

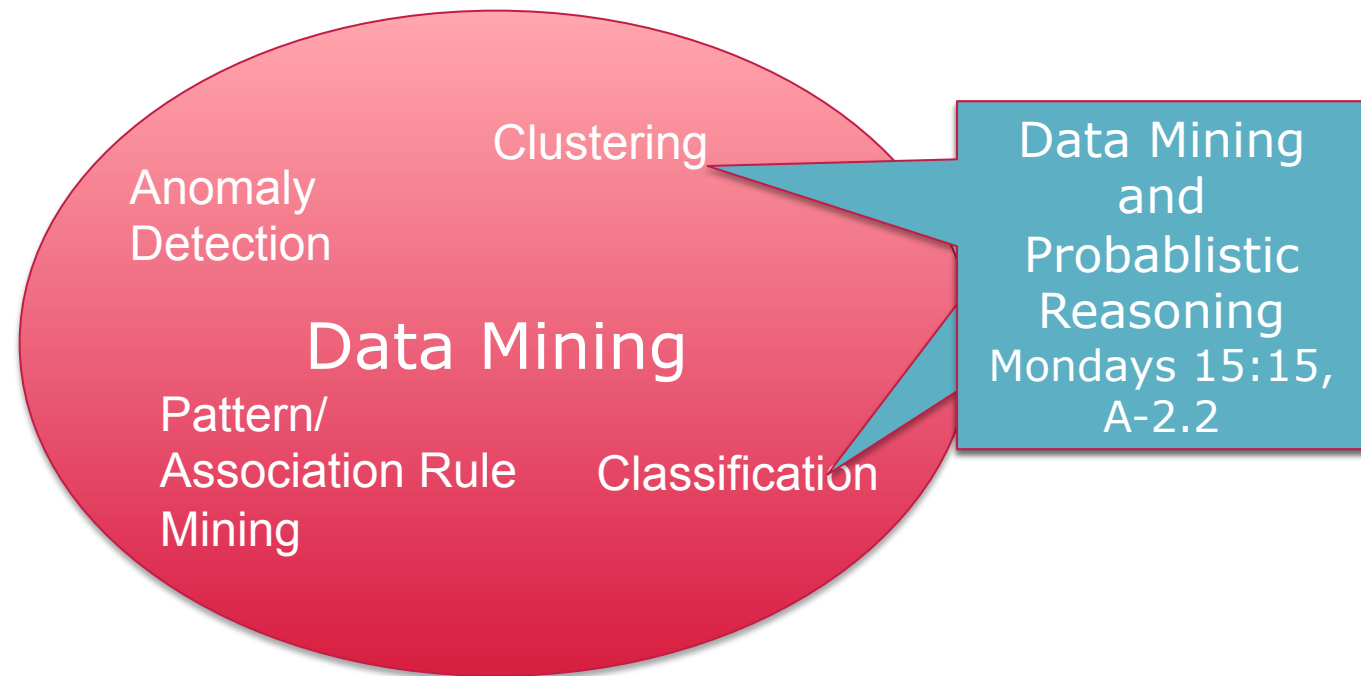
# Introduction to Algorithms for Pattern Mining

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# Pattern Mining

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- Data Mining: "...extract knowledge from a data set in human-understandable structure..."
- Pattern: frequently occurring event or item combinations



# Pattern Mining Applications

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- Shopping basket analysis

- Which products are likely to be bought together?

**Wird oft zusammen gekauft**



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- Web mining

- Web content mining, web structure mining, web usage mining

- Software bug mining

- Identify copy and paste code for bug isolation
  - Extract application specific programming rules

- Mining data streams

- Mining multimedia data

# Frequent Pattern Mining

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- Frequent pattern
  - holding **support** 25%
  - {milk},{bread}, {beer}, {diaper}
  - {milk, bread}...
- Maximal frequent pattern
  - no proper super-itemset is frequent
  - {milk, bread}, {beer, diaper, bread}
- Closed frequent pattern
  - no proper super-itemset has the same support
  - {milk, bread}, {beer}, {beer, diaper, bread}

TID	transaction
1	bread, milk, tea
2	beer, diaper, bread
3	beer, diaper, bread, milk
4	flour, milk, bread
5	beer

# Association Rules

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## ■ Association Rules

□ For each frequent itemset  $a$  generate rules:  $l \rightarrow a - l$   
 where  $l \subset a, l \neq \emptyset$

□ Output rules with minimum **confidence**  $\text{conf}(l \rightarrow a - l) = \frac{\text{sup}(a)}{\text{sup}(l)}$

## ■ Example

□ holding **confidence** 60%

□ Positive Rules

□  $\{\text{beer}\} \rightarrow \{\text{diaper}\}, 100\%$

□  $\{\text{bread}\} \rightarrow \{\text{milk}\}, 75\%$

□ Negative Rules

□  $\{\text{tea}\} \rightarrow \text{NOT } \{\text{coffee}\}$

## ■ Correlation Coefficient, Lift, ...

TID	transaction
1	bread, milk, tea
2	beer, diaper, bread
3	beer, diaper, bread, milk
4	flour, milk, bread
5	beer

# FP Mining Algorithms

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- Naive approach: scan transaction table for **each** combination for retrieving its support →  $2^n$  scans
- Pruning by the intuition “all subsets of a frequent pattern must also be frequent”
  - 1. Extract all existing relevant itemset frequencies holding minimum support
  - 2. Discover relationships
- Mining Algorithms:
  - Apriori [vldb94]
  - FP-Growth [sigmod00]
  - Eclat [tkde00]

# Apriori [Agrawal93]

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- Bottom-Up approach with multiple passes
- Precondition: all itemsets are sorted lexicographically
- Process:
  - Identify frequent items (1-itemsets)
  - Generate  $k+1$ -candidates by combining frequent  $k$ -itemsets that have the first  $k-1$  items in common
  - Prune candidates with non-frequent subsets
  - Verify remaining  $k$ -candidates

# Apriori Example

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- minimum support = 25%

## 1. Pass:

- {bread}, {milk}, {beer}, {diaper}

## 2. Pass: Combine all 1-frequent-itemsets

- Candidates: {bread, milk}, {beer, bread}, {bread, diaper}, {beer, milk},...
- After scan: {bread, milk}, {beer, bread}, {bread, diaper}, {beer, diaper}

## 3. Pass: Combine all 2-frequent-itemsets that have the first item in common

- Candidates: {bread, milk, diaper}, {beer, bread, diaper}
- Prune {bread, diaper, milk} because {diaper, milk} is not frequent

TID	transaction
1	bread, milk, tea
2	beer, diaper, bread
3	beer, diaper, bread, milk
4	flour, milk, bread
5	beer



# Challenges

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- Efficient generation of negative association rules
  - Needs tracking non-frequent items as well
- Considering Multi-set semantics
- Non-redundant parallelization

# Grading process

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- 3 LP
- groups of two (limited to 3 groups)
- Grading
  - Implementation of one algorithm, one use case and, one extension
  - 2 presentations
    - Paper presentation and first algorithm evaluations
    - Use case and extension evaluation
  - 6 pages evaluation report

- Algorithms:
  - AprioriTID, FPGrowth, Eclat
- Suggested extensions
  - Quantitative association rules [sigmod96], negative associations [tois04], high utility itemsets[kdd10], ...
  - Efficiency or scalability boost (paralellizing)
- Suggested data sources/ use cases
  - DBpedia (any other linked data resource) [smer11]
  - [www.data-mining-cup.de](http://www.data-mining-cup.de)
  - Source code of large projects
  - [www.data.gov](http://www.data.gov)

# Application

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- Send mail to [ziawasch.abedjan@hpi.uni-potsdam.de](mailto:ziawasch.abedjan@hpi.uni-potsdam.de)
- Subject [APM Seminar]
- Deadline: April 13<sup>th</sup>
- Notification: April 14<sup>th</sup>
  
- Limited to 6 participants = 3 teams
  - Random selection if more applicants
- Send ranked wishes on algorithms
  - You may also already propose extension and use case
  - You may include desired teammate (Both should write an e-mail)

# Time Schedule

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- April 10th: first seminar, topic presentation
- April 13th: **application deadline**
- April 14th: notification
- April 17th: mandatory consulting
- April 24th: mandatory consulting
- May 1st: workers unite
- May 8th: mandatory consulting
- May 15th: **intermediate presentation**
- May 22nd: mandatory consulting
- ...
- July 10th: **final presentation**
- July 14th: **short paper deadline**

# References

- [vldb94] R. Agrawal & R. Srikant, fast algorithms for mining association rules
- [vldb95] J. Han & Y. Fu, Mining multiple-level association rules in large data bases
- [sigmod96] R. Srikant & R. Agrawal, Mining quantitative association rules in large relational tables
- [sigmod00] J. Han & J. Pei & Y. Yin, Mining frequent patterns without candidate generation
- [tkde00] M. J. Zaki, Scalable algorithms for association mining
- [smer11] Z. Abedjan, F. Naumann, Context and target configurations for mining RDF data
- [kdd10] V. Tseng & C. Wu & B. Shie & P. S. Yu, UP-Growth: an efficient algorithm for high utility itemset mining
- [tois04] X. Wu & C. Zhang & S. Zhang, Efficient mining of both positive and negative association rules