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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?

recommender systems

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Recommender system - Wikipedia, the free encyclopedia

Recommender systems form a specific type of information filtering (IF) technique that attempts to present information items (movies, music, books, news, ... en.wikipedia.org/wiki/Recommendation system - 33k - Cached - Similar pages

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SVD Recommendation System in Ruby - igvita.com

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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

[Cosley et al, Proceedings of CHI 2003, "Is seeing believing? How recommender Interfaces Affect User Opinions"]

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) selfsustaining



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]





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



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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]

