User-Oriented Context Suggestion

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Recomendación Clásica

Users X *Items* → *Ratings*

Recomendación Context-Aware (CARS)

R: Users X *Items* X Contexts → *Ratings*

¿En qué podemos utilizar el contexto?

- Recomendar items utilizando el contexto provee mayor información al modelo.

- *Context Suggestion.*

- *“The right item should be delivered to the right person at the right time and in the right place.”*

¿En qué podemos utilizar el contexto?

Figure 1: Different User Experience in Movie domain

¿En qué podemos utilizar el contexto?

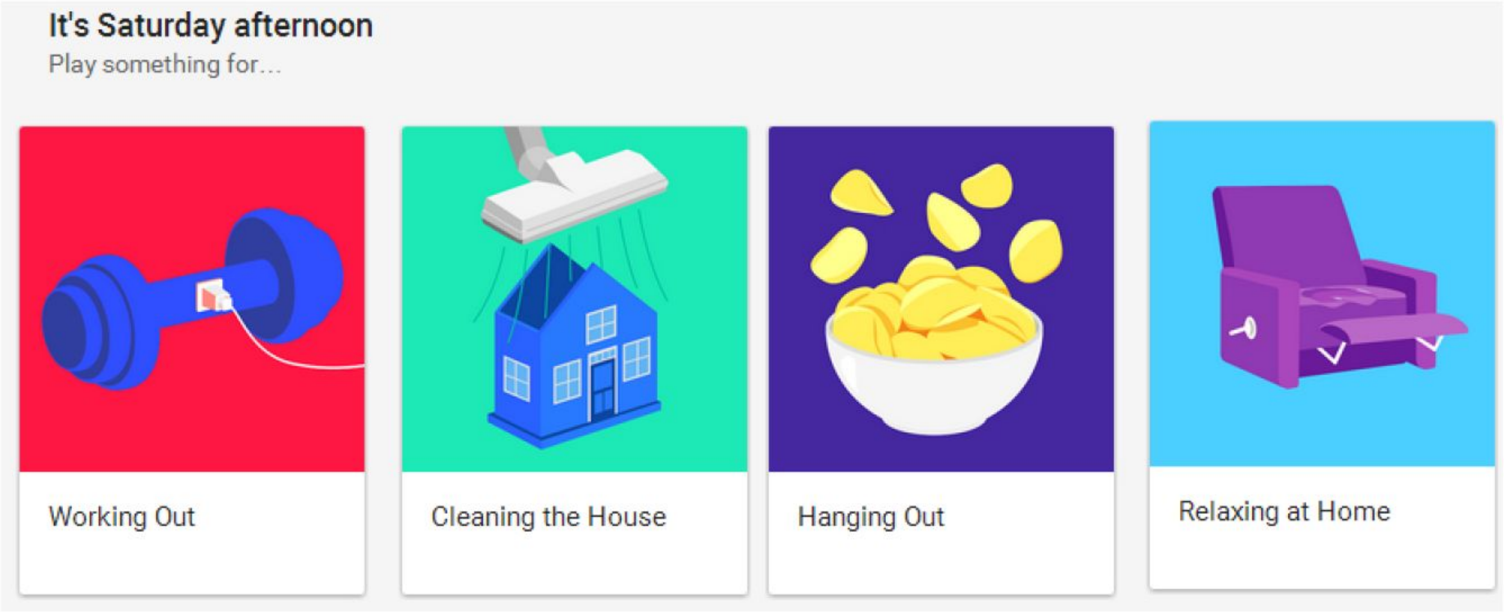


Figure 2: Context Suggestion in Google Music

Posibles usos de Context Suggestion

Table 1: Uses of Context Suggestion

	Inputs	**Outputs**
Context Suggestion	user	a list of contexts
	item	a list of contexts
	user, item	a list of contexts
Context Suggestion As Explanations	user	items + contexts
	item	users + contexts
Bundle Suggestion	user, item	contexts + items
	user, item	contexts + users

Configuraciones del Problema

- *Contextual Dimensions*

- *Contextual Condition*

Configuraciones del Problema

Table 2: Sample of Context-aware Movie Data Set

User	**Item**	**Rating**	**Time**	**Location**
U1	T1	3	Weekend	Home
U1	T2	4	Weekend	Cinema
U1	T1	5	Weekday	Cinema
U2	T2	3	Weekday	Cinema
U2	T3	4	Weekday	Home
U2	T4	5	Weekend	Home

Configuraciones del Problema

- ¿Cómo obtengo la evaluación del usuario al contexto?

- Dos posibles formas
  - Utilizar la frecuencia de uso del contexto
  - Utilizar el promedio de las evaluaciones

Configuraciones del Problema

Table 3: User-Context Rating Data Matrix

	Weekend	Weekday	Home	Cinema
U1	3.5	5	3	4.5
U2	5	3.5	4.5	3

Acercamientos Experimentales

- Se consiguieron datasets en formato **Table 2**
- Los partieron en dos (Training, Testing)
- Las particiones, las transformaron al formato UC rating matrix (**Table 3**)
- Se probaron distintos algoritmos y distintas métricas para probar cuál funcionaba mejor.

Algoritmos

- *Context Average*
- *User-Context Average*
- *Recommenders Based on UC Rating Matrix*
- *Contextual Rating Deviations*
- *UI-Oriented Context Suggestion*

Recommenders Based on UC Rating Matrix

- Utilizaron el *biased matrix factorization* de Koren et al.

$$\widehat{r}_{uc} = \mu + b_u + b_c + p_u^T q_c$$

Contextual Rating Deviations

- Utilizan algoritmos diseñados para *Context Aware*
- *Context Aware Matrix Factorization (CAMF)*
- *CAMF_C **(2)***
- *CAMF_CU **(3)***

Contextual Rating Deviations

$$\widehat{r}_{uic_1c_2...c_N} = \mu + b_u + b_i + \sum_{j=1}^{N} CRD(c_j) + p_u^T q_i \qquad (2)$$

$$\widehat{r}_{uic_1c_2...c_N} = \mu + \sum_{j=1}^{N} CRD(c_j, u) + b_i + p_u^T q_i \qquad (3)$$

UI-Oriented Context Suggestion

Table 5: Predictions By UI-Oriented Context Suggestion

User	Item	Weekend	Weekday	Home	Cinema
U1	T1	3	5	3	4
U2	T2	5	3	4	3
U1	T3	3	4	4	4
U2	T4	4	4	3	3

UI-Oriented Context Suggestion

Table 6: User-Context Predictions

	Weekend	Weekday	Home	Cinema
U1	3	4.5	3.5	4
U2	4.5	3.5	3.5	3

Evaluación y Resultados

Datasets

Table 4: Descriptions of Multidimensional Context-aware Data Sets

	Restaurant	Music	LDOS-CoMoDa	Frappe
# of users	50	42	112	957
# of items	40	139	1232	4082
# of ratings	2,309	3,938	2294	87,580
rating scale	1-5	1-5	1-5	Raw frequency
rating sparsity	9.62E-02	7.49E-06	8.12E-07	3.11E-04
# of context dimensions	2	8	6	3
# of context conditions	7	34	32	12
context dimensions	Time, Location	DrivingStyle, Landscape, Mood, NaturalPhenomena, RoadType, Sleepiness, TrafficConditions, Weather	time, location, dayOfWeek, mood, dominantEmo, endEmo	Time of the day, Day of the week, Location

Evaluación y Resultados

Datasets

Table 7: Data Description of UC Rating Matrix

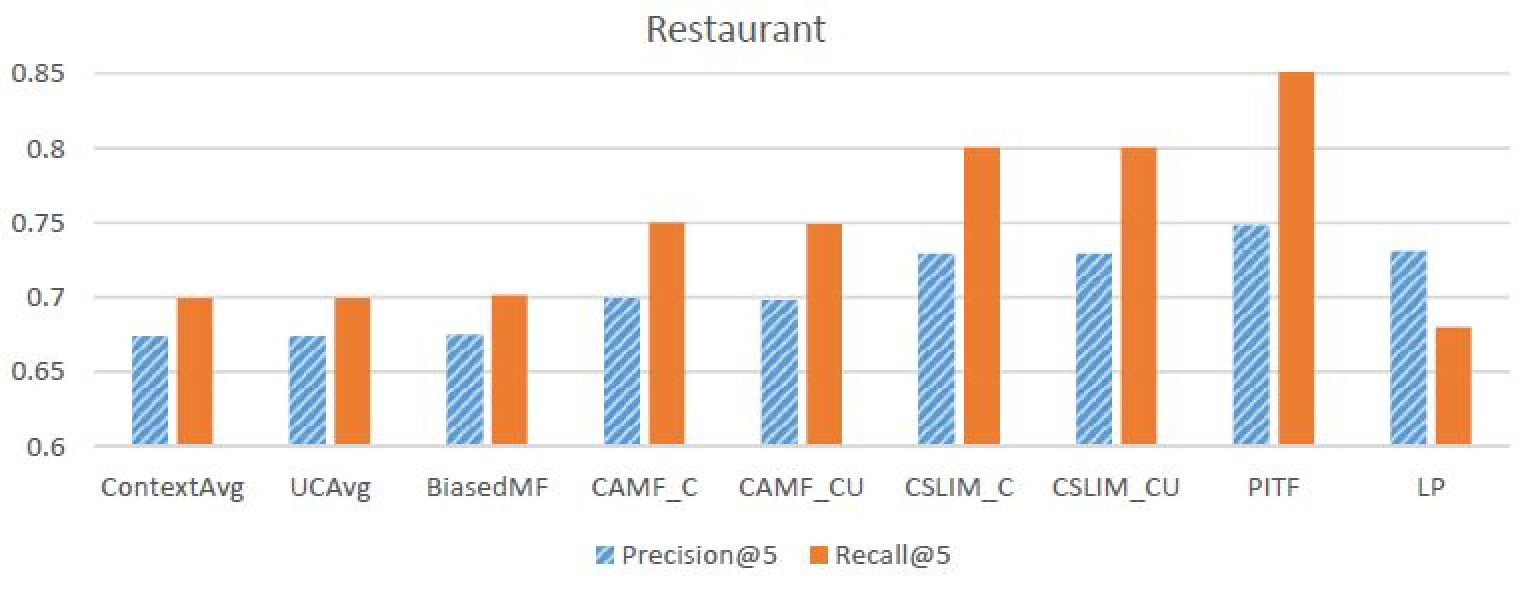
	Restaurant	Music	LDOS-CoMoDa	Frappe
# of users	50	42	112	957
# of conditions	7	34	32	12
# of ratings	327	1015	1484	6681
rating density	93.4%	71.1%	41.4%	58.1%
rating density by context	14.3%	2.9%	3.0%	8.3%

Evaluación y Resultados

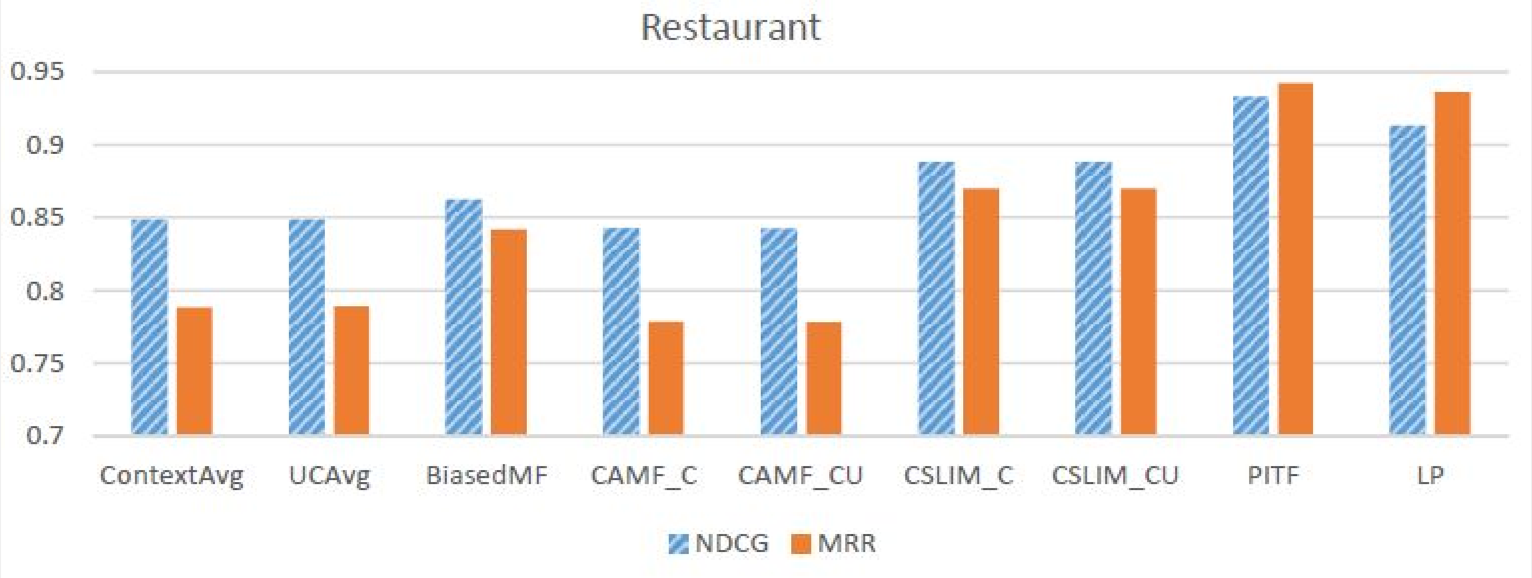
Evalaución

- *5-fold cross-validation*
- *Precision@5 vs Recall@5*
- *NDCG vs MRR*

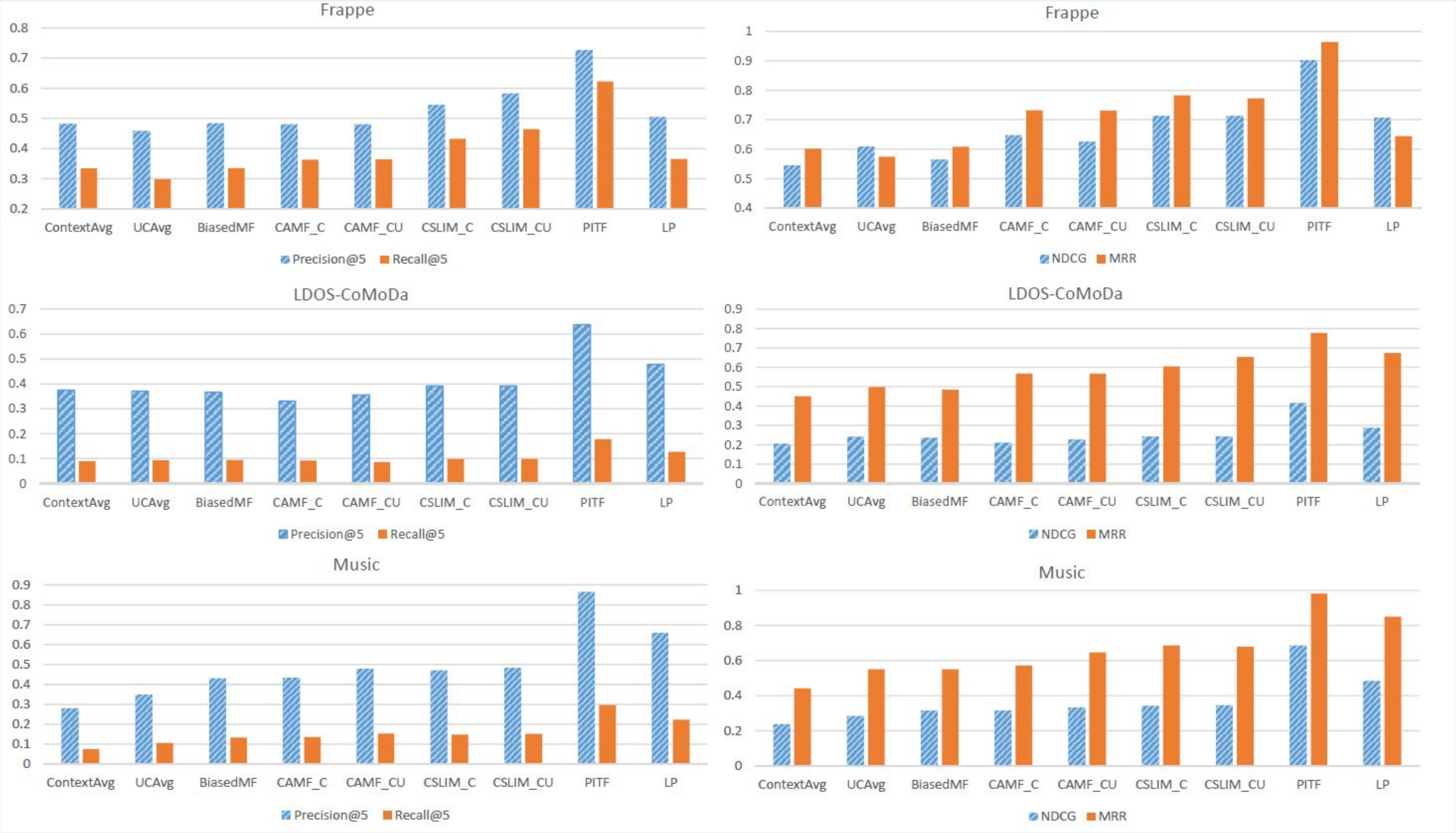
Evaluación y Resultados



Evaluación y Resultados



Evaluación y Resultados



Conclusiones

- PITF es el mejor algoritmo hasta el momento
- *“user-personalization is required in the task of context suggestion”*
- *“Context Suggestion is still a novel and promising research direction”*

Referencias

User-Oriented Context Suggestion
https://www.researchgate.net/publication/303680796_User-Oriented_Context_Suggestion

Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix factorization techniques for recommender systems. Computer IEEE Magazine, 42(8), 30-37.