Teaching AI & Business Analytics to MBAs

How to Develop Insightful Understanding of (AI) Recommendation Systems

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- Driving our own teaching, research, and development:
- “…Innovators around the world can work in parallel, exploring novel combinations of software components…
  …The component parts of these technologies can be combined and recombined by innovators to create new devices and applications…”
- Why was innovation so rapid on the Internet? The reason is that the component parts were all bits…”

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Collaborative Filtering as an AI “Component”

Our Pedagogical Motivation:

Why is it critical to make sure that our MBA students be familiar with what actually happens behind the scenes of a common machine-learning algorithm?

- Fostering personal confidence
- Building trust of that AI system
- Ability to improve on the current method
- Diagnose the sources of potential AI errors
- Verify that the methods are working as they should
- Understand why interpretability is often the first casualty when adopting complex predictors, …

Looking at Recommender Systems Design

Commonly used by online merchants to identify interesting products for their customers

- Consumers’ benefit?
- Merchants’ benefit?
Collaborative Filtering

- Users provide ratings (Labels) on items
  - This way, they not only give the algorithm information about the **quality of the items**, but also about themselves (i.e., the types of movies, shoes, cars, or drinks they have consumed, and which they like or dislike.)

Everyday Examples of Collaborative Filtering...

- Bestseller lists
- Many weblogs
- Top 40 music/book lists
- “Read any good books lately?”
- The “recent returns” shelf at the library
- “Have you seen any good Netflix show lately?”
- Unmarked but well-used paths thru the woods
- The printer/coffee room at work (at the Pre-Covid Time…)
Collaborative Filtering...

- **Common insight**: personal tastes are *correlated*:
  - If Alice and Bob both like X and Alice likes Y, then Bob is more likely to like Y
  - Especially (perhaps):
    - if Bob knows Alice, or if they live nearby, or if they share a few **common features** *(Age, Gender, Education, Hobbies, Social Media Channel, Zip Code, Religion,…)*,
    - then they are likely to share a similar taste

The Machine Learning Output:

- Each user gets a small set of items that the user has not seen before but is expected to like

- This contrasts with the **content based filtering methods (CB)** that use **features vectors to** recommend items with similar features to the items that a user *has labeled at liked* in the past
The Advantage of (Basic) Collaborative Filtering

- CF methods do not need any data on the feature vectors of the items or demographic characteristics of the users.
- All they need are the labels user's assign to each product (±), or how many stars were given by that user.
- What is needed:
  - A database of user ratings which helps finding similar users.
  - A decision rule defining:
    - ‘similarity’,
    - and ‘the recommendation’.

From: William W. Cohen (CMU):
- Cosine with "inverse user frequency" \( f_j = \log(n/n_j) \), where

\[
 w(a, i) = \frac{\sum_j f_j \sum_j f_j v_{a,j} v_{i,j} - (\sum_j f_j v_{a,j}) (\sum_j f_j v_{i,j})}{\sqrt{UV}}
\]

where

\[
 U = \sum_j f_j (\sum_j f_j v_{a,j}^2 - (\sum_j f_j v_{a,j})^2)
\]

\[
 V = \sum_i f_i (\sum_i f_i v_{i,j}^2 - (\sum_i f_i v_{i,j})^2)
\]
Why Bother with CF Algorithmic Intuition?

- In recent years, significant efforts have been dedicated towards the development of AI models that are inherently interpretable.
- The recommendation rule must be an interpretable model -- whose computation process should be well understood by human users (Letham et al. 2015).


A More Intuitive Example:

<table>
<thead>
<tr>
<th></th>
<th>Alice</th>
<th>Bob</th>
<th>Chris</th>
<th>Devin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Justin Bieber</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Red Hot Chili Peppers</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>The Beatles</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>One Direction</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>?</td>
</tr>
</tbody>
</table>

"+" represents like and "-" represents dislike

The decision problem:

* Will Devin like One Direction or not?
Our New CF Software Tool (*Movie Recommendation*)

- **The Objective:**
  - Provide MBA students with a Hands-On experience in using CF
- **Our Design Principles:**
  - Faculty can specify the randomized data set:
    - Proportion of Positive, Negative, Not seen,…
  - A set of “CF Rules” to be used by our students
  - More rules are added over time
  - The code/rules are hidden

Sample Screen Shot
The Students Homework Assignment:

1. Run the system, and discover the logic of Rules A to E
2. Discuss the relative ‘power’, and limitations, of each rule
3. Design, or enhance, two more Recommendation Rules
4. Explain the rule you prefer, and why?
5. Key limitations of the CF approach?
6. .....
Some CF Issues

- **Sparsity** problem
- **First-rater** problem
- **Privacy** problem
- How to combine CF with CB recommenders:
  - Use CB approach to score some unrated items
  - Then use CF for recommendations
- The pleasure of **Serendipity**

Methodical Conclusions:

- Not a trivial undertaking for all students
  - Must plan ‘the experiments’ carefully
  - Gain insights to the logic, and the limitations of CF
  - Student found the ‘hands-on part’ challenging, yet highly rewarding
- Valuable hands-on learning of the “AI Interpretability” challenge
  - Understanding AI insightfully builds sustained Users’ Confidence

==> Will gladly share our new **CF Experimental SW tool** with other IS faculty
Thank you

- Questions?

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