# Bike Sharing Demand
# Forecast use of a city bikeshare system

Dong Zhu

Deakin University

(None)

# Overview

# Problem Definition

**Definition**

Bike-sharing systems are a means of renting bikes, through which people can rent a bike from any place and return it when they arrive at their destination. The bike-sharing system clearly records the time of travel, the place of departure, the place of arrival and the time. Therefore, it can be used to study mobility in cities. In this project, historical usage patterns were combined with weather data to predict bike rental demand in Washington, D.C.

- Researchers can use bike sharing systems as a sensor network, which can be used for studying mobility in a city.
- This is a Supervised regression machine learning task.
- 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.

# Data exploration

# Check for missing vaules



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   datetime    10886 non-null  object
 1   season      10886 non-null  int64
 2   holiday     10886 non-null  int64
 3   workingday  10886 non-null  int64
 4   weather     10886 non-null  int64
 5   temp        10886 non-null  float64
 6   atemp       10886 non-null  float64
 7   humidity    10886 non-null  int64
 8   windspeed   10886 non-null  float64
 9   casual      10886 non-null  int64
 10  registered  10886 non-null  int64
 11  count       10886 non-null  int64
dtypes: float64(3), int64(8), object(1)
memory usage: 1020.7+ KB
None
```

Figure 1: Training data information

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6493 entries, 0 to 6492
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   datetime    6493 non-null   object
 1   season      6493 non-null   int64
 2   holiday     6493 non-null   int64
 3   workingday  6493 non-null   int64
 4   weather     6493 non-null   int64
 5   temp        6493 non-null   float64
 6   atemp       6493 non-null   float64
 7   humidity    6493 non-null   int64
 8   windspeed   6493 non-null   float64
dtypes: float64(3), int64(5), object(1)
memory usage: 456.7+ KB
None
```

Figure 2: Test data information

# Check for outliers



## Statistical description

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **season** | 10886.0 | 2.506614 | 1.116174 | 1.00 | 2.0000 | 3.000 | 4.0000 | 4.0000 |
| **holiday** | 10886.0 | 0.028569 | 0.166599 | 0.00 | 0.0000 | 0.000 | 0.0000 | 1.0000 |
| **workingday** | 10886.0 | 0.680875 | 0.466159 | 0.00 | 0.0000 | 1.000 | 1.0000 | 1.0000 |
| **weather** | 10886.0 | 1.418427 | 0.633839 | 1.00 | 1.0000 | 1.000 | 2.0000 | 4.0000 |
| **temp** | 10886.0 | 20.230860 | 7.791590 | 0.82 | 13.9400 | 20.500 | 26.2400 | 41.0000 |
| **atemp** | 10886.0 | 23.655084 | 8.474601 | 0.76 | 16.6650 | 24.240 | 31.0600 | 45.4550 |
| **humidity** | 10886.0 | 61.886460 | 19.245033 | 0.00 | 47.0000 | 62.000 | 77.0000 | 100.0000 |
| **windspeed** | 10886.0 | 12.799395 | 8.164537 | 0.00 | 7.0015 | 12.998 | 16.9979 | 56.9969 |
| **casual** | 10886.0 | 36.021955 | 49.960477 | 0.00 | 4.0000 | 17.000 | 49.0000 | 367.0000 |
| **registered** | 10886.0 | 155.552177 | 151.039033 | 0.00 | 36.0000 | 118.000 | 222.0000 | 886.0000 |
| **count** | 10886.0 | 191.574132 | 181.144454 | 1.00 | 42.0000 | 145.000 | 284.0000 | 977.0000 |

Figure 3: Data description

# Check for outliers

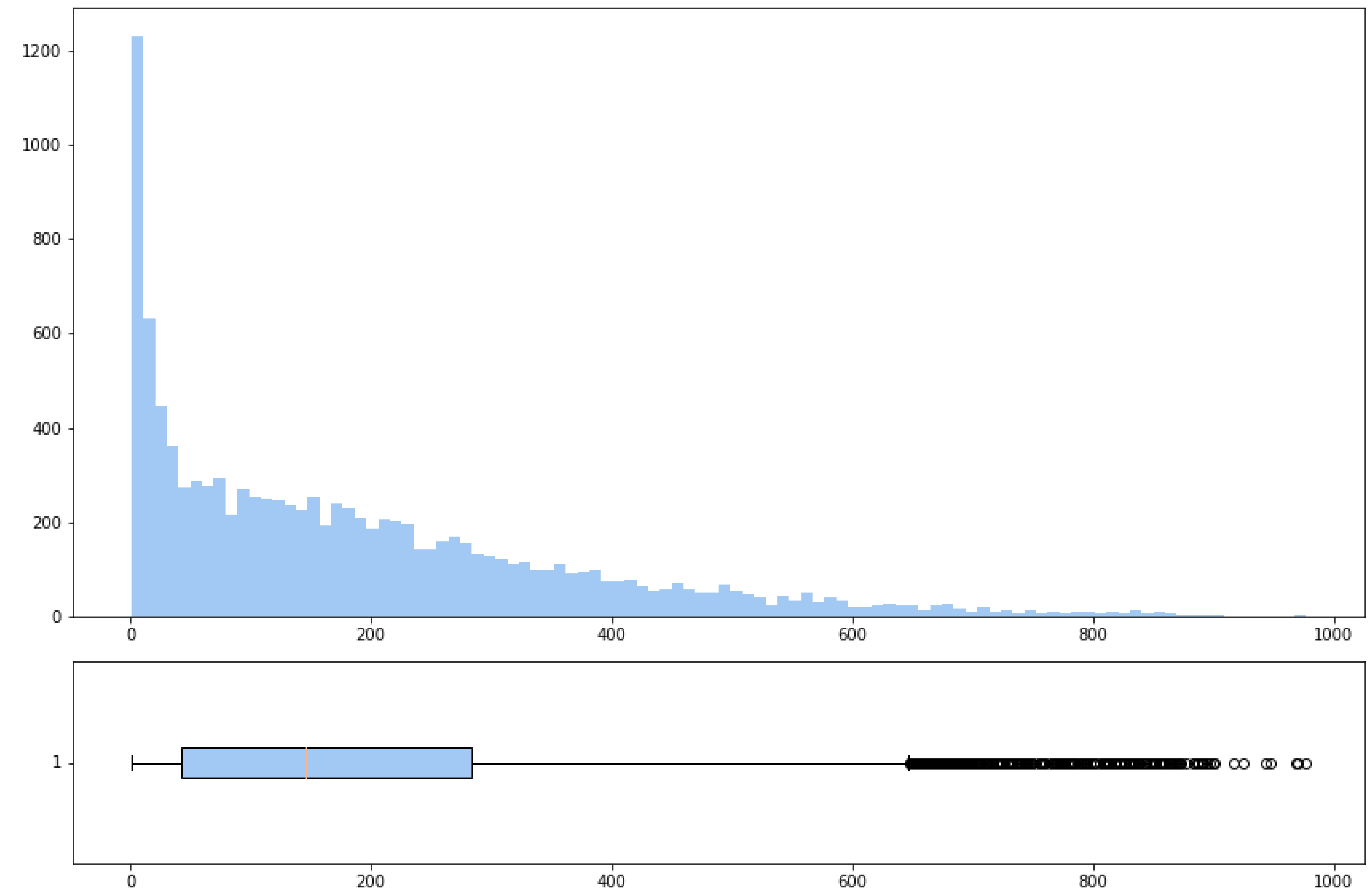



Figure 4: The distribution of the label "count"

# Check for outliers



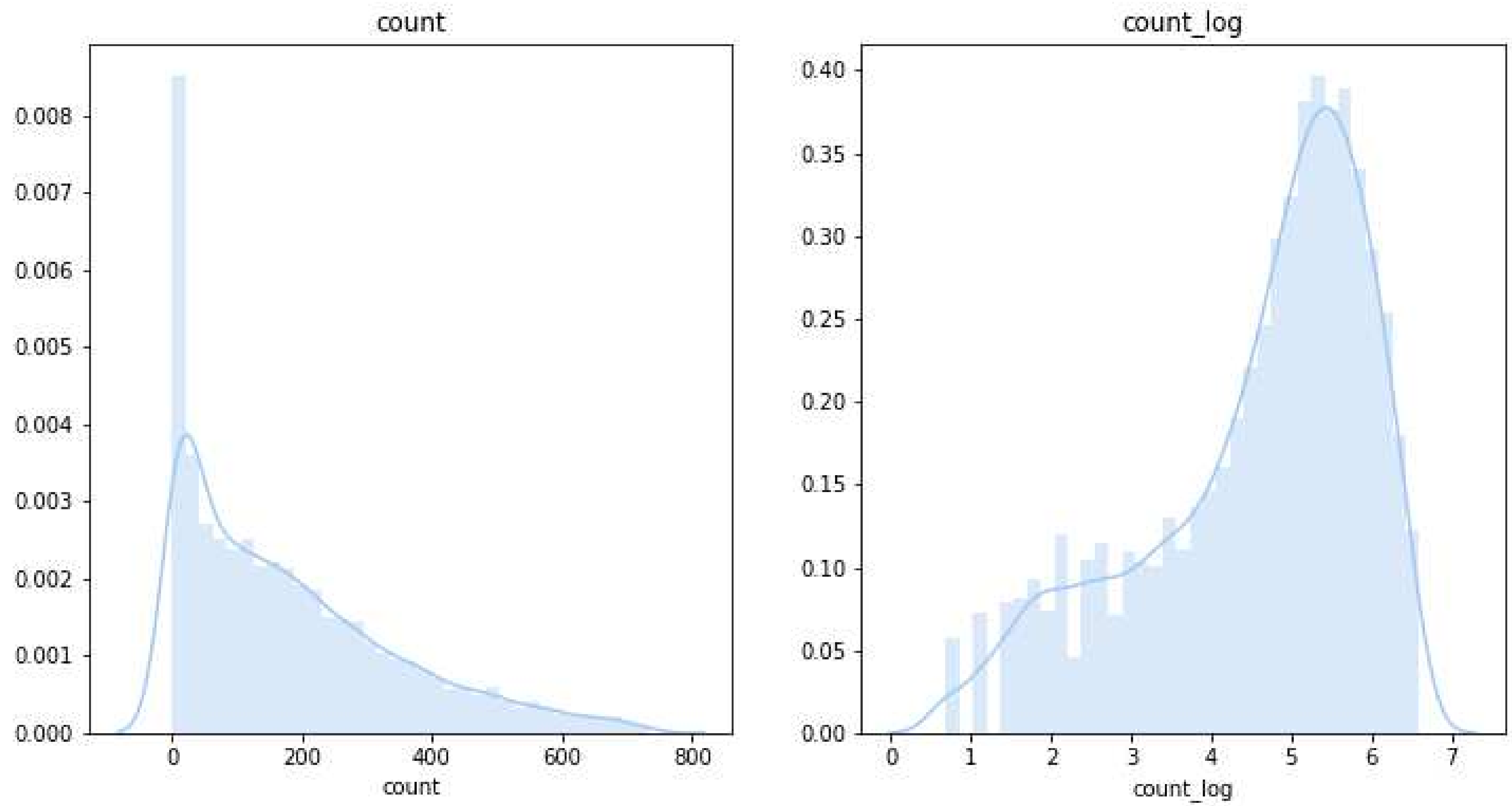



Figure 5: Count distribution compare

# Check for outliers



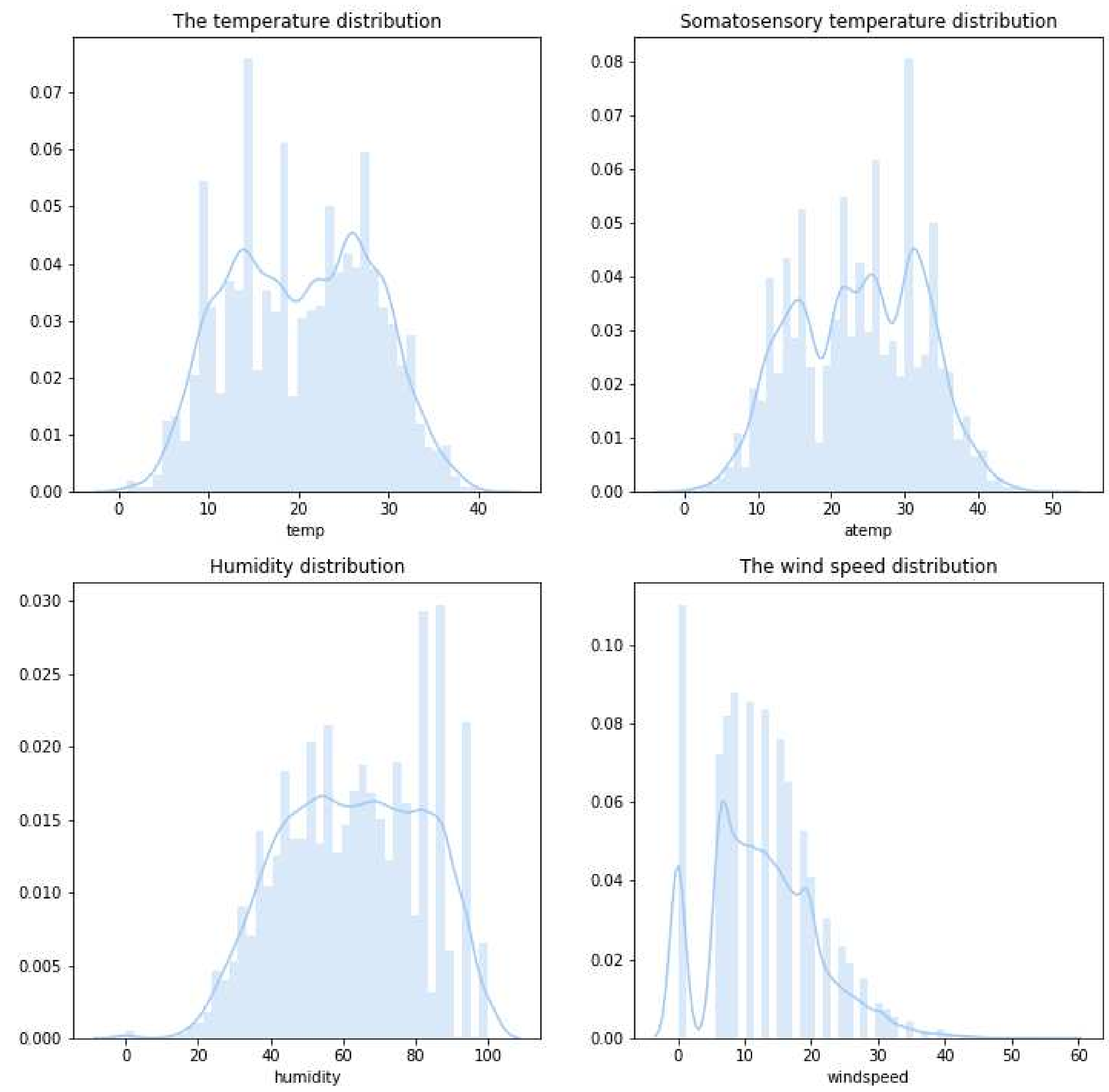



Figure 6: Main features distribution

# Check for outliers



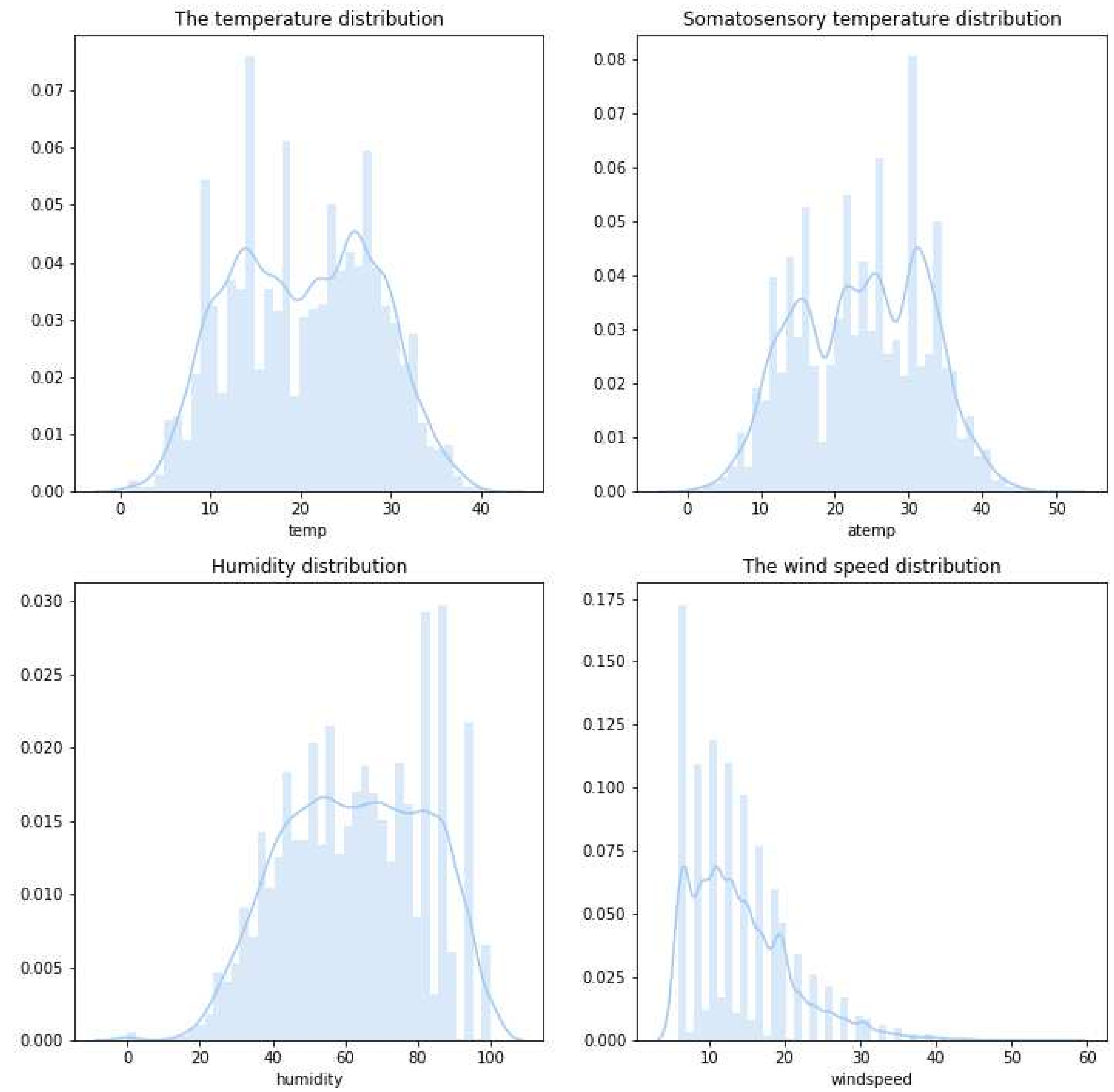



Figure 7: Main features distribution

# Data visualization

- there are two peaks in the graph, one is from 7-8 in the morning, the other is from 5-6 in the afternoon, which is the morning peak and the evening peak respectively, which is in line with the actual situation.

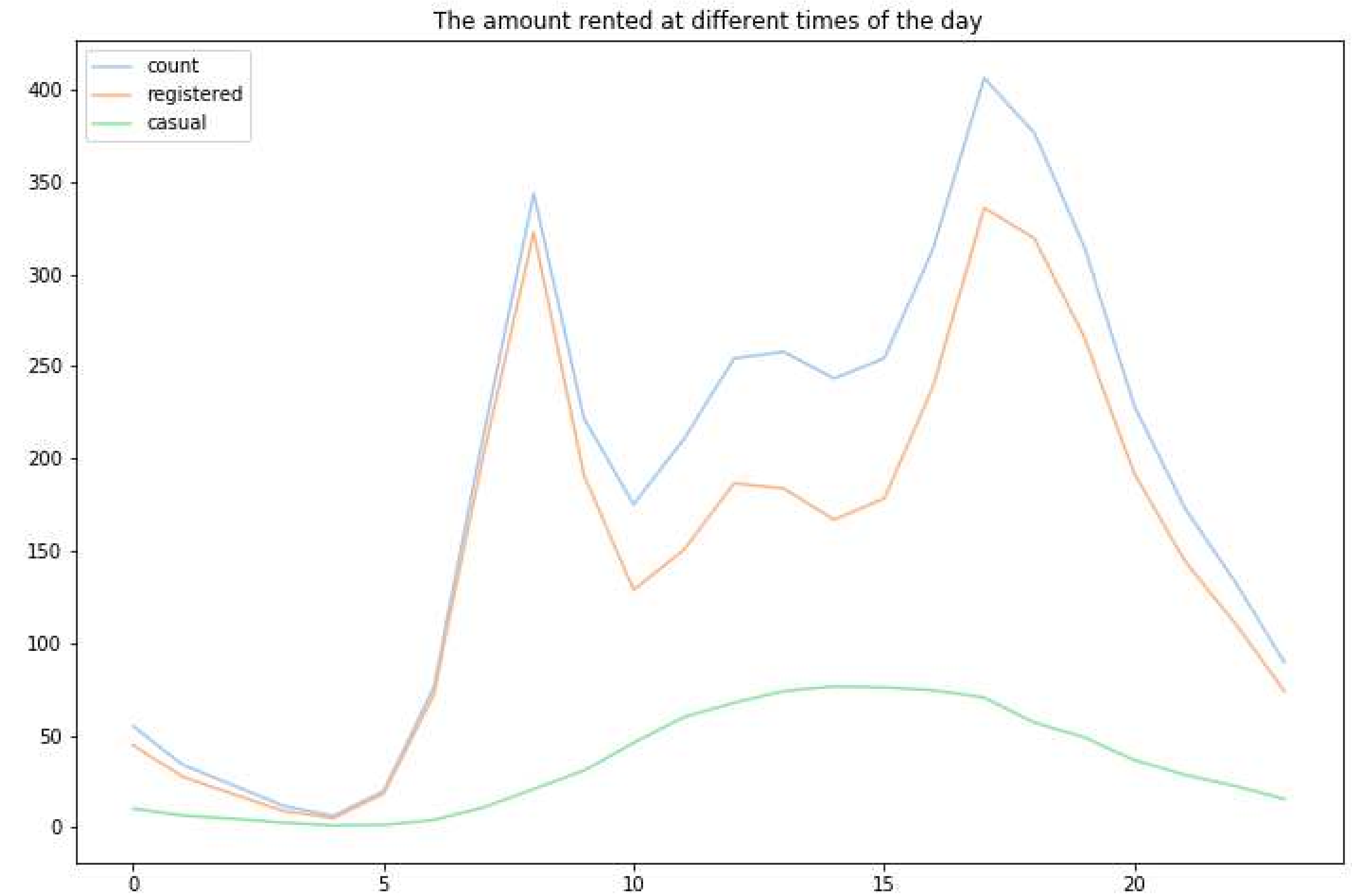



Figure 8: The amount rented at different times of the day

# Time characteristic analysis



- from Monday to Friday, 8 in the morning of the day - 9 am and 5 to 7 PM, usage is more, may be caused by time going to work in the morning and evening after work time, include the reason of eating out at the same time, for the weekend, time is more focused, basic usage around 11 PM to 5 PM, This time is supposed to be everyone's leisure time.

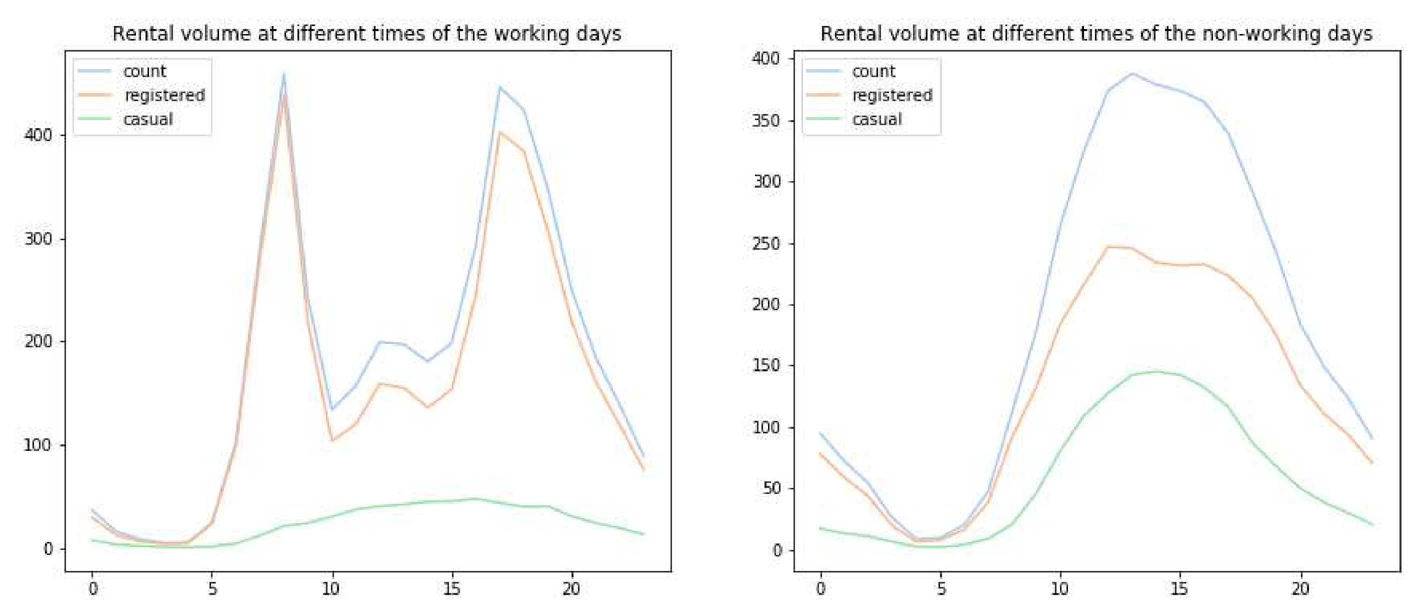



Figure 9: Rental amount at different times of the non-working days and the non-working days

# Time characteristic analysis

- As can be seen from the above diagram, the usage is obviously lower in spring, probably due to the lower temperature.

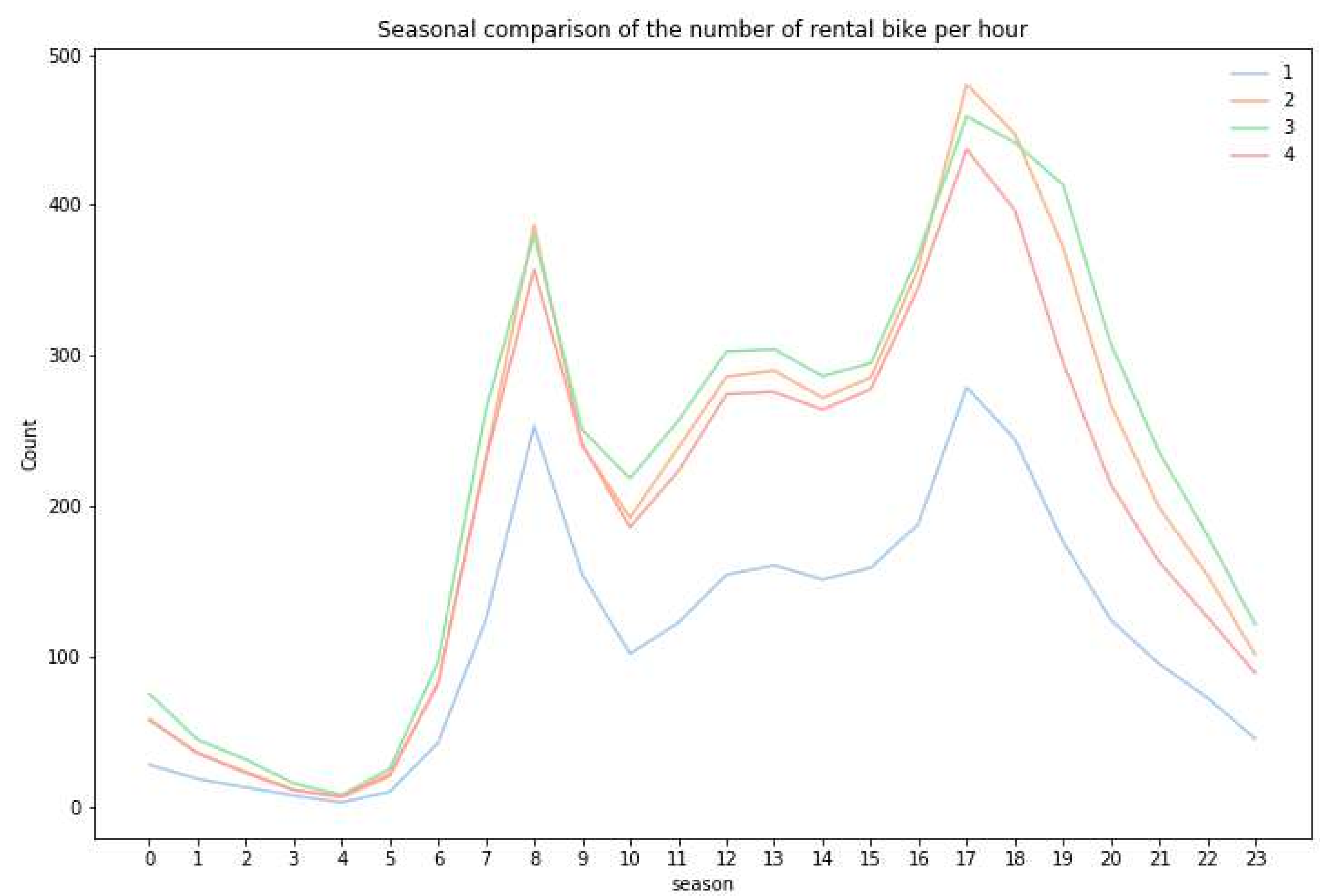



Figure 10: Seasonal comparison of the number of rental bike per hour

# Step One - Group Feature Extraction

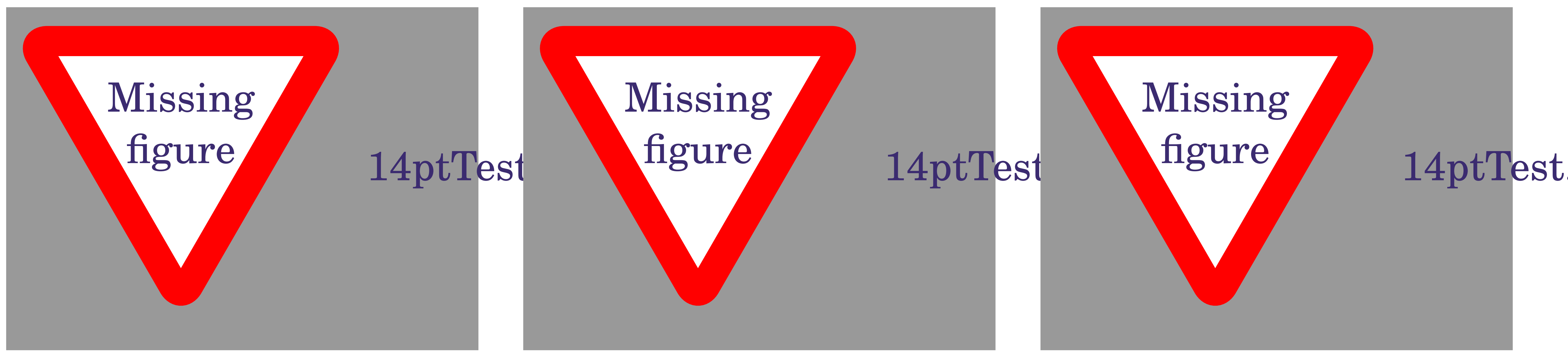


- Suppose $f_1$, $f_2$, $f_3$ are three features of $G_q$.

  $f_1$: $\{x_1, x_2, x_3, x_4, x_5, x_2, x_3, x_4, x_1, x_2\}$

  $f_2$: $\{y_2, y_2, y_1, y_2, y_3, y_3, y_5, y_4, y_4, y_2\}$

  $f_3$: $\{z_1, z_4, z_2, z_4, z_5, z_3, z_1, z_2, z_4, z_2\}$




(a) $f_1$ (b) $f_2$ (c) $f_3$

Figure 11: Histogram of $G_q$ on three features

# Step Two - Outlying Degree Scoring



- Calculate Earth Mover Distance
  - Represent one feature among different groups
  - Purpose: calculate the minimum mean distance

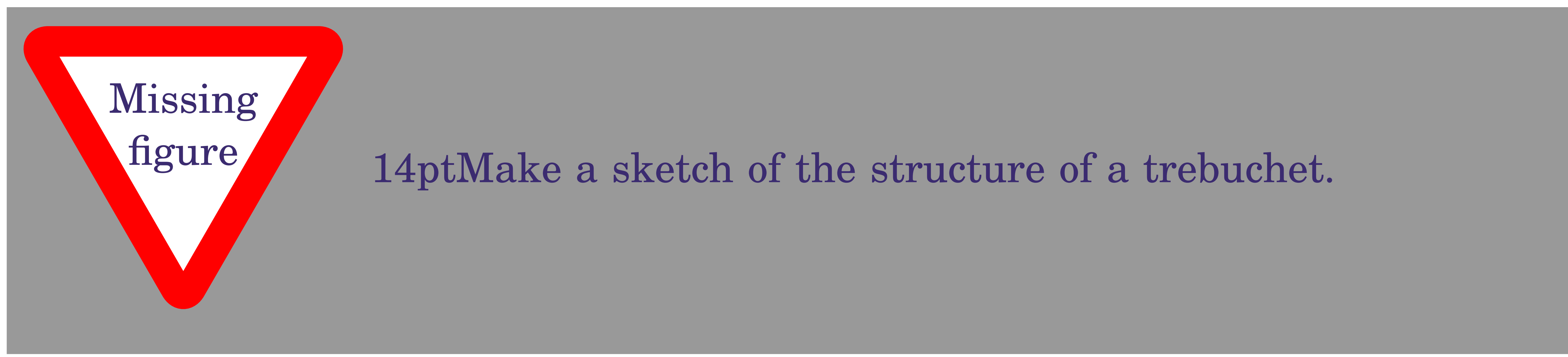



Figure 12: EMD of one feature

# Step Two - Outlying Degree Scoring

- Calculate the outlying degree

$$OD(G_q) = \sum_1^n EDM(h_{q_s}, h_{k_s})$$

  - n ⇔ the number of contrast groups.
  - $h_{k_s}$ ⇔ the histogram representation of $G_k$ in the subspace s.

# Step Three - Outlying Aspects Identification

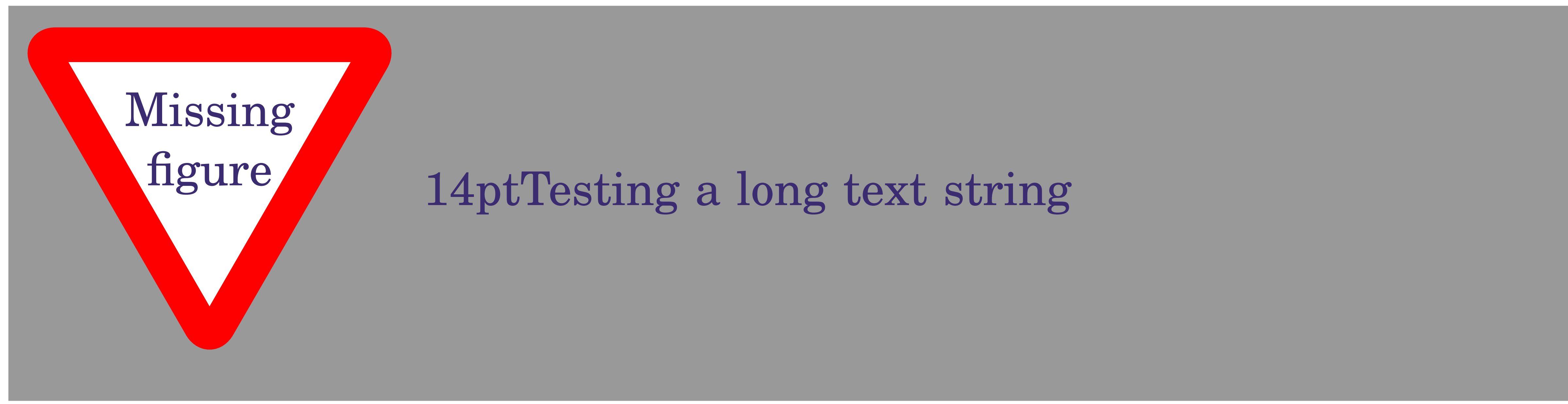


- Identify group outlying aspects mining based on the value of outlying degree.
- The greater the outlying degree is, the more likely it is group outlying aspect.

# Pseudo code



- Pseudo code of GOAM algorithm



# Illustration

Table 1: Original Dataset

| $G_1$ | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $G_2$ | $F_1$ | $F_2$ | $F_3$ | $F_4$ |
|---|---|---|---|---|---|---|---|---|---|
| | 10 | 8 | 9 | 8 | | 7 | 7 | 6 | 6 |
| | 9 | 9 | 7 | 9 | | 8 | 9 | 9 | 8 |
| | 8 | 10 | 8 | 8 | | 6 | 7 | 8 | 9 |
| | 8 | 8 | 6 | 7 | | 7 | 7 | 7 | 8 |
| | 9 | 9 | 9 | 8 | | 8 | 6 | 6 | 7 |
| $G_3$ | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $G_4$ | $F_1$ | $F_2$ | $F_3$ | $F_4$ |
| | 8 | 10 | 8 | 8 | | 9 | 8 | 8 | 8 |
| | 9 | 9 | 7 | 9 | | 7 | 7 | 7 | 9 |
| | 10 | 9 | 10 | 7 | | 8 | 6 | 6 | 8 |
| | 9 | 10 | 8 | 6 | | 9 | 8 | 8 | 7 |
| | 9 | 9 | 7 | 9 | | 8 | 7 | 9 | 8 |

# Illustration



Table 2: outlying degree of each possible subspaces

| Feature | Outlying Degree | Feature | Outlying Degree |
|---|---|---|---|
| $\{F_1\}$ | 4.351 | $\{F_2,F_3\}$ | 4.023 |
| $\{F_2\}$ | 2.012 | $\{F_3,F_4\}$ | 4.324 |
| $\{F_3\}$ | 1.392 | $\{F_2,F_4\}$ | 2.018 |
| $\{F_4\}$ | 2.207 | $\{F_2,F_3,F_4\}$ | 2.012 |

- Search process:

  $OD(\{F_1\}) > \alpha$, save to $T_1$.

  $OD(\{F_2\}) < \alpha$, save to $C_1$.

  $OD(\{F_3\}) < \alpha$, save to $C_2$.

  $OD(\{F_4\}) < \alpha$, save to $C_3$.

  $OD(\{F_2,F_3\}) > \alpha$, save to $N_1$.

  $OD(\{F_3,F_4\}) > \alpha$, save to $N_2$.

  $OD(\{F_2,F_4\}) < \alpha$, remove.

  $OD(\{F_2,F_3,F_4\}) < \alpha$, remove.

# Strengths of GOAM Algorithm



- Reduction of Complexity
  - Bottom-up search strategy.
  - Reduce the size of candidate subspaces.
- Efficiency
  - Before: $O(2^d)$
    Now: $O(d * n^2)$

# Evaluation Results

# Evaluation



- $Accuracy = \frac{P}{T}$

  P: Identified outlying aspects

  T: Real outlying aspects

# Synthetic Dataset

- Synthetic Dataset and Ground Truth

Table 3: Synthetic Dataset and Ground Truth

| Query group | $\mathbf{F_1}$ | $\mathbf{F_2}$ | $F_3$ | $\mathbf{F_4}$ | $F_5$ | $F_6$ | $F_7$ | $F_8$ |
|---|---|---|---|---|---|---|---|---|
| $i_1$ | **10** | **8** | 9 | **7** | 7 | 6 | 6 | 8 |
| $i_2$ | **9** | **9** | 7 | **8** | 9 | 9 | 8 | 9 |
| $i_3$ | **8** | **10** | 8 | **9** | 6 | 8 | 7 | 8 |
| $i_4$ | **8** | **8** | 6 | **7** | 8 | 8 | 6 | 7 |
| $i_5$ | **9** | **9** | 9 | **7** | 7 | 7 | 8 | 8 |
| $i_6$ | **8** | **10** | 8 | **8** | 6 | 6 | 8 | 7 |
| $i_7$ | **9** | **9** | 7 | **9** | 8 | 8 | 8 | 7 |
| $i_8$ | **10** | **9** | 10 | **7** | 7 | 7 | 7 | 7 |
| $i_9$ | **9** | **10** | 8 | **8** | 7 | 6 | 7 | 7 |
| $i_{10}$ | **9** | **9** | 7 | **7** | 7 | 8 | 8 | 8 |

# Synthetic Dataset Results

Table 4: The experiment result on synthetic dataset

| Method | Truth Outlying Aspects | Identified Aspects | Accuracy |
|---|---|---|---|
| GOAM | $\{F_1\}$, $\{F_2 F_4\}$ | $\{F_1\}$, $\{F_2 F_4\}$ | 100% |
| Arithmetic Mean based OAM | $\{F_1\}$, $\{F_2 F_4\}$ | $\{F_4\}$, $\{F_2\}$ | 0% |
| Median based OAM | $\{F_1\}$, $\{F_2 F_4\}$ | $\{F_2\}$, $\{F_4\}$ | 0% |

# NBA Dataset

## Data Collection

### Source

*Yahoo Sports* website (`http://sports.yahoo.com.cn/nba`)

### Data

- Extract NBA teams' data until March 30, 2018;
- 6 divisions;
- 12 features (eg: *Point Scored*).

# NBA Dataset

The detail features are as follows:

Table 5: Collected data of Brooklyn Nets Team

| Pts | FGA | FG% | 3FA | 3PT% | FTA | FT% | Reb | Ass | To | Stl | Blk |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 18 | 12 | 42 | 2.00 | 50 | 7.00 | 100 | 0 | 4 | 3 | 0 | 0 |
| 15.7 | 14.07 | 41 | 5.45 | 32 | 3.05 | 75 | 3.98 | 5.1 | 2.98 | 0.69 | 0.36 |
| 14.5 | 11.1 | 47 | 0.82 | 26 | 4.87 | 78 | 6.82 | 2.4 | 1.74 | 0.92 | 0.66 |
| 13.5 | 10.8 | 42 | 5.37 | 37 | 3.38 | 77 | 6.66 | 2 | 1.38 | 0.83 | 0.42 |
| 12.7 | 10.59 | 39 | 5.36 | 33 | 3.37 | 82 | 3.24 | 6.6 | 1.56 | 0.89 | 0.31 |
| 12.6 | 10.93 | 40 | 6.94 | 37 | 1.70 | 84 | 4.27 | 1.5 | 1.06 | 0.61 | 0.44 |
| 12.2 | 10.39 | 44 | 3.42 | 35 | 2.70 | 72 | 3.79 | 4.1 | 2.15 | 1.12 | 0.32 |
| 10.6 | 7.85 | 49 | 4.51 | 41 | 1.35 | 83 | 3.34 | 1.6 | 1.15 | 0.45 | 0.24 |

- Data Preprocess

Table 6: The bins that used to discrete data of each feature

| Labels | Pts | FGA | FG% | 3FA | 3PT% | FTA |
|---|---|---|---|---|---|---|
| low | [0,5] | [0,4] | [0,0.35] | [0,1.0] | [0,0.2] | [0,1.0] |
| medium | (5,10] | (4,7] | (0.35,0.45] | (1.0,2.5] | (0.2,0.3] | (1.0,1.5] |
| high | (10,15] | (7,10] | (0.45,0.5] | (2.5,3.5] | (0.3,0.35] | (1.5,2.5] |
| very high | (15,+∞] | (10,+∞] | (0.5,1] | (3.5,+∞] | (0.35,1] | (2.5,+∞] |
| Labels | FT% | Reb | Ass | To | Stl | Blk |
| low | [0,0.6] | [0,2.0] | [0,1.0] | [0,0.6] | [0,0.2] | [0,0.25] |
| medium | (0.6,0.65] | (2,5] | (1,2] | (0.6,0.9] | (0.2,0.5] | (0.25,0.5] |
| high | (0.65,0.75] | (5,6] | (2,4] | (0.9,1.7] | (0.6,0.75] | (0.5,0.7] |
| very high | (0.75,1] | (6,+∞] | (4,+∞] | (1.7,+∞] | (0.75,+∞] | (0.7,+∞] |

# NBA Dataset Results



Table 7: The identified outlying aspects of groups

| Teams | Trivial Outlying Aspects | NonTrivial Outlying Aspects |
|---|---|---|
| Cleveland Cavaliers | {3FA} | {FGA, FT%}, {FGA, FG%} |
| Orlando Magic | {Stl} | None |
| Milwaukee Bucks | {To}, {FTA} | {FGA, FTA}, {3FA, FTA} |
| Golden State Warriors | {FG%} | {FT%, Blk}, {FGA, 3PT%, FTA} |
| Utah Jazz | {Blk} | {3FA, 3PT%} |
| New Orleans Pelicans | {FT%}, {FTA} | {FTA, Stl}, {FTA, To} |

# Conclusion

# Conclusion



- Formalize the problem of *Group Outlying Aspects Mining* by extending outlying aspects mining;
- Propose a novel method GOAM algorithm to solve the *Group Outlying Aspects Mining* problem;
- Utilize the pruning strategies to reduce time complexity.

# Questions?



# Contact Information

Associate Professor Gang Li

School of Information Technology

Deakin University, Australia

gangli@tulip.org.au

Team for Universal Learning and Intelligent Processing