

Sistemas Recomendadores Híbridos

IIC 3633 - Sistemas Recomendadores

Denis Parra

Profesor Asistente, DCC, PUC CHile

TOC

En esta clase

1. Motivación
2. Clasificación General
3. Modelos de Hibridización
4. Ejemplos

Motivación

Diferentes métodos tienen 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 y permite con facilidad para extraer features del contenido. Sin embargo, también sufre de "new user problem", es menos preciso de el F.C. y presenta sobre-especialización.
- Knowledge-based: No los hemos visto hasta ahora. Casos típicos son Constrain-Based y Case-Based. Basados en un paradigma más interactivo, también los llaman "Conversacionales" (Burke, 2002). Su principal debilidad es el costo de mantener las reglas actualizadas.

Categorización de RecSys de 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.

Ref: Burke, R. (2002). Hybrid recommender systems: Survey and experiments. User modeling and user-adapted interaction, 12(4), 331-370.

Knowledge-Based Systems I

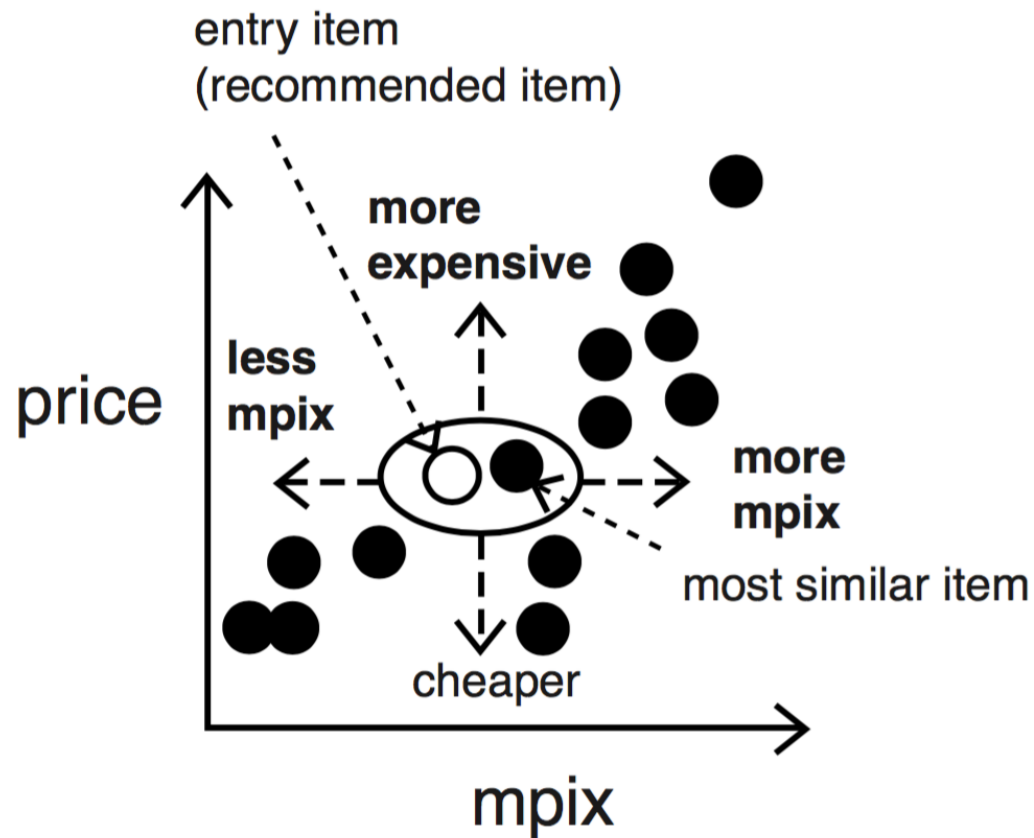


Figure 4.3. Critique-based navigation: items recommended to the user can be critiqued regarding different item properties (e.g., *price* or *mpix*).

Ref: Jannach, D., Zanker, M., Felfernig, A., & Friedrich, G. (2010). Recommender systems: an introduction. Cambridge University Press.

Knowledge-Based Systems II

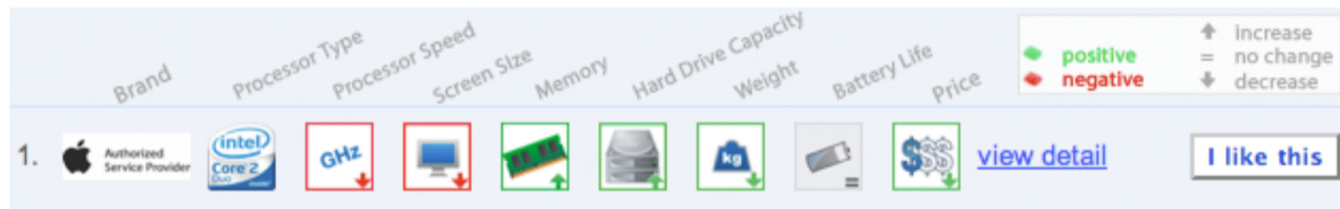


Fig. 7: The critiquing systems by Zhang et al. [2008], which visualizes compound critiques with icons and colors.

Ref: Jiyong Zhang, Nicolas Jones, and Pearl Pu. 2008. A visual interface for critiquing-based recom-mender systems. In Proceedings of the 9th Conference on Electronic Commerce (EC '08). 230–239.

Modelo Caja Negra de RecSys (Jannach et al. 2010)

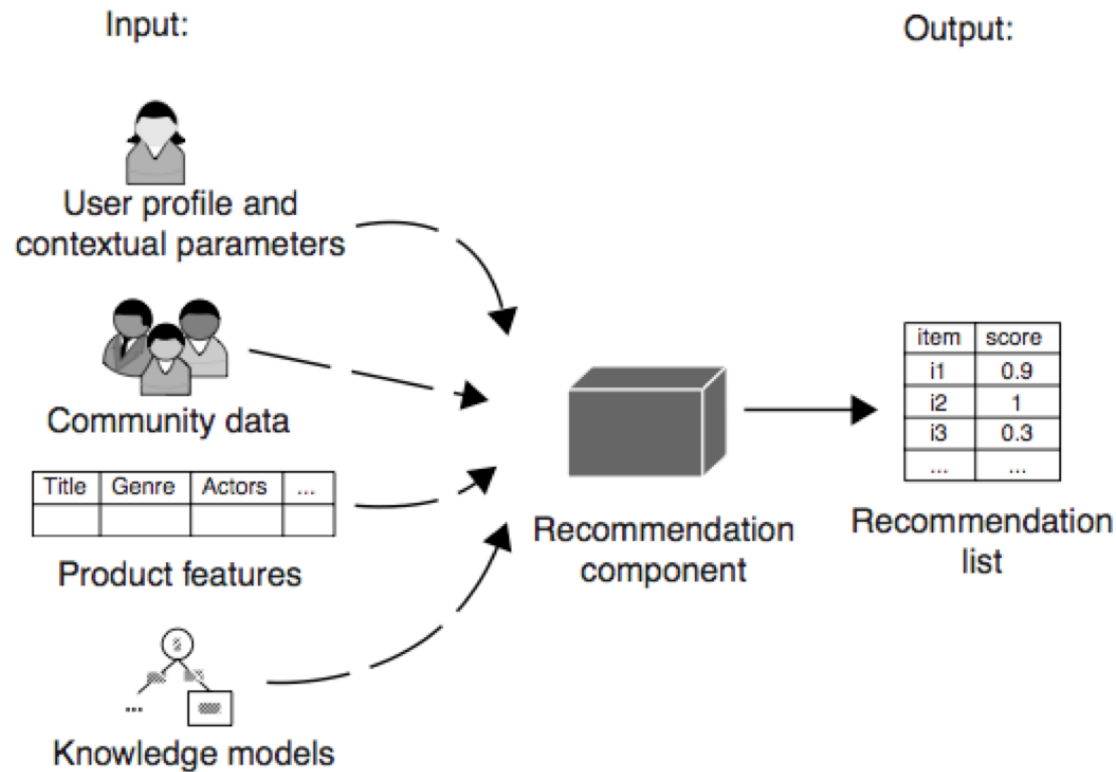


Figure 5.1. Recommender system as a black box.

Ref: Jannach, D., Zanker, M., Felfernig, A., & Friedrich, G. (2010). Recommender systems: an introduction. Cambridge University Press.

Combinar Métodos Content-based y Filtrado Colaborativo

Según (Adomavicius et al., 2005)

- Implementar métodos CF y CB separadamente y combinar las predicciones
- Incorporar características de métodos CB dentro de un método CF
- Incorporar características colaborativas dentro de modelo CB
- Construir un modelo que de manera unificada incorpore características basadas en contenido y colaborativas

Ref: Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. Knowledge and Data Engineering, IEEE Transactions on, 17(6), 734-749.

Cómo combinar Métodos de Recomendación?

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.

Hibridización Monolítica

Table III: Hybridization Methods

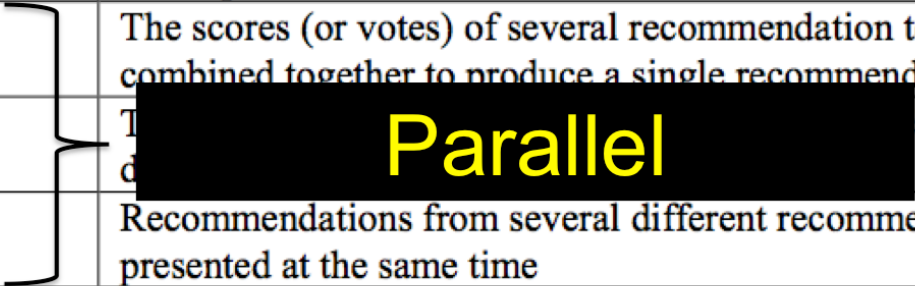
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Feature combination	Features from several recommenders are thrown together.
Cascade	One recommender's output is used as input to another.
Feature augmentation	One recommender's output is used to augment the input of another.
Meta-level	The model learned by one recommender is used as input to another.

Monolithic

Monolithic

Hibridización Paralela

Table III: Hybridization Methods

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Hibridización Pipeline

Table III: Hybridization Methods

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Mixed	Recommendations from several different recommenders are presented at the same time
Feature combination	Features from different recommendation data sources are thrown together to form a new feature set.
Cascade	Output from one technique is used as an input feature to another.
Feature augmentation	Output from one technique is used as an input feature to another.
Meta-level	Output from one technique is used as input to another.

Pipeline

Pipeline

Hibridización Monolítica

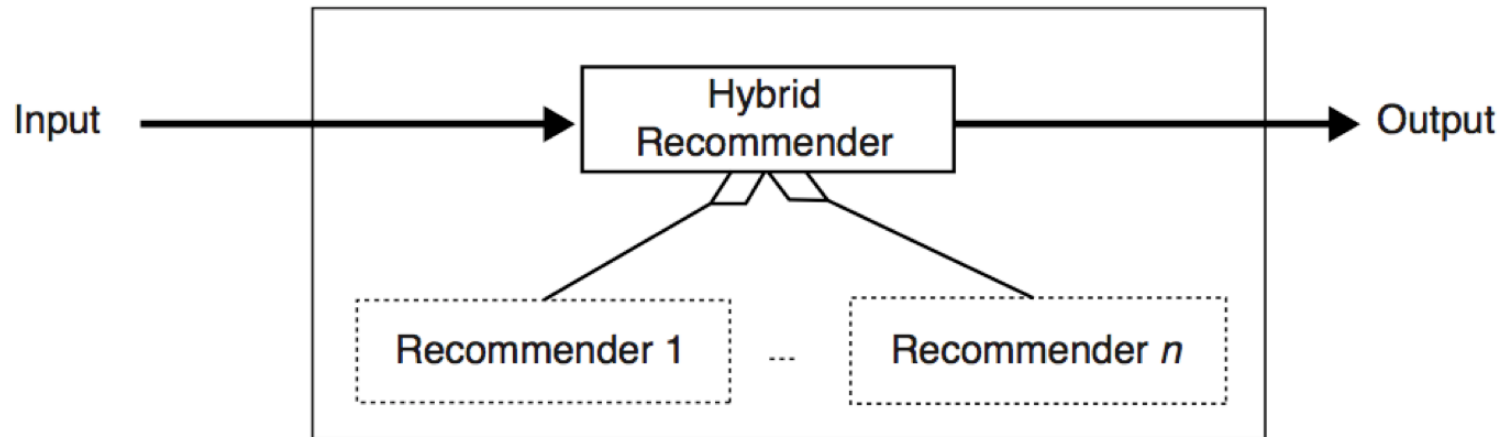


Figure 5.2. Monolithic hybridization design.

Estrategias de Combinación:

- Feature Combination
- Feature Augmentation

H. Monolítica: Feature Combination

Table 5.2. *Community and product knowledge.*

User	Item1	Item2	Item3	Item4	Item5	Item	Genre
Alice		1		1		Item1	romance
User1		1	1		1	Item2	mystery
User2	1	1			1	Item3	mystery
User3	1		1			Item4	mystery
User4					1	Item5	fiction

H. Monolítica: Feature Combination I

Table 5.3. *Hybrid input features.*

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

H. Monolítica: 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

H. Monolítica: Feature Augmentation

- A diferencia de "feature combination", este híbrido no sólo combina y procesa distintos tipos de entrada, sino que aplica algunos pasos de transformación más compleja.



Customers Who Bought This Item Also Bought



H. Monolítica: Feature Augmentation

The Measure of All Things: The Seven-Year Odyssey and Hidden Error That Transformed the World Paperback – October 1, 2003
by **Ken Alder** (Author)
★★★★☆ 39 customer reviews

See all 11 formats and editions

Format	Price	Used	New	Collectible
Hardcover	from \$0.01	166 Used from \$0.01	29 New from \$1.68	6 Collectible from \$9.85
Paperback	\$20.74 ✓Prime	44 Used from \$1.18	33 New from \$14.86	3 Collectible from \$6.90

Customers Who Bought This Item Also Bought

- King Lear (Norton Critical Editions)**
William Shakespeare
★★★★☆ (5)
Paperback
\$13.95 ✓Prime
- A Philosophical Enquiry into the Origin of Our ...**
Edmund Burke
★★★★★ (10)
Paperback
\$10.30 ✓Prime
- Critique of Judgment**
Immanuel Kant
★★★★☆ (3)
Paperback
\$21.03 ✓Prime
- Sherlock Holmes: Selected Stories ...**
Arthur Conan Doyle
★★★★★ (5)
Paperback

Usar estas
“features” en
un nuevo
recomendador

Hibridización Paralela

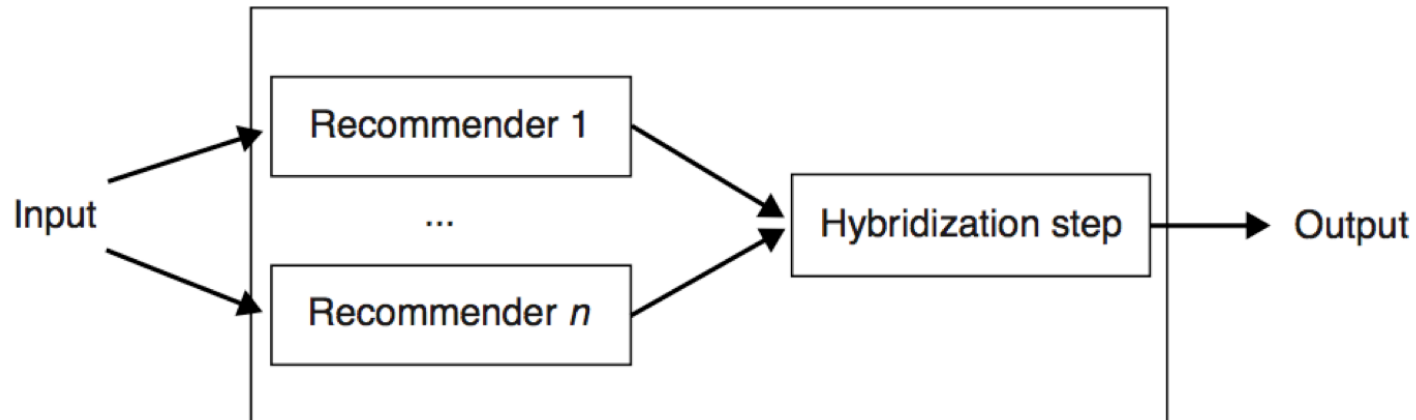


Figure 5.3. Parallelized hybridization design.

Tres mecanismos principales:

- Weighted
- Mixed
- Switching

H. Paralela: Weighted I

- La idea principal calcular una suma ponderada de los scores de items recomendados por diferentes recomendadores.

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

- La métrica de error MAE es ajustada:

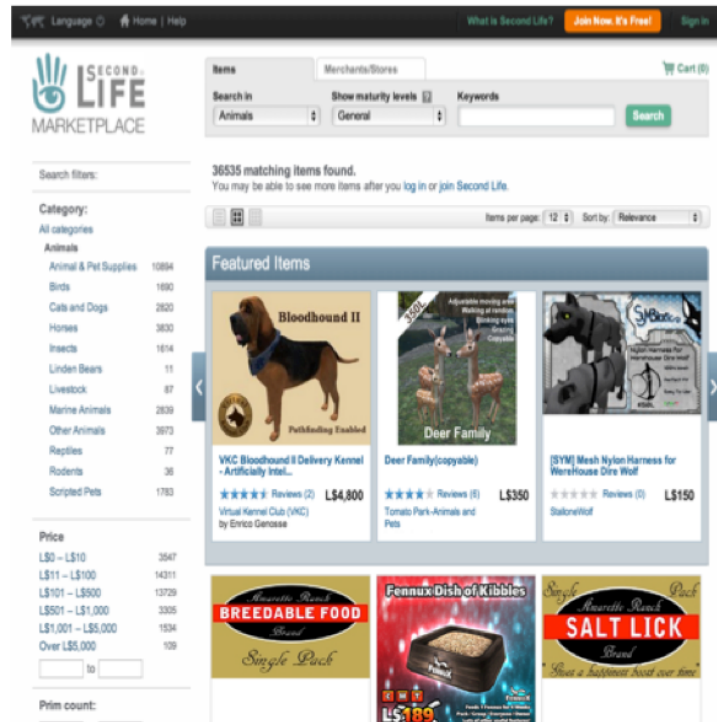
$$MAE = \frac{\sum_{r_i \in R} \sum_{k=1}^n \beta_k \times |rec_k(u, i) - r_i|}{|R|}$$

H. Paralela: Weighted II

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

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

H. Paralela: Weighted III



(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.

H. Paralela: Weighted IV

- Ejemplo

Table 5.6. *Recommendations of weighted hybrid.*

item	rec_1 score	rec_1 rank	rec_2 score	rec_2 rank	rec_w score	rec_w 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		0	

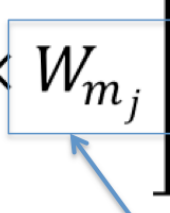
H. Paralela: Weighted V

- Asumiendo que Alice compró ítems 1 y 4

Table 5.7. *Dynamic weighting parameters, absolute errors, and MAEs for user Alice.*

β_1	β_2	item	r_i	rec_1	rec_2	error	MAE
0.1	0.9	Item1	1	0.5	0.8	0.23	0.61
		Item4	1	0.1	0	0.99	
0.3	0.7	Item1	1	0.5	0.8	0.29	0.63
		Item4	1	0.1	0	0.97	
0.5	0.5	Item1	1	0.5	0.8	0.35	0.65
		Item4	1	0.1	0	0.95	
0.7	0.3	Item1	1	0.5	0.8	0.41	0.67
		Item4	1	0.1	0	0.93	
0.9	0.1	Item1	1	0.5	0.8	0.47	0.69
		Item4	1	0.1	0	0.91	

H. Paralela: Mixed I

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


M : The set of all methods available to fuse

$rank_{rec_i, m_j}$: rank-position in the list of a recommended item

rec_i : recommended item i

m_j : recommendation method j

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

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

Slider
weight



H. Paralela: Mixed II

Tune weights of the recommender methods: (b)

Most bookmarked papers 0.4

Similar to your favorite articles 0.8

Frequently cited authors in ACM DL 0.4

Update Recommendation List →

* Hover over circles to explore articles
* Click on the diagram to highlight subsets (c)

Similar to your favorite articles

Articles in top30
Articles not in top30

Most bookmarked papers

2. Can't see the forest for the trees? A citation recommendation system

(a)

2. Can't see the forest for the trees? A citation recommendation system 
by C. Lee Giles, Cornelia Caragea, Adrian Silvescu, Prasenjit Mitra [\[see abstract\]](#)

3. When thumbnails are and are not enough: Factors behind users 
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7. Gendered Artifacts and User Agency 
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8. Two Paths to Motivation through Game Design Elements: Reward-Based Gamification and Meaningful Gamification 
by Scott Nicholson [\[see abstract\]](#)

9. Automatic Identifying Search Tactic in Individual Information Seeking: A Hidden Markov Model Approach 
by Zhen Yue, Shuguang Han, Daqing He [\[see abstract\]](#)

11. Old Maps and Open Data Networks 
by Werner Robitza, Carl Lagoze, Bernhard Haslhofer, Keith Newman, Amanda Stefanik [\[see abstract\]](#)

14. Effects of User Identity Information On Key Answer Outcomes in Social Q&A 
by Erik Choi, Craig Scott, Chirag Shah [\[see abstract\]](#)

15. Ebooks and cross generational perceived privacy issues 
Jennifer Sue Thiele, Renee Kapusniak [\[see abstract\]](#)

16. Toward a mesoscopic analysis of the temporal evolution of scientific collaboration networks

H. Paralela: Mixed III

Traditional Ranked List

Papers sorted by
Relevance.
It combines 3
recommendation
approaches.



(a)

2. Can't see the forest for the trees? A citation recommendation system  [\[see abstract\]](#)
by C. Lee Giles, Cornelia Caragea, Adrian Silvescu, Prasenjit Mitra

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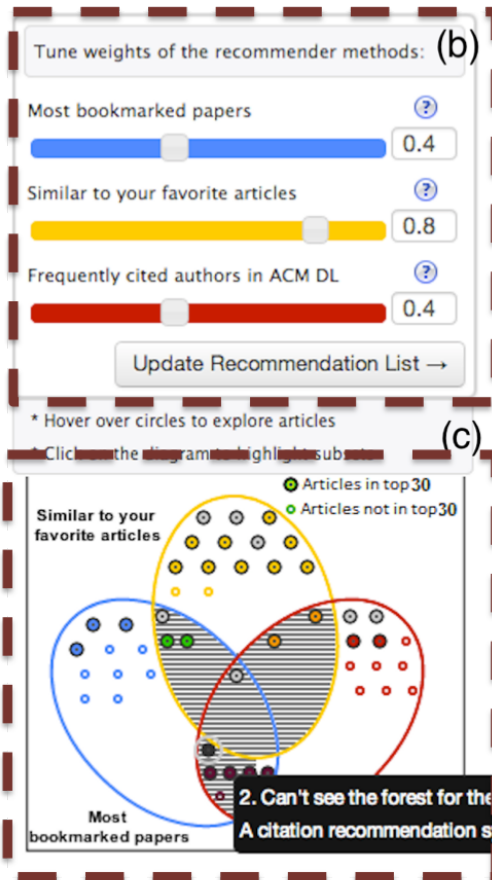
11. Old Maps and Open Data Networks  [\[see abstract\]](#)
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H. Paralela: Mixed IV



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

H. Paralela: Switching I

- De un grupo de recomendadores, **activar un recomendador a la vez**.
- Podría ser especialmente útil **considerando los learning rate de algunos 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**.

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

H. Paralela: Switching II

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

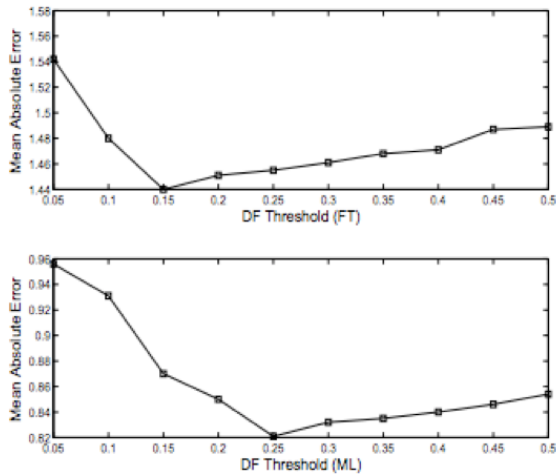


Figure 1: Determining the optimal value of DF .

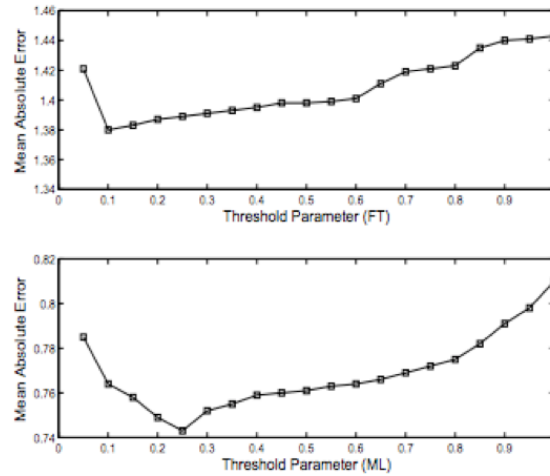


Figure 2: Determining the optimal value of α .

Hibridización Pipeline

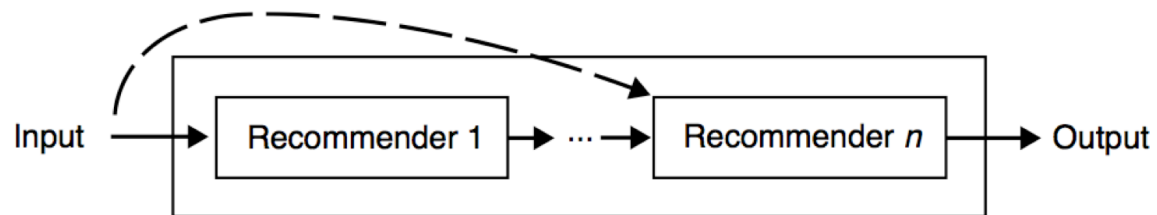


Figure 5.4. Pipelined hybridization design.

Dos mecanismos principales:

- Cascade
- Meta-Level

H. Pipeline: Cascade

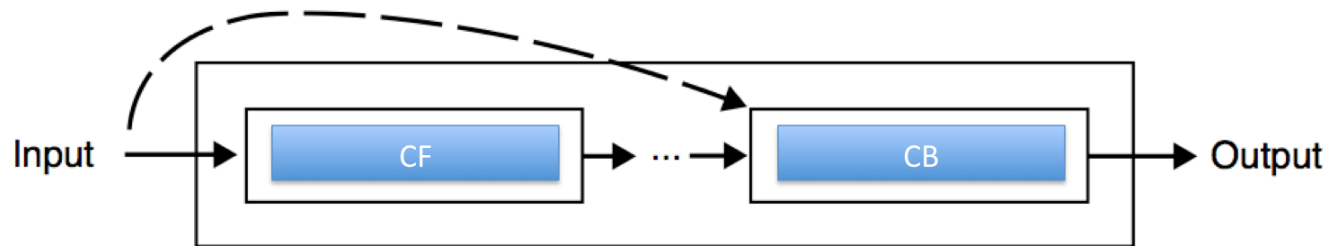


Figure 5.4. Pipelined hybridization design.

H. Pipeline: Cascade (Moodplay)



H. Pipeline: Cascade (Moodplay)

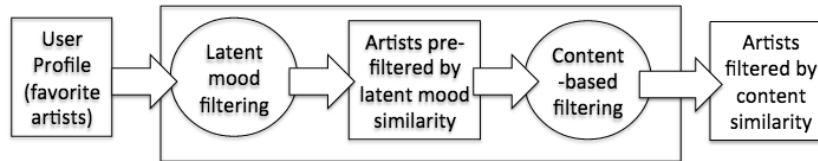
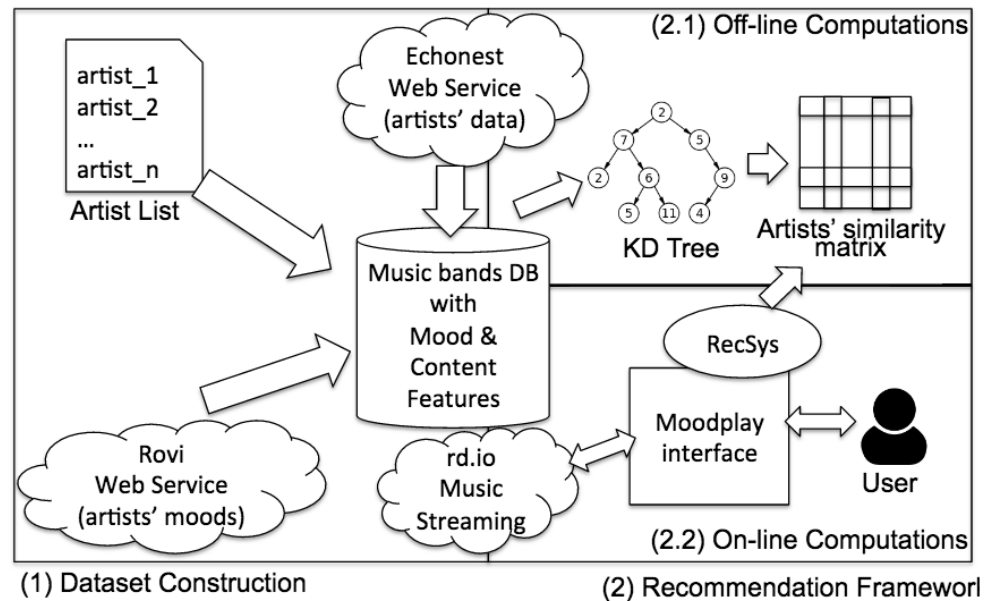


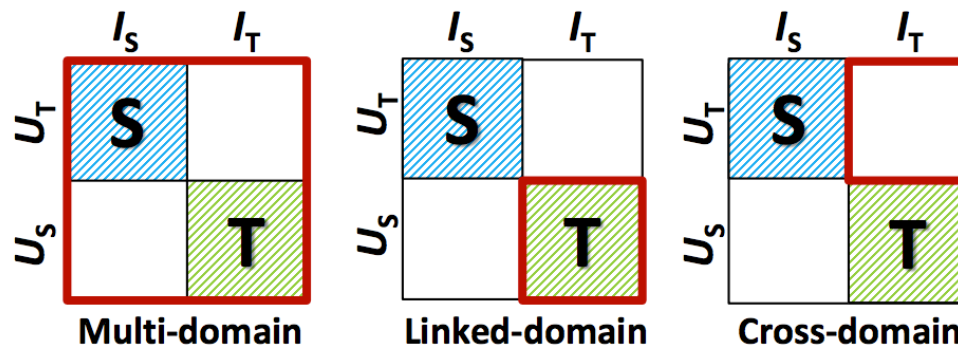
Fig. 4 Schematic representing our hybrid cascading recommender which pre-filters based on mood larity and then post-filters based on content similarity.



H. Pipeline: Meta-Level

El modelo aprendido por un recomendador es usado para un segundo recomendador.
Transfer Learning:

Cross-domain recommendation tasks



-  = data from source domain
-  = data from target domain
-  = target of recommendations

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Tutorial on Cross-domain recommender systems http://recsys.acm.org/wp-content/uploads/2014/10/recsys2014-tutorial-cross_domain.pdf

Referencias

- Burke, R. (2002). Hybrid recommender systems: Survey and experiments. *User modeling and user-adapted interaction*, 12(4), 331-370.
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