Recomendación Contextual

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Sistemas Recomendadores
IIC 3633

2do Semestre 2015

Agenda Semestral

6 - 8 Oct	User centric evaluation + User interfaces	Prof. Denis Parra
13 - 15 Oct	Context-aware recommenders / social + location	Prof. Denis Parra
20 - 22 Oct	Active Learning in Recommender Systems	Javier Machin
27 - 29 Oct	Reinforcement Learning Recommender Systems	Gabriel della Maggiora
3 - 5 Nov	Graph-based recommendation	Juan Pablo Salazar y Christopher Arenas
10 - 12 Nov	Applications: music	Miguel Fadic
17 - 19 Nov	Modelos graficos probabilisticos para sistemas recomendadores	Laura Cruz (invitada)

Temas de Recomendación por Revisar

- Evaluación centrada en el usuario (transparency, explainability, user control, etc.)
- Interfaces Gráficas para presentar recomendaciones (conectado con evaluación centrada en el usuario)
- Recomendación basada en contexto (tiempo, ubicación, dispositivo, etc.)
- Recomendaciones considerando relaciones sociales
- Métodos de Recomendación basados en grafos (basados en PageRank, SimRank, por ejemplo)

Temas de Recomendación por Revisar II

- Machine Learning
  - Markov Models para modelar secuencias
  - Multiarmed bandits (active/reinforcement learning)
  - Learning to Rank
- Dominios especiales: Música, Educación, Turismo, Dispositivos Móviles
- Recomendaciones a grupos

Idea 1: MovieCity

- Problema: Rankear con Implicit Feedback y Context-aware Recommendation
- Opción:
  - Analizar en detalle el dataset
  - Testear varios algoritmos
    - Implicit Feedback (Hu & Koren)
    - Context-aware recommendation (Baltrunas, Karatzoglou, Rendle)

CONTEXTO

- Un factor importante a considerar al realizar recomendaciones

Definiciones

- Information Retrieval:
  - Lawrence (2000) and Maamar (2004) describe scenarios where context could be useful
  - Current shortcoming: Focused on short-term and not long-term information needs
- Marketing and Management: purchasing process dependent upon context such as time (when to deliver experience), spatial (where) and technological (how to deliver) (Prahalad 2004)

Otros Ejemplos de contexto

- Ranganathan & Campbelll (2003) identificaron:
- …context denotes additional information to what is traditionally represented in a user model, such as:
  - demographics or interests, and refers to "physical contexts (e.g., location, time),
  - environmental contexts (weather, light and sound levels),
  - informational contexts (stock quotes, sports scores),
  - personal contexts (health, mood, schedule, activity),
  - social contexts (group activity, social activity, whom one is in a room with),
  - application contexts (emails, websites visited) and
  - system contexts (network traffic, status of printers)"

Cómo Obtener Información Contextual

- Explícitamente: Encuestas
- Implicitamente: Información de dispositivos (hora, ubicación, temperatura, etc)
- Infiriendo: e.g. distintos usuarion que está viendo películas con la misma cuenta de movie city (Naïve Bayes o redes Bayesianas, Palmisano et al. 2008)

Ejemplos de Recomendación Contextual en Ambientes Ubicuos

- Para Shilit et al. (1994) los aspectos más importantes son:
  - Dónde estás (where you are),
  - Con quién estás (who you are with), y
  - Qué recursos hay alrededor (what resources are nearby.)

Definiciones II

- Contexto es definido de distintas formas en diferentes disciplinas (Adomavicious & Tuzhilin)
- Data Mining: context is sometimes defined as those events which characterize the life stages of a customer and that can determine a change in his/her preferences, status, and value for a company:
  – new job,
  – the birth of a child,
  – marriage, divorce,
  – and retirement

Definiciones III

- E-commerce Personalization
  - Intent of buying (Palmisano et al. (2008) built separate user profiles depending on context)
- Ubiquitous and mobile context-aware systems :
  - location, but also date, season (Brown et al. 1997, 2005) and temperature, emotional status

Resumen y características

- Observable / Parcialmente / No Observable
- Estático / Dinámico

How Contextual Factors Change	Knowledge of the RS about the Contextual Factors		
	Fully Observable	Partially Observable	Unobservable
Static	Everything Known about Context	Partial and Static Context Knowledge	Latent Knowledge of Context
Dynamic	Context Relevance Is Dynamic	Partial and Dynamic Context Knowledge	Nothing Is Known about Context

Figure 1. Contextual Information Dimensions.

Adomavicius, G., Mobasher, B., Ricci, F. , & Tuzhilin, A. (2008) Context-Aware Recommender Systems. AAAI Magazine.

Paradigmas para incorporar contexto

- Técnicas de Pre-Filtrado
- Técnicas de Post-Filtrado
- Modelado Contextual

Paradigmas para incorporar contexto

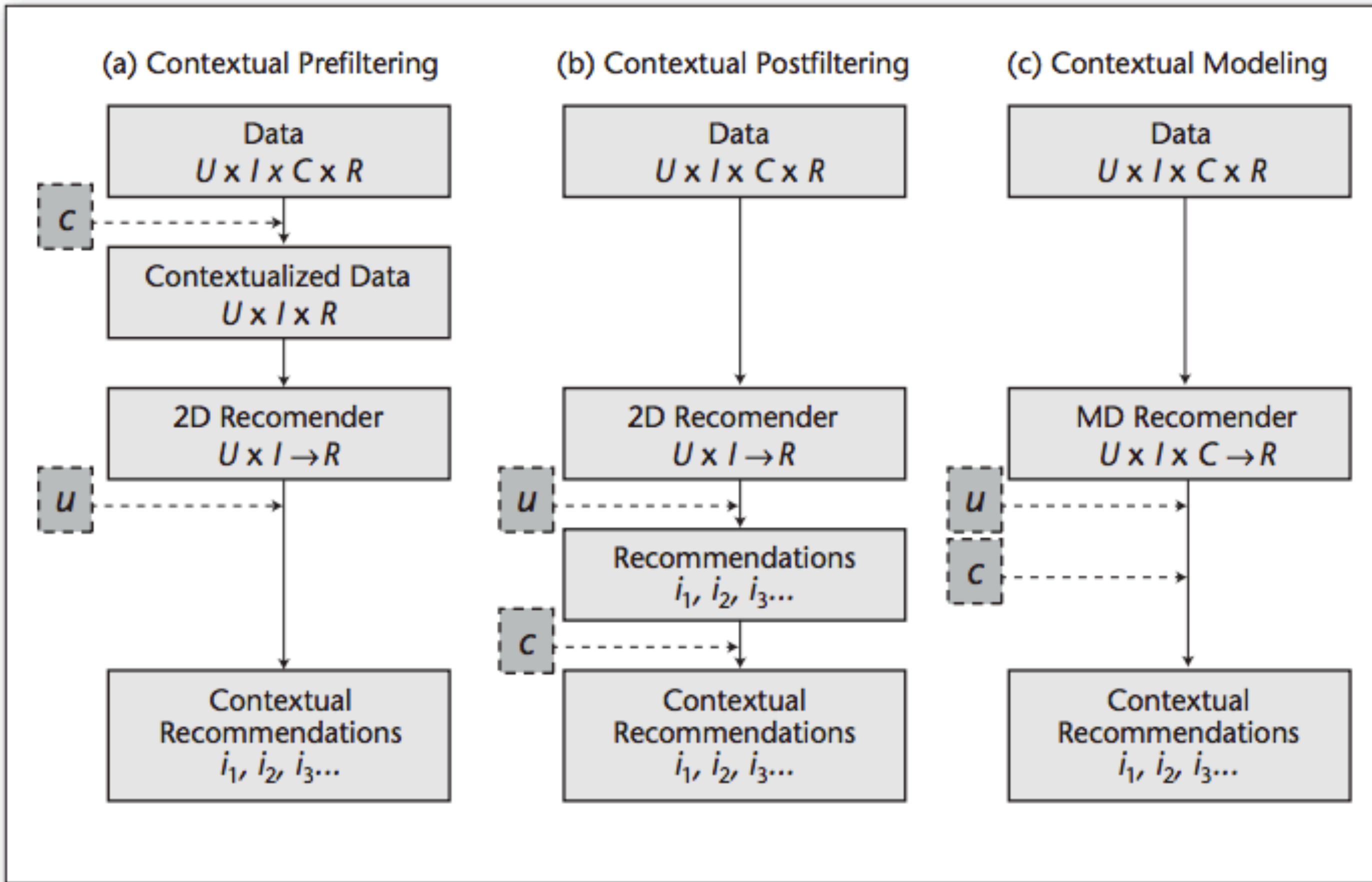
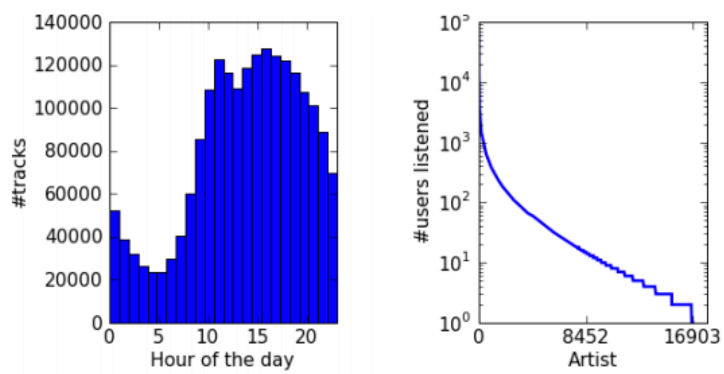


Figure 2. Paradigms for Incorporating Context in Recommender Systems.

Adomavicius, G., Mobasher, B., Ricci, F. , & Tuzhilin, A. (2008) Context-Aware Recommender Systems. AAAI Magazine.

Caso de Pre-Filtrado

Baltrunas, L., & Amatriain, X. (2009, October). Towards time-dependant recommendation based on implicit feedback. In Workshop on context-aware recommender systems (CARS'09)



(a) #tracks per hour. (b) Popularity of an artist.

Figure 1: Last.fm data information

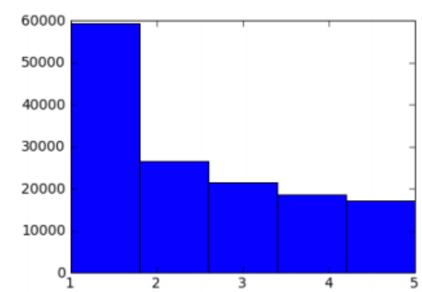
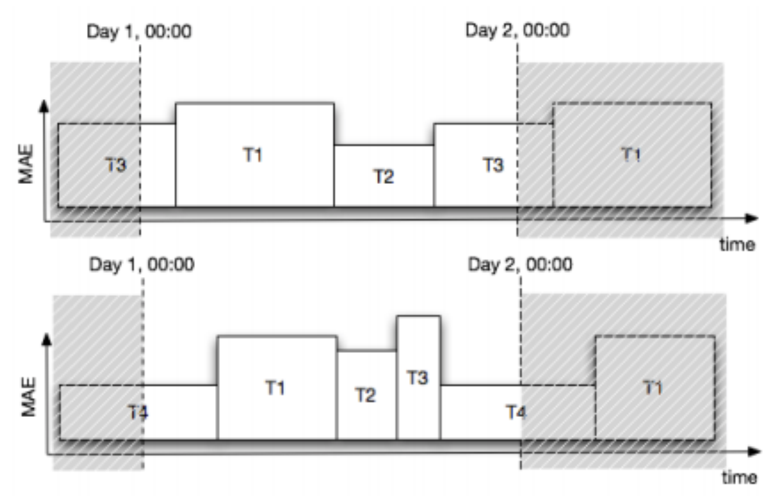


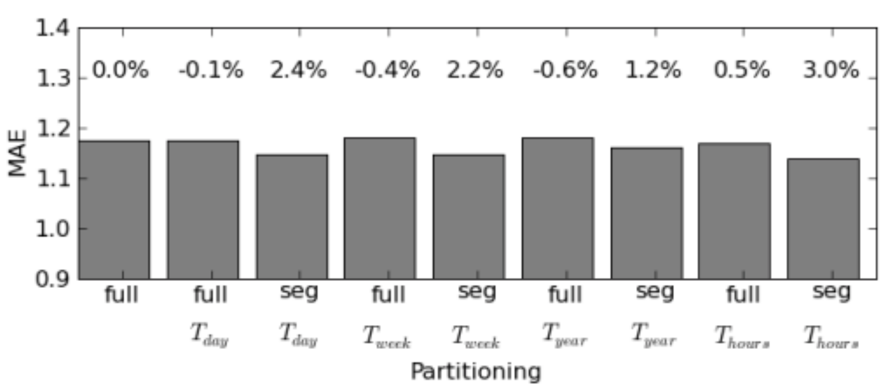
Figure 2: Rating distribution for the data set.

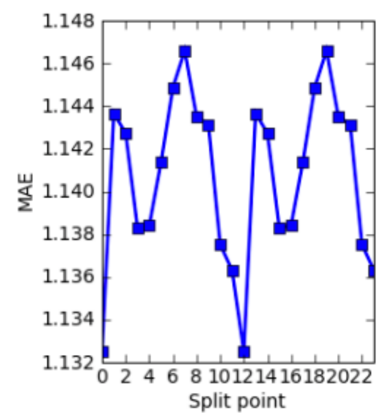
Dataset/Evaluación

#users	338
#tracks	322871
#artists	16904
#entries	1970029
#ratings (after normalization)	143091
average mean repetition of a track for a user	3.09
average mean repetition of an artist for a user	19.87

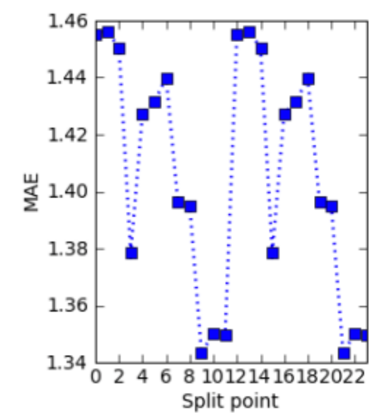
Table 1: Summary of the data set







(a) True error E



(b) Cross-validation

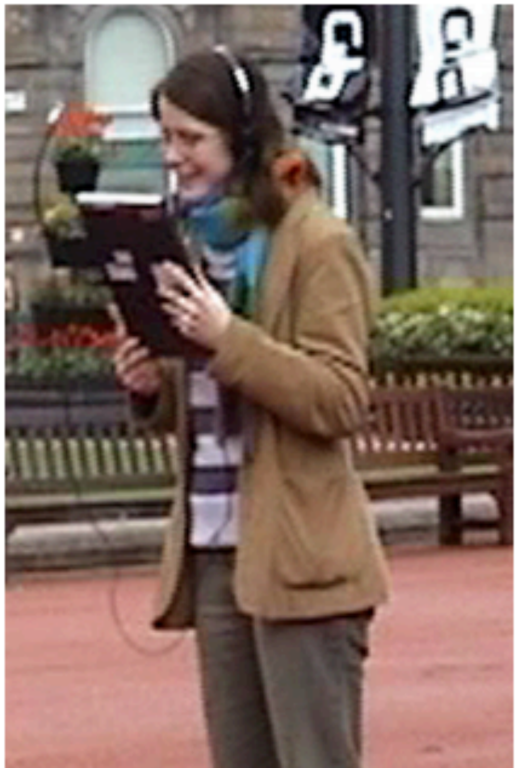
Caso de Estudio I: Sharing the Square (2005)

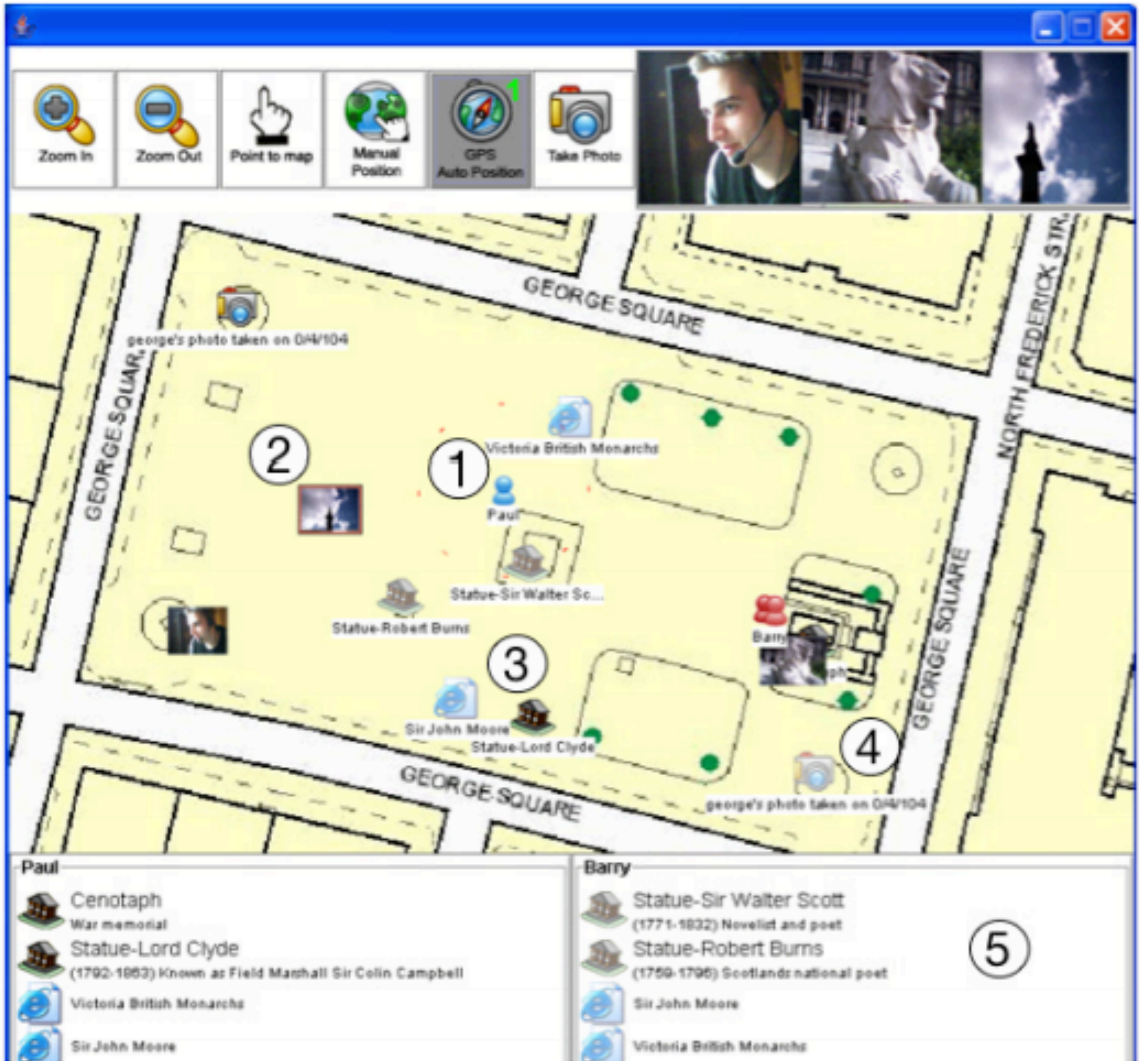
Sharing the square: Collaborative Leisure in the City Streets

Barry Brown[1], Matthew Chalmers[1], Marek Bell[1], Malcolm Hall[1], Ian MacColl[2], Paul Rudman[1]
[1]Department of Computing Science, University of Glasgow, Glasgow, UK [2]School of IT and Enginnering, University of Queensland, Brisbane, Australia

Abstract. Sharing events with others is an important part of many enjoyable experiences. While most existing co-presence systems focus on work tasks, in this paper we describe a lightweight mobile system designed for sharing leisure. This system allows city visitors to share their experiences with others both far and near, through tablet computers that share photographs, voice and location. A collaborative filtering algorithm uses historical data of previous visits to recommend photos, web pages and places to

Sharing the Square (2005) II





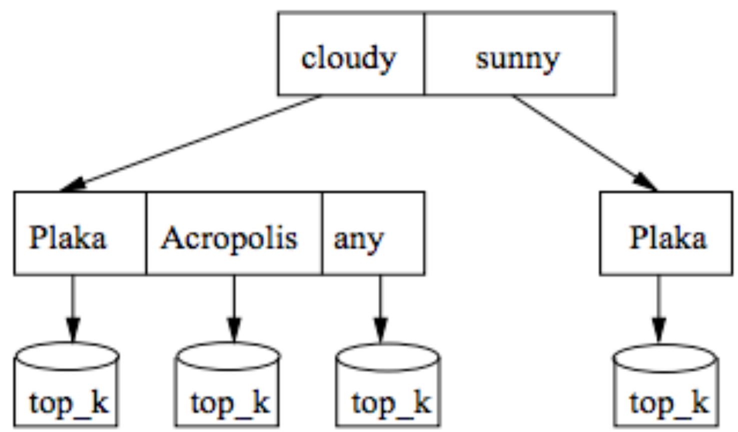
Definiciones

- Databases: Adapt answers of database queries depending on context, Stephanidis (2007), Agrawal (2006), and Mokbel's CareDB (2009)

Query 2 *Look for $Mary's$ most preferable restaurants (in the current context).*

The execution of *Query 2* leads to the execution of the following subqueries (we suppose that $CS(current) = \{Acropolis, sunny\}$):

- *SELECT R.name, FL.score FROM Users U, Restaurants R, $Fact\_Location$ FL, Location L WHERE U.name $='Mary'$ AND U.uid $=$ FL.uid AND R.rid $=$ FL.rid AND L.lid $=$ FL.lid AND current_location $='Acropolis'$;*
  and
- *SELECT R.name, FW.score FROM Users U, Restaurants R, $Fact\_Weather$ FW WHERE U.name $='Mary'$ AND U.uid $=$ FW.uid AND R.rid $=$ FW.rid AND current_weather $='sunny'$;*



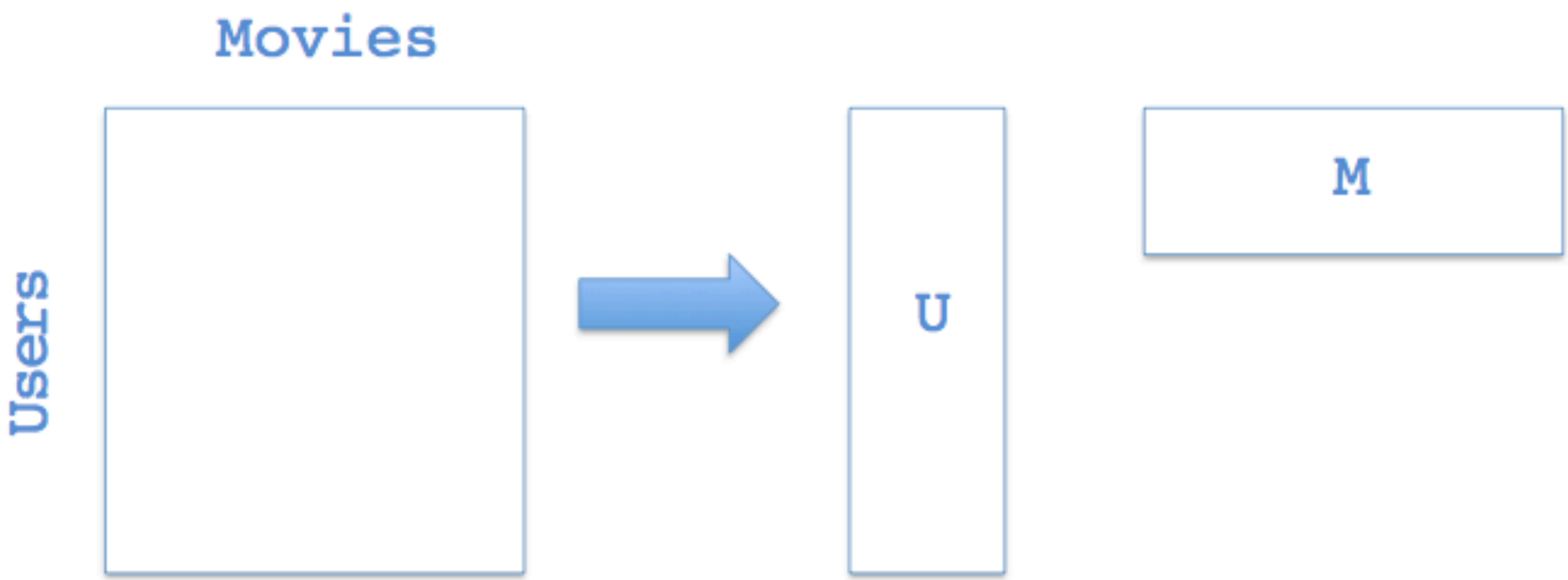
Caso de Modelado Contextual II

- Karatzoglou, A., Amatriain, X., Baltrunas, L., & Oliver, N. (2010, September). Multiverse recommendation: n-dimensional tensor factorization for context-aware collaborative filtering. In Proceedings of the fourth ACM conference on Recommender systems (pp. 79-86). ACM.

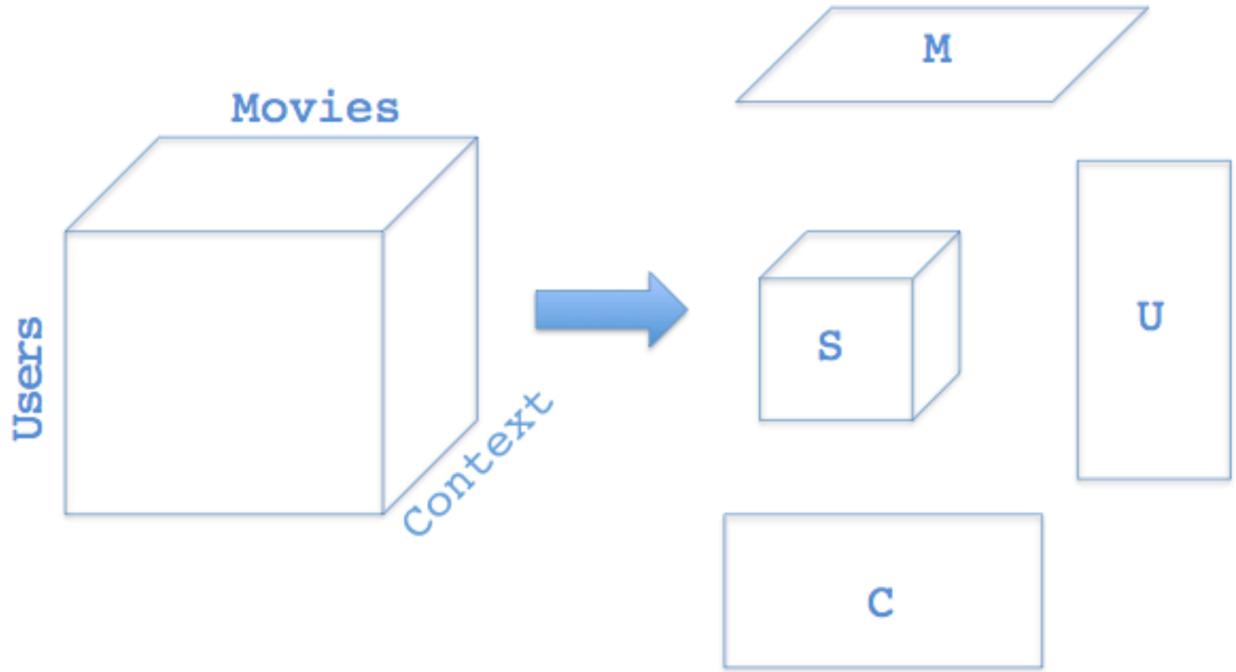
FM Tradicional

Find $U \in R^{n \times d}$ and $M \in R^{d \times m}$ so that $F = UM$

$$\text{minimize}_{U,M} L(F, Y) + \lambda \Omega(U, M)$$



Matriz -> Tensor



$$F_{ijk} = S \times_U U_{i*} \times_M M_{j*} \times_C C_{k*}$$

$$R[U, M, C, S] := L(F, Y) + \Omega[U, M, C] + \Omega[S]$$

$$\Omega[F] = \lambda_M \|M\|_F^2 + \lambda_U \|U\|_F^2 + \lambda_C \|C\|_F^2 \qquad \Omega[S] := \lambda_S \|S\|_F^2$$

Loss Function

- Opción 1: Cuadrado del error

$$l(f, y) = \frac{1}{2}(f - y)^2 \qquad L(F, Y) = \sum_{i}^{n} \sum_{j}^{m} l(f_{ij}, y_{ij})$$

- Opción 2: Error Absoluto

$$l(f, y) = |f - y| \qquad L(F, Y) = \sum_{i}^{n} \sum_{j}^{m} l(f_{ij}, y_{ij})$$

Dataset / Evaluación

$$MAE = \frac{1}{K}\sum_{ijk}^{n,m,c} D_{ijk}|Y_{ijk} - F_{ijk}|$$

Data set	Users	Movies	Context Dim.	Ratings	Scale
Yahoo!	7642	11915	2	221K	1-5
Adom.	84	192	5	1464	1-13
Food	212	20	2	6360	1-5

Table: Data set statistics

Baselines

- Modelos a comparar:

Pre-filtering based approach, (*G. Adomavicius et.al*), computes recommendations using *only* the ratings made in the same context as the target one

Item splitting method (*L. Baltrunas, F. Ricci*) which identifies items which have significant differences in their rating under different context situations.

Con/Sin contexto

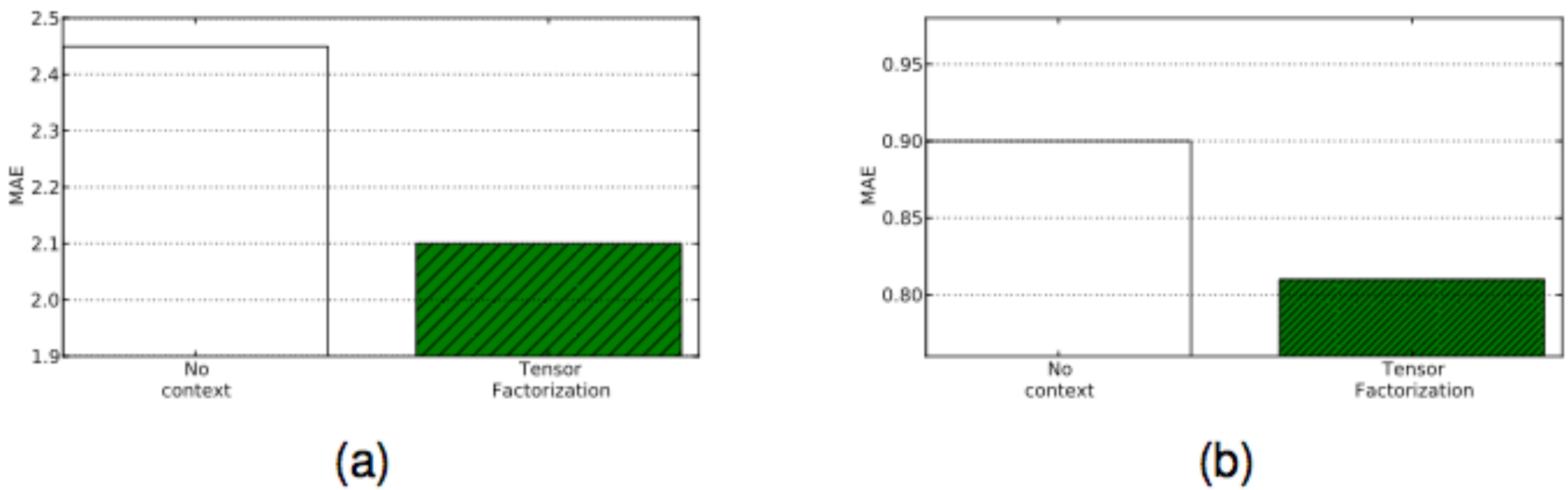


Figure: Comparison of matrix (no context) and tensor (context) factorization on the Adom and Food data.

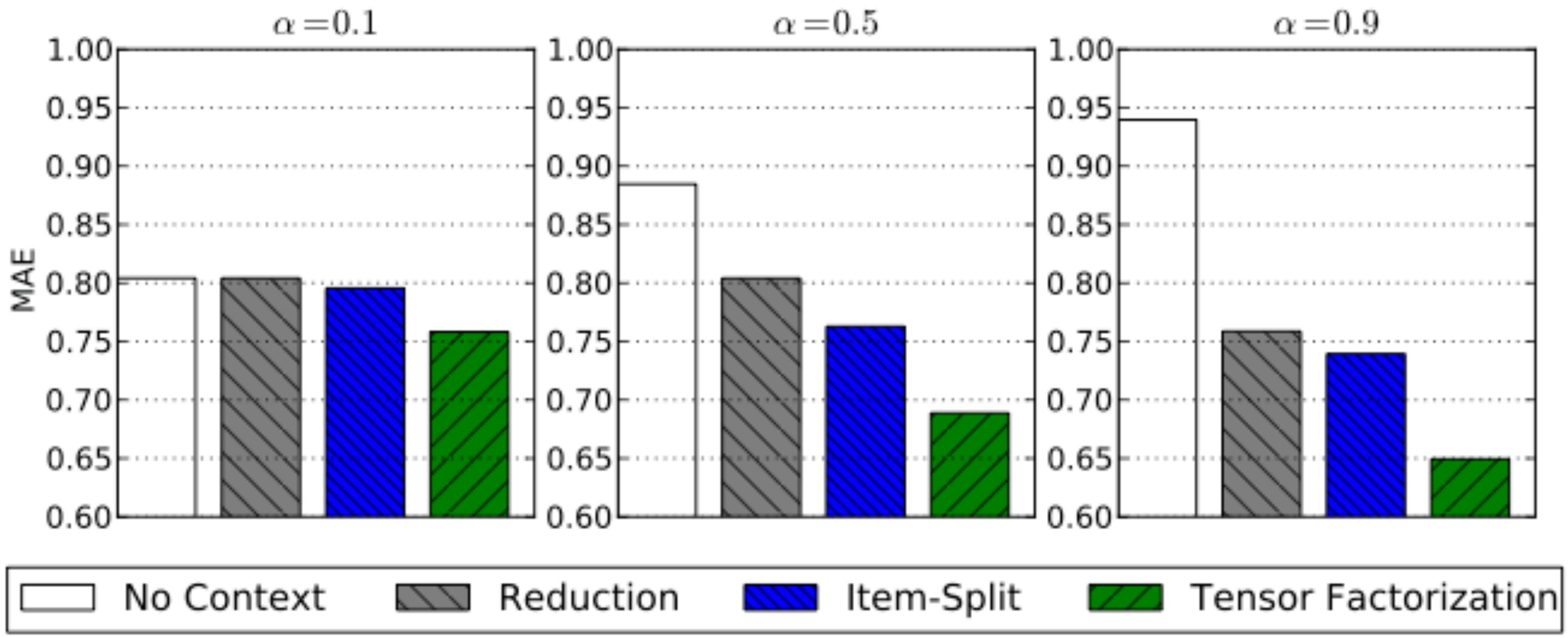
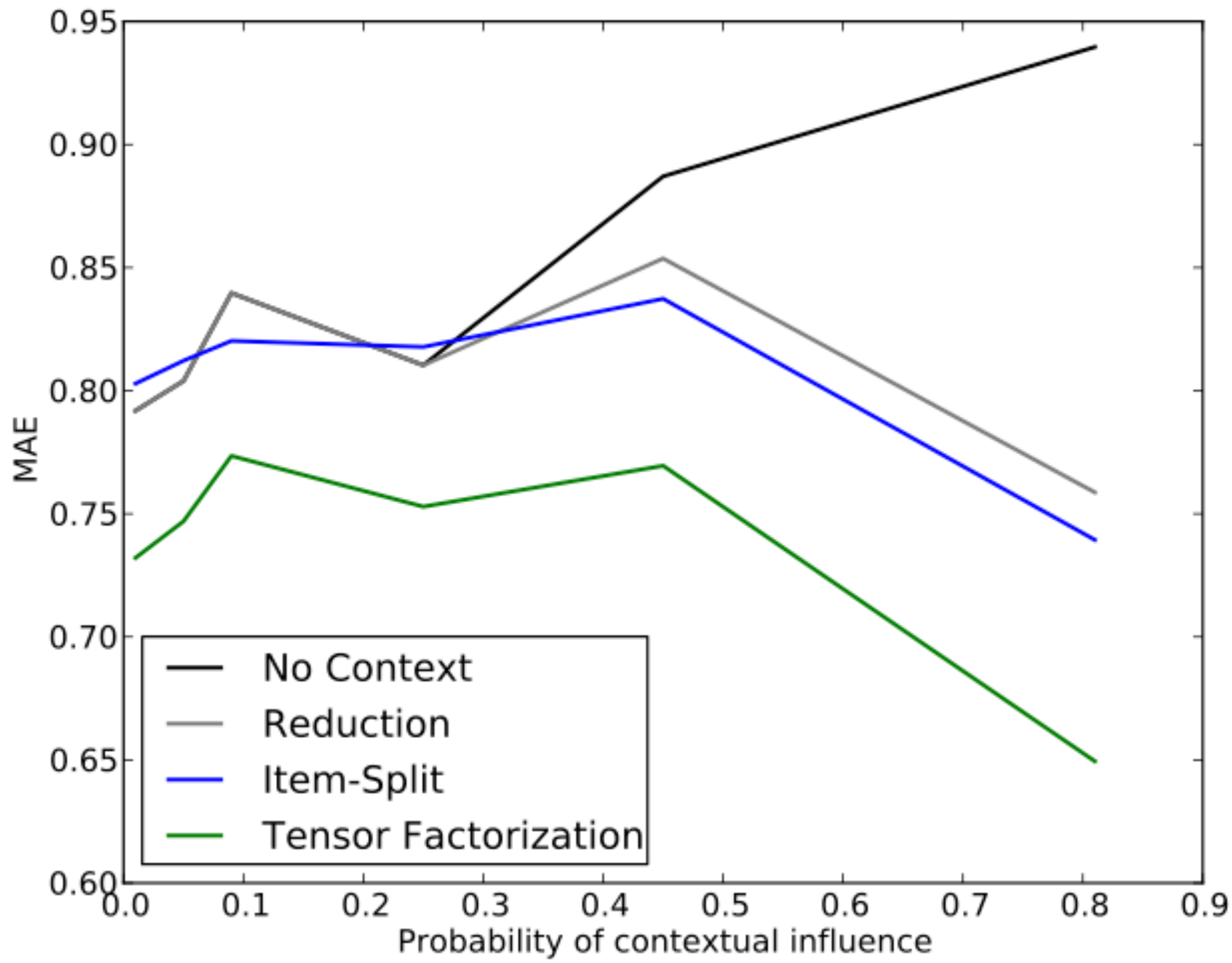


Figure: Comparison of context-aware methods on the Yahoo! artificial data

Wrt Probabilidad de la inf. contextual



En otros dataset

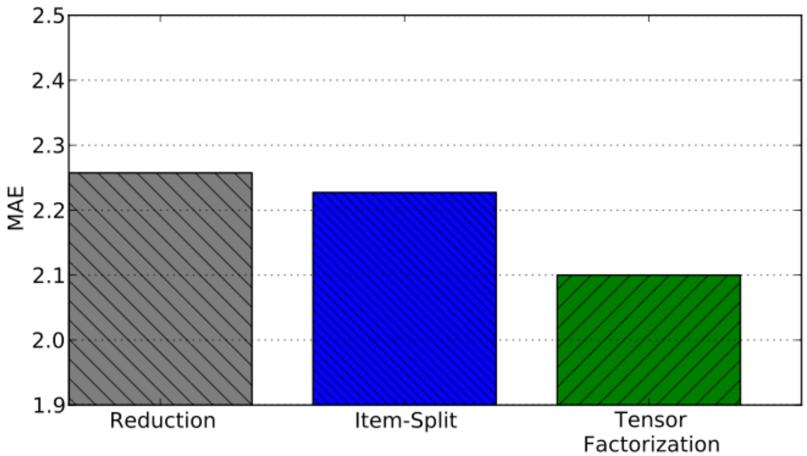


Figure: Comparison of context-aware methods on the Adom data.

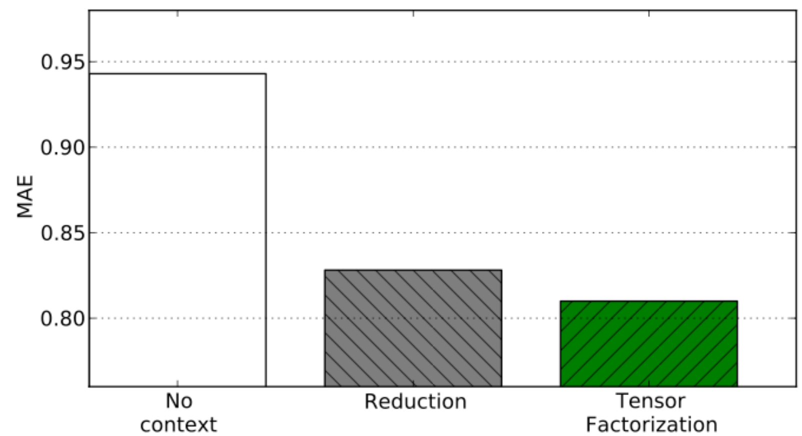


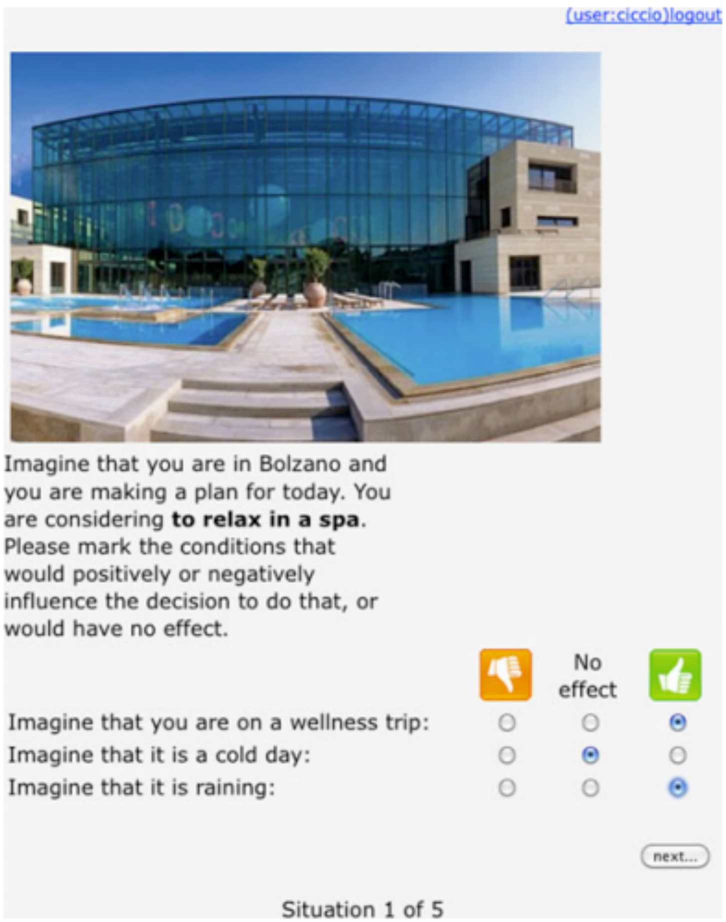
Figure: Comparison of context-aware methods on the Food data.

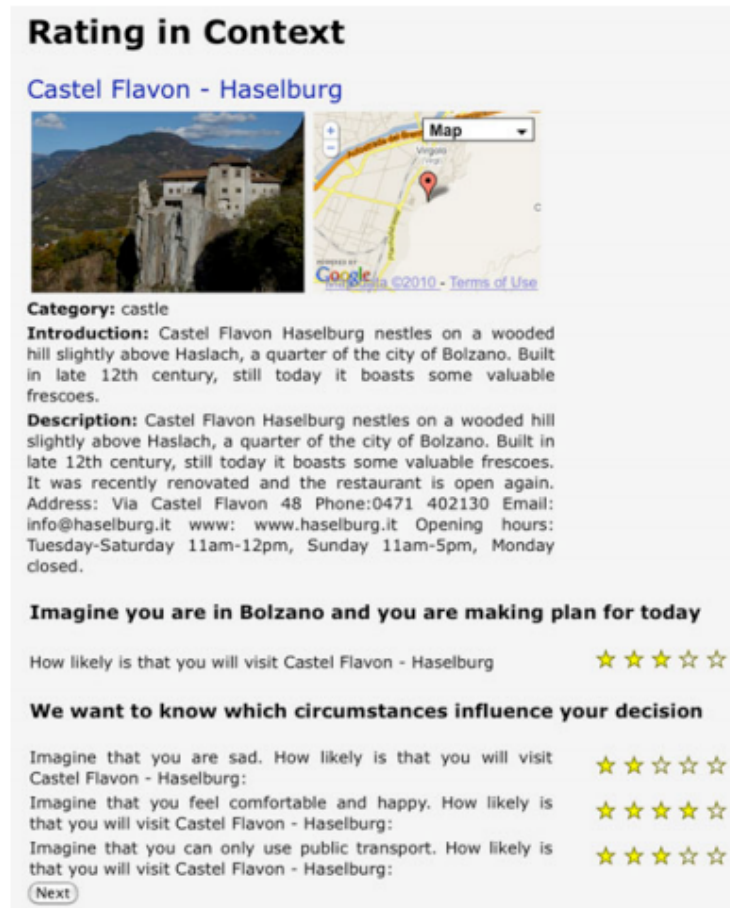
Caso de Estudio III

- Linas Baltrunas, Bernd Ludwig, Stefan Peer, and Francesco Ricci. 2012. Context relevance assessment and exploitation in mobile recommender systems. Personal Ubiquitous Comput. 16, 5 (June 2012), 507-526. DOI=10.1007/s00779-011-0417-x

Turismo: Points of Interest

- Preference elicitation





Contexts Used

Table 1 Context factors used in the web survey

Context factor	Conditions	Context factor	Conditions	Context factor	Conditions	Context factor	Conditions
Budget	Budget traveler	Crowdedness	Not crowded	Companion	With girl/ boyfriend	Season	Spring
	High spender		Crowded		With family		Summer
	Price for quality		Empty		With children		Autumn
Time of the day	Morning time		Health care		Alone		Winter
	Afternoon	Travel goal	Cultural experience		With friends	Transport	Public transport
	Night time		Scenic/landscape	Weather	Snowing		No means of transp.
Day of the week	Weekend		Education		Clear sky		Bicycle
	Working day		Hedonistic/fun		Sunny		Car
Distance to POI	Near by		Social event		Rainy	Temperature	Warm
	Far away		Religion		Cloudy		Cold
Knowledge	New to city		Activity/sport	Mood	Happy		Hot
About area	Citizen of the city		Visiting friends		Active	Time available	Half day
	Returning visitor		Business		Sad		More than a day
							One day

Opciones de la interfaz

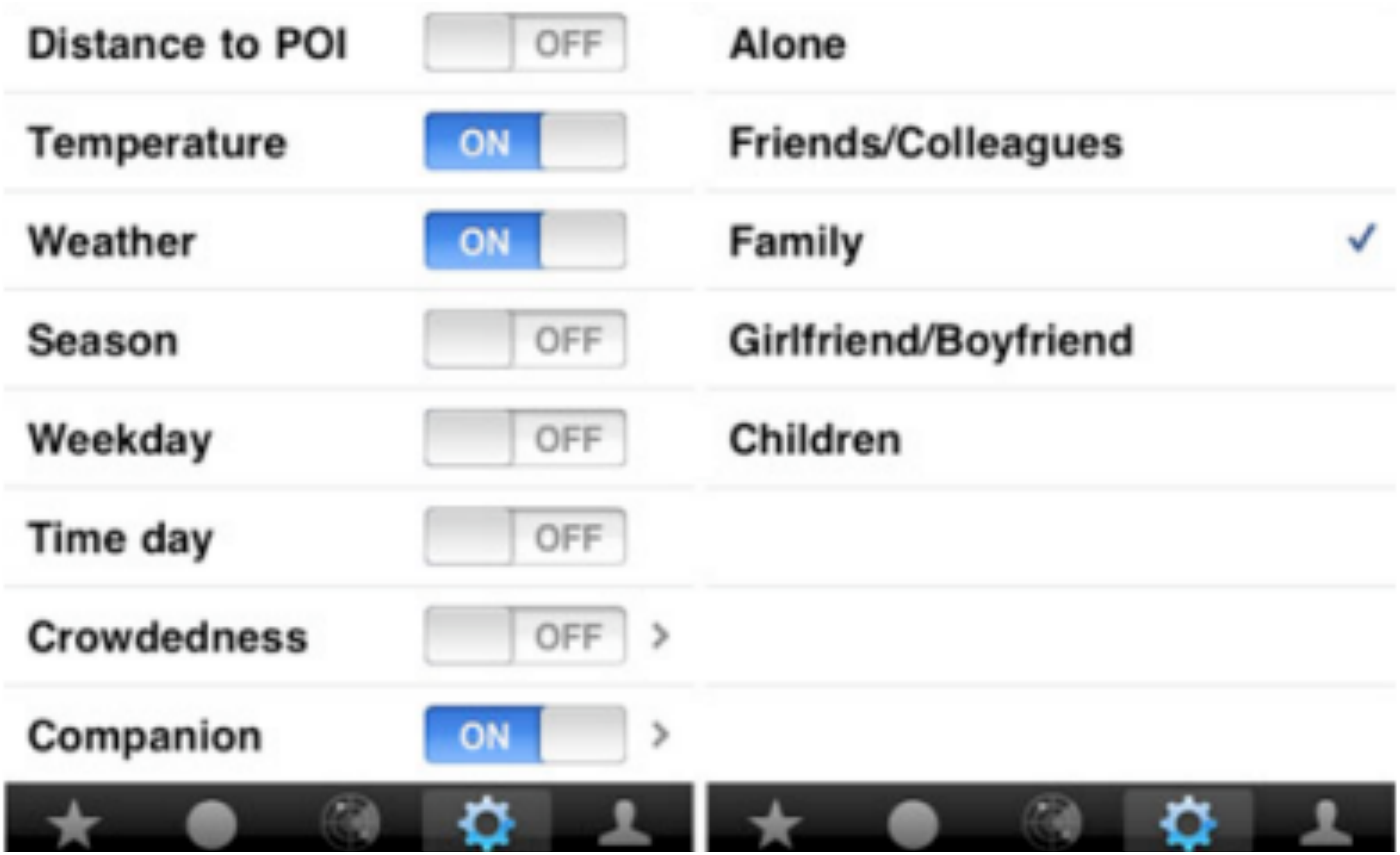


Fig. 9 Details for a suggestion

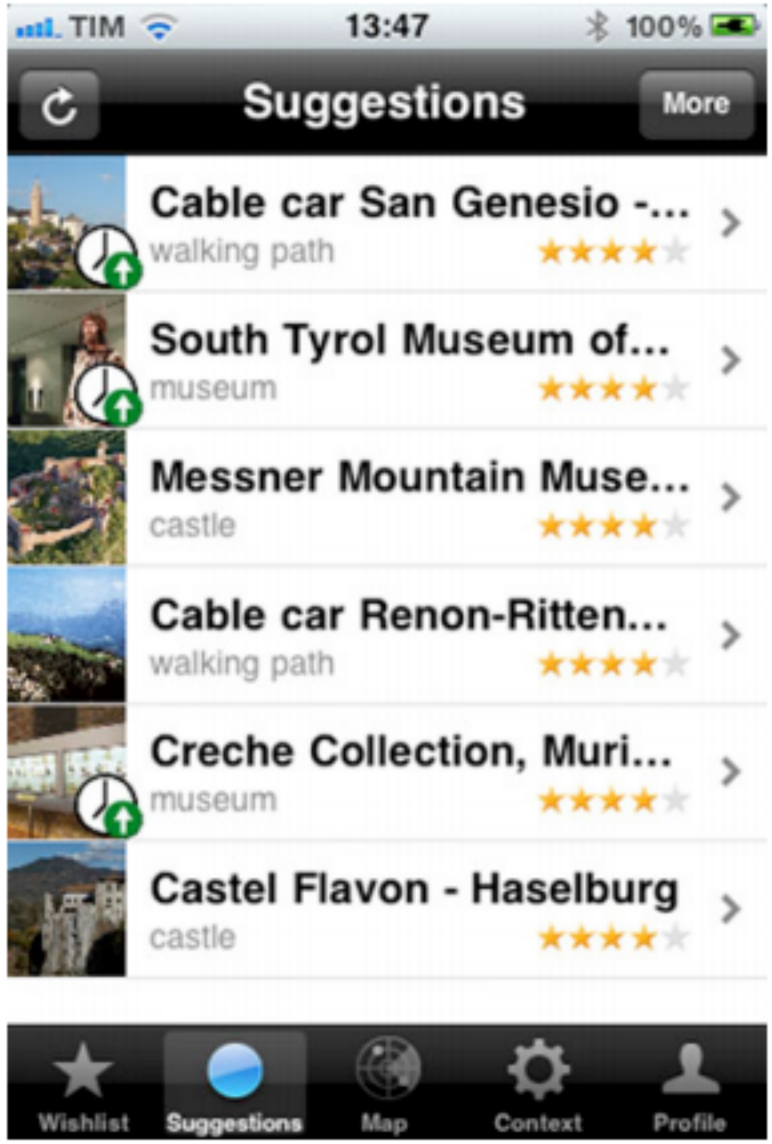
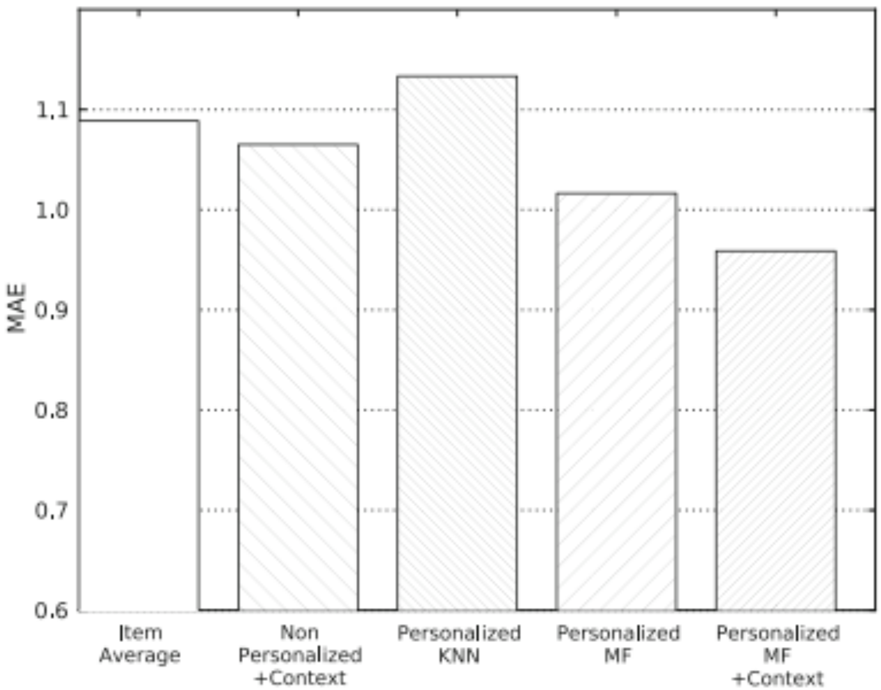
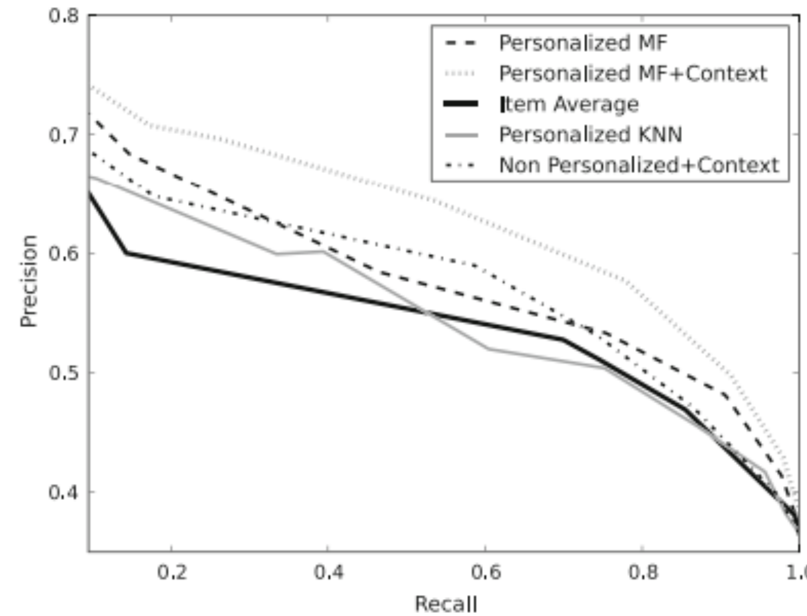


Fig. 8 Suggestions GUI

Resultados



(a) MAE of different models

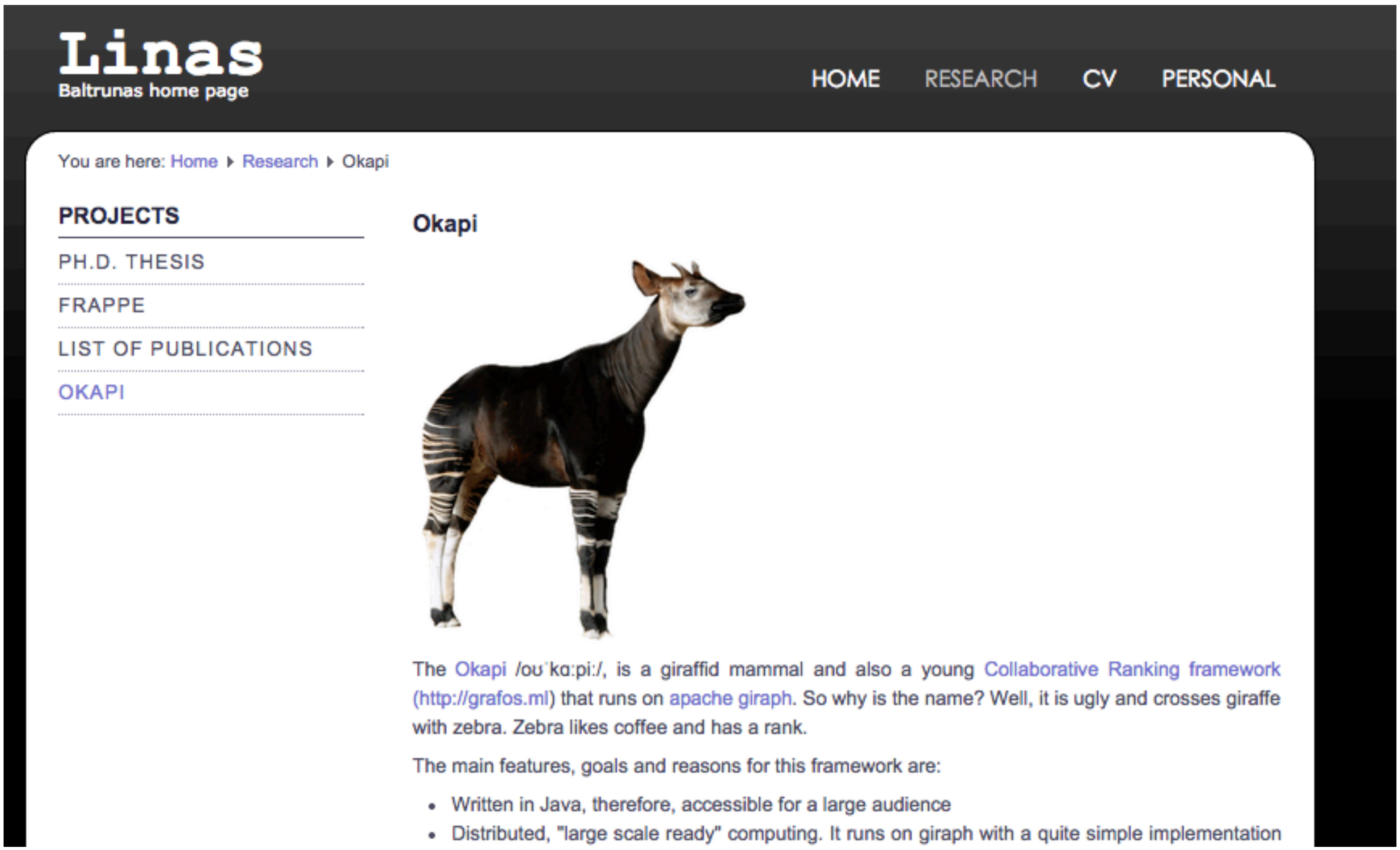


(b) Precision and Recall of different methods

Fig. 6 Performance of different methods

Linas' Recommendation OKAPI

- http://baltrunas.info/research-menu/okapi



Caso de Estudio IV

- Braunhofer, M., Kaminskas, M., & Ricci, F. (2011, October). Recommending music for places of interest in a mobile travel guide. In Proceedings of the fifth ACM conference on Recommender systems (pp. 253-256). ACM.
- Objetivo: Selecting the right music depending on the POI (point of interest)

Screenshot of Playing Guide

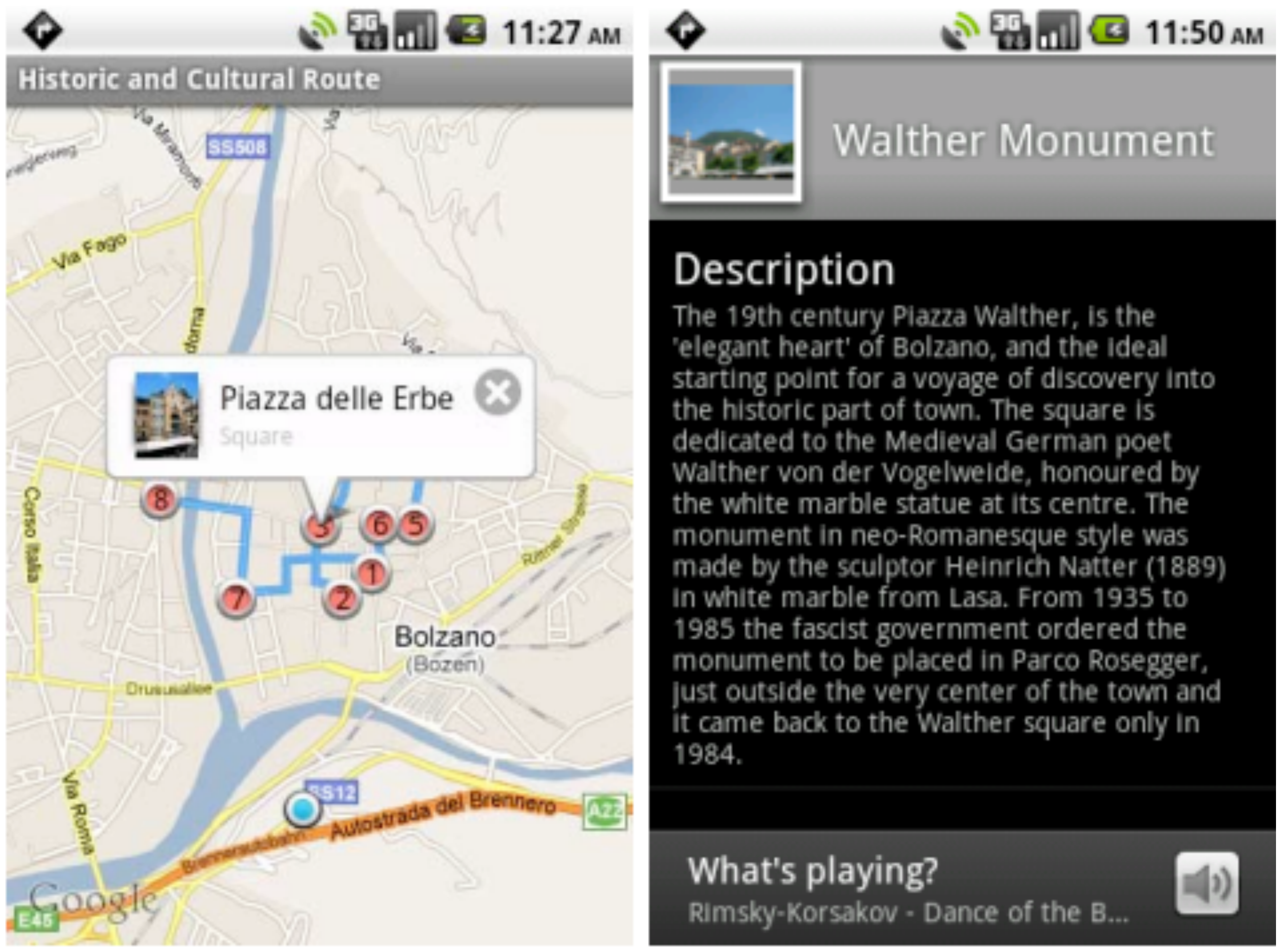


Figure 1: Sample screenshots of the application

Similarity between track (d2) and POI (d1)

- Weighted Jaccard-similarity

$$w_{t,d} = \begin{cases} -\log p_t & \text{if } tf_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases},$$

$$sim(d_1, d_2) = \frac{\sum_{i=1}^{M} \min(\vec{V}_i(d_1), \vec{V}_i(d_2))}{\sum_{i=1}^{M} \max(\vec{V}_i(d_1), \vec{V}_i(d_2))}.$$

Resultados

	Group of music tracks	
Rating acquisition condition	MATCH	MUSIC
In context (mobile)	3.78	3.34
Without context (web)	3.22	2.95

Table 1: Mean ratings for the music tracks in MATCH and MUSIC groups

Post-study survey

Statement	MATCH mean (SD)	MUSIC mean (SD)
1. It was simple to use this system.	6.08 (0.51)	6.46 (0.66)
2. I am able to complete my work quickly using this system.	5.58 (1.00)	5.54 (1.27)
3. I feel comfortable using this system.	6.00 (0.60)	5.92 (1.12)
4. It was easy to learn to use this system.	6.17 (0.83)	6.54 (0.78)
5. Whenever I make a mistake using the system, I recover easily and quickly.	5.60 (1.07)	5.20 (1.62)
6. The information provided with this system is clear.	5.90 (1.29)	5.92 (1.04)

Post-study survey II

7. It is easy to find the information I needed.	6.00 (1.18)	5.77 (0.93)
8. The organization of information on the system screens is clear.	6.08 (1.24)	6.31 (1.11)
9. The interface of this system is pleasant.	6.25 (0.62)	6.69 (0.63)
10. I like using the interface of this system.	6.17 (0.83)	6.38 (0.65)
11. The music was correctly selected for each POI.	**5.00** (0.74)	**4.08** (1.38)
12. I liked the music played for each POI.	5.08 (0.67)	4.38 (1.98)
13. I would recommend it to a friend.	6.00 (0.74)	5.92 (1.19)
14. Overall, I am satisfied with this system.	6.00 (0.74)	6.00 (0.82)

Proxima clase

- Using Factorization Machines for context-aware recommendation
- Results of a study conducted last year in this same class
- Estudios adicionales sobre recomendación contextual