

Content-based recommendation

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Collaborative filtering

- Leverages item ratings
- Agnostic to item content

Content-based filtering

- · Leverages item content
- · Agnostic to item ratings

Applicable **to any kind of item** (e.g., text,
audio, video, food)

Applicable even in extreme cold-start scenarios

Same basic idea

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- Stable preferences
 - News: I prefer technology, travel
 - Music: I prefer rock, grunge, folk
 - Clothing: I prefer cotton, casual
 - Movies: I prefer sci-fi, thrillers

Advantages



- No need for data on other users
- No cold-start or sparsity problems
- Able to recommend to users with unique tastes
- Able to recommend new and unpopular items
 - No first-rater problem
- Can provide explanations of recommended items by relevant content features
 - More on explanations later in the course

Challenges and drawbacks

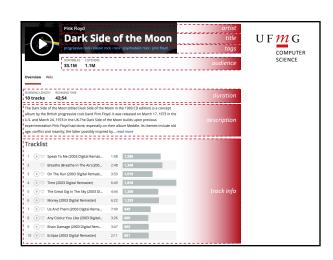


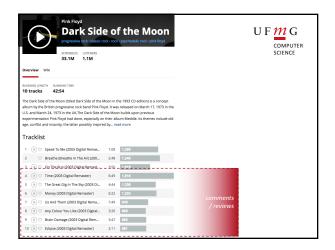
- Content-based techniques in general...
 - Depend on well-structured attributes that align with preferences (consider paintings)
 - Depend on having a reasonable distribution of attributes across items (and vice versa)
 - Unlikely to find surprising connections (e.g., chili peppers or lemon with chocolate)
 - Harder to find complements than substitutes

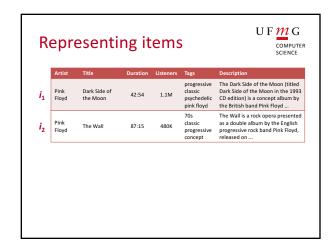
What is "content"?

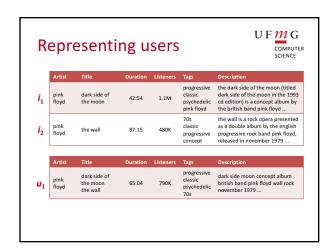


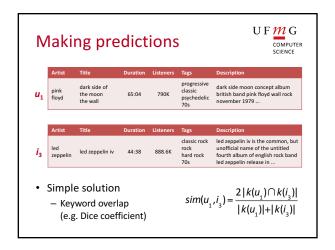
- It can be structured text
 - Artist: Pink FloydGenre: RockYear: 1973
- · It can be unstructured text
 - Several techniques to extract content features
 - Several techniques to compute item similarity
- · It can be derived from binary data
 - Audio, video, image











Are we done yet?

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Tokenization

• How to split...

- information retrieval?

• information + retrieval

- 信息检索?

• 信息 + 检索

• We can analyze term statistics

- Probability of segmentation

• Also applicable in other scenarios

- Domain names, hashtags, etc.

Term normalization

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- · I am interested in "information retrieval"
 - i₁ contains "retrieval"
 - i₂ contains "retrieving"
 - $-i_3$ contains "retrieved"

•••

- Stemming reduces words to a root form
 - "retrieval" → "retriev"
 - "retrieving" → "retriev"
 - "retrieved" → "retriev"

Term frequency

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- I am interested in "information retrieval"
 - $-i_1$ contains "information retrieval" once
 - $-i_2$ contains "information retrieval" ten times
- Intuitively, *term frequency* denotes how much the item is about the particular term
 - Also applicable to n-grams

Term frequency



- · I am interested in "information retrieval"
 - i₁ contains "information retrieval" once
 - i₁ has a total of 10 terms
 - $-i_2$ contains "information retrieval" ten times
 - *i*₂ has a total of 100,000 terms
- Intuitively, long items may yield high frequency terms by chance
 - Content *length normalization* may help (next class)

Term proximity



- I am interested in "information retrieval"
 - i₁ contains "information retrieval"
 - i₂ contains "retrieval of spatial memory in the hippocampus ... the theory of constructive recollection asserts that information ..."
- Once again, co-occurrence stats may help
 - Index "information retrieval" as a unit
 - Or record the position of each term
- Alternatively, we can identify concepts

Term informativeness



- I am interested in "information retrieval"
 - i₁ contains "information"
 - i₂ contains "retrieval"
- Which item should be ranked first?
 - "information" occurs in 35% of all items
 - "retrieval" occurs in 0.1% of all items
- Intuitively, the scarcity of a term makes its occurrence more informative

Content structure



- I am interested in "information retrieval"
 - $-i_1$ contains "information retrieval" in the title
 - $-i_2$ contains "information retrieval" in the body
 - $-i_3$ contains "information retrieval" in the URL
- Different fields may convey a different measure of the informativeness of a term
 - Field-based term weighting may help
 - Typically a machine learning task

Content enrichment



- · I am interested in "information retrieval"
 - i₁ contains "search engines"
 - i₂ contains "recommender systems"
- How can they be retrieved?
 - Leverage external databases
 - Lexical databases, knowledge bases
 - Leverage user-generated content
 - Tags, anchor-text (user annotations)
 - Views, clicks, purchases (user feedback)

Content quality



- I am interested in "information retrieval"
 - $-i_1$ is a book by Manning et al. (authority)
 - $-i_2$ is an entry in Wikipedia (readability)
 - $-i_3$ is a spam page (trustworthiness)
 - $-i_4$ is a best seller (popularity)
 - $-i_5$ is brand new (freshness)
- · Several measures of "quality"
 - A-priori notion of relevance, helping distinguish between items with similar topicality

Summary



- CB recommendation works for new items
 - Not for new users (still need ratings)
- Keywords alone may not suffice
 - Freshness, usability, aesthetics, writing style
 - Content may also be limited / too short
 - Content may not be automatically extractable
- Overspecialization
 - Algorithms tend to propose "more of the same"

Writing Assignment #4 Due May 1st @ 23:55



- Write a one-page summary describing the following paper:
 - Performance of recommender algorithms on topn recommendation tasks (RecSys 2010)
 by Paolo Cremonesi, Yehuda Koren, Roberto Turrin