Bike Sharing Demand

Forecast use of a city bikeshare system

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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.

Outlying Aspects Mining vs Outlier Detection

Player	3PT%	FTA	FT%	To
P_1	65	4	33	8
P_2	78	1	65	5
P_3	58	6	46	3
P_4	68	1.2	85	6.2
P_5	58	6.2	36	3.4

Outlying Aspects Mining

- Explain the distinctive aspects of the query object.
- The query object may (or may not) be an outlier.

Outlier Detection

- Find out all unusual objects in the whole dataset.
- No explanation on how they are different.

Group Outlying Aspects Mining

Defn

Group outlying aspects mining aims to identify the outstanding features of the group of query object.

- Doctors desire to identify the merits & demerits between a group of cancer patients and normal people.
- NBA coaches are passionate about exploring the obvious advantages & disadvantages of the team.

Figure 1: Medical

Figure 2: NBA-Team

Problem Formalization

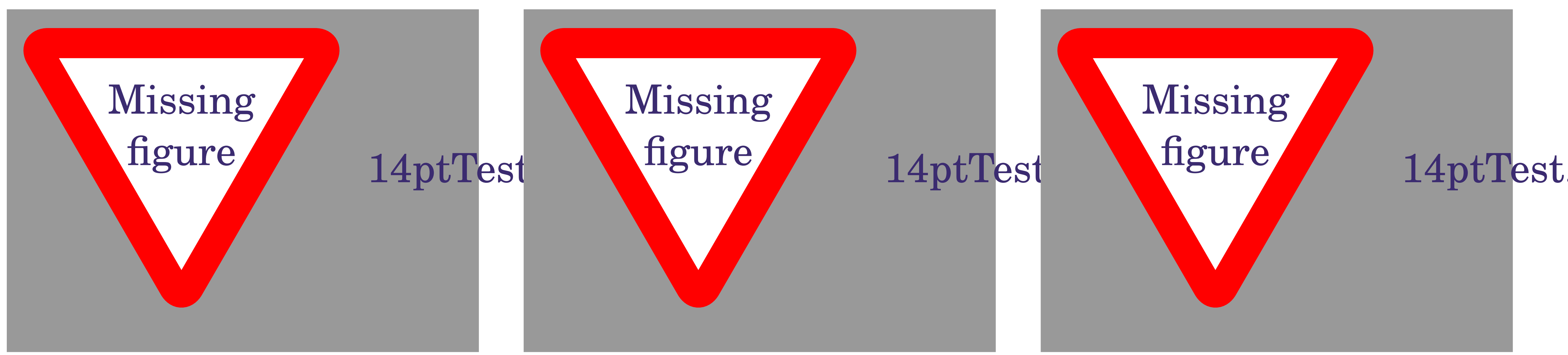
Defn

Group outlying aspects mining aims to identify the top-k group outlying subspace $s \subseteq F$ in which the query group G_q is distinctive with other groups.

- $G = \{G_q, G_2, G_3, ..., G_n\}$ ⇔ a set of groups.
- G_q ⇔ the query group.
- Other groups ⇔ comparison groups.
- Each object in the group has d features $F = \{f_1, f_2, ..., f_d\}$.

Term Definition

- Top-k group outlying subspaces
  - $\rho_s(\cdot) \Rightarrow$ outlying scoring function.
  - $\rho_s(\cdot)$ quantifies the outlying degree of the query group G_q in the subspace s.
  - Order by DESC using scoring function $\rho(\cdot)$ to identify top K group outlying subspaces.



(a) Original Feature Spaces (b) Group Outlying Spaces (c) Another Subspaces

Term Definition

- Trivial Outlying Features
  - One-dimension subspaces.
  - G_q's outlying degree $\rho(\cdot) > \alpha$.

Table 1: $\alpha = 4$

Feature	Outlying Degree
$\{F_1\}$	4.351
$\{F_3, F_4\}$	4.024
$\{F_2, F_4\}$	2.318
$\{F_2\}$	2.002
$\{F_3\}$	1.028

Term Definition

- Non-Trivial Outlying Subspaces
  - Multi-dimension subspaces.
  - G_q's outlying degree $\rho(\cdot) > \alpha$.

Table 2: $\alpha = 4$

Feature	Outlying Degree
$\{F_1\}$	4.351
$\{F_3, F_4\}$	4.024
$\{F_2, F_4\}$	2.318
$\{F_2\}$	2.002
$\{F_3\}$	1.028

Related Work and Challenges

Related Work - Outlying Aspects Mining

- Existing Methods - Feature selection
  - To distinguish two classes: the query point (positive) & rest of data (negative)

Disadvantages

- Positive and negative classes are Not balanced.
- Not quantify the outlying degree accurately.
- Not identify group outlying aspects.

Advantages

- Easy to operate.
- Resolve dimensionality bias.

Related Work - Outlying Aspects Mining

- Existing Methods - Score-and-search
  - Define an outlying score function.
  - Search subspaces.

Disadvantages

- Dimensionality bias.
- Search efficiency is Not high (dataset is large).
- Not identify group outlying aspects.

Advantages

- Quantify the outlying degree correctly.
- High Comprehensibility.

Group Outlying Aspects Mining

- Focus on differences between groups.
- Multiple points.

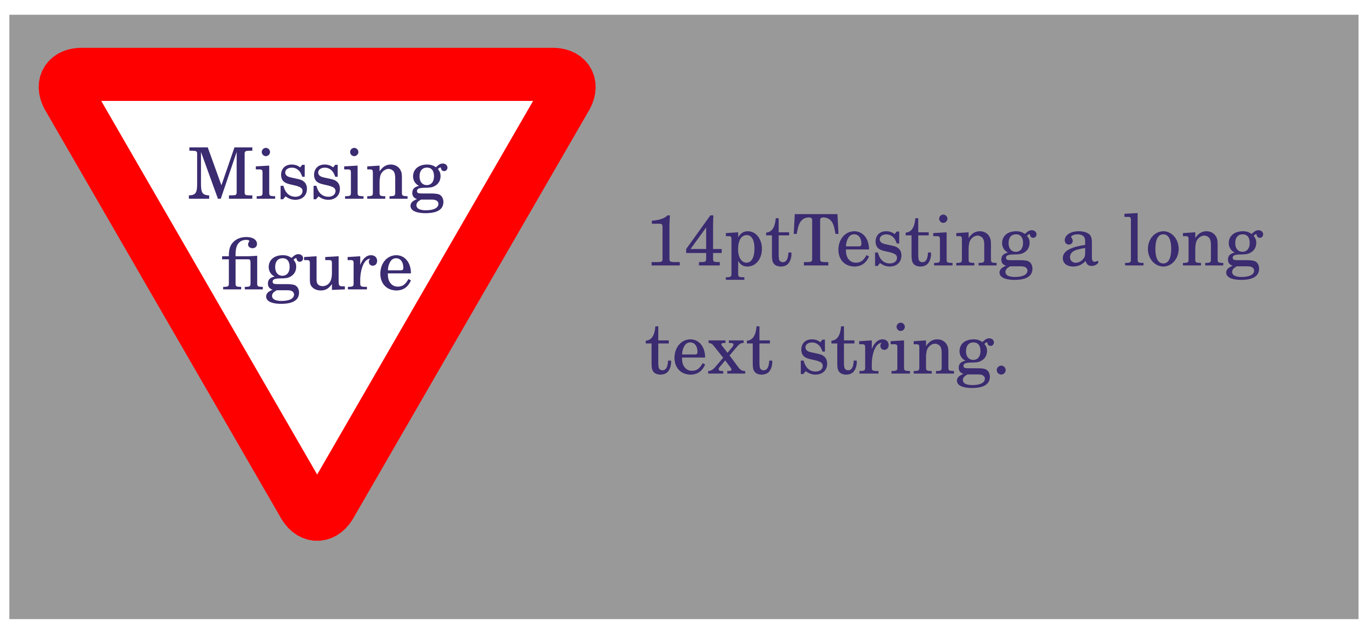


Figure 3: Group Outlying Aspects Target

Outlying Aspects Mining

- Concentrates on differences between objects.
- One point.

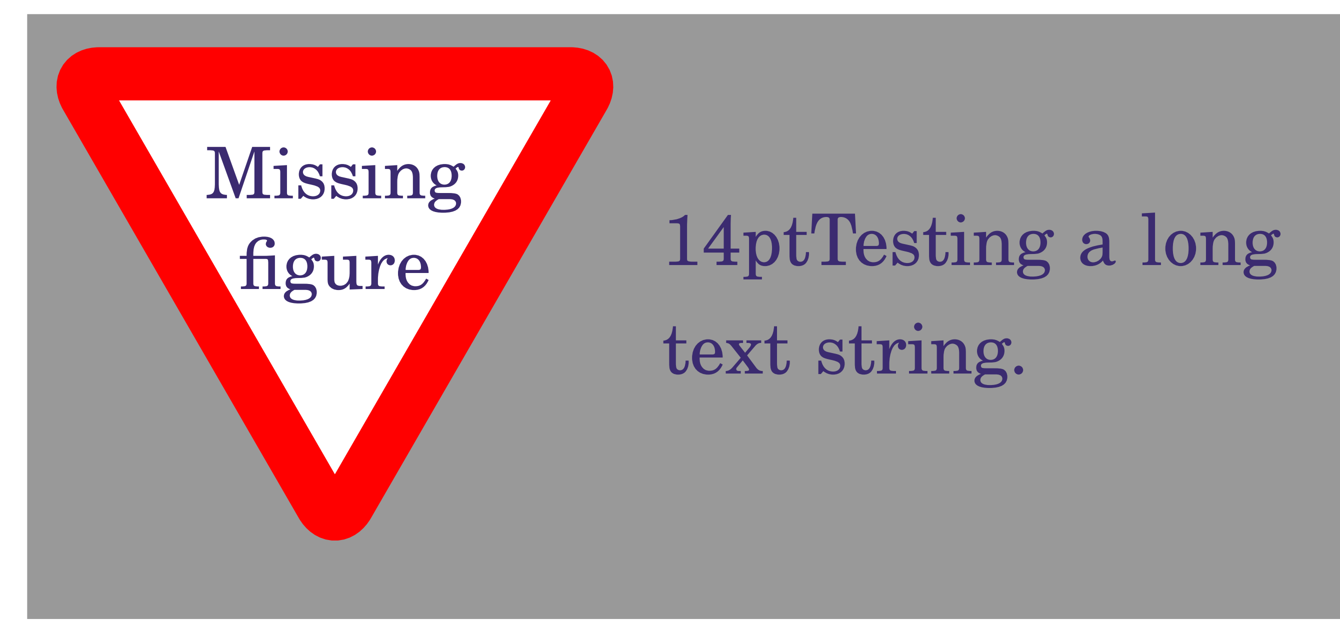


Figure 4: Outlying Aspects Target

Challenges (1)

- How to represent the group features.
  - Can be affected by outlier values.
  - Can Not reflect the overall distribution of group features.

Challenges (2)

- How to evaluate the outlying degree in different aspects.
  - Need design a scoring function when necessary.
  - Adopting an appropriate scoring function (without dimension bias) remains a problem.

Challenges (3)

- How to improve the efficiency.
  - When the dimension of the data is high, the candidate subspace grows exponentially.
  - It will easily go beyond the limits of the computation resources.

GOAM Algorithm

Framework of GOAM algorithm:

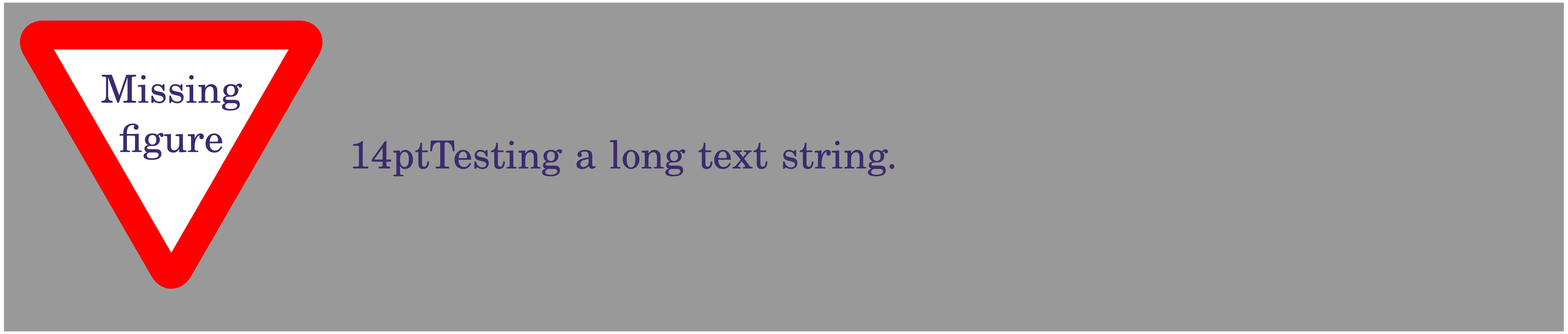


Figure 5: Framework of GOAM Algorithm

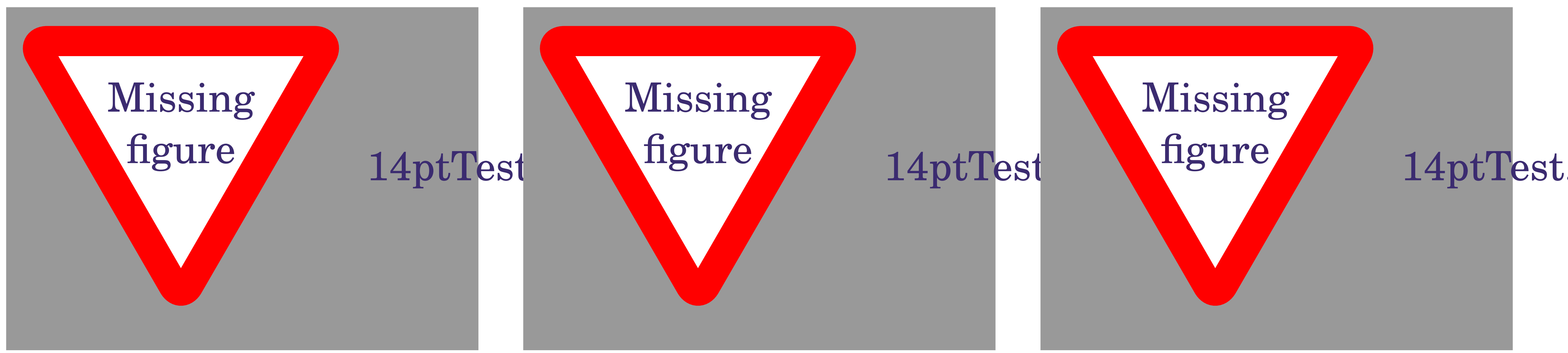
Step One - Group Feature Extraction

- 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 6: 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

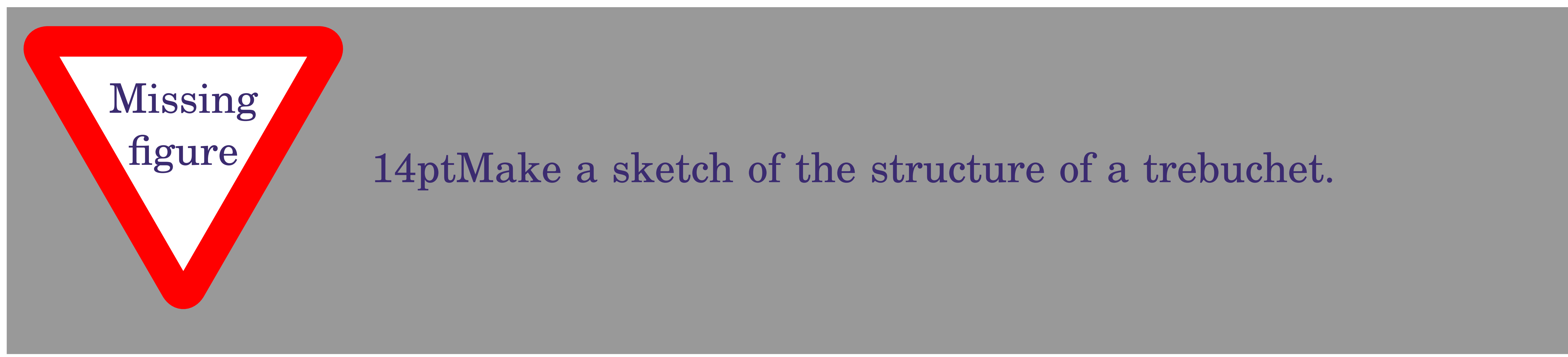


Figure 7: EMD of one feature

Step Two - Outlying Degree Scoring

- Calculate the outlying degree

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

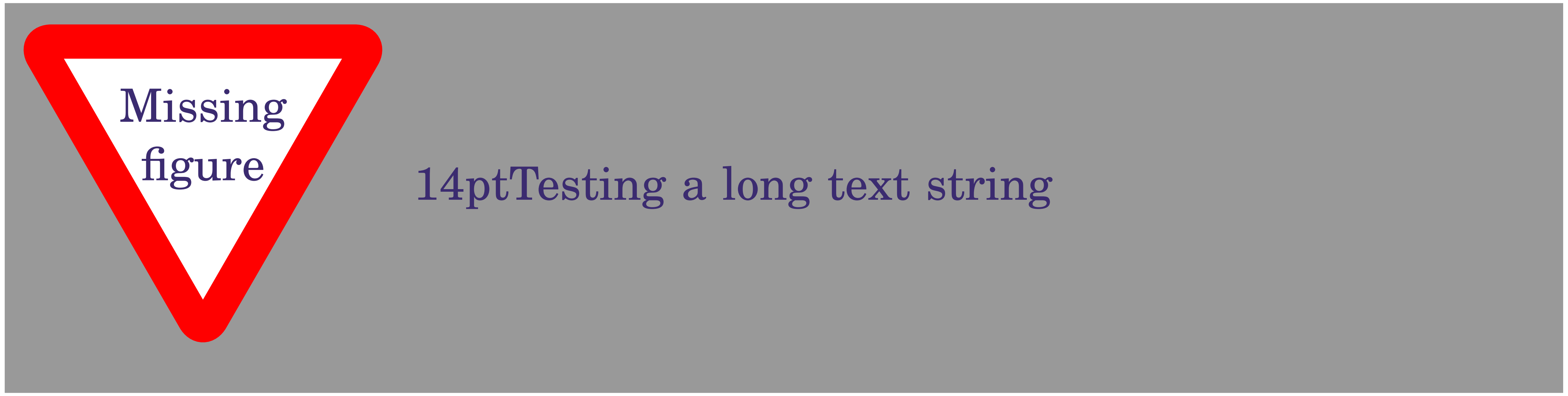
  - n ⇔ the number of contrast groups.
  - h_{k_s} ⇔ the histogram representation of G_k in the subspace s.

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 3: 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 4: 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 and Ground Truth

Table 5: 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 6: The experiment result on synthetic dataset

Method	Truth Outlying Aspects	Identified Aspects	Accuracy
GOAM	$\{F_1\}$, $\{F_2F_4\}$	$\{F_1\}$, $\{F_2F_4\}$	100%
Arithmetic Mean based OAM	$\{F_1\}$, $\{F_2F_4\}$	$\{F_4\}$, $\{F_2\}$	0%
Median based OAM	$\{F_1\}$, $\{F_2F_4\}$	$\{F_2\}$, $\{F_4\}$	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*).

The detail features are as follows:

Table 7: 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

NBA Dataset

- Data Preprocess

Table 8: 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 9: 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?

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