Evaluation of Recommender Algorithms for an Internet Information Broker

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

WEBKDD 2002
Edmonton, Alberta, Canada

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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
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
  – 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-occurrence 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