

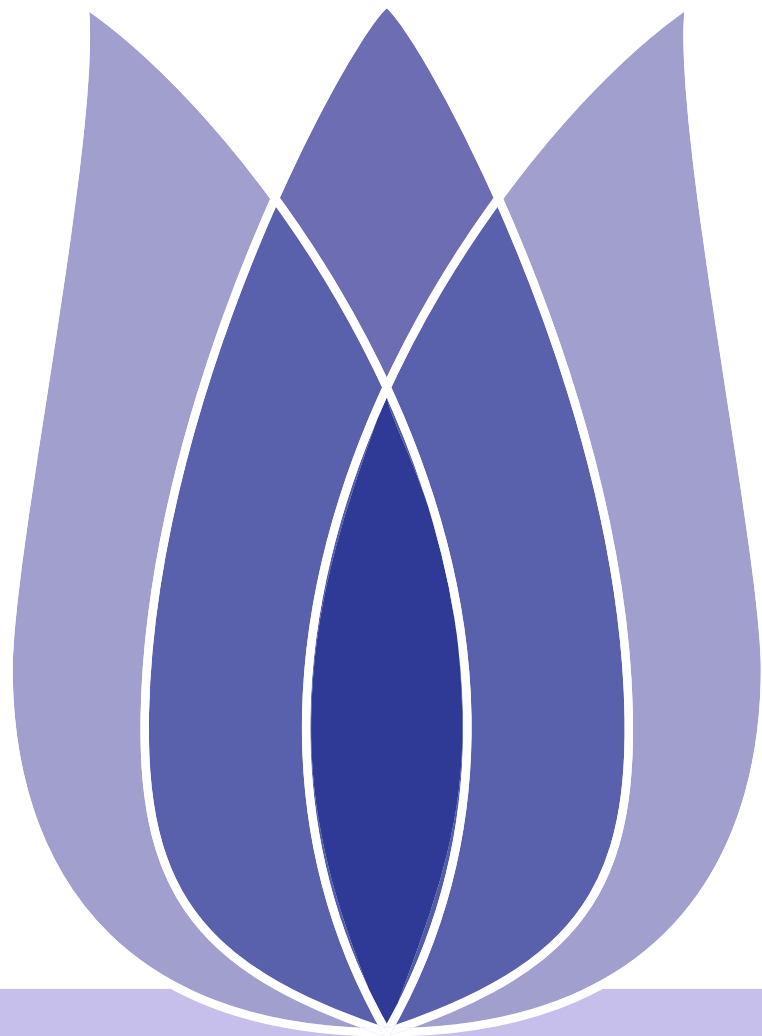


# Group Outlying Aspects Mining

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(None)





# Overview



# Problem Definition



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# Outlying Aspects Mining

Defn

Outlying Aspects Mining aims to identify the outstanding features of the query object.

- A teacher may be interested in the **characteristics** that make **one student distinctive** from others.
- NBA coaches would prefer to find out the strengths and weaknesses of the player (a query object).

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 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
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$P_5$	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

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.

Defn

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





# 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



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## 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.

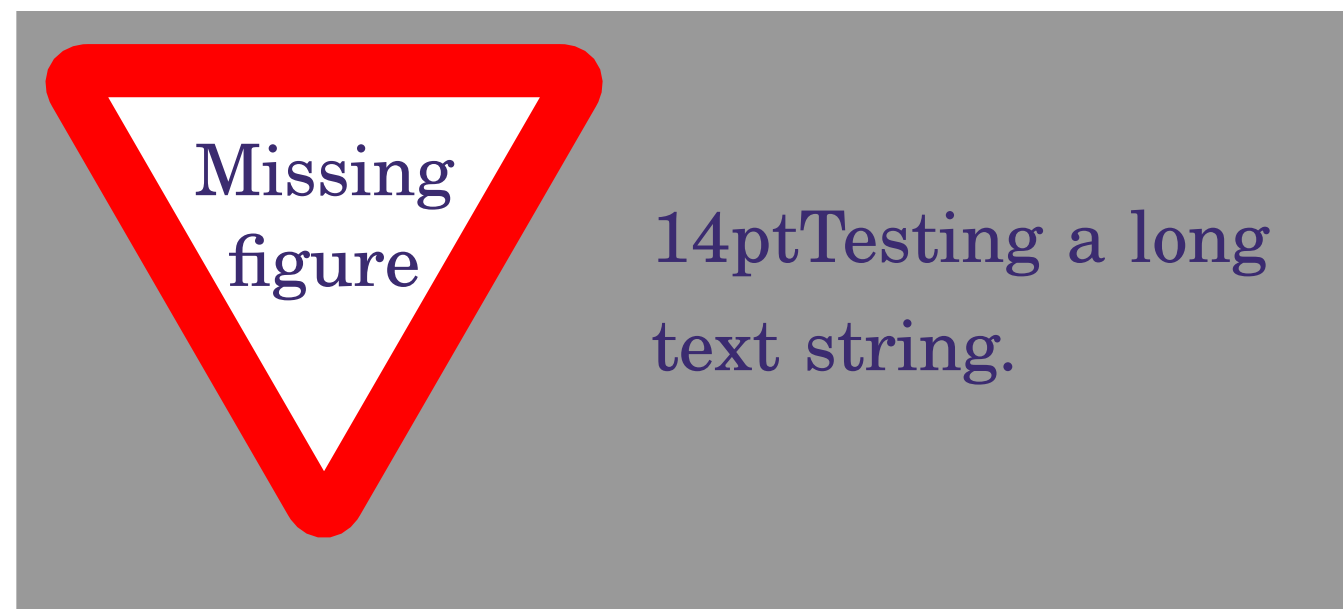


Figure 3: Group Outlying Aspects Target

## Outlying Aspects Mining

- Concentrates on differences between **objects**.
- **One** point.

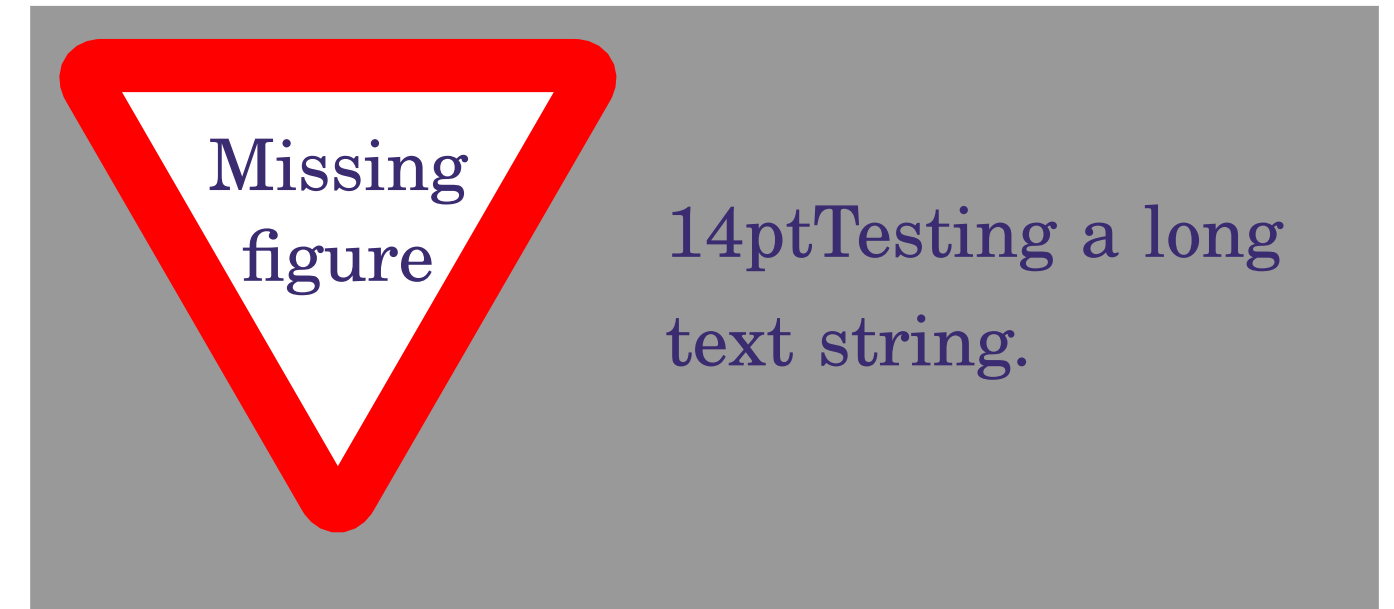


Figure 4: Outlying Aspects Target





## 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



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Framework of GOAM algorithm:

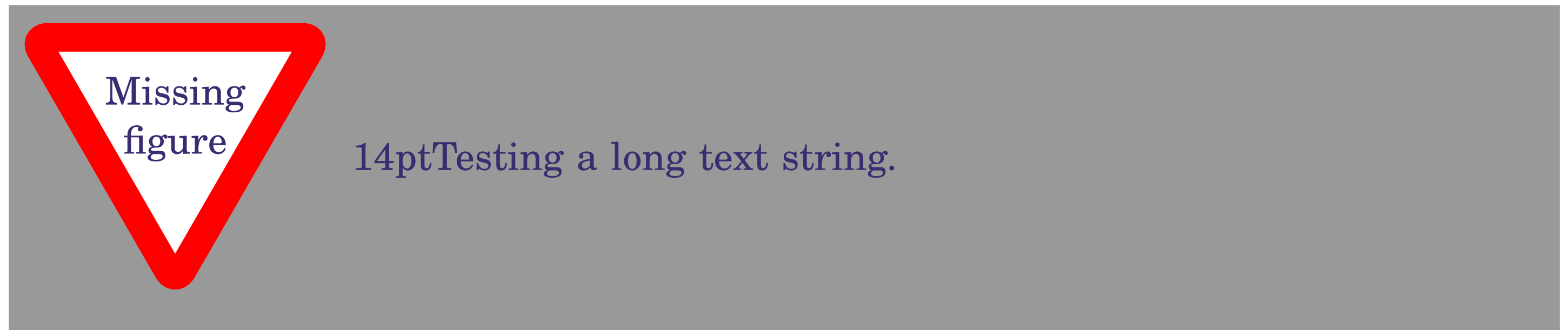


Figure 5: Framework of GOAM Algorithm



## Step One - Group Feature Extraction

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

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

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

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

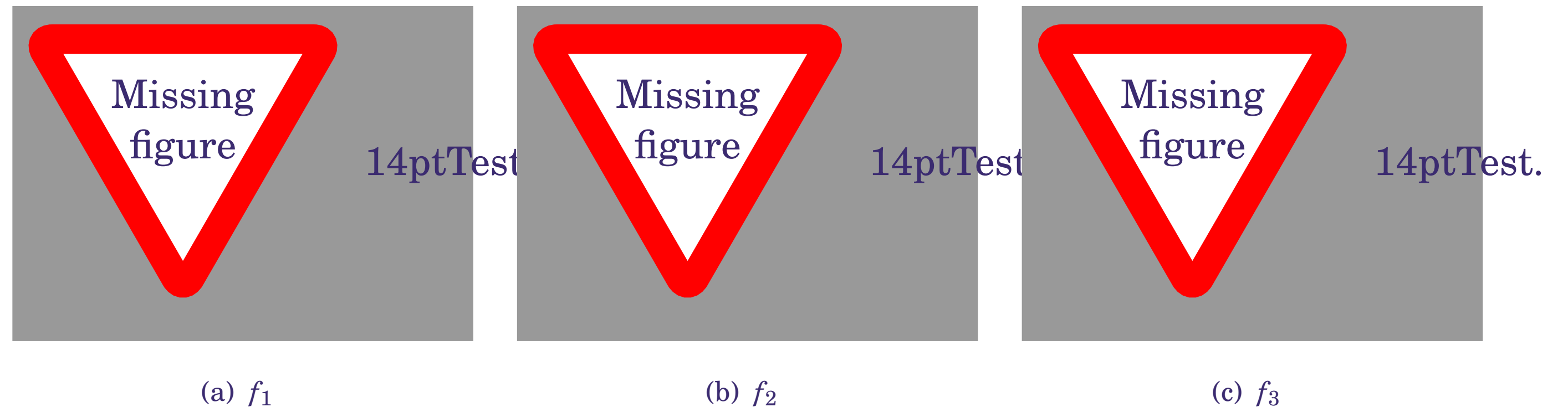


Figure 6: Histogram of  $G_q$  on three features



## Step Two - Outlying Degree Scoring

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

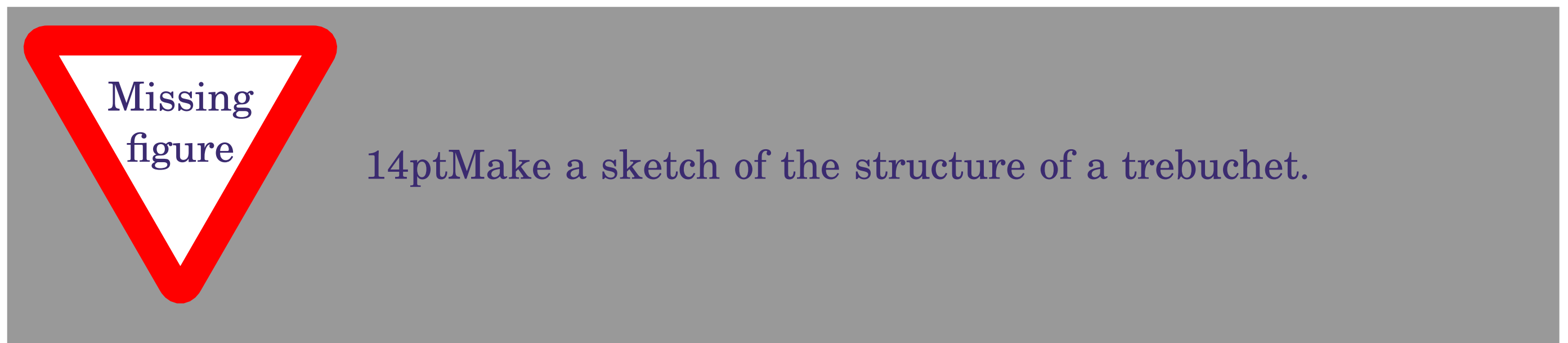


Figure 7: EMD of one feature





## Step Two - Outlying Degree Scoring

- Calculate the outlying degree

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

- ◆  $n \Leftrightarrow$  the number of contrast groups.
- ◆  $h_{k_s} \Leftrightarrow$  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

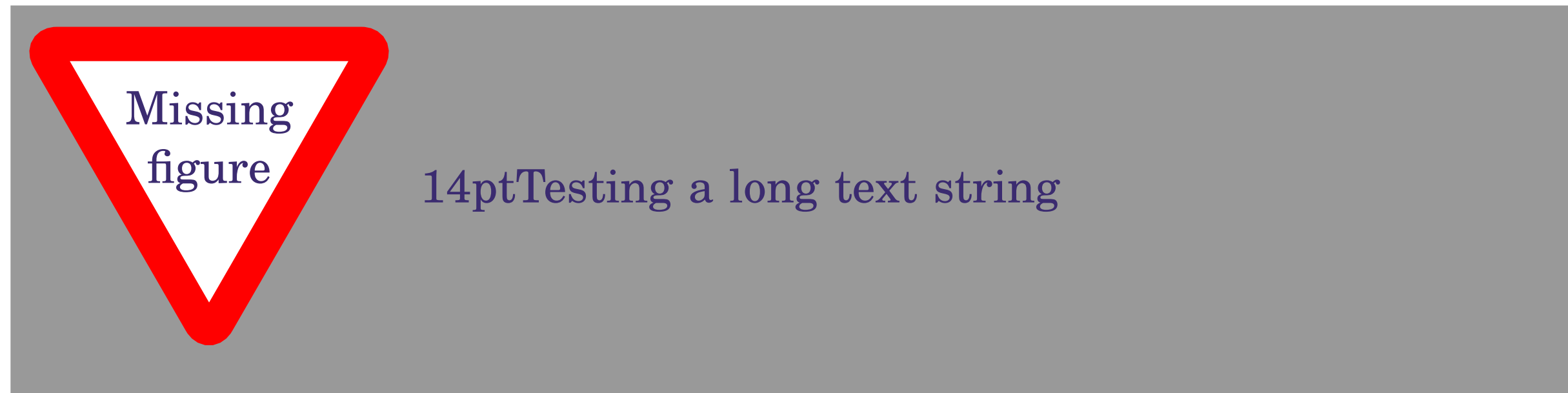




Table 3: Original Dataset

$G_1$	$F_1$	$F_2$	$F_3$	$F_4$	$G_2$	$F_1$	$F_2$	$F_3$	$F_4$
	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



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# 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	<b>F<sub>1</sub></b>	<b>F<sub>2</sub></b>	<i>F<sub>3</sub></i>	<b>F<sub>4</sub></b>	<i>F<sub>5</sub></i>	<i>F<sub>6</sub></i>	<i>F<sub>7</sub></i>	<i>F<sub>8</sub></i>
<i>i<sub>1</sub></i>	<b>10</b>	<b>8</b>	9	<b>7</b>	7	6	6	8
<i>i<sub>2</sub></i>	<b>9</b>	<b>9</b>	7	<b>8</b>	9	9	8	9
<i>i<sub>3</sub></i>	<b>8</b>	<b>10</b>	8	<b>9</b>	6	8	7	8
<i>i<sub>4</sub></i>	<b>8</b>	<b>8</b>	6	<b>7</b>	8	8	6	7
<i>i<sub>5</sub></i>	<b>9</b>	<b>9</b>	9	<b>7</b>	7	7	8	8
<i>i<sub>6</sub></i>	<b>8</b>	<b>10</b>	8	<b>8</b>	6	6	8	7
<i>i<sub>7</sub></i>	<b>9</b>	<b>9</b>	7	<b>9</b>	8	8	8	7
<i>i<sub>8</sub></i>	<b>10</b>	<b>9</b>	10	<b>7</b>	7	7	7	7
<i>i<sub>9</sub></i>	<b>9</b>	<b>10</b>	8	<b>8</b>	7	6	7	7
<i>i<sub>10</sub></i>	<b>9</b>	<b>9</b>	7	<b>7</b>	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



## ■ 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,+∞]



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



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## 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

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