Sistemas Híbridos de Recomendación

IIC3633 RecSys
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Resumen

- Motivacion
- Clasificación General
- Modelos de Hibridización
- Ejemplos

Motivación

- Diferentes métodos tienen gran distintas debilidades y fortalezas
  - Filtrado Colaborativo es preciso, pero sufre de sparsity, cold start y new item problem
  - Filtrado Basado en contenido no sufre tanto por sparsity, pero sí por new user, facilidad para extraer features del contenido y sobre especialización
  - Knowledge-based: No los hemos visto hasta ahora. Casos típicos son Constrait-Based y Case-Based. Basados en un paradigma más interactivo, también los llaman “Conversational” (Burke, 2002).

Burke 2002

Table I: 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.

Sistema Recomendador "Caja Negra"

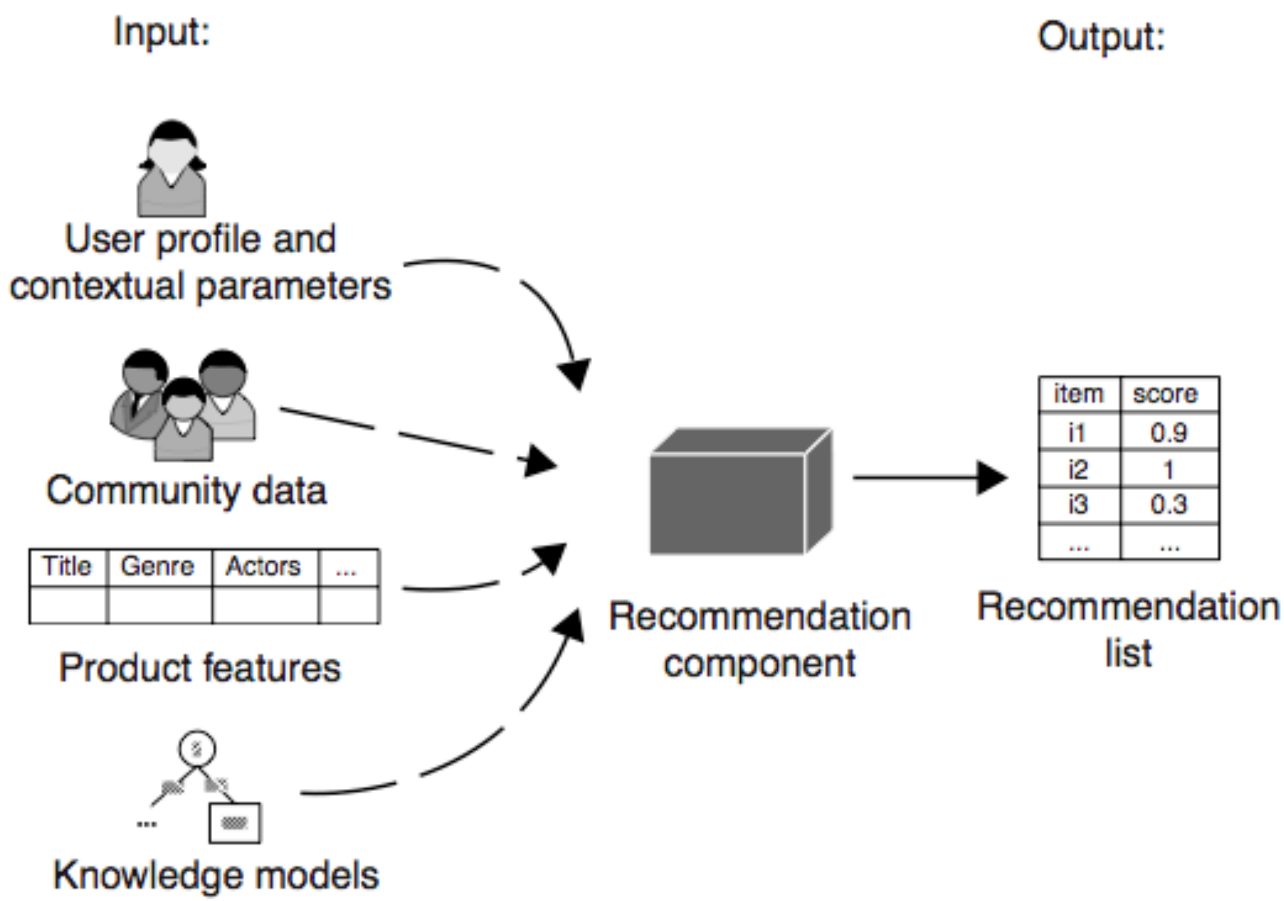

Figure 5.1. Recommender system as a black box.

Figura sacado de Jannach et al. 2012

De Adomavicius et al. 2005

Formas de combinar CF y CB:

1. Implementar métodos CF y CB separadamente y combinar las prediccion
2. Incorporar características de métodos CB dentro de un método CF
3. Incorporar características colaborativas dentro de modelo CB
4. Construir un modelo que de manera unificada incorpore características basadas en contenido y colaborativas

Cómo combinar los métodos?

- Burke (2002) distingue 7 estrategias de hibridización
- Jannach (2012) resume las 7 estrategias en 3 diseños generales
  – Monolítico
  – Paralelizado
  – Pipeline

7 Estrategias de Hibridización, Burke 2002

Table III: Hybridization Methods

Hybridization method	Description
Weighted	The scores (or votes) of several recommendation techniques are combined together to produce a single recommendation.
Switching	The system switches between recommendation techniques depending on the current situation.
Mixed	Recommendations from several different recommenders are presented at the same time
Feature combination	Features from different recommendation data sources are thrown together into a single recommendation algorithm.
Cascade	One recommender refines the recommendations given by another.
Feature augmentation	Output from one technique is used as an input feature to another.
Meta-level	The model learned by one recommender is used as input to another.

7 Estrategias de Hibridizacion

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Parallel

7 Estrategias de Hibridizacion

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7 Estrategias de Hibridizacion

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Diseño Híbrido Monolítico

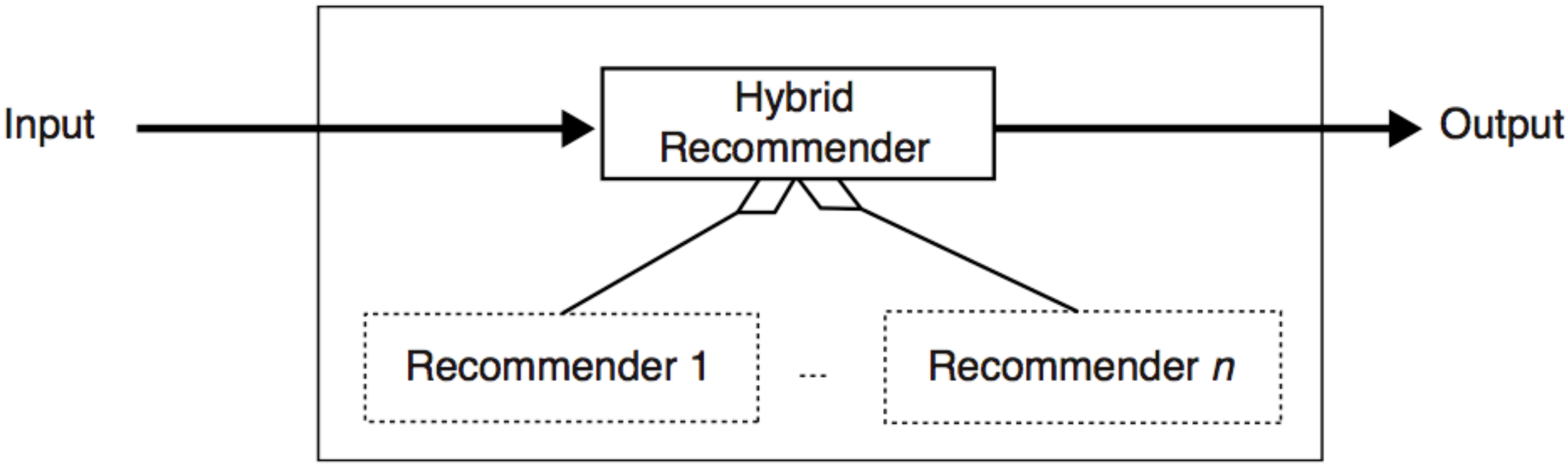


Figure 5.2. Monolithic hybridization design.

Estrategias de Combinación:

- Feature Combination
- Feature Augmentation

Híbrido: Feature Combination

Table 5.3. *Hybrid input features*.

Feature	Alice	User1	User2	User3	User4
User likes many *mystery* books	true	true			
User likes some *mystery* books			true	true	
User likes many *romance* books					
User likes some *romance* books			true	true	
User likes many *fiction* books					
User likes some *fiction* books		true	true		true

Híbrido: Feature Combination II

Table 5.4. *Different types of user feedback.*

User	R_{nav}	R_{view}	R_{ctx}	R_{buy}
Alice	n_3, n_4	i_5	k_5	$\emptyset$
User1	n_1, n_5	i_3, i_5	k_5	i_1
User2	n_3, n_4	i_3, i_5, i_7	$\emptyset$	i_3
User3	n_2, n_3, n_4	i_2, i_4, i_5	k_2, k_4	i_4

Híbrido: Feature Augmentation

Híbrido: Feature Augmentation

Usar estas "features" en un nuevo recomendador

Diseño Híbrido Paralelizado

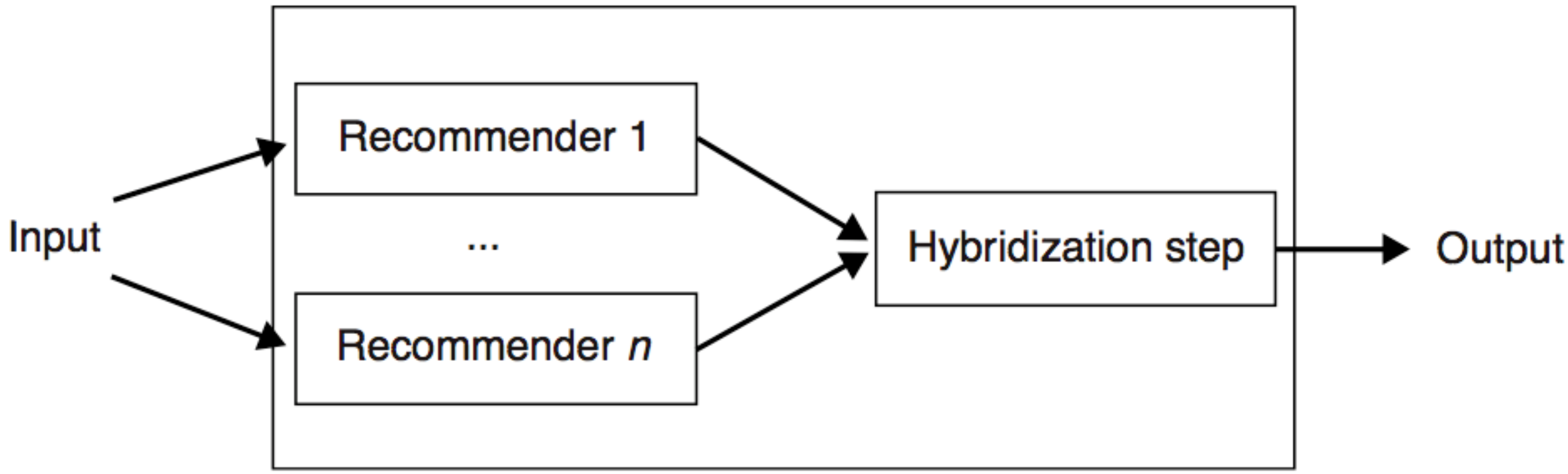


Figure 5.3. Parallelized hybridization design.

Estrategias de Combinación:

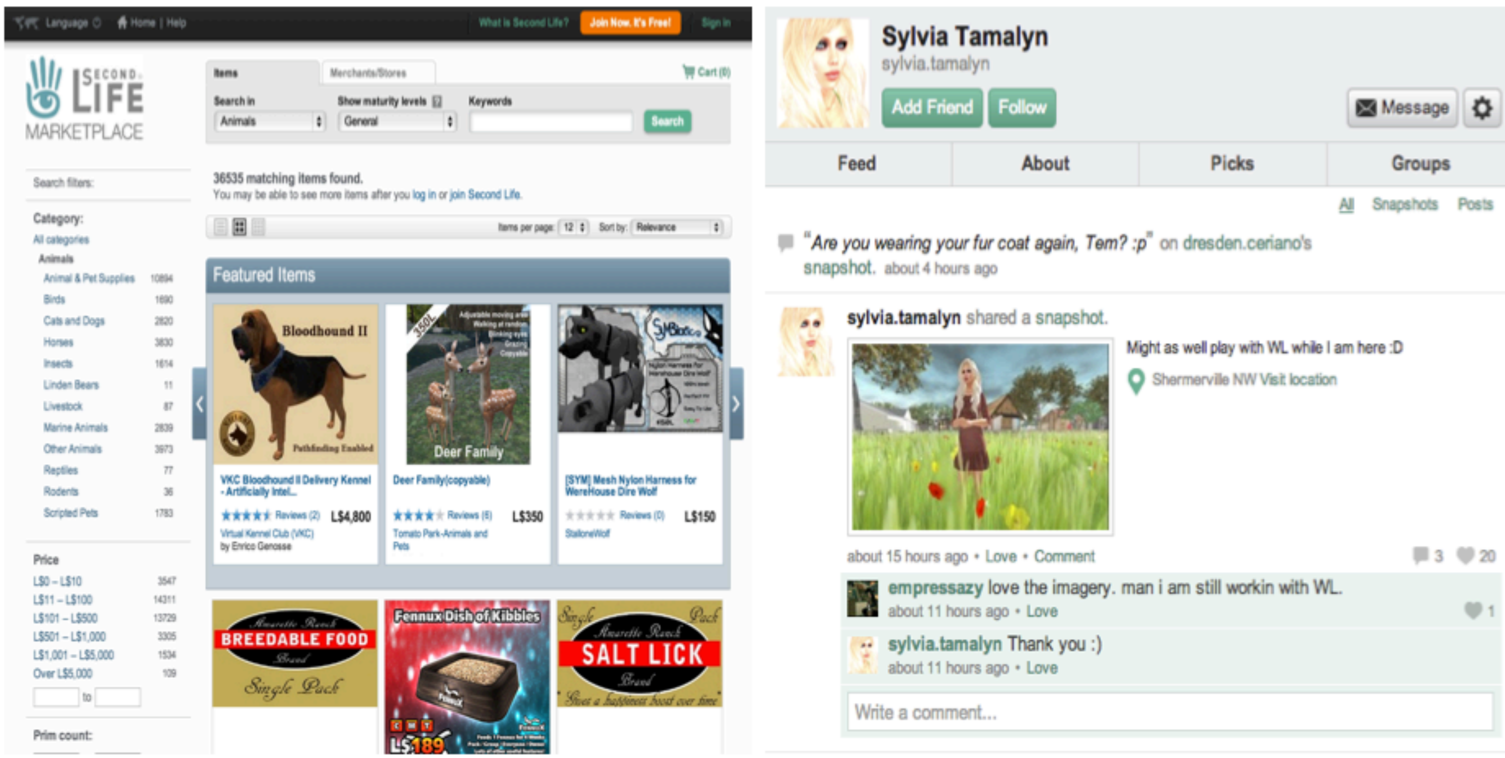
- Weighted
- Mixed
- Swtiching

Híbrido Paralelo: Weighted

$$W_{rec_i} = \sum_{s_j \in S} (W_{rec_i, s_j} \cdot W_{s_j})$$

rec_i	Item recomendado i
W_{rec_i}	Score combinado del item i
W_{rec_i, s_j}	Score del item I por el recomendador S_j
W_{s_j}	Peso del recomendador S_j

Caso de Estudio: SL Item Recommender



(a) SecondLife store

(b) SecondLife social stream

Fig. 1. Examples for a store in the marketplace and a social stream of an user in the online social network of the virtual world SecondLife.

Resultados de Distintas Features

Sets		$nDCG@10$	$P@10$	$R@10$	D	UC
Most Popular		.0082	.0021	.0122	.5945	100.00%
Market	Content	.0239	.0073	.0306	.6367	56.17%
Social	Content	.0067	.0015	.0096	.6877	78.67%
	Network	**.1597**	**.0550**	**.2041**	.6316	63.76%
	Combined	.1135	.0390	.1464	.6746	91.04%
Location	Content	.0053	.0014	.0083	**.6928**	99.90%
	Network	.0025	.0007	.0040	.6847	37.20%
	Combined	.0054	.0014	.0081	.6925	99.90%
Combined		.1085	.0363	.1395	.6722	**100.00%**
Combined Top 3		.1168	.0361	.1330	.6620	98.88%

Table 3: Results of the hybrid recommendation approaches.

Híbrido Paralelo: Mixed

$$src(rec_i) = \left[\sum_{m_m \in M} \frac{1}{rank_{rec_i, m_j}} \times \boxed{W_{m_j}} \right] \times |M_{rec_i}|$$

Slider weight

M: The set of all methods available to fuse

$rank_{reci,mj}$: rank–position in the list of a recommended item

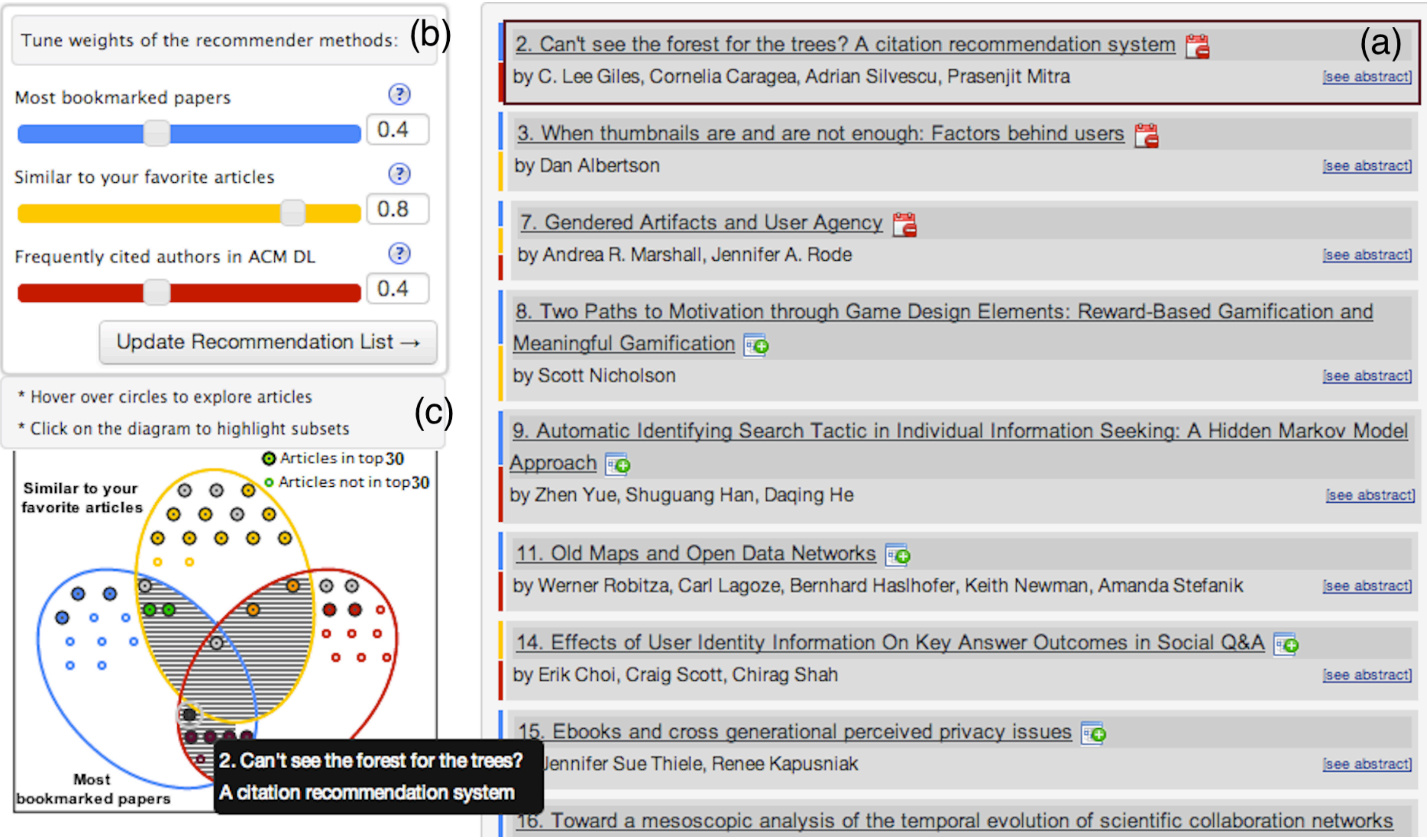
rec_i : recommended item *i*

m_j, : recommendation method j

W_{mj} : weight given by the user to the method m_j using the controllable interface

$|M_{reci}|$ represents the number of methods by which item rec_i was recommended

Caso de Estudio: SetFusion

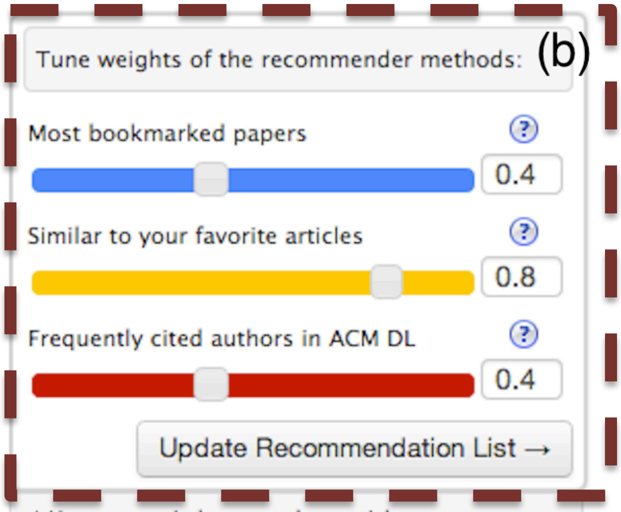


Our Proposed Interface - II

Traditional Ranked List

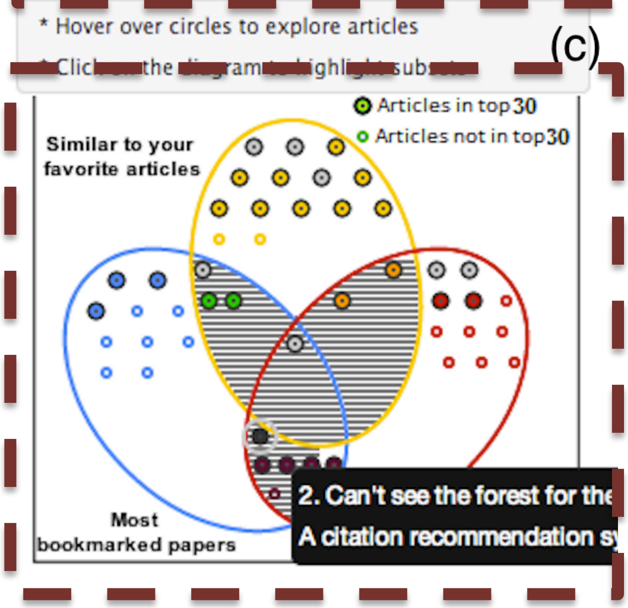
Papers sorted by Relevance.
It combines 3 recommendation approaches.

Our Proposed Interface - III



Sliders

Allow the user to control the importance of each data source or recommendation method



Interactive Venn Diagram

Allows the user to inspect and to filter papers recommended. Actions available:

- Filter item list by clicking on an area
- Highlight a paper by mouse-over on a circle
- Scroll to paper by clicking on a circle
- Indicate bookmarked papers

Híbrido Paralelo: Switching

- De un grupo de recomendadores, activar un recomendador a la vez
- Podría ser especialmente útil considerando el learning rate de alguno métodos
- Ejemplo: Elegir entre un clasificador Bayesiano y un recomendador Item-based como en:
  - Ghazanfar, M., & Prugel-Bennett, A. (2010). An Improved Switching Hybrid Recommender System Using Naive Bayes Classifier and Collaborative Filtering.

$$P(C_j|d) = \frac{P(C_j)\prod_{i=1}^{h} P(F_i|C_j)}{P(F_1,\cdots,F_h)}.$$

Switching: DF y alfa (Prob)

Table 1: A comparison of proposed algorithm with existing in terms of cost (based on [31]), accuracy metrics, and coverage

Algorithm	On-line Cost	Best MAE		ROC-Sensitivity		Coverage	
		(ML)	(FT)	(ML)	(FT)	(ML)	(FT)
$UBCF_{DV}$	$O(M^2N) + O(NM)$	0.766	1.441	0.706	0.563	99.424	93.611
IBCF	$O(N^2)$	0.763	1.421	0.733	0.605	99.221	92.312
IDemo4	$O(N^2)$	0.749	1.407	0.739	0.621	99.541	94.435
Rec_{NBCF}	$O(N^2) + O(Mf)$	**0.696**	**1.341**	**0.778**	**0.657**	**100**	**99.992**
NB	$O(Mf)$	0.808	1.462	0.703	0.571	100	99.992
NH	$O(N^2) + O(Mf)$	0.785	1.438	0.712	0.586	100	99.992
CB	$O(M^2N) + O(NM) + O(Mf)$	0.721	1.378	0.741	0.611	100	**99.995**

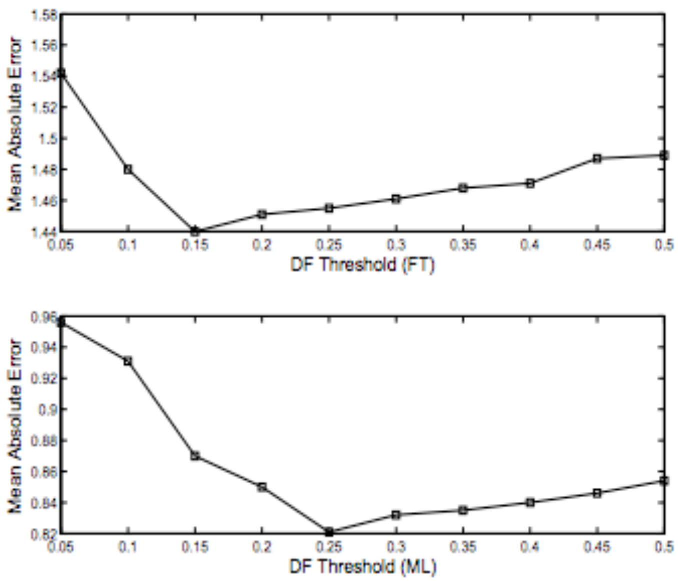


Figure 1: Determining the optimal value of DF.

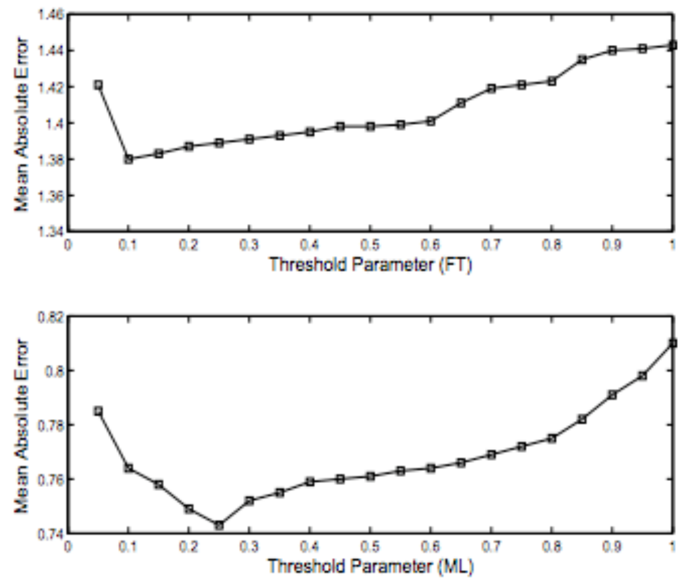


Figure 2: Determining the optimal value of α.

Diseño Híbrido Pipeline

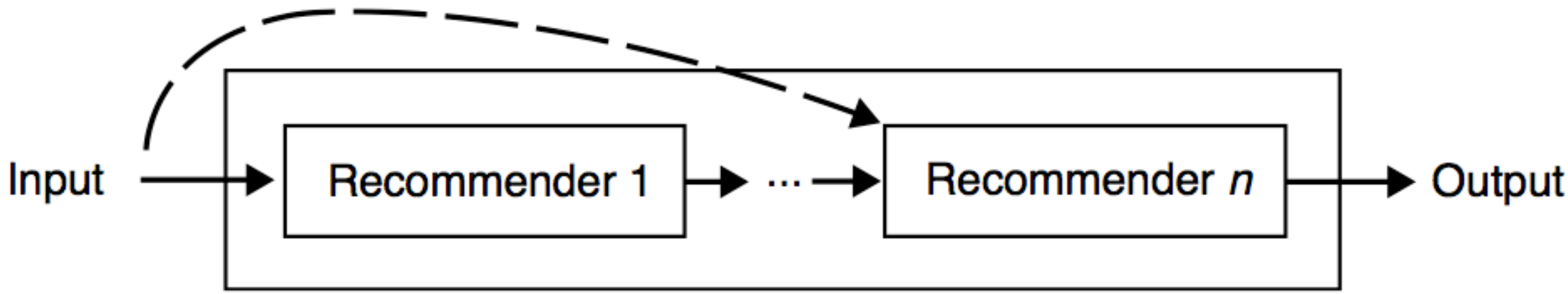


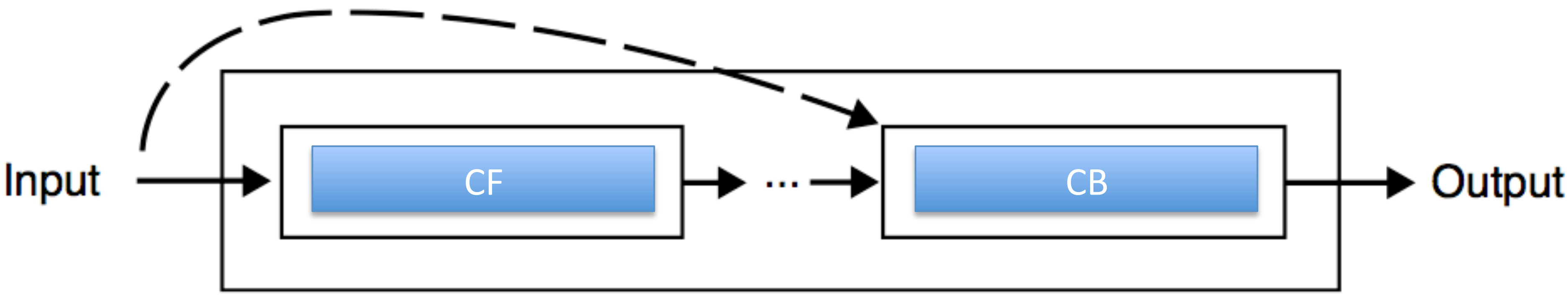
Figure 5.4. Pipelined hybridization design.

Estrategias de Combinación:

- Cascade
- Feature Augmentation

Híbrido Cascade

- El más sencillo: usar los resultados de un recomendador y refinarlos con un segundo recomendador



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Referencias

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