

# STATISTICAL PROGRAMMING PYTHON

# Machine Learning: association rules

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# **Summary**



- Machine Learning overview
- Unsupervised learning
  - clustering
    - KMeans
    - hierarchical clustering
  - dimensionality reduction
    - feature selection
    - feature extraction
      - PCA: principal component analysis
      - LDA: linear discriminant analysis
  - association rules
- Supervised learning
  - classification
  - regression



# Machine learning: algorithms

#### Supervised learning:

Classification: classification trees...

- Regression: linear regression, logistic regression, stepwise regression,

regression trees...

#### Unsupervised learning:

Clustering: k-means, k-medians, hierarchical clustering...

- Dimensionality reduction: principal component analysis, discriminant

analysis...

Association rule: a priori agorithm...



# **Machine Learning: use cases**

#### Supervised learning:

Classification: customer retention, fraud detection, image classification...

- Regression: market forecasting, population growth prediction...

#### Unsupervised learning:

- clustering: customer segmentation, recommender systems...

dimensionality reduction: structure discovery, big data visualization...

association rule: targetted marketing...

# **Summary**



- Machine Learning overview
- Unsupervised learning
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    - feature selection
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      - LDA: linear discriminant analysis
  - association rules
- Supervised learning
  - classification
  - regression

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#### **Association rules: overview**

#### Goal:

Find association relationships in large data sets.

#### How does it work?

When we look for association rules, some parameters have to be defined:

- **support** of an itemset: percentage of the data set which contains this itemset

- **confidence** of a rule A => B: P(A and B)/P(A). It means, the rule is true for at least that confidence value.

- **lift of a rule** (A => B): support(A U B)/(support(A) \* support(B)). Lift > 1 means both occurrences are dependent on one other

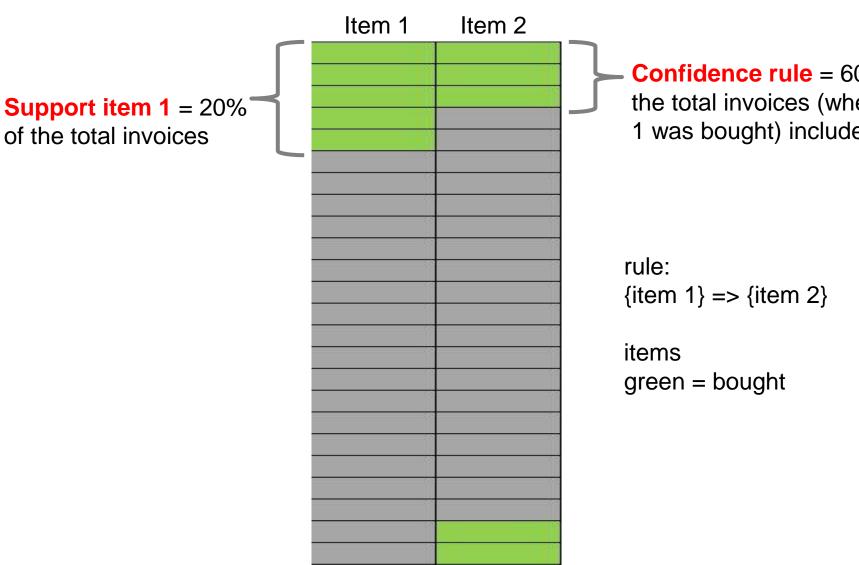
**Example**: rules with support 0.40 and confidence 0.80 {peanuts, coke} => {chips} means that:

- at least, a 40% of the cases included peanuts and coke
- in the cases where peanuts and coke were sold, chips were sold as well at least in a 80% of these transactions.

#### **Usages:**

Market analysis
Click stream tracking
Online recommendation engines



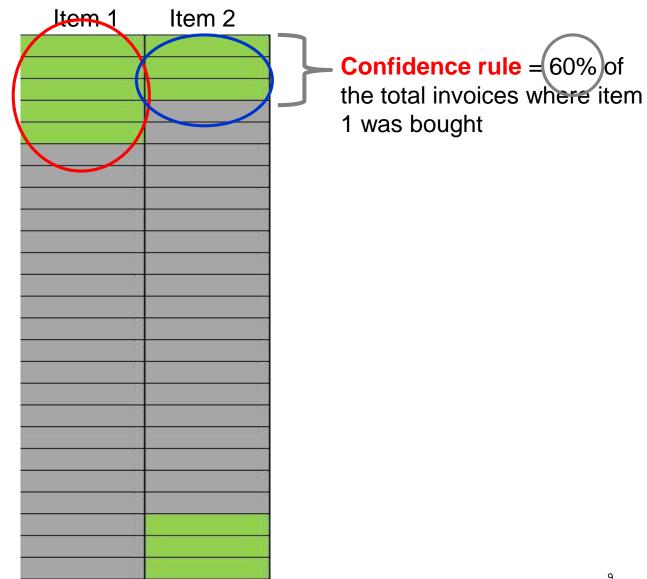


Confidence rule = 60% of the total invoices (where item 1 was bought) include ítem 2

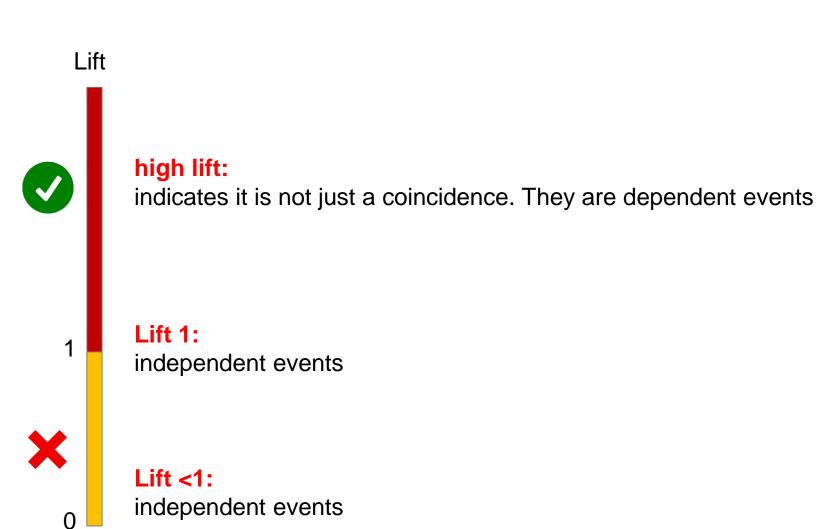














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#### **Association rules: data structure**

#### Mode 1: Sparse vectors

1, 1, 19	
2, 5, 35, 42, 44	l,
3, 10, 17, 26, 27, 28, 3	31, 32
4, 2, 5, 18, 22, 27, 46	
5, 23, 24, 40, 41, 43	

Mode 3: Items tables

All of them are equivalent

## Mode 2: Full binary vectors

1,4,1	
1,2,19	9
2,5,42	2
2,5,5	
2,5,44	1
2,2,35	5
3,4,28	3
3,4,27	7
3,2,32	2
3,1,10	0
3,4,17	7
3,2,3	1
3,4,26	5
4,3,22	2
4,3,18	3
4,3,27	7
4,4,46	5
4,2,5	
4,5,2	
5,2,23	3
5,3,24	1
5,5,43	1
5,1,43	3
5,1,40	0



1 4 1

#### **Association rules: data structure**

#### Mode 1: Sparse vectors

1, 1, 19	
2, 5, 35, 42, 44	
3, 10, 17, 26, 27, 28, 3	1, 32
4, 2, 5, 18, 22, 27, 46	
5, 23, 24, 40, 41, 43	

Mode 3: Items tables

All of them are equivalent

#### Mode 2: Full binary vectors

# Challenge

- How many transactions are there?
- Which is the number of different items in transaction #4?
- Which is the number of sold items in transaction #2?

Τ.			
1,	,2	,19	)
2	,5	,42	2
2	,5	,5	
2	,5	,44	1
2	,2	,35	5
3	,4	,28	3
3	,4	,27	7
3	,2	,32	2
3	,1	,10	)
3	,4	,17	7
3	,2	,31	L
3	,4	,26	5
4	,3	,22	2
4	,3	,18	3
4	,3	,27	7
4	,4	,46	5
4	,2	,5	
4	,5	,2	
		,23	3
5	,3	,24	1
5	,5	,41	L
5	,1	,43	3
5	,1	,40	)



#### Association rules: data structure

#### Mode 1: Sparse vectors

1	1, 19	
	5, 35, 42, 44	
3,	10, 17, 26, 27, 28, 3	1, 32
4,	10, 17, 26, 27, 28, 3 2, 5, 18, 22, 27, 46	
5	23, 24, 40, 41, 43	



#### Mode 3: Items tables

#### Mode 2: Full binary vectors

First receipt: item 1 (4 units) and ítem 19 (2 ítems)

ítem 5 (5 units), ítem 35 (2 units), ítem 42 (5 units) and item 44 (5 items) Second receipt:

2,	,5
255	,44
25-0	,35
3,4	,28
3,4	,27
3,2	,32
3,1	,10
3,4	,17
3,2	,31
3,4	,26
4,3	,22
	,18
	,27
4,4	,46
1000	,5
4,	,2
5,	,23
5,	3,24
	,41
	,43
5,1	,40



1.4.1

#### **Association rules: data structure**

#### Mode 1: Sparse vectors

1, 1, 19	
2, 5, 35, 42, 44	
3, 10, 17, 26, 27, 28, 3	31, 32
4, 2, 5, 18, 22, 27, 46	
5, 23, 24, 40, 41, 43	

#### Mode 3: Items tables

Required structure for the association analysis algorithm:

index: transaction lds

columns: products with 1s or 0s

## Mode 2: Full binary vectors

First receipt: item 1 (4 units) and ítem 19 (2 ítems)

Second receipt: ítem 5 (5 units), ítem 35 (2 units), ítem 42 (5 units) and item 44 (5 items)

. . .

1,2,19	
2,5,42	
2,5,5	
2,5,44	
2,2,35	
3,4,28	
3,4,27	
3,2,32	
3,1,10	
3,4,17	
3,2,31	
3,4,26	
4,3,22	
4,3,18	
4,3,27	
4,4,46	
4,2,5	
4,5,2	
5,2,23	
5,3,24	
5,5,41	
5,1,43	
5,1,40	



# **Selecting the support and confidence parameters**





#### **Association rules**



```
from mlxtend.frequent_patterns import apriori, association_rules
```

```
frequent_itemsets = apriori(...)
```

Arguments in apriori command:

- df: dataframe in "Full binary vectors" format # columns: products. index: transactions IDs
- min\_support: number
- use\_colnames: True or False (default) # False: column indices. True: column names

```
rules = association_rules(frequent_itemsets, ...)
```

Arguments in association\_rules command:

- df: frequent itemsets
- metric: "lift" or "confidence" (default)
- min\_threshold: number (default: 0.8)



## **Programming challenge ARUL.1**

File: association\_rules\_20000\_XXX.csv

- 1. Give the correct structure to the data file in Python Note: check the command set\_index
- 2. Find a set of some rules
- 3. Try to quantify for some rule the number of non-sold units that we could try to sell doing recommendations



# **Programming challenge ARUL.2**

File: "Online Retail\_Association rules\_v2.csv"

1. Show the 3 items which have produced the highest income



# Programming challenge ARUL.2

File: "Online Retail\_Association rules\_v2.csv"

- 1. Show the 3 items which have produced the highest income
- 2. Give a calendar heatmap for the number of sold items per day in United Kingdom during December 2010 and January 2011



#### **Programming challenge ARUL.2**

File: "Online Retail\_Association rules\_v2.csv"

- 1. Show the 3 items which have produced the highest income
- 2. Give a calendar heatmap for the number of sold items per day in United Kingdom during December 2010 and January 2011
- 3. Create the required structure to apply a association rules analysis for the invoices in France.
  - After this, calculate all the rules with lift > 1 for products sold in a 7% of the transactions at least.
- 4. For all the previous rules, extract the rules with lift > 6 and confidence is, at least, 80%.

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#### **Association rules: exercise**

#### **Programming challenge ARUL.2**

File: "Online Retail\_Association rules\_v2.csv"

- 1. Show the 3 items which have produced the highest income
- 2. Give a calendar heatmap for the number of sold items per day in United Kingdom during December 2010 and January 2011
- 3. Create the required structure to apply a association rules analysis for the invoices in France.
  - After this, calculate all the rules with lift > 1 for products sold in a 7% of the transactions at least.
- 4. For all the previous rules, extract the rules with lift > 6 and confidence is, at least, 80%.
- 5. For the rule "ALARM CLOCK BAKELIKE GREEN" => "ALARM CLOCK BAKELIKE RED", how much extra money can I win if all the clients are moved to the second part as well?

# Session Wrap-up









apriori()
association\_rules()