BIG DATA IN MACHINE LEARNING

Bài 9: PySpark ML – Clustering, Recommender System

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https://fcse.edu.vn/lap-trinh-va-cntt/Big-Data-la-Machine-Learning-125

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Nội dung

1. **Clustering K-Means**
2. **Recommender System – ALS**
3. **Association rules - FPGrowth**

Clustering K-Means

❑Clustering

- Input: Unlabled data
- Apply: Unsupervised learning Algorithm
- Output: Các cluster có thể của data

❑Nghĩa là, chúng ta có data chỉ chứa các feature và muốn tìm ra các pattern trong dữ liệu giúp có thể tạo ra các group/cluster.

Clustering K-Means

❑Bản chất

- Về mặt bản chất: vấn đề là khó có thể đánh giá các group/cluster theo "mức độ chính xác" ("correctness").
- Phần lớn công việc diễn giải các cluster này dựa vào "domain knowledge".
- Ngoài ra, tùy thuộc vào thuật toán phân cụm (clustering algorithm), chúng ta có thể quyết định trước số lượng cụm muốn tạo.
- Rất nhiều vấn đề phân cụm không có cách tiếp cận hoặc trả lời đúng 100%, đó là bản chất của việc học tập không giám sát!

Clustering K-Means

- Ví dụ:
  - Nếu chúng ta có dữ liệu khách hàng, sau đó được yêu cầu phân cụm thành các nhóm riêng biệt.
  - Việc phân nhóm này sẽ tùy thuộc vào chúng ta quyết định những gì sẽ đại diện cho các nhóm. Công việc này đôi khi dễ dàng, đôi khi rất khó khăn.

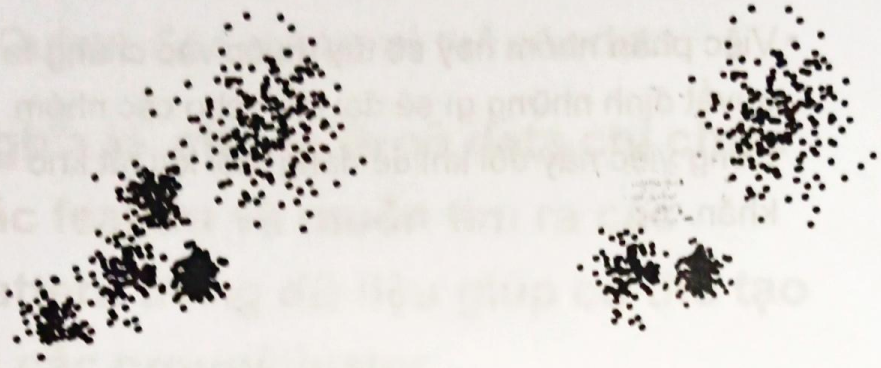
Clustering K-Means

❑K-Means

- K Means Clustering là một thuật toán thuộc nhóm unsupervised learning, cố gắng nhóm các cụm tương tự lại với nhau dựa trên dữ liệu.
- Vì vậy, một vấn đề phân cụm điển hình là:
  - Cụm các tài liệu tương tự
  - Cụm khách hàng dựa trên các thuộc tính
  - Phân khúc thị trường
  - Xác định các nhóm (vật lý) tương tự

Clustering K-Means

- Mục tiêu tổng thể là phân chia dữ liệu thành các nhóm riêng biệt sao cho các đối tượng trong mỗi nhóm tương tự nhau.

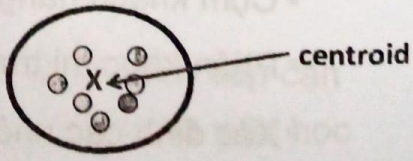


có 2 cách để phân loại cụm:
+ elbow method : page version 2
+ silhouette : page version 3

Clustering K-Means

❑K-Means Algorithm

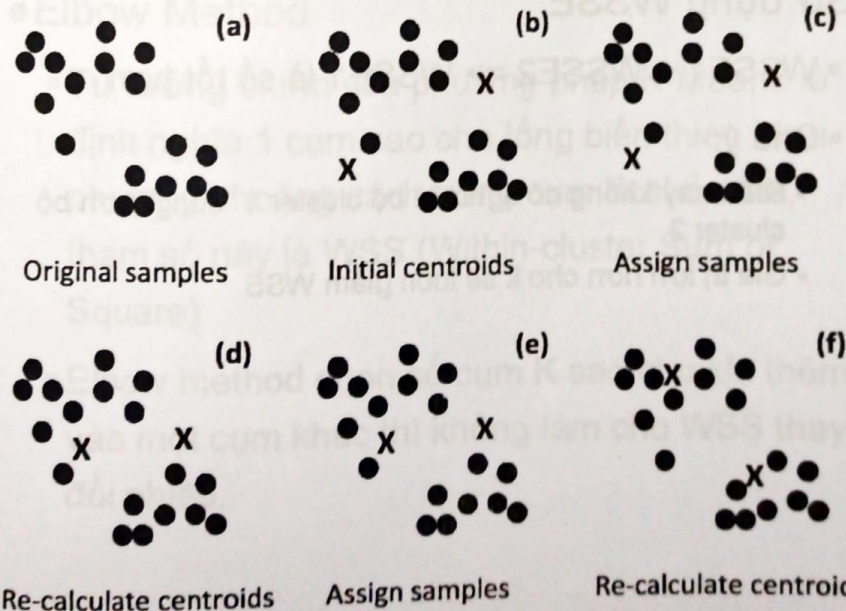
- Lựa chọn k centroid ban đầu (cluster center)
- Lặp:
  - Gán từng mẫu với centroid gần nhất
  - Tính toán trung bình của các cluster để xác định centroid mới
- Cho đến khi:
  - Đạt được tiêu chí dừng



Clustering K-Means

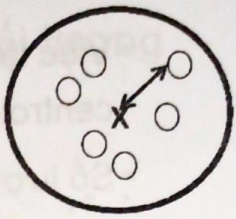
- Tiêu chí dừng
  - Việc lặp sẽ dừng khi không có sự thay đổi các centroid
  - Số lượng các mẫu thay đổi cluster dưới ngưỡng (threshold)

Clustering K-Means



Clustering K-Means

- Tính toán kết quả cluster
  - error = khoảng cách giữa sample và centroid
  - squared error = error^2
  - Tính tổng các squared error giữa tất cả các sample và centroid



=> Tính tổng trên tất cả các cluster => WSSE

Within-Cluster Sum of Squared Error

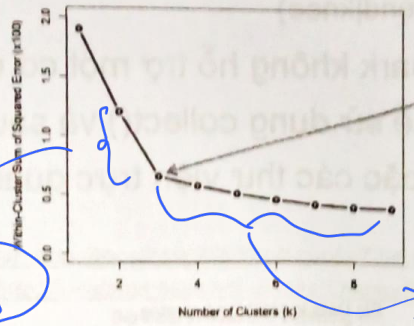
Clustering K-Means

- Sử dụng WSSE
  - WSSE1 < WSSE2 => WSSE1 là số tốt hơn
  - Chú ý:
    - Điều này không có nghĩa là bộ cluster 1 "đúng" hơn bộ cluster 2
    - Giá trị lớn hơn cho k sẽ luôn giảm WSS

K càng lớn thì WSS càng nhỏ

Clustering K-Means

- Chọn K
  - Không có câu trả lời dễ dàng cho việc chọn giá trị tốt nhất của K
  - Một cách là dùng phương pháp khuỷu tay (elbow method)



Đề xuất chọn K = 3

WSS thay đổi nhiều khúc này

khúc này thay đổi ít

13

có 2 cách chọn K
+ theo sếp
+ theo pp khuỷu tay

Clustering K-Means

- Elbow Method
  - Tư tưởng chính của phương pháp K-Means là định nghĩa 1 cụm sao cho tổng biến thiên bình phương khoảng cách trong cụm là nhỏ nhất, tham số này là WSS (Within-cluster Sum of Square)
  - Elbow method chọn số cụm K sao cho khi thêm vào một cụm khác thì không làm cho WSS thay đổi nhiều.

Clustering K-Means

- Elbow Method
  - Qui trình triển khai Elbow method như sau:
    - Triển khai thuật toán K-Means với các số cụm K thay đổi (ví dụ từ 2 đến 10)
    - Với mỗi giá trị K, tính giá trị WSS
    - Vẽ Elbow curve theo các giá trị K.
    - Dựa vào Elbow curve chọn số K thích hợp, là vị trí ở khúc cua (bend|knee)
  - Chú ý: Pyspark không hỗ trợ một cơ chế vẽ, nhưng có thể sử dụng collect() và sau đó vẽ bằng matplotlib hoặc các thư viện trực quan khác.

Clustering K-Means

- Nhưng không nên coi đây là một quy tắc nghiêm ngặt khi chọn giá trị K. Việc phân nhóm còn phụ thuộc vào bối cảnh của tình huống chính xác (domain knowledge)

Clustering K-Means

❑Triển khai K-Means

- pyspark.ml.classification.clustering. KMeans

Without Scaler: http://localhost:8888/notebooks/Chapter9/demo_Kmeans.ipynb

With Scaler: http://localhost:8888/notebooks/Chapter9/demo_Kmeans_Scaler.ipynb

Clustering K-Means

- Ví dụ: Thực hiện bài toán phân cụm với dữ liệu 5000_points.txt. Với số cụm dao động từ 2 – 10.
  - Đọc dữ liệu

```
# Loads data.
data = spark.read.csv("5000_points.txt", header=False,
                      inferSchema=True, sep="\t")

data.show(3)
```

```
+------+------+
|   _c0|   _c1|
+------+------+
|664159|550946|
|665845|557965|
|597173|575538|
+------+------+
only showing top 3 rows
```

Clustering K-Means

- Chuẩn hóa dữ liệu (nếu cần)

```
from pyspark.sql.functions import col
data = data.select(col("_c0").alias("x"), col("_c1").alias("y"))

data.show(3)

+------+------+
|     x|     y|
+------+------+
|664159|550946|
|665845|557965|
|597173|575538|
+------+------+
only showing top 3 rows
```

Clustering K-Means

- Chuyển đổi dữ liệu

```
from pyspark.ml.linalg import Vectors
from pyspark.ml.feature import VectorAssembler

data.columns

['x', 'y']

vec_assembler = VectorAssembler(inputCols = data.columns,
                                outputCol='features')

final_data = vec_assembler.transform(data)
```

Clustering K-Means

- Scale dữ liệu (nếu cần)

```
from pyspark.ml.feature import StandardScaler

scaler = StandardScaler(inputCol="features", outputCol="scaledFeatures",
                        withStd=True, withMean=False)

# Compute summary statistics by fitting the StandardScaler
scalerModel = scaler.fit(final_data)

# Normalize each feature to have unit standard deviation.
final_data = scalerModel.transform(final_data)

final_data.show(3, False)
```

```
+------+------+------------------+------------------------------------------+
|x     |y     |features          |scaledFeatures                            |
+------+------+------------------+------------------------------------------+
|664159|550946|[664159.0,550946.0]|[2.716775610700365,2.336092297255214]    |
|665845|557965|[665845.0,557965.0]|[2.7236722780340017,2.3658538924649704]  |
|597173|575538|[597173.0,575538.0]|[2.4427660270639544,2.440366004250274]   |
+------+------+------------------+------------------------------------------+
only showing top 3 rows
```


Clustering K-Means

- Xây dựng model
  - Chọn k thích hợp (trong khoảng từ 2-10)

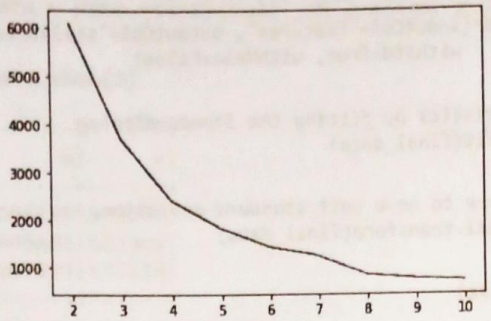
```
from pyspark.ml.clustering import KMeans

# Trains a k-means model.
k_list = []
wssse_list = []
for k in range(2,11):
    # kmeans = KMeans(featuresCol='features',k=k)
    kmeans = KMeans(featuresCol='scaledFeatures',k=k)
    model = kmeans.fit(final_data)
    wssse = model.computeCost(final_data)
    k_list.append(k)
    wssse_list.append(wssse)
    print("With k =", k, "Set Sum of Squared Errors = " + str(wssse))
```

Clustering K-Means

- Xây dựng model (tt)

```
plt.plot(k_list, wssse_list)
plt.show()
```




```
With k = 2 Set Sum of Squared Errors = 6086.719508212722
With k = 3 Set Sum of Squared Errors = 3706.746994293558
With k = 4 Set Sum of Squared Errors = 2406.331723769621
With k = 5 Set Sum of Squared Errors = 1817.0452245537108
With k = 6 Set Sum of Squared Errors = 1431.651801147981
With k = 7 Set Sum of Squared Errors = 1239.5344779608115
With k = 8 Set Sum of Squared Errors = 844.1587813075814
With k = 9 Set Sum of Squared Errors = 758.2190969540461
With k = 10 Set Sum of Squared Errors = 716.2779344197979
```


Clustering K-Means

- Xây dựng model (tt)

```
# Trains a k-means model.
kmeans = KMeans(featuresCol='scaledFeatures',k=10)
model = kmeans.fit(final_data)

# Evaluate clustering by computing Within Set Sum of Squared Errors.
wssse = model.computeCost(final_data)
print("Within Set Sum of Squared Errors = " + str(wssse))

Within Set Sum of Squared Errors = 716.2779344197979

# Shows the result.
centers = model.clusterCenters()
print("Cluster Centers: ")
for center in centers:
    print(center)
```

```
Cluster Centers:
[3.48538772 0.66860987]
[0.96278248 2.3742748 ]
[2.47672914 2.43665775]
[1.70360373 0.71250277]
[3.28321464 1.37765613]
[2.48029822 1.6930302 ]
[1.33679274 3.4704405 ]
[2.77092183 3.63555263]
[3.45308435 2.676229  ]
[1.14099447 1.58997597]
```

Clustering K-Means

- Dự đoán kết quả

```
predictions = model.transform(final_data)

predictions.select("prediction").show(5)
```

```
+----------+
|prediction|
+----------+
|         2|
|         2|
|         2|
|         2|
|         2|
+----------+
only showing top 5 rows
```

```
predictions.groupBy('prediction').count().show()
```

```
+----------+-----+
|prediction|count|
+----------+-----+
|         1|  640|
|         6|  358|
|         3|  667|
|         5|  341|
|         9|  349|
|         4|  349|
|         8|  650|
|         7|  397|
|         2|  320|
|         0|  929|
+----------+-----+
```


Clustering K-Means

- Dự đoán kết quả (tt)

```
final_data.show(3, False)
```

```
+------+------+------------------+------------------------------------+
|x     |y     |features          |scaledFeatures                      |
+------+------+------------------+------------------------------------+
|664159|550946|[664159.0,550946.0]|[2.716775610700365,2.336092297255214]|
|665845|557965|[665845.0,557965.0]|[2.7236722780340017,2.3658538924649704]|
|597173|575538|[597173.0,575538.0]|[2.4427660270639544,2.440366004250274]|
+------+------+------------------+------------------------------------+
only showing top 3 rows
```

```
temp = final_data.select("scaledFeatures").rdd.map(lamòda x: x[0].toArray().tolist()).toDF()

temp.show(3)
```

```
+------------------+------------------+
|                _1|                _2|
+------------------+------------------+
| 2.716775610700365| 2.336092297255214|
|2.7236722780340017|2.3658538924649704|
|2.4427660270639544| 2.440366004250274|
+------------------+------------------+
only showing top 3 rows
```

Clustering K-Means

- Dự đoán kết quả (tt)

```
temp=temp.withColumn('row_index', f.monotonically_increasing_id())
data_result=data_result.withColumn('row_index', f.monotonically_increasing_id())
temp = temp.join(data_result, on=["row_index"]).sort("row_index").drop("row_index")
```

```
temp.show(3)
```

```
+------------------+------------------+----------+
|                _1|                _2|prediction|
+------------------+------------------+----------+
| 2.716775610700365| 2.336092297255214|         2|
|2.7236722780340017|2.3658538924649704|         2|
|2.4427660270639544| 2.440366004250274|         2|
+------------------+------------------+----------+
only showing top 3 rows
```

```
temp = temp.select(col("_1").alias("x_scale"), col("_2").alias("y_scale"), "prediction")
```

```
df = temp.toPandas()
```

Clustering K-Means

- Trực quan hóa dữ liệu

```
df = temp.toPandas()

centers_df = pd.DataFrame(centers)
centers_df.head()
```

	0	1
0	3.485388	0.668610
1	0.962782	2.374275
2	2.476729	2.436658
3	1.703604	0.712503
4	3.283215	1.377656

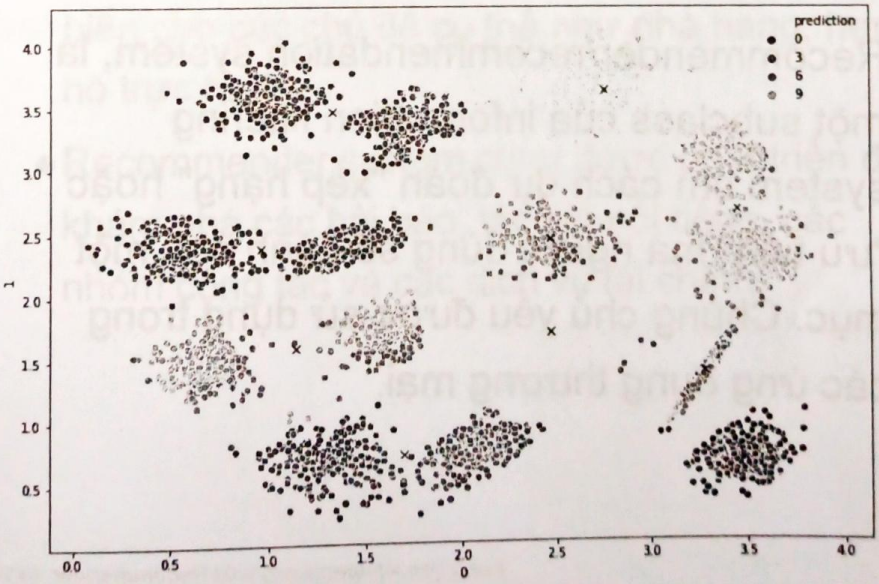
Clustering K-Means

- Trực quan hóa dữ liệu (tt)

```
plt.figure(figsize=(12,8))
sns.scatterplot(x="x_scale", y="y_scale", data = df,
                hue="prediction",
                # size = "prediction",
                palette="Set1")
sns.scatterplot(data = centers_df, x=0, y=1, color="black", marker="x")
plt.show()
```


Clustering K-Means

- Trực quan hóa dữ liệu (tt)



Nội dung

1. Clustering K-Means
2. Recommender System – ALS
3. Association rules - FPGrowth

Recommender System

❑Giới thiệu

- Recommender/recommendation system, là một subclass của information filtering system tìm cách dự đoán "xếp hạng" hoặc "ưu tiên" mà người dùng sẽ dành cho một mục. Chúng chủ yếu được sử dụng trong các ứng dụng thương mại.

https://en.wikipedia.org/wiki/Recommender_system

Recommender System

- Recommender systems được sử dụng trong nhiều lĩnh vực: tạo danh sách phát nhạc/video cho các dịch vụ như Netflix, YouTube & Spotify, đề xuất sản phẩm cho các dịch vụ như Amazon, đề xuất nội dung cho các nền tảng truyền thông xã hội (social media platform) Facebook & Twitter. Những system có thể hoạt động bằng cách sử dụng một single input (như music), hay multiple input trong và trên các nền tảng như news, books,... và truy vấn tìm kiếm (search query).

Recommender System

- Ngoài ra, còn có các recommender system phổ biến cho các chủ đề cụ thể như nhà hang, hẹn hò trực tuyến.., homestay
- Recommender system cũng được phát triển để khám phá các bài báo, tác giả nổi tiếng, các nhóm cộng tác và các dịch vụ tài chính.

Đánh giá sản phẩm
+ Bảng chấm điểm sao (1 sao, 2 sao, ... 5 sao ấy)
+ Comment của người dùng

Recommender System

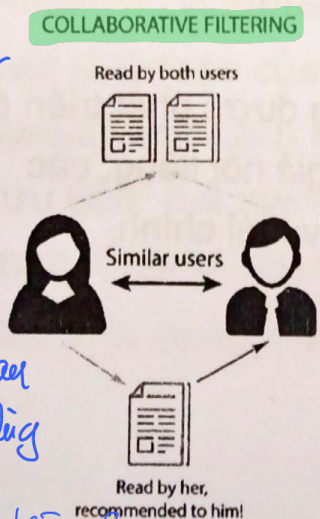
❑ Một cách tổng quát

- Recommender system là các thuật toán nhằm đề xuất các item có liên quan cho người dùng (Item có thể là phim để xem, văn bản để đọc, sản phẩm cần mua hoặc bất kỳ thứ gì khác tùy thuộc vào ngành).
- Recommender system thực sự quan trọng trong một số lĩnh vực vì chúng có thể tạo ra một khoản thu nhập khổng lồ hoặc cũng là một cách để nổi bật đáng kể so với các đối thủ cạnh tranh.

- Khi xây dựng recommend system: phải xây dựng model để dự đoán sao ra sản phẩm còn đang bán chứ (tức dữ liệu phải thập trong khoảng time, tức phải đang trong) + sản phẩm phải còn trong kho, còn kinh doanh thì mới đề xuất chứ k còn bán, kinh doanh thì phải đề xuất, tức train data phải theo trending.

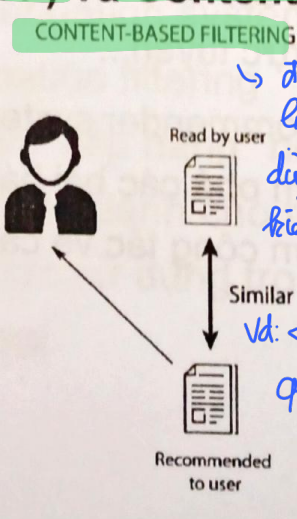
Recommender System

❑ Có hai recommender system phổ biến nhất là Collaborative Filtering (CF) và Content-Based



đề xuất dựa theo sở thích giống nhau giữa những người dùng

+ Dựa trên những người dùng



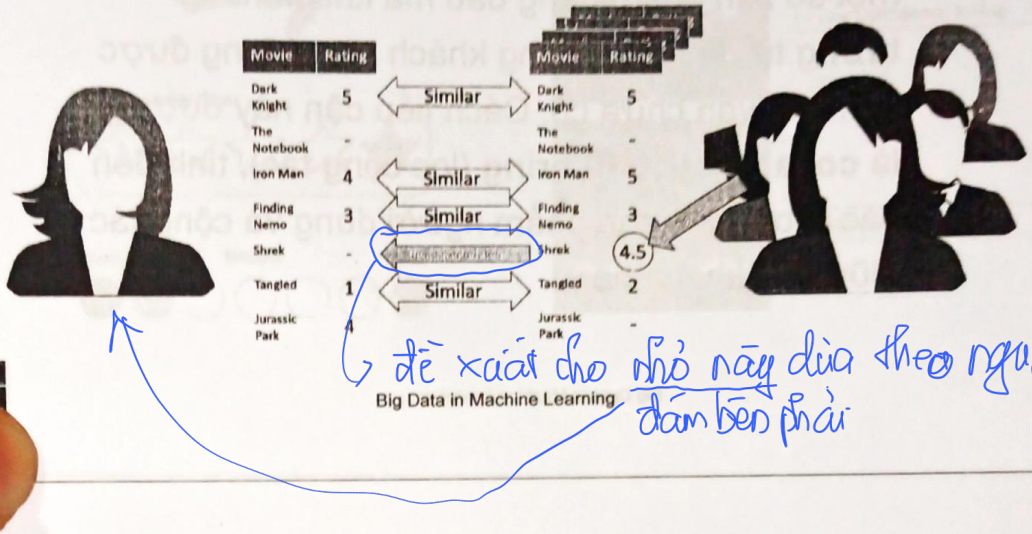
↳ đề xuất dựa theo lịch sử những gì mà người dùng quan tâm + tương tự trong quá khứ

vd: trên FB, google quảng cáo liên quan

+ Dựa theo lịch sử của 1

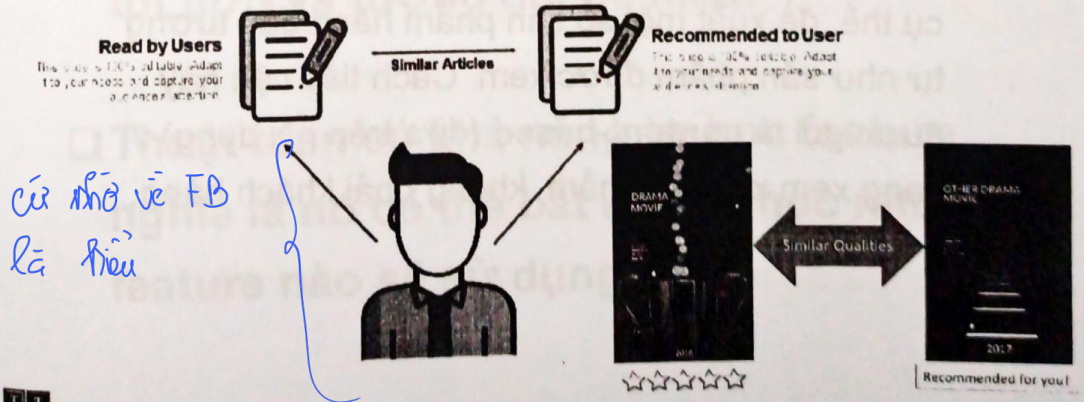
Recommender System

- Collaborative filtering tạo ra các đề xuất dựa trên kiến thức của người dùng về thái độ đối với các item, nó sử dụng kiến thức của số đông ("wisdom of the crowd") để đề xuất các item.



Recommender System

- Content-based recommender system tập trung vào các thuộc tính của item và cung cấp cho người dùng các đề xuất dựa trên sự tương tự giữa chúng.



Recommender System

- Ví dụ:
  - Xem xét lịch sử giao dịch của khách hàng. Đối với một khách hàng cụ thể, hãy tìm những khách hàng có lịch sử giao dịch tương tự và giới thiệu một số sản phẩm hàng đầu mà khách hàng tương tự đã mua nhưng khách hàng đang được xem xét vẫn chưa có. Cách tiếp cận này được gọi là **collaborative filtering** (lọc cộng tác), tính đến các tương tác sản phẩm người dùng và cộng tác giữa các khách hàng.

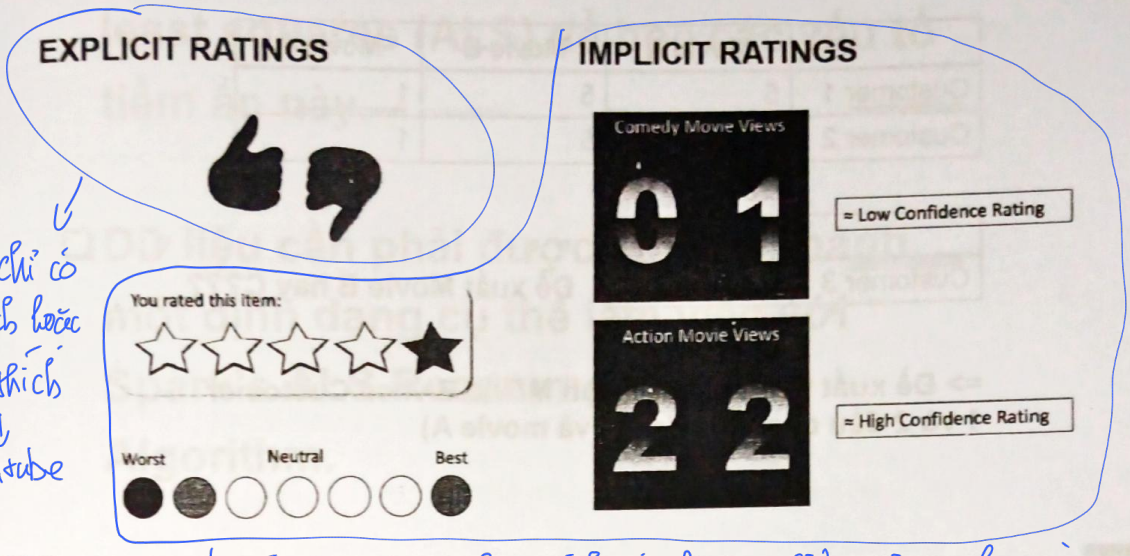
- Khách hàng chỉ có 2 loại
  + Khen ghê lắm : 5*
  + Chê ghê lắm : 1*
  + Khoảng [2,3]* rất ít
  + K° thể điền dữ liệu giả vào, do k° phải chính mình sử dụng nên điền vào sẽ làm giảm sức mạnh của model

Recommender System

- Ví dụ:
  - Xem xét bộ sản phẩm và sử dụng thông tin sản phẩm để tìm sản phẩm tương tự. Do đó, khi người dùng mở một liên kết đến một sản phẩm cụ thể, đề xuất một số sản phẩm hàng đầu tương tự như sản phẩm được xem. Cách tiếp cận này được gọi là **content-based** (dựa trên nội dung) vì đang xem xét sản phẩm, không phải khách hàng.

Recommender System

- Rating: có 2 loại là explicit và implicit



chỉ có thích hoặc k thích → youtube

→ này mua hàng online đánh giá theo *, tiền, shopee hay sai

Recommender System

- Nói chung, Collaborative filtering (CF) được sử dụng nhiều hơn các content-based system vì nó thường cho kết quả tốt hơn và tương đối dễ hiểu.

- Thuật toán có khả năng tự học feature, nghĩa là nó có thể bắt đầu tự học những feature nào sẽ sử dụng.

Recommender System

- Ví dụ:

3 phim A, B, C

	Movie A	Movie B	Movie C
Customer 1	5	5	1
Customer 2	5	5	1

3 khách hàng

	Movie A
Customer 3	5

Đề xuất Movie B hay C???

=> Đề xuất Customer 3 chọn Movie B vì cả Customer 1 và 2 đều chọn movie B (và movie A)

- Khi hệ thống đề xuất, giả sử ta quy định 3 đề xuất thì model sẽ chọn 3 đề xuất có điểm cao nhất, tuy nhiên ta cũng phải đưa ra ngưỡng ví dụ 3 đề xuất này phải 3 * trở lên

Recommender System

- Những kỹ thuật này nhằm mục đích điền vào các mục còn thiếu của ma trận kết hợp user-item (user-item association matrix).

dòng là user cột là item

- spark.ml hiện hỗ trợ model cho collaborative filtering, trong đó người dùng và sản phẩm được mô tả bằng một nhóm nhỏ các yếu tố tiềm ẩn (latent factor) có thể được sử dụng để dự đoán các mục bị thiếu.

Recommender System

- spark.ml sử dụng thuật toán alternating least squares (ALS) để học các yếu tố tiềm ẩn này.
- Dữ liệu cần phải được chuyển thành một định dạng cụ thể làm việc với Spark's ALS Recommendation Algorithm.

Recommender System

- ALS về cơ bản là một cách tiếp cận Matrix Factorization để thực hiện recommendation algorithm mà chúng ta phân tách ma trận user/item lớn thành các yếu tố user và yếu tố item có chiều thấp hơn.

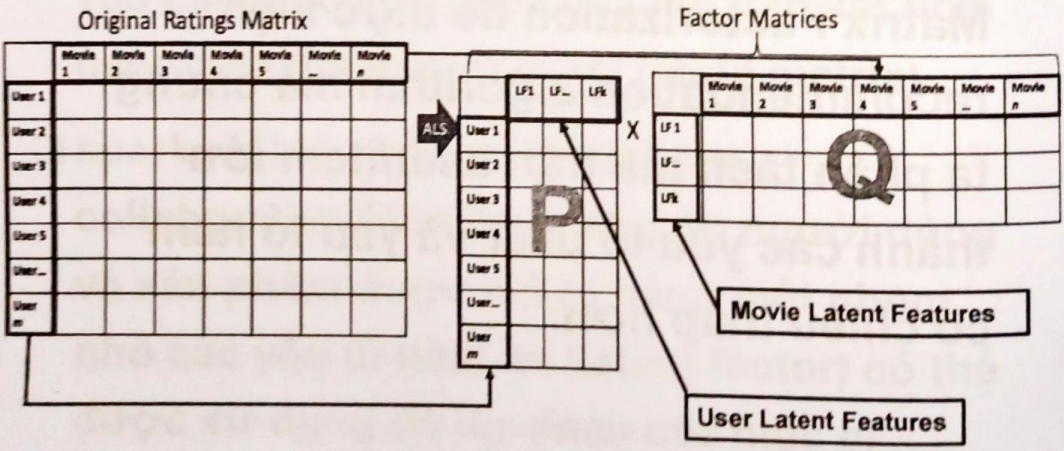
❑ ALS

- Diễn giải với bài toán Users-Products
  - Matrix R_{mxn}
    - m: số lượng user
    - n: số lượng product
  - Phân rã thành P_{mxk} và Q_{kxn} sao cho
    - Với *i*_th product và *u*_th user có thể dự đoán product rating $r_{iu} = q^T_i p_u$ => đưa ra đề xuất.
    - Có nghĩa là mỗi user và mỗi product được mô tả bằng vectors của các latent variable là p và q, mỗi biến có chiều dài là k. Và ma trận P và Q lưu trữ các latent variable (là unobservable variable, ví dụ: một số rating đã biết và một số rating không biết)

m là số lg user
k là số lg nhân tố ẩn
n là số lg product

https://stats.stackexchange.com/questions/...

❑ ALS



Recommender System

❑ALS

Original Ratings Matrix

	Horror Mov1	Horror Mov2	Horror Mov3	Drama Mov1	Drama Mov2	Movie ...	Drama MovN
User 1	5	5	1	1	1	...	1
User 2	4	4	1	1	1	...	1
User 3	4	5	1	1	1	...	1
User 4	2	2	1	1	1	...	1
User 5	1	1	1	5	5	...	5
User...	...	...	...	...	...	...	...
User m	1	1	1	4	5	...	5

ALS

	LF1	LF...	LFk
User 1	2.2	...	.00
User 2	1.9	...	.00
User 3	2.1	...	.01
User 4	.90	...	.01
User 5	.01	...	2.3
User...	...	...	...
User m	.00	...	2.2

P

X

Horror Movies Scored High | Dramas Scored Low

	Horror Mov1	Horror Mov2	Horror Mov3	Drama Mov1	Drama Mov2	Movie ...	Drama MovN
LF 1	2.1	2.2	.01	.04	.04	...	.1
LF ...	...	...	...	...	...	...	...
LFk	.1	.01	.04	2.3	2.1	...	2.2

Q

Horror Movies Scored Low | Dramas Scored High

pygspark die xuất k = 10

Recommender System

❑ALS

Original Matrix

	Movie 1	Movie 2	Movie3	Movie...	Movie n
User 1	5	4.8	4.9	...	4.9
User 2	4.5	4.3	4.4	...	4.3
User 3	4.8	4.6	4.7	...	4.6
User 4	2.1	1.98	2	...	2
User 5	4.1	4	4	...	4
User...	...	...	...	...	...
User m	4.6	4.4	4.5	...	4.4
Avg Rating	4.2	4.0	4.1	...	4

ALS

Factor Matrices

	LF 1	LF...	LF k
User 1	2.2	...	0.0
User 2	1.95	...	0.0
User 3	2.1	...	0.01
User 4	0.90	...	0.01
User 5	1.8	...	0.03
User...	...	...	...
User m	2.0	...	0.02

P

X

	Movie 1	Movie 2	Movie3	Movie...	Movie n
LF 1	2.3	2.2	2.3	...	2.21
LF...	...	...	...	...	...
LF k	0.1	0.01	0.02	...	0.02

Q

❑Triển khai ALS

- pyspark.ml.recommendation.ALS

http://localhost:8888/notebooks/Chapter3/demo_Recommender.ipynb

- Ví dụ: Movies Rating
  - Đọc dữ liệu

```
data = spark.read.csv('movielens_ratings.csv',inferSchema=True,header=True)

data.show(5, False)
```

```
+-------+------+------+
|movieId|rating|userId|
+-------+------+------+
|2      |3.0   |0     |
|3      |1.0   |0     |
|5      |2.0   |0     |
|9      |4.0   |0     |
|11     |1.0   |0     |
+-------+------+------+
only showing top 5 rows
```

```
# Distinct users and movies
users = data.select("userId").distinct().count()
movies = data.select("movieId").distinct().count()
numerator = data.count()

display(numerator, users, movies)
```

```
1501

30

100
```

Recommender System

- Chuẩn hóa dữ liệu, chuyển đổi dữ liệu (nếu cần)
- Chia dữ liệu train-test

```
# Smaller dataset so we will use 0.8 / 0.2
(training, test) = data.randomSplit([0.8, 0.2])
```


Recommender System

- Xây dựng model

* Lưu ý: đừng sài kĩ thuật grid search
↳ nên sài random search cho bộ tham số

```
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.recommendation import ALS

als = ALS(maxIter=5, regParam=0.01,
          userCol="userId",
          itemCol="movieId",
          ratingCol="rating")
model = als.fit(training)
```

3 này bắt buộc

- implicitPrefs: nếu cái liên tiếp coi
- alpha: bước nhảy, default = 1
- nonnegative: có nhận giá trị âm k? nếu muốn chỉ nhận giá trị dg thì set = true, default = false

- maxIter: số lần lặp, default = 10
- regParam: [0, 1], default = 1
- 1 tham số nữa là rank: default = 10, này là k value á
- numBlocks: số partition, default = 10, số RDD á mấy má

Recommender System

▪ Đánh giá kết quả

```
# Evaluate the model by computing the RMSE on the test data
predictions = model.transform(test)

predictions.show(5)
```

```
+-------+------+------+----------+
|movieId|rating|userId|prediction|
+-------+------+------+----------+
|     31|   1.0|     5|  2.424184|
|     31|   3.0|     7| 1.7320327|
|     31|   2.0|    25| 1.9922988|
|     31|   3.0|    14|-0.4973545|
|     85|   1.0|    23|  5.652081|
+-------+------+------+----------+
only showing top 5 rows
```

```
evaluator = RegressionEvaluator(metricName="rmse",
                                labelCol="rating",
                                predictionCol="prediction")

rmse = evaluator.evaluate(predictions)
print("Root-mean-square error = " + str(rmse))
```

```
Root-mean-square error = 1.6706362678979425
```

```
#On average, this model is ~ 1.7 from perfect recommendations.
```

→ rating thì [1,5] mà sai số gần bằng 2 thì model sida lắm

Recommender System

▪ Dự đoán

```
userId = 27
single_user = test.filter(test['userId']==userId).select(['movieId','userId'])

reccomendations = model.transform(single_user)

# prediction
reccomendations.orderBy('prediction',ascending=False).show()
```

```
+-------+------+----------+
|movieId|userId|prediction|
+-------+------+----------+
|     90|    27|  4.205997|
|     94|    27| 3.3630939|
|     98|    27| 1.9856262|
|     55|    27| 1.8030219|
|     40|    27|  1.730906|
|     66|    27| 1.7132561|
|      9|    27| 1.7111484|
|     92|    27| 1.6712735|
|     24|    27| 1.5636977|
|     70|    27| 1.5062279|
|     64|    27| 1.1982841|
|     59|    27|0.87414837|
|     72|    27|0.18111625|
+-------+------+----------+
```

```
single_user.show()
```

```
+-------+------+
|movieId|userId|
+-------+------+
|      9|    27|
|     24|    27|
|     40|    27|
|     55|    27|
|     59|    27|
|     64|    27|
|     66|    27|
|     70|    27|
|     72|    27|
|     90|    27|
|     92|    27|
|     94|    27|
|     98|    27|
+-------+------+
```

Recommender System

- Đưa ra đề xuất cho tất cả user

```
# Get 20 recommendations which have highest rating.
user_recs = model.recommendForAllUsers(20)


for user in user_recs.head(2):
    print(user)
    print("\n")
```

```
Row(userId=28, recommendations=[Row(movieId=92, rating=5.118626117706299), Row(movieId=81,
rating=4.832043170928955), Row(movieId=12, rating=4.752755165100098), Row(movieId=53,
rating=4.616611003875732), Row(movieId=89, rating=4.304506301879883), Row(movieId=74,
rating=4.064364910125732), Row(movieId=2, rating=3.830737352371216), Row(movieId=49,
rating=3.7942352294921875), Row(movieId=82, rating=3.71313214302063), Row(movieId=30,
rating=3.5869648456573486), Row(movieId=4, rating=3.494983196258545), Row(movieId=68,
rating=3.4522364139556885), Row(movieId=24, rating=3.1765313148498535), Row(movieId=23,
rating=3.1444807052612305), Row(movieId=51, rating=3.142695426940918), Row(movieId=77,
rating=2.927616596221924), Row(movieId=62, rating=2.917660713195801), Row(movieId=22,
rating=2.882833957672119), Row(movieId=0, rating=2.7797999382019043), Row(movieId=9,
rating=2.740954637527466)]) Row(userId=26, recommendations=[Row(movieId=32,
rating=6.711236953735352), Row(movieId=30, rating=5.319496154785156), Row(movieId=94,
rating=5.201180458068848), Row(movieId=98, rating=5.186388969421387), Row(movieId=22,
rating=5.1540913581848145), Row(movieId=74, rating=5.077207088470459), Row(movieId=7,
rating=4.8612518310546875), Row(movieId=75, rating=4.7022175788879395), Row(movieId=88,
rating=4.6973724365234375), Row(movieId=23, rating=4.655683517456055), Row(movieId=90,
rating=4.458372116088867), Row(movieId=54, rating=4.276267051696777), Row(movieId=68,
rating=4.1668806076049805), Row(movieId=73, rating=3.908524751663208), Row(movieId=18,
rating=3.8087682723999023), Row(movieId=77, rating=3.8087258338928223), Row(movieId=53,
rating=3.7034876346588135), Row(movieId=10, rating=3.54668927192688), Row(movieId=87,
rating=3.53151798248291), Row(movieId=69, rating=3.2649927139282227)])
```


Recommender System

- Đưa ra đề xuất cho một user cụ thể

```
userId = 27
user_recs.filter(user_recs["userId"] == 27).show(truncate=False)
```

```
|userId|recommendations | +------+-----------------------------------
-----------------------------------------------------------------------
-+ |27 |[[38, 3.841758], [18, 3.8377333], [80, 3.7730618], [65,
3.2105079], [66, 3.184661], [19, 3.1673741], [51, 3.0379815], [27,
3.0274985], [55, 2.5979254], [81, 2.5484018], [11, 2.390921], [85,
2.389595], [32, 2.3870957], [33, 2.3860118], [94, 2.3158324], [83,
2.2594254], [30, 2.255559], [35, 1.9348334], [87, 1.9159526], [2,
1.8787222]]| +------+------------------------------------------------
```

Nội dung

1. Clustering K-Means
2. Recommender System – ALS
3. Association rules - FPGrowth

Association rules

❑Association rule learning

- Là một phương pháp Machine Learning dựa trên trên quy tắc để khám phá mối quan hệ thú vị giữa các biến trong cơ sở dữ liệu lớn. Nó dùng để xác định các quy tắc mạnh được phát hiện trong cơ sở dữ liệu bằng cách sử dụng một số thuật toán thú vị.

https://en.wikipedia.org/wiki/Association_rule_learning

Association rules

- **Market Basket Analysis, association rules mining, là một phương pháp rất hữu ích để hiểu rõ hơn về các bộ dữ liệu giao dịch (transactional data set) và đề xuất sản phẩm.**
  - Ví dụ: Dữ liệu giao dịch trong một siêu thị. Đối với mỗi khách hàng, chúng ta biết những sản phẩm riêng lẻ mà khách hàng đã mua. Với association rules mining, chúng ta có thể xác định các mặt hàng thường được mua cùng nhau.

Association rules

- **Frequent Pattern Mining (FPM)**
  - Khai thác các item, itemset, subsequence, hoặc substructure thường xuyên xuất hiện là một trong những bước đầu tiên để phân tích một tập dữ liệu quy mô lớn, vốn là một chủ đề nghiên cứu tích cực trong khai thác dữ liệu.
  - Thuộc nhóm Association rule learning

❑ FP-growth algorithm (FP: frequent pattern)

- Là thuật toán trong nhóm FPM dùng để phân tích luật kết hợp.
- Thuật toán
  - Cung cấp dữ liệu transactions
  - Bước đầu tiên là tính toán tần số xuất hiện của các item và xác định các frequent item.
  - Bước thứ hai sử dụng suffix tree (FP-tree) để mã hóa các giao dịch mà không tạo ra các bộ ứng cử viên rõ ràng.
  - Sau bước thứ hai, các frequent itemset có thể được trích xuất từ FP-tree

TID	Items
1	{a,b}
2	{b,c,d}
3	{a,c,d,e}
4	{a,d,e}
5	{a,b,c}
6	{a,b,c,d}
7	{a}
8	{a,b,c}
9	{a,b,d}
10	{b,c,e}

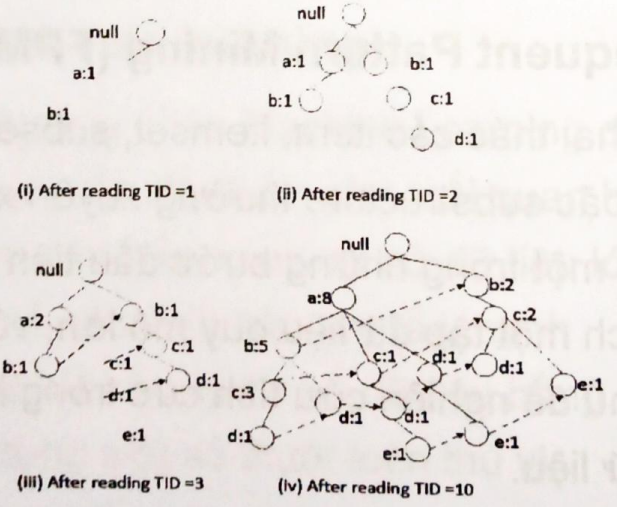


Fig. 7. Construction of an FP-tree - Based on [28]

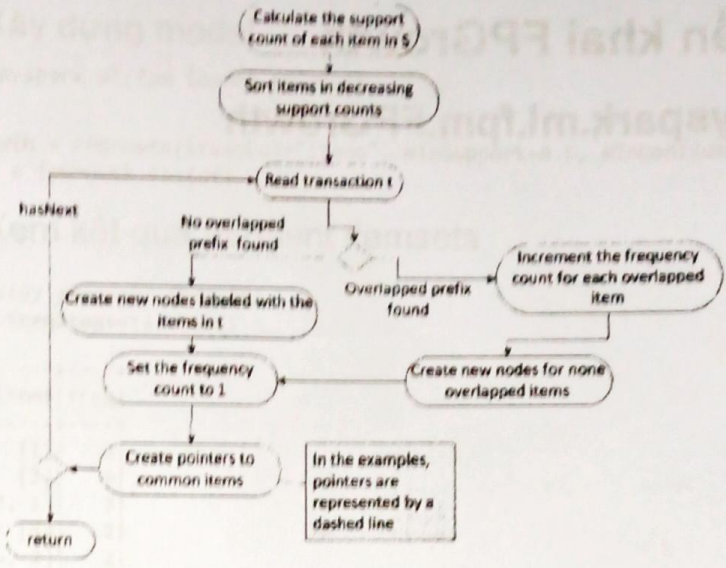


Fig. 8. Activity diagram - Construction of the FP-Tree - Notation: [27]

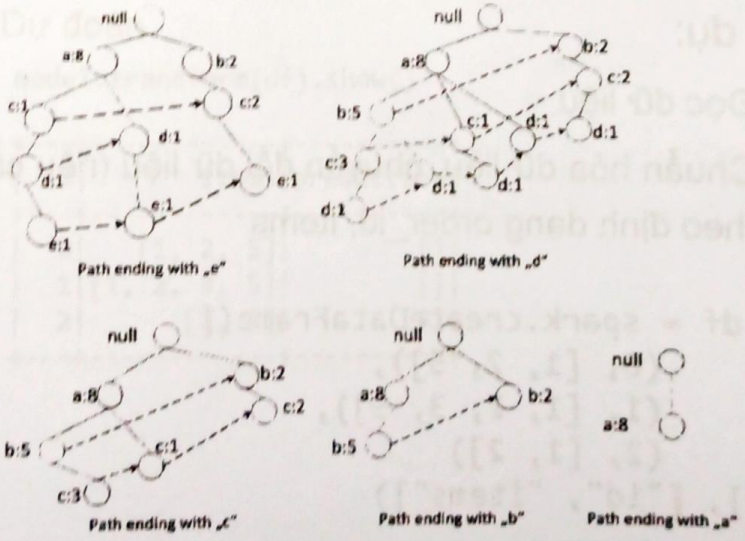


Fig. 9. Subproblems - Based on [28]

Association rules

❑ Triển khai FPGrowth

- pyspark.ml.fpm.FPGrowth

Association rules

- Ví dụ:
  - Đọc dữ liệu
  - Chuẩn hóa dữ liệu, chuyển đổi dữ liệu (nếu cần) theo định dạng order_id, items

```
df = spark.createDataFrame([
    (0, [1, 2, 5]),
    (1, [1, 2, 3, 5]),
    (2, [1, 2])
], ["id", "items"])
```

Association rules

- Xây dựng model

```
from pyspark.ml.fpm import FPGrowth

fpGrowth = FPGrowth(itemsCol="items", minSupport=0.5, minConfidence=0.6)
model = fpGrowth.fit(df)
```

- Xem kết quả frequent itemsets

```
# Display frequent itemsets.
model.freqItemsets.show()
```

```
+---------+----+
|    items|freq|
+---------+----+
|      [1]|   3|
|      [2]|   3|
|   [2, 1]|   3|
|      [5]|   2|
|   [5, 2]|   2|
|[5, 2, 1]|   2|
|   [5, 1]|   2|
+---------+----+
```

Association rules

- Dự đoán

```
model.transform(df).show()
```

```
+---+------------+----------+
| id|       items|prediction|
+---+------------+----------+
|  0|   [1, 2, 5]|        []|
|  1|[1, 2, 3, 5]|        []|
|  2|      [1, 2]|       [5]|
+---+------------+----------+
```

Chapter 9: K-Means Clustering

Ex1: 3D points

Dataset: data3D.csv.

Requirement:

- Read dataset
- Pre-process data
- Use K-means clustering algorithm to cluster 3D points in data3D.csv.

In [8]:
```
import findspark
findspark.init()
```

In [9]:
```
import pyspark
```

In [10]:
```
from pyspark.sql import SparkSession
```

In [11]:
```
spark = SparkSession.builder.appName('kmeans_3D_point').getOrCreate()
```

In [12]:
```
# Loads data.
data = spark.read.csv("data3D.csv", header=True,
                      inferSchema=True)
```

In [13]:
```
data.show(3)
```

```
+------+-----------------+------------------+------------------+
|    id|                x|                 y|                 z|
+------+-----------------+------------------+------------------+
|point0|5.647627534046943|-6.356222340123802|-7.240816026826695|
|point1|4.414367138680041|-10.32624175635328| 8.963324308916228|
|point2|5.005396944639823|-9.301070062115645| 10.35473056351597|
+------+-----------------+------------------+------------------+
only showing top 3 rows
```

In [14]:
```
from pyspark.sql.functions import col
```

In [17]:
```
data = data.select(['x', 'y', 'z'])
```

In [18]:
```
data.show(3)
```

```
+-----------------+------------------+------------------+
|                x|                 y|                 z|
+-----------------+------------------+------------------+
|5.647627534046943|-6.356222340123802|-7.240816026826695|
|4.414367138680041|-10.32624175635328| 8.963324308916228|
|5.005396944639823|-9.301070062115645| 10.35473056351597|
+-----------------+------------------+------------------+
only showing top 3 rows
```

Format from data

In [19]:
```
from pyspark.ml.linalg import Vectors
from pyspark.ml.feature import VectorAssembler
```

In [20]:
```
data.columns
```

Out[20]:
```
['x', 'y', 'z']
```

In [21]:
```
vec_assembler = VectorAssembler(inputCols = data.columns,
                                outputCol='features')
```

In [25]:
```
final_data = vec_assembler.transform(data)
```

Scale the Data

In [22]:
```
from pyspark.ml.feature import StandardScaler
```

In [23]:
```
scaler = StandardScaler(inputCol="features",
                        outputCol="scaledFeatures",
                        withStd=True,
                        withMean=False)
```

In [26]:
```
# Compute summary statistics by fitting the StandardScaler
scalerModel = scaler.fit(final_data)
```

In [27]:
```
# Normalize each feature to have unit standard deviation.
final_data = scalerModel.transform(final_data)
```

In [28]:
```
final_data.show(3, False)
```

```
+-----------------+-----------------+-----------------+-----------------------------------------------------
----------------+
|x                |y                |z                |features                                             |
|scaledFeatures                                                                                               |
+-----------------+-----------------+-----------------+-----------------------------------------------------
----------------+
|5.647627534046943|-6.356222340123802|-7.240816026826695|[5.647627534046943,-6.
356222340123802,-7.240816026826695]|[1.0159673512169811,-0.81335799160424,-1.13
00631023636807] |
|4.414367138680041|-10.32624175635328|8.963324308916228 |[4.414367138680041,-1
0.32624175635328,8.963324308916228] |[0.7941127247055396,-1.3213715327025133,1.
3988923401033817]|
|5.005396944639823|-9.301070062115645|10.35473056351597 |[5.005396944639823,-9.
301070062115645,10.35473056351597] |[0.9004347126254774,-1.1901880174546189,1.6
160469899240197]|
+-----------------+-----------------+-----------------+-----------------------------------------------------
----------------+
only showing top 3 rows
```

Train the Model and Evaluate

Seleck k with minimun WSSSE: k between 2 - 10

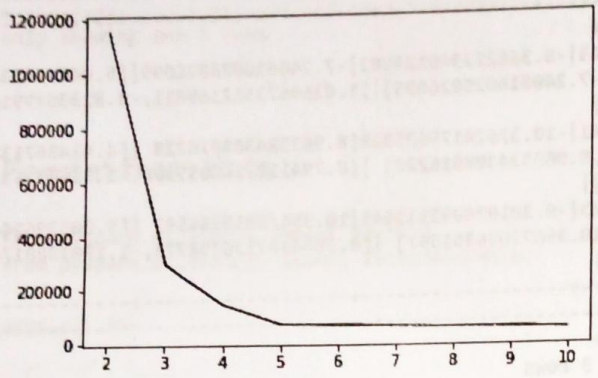
In [29]:
```
from pyspark.ml.clustering import KMeans
```

In [31]:
```
# Trains a k-means model.
k_list = []
wssse_list = []
for k in range(2,11):
    kmeans = KMeans(featuresCol='scaledFeatures',k=k)
    model = kmeans.fit(final_data)
    wssse = model.computeCost(final_data)
    k_list.append(k)
    wssse_list.append(wssse)
    print("With k =", k, "Set Sum of Squared Errors = " + str(wssse))
```

```
With k = 2 Set Sum of Squared Errors = 1155067.2563008904
With k = 3 Set Sum of Squared Errors = 297656.40920043044
With k = 4 Set Sum of Squared Errors = 146718.50451770602
With k = 5 Set Sum of Squared Errors = 72720.18504204818
With k = 6 Set Sum of Squared Errors = 68583.68208541229
With k = 7 Set Sum of Squared Errors = 64483.499921190276
With k = 8 Set Sum of Squared Errors = 60180.384358530224
With k = 9 Set Sum of Squared Errors = 58364.71279295459
With k = 10 Set Sum of Squared Errors = 52251.866281251554
```

In [32]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [33]:
```
plt.plot(k_list, wssse_list)
plt.show()
```



- According to Elbow Method, we choose k = 5. Look like there is very little gain after k=5, so we stick to that choice when processing the full data set.

Select k = 5

In [34]:
```
# Trains a k-means model.
kmeans = KMeans(featuresCol='scaledFeatures',k=5)
model = kmeans.fit(final_data)
```

In [35]:
```
# Evaluate clustering by computing Within Set Sum of Squared Errors.
wssse = model.computeCost(final_data)
print("Within Set Sum of Squared Errors = " + str(wssse))
```

```
Within Set Sum of Squared Errors = 72720.18504204816
```

In [36]:
```
# Shows the result.
centers = model.clusterCenters()
print("Cluster Centers: ")
for center in centers:
    print(center)
```

```
Cluster Centers:
[-1.59030525  0.93719373  0.31581855]
[ 1.19780483 -0.7365009  -0.99420908]
[ 0.74896823 -1.2269015   1.46702482]
[-0.45182036  1.15367577  0.72369935]
[ 0.35333753 -0.87989287 -1.0735622 ]
```

In [37]:
```
predictions =  model.transform(final_data)
```

In [38]:
```
predictions.select("prediction").show(5)
```

```
+----------+
|prediction|
+----------+
|         1|
|         2|
|         2|
|         2|
|         0|
+----------+
only showing top 5 rows
```

In [ ]:
```
# Check number points of each cluster
```

In [60]:
```
predictions.groupBy('prediction').count().show()
```

```
+----------+------+
|prediction| count|
+----------+------+
|         1|199987|
|         3|200017|
|         4|200013|
|         2|200000|
|         0|199983|
+----------+------+
```

In [ ]:
```
# Our clustering algorithm created 5 equally sized clusters with K=5
```

In [39]:
```
data_result = predictions.select("prediction")
data_result.columns
```

Out[39]:
```
['prediction']
```

In [40]:
```
type(data_result)
```

Out[40]:
```
pyspark.sql.dataframe.DataFrame
```

In [41]:
```
final_data.show(3, False)
```

```
+----------------+------------------+------------------+------------------------------------------------------------
-----------------------------+------------------------------------------------------------------------------
----------------+
|x               |y                 |z                 |features                                                  |
|scaledFeatures
+----------------+------------------+------------------+------------------------------------------------------------
-----------------------------+------------------------------------------------------------------------------
----------------+
|5.647627534046943|-6.356222340123802|-7.240816026826695|[5.647627534046943,-6.356222340123802,-7.240816026826695]|[1.0159673512169811,-0.81335799160424,-1.1300631023636807] |
|4.414367138680041|-10.32624175635328|8.963324308916228 |[4.414367138680041,-10.32624175635328,8.963324308916228] |[0.7941127247055396,-1.3213715327025133,1.3988923401033817]|
|5.005396944639823|-9.301070062115645|10.35473056351597 |[5.005396944639823,-9.301070062115645,10.35473056351597] |[0.9004347126254774,-1.1901880174546189,1.6160469899240197]|
+----------------+------------------+------------------+------------------------------------------------------------
-----------------------------+------------------------------------------------------------------------------
----------------+
only showing top 3 rows
```

In [42]:
```
temp = final_data.select("scaledFeatures").rdd.map(lambda x: \
                                                   x[0].toArray().tolist()).toDF()
```

In [43]:
```
temp.show(3)
```

```
+------------------+-------------------+------------------+
|                _1|                 _2|                _3|
+------------------+-------------------+------------------+
|1.0159673512169811|   -0.81335799160424|-1.1300631023636807|
|0.7941127247055396|-1.3213715327025133| 1.3988923401033817|
|0.9004347126254774|-1.1901880174546189| 1.6160469899240197|
+------------------+-------------------+------------------+
only showing top 3 rows
```

In [44]:
```
import pyspark.sql.functions as f
```

In [45]:
```
# since there is no common column between these two dataframes add row_index so 
temp=temp.withColumn('row_index', f.monotonically_increasing_id())
data_result=data_result.withColumn('row_index',
                                   f.monotonically_increasing_id())

temp = temp.join(data_result,
                 on=["row_index"]).sort("row_index").drop("row_index")
```

In [46]:
```
temp.show(3)
```

```
+------------------+-------------------+------------------+----------+
|                _1|                 _2|                _3|prediction|
+------------------+-------------------+------------------+----------+
|1.0159673512169811|  -0.81335799160424|-1.1300631023636807|         1|
|0.7941127247055396|-1.3213715327025133| 1.3988923401033817|         2|
|0.9004347126254774|-1.1901880174546189| 1.6160469899240197|         2|
+------------------+-------------------+------------------+----------+
only showing top 3 rows
```

In [48]:
```
temp = temp.select(col("_1").alias("x_scale"),
                   col("_2").alias("y_scale"),
                   col("_3").alias("z_scale"),
                   "prediction")
```

In [49]:
```
df = temp.toPandas()
```

In [54]:
```
df.head(3)
```

Out[54]:

	x_scale	y_scale	z_scale	prediction
0	1.015967	-0.813358	-1.130063	1
1	0.794113	-1.321372	1.398892	2
2	0.900435	-1.190188	1.616047	2

In [50]:
```
centers_df = pd.DataFrame(centers)
centers_df.head()
```

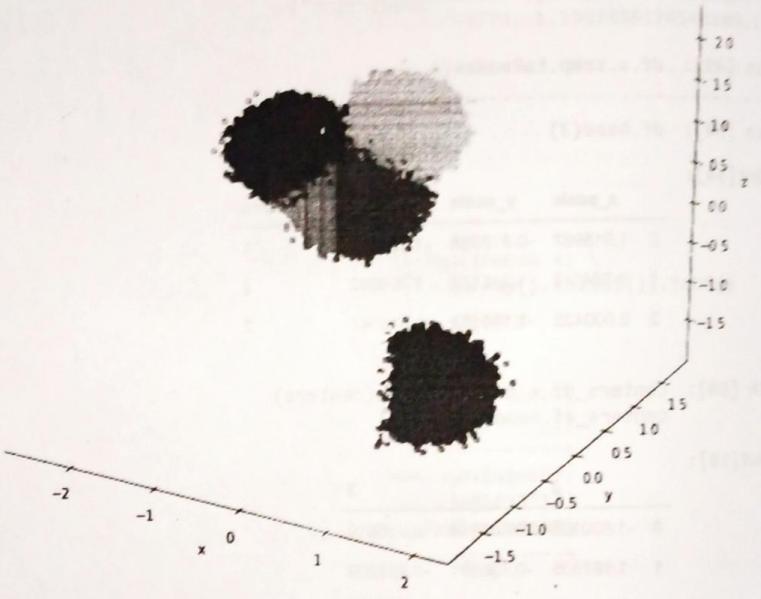
Out[50]:

	0	1	2
0	-1.590305	0.937194	0.315819
1	1.197805	-0.736501	-0.994209
2	0.748968	-1.226902	1.467025
3	-0.451820	1.153676	0.723699
4	0.353338	-0.879893	-1.073562

In [55]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
```

```
In [59]: threedee = plt.figure(figsize=(12,10)).gca(projection='3d')
         threedee.scatter(df.x_scale, df.y_scale,
                          df.z_scale,
                          c=df.prediction)
         threedee.set_xlabel('x')
         threedee.set_ylabel('y')
         threedee.set_zlabel('z')

         plt.show()
```



Combine results

In [51]:
```
# since there is no common column between these two dataframes add row_ind
final_data=final_data.withColumn('row_index',
                                 f.monotonically_increasing_id())
temp=temp.withColumn('row_index',
                     f.monotonically_increasing_id())
final_data = final_data.join(temp,
                             on=["row_index"]).sort("row_index").drop("row_index
```

In [52]:
```
final_data.show(3, False)
```

```
+-----------------+-----------------+-----------------+----------------------
----------------------------------+----------------------------------------
---------------+-----------------+-----------------+------------------+---
-------+
|x                |y                |z                |features
                                  |x_scale
|y_scale          |z_scale          |prediction|
+-----------------+-----------------+-----------------+----------------------
----------------------------------+----------------------------------------
---------------+-----------------+-----------------+------------------+---
-------+
|5.647627534046943|-6.356222340123802|-7.240816026826695|[5.647627534046943,-6.
356222340123802,-7.240816026826695]|[1.0159673512169811,-0.81335799160424,-1.13
00631023636807] |1.0159673512169811|-0.81335799160424  |-1.1300631023636807|1
|
|4.414367138680041|-10.32624175635328|8.963324308916228 |[4.414367138680041,-1
0.32624175635328,8.963324308916228] |[0.7941127247055396,-1.3213715327025133,1.
3988923401033817]|0.7941127247055396|-1.3213715327025133|1.3988923401033817 |2
|
|5.005396944639823|-9.301070062115645|10.35473056351597 |[5.005396944639823,-9.
301070062115645,10.35473056351597] |[0.9004347126254774,-1.1901880174546189,1.6
160469899240197]|0.9004347126254774|-1.1901880174546189|1.6160469899240197 |2
|
+-----------------+-----------------+-----------------+----------------------
----------------------------------+----------------------------------------
---------------+-----------------+-----------------+------------------+---
-------+
only showing top 3 rows
```

Chapter 9: K-Means Clustering

Ex2: Clustering Consulting Project - Hack_data

A large technology firm needs your help, they've been hacked! Luckily their forensic engineers have grabbed valuable data about the hacks, including information like session time,locations, wpm typing speed, etc. The forensic engineer relates to you what she has been able to figure out so far, she has been able to grab meta data of each session that the hackers used to connect to their servers. These are the features of the data:

- 'Session_Connection_Time': How long the session lasted in minutes
- 'Bytes Transferred': Number of MB transferred during session
- 'Kali_Trace_Used': Indicates if the hacker was using Kali Linux
- 'Servers_Corrupted': Number of server corrupted during the attack
- 'Pages_Corrupted': Number of pages illegally accessed
- 'Location': Location attack came from (Probably useless because the hackers used VPNs)
- 'WPM_Typing_Speed': Their estimated typing speed based on session logs.

The technology firm has 3 potential hackers that perpetrated the attack. Their certain of the first two hackers but they aren't very sure if the third hacker was involved or not. They have requested your help! Can you help figure out whether or not the third suspect had anything to do with the attacks, or was it just two hackers? It's probably not possible to know for sure, but maybe what you've just learned about Clustering can help!

One last key fact, the forensic engineer knows that the hackers trade off attacks. Meaning they should each have roughly the same amount of attacks. For example if there were 100 total attacks, then in a 2 hacker situation each should have about 50 hacks, in a three hacker situation each would have about 33 hacks. The engineer believes this is the key element to solving this, but doesn't know how to distinguish this unlabeled data into groups of hackers.

Chapter 9: K-means Clustering

Ex 2: Clustering Consulting Project - Hack_data - Solutions

A large technology firm needs your help, they've been hacked! Luckily their forensic engineers have grabbed valuable data about the hacks, including information like session time,locations, wpm typing speed, etc. The forensic engineer relates to you what she has been able to figure out so far, she has been able to grab meta data of each session that the hackers used to connect to their servers. These are the features of the data:

- 'Session_Connection_Time': How long the session lasted in minutes
- 'Bytes Transferred': Number of MB transferred during session
- 'Kali_Trace_Used': Indicates if the hacker was using Kali Linux
- 'Servers_Corrupted': Number of server corrupted during the attack
- 'Pages_Corrupted': Number of pages illegally accessed
- 'Location': Location attack came from (Probably useless because the hackers used VPNs)
- 'WPM_Typing_Speed': Their estimated typing speed based on session logs.

The technology firm has 3 potential hackers that perpetrated the attack. Their certain of the first two hackers but they aren't very sure if the third hacker was involved or not. They have requested your help! Can you help figure out whether or not the third suspect had anything to do with the attacks, or was it just two hackers? It's probably not possible to know for sure, but maybe what you've just learned about Clustering can help!

One last key fact, the forensic engineer knows that the hackers trade off attacks. Meaning they should each have roughly the same amount of attacks. For example if there were 100 total attacks, then in a 2 hacker situation each should have about 50 hacks, in a three hacker situation each would have about 33 hacks. The engineer believes this is the key element to solving this, but doesn't know how to distinguish this unlabeled data into groups of hackers.

In [1]:
```
import findspark
findspark.init()
```

In [2]:
```
from pyspark.sql import SparkSession
spark = SparkSession.builder.appName('hack_find').getOrCreate()
```

In [3]:
```
from pyspark.ml.clustering import KMeans

# Loads data.
dataset = spark.read.csv("hack_data.csv", header=True,
                         inferSchema=True)
```

In [4]:
```
dataset.head()
```

Out[4]:
```
Row(Session_Connection_Time=8.0, Bytes Transferred=391.09, Kali_Trace_Used=1, S
ervers_Corrupted=2.96, Pages_Corrupted=7.0, Location='Slovenia', WPM_Typing_Spe
ed=72.37)
```

In [5]:
```
dataset.describe().show()
```

```
+-------+----------------------+------------------+------------------+--------
---------+-----------------+-----------+------------------+
|summary|Session_Connection_Time| Bytes Transferred|   Kali_Trace_Used|Servers_
Corrupted|   Pages_Corrupted|   Location|  WPM_Typing_Speed|
+-------+----------------------+------------------+------------------+--------
---------+-----------------+-----------+------------------+
|  count|                   334|               334|               334|
334|              334|        334|               334|
|   mean|     30.008982035928145| 607.2452694610777|0.5119760479041916|5.258502
994011977|10.838323353293413|       null|57.342395209580864|
| stddev|     14.088200614636158|286.33593163576757|0.5006065264451406| 2.30190
693339697|  3.06352633036022|       null| 13.41106336843464|
|    min|                   1.0|              10.0|                 0|
1.0|               6.0|Afghanistan|              40.0|
|    max|                  60.0|            1330.5|                 1|
10.0|              15.0|   Zimbabwe|              75.0|
+-------+----------------------+------------------+------------------+--------
---------+-----------------+-----------+------------------+
```

In [6]:
```
dataset.columns
```

Out[6]:
```
['Session_Connection_Time',
 'Bytes Transferred',
 'Kali_Trace_Used',
 'Servers_Corrupted',
 'Pages_Corrupted',
 'Location',
 'WPM_Typing_Speed']
```

In [7]:
```
from pyspark.ml.linalg import Vectors
from pyspark.ml.feature import VectorAssembler
```

In [8]:
```
feat_cols = ['Session_Connection_Time',
             'Bytes Transferred',
             'Kali_Trace_Used',
             'Servers_Corrupted',
             'Pages_Corrupted','WPM_Typing_Speed']
```

In [9]:
```
vec_assembler = VectorAssembler(inputCols = feat_cols,
                                outputCol='features')
```

In [10]:
```
final_data = vec_assembler.transform(dataset)
```

In [11]:
```
from pyspark.ml.feature import StandardScaler
```

```
In [12]: scaler = StandardScaler(inputCol="features",
                                 outputCol="scaledFeatures",
                                 withStd=True,
                                 withMean=False)
```

```
In [13]: # Compute summary statistics by fitting the StandardScaler
         scalerModel = scaler.fit(final_data)
```

```
In [14]: # Normalize each feature to have unit standard deviation.
         cluster_final_data = scalerModel.transform(final_data)
```

** Time to find out whether its 2 or 3! **

```
In [15]: kmeans3 = KMeans(featuresCol='scaledFeatures',k=3)
         kmeans2 = KMeans(featuresCol='scaledFeatures',k=2)
```

```
In [16]: model_k3 = kmeans3.fit(cluster_final_data)
         model_k2 = kmeans2.fit(cluster_final_data)
```

```
In [17]: wssse_k3 = model_k3.computeCost(cluster_final_data)
         wssse_k2 = model_k2.computeCost(cluster_final_data)
```

```
In [18]: print("With K=3")
         print("Within Set Sum of Squared Errors = " + str(wssse_k3))
         print('--'*30)
         print("With K=2")
         print("Within Set Sum of Squared Errors = " + str(wssse_k2))
```

```
With K=3
Within Set Sum of Squared Errors = 434.1492898715845
------------------------------------------------------------
With K=2
Within Set Sum of Squared Errors = 601.7707512676716
```

Not much to be gained from the WSSSE, after all, we would expect that as K increases, the WSSSE decreases. We could however continue the analysis by seeing the drop from K=3 to K=4 to check if the clustering favors even or odd numbers. This won't be substantial, but its worth a look:

In [19]:
```
for k in range(2,9):
    kmeans = KMeans(featuresCol='scaledFeatures',k=k)
    model = kmeans.fit(cluster_final_data)
    wssse = model.computeCost(cluster_final_data)
    print("With K={}".format(k))
    print("Within Set Sum of Squared Errors = " + str(wssse))
    print('--'*30)
```

```
With K=2
Within Set Sum of Squared Errors = 601.7707512676716
------------------------------------------------------------
With K=3
Within Set Sum of Squared Errors = 434.1492898715845
------------------------------------------------------------
With K=4
Within Set Sum of Squared Errors = 414.8171173373783
------------------------------------------------------------
With K=5
Within Set Sum of Squared Errors = 247.80143915458297
------------------------------------------------------------
With K=6
Within Set Sum of Squared Errors = 232.65169349742308
------------------------------------------------------------
With K=7
Within Set Sum of Squared Errors = 219.57683951525962
------------------------------------------------------------
With K=8
Within Set Sum of Squared Errors = 206.34236284345502
------------------------------------------------------------
```

** Nothing definitive can be said with the above, but wait! The last key fact that the engineer mentioned was that the attacks should be evenly numbered between the hackers! Let's check with the transform and prediction columns that result form this! Congratulations if you made this connection, it was quite tricky given what we've covered!**

In [20]:
```
model_k3.transform(cluster_final_data).groupBy('prediction').count().show()
```

```
+----------+-----+
|prediction|count|
+----------+-----+
|         1|  167|
|         2|   83|
|         0|   84|
+----------+-----+
```

In [21]:
```
model_k2.transform(cluster_final_data).groupBy('prediction').count().show()
```

```
+----------+-----+
|prediction|count|
+----------+-----+
|         1|  167|
|         0|  167|
+----------+-----+
```

It was 2 hackers, in fact, our clustering algorithm created two equally sized clusters with K=2, no way that is a coincidence!

In [ ]:

Chapter 9: Recommender

Ex3: Musical Instruments

Dataset: Musical_Instruments_5.json

Read more about dataset: http://jmcauley.ucsd.edu/data/amazon/ (http://jmcauley.ucsd.edu/data/amazon/)

Requirement:

- Read dataset
- Pre-process data
- Use "asin" (ProductID), "reviewerID" and overall (User's reviews for each product - rating) to build model to predict overalls => Give recommendation for users.

In [1]:
```
import findspark
findspark.init()
```

In [2]:
```
from pyspark.sql import SparkSession
```

In [3]:
```
spark = SparkSession.builder.appName('Recommendation_system').getOrCreate()
```

In [4]:
```
data = spark.read.json("Musical_Instruments_5.json")
```

In [5]:
```
data.show(5,truncate=True)
```

```
+----------+--------+-------+--------------------+-----------+--------------+--
----------------+--------------------+--------------+
|      asin| helpful|overall|          reviewText| reviewTime|    reviewerID|
reviewerName|             summary|unixReviewTime|
+----------+--------+-------+--------------------+-----------+--------------+--
----------------+--------------------+--------------+
|1384719342|  [0, 0]|    5.0|Not much to write...|02 28, 2014|A2IBPI20UZIR0U|ca
ssandra tu "Yea...|                good|    1393545600|
|1384719342|[13, 14]|    5.0|The product does ...|03 16, 2013|A14VAT5EAX3D9S|
Jake|                Jake|    1363392000|
|1384719342|  [1, 1]|    5.0|The primary job o...|08 28, 2013|A195EZSQDW3E21|Ri
ck Bennette "Ri...|It Does The Job Well|    1377648000|
|1384719342|  [0, 0]|    5.0|Nice windscreen p...|02 14, 2014|A2C00NNG1ZQQG2|Ru
styBill "Sunday...|GOOD WINDSCREEN F...|    1392336000|
|1384719342|  [0, 0]|    5.0|This pop filter i...|02 21, 2014| A94QU4C90B1AX|
SEAN MASLANKA|No more pops when...|    1392940800|
+----------+--------+-------+--------------------+-----------+--------------+--
----------------+--------------------+--------------+
only showing top 5 rows
```

In [6]:
```
data_sub = data.select(['asin', 'overall', 'reviewerID'])
```

In [7]:
```
data_sub.count()
```

Out[7]: 10261

In [8]:
```
from pyspark.sql.functions import col, udf
from pyspark.sql.functions import isnan, when, count, col
```

In [10]:
```
data_sub.show(5, truncate=True)
```

```
+----------+-------+--------------+
|      asin|overall|    reviewerID|
+----------+-------+--------------+
|1384719342|    5.0|A2IBPI20UZIR0U|
|1384719342|    5.0|A14VAT5EAX3D9S|
|1384719342|    5.0|A195EZSQDW3E21|
|1384719342|    5.0|A2C00NNG1ZQQG2|
|1384719342|    5.0| A94QU4C90B1AX|
+----------+-------+--------------+
only showing top 5 rows
```

In [11]:
```
data_sub.select([count(when(col(c).isNull(), c)).alias(c) for c in
                 data_sub.columns]).toPandas().T
```

Out[11]:

	0
asin	0
overall	0
reviewerID	0

In [12]:
```
# Distinct users and movies
users = data_sub.select("reviewerID").distinct().count()
products = data_sub.select("asin").distinct().count()
numerator = data_sub.count()
```

In [13]:
```
display(numerator, users, products)
```

```
10261

1429

900
```

In [14]:
```
# Number of ratings matrix could contain if no empty cells
denominator = users * products
denominator
```

Out[14]: 1286100

In [15]:
```
#Calculating sparsity
sparsity = 1 - (numerator*1.0 / denominator)
print ("Sparsity: "), sparsity

Sparsity:
```

Out[15]:
```
(None, 0.992021615737501)
```

In [16]:
```
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.recommendation import ALS
```

In [17]:
```
# Converting String to index
from pyspark.ml.feature import StringIndexer
from pyspark.ml import Pipeline
from pyspark.sql.functions import col
```

In [18]:
```
# Create an indexer
indexer = StringIndexer(inputCol='asin',
                        outputCol='asin_idx')

# Indexer identifies categories in the data
indexer_model = indexer.fit(data_sub)

# Indexer creates a new column with numeric index values
data_indexed = indexer_model.transform(data_sub)

# Repeat the process for the other categorical feature
indexer1 = StringIndexer(inputCol='reviewerID',
                         outputCol='reviewerID_idx')
indexer1_model = indexer1.fit(data_indexed)
data_indexed = indexer1_model.transform(data_indexed)
```

In [19]:
```
data_indexed.show(5, truncate=True)
```

```
+----------+-------+--------------+---------+--------------+
|      asin|overall|    reviewerID|asin_idx|reviewerID_idx|
+----------+-------+--------------+---------+--------------+
|1384719342|    5.0|A2IBPI20UZIR0U|    781.0|          72.0|
|1384719342|    5.0|A14VAT5EAX3D9S|    781.0|         359.0|
|1384719342|    5.0|A195EZSQDW3E21|    781.0|         436.0|
|1384719342|    5.0|A2C00NNG1ZQQG2|    781.0|        1216.0|
|1384719342|    5.0| A94QU4C90B1AX|    781.0|        1137.0|
+----------+-------+--------------+---------+--------------+
only showing top 5 rows
```

In [20]:
```
data_indexed.select([count(when(col(c).isNull(), c)).alias(c) for c in
                     data_indexed.columns]).toPandas().T
```

Out[20]:

	0
asin	0
overall	0
reviewerID	0
asin_idx	0
reviewerID_idx	0

In [21]:
```
# Smaller dataset so we will use 0.8 / 0.2
(training, test) = data_indexed.randomSplit([0.8, 0.2])
```

In [22]:
```
# Creating ALS model and fitting data
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.recommendation import ALS
```

In [23]:
```
als = ALS(maxIter=5,
          regParam=0.09,
          rank = 25,
          userCol="reviewerID_idx",
          itemCol="asin_idx",
          ratingCol="overall",
          coldStartStrategy="drop",
          nonnegative=True)
model = als.fit(training)
```

In [24]:
```
# Evaluate the model by computing the RMSE on the test data
predictions = model.transform(test)
```

In [25]:
```
predictions.select(["asin_idx", "reviewerID_idx",
                    "overall", "prediction"]).show(5)
```

```
+--------+--------------+-------+----------+
|asin_idx|reviewerID_idx|overall|prediction|
+--------+--------------+-------+----------+
|   148.0|          34.0|    4.0|  3.732204|
|   148.0|         502.0|    5.0| 3.8744607|
|   148.0|        1377.0|    5.0| 2.8333657|
|   148.0|          30.0|    3.0|  4.517724|
|   463.0|         671.0|    5.0|  4.361149|
+--------+--------------+-------+----------+
only showing top 5 rows
```

In [29]:
```
evaluator = RegressionEvaluator(metricName="rmse",
                                labelCol="overall",
                                predictionCol="prediction")
rmse = evaluator.evaluate(predictions)
print("Root-mean-square error = " + str(rmse))
```

```
Root-mean-square error = 1.1928346794514073
```

In [ ]:
```
# On average, this model is ~ 1.2 from perfect recommendations.
```

Providing Recommendations: for all users

In [33]:
```
# get 20 recommendations which have highest rating.
user_recs = model.recommendForAllUsers(20)
```

In [35]:
```
for user in user_recs.head(5):
    print(user)
    print("\n")
```

```
Row(reviewerID_idx=471, recommendations=[Row(asin_idx=357, rating=5.99492979049
6826), Row(asin_idx=402, rating=5.971096515655518), Row(asin_idx=328, rating=5.
91753625869751), Row(asin_idx=544, rating=5.729032039642334), Row(asin_idx=476,
rating=5.716101169586182), Row(asin_idx=232, rating=5.712975978851318), Row(asi
n_idx=852, rating=5.712711811065674), Row(asin_idx=888, rating=5.70264530181884
8), Row(asin_idx=360, rating=5.70063591003418), Row(asin_idx=427, rating=5.6923
59924316406), Row(asin_idx=346, rating=5.683685302734375), Row(asin_idx=746, ra
ting=5.678509712219238), Row(asin_idx=829, rating=5.665043830871582), Row(asin_
idx=368, rating=5.654289245605469), Row(asin_idx=805, rating=5.63354778289794
9), Row(asin_idx=350, rating=5.57622766494751), Row(asin_idx=723, rating=5.5738
38233947754), Row(asin_idx=396, rating=5.543375492095947), Row(asin_idx=632, ra
ting=5.540017127990723), Row(asin_idx=734, rating=5.527731895446777)])


Row(reviewerID_idx=1342, recommendations=[Row(asin_idx=731, rating=6.3991994857
78809), Row(asin_idx=427, rating=6.240170001983643), Row(asin_idx=746, rating=
6.126894950866699), Row(asin_idx=328, rating=6.101090431213379), Row(asin_idx=2
32, rating=6.0971221923828125), Row(asin_idx=852, rating=6.052910327911377), Ro
w(asin_idx=476, rating=6.034964561462402), Row(asin_idx=645, rating=6.031756877
89917), Row(asin_idx=544, rating=6.0315022468566895), Row(asin_idx=829, rating=
6.031264781951904), Row(asin_idx=682, rating=6.015640735626221), Row(asin_idx=8
53, rating=6.006399154663086), Row(asin_idx=734, rating=6.0043182373046875), Ro
w(asin_idx=346, rating=5.98906135559082), Row(asin_idx=723, rating=5.9865040779
11377), Row(asin_idx=766, rating=5.969595432281494), Row(asin_idx=888, rating=
5.9575724601745605), Row(asin_idx=791, rating=5.956635475158691), Row(asin_idx=
402, rating=5.906132698059082), Row(asin_idx=809, rating=5.890671253204346)])


Row(reviewerID_idx=463, recommendations=[Row(asin_idx=746, rating=5.70749330520
6299), Row(asin_idx=476, rating=5.547768592834473), Row(asin_idx=544, rating=5.
540889739990234), Row(asin_idx=368, rating=5.476436614990234), Row(asin_idx=80
5, rating=5.46685266494751), Row(asin_idx=731, rating=5.438949108123779), Row(a
sin_idx=465, rating=5.411510944366455), Row(asin_idx=427, rating=5.398251056671
143), Row(asin_idx=698, rating=5.384541988372803), Row(asin_idx=853, rating=5.3
731842041015625), Row(asin_idx=306, rating=5.3723273277282715), Row(asin_idx=18
3, rating=5.372140407562256), Row(asin_idx=664, rating=5.357931613922119), Row
(asin_idx=232, rating=5.35223913192749), Row(asin_idx=328, rating=5.33652114868
1641), Row(asin_idx=678, rating=5.331408977508545), Row(asin_idx=829, rating=5.
323209285736084), Row(asin_idx=518, rating=5.315012454986572), Row(asin_idx=90,
rating=5.2987165451049805), Row(asin_idx=791, rating=5.295729637145996)])


Row(reviewerID_idx=833, recommendations=[Row(asin_idx=734, rating=6.09094333648
6816), Row(asin_idx=476, rating=5.975735187530518), Row(asin_idx=465, rating=5.
958075523376465), Row(asin_idx=746, rating=5.939692974090576), Row(asin_idx=36
8, rating=5.900303840637207), Row(asin_idx=437, rating=5.891534328460693), Row
(asin_idx=396, rating=5.8877973556518555), Row(asin_idx=853, rating=5.885824680
328369), Row(asin_idx=427, rating=5.86740779876709), Row(asin_idx=402, rating=
5.852911949157715), Row(asin_idx=888, rating=5.833059310913086), Row(asin_idx=6
84, rating=5.827024936676025), Row(asin_idx=791, rating=5.814032554626465), Row
(asin_idx=705, rating=5.810422420501709), Row(asin_idx=645, rating=5.8077998161
31592), Row(asin_idx=346, rating=5.799132347106934), Row(asin_idx=632, rating=
5.797298908233643), Row(asin_idx=829, rating=5.776956081390381), Row(asin_idx=8
```

```
09, rating=5.772419452667236), Row(asin_idx=662, rating=5.757423400878906)])
```

```
Row(reviewerID_idx=496, recommendations=[Row(asin_idx=232, rating=5.53647279739
3799), Row(asin_idx=731, rating=5.501907825469971), Row(asin_idx=427, rating=5.
453770160675049), Row(asin_idx=791, rating=5.439143657684326), Row(asin_idx=74
6, rating=5.427332878112793), Row(asin_idx=853, rating=5.397946834564209), Row
(asin_idx=476, rating=5.383556842803955), Row(asin_idx=829, rating=5.3825254440
30762), Row(asin_idx=368, rating=5.379194736480713), Row(asin_idx=886, rating=
5.36549186706543), Row(asin_idx=632, rating=5.29641056060791), Row(asin_idx=46
5, rating=5.287215709686279), Row(asin_idx=698, rating=5.279950141906738), Row
(asin_idx=734, rating=5.271482467651367), Row(asin_idx=293, rating=5.2693777084
35059), Row(asin_idx=274, rating=5.261102199554443), Row(asin_idx=678, rating=
5.249166488647461), Row(asin_idx=402, rating=5.2356858253479), Row(asin_idx=54
4, rating=5.224824905395508), Row(asin_idx=805, rating=5.2206926345825195)])
```

Converting back to string form

In [38]:
```
import pandas as pd
recs=model.recommendForAllUsers(10).toPandas()
nrecs=recs.recommendations.apply(pd.Series) \
            .merge(recs, right_index = True, left_index = True) \
            .drop(["recommendations"], axis = 1) \
            .melt(id_vars = ['reviewerID_idx'], value_name = "recommendation") \
            .drop("variable", axis = 1) \
            .dropna()
nrecs=nrecs.sort_values('reviewerID_idx')
nrecs=pd.concat([nrecs['recommendation'].apply(pd.Series),
                 nrecs['reviewerID_idx']], axis = 1)
nrecs.columns = [
        'ProductID_index',
        'Rating',
        'UserID_index'
    ]
```

In [41]:
```
md=data_indexed.select(['reviewerID', 'reviewerID_idx',
                        'asin', 'asin_idx'])
md=md.toPandas()
dict1 =dict(zip(md['reviewerID_idx'],md['reviewerID']))
dict2=dict(zip(md['asin_idx'],md['asin']))
nrecs['reviewerID']=nrecs['UserID_index'].map(dict1)
nrecs['asin']=nrecs['ProductID_index'].map(dict2)
nrecs=nrecs.sort_values('reviewerID')
nrecs.reset_index(drop=True, inplace=True)
new=nrecs[['reviewerID','asin','Rating']]
new['recommendations'] = list(zip(new.asin, new.Rating))
res=new[['reviewerID','recommendations']]
res_new=res['recommendations'].groupby([res.reviewerID])\
                              .apply(list).reset_index()
```

```
c:\program files\python36\lib\site-packages\ipykernel_launcher.py:10: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stab
le/user_guide/indexing.html#returning-a-view-versus-a-copy (http://pandas.pydat
a.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y)
  # Remove the CWD from sys.path while we load stuff.
```

[42]:
```
res_new
```

Out[42]:

	reviewerID	recommendations
0	A00625243BI8W1SSZNLMD	[(B0002GXRF2, 5.8296637535095215), (B001CJ2QZU...
1	A10044ECXDUVKS	[(B001L8KE06, 5.229329586029053), (B004PFWZHM,...
2	A102MU6ZC9H1N6	[(B0002GXRF2, 5.819663047790527), (B000MWWT6E,...
3	A109JTUZXO61UY	[(B001IM5KFY, 5.880716323852539), (B0002BACB4,...
4	A109ME7C09HM2M	[(B000RYE5Y6, 6.396268844604492), (B000MWWT6E,...
...	...	...
1424	AZJPNK73JF3XP	[(B001CJ2QZU, 5.473949432373047), (B003AYEAHC,...
1425	AZMHABTPXVLG3	[(B004T6M7DE, 3.672528028488159), (B0002CZVI2,...
1426	AZMIKIG4BB6BZ	[(B000RYE5Y6, 5.908489227294922), (B003AYEAHC,...
1427	AZPDO6FLSMLFP	[(B000RYE5Y6, 5.2437310218811035), (B0000AQRST...
1428	AZVME8JMPD3F4	[(B000WGJ71U, 4.245903015136719), (B000RKL8R2,...

1429 rows × 2 columns

Chapter 9: Recommender

Ex4: Beauty

Dataset: Beauty_5.json.json

Read more about dataset: http://jmcauley.ucsd.edu/data/amazon/ (http://jmcauley.ucsd.edu/data/amazon/)

Requirement:

- Read dataset
- Pre-process data
- Use "asin" (ProductID), "reviewerID" and overall (User's reviews for each product - rating) to build model to predict overalls => Give recommendation for users.

In [1]:
```
import findspark
findspark.init()
```

In [2]:
```
from pyspark.sql import SparkSession
```

In [3]:
```
spark = SparkSession.builder.appName('Recommendation_Beauty').getOrCreate()
```

In [4]:
```
data = spark.read.json("Beauty_5.json")
```

In [5]:
```
data.show(5,truncate=True)
```

```
+----------+-------+-------+--------------------+-----------+--------------+---
---------+--------------------+--------------+
|      asin|helpful|overall|          reviewText| reviewTime|    reviewerID|rev
iewerName|             summary|unixReviewTime|
+----------+-------+-------+--------------------+-----------+--------------+---
---------+--------------------+--------------+
|7806397051| [3, 4]|    1.0|Very oily and cre...|01 30, 2014|A1YJEY40YUW4SE|
Andrea|Don't waste your ...|    1391040000|
|7806397051| [1, 1]|    3.0|This palette was ...|04 18, 2014| A60XNB876KYML|  J
essica H.|         OK Palette!|    1397779200|
|7806397051| [0, 1]|    4.0|The texture of th...| 09 6, 2013|A3G6XNM240RMWA|
Karen|       great quality|    1378425600|
|7806397051| [2, 2]|    2.0|I really can't te...| 12 8, 2013|A1PQFP6SAJ6D80|
Norah|Do not work on my...|    1386460800|
|7806397051| [0, 0]|    3.0|It was a little s...|10 19, 2013|A38FVHZTNQ271F|
Nova Amor|          It's okay.|    1382140800|
+----------+-------+-------+--------------------+-----------+--------------+---
---------+--------------------+--------------+
only showing top 5 rows
```

In [6]:
```
data_sub = data.select(['asin', 'overall', 'reviewerID'])
```

In [7]:
```
data_sub.count()
```

Out[7]:
```
198502
```

In [8]:
```
from pyspark.sql.functions import col, udf
from pyspark.sql.functions import isnan, when, count, col
```

In [9]:
```
data_sub.show(5, truncate=True)
```

```
+----------+-------+--------------+
|      asin|overall|    reviewerID|
+----------+-------+--------------+
|7806397051|    1.0|A1YJEY40YUW4SE|
|7806397051|    3.0| A60XNB876KYML|
|7806397051|    4.0|A3G6XNM240RMWA|
|7806397051|    2.0|A1PQFP6SAJ6D80|
|7806397051|    3.0|A38FVHZTNQ271F|
+----------+-------+--------------+
only showing top 5 rows
```

In [10]:
```
data_sub.select([count(when(col(c).isNull(), c)).alias(c) for c in
                 data_sub.columns]).toPandas().T
```

Out[10]:

	0
asin	0
overall	0
reviewerID	0

In [11]:
```
# Distinct users and movies
users = data_sub.select("reviewerID").distinct().count()
products = data_sub.select("asin").distinct().count()
numerator = data_sub.count()
```

In [12]:
```
display(numerator, users, products)
```

```
198502

22363

12101
```

In [13]:
```
# Number of ratings matrix could contain if no empty cells
denominator = users * products
denominator
```

Out[13]:
```
270614663
```

In [14]:
```
#Calculating sparsity
sparsity = 1 - (numerator*1.0 / denominator)
print ("Sparsity: "), sparsity
```

Sparsity:

Out[14]: (None, 0.9992664772935825)

In [15]:
```
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.recommendation import ALS
```

In [16]:
```
# Converting String to index
from pyspark.ml.feature import StringIndexer
from pyspark.ml import Pipeline
from pyspark.sql.functions import col
```

In [17]:
```
# Create an indexer
indexer = StringIndexer(inputCol='asin',
                        outputCol='asin_idx')

# Indexer identifies categories in the data
indexer_model = indexer.fit(data_sub)

# Indexer creates a new column with numeric index values
data_indexed = indexer_model.transform(data_sub)

# Repeat the process for the other categorical feature
indexer1 = StringIndexer(inputCol='reviewerID',
                         outputCol='reviewerID_idx')
indexer1_model = indexer1.fit(data_indexed)
data_indexed = indexer1_model.transform(data_indexed)
```

In [18]:
```
data_indexed.show(5, truncate=True)
```

```
+----------+-------+--------------+--------+--------------+
|      asin|overall|    reviewerID|asin_idx|reviewerID_idx|
+----------+-------+--------------+--------+--------------+
|7806397051|    1.0|A1YJEY40YUW4SE|  6959.0|       18008.0|
|7806397051|    3.0| A60XNB876KYML|  6959.0|       10825.0|
|7806397051|    4.0|A3G6XNM240RMWA|  6959.0|        5924.0|
|7806397051|    2.0|A1PQFP6SAJ6D80|  6959.0|       12357.0|
|7806397051|    3.0|A38FVHZTNQ271F|  6959.0|        6087.0|
+----------+-------+--------------+--------+--------------+
only showing top 5 rows
```

In [19]:
```
data_indexed.select([count(when(col(c).isNull(), c)).alias(c) for c in
                     data_indexed.columns]).toPandas().T
```

Out[19]:

	0
asin	0
overall	0
reviewerID	0
asin_idx	0
reviewerID_idx	0

In [20]:
```
# Smaller dataset so we will use 0.8 / 0.2
(training, test) = data_indexed.randomSplit([0.8, 0.2])
```

In [21]:
```
# Creating ALS model and fitting data
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.recommendation import ALS
```

In [22]:
```
als = ALS(maxIter=5,
          regParam=0.09,
          rank = 25,
          userCol="reviewerID_idx",
          itemCol="asin_idx",
          ratingCol="overall",
          coldStartStrategy="drop",
          nonnegative=True)
model = als.fit(training)
```

In [23]:
```
# Evaluate the model by computing the RMSE on the test data
predictions = model.transform(test)
```

In [24]:
```
predictions.select(["asin_idx", "reviewerID_idx",
                    "overall", "prediction"]).show(5)
```

```
+--------+--------------+-------+----------+
|asin_idx|reviewerID_idx|overall|prediction|
+--------+--------------+-------+----------+
|   148.0|        9492.0|    5.0| 4.2765565|
|   148.0|        5258.0|    3.0| 3.6554668|
|   148.0|        5909.0|    4.0| 3.1009164|
|   148.0|       14415.0|    5.0| 3.8484008|
|   148.0|       19062.0|    5.0| 3.4705784|
+--------+--------------+-------+----------+
only showing top 5 rows
```

In [25]:
```
evaluator = RegressionEvaluator(metricName="rmse",
                                labelCol="overall",
                                predictionCol="prediction")

rmse = evaluator.evaluate(predictions)
print("Root-mean-square error = " + str(rmse))
```

```
Root-mean-square error = 1.3504136630485968
```

In [26]:
```
# On average, this model is ~ 1.35 from perfect recommendations.
```

Providing Recommendations: for all users

In [27]:
```
# get 20 recommendations which have highest rating.
user_recs = model.recommendForAllUsers(20)
```

In [28]:
```
for user in user_recs.head(5):
    print(user)
    print("\n")
```

```
Row(reviewerID_idx=1580, recommendations=[Row(asin_idx=9900, rating=7.452762603
759766), Row(asin_idx=7885, rating=7.445200443267822), Row(asin_idx=8386, ratin
g=7.283047199249268), Row(asin_idx=7300, rating=7.233673572540283), Row(asin_id
x=9998, rating=7.199503421783447), Row(asin_idx=9432, rating=7.078475952148437
5), Row(asin_idx=8888, rating=7.067144870758057), Row(asin_idx=8747, rating=7.0
503754615783691, Row(asin_idx=7840, rating=7.049852371215821, Row(asin_idx=314
3, rating=7.045359134674072), Row(asin_idx=12100, rating=7.037707328796387), Ro
w(asin_idx=11372, rating=7.035341739654541), Row(asin_idx=6793, rating=7.007732
391357422), Row(asin_idx=6539, rating=6.991481781005859), Row(asin_idx=8643, ra
ting=6.974045753479004), Row(asin_idx=8691, rating=6.971042156219482), Row(asin
_idx=10728, rating=6.964417457580566), Row(asin_idx=10466, rating=6.94252109527
5879), Row(asin_idx=10039, rating=6.9183573722839355), Row(asin_idx=7585, ratin
g=6.905022621154785)])


Row(reviewerID_idx=4900, recommendations=[Row(asin_idx=10071, rating=6.86618375
7781982), Row(asin_idx=10450, rating=6.866183757781982), Row(asin_idx=12002, ra
ting=6.856912612915039), Row(asin_idx=10013, rating=6.856446743011475), Row(asi
n_idx=8386, rating=6.838607311248779), Row(asin_idx=10958, rating=6.82022857666
0156), Row(asin_idx=10279, rating=6.657992362976074), Row(asin_idx=7885, rating
=6.617455005645752), Row(asin_idx=11977, rating=6.580188274383545), Row(asin_id
x=9703, rating=6.570758819580078), Row(asin_idx=9665, rating=6.53776121139526
4), Row(asin_idx=8603, rating=6.454494953155518), Row(asin_idx=7300, rating=6.4
27910327911377), Row(asin_idx=9549, rating=6.423874855041504), Row(asin_idx=112
27, rating=6.382607936859131), Row(asin_idx=9802, rating=6.360374927520752), Ro
w(asin_idx=3422, rating=6.358455181121826), Row(asin_idx=6136, rating=6.3500509
26208496), Row(asin_idx=6396, rating=6.349891662597656), Row(asin_idx=8972, rat
ing=6.346033573150635)])


Row(reviewerID_idx=5300, recommendations=[Row(asin_idx=10450, rating=7.88202285
7666016), Row(asin_idx=10071, rating=7.882022857666016), Row(asin_idx=10279, ra
ting=7.857653617858887), Row(asin_idx=12002, rating=7.836369514465332), Row(asi
n_idx=10013, rating=7.834311485290527), Row(asin_idx=10958, rating=7.7301292419
43359), Row(asin_idx=7885, rating=7.546260833740234), Row(asin_idx=7300, rating
=7.035318374633789), Row(asin_idx=4299, rating=7.0198140144348145), Row(asin_id
x=8386, rating=6.878007888793945), Row(asin_idx=9545, rating=6.74942064285278
3), Row(asin_idx=10466, rating=6.746596813201904), Row(asin_idx=7082, rating=6.
730844497680664), Row(asin_idx=11673, rating=6.722889423370361), Row(asin_idx=9
409, rating=6.704495906829834), Row(asin_idx=8347, rating=6.698277950286865), R
ow(asin_idx=7361, rating=6.693828582763672), Row(asin_idx=7920, rating=6.614742
279052734), Row(asin_idx=7900, rating=6.586149215698242), Row(asin_idx=4710, ra
ting=6.5770463943481445)])


Row(reviewerID_idx=6620, recommendations=[Row(asin_idx=10071, rating=7.87718248
3673096), Row(asin_idx=10450, rating=7.877182483673096), Row(asin_idx=12002, ra
ting=7.858290672302246), Row(asin_idx=10013, rating=7.858236789703369), Row(asi
n_idx=10958, rating=7.803875923156738), Row(asin_idx=7885, rating=7.77376794815
0635), Row(asin_idx=10279, rating=7.713746547698975), Row(asin_idx=7300, rating
=7.360595703125), Row(asin_idx=8386, rating=7.12551736831665), Row(asin_idx=943
2, rating=7.098012924194336), Row(asin_idx=7591, rating=7.043422222137451), Row
(asin_idx=9665, rating=7.017157554626465), Row(asin_idx=9784, rating=6.98062896
```

```
7285156), Row(asin_idx=6396, rating=6.968845367431641), Row(asin_idx=8347, rating=6.9
ng=6.954199314117432), Row(asin_idx=9900, rating=6.791838645935059), Row(asin_idx=8
dx=5677, rating=6.754838943481445), Row(asin_idx=7421, rating=6.73906898498535
2), Row(asin_idx=6098, rating=6.733091831207275), Row(asin_idx=8407, rating=6.7
07345008850098)])

Row(reviewerID_idx=7240, recommendations=[Row(asin_idx=8386, rating=6.249364852
905273), Row(asin_idx=7300, rating=6.18107795715332), Row(asin_idx=7885, rating
=6.09645414352417), Row(asin_idx=9900, rating=6.0728325843811035), Row(asin_idx
=8888, rating=5.873400688171387), Row(asin_idx=10450, rating=5.83579730987548
8), Row(asin_idx=10071, rating=5.835797309875488), Row(asin_idx=10013, rating=
5.817392349243164), Row(asin_idx=12002, rating=5.816351413726807), Row(asin_idx
=6396, rating=5.768041610717773), Row(asin_idx=10728, rating=5.76656913757324
2), Row(asin_idx=10958, rating=5.7658257484436035), Row(asin_idx=9784, rating=
5.753474235534668), Row(asin_idx=7082, rating=5.733229637145996), Row(asin_idx=
8406, rating=5.722962379455566), Row(asin_idx=6098, rating=5.7152099609375), Ro
w(asin_idx=9220, rating=5.712944984436035), Row(asin_idx=8681, rating=5.7128973
00720215), Row(asin_idx=11521, rating=5.710545539855957), Row(asin_idx=10279, r
ating=5.710353374481201)])
```

Converting back to string form

In [29]:
```
import pandas as pd
recs=model.recommendForAllUsers(10).toPandas()
nrecs=recs.recommendations.apply(pd.Series) \
            .merge(recs, right_index = True, left_index = True) \
            .drop(["recommendations"], axis = 1) \
            .melt(id_vars = ['reviewerID_idx'], value_name = "recommendation") \
            .drop("variable", axis = 1) \
            .dropna()
nrecs=nrecs.sort_values('reviewerID_idx')
nrecs=pd.concat([nrecs['recommendation']\
                 .apply(pd.Series), nrecs['reviewerID_idx']], axis = 1)
nrecs.columns = [
        'ProductID_index',
        'Rating',
        'UserID_index'
    ]
```

In [30]:
```
md=data_indexed.select(['reviewerID', 'reviewerID_idx', 'asin', 'asin_idx'])
md=md.toPandas()
dict1 =dict(zip(md['reviewerID_idx'],md['reviewerID']))
dict2=dict(zip(md['asin_idx'],md['asin']))
nrecs['reviewerID']=nrecs['UserID_index'].map(dict1)
nrecs['asin']=nrecs['ProductID_index'].map(dict2)
nrecs=nrecs.sort_values('reviewerID')
nrecs.reset_index(drop=True, inplace=True)
new=nrecs[['reviewerID','asin','Rating']]
new['recommendations'] = list(zip(new.asin, new.Rating))
res=new[['reviewerID','recommendations']]
res_new=res['recommendations'].groupby([res.reviewerID])\
                                .apply(list).reset_index()
```

```
c:\program files\python36\lib\site-packages\ipykernel_launcher.py:10: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stab
le/user_guide/indexing.html#returning-a-view-versus-a-copy (http://pandas.pydat
a.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
y)
  # Remove the CWD from sys.path while we load stuff.
```

In [31]:
```
res_new
```

Out[31]:

	reviewerID	recommendations
0	A00414041RD0BXM6WK0GX	[(B00161IKD6, 4.968151092529297), (B000P8559S,...
1	A00473363TJ8YSZ3YAGG9	[(B001FO2GW0, 4.339757919311523), (B006J6R23M,...
2	A00700212KB3K0MVESPIY	[(B000ALBJ40, 6.009731292724609), (B00H8JPMX6,...
3	A0078719IR14X3NNUG0F	[(B000PHP8L4, 7.588184833526611), (B000ALBJ40,...
4	A01198201H0E3GHV2Z17I	[(B00HHECHLC, 6.440869331359863), (B000VOHH56,...
...	...	...
22356	AZZNK89PXD006	[(B0009OAHQY, 3.877105236053467), (B000052YMG,...
22357	AZZQXL8VDCFTV	[(B001CB2OQO, 6.011270523071289), (B0013YYNDM,...
22358	AZZT1ERHBSNQ8	[(B000C1ZFBG, 6.335065841674805), (B0013YYNDM,...
22359	AZZU6NXB8YJN9	[(B0042PE8LQ, 4.932450771331787), (B00161IKD6,...
22360	AZZZLM1E5JJ8C	[(B00HB831SM, 5.787951946258545), (B00HAPQT7Q,...

22361 rows × 2 columns

In [32]:
```
res_new.to_csv("beauty.csv")
```

Chapter 9: Frequent Pattern Mining

Ex5: instacart_online_grocery_shopping_2017_05_01

Dataset: link download https://www.instacart.com/datasets/grocery-shopping-2017 (https://www.instacart.com/datasets/grocery-shopping-2017)

Requirement:

- Read data
- Pre-process data
- Apply FPGrowth algorithm to find association rules from this dataset. Find the most popular items in a basket.

In [1]:
```
import findspark
findspark.init()
```

In [2]:
```
import pyspark
```

In [3]:
```
from pyspark import SparkContext
from pyspark.conf import SparkConf
from pyspark.sql import SparkSession
```

In [4]:
```
sc = SparkContext()
```

In [5]:
```
spark = SparkSession.builder.appName('ex_demo').getOrCreate()
```

In [6]:
```
from pyspark.ml.fpm import FPGrowth
```

In [7]:
```
# Loads data.
data = spark.read.csv('instacart_2017_05_01/order_products__train.csv',
                      header=True,
                      inferSchema=True)
```

In [8]:
```
data.count()
```

Out[8]:
```
1384617
```

In [9]: data.show()

```
+--------+----------+-----------------+---------+
|order_id|product_id|add_to_cart_order|reordered|
+--------+----------+-----------------+---------+
|       1|     49302|                1|        1|
|       1|     11109|                2|        1|
|       1|     10246|                3|        0|
|       1|     49683|                4|        0|
|       1|     43633|                5|        1|
|       1|     13176|                6|        0|
|       1|     47209|                7|        0|
|       1|     22035|                8|        1|
|      36|     39612|                1|        0|
|      36|     19660|                2|        1|
|      36|     49235|                3|        0|
|      36|     43086|                4|        1|
|      36|     46620|                5|        1|
|      36|     34497|                6|        1|
|      36|     48679|                7|        1|
|      36|     46979|                8|        1|
|      38|     11913|                1|        0|
|      38|     18159|                2|        0|
|      38|      4461|                3|        0|
|      38|     21616|                4|        1|
+--------+----------+-----------------+---------+
only showing top 20 rows
```

In [10]:
```
# Pre-processing data
from pyspark.sql.functions import collect_list, col, count, collect_set
```

In [11]:
```
data.createOrReplaceTempView("order_products_train")
```

In [12]:
```
products = spark.sql("select distinct product_id from order_products_train")
products.count()
```

Out[12]: 39123

In [13]:
```
rawData = spark.sql("select * from order_products_train")
baskets = rawData.groupBy('order_id').agg(collect_set('product_id')\
                                          .alias('items'))
baskets.createOrReplaceTempView('baskets')
```

In [14]:
```
baskets.show(5, truncate=False)
```

```
+--------+--------------------------------------------------------------------------
----------------------------------------------------------------------------------
------------------------------------------------------------------------+
|order_id|items
|
+--------+--------------------------------------------------------------------------
----------------------------------------------------------------------------------
------------------------------------------------------------------------+
|1342    |[30827, 3798, 14966, 21137, 46129, 33081, 13176, 7862]
|
|1591    |[48246, 44116, 24852, 5194, 9130, 48823, 46473, 40310, 32520, 22105,
16900, 27681, 4103, 44008, 17758, 41671, 25316, 45061, 38805, 48205, 25237, 196
04, 5384, 27344, 17203, 18792, 12986, 39758, 34358, 31215, 9387]|
|4519    |[29270]
|
|4935    |[45190]
|
|6357    |[33731, 14669, 43789, 37524, 39408, 43129, 24852, 48745, 38772]
|
+--------+--------------------------------------------------------------------------
----------------------------------------------------------------------------------
------------------------------------------------------------------------+
only showing top 5 rows
```

In [15]:
```
type(baskets)
```

Out[15]:
```
pyspark.sql.dataframe.DataFrame
```

In [16]:
```
fpGrowth = FPGrowth(itemsCol="items", minSupport=0.003,
                    minConfidence=0.003)
model = fpGrowth.fit(baskets)
```

In [17]:
```
# Display frequent itemsets.
model.freqItemsets.show()
```

```
+--------------------+-----+
|               items| freq|
+--------------------+-----+
|             [13629]|  772|
|              [5194]|  475|
|             [24852]|18726|
|             [13176]|15480|
|             [35921]|  769|
|             [20345]|  473|
|             [21137]|10894|
|      [21137, 13176]| 3074|
|      [21137, 24852]| 2174|
|             [23165]|  764|
|             [13380]|  473|
|              [7969]|  472|
|             [21903]| 9784|
|      [21903, 21137]| 1639|
|[21903, 21137, 13...|  587|
|      [21903, 13176]| 2236|
|      [21903, 24852]| 2000|
|             [32478]|  763|
|             [47626]| 8135|
|      [47626, 21137]| 1017|
+--------------------+-----+
only showing top 20 rows
```

In [18]:
```
# transform examines the input items against all the association rules and summa
# consequents as prediction
mostPopularItemInABasket = model.transform(baskets)
```

In [19]:
```
mostPopularItemInABasket.show()
```

```
+--------+--------------------+--------------------+
|order_id|               items|          prediction|
+--------+--------------------+--------------------+
|    1342|[30827, 3798, 149...|[21903, 47626, 47...|
|    1591|[48246, 44116, 24...|[21137, 21903, 47...|
|    4519|             [29270]|                  []|
|    4935|             [45190]|                  []|
|    6357|[33731, 14669, 43...|[21137, 21903, 47...|
|   10362|[28522, 43789, 12...|[21137, 47626, 47...|
|   19204|[45255, 37285, 48...|                  []|
|   29601|[2716, 48057, 219...|[21137, 21903, 47...|
|   31035|[40723, 8174, 131...|[21137, 21903, 47...|
|   40011|[27292, 35213, 21...|[21137, 13176, 24...|
|   46266|[38558, 48642, 13...|[47626, 47766, 47...|
|   51607|[41390, 42752, 17...|                  []|
|   58797|[30827, 8803, 326...|[21137, 21903, 47...|
|   61793|[26348, 6184, 433...|[21137, 16797, 39...|
|   67089|[47766, 29388, 21...|[47626, 21137, 47...|
|   70863|[34791, 2618, 173...|      [13176, 24852]|
|   88674|[25659, 16262, 22...|                  []|
|   91937|[20708, 38200, 26...|                  []|
|   92317|[18105, 34969, 17...|[13176, 21903, 21...|
|   99621|[21616, 43789, 38...|[26209, 21137, 47...|
+--------+--------------------+--------------------+
only showing top 20 rows
```

Use product_name instead of product_id

In [20]:
```
product_data = spark.read.csv('instacart_2017_05_01/products.csv',
                              header=True, inferSchema=True)
```

In [21]:
```
product_data.show(5, truncate=False)
```

```
+----------+------------------------------------------------------------------+-
-------+-------------+                                                        |a
|product_id|product_name
isle_id|department_id|                                                        +-
+----------+------------------------------------------------------------------+-
-------+-------------+                                                        |6
|1         |Chocolate Sandwich Cookies
1      |19          |                                                        |1
|2         |All-Seasons Salt
04     |13          |                                                        |9
|3         |Robust Golden Unsweetened Oolong Tea
4      |7           |                                                        |3
|4         |Smart Ones Classic Favorites Mini Rigatoni With Vodka Cream Sauce
8      |1           |                                                        |5
|5         |Green Chile Anytime Sauce
|13          |
+----------+------------------------------------------------------------------+-
-------+-------------+
only showing top 5 rows
```

In [22]:
```
product_data.createOrReplaceTempView("products")
```

In [23]:
```
rawData_1 = spark.sql('''select p.product_name, o.order_id from products p
                         inner join order_products_train o
                         where o.product_id = p.product_id''')
baskets_1 = rawData_1.groupBy('order_id').agg(collect_set('product_name')\
                                              .alias('items'))
baskets_1.createOrReplaceTempView('baskets')
```

In [24]:
```
baskets_1.head(3)
```

Out[24]:
```
[Row(order_id=1342, items=['Raw Shrimp', 'Seedless Cucumbers', 'Versatile Stain
Remover', 'Organic Strawberries', 'Organic Mandarins', 'Chicken Apple Sausage',
'Pink Lady Apples', 'Bag of Organic Bananas']),
 Row(order_id=1591, items=['Cracked Wheat', 'Strawberry Rhubarb Yoghurt', 'Orga
nic Bunny Fruit Snacks Berry Patch', 'Goodness Grapeness Organic Juice Drink',
'Honey Graham Snacks', 'Spinach', 'Granny Smith Apples', 'Oven Roasted Turkey B
reast', 'Pure Vanilla Extract', 'Chewy 25% Low Sugar Chocolate Chip Granola',
'Banana', 'Original Turkey Burgers Smoke Flavor Added', 'Twisted Tropical Tango
Organic Juice Drink', 'Navel Oranges', 'Lower Sugar Instant Oatmeal  Variety',
'Ultra Thin Sliced Provolone Cheese', 'Natural Vanilla Ice Cream', 'Cinnamon Mu
ltigrain Cereal', 'Garlic', 'Goldfish Pretzel Baked Snack Crackers', 'Original
Whole Grain Chips', 'Medium Scarlet Raspberries', 'Lemon Yogurt', 'Original Pat
ties (100965) 12 Oz Breakfast', 'Nutty Bars', 'Strawberry Banana Smoothie', 'Gr
een Machine Juice Smoothie', 'Coconut Dreams Cookies', 'Buttermilk Waffles', 'U
ncured Genoa Salami', 'Organic Greek Whole Milk Blended Vanilla Bean Yogurt']),
 Row(order_id=4519, items=['Beet Apple Carrot Lemon Ginger Organic Cold Pressed
Juice Beverage'])]
```

In [25]:
```
fpGrowth_1 = FPGrowth(itemsCol="items",
                      minSupport=0.003,
                      minConfidence=0.003)
model_1 = fpGrowth.fit(baskets_1)
```

In [26]:
```
# Display frequent itemsets.
model_1.freqItemsets.show(truncate=False)
```

```
+------------------------------------------------------------------------+-----+
|items                                                                   |freq |
+------------------------------------------------------------------------+-----+
|[Organic Tomato Basil Pasta Sauce]                                      |772  |
|[Organic Spinach Bunch]                                                 |475  |
|[Banana]                                                                |18726|
|[Bag of Organic Bananas]                                                |15480|
|[Organic Large Grade A Brown Eggs]                                      |769  |
|[Organic Blue Corn Tortilla Chips]                                      |473  |
|[Organic Strawberries]                                                  |10894|
|[Organic Strawberries, Bag of Organic Bananas]                          |3074 |
|[Organic Strawberries, Banana]                                          |2174 |
|[Organic Leek]                                                          |764  |
|[Thin Crust Pepperoni Pizza]                                            |473  |
|[Lime]                                                                  |472  |
|[Organic Baby Spinach]                                                  |9784 |
|[Organic Baby Spinach, Organic Strawberries]                            |1639 |
|[Organic Baby Spinach, Organic Strawberries, Bag of Organic Bananas]    |587  |
|[Organic Baby Spinach, Bag of Organic Bananas]                          |2236 |
|[Organic Baby Spinach, Banana]                                          |2000 |
|[Reduced Fat 2% Milk]                                                   |763  |
|[Large Lemon]                                                           |8135 |
|[Large Lemon, Organic Strawberries]                                     |1017 |
+------------------------------------------------------------------------+-----+
only showing top 20 rows
```

In [27]:
```
mostPopularItemInABasket_1 = model_1.transform(baskets_1)
```

In [28]: `mostPopularItemInABasket_1.head(3)`

Out[28]:
```
[Row(order_id=1342, items=['Raw Shrimp', 'Seedless Cucumbers', 'Versatile Stain
Remover', 'Organic Strawberries', 'Organic Mandarins', 'Chicken Apple Sausage',
'Pink Lady Apples', 'Bag of Organic Bananas'], prediction=['Organic Baby Spinac
h', 'Large Lemon', 'Organic Avocado', 'Organic Hass Avocado', 'Strawberries',
'Limes', 'Organic Raspberries', 'Organic Blueberries', 'Organic Whole Milk', 'O
rganic Cucumber', 'Organic Zucchini', 'Organic Yellow Onion', 'Organic Garlic',
'Seedless Red Grapes', 'Asparagus', 'Organic Grape Tomatoes', 'Organic Red Onio
n', 'Organic Baby Carrots', 'Honeycrisp Apple', 'Organic Cilantro', 'Organic Le
mon', 'Sparkling Water Grapefruit', 'Raspberries', 'Organic Fuji Apple', 'Small
Hass Avocado', 'Organic Baby Arugula', 'Organic Large Extra Fancy Fuji Apple',
'Original Hummus', 'Organic Blackberries', 'Organic Gala Apples', 'Fresh Caulif
lower', 'Organic Half & Half', 'Michigan Organic Kale', 'Organic Small Bunch Ce
lery', 'Organic Garnet Sweet Potato (Yam)', 'Organic Tomato Cluster', 'Carrot
s', 'Organic Peeled Whole Baby Carrots', 'Organic Italian Parsley Bunch', 'Orga
nic Red Bell Pepper', 'Organic Granny Smith Apple', 'Hass Avocados', 'Apple Hon
eycrisp Organic', 'Spring Water', 'Organic Unsweetened Almond Milk', 'Unsweeten
ed Almondmilk', 'Organic Ginger Root', 'Organic Whole String Cheese', 'Organic
Navel Orange', 'Large Alfresco Eggs', "Organic D'Anjou Pears", 'Organic Kiwi',
'Organic Grade A Free Range Large Brown Eggs', 'Organic Lacinato (Dinosaur) Kal
e', 'Organic Carrot Bunch', 'Organic Broccoli', 'Organic Black Beans', 'Banan
a', 'Broccoli Crown', 'Organic Banana']),
 Row(order_id=1591, items=['Cracked Wheat', 'Strawberry Rhubarb Yoghurt', 'Orga
nic Bunny Fruit Snacks Berry Patch', 'Goodness Grapeness Organic Juice Drink',
'Honey Graham Snacks', 'Spinach', 'Granny Smith Apples', 'Oven Roasted Turkey B
reast', 'Pure Vanilla Extract', 'Chewy 25% Low Sugar Chocolate Chip Granola',
'Banana', 'Original Turkey Burgers Smoke Flavor Added', 'Twisted Tropical Tango
Organic Juice Drink', 'Navel Oranges', 'Lower Sugar Instant Oatmeal  Variety',
'Ultra Thin Sliced Provolone Cheese', 'Natural Vanilla Ice Cream', 'Cinnamon Mu
ltigrain Cereal', 'Garlic', 'Goldfish Pretzel Baked Snack Crackers', 'Original
Whole Grain Chips', 'Medium Scarlet Raspberries', 'Lemon Yogurt', 'Original Pat
ties (100965) 12 Oz Breakfast', 'Nutty Bars', 'Strawberry Banana Smoothie', 'Gr
een Machine Juice Smoothie', 'Coconut Dreams Cookies', 'Buttermilk Waffles', 'U
ncured Genoa Salami', 'Organic Greek Whole Milk Blended Vanilla Bean Yogurt'],
prediction=['Organic Strawberries', 'Organic Baby Spinach', 'Large Lemon', 'Org
anic Avocado', 'Organic Hass Avocado', 'Strawberries', 'Limes', 'Organic Raspbe
rries', 'Organic Blueberries', 'Organic Whole Milk', 'Organic Cucumber', 'Organ
ic Zucchini', 'Organic Yellow Onion', 'Organic Garlic', 'Seedless Red Grapes',
'Asparagus', 'Organic Grape Tomatoes', 'Organic Red Onion', 'Yellow Onions', 'O
rganic Baby Carrots', 'Honeycrisp Apple', 'Organic Cilantro', 'Sparkling Water
Grapefruit', 'Raspberries', 'Organic Fuji Apple', 'Small Hass Avocado', 'Brocco
li Crown', 'Organic Baby Arugula', 'Red Peppers', 'Organic Large Extra Fancy Fu
ji Apple', 'Original Hummus', 'Organic Blackberries', 'Organic Gala Apples', 'F
resh Cauliflower', 'Organic Half & Half', 'Michigan Organic Kale', 'Organic Sma
ll Bunch Celery', 'Organic Garnet Sweet Potato (Yam)', 'Organic Tomato Cluste
r', 'Green Bell Pepper', 'Carrots', 'Organic Peeled Whole Baby Carrots', 'Half
& Half', 'Cucumber Kirby', 'Organic Red Bell Pepper', 'Organic Granny Smith App
le', 'Blueberries', '100% Whole Wheat Bread', 'Apple Honeycrisp Organic', 'Red
Vine Tomato', 'Unsweetened Almondmilk', 'Boneless Skinless Chicken Breasts', 'O
rganic Whole String Cheese', 'Roma Tomato', 'Bunched Cilantro', 'Jalapeno Peppe
rs', "Organic D'Anjou Pears", 'Orange Bell Pepper', 'Grape White/Green Seedles
s', 'Red Raspberries', 'Clementines, Bag', 'Unsweetened Original Almond Breeze
Almond Milk', 'Bartlett Pears']),
 Row(order_id=4519, items=['Beet Apple Carrot Lemon Ginger Organic Cold Pressed
Juice Beverage'], prediction=[])]
```

In [29]:
```
type(mostPopularItemInABasket_1)
```

Out[29]:
```
pyspark.sql.dataframe.DataFrame
```

In [30]:
```
# chuyển list array thành string
from pyspark.sql.types import StringType
```

In [31]:
```
mostPopularItemInABasket_1.printSchema()
```

```
root
 |-- order_id: integer (nullable = true)
 |-- items: array (nullable = true)
 |    |-- element: string (containsNull = true)
 |-- prediction: array (nullable = true)
 |    |-- element: string (containsNull = true)
```

In [33]:
```
mostPopularItemInABasket_1.createOrReplaceTempView("popular_items")
```

In [34]:
```
DF_cast = mostPopularItemInABasket_1.select('order_id',
                          mostPopularItemInABasket_1.items.cast(StringType()),
                          mostPopularItemInABasket_1.prediction.cast(StringType()))

DF_cast.printSchema()
```

```
root
 |-- order_id: integer (nullable = true)
 |-- items: string (nullable = true)
 |-- prediction: string (nullable = true)
```

In [35]:
```
DF_cast.head(3)
```

Out[35]:
```
[Row(order_id=1342, items='[Raw Shrimp, Seedless Cucumbers, Versatile Stain Rem
over, Organic Strawberries, Organic Mandarins, Chicken Apple Sausage, Pink Lady
Apples, Bag of Organic Bananas]', prediction="[Organic Baby Spinach, Large Lemo
n, Organic Avocado, Organic Hass Avocado, Strawberries, Limes, Organic Raspberr
ies, Organic Blueberries, Organic Whole Milk, Organic Cucumber, Organic Zucchin
i, Organic Yellow Onion, Organic Garlic, Seedless Red Grapes, Asparagus, Organi
c Grape Tomatoes, Organic Red Onion, Organic Baby Carrots, Honeycrisp Apple, Or
ganic Cilantro, Organic Lemon, Sparkling Water Grapefruit, Raspberries, Organic
Fuji Apple, Small Hass Avocado, Organic Baby Arugula, Organic Large Extra Fancy
Fuji Apple, Original Hummus, Organic Blackberries, Organic Gala Apples, Fresh C
auliflower, Organic Half & Half, Michigan Organic Kale, Organic Small Bunch Cel
ery, Organic Garnet Sweet Potato (Yam), Organic Tomato Cluster, Carrots, Organi
c Peeled Whole Baby Carrots, Organic Italian Parsley Bunch, Organic Red Bell Pe
pper, Organic Granny Smith Apple, Hass Avocados, Apple Honeycrisp Organic, Spri
ng Water, Organic Unsweetened Almond Milk, Unsweetened Almondmilk, Organic Ging
er Root, Organic Whole String Cheese, Organic Navel Orange, Large Alfresco Egg
s, Organic D'Anjou Pears, Organic Kiwi, Organic Grade A Free Range Large Brown
Eggs, Organic Lacinato (Dinosaur) Kale, Organic Carrot Bunch, Organic Broccoli,
Organic Black Beans, Banana, Broccoli Crown, Organic Banana]"),
 Row(order_id=1591, items='[Cracked Wheat, Strawberry Rhubarb Yoghurt, Organic
Bunny Fruit Snacks Berry Patch, Goodness Grapeness Organic Juice Drink, Honey G
raham Snacks, Spinach, Granny Smith Apples, Oven Roasted Turkey Breast, Pure Va
nilla Extract, Chewy 25% Low Sugar Chocolate Chip Granola, Banana, Original Tur
key Burgers Smoke Flavor Added, Twisted Tropical Tango Organic Juice Drink, Nav
el Oranges, Lower Sugar Instant Oatmeal  Variety, Ultra Thin Sliced Provolone C
heese, Natural Vanilla Ice Cream, Cinnamon Multigrain Cereal, Garlic, Goldfish
Pretzel Baked Snack Crackers, Original Whole Grain Chips, Medium Scarlet Raspbe
rries, Lemon Yogurt, Original Patties (100965) 12 Oz Breakfast, Nutty Bars, Str
awberry Banana Smoothie, Green Machine Juice Smoothie, Coconut Dreams Cookies,
Buttermilk Waffles, Uncured Genoa Salami, Organic Greek Whole Milk Blended Vani
lla Bean Yogurt]', prediction="[Organic Strawberries, Organic Baby Spinach, Lar
ge Lemon, Organic Avocado, Organic Hass Avocado, Strawberries, Limes, Organic R
aspberries, Organic Blueberries, Organic Whole Milk, Organic Cucumber, Organic
Zucchini, Organic Yellow Onion, Organic Garlic, Seedless Red Grapes, Asparagus,
Organic Grape Tomatoes, Organic Red Onion, Yellow Onions, Organic Baby Carrots,
Honeycrisp Apple, Organic Cilantro, Sparkling Water Grapefruit, Raspberries, Or
ganic Fuji Apple, Small Hass Avocado, Broccoli Crown, Organic Baby Arugula, Red
Peppers, Organic Large Extra Fancy Fuji Apple, Original Hummus, Organic Blackbe
rries, Organic Gala Apples, Fresh Cauliflower, Organic Half & Half, Michigan Or
ganic Kale, Organic Small Bunch Celery, Organic Garnet Sweet Potato (Yam), Orga
nic Tomato Cluster, Green Bell Pepper, Carrots, Organic Peeled Whole Baby Carro
ts, Half & Half, Cucumber Kirby, Organic Red Bell Pepper, Organic Granny Smith
Apple, Blueberries, 100% Whole Wheat Bread, Apple Honeycrisp Organic, Red Vine
Tomato, Unsweetened Almondmilk, Boneless Skinless Chicken Breasts, Organic Whol
e String Cheese, Roma Tomato, Bunched Cilantro, Jalapeno Peppers, Organic D'Anj
ou Pears, Orange Bell Pepper, Grape White/Green Seedless, Red Raspberries, Clem
entines, Bag, Unsweetened Original Almond Breeze Almond Milk, Bartlett Pear
s]"),
 Row(order_id=4519, items='[Beet Apple Carrot Lemon Ginger Organic Cold Pressed
Juice Beverage]', prediction='[]')]
```

In [36]:
```
DF_cast.write.csv('mostPopularItemInABasket.csv')
```