CONTRIBUTION TO PROACTIVITY IN MOBILE CONTEXT-AWARE RECOMMENDER SYSTEMS

Author: Daniel Gallego Vico

Director: Gabriel Huecas Fernández-Toribio
“Information overload occurs when a person is exposed to more information than the brain can process at one time”

[Palladino, 2007]
Recommender Systems are powerful information filtering tools providing suggestions for items to be of use to a user.
“We use recommendation algorithms to personalize the online store for each customer”

[Linden et al., 2003]

“75% of what people watch is from some sort of recommendation”

[Amatriain, 2012]
But items are just the beginning...
Social data information can be used to increase the level of personalization:

- Behavior
- Tastes
- Consumption trends
- Social links
- ...
**Recommend System**

Transaction
Action in the system (request...)
with a specific context

**Item**

Transaction
Related to item (feedback, tag...)
with a specific context

**Features**

**User**

Transaction
Social relationship
(following...)

**Profile**
“Recommendation techniques can increase the usability of mobile systems providing personalized and more focused content”

[Ricci, 2010]
“Context: any information used to characterize the situation of an entity”

“Entity: person, place, or object considered relevant to the interaction between user and application, including the user and application themselves”

Context-aware Recommender Systems (CARS)
[Adomavicius & Tuzhulin, 2005] [Verbert et al., 2012]

Mobile CARS
• Motivation and open challenges

• Research methodology

• Contributions

• Conclusions
Recommendations are made to the user

- when the current situation is appropriate
- without the need for an explicit request
Research question

How could proactivity be incorporated into current mobile CARS and what are the UX implications?
Open challenges

1. What kind of architecture is suitable for building mobile CARS in scenarios with rich social data?

2. How can proactivity be incorporated into mobile CARS?

3. Which UX factors need to be considered in the implementation of proactive mobile CARS?
• Motivation and open challenges

• **Research methodology**

• Contributions

• Conclusions
1. Design as an artifact
2. Problem relevance
3. Design evaluation
4. Research contributions
5. Research rigor
6. Design as a search process
7. Communication of research

[Hevner et al. 2004]
Research chronology

2010
- ICCT
- JITEL

2011
- ISTP
- PEMA
- RecSys
- IJCISIM

2012
- ICDS
- MUSIC
- FIE

2013
- JSA
- JET
- EPI
- FIE
- WCCIT

Bankinter RecSys
Research stay at TUM
GLOBAL excursion

Conferences
Journals
• Motivation and open challenges

• Research methodology

• **Contributions**

• Conclusions
Architecture for social mobile CARS

Model for proactivity in mobile CARS

Proactivity impact in mobile CARS user experience

Methods to incorporate proactivity into mobile CARS
Architecture for social mobile CARS
Objectives

• Architecture
  • Mash-up of several social sources for recommendation
  • Privacy
  • Multi-device and Cross-platform

• Suitable contextual recommendation model
  • Social data analysis available at recommendation time
  • Avoid cold start problem

• Validation
**Architecture**

- **Client**
  - Mobile app
  - REST API
  - Application Manager
  - Recommender

- **Server**
  - Data Anonymization
  - Social Data Source 1
  - Social Data Source 2
  - Social Data Source 3
  - Social Data Source N

**Process Flow**

- **Contextual information** from Mobile app to REST API
- **Request recommendation** from REST API to Application Manager
- **Display recommendation** from Application Manager to Mobile app
- **User feedback** from Mobile app to REST API
- **Target user profile** from Application Manager to Recommender
- **Personalized recommendation** from Recommender to Application Manager
- **User profiles** from Application Manager to Data Anonymization
- **Transactions** and **Items** from Data Anonymization to Social Data Sources

Architecture

Client

Mobile app

Contextual information
Request recommendation
Display recommendation
User feedback

REST API

Application Manager

Target user profile
Personalized recommendation

Recommender

User profiles
Transactions
Items

Server

Data Anonymization

Social Data Source 1
Social Data Source 2
Social Data Source 3
Social Data Source N
Recommendation model

Phase I: Social Context Generation
- User Profiles
  - User Profile Clustering
  - Social Clusters
  - Items Assignment
  - Clusters Trends Map
- Item, Transactions
- Target User Profile
  - User’s Cluster Discovery

Phase II: Location Context Filtering
- Mobile Device Context Information
- User’s Location Acquisition
  - User’s location
  - Location based Filtering
  - Geo-Located User’s Cluster Trends Map

Phase III: User Context Filtering
- User context
  - Ranking Generation
  - Personalized Recommendation

Mobile User Interface
- User Feedback
  - Display Recommendation
Validation: banking scenario

- “Perdidos en la Gran Ciudad” project

Objective:
- Recommend **places** using banking data

Place
- Entities with credit card payments
- Restaurants, supermarkets, cinemas, stores…
Evaluation: demographics

- Deployed in **Bankinter Labs** environment

- Banking data sample
  - 2.5 million credit card transactions
  - 222,000 places information
  - 34,000 anonymous customer’s profiles
    - 57% male, 43% female
    - Average age: 51
    - Average expense per year: 11,719€
Evaluation: social clustering results

Cluster size (users) vs. Average credit card expense per year (€)
Validation: publications

- **International journals**
  1. *Generating Awareness from Collaborative Working Environment using Social Data*
     Daniel Gallego, Iván Martínez and Joaquín Salvachúa. IJCISIM, 2012

- **International conferences**
  1. *An Empirical Case of a Context-aware Mobile Recommender System in a Banking Environment*
     Daniel Gallego and Gabriel Huecas. MUSIC, 2012
     Daniel Gallego, Gabriel Huecas and Joaquín Salvachúa. ICDS, 2012
Model for proactivity in mobile CARS
Objectives

- Generality
- Proactive and request-response recommendations supported
- Relationship between appropriateness situation and item suitability
- Feedback to learn user behavior
Recommendation model

Phase I: Situation
When to make a recommendation?

- Calculate score by weighted combination of context attributes
  - User Context
  - Temporal Context
  - Geographical Context
  - Social Context

Score $S_1$ influences $T_2$}

Abort ($S_1 = 0$)

Phase II: Items
Which item(s) to recommend?

- S1 > threshold $T_1$?
  - Score $S_1$
  - Forced Rec. ($S_1 = 1$)
  - Calculate score for each candidate item
    - Apply contextual or non-contextual recommender system
  - Score $S_2$

- S2 > threshold $T_2$?

Display Recommendation
How to show the recommendation?

Feedback influences $T_1$ & $T_2$

$T_2 = 1 - S_1$
Validation: publications

- **International indexed journal**
  1. Proactivity and context-awareness: future of recommender systems design

- **International conferences**
  1. Enhanced Recommendations for e-Learning Authoring Tools based on a Proactive Context-aware Recommender
     Daniel Gallego, Enrique Barra, Aldo Gordillo and Gabriel Huecas. FIE, 2013

  2. A Model for Proactivity in Mobile, Context-aware Recommender Systems
     Wolfgang Woerndl, Johannes Huebner, Roland Bader, and Daniel Gallego. RecSys, 2011
Proactivity impact in mobile CARS user experience
Objectives

• **How** to show proactive recommendations?
  - Design **suitable user interfaces** to generate proactive recommendations in mobile CARS
  - Develop a mobile CARS following the previous model

• **Empirical evaluation among users**
  - Extract valuable **outcomes** about proactivity impact in mobile CARS user experience
Proactive notification: Status bar

- Based on Android push notifications

- Stimulus
  - Visual
  - Acoustic
  - Tactile

- User feedback
  - Ignore
  - Not now
  - Expand
Proactive notification: Widget

- Based on Android app widgets
  - Always visible in Home screen

- Stimulus
  - Visual 📺

- User feedback
  - Ignore
  - Not now
  - Expand
• **Objective**
  - Evaluate UX of proactive mobile interfaces

• **Scenario: restaurant recommendations**

• **On-line survey to**
  - Compare both mobile proactive approaches
    - *A/B testing methodology*
    - Study the acceptance of the mobile result visualization methods
Evaluation: demographics

- **58 test users**
  - 72% male, 28% female
  - Average age 29
  - 76% owned a smartphone

- Split up randomly into
  - $\alpha$ group evaluated first Status bar, then Widget
  - $\beta$ group evaluated first Widget, then Status bar
Results: proactivity impact

- Scenarios S1 and S2
  - Compare users reaction whether a necessity exists or not
- Application **ignored when** recommendation **not needed**
- But users give **feedback** on their **active rejection**
Results: proactivity impact

- Scenarios S3 and S4
  - Compare users’ reaction whether they are in a hurry or not

- **Time pressure** situations ⇒ **poor user feedback**
- **Activity influences appropriateness** of proactive recommendations
Results: proactivity impact

- Scenarios S5 and S6
  - Compare users reaction with user-request approach

- In situations corresponding to traditional recommendation scenarios proactive ones have also high acceptance
• **Widget solution** considered **better** to achieve proactivity by users

• When comparing both, Widget always had higher acceptance
• International indexed journal
     Daniel Gallego, Wolfgang Woerndl and Gabriel Huecas. JSA, 2013

• International conference
Methods to incorporate proactivity into mobile CARS
Objectives

• Include **proactivity** in the recommendation model for mobile CARS in **social** scenarios

• Define context-aware **methods** to calculate the appropriateness of a situation

• Validation in **real scenario**
Merged recommendation model

Phase I: Social Context Generation
- User Profiles
- Items, Transactions
- Target User Profile
- User Profile Clustering
- Items Assignment
- User's Cluster Discovery
- Social Clusters
- Clusters Trends Map

Phase II: Situation Assessment
- Location Context
- Score S1
- Score S2
- User Context
- User's Cluster Trends Map
- Cluster Trends Map
- Forced Rec. (S1 = 1)
- Abort (S1 = 0)
- S1 > T1?

Phase III: Item Assessment
- User's Cluster Trends Map
- Location Context Rating
- Located User's Cluster Trends Map
- User Context Rating
- Rated Items (Score S2)
- S2 > T2?
- Personalized Recommendation

Display Recommendation

Recommender

User Interface
Merged recommendation model

Phase I: Social Context Generation
- User Profiles
- Items, Transactions
- Target User Profile
  - User Profile Clustering
  - Items Assignment
  - User’s Cluster Discovery
  - Social Clusters
  - Clusters Trends Map

Phase II: Situation Assessment
- Location Context
- Score S1
- Score S2
- User Context
- User’s Cluster Trends Map
- Abort (S1 = 0)
- Forced Rec. (S1 = 1)

Phase III: Item Assessment
- User’s Cluster Trends Map
- Location Context Rating
- Located User’s Cluster Trends Map
- User Context Rating
- Rated Items (Score S2)

Display Recommendation

Recommendation

User Interface

User Feedback
Determination of appropriateness: definitions

• For any contextual model
  • Each feature has a weight
  • Each feature value has an appropriateness factor

• Feature weight

\[ f.weight \in [1..5] \subset \mathbb{Q} \]

\[ \begin{align*}
1 & \Rightarrow \text{feature definitely not important} \\
\vdots & \quad \vdots \\
5 & \Rightarrow \text{feature very important}
\end{align*} \]

• Appropriateness factor

\[ \text{app}(f.value) \in [1..5] \subset \mathbb{Q} \]

\[ \begin{align*}
1 & \Rightarrow \text{recommendation not at all appropriate} \\
\vdots & \quad \vdots \\
5 & \Rightarrow \text{recommendation very appropriate}
\end{align*} \]
Determination of appropriateness: methods

- **Situation model recommendation score**

\[ SRS_M = \sum_{f \in F_M} \text{app}(f.\text{value}) \times f.\text{weight} \]

\[ w_M = \sum_{f \in F_M} f.\text{weight} \]

- **Context influence factor**

\[ i_c \in [0,1] \subseteq \mathbb{Q} \rightarrow \sum_{M} i_c = 1 \]

- **Situation decision score S1**

\[ S1 = i_{social} \times SRS_{social} + i_{location} \times SRS_{location} + i_{user} \times SRS_{user} \]
Validation: ViSH scenario

- Virtual Science Hub
  - e-learning social network

- Allows collaboration among teachers/scientists to
  - Share and create enhanced educational content
  - Improve science curriculum of pupils in the 14-18 age range

- Proactive mobile CARS recommends
  - Learning objects
  - People with similar interests
**ViSH context features for proactivity**

<table>
<thead>
<tr>
<th>Feature</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Social context</strong></td>
<td></td>
</tr>
<tr>
<td>Social clusters</td>
<td>Generated, not generated</td>
</tr>
<tr>
<td><strong>Location context</strong></td>
<td></td>
</tr>
<tr>
<td>Geographical</td>
<td>User is in or out his city/working area</td>
</tr>
<tr>
<td>Temporal</td>
<td>Morning, Afternoon, Evening, Night</td>
</tr>
<tr>
<td><strong>User Context</strong></td>
<td></td>
</tr>
<tr>
<td>Activity</td>
<td>Away</td>
</tr>
<tr>
<td></td>
<td>Idle</td>
</tr>
<tr>
<td></td>
<td>Browsing the platform</td>
</tr>
<tr>
<td></td>
<td>After filling in the profile</td>
</tr>
<tr>
<td></td>
<td>While creating new content</td>
</tr>
<tr>
<td></td>
<td>While editing content</td>
</tr>
<tr>
<td></td>
<td>While looking for content</td>
</tr>
<tr>
<td></td>
<td>After finishing the creation of new content</td>
</tr>
<tr>
<td></td>
<td>While viewing content created by others</td>
</tr>
<tr>
<td></td>
<td>After viewing content created by others</td>
</tr>
</tbody>
</table>
• **Objective**
  - Obtain e-learning user model with values of
    - Appropriateness of feature values
    - Feature weights

• **On-line survey to**
  - Measure the impact of proactive recommendations in educators daily work
    - 5-point Likert scale questions methodology
Evaluation: demographics

- **104 test users**
  - 64% European teachers
  - 36% European scientists
  - 52 men and 52 women
  - Average age 40

- **Usage frequency of recommender systems**
  - 31.73% never
  - 29.81% hardly
  - 29.92% regularly
  - 11.54% frequently
Results: feature weights

Geographical Temporal Device Activity

Definitely not important Not important Neutral Important Very important

Less important contextual feature

Most important contextual feature

1 2 3 4
Results: appropriateness of feature values

- At work: Very appropriate
- Out of work: Not appropriate
- Morning: Appropriate
- Afternoon: Neutral
- Evening: Not at all appropriate
- Night: Very appropriate
- Desktop: Neutral
- Tablet: Very appropriate
- Smartphone: Appropriate

- Away: Not at all appropriate
- Idle: Not at all appropriate
- Browsing: Very appropriate
- After filling in the profile: Very appropriate
- While creating new content: Appropriate
- While editing content: Neutral
- While looking for content: Neutral
- After creating new content: Not at all appropriate
- While viewing others’ content: Neutral
- After viewing others’ content: Very appropriate

Colors:
- Red: Not at all appropriate
- Orange: Not appropriate
- Green: Neutral
- Light blue: Appropriate
- Blue: Very appropriate
Validation: publications

- International journal
  1. Methods to Incorporate Proactivity into Context-Aware Recommender Systems for E-Learning  
     Daniel Gallego, Enrique Barra, Pedro Rodríguez and Gabriel Huecas. JET, 2013

- International conferences
  1. Incorporating Proactivity to Context-Aware Recommender Systems for E-Learning  
     Daniel Gallego, Enrique Barra, Pedro Rodríguez and Gabriel Huecas. WCCIT, 2013

     Daniel Gallego, Enrique Barra, Sandra Aguirre and Gabriel Huecas. FIE, 2012
• Motivation and open challenges
• Research methodology
• Contributions

• **Conclusions**
Contributions

- General architecture for mobile CARS with rich social data
- Implementation in real ubiquitous and social scenario
- Novel model for proactivity in mobile CARS
- Mobile user interfaces for proactive recommendations
- Outcomes on proactivity impact regarding UX
- Methods for incorporating proactivity into mobile CARS
- Implementation of proactive mobile CARS in a social network
Validation: research projects

Perdidos en la gran ciudad

bankinter.
Validation: research projects
Validation: dissemination of results

- 2 international indexed journals
- 2 international journals
- 9 international conferences
- 1 national conference
Open challenges addressed

- **What kind of architecture is suitable for building mobile CARS in scenarios with rich social data?**
  - Social data analysis available at recommendation time
    - Social contextual pre-filtering \(\Rightarrow\) slow changes
    - Location and User contextual post-filtering \(\Rightarrow\) rapid changes
  - Social data sources as separate modules
    - Anonymization \(\Rightarrow\) privacy
  - API REST for managing recommendations
    - Multi-device and cross-platform
Open challenges addressed

• How can proactivity be incorporated into mobile CARS?

  • Recommendation model
    • Contextual situation assessment, then item assessment
    • Relation between situation appropriateness and item suitability
    • Feedback to learn from user’s behavior

  • Methods
    • Weight of contextual features
    • Appropriateness of contextual feature values
    • Situation decision for proactivity as a combination of both
Open challenges addressed

• Which UX factors need to be considered in the implementation of proactive mobile CARS?
  • Current user activity is the most influential
    • Other factors are more scenario-dependent
  • Different proactive notifications offered to the user
    • E.g. Widget less annoying than Status bar notification
Future work

- Long-term experience with proactive recommendations
- Different recommendation profiles for the same user
- Novel user interfaces for proactive mobile CARS
- Improve current methods to incorporate proactivity
- Application to different scenarios
Thank you

Questions?