Ranking & UB-CF

IIC 3633 - Sistemas Recomendadores

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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.

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

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

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

$$R : \; conjunto\ recomendado\ de\ items$$

$$C : \; conjunto\ de\ usuarios$$

$$S : \; conjunto\ de\ items$$

1. Un Poco de Historia

1.1 En 1992 Xerox PARC Tapestry

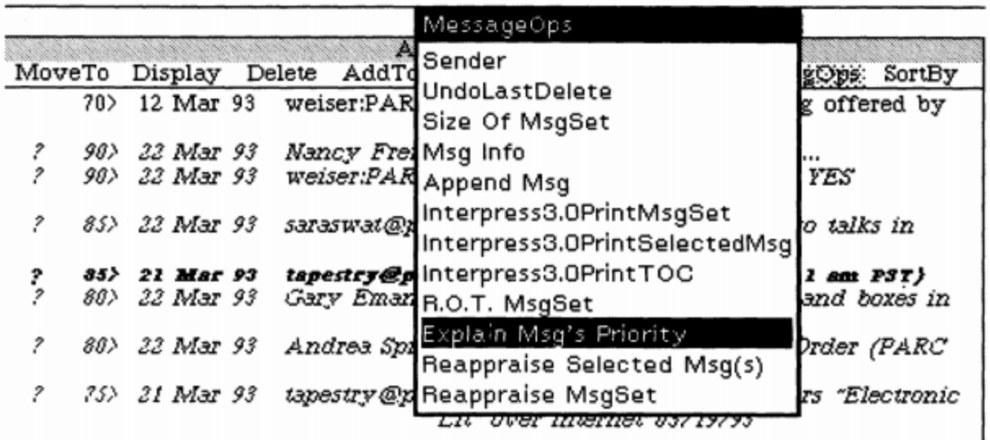


Figure 2. Requesting an explanation for a message's priority.

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

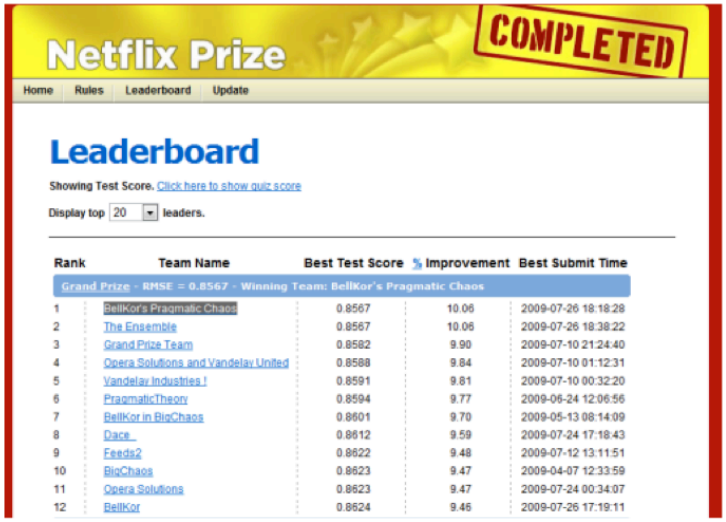
Figure 3. An explanation of priorities assigned to a message by various appraisers.

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

1.2 MovieLens

NetFlix Prize (2007-2009)



Netflix Prize COMPLETED

Home | Rules | Leaderboard | Update

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

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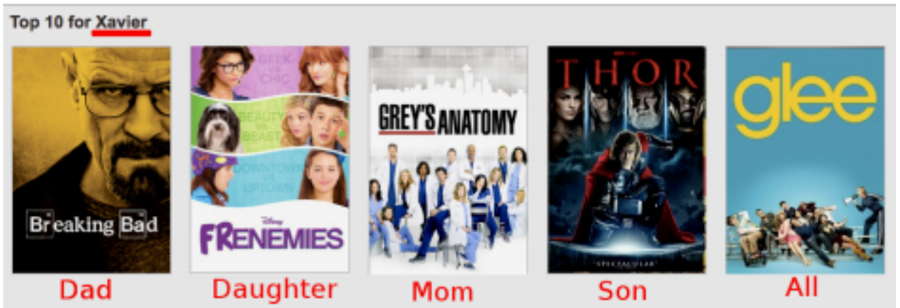
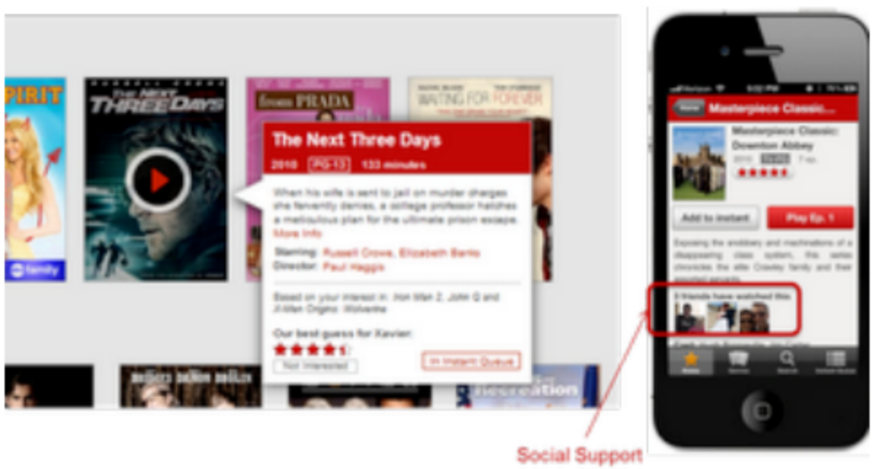
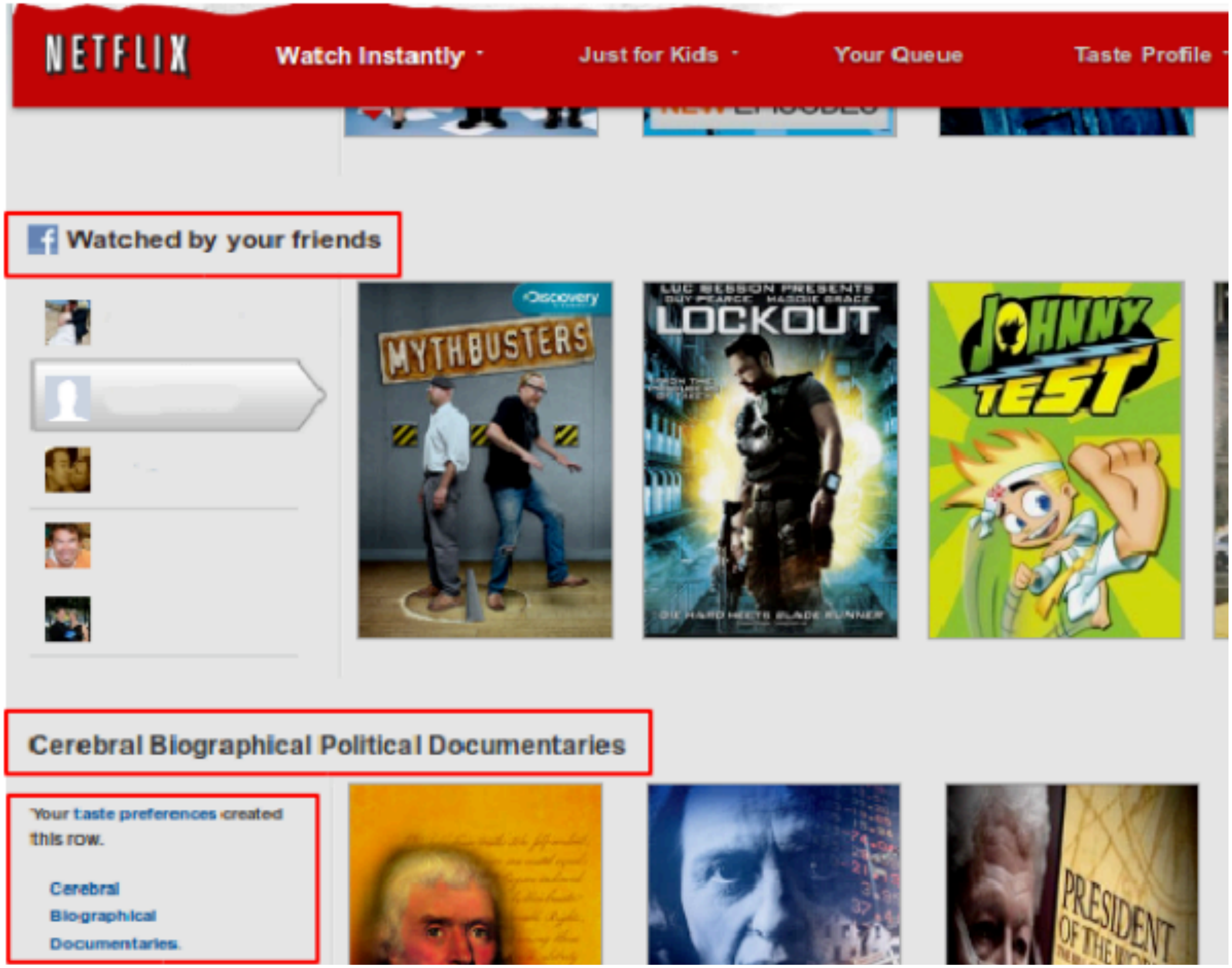
1.3 Netflix en 2012





Link to [Amatriain 2012]

1.3 Netflix en 2012 (continuación)



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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.

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

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%.

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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)

Filtrado Colaborativo basado en el usuario

Dos tareas son necesarias:

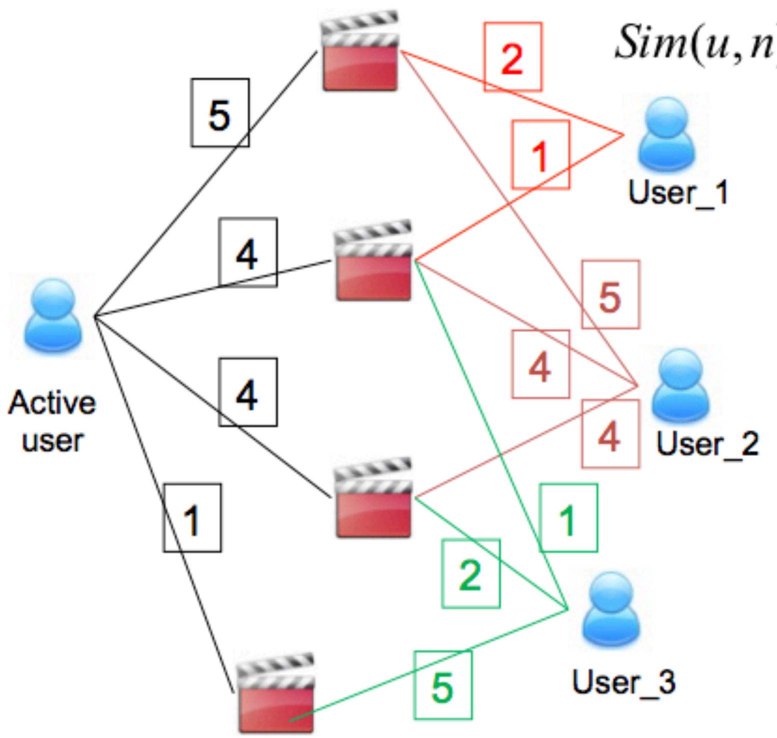
- KNN: Encontrar los K vecinos más cercanos (KNN) al usuario a:

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

- **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



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

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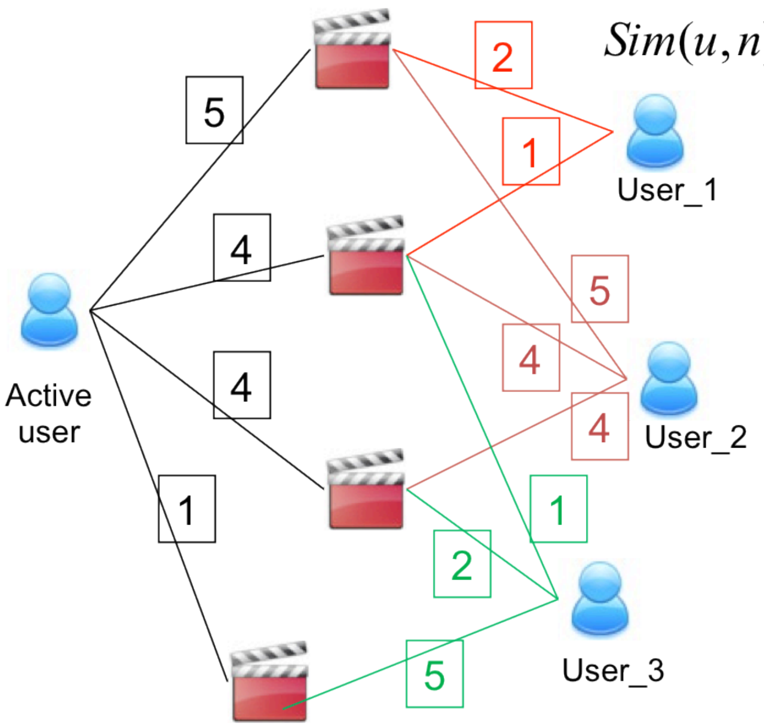
Ejemplo: Correlación de Pearson

SOLUCION

Ejemplo: Correlación de Pearson



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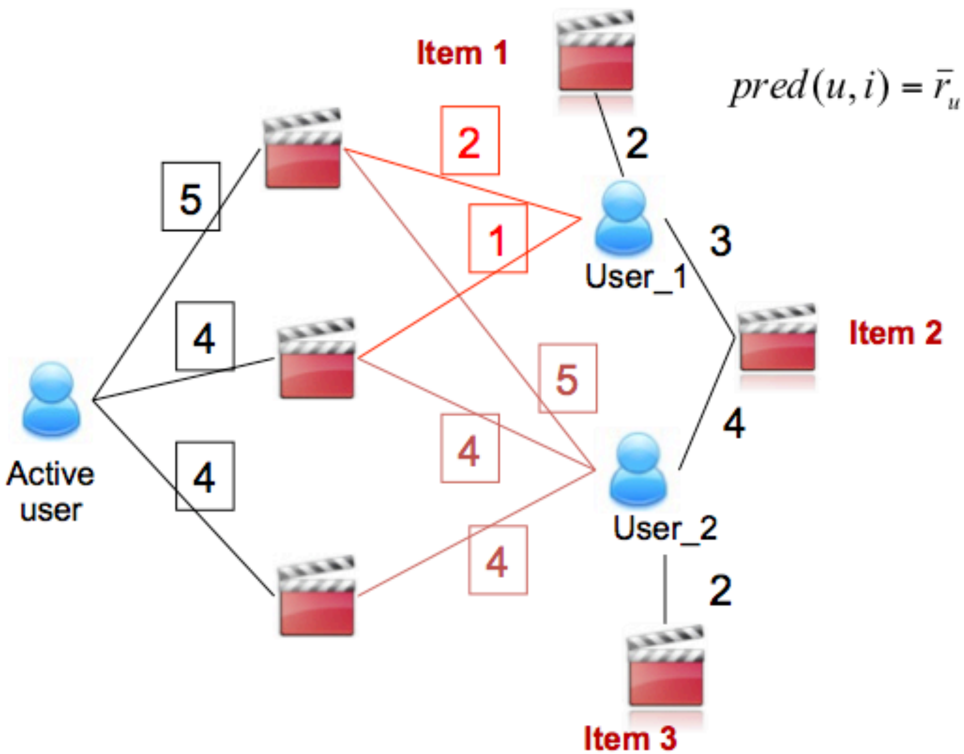
	active user
user_1	0.4472136
user_2	0.49236596
user_3	-0.91520863

Ejemplo Paso 2: Predicción del rating



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

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Ejemplo Paso 2: Predicción del rating

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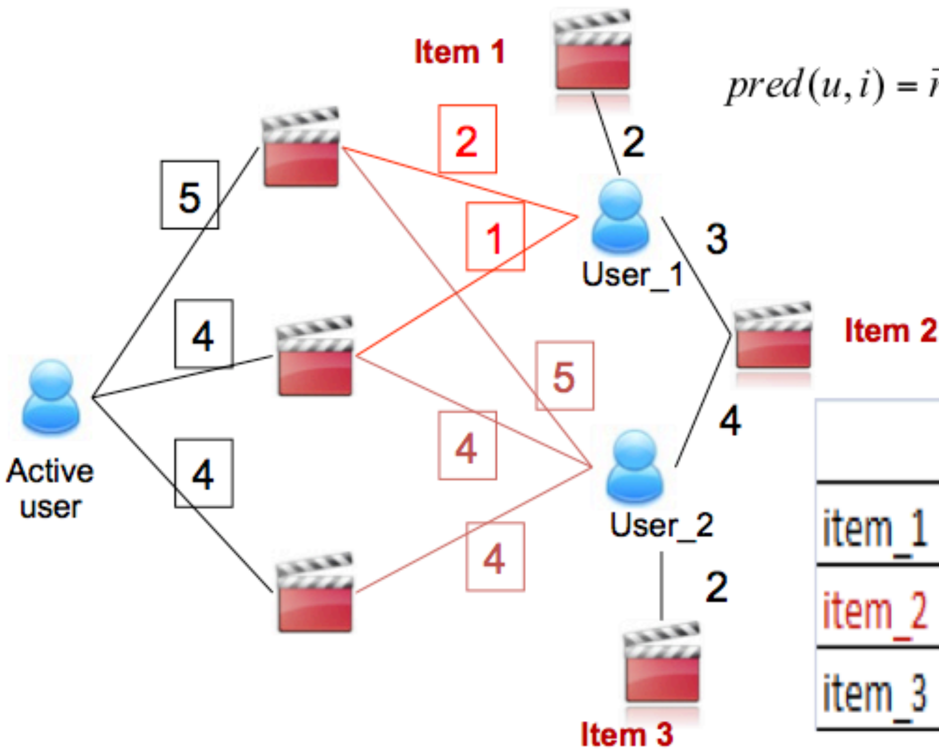

$$pred(u,i) = \bar{r}_u + \frac{\sum_{n \subset neighbors(u)} userSim(u,n) \cdot (r_{ni} - \bar{r}_n)}{\sum_{n \subset neighbors(u)} userSim(u,n)}$$

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

Referencias

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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.