
Statistic Machine Learning Project

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Abstract

1 To fulfill the demand of public bike that more fossil based transportation cans be
2 replaced by bike and contribute to alleviating climate change, the city of Wash-
3 ington D.C. has recorded the observations high bike demand along with temporal
4 and meteorological features. With this data, this project study is dedicated to help
5 the city to predict the necessity of increasing number of bikes at certain hours.
6 To achieve this goal, methods including Logistic Regression, KNN, bagging and
7 boosting are deployed to predict the target label with given feature. Number of
8 group members: 3.

9 1 Study case and Data

10 To further understand and practice the knowledge we have obtained from lectures. A case of
11 classification problem was given that we can apply different methods on the data and understand the
12 characteristics and behaviours of these methods.

13 1.1 Case and data description

14 To help the city of Washington, D.C. understand whether increasing the number of public bikes is
15 necessary at some certain hour, a machine learning model is expected to predict the public bike
16 demand for given temporal and meteorological features.

17
18 A data set contains 1600 random obeservations is provided for the model training. The target variable
19 is binary for "high" or "low" demand for increasing bikes' number. The description of the features
20 are given in Table 1

21 1.2 Exploratory data analysis

22 Exploratory data analysis has been conducted to gain the knowledge of relations among features in
23 the dataset. Also, following questions in the project introduction are answered in this section.

- 24 1. Which are the numerical features and which are the categorical features?
25 2. Is there any trend to need increase in the availability of bycycles?

26 Out of that the ways to treat categorical features are different from numerical features, the features
27 are sorted into two groupd, numerical and categorical. This sort of them can be identified according
28 to Table 1. The two groups are shown in Table 2, which also answers Quesiton 1.

29 For categorical features, first step done was to see the label balance. The result is shown in Figure 1.
30 One thing to be noted is that the feature "snow" has only one label. A flat feature will not have input

Table 1: Labels and features in the data set [1]

Feature Name	Description
midrule increase_stock (prediction label)	low_bike_demand – no need to increase the number of bikes high_bike_demand – the number of bikes needs to be increased
midrule hour_of_day	Hour of the day (from 0 to 23)
day_of_week	Day of the week (from 0 – Monday to 6 – Sunday)
month	Month (from 0 – January to 12 – December)
holiday	If it is a holiday or not (0 – no holiday, 1 – holiday)
weekday	If it is a weekday or not (0 – weekend, 1 – weekday)
summertime	If it is summertime or not (0 – no summertime, 1 – summertime)
temp	Temperature in Celsius degrees
dew	Dew point in Celsius degrees
humidity	Relative humidity (percentage)
precip	Precipitation in mm
snow	Amount of snow in the last hour in mm
snow_depth	Accumulated amount of snow in mm
windspeed	Wind speed in km/h
cloudcover	Percentage of the city covered in clouds
visibility	Distance in km at which objects or landmarks can be clearly seen and identified

Table 2: Categorical and numerical features.

Categorical features	Numerical features
holiday	month
weekday	temp
summertime	dew
snow	humidity
increase_stock	precip
hour_of_day	snow_depth
day_of_week	windspeed
	cloudcover

31 to the model, thus it was excluded from training set. This will be also seen in the correlation analysis.
 32 Similarly, histogram plot was generated to visualize the distribution of numerical features (shown in
 33 Figure 2).

34 To understand the correlation among features, mostly between targets and other features, correlation
 35 analysis has been done plotting correlation maps, shown in Figure 3

36 Droping out the smaller correlated features ($correlation \geq 0.1$), the left ones are: "temp", "humidity",
 37 "hour_of_day", "summertime", "dew", "weekday", and "visibility". To more intuitively see if any
 38 features can help separate the target label. Figure 4 was plotted.

39 Finally, with all analysis and figures above, the Question 2 can be answered.

40 It is seen that the label "1" ("high_bike_demand") is concentrated around daytime, growth starts
 41 from early morning, drops till late evening after reaching its peak at 15:00 to 16:00. Weekday has
 42 more "high_bike_demand" than weekends.

43 Temperature also has impact on bike demand, more bike are needed when temperature is in a comfort-
 44 able region, 20 – 30 degC in data. This can also interprets the trend in the summertime, temperature is
 45 higher in summer, similarly for dew point.

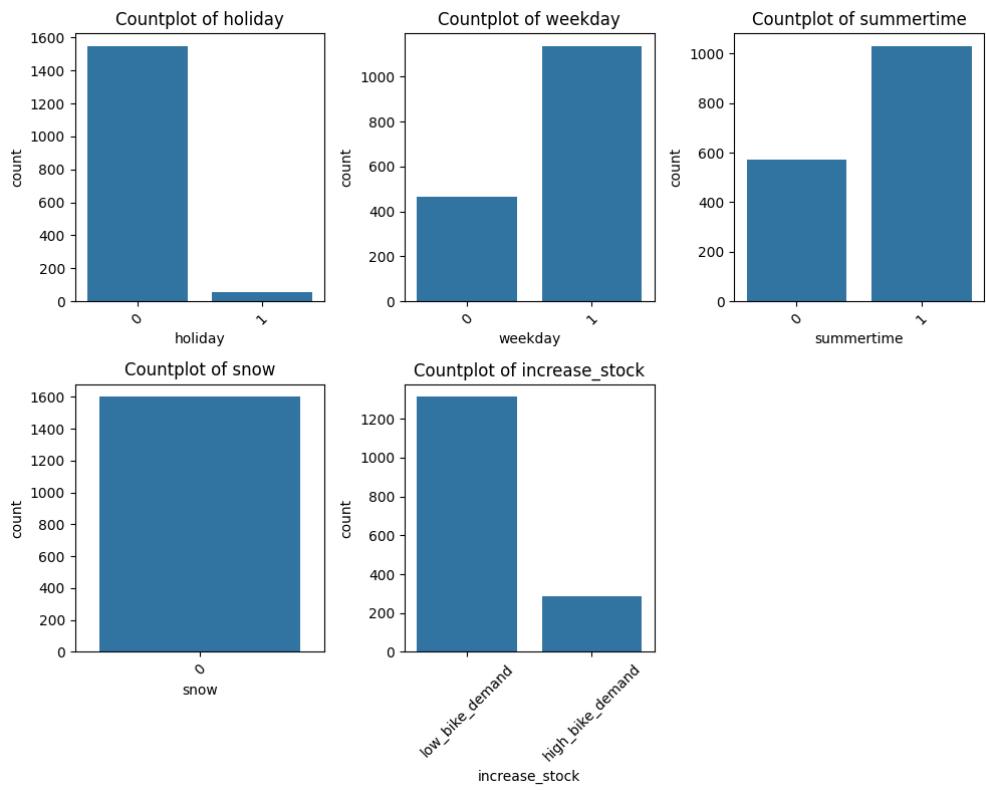


Figure 1: Label counts for categorical features

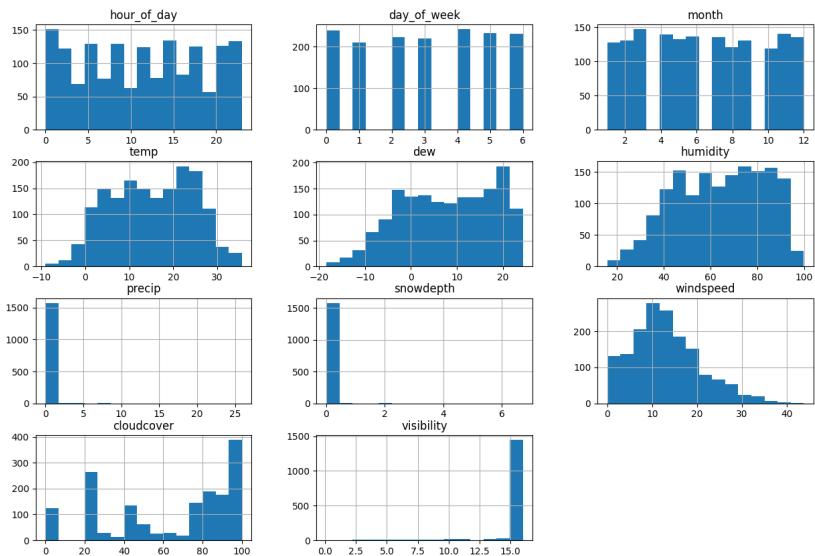


Figure 2: histograms of numerical features

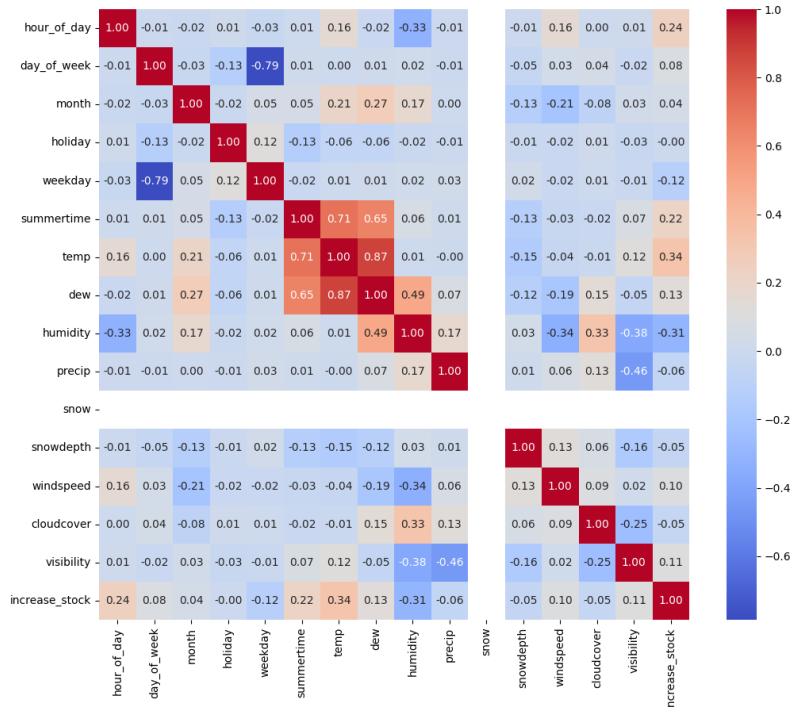


Figure 3: Correlation among features

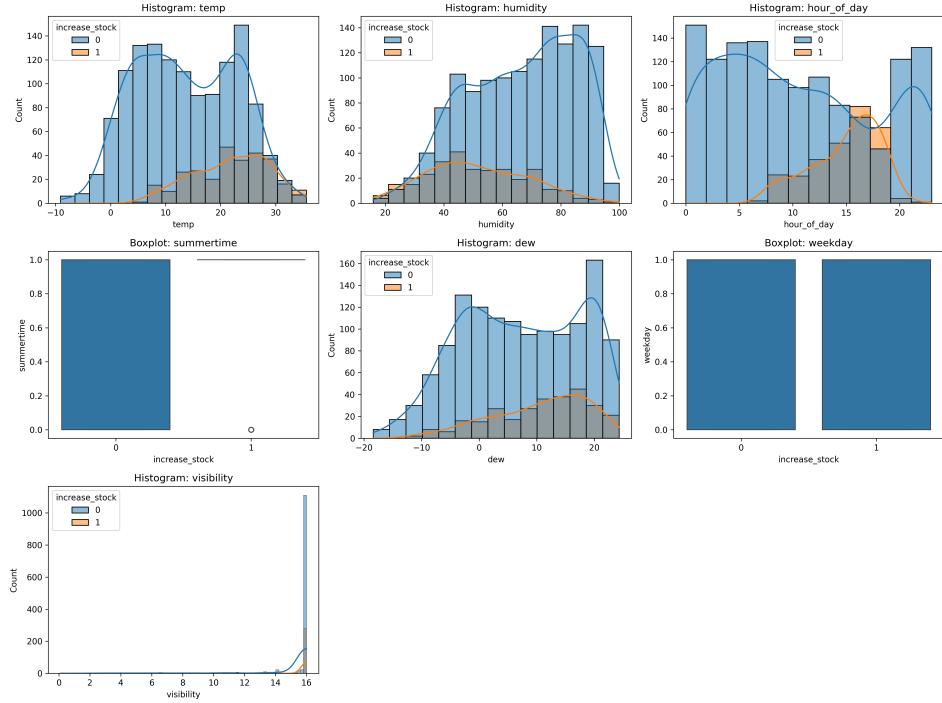


Figure 4: Boxes and Histograms for features with different targets laebls

46 **2 Methodology**

47 **2.1 Machine learning models**

48 **2.1.1 Boosting**

49 Boosting is an ensemble method which is built on the idea that even a weak model can capture some
50 patterns between target variables and given features. Starting from a base model, optimizing it based
51 on the returned error can produce a new model which would become the base for next model. By
52 ensembling the predictions from these models, the intention of boosting is to reduce bias[2].
53

54 In this study, three mainstream boosting algorithm were deployed, **AdaBoost**[2], **GradientBoost**[2],
55 and **CatBoost**[3]. The methods can be expressed as following equations.

$$\text{AdaBoost: } \hat{y}_{\text{boost}}^{(B)}(\mathbf{x}) = \text{sign} \left(\sum_{b=1}^B \alpha^{(b)} \hat{y}^{(b)}(\mathbf{x}) \right) \quad (1)$$

$$\text{GradientBoost: } f^{(B)}(\mathbf{x}) = \sum_{b=1}^B \alpha^{(b)} f^{(b)}(\mathbf{x}), \quad (2)$$

$$\text{CatBoost: } f^{(B)}(\mathbf{x}) = \sum_{b=1}^B \eta^{(b)} T^{(b)}(\mathbf{x}) \quad (3)$$

56 **2.2 Validation**

57 K-fold method with 5 subset was used for cross-validation to the deployed models. Considering that
58 label are imbalanced in the target variable, metrics like accuracy would not be a good choice for
59 performance measurement. F-score, given by equation 4, is used for measuring the performance in this
60 case.

$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} = \frac{2TP}{2TP + FP + FN} \quad (4)$$

61 **3 Results**

62 **3.1 Boosting**

63 Three boosting models were applied in this study, AdaBoostingClassifier and GradientBoostingClassifier
64 from *Scikit-learn*, and CatBoostClassifier. Their performance is shown in Table 3

Table 3: Boosting models performance

Model	Precision		Recall		F1 Score		Train Time (s)
	1	0	1	0	1	0	
AdaBoostClassifier	0.6427	0.9161	0.6298	0.9184	0.6334	0.9170	0.0035
GradientBoostingClassifier	0.7729	0.9238	0.6555	0.9549	0.7084	0.9391	0.0890
CatBoostClassifier	0.7828	0.9317	0.6932	0.9549	0.7337	0.9431	0.5812

65 According to the performance, CatBoostClassifier was chosen to be optimized on
66 Hyperparameters, where *GridSearch* was used. The result is shown in Table 4.

Table 4: f1-score of best models

Class	Cat Boost	KNN	Logistic Regression	Support
0	0.93	0.92	0.94	270
1	0.61	0.57	0.62	50

67 **4 Discussion**68 **5 Conclusion**69 **References**

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79 **A Appendix**