

Hybrid Recommendation

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with slides of Danielle Lee

IS2480 Adaptive Information Systems

Three basic recommendation engines

- **Collaborative Filtering:** exploiting other likely-minded community data to derive recommendations
 - Effective, Novel and Serendipitous recommendations
 - Data Sparsity, cold-start problem and ad-hoc users
- **Content-based approach:** relying on product (information) features and textual descriptions
- **Knowledge-based approach :** reasoning on explicit knowledge models from the domain
 - Ability to generate recommendation with a small set of user preference and suggest reasonable recommendations
 - Easy to generate too obvious or boring recommendation and plasticity problems.
- Each engine also have variations
 - Content vs. metadata in CBF
 - Peers vs. friends in CF

Input Data Requirements of Recommendation Techniques

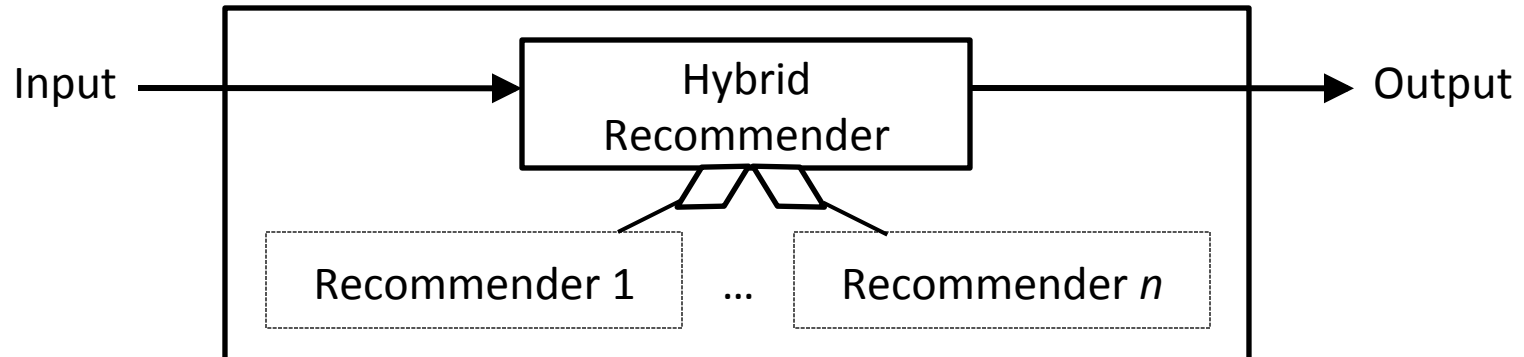
	User Profile & Contextual Parameters	Community Data	Product Features	Knowledge models
Collaborative Filtering	Yes	Yes	No	No
Content-based	Yes	No	Yes	No
Knowledge-based	Yes	No	Yes	Yes

Different engines and their variations typically use different sources of data. It could be wise to combine the approaches to use more data

Hybridization Designs

- Monolithic Hybridization
 - Incorporating aspects of several recommendation strategies in one algorithm implementation
- Parallelized Hybridization
 - Operating independently of one another and produce separate recommendation lists. Then their output is combined into a final set of recommendations
- Pipelined Hybridization
 - Several recommender systems are joined together in a pipeline architecture. The output of one recommender becomes part of the input of the subsequent one.

Monolithic Hybridization

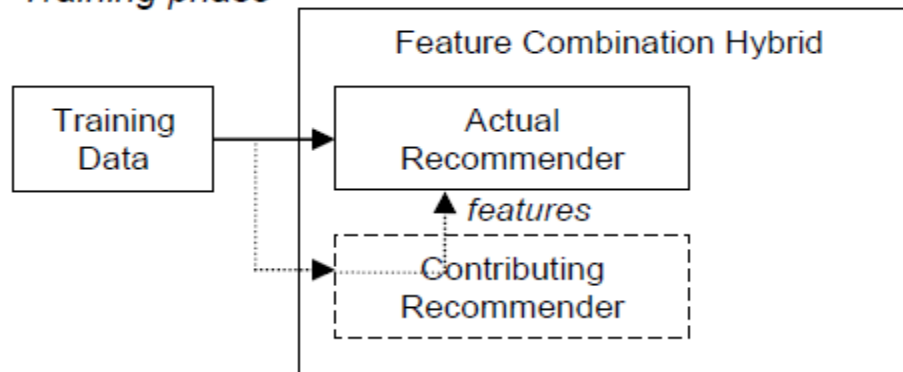


- Built-in modification of recommendation algorithm to exploit different types of input data
- Apply one approach (i.e. CBF) but enhance with the knowledge sources that are typically used by other (CoF)
- Feature combination hybrids
 - Ex) Basu, et al. (1998), Zanker and Jessenitschnig (2009), Pazzani (1999)
- Feature augmentation hybrids
 - Melville, et al. (2002), Mooney and Roy (1999), and Torres et al. (2004)

Monolithic Hybridization

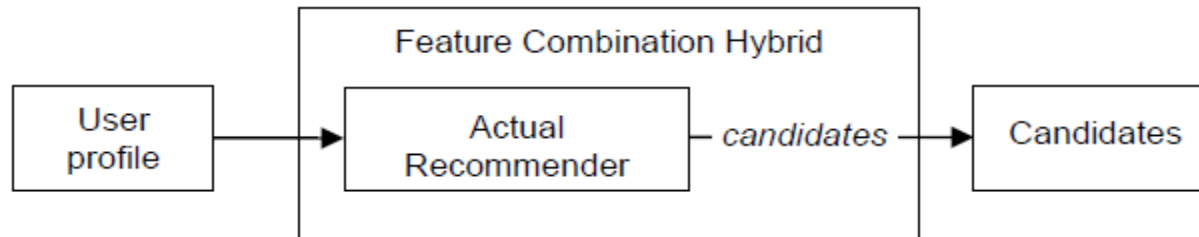
- Feature combination hybrids

Training phase

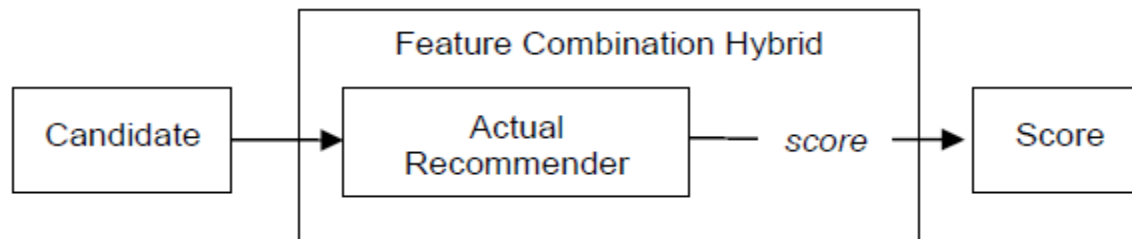


Content-based approach is trained using features extracted from collaborative sources

Candidate generation



Scoring



Example (1)

User	Item1	Item2	Item3	Item4	Item5
Alice		1		1	
User1		1	1		1
User2	1	1			1
User3	1		1		
User4					1

Item	Genre
Item1	Romance
Item2	Mystery
Item3	Mystery
Item4	Mystery
Item5	Fiction

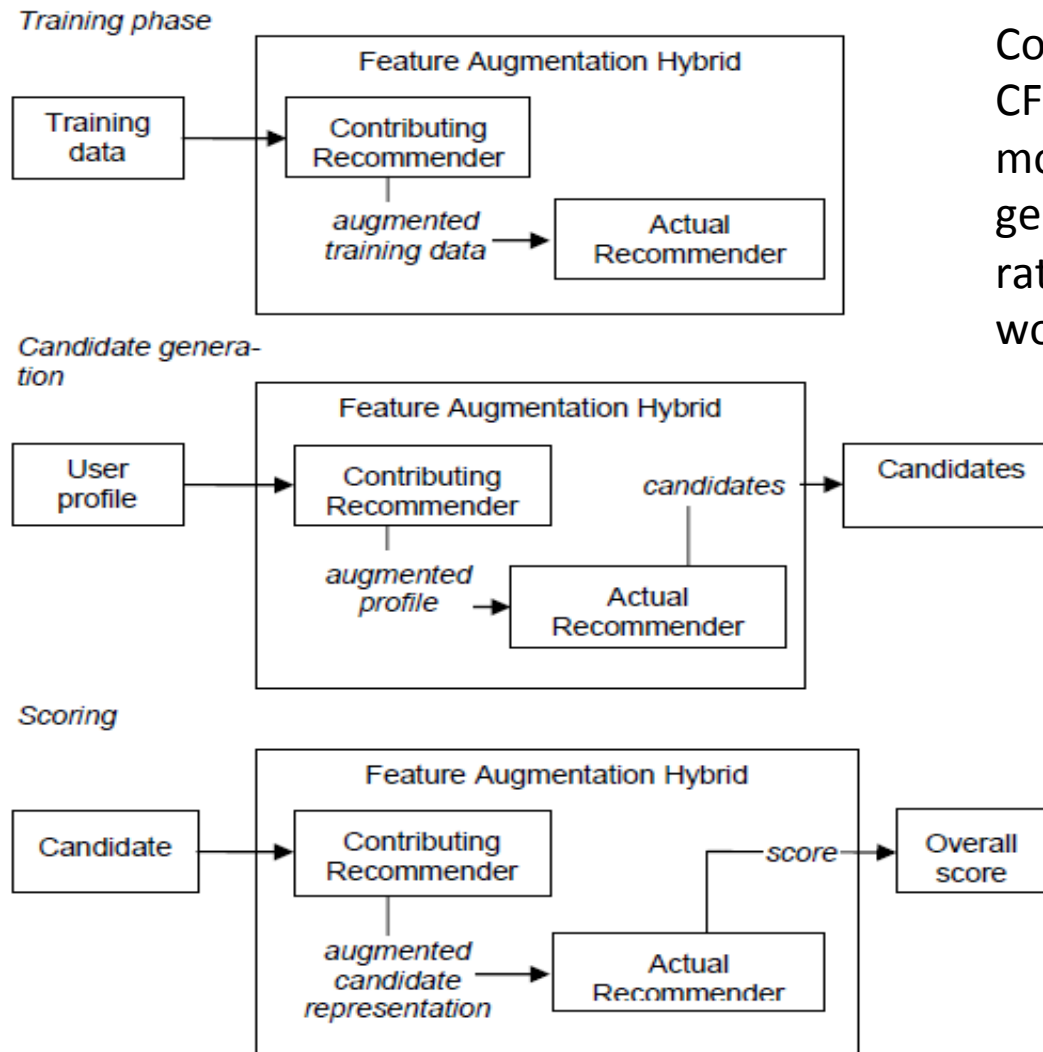
Example (1)

Feature	Alice	User1	User2	User3	User4
User likes many <i>mystery</i> books	true	true			
User likes some <i>mystery</i> books			true	true	
User likes many <i>romance</i> books					
User likes some <i>romance</i> books			true	true	
User likes many <i>fiction</i> books					
User likes some <i>fiction</i> books		true	true		true

Legend: If a user bought mainly books of genre X (two-thirds of the total purchases and at least two books), we say that 'Users likes many X books'

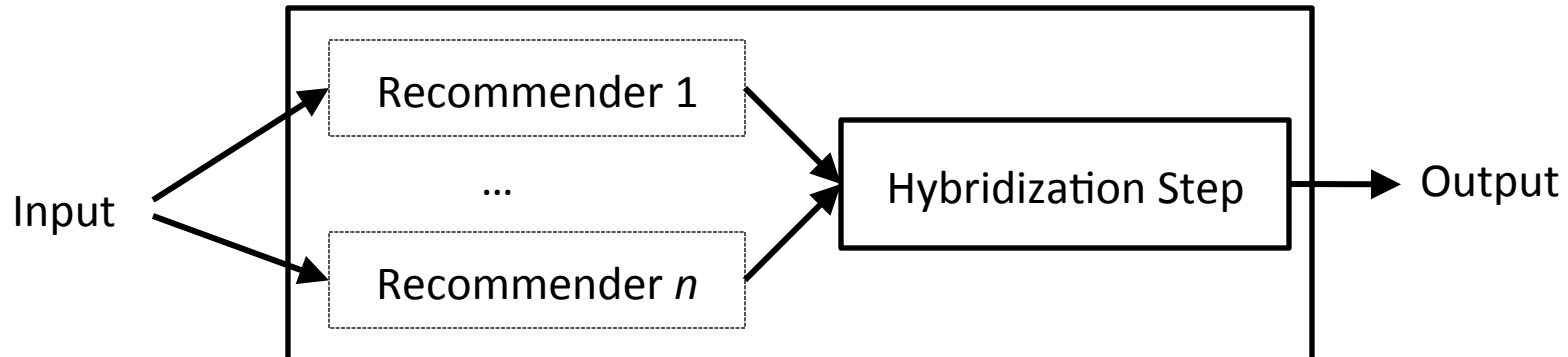
Monolithic Hybridization

- Feature augmentation hybrids



Content-boosted CF: content-based model used to generate missed ratings. Then CF works

Parallelized Hybridization

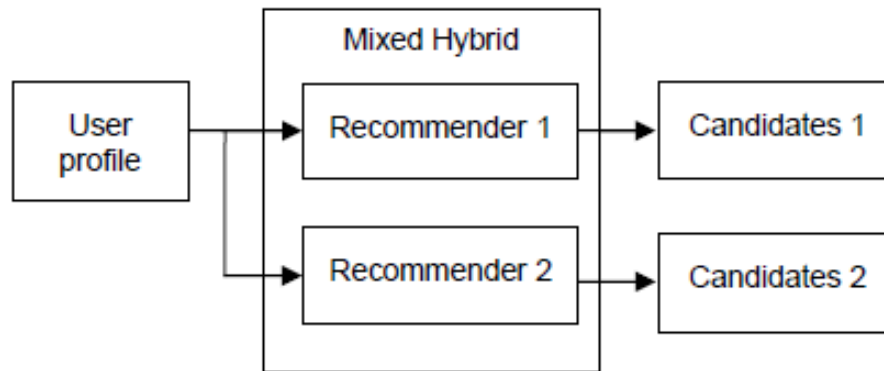


- Employ several recommenders side by side and employ a specific hybridization technique to aggregate the outputs.
- Mixed Hybrids
 - Cotter & Smyth (2000), Zanker, et al. (2007)
- Weighted Hybrids
 - Zanker and Jessenitschnig (2009), Claypool, et al. (1999)
- Switching Hybrids
 - Zanker and Jessenitschnig (2009), van Setten (2005)

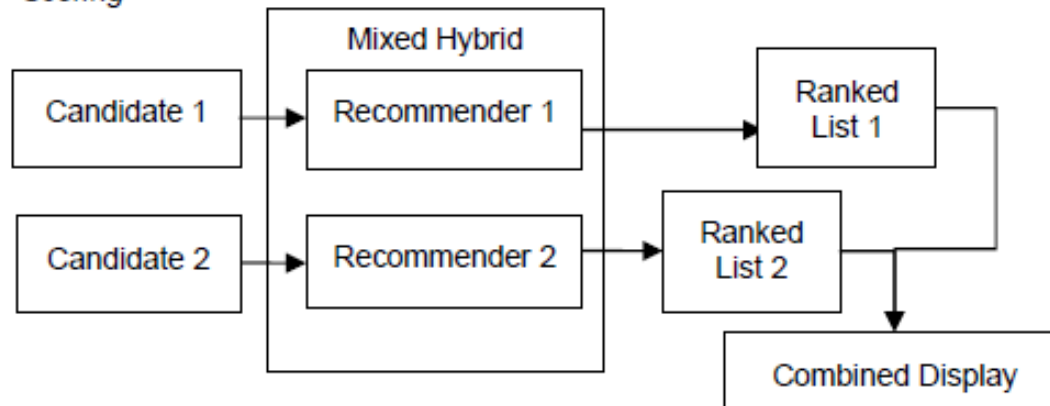
Parallelized Hybridization

- Mixed Hybrid: combines results of different recommenders at user interface level

Candidate generation



Scoring



Example of Combination

Tune weights of the recommender methods:

(1)

(M1) Author Impact 0.5

(M2) Similar Content 0.25

(M3) Articles by Co-authors 0.25

Update Recommendation List →

Venn Diagram Browser

- * Click on the diagram to highlight subsets
- * Hover over circles to explore articles
- * Circles with black border are top 20 papers

(2)

(M2) Similar Content

(M1) Author Impact (M3) Articles of Coauthors

Showing Top 20 recommended articles:

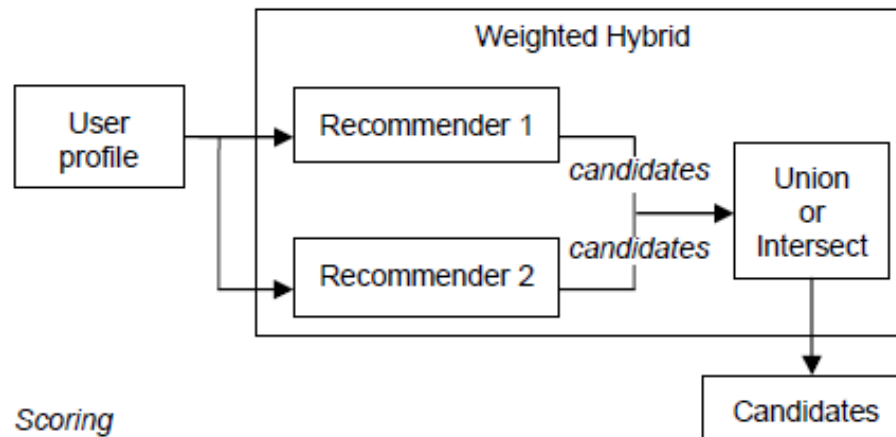
1. [Major Life Changes and Behavioral Markers in Social Media: Case of Childbirth](#)
by Eric Horvitz, Scott Counts, Munmun De Choudhury with method(s): M1
2. [Sometimes When We Touch: How Arm Embodiments Change Reaching and Collaboration on Digital Tables](#)
by Carl Gutwin, Andre Doucette, Miguel Nacenta, Regan Mandryk with method(s): M1/M2
3. [Using Facebook after losing a job: Differential benefits of strong and weak ties](#)
by Moira Burke, Robert E. Kraut with method(s): M3
4. [Exploring Pet Video Chat: The Remote Awareness and Interaction Needs of Families with Dogs and Cats](#)
by Carman Neustaedter, Jennifer Golbeck with method(s): M2
5. [KinectArms: a Toolkit for Capturing and Displaying Arm Embodiments in Distributed Tabletop Groupware](#)
by Michael Kalyn, Zenja Ivkovic, Anthony Tang, Carl Gutwin, Aaron Genest with method(s): M1
6. [ACES: A Cross-Discipline Platform and Method for Communication and Language Research](#)
by Joshua Hallpern, Marina Danilevsky, Andrew Harris, Sunah Suh, Reed LaBotz, Karrie Karahalios with method(s): M2/M3
7. [Keeping Eyes on the Prize: Officially Sanctioned Rule Breaking in Mass Collaboration Systems](#)
by Elisabeth Joyce, Jacqueline Pike, Brian Butler with method(s): M3
8. [How and Why Teenagers Use Video Chat](#)
by Tatiana Buhler, Carman Neustaedter, Serena Hillman with method(s): M2
9. [Social Navigation for Loosely-Coupled Information Seeking in Tightly-Knit Groups using WebWear](#)
by Gordon McCalla, Carl Gutwin, Scott Bateman with method(s): M1

Image showing the condition of an interactive controllable interface. In addition to browsing a list the articles, the user can control (sliders at the top

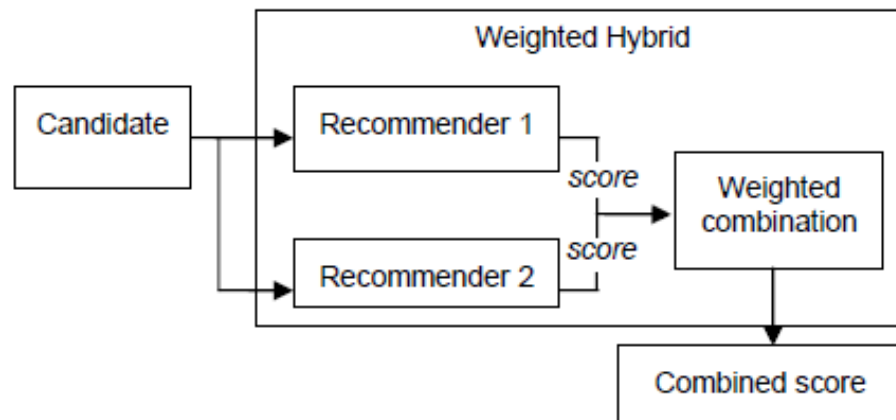
Parallelized Hybridization

- Weighted Hybrids: Combines recommendations by computing weighted sums of their scores

Candidate generation



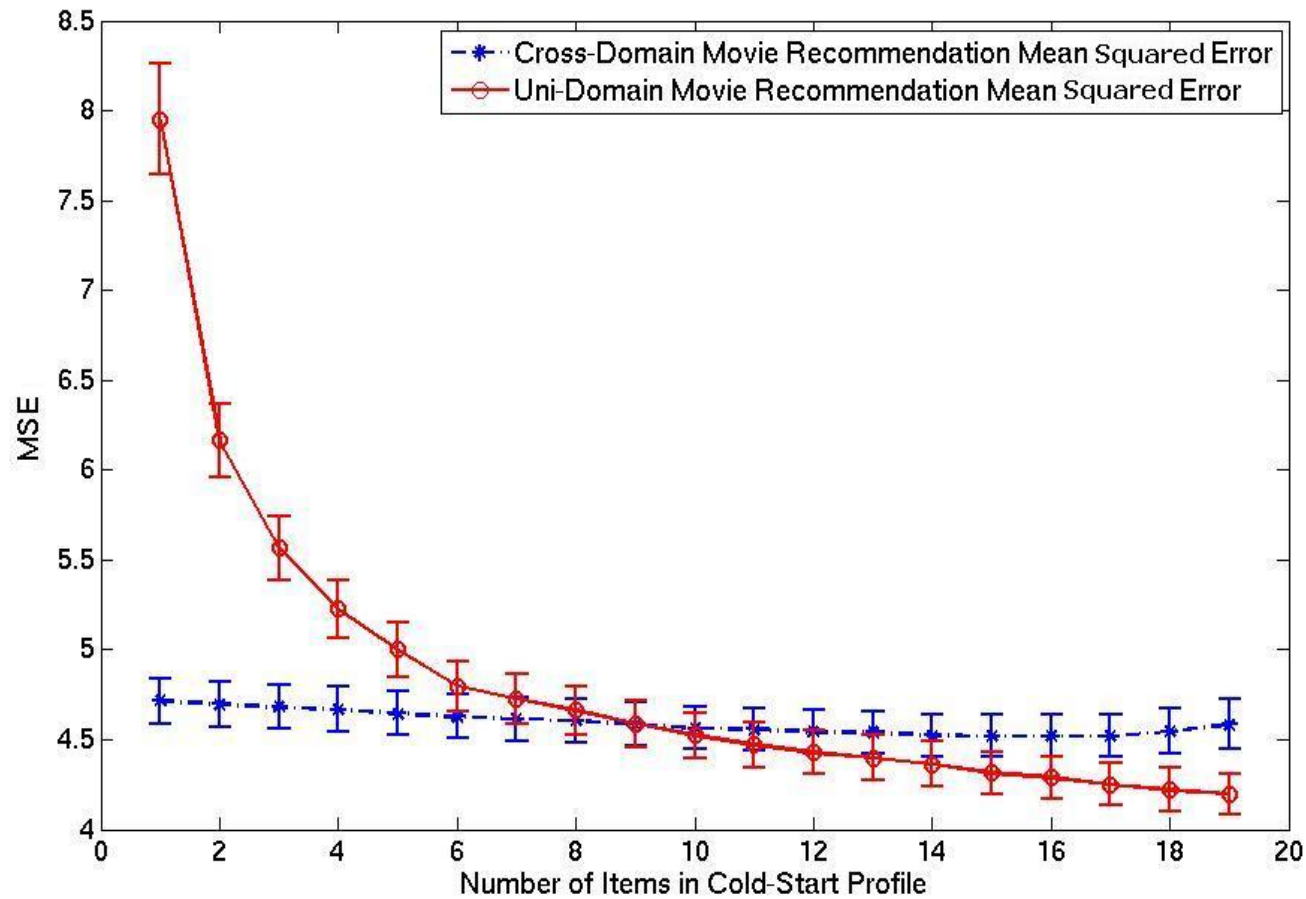
Scoring



Parallelized Hybridization

	rec1 score	rec1 rank	rec2 score	rec2 rank	recw score	recw rank
Item1	0.5	1	0.8	2	0.65	1
Item2	0		0.9	1	0.45	2
Item3	0.3	2	0.4	3	0.35	3
Item4	0.1	3	0		0.05	
Item5			0		0	

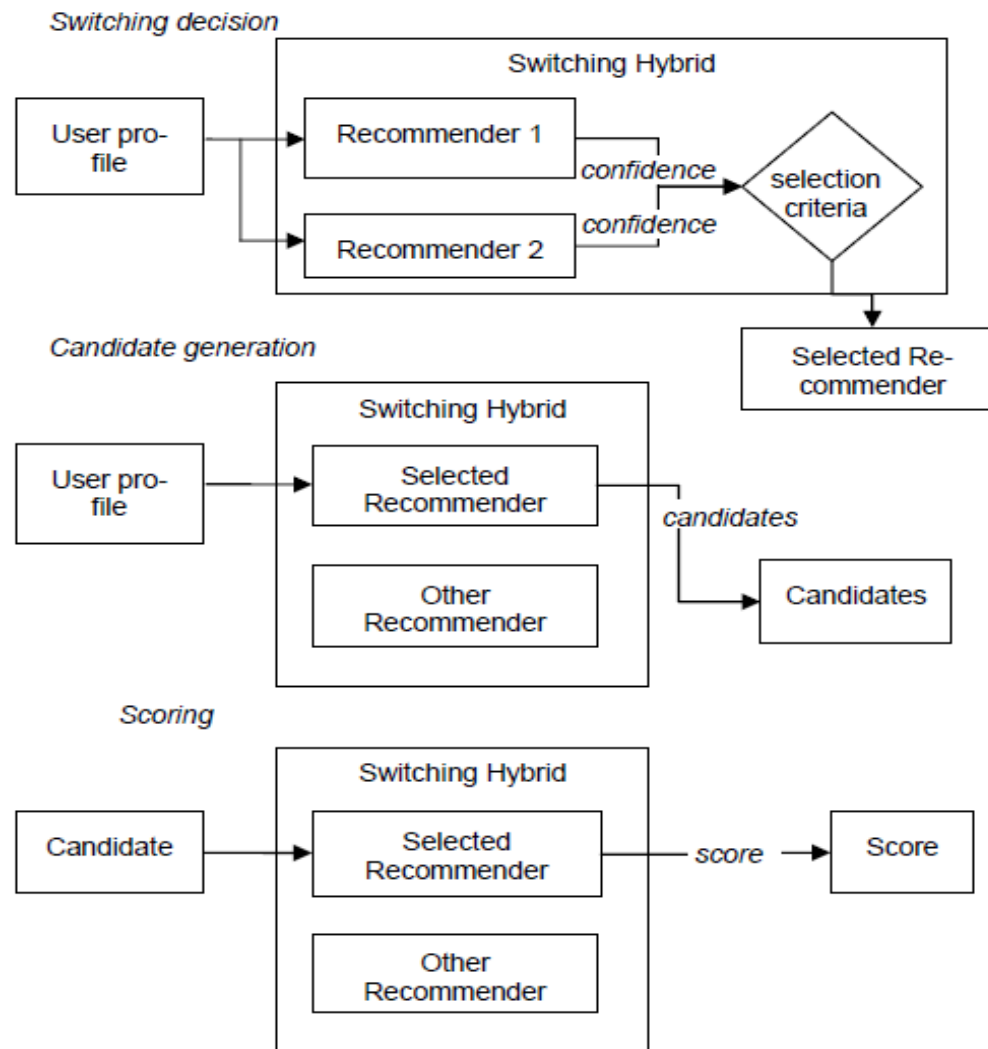
Parallelized Hybridization



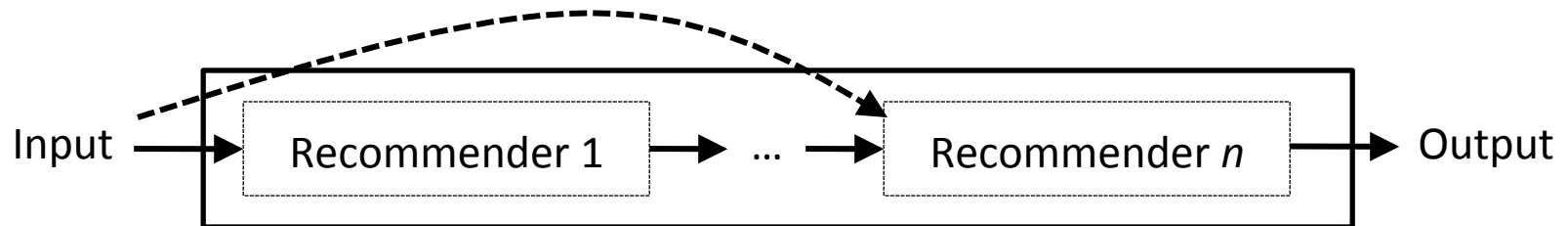
Why switching might be better than weighting?

Parallelized Hybridization

- Switching hybrids



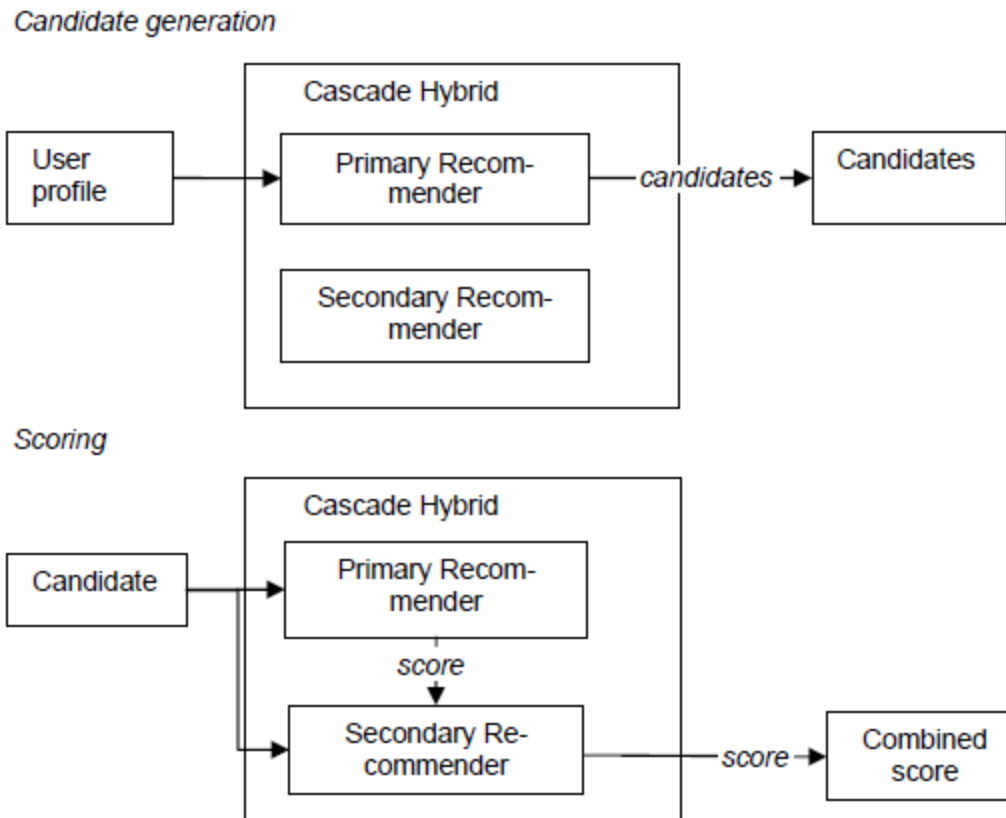
Pipelined Hybridization



- A staged process in which several techniques sequentially build on each other before the final one produces recommendations
- Cascade Hybrids
 - Zanker and Jessenitschnig (2009)
- Meta-level Hybrids
 - Zanker (2008), Pazzani (1999)

Pipelined Hybridization

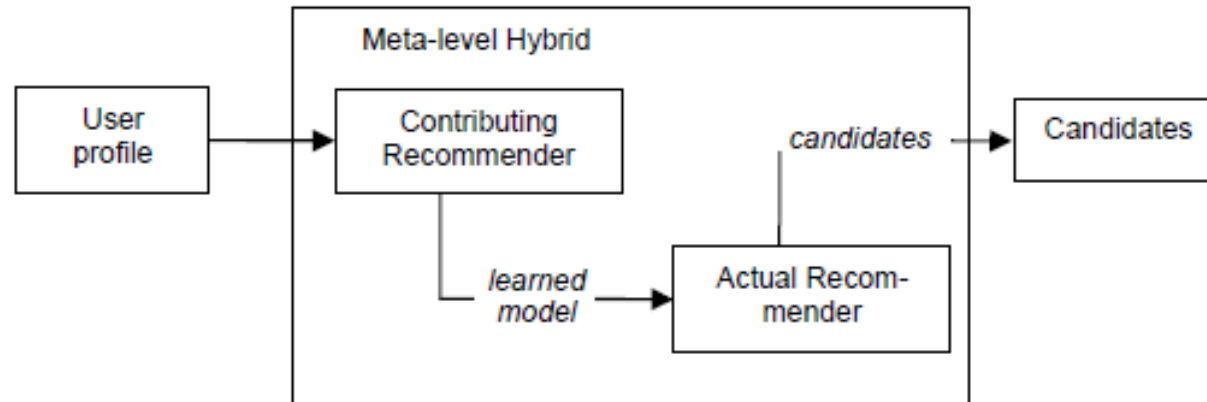
- Cascade hybrids: based on a sequenced order of techniques.



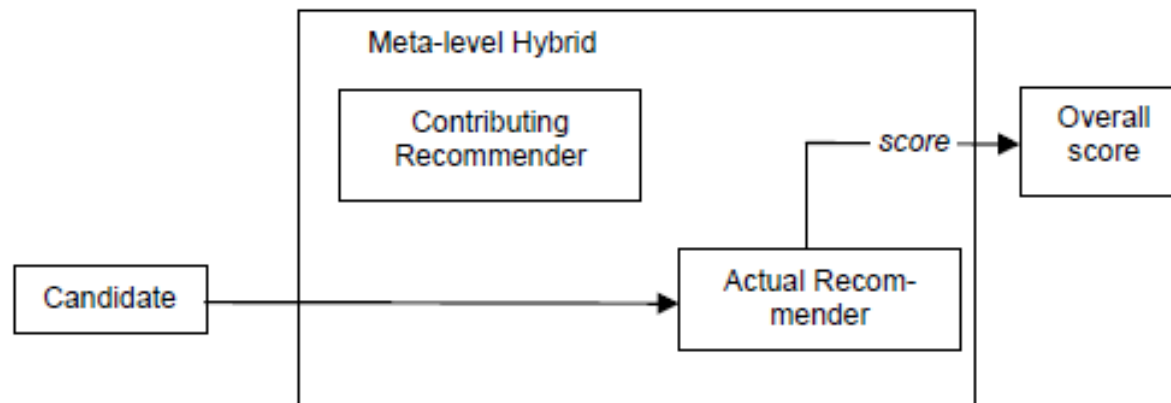
Pipelined Hybridization

- Meta-Level Hybrids: one recommender builds a model that is exploited by the principal recommender

Candidate generation



Scoring



Hybridization Summary

	Weight.	Mixed	Switch.	FC	Cascade	FA	Meta
CF/CN	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Existing implementation
CF/DM	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Not possible
CF/KB	Existing implementation	Existing implementation	Existing implementation	Not possible	Existing implementation	Existing implementation	Existing implementation
CN/CF	Redundant	Redundant	Redundant	Redundant	Existing implementation	Existing implementation	Existing implementation
CN/DM	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Not possible
CN/KB	Existing implementation	Existing implementation	Existing implementation	Not possible	Existing implementation	Existing implementation	Existing implementation
DM/CF	Redundant	Redundant	Redundant	Redundant	Existing implementation	Existing implementation	Not possible
DM/CN	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Existing implementation
DM/KB	Existing implementation	Existing implementation	Existing implementation	Not possible	Existing implementation	Existing implementation	Existing implementation
KB/CF	Redundant	Redundant	Redundant	Redundant	Existing implementation	Existing implementation	Existing implementation
KB/CN	Redundant	Redundant	Redundant	Redundant	Existing implementation	Existing implementation	Existing implementation
KB/DM	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Existing implementation	Not possible

FC = Feature Combination, FA = Feature Augmentation

CF = collaborative, CN = content-based, DM = demographic, KB = knowledge-based

Redundant
Not possible
Existing implementation