

# 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 & Campbell (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
- Implícitamente: Información de dispositivos (hora, ubicación, temperatura, etc)
- Infiriendo: e.g. distintos usuarios que están 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

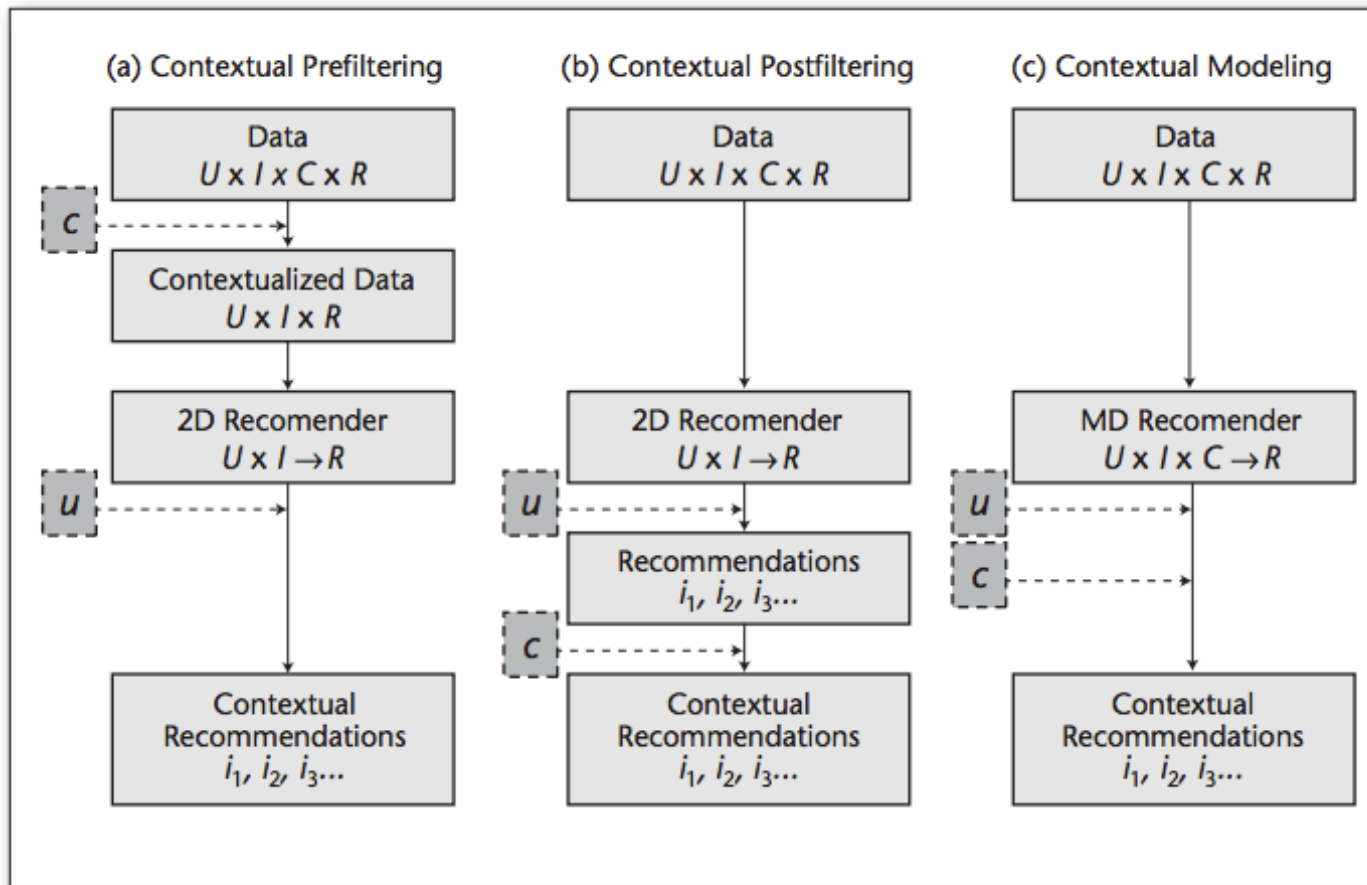


Figure 2. Paradigms for Incorporating Context in Recommender Systems.

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)

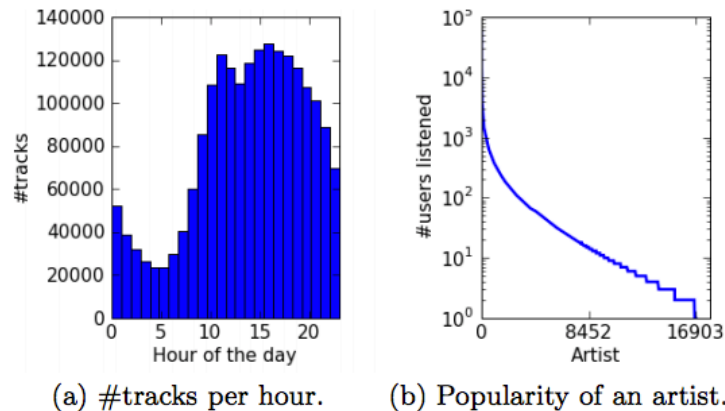


Figure 1: Last.fm data information

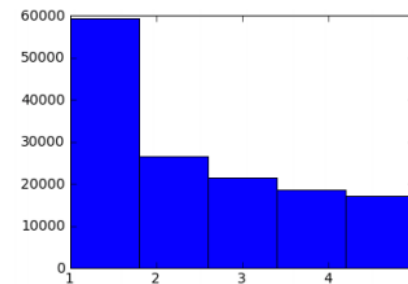


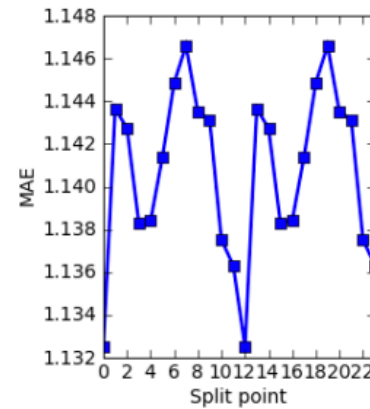
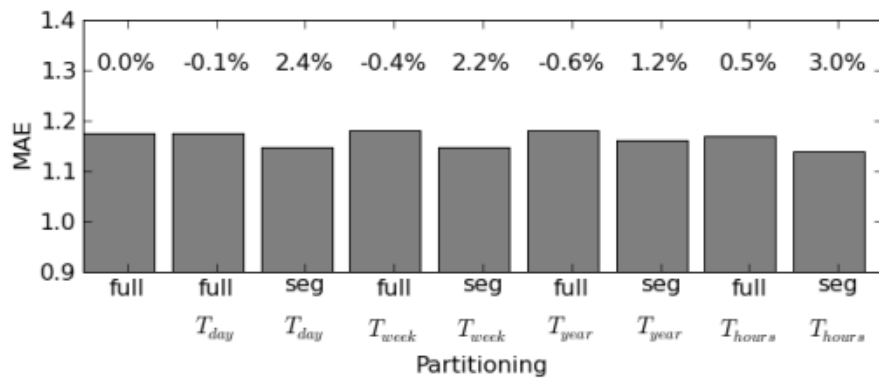
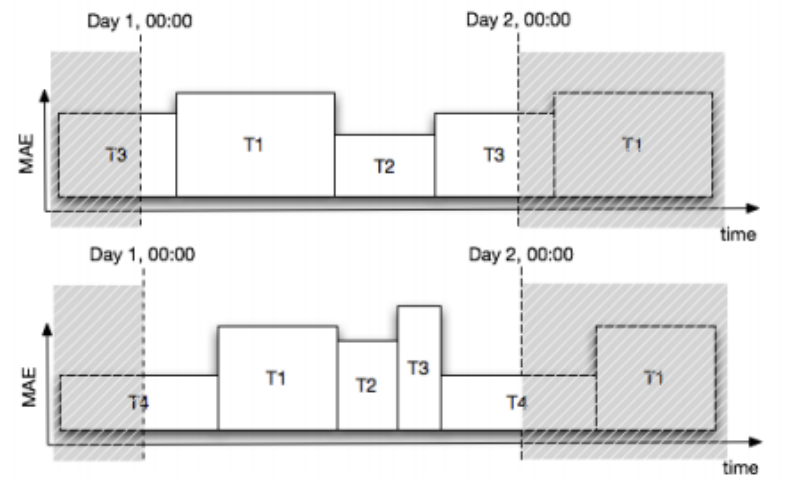
Figure 2: Rating distribution for the data set.



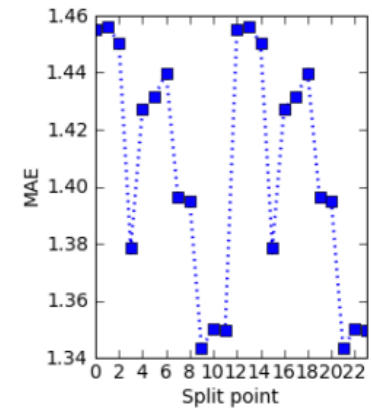
# Dataset/Evaluación

#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)

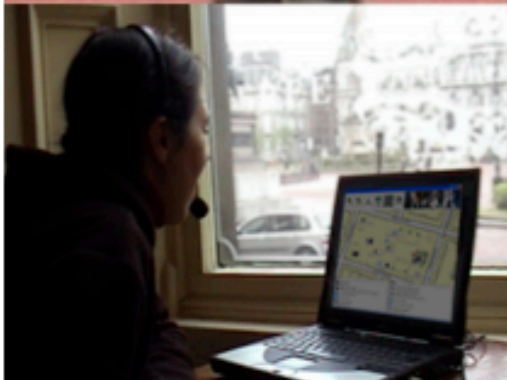
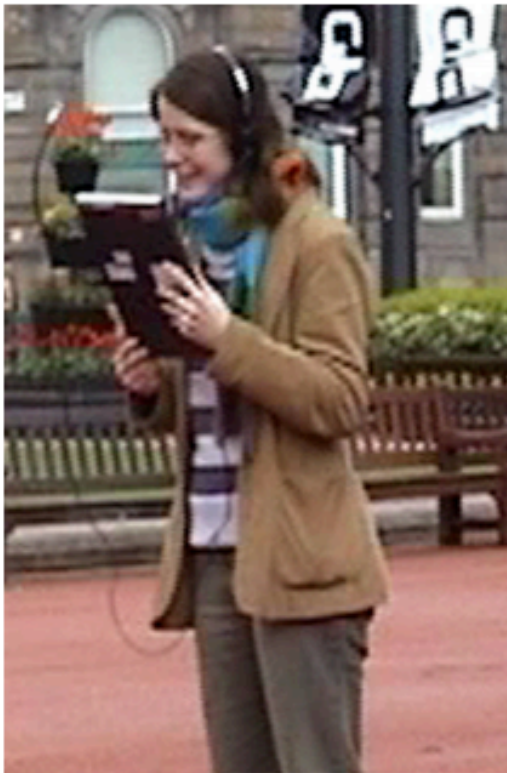
## Sharing the square: Collaborative Leisure in the City Streets

Barry Brown<sup>1</sup>, Matthew Chalmers<sup>1</sup>, Marek Bell<sup>1</sup>, Malcolm Hall<sup>1</sup>, Ian MacColl<sup>2</sup>, Paul Rudman<sup>1</sup>

<sup>1</sup>Department of Computing Science, University of Glasgow, Glasgow, UK <sup>2</sup>School of IT and Engineering, 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



The screenshot shows a mobile application interface for a location-based service. At the top, there is a toolbar with icons for 'Zoom In', 'Zoom Out', 'Point to map', 'Manual Position', 'GPS Auto Position', and 'Take Photo'. Below the toolbar is a map of George Square, which is a large open square in Edinburgh, Scotland. The map is overlaid with several icons and labels. A blue location pin labeled 'Paul' is positioned near the center of the square. Other landmarks are labeled, including 'Statue-Sir Walter Scott', 'Statue-Robert Burns', 'Statue-Lord Clyde', and 'Victoria British Monarchs'. There are also two 'george's photo taken on 04/10/04' icons on the map. The map is divided into five numbered regions (1-5) by dashed lines. At the bottom of the screen, there are two panels: 'Paul' and 'Barry'. The 'Paul' panel lists 'Cenotaph War memorial' and 'Statue-Lord Clyde (1792-1863) Known as Field Marshall Sir Colin Campbell'. The 'Barry' panel lists 'Statue-Sir Walter Scott (1771-1832) Novelist and poet', 'Statue-Robert Burns (1759-1796) Scotland's national poet', 'Sir John Moore', and 'Victoria British Monarchs'. A fifth numbered region (5) is also visible at the bottom right of the map area.

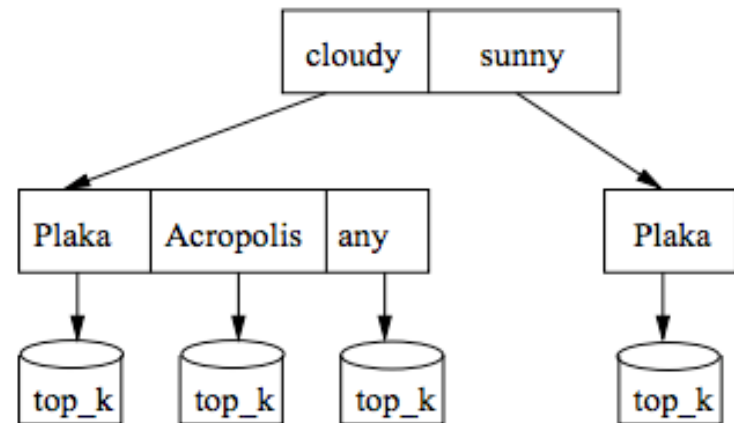
# Definiciones

- 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';*



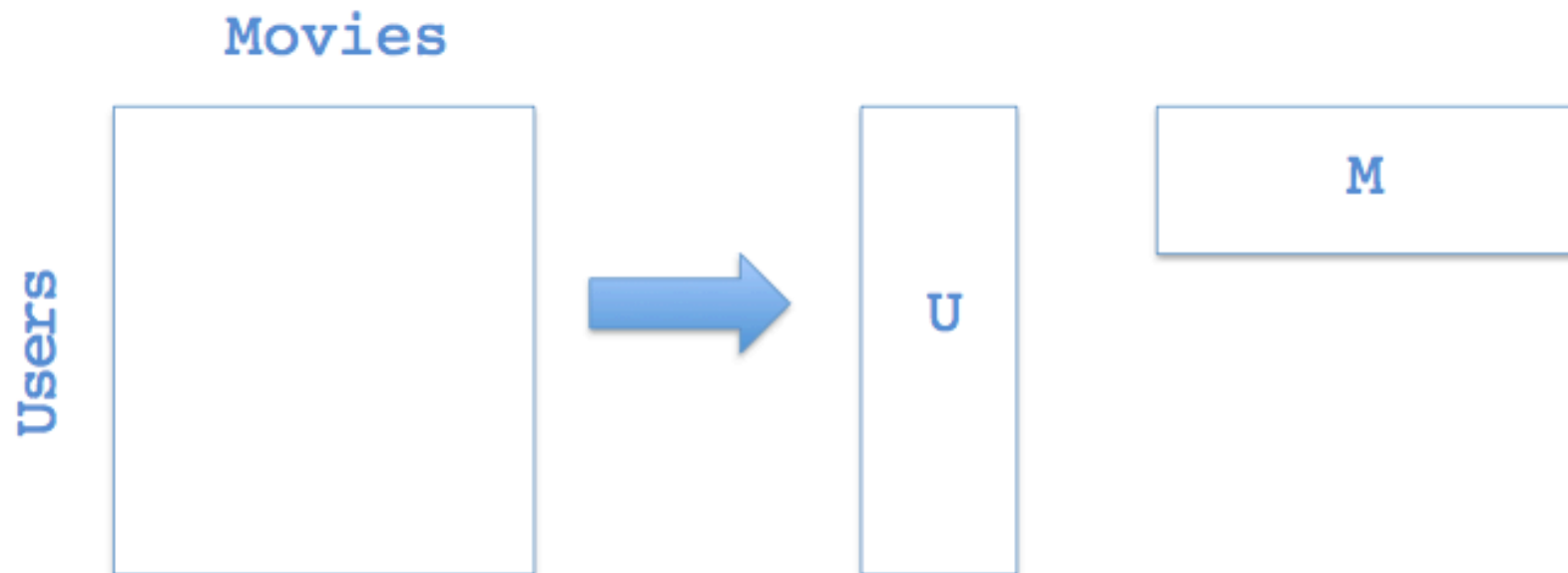
# Caso de Modelado Contextual II

- 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.

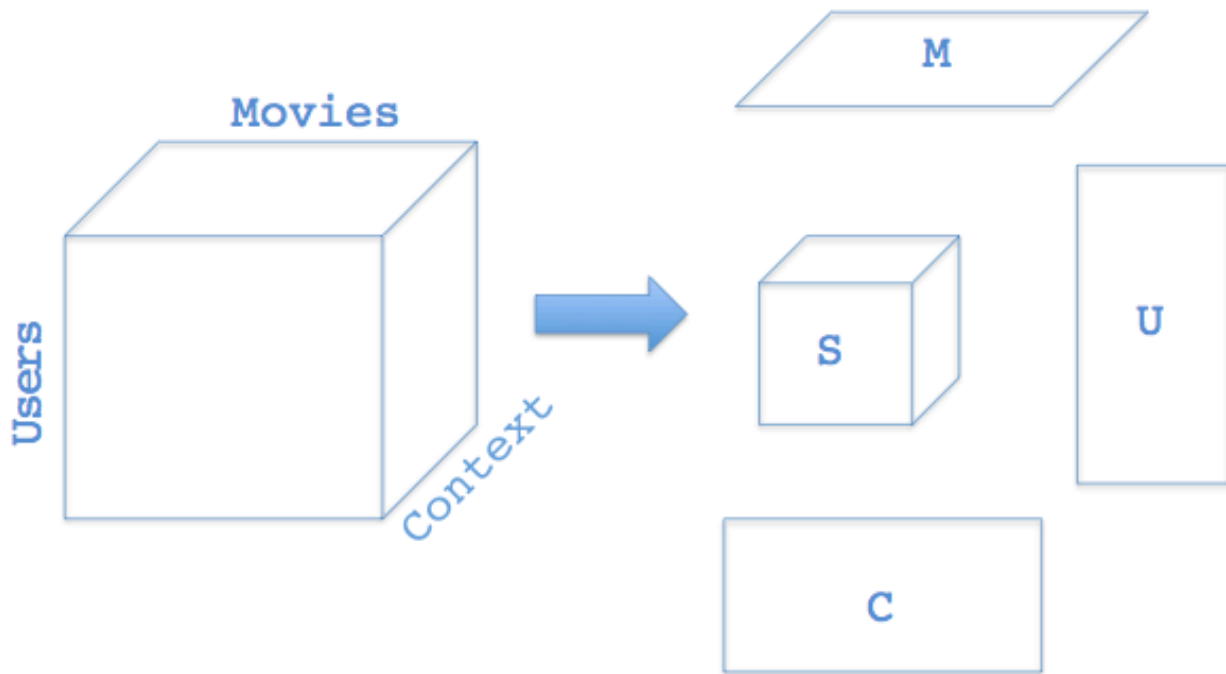
# FM Tradicional

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



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

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

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

$$\Omega[S] := \lambda_S \|S\|_F^2$$

# Loss Function

- Opción 1: Cuadrado del error

$$l(f, y) = \frac{1}{2}(f - y)^2 \quad L(F, Y) = \sum_i^n \sum_j^m l(f_{ij}, y_{ij})$$

- Opción 2: Error Absoluto

$$l(f, y) = |f - y| \quad L(F, Y) = \sum_i^n \sum_j^m l(f_{ij}, y_{ij})$$



# 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

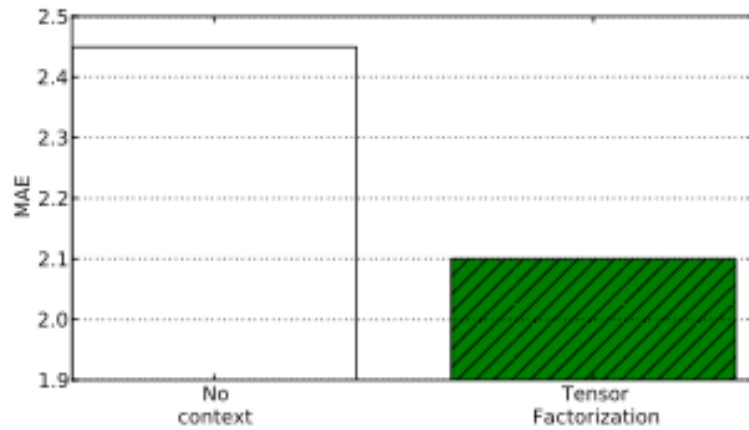
# Baselines

- Modelos a comparar:

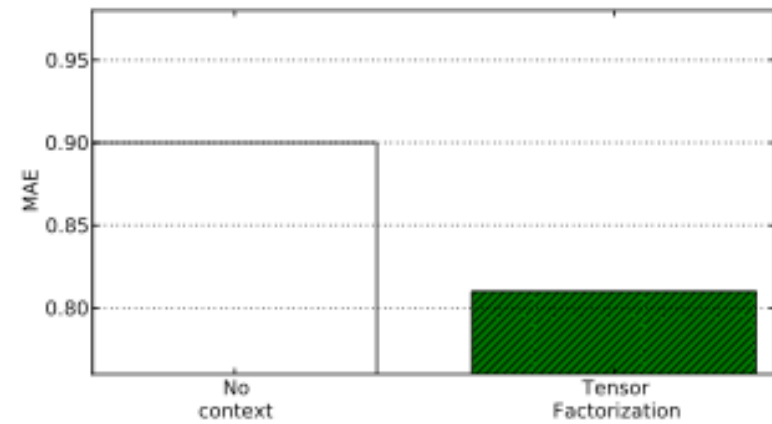
Pre-filtering based approach, (*G. Adomavicius et.al*), computes recommendations using *only* the ratings made in the same context as the target one

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

# Con/Sin contexto



(a)



(b)

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

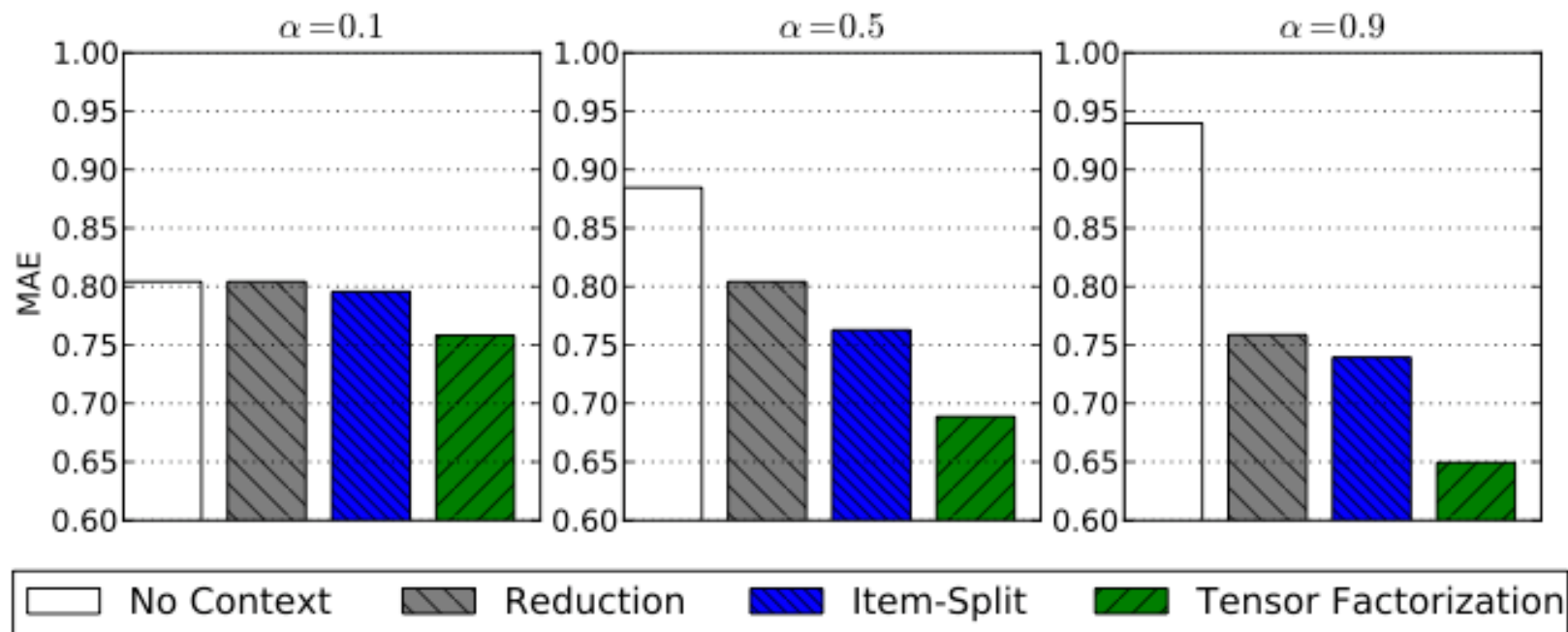
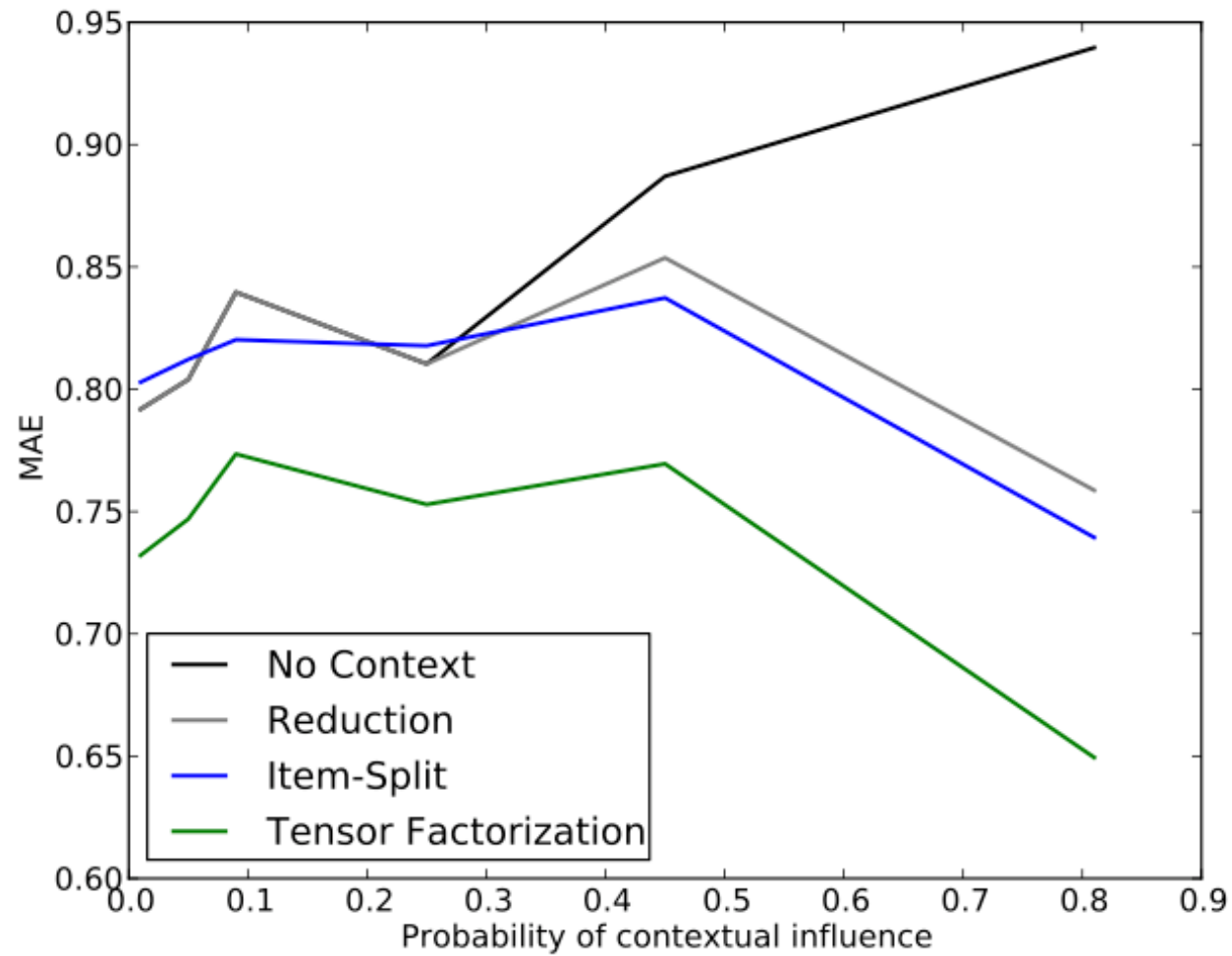


Figure: Comparison of context-aware methods on the Yahoo! artificial data

# Wrt Probabilidad de la inf. contextual



# En otros dataset

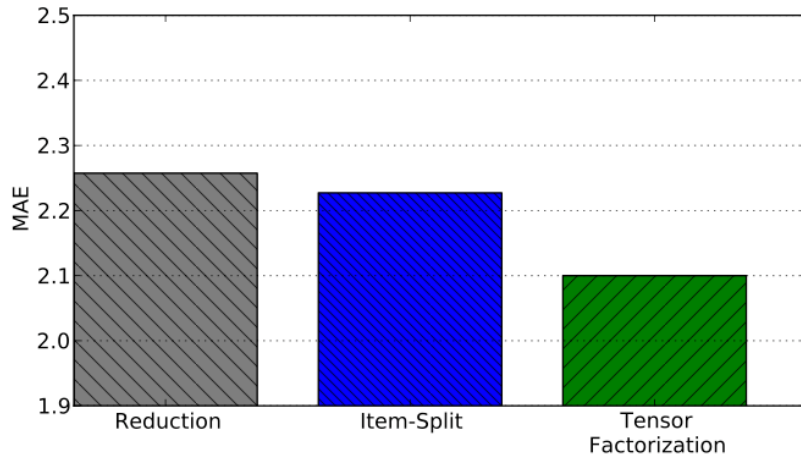


Figure: Comparison of context-aware methods on the Adom data.

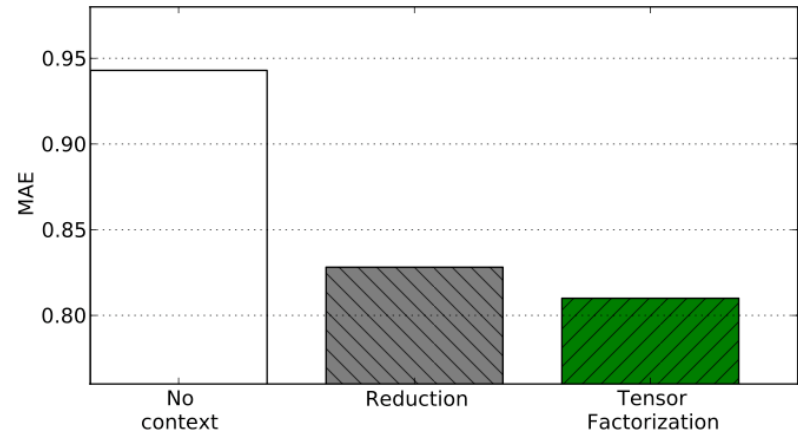


Figure: Comparison of context-aware methods on the Food data.


# 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

(user:ciccio)logout



Imagine that you are in Bolzano and you are making a plan for today. You are considering **to relax in a spa**. Please mark the conditions that would positively or negatively influence the decision to do that, or would have no effect.


		No effect	
Imagine that you are on a wellness trip:	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>
Imagine that it is a cold day:	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>
Imagine that it is raining:	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>

next...

Situation 1 of 5

## Rating in Context

### Castel Flavon - Haselburg



**Category:** castle

**Introduction:** Castel Flavon Haselburg nestles on a wooded hill slightly above Haslach, a quarter of the city of Bolzano. Built in late 12th century, still today it boasts some valuable frescoes.

**Description:** Castel Flavon Haselburg nestles on a wooded hill slightly above Haslach, a quarter of the city of Bolzano. Built in late 12th century, still today it boasts some valuable frescoes. It was recently renovated and the restaurant is open again. Address: Via Castel Flavon 48 Phone:0471 402130 Email: info@haselburg.it www: www.haselburg.it Opening hours: Tuesday-Saturday 11am-12pm, Sunday 11am-5pm, Monday closed.

**Imagine you are in Bolzano and you are making plan for today**

How likely is that you will visit Castel Flavon - Haselburg ★ ★ ★ ★ ☆

**We want to know which circumstances influence your decision**

Imagine that you are sad. How likely is that you will visit Castel Flavon - Haselburg: ★ ★ ★ ★ ☆

Imagine that you feel comfortable and happy. How likely is that you will visit Castel Flavon - Haselburg: ★ ★ ★ ★ ☆

Imagine that you can only use public transport. How likely is that you will visit Castel Flavon - Haselburg: ★ ★ ★ ★ ☆

Next

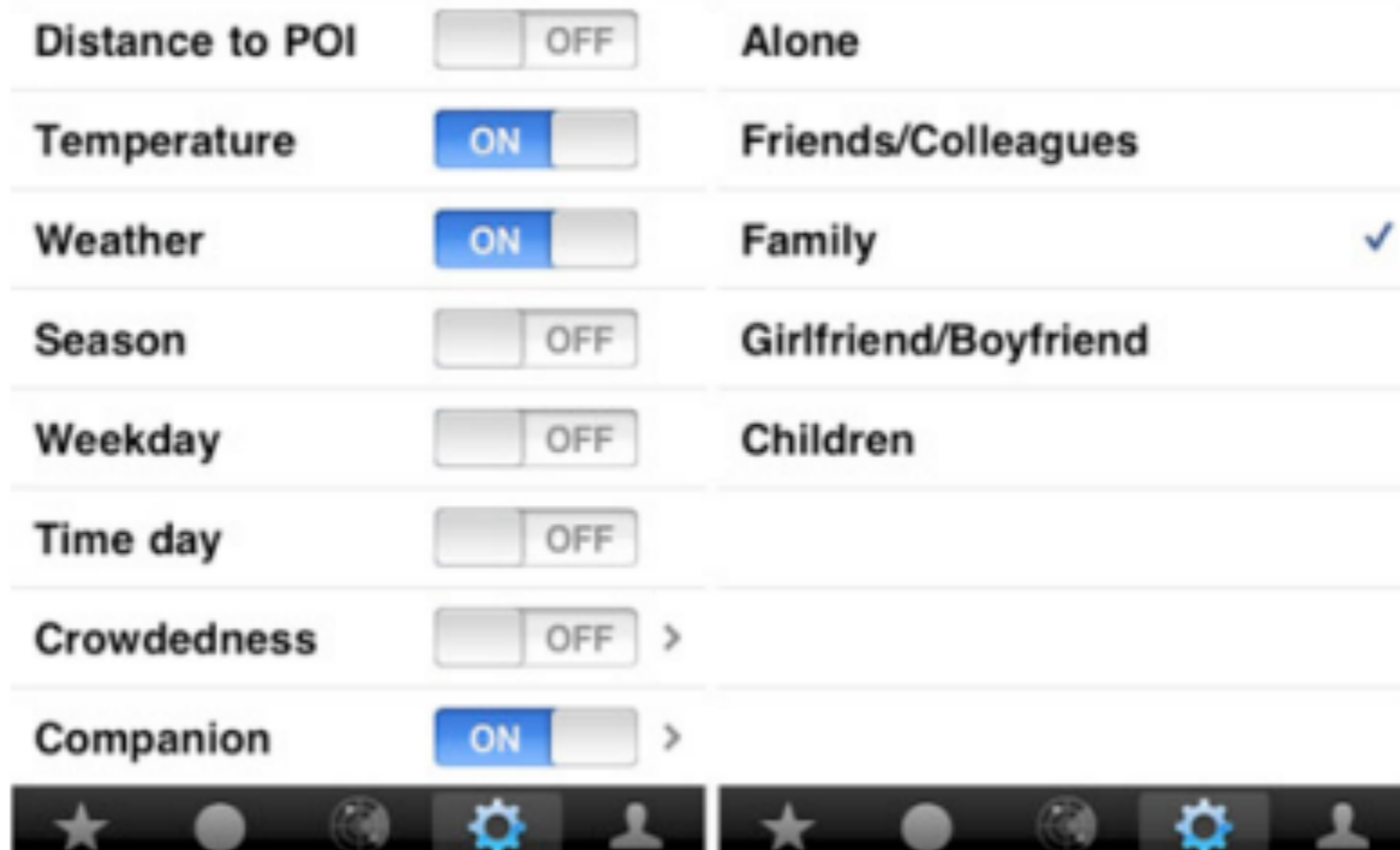


# Contexts Used

**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
Time of the day	Price for quality	Travel goal	Empty	Weather	With children	Transport	Autumn
	Morning time		Health care		Alone		Winter
	Afternoon		Cultural experience		With friends		Public transport
Day of the week	Weekend	Education	Scenic/landscape	Snowing	Clear sky	Temperature	No means of transp. Bicycle
							Working day
Distance to POI	Near by	Social event	Religion	Rainy	Happy	Time available	Warm
	Far away						Activity/sport
Knowledge About area	New to city	Visiting friends	Mood	Active	Sad	Time available	Hot
	Citizen of the city						Business
	Returning visitor						More than a day One day

# Opciones de la interfaz





**Fig. 9** Details for a suggestion

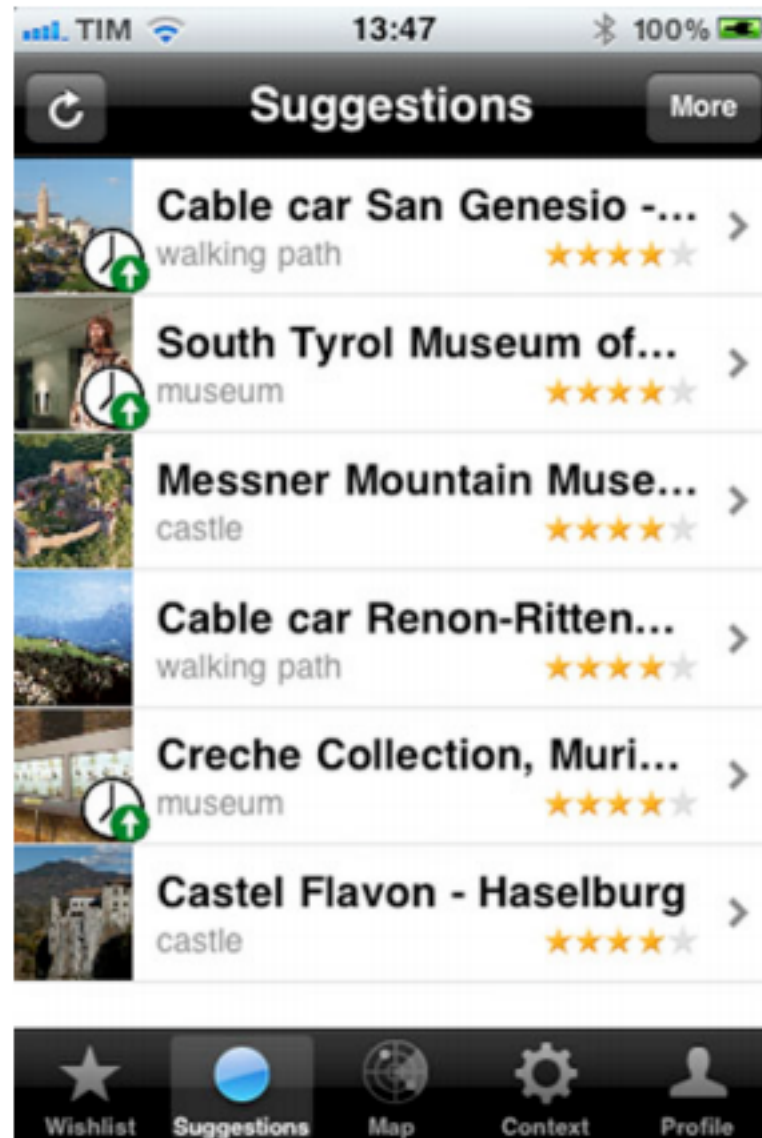
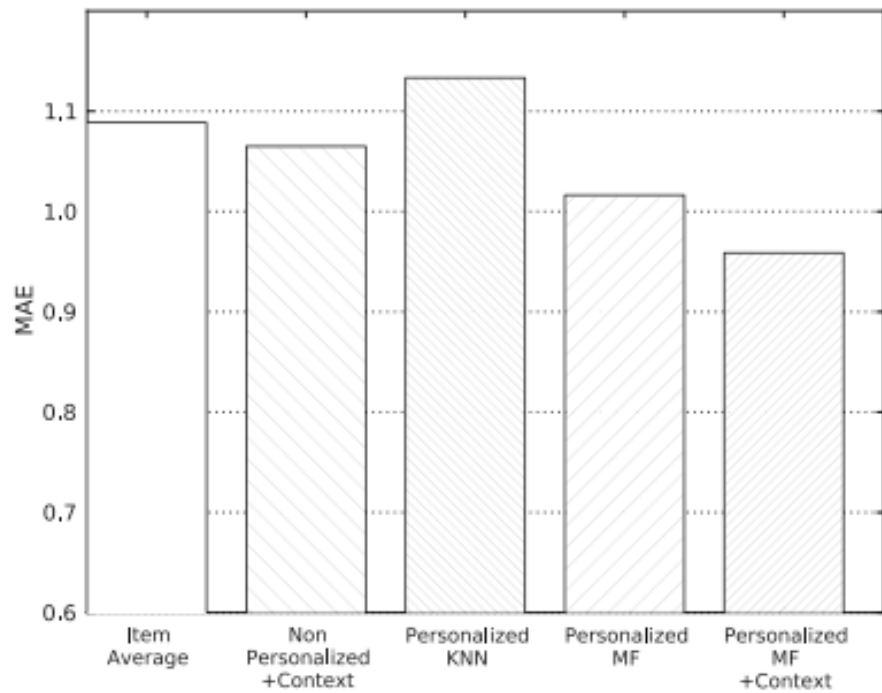
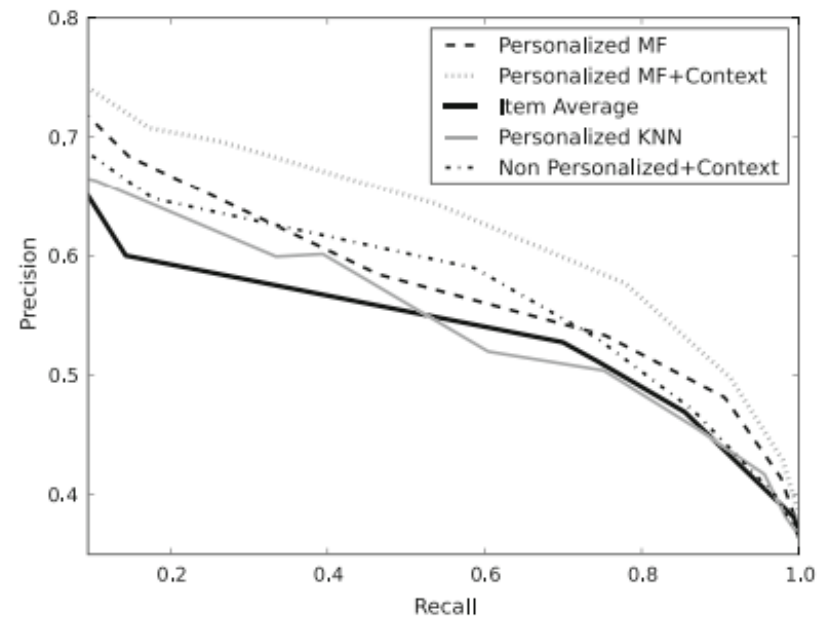


Fig. 8 Suggestions GUI

# Resultados



(a) MAE of different models



(b) Precision and Recall of different methods

Fig. 6 Performance of different methods

# Linus' Recommendation OKAPI

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

**Linus**  
Baltrunas home page

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**Okapi**



The **Okapi** /ou'ka:pi:/, is a giraffid mammal and also a young [Collaborative Ranking framework](#) (<http://grafos.ml>) that runs on [apache giraph](#). So why is the name? Well, it is ugly and crosses giraffe with zebra. Zebra likes coffee and has a rank.

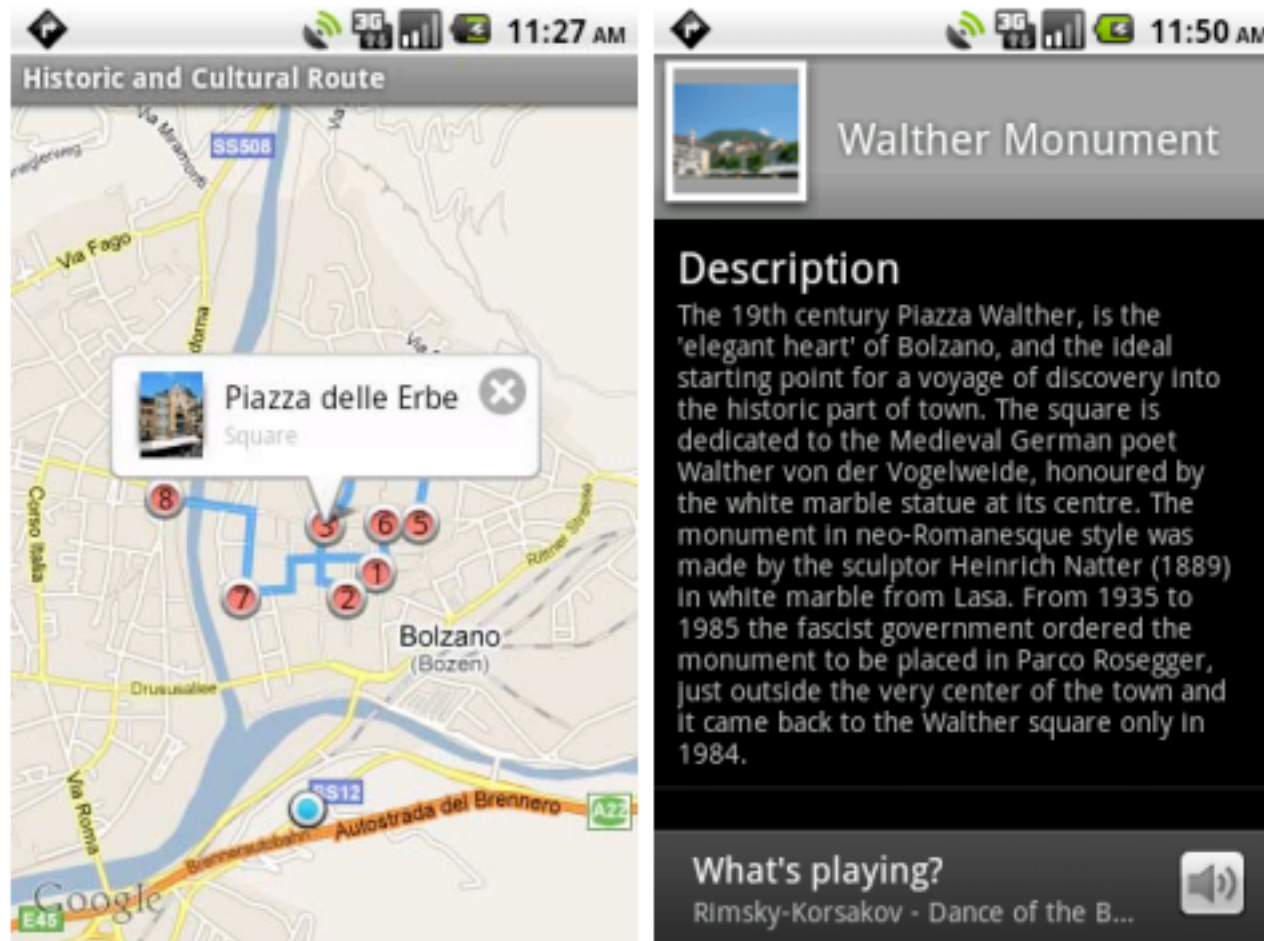
The main features, goals and reasons for this framework are:

- Written in Java, therefore, accessible for a large audience
- Distributed, "large scale ready" computing. It runs on giraph with a quite simple implementation

# Caso de Estudio IV

- Braunhofer, M., Kaminskis, 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

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

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

# Resultados

Rating acquisition condition	Group of music tracks	
	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.	<b>5.00</b> (0.74)	<b>4.08</b> (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