A Case-Based Reasoning Approach

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1 Collaborative Recommendation

Examples  GroupLens (Resnick, et al. 1994), Ringo/Firefly (Shardanand & Maes, 1995)
Technique Use ratings of products to correlate users. Use ratings of similar users to 
predict ratings of unseen items.
Problems  Cold start
  System needs a large body of users to predict well.
  Early rater
  New items can't be recommended until they are rated.
  Gray sheep
  Users with no close neighbors get poor recommendations.

2 Case-Based Recommendation

Examples  WEBSELL (Stahl & Bergmann, 2000), Entree recommender (Burke, 1999)
Technique Use a similarity metric to order products based on user input.
Problem  Not enough knowledge/data for total order.

3 Answer = Hybrid Recommendation

Examples  Daily Learner (Billsus, 2000), Fab (Balabanovic, 1997), PTV (Cotter & Smyth, 2000)
Techniques  Recommendation
  Collaborative, content-based, demographic, knowledge-based, case-based
  Combination
  Switch, mix, combine, meta-level, cascade
4 Semantic Ratings

Opportunity In Entree, critique-based navigation yields "semantic ratings": knowledge of the "why" behind a user's likes and dislikes.

Solution Inter-rating similarities provide a richer similarity metric for raters: a case-based alternative to standard collaborative filtering.

Entree Restaurant Recommender

http://infolab.ils.nwu.edu/entree/
5 Experiments

Methodology
Split session data into training and test groups
Select active users for testing
Divide each session into profile and test data
Simulate cascaded recommendation task
- Profile = items rated so far, Test = items in retrieved set
- Based on profile, predict ratings for test items
- Try to select the positively-rated item

Techniques
Case-based comparison of users using the semantic ratings (labeled "Heuristic")
Collaborative filtering using correlation of binary ratings (labeled "Correlation")
Vector space model treating restaurant / rating pairs treated as unique features (labeled "Sparse")
Average rating of each restaurant used as prediction

6 Results

Large sessions
15-rating sessions (n=4600)

Smaller sessions
10-rating sessions (50% sample, n=17,000)

Small sessions
5-rating sessions (20% sample, n=5669)

Data
The data on which this research is based is available in the UCI KDD archive at <URL http://kdd.ics.uci.edu/en>
**Future work**

**Field**  
Field as part of e-commerce recommendation service

**Profiles**  
Experiment with larger multi-session profiles

**Learning**  
Acquisition of inter-rating similarity metric

*As of January 2001, I will be joining the Department of Management Science/Information Systems at California State University, Fullerton*