Provenance for Data Mining

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Outline

1 Motivation

2 Provenance for Data Mining

3 Frequent Itemset Provenance

4 Multidimensional Scaling Provenance

5 Conclusions
Data Mining / KDD

Goals
Extract useful information from data

Approach

1. Preprocessing
   - Cleaning
   - Feature Extraction
   - ...

2. Apply algorithms to extract information
   - Clustering, Frequent Itemset Mining, Classification, ...
   - Most approaches: Reduce size/Summarize data
Dilemmas

- Purpose of data mining necessitates summarization
  - “Needle in the haystack”
  - Loss of information
- Makes interpreting “raw” results harder
- User point of view: DM algorithm is black box
How to solve Dilemmas?

- Selective access to input data result is based on
  - Inputs to mining algorithm
  - Inputs to preprocessing
  - Contextual information

- Understand importance of inputs for results
  - Input data
  - Parameter settings

- Understand how data mining algorithm generates result from inputs

- Understand missing results
How to solve Dilemmas?

- Selective access to input data result is based on *(Data Provenance+)*
  - Inputs to mining algorithm
  - Inputs to preprocessing
  - Contextual information
- Understand importance of inputs for results *(Responsibility)*
  - Input data
  - Parameter settings
- Understand how data mining algorithm generates result from inputs *(Process provenance)*
- Understand missing results *(Missing answers)*
Related Work

Provenance

- Database provenance, Workflow provenance, Missing answers, Responsibility, ...

Data Mining

- Enriching mining results with additional information
  - Contextual information for frequent itemsets\(^a\)
- Visualization techniques\(^b\)
- Determining effect of parameter settings/inputs on result
  - e.g., K-means cluster stability based on parameter settings\(^c\)

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\(^a\)Q. Mei et al. “Generating semantic annotations for frequent patterns with context analysis”. In: *SIGKDD*. 2006, pp. 337–346.


Contributions

- Analyze requirements and use cases for data mining provenance (DMProv)
- Discuss applicability of existing approaches
- Outline challenges and sketch research directions
- Exemplify concepts on two concrete mining algorithms
  - Frequent Itemset Mining (FIM)
  - Multidimensional Scaling (MDS)
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Why-Provenance

- Here Why-Provenance means all models based on influence
  - Subset of the input that caused output to appear in result
- “Caused by” modelled as
  - Sufficiency
  - Necessity
  - Preservation of Equivalence / Computability
  - Causality

Useful for Data Mining?

- Provenance concepts seem applicable to data mining
- Have to deal with large provenance size (summarization)
- Can abstract processing of classes of mining algorithms?
  - Do not reinvent provenance tracking for each algorithm!
Fine-Grained Provenance

Tracing Through Preprocessing Steps

- Track back data mining results to inputs of preprocessing
- ETL tools are used for preprocessing
- ⇒ can use database or workflow provenance approaches?
Contextual Information as Provenance

- Mining algorithms often applied to a subset of available data
- **Contextual Data**: data related to the mining inputs
  - Automatic detection
  - User provided
- Contextual data often more usable and concise than provenance
- Which contextual data is of interest will differ
  - per use-case
  - maybe even per query
- ⇒ Should support contextual data per provenance query/generation
  - Need flexible mechanism to select context (declarative?)
Measuring Amount of Influence

- Single mining result influenced by large subset of input (all)
  - e.g., clustering
- Amount of influence differs significantly (Responsibility)

DB Responsibility Model

- **Causality**
- **Counterfactual cause** $i$ for output $o$
  - Removing $i$ removes $o$ from result
- **Actual cause** $i$ for output $o$
  - **Contingency** $C$: Set of inputs to remove before $i$ becomes CC for $o$
- **Responsibility**: $\frac{1}{\text{size of minimal contingency}}$

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DMProv and Data Responsibility

Applicability for Data Mining

- Reduce size of provenance
  - only return top-k responsible inputs in provenance
  - only return input with responsibility over threshold
- However: Output variables are not boolean

Solution Sketch

- Consider every input as a cause
- Consider every set of inputs as a contingency
- Measure amount of change
  - e.g., distance between cluster means
- Responsibility is sum of $\frac{1}{\text{size of contingency}} \cdot d(o, o')$ over all contingencies normalized by number of contingencies
Data vs. Parameter Responsibility

Effect of Parameter Settings

- Mining results do depend on
  - Data
  - Parameter settings
- Define new responsibility type using both data and parameters
- Related Work: Robustness against parameter changes only
  - stability of clusterings

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So far only data provenance

Understand how mining algorithm combines inputs to produce an output

Applicability of workflow and program analysis provenance techniques
  - Either too detailed or too coarse grained
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One of the most prevalent mining tasks

**Input**: set of transactions (sets of items)
  - Fixed domain $\mathcal{D}$

**Output**: subsets of $\mathcal{D}$ (frequent itemsets)
  - appear in fraction larger $\sigma$ (minimum support) of the transactions
### FIM Example

#### Transaction

<table>
<thead>
<tr>
<th>TID</th>
<th>Items</th>
<th>CID</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>{Coffee-mate, Coffee, Diaper, Beer}</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>{Diaper, Bread, Beer}</td>
<td>2</td>
</tr>
<tr>
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</tr>
<tr>
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</tr>
<tr>
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</tr>
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#### FIM

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<tbody>
<tr>
<td>1</td>
<td>{Coffee}</td>
<td>4</td>
</tr>
<tr>
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**Intuition**

- The transactions containing a frequent itemset $I$ caused $I$ to be frequent
- Define the Why-provenance as this set

**Definition (Why-Provenance for FI)**

- Given transaction base $D$, minimum support $\sigma$, itemset $I$
- $W(I) = \{ t \mid I \subseteq t \land t \in D \}$
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FIM Provenance with Context

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Example (Beer and Diaper)

- Beer and Diaper is frequent
- but why?

Summary of inputs in provenance using contextual information

Will need different context for different use cases
**FIM Provenance with Context**

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**Example (Beer and Diaper)**

- Beer and Diaper is frequent
- but why?
- Why-provenance ⇒ it appeared in this set of transactions

**Not very useful!**

Unfeasible if \( D \) is large

Because male customers in age group 20−40 bought it

More useful and concise

Summarization of inputs in provenance using contextual information

Will need different context for different use cases
Example (Beer and Diaper)

- Beer and Diaper is frequent
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  - Not very useful!
  - Unfeasible if \(D\) is large
- Because male customers in age group 20 – 40 bought it
FIM Provenance with Context

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  - Not very useful!
  - Unfeasible if $D$ is large
- Because male customers in age group 20 – 40 bought it
  - More useful and concise
  - Summarization of inputs in provenance using contextual information
  - Will need different context for different use cases
FIM Provenance

- Why-Provenance for FIM
- Declarative selection of context
- I-Provenance
  - Prefix compressed tree representation of provenance
  - Precise modelling of interdependencies of items in provenance within transactions
- Database-based provenance generation and querying
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Multidimensional Scaling (MDS)

Approach

- **Input**: Set of observation with pair-wise similarities
- **Output**: Mapping into $n$-dim space that tries to preserve similarities
  - Optimization problem
- **Use-case Marketing**:
  - Customers rate products pairs according to similarity
  - MDS to generate layout (perceptual map) depicting similarity of products

Example

```
A  B  C  D
A  -  -  -  -
B  2  -  -  -
C  2  4  -  -
D  3  3  3  -
```

A

B

C

D

A

B

C

D

A

B

C

D

A

B

C

D

A

B

C

D
Data vs. Parameter Responsibility

Problem
- If two items are close in the layout then
  - either they are similar
  - or because it minimized the fitness function
  - or some combination of both

Using Provenance
- Why-provenance
  - Show (difference to) original similarities for subset of the data
- Data vs. Parameter Responsibility
  - Influence of actual data properties
  - Parameter settings
  - Idiosyncrasies of the algorithm
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## Challenges

### Why-Provenance
- Common model that generalizes processing of large classes of mining algorithms
- Dealing with large (potentially overlapping) provenance

### Context and Preprocessing
- Dynamic handling of contextual data
- Tracing through preprocessing steps

### Responsibility
- Computational complexity
- How to model parameter vs. data responsibility?
## Conclusions

### Take Away Messages
- Data Mining is interesting and challenging application domain for provenance
- No previous work

### Future Work
- Extend preliminary results on FIM
- Clustering (responsibility)
- MDS (parameter vs. data responsibility)
Questions?

- This is a vision paper
- so let’s discuss!