Sales of Books Forecast

Lin Jiahong

Nanjing University of Science and Technology

(None)

Overview

Problem Definition

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

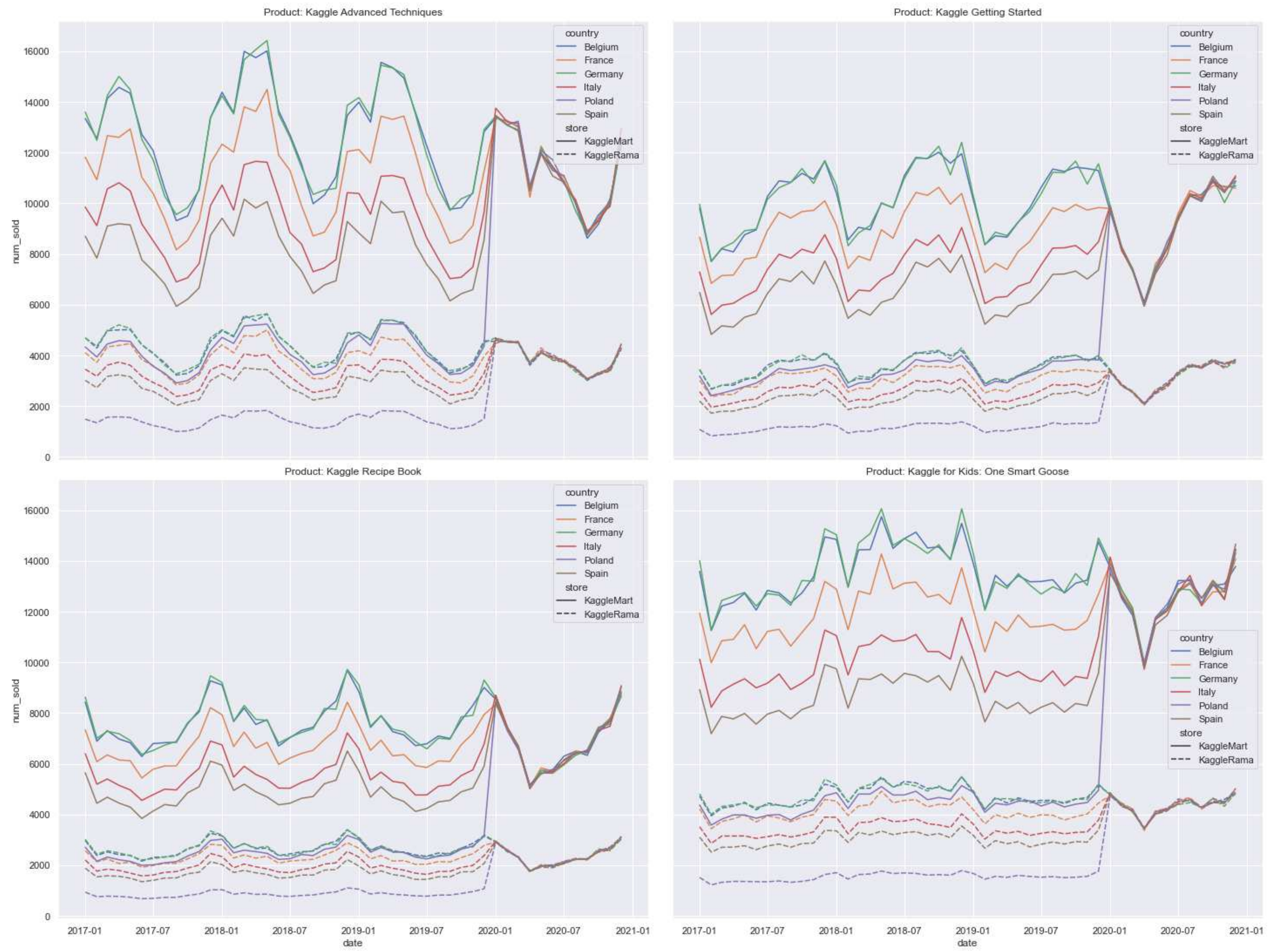


Figure 1: Monthly sales

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

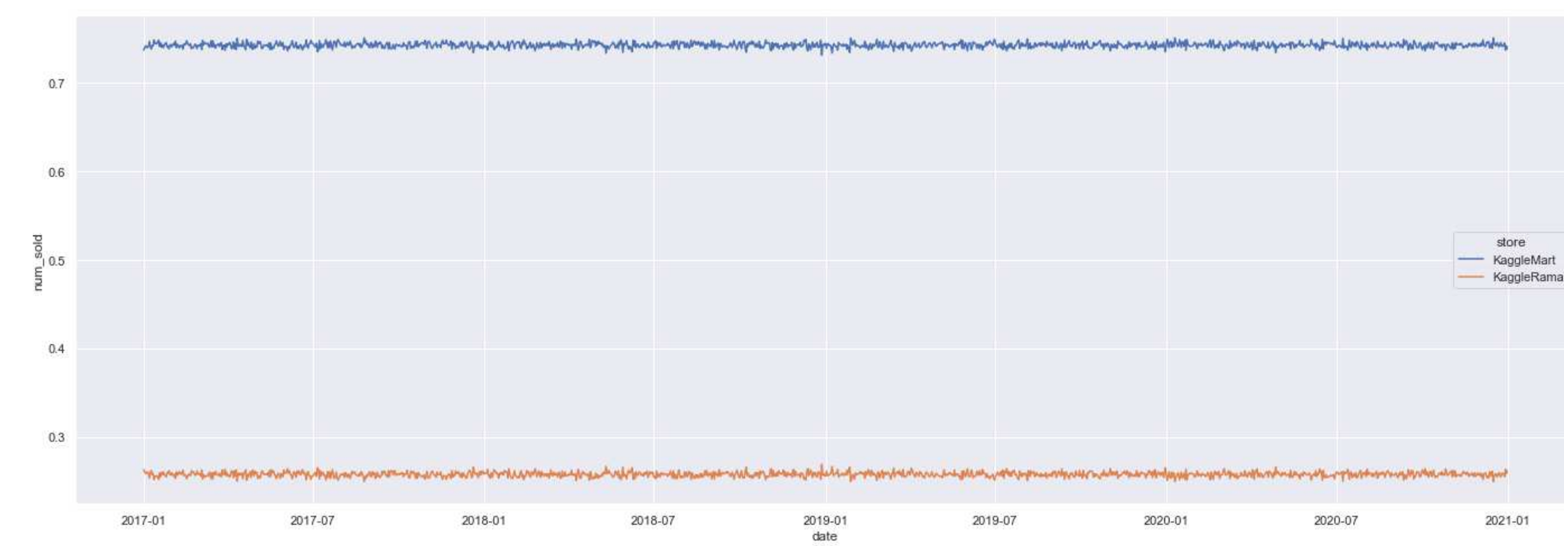


Figure 2: Stores ratio

Aggregating Time Series(Store)

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

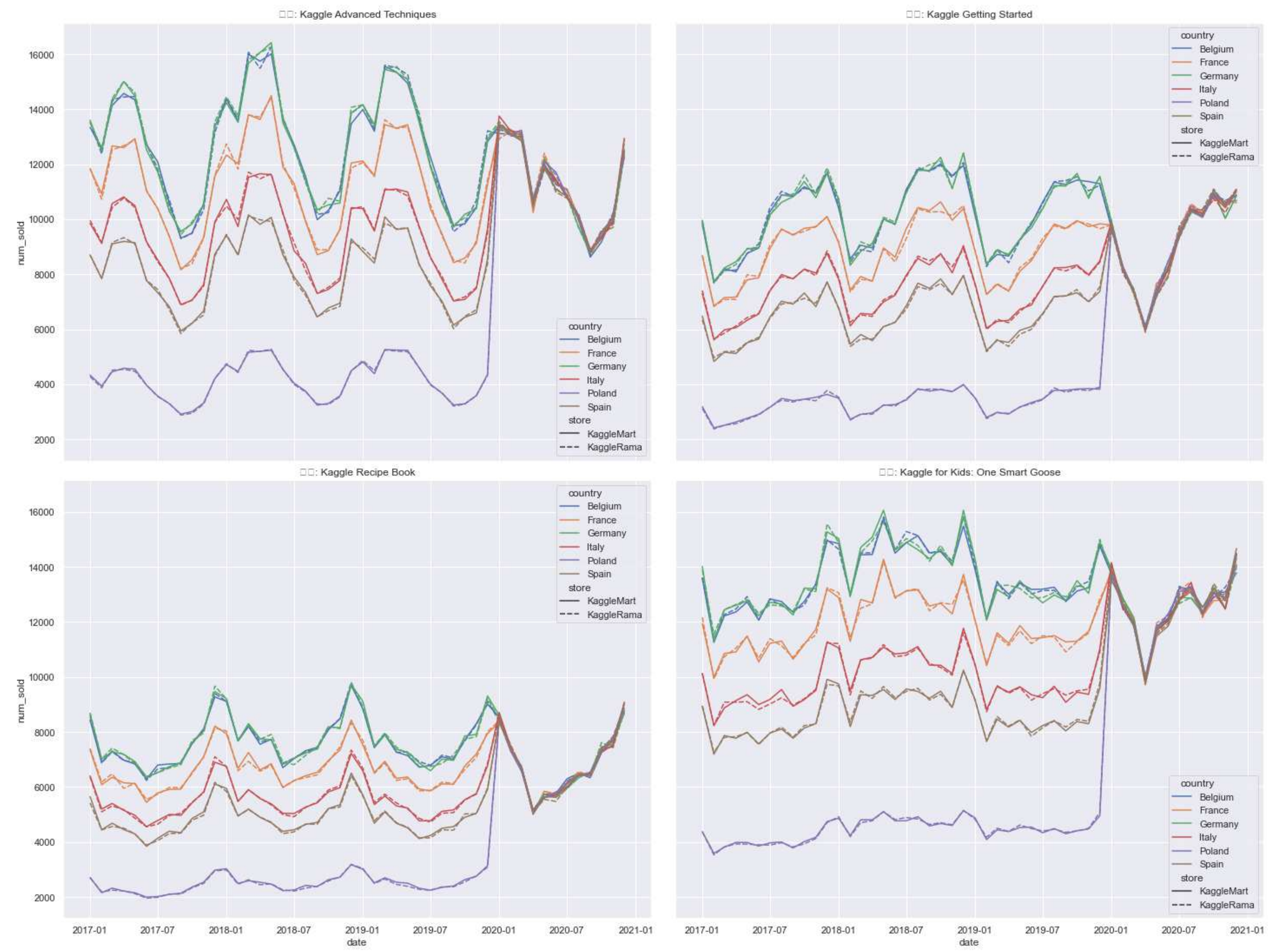


Figure 3: Stores ratio trend

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

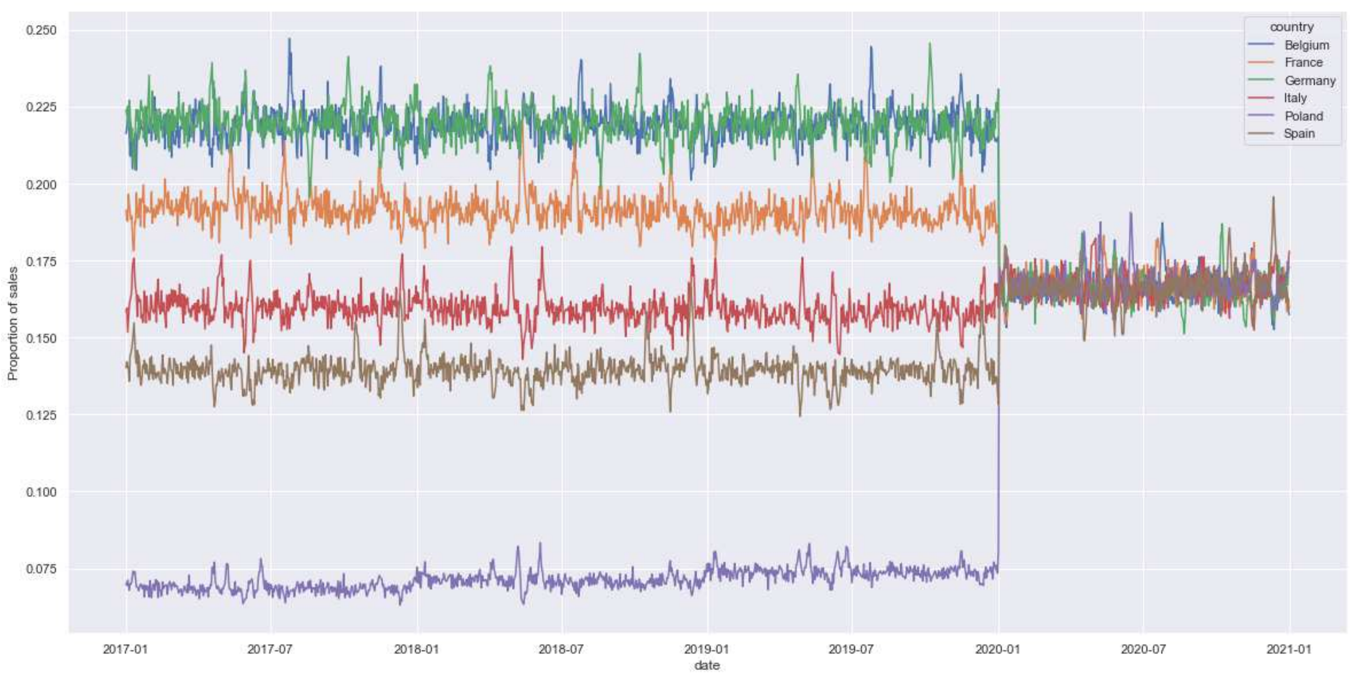


Figure 4: Countries ratio

Aggregating Time Series(Country)

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

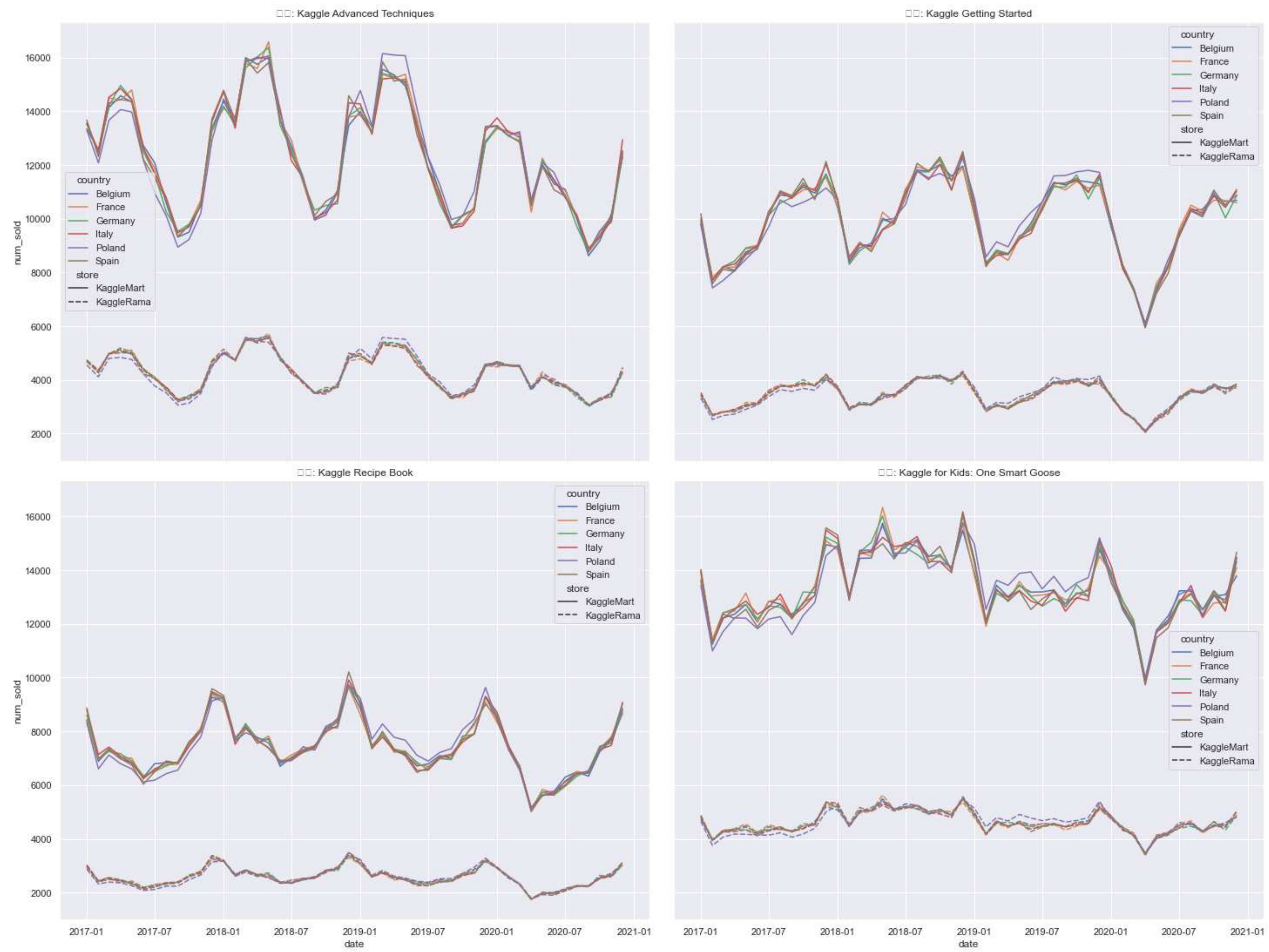


Figure 5: Countries ratio trend

Aggregating Time Series(Country and Store)

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

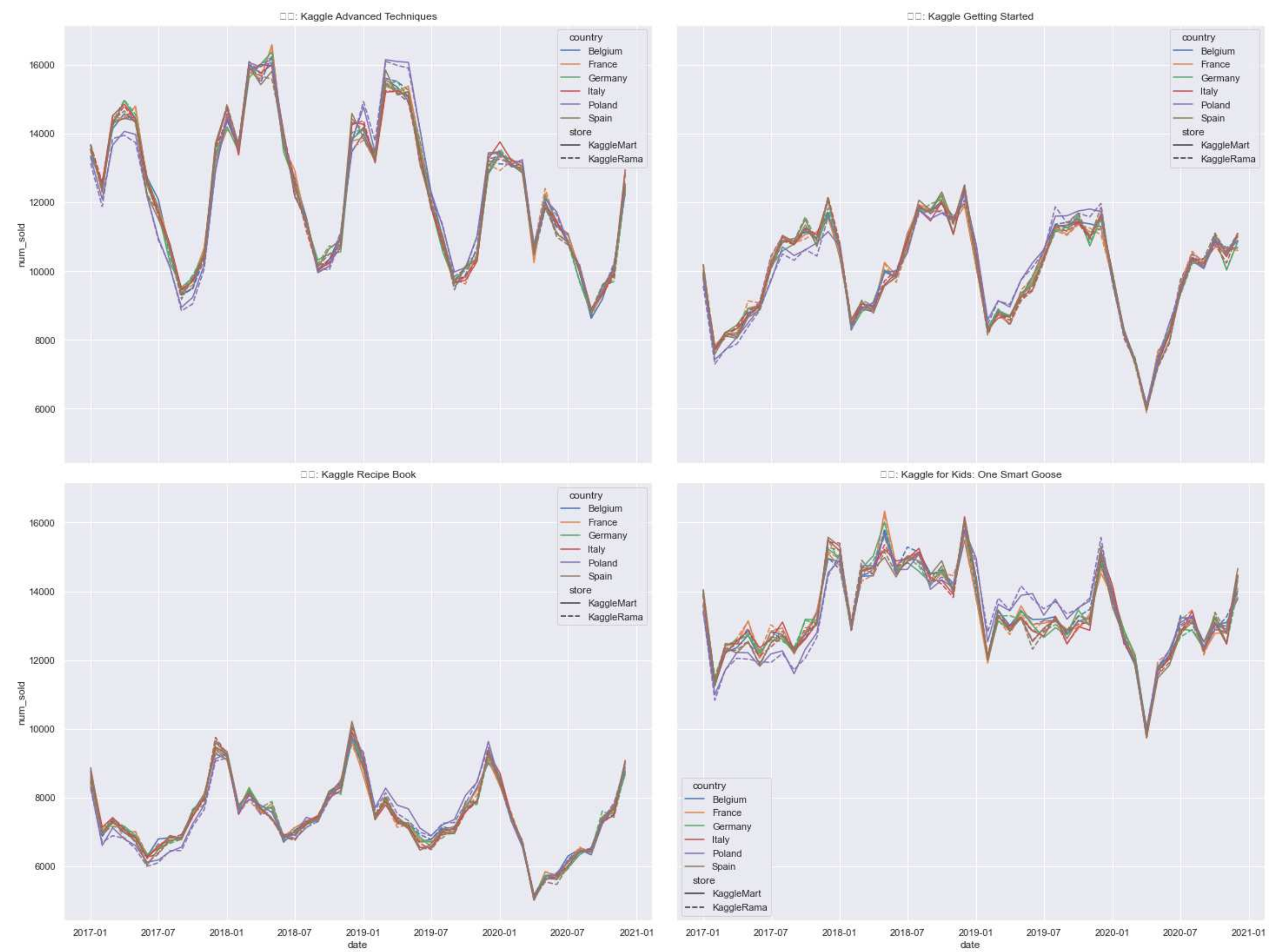


Figure 6: Countries and Store trend

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

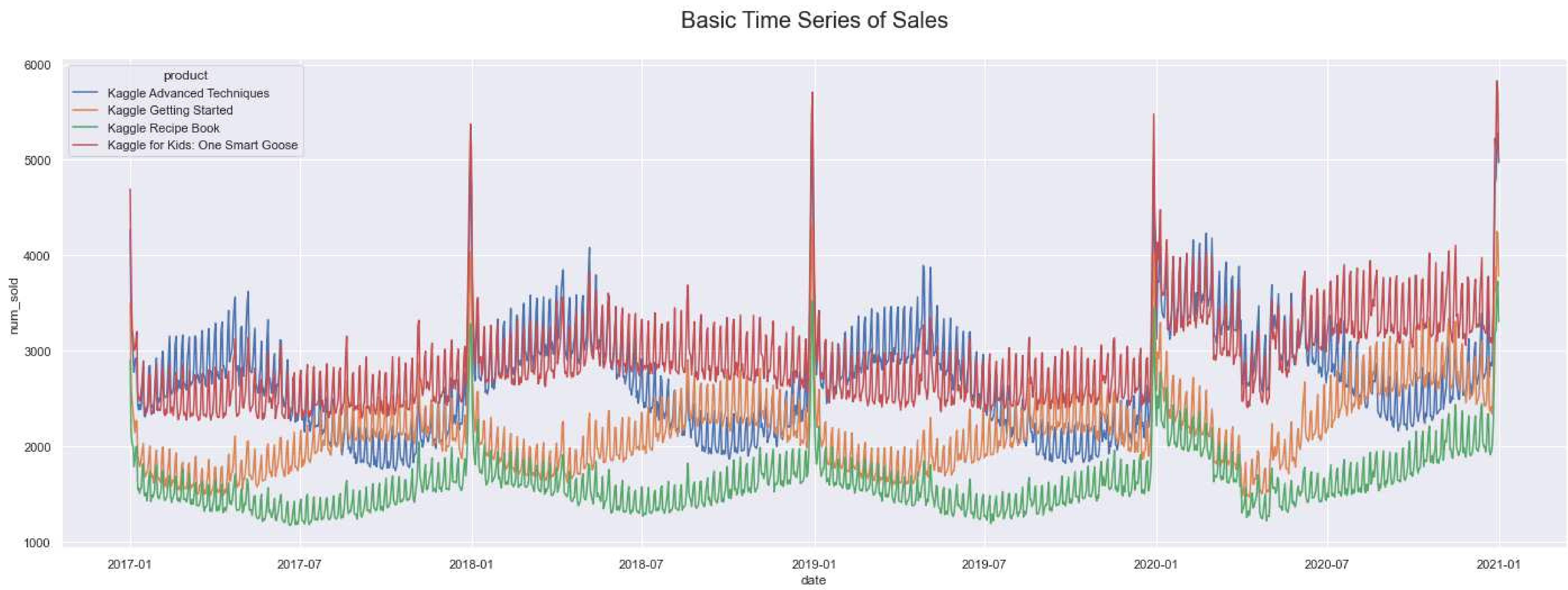


Figure 7: Sales of Product

Aggregating Time Series(Product)

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

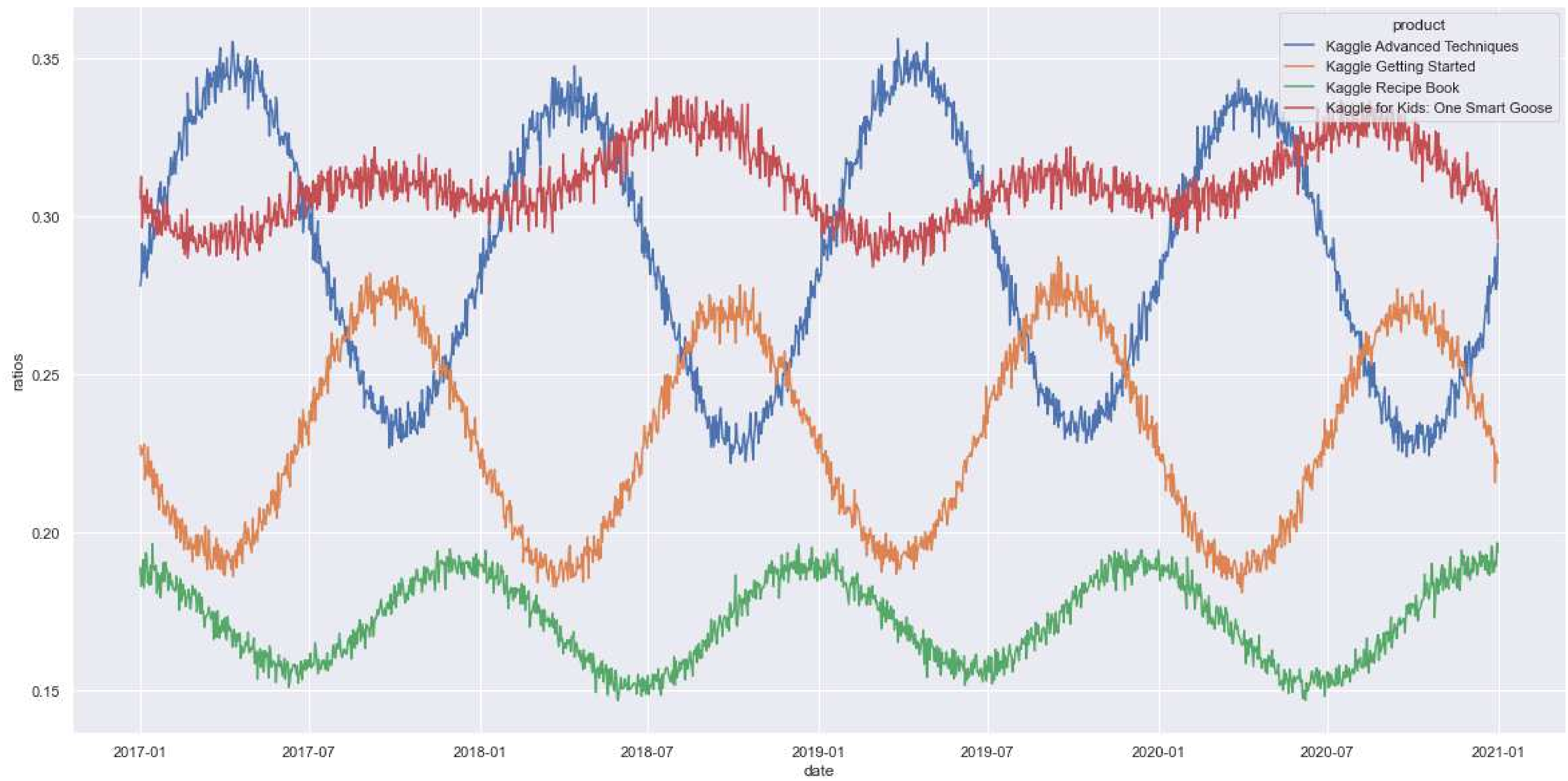


Figure 8: Product ratio trend

Aggregated Time Series

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

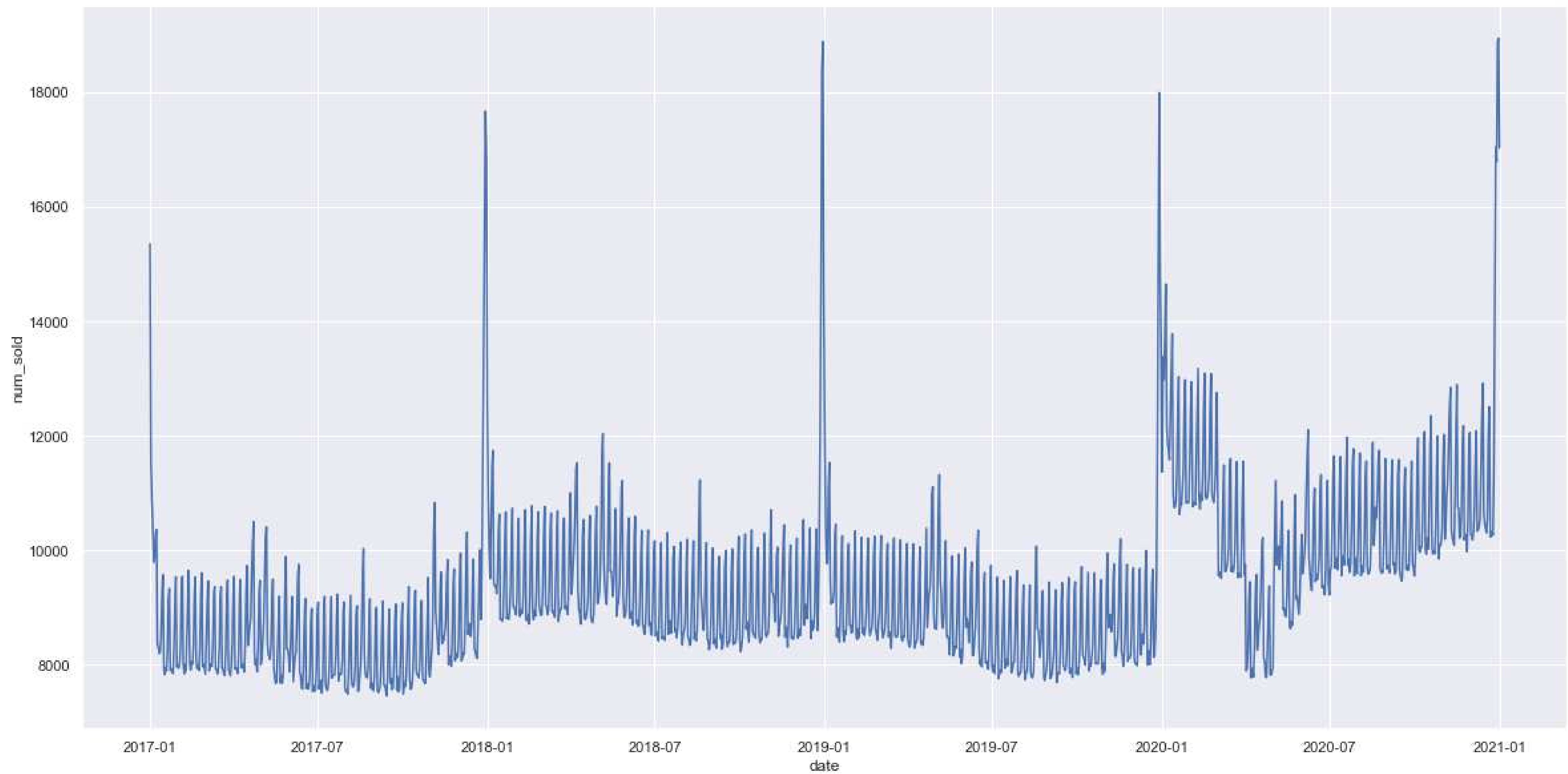


Figure 9: Aggregated time series

Feature Extraction

Framework of GOAM algorithm:

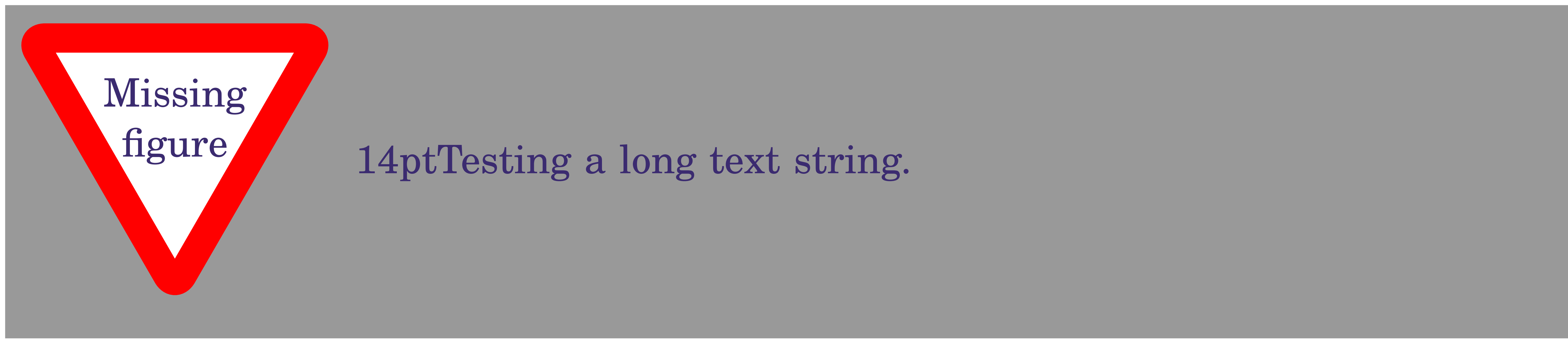


Figure 10: Framework of GOAM Algorithm

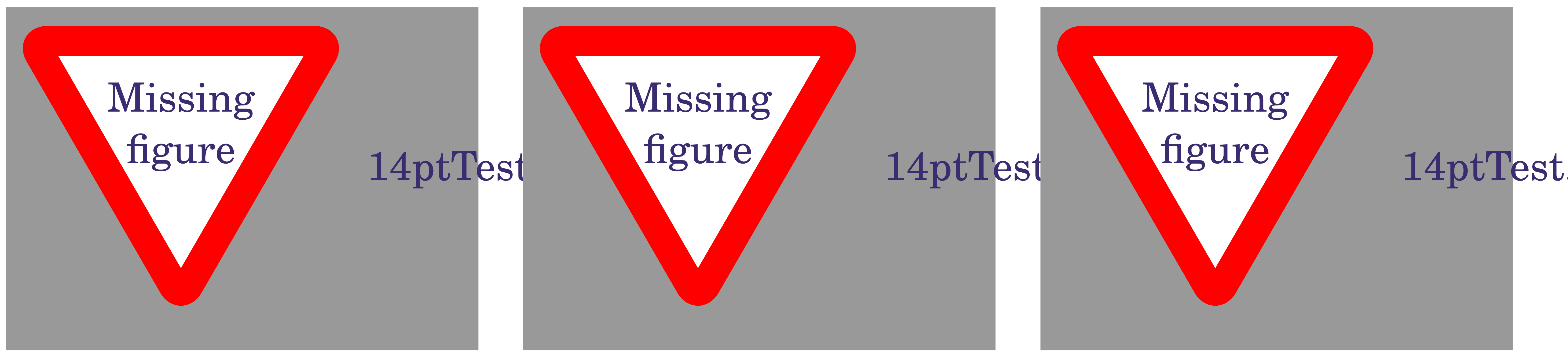
Step One - Group Feature Extraction

- 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

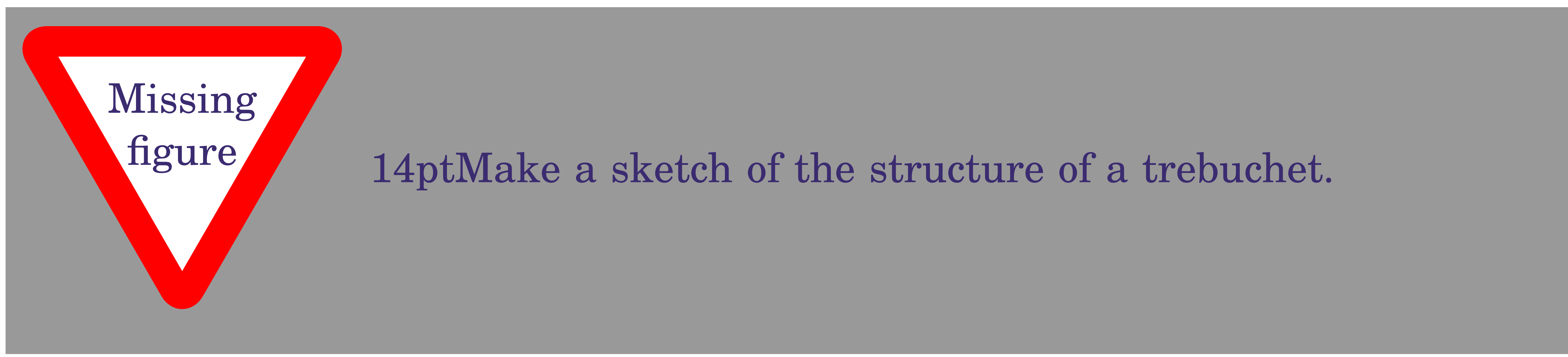


Figure 12: EMD of one feature

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

14ptTesting a long text string

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

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

- 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*).

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}

Problem Definition
Data Analysis
Feature Extraction
Model Train
Conclusion

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