Evaluation of Recommender Algorithms for an Internet Information Broker

based on Simple Association Rules and on the Repeat-Buying Theory

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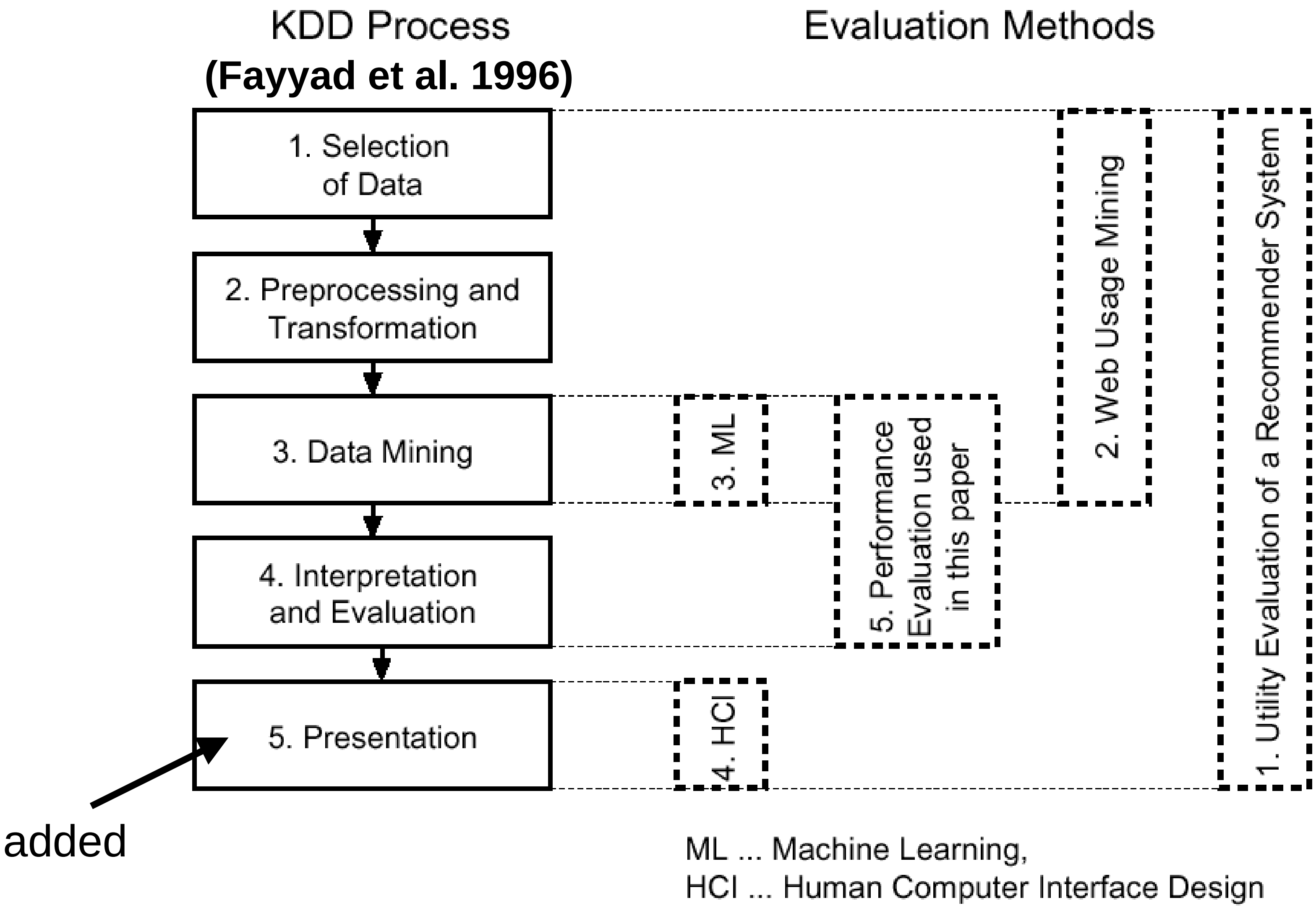
Introduction

- Research questions
  - *Are frequent itemsets (association rules) useful to build recommender systems for information brokers?*
  - *How does a recommender based on association rules perform compared to a recommender based on the repeat-buying theory known from marketing research?*
- Framework for evaluation
- Item-to-item correlation type recommender
- Association rules / Repeat-buying theory
- Experimental setup
- Results and conclusion

Framework for Evaluation



Performance Measures for Recommender Algorithms

- **From Machine Learning**
  - Accuracy
  - Coverage
  - MAE

- **From Information Retrieval**
  - Precision / recall
  - F-measure (F1) / E-measure

- **Other measures**
  - Receiver Operating Characteristic (ROC)
  - Mobasher's R

Item-to-item Correlation Type of Recommender

- Recommendations can be based on many sources of information (e.g. Ansari et al 2000):
  - Expert evaluations
  - Expressed preferences
  - Individual characteristics

  explicit, observations
  - Item characteristics (content based)
  - Expressed preferences of other people (collaborative)

- We analyze non-personalized transactions where items are used together.

Association Rules (Agrawal et al, 1993)

- Support-Confidence Framework
- **Model assumptions**: none
- We use only Rules with 1 item in the antecedent for recommendations

- **Criticism**: confidence ignores the frequency of the consequent.
  Other measures of interestingness are
  - Lift - symmetric measure of co-occurrence (deviation from independence)
  - Conviction - deviation of the implication from independence

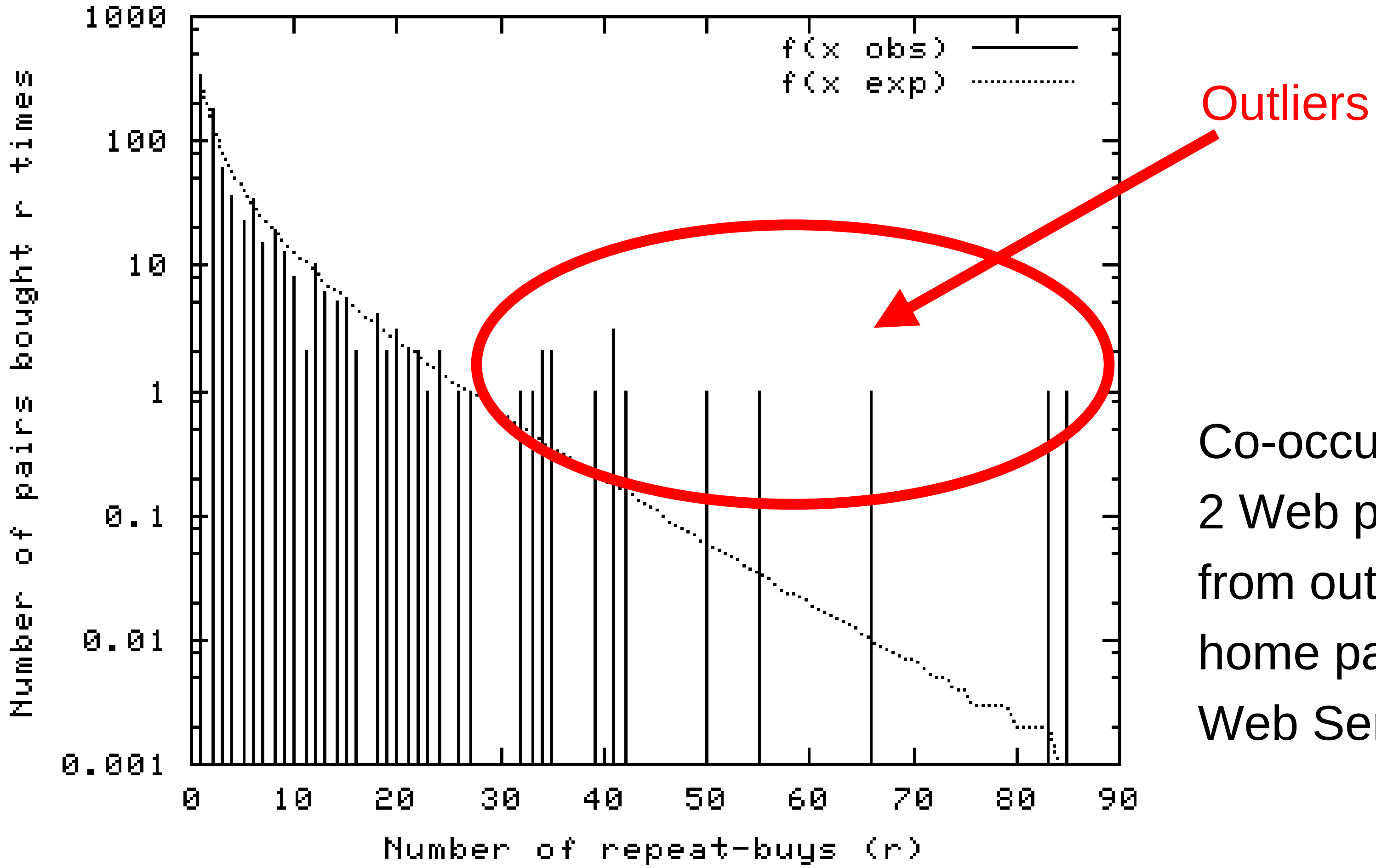
Repeat-buying Theory (Ehrenberg 1988)

- **Model assumptions**:
  - Stationary (in the analyzed time period)
  - "Purchases" of items follow independent Poisson processes
  - Distribution of the parameters follows a Gamma-distribution
  - Used for panel data for consumer products (scanner data)

- LSD (NBD) gives the probability that an item (combination of items) is "purchased" 1,2,...,r times by pure chance.

Repeat-buying Theory (Recommender)

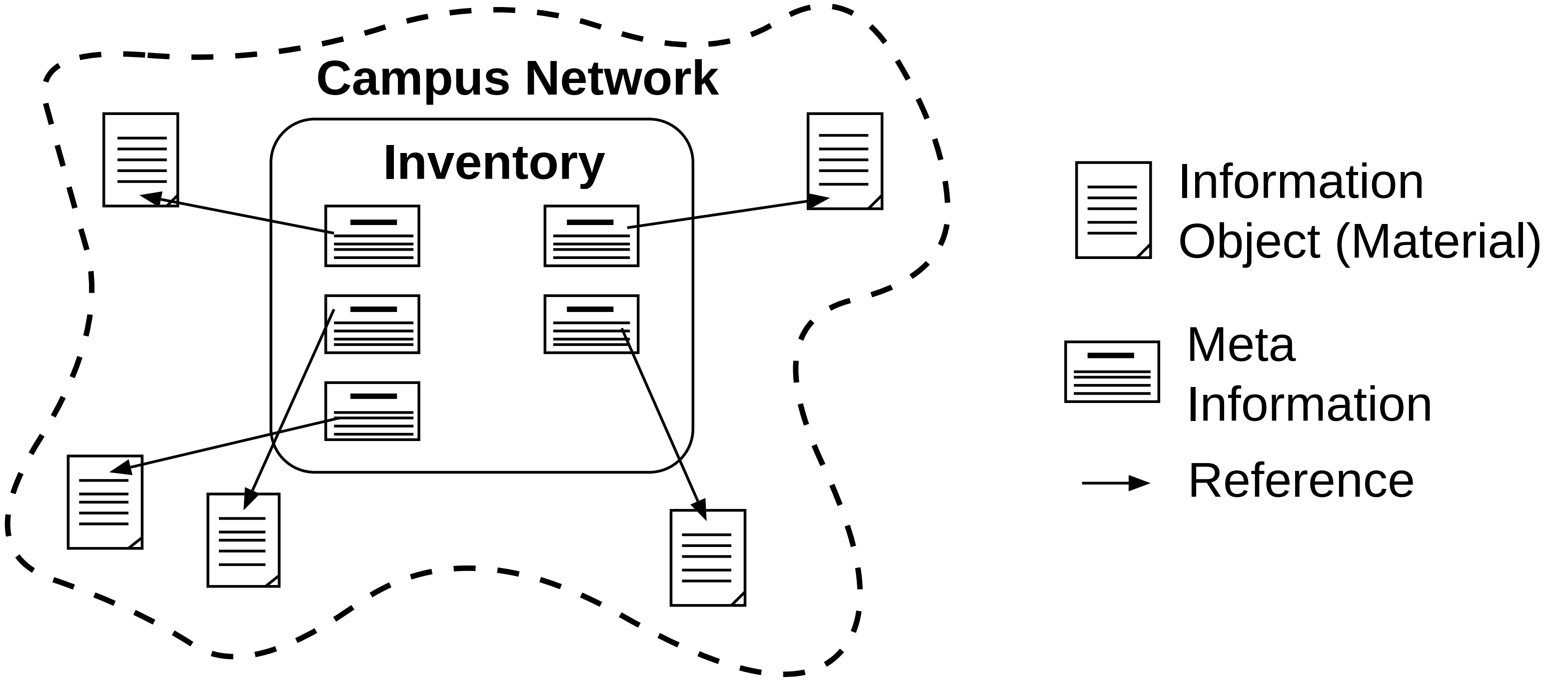
- Users "purchase" some items more often together than predicted
- Filter outliers as potential recommendations



Co-occurence of 2 Web pages from out Dept.'s home page in the Web Server's log

Experimental Setup (Info. Broker)

- Educational Internet Information Broker for lecture notes, research material, enrollment information,...



Experimental Setup (Data Set)

- **Available Data:**

6 months of transaction data (January - June 2002)

Transactions:	25522
Items:	3774
Co-occurrences:	114128

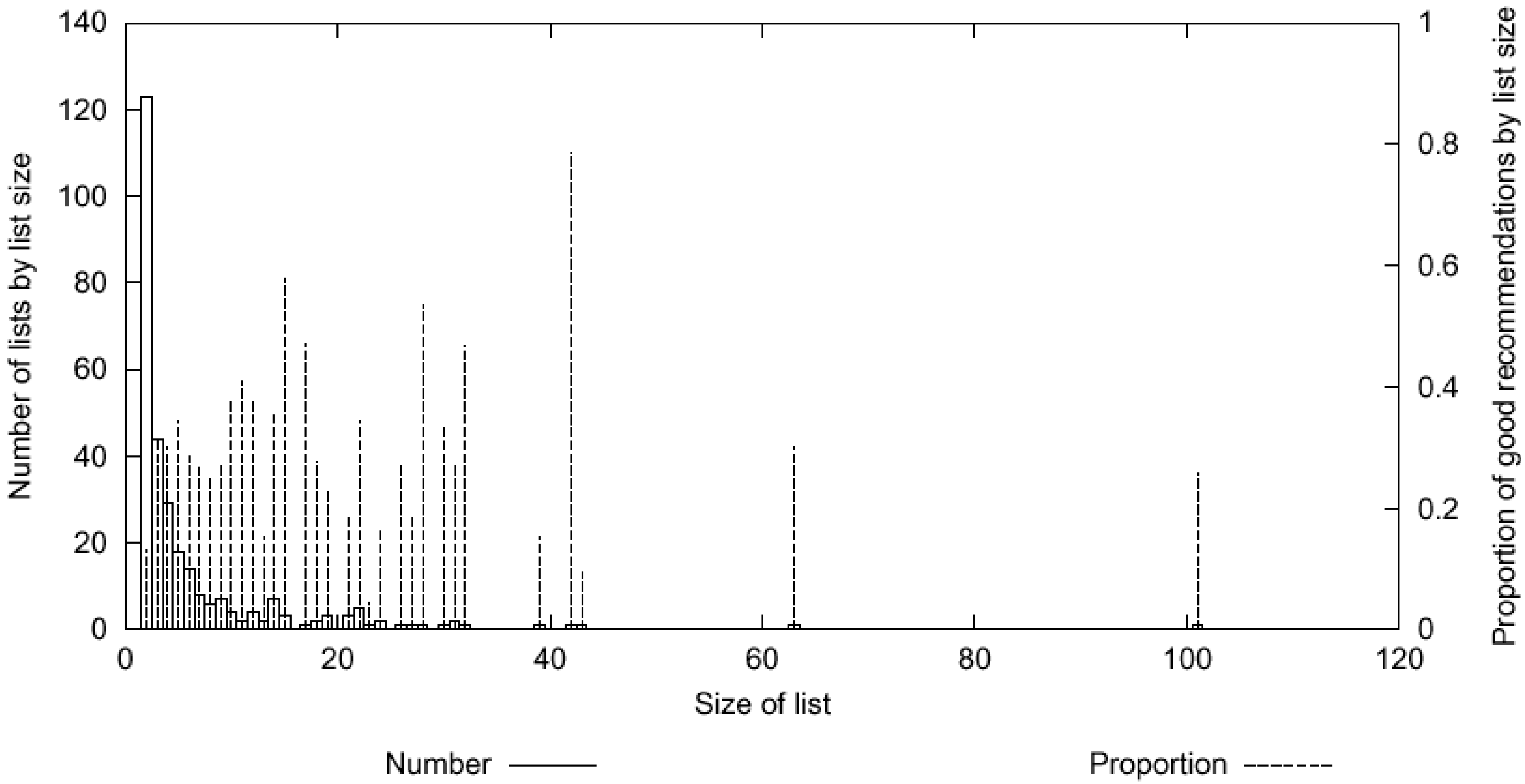
- **Data Set:**

co-occurrence lists for 300 items randomly selected

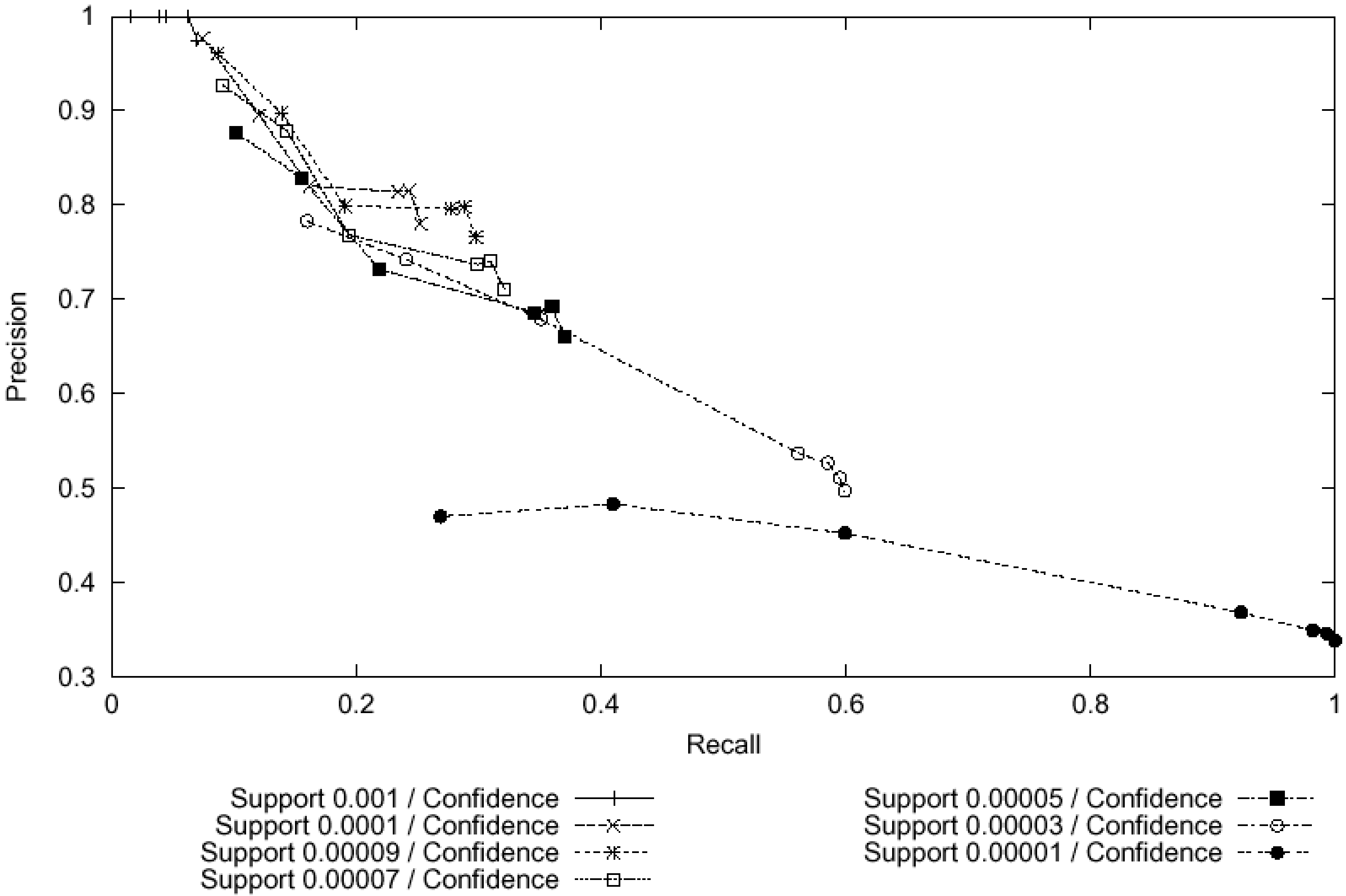
9 users from the target group evaluated 1661 co-occurrences

561 "recommend" - 1100 "don't recommend"

Experimental Setup (Evaluated Data)

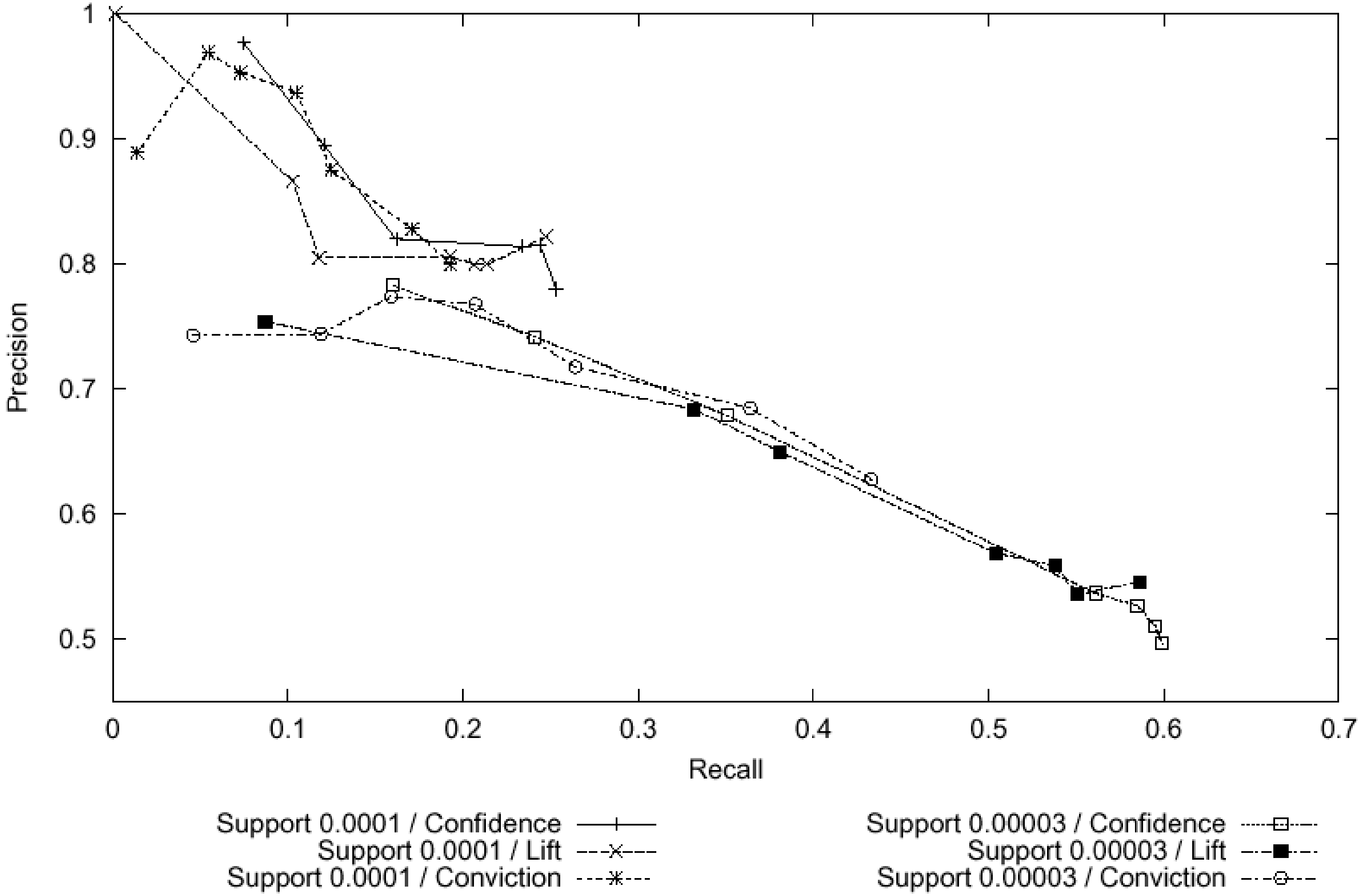


Results (Support for Association Rules)



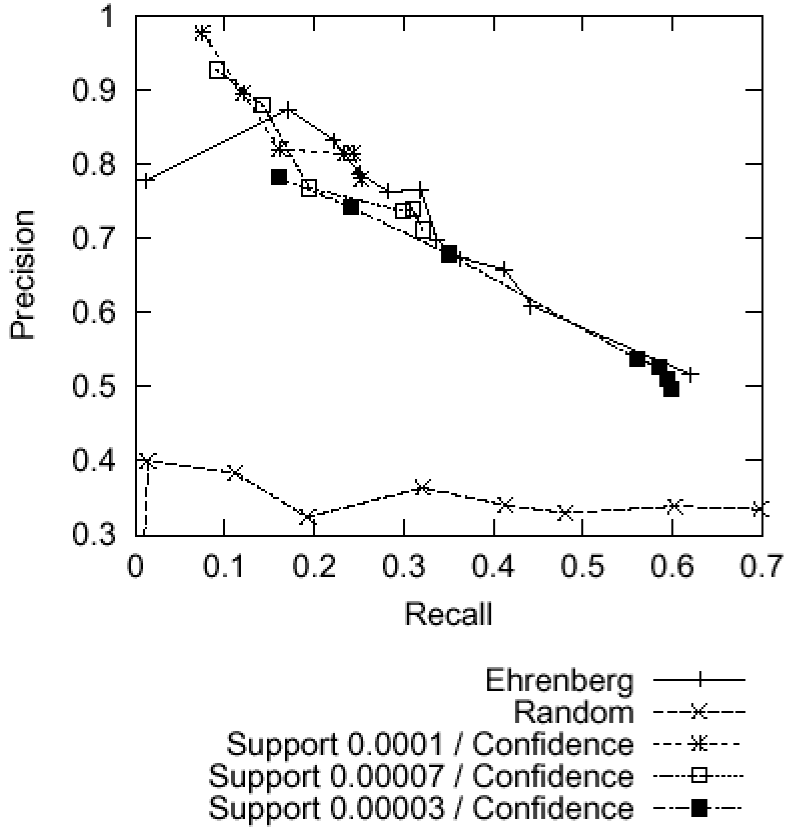
- Low support necessary for reasonable recall

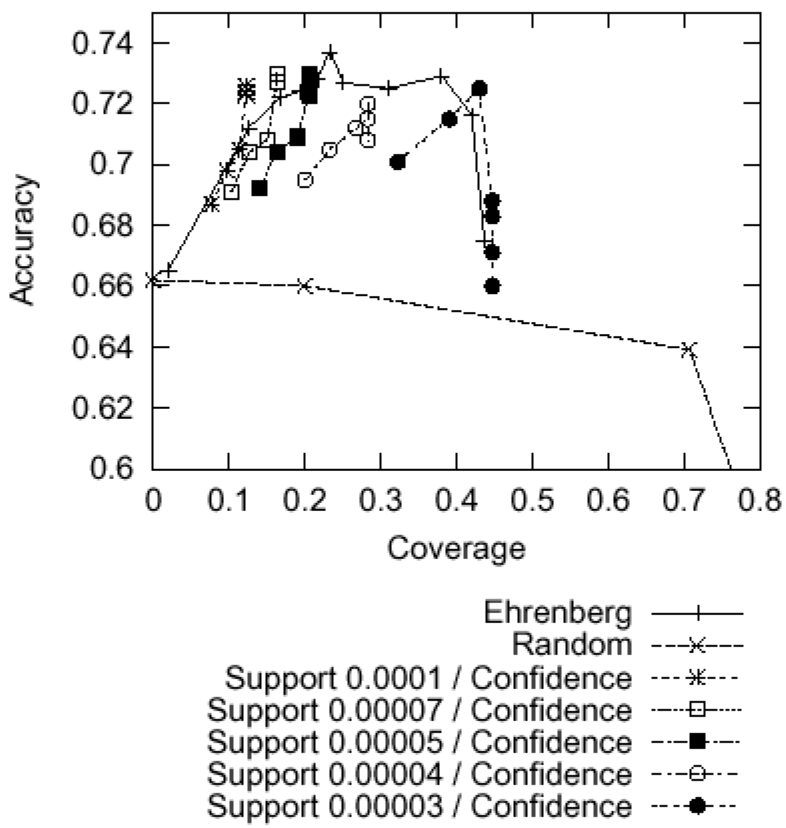
Results (Lift / Conviction)



- Lift / conviction don't perform sig. better than confidence.

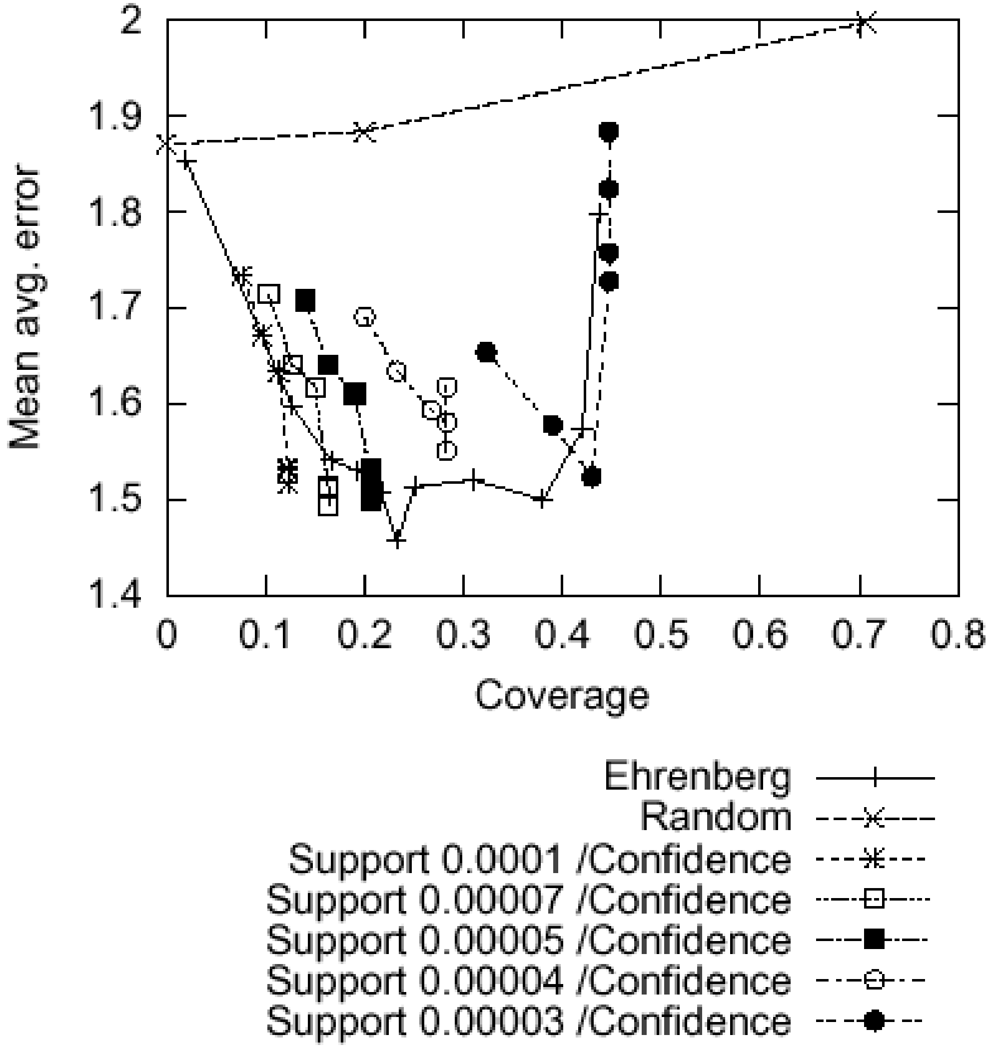
Results (Precision, Accuracy)





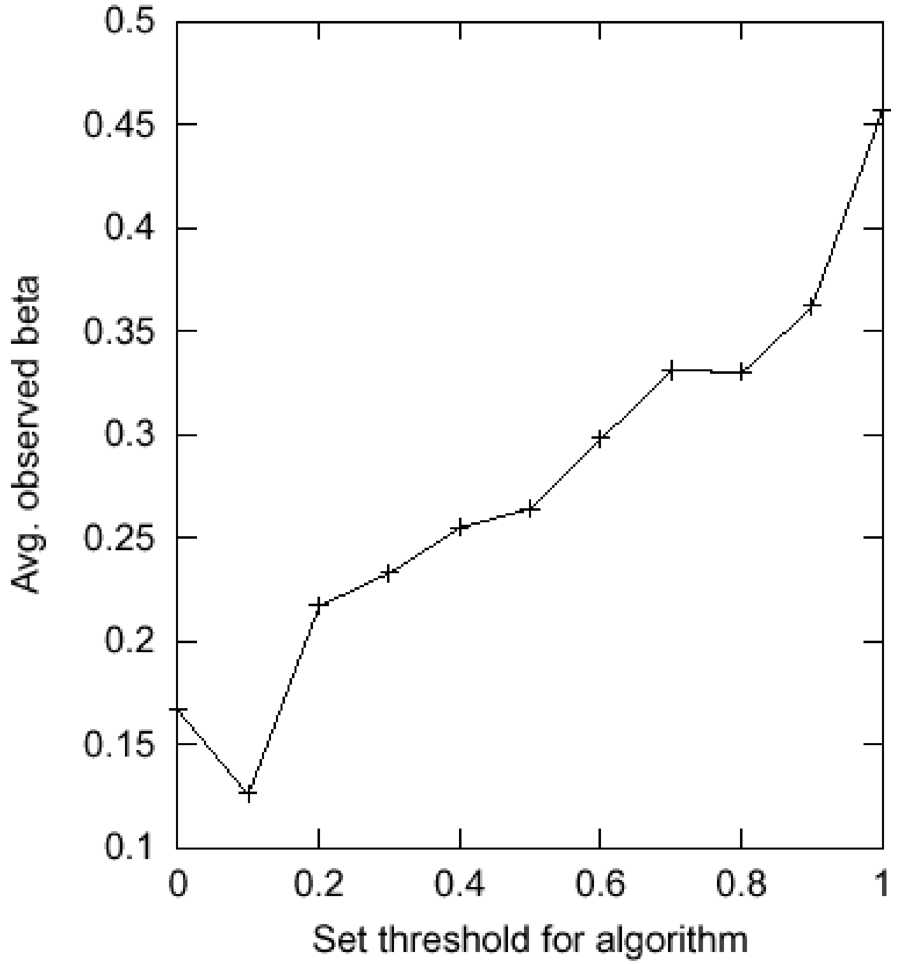
- Perform better than a random choice
- Support-Confidence sensitive to misspecification (conf)

Results (MAE)



- Support-Confidence sensitive to misspecification (conf)
- Repeat-buying seems more robust

Results (Parameter of the Repeat-buying Recommender)



- Expected error II rate is below the avg. rate (exception thresholds 0, 0.1, 0.2)

Conclusion

- Frequent itemsets represent useful recommendations Accuracy >70%, Precision 60-90%
- Both algorithms perform very similar with adequate parameters.
- Repeat-buying algorithm seems more robust to misspecification
- Model assumptions of the repeat-buying theory need to be checked.
- Datasets from other applications are needed to confirm findings