

How Does the Apriori Algorithm Work?

The Apriori algorithm operates on a straightforward premise. When the support value of an item set exceeds a certain threshold, it is considered a frequent item set. Take into account the following steps. To begin, set the support criterion, meaning that only those things that have more than the support criterion are considered relevant.

- Step 1: Create a list of all the elements that appear in every transaction and create a frequency table.
- Step 2: Set the minimum level of support. Only those elements whose support exceeds or equals the threshold support are significant.
- Step 3: All potential pairings of important elements must be made, bearing in mind that AB and BA are interchangeable.
- Step 4: Tally the number of times each pair appears in a transaction.
- Step 5: Only those sets of data that meet the criterion of support are significant.
- Step 6: Now, suppose you want to find a set of three things that may be bought together. A rule, known as self-join, is needed to build a three-item set. The item pairings OP, OB, PB, and PM state that two combinations with the same initial letter are sought from these sets.

The rapid rise of e-commerce apps has increased the accumulation of data. To forecast outcomes, [data mining](#), also known as KDD (Knowledge Discovery in Databases), is used to detect irregularities, linkages, [trends and patterns in data](#).

An algorithm known as Apriori is a common one in data mining. It's used to identify the most frequently occurring elements and meaningful associations in a dataset. As an example, products brought in by consumers to a shop may all be used as inputs in this system.

An effective Market Basket Analysis is critical since it allows consumers to purchase their products with more convenience, resulting in a rise in market sales. Furthermore, it has been applied in healthcare to aid in the identification of harmful medication responses. A [clustering algorithm](#) is generated that identifies which combinations of drugs and patient factors are associated with adverse drug reactions.

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Apriori Property

In 1994, R. Agrawal and R. Srikant developed the Apriori method for identifying the most frequently occurring itemsets in a dataset using the boolean association rule. Since it makes

use of previous knowledge about common itemset features, the method is referred to as Apriori. This is achieved by the use of an iterative technique or level-wise approach, in which k-frequent itemsets are utilized to locate k+1 itemsets.

An essential feature known as the Apriori property is utilized to boost the effectiveness of level-wise production of frequent itemsets. This property helps by minimizing the search area, which in turn serves to maximize the productivity of level-wise creation of frequent patterns.

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 1. OPB is the result of OP and OB.
 2. PBM is the result of PB and PM.
- Step 7: When the threshold criterion is applied again, you'll get the significant itemset.

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Steps for Apriori Algorithm

The Apriori algorithm has the following steps:

- Step 1: Determine the level of transactional database support and establish the minimal degree of assistance and dependability.

- **Step 2:** Take all of the transaction's supports that are greater than the standard or chosen support value.
- **Step 3:** Look for all rules with greater precision than the cutoff or baseline standard, in these subgroups.
- **Step 4:** It is best to arrange the rules in ascending order of strength.

Methods to Improve Apriori Efficiency

The algorithm's efficiency may be improved in a variety of ways.

- **Hash-Based Technique**

Using a hash-based structure known as a hash table, the k-itemsets and their related counts are generated. The table is generated using a hash function.

- **Transaction Reduction**

There are fewer transactions to scan throughout each loop when using this strategy. Items that are not often used in a process are either tagged or deleted.

- **Partitioning**

Two database searches are all that is needed to find the frequently occurring itemsets using this approach. For any item set to be considered "possibly frequent" in the database, it must be prevalent in at least a few of the database subdivisions.

- **Sampling**

A random sample S is selected from database D, and then a search is conducted for frequent itemsets within that sample S. Global frequent itemsets may be misplaced. By reducing the min sup, this may be decreased.

- **Dynamic Itemset Counting**

During the screening of the dataset, this approach may add new iterations at any indicated starting position of the directory.

Advantages of Apriori

- An algorithm that is simple to grasp.
- The Merge and Squash processes are simple to apply on big itemsets in huge databases.

Disadvantages of Apriori

- It requires a significant amount of calculations if the itemsets are extremely big and the minimal support is maintained to a bare minimum.
- A full scan of the whole database is required.

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Introduction to Apriori Algorithm in Python

The Apriori algorithm is a classical [algorithm](#) in [Data Mining](#) that is used for mining frequent itemsets and association rule mining.

What is Association Rule Mining?

As mentioned before, the Apriori algorithm is used for [association rule mining](#). Now, what is association rule mining? Association rule mining is a technique to identify frequent patterns and associations among a set of items.

For example, understanding customer buying habits. By finding [correlations](#) and associations between different items that customers place in their 'shopping basket,' recurring patterns can be derived.

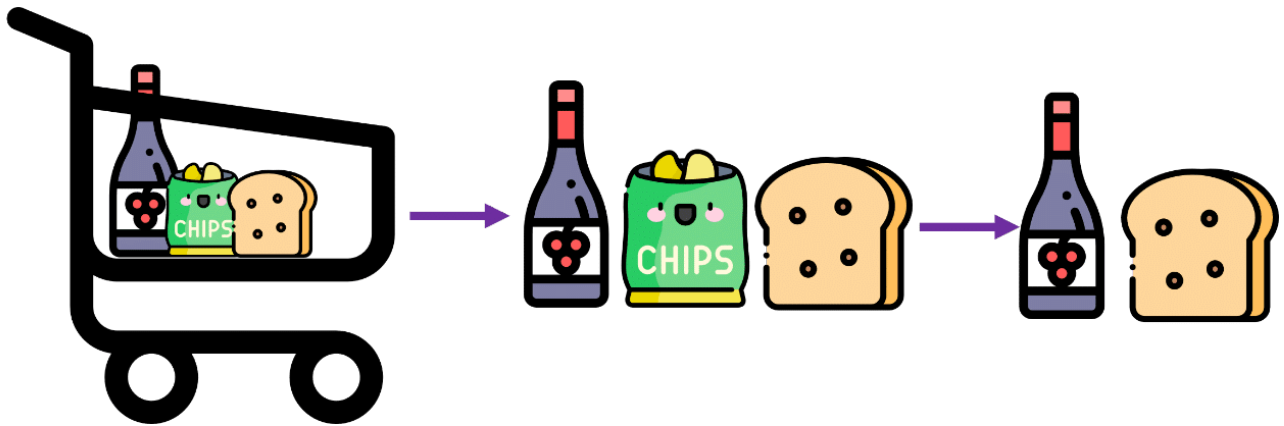


Say, Joshua goes to buy a bottle of wine from the supermarket. He also grabs a couple of chips as well. The manager there analyses that, not only Joshua, people often tend to buy wine and chips together. After finding out the [pattern](#), the manager starts to arrange these items together and notices an increase in sales.

This process of identifying an association between products/items is called association rule mining. To implement association rule mining, many algorithms have been developed. The Apriori algorithm is one of the most popular and arguably the most efficient algorithms among them. Let us discuss what an Apriori algorithm is.

What Is an Apriori Algorithm?

Apriori algorithm assumes that any subset of a frequent itemset must be frequent.



Say, a transaction containing {wine, chips, bread} also contains {wine, bread}. So, according to the principle of Apriori, if {wine, chips, bread} is frequent, then {wine, bread} must also be frequent.

How Does the Apriori Algorithm Work?

The key concept in the Apriori algorithm is that it assumes all subsets of a frequent itemset to be frequent. Similarly, for any infrequent itemset, all its supersets must also be infrequent.

Let us try and understand the workings of an Apriori algorithm with the help of a very famous business scenario, market basket analysis.

Here is a dataset consisting of six transactions in an hour. Each transaction is a combination of 0s and 1s, where 0 represents the absence of an item and 1 represents the presence of it.

Transaction ID	Win e	Chip s	Brea d	Mil k
1	1	1	1	1
2	1	0	1	1
3	0	0	1	1
4	0	1	0	0
5	1	1	1	1
6	1	1	0	1

We can find multiple rules in this scenario. For example, in a transaction of wine, chips, and bread, if wine and chips are bought, then customers also buy bread.

{wine, chips} => {bread}

To select the interesting rules out of multiple possible rules from this small business scenario, we will be using the following measures:

- Support
- Confidence
- [List](#)
- Conviction

Support

Support of item x is nothing but the ratio of the number of transactions in which item x appears to the total number of transactions.

i.e.,

$$\text{Support(wine)} = \frac{\text{Number of transactions in which the item wine appears}}{\text{Total number of transactions}}$$

$$\text{Support(wine)} = \frac{4}{6} = 0.66667$$

Confidence

Confidence (x => y) signifies the likelihood of the item y being purchased when item x is purchased. This method takes into account the popularity of item x.

i.e.,

$$\text{Conf}(\{\text{wine, chips}\} \Rightarrow \{\text{bread}\}) = \frac{\text{support(wine,chips,bread)}}{\text{support(wine,chips)}}$$

$$\text{Conf}(\{\text{wine, chips}\} \Rightarrow \{\text{bread}\}) = \frac{\frac{2}{6}}{\frac{4}{6}} = 0.667$$

Lift

Lift (x => y) is nothing but the ‘interestingness’ or the likelihood of the item y being purchased when item x is sold. Unlike confidence (x => y), this method takes into account the popularity of the item y.

i.e.,

$$\text{lift}(\{\text{wine, chips}\} \Rightarrow \{\text{bread}\}) = \frac{\text{support(wine,chips,bread)}}{\text{support(wine,chips)}}$$

$$\text{lift}(\{\text{wine, chips}\} \Rightarrow \{\text{bread}\}) = \frac{\frac{2}{6}}{\frac{4}{6} * \frac{4}{6}} = 1$$

- Lift ($x \Rightarrow y$) = 1 means that there is no correlation within the itemset.
- Lift ($x \Rightarrow y$) > 1 means that there is a positive correlation within the itemset, i.e., products in the itemset, x and y, are more likely to be bought together.
- Lift ($x \Rightarrow y$) < 1 means that there is a negative correlation within the itemset, i.e., products in itemset, x and y, are unlikely to be bought together.

Conviction

Conviction of a rule can be defined as follows:

$$\text{conv}(x \Rightarrow y) = \frac{1 - \text{supp}(y)}{1 - \text{conf}(x \Rightarrow y)}$$

i.e.,

$$\text{conv}(\{\text{wine, chips}\} \Rightarrow \{\text{bread}\}) = \frac{1 - \text{supp}(\text{bread})}{1 - \text{conf}(\{\text{wine, chips}\} \Rightarrow \{\text{bread}\})} = \frac{1 - \frac{4}{6}}{1 - \frac{2}{3}} = 1$$

Its value range is $[0, +\infty]$.

- Conv($x \Rightarrow y$) = 1 means that x has no relation with y.
- Greater the conviction higher the interest in the rule.

Now that we know the methods to find out the interesting rules, let us go back to the example.

Before we get started, let us fix the support threshold to 50 percent.

Step 1: Create a frequency table of all the items that occur in all transactions

Item	Frequency
Wine	4
Chips	4
Bread	4
Milk	5

Step 2: Find the significant items based on the support threshold

Support threshold = 3

Item	Frequency
Wine	4
Chips	4
Bread	4
Milk	5

Step 3: From the significant items, make possible pairs irrespective of the order

Item	Frequency
Wine, Chips	3
Wine, Bread	3
Wine, Milk	4
Chips, Bread	2
Chips, Milk	3
Bread, Milk	4

Step 4: Again, find the significant items based on the support threshold

Item	Frequency
Wine, Milk	4
Bread, Milk	4

Step 5: Now, make a set of three items that are bought together based on the significant items from Step 4

Item	Frequency
Wine, Bread, Milk	3

{Wine, Bread, Milk} is the only significant item set we have got from the given data. But in real-world scenarios, we would have dozens of items to build rules from. Then, we might have to make four/five-pair itemsets.

Watch Apriori Algorithm Tutorial

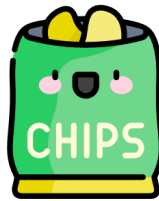
Hands-on: Apriori Algorithm in Python- Market Basket Analysis

Problem Statement

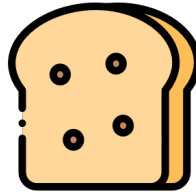
The manager of a retail store is trying to find out an association rule between six items, to figure out which items are more often bought together so that he can keep the items together in order to increase sales.



Wine



Chips



Bread



Milk



Butter

Dataset

Below is the transaction data from Day 1. This dataset contains 6 items and 22 transaction records.

	A	B	C	D	E	F
1	Wine	Chips	Bread	Butter	Milk	Apple
2	Wine		Bread	Butter	Milk	
3			Bread	Butter	Milk	
4		Chips				Apple
5	Wine	Chips	Bread	Butter	Milk	Apple
6	Wine	Chips			Milk	
7	Wine	Chips	Bread	Butter		Apple
8	Wine	Chips			Milk	
9	Wine		Bread			Apple
10	Wine		Bread	Butter	Milk	
11		Chips	Bread	Butter		Apple
12	Wine			Butter	Milk	Apple
13	Wine	Chips	Bread	Butter	Milk	
14	Wine		Bread		Milk	Apple
15	Wine		Bread	Butter	Milk	Apple
16	Wine	Chips	Bread	Butter	Milk	Apple
17		Chips	Bread	Butter	Milk	Apple
18		Chips		Butter	Milk	Apple
19	Wine	Chips	Bread	Butter	Milk	Apple
20	Wine		Bread	Butter	Milk	Apple
21	Wine	Chips	Bread		Milk	Apple
22		Chips				

Environment Setup:

Before we move forward, we need to install the 'apyori' package first.

pip install apyori

Anaconda Prompt

```
(base) C:\Users\intellipaat>pip install apyori
Collecting apyori
  Downloading https://files.pythonhosted.org/packages/25/fd/0561e2dd29aedd544bad2d1991636e38700cdaef9530490b863741f35295/apyori-1.1.1.tar.gz
Building wheels for collected packages: apyori
  Running setup.py bdist_wheel for apyori ... done
  Stored in directory: C:\Users\intellipaat\AppData\Local\pip\Cache\wheels\7b\2a\35\c0c3749c1a36d4f454ea22d8396e1b854b86340d63cbbb7949
Successfully built apyori
Installing collected packages: apyori
Successfully installed apyori-1.1.1
```

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AFGHANISTAN+1268	AG	ANTIGUA	AND	BARBUDA+1264	AI	
ANGUILLA+355	AL	ALBANIA+374	AM	ARMENIA+599	AN	
NETHERLANDS		ANTILLES+244	AO	ANGOLA+672	AQ	
ANTARCTICA+54	AR	ARGENTINA+1684	AS	AMERICAN SAMOA+43	AT	
AUSTRIA+61	AU	AUSTRALIA+297	AW	ARUBA+994	AZ	
AZERBAIJAN+387	BA	BOSNIA	AND	HERZEGOVINA+1246	BB	
BARBADOS+880	BD	BANGLADESH+32	BE	BELGIUM+226	BF	
BURKINA FASO+359	BG	BULGARIA+973	BH	BAHRAIN+257	BI	
BURUNDI+229	BJ	BENIN+590	BL	SAINT BARTHELEMY+1441	BM	
BERMUDA+673	BN	BRUNEI DARUSSALAM+591	BO	BOLIVIA+55	BR	
BRAZIL+1242	BS	BAHAMAS+975	BT	BHUTAN+267	BW	
BOTSWANA+375	BY	BELARUS+501	BZ	BELIZE+61	CC	COCOS
(KEELING ISLANDS+243	CD	CONGO, THE DEMOCRATIC REPUBLIC OF				
THE+236	CF	CENTRAL AFRICAN REPUBLIC+242	CG	CONGO+41	CH	
SWITZERLAND+225	CI	COTE D IVOIRE+682	CK	COOK ISLANDS+56	CL	
CHILE+237	CM	CAMEROON+86	CN	CHINA+57	CO	
COLOMBIA+506	CR	COSTA RICA+53	CU	CUBA+238	CV	CAPE
VERDE+61	CX	CHRISTMAS ISLAND+357	CY	CYPRUS+420	CZ	CZECH
REPUBLIC+49	DE	GERMANY+253	DJ	DJIBOUTI+45	DK	
DENMARK+1767	DM	DOMINICA+1809	DO	DOMINICAN		
REPUBLIC+213	DZ	ALGERIA+593	EC	ECUADOR+372	EE	
ESTONIA+20	EG	EGYPT+291	ER	ERITREA+34	ES	SPAIN+251
ETHIOPIA+358	FI	FINLAND+679	FJ	FIJI+500	FK	FALKLAND ISLANDS
(MALVINAS+691	FM	MICRONESIA, FEDERATED STATES OF+298	FO	FAROE		

ISLANDS+33 FR	FRANCE+241 GA	GABON+1473 GD
GRENADA+995 GE	GEORGIA+233 GH	GHANA+350 GI
GIBRALTAR+299 GL	GREENLAND+220 GM	GAMBIA+224 GN
GUINEA+240 GQ	EQUATORIAL GUINEA+30 GR	GREECE+502 GT
GUATEMALA+1671 GU	GUAM+245 GW	GUINEA-BISSAU+592 GY
GUYANA+852 HK	HONG KONG+504 HN	HONDURAS+385 HR
CROATIA+509 HT	HAITI+36 HU	HUNGARY+62 ID
INDONESIA+353 IE	IRELAND+972 IL	ISRAEL+44 IM
ISLE OF MAN+964 IQ	IRAQ+98 IR	IRAN, ISLAMIC REPUBLIC OF+354 IS
ICELAND+39 IT	ITALY+1876 JM	JAMAICA+962 JO
JORDAN+81 JP	JAPAN+254 KE	KENYA+996 KG
KYRGYZSTAN+855 KH	CAMBODIA+686 KI	KIRIBATI+269 KM
SAINT KITTS AND NEVIS+850 KP	COMOROS+1869 KN	KOREA DEMOCRATIC PEOPLES REPUBLIC OF+82 KR
KOREA REPUBLIC OF+965 KW	KUWAIT+1345 KY	CAYMAN ISLANDS+7 KZ
KAZAKSTAN+856 LA	LAO PEOPLES DEMOCRATIC REPUBLIC+961 LB	LEBANON+1758 LC
SAINT LUCIA+423 LI	LIECHTENSTEIN+94 LK	SRI LANKA+231 LR
LIBERIA+266 LS	LESOTHO+370 LT	LITHUANIA+352 LU
LUXEMBOURG+371 LV	LATVIA+218 LY	LIBYAN ARAB JAMAHIRIYA+212 MA
MOROCCO+377 MC	MONACO+373 MD	MOLDOVA, REPUBLIC OF+382 ME
MONTENEGRO+1599 MF	SAINT MARTIN+261 MG	MADAGASCAR+692 MH
MARSHALL ISLANDS+389 MK	MACEDONIA, THE FORMER YUGOSLAV REPUBLIC OF+223 ML	MALI+95 MM
MACAU+1670 MP	MYANMAR+976 MN	MONGOLIA+853 MO
MAURITANIA+1664 MS	NORTHERN MARIANA ISLANDS+222 MR	MAURITIUS+960 MV
MAURITIUS+960 MV	MONTSERRAT+356 MT	MALTA+230 MU
MEXICO+60 MY	MALDIVES+265 MW	MALAWI+52 MX
NEW ZEALAND+968 OM	MALAYSIA+258 MZ	MOZAMBIQUE+264 NA
PERU+689 PF	CALEDONIA+227 NE	NAMIBIA+687 NC
PHILIPPINES+92 PK	NIGER+234 NG	NIGERIA+505 NI
PAKISTAN+48 PL	NICARAGUA+31 NL	NORWAY+977 NP
POLAND+508 PM	NETHERLANDS+47 NO	SAINT PIERRE
SAINT PIERRE	NEPAL+674 NR	NAURU+683 NU
SAINT PIERRE	NIUE+64 NZ	NEW ZEALAND+968 OM
SAINT PIERRE	OMAN+507 PA	PANAMA+51 PE
SAINT PIERRE	FRENCH POLYNESIA+675 PG	PAPUA NEW GUINEA+63 PH
SAINT PIERRE	PAKISTAN+48 PL	POLAND+508 PM

AND MIQUELON+870 PN PITCAIRN+1 PR PUERTO RICO+351 PT
 PORTUGAL+680 PW PALAU+595 PY PARAGUAY+974 QA
 QATAR+40 RO ROMANIA+381 RS SERBIA+7 RU RUSSIAN
 FEDERATION+250 RW RWANDA+966 SA SAUDI ARABIA+677 SB
 SOLOMON ISLANDS+248 SC SEYCHELLES+249 SD SUDAN+46 SE
 SWEDEN+65 SG SINGAPORE+290 SH SAINT HELENA+386 SI
 SLOVENIA+421 SK SLOVAKIA+232 SL SIERRA LEONE+378 SM SAN
 MARINO+221 SN SENEGAL+252 SO SOMALIA+597 SR
 SURINAME+239 ST SAO TOME AND PRINCIPE+503 SV EL
 SALVADOR+963 SY SYRIAN ARAB REPUBLIC+268 SZ
 SWAZILAND+1649 TC TURKS AND CAICOS ISLANDS+235 TD
 CHAD+228 TG TOGO+66 TH THAILAND+992 TJ
 TAJIKISTAN+690 TK TOKELAU+670 TL TIMOR-LESTE+993 TM
 TURKMENISTAN+216 TN TUNISIA+676 TO TONGA+90 TR
 TURKEY+1868 TT TRINIDAD AND TOBAGO+688 TV TUVALU+886 TW
 TAIWAN, PROVINCE OF CHINA+255 TZ TANZANIA, UNITED REPUBLIC
 OF+380 UA UKRAINE+256 UG UGANDA+598 UY URUGUAY+998 UZ
 UZBEKISTAN+39 VA HOLY SEE (VATICAN CITY STATE+1784 VC SAINT
 VINCENT AND THE GRENADINES+58 VE VENEZUELA+1284 VG VIRGIN
 ISLANDS, BRITISH+1340 VI VIRGIN ISLANDS, U.S.+84 VN VIET
 NAM+678 VU VANUATU+681 WF WALLIS AND FUTUNA+685 WS
 SAMOA+381 XK KOSOVO+967 YE YEMEN+262 YT
 MAYOTTE+27 ZA SOUTH AFRICA+260 ZM ZAMBIA+263 ZW
 ZIMBABWE

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Market Basket Analysis Implementation within Python

With the help of the apyori package, we will be implementing the Apriori algorithm in order to help the manager in [market basket analysis](#).



Business Scenario

Step 1: Import the libraries

```
In [1]: #Importing the required datasets
import numpy as np
import pandas as pd
from apyori import apriori
```

Step 2: Load the dataset

```
In [2]: #Loading the dataset
store_data = pd.read_csv('Day1.csv', header=None)
```

Step 3: Have a glance at the records

```
In [3]: #Having a glance at the records
store_data
```

Out[3]:

	0	1	2	3	4	5
0	Wine	Chips	Bread	Butter	Milk	Apple
1	Wine	NaN	Bread	Butter	Milk	NaN
2	NaN	NaN	Bread	Butter	Milk	NaN
3	NaN	Chips	NaN	NaN	NaN	Apple
4	Wine	Chips	Bread	Butter	Milk	Apple
5	Wine	Chips	NaN	NaN	Milk	NaN
6	Wine	Chips	Bread	Butter	NaN	Apple
7	Wine	Chips	NaN	NaN	Milk	NaN
8	Wine	NaN	Bread	NaN	NaN	Apple
9	Wine	NaN	Bread	Butter	Milk	NaN
10	NaN	Chips	Bread	Butter	NaN	Apple
11	Wine	NaN	NaN	Butter	Milk	Apple
12	Wine	Chips	Bread	Butter	Milk	NaN
13	Wine	NaN	Bread	NaN	Milk	Apple
14	Wine	NaN	Bread	Butter	Milk	Apple
15	Wine	Chips	Bread	Butter	Milk	Apple
16	NaN	Chips	Bread	Butter	Milk	Apple
17	NaN	Chips	NaN	Butter	Milk	Apple
18	Wine	Chips	Bread	Butter	Milk	Apple
19	Wine	NaN	Bread	Butter	Milk	Apple
20	Wine	Chips	Bread	NaN	Milk	Apple
21	NaN	Chips	NaN	NaN	NaN	NaN

Step 4: Look at the shape

```
In [4]: store_data.shape
```

Out[4]: (22, 6)

Step 5: Convert Pandas DataFrame into a list of lists

```
In [5]: #Converting the pandas dataframe into a list of lists
records = []
for i in range(0, 22):
    records.append([str(store_data.values[i,j]) for j in range(0, 6)])
```

Step 6: Build the Apriori model

```
In [7]: #Building the first apriori model
association_rules = apriori(records, min_support=0.50, min_confidence=0.7, min_lift=1.2, min_length=2)
association_results = list(association_rules)
```

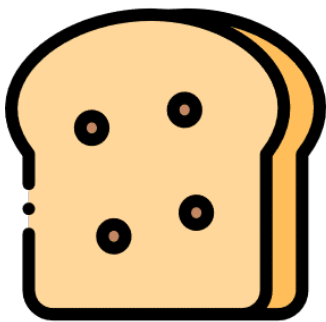
Step 7: Print out the number of rules

```
In [8]: #Getting the number of rules
print(len(association_results))
```

Step 8: Have a glance at the rule

```
In [10]: #Glancing at the first rule  
print(association_results)
```

```
[RelationRecord(items=frozenset({'Milk', 'Butter', 'Bread'}), support=0.5, ordered_statistics=[OrderedStatistic(items_base=frozenset({'Milk', 'Bread'}), items_add=frozenset({'Butter'}), confidence=0.8461538461538461, lift=1.241025641025641)])]
```



Bread



Milk



Butter

The support value for the first rule is 0.5. This number is calculated by dividing the number of transactions containing ‘Milk,’ ‘Bread,’ and ‘Butter’ by the total number of transactions.

The confidence level for the rule is 0.846, which shows that out of all the transactions that contain both “Milk” and “Bread”, 84.6 % contain ‘Butter’ too.

The lift of 1.241 tells us that ‘Butter’ is 1.241 times more likely to be bought by the customers who buy both ‘Milk’ and ‘Butter’ compared to the default likelihood of sale of ‘Butter.’

Limitations of Apriori Algorithm

Despite being simple one, Apriori algorithms have some limitations including:

- Waste of time when it comes to handling a large number of candidates with frequent itemsets.
- The efficiency of this algorithm goes down when there is a large number of transactions going on through a limited memory capacity.
- Requires high computation power and needs to scan the entire database.

Improvements

The following are the ways to improve the efficiency of the algorithm:

- Use hashing techniques to reduce the number of database scans.
- Do not take the infrequent transaction further into consideration.

- If a purchase is frequent in one partition, it should be frequent in another partition.
- Try to pick up random samples to improve the accuracy of your algorithm.
- Use dynamic itemset counting to introduce new candidate itemsets while the scanning of the database is performed.

Applications of Apriori Algorithm

Some of the popular applications of the algorithm are:


- Used in forest departments to understand the intensity and probability of forest fires.
- Used by Google and other search engines for their auto-complete features.
- The Healthcare department used such [algorithms](#) to analyze the patients' database and predict which patients might develop blood pressure, diabetes, or other common disease.
- Used to categorize students based on their specialties and performance to improve their academic performance.
- E-commerce websites use it in their [recommendation systems](#) to provide a better user experience.

What Did We Learn?

In this tutorial, we have learned what association rule mining is, and what the Apriori algorithm is, and with the help of an Apriori algorithm example, we learned how the Apriori algorithm works. In the end, we have built an Apriori model in Python programming language on market basket analysis. [Python Programming Course](#) is one of the most demanding skills right now in the market.

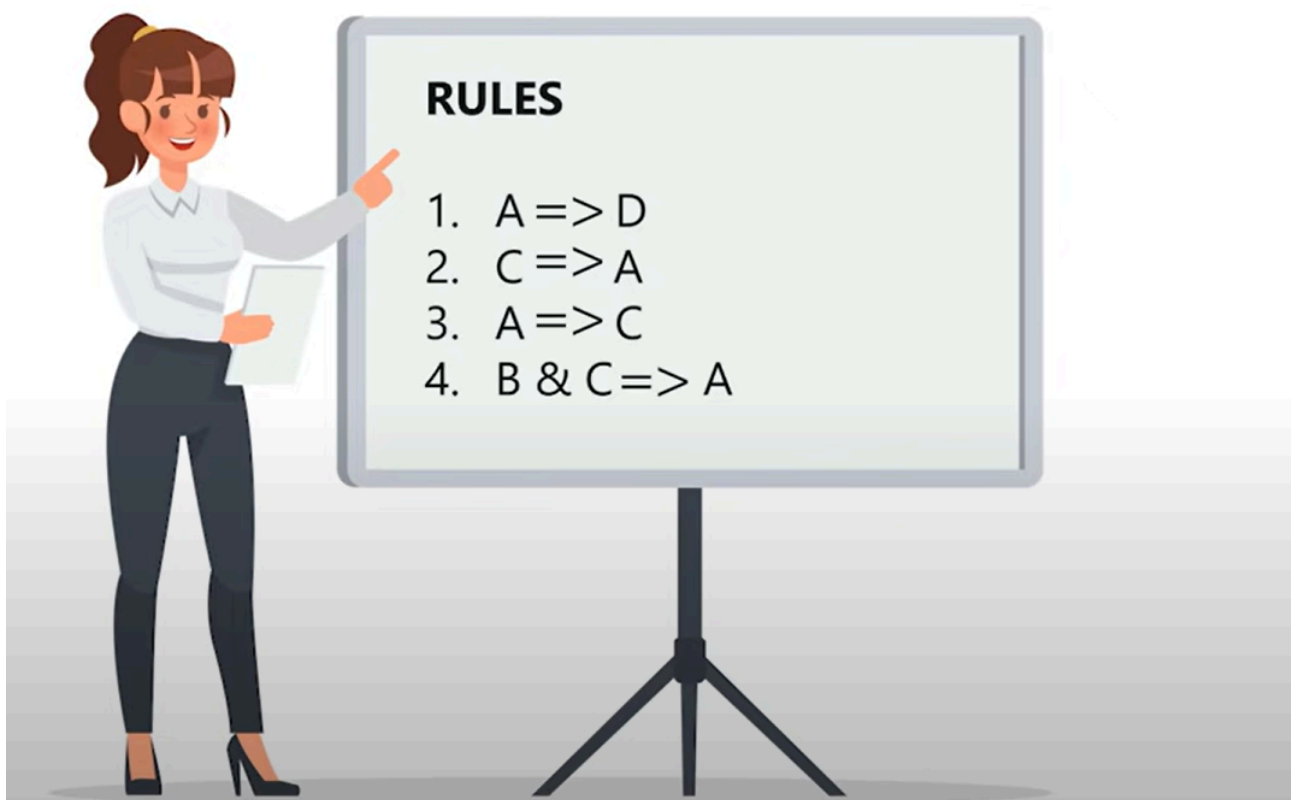
Example

Association Rule Mining



Transaction at a Local Market

T1	A	B	C
T2	A	C	D
T3	B	C	D
T4	A	D	E
T5	B	C	E



Rule	Support	Confidence	Lift
$A \Rightarrow D$	2/5	2/3	10/9
$C \Rightarrow A$	2/5	2/4	5/6
$A \Rightarrow C$	2/5	2/3	5/6
$B, C \Rightarrow A$	1/5	1/3	5/9

Apriori algorithm uses frequent item sets to generate association rules. It is based on the concept that a subset of a frequent itemset must also be a frequent itemset.



But what is a frequent item set?

Frequent Itemset is an itemset whose support value is greater than a threshold value.

TID	Items
T1	1 3 4
T2	2 3 5
T3	1 2 3 5
T4	2 5
T5	1 3 5

Min. Support count = 2

TID	Items
T1	1 3 4
T2	2 3 5
T3	1 2 3 5
T4	2 5
T5	1 3 5



C1	
Itemset	Support
{1}	3
{2}	3
{3}	4
{4}	1
{5}	4

Apriori Algorithm - 1st Iteration

C1	
Itemset	Support
{1}	3
{2}	3
{3}	4
{4}	1
{5}	4



F1	
Itemset	Support
{1}	3
{2}	3
{3}	4
{5}	4

Item sets with support value less than min. support value (i.e. 2) are eliminated