Pattern-Based Classification: A Unifying Perspective

LeGo
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Observations

The LeGo schema

General schema

Augment/replaces *data mining* step in KDD

Topic of this workshop
Observations (cont.)

DB → Pattern Mining → PS → Feature Selection → PS → Model Induction → M

- Frequent
- Closed
- Correlating
- Exhaustive
- Heuristic
- Decision Tree
- Decision List
- SVM
Observations (cont.)

DB → Pattern Mining → PS → Feature Selection → PS → Model Induction → M

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- SVM

No overview

Ramamohanarao et al ‘07
Observations (cont.)

No overview → reinventions → revisited dead ends → lost progress
Observations (cont.)

- DB → Pattern Mining
- PS → Feature Selection
- PS → Model Induction

Frequent
Closed
Correlating
Exhaustive
Heuristic
Decision Tree
Decision List
SVM

No overview → reinventions → revisited dead ends → lost progress
What patterns and how?

- Which pattern type
  - Itemsets
  - Multi-itemsets
  - Sequences
  - Trees
  - Graphs

- Which data-structure
  - FP-Trees
  - ZBDDs
  - TID-Lists
  - Bit-Vectors
What patterns and how?

- **Which pattern type**
  - Independent of Pattern Type
  - Sequences ⊂ Trees ⊂ Graphs

- **Which data-structure**
  - FP-Trees
  - ZBDDs
  - TID-Lists
  - Bit-Vectors

Results hold for **lattices** (itemsets) or even **partial orders** (graphs)
What patterns and how?

- Which pattern type
  - Results hold for
    - **lattices** (itemsets) or even
      - **partial orders** (graphs)
    - Independent of Pattern Type
  - Sequences ⊆ Trees ⊆ Graphs

- Which data-structure
  - Independent of Data Structure
Why mine explicit patterns?

Attributes: \{A_1, \ldots, A_d\}

Values: \(V(A) = \{v_1, \ldots, v_r\}\)

Rules:

\[ A_1 = v_2 \Rightarrow A_4 = v_1 \]
\[ A_3 = v_2 \Rightarrow A_2 = v_1 \]

Decision Trees:

\[ A_1 = v_2 \]
\[ A_4 = v_1 \]
\[ A_3 = v_2 \]

Traditional classification

EXCURSUS

Why should we care in the first place?

EXCURSUS

Why should we care in the first place?

apart from attending the workshop

\[ A_4 = v_1 \quad A_3 = v_2 \]
Why mine explicit patterns?

Traditional classification

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Values: V(A) = \{v_1, \ldots, v_r\}

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\[ A_1 = v_2 \land A_4 = v_1 \Rightarrow + \]
\[ A_3 = v_2 \land A_2 = v_1 \Rightarrow - \]

Decision Trees:

\[ A_1 = v_2 \]
\[ A_4 = v_1 \]
\[ A_3 = v_2 \]
Why mine explicit patterns?

Pattern based classification

Transactions are Structured

\[ t \subseteq \{i_1, \ldots, i_3\} \]

- Patterns provide instance description
- Models can be built independent of data type
- Yield interpretable classifiers
- Alternatives are opaque (Kernels, NN, ...)
Thus leverage pattern mining techniques

**Advantages:**

- 15 years of research → fast and scaleable
- Described in structured language → persistent, not opaque

**Challenge(s):**

- *(Re-)*Entangle instance description and classification
Roadmap

Class-sensitive patterns & the mining thereof

- Model-independence
  - Post-processing
  - Iterative Mining

- Model-dependence
  - Post-processing
  - Iterative Mining
We will probably miss some approaches that should have been included in the presentation, which just proves our point.
Should we use frequent patterns?

- Well-researched
- Frequent $\rightarrow$ expected to hold on unseen
- Efficient mining

- Which threshold?
- Frequent $\rightarrow$ no/anti-correlation w/classes
- (Too) many patterns
Class-sensitive patterns
Taking relationship to class-labels into account

Taking no sides/not subscribing to particular universe

Interesting Rules ’98 (IR)
Nuggets ’94
Contrast Sets ’99 (CS)
Discriminative Patterns ’07 (DP)

Jumping Emerging Patterns ’01 (JEP)
Subgroup Descriptions ’96 (SGD)
Correlating Patterns ’00 (CP)

Emerging Patterns ’99 (EP)
Version Space Patterns ’01

Class-Association Rules ’98 (CAR)
Evaluating class-sensitivity

- Confidence, Lift, WRAcc (Novelty), $X^2$, Correlation Coefficient, Information Gain, Fisher Score

- Some of them mathematically equivalent, some semantically

- Lavrac et al. ‘09
How to mine them?

- Mining frequent patterns & post-processing
  - Liu et al. ’98 (CAR)
  - Kavask et al. ’06 (SGD)
  - Atzmüller et al. ’06 (SGD)
  - Cheng et al. ’07 (DP)

- Bounding specific measure
  - Wrobel ’97 (SGD)
  - Bay et al. ’99 (CS)
  - Wang et al. ’05 (CAR)
  - Arunasalam et al. ’06 (CAR)
  - Nowozin et al. ’07 (CAR)
  - Cheng et al. ’08 (DP)
    (1 bound)

<table>
<thead>
<tr>
<th>CAR</th>
<th>- Class Association Rules</th>
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<tbody>
<tr>
<td>CS</td>
<td>- Contrast Sets</td>
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<tr>
<td>DP</td>
<td>- Discriminative Patterns</td>
</tr>
<tr>
<td>SGD</td>
<td>- SubGroup Descriptions</td>
</tr>
</tbody>
</table>
How to? (cont.)

- General Branch-and-bound
  - Webb ’95 (CAR)
  - Klösgen ’95 (SGD)
  - Morishita et al. ’00 (2-bounds)
  - Grosskreutz et al. ’08 (SGD)
  - Nijssen et al. ’09 (4-bounds)*

- Iterative deepening
  - Bringmann et al. ’06 (CP)
  - Cerf et al. ’08 (CAR)
  - Yan et al. ’08 (DP)

- Sequential sampling
  - Scheffer et al. ’02 (SGD)

*) itemset-specific, constraint programming

Earlier than most specifics, subsumes them!
What traversal strategy

Seriously?
Result sets

- Are still too big
- May include irrelevant patterns
- May include much redundancy
The (extended) LeGo

DB → Pattern Mining → PS → Feature Selection → PS → Model Induction → M

Pattern set constraint → Model constraint
The (extended) LeGo
The (extended) LeGo

Model-Independent Iterative Mining

Model-Independent Post-Processing

DB → Pattern Mining → PS → Feature Selection → PS → Model Induction → M

Model constraint
The (extended) LeGo

- Model-Independent Iterative Mining
- Model-Independent Post-Processing
- Optimisation Criteria
- Mining Constraint
The (extended) LeGo

Model-Independent Iterative Mining

Pattern Mining

PS

Feature Selection

PS

Model Induction

DB

Model-Dependent Iterative Mining

Model-Independent Post-Processing

Model-Dependent Post-Processing
Model-independence

- Only patterns affect other patterns’ selection
- Modular: usable in any classifier (often SVM)
Mine large set of patterns
Select subset
  - Exhaustively: too expensive
  - Heuristically: usually ordered
Use measure to quantify combined worth
• Pattern sets can be scored based on

  • **TID lists** of patterns only
    • significance: incorporate support/class-sensitivity
    • redundancy: similarity between TID lists

  • **Pattern structure** & TID lists
    • using a **pattern distance** measure
    • by computing how well the patterns **compress** data

★ computable for all data types

★ requires specialization
Knobbe et al. '06

- Exhaustive enumeration
- Explicit size constraint
- Boundable pruning
- Implicit redundancy control

De Raedt et al. '07

- Exhaustive enumeration
- Arbitrary constraints
- Monotone, boundable pruning
- Explicit redundancy control

Extremely large search space -> scalability issues

Counter-intuitive result: all sets

Model independent Post-Processing

Exhaustive

**DISCLAIMER**

The following algorithms should be considered illustrating examples, NOT recommendations!

other approaches vary
Knobbe et al. ’06
- Exhaustive enumeration
- **Explicit size constraint**
- Boundable pruning
- Implicit redundancy control (entropy)

De Raedt et al. ’07
- Exhaustive enumeration
- Arbitrary constraints
- Monotone, boundable pruning
- Explicit redundancy control

- Extremely large search space -> scalability issues
- Counter-intuitive result: all sets
Heuristic Search Strategies

- **Fixed Order:** Scan patterns in (possibly random) fixed order, add each pattern that improves running score ($O(n)$)

- **Greedy:** Repeatedly reorder patterns to pick pattern that improves score most ($O(n^2)$)
Model independent Post-Processing

Heuristic Search Strategies

- **Fixed Order**: Scan patterns in (possibly random) fixed order, add each pattern that improves running score (O(n))

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Model independent Post-Processing

**Example I**
(Siebes et al ‘06)

- Score pattern set by MDL encoding of \( db \): 
  \[
  L_C(db) = L(C,S_C)(db) + L(CT_C)
  \]

- Order patterns by size and support
- Fixed order scan
  - Pick first improving score
  - Some pruning
- Also:
  - Bringmann et al ’07
  - Al Hasan et al ‘07
Significance $S$ traded off against redundancy $L$:

$$G_{gen}(\mathcal{P}^k) = \sum_{i=1}^{k} S(p_i) - L(P^k)$$

Use TIDs only

Greedy:
- Add pattern improving $G$ most
- Until $|S| = k$

Also:
- Garriga et al ’07
- Cheng et al ’07
- Miettinen et al ’08
- Bringmann et al ’09
- Thoma et al ’09
Model independent
Iterative Mining

- Mine (set of) pattern(s)
- Adjust scoring function according to pattern
- Re-Mine
Sequential Mining
(Cheng et al ‘08)

- Information Gain
- Sequential covering:
  - Mine most discriminating pattern
  - Add to set
  - Remove covered instances
  - Until |S| = k

Also:
- Rückert et al ‘07
- Thoma et al ‘09

Model independent Iterative Mining
Model dependence

- Final model influences patterns’ selection
- Can be used in any model, optimized for one
- Less modular, stages need to coordinate
Model dependent techniques

Model types

- **Votes** of patterns
  - Weighted votes
  - Compression-based

- Ordered **list** of patterns
  - Some of which can be compressed into trees

- **Tree** of patterns
Model dependent

**Post-Processing**

- Mine large set of patterns
- Post-process depending on model constraints
  (Check on model effectiveness)
Model dependent Post-Processing

Fixed order scan

- Sorting order
  - Confidence/support
  - Growth rate/support
  - Size/support
  - $X^2$/support
  - Unimportant - every pattern above threshold chosen

- Patterns chosen
  - Independent of particular classes
  - Per class
Model dependent Post-Processing

Example I
(Zaki et al '03)

- Model: weighted vote
- Fix measure for predictive strength
- Filter patterns on strength threshold

Also:
- Wang et al '05
- Arunasalam et al ‘06
Model dependent Post-Processing

Example II
(Liu et al ’98)

- Model: ordered list
- Order: confidence/support
- Hill-climbing:
  - Pick first pattern correctly predicting at least one training instance
  - Remove covered training data
- Also:
  - Dong et al ’99
  - Li et al ’01
  - Zimmermann et al ’05
  - Van Leeuwen et al ’06

Fixed Order: 5
Model dependent Post-Processing

Example II
(Liu et al '98)

- **Model:** ordered list
- **Order:** confidence/support
- **Hill-climbing:**
  - Pick first pattern correctly predicting at least one training instance
  - Remove covered training data

**Also:**
- Dong et al '99
- Li et al '01
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- Van Leeuwen et al '06

Siebes et al '06!
Model dependent Post-Processing

Example II
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Fixed Order: 8
Model dependent Post-Processing

Example III
(Nijssen et al '07)

- Model: patterns as tree
- Mine/filter patterns based on model constraints
- Each itemset a DT branch
- Scan lattice bottom up, enforcing model constraints

Also:
- Gay et al '07
Model dependent
Iterative Mining

- Clearest connection to ML
- Features made-to-fit
- Overfitting danger
Model dependent Iterative Mining

Sequential Covering
(Galiano et al ‘04)

- Model: ordered list
- Algorithm:
  - Mine patterns
  - Select set of mutually exclusive patterns
  - Remove covered data
- Also:
  - Yin et al ‘03

Sequential Mining: 2
Model dependent Iterative Mining

Decision Tree Construction
(Bringmann et al ‘05)

- Model: tree of patterns
- Algorithm:
  - Mine most discriminating pattern (information gain)
  - Split data into covered and uncovered
- Also:
  - Geamsakul et al ‘03
  - Fan et al ‘08
Lazy Learning
(Li et al ’00)

- Model: weighted vote
- For each testing instance:
  - Project db on syntactic elements
  - Mine highly predictive patterns
- Also:
  - Veloso et al ’06
Model dependent Iterative Mining

Boosting/Regression
(Nowozin et al ’07)

- Model: weighted vote
- Algorithm
  - Mine predictive pattern
  - Re-weight mis-classified training instances as in Linear Programming Boosting
- Weights derived from mining
- Also:
  - Saigo et al ‘08

Boosting-Like: 2
Conclusions

Let’s Count

Model-Independent Post-Processing
- Fixed Order: 3
- Greedy: 6

Model-Dependent Post-Processing
- Threshold Selection: 3
- Fixed Order: 5
- Decision Tree Construction: 2

Model-Independent Iterative Mining
- Sequential Mining: 3

Model-Dependent Iterative Mining
- Sequential Mining: 2
- Lazy Learners: 2
- DT Construction: 3
- Boosting-Like: 2
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Model-Dependent Post-Processing
- Fixed Order: 8

Decision Tree Construction: 2

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Model-Dependent Iterative Mining
- Sequential Mining: 2
- Lazy Learners: 2
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Let’s Count

Post-Processing

- Fixed Order: 11
- Greedy: 6
- Decision Tree Construction: 2

Model-Independent Iterative Mining

- Sequential Mining: 3

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- Sequential Mining: 2
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Conclusions

Let’s Count

WE BROUGHT YOU 31

LeGo techniques
Conclusions

- Large number of existing LeGo approaches
- Two main dimensions
  - Model (in)dependence
  - Post-Processing & Iterative Mining
  - Boundaries blur
- Mostly very flexible
- Few studies in relative effectiveness
  - Deshpande et al ’05
  - Wale et al ’08
  - Janssen et al ’09
### The exact picture

**Model independent PP**

<table>
<thead>
<tr>
<th>TID Score</th>
<th>Pattern Structure Score</th>
<th>Search</th>
<th>Score used</th>
</tr>
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<td>Score used</td>
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<tr>
<td>Sig</td>
<td>Red</td>
<td>Distance</td>
<td>Compress</td>
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<tr>
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</table>

Some greedy algorithms approximate a well-defined global optimum.
# The exact picture

## Model dependent PP

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Order</th>
<th>Selection</th>
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<tbody>
<tr>
<td>Voting</td>
<td></td>
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</tr>
<tr>
<td>Compress</td>
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<tr>
<td>List</td>
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<td>Conf.</td>
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<tr>
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<td>Per class</td>
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<tr>
<td>Indep</td>
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</table>

### Voting

- Liu et al '98
  - X
- Dong et al '99
  - X
- Li et al '01
  - X
- Zaki et al '03
  - X
- Wang et al '05
  - X
- Zimmermann et al '05
  - X
- Van Leeuwen et al '06
  - X
- Arunasalam et al '06
  - X

### Compress

- Dong et al '99
  - X

### List

- Dong et al '99
  - X

### Conf.

- Dong et al '99
  - X

### Growth

- Dong et al '99
  - X

### $X^2$

- Dong et al '99
  - X

### Threshold

- Dong et al '99
  - X

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- Dong et al '99
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- Dong et al '99
  - X