Bike Sharing Demand

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Problem Definition

Bike Sharing Demand

Defn

Bike sharing demand aims to forecast the use of the bikeshare system throughout the city.

- Dataset comprises of the hourly rental data spanning two year having data fields such as datetime, seasontemp etc.
- predict the total count of bikes rented during each hour

Data Summary

- Training Set provides the data and usage of the first 19 days of each month
- Test Set provides the data from the 20th to the end of the month

```
train_df.head()
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13	16
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	32	40
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5	27	32
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3	10	13
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0	1	1

```
train_df.dtypes
```

```
datetime        object
season           int64
holiday          int64
workingday       int64
weather          int64
temp           float64
atemp          float64
humidity         int64
windspeed      float64
casual           int64
registered       int64
count            int64
dtype: object
```

- No missing values in the dataset

Exploratory Data Analysis

Dataset Description

- Data Fields
  - datetime - hourly date + timestamp
  - season - 1 = spring, 2 = summer, 3 = fall, 4 = winter
  - holiday - whether the day is considered a holiday
  - workingday - whether the day is neither a weekend nor holiday
  - weather - 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 - temperature in Celsius
  - atemp - "feels like" temperature in Celsius
  - humidity - relative humidity
  - windspeed - wind speed
  - casual - number of non-registered user rentals initiated
  - registered - number of registered user rentals initiated
  - count - number of total rentals

Data Preprocessing

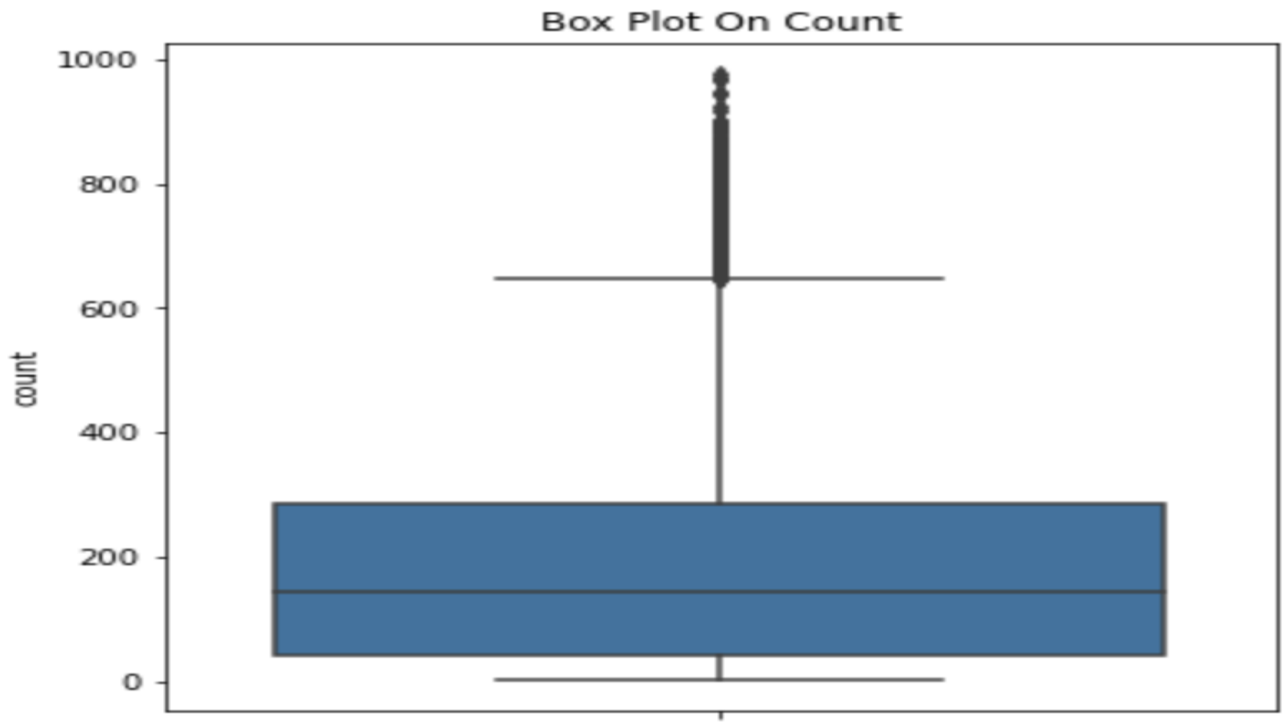
- Season, holiday, workingday, and weather are int type, but category type is more suitable, so convert to category type
- split datetime into separate year, month, day, hour and dayofweek columns
- Analyse the missing values
- Remove datetime

Analysis of the features

- Category Features : Hour, weekday, month, Season, holiday, Workingday, weather
- Numerical Features: temp, atemp, humidity, windspeed, registered and causal

Outliers Analysis

- From the Boxplot of count column, it is clearly visible that most of the data lies between 30-300 and a huge numbers of outliers are presesnt in the plot.
- Use the 3 sigma principle to remove outliers



Data Visualization between count vs. month and season

- The use of shared bicycles from November to April will be a little less than in other months, which may be due to seasonal reasons.

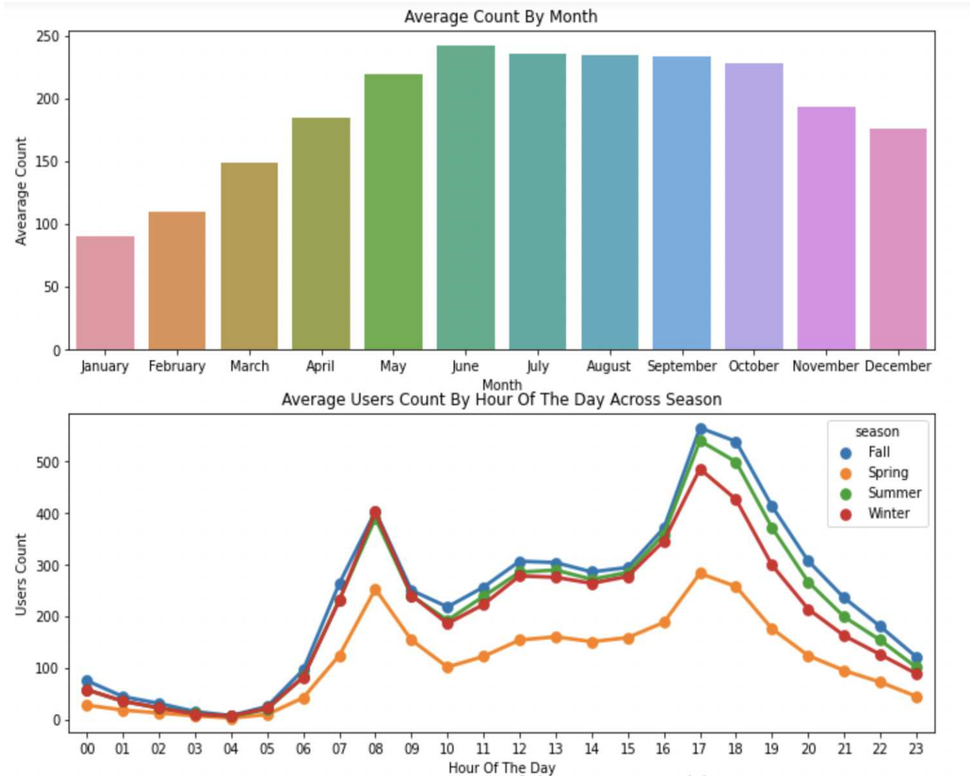


Figure 1: Data Visualization between count vs. month and season

Data Visualization between count vs. weekdays and usertype

- The use of shared bicycles in winter and spring is relatively small compared to summer and autumn, which is mutually confirmed with the conclusions generated in the above months.

Histogram Plot of Count

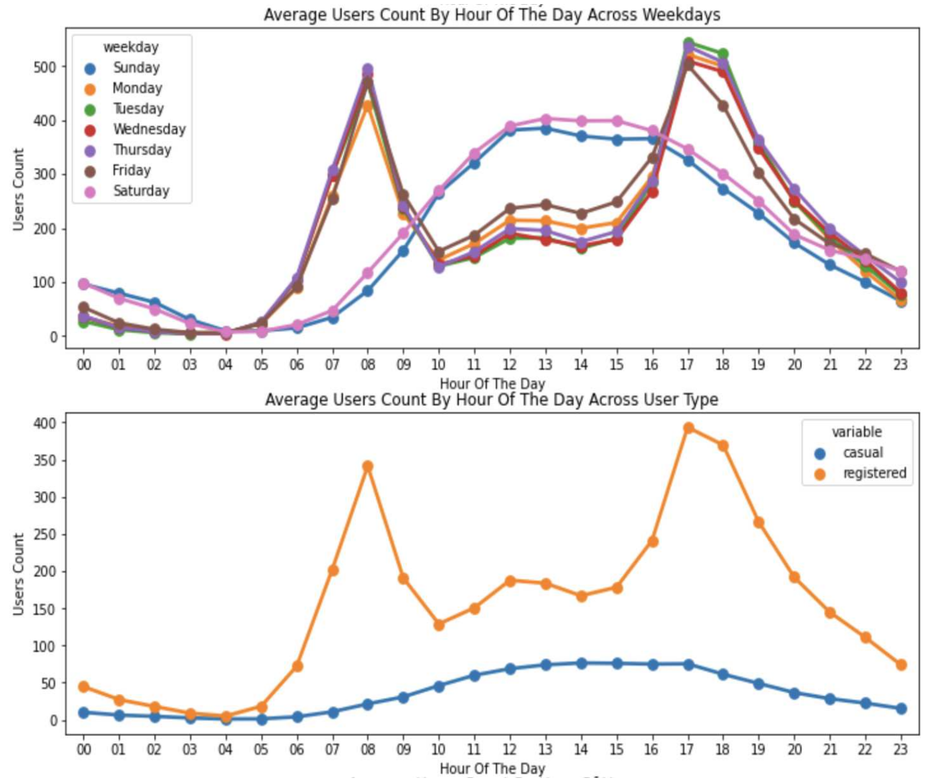


Figure 2: Data Visualization between count vs. weekdays and usertype

Data Visualization of count and [temp, windspeed, humidity]

- From the scatter plot, windspeed has many values of 0 and is separated from other values, so it is predicted that this is not an actual measured value.

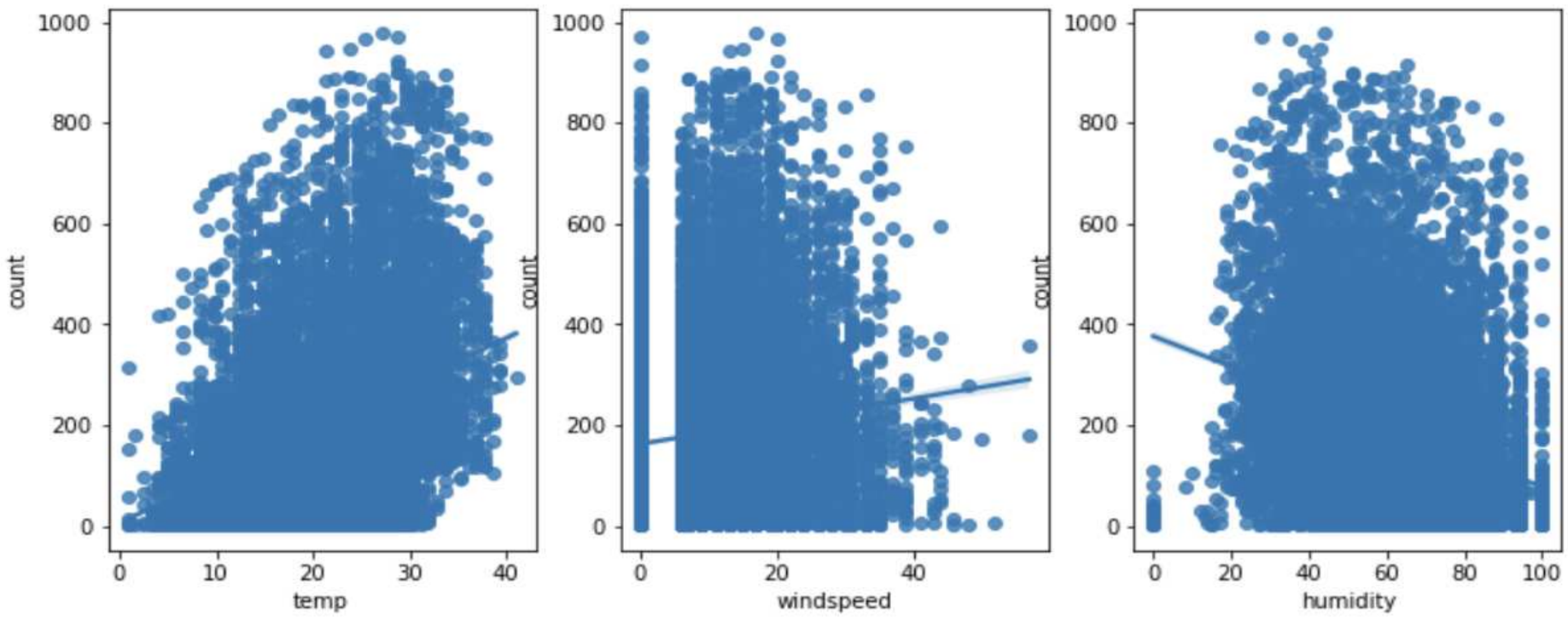


Figure 3: Scatter Plot

Correlation Matrix

- Heatmap of the correlation matrix between count and [temp, atemp, humidity, windspeed, casual, registered].

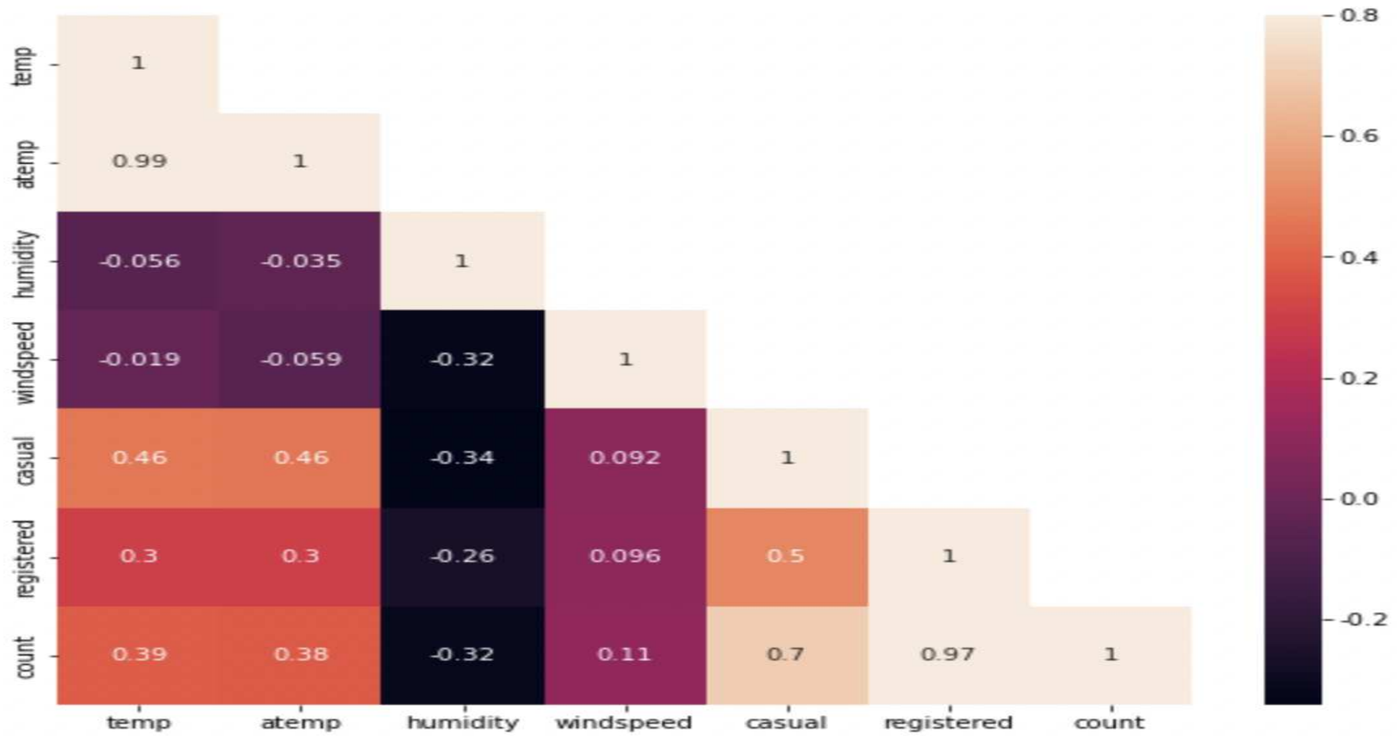


Figure 4: Heatmap

Feature Engineering

Based on the above heatmap, we can see that some of the features have no relation with the response variable. we can drop those columns.

- humidity, temp are negatively correlated with count
- There is a strong correlation between temp and atemp, if both are included in the model, it will cause multicollinearity problems, so one of the features must be deleted. We remove the atemp feature because it has a weaker correlation with count than temp.
- Casual, Registered are not considered and removed during model building
- humidity, temp and windspeed features are considered during future modelling
- fill in the zero values in the windspeed feature: usage is high when the wind speed is 0, which may be caused by null filling. Therefore, a random forest model is used here to fill in the zero values.

Skewness in Data Distribution

- From the histogram plot, we can say that count data is skewed (concentrated on the one side) and the data is not equally distributed.
- Solution is to log-transform the count variable after removing outlier data points.

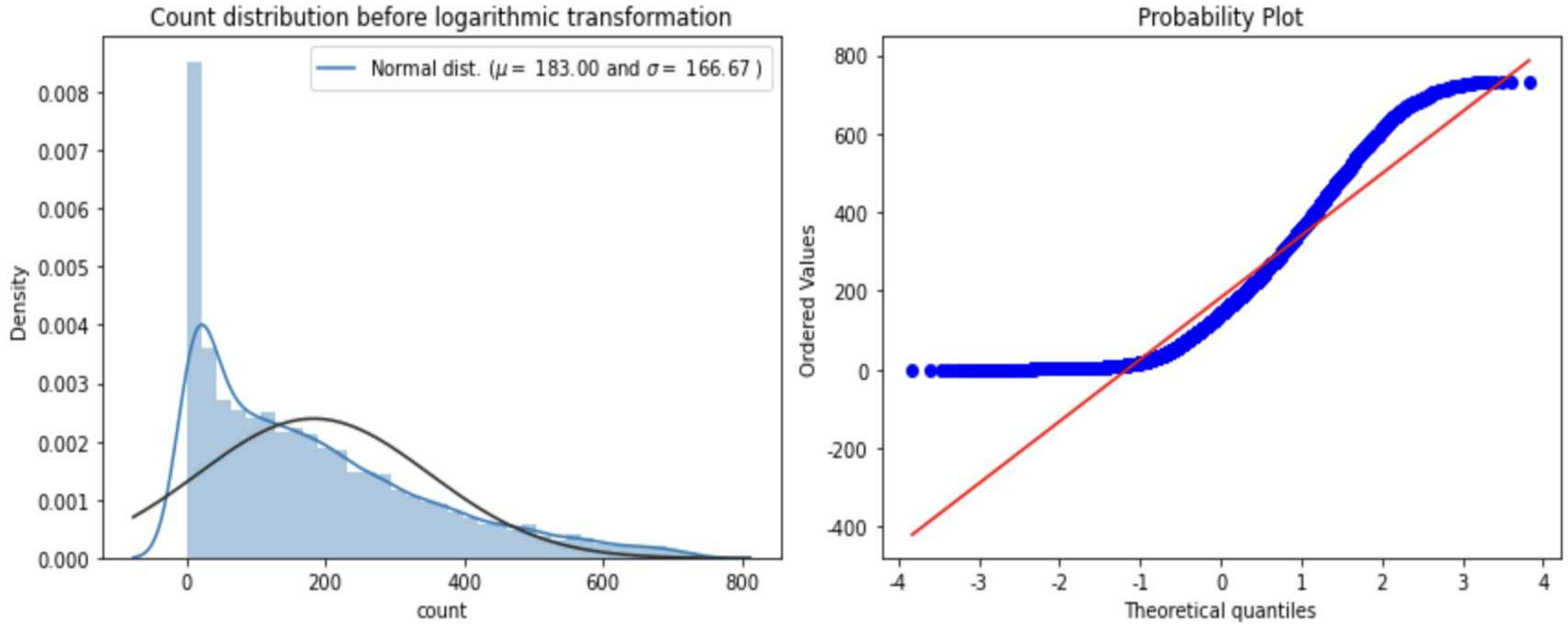


Figure 5: Count distribution before logarithmic transformation

Solution to Skewness in Data Distribution

- Solution is to log-transform the count variable after removing outlier data points.

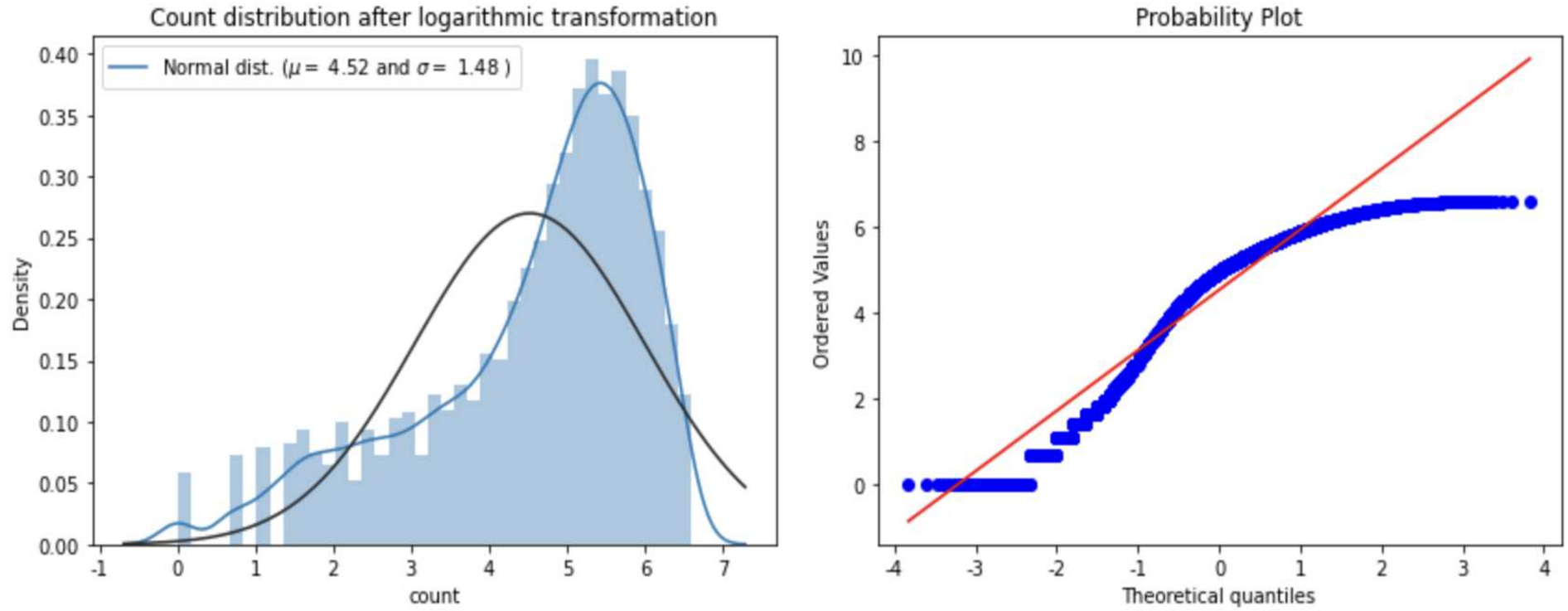


Figure 6: Count distribution after logarithmic transformation

Predictive Modelling

Data Preparation

- Split the dataset into train set and test set
- Train Data size : 0.7
- Test Data size : 0.3

Predictions with linear Model

- Linear Regression
- Ridge Regression
- Lasso Regression
- Logistic Regression
- ElasticNet

Predictions with Ensemble learning Models

- Bagging Regressor
- Random Forest Regressor
- Gradient Boosting Regressor
- AdaBoost Regressor

Evaluation Results

Evaluation

- Evaluation Indicators: root mean square error is required (Root Mean Squared Logarithmic Error, RMSLE) to evaluate the quality of the model.

$$RMSLE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[\log(p_i + 1) - \log(a_i + 1)]^2}$$

Among them, n is the number of samples in the test set, p_i is the test value, and a_i is the actual value. The smaller the root mean square error, the better the fitting effect of the data, and the closer the test value is to the actual value.

Model Evaluation Results

Table 1: Model Evaluation Results

Model	Accuracy
Random Forest Regression	0.376319
Bagging Regression	0.395248
GBRT	0.430378
AdaBoost Regression	0.703528
Ridge Regression	1.045335
Lasso Regression	1.045453
ElasticNet Regression	1.045489
Linear Regression	1.046341
Logistic Regression	1.131105

Conclusion

Conclusion

- Basic modelling of the data
- Results can be further enhanced

Questions?

Contact Information

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