# Hybrid Recommender Systems

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# Disclaimer

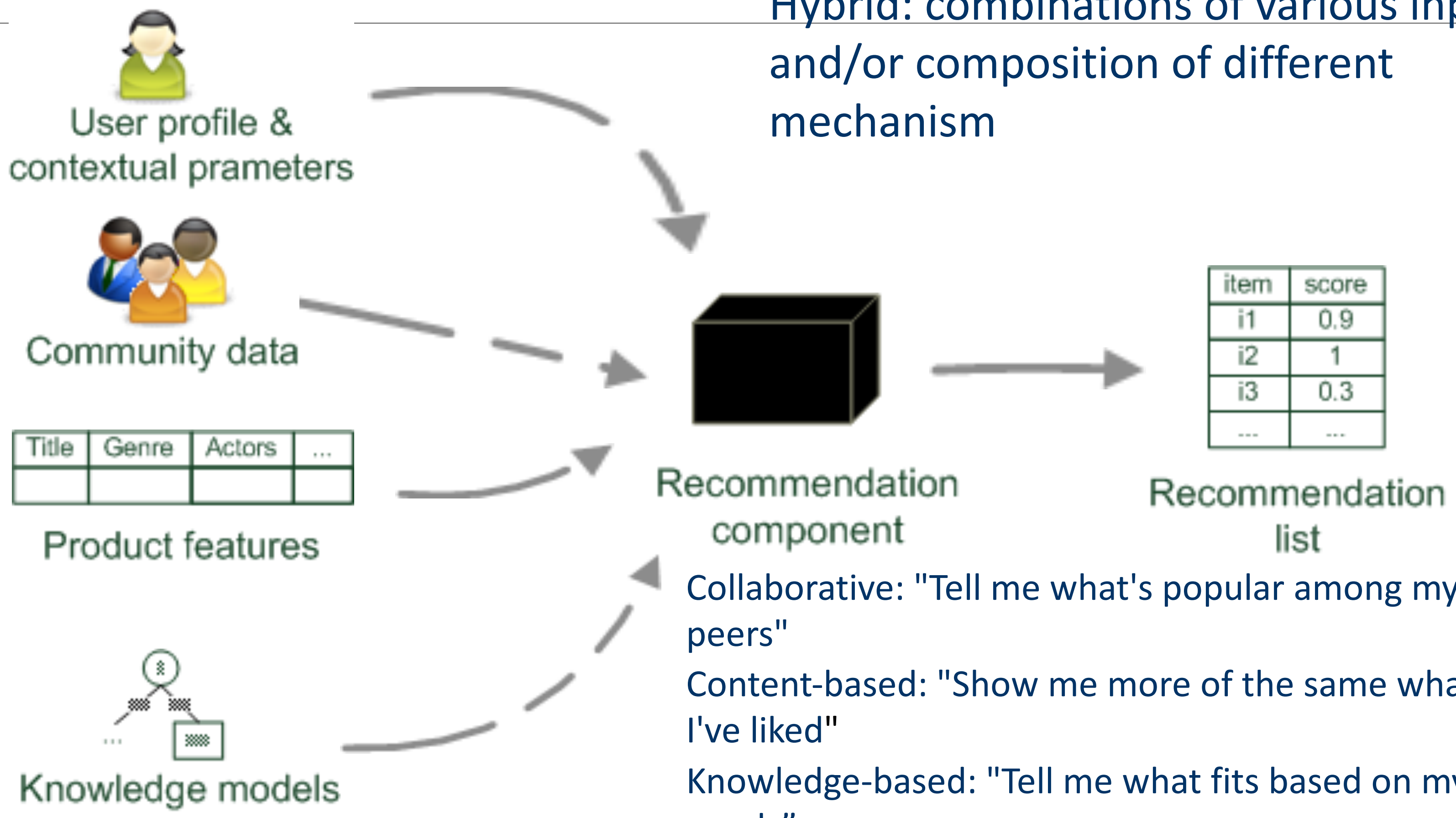
- **Some of this material/slides are adapted from several:**
  - Presentations found on the internet;
  - Papers
  - Books;
  - Web sites
  - …

# Hybrid Recommender Systems

- ❑ Combine different recommendation techniques to overcome the limitations presented by each method when implemented individually
- ❑ Can be implemented in various ways, such as:
  - ✓ Based on content filtering and collaborative filtering separately, and then combining their predictions
  - ✓ Adding content-based features to a collaborative approach (and vice versa)
  - ✓ Unifying the approaches into one model
  - ✓ …..

# Hybrid recommender systems

Hybrid: combinations of various inputs and/or composition of different mechanism



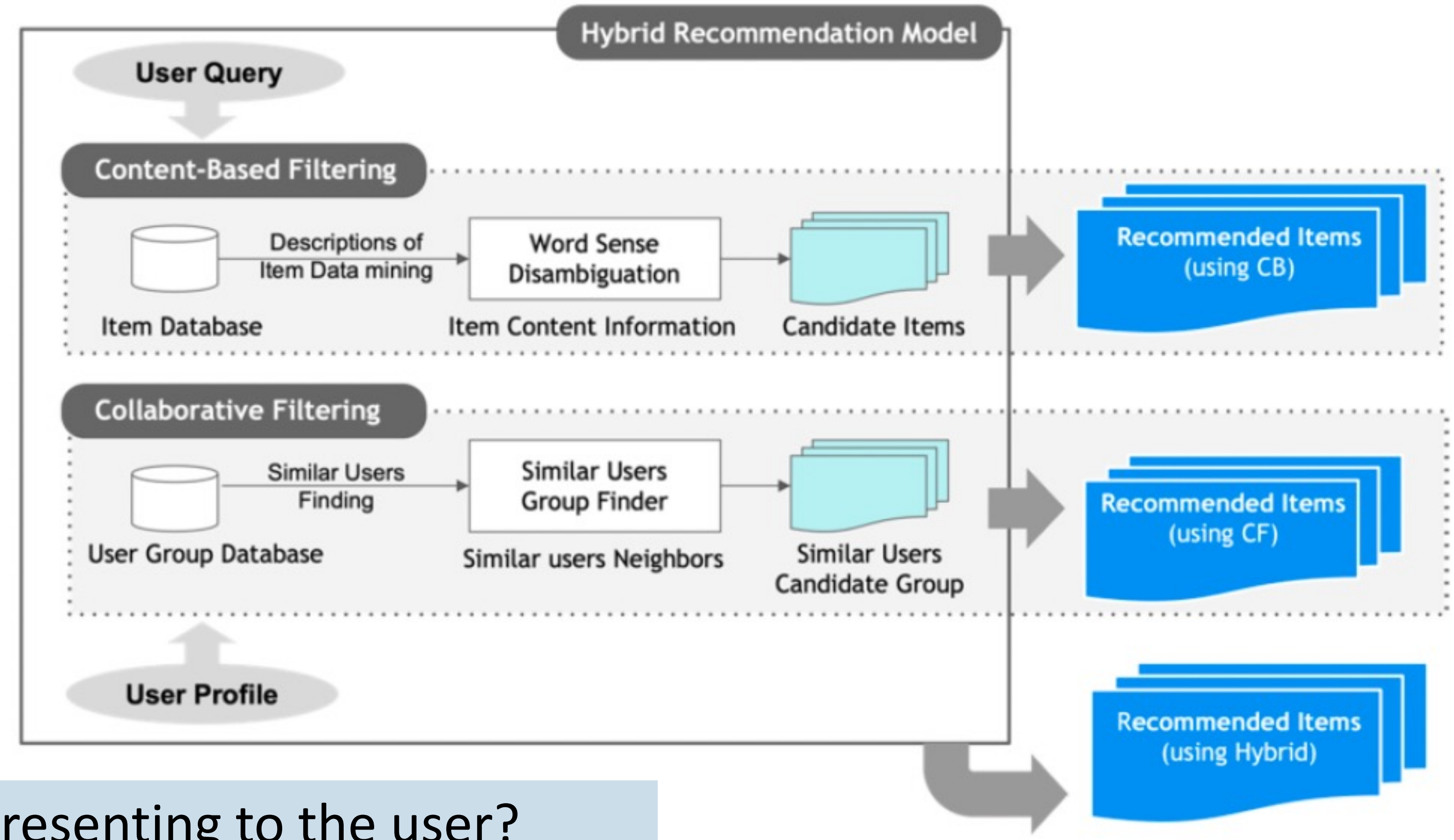

Collaborative: "Tell me what's popular among my peers"

Content-based: "Show me more of the same what I've liked"

Knowledge-based: "Tell me what fits based on my needs”

…….

# Hybrid Filtering

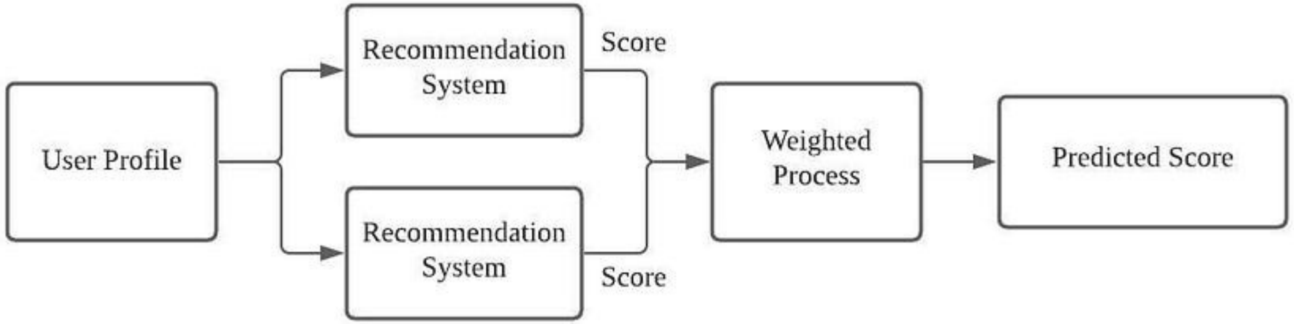



How are items presenting to the user?

# Hybrid Recommendation Methods

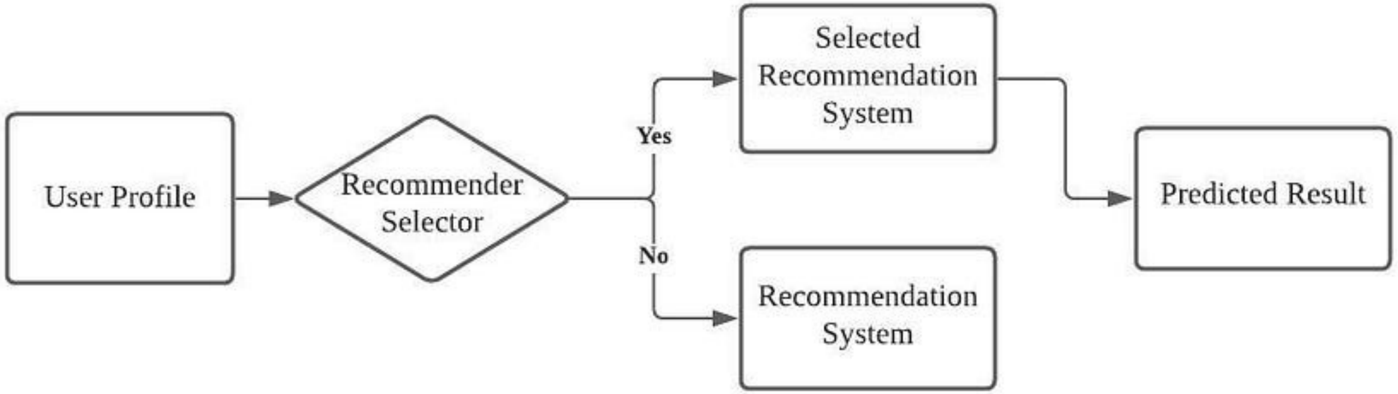
# Weighted

- The recommended item is determined by the combination of the system's individual recommendation techniques results
- Each component of the hybrid system scores a given item, and these scores are calculated from the results of all available recommendation techniques in the system
- It combines the results of different recommendations to generate a list or prediction of recommendations, integrating the scores from each of the techniques in use through a linear formula
- Some systems have fixed weights, and others have variable weights, adjusting the recommendation to the user preferences



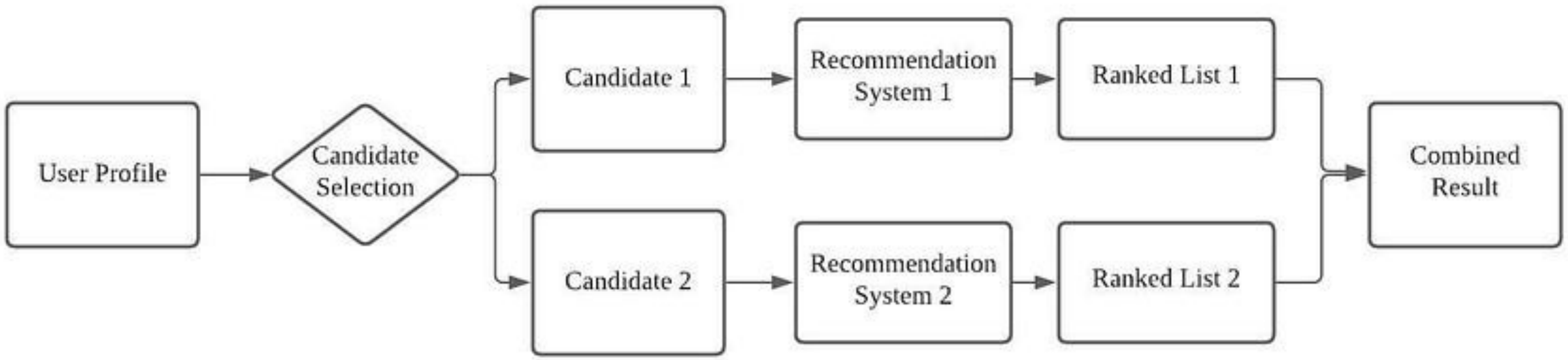
# Switching

- The system switches recommendation algorithms based on the interpretation of system data
- Based on the current situation, the hybrid systems switch between recommendation techniques
- For example may use CBF initially, switching to CF when the system has sufficient user data to mitigate the cold-start problem



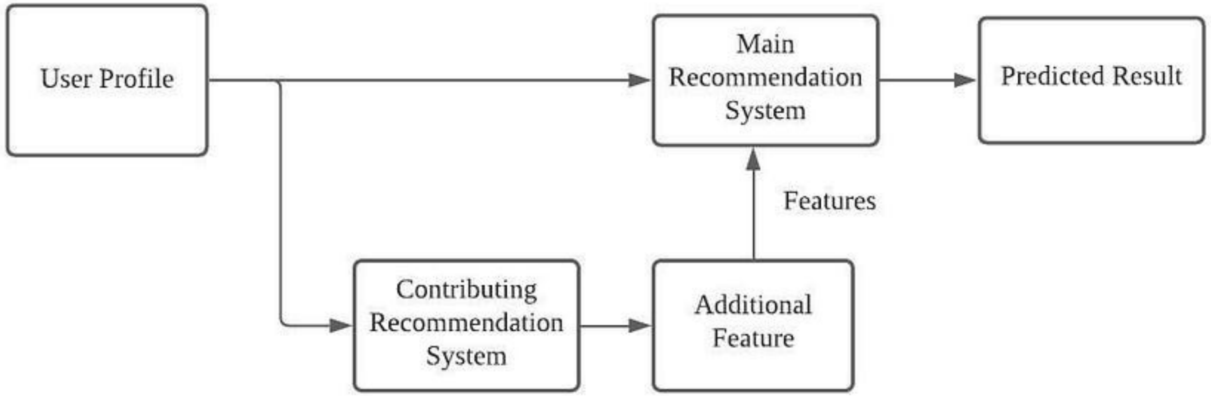
# Mixed

- Used when a large number of recommendations need to be made simultaneously
- Can employ multiple techniques together, avoiding the item cold start initialization problem
- In this type of system, recommendations from several different filtering techniques are presented simultaneously



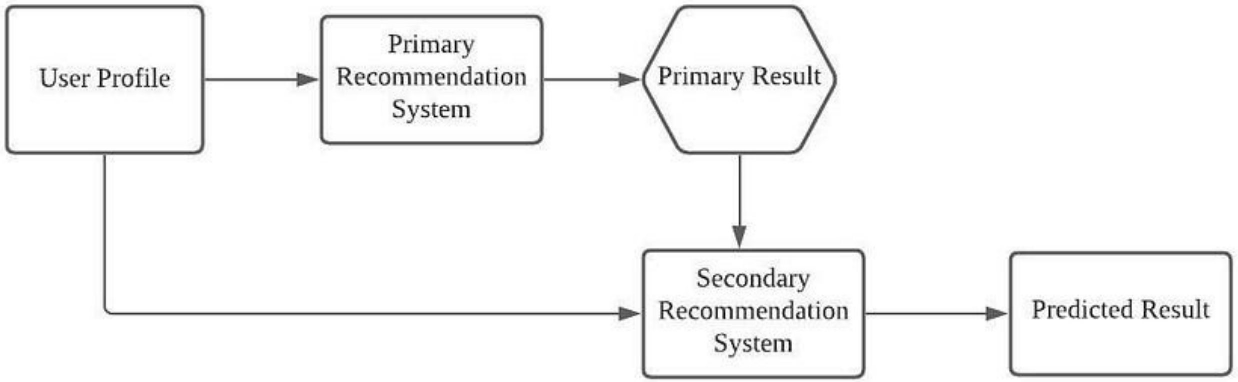
# Feature Combination

- Involves unifying characteristics from different recommendation techniques into a single algorithm
- One way of combining two RSs techniques, is to use one CF recommender (or any other type) output, as an additional feature data provider
- This extra data is supplied to another recommender, normally a CBF, together with the initial data, and the output is the final recommendation.
- For example the rating input produced by the collaborative filtering-based system in a content-based system can be treated as an item



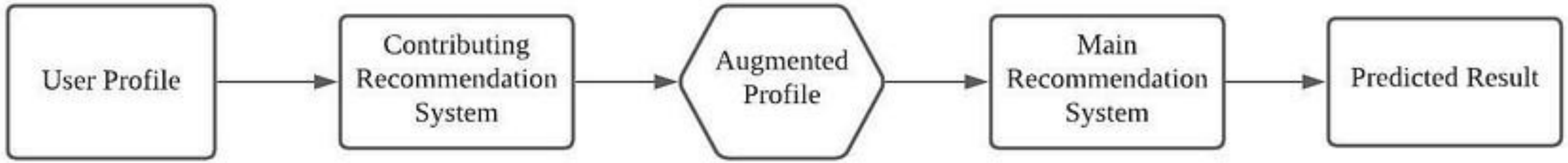
# Cascade

- Involves the first recommendation technique generating an approximate list of recommendations, which is then refined by the next recommendation technique
- One algorithm filters the recommendations generated by another algorithm (e.g., items that have been classified with identical ratings by the first technique may be reclassified by the second technique of the system)
- This approach prevents the application of the second technique to items eliminated undoubtedly by the first filtering technique, rendering this approach, more efficient than other approaches which use complete data in all recommenders



# Feature Augmentation

- involves using a first recommendation technique to produce a rating or classification of an item
- which is then integrated as input into the recommendation process of the second technique
- This type of hybrid system uses one recommendation technique to rate an item and delivers that information to be used by the following recommendation technique
- This hybrid RS is used to improve recommender performance without changing its internals, only with the inclusion of the first RS provided data



# Meta-level

- Involves using the learned model as a parameter input to another system
- The generated model is always richer in information compared to a single classification.
- Approach combine two recommendation techniques is by using as input for the second recommender technique, the model produced by the first technique
- The main difference from feature augmentation is that instead of using only some feature data as input for the second technique, this approach uses the entire model

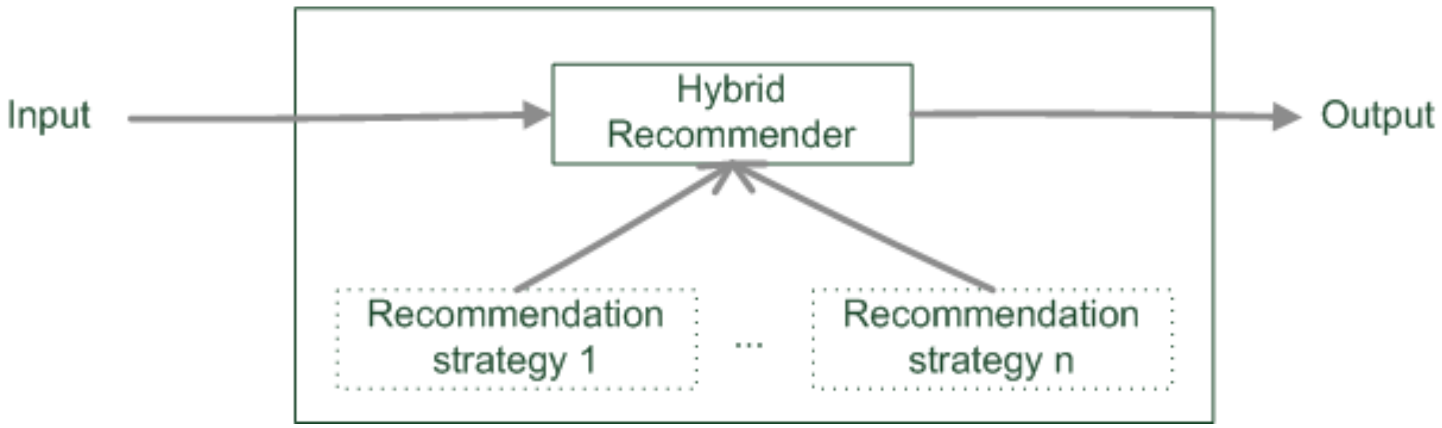
# Hybrid Recommendation Design

# Hybrid recommender design

- Different hybridization designs
  - Monolithic exploiting different features
  - Parallel use of several systems
  - Pipelined invocation of different systems

# Monolithic hybridization

Only a single recommendation component




Hybridization is "virtual" in the sense that

- Features/knowledge sources of different paradigms are combined

# Monolithic hybridization: Feature combination

- Combination of several knowledge sources
  - ✓ For example Ratings and user demographics or explicit requirements and needs used for similarity computation
- "Hybrid" content features:
  - ✓ Social features: Movies liked by user
  - ✓ Content features: Comedies liked by user, dramas liked by user
  - ✓ Hybrid features: user likes many movies that are comedies, …

“the common knowledge engineering effort that involves inventing good features to enable successful learning”

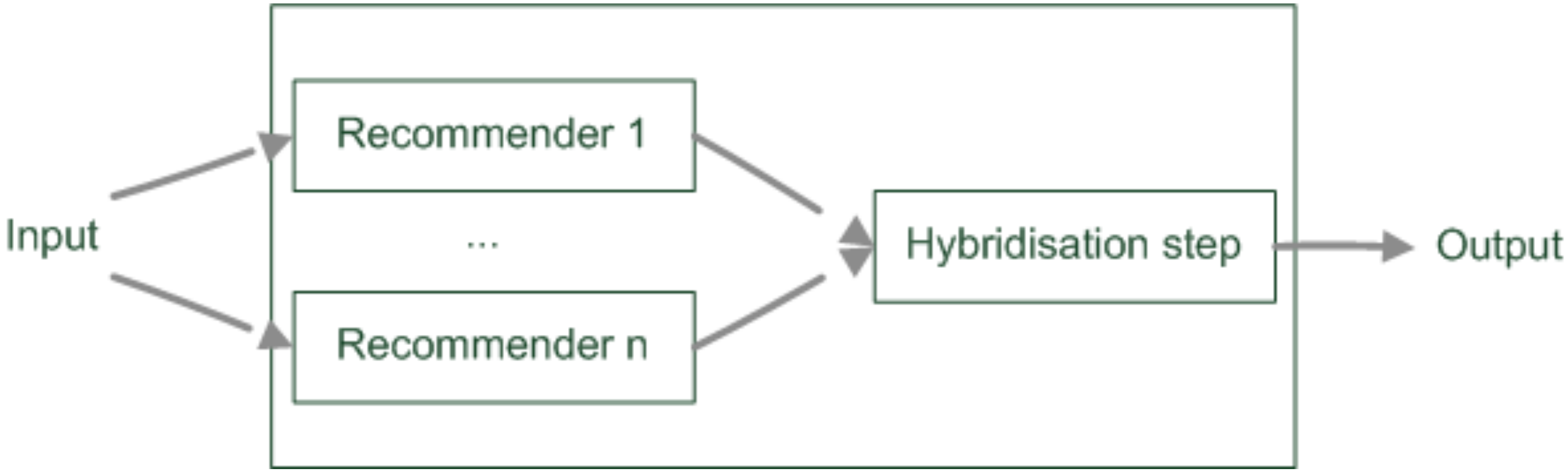
Feature augmentation can also be used

# Parallelized hybridization

- Output of several existing implementations combined

  Least invasive design

- Some weighting or voting scheme
  - Weights can be learned dynamically
  - Extreme case of dynamic weighting is switching



# Parallelized hybridization: Weighted

- ✓ Compute weighted sum: $rec_{weighted}(u,i) = \sum_{k=1}^{n} \beta_k \times rec_k(u,i)$

| Recommender 1 | | |
|---|---|---|
| Item1 | 0.5 | 1 |
| Item2 | 0 | |
| Item3 | 0.3 | 2 |
| Item4 | 0.1 | 3 |
| Item5 | 0 | |

| Recommender 2 | | |
|---|---|---|
| Item1 | 0.8 | 2 |
| Item2 | 0.9 | 1 |
| Item3 | 0.4 | 3 |
| Item4 | 0 | |
| Item5 | 0 | |

| Recommender weighted(0.5:0.5) | | |
|---|---|---|
| Item1 | 0.65 | 1 |
| Item2 | 0.45 | 2 |
| Item3 | 0.35 | 3 |
| Item4 | 0.05 | 4 |
| Item5 | 0.00 | |

# Parallelized hybridization: Switching

- Requires an "oracle" that decides on recommender

$$\exists_1 k : 1 \ldots n \; rec_{switching}(u,i) = rec_k(u,i)$$

- Example:
  - Ordering on recommenders and switch based on some quality criteria
  - For example  if too few ratings in the system use knowledge-based, else collaborative
  - More complex conditions based on contextual parameters, apply classification techniques

Question: Special case of dynamic weights?

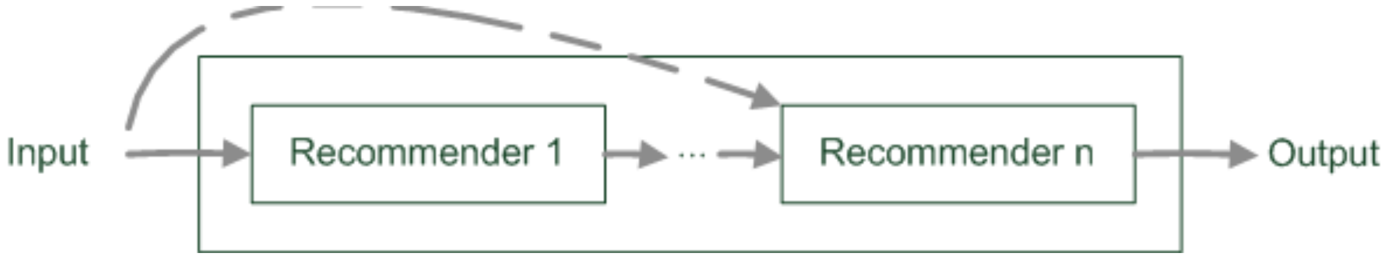
# Parallelized hybridization: Mixed

- Combines the results of different recommender systems at the level of user interface
- Results of different techniques are presented together
- Recommendation result for user $u$ and item $i$ is the set of tuples $< score, k >$ for each of its $n$ constituting recommenders $rec_k$

$$rec_{mixed} = \bigcup_{k=1}^{n} \langle rec_k(u,i), k \rangle$$

# Pipelined hybridization

- One recommender system pre-processes some input for the subsequent one
  - Cascade
  - Meta-level
- Refinement of recommendation lists (cascade)
- Learning of model (e.g. collaborative knowledge-based meta-level)



# Example Dynamic Weighted

# Dynamic Weighted

- This weighted hybrid recommendation relies on the linear combination of content-based recommendation values with collaborative recommendation
- Weighted recommendation utilizes the available recommendation techniques in the system and combines them to generate a recommendation list or prediction for the user
- By using this methodology, the cold start problem of collaborative filtering is addressed by combining collaborative and content data of items so that users who have provided few ratings or are new to the system can receive relevant recommendations, and the recommendations are more accurate and unexpected.
- In weighted hybrid systems, the outputs of various recommendation systems are combined using a set of weights

$$P_{u,i} = \alpha_1 \times P_{u,i}^{(1)} + \cdots + \alpha_n \times P_{u,i}^{(n)}$$

# Dynamic Weighted

- Each technique contributes to the result of the hybrid recommendation
- Each of these components is weighted according to a parameter called confidence, which varies between 0 and 1
- Since most RSs follow collaborative filtering, content filtering, or both (in terms of hybrid filtering), only these techniques will be considered
- Thus, the confidence ($\alpha_u$) of the collaborative filtering prediction (${P_{u,i}}^{(CF)}$) should increase as the number of items rated by user $u$ increases
- The confidence of the content-based filtering system (${P_{u,i}}^{(CBF)}$) can thus be defined as 1− $\alpha_u$

$$P_{u,i} = \alpha_u \times P_{u,i}^{(CF)} + (1 - \alpha_{u)} \times P_{u,i}^{(CBF)}$$

This does not mean that the recommendation of the content-based filtering system decreases when a user rates more items, but rather that the confidence in the recommendation of the collaborative filtering system becomes dominant

# Dynamic Weighted

- Another example:
- $\alpha_u$ It is given by formula, where $k \in \mathbb{N}$ is the number of neighbors used in collaborative filtering classification and $t_u$ is the number of items from $I \backslash I_u$
- If the number of items not rated by user $u$ is greater than the neighborhood, then $t_u$ = $k$
- The ratio between $t_u$ and $k$ is the confidence factor for each user $u$

$$\alpha_u = \frac{t_u}{k} \times 0{,}9$$

- For the construction of the RS, the described methodologies are implemented individually and then combined, allowing the construction of a weighted Hybrid RS

# References

Serão colocadas depois da entrega do primeiro trabalho