Graduate Certificate in Big Data Analytics

Content-Based Recommender Systems

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Agenda

- Basics of Content-based Recommender Systems
- Item Representation and Similarity
- Some Example Applications
- Advantages and Issues

Content-based Recommendation

The system learns to recommend items that are **similar** to the ones that the user liked in the past.

Item features

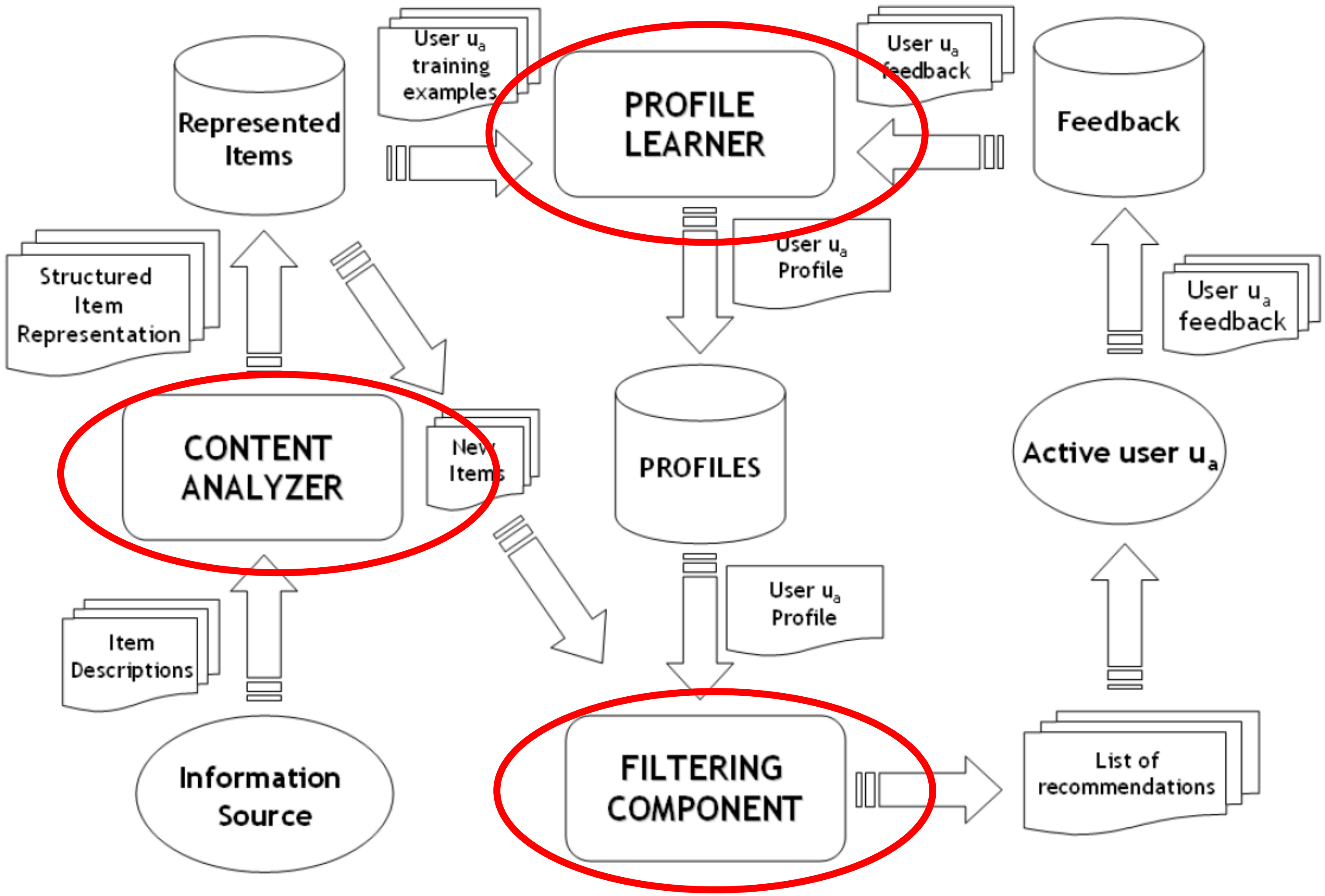
- In contrast, *collaborative* recommendation identifies **users** whose preferences are similar to those of the given user and recommends items they have liked.
- Recommending news, books, movies, music, products and services in e-commerce, etc.

Basics of Content-based Recommendation

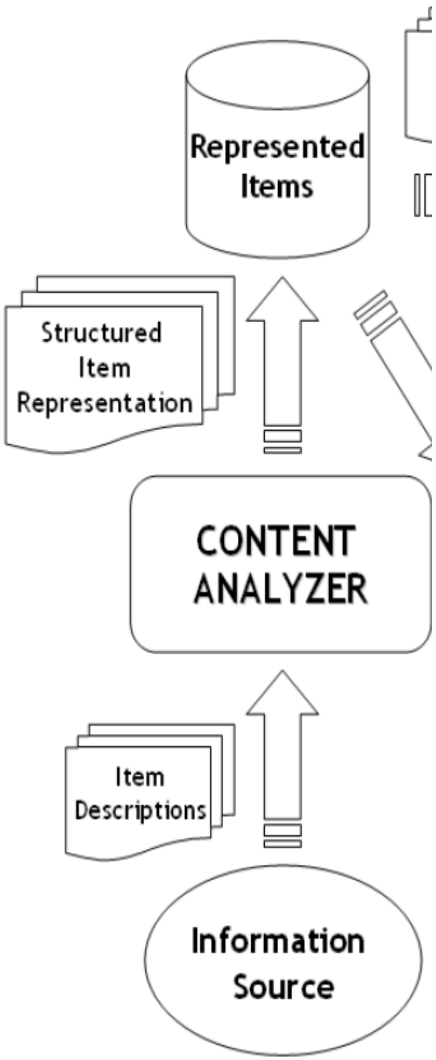
- Inputs:
  - Profile of the user's preferences and interests
  - Description of a content item
- Output: a relevance score representing the user's level of interest in that object

➔ Ranking, filtering of content items

High Level Architecture

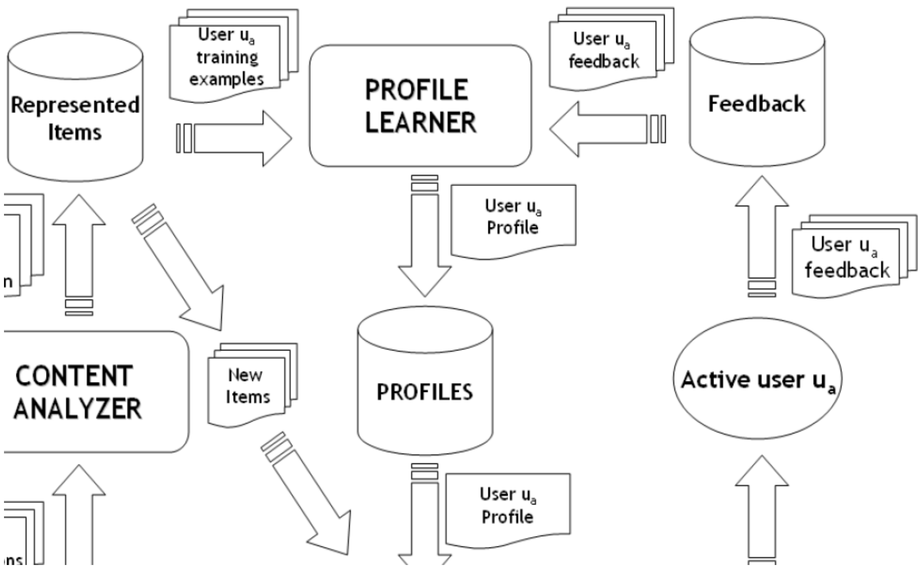


Content Analyzer



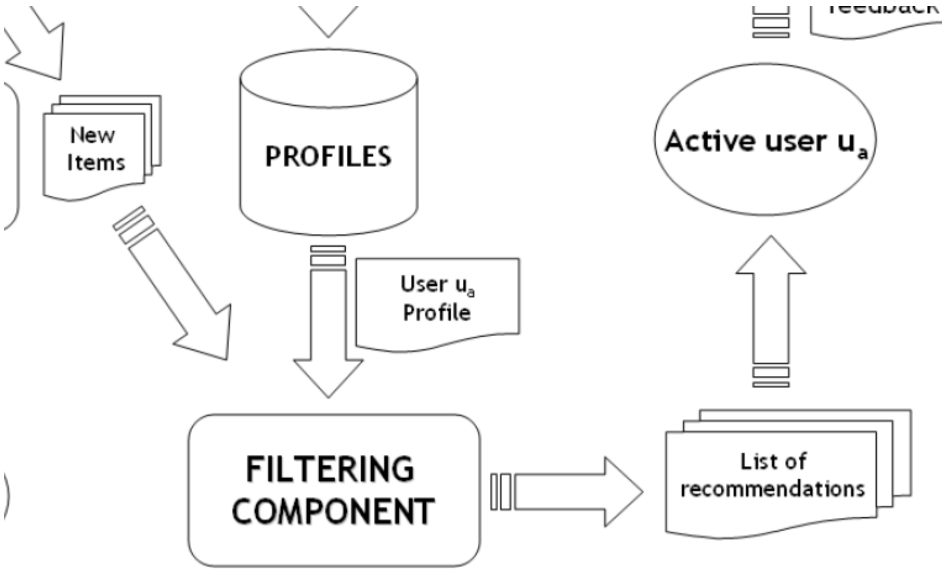
- Input: The content of items (web pages, news, product descriptions, etc)
- Pre-processing step to extract structured relevant information from content -- **feature extraction** to the target space

Profile Learner



- Defined by user
- Or infer a model of user interests from items liked or disliked by the user (machine learning) e.g. relevance feedback method - feedback (training examples) provided by the user

Filtering Component



- Matching user profile against item representations using similarity metrics (eg. Cosine similarity)
- Result: binary or continuous relevance judgement, a (ranked) list of potentially interesting items

User Profile - Feedbacks

- Feedbacks – user's reactions to items, together with the related item descriptions
  - Positive feedbacks – inferring features the user liked
  - Negative feedbacks – inferring features the user 's not interested in
- Explicit **Feedbacks** – The user explicitly evaluates items.
  - Like/dislike
  - Ratings
  - Text comments
- Implicit **Feedbacks** – no active user involvement; derived by monitoring and analyzing user's activities
  - Assigning a relevance score to specific user actions on an item (e.g. saving, discarding, printing, bookmarking, etc.)

Item Representation

- A set of *features*, or *attributes*, *properties*.
- Features may be manually assigned, e.g. features for movies - *actors, directors, genres, subject matter*, etc.
- For items like web pages, emails, news articles, and product descriptions, features are extracted from text – **vector space model**
  - Keyword-based profiles
  - Not able to capture the semantics of user interests
  - Language ambiguity like *polysemy* and *synonymy* - typical NLP problem

Vector Space Model

Documents

Lost glamor

High tea at Raffles!

Not what it was, but still a place to go to.

Amazing service
Rated 5 by travel-gini on Feb 26, 2013

Great location with a little bit of history, the staff make this hotel though
Have a drink in the Long Bar, throw your nutshells on the floor, then go to the Tiffin Room for the best curry in the world. About £40a head for food but the choice is brilliant and when my wife mentioned it was her birthday at the end of the meal a cake was presented, what amazing service.

Stayed February 2013

Term Document Matrix

	amazing	service	lost	glamour	disappoint	brilliant	super	expensive	noisy	…
Doc1	1	1	0	0	0	1	0	0	0	
Doc2	0	0	1	1	1	0	0	1	0	
Doc3	0	0	0	1	0	0	1	0	0	
Doc4	0	0	0	0	2	0	0	1	1	
…										

Vector Space Model

- Keyword-based, “bag-of-words” approach
- Each item (***document***) is represented by a vector in a n-dimensional space
- Each dimension corresponds to a ***term*** from the vocabulary of a given document collection (***corpus***)
- Documents are pre-processed by operations like *tokenization, case lowering, stop-words removal, stemming*
- Usually using ***TF-IDF*** (Term Frequency - Inverse Document Frequency) *weighting*

TF-IDF Weighting

- To modify the frequency of a word in a document by the perceived importance of the word(the *inverse document frequency)*, widely used in information retrieval
  - When a word appears in many documents, it's considered unimportant.
  - When the word is relatively unique and appears in few documents, it's important.

$$tf\text{-}idf_{t,d} = tf_{t,d} * idf_t \qquad idf_t = \log \frac{N}{df_t}$$

- $tf_{t,d}$: term frequency – number of occurrences of term t in document d
- idf_t : inverted document frequency of term t
- N : the total number of documents in the corpus
- df_t : the document frequency of term t, i.e., the number of documents that contain the term.

tf-idf Example

TERM VECTOR MODEL BASED ON $w_i = tf_i * IDF_i$											
Query, Q: "gold silver truck" D_1: "Shipment of gold damaged in a fire" D_2: "Delivery of silver arrived in a silver truck" D_3: "Shipment of gold arrived in a truck" D = 3; IDF = $\log(D/df_i)$											
		Counts, tf_i						Weights, $w_i = tf_i * IDF_i$			
Terms	Q	D_1	D_2	D_3	df_i	D/df_i	IDF_i	Q	D_1	D_2	D_3
a	0	1	1	1	3	3/3 = 1	0	0	0	0	0
arrived	0	0	1	1	2	3/2 = 1.5	0.1761	0	0	0.1761	0.1761
damaged	0	1	0	0	1	3/1 = 3	0.4771	0	0.4771	0	0
delivery	0	0	1	0	1	3/1 = 3	0.4771	0	0	0.4771	0
fire	0	1	0	0	1	3/1 = 3	0.4771	0	0.4771	0	0
gold	1	1	0	1	2	3/2 = 1.5	0.1761	0.1761	0.1761	0	0.1761
in	0	1	1	1	3	3/3 = 1	0	0	0	0	0
of	0	1	1	1	3	3/3 = 1	0	0	0	0	0
silver	1	0	2	0	1	3/1 = 3	0.4771	0.4771	0	0.9542	0
shipment	0	1	0	1	2	3/2 = 1.5	0.1761	0	0.1761	0	0.1761
truck	1	0	1	1	2	3/2 = 1.5	0.1761	0.1761	0	0.1761	0.1761

Note that in this example, stopwords and very common words are not removed, and terms are not reduced to root terms.

http://www.miislita.com/term-vector/term-vector-3.html

Cosine Similarity

- A similarity measure between two vectors by measuring the cosine of the angle between them

$$Sim(D_i, D_j) = \frac{D_i \bullet D_j}{|D_i| * |D_j|} = \frac{\sum_k w_{ki} w_{kj}}{\sqrt{\sum_k w_{ki}^2 \sum_k w_{kj}^2}}$$

- Example: Given 3 document vectors shown here

D_1	D_2	D_3
0	0	0
0	0	0.1761
0	0.4771	0
0	0	0.4771
0	0.4771	0
0.1761	0.1761	0
0	0	0
0	0	0
0.4771	0	0.9542
0	0.1761	0
0.1761	0	0.1761

$$|D_1| = \sqrt{0.1761^2 + 0.4771^2 + 0.1761^2} = \sqrt{0.2896} = 0.5382$$

$$|D_2| = \sqrt{0.4771^2 + 0.4771^2 + 0.1761^2 + 0.1761^2} = \sqrt{0.5173} = 0.7192$$

$$|D_3| = \sqrt{0.1761^2 + 0.4771^2 + 0.9542^2 + 0.1761^2} = \sqrt{1.2001} = 1.0955$$

$Sim(D_1, D_2)$ = (0.1761*0.1761)/(0.5382*0.7192)=0.0801

$Sim(D_1, D_3)$ = (0.4771*0.9542+0.1761*0.1761)/(0.5382*1.0955)=0.8246

Example Application: Web Recommenders

- Tracking the user's browsing behaviour to recommend web pages
- Personalized model – keywords related to the user's interests
- Explicit preferences
  - user providing positive and negative feedback on pages
- Inferred preferences
  - from actions like bookmarking a page
  - From web pages the user visits, and pages one link away from them
- What about forgetting?
  - Short-term vs long-term profile – e.g. short-term model based on tf-idf, long-term model based on a naïve Bayesian classifier
  - Temporal decay of interests

Example Application: Movie Recommenders

- Content-based movie recommender systems.
  - Usually text categorization to learn a user model from the synopses of movies rated by the user (but not restricted to such methods only)
  - User to rate a minimum number of movies into categories such as *terrible*, *bad*, *below average*, *above average*, *good*, and *excellent*
  - E.g. INTIMATE, Movies2GO

The titles listed in the 'More like this' section are generated from a variety of information, including genres, country of origin, actors, and much more. Different devices may give slightly different options in the 'More like this' section, to offer a wider range of suggestions for what to watch next.

Example Application: Music Recommenders

- Content-based music recommendation systems
  - Pandora Internet Radio
    - Music Genome Project database: manual content-based description (>400 musical attributes) about qualities of melody, harmony, rhythm, form, composition and lyrics
    - Annotated by experts in music theory (hard to scale)
    - User feedback using thumbs-up or thumbs-down, add music to a station (as positive example)
  - FOAFing the Music
    - Content-based descriptions extracted from music related RSS feeds and the audio itself

Advantages Against CF Approach

	Content-based	Collaborative Filtering
User independence	Just needs the active user's information to build his profile	Requires ratings from other users to find users with similar tastes (rated same items similarly)
Transparency	Recommendations can be explained by listing content features that caused an item to appear in the recommendation list.	Black box (unknown users with similar tastes like that item)
New item	Can recommend items not yet rated by any user.	new item has to be rated by sufficient number of users to get recommended.

Disadvantages

- **Limited content analysis**
  - Limited number and type of features; not sufficient to differentiate what user likes from what he does not like.
  - May need domain knowledge (ontologies)
- **New User**
  - Enough ratings/interactions needed to form user profile for reliable recommendations
- **Over-specialization**
  - Recommended items are ***similar*** to items that user rated high.
  - *Serendipity* problem: rarely anything ***novel*** recommended

Semantic Representation of Content

- To overcome the issue of string-matching keyword-based representation
- Bring **semantics** into recommendation
  - Using knowledge sources (e.g. lexicon, taxonomy, ontology, etc)
  - To move from vectors of keywords to vectors of concepts, synsets (WordNet), categories/classes
- Common-sense and domain-specific knowledge may help, too.
  - Augmenting text representation with natural concepts derived from Wikipedia
  - Still in research
- Or, explore innovative representation using **word embeddings**!

Novel Representation of Content

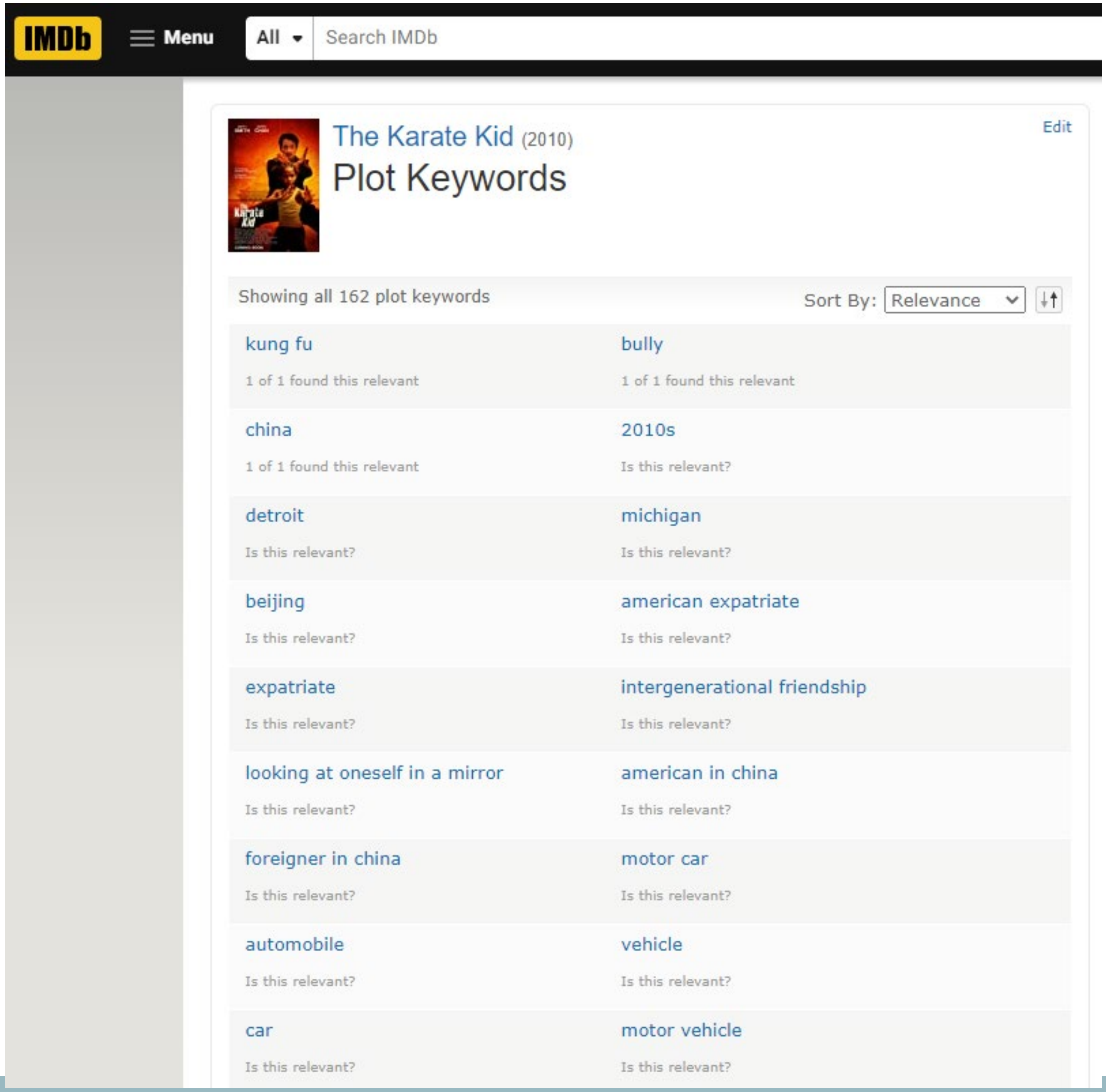
- With user generated content like ***folksonomy***, a taxonomy generated by users who collaboratively annotate and categorize resources of interests with freely chosen keywords called ***tags***

Tag-Based Representation

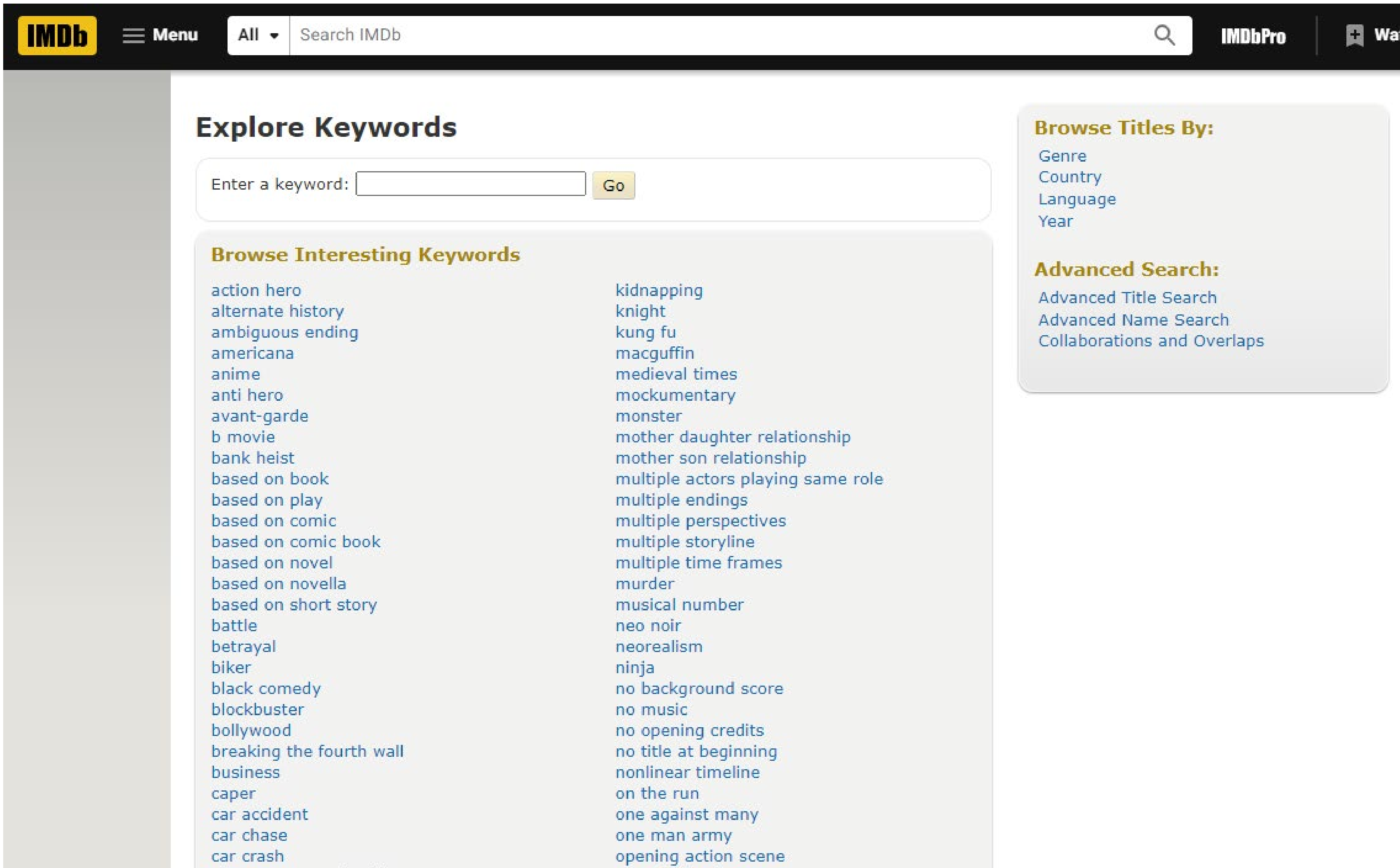
- Using tags to represent content instead of keywords extracted from descriptions
- E.g. tag-based movie recommendation
- Issues
  - Polysemy and synonymy of tags
  - Users with different expertise and purposes
  - resulting in tags with various levels of abstraction to describe a resource
  - Chaotic proliferation of tags

Movies: Plot Keywords (Tags)

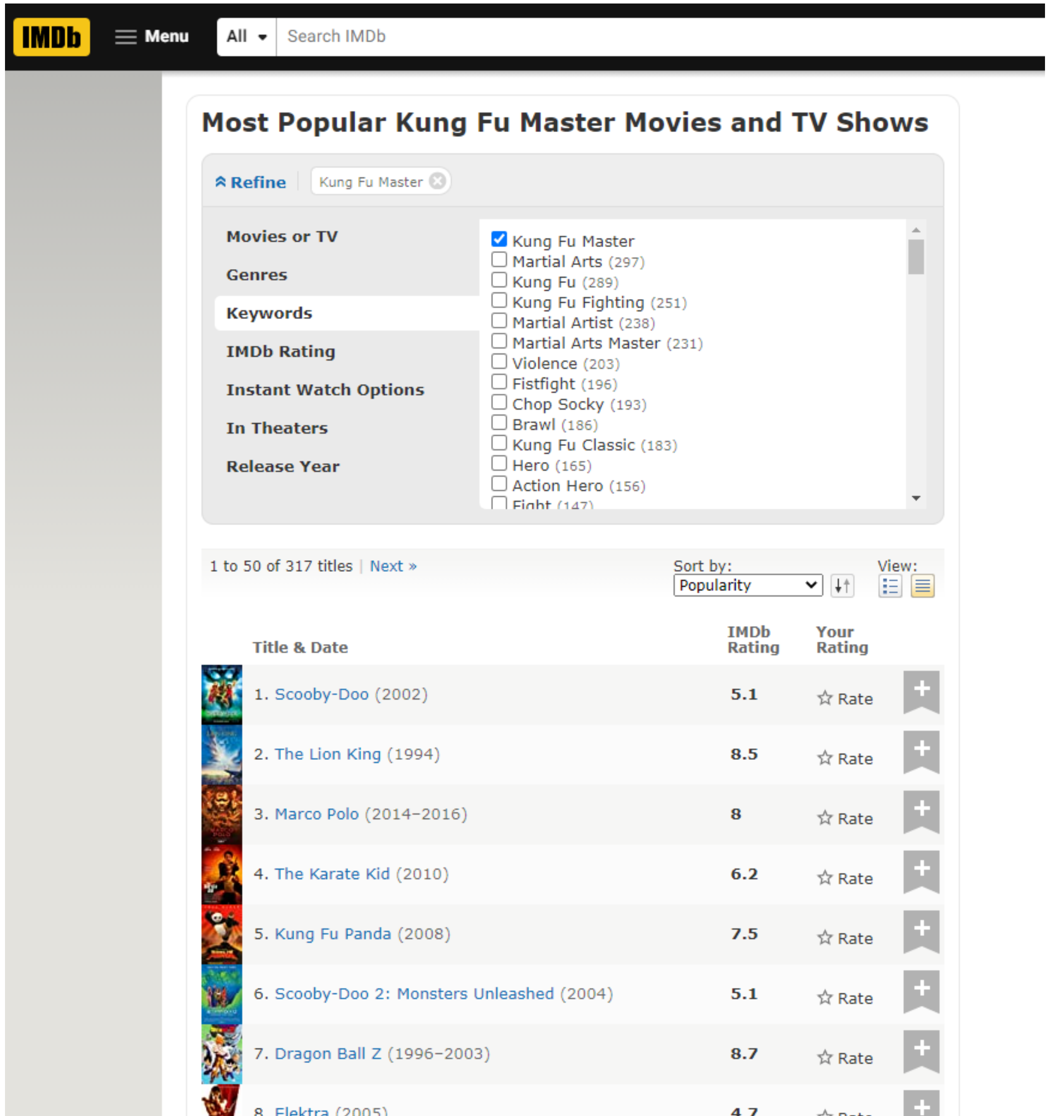
- *IMDB: A keyword is a word (or group of connected words) attached to a title (movie / TV series / TV episode) to describe any notable* ***object, concept, style or action*** *that takes place during a title. The main purpose of keywords is to allow visitors to easily search and discover titles.*
- *Contributed by users.*



IMDb: Plot Keyword-based Browsing



IMDb: Plot Keyword-based Browsing



Social Tags

- To relieve the new user problem
- Tags from items rated by the user
- Tags adopted by other users who rated the same items (*social* tags)
- Include social tags in the user profile

➔ hybrid approach combining content-based and collaborative approaches

Serendipity

- To overcome the problem of over-specialization, and achieve ***diversity*** of recommendations
- Relevant, and novel/unexpected

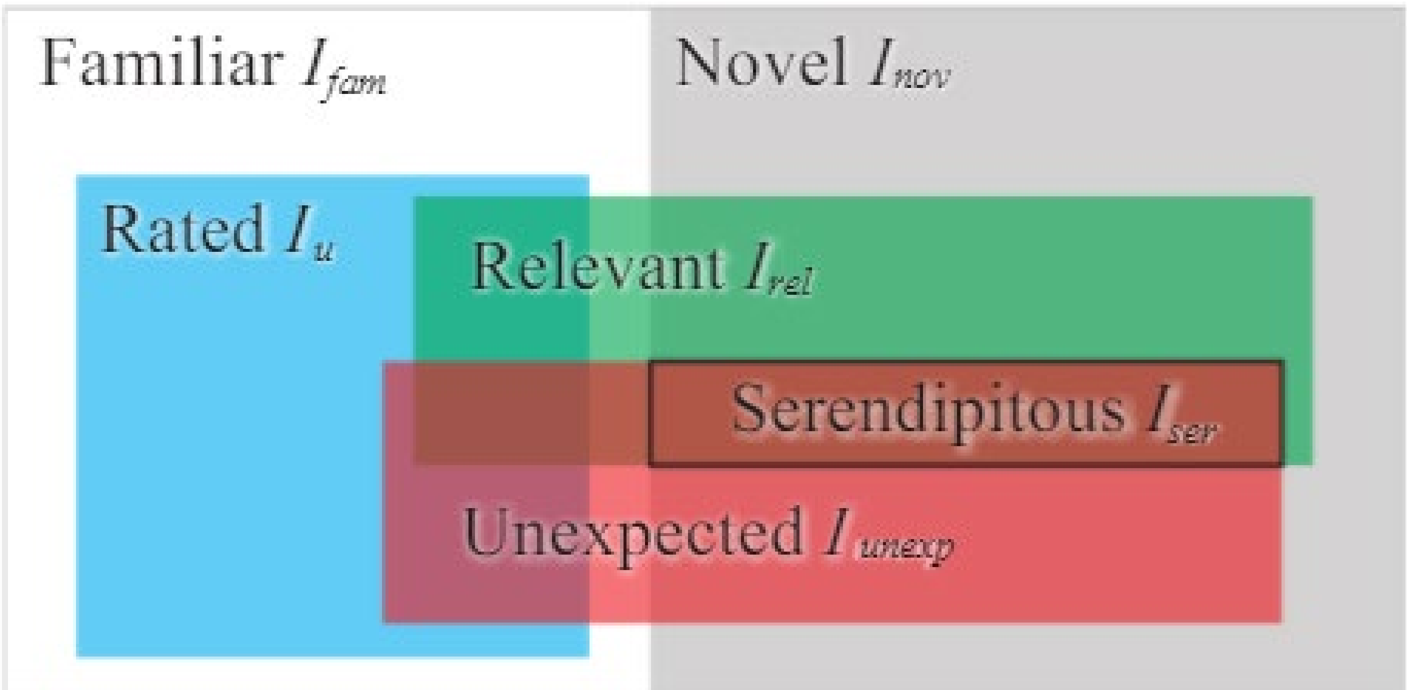
serendipity

noun [U] • formal

UK /ˌser.ənˈdɪp.ə.ti/ US /ˌser.ənˈdɪp.ə.t̬i/

the fact of finding interesting or valuable things by chance

The Concept of Serendipity



Kotkov, Denis, Shuaiqiang Wang, and Jari Veijalainen. "A survey of serendipity in recommender systems." *Knowledge-Based Systems* 111 (2016): 180-192.

Ways to Serendipity

- Introduce randomness
  - Completely random item
  - Bounded random selection: from K best matches
- Avoid recommending items that are too similar to what the user has seen, i.e. filter off those above a similarity threshold
- How to evaluate? User-centric methods probably.