Association Analysis

a.k.a. Market-Basket Analysis Affinity Analysis

The Famous Example

- June 1992 Study by NCR (now TeraData) for Osco Drug searched for product associations
 - Beer and Diapers likely to be purchased together
 - (and many others, including Fruit Juice and Cough Syrup)



Association Analysis

- Unsupervised: No target outcome for training. Searching for patterns in the data.
- Association Analysis gives us sets of products that are likely to be purchased together.
- Used in retail for coupon marketing, targeted upselling, and product placement.
- Flexible analytics tool that can be used in many situations!

Association Rules

Data comes in the form of transactions:

Transaction	Items
ID	
10001	Bread, Juice
10002	Diapers, Beer, Eggs, Formula
10003	Milk, Diapers, Bread, Formula
10004	Juice, Diapers, Milk, Eggs
10005	Soda, Milk, Eggs, Bread
10006	Formula, Juice, Diapers, Bread

Question: are there any relationships between items that might be hiding in these transactions?

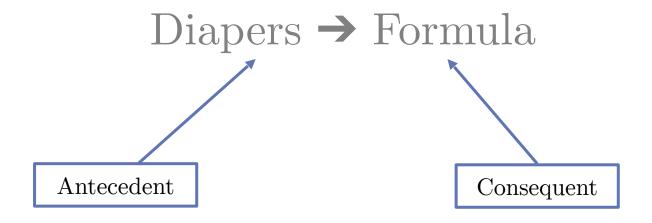
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Diapers → Formula?

An Association Rule



Interpretation: Someone who buys diapers is also likely to (simultaneously) buy formula.

- The strength of an association rule A → B is quantified using three statistics:
 - Support: $P(A \cap B) = P(A \text{ and } B)$
 - Measures how often we find instances of this rule in the training data.

• Confidence:
$$P(B|A) = \frac{P(A \cap B)}{P(A)}$$

• Measures what percent of transactions containing A also contain B.

• Lift:
$$\frac{P(B|A)}{P(B)} = \frac{P(A \cap B)}{P(A)P(B)}$$

- Measures how much more likely we are to buy B given that we also buy A than we are to buy B at random.
- Want Lift values greater than 1!!

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Diapers → Formula?

Support: How often does this "rule" present itself?

P(Diapers and Formula)

In 50% of the transactions

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10005	Soda, Milk, Eggs, Bread
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Diapers → Formula?

Confidence: Given one buys Diapers, what is chance they also buy Formula? P(Formula | Diapers)

75% of Diaper purchases also contained Formula

Transaction ID	Items
10001	Bread, Juice
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Diapers → Formula?

Lift: How much more likely are we to see Formula with Diapers than see Formula overall? P(Formula|Diapers)/P(Formula)

We are (0.75/0.5 =) 1.5 times more likely to see a formula purchase with Diapers than we are to see one at random.

Some Post-Hoc Takeaways

Product $A \rightarrow$ Product B

- <u>Product B as consequent</u>: Determine what can be done to boost its sales.
 - Product placement
 - Optimize upselling
 - Coupons for related products
- <u>Product A as antecendent:</u> Determine what other products would be affected by changes to Prod A.
 - Discontinuations
 - Price changes
 - Cannibalization

Direction of Association Rules

 $A \rightarrow B$ vs. $B \rightarrow A$

Same Support
Same Lift
Different Confidence
NO TIME COMPONENT

We DO NOT say "those who buy A will THEN buy B."

Finding Association Rules

- Most algorithms have two parts:
 - Itemset generation find all sets of items that satisfy some minimum support.
 - Rule generation determine which sets generated in step 1 satisfy some minimum confidence.
 - For more details of each part, see text by Tan, Steinbach, and Kumar
- To perform this analysis in any programming software, you need to specify:
 - "The basket" something that identifies the basket of items being purchased simultaneously by a single customer.
 - "The items" whatever column itemizes the transaction of each basket.
- The format for each software package/library will surely be different. Read the documentation!

SAS Viya Code

```
cas;
caslib _all_ assign;

proc mbanalysis data=public.grocery pctsupport=.5;
    customer transaction;
    target item;
    output out=casuser.setmb
        outfreq=casuser.freqmb
        outrule=casuser.mba_rules;
run;
```

SAS Viya Code

```
cas;
caslib _all_ assign;

proc mbanalysis data=public.grocery pctsupport=.5;
    customer transaction; #TheBasket"
    target item; #TheItems
    output out=casuser.setmb
        outfreq=casuser.freqmb
        outrule=casuser.mba_rules;
run;
```

You must specify either of the following options:

proc mbanalysis

★ SUPPORT=number

specifies the minimum level of support (minimum frequency of an item) for a rule, where *number* must be an integer greater than or equal to 0. This option overrides the specification of the PCTSUP= option.

- **★ PCTSUP**=number
- \star **SUPPCT**=number
- ★ SUP_PCT=number
- **★ PCTSUPPORT**=number

specifies the minimum level of support for a rule as a percentage of the number of baskets in the input data table, where *number* must be a real number between 0 and 100, inclusive. This option is ignored if the SUPPORT= option is specified.

You can also specify the following options:

★ CONF=number

specifies the minimum confidence for the rules, where *number* must be a real number between 0 and 100.

By default, CONF=50

 \star ITEMS=number

specifies the number of items in a rule, where *number* must be an integer between 1 and 100. By default, ITEMS=2 when either an OUT= or OUTRULE= option is specified in the OUTPUT statement; otherwise, ITEMS=1 by default.

★ LIFT=number

specifies the minimum lift value necessary to generate a rule, where *number* must be a positive, real number between 0 and 100, inclusive. By default, LIFT=1.

MBA_RULES Output Dataset

RULEID	LHS	RHS	COUNT	SUPPORT	CONF	LIFT	ITEM1	ITEM2	RULE
9	1	1	62	0.630	51.240	2.129	brown	whole milk	brown ==> whole milk
16	1	1	50	0.508	51.546	6.243	other	citrus fruit	other ==> citrus fruit
20	1	1	52	0.529	56.522	3.090	cream	other vegetables	cream ==> other vegetables
28	1	1	69	0.702	54.762	2.275	frozen	whole milk	frozen ==> whole milk
37	1	1	66	0.671	51.163	2.126	newspa	whole milk	newspa ==> whole milk
40	1	1	98	0.996	53.846	2.944	rolls/	other vegetables	rolls/ ==> other vegetables
41	1	1	66	0.671	60.000	3.280	whippe	other vegetables	whippe ==> other vegetables
42	1	1	56	0.569	57.732	5.465	other	root vegetables	other ==> root vegetables

Unique Rule Identifier

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Number of items on the Left Hand Side (LHS) of the rule and the RHS

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Number of grocery baskets in which the rule appears

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Support, Confidence and Lift of the Rule

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All items involved in the rule are listed in separate columns.

Network Visualization

```
proc fedsql sessref = casauto;
   create table casuser.mba_network as
       select t1.item as t1 item,
           t1.count as item count,
           t1.support as item support,
          t.2. *
   from casuser.freqmb as t1 inner join casuser.mba rules as t2
       on t1.item=t2.item1;
   create table casuser.mba network2 as
       select tl.item as tl item,
           t1.count as item count,
           t1.support as item support
   from casuser.freqmb as t1 inner join casuser.mba_rules as t2
       on t1.item=t2.item2;
quit;
data casuser.mba network final;
                                                     Create Network
   set casuser.mba_network casuser.mba network2;
                                                   Dataset from Output
run;
proc casutil;
```

promote casdata='mba_network_final'
incaslib ='casuser'
outcaslib='casuser'
casout ='mba_assocs_network';
run;

Promote Dataset for Visual Studio

ANALYTICS LIFE CYCLE

Manage Data

Prepare Data

Explore and Visualize

Build Models

Manage Models

Share and Collaborate

Develop SAS Code

ADMINISTRATION

Build Custom Graphs

Build Custom Themes

Explore Lineage

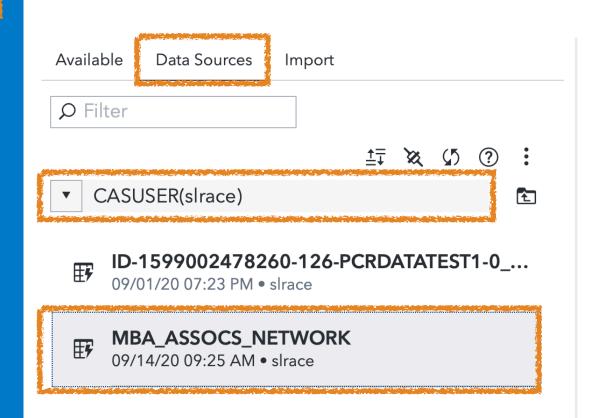
Manage Environment

Manage Workflows

Explore and Visualize

Explore data, apply predictive analytics, and build interactive reports with SAS Visual Analytics.





ANALYTICS LIFE CYCLE

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Build Custom Graphs

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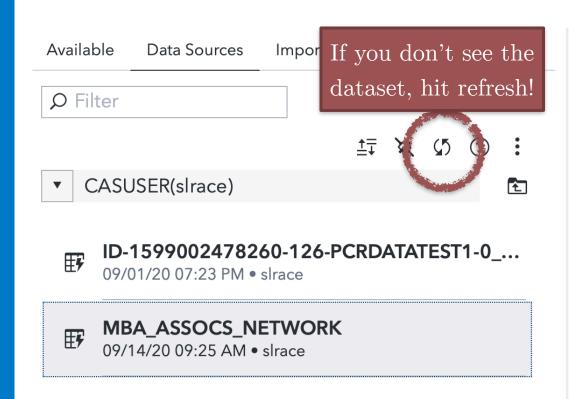
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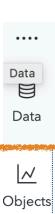
Explore and Visualize

Explore data, apply predictive analytics, and build interactive reports with SAS Visual Analytics.

New Report

Start with Data





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Suggest

 \equiv

Outline

Objects





Slider

■ Text input

∨ Analytics

Automated explanation

 $\parallel_{X}^{"}$ Automated prediction

Forecasting

✗ Network analysis

Path analysis

Text topics



Data Koles

Network analysis - Item Name 1

∨ Source

Item Name

∨ Target

₪ Item2

∨ Size

∨ Color

+ Add

∨ Link width

⊗ Lift

