous variable.
    # Let's convert them to categories
      names = c("season", "holiday", "workingday", "weather")
      bike[,names] = lapply(bike[,names], factor)
      bike_test[,names] = lapply(bike_test[,names], factor)

      str(bike)
      str(bike_test)

# ------------------- Step 3: Data Preparation ends here␣
↪--------------------------
```

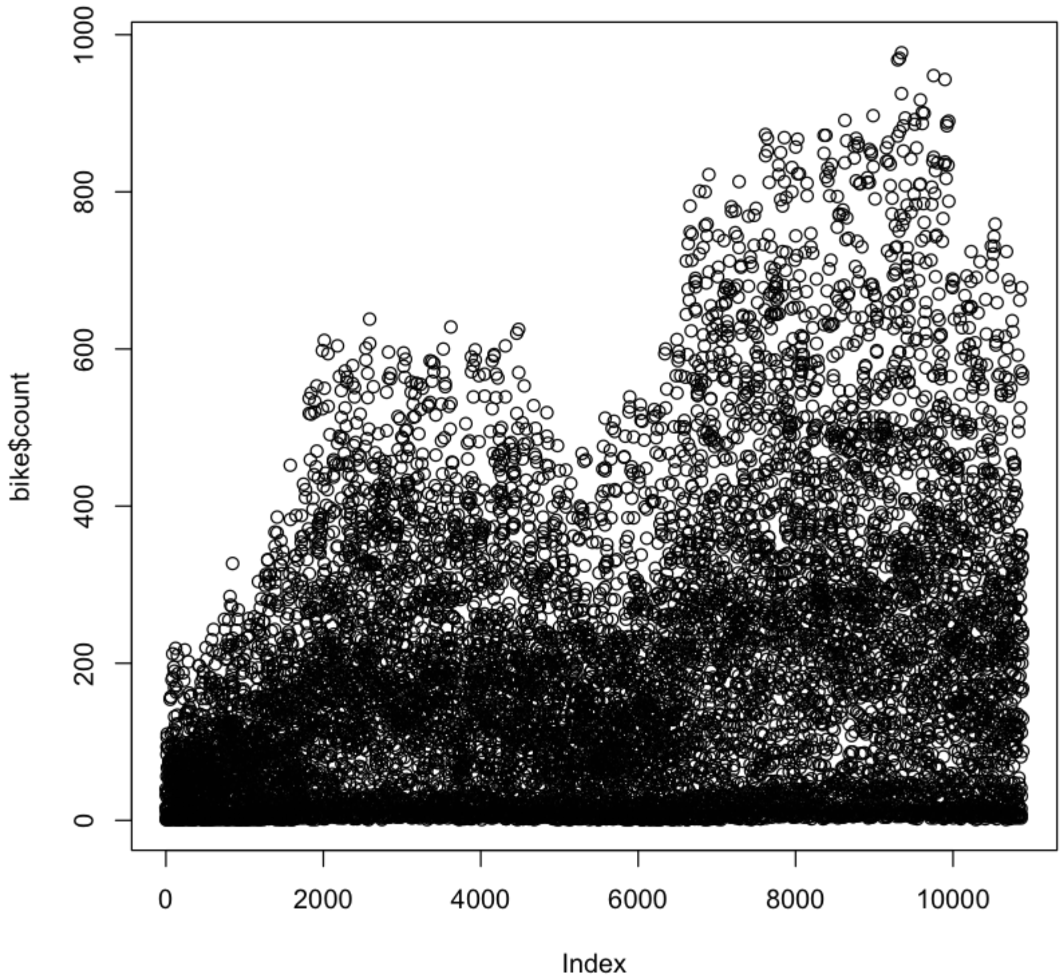
```
'data.frame':	10886 obs. of  16 variables:
 $ season    : Factor w/ 4 levels "1","2","3","4": 1 1 1 1 1 1 1 1 1 1 ...
 $ holiday   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
 $ workingday: Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
 $ weather   : Factor w/ 4 levels "1","2","3","4": 1 1 1 1 1 2 1 1 1 1 ...
 $ temp      : num  9.84 9.02 9.02 9.84 9.84 ...
 $ atemp     : num  14.4 13.6 13.6 14.4 14.4 ...
 $ humidity  : int  81 80 80 75 75 75 80 86 75 76 ...
 $ windspeed : num  0 0 0 0 0 ...
 $ casual    : int  3 8 5 3 0 0 2 1 1 8 ...
 $ registered: int  13 32 27 10 1 1 0 2 7 6 ...
 $ count     : int  16 40 32 13 1 1 2 3 8 14 ...
 $ date      : Date, format: "2011-01-01" "2011-01-01" ...
 $ year      : Factor w/ 2 levels "2011","2012": 1 1 1 1 1 1 1 1 1 1 ...
 $ month     : Factor w/ 12 levels "1","2","3","4",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ hour      : Factor w/ 24 levels "0","1","2","3",..: 1 2 3 4 5 6 7 8 9 10 ...
 $ wkday     : Factor w/ 7 levels "1","2","3","4",..: 7 7 7 7 7 7 7 7 7 7 ...
'data.frame':	6493 obs. of  13 variables:
 $ season    : Factor w/ 4 levels "1","2","3","4": 1 1 1 1 1 1 1 1 1 1 ...
 $ holiday   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
 $ workingday: Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 2 ...
 $ weather   : Factor w/ 4 levels "1","2","3","4": 1 1 1 1 1 1 1 1 1 2 ...
 $ temp      : num  10.7 10.7 10.7 10.7 10.7 ...
 $ atemp     : num  11.4 13.6 13.6 12.9 12.9 ...
 $ humidity  : int  56 56 56 56 56 60 60 55 55 52 ...
 $ windspeed : num  26 0 0 11 11 ...
 $ date      : Date, format: "2011-01-20" "2011-01-20" ...
 $ year      : Factor w/ 2 levels "2011","2012": 1 1 1 1 1 1 1 1 1 1 ...
 $ month     : Factor w/ 12 levels "1","2","3","4",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ hour      : Factor w/ 24 levels "0","1","2","3",..: 1 2 3 4 5 6 7 8 9 10 ...
 $ wkday     : Factor w/ 7 levels "1","2","3","4",..: 5 5 5 5 5 5 5 5 5 5 ...
```

[ ]:
```
# ------------- Step 4: Exploratory Data Analysis -----------
    # 4a. Outlier Analysis

    # 4a(1). Visualize continuos variables wrt target variable

    # 4a(2). Visualize categorical variables wrt target variable
```

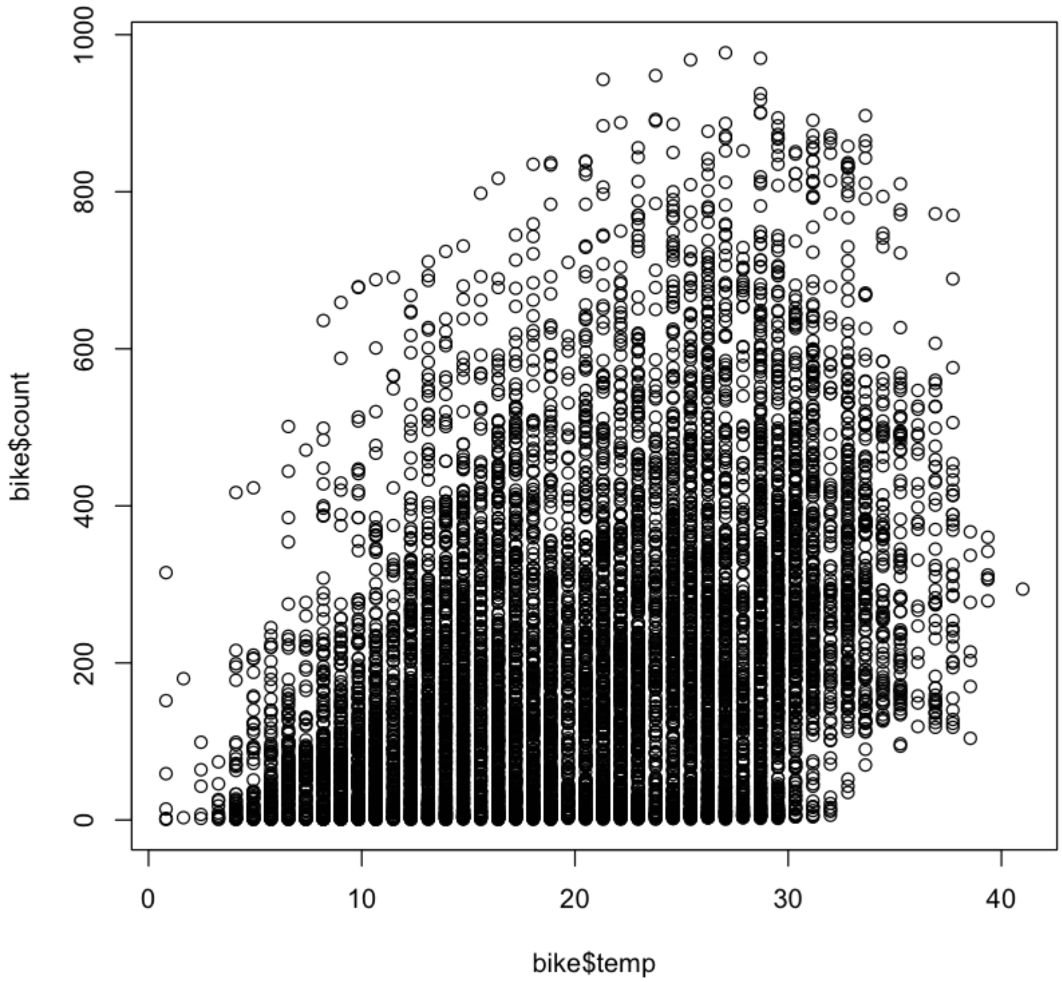
[ ]:
```
# 4b. Correlation Analysis

# --------------- Explore Continuous Variables----------------
    # 4b(1). Explore continous features
        # i. Check distribution of target variable
        # ii. Explore correlation between independent continuous variables with␣
↪target variable
        # iii. Plot heatmap for correlation matrix (to check for␣
↪multicolinearity)
        # iv. Visualize the relationship among all continuous variables using␣
↪pairplots
        # v. Explore relationship between independent continuous variables and␣
↪dependent variables using Joint Plot
```

[8]:
```
# 4b(1) i. Check distribution of target variable
          hist(bike$count)
          plot(bike$count)
   # Inference: Target variable "count" is almost normally distributed.
```

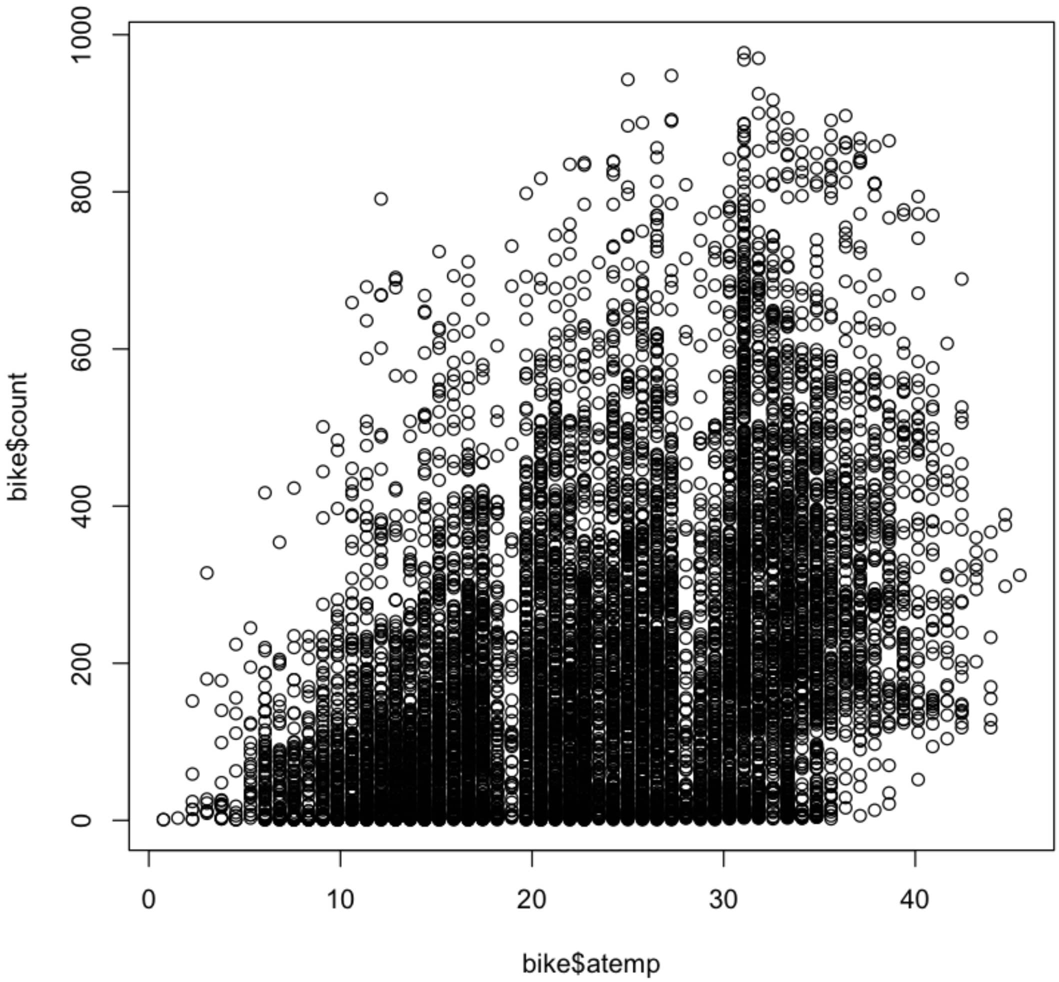

Histogram of bike$count
Frequency
0
500
1000
1500
2000
2500
3000
0
200
400
600
800
1000
bike$count

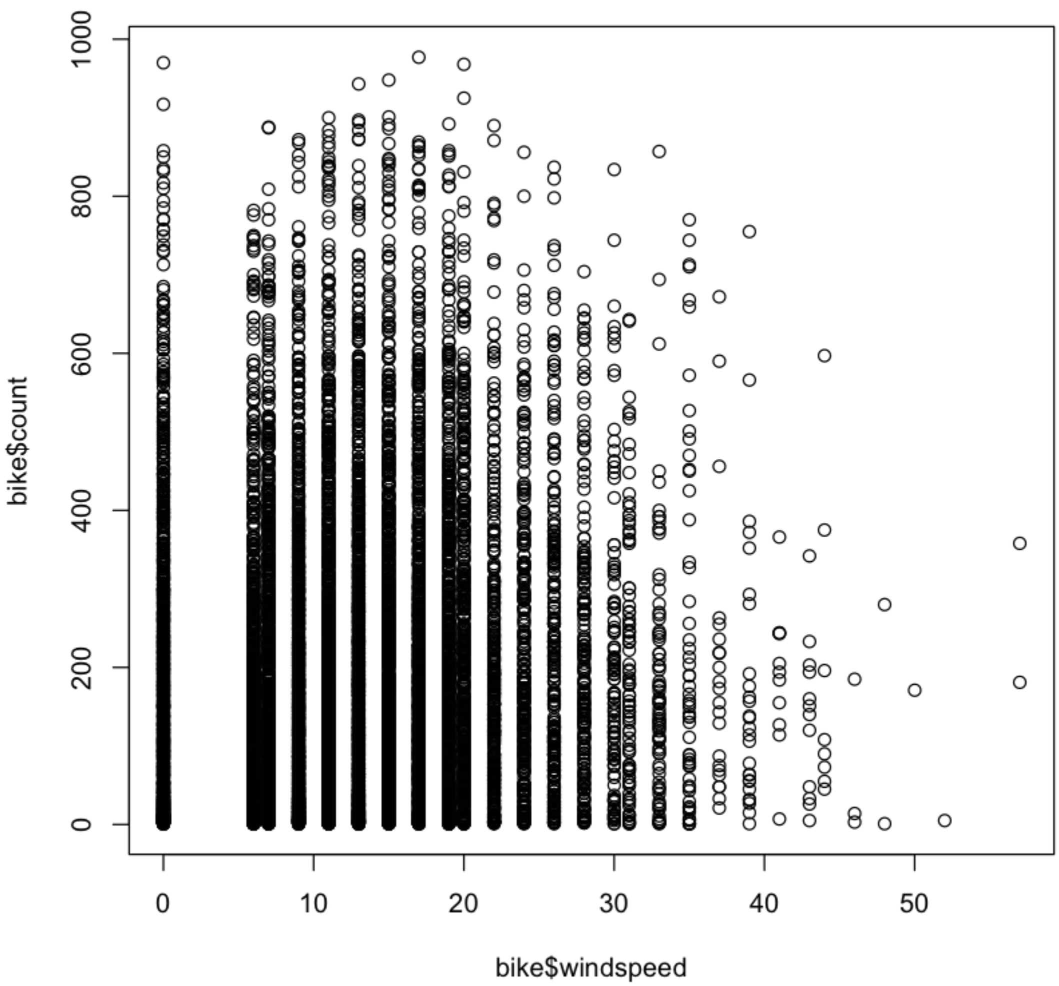


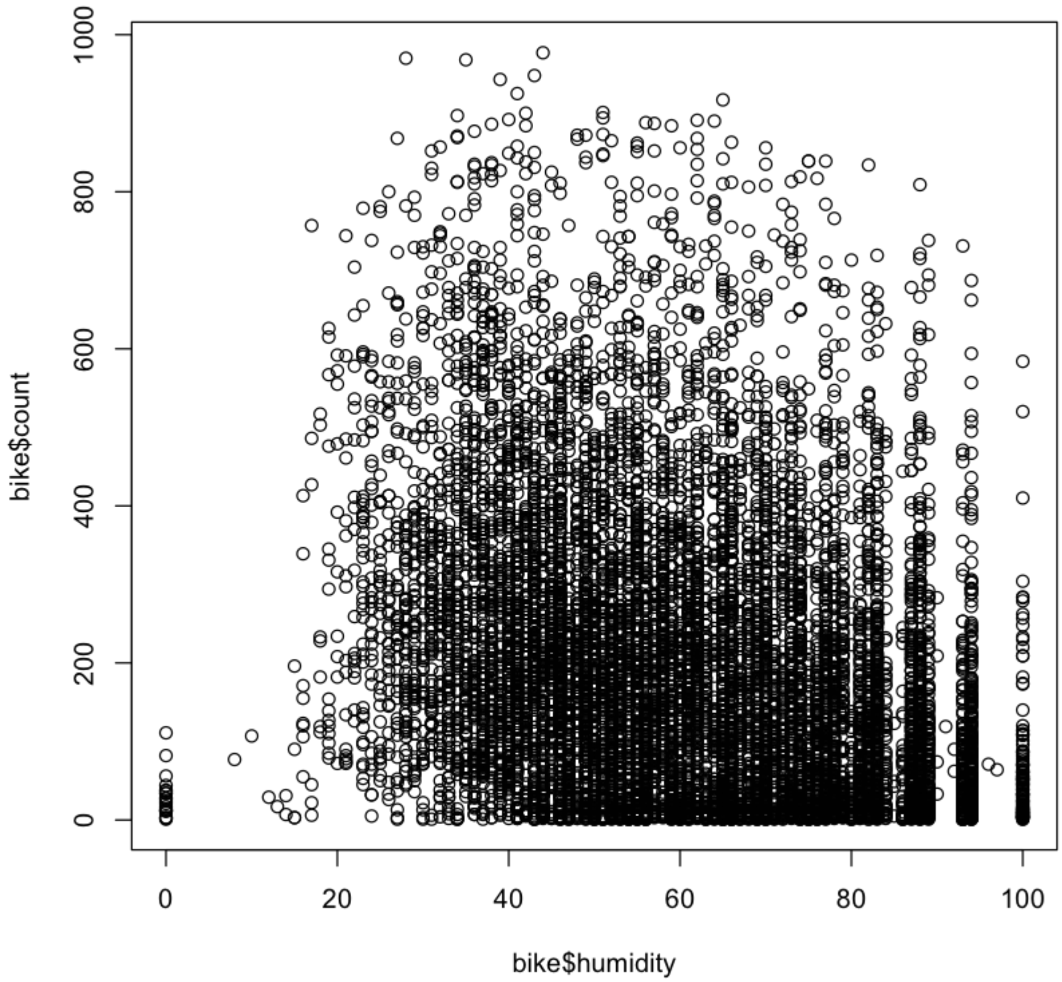
[9]:
```
# 4b(1) ii. Explore correlation between independent continuous variables with␣
↪target variable
        plot(bike$temp,bike$count)
        plot(bike$atemp,bike$count)
        plot(bike$windspeed,bike$count)
        plot(bike$humidity,bike$count)
```



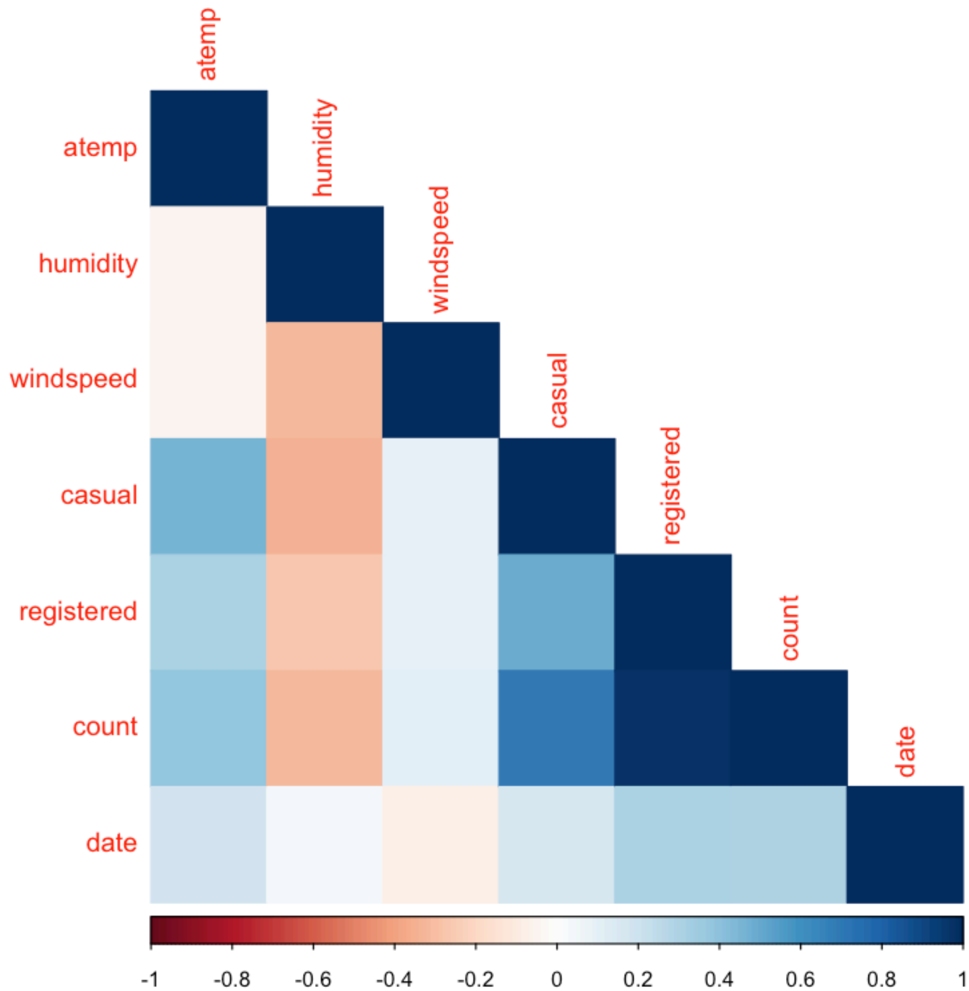
bike$count
0
200
400
600
800
1000
0
10
20
30
40
bike$temp


bike$count
1000
800
600
400
200
0
0
10
20
30
40
bike$atemp

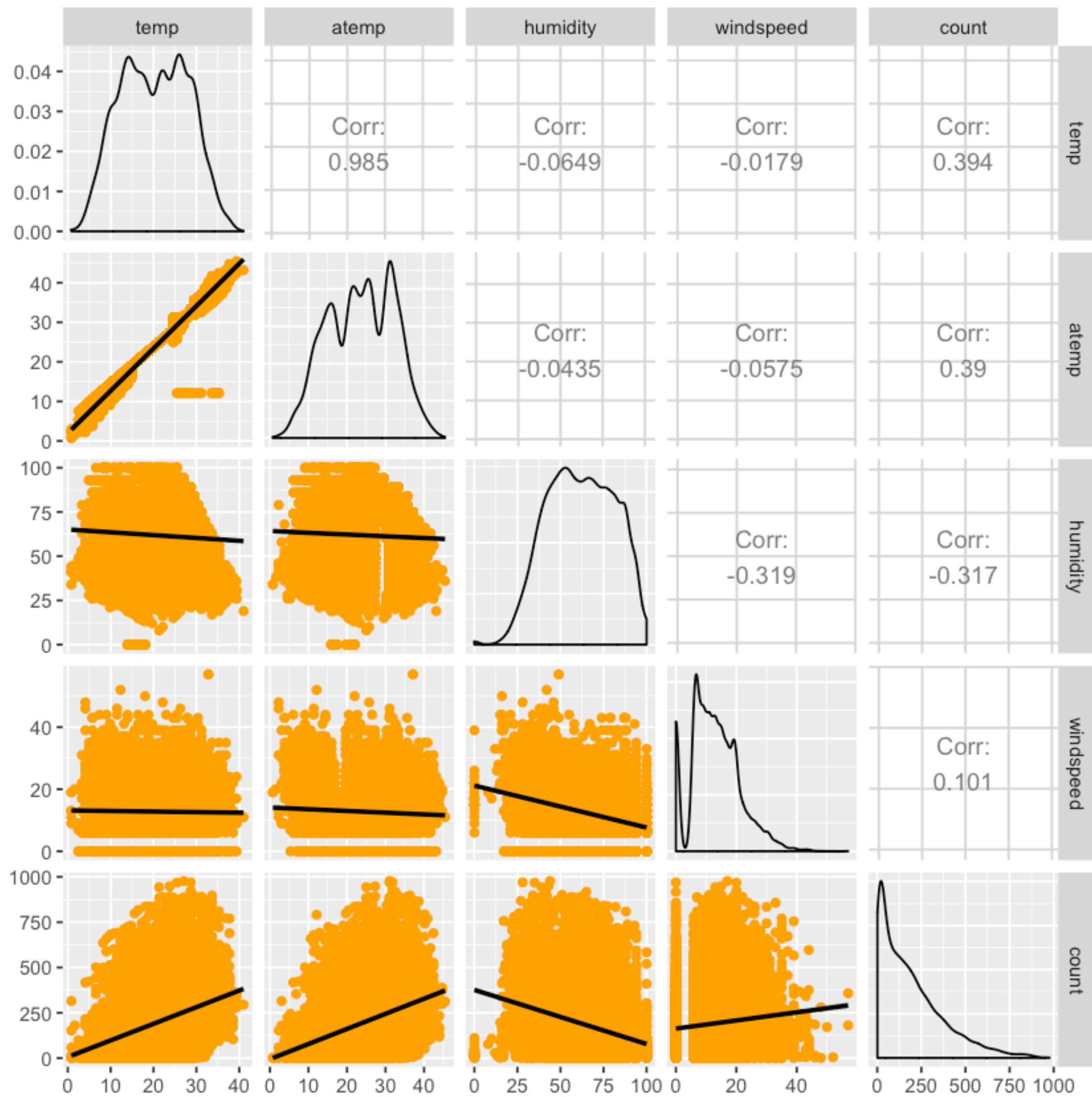

bike$count
bike$windspeed
0
200
400
600
800
1000
0
10
20
30
40
50



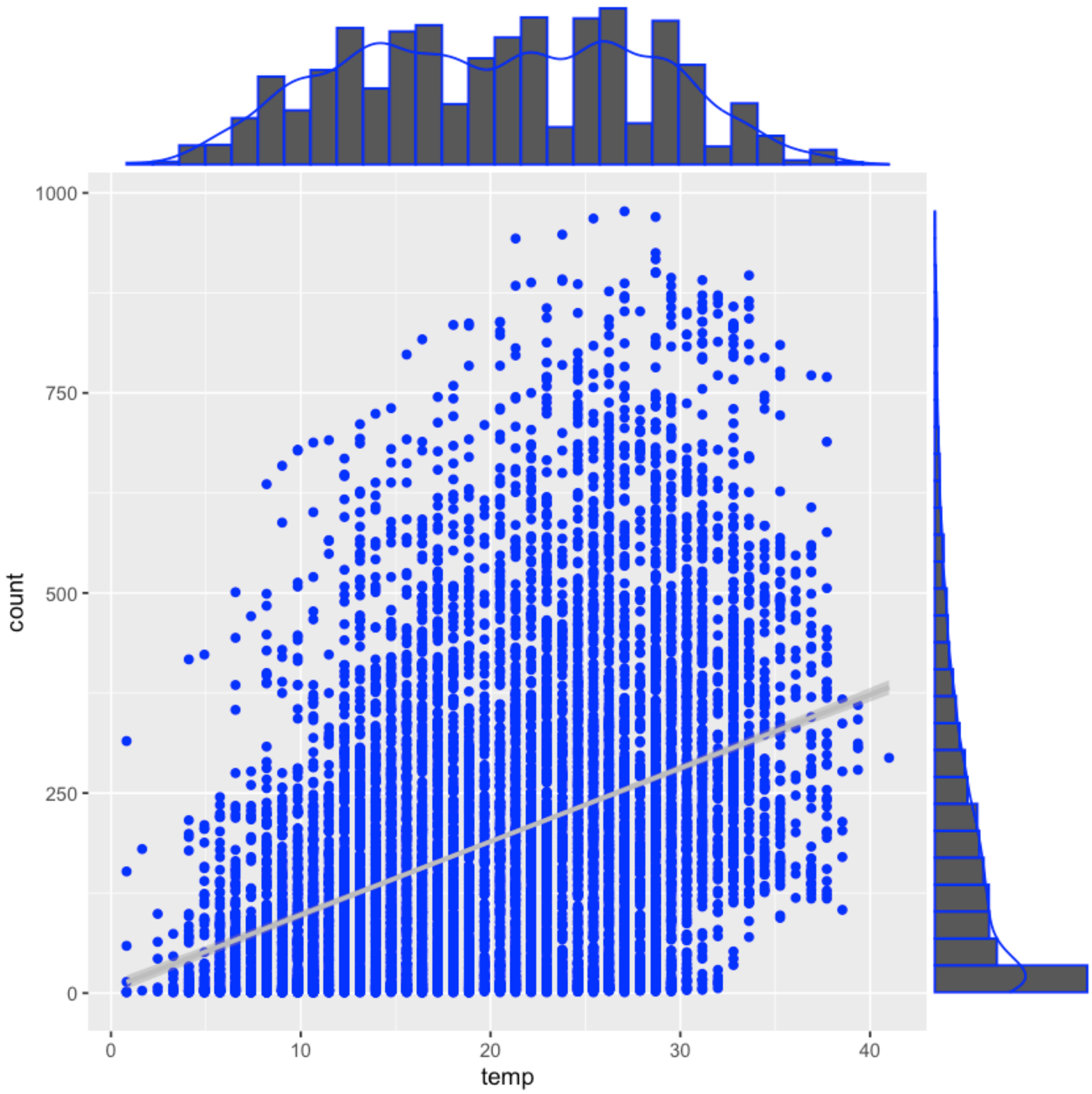
[10]:
```
# 4b(1) iii. Plot heatmap for correlation matrix (to check for␣
↪multicolinearity)
        corr <- as.data.frame(lapply(bike[c(6:12)], as.numeric))
        corrplot(cor(corr), method = "color", type='lower')
    # Inference:
        # i. temp and atemp are highly correlated, we would need to drop one of␣
↪them to remove multicolinearity.
        # ii. We can also drop Registered and Casual from our analysis as␣
↪Counts are categorized as Registered and Casual
             # and we will be predicting "Count" variable only.
```



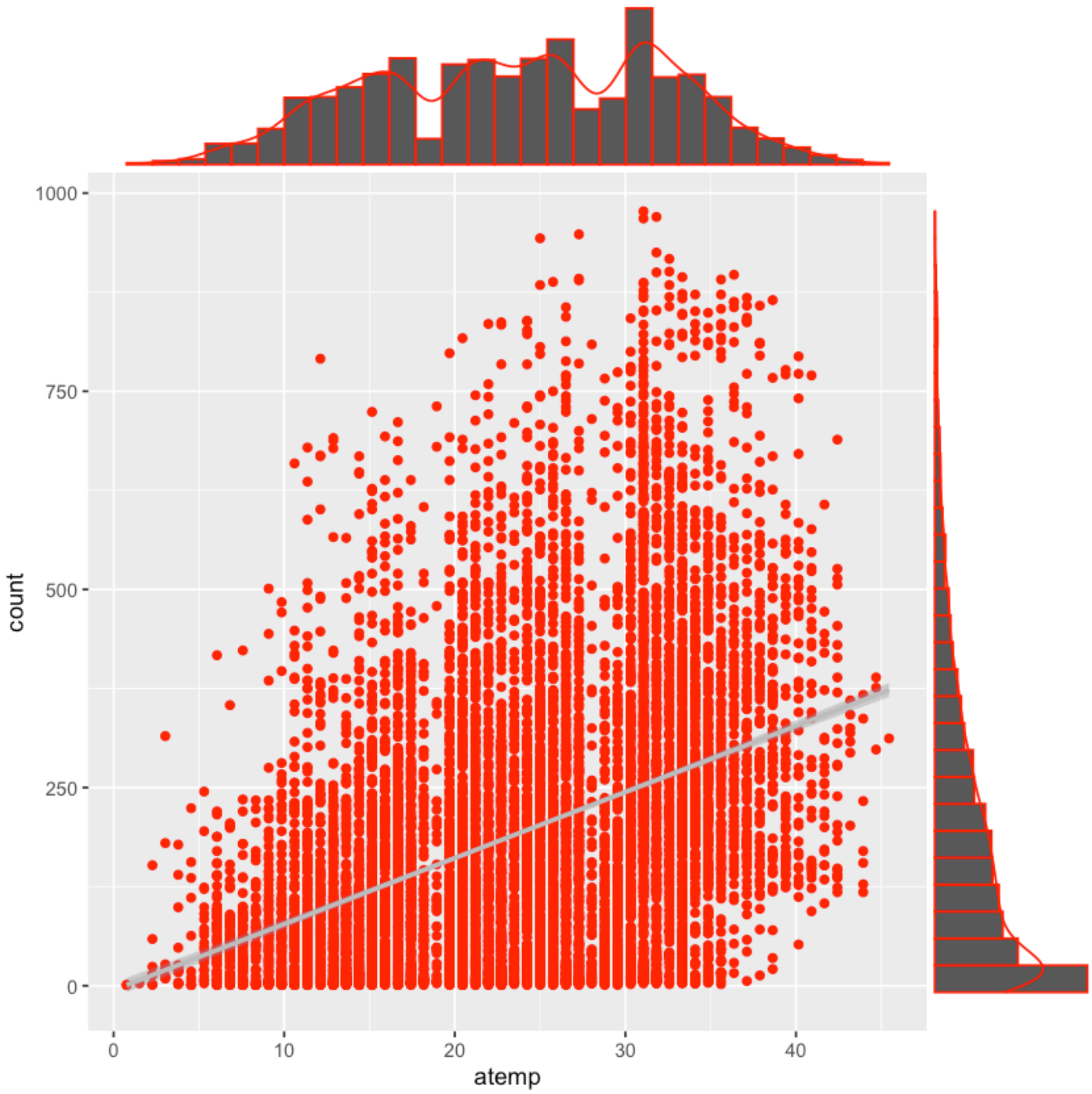
[11]:
```
# 4b(1) iv. Visualize the relationship among all continuous variables using␣
↪pairplots
        ggpairs(bike[c(5:8, 11)], lower=list(continuous=wrap("smooth",␣
↪colour="orange")) )
```



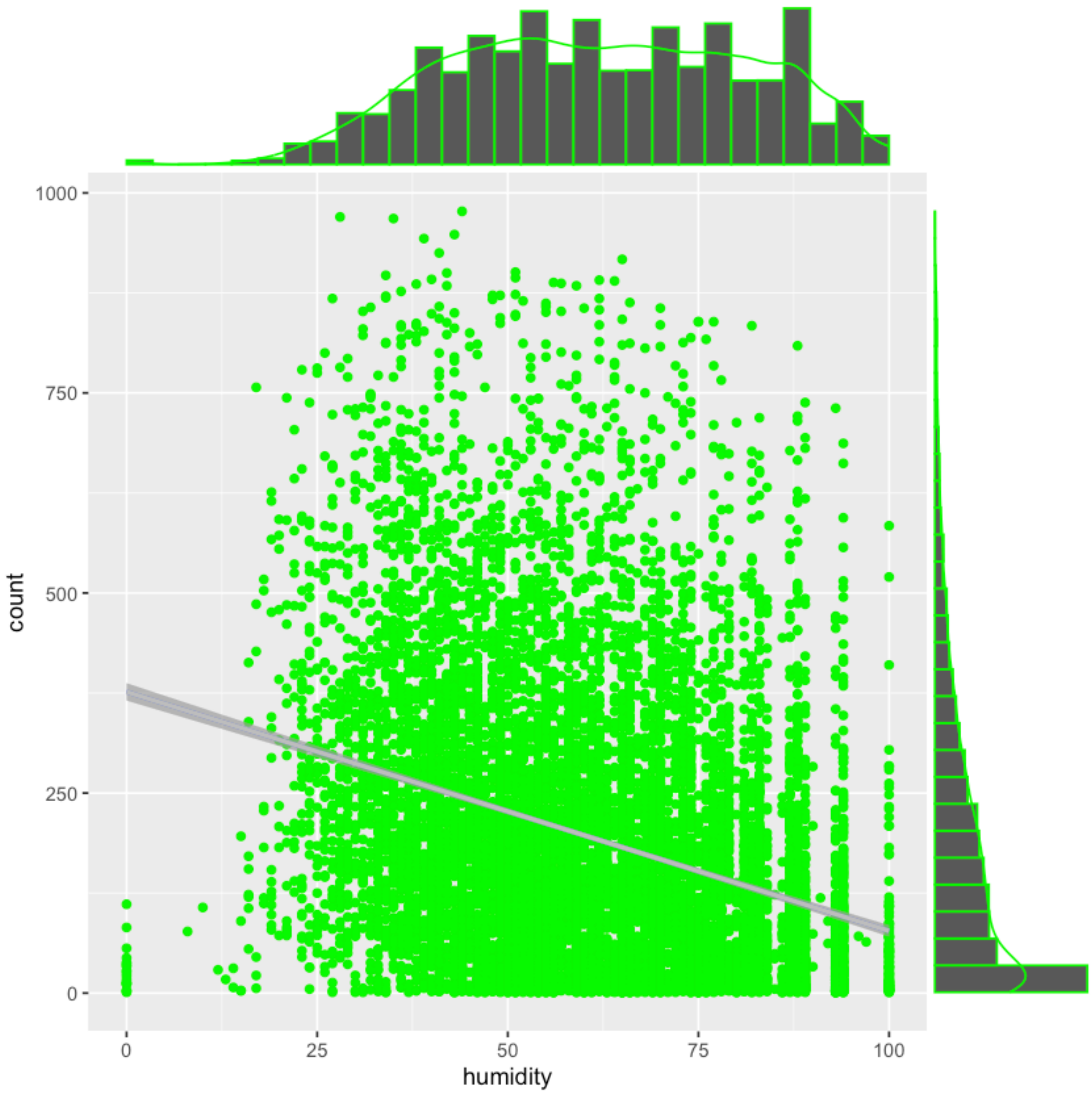
[15]:
```
# 4b(1) v. Explore relationship between independent continuous variables and␣
↪dependent variables using Joint Plot

        # 1. temp vs Count
        plot_center = ggplot(bike, aes(x=temp,y=count)) +␣
↪geom_point(colour="blue") + geom_smooth(method="lm", colour="grey")
        ggMarginal(plot_center, type="densigram", colour="blue")
        # Inference: temp has good correlation with count.
```



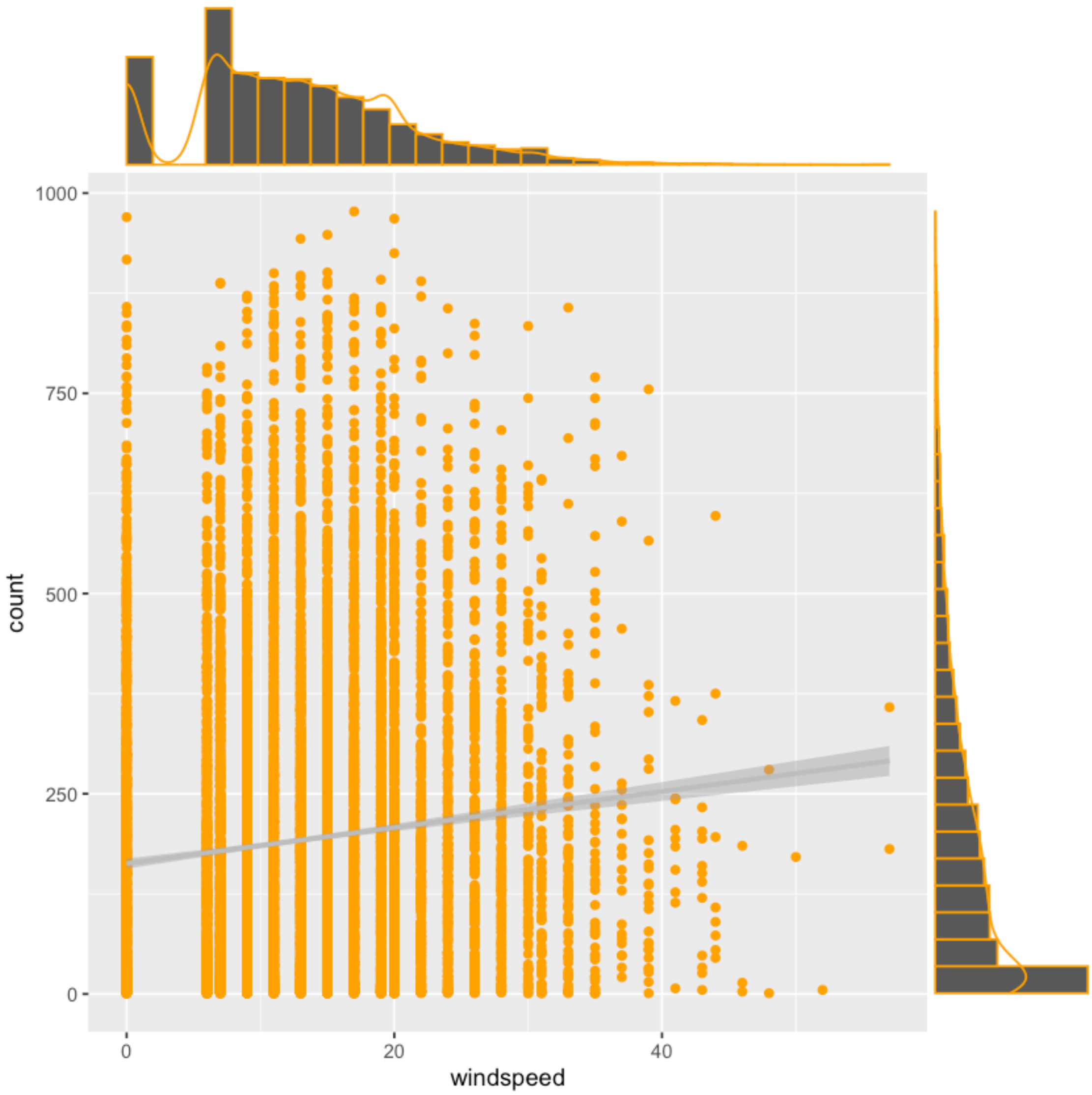
[16]:
```
# 4b(1).v.2. atemp vs Count
        plot_center = ggplot(bike, aes(x=atemp,y=count)) +
 ↪geom_point(colour="red") + geom_smooth(method="lm", colour="grey")
        ggMarginal(plot_center, type="densigram", colour="red")
        # Inference: atemp has good correlation with count.
```



[17]:
```
# 4b(1).v.3. humidity vs Count
        plot_center = ggplot(bike, aes(x=humidity,y=count)) +␣
 ↪geom_point(colour="green") + geom_smooth(method="lm") +␣
 ↪geom_smooth(method="lm", colour="grey")
        ggMarginal(plot_center, type="densigram", colour="green")
        # Inference: Humidity has low correlation with count.
```



[18]:
```
# 4b(1).v.4. windspeed vs Count
        plot_center = ggplot(bike, aes(x=windspeed,y=count)) +␣
↪geom_point(colour="orange") + geom_smooth(method="lm", colour="grey")
        ggMarginal(plot_center, type="densigram", colour="orange")
```



[ ]:
```
# 4b(1) Inferences Summary - Analysis of continous variables
        # 1. Target variable 'count' is almost normally distributed.
        # 2. From correlation with dependent variable "count", we can see that␣
↪'casual','registered' are very
             # highly correlated to cnt. Needs to be dropped from the dataset.
        # 3. 'humidity' has low correlation with 'count'. For now, lets keep it.
        # 4. atemp and temp has good correlation with 'count'
        # 5. From heatmap, we can see that atemp and temp are highly correlated.
↪ So we need to drop 1 to remove multicollinearity.
        # 6. Since, as seen from jointplot, p(atemp) < p(temp), we can drop␣
↪'temp' and retain 'atemp' in the dataset.
```

[ ]:
```
# --------------- Explore Catogorical Variables----------------
    # 4b(2) Explore categorical features
          # i. Check distribution of categorical variables
          # ii. Check how individual categorical features affects the target␣
↪variable
          # iii. Explore trends over time
```

[ ]:
```
# 4c. Drop some variables from the dataset based on the analysis so far
        # drop temp, casual, registered and date
        bike_subset = bike[-c(5,9:10, 12)]
        head(bike_subset,5)
```

[ ]:
```
#------ Step 4: Exploratory Data Analysis ENDS Here------------------
# Final observations:
#1.) 'casual' and 'registered' needs to be dropped from the dataset
#2.) 'atemp' and 'temp' are very strongly correlated . Drop 'atemp' from the␣
↪dataset (since it has higher p-value
        #than 'temp')
#3.) 'date' does not seem to have any affect on count of bikes, it can be␣
↪dropped from the dataset
#------------------------------------------------------------
```

[ ]:
```
#----------Part 5 : Model Builing starts here ----------------------
    # 5a. Split data into test and train set
    # 5b. Linear Regression
    # 5c. Random Forest
    # 5d. Gradient Boosting
```

[19]:
```
# 5a. Split data into test and train set
        sample_size = floor(0.8 * nrow(bike))
        set.seed(1)
        train_index = sample(nrow(bike), size = sample_size)
        train <- bike[train_index, ]
        test <- bike[-train_index, ]
```

[22]:
```
# 5b. Linear Regression
        # Fit Linear Model
        train_subset = train[-c(5,9:10, 12)]
        test_subset = test[-c(5,9:10, 12)]

        lm_fit = lm(count ~ ., data = train_subset)
        summary(lm_fit)

        # Choosing the best model by AIC in a Stepwise Algorithm
        # The step() function iteratively removes insignificant features from␣
↪the model.
        step(lm_fit)
        summary(lm_fit)
```

```r
# Calculate Train RMSLE
y_act_train <- abs(train_subset$count)
y_pred_train <- abs(predict(lm_fit, train_subset))
lm_train_RMSLE = rmsle(y_act_train, y_pred_train)

# Calculate Test RMSLE
y_act_test <- abs(test_subset$count)
y_pred_test <- abs(predict(lm_fit, test_subset))
lm_test_RMSLE = rmsle(y_act_test, y_pred_test)

# Save the results
lm_results = predict(lm_fit, bike_test)
hist(lm_results)
```

```
Call:
lm(formula = count ~ ., data = train_subset)

Residuals:
    Min      1Q  Median      3Q     Max
-354.13  -61.80   -6.72   51.10  432.28

Coefficients: (4 not defined because of singularities)
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  -88.06071    9.41903  -9.349  < 2e-16 ***
season2       76.02615    7.50253  10.133  < 2e-16 ***
season3       85.24449    7.28896  11.695  < 2e-16 ***
season4       75.84881    5.62763  13.478  < 2e-16 ***
holiday1      15.21998    7.81590   1.947  0.05153 .
workingday1   16.46915    4.06865   4.048 5.21e-05 ***
weather2     -12.18425    2.67532  -4.554 5.33e-06 ***
weather3     -69.93783    4.47891 -15.615  < 2e-16 ***
weather4    -178.26616  100.80800  -1.768  0.07703 .
atemp          4.15523    0.27807  14.943  < 2e-16 ***
humidity      -0.79181    0.07847 -10.091  < 2e-16 ***
windspeed     -0.36893    0.14426  -2.557  0.01056 *
year2012      87.60396    2.18764  40.045  < 2e-16 ***
month2        10.99388    5.39353   2.038  0.04155 *
month3        31.14268    5.73979   5.426 5.93e-08 ***
month4       -23.36018    5.81874  -4.015 6.00e-05 ***
month5         8.92497    5.39782   1.653  0.09828 .
month6              NA         NA      NA       NA
month7       -33.47592    5.52279  -6.061 1.41e-09 ***
month8       -22.39220    5.38767  -4.156 3.27e-05 ***
month9              NA         NA      NA       NA
month10       24.88559    5.68662   4.376 1.22e-05 ***
month11        2.20392    5.35091   0.412  0.68044
month12             NA         NA      NA       NA
```

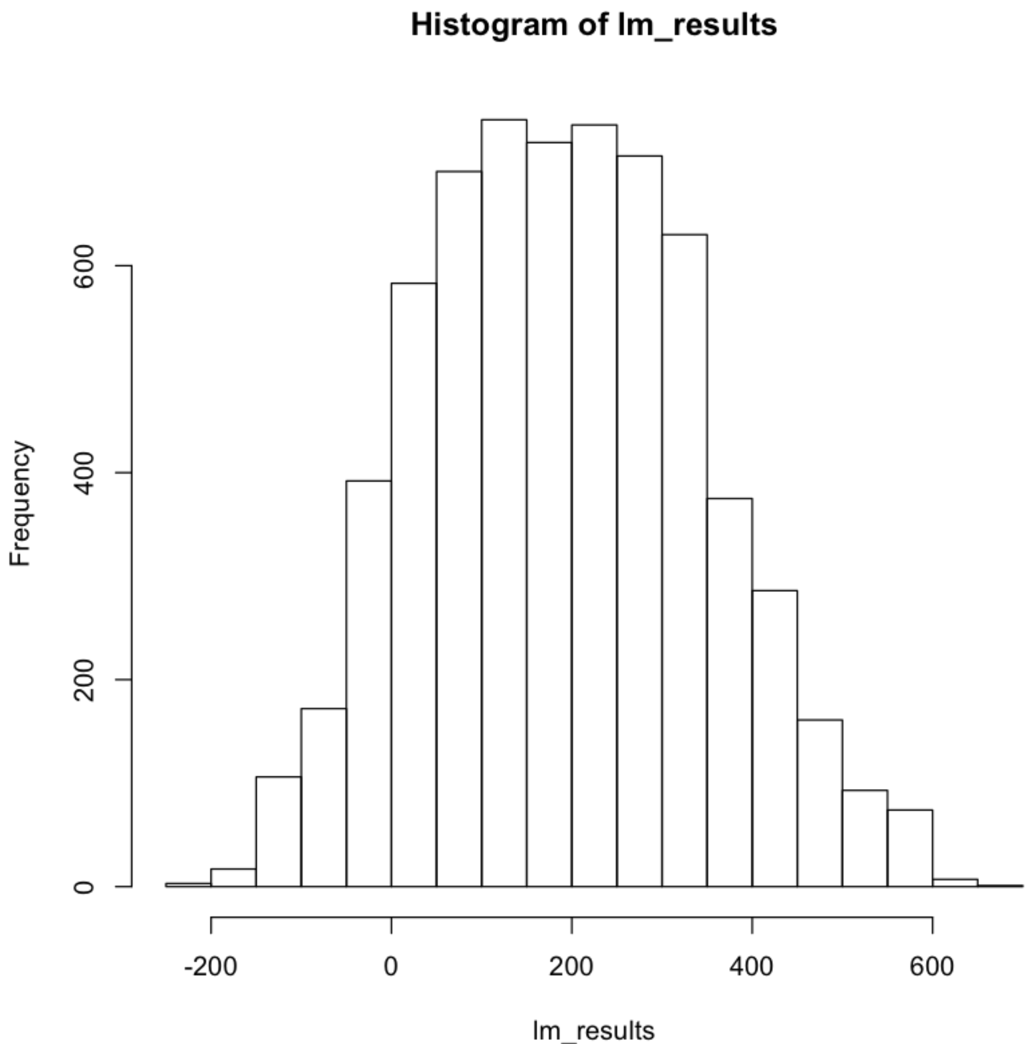
```
hour1        -11.56700    7.48918  -1.544  0.12250
hour2        -24.20057    7.45303  -3.247  0.00117 **
hour3        -37.65763    7.55672  -4.983 6.37e-07 ***
hour4        -38.36125    7.44394  -5.153 2.62e-07 ***
hour5        -23.58264    7.47710  -3.154  0.00162 **
hour6         36.34707    7.41526   4.902 9.68e-07 ***
hour7        170.36551    7.39766  23.030  < 2e-16 ***
hour8        311.27579    7.44319  41.820  < 2e-16 ***
hour9        164.66110    7.38386  22.300  < 2e-16 ***
hour10       114.20073    7.46609  15.296  < 2e-16 ***
hour11       141.94037    7.50231  18.920  < 2e-16 ***
hour12       179.11916    7.56096  23.690  < 2e-16 ***
hour13       178.36299    7.65620  23.297  < 2e-16 ***
hour14       163.86705    7.63461  21.464  < 2e-16 ***
hour15       170.24754    7.57631  22.471  < 2e-16 ***
hour16       233.35385    7.60976  30.665  < 2e-16 ***
hour17       389.19729    7.65071  50.871  < 2e-16 ***
hour18       361.87509    7.57348  47.782  < 2e-16 ***
hour19       246.72022    7.42580  33.225  < 2e-16 ***
hour20       164.41265    7.51298  21.884  < 2e-16 ***
hour21       114.40167    7.44445  15.367  < 2e-16 ***
hour22        75.69491    7.45131  10.159  < 2e-16 ***
hour23        37.52871    7.37358   5.090 3.66e-07 ***
wkday2       -12.53471    4.16922  -3.006  0.00265 **
wkday3        -9.06690    4.11349  -2.204  0.02754 *
wkday4        -5.40134    4.11238  -1.313  0.18907
wkday5        -3.99999    4.07558  -0.981  0.32640
wkday6              NA         NA      NA       NA
wkday7        16.55806    3.99635   4.143 3.46e-05 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 100.5 on 8659 degrees of freedom
Multiple R-squared:  0.6934,Adjusted R-squared:  0.6917
F-statistic:   408 on 48 and 8659 DF,  p-value: < 2.2e-16



Start:  AIC=80337.58
count ~ season + holiday + workingday + weather + atemp + humidity +
    windspeed + year + month + hour + wkday


Step:  AIC=80337.58
count ~ season + holiday + weather + atemp + humidity + windspeed +
    year + month + hour + wkday
```

```
Step:  AIC=80337.58
count ~ holiday + weather + atemp + humidity + windspeed + year +
    month + hour + wkday

            Df Sum of Sq       RSS   AIC
- holiday    1       330  87440395 80336
<none>                    87440065 80338
- windspeed  1     66045  87506111 80342
- wkday      6    287513  87727579 80354
- humidity   1   1028198  88468263 80437
- atemp      1   2254957  89695022 80557
- weather    3   2485536  89925602 80576
- month     11   5549955  92990020 80851
- year       1  16193442 103633507 81815
- hour      23 102266438 189706503 87036

Step:  AIC=80335.61
count ~ weather + atemp + humidity + windspeed + year + month +
    hour + wkday

            Df Sum of Sq       RSS   AIC
<none>                    87440395 80336
- windspeed  1     66045  87506441 80340
- wkday      6    291781  87732176 80353
- humidity   1   1028605  88469000 80435
- atemp      1   2254678  89695074 80555
- weather    3   2485209  89925605 80574
- month     11   5553725  92994121 80850
- year       1  16193145 103633541 81813
- hour      23 102271521 189711917 87034

Call:
lm(formula = count ~ weather + atemp + humidity + windspeed +
    year + month + hour + wkday, data = train_subset)

Coefficients:
(Intercept)     weather2     weather3     weather4        atemp     humidity
   -88.1022     -12.1887     -69.9304    -178.0143       4.1544      -0.7919
  windspeed     year2012       month2       month3       month4       month5
    -0.3689      87.6027      11.0857      31.2433      52.7041      85.0598
     month6       month7       month8       month9      month10      month11
    76.1375      51.8193      62.9666      85.2886     100.7816      78.0935
    month12        hour1        hour2        hour3        hour4        hour5
    75.9544     -11.5714     -24.1994     -37.6623     -38.3622     -23.5839
      hour6        hour7        hour8        hour9       hour10       hour11
    36.3411     170.3596     311.2796     164.6600     114.2076     141.9441
     hour12       hour13       hour14       hour15       hour16       hour17
   179.1188     178.3688     163.8666     170.2423     233.3501     389.2004
```

```
    hour18      hour19      hour20      hour21      hour22      hour23
  361.8761    246.7257    164.4022    114.4089     75.6880     37.5286
    wkday2      wkday3      wkday4      wkday5      wkday6      wkday7
    3.7447      7.4038     11.0473     12.4676     16.4273     16.5561
```

```
Call:
lm(formula = count ~ ., data = train_subset)

Residuals:
    Min      1Q  Median      3Q     Max
-354.13  -61.80   -6.72   51.10  432.28

Coefficients: (4 not defined because of singularities)
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  -88.06071    9.41903  -9.349  < 2e-16 ***
season2       76.02615    7.50253  10.133  < 2e-16 ***
season3       85.24449    7.28896  11.695  < 2e-16 ***
season4       75.84881    5.62763  13.478  < 2e-16 ***
holiday1      15.21998    7.81590   1.947  0.05153 .
workingday1   16.46915    4.06865   4.048 5.21e-05 ***
weather2     -12.18425    2.67532  -4.554 5.33e-06 ***
weather3     -69.93783    4.47891 -15.615  < 2e-16 ***
weather4    -178.26616  100.80800  -1.768  0.07703 .
atemp          4.15523    0.27807  14.943  < 2e-16 ***
humidity      -0.79181    0.07847 -10.091  < 2e-16 ***
windspeed     -0.36893    0.14426  -2.557  0.01056 *
year2012      87.60396    2.18764  40.045  < 2e-16 ***
month2        10.99388    5.39353   2.038  0.04155 *
month3        31.14268    5.73979   5.426 5.93e-08 ***
month4       -23.36018    5.81874  -4.015 6.00e-05 ***
month5         8.92497    5.39782   1.653  0.09828 .
month6              NA         NA      NA       NA
month7       -33.47592    5.52279  -6.061 1.41e-09 ***
month8       -22.39220    5.38767  -4.156 3.27e-05 ***
month9              NA         NA      NA       NA
month10       24.88559    5.68662   4.376 1.22e-05 ***
month11        2.20392    5.35091   0.412  0.68044
month12             NA         NA      NA       NA
hour1        -11.56700    7.48918  -1.544  0.12250
hour2        -24.20057    7.45303  -3.247  0.00117 **
hour3        -37.65763    7.55672  -4.983 6.37e-07 ***
hour4        -38.36125    7.44394  -5.153 2.62e-07 ***
hour5        -23.58264    7.47710  -3.154  0.00162 **
hour6         36.34707    7.41526   4.902 9.68e-07 ***
hour7        170.36551    7.39766  23.030  < 2e-16 ***
hour8        311.27579    7.44319  41.820  < 2e-16 ***
```

```
hour9        164.66110    7.38386  22.300  < 2e-16 ***
hour10       114.20073    7.46609  15.296  < 2e-16 ***
hour11       141.94037    7.50231  18.920  < 2e-16 ***
hour12       179.11916    7.56096  23.690  < 2e-16 ***
hour13       178.36299    7.65620  23.297  < 2e-16 ***
hour14       163.86705    7.63461  21.464  < 2e-16 ***
hour15       170.24754    7.57631  22.471  < 2e-16 ***
hour16       233.35385    7.60976  30.665  < 2e-16 ***
hour17       389.19729    7.65071  50.871  < 2e-16 ***
hour18       361.87509    7.57348  47.782  < 2e-16 ***
hour19       246.72022    7.42580  33.225  < 2e-16 ***
hour20       164.41265    7.51298  21.884  < 2e-16 ***
hour21       114.40167    7.44445  15.367  < 2e-16 ***
hour22        75.69491    7.45131  10.159  < 2e-16 ***
hour23        37.52871    7.37358   5.090 3.66e-07 ***
wkday2       -12.53471    4.16922  -3.006  0.00265 **
wkday3        -9.06690    4.11349  -2.204  0.02754 *
wkday4        -5.40134    4.11238  -1.313  0.18907
wkday5        -3.99999    4.07558  -0.981  0.32640
wkday6              NA         NA      NA       NA
wkday7        16.55806    3.99635   4.143 3.46e-05 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 100.5 on 8659 degrees of freedom
Multiple R-squared:  0.6934,Adjusted R-squared:  0.6917
F-statistic:   408 on 48 and 8659 DF,  p-value: < 2.2e-16


Warning message in predict.lm(lm_fit, test_subset):
prediction from a rank-deficient fit may be misleadingWarning message in
predict.lm(lm_fit, bike_test):
```

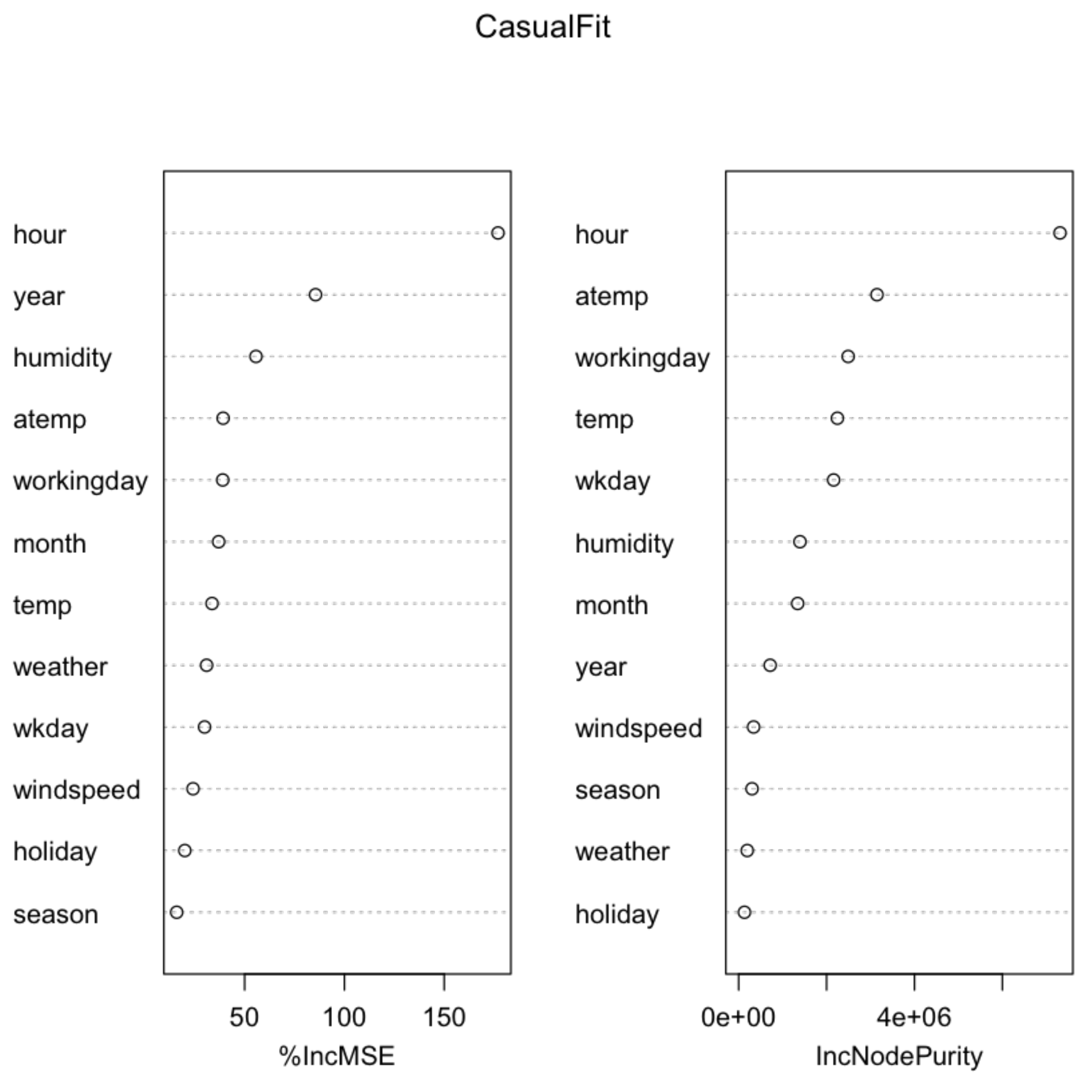


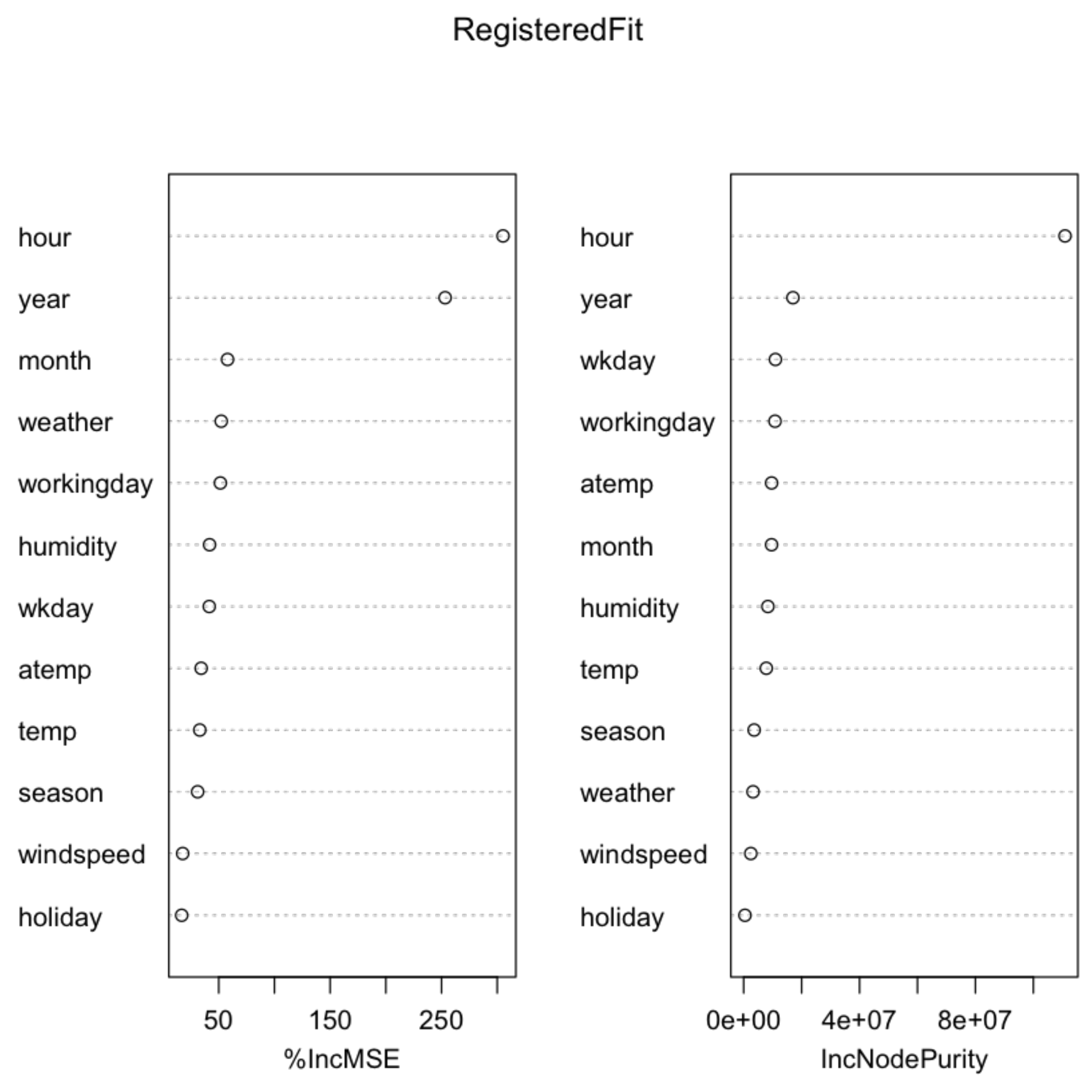
[24]:
```
# 5b. Random Forest
        Ntree=500
        Mtry = 5
        myImportance = TRUE

        # Predict Casual Counts
        set.seed(1)
        CasualData <- subset(train, select = -c(count, registered, date))
        CasualFit <- randomForest(casual ~ ., data=CasualData, ntree=Ntree,␣
↪mtry=Mtry,
                                importance=myImportance)
```

```
        # Predict Registered Counts
        RegisteredData <- subset(train, select = -c(count, casual, date))
        RegisteredFit <- randomForest(registered ~ ., data=RegisteredData,␣
↪ntree=Ntree, mtry=Mtry,
                                importance=myImportance)
```

[25]:

```
varImpPlot(CasualFit)
        varImpPlot(RegisteredFit)

    #Inference - Casual Fit: season, holiday, windspeed and weather are not␣
↪much significant here.
    #Inference - Registered Fit: season, holiday, windspeed and temp are not␣
↪much significant here.
```





[26]:
```
casualFitFinal <- randomForest(casual ~ hour + year + humidity + month + temp +␣
↪atemp + workingday + wkday,
                               data=CasualData, ntree=Ntree,␣
↪mtry=Mtry,importance=myImportance)
        RegisteredFitFinal <- randomForest(registered ~ hour + year + month +␣
↪weather + workingday + humidity + atemp
                                          + wkday, data=RegisteredData,␣
↪ntree=Ntree, mtry=Mtry,importance=myImportance)
```

[46]:
```
# Prediction on train data

            # Prediction on train data - casual users
            PredTrainCasual = round(predict(CasualFit, train),0)
            PredTrainCasualFinal = round(predict(casualFitFinal, train),0)
```

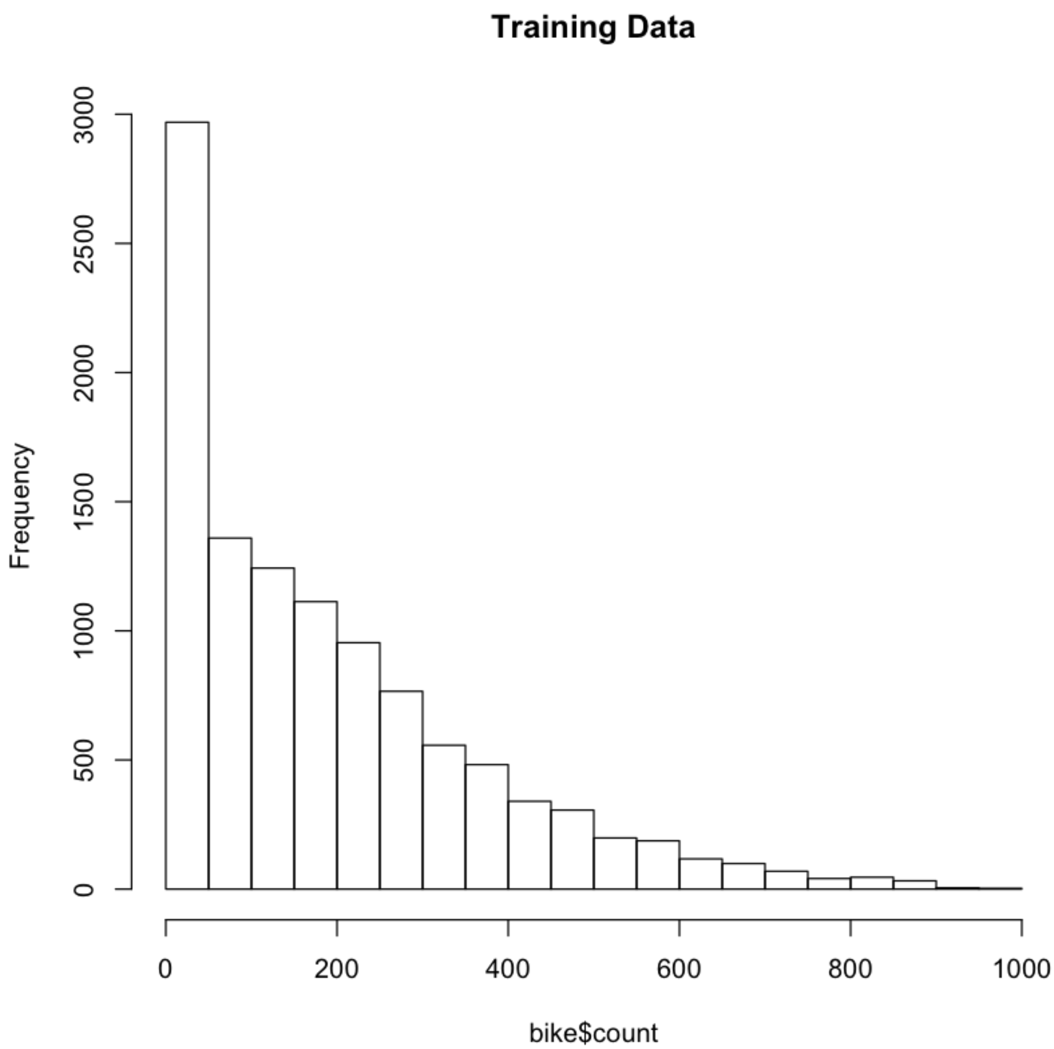
```
            # Prediction on train data - Registered users
            PredTrainRegistered = round(predict(RegisteredFit, train),0)
            PredTrainRegisteredFinal = round(predict(RegisteredFitFinal,␣
 ↪train),0)

            # Sum up Casual and Registered to get Total Count
            PredTrainCount = PredTrainCasual+PredTrainRegistered
            PredTrainCountFinal = PredTrainCasualFinal+PredTrainRegisteredFinal

            # Calculate Train RMSLE
            rf_train_rmsle_full = rmsle(train$count, PredTrainCount)
            rf_train_rmsle2_reduced = rmsle(train$count, PredTrainCountFinal)


        # Prediction on test data
            # Prediction on test data - casual users
            PredTestCasual = round(predict(CasualFit, test),0)
            PredTestCasualFinal = round(predict(casualFitFinal, test),0)

            # Prediction on test data - registered users
            PredTestRegistered = round(predict(RegisteredFit, test),0)
            PredTestRegisteredFinal = round(predict(RegisteredFitFinal, test),0)

            # Sum up Casual and Registered to get Total Count
            PredTestCount = PredTestCasual+PredTestRegistered
            PredTestCountFinal = PredTestCasualFinal+PredTestRegisteredFinal

            # Calculate Train RMSLE
            rf_test_rmsle_full = rmsle(test$count, PredTestCount)
            rf_test_rmsle2_reduced = rmsle(test$count, PredTestCountFinal)
```

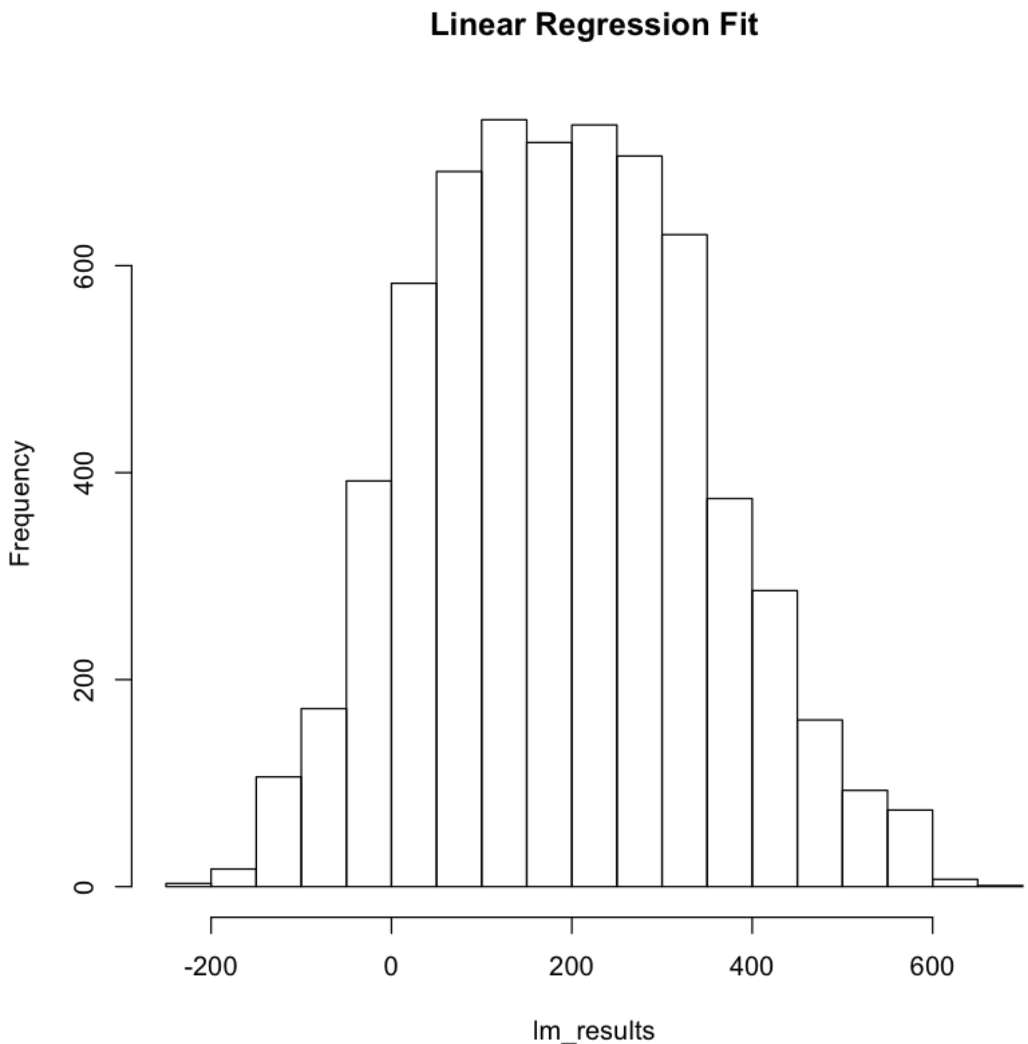
[42]:
```
cat("Training RMSLE - Linear Regression: ", lm_train_RMSLE)
cat("\nTraining RMSLE - Random Forest (Full Model): ", rf_train_rmsle_full)
cat("\nTraining RMSLE - Random Forest (Reduced Model): : ",␣
 ↪rf_train_rmsle2_reduced)

cat("\n\nTest RMSLE - Linear Regression: ", lm_test_RMSLE)
cat("\nTest RMSLE - Random Forest (Full Model): ", rf_test_rmsle_full)
cat("\nTest RMSLE - Random Forest (Reduced Model): ", rf_test_rmsle2_reduced)
```

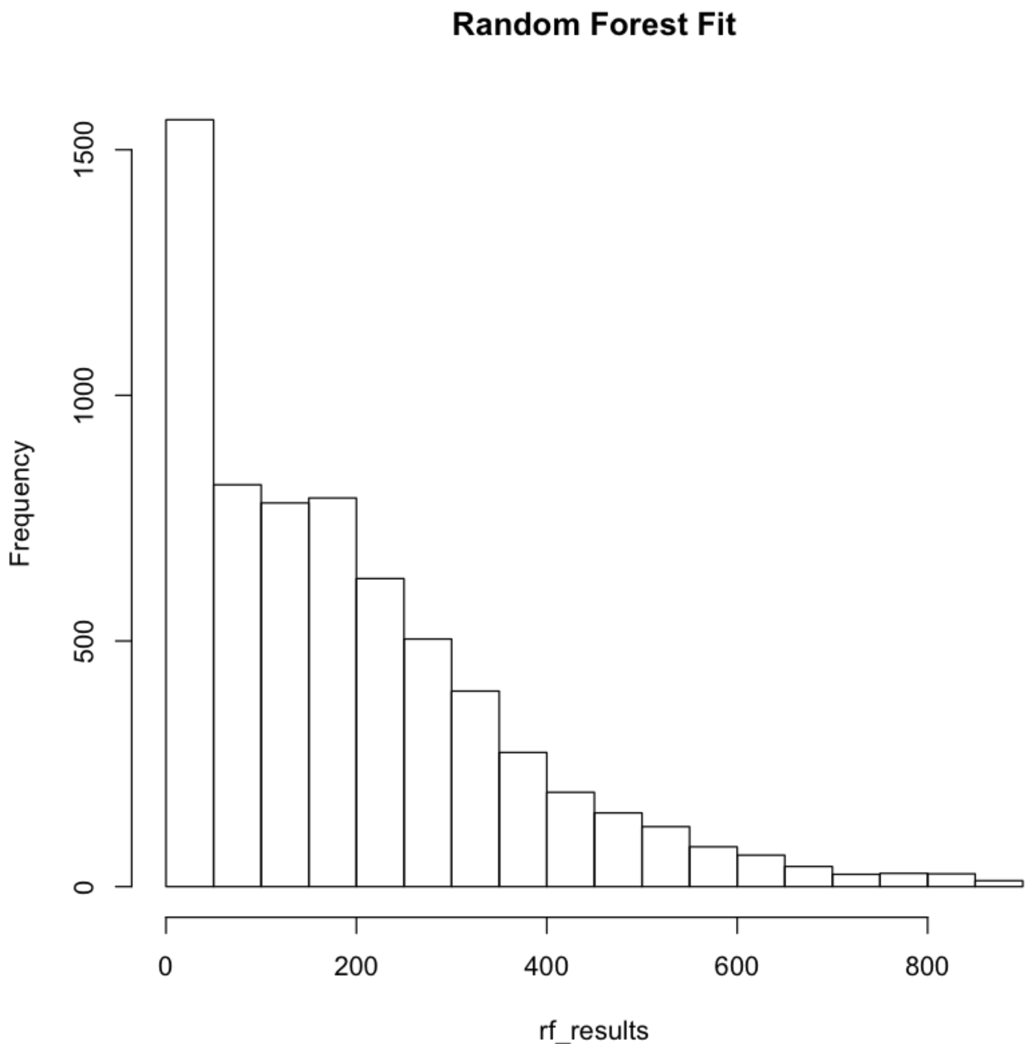
```
Training RMSLE - Linear Regression:  1.031166
Training RMSLE - Random Forest (Full Model):  0.2706077
Training RMSLE - Random Forest (Reduced Model): :  0.2091858

Test RMSLE - Linear Regression:  0.9982687
Test RMSLE - Random Forest (Full Model):  0.4446371
```

[50]:

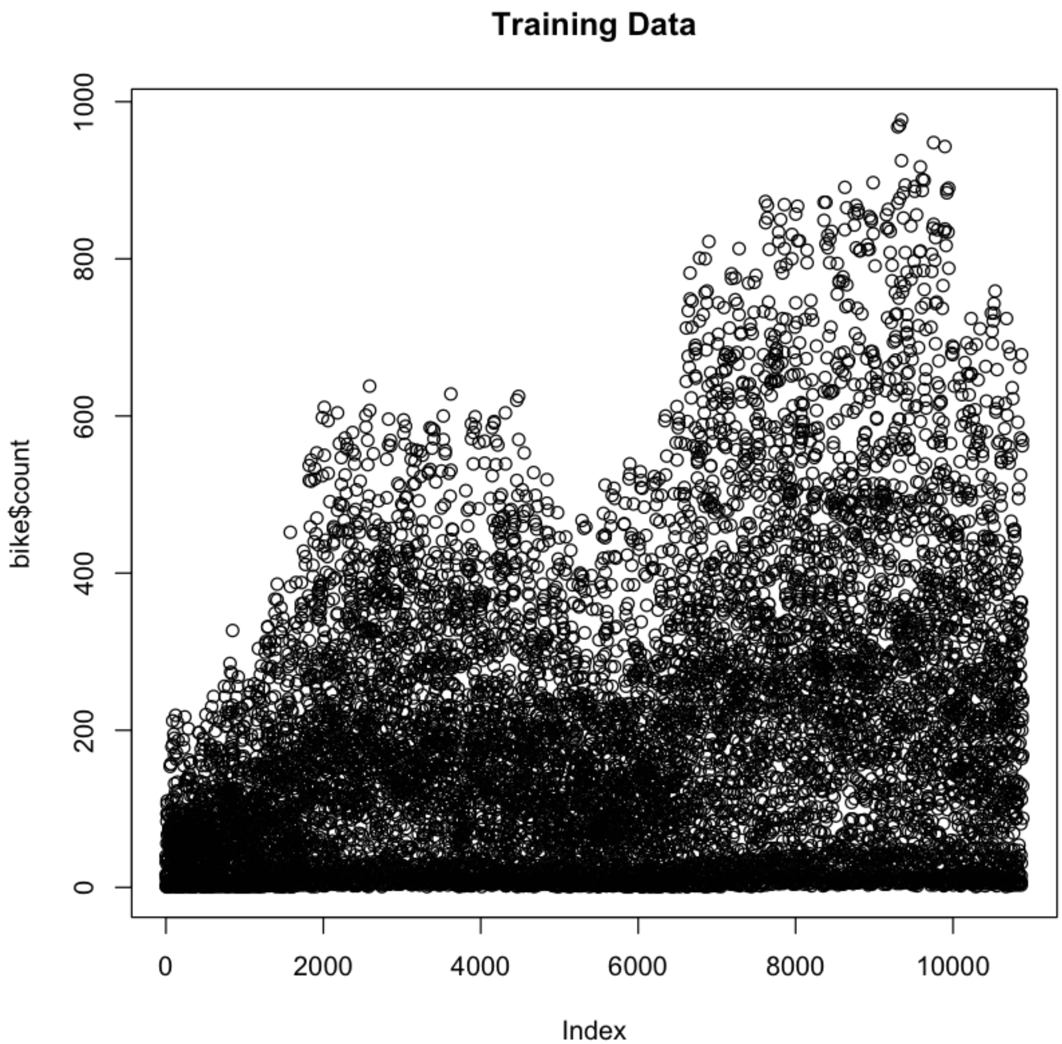
```
# Save the RF results
        #rf_test_casual = round(predict(casualFitFinal, bike_test),0)
        #rf_test_registered = round(predict(RegisteredFitFinal, bike_test),)
        #rf_results = rf_test_casual + rf_test_registered

        hist(bike$count, main="Training Data")
        hist(lm_results, main="Linear Regression Fit")
        hist(rf_results, main="Random Forest Fit")

        # Inference: The distribution of predicted count looks similar to that␣
 ↪of train data.
```

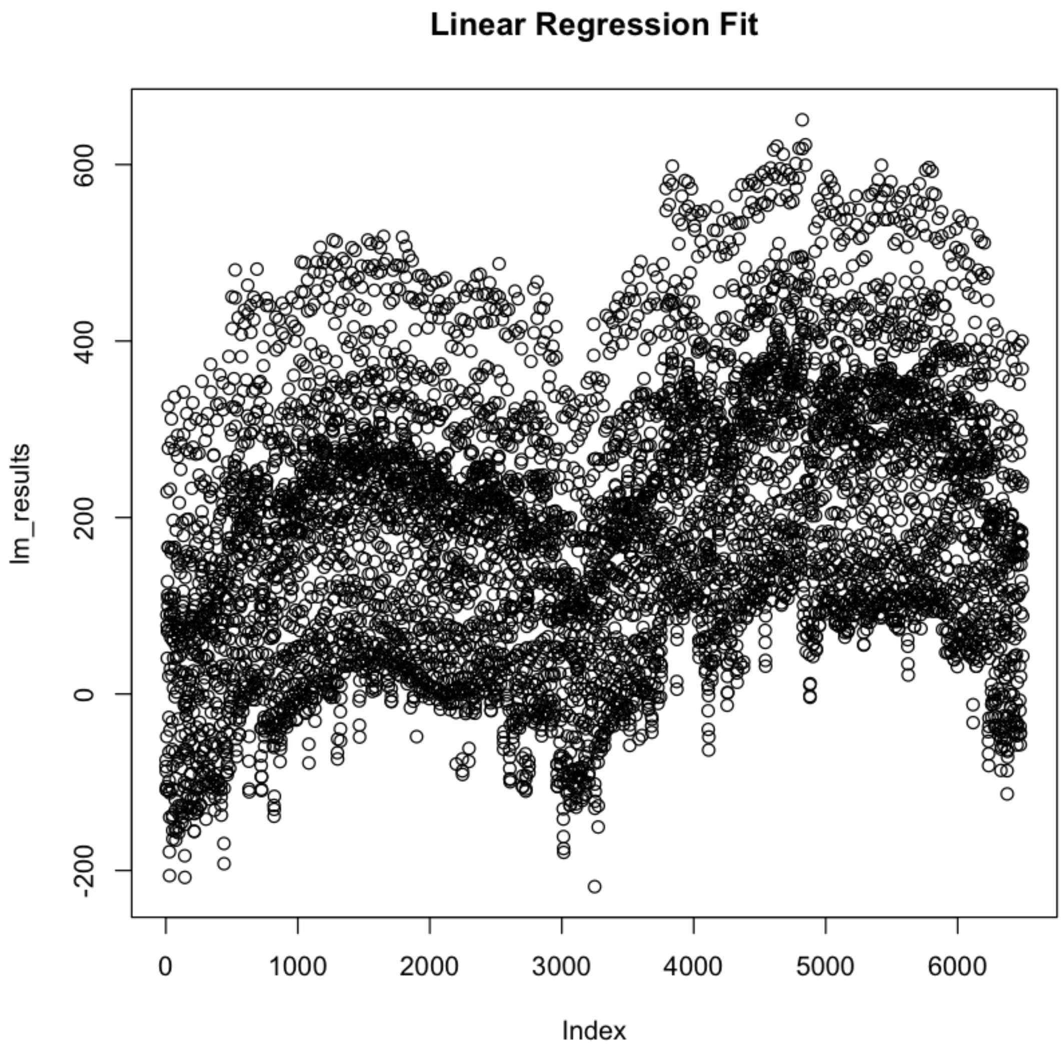


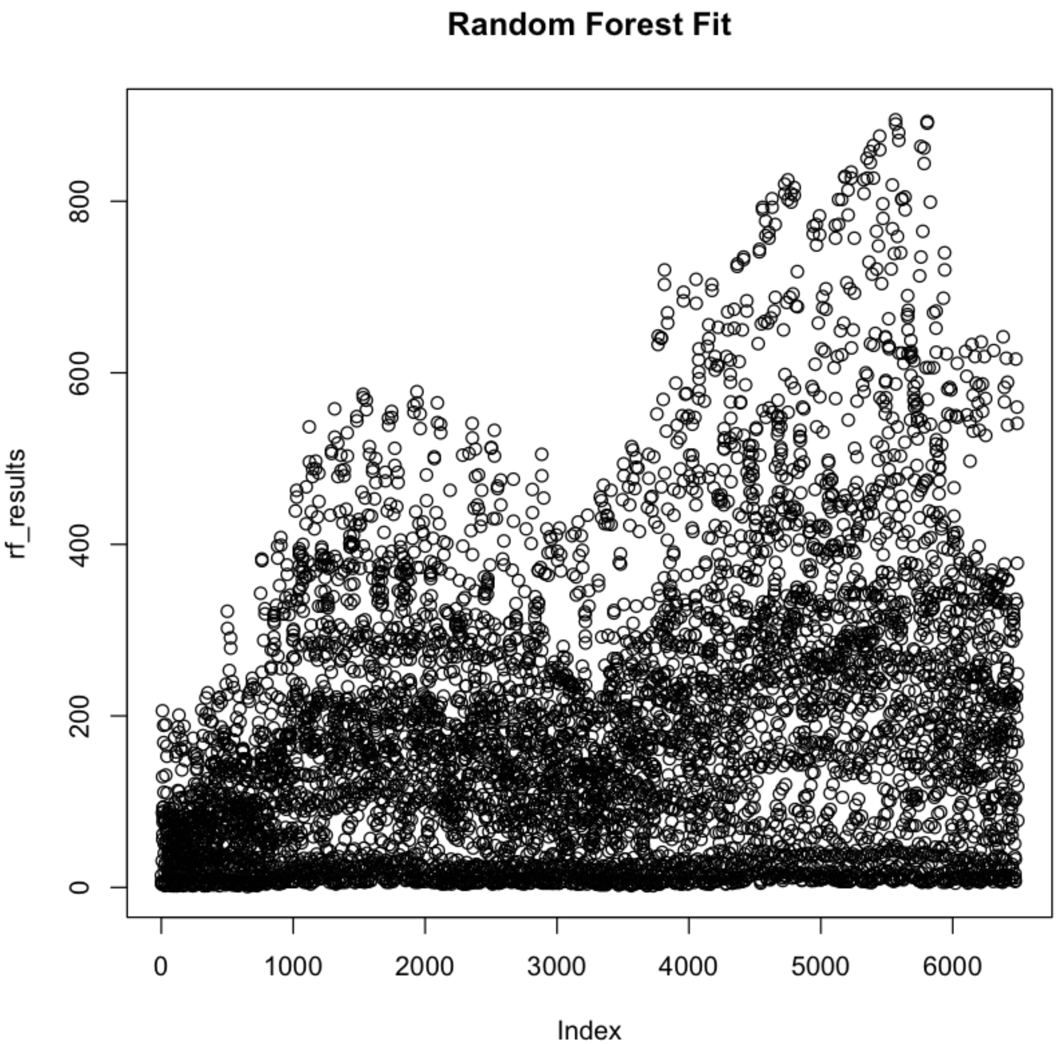

Linear Regression Fit
Frequency
0
200
400
600
-200
0
200
400
600
lm_results



[52]:
```
plot(bike$count, main="Training Data")
        plot(lm_results, main="Linear Regression Fit")
        plot(rf_results, main="Random Forest Fit")

        # Histograms and plots clearly shows that Random Forest fits better␣
 ↪than Linear Regression.
```


Training Data
bike$count
0
200
400
600
800
1000
0
2000
4000
6000
8000
10000
Index


Linear Regression Fit
lm_results
Index
600
400
200
0
-200
0
1000
2000
3000
4000
5000
6000


Random Forest Fit
rf_results
0
200
400
600
800
0
1000
2000
3000
4000
5000
6000
Index

[ ]: