

Finding Meaningful Correlations

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- An unsupervised learning technique
  - No labels necessary
  - Useful for data discovery
- Finds "significant" correlations/associations/relations
  - Shopping cart: Coffee and sugar
  - Medical: High plasma glucose and diabetes
- Expresses them as "if then rules"
  - If "antecedent" then "consequent"
  - Significance measures
- BigML: "Magnum Opus" from Geoff Webb

# Clusters



date	customer	account	auth	class	zip	amount
Mon	Bob	3421	pin	clothes	46140	135
Tue	Bob	3421	sign	food	46140	401
Tue	Alice	2456	pin	food	12222	234
Wed	Sally	6788	pin	gas	26339	94
Wed	Bob	3421	pin	tech	21350	2459
Wed	Bob	3421	pin	gas	46140	83
Thr	Sally	6788	sign	food	26339	51

# Clusters



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Wed	Sally	6788	pin	gas	26339	94	<b>←</b> '
Wed	Bob	3421	pin	tech	21350	2459	
Wed	Bob	3421	pin	gas	46140	83	<b>←</b>
Thr	Sally	6788	sign	food	26339	51	

similar

# Anomaly Detection



date	customer	account	auth	class	zip	amount
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anomaly



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{customer = Bob, account = 3421}



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#### Rules:

Antecedent —— Consequent

#### Use Cases



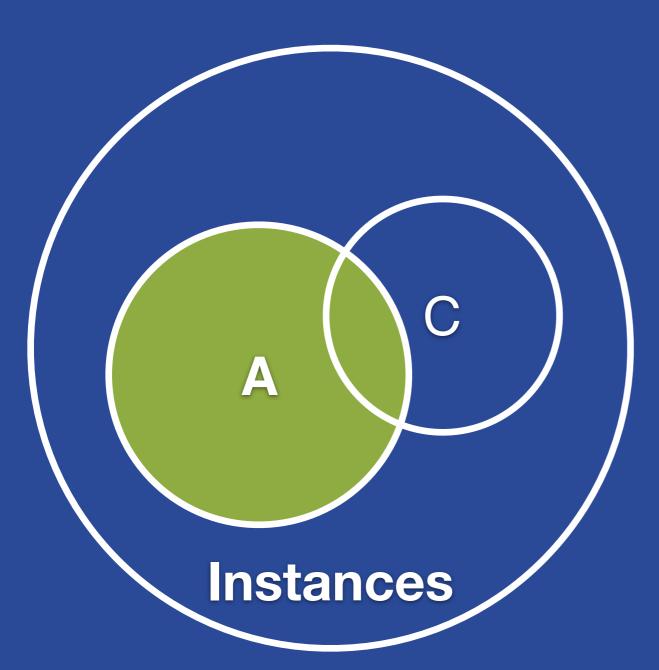
- Market Basket Analysis: Items that go together
- Data Discovery: how do instances relate?
- Behaviors that occur together
  - Web usage patterns
  - Intrusion detection
  - Fraud detection
- Bioinformatics
  - gene expression associated with outcomes
- Medical risk factors

# What is interesting?



- In-frequent patterns can be strong, but are they interesting?
  - X Vodka and caviar
  - Storms and high water sales
- Frequent patterns can be strong, but are they interesting?
  - Coffee and milk
  - ✓ High plasma glucose and diabetes
- "Frequency" isn't the answer...
  - Depends on the data and domain
  - We need better metrics to define what is interesting

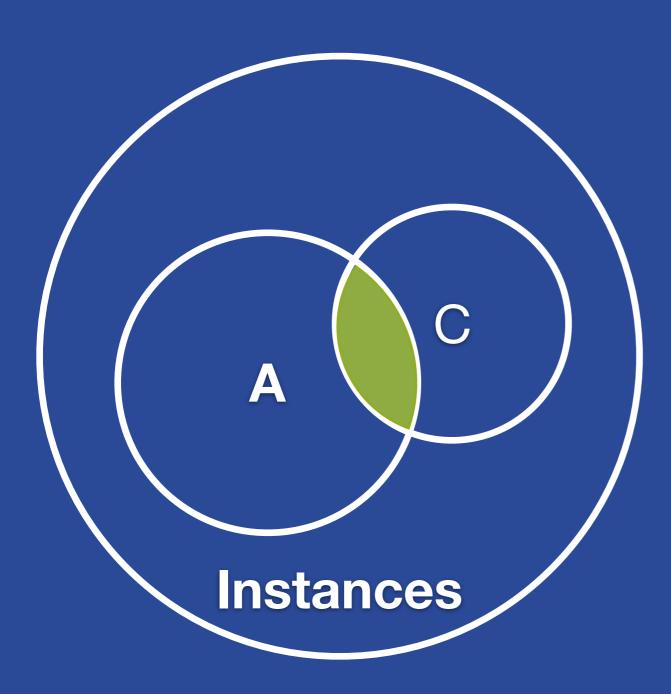




#### Coverage

Percentage of instances which match antecedent "A"

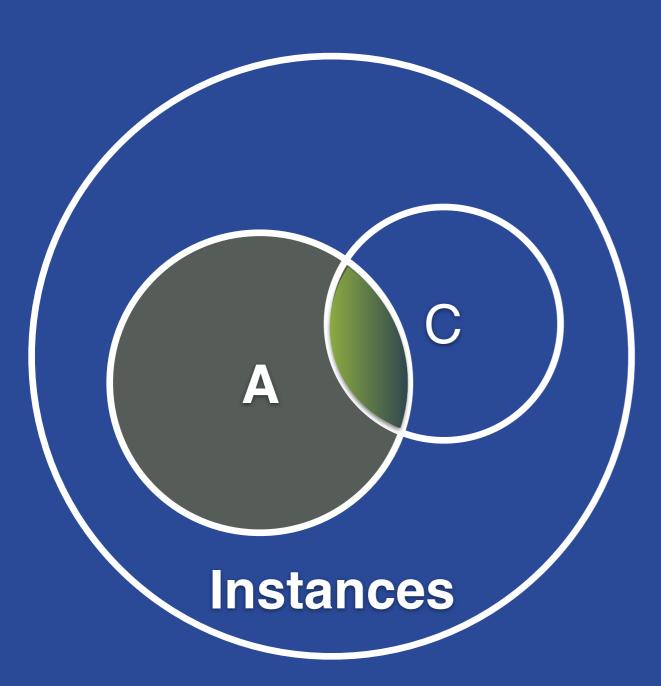




#### **Support**

Percentage of instances which match antecedent "A" and Consequent "C"





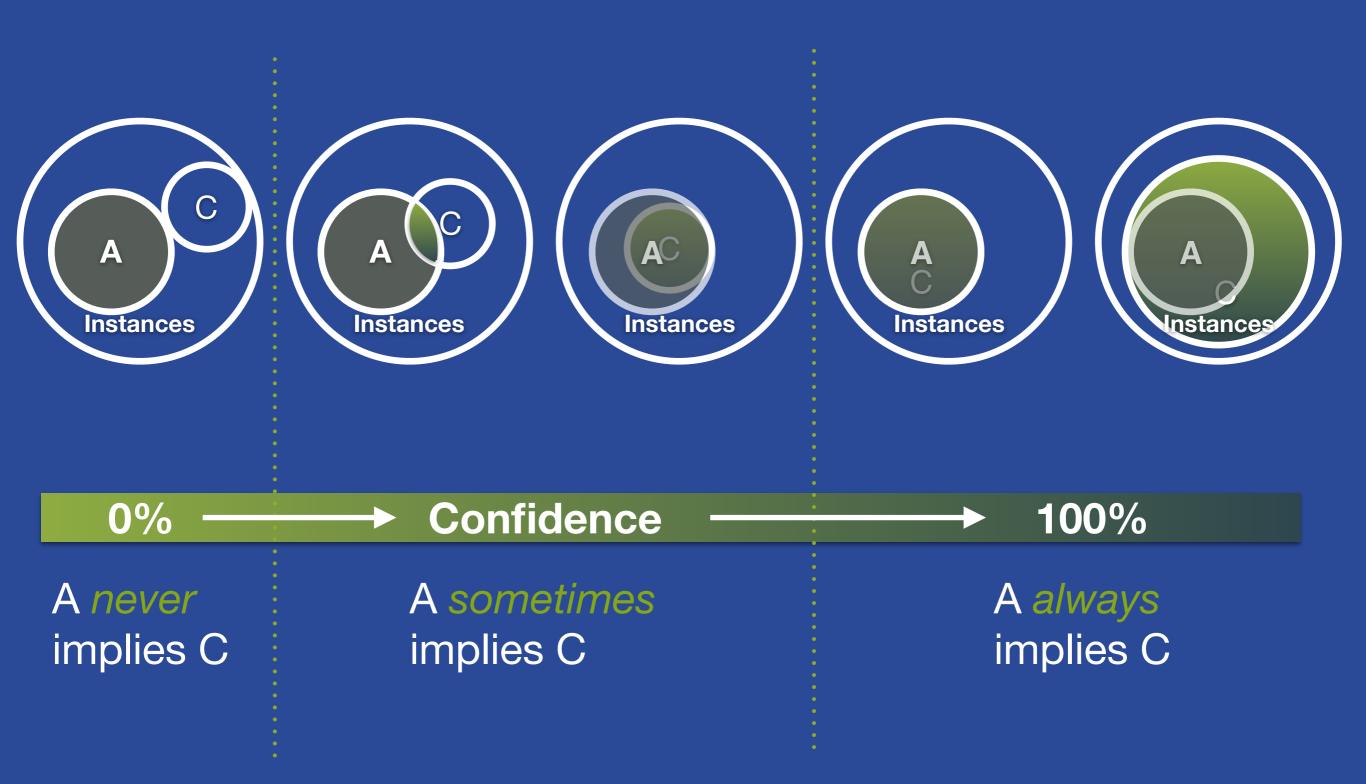
#### Confidence

Percentage of instances in the antecedent which **also** contain the consequent.

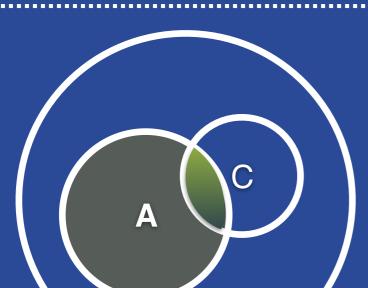
Support

Coverage









Independent

#### Lift

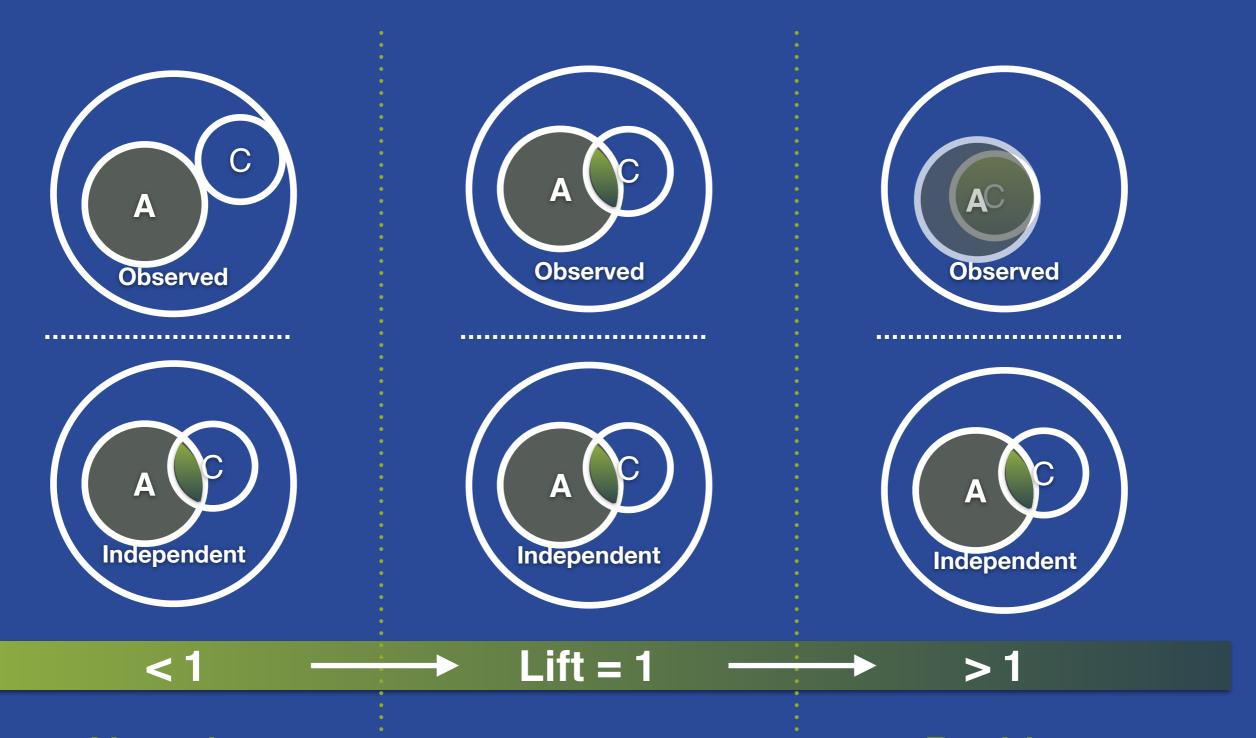
Ratio of observed support to support if A and C were statistically independent.

$$\frac{\text{Support}}{p(A) * p(C)} == \frac{\text{Confidence}}{p(C)}$$

#### Problem:

if p(C) is "small" then... lift may be large.



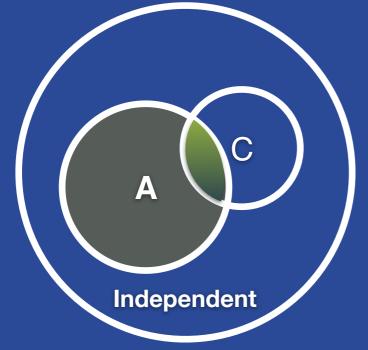


Negative Correlation

**No Correlation** 

Positive Correlation





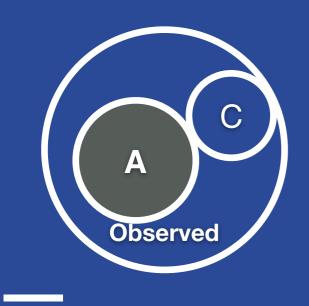
#### Leverage

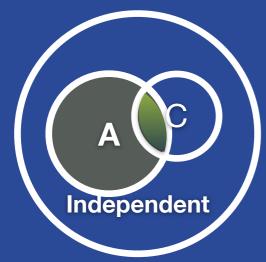
Difference of observed support and support if A and C were statistically independent.

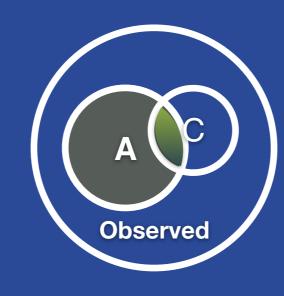
Support - [p(A) \* p(C)]

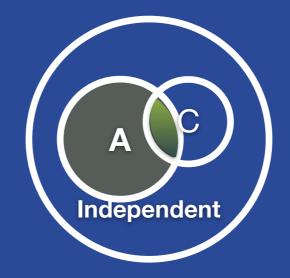


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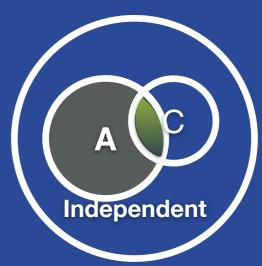












1.... < 0

Leverage = 0

>0

Negative Correlation

**No Correlation** 

Positive Correlation

# Magnum Opus



- Select measure of interest: Levarage, Lift, etc.
- System finds the top-k associations on that measure within constraints
  - Must be statistically significant interaction between antecedent and consequent
  - Every item in the antecedent must increase the strength of association

## Basic AD Configuration



- 1. Search Strategy: Support/Coverage/Confidence/Lift/Leverage
- 2. Max Number of Associations: 1 to 500 (default 100)
- 3. Max Items in Antecedent: 1 to 10 (default 4)
- 4. Complement Items: True / False
  - False: Coffee and...
  - True: **Not** Coffee and....
- 5. Missing Items: True / False
  - False: Loan Description contains "Ferrari" and...
  - True: Loan Description is missing and...

## Data Types



A B C

text

123

1, 2.0, 3, -5.4

numeric

true, yes, red, mammal

categorical

**DATE-TIME** 

2013-09-25 10:02

date-time

Be not afraid of greatness: some are born great, some achieve greatness, and some have greatness thrust upon 'em.

text

YYYY-MM-DD

**YEAR** 

2013

YYYY-MM-DD

**MONTH** 

September

YYYY-MM-DD

DAY-OF-MONTH

25

M-T-W-T-F-S-D

**DAY-OF-WEEK** 

Wednesday

HH:MM:SS

**HOUR** 

10

HH:MM:SS

**MINUTE** 

02

"great"

"afraid"

"born"

"some"

appears 2 times

appears 1 time

appears 1 time

appears 2 times

## Items Type



coffee, sugar, milk, honey, dish soap, bread

items

items

- Canonical example: shopping cart contents
- Single feature describing a list of items
- Each item separated by a comma (default)

#### Use Cases





- Dataset of 9,834 grocery cart transactions
- Each row is a list of all items in a cart at checkout

GOAL: Discover "interesting" rules about what store items are typically purchased together.



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# Association Demo #1

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#### Use Cases





- Dataset of diagnostic measurements of 768 patients.
- Each patient labelled True/False for diabetes.

GOAL: Find general rules that indicate diabetes.

# Association Demo #2

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### Medical Risks



#### **Decision Tree**

If plasma glucose > 155 and bmi > 29.32 and diabetes pedigree > 0.32 and insulin <= 629 and age <= 44

then diabetes = TRUE

#### **Association Rule**

If **plasma glucose** > 146 then **diabetes** often TRUE

# Association Demo #3

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### Your Turn!



- Starting from the 1-click Diabetes cluster (gmeans)
- Create a Batch Centoid and output as a Dataset
- Create an Association Discovery:
  - Specify the consequent as the cluster assignment
- Can you generalize any of the cluster groups?

