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Lecture 11:  
Explanations and Interface Variations  
SI583: Recommender Systems
Recap: Evaluation Metrics

- Thresholds
  - precision, recall, …

- Ranked lists
  - precision-recall, scores, ..

- Numeric predictions
  - MAE, RMSE
Are we evaluating the right thing?

- How “good” is this recommender? What factors will you consider?
Recommended for You

These recommendations are based on items you own and more.

view: All | New Releases | Coming Soon

1. Auction Theory
   by Vijay Krishna
   Average Customer Review: ★★★★★
   In Stock
   Publication Date: March 1, 2002
   Our Price: $52.46 Used & new from $52.46
   Add to cart
   Add to Wish List

I Own It  Not interested  ★★★★★ Rate it
Recommended because you purchased Putting Auction Theory to Work and more (edit)

2. Canon Matte Photo Paper (8.5x11, 50 Sheets)
   by Canon
   Average Customer Review: ★★★★★
   Signed by Verisign, I
Why the MAE/RMSE might mislead

- Predictive accuracy doesn’t help if it recommends seen items
  - recommenders can get stuck recommending just one small category/cluster
- Users like *diversity* and *serendipity*
- Interface can influence ratings (and thus, measured MSE)
- Trust, confidence important
- Users experience a dialogue/process, not just a *single, one-way, recommendation*
Rest of this class

- Impact of interface features on ratings
- Human-Recommender Interaction conceptual model
- Incorporating explanations: why and how
Effect of the interface on ratings


- Studies choices in MovieLens interface:
  - Does the rating scale matter?
  - How consistent are ratings over time? Can recommender prompts affect this?
  - Does the displayed prediction affect the submitted rating?

- Controlled experiments and survey
Effect of interfaces: Cosley et al findings

Rating scales:
- slightly better predictive accuracy with more stars.
- binary (Like/Dislike) scale results in a positive bias

Rating consistency
- Fairly high consistency on rerated movies (60%)
- Increases when users are prompted with accurate “predicted” value
Effect of interfaces: Cosley et al findings

- Effect of displayed predictions:
  - Predictions were randomly perturbed: raised/lowered/left alone
  - Actual ratings were correlated with the perturbation

- Implication: Displayed prediction influences users’ rating
  - also: manipulation can be (somewhat) self-sustaining
User-centered view

- Consider recommender design within the context of the users’ goals

- Human-Recommender Interaction model [McNee, Riedl, Konstan]
  - describe/categorize attributes of the context
  - describe attributes/features that influence user satisfaction
  - suggest a design process around these
HRI Model [from McNee et al]

Recommendation Dialogue
- Correctness
- Transparency
- Saliency
- Serendipity
- Quantity
- Usefulness
- Spread
- Usability

Recommender Personality
- Personalization
- Boldness
- Adaptability
- Trust / First Impressions
- Risk Taking / Aversion
- Affirmation
- Pigeonholing
- Freshness

End User’s Information Seeking Task
- Concreteness of Task
- Task Compromising
- Recommender Appropriateness
- Expectations of Recommender Usefulness
- Recommender Importance in Meeting Need

Users & Tasks
- Analyze
- Create Mapping
- Metrics
- Benchmark

HRI
- Recommender Algorithms

McNee et al.
HRI model

- Factors describing context
  - concreteness of task
  - expectation of usefulness, etc.

- Different contexts may lead to different evaluation criteria

- Examples?
HRI model

Factors influencing satisfaction:

– In one interaction
  • Correctness, usefulness, serendipity (maybe), transparency, diversity of recommended list..

– Over time
  • Personalization, trust, adaptability, freshness..
Implications

- In studies, users sometime prefer rec. lists that are worse on standard metrics
- Different algorithms better for different goals => recommenders may need multiple CF algorithms
- Interface should provide a way to express context information
- Explaining recommendations can help generate trust, adaptability
Explanations in recommender systems

- Moving away from the black-box oracle model

- *justify* why a certain item is recommended

- maybe also *converse* to reach a recommendation
Why have explanations? [Tintarev & Masthoff]

- Transparency
- “Scrutability”: correct errors in learnt preference model
- Trust/Confidence in system
- Effectiveness & efficiency (speed)
- Satisfaction/enjoyment
Example: explanations for transparency and confidence

- “Movie X was recommended to you because it is similar to movie Y, Z that you recently watched”

- “Movie X was recommended to you because you liked other comedies”

- “Other users who bought book X also bought book Y”
Generating explanations

- Essentially, explain the steps of the CF algorithm, picking the most prominent “neighbors”
  - User-user
  - Item-item

- Harder to do for SVD and other abstract model-fitting recommender algorithms
Conversational recommenders

Example transcript: (from [McSherry, “Explanation in Recommender Systems, AI Review 2005]):

- **Top case**: please enter your query
- **User**: Type = wandering, month = aug
- **Top Case**: the target case is “aug, tyrol, ...”
  other competing cases include “....”
- **Top case**: What is the preferred location?
- **User**: why?
- **Top case**: It will help eliminate ... alternatives
- **User**: alps..
Conversational recommenders

- One view: CF using some navigational data as well as ratings

- More structured approach: incremental collaborative filtering
  - similarity metric changes as the query is refined

- e.g., incremental Nearest-Neighbor algorithm [McSherry, AI Review 2005]