CS-4053 Recommender System

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Lecture 3: Content-based Recommender System

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Content-based Recommendations: Preamble

- The basic idea of a content-based recommender system is to match user with items that are similar to what they rated highly in the past
- The similarity is not on the basis of rating correlations across users
- The attributes of the items are used to find similarity

Content-based Recommendations: Preamble

- These type of recommendation systems can work well in cases where personalized recommendations are needed
  - Movie recommendations e.g. a user liking a movie of a certain director more
  - Websites or blogs *e.g.* recommending similar news or article to the user to the one he is querying or interested in

Content-based Recommendations: Preamble

- What exactly do we mean by **content**?

- **Content** are explicit attributes or characteristics of the item e.g. for a movie:
  - **Genre**: Action / Superhero
  - **Actor**: Robert Downey Jr.
  - **Year**: 2019

- It can also be textual content (title, description, table of content, *etc.*)
  - Several techniques to compute the distance between two textual documents
  - Can use NLP techniques to extract content features

- Can be extracted from the signal itself (audio, image)

Content-based Recommender System

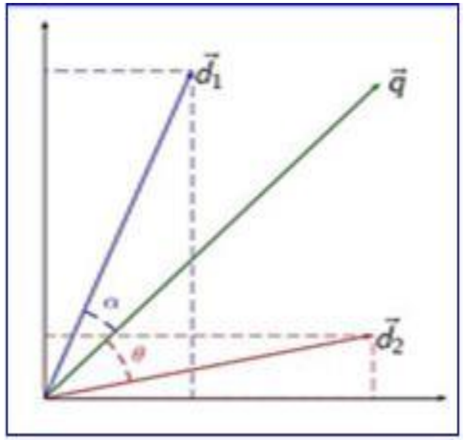
- Formally, a **content-based recommender systems** try to match users to items that are *similar* to what they have liked in the past

- This *similarity* is not necessarily based on rating correlations across users but on the basis of the attributes of the objects liked by the user

Vector Space Model

- In a vector space model, each item is saved as a vector of its attributes (features) in n-dimensional space
- The angle between two vectors give similarity between the contents of these items
- Each user is saved as a user profile vector and the similarity is calculated the same way

Vector Space Model



User profile and Item feature vectors in 2-D vector space

Content-based Filtering: Approach

- Content-based systems are common for recommending text-based products *e.g.* news articles, wiki pages

- A lazy approach is to recommend an item containing content that is most similar to that present in user's highly rated items
  - Also called **lazy approach**

- More novel approaches involve training a classifier *(decision trees, neural networks etc.)* to predict a rating given a set of features as input

Content-based Filtering: Approach

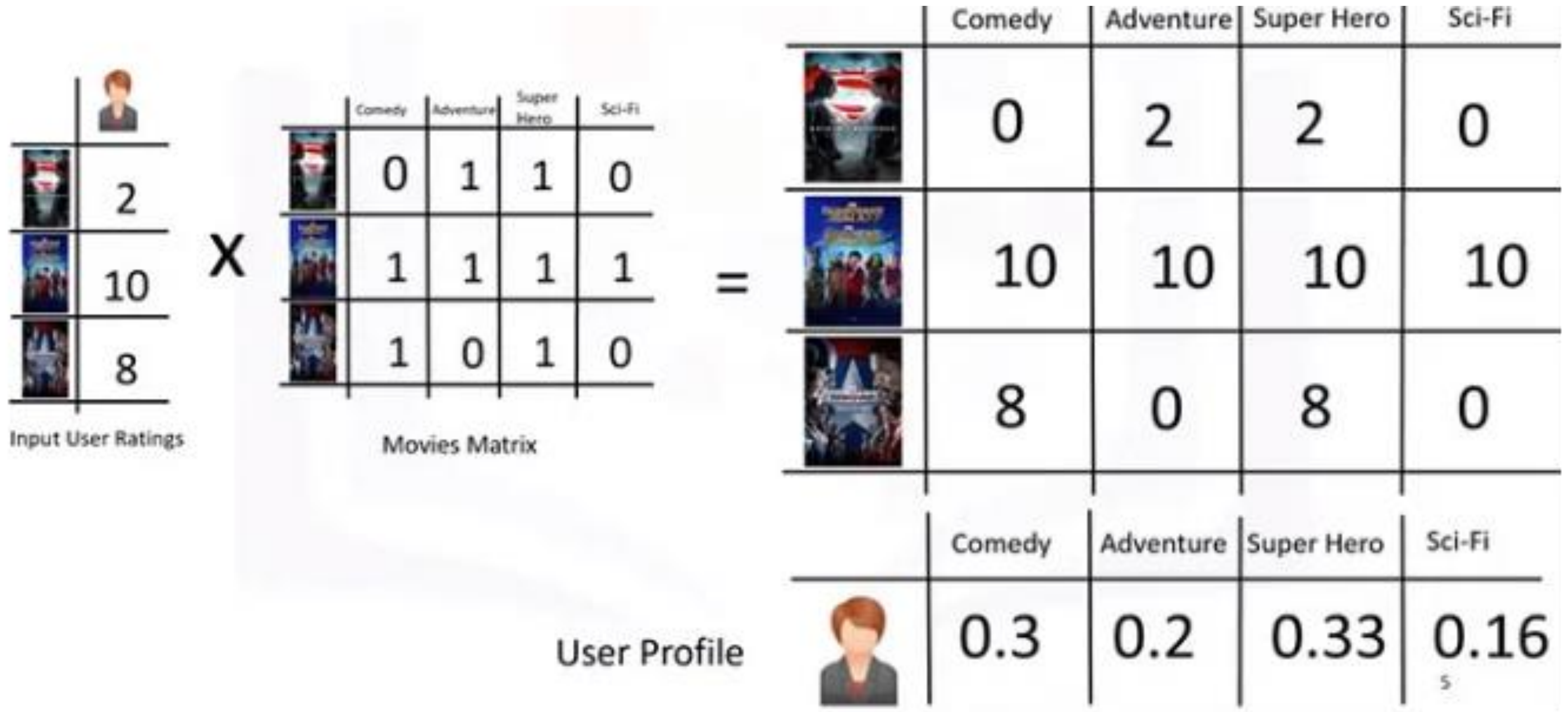
- **Input**
  - A vector containing attributes for each unrated (unseen) item
  - A user profile vector expressing their taste using already rated items
- **Output**
  - A weighted matrix depicting user's measure of *liking* of each attribute for all items
  - A recommendation vector containing predicted ratings for unseen items

Content-based Filtering: Example

- We have an input of user ratings for a set of movies and their attributes

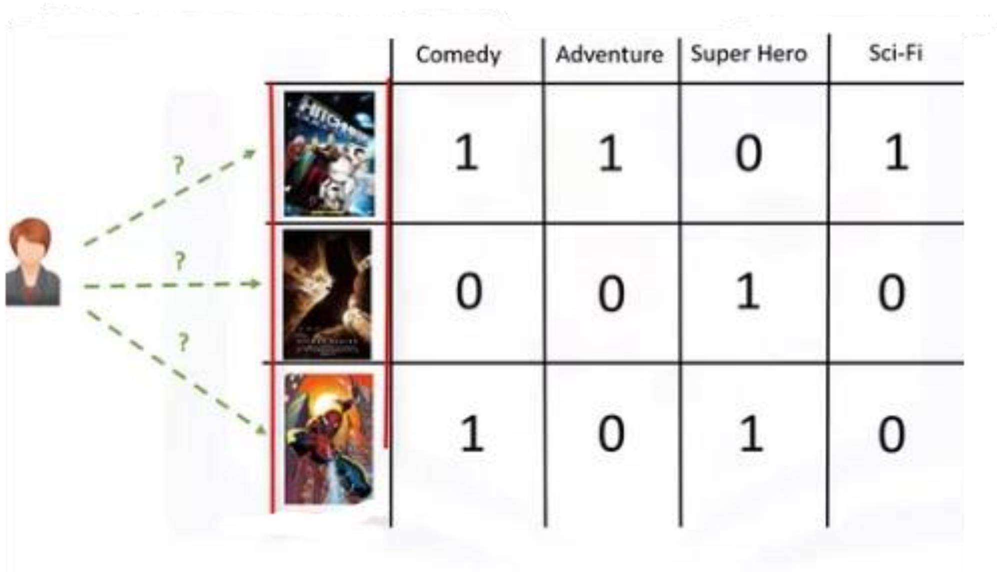
Content-based Filtering: Example

- We first create a user profile based on already rated items (and attributes)



Content-based Filtering: Example

- Which one of the yet unrated movies should we be recommending?



	Comedy	Adventure	Super Hero	Sci-Fi
	1	1	0	1
	0	0	1	0
	1	0	1	0

Content-based Filtering: Example

- We can recommend the movie that gives us the maximum weighted average

Content-based Filtering: Example

- Maximum weighted average can also be expressed as raw predicted rating

6.6

3.3

6.3

Content-based Filtering: Exercise

- **Task:** Find Cosine similarity between user profile and movie matrix and compare with previous results.

Content-based Filtering: Example

- Let us assume that a user clicks and reads a blog on a website
- The objective is to recommend **two** similar blogs to the user
- We can calculate the **TF** (term frequency) and **IDF** (inverse document frequency) of the blogs in order to find their relative importance based on how similar they are to the current blog

Content-based Filtering: Example

- Term Frequency (**TF)** is simply the number of times a term (feature) appears in the document (item)

- We generally use transformed **TF** in order to de-emphasize the effect of frequency on relevance of the term. Hence:

$$TF_{tk,\, dj} = \frac{freq(tk)}{max(ti, dj)}$$

- Inverse Document Frequency **(IDF)** helps us find the overall relevance of a term

$$IDF_{tk} = log_{10} \frac{N}{n_k}$$

Content-based Filtering: Example

- Let us assume that **Blog 1** is being read by the user and contains the given three terms with their frequencies

Blog	Business	Invention	Hospital
Blog 1	31	27	0

Content-based Filtering: Example

- The given table contains retrieved blog along with information for all other blogs (from which two are to be recommended)

Blog	Business	Invention	Hospital
Blog 1	31	27	0
Blog 2	29	61	3
Blog 3	52	99	6
Blog 4	10	29	5
Blog 5	13	41	7

- Assume that the corpus contains **50000** documents (blogs) on the website and **2500** of them contain the term **Business**, **1200** contain **Invention** and **800** contain **Hospital**

Content-based Filtering: Example

- The given table contains retrieved blog along with information for all other blogs (from which two are to be recommended)

Blog	Business	Invention	Hospital
Blog 1	31	27	0
Blog 2	29	61	3
Blog 3	52	99	6
Blog 4	10	29	5
Blog 5	13	41	7
Doc. Freq.	**2500**	**1200**	**800**

- **N = 50000**

Content-based Filtering: Example

- We first calculate TF for each attribute of every blog *e.g.*

$$\boldsymbol{TF}_{Business,\ Blog2} = \frac{freq(Business,Blog2)}{max(freq(any\ other\ term,\ Blog2))} = \frac{29}{61} = \mathbf{0.47}$$

Blog	Business	Invention	Hospital
Blog 1	31	27	0
Blog 2	0.47	61	3
Blog 3	52	99	6
Blog 4	10	29	5
Blog 5	13	41	7
Doc. Freq.	**2500**	**1200**	**800**

Content-based Filtering: Example

- We calculate TF for all other attributes in the same manner

$$\boldsymbol{TF}_{Business,\ Blog2} = \frac{freq(Business, Blog2)}{\max(freq_i, Blog2)} = \frac{29}{61} = \mathbf{0.47}$$

Blog	Business	Invention	Hospital
Blog 1	1.14	0.87	0
Blog 2	0.47	2.10	0.04
Blog 3	0.52	1.90	0.06
Blog 4	0.34	2.9	0.17
Blog 5	0.31	3.15	0.17
Doc. Freq.	**2500**	**1200**	**800**

Content-based Filtering: Example

- We also need to calculate **IDF** for each attribute e.g.

$$\boldsymbol{IDF}_{Business} = log_{10}\left(\frac{\mathbf{50000}}{\mathbf{2500}}\right) = \mathbf{1.30}$$

Blog	Business	Invention	Hospital
Blog 1	1.14	0.87	0
Blog 2	0.47	2.10	0.04
Blog 3	0.52	1.90	0.06
Blog 4	0.34	2.9	0.17
Blog 5	0.31	3.15	0.17
Doc. Freq.	**2500**	**1200**	**800**
IDF	**1.30**	**1.61**	**1.79**

Content-based Filtering: Example

- Let us calculate the TF-IDF weights for each term in every blog e.g.

$$\boldsymbol{TF\text{–}IDF_{tk,\ dj}} = TF\text{–}IDF_{Business,\ Blog2} = 0.47 \ * 1.30 = \mathbf{0.61}$$

Blog	Business	Invention	Hospital
Blog 1	1.14	0.87	0
Blog 2	**0.61**	2.10	0.04
Blog 3	0.52	1.90	0.06
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Content-based Filtering: Example

- Let us calculate the TF-IDF weights for each term in every blog e.g.

$$\boldsymbol{TF\text{–}IDF_{tk,\,dj}} = TF\text{–}IDF_{Business,\,Blog2} = 0.47 * 1.30 = \mathbf{0.61}$$

Blog	Business	Invention	Hospital
Blog 1	1.48	1.40	0
Blog 2	0.61	3.38	0.07
Blog 3	0.67	3.05	0.10
Blog 4	0.44	4.66	0.30
Blog 5	0.40	5.07	0.30
Doc. Freq.	**2500**	**1200**	**800**
IDF	**1.30**	**1.61**	**1.79**

Content-based Filtering: Example

- Let us first find the length of each vector and then use it calculate the normalized TF-IDF weights e.g.

$$\boldsymbol{Length_{Blog1}} = \sqrt{1.48^2 + 1.40^2 + 0^2} = \mathbf{2.03}$$

Blog	Business	Invention	Hospital	Magnitude
Blog 1	1.48	1.40	0	**2.03**
Blog 2	0.61	3.38	0.07	3.43
Blog 3	0.67	3.05	0.10	3.12
Blog 4	0.44	4.66	0.30	4.69
Blog 5	0.40	5.07	0.30	5.09
Doc. Freq.	**2500**	**1200**	**800**	
IDF	**1.30**	**1.61**	**1.79**	

Content-based Filtering: Example

- Let us first find the length of each vector and then use it calculate the normalized TF-IDF weights e.g.

$$w_{Business,\ Blog1} = \frac{TF\text{–}IDF_{Business,\ Blog1}}{Length_{Blog1}} = \mathbf{0.73}$$

Blog	Business	Invention	Hospital	Magnitude
Blog 1	0.73	0.68	0	2.03
Blog 2	0.17	0.98	0.02	3.43
Blog 3	0.21	0.97	0.03	3.12
Blog 4	0.09	0.99	0.06	4.69
Blog 5	0.07	0.99	0.05	5.09
Doc. Freq.	**2500**	**1200**	**800**	
IDF	**1.30**	**1.61**	**1.79**	

Content-based Filtering: Example

- Calculate the Cosine Similarity between the weighted user profile (Blog1) and each weighted item profile (all other blogs) to recommend blogs

Blog	Business	Invention	Hospital	Magnitude
Blog 1	0.73	0.68	0	2.03
Blog 2	0.17	0.98	0.02	3.43
Blog 3	0.21	0.97	0.03	3.12
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Content-based Filtering: Example

- Calculate the Cosine Similarity between the weighted user profile (Blog1) and each weighted item profile (all other blogs) to recommend blogs

$$Cosine_{(Blog1,\ Blog2)} = \frac{(0.73 * 0.17) + (0.68 * 0.98) + (0 * 0.02)}{\sqrt{0.73^2 + 0.68^2 + 0^2}\ .\ \sqrt{0.17^2 + 0.98^2 + 0.02^2}} = \mathbf{0.79}$$

Blog	Business	Invention	Hospital	Magnitude	Cosine Similarity
Blog 1	0.73	0.68	0	2.03	
Blog 2	0.17	0.98	0.02	3.43	0.79
Blog 3	0.21	0.97	0.03	3.12	
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Blog 3	0.21	0.97	0.03	3.12	**0.82**
Blog 4	0.09	0.99	0.06	4.69	**0.74**
Blog 5	0.07	0.99	0.05	5.09	**0.73**
Doc. Freq.	**2500**	**1200**	**800**		
IDF	**1.30**	**1.61**	**1.79**		

Content-based Filtering: Example

- Based on Cosine Similarities, **Blog 2** and **Blog 3** will be recommended to the user for reading

Blog	Business	Invention	Hospital	Magnitude	Cosine Similarity
Blog 1	0.73	0.68	0	2.03	
Blog 2	0.17	0.98	0.02	3.43	**0.79**
Blog 3	0.21	0.97	0.03	3.12	**0.82**
Blog 4	0.09	0.99	0.06	4.69	**0.74**
Blog 5	0.07	0.99	0.05	5.09	**0.73**
Doc. Freq.	**2500**	**1200**	**800**		
IDF	**1.30**	**1.61**	**1.79**		

Content-based Filtering: Pros and Cons

Pros

- Scalable in terms of new users
- Highly personalized recommendations
- Partially solves cold start problem *i.e.* solves for new item
- Recommendations are explainable

Cons

- Not easy to hand-engineer meaningful attributes
- Has little to no serendipity
- Suffers from cold start user problem