6-1: Introduction to Item-Item Collaborative Filtering

Learning Objectives

- To understand the motivation, history, and intuition behind item-item CF algorithms
- To gain a basic understanding of the algorithm idea, preparing you to master the details later this module
- To understand some of the practical strengths and weaknesses of the algorithm

Motivation

- User-User CF was great, except …
- Issues of Sparsity
  - With large item sets, small numbers of ratings, too often there are points where no recommendation can be made (for a user, for an item to a set of users, etc.)
  - Many solutions proposed here, including “filterbots”, item-item, and dimensionality reduction

Motivation (2)

- Computational performance
  - With millions of users (or more), computing all-pairs correlations is expensive
  - Even incremental approaches were expensive
  - And user profiles could change quickly – needed to compute in real time to keep users happy

The Item-Item Insight

- Item-Item similarity is fairly stable …
  - This is dependent on having many more users than items
    - Average item has many more ratings than an average user
    - Intuitively, items don't generally change rapidly – at least not in ratings space (special case for time-bound items)
- Item similarity is a route to computing a prediction of a user's item preference

A little more detail …

- Two step process:
  - Compute similarity between pairs of items
    - Correlation between rating vectors
      - co-rated cases only (only useful for multi-level ratings)
    - Cosine of item rating vectors
      - can be used with multi-level or unary ratings
    - Adjusted cosine (normalize each user's ratings)
      - to adjust for differences in rating scales
    - Some use conditional probability (unary)
  - Predict user-item rating
    - Weighted sum of rated "item-neighbors"
    - Linear regression to estimate rating

Item-Item Top-N

- Item-Item similarity model can be used to compute top-N directly:
  - Simplify model by limiting items to small "neighborhoods" of k most-similar items (e.g., 20)
  - For a profile set of items, compute/merge/sort the k-most similar items for each profile item
    - Straightforward matrix operation from Deshpande and Karypis

Benefits of Item-Item

- It actually works quite well
  - Good MAE performance on prediction; good rank performance on top-N
- Efficient implementation
  - At least in cases where |U| >> |I|
  - Benefits of precomputability
- Broad applicability and flexibility
  - As easy to apply to a shopping cart as to a user profile

Core Assumptions/Limitations

- Item-item relationships need to be stable …
  - Mostly just a corollary of stable user preferences
  - Could have special cases that are difficult (e.g., calendars, short-lived books, etc.)
  - Many of these issues are general temporal issues
- Main limitation/complaint: lower serendipity
  - This is a user/researcher complaint, not fully studied; intuition is clear

Moving Forward

- Next Lectures
  - Breaking down the core item-item algorithm
  - Looking at the special cases of unary/binary ratings
  - Programming item-item (for programmers)

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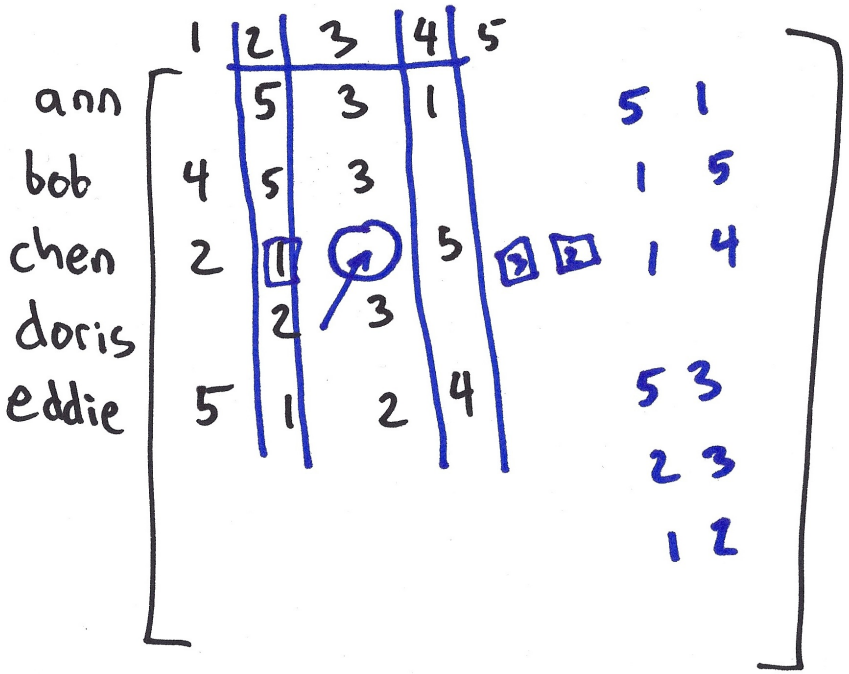
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