

# Lecture 18

- Hybrid Recommendation Techniques

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IT492: Recommendation Systems (AY 2023/24) — Dr. Arpit Rana

# Recommendation Techniques

Technique	Background	Input	Process
Collaborative	Ratings from $U$ of items in $I$ .	Ratings from $u$ of items in $I$ .	Identify users in $U$ similar to $u$ , and extrapolate from their ratings of $i$ .
Content-based	Features of items in $I$	$u$ 's ratings of items in $I$	Generate a classifier that fits $u$ 's rating behavior and use it on $i$ .
Demographic	Demographic information about $U$ and their ratings of items in $I$ .	Demographic information about $u$ .	Identify users that are demographically similar to $u$ , and extrapolate from their ratings of $i$ .
Utility-based	Features of items in $I$ .	A utility function over items in $I$ that describes $u$ 's preferences.	Apply the function to the items and determine $i$ 's rank.
Knowledge-based	Features of items in $I$ . Knowledge of how these items meet a user's needs.	A description of $u$ 's needs or interests.	Infer a match between $i$ and $u$ 's need.

# Trade-offs between Recommendation Techniques

Technique	Pluses	Minuses
Collaborative filtering (CF)	<p>A. Can identify cross-genre niches.</p> <p>B. Domain knowledge not needed.</p> <p>C. Adaptive: quality improves over time.</p> <p>D. Implicit feedback sufficient</p>	<p>I. New user ramp-up problem</p> <p>J. New item ramp-up problem</p> <p>K. 'Gray sheep' problem</p> <p>L. Quality dependent on large historical data set.</p> <p>M. Stability vs. plasticity problem</p>
Content-based (CN)	B, C, D	I, L, M
Demographic (DM)	A, B, C	<p>I, K, L, M</p> <p>N. Must gather demographic information</p>
Utility-based (UT)	<p>E. No ramp-up required</p> <p>F. Sensitive to changes of preference</p> <p>G. Can include non-product features</p>	<p>O. User must input utility function</p> <p>P. Suggestion ability static (does not learn)</p>
Knowledge-based (KB)	<p>E, F, G</p> <p>H. Can map from user needs to products</p>	<p>P</p> <p>Q. Knowledge engineering required.</p>

## Comparison of Collaborative and Content-based Methods

Criteria	Collaborative	Content-based
Cold-start User	Yes	Yes
Cold-start Item	Yes	No
Limited Content Analysis	No	Yes
Over-specialization	No	Yes
Sparsity	Yes	No
Popularity Bias	Yes	No
Interpretability	Less	More

# Definition

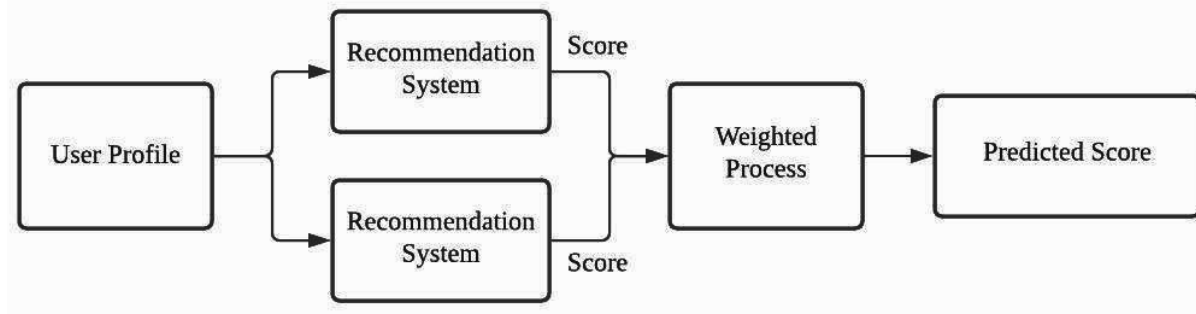
Hybrid recommender systems -

- combine two or more recommendation strategies
- to benefit from their complementary advantages

# Weighted Hybrid Recommender

A weighted hybrid recommender is one in which -

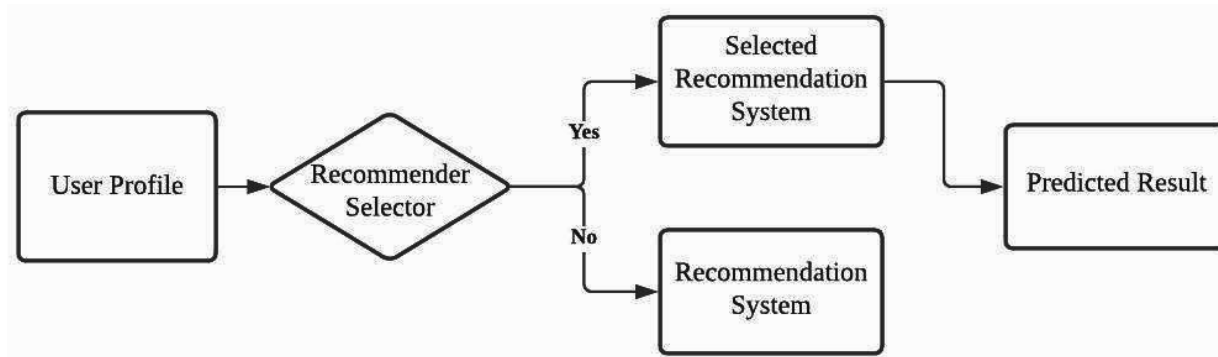
- the score of a recommended item is computed from the results of all of the available recommendation techniques present in the system
- e.g., the simplest combined hybrid would be a linear combination of recommendation scores
- The implicit assumption is that the relative value of the different techniques is more or less uniform across the space of possible items



# Switching Hybrid Recommender

A switching hybrid builds in item-level sensitivity to the hybridization strategy:

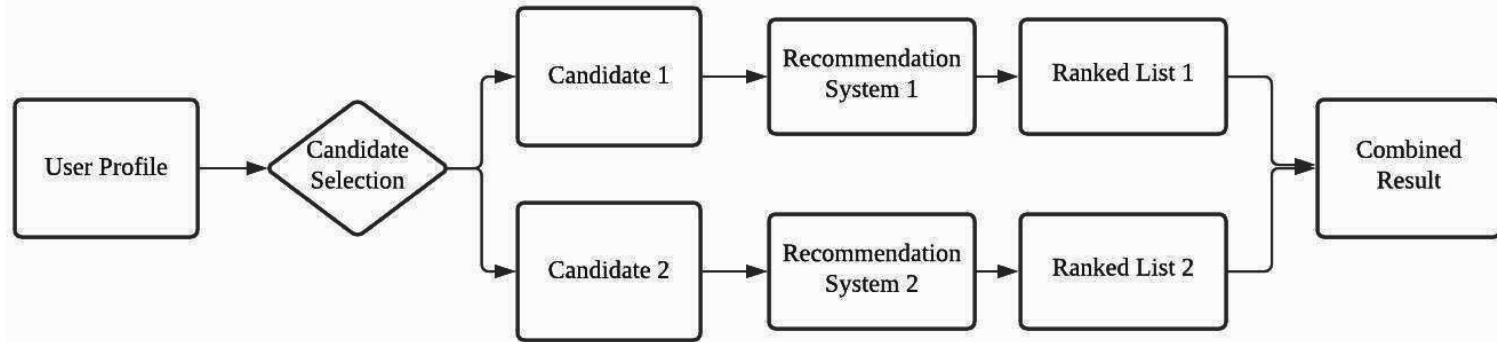
- the system uses some criterion to switch between recommendation techniques
- the switching criteria must be determined, and this introduces another level of parameterization.
- the benefit is that the system can be sensitive to the strengths and weaknesses of its constituent recommenders



# Mixed Hybrid Recommender

Mixed hybrids are used where it is practical to make large number of recommendations simultaneously,

- recommendations from more than one technique are presented together
- to rank the items or to select a single best recommendation, some kind of combination technique must be employed

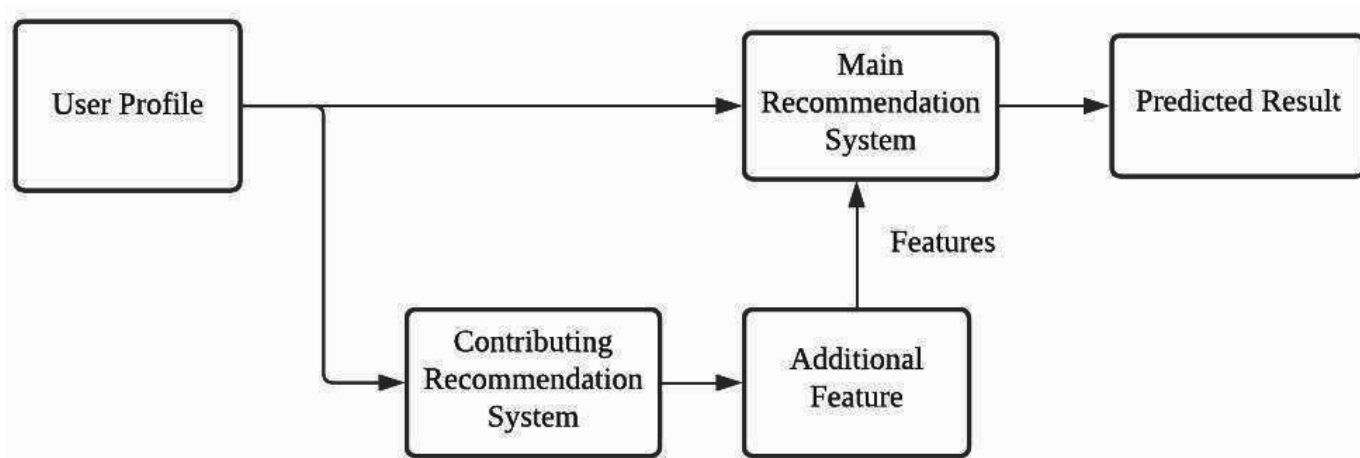




# Feature Combination

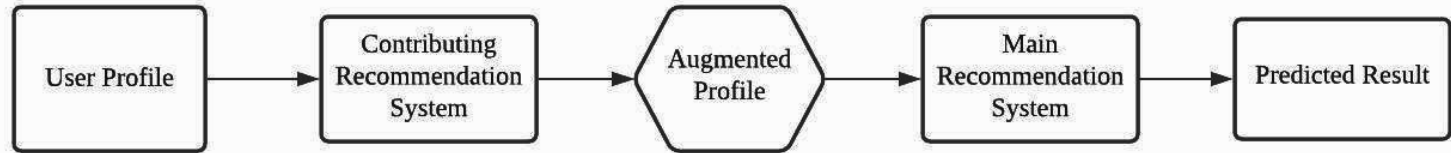
Another way to achieve the content/collaborative merger is -

- to treat collaborative information as simply additional feature data associated with each example, and
- use content-based techniques over this augmented data set



# Feature Augmentation

- A contributing recommendation model is employed to generate a rating or classification of the user/item profile,
- which is further used in the main recommendation system to produce the final predicted result



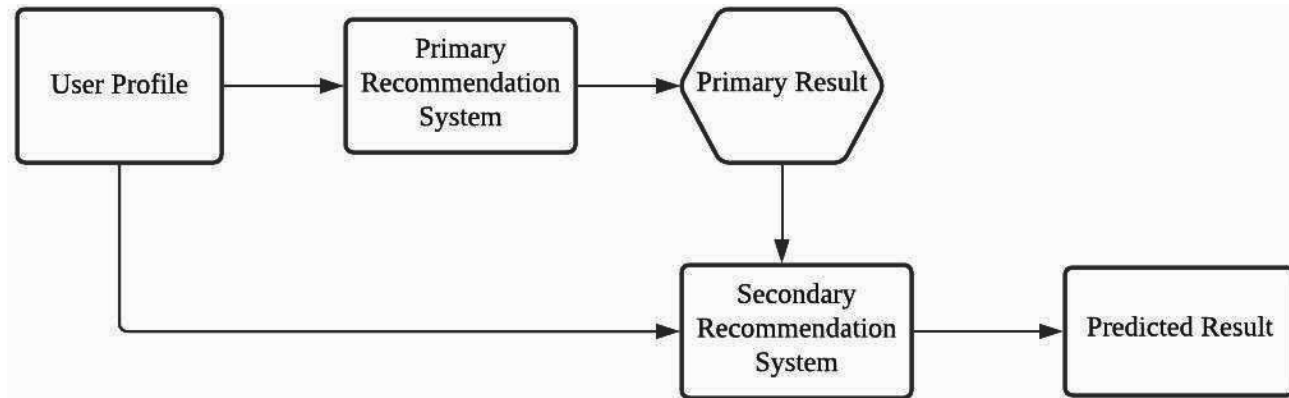
## Meta-level

- It is similar to the feature augmentation, such that the contributing model is providing augmented dataset to the main recommendation model
- Different from the feature augmentation hybrid,
  - meta-level replaces the original dataset with a learned model from the contributing model as the input to the main recommendation model

# Cascade Hybrid Recommender

In this technique,

- one recommendation technique is employed first to produce a coarse ranking of candidates and,
- a second technique refines the recommendation from among the candidate set.



## Next Lecture

- Re-ranking Techniques for Recommendations