Ranking & UB-CF

IIC3633 - Sistemas Recomendadores

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TOC

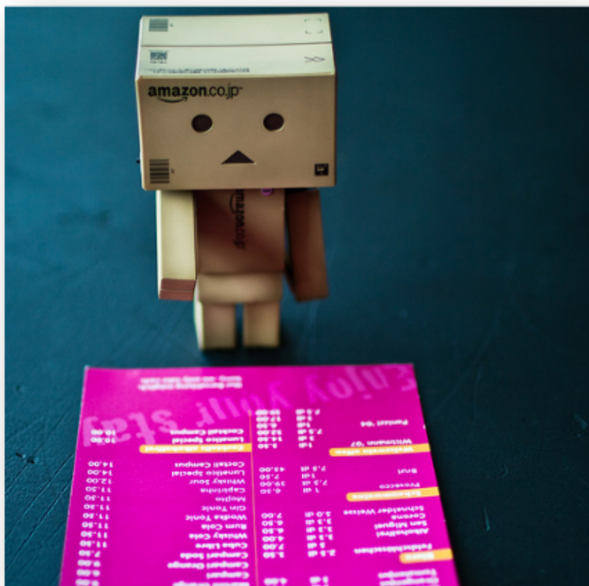
En esta clase

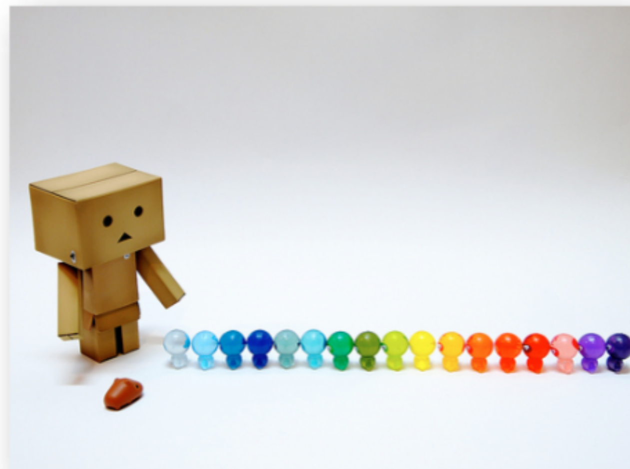
1. Actividades principales del semestre: Blog, Tarea 1, Presentacion, Proyecto Final
2. Definición y un poco de Historia
3. Ranking No Personalizado
4. User-Based Collaborative Filtering
5. Referencias

Definición

Recommender Systems aim to help a user or a group of users in a system to select items from a crowded item or information space.
(MacNee et. al 2006)

R. Burke tenía su propia definición, similar a esta, pero agregaba ...in a personalized way.





3/24

¿Por qué nos interesan los RecSys en estos días?

- Los Sistemas Recomendadores (RecSys) han ganado mucha popularidad en varios dominios y aplicaciones donde la gente debe tomar decisiones sobre una gran cantidad de información.

4/24

El problema de recomendación formalizado (Adomavicius et al. 2007)

$$\forall c \in C, s'_c = \underset{s \in S}{\operatorname{argmax}}\, u(c, s)$$

$$u : C \times S \rightarrow R,\ funcion\ de\ utilidad$$

$$R :\ conjunto\ recomendado\ de\ items$$
$$C :\ conjunto\ de\ usuarios$$
$$S :\ conjunto\ de\ items$$

5/24

1. Un Poco de Historia

Recomendaciones estilo Amazon.com

6/24

1.1 En 1992 Xerox PARC Tapestry

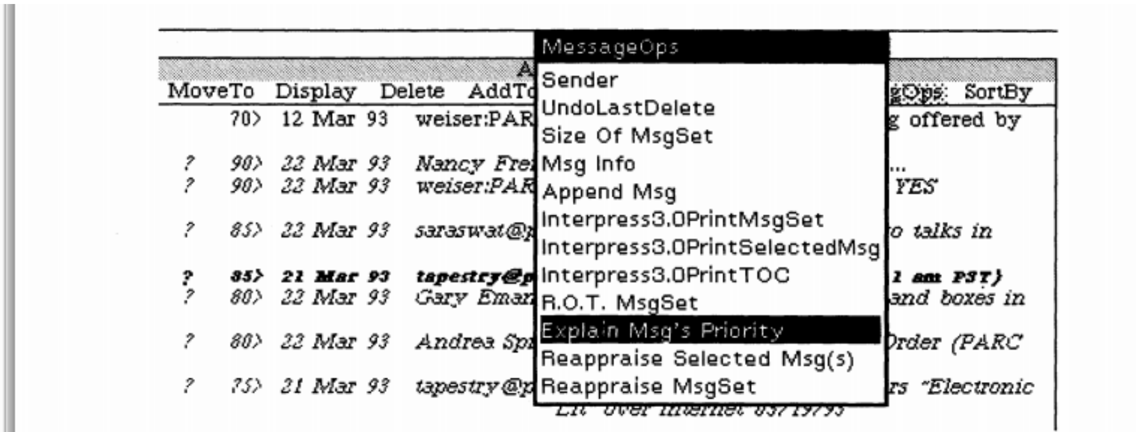


Figure 2. Requesting an explanation for a message's priority.

Annotations for message $ XNS-SMTP-Gateway:Parc:Xerox
appraiser terry$text:Bakersfield => priority 85
appraiser terry$Subject:Briefs←California => priority 55
appraiser terry$sender:tapestry => priority 10

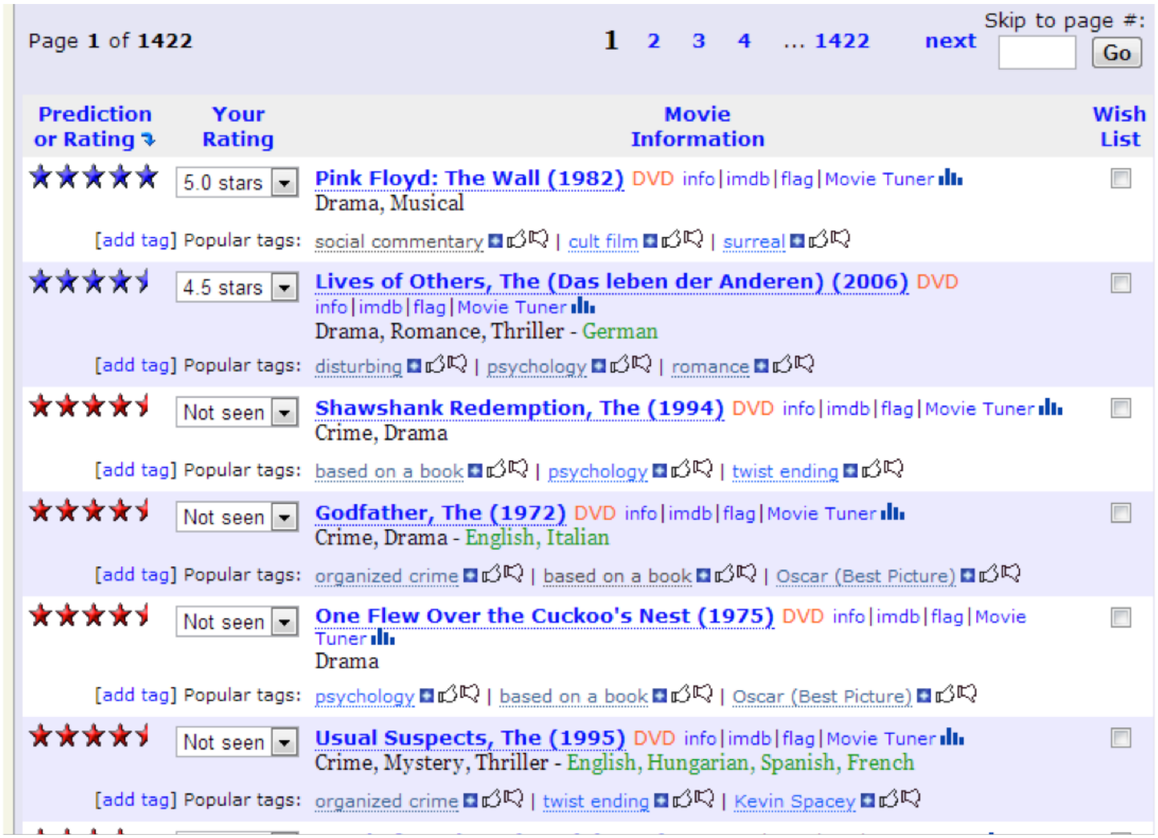
Figure 3. An explanation of priorities assigned to a message by various appraisers.

am curious as to why this particular message was assigned priority 85. So I select the message by left-clicking on its summary, and then I click the "MsgOps" button at the top of the window. This produces a pop-up menu from which I select the "Explain Msg's Priority" option (see Figure 2.). The resulting textual explanation is shown in Figure 3.

Link to PDF file

7/24

1.2 MovieLens



Link to [Amatriain 2012]

8/24

NetFlix Prize (2007-2009)

Leaderboard

Showing Test Score. Click here to show quiz score

Display top 20 leaders.

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos				
1	BellKor's Pragmatic Chaos	0.8567	10.06	2009-07-26 18:18:28
2	The Ensemble	0.8567	10.06	2009-07-26 18:38:22
3	Grand Prize Team	0.8582	9.90	2009-07-10 21:24:40
4	Opera Solutions and Vandelay United	0.8588	9.84	2009-07-10 01:12:31
5	Vandelay Industries !	0.8591	9.81	2009-07-10 00:32:20
6	PragmaticTheory	0.8594	9.77	2009-06-24 12:06:56
7	BellKor in BigChaos	0.8601	9.70	2009-05-13 08:14:09
8	Dace_	0.8612	9.59	2009-07-24 17:18:43
9	Feeds2	0.8622	9.48	2009-07-12 13:11:51
10	BigChaos	0.8623	9.47	2009-04-07 12:33:59
11	Opera Solutions	0.8623	9.47	2009-07-24 00:34:07
12	BellKor	0.8624	9.46	2009-07-26 17:19:11

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
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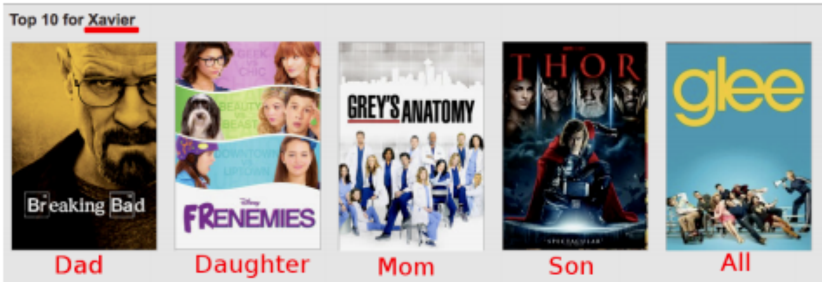
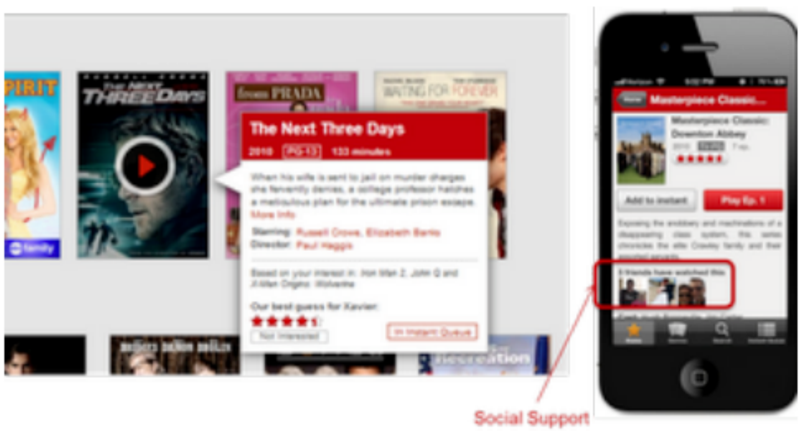
9/24

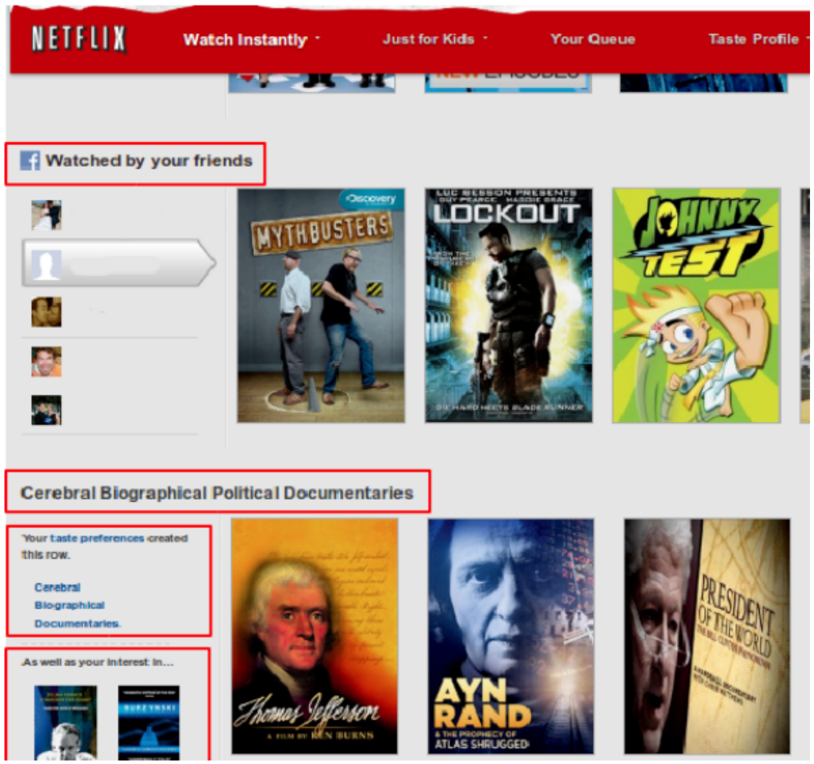
1.3 Netflix en 2012





Link to [Amatriain 2012]

1.3 Netflix en 2012 (continuación)



Link to [Amatriain 2012]

11/24

Ranking no personalizado (Blog de Evan Miller, 2009)

1. Popularidad.
2. Score: (Ratings Positivos) - (Ratings Negativos)
3. Score: (Rating Promedio) = (Ratings Positivos)/(Total de Ratings)
4. Score: **Considerando Ratings positivos y negativos**, Limite inferior del Intervalo de Confianza del Wilson Score, para un parámetro Bernoulli.

$$\left(\hat{p} + \frac{z_{\alpha/2}^2}{2n} \pm z_{\alpha/2}\sqrt{[\hat{p}(1-\hat{p}) + z_{\alpha/2}^2/4n]/n}\right)/(1+z_{\alpha/2}^2/n).$$

Donde $\hat{p}$ es la proporción (estimada) de ratings positivos, $z_{\alpha/2}$ es el $(1-\alpha/2)$ cuantil de la distribución normal, y n el número de ratings. α, también llamado nivel de significancia estadístico, generalmente se considera 95%.

12/24

Clasificacion(es)

1. Considerando los Datos usados
   1. Basado en Reglas (Rule-based)
   2. Basado en Contenido (Content-based)
   3. Filtrado Colaborativo (el usuario y sus vecinos)
2. Considerando el Modelo
   1. Memory-based (KNN)
   2. Model-based (Representación latente)

Simplificación del Problema: Predicción de Ratings

Predict!

	Item 1	Item 2	…	Item m
User 1	1	5		4
User 2	5	1		?
…				
User n	2	5		?

- How good is my prediction?

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{r}_{ui} - r_{ui})^2}{n}}$$

14/24

Filtrado Colaborativo basado en el usuario

Dos tareas son necesarias:

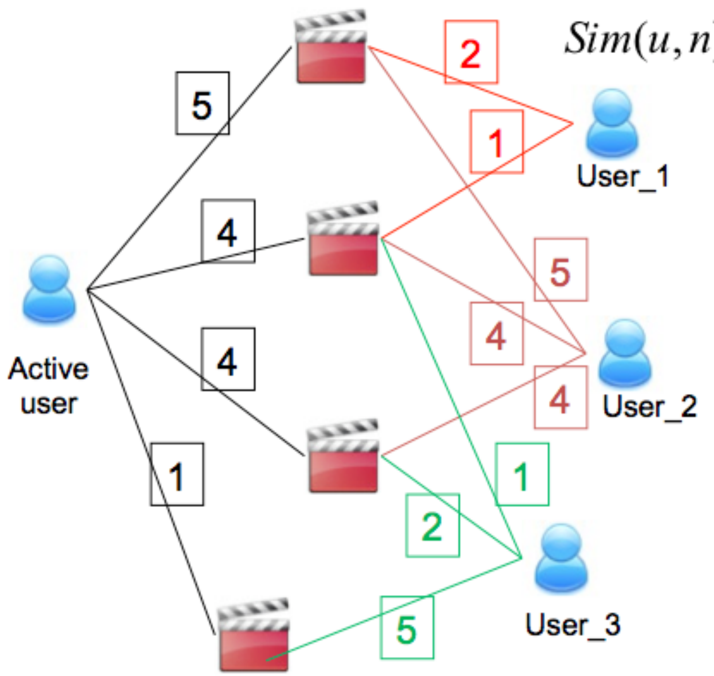
- KNN: Encontrar los K vecinos más cercanos (KNN) al usuario a:

$$Similaridad(a, i) = w(a, i), i \in K$$

- **Predecir** el rating que un usuario a dará a un ítem j :

$$p_{a,j} = \bar{v}_a + \alpha \sum_{i=1}^{n} w(a, i)(v_{i,j} - \bar{v}_i)$$

Ejemplo: Correlación de Pearson



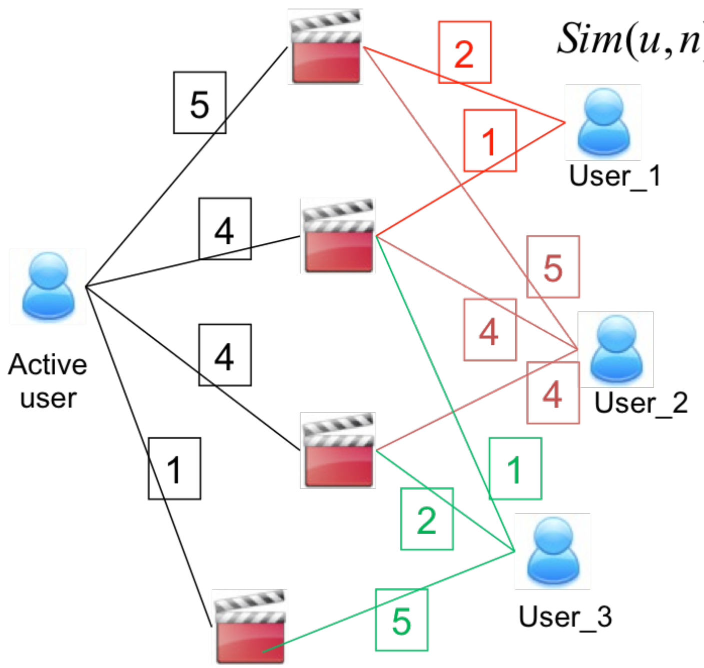
$$Sim(u,n) = \frac{\sum_{i \subset CR_{u,n}} (r_{ui} - \bar{r}_u)(r_{ni} - \bar{r}_n)}{\sqrt{\sum_{i \subset CR_{u,n}} (r_{ui} - \bar{r}_u)^2} \sqrt{\sum_{i \subset CR_{u,n}} (r_{ni} - \bar{r}_n)^2}}$$

16/24

Ejemplo: Correlación de Pearson

SOLUCION

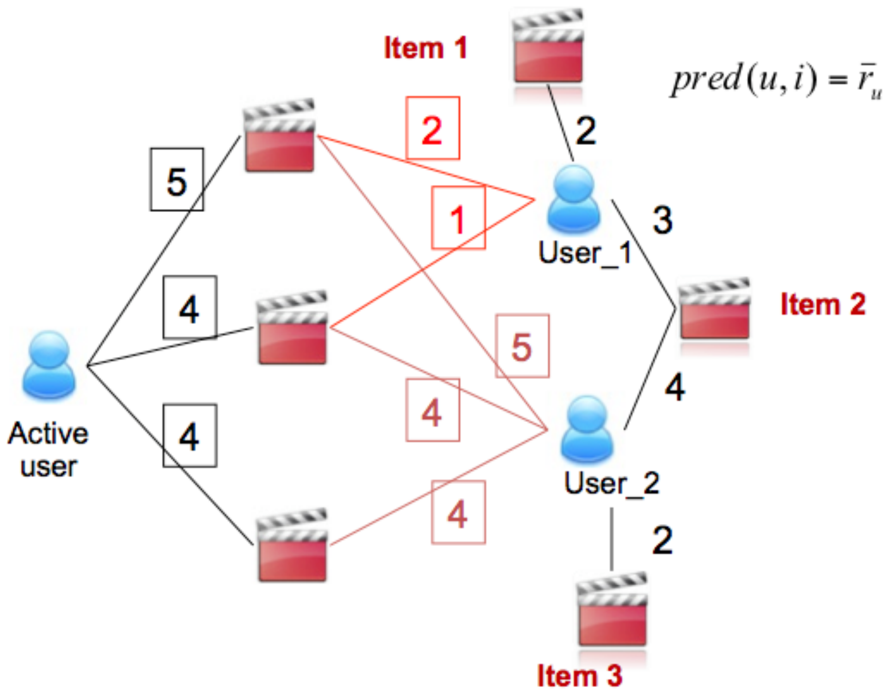
Ejemplo: Correlación de Pearson



$$Sim(u,n) = \frac{\sum_{i \subset CR_{u,n}} (r_{ui} - \bar{r}_u)(r_{ni} - \bar{r}_n)}{\sqrt{\sum_{i \subset CR_{u,n}} (r_{ui} - \bar{r}_u)^2} \sqrt{\sum_{i \subset CR_{u,n}} (r_{ni} - \bar{r}_n)^2}}$$

	active user
user_1	0.4472136
user_2	0.49236596
user_3	-0.91520863

Ejemplo Paso 2: Predicción del rating



$$pred(u,i) = \bar{r}_u + \frac{\sum_{n \subset neighbors(u)} userSim(u,n) \cdot (r_{ni} - \bar{r}_n)}{\sum_{n \subset neighbors(u)} userSim(u,n)}$$

19/24

Ejemplo Paso 2: Predicción del rating

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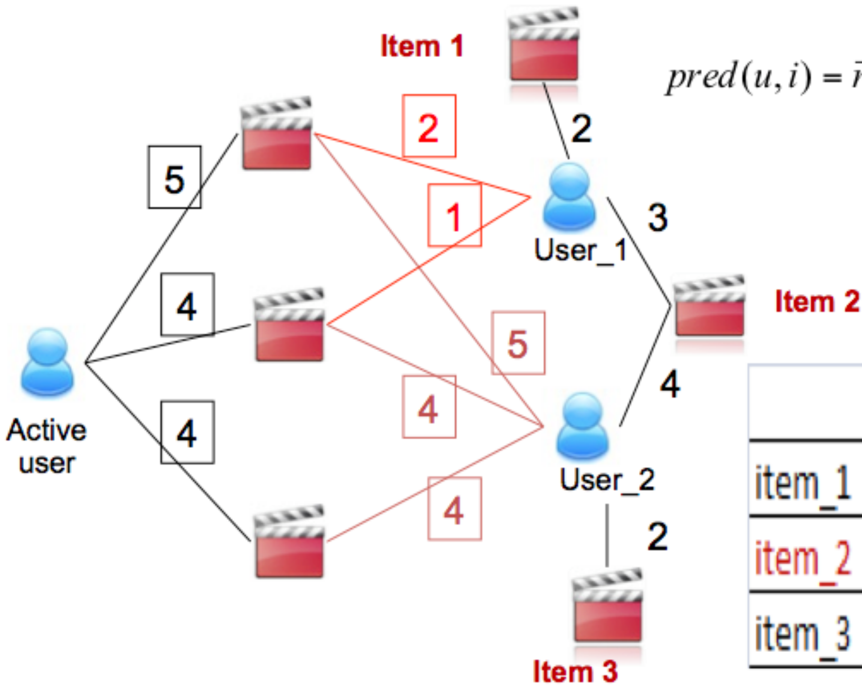
Ejemplo Paso 2: Predicción del rating

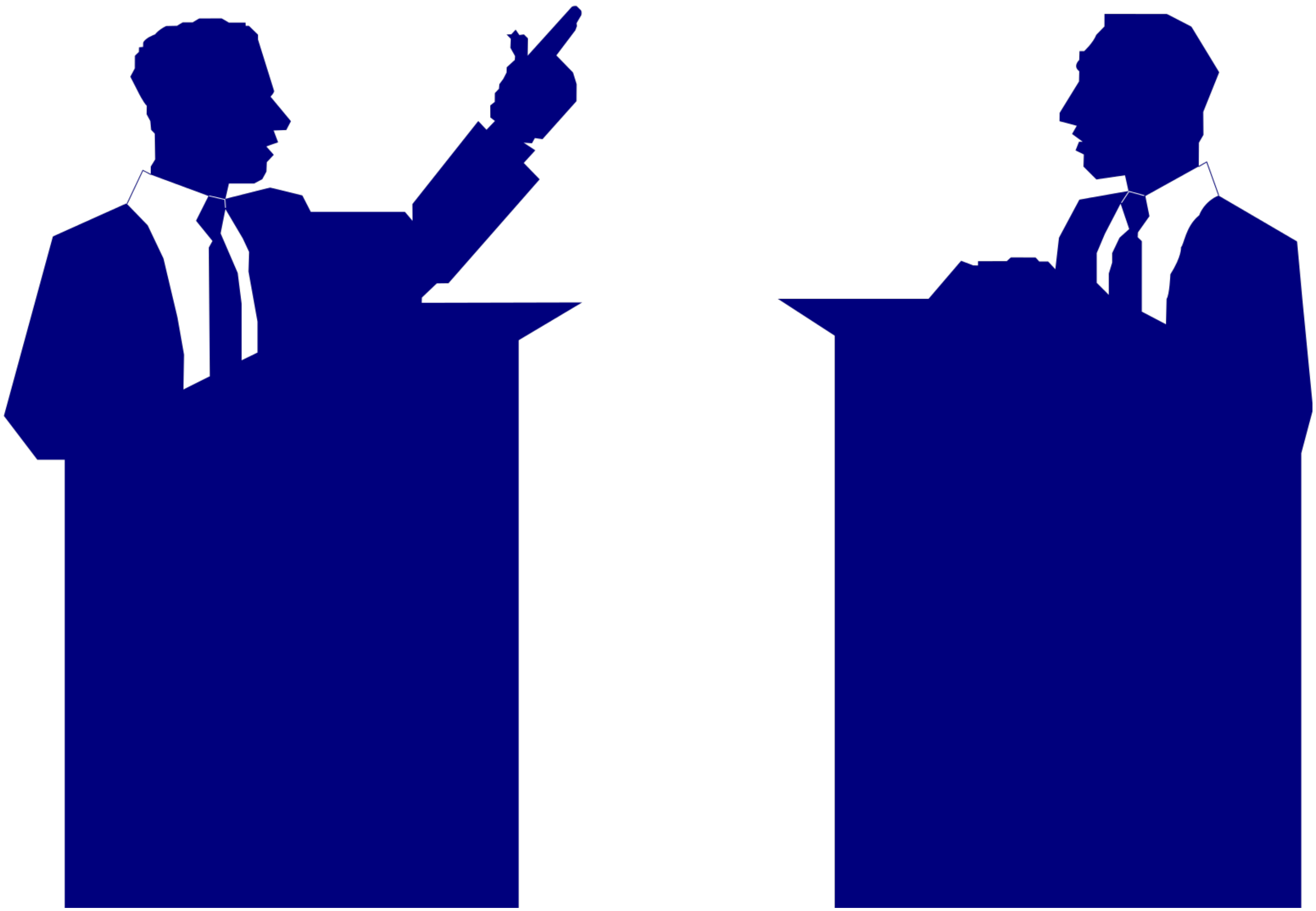


$$pred(u,i) = \bar{r}_u + \frac{\sum_{n \subset neighbors(u)} userSim(u,n) \cdot (r_{ni} - \bar{r}_n)}{\sum_{n \subset neighbors(u)} userSim(u,n)}$$

	User_1	User_2	predicted interest
item_1	2	-	3.262013982
item_2	3	4	3.56331003
item_3	-	2	2.277268083

21/24

¿Discusión: cuáles son los pro y cons de este método?



22/24

¿Discusión: cuáles son los pro y cons de este método?

PROS:

- Very simple to implement
- Content-agnostic
- Compared to other techniques such as content-based, is more accurate. There is also the Item KNN.

CONS:

- Sparsity
- Cold-start
- New Item

Referencias

- 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.
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- Miller, B. N., Albert, I., Lam, S. K., Konstan, J. A., & Riedl, J. (2003, January). MovieLens unplugged: experiences with an occasionally connected recommender system. In Proceedings of the 8th international conference on Intelligent user interfaces (pp. 263-266). ACM.
- Parra, D., & Sahebi, S. (2013). Recommender systems: Sources of knowledge and evaluation metrics. In Advanced Techniques in Web Intelligence-2 (pp. 149-175). Springer Berlin Heidelberg.