Sales of Books Forecast

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Overview

Problem Definition

Sales of Books Forecast

Defn Sales of Books Forecast aims to predict the sales of books in 2021 through the book sales data from 2017 to 2020.

- Data covers different countries and different stores.
- There are cyclical and seasonal changes in book sales.

Data	row_num	date	country	store	product
train	70128	1461	6	2	4
test	17520	365	6	2	4

Data Analysis

Overall data

- Country - Belgium,France,Germany,Italy,Poland,Spain
- Product - [Kaggle Advanced Techniques],[Kaggle Getting Started],[Kaggle Recipe Book],[Kaggle for Kids: One Smart Goose]
- Stores - KaggleMart,KaggleRama
- Time line

Data	Earliest date	Latest date
train	2017 – 01 – 01	2020 – 12 – 31
test	2021 – 01 – 01	2021 – 12 – 31

Monthly sales statistics

- the patterns in sales of all countries and stores are identical.the magnitudes of sales are different

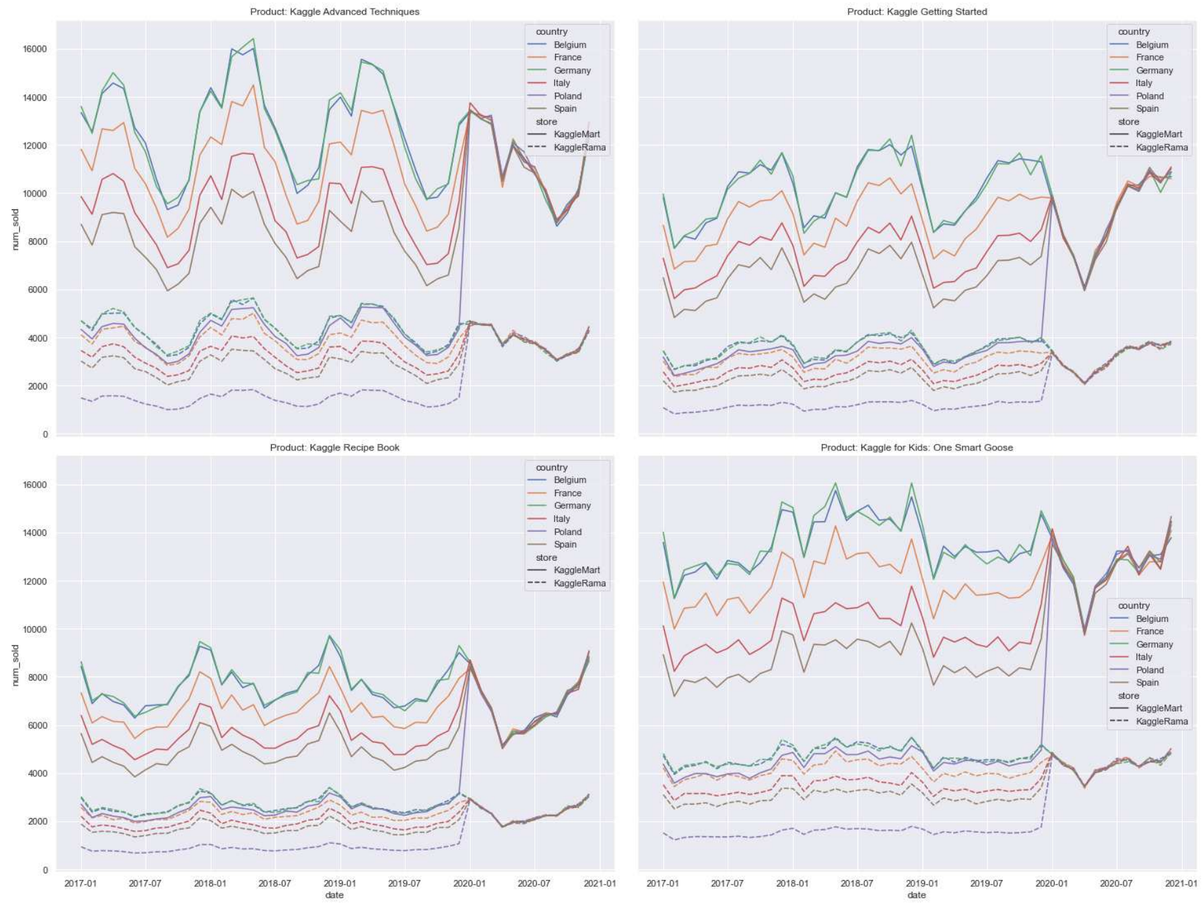


Figure 1: Monthly sales

Aggregating Time Series(Store)

- Store-KaggleMart appears to consistantly have 74.25% of the total number of sales

Store	ratio
KaggleMart	0.742515
KaggleRama	0.257485

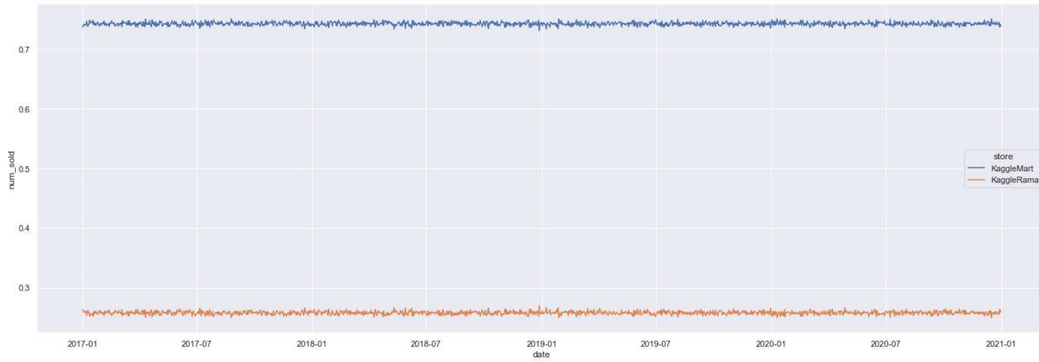


Figure 2: Stores ratio

Aggregating Time Series(Store)

- To compare the trend of the two stores, multiply the sales data of the two stores by a constant.

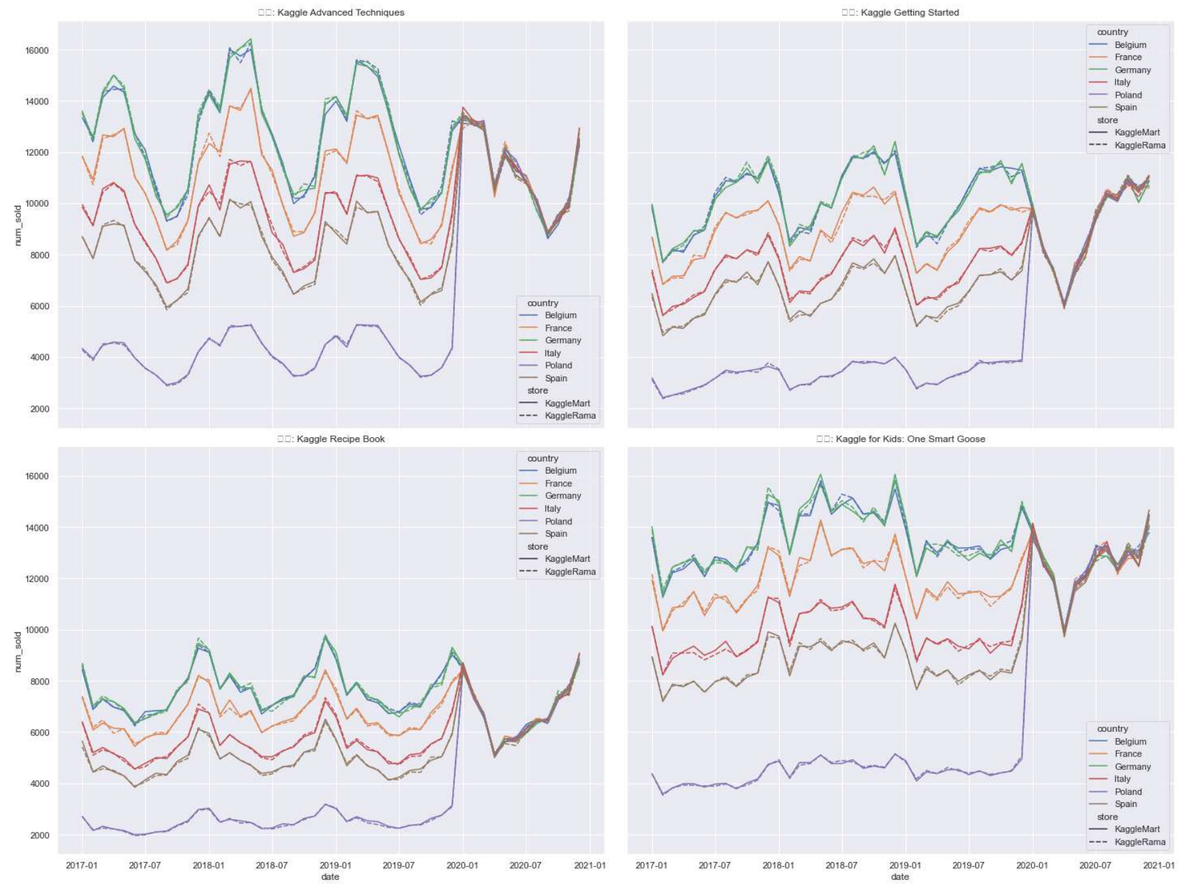


Figure 3: Stores ratio trend

Aggregating Time Series(Country)

- Country-The ratio of total sales in different countries also fluctuates little.

Country	ratio
Belgium	0.218930
France	0.191360
Germany	0.219586
Italy	0.159383
Poland	0.071348
Spain	0.139393

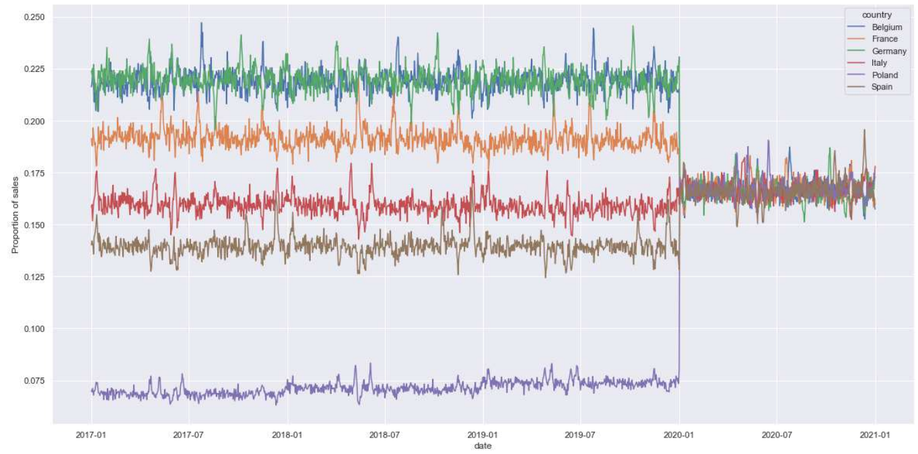


Figure 4: Countries ratio

Aggregating Time Series(Country)

- Multiply all countries by a constant so they are comparable with Belgium.

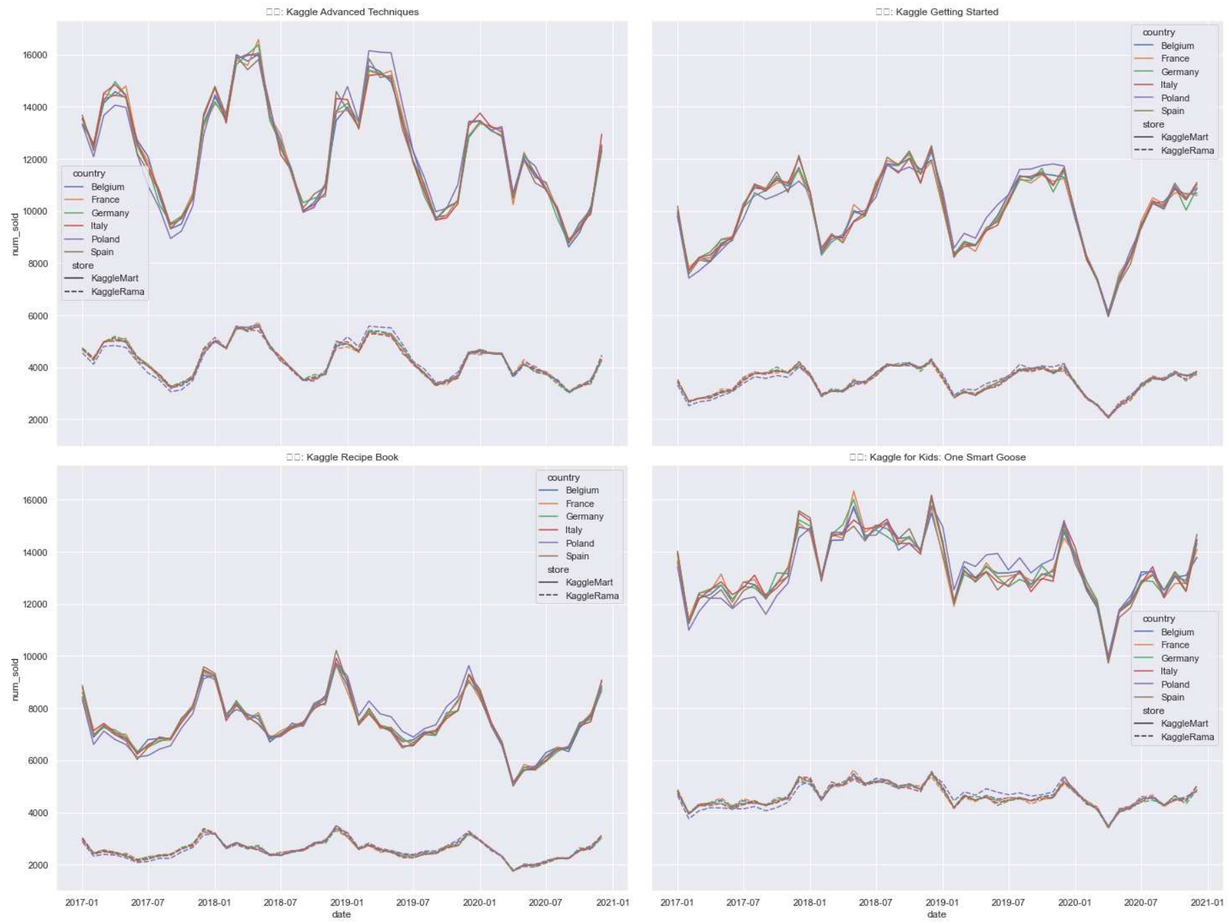


Figure 5: Countries ratio trend

Aggregating Time Series(Country and Store)

- In the plots make all time series inline with the Belgium KaggleMart store by multiplying by a constant.

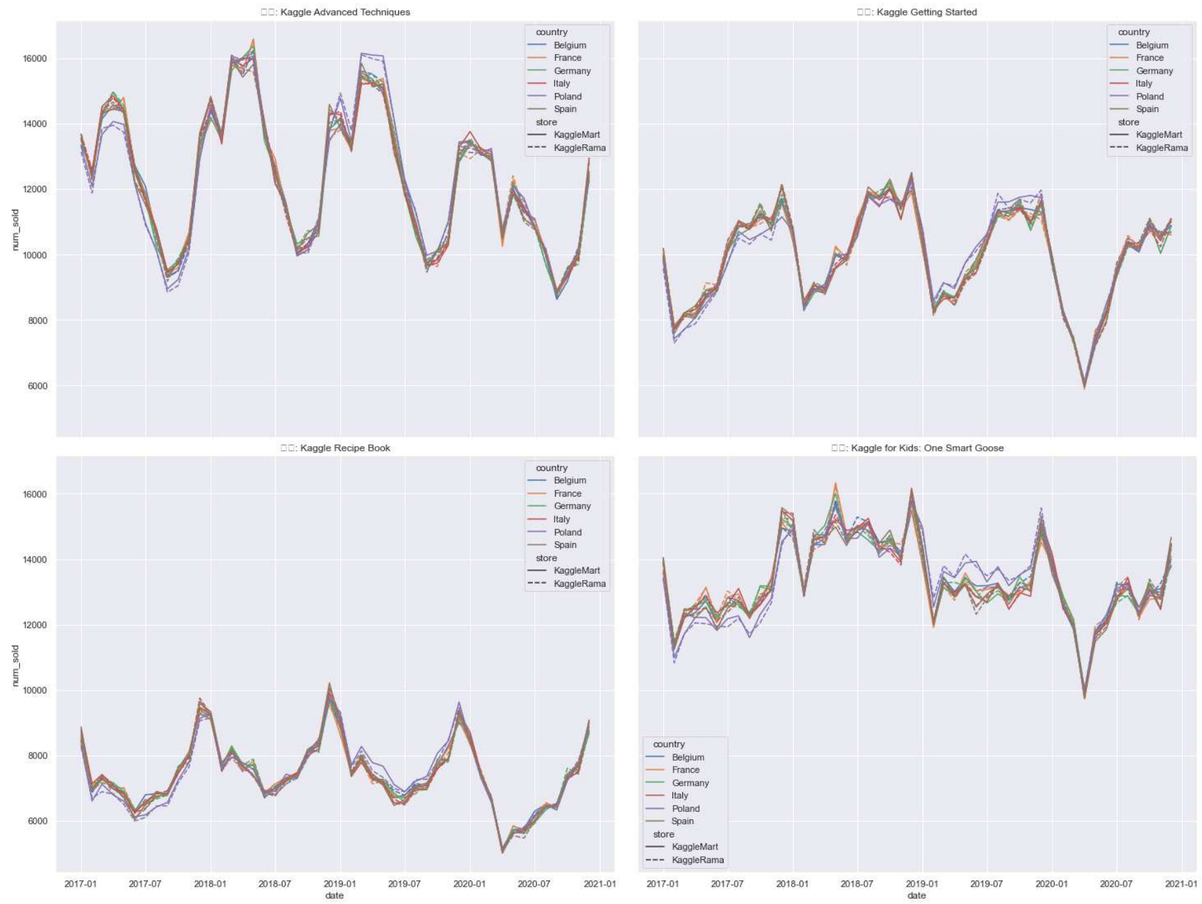


Figure 6: Countries and Store trend

Aggregating Time Series(Product)

- The change trend of the sales volume of the four books is cyclical.

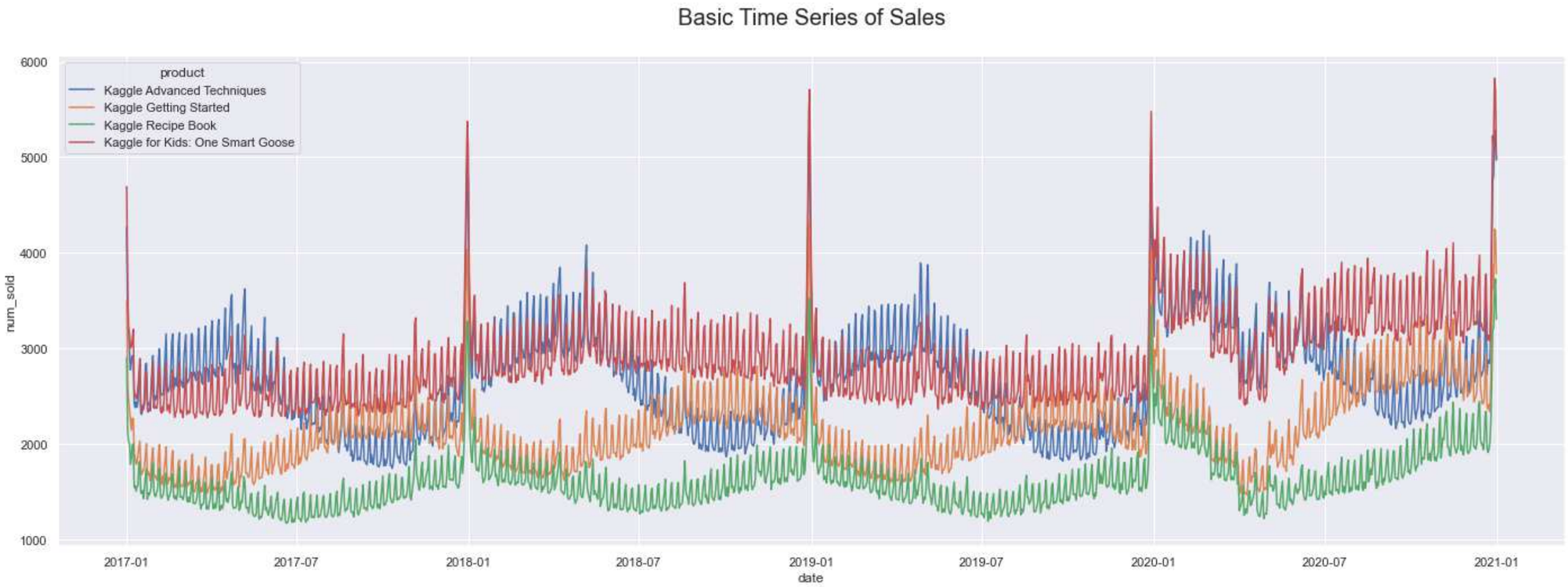


Figure 7: Sales of Product

Aggregating Time Series(Product)

- The change trend of the sales proportion of the four books has rules.

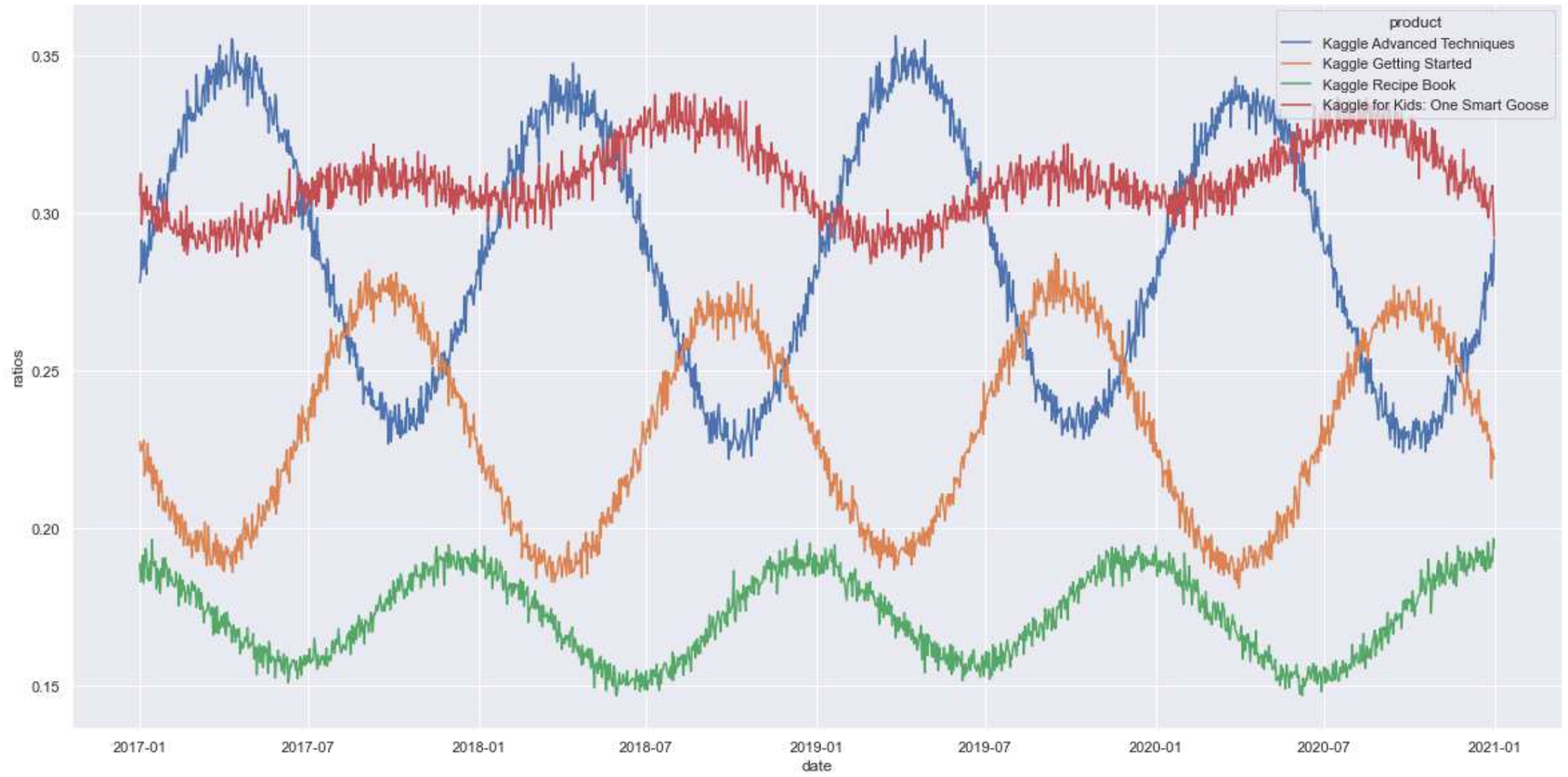


Figure 8: Product ratio trend

Aggregated Time Series

- aggregate the sales timeline to consider how to forecast the overall sales volume.

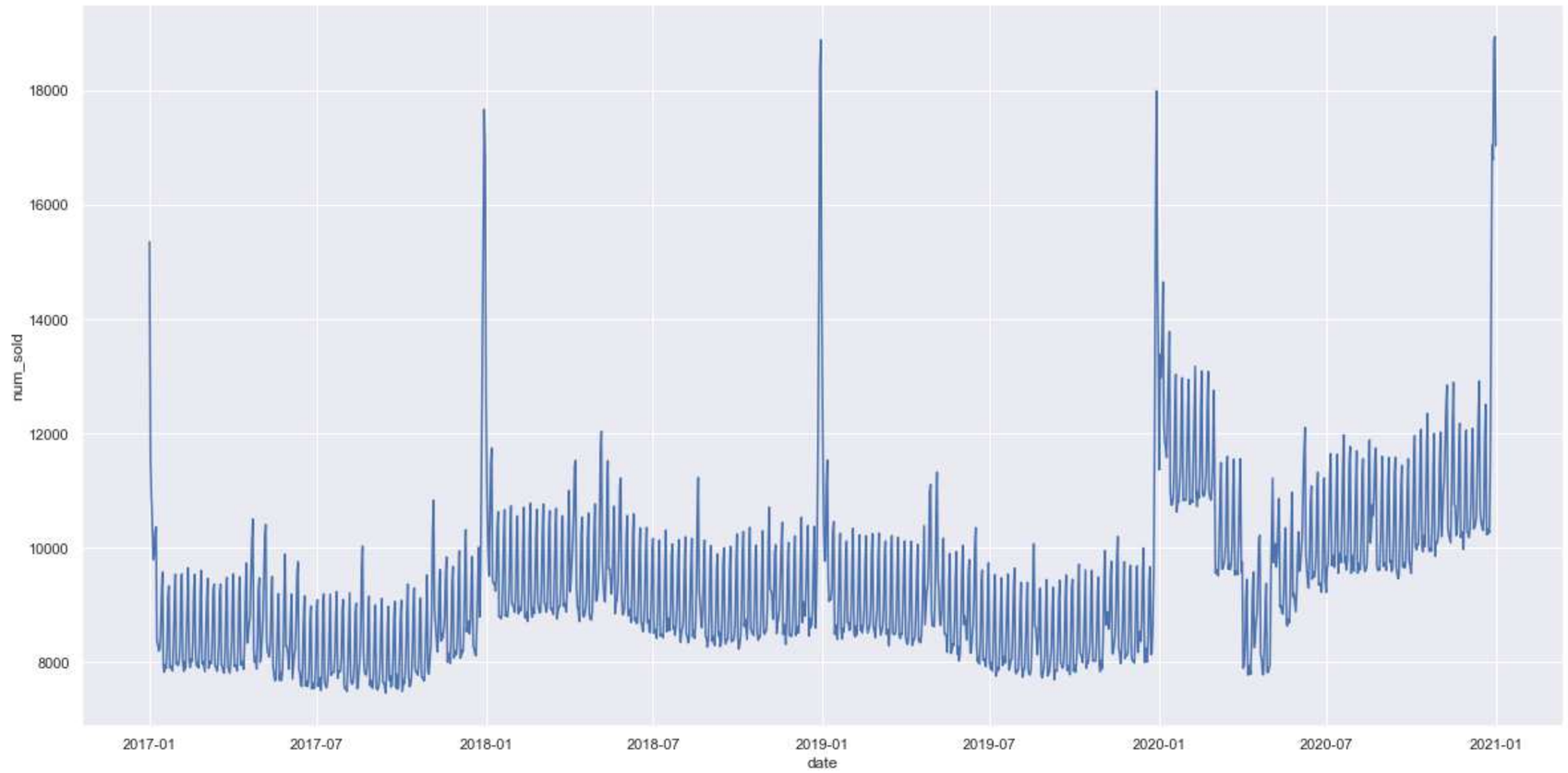


Figure 9: Aggregated time series

Feature Extraction

Framework of GOAM algorithm:

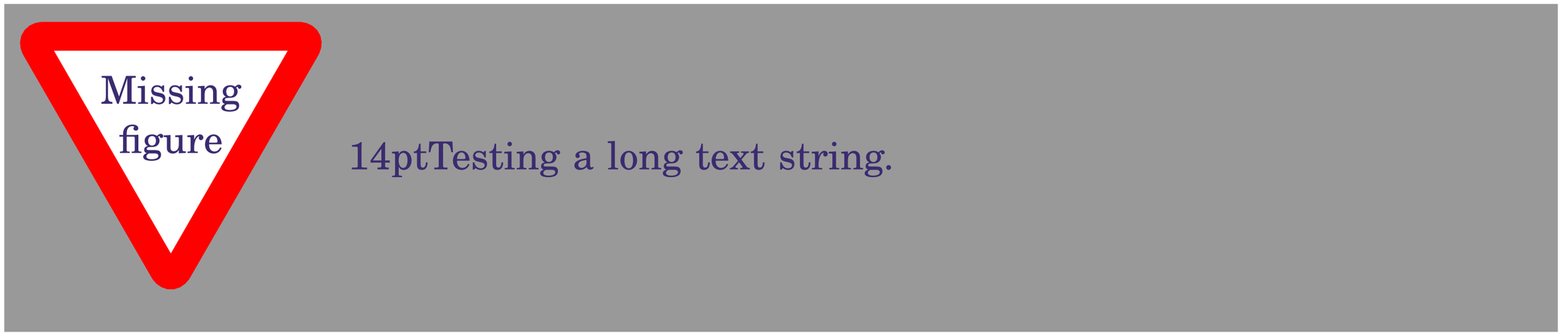


Figure 10: Framework of GOAM Algorithm

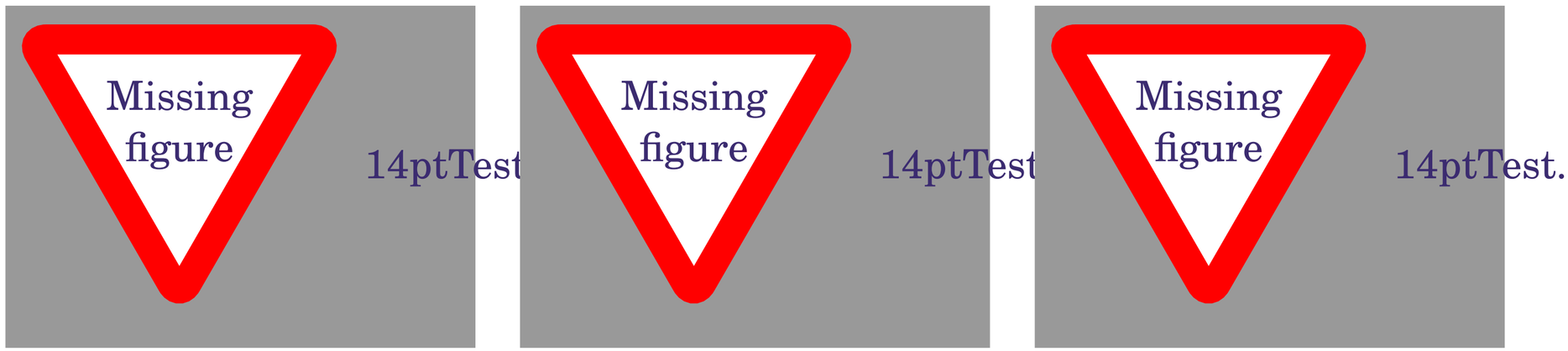
Step One - Group Feature Extraction

- 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 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

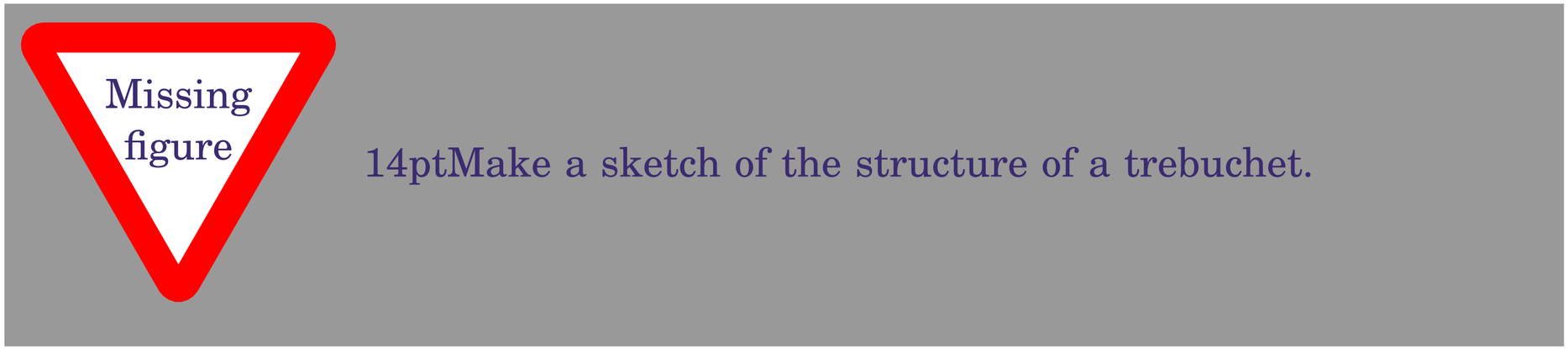


Figure 12: EMD of one feature

Step Two - Outlying Degree Scoring

- Calculate the outlying degree

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

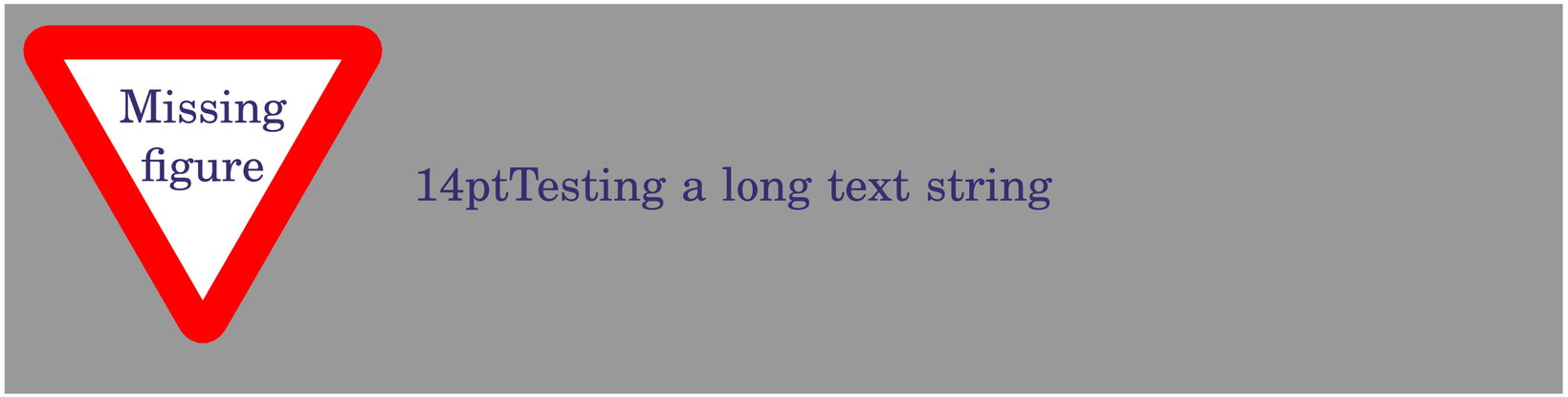
  - n ⇔ the number of contrast groups.
  - h_{k_s} ⇔ the histogram representation of G_k in the subspace s.

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: $O(d * n^2)$

Model Train

Evaluation

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

  P: Identified outlying aspects

  T: Real outlying aspects

- 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	$\{F_1\}$, $\{F_2F_4\}$	$\{F_1\}$, $\{F_2F_4\}$	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 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?

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