

# **Sistemas Recomendadores Híbridos**

## **IIC 3633 - Sistemas Recomendadores**

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# Memo del Semestre

- **Tarea 1:** Deadline nuevo, Jueves 8 de Septiembre.
- **Lecturas en el semestre:** Ya fueron actualizadas en el sitio web del curso.

Week	Fecha semana	Clase Martes	Clase Jueves	Presentador 1	Presentador 2	Presentador 3
I	2 - 4 Ago	Intro + CF	CF + Clustering			
II	9 - 11 Ago	CF item-based	Slope One + RecSys			
III	16 - 18 Ago	Evaluacion de RecSys	Evaluacion de RecSys			
IV	23 - 25 Ago	Content-based	Tag-based			
V	30 Ag - 1 Sept	Hybrid	Context-aware			
VI	6 - 8 Sept	Factorizacion Matricial	Implicit Feedback			
VII	13 - 15 Sept	student presentation (Context, MF)	RECSYS Conf	V. Dominguez	J. Schellman	P. Lopez
VIII	20 - 22 Sept	RECSYS Conf	student presentation (IF, MF)	F. Lucchini	V. Claro	V. Castillo
IX	27 - 29 Sept	Presentaciones: Proy. Final	Presentaciones: Proy. Final			
X	4 - 6 Oct	User-centric RecSys/Interfaces	student presentation	J. Lee	C. Kutscher	R. Carmona
XI	11 - 13 Oct	Active Learning/Ranking	student presentation	F. Rojos	J. Navarro	N. Morales
XII	18 - 20 Oct	Graph-based	student presentation	P. Messina	S. Martí	J. Castro
XIII	25 - 27 Oct	Applications: Social/Trust/Music	student presentation	J.M. Herrera	V. Dragicevic	L. Zorich
XIV	1 - 3 Nov	Applications: POI/Tourism	student presentation	P. Sanabria	T. Hepner	M. Troncoso
XV	8 - 10 Nov	Applications: Educ/Soft.Eng.	student presentation	R. Perez	P. Sanabria	J. Diaz
XVI	15 - 17 Nov	Deep Learning	student presentation	Felipe del Rio	L. Pose	G. Sepulveda
XVII	29 Nov - 1 Dic	Presentacion Final	Presentacion Final			

# 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 Constraint-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.

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

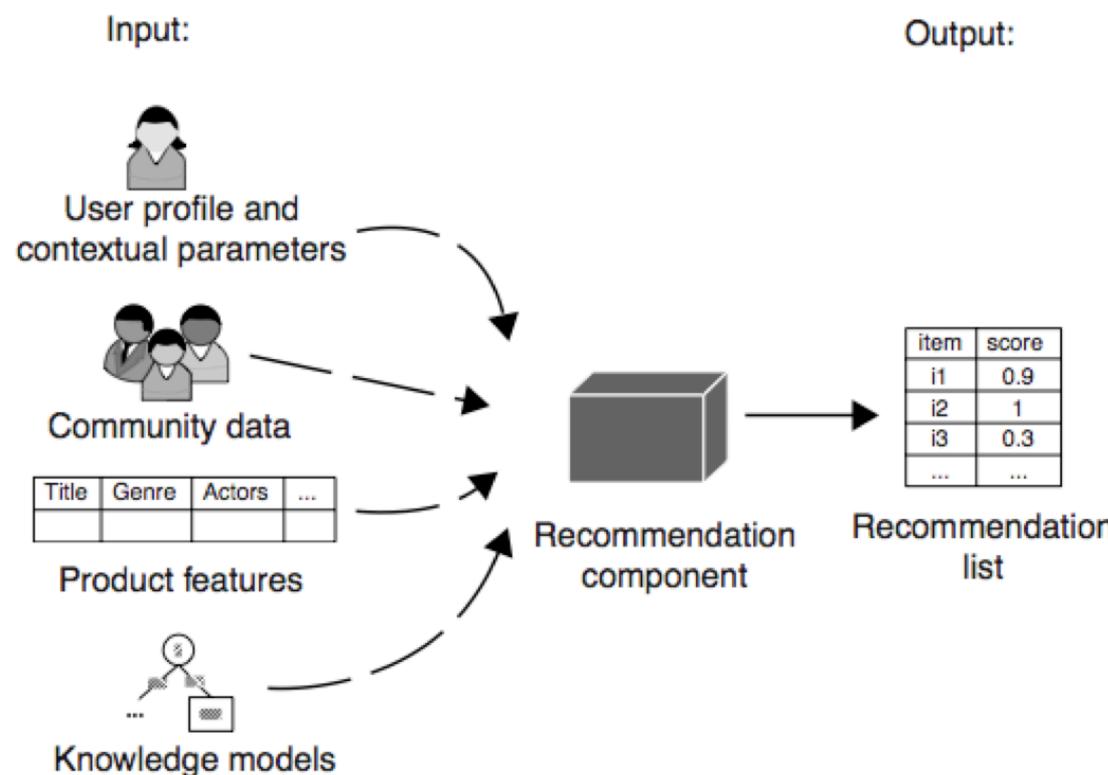


Figure 5.1. Recommender system as a black box.

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**

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 recommenders are thrown together.
Cascade	One recommender feeds its output to another.
Feature augmentation	Features from one recommender are added to another.
Meta-level	The model learned by one recommender is used as input to another.

# Hibridización Paralela

**Table III: Hybridization Methods**

Hybridization method	Description
Weighted	The scores (or votes) of several recommendation techniques are combined together to produce a single recommendation.
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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.

Parallel

# Hibridización Pipeline

**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 into a single feature space.
Cascade	→ Pipeline → given by another.
Feature augmentation	Output from one technique is used as an input feature to another.
Meta-level	→ Pipeline → as input to

# Hibridización Monolítica

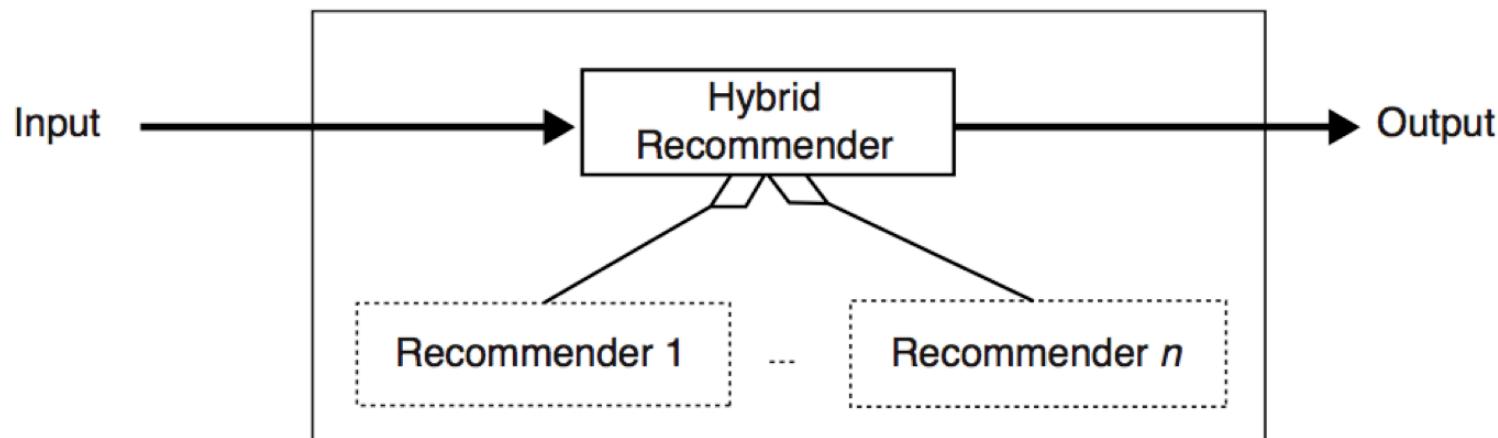


Figure 5.2. Monolithic hybridization design.

Estrategias de Combinación:

- Feature Combination
- Feature Augmentation

# H. Monolítica: Feature Combination I

Table 5.3. *Hybrid input features.*

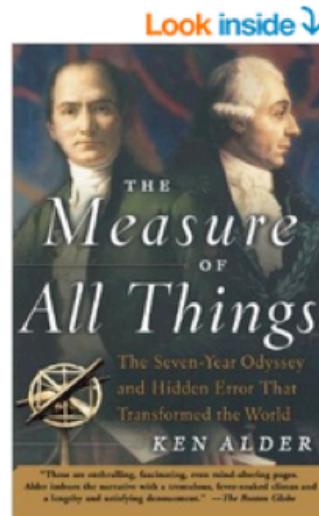
Feature	Alice	User1	User2	User3	User4
User likes many <i>mystery</i> books	true	true			
User likes some <i>mystery</i> books			true	true	
User likes many <i>romance</i> books					
User likes some <i>romance</i> books			true	true	
User likes many <i>fiction</i> books					
User likes some <i>fiction</i>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



Look inside ↴

## The Measure of All Things: The Seven-Year Odyssey and Hidden Error That Transformed the World Paperback – October 1, 2003

by Ken Alder (Author)

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► Immanuel Kant  
★★★★★ 5 (3)  
Paperback  
\$21.03 ✓Prime



Sherlock Holmes: Selected  
Stories ...  
► Arthur Conan Doyle  
★★★★★ 5 (5)  
Paperback

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# 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

Hardcover from \$0.01	Paperback \$20.74 Prime
166 Used from \$0.01 29 New from \$1.68 6 Collectible from \$9.85	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 Ideas of the Beautiful  
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

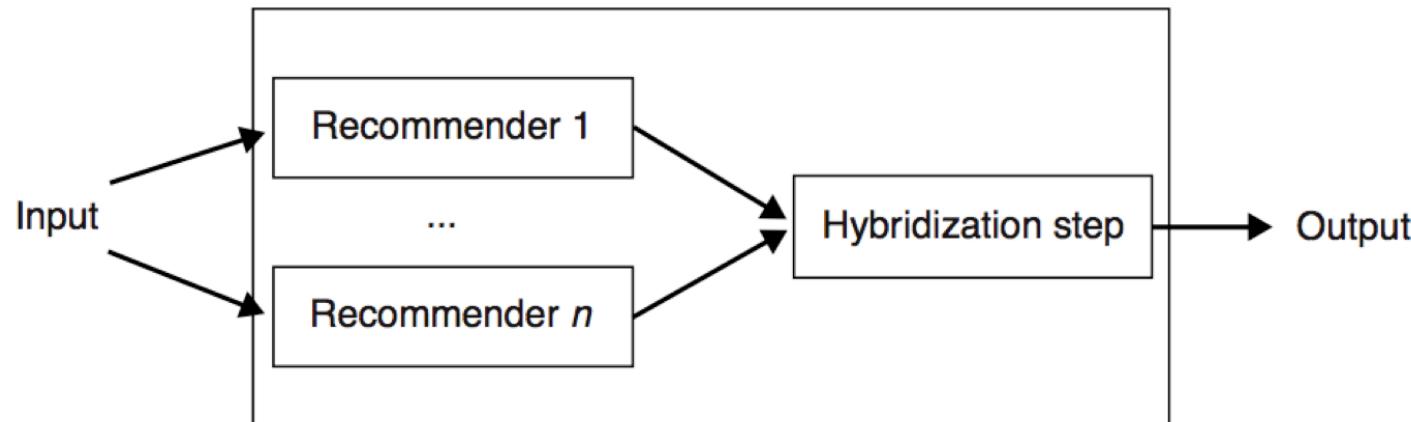


Figure 5.3. Parallelized hybridization design.

Tres mecanismos principales:

- Weighted
- Mixed
- Switching

## H. Paralela: Weighted I

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

$rec_i$	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 II

The screenshot shows the SecondLife Marketplace store interface. At the top, there are links for Language, Home, Help, and Sign In. Below that is a search bar with fields for Items, Merchants/Stores, Search in (Animals), Show maturity levels, Keywords, and a Search button. A cart icon shows 0 items. The main area displays '36535 matching items found.' and a message about logging in. On the left, there's a sidebar with 'Category:' filters for All categories, Animals (with sub-options like Animal & Pet Supplies, Birds, Cats and Dogs, etc.), and Price filters (L\$0 - L\$10, L\$11 - L\$100, etc.). The right side shows 'Featured Items' for animals, including 'Bloodhound II' (L\$4,800), 'Deer Family' (L\$350), and 'SYM Mesh Nylon Harness for WereHouse Dire Wolf' (L\$150). Below these are items like 'BREEDABLE FOOD' and 'Fennux Dish of Kibbles'.

(a) SecondLife store

The screenshot shows a user's social stream on SecondLife. At the top, it displays the user's profile picture, name 'Sylvia Tamalyn', and handle 'sylvia.tamalyn'. Below that are buttons for Add Friend, Follow, Message, and Settings. The main feed shows a post from 'dresden.ceriano' with a caption: "Are you wearing your fur coat again, Tem? :p" on a snapshot taken about 4 hours ago. Another post from 'sylvia.tamalyn' shows a snapshot of her in a field, with the caption: "Might as well play with WL while I am here :D" and a location tag for Shermerville NW. There are comments from other users: 'empressazy' and 'sylvia.tamalyn' both saying they love the imagery and are working with WL. A comment input field at the bottom says 'Write a comment...'

(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: 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

**(b)**

Tune weights of the recommender methods:

- 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

Most bookmarked papers

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

Articles in top 30  
Articles not in top 30

**(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 by Dan Albertson [\[see abstract\]](#)

7. Gendered Artifacts and User Agency by Andrea R. Marshall, Jennifer A. Rode [\[see abstract\]](#)

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 Robitz, 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 by Jennifer Sue Thiele, Renee Kapusniak [\[see abstract\]](#)

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

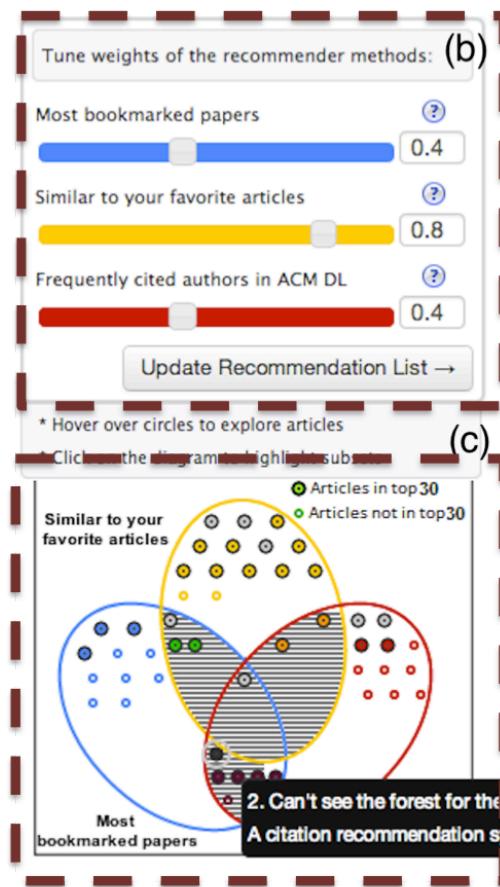
# H. Paralela: Mixed III

## Traditional Ranked List

Papers sorted by Relevance.  
It combines 3 recommendation approaches.

2. Can't see the forest for the trees? A citation recommendation system		(a)
by C. Lee Giles, Cornelia Caragea, Adrian Silvescu, Prasenjit Mitra		<a href="#">[see abstract]</a>
3. When thumbnails are and are not enough: Factors behind users		
by Dan Albertson		<a href="#">[see abstract]</a>
7. Gendered Artifacts and User Agency		
by Andrea R. Marshall, Jennifer A. Rode		<a href="#">[see abstract]</a>
8. Two Paths to Motivation through Game Design Elements: Reward-Based Gamification and Meaningful Gamification		
by Scott Nicholson		<a href="#">[see abstract]</a>
9. Automatic Identifying Search Tactic in Individual Information Seeking: A Hidden Markov Model Approach		
by Zhen Yue, Shuguang Han, Daqing He		<a href="#">[see abstract]</a>
11. Old Maps and Open Data Networks		
by Werner Robitzka, Carl Lagoze, Bernhard Haslhofer, Keith Newman, Amanda Stefanik		<a href="#">[see abstract]</a>
14. Effects of User Identity Information On Key Answer Outcomes in Social Q&A		
by Erik Choi, Craig Scott, Chirag Shah		<a href="#">[see abstract]</a>
15. Ebooks and cross generational perceived privacy issues		
by Jennifer Sue Thiele, Renee Kapusniak		<a href="#">[see abstract]</a>
16. Toward a mesoscopic analysis of the temporal evolution of scientific collaboration networks		

## 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 |

- 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)
<i>UBCF<sub>DV</sub></i>	$O(M^2N) + O(NM)$	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
<i>Rec<sub>NBCF</sub></i>	$O(N^2) + O(Mf)$	<b>0.696</b>	<b>1.341</b>	<b>0.778</b>	<b>0.657</b>	<b>100</b>	<b>99.992</b>
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	<b>99.995</b>

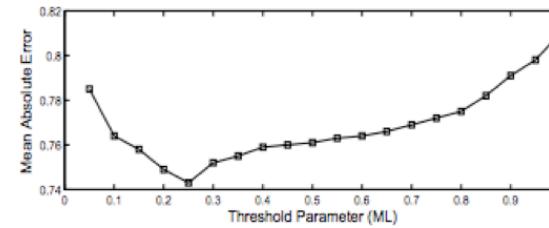
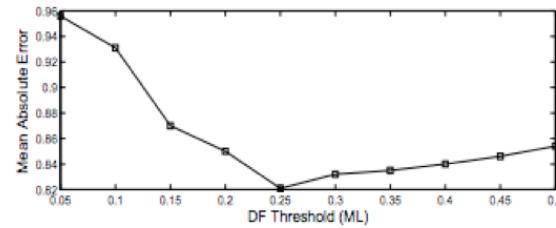
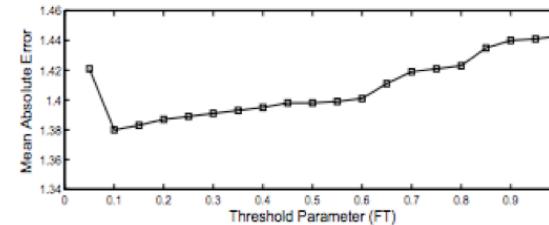
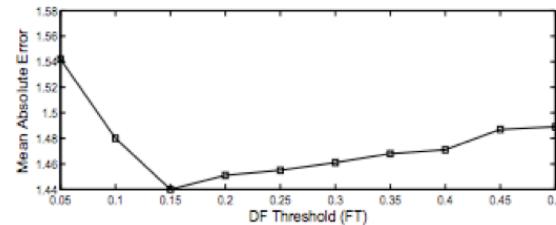


Figure 1: Determining the optimal value of  $DF$ .

Figure 2: Determining the optimal value of  $\alpha$ .

# Hibridización Pipeline

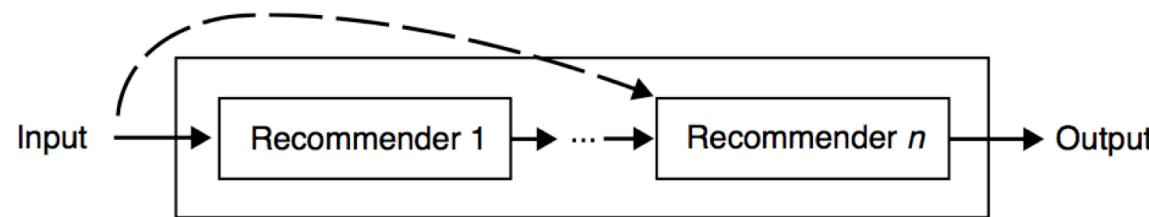


Figure 5.4. Pipelined hybridization design.

Dos mecanismos principales:

- Cascade
- Meta-Level

## H. Pipeline: Cascade

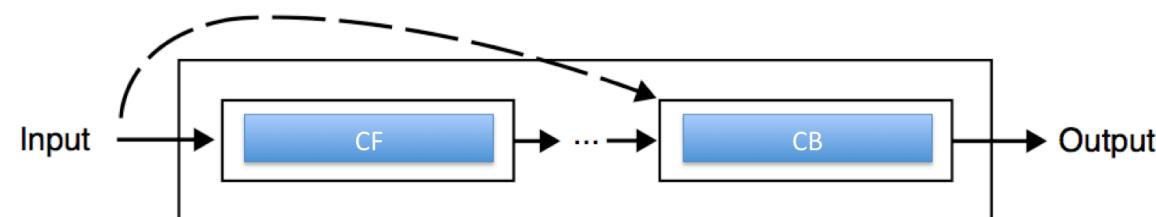
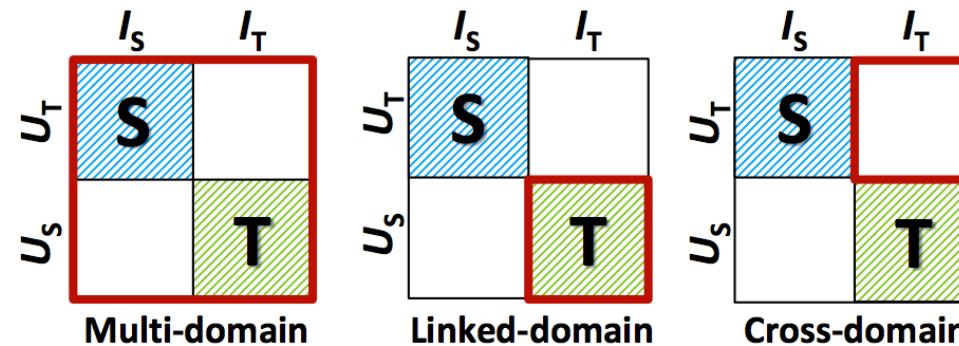


Figure 5.4. Pipelined hybridization design.

# H. Pipeline: 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](http://recsys.acm.org/wp-content/uploads/2014/10/recsys2014-tutorial-cross_domain.pdf)

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# Referencias

- Burke, R. (2002). Hybrid recommender systems: Survey and experiments. *User modeling and user-adapted interaction*, 12(4), 331-370.
- 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.
- Burke, R. (2007). Hybrid web recommender systems. In *The adaptive web* (pp. 377-408). Springer Berlin Heidelberg.
- Jannach, D., Zanker, M., Felfernig, A., & Friedrich, G. (2010). *Recommender systems: an introduction*. Cambridge University Press. Chicago

