CONTRIBUTION TO PROACTIVITY IN MOBILE CONTEXT-AWARE RECOMMENDER SYSTEMS

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"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.
“75% of what people watch is from some sort of recommendation.” [Amatriain, 2012]

“We use recommendation algorithms to personalize the online store for each customer.” [Linden et al., 2003]

But items are just the beginning...

Social data information can be used to increase the level of personalization.

Rich user profile
- Behavior
- Tastes
- Consumption trends
- Social links
“Recommendation techniques can increase the usability of mobile systems providing personalized and more focused content” [Ricci, 2010]

Ubiquitous environment

Device used Activity Location

“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” [Dey, 2001]

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

Mobile CARS

"Recommendation techniques can increase the usability of mobile systems providing personalized and more focused content" [Ricci, 2010]
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- Motivation and open challenges
- Research methodology
- Contributions
- Conclusions

Proactivity

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?

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Design science: guidelines

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]
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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

Recommendation model

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

Validation: publications

- International journals
  1. Generating Awareness from Collaborative Working Environment using Social Data
     Daniel Gallego, Ivan Martinez 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
  2. Generating Context-aware Recommendations using Banking Data in a Mobile Recommender System
     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

\[ T_2 = 1 - S_1 \]
### Validation: publications

<table>
<thead>
<tr>
<th>International indexed journal</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Proactivity and context-awareness: future of recommender systems design</td>
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<tr>
<th>International conferences</th>
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</thead>
<tbody>
<tr>
<td>1. Enhanced Recommendations for e-Learning Authoring Tools based on a Proactive Context-aware Recommender</td>
</tr>
<tr>
<td>Daniel Gallego, Enrique Barra, Aldo Gordillo and Gabriel Huecas. FIE, 2013</td>
</tr>
<tr>
<td>2. A Model for Proactivity in Mobile, Context-aware Recommender Systems</td>
</tr>
<tr>
<td>Wolfgang Woerndl, Johannes Huebner, Roland Badir, and Daniel Gallego. RecSys, 2011</td>
</tr>
</tbody>
</table>

### Proactivity impact in mobile CARS user experience

<table>
<thead>
<tr>
<th>Objectives</th>
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<tbody>
<tr>
<td>• <strong>How</strong> to show proactive recommendations?</td>
</tr>
<tr>
<td>- Design suitable user interfaces to generate proactive recommendations in mobile CARS</td>
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<td>- Develop a mobile CARS following the previous model</td>
</tr>
<tr>
<td>• <strong>Empirical</strong> evaluation among users</td>
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<td>- Extract valuable outcomes about proactivity impact in mobile CARS user experience</td>
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</tbody>
</table>
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

Evaluation: description

- 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
  - **α** group evaluated first Status bar, then Widget
  - **β** 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

- **Scenarios S3 and S4**
  - Compare users reaction whether they are in a hurry or not
  - **Time pressure situations lead to 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

Results: comparison

- Widget solution considered better to achieve proactivity by users
- When comparing both, Widget always had higher acceptance

Validation: publications

- 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
Determination of appropriateness: definitions

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

- Feature weight
  \[ f_{\text{weight}} \in [1, 5] \subseteq \mathbb{Q} \]
  - 1 \( \Rightarrow \) feature definitely not important
  - 5 \( \Rightarrow \) feature very important

- Appropriateness factor
  \[ \text{app}_{(f, \text{value})} \in [1, 5] \subseteq \mathbb{Q} \]
  - 1 \( \Rightarrow \) recommendation not at all appropriate
  - 5 \( \Rightarrow \) recommendation very appropriate

Determination of appropriateness: methods

- Situation model recommendation score
  \[ SRS_{sit} = \frac{\sum_{f_{\text{weight}}} \text{app}_{(f, \text{value})} \times f_{\text{weight}}}{\sum_{f_{\text{weight}}} f_{\text{weight}}} \]

- Context influence factor
  \[ \iota_f \in [0,1] \subseteq \mathbb{Q} \rightarrow \sum_{f_{\text{weight}}} \iota_f = 1 \]

- Situation decision score S1
  \[ S1 = f_{\text{context}} \times SRS_{sit} + f_{\text{location}} \times SRS_{location} + f_{\text{device}} \times SRS_{device} \]
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>Social context</td>
<td>Generated, not generated</td>
</tr>
<tr>
<td>Location context</td>
<td>User is in or out of working area</td>
</tr>
<tr>
<td>Temporal</td>
<td>Morning, Afternoon, Evening, Night</td>
</tr>
<tr>
<td>Device</td>
<td>Desktop, Tablet, Smartphone</td>
</tr>
<tr>
<td>Activity</td>
<td>Away, Idle, Browsing the platform, After filling in the profile, While creating new content, While editing content, While looking for content, After finishing the creation of new content, After viewing content created by others, After viewing content created by others.</td>
</tr>
</tbody>
</table>

Evaluation: description

- 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
  - 26% 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

- The figure shows the distribution of weights for geographical, temporal, device, and activity features.
- The x-axis represents the percentage of users who consider each feature to be either not important, neutral, important, or very important.
- The y-axis represents the percentage of users.

Results: appropriateness of feature values

- The figure shows the appropriateness of feature values for different contexts such as filling in the profile, creating new content, editing content, looking for content, creating new content again, viewing others' content, and viewing content.
- The x-axis represents the percentage of users.
- The y-axis represents the appropriateness level, ranging from not at all appropriate to very appropriate.
Validation: publications

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

- International conferences
  1. Incorporating Proactivity to Context-Aware Recommender Systems for E-Learning
     Daniel Gallego, Enrique Barra, Pedro Rodriguez and Gabriel Huecas. WCCIT, 2013
     Daniel Gallego, Enrique Barra, Sandra Aguirre and Gabriel Huecas. FIE, 2012

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- Research methodology
- Contributions
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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: 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 → slow changes
    - Location and user contextual post-filtering → rapid changes
  - Social data sources as separate modules
    - Anonymization → privacy
  - API REST for managing recommendations
    - Multi-device and cross-platform

- 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

- 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?