# Minimum Variance Associations - Discovering Relationships in Numerical Data 

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## Frequent pattern mining

## Frequent itemset mining

Given a binary table find all sets of attributes such that

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\operatorname{supp}(I)=\frac{|\{t \in \mathcal{D}: t[I]=(1,1, \ldots, 1)\}|}{|\mathcal{D}|} \geq \min _{\text {supp }}
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- Defined for binary datasets
- Easy extension to categorical attributes
- Applicable to: trees, graphs, etc.
- but... how to do it for numerical attributes?


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- Discretization
- information loss
- rules split among many intervals


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- Discretization
- information loss
- rules split among many intervals
- Recently a few other approaches:
- definitions of support for numeric data [Steinbach]
- using ranks [Calders, Goethals, Jaroszewicz]
- using polynomials [Jaroszewicz, Korzeń]
- equations discovery [Langley, Dzeroski, Todorovski]

A framework for pattern mining analogous to association rules

- Handles numeric data directly
- Able to discover arbitrary nonlinear relationships


## Minimum Variance Associations: main idea

Trivial examples:

$$
x=y
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x^{2}+y^{2}=1
$$



Pattern:

$$
\begin{aligned}
& F(x, y)=x^{2}+y^{2}-1 \\
& =0 \text { for all transactions }
\end{aligned}
$$

## Minimum Variance Itemsets

Attributes $x_{1} x_{2} \ldots x_{n}$ are related if there exists a function $F\left(x_{1} \ldots x_{n}\right)$ which has low variance

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\sum_{t \in \mathcal{D}} F^{2}\left(t\left[x_{1} \ldots x_{n}\right]\right) \approx 0
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These are our itemsets

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## Problem

$F \equiv 0$ trivially satisfies all cases.

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subject to additional constraint:
If $x_{1}, x_{2}, \ldots, x_{n}$ were statistically independent then

$$
\sum_{t \in \mathcal{D}} F^{2}\left(t\left[x_{1} \ldots x_{n}\right]\right)=1
$$

## How to find $F$ with minimum variance?

(1) Assume $F$ is a polynomial:

$$
F(x, y)=c_{0}+c_{1} x+c_{2} y+c_{3} x y+c_{4} x^{2}+c_{5} y^{2}
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(2) Compute two matrices $\mathbf{S}_{\text {Data }}$ and $\mathbf{S}_{\text {Indep }}$ :

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\begin{aligned}
\mathbf{S}_{\text {Data }}[1,3] & =\sum_{\mathcal{D}} x \cdot x y \\
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(3) The coefficient vector $\mathbf{c}=\left[c_{0}, \ldots, c_{n}\right]$ is a solution of the Generalized Eigenvalue Problem

$$
\mathbf{S}_{\text {Data }} \cdot \mathbf{c}=\lambda \mathbf{S}_{\text {Indep }} \cdot \mathbf{c}
$$

## Mining algorithm

## Monotonicity property <br> Adding attributes decreases the minimum variance

If an itemset is good, all its supersets are also good.

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## Monotonicity property

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## Solution

Find smallest itemsets with given minimum variance.
Simple modification of standard itemset mining algorithms.

## Rules

Two types of rules:
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Equality rules: $\quad F(X)=G(Y)$

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Regression rules: $\quad y=F(X)$
Equality rules: $\quad F(X)=G(Y)$

Variance of rule $F(X)=G(Y)$ is higher than of itemset $X \cup Y$
Like standard association rules:
(1) First mine itemsets
(2) Find rules for each itemset

## Simple example

$$
x^{2}+y^{2}=1
$$


itemset: $\quad-1.99+1.99 x^{2}+1.99 y^{2}$
equality rule: $\quad 1.99 y^{2}=1.99-1.99 x^{2}$
regression rule: none

## Examples: extrasolar planets

Itemsets and rules corresponding to:

- Trigonometric identity between distance and angular distance
- Kepler's law


## Examples: more interesting relationships

sonar dataset, attributes 15 and 44


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- No good regression rule
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- Correlation coefficient $=-0.114$
- No good regression rule
- No good equality rule
- A minimum variance itemset with variance 0.0001
sonar dataset, attributes 15 and 44
A minimum variance itemset with variance 0.0001


3 attribute patterns, degree $=3$


## Performance: comparison with Lagrange equation discoverer



## Conclusions:

- Association rule-like framework for numerical data
- Arbitrary non-linear relationships can be discovered efficiently

Future research:

- Background knowledge
- Combine with equation discovery

