Context and Intention-Awareness in POIs Recommender Systems[1]

Hernani Costa[1] Barbara Furtado[2] Durval Pires[2]
Luis Macedo[1] Amilcar Cardoso [1]

Cognitive & Media Systems Group
CISUC, University of Coimbra

[1]{hpcosta, macedo, amilcar}@dei.uc.pt

[2]{bfurtado, durval}@student.dei.uc.pt

Dublin, September, 2012

[1]supported by the FCT project PTDC/EIA-EIA/108675/2008.

Introduction

With the technological advance registered in the last decades, there has been an exponential growth of the information available, for instance in location-based services (van Setten et al. (2004))

Introduction

With the technological advance registered in the last decades, there has been an exponential growth of the information available, for instance in location-based services (van Setten et al. (2004))

Personal Assistant Agents can help humans to cope with the task of selecting the relevant information

Introduction

With the technological advance registered in the last decades, there has been an exponential growth of the information available, for instance in location-based services (van Setten et al. (2004))

Personal Assistant Agents can help humans to cope with the task of selecting the relevant information

In order to perform well, these agents *should consider* not only their preferences, but also their context and intentions when selecting information (Ponce-Medellin et al. (2009))

Introduction

However, most of Recommender Systems (RS) approaches focus on

- item *x* user (Content-Based)
- user *x* user (Collaborative Filtering)

In other words, traditional RS consider only two types of entities, users and items

Introduction

Still...

the most relevant information for the user may not only depend on his preferences, but also in his context (Woerndl and Schlichter (2007); Adomavicius et al. (2011))

Introduction

Still...

the most relevant information for the user may not only depend on his preferences, but also in his context (Woerndl and Schlichter (2007); Adomavicius et al. (2011))

But...

the very same content can be relevant to a user in a particular context, and completely irrelevant in a different one

Introduction

Still...

the most relevant information for the user may not only depend on his preferences, but also in his context (Woerndl and Schlichter (2007); Adomavicius et al. (2011))

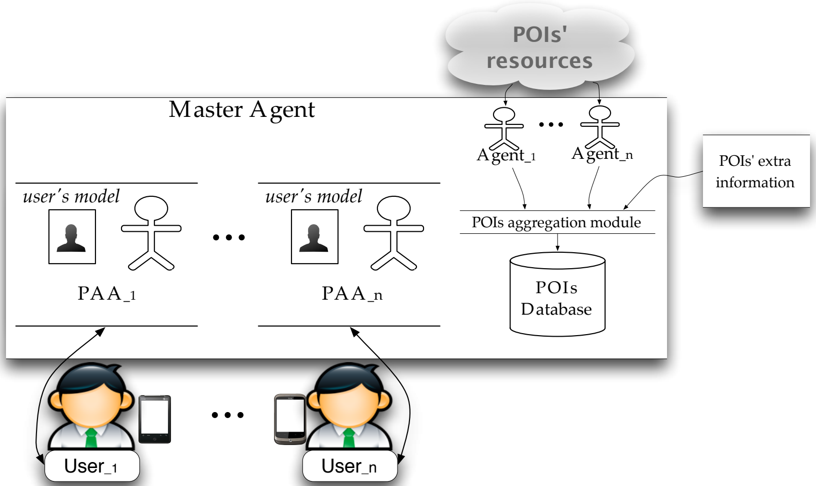
But...

the very same content can be relevant to a user in a particular context, and completely irrelevant in a different one

For this reason...

we believe that it is important to have the user's context and intentions in consideration during the recommendation process

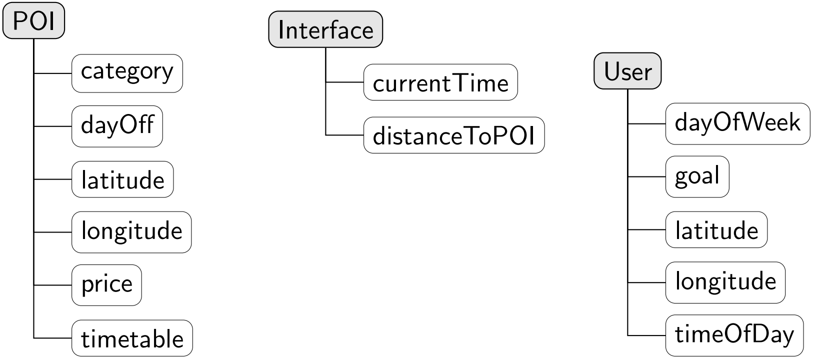
System's Architecture



Set-Up

- Area of Work
  - Coimbra's Downtown
- Web Agent Gowalla
  - retrieved POIs from Gowalla service
- Extra Information for ≈500 POIs
  - dayOff, timetable, average price
  - as well as some of the attributes missing

Main attributes used to defined the context



Set-Up

- Definition of Run
  - combination of the user's context and goal (i.e., intention) with the POIs' context (all the POIs in the radius of 350m)

Set-Up

- Definition of Run
  - combination of the user's context and goal (i.e., intention) with the POIs' context (all the POIs in the radius of 350m)

- User's Context
  i) proximity related to a specific POI
  $\langle \texttt{near} \leq 100m > \texttt{average} \leq 200m > \texttt{far} \rangle$
  ii) current time of day $\langle$`morning, afternoon or night`$\rangle$
  iii) current day of the week
  iv) user's goal $\langle$`coffee, lunch, dinner or party`$\rangle$

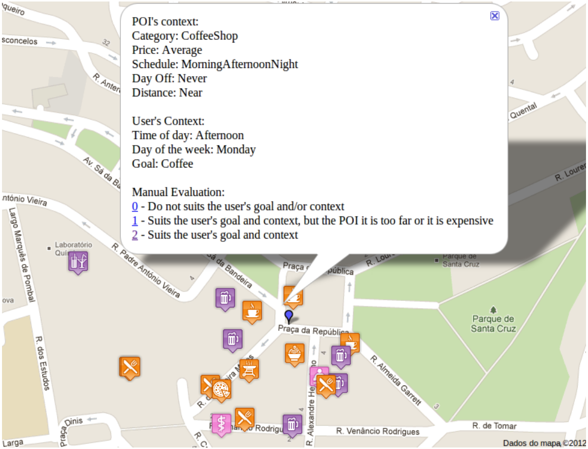
Set-Up

- Definition of Run
  - combination of the user's context and goal (i.e., intention) with the POIs' context (all the POIs in the radius of 350m)

- User's Context
  i) proximity related to a specific POI ⟨near$\leq 100m >$average$\leq 200m >$far⟩
  ii) current time of day ⟨morning, afternoon or night⟩
  iii) current day of the week
  iv) user's goal ⟨coffee, lunch, dinner or party⟩

- POI's Context
  a) category e.g., SandwichShop, Vegetarian and WineBar (≈105)
  b) price ⟨cheap, average or expensive⟩
  c) timetable ⟨morning, afternoon, night, or combinations⟩
  d) day off ⟨a day of the week or combinations⟩

Set-Up



User's profile

- distance=near
- price=cheap

Goal

Verify how machine learning techniques suit the task of predicting the user's profile

More precisely, the **Naïve Bayes Updateable** algorithm

Results Analysis Outline

1. Cross validation
2. Manual Evaluation
3. Comparison between
   Manual Evaluation with System's Recommendations

Results Analysis

Cross Validation

- Weka[2] library integrated in Java

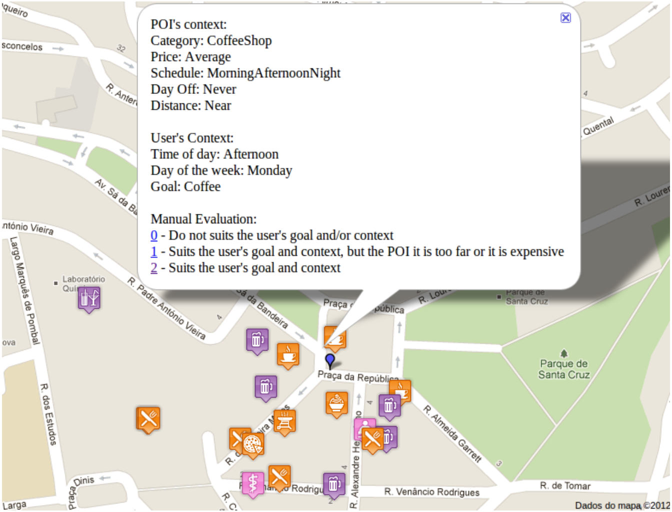
- Classifier's statistics

Correctly Classified Instances	9246	**63.2594%**
Incorrectly Classified Instances	5370	**36.7406%**
Kappa statistic	0.3909	
Mean absolute error	0.1729	
Root mean squared error	0.3163	
Relative absolute error	73.0797%	
Root relative squared error	91.9724%	
Total Number of Instances	**14616**	

[2] http://www.cs.waikato.ac.nz/ml/weka

Results Analysis

Manual Evaluation



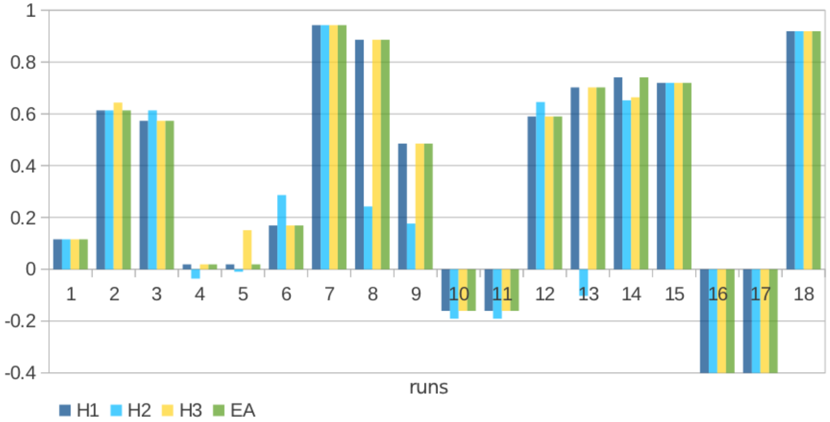
Results Analysis

Manual Evaluation

- Three human judges evaluated 18 runs, each
- Exact Agreement between them $= 93.3\%$

Results Analysis

Correlation between Manual vs. Automatic Recommendations (Exact Agreement)

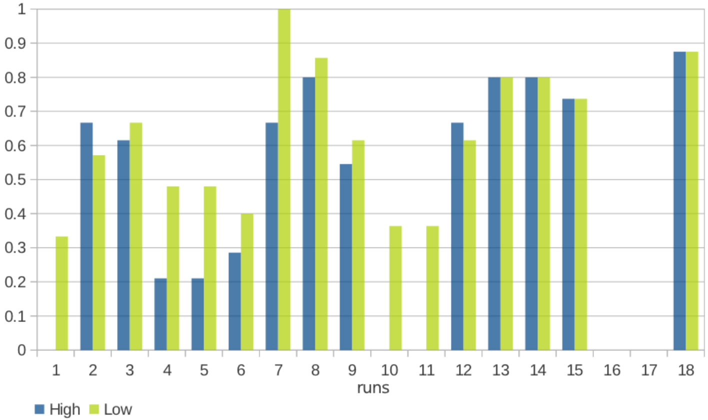


Caption

- H1, H2, H3 $\rightarrow$ *Human Judges*
- EA $\rightarrow$ *Exact Agreement*

Results Analysis

System's Recommendations (F-Measure)



Caption

- High filter → *score 2*
- Low filter → *score 2 and 1*

Conclusions

- System's architecture
  - combines context and intentions in the recommendation process

Conclusions

- System's architecture
  - combines context and intentions in the recommendation process
- Analysed the recommendations' accuracy
  - cross-validation test
  - exact agreement between the human judges
  - correlation analysis between manual evaluations and the output values given by the PAA

Conclusions

- System's architecture
  - combines context and intentions in the recommendation process
- Analysed the recommendations' accuracy
  - cross-validation test
  - exact agreement between the human judges
  - correlation analysis between manual evaluations and the output values given by the PAA
- Machine learning can be a powerful tool to be used in location-based services

Conclusions

- System's architecture
  - combines context and intentions in the recommendation process
- Analysed the recommendations' accuracy
  - cross-validation test
  - exact agreement between the human judges
  - correlation analysis between manual evaluations and the output values given by the PAA
- Machine learning can be a powerful tool to be used in location-based services
- Results in general, can be considered very promising
  - a good starting point to develop a real usable application

Future Work

- Internal improvements

- External improvements

Future Work

- Internal improvements
  - use new information sources
  - take into account new attributes (e.g., POI's quality)
  - create a baseline to test and compare other ML algorithms, e.g., BayesNet, J48 (Witten et al. (2011))
  - analyse other users' profiles
- External improvements

Future Work

- Internal improvements
  - use new information sources
  - take into account new attributes (e.g., POI's quality)
  - create a baseline to test and compare other ML algorithms, e.g., BayesNet, J48 (Witten et al. (2011))
  - analyse other users' profiles
- External improvements
  - improve the recommendations' accuracy by using more data in the training process
  - possibility of changing the values of some attributes (e.g., choose user's *budget* or what is *near*, *far*, etc.)
  - analyse the system's accuracy when applying selective attention metrics, e.g., surprise (Macedo (2010)), in the recommendation outputs

References I

Adomavicius, G., Mobasher, B., Ricci, F., and Tuzhilin, A. (2011). Context-Aware Recommender Systems. *AI Magazine*, 32(3):67–80.

Macedo, L. (2010). A Surprise-based Selective Attention Agent for Travel Information. In *Proc. 9th Int. Conf. on Autonomous Agents and Multiagent Systems, 6th Workshop on Agents in Traffic and Transportation*, AAMAS'10, pages 111–120, Toronto, Canada.

Ponce-Medellin, R., González-Serna, G., Vargas, R., and Ruiz, L. (2009). Technology Integration around the Geographic Information: A State of the Art. *International Journal of Computer Science Issues*, 5:17–26.

van Setten, M., Pokraev, S., and Koolwaaij, J. (2004). Context-Aware Recommendations in the Mobile Tourist Application COMPASS. In *Proc. 3rd Conf. on Adaptive Hypermedia and Adaptive Web-Based Systems*, pages 235–244, Berlin, Germany. Springer.

Witten, I. H., Frank, E., and Hall, M. A. (2011). *Data Mining: Practical Machine Learning Tools and Techniques: Practical Machine Learning Tools and Techniques*. The Morgan Kaufmann Series in Data Management Systems. Elsevier Science, CA, USA.

Woerndl, W. and Schlichter, J. (2007). Introducing Context into Recommender Systems. In *Proc. AAAI 2007, Workshop on Recommender Systems in e-Commerce*, pages 22–23, Vancouver, Canada. AAAI press.


Information Overload
Naïve Bayes
Intentions
Preferences
Evaluation
Recall
Recommender Systems
Artificial Intelligence
Ubiquitous Computing
Machine Learning
Content-Based
Cross-Validation
Multiagent Systems
F-Measure
Collaborative Filtering
Algorithms
Precision
Validation
Personal Assistant Agents
Location-Based Services
User Modeling
Context