Teaching AI & Business Analytics to MBAs

How to Develop Insightful Understanding of (AI) Recommendation Systems

The 2021 IT & Business Analytics Teaching Conference
Georgia Tech, Scheller College of Business

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Combinatorial Innovation: *Hal Varian,* AER (2010)

- 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…*
- *You never run out of HTML…"*

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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, …

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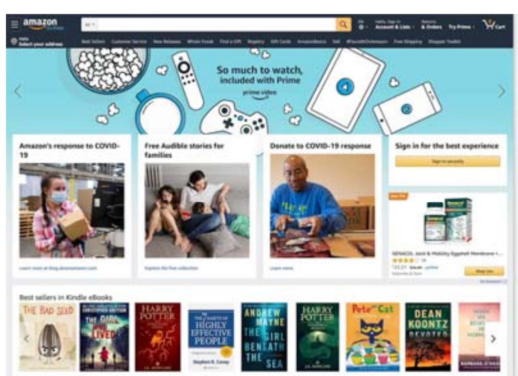
Looking at Recommender Systems Design

- Commonly used by online merchants to identify interesting products for their customers
  - Consumers’ benefit?
  - Merchants’ benefit?



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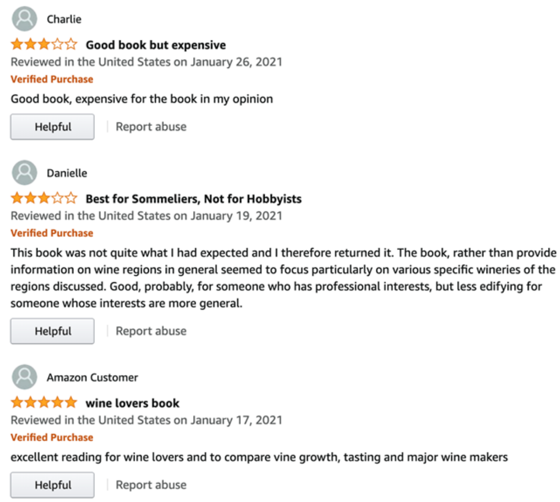
Collaborative Filtering

- 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.)



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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…)

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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 <u>but is expected to like</u>
- 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 **-**), 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*'

Algorithms for Collaborative Filtering: Memory-Based Algorithms (Breese et al, UAI98)

From: William W. Cohen (CMU):

- Cosine with "inverse user frequency" $f_i = log(n/n_j)$, where
  - n is number of users,
  - n_j is number of users voting for item j
  - $V_{i,j}$ ratings,…

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

where

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

$$V = \sum_i f_j(\sum_i f_j v_{i,j}^2 - (\sum_i f_j v_{i,j})^2)$$

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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)

Letham B, Rudin C, McCormick TH, Madigan D, et al. (2015) Interpretable classifiers using rules and Bayesian analysis: Building a better stroke prediction model. ***The Annals of Applied Statistics*** 9(3):1350-1371.

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A More Intuitive Example:

	Alice	Bob	Chris	Devin
Justin Bieber	+	-	+	+
Red Hot Chili Peppers	-	+	+	+
The Beatles	+	+	+	+
One Direction	+	+	-	?

The decision problem:

* Will Devin like **One Direction** or not?

"+" represents like and "-" represents dislike

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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

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Sample Screen Shot

Data

Number of Movies: (5-15)

5

Number of Viewers: (5-15)

5

Submit

	New User	Bob	Chris	Kate	Devin
The Godfather	Dislike	Like	Dislike	Like	No Data
Yes Man	Dislike	Dislike	Dislike	Like	Dislike
Apocalypse Now	?	Like	No Data	No Data	Dislike
Jaws	No Data	Like	Dislike	No Data	Like
The Shawshank Redemption	Dislike	No Data	Dislike	Dislike	No Data

Value Function: (A-E)

A

Submit

Value function: 1
Score List:
Bob .... : 2
Kate .... : 1

The most similar to New User is Bob with the similarity score 2

Apocalypse Now is NOT recommended

Export to PDF

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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. …..

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Blackboard Design

Method/Value Function	A	B	C	D	E
Similarity Score Calculation					
Recommendation made by					
In Case of Conflicting Preferences from the Most (Dis)similar Users					

How to **improve** on these rule set?
Business applications of such **Recommendation Systems** in practice?

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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

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Thank you

- Questions?

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