Context and Intention-Awareness in POIs Recommender Systems

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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))
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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))
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
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))
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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

Master Agent

user’s model

PAA_1

user’s model

PAA_n

POIs' resources

Agent_1

Agent_n

POIs aggregation module

POIs Database

POIs' extra information

User_1

User_n

...
Set-Up

- **Area of Work**
  - Coimbra’s Downtown

- **Web Agent Gowalla**
  - retrieved POIs from Gowalla service

- **Extra Information for \( \approx 500 \) POIs**
  - dayOff, timetable, average price
  - as well as some of the attributes missing
Main attributes used to defined the context

- **POI**
  - category
  - dayOff
  - latitude
  - longitude
  - price
  - timetable

- **Interface**
  - currentTime
  - distanceToPOI

- **User**
  - dayOfWeek
  - goal
  - latitude
  - longitude
  - timeOfDay
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)
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User’s Context

1. proximity related to a specific POI
   - near \( \leq 100 \, m \), average \( \leq 200 \, m \), far
2. current time of day (morning, afternoon, or night)
3. current day of the week
4. user’s goal (coffee, lunch, dinner, or party)
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- **POI’s Context**
  1. category e.g., SandwichShop, Vegetarian and WineBar \((\approx 105)\)
  2. price \(\text{cheap, average or expensive}\)
  3. timetable \(\text{morning, afternoon, night, or combinations}\)
  4. day off \(\text{a day of the week or combinations}\)
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
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

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\(^2\)http://www.cs.waikato.ac.nz/ml/weka
Results Analysis

Manual Evaluation

POI's context:
Category: CoffeeShop
Price: Average
Schedule: Morning, Afternoon, Night
Day Off: Never
Distance: Near

User's Context:
Time of day: Afternoon
Day of the week: Monday
Goal: Coffee

Manual Evaluation:
0 - Do not suit the user's goal and/or context
1 - Suits the user's goal and context, but the POI it is too far or it is expensive
2 - Suits the user's goal and context
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 $\rightarrow$ score 2
- Low filter $\rightarrow$ score 2 and 1
Conclusions

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

Results in general, can be considered very promising – a good starting point to develop a real usable application.
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- 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
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Future Work

- Internal improvements

- External improvements
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- **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
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The end

Naïve Bayes

Recommendation Systems

Artificial Intelligence

Machine Learning

Personal Assistant Agents

Location-Based Services

User Modeling

Context

Evaluation

Preferences

Intention

Information Overload

Recall

Content-Based

Cross-Validation

Multiagent Systems

F-Measure

Collaborative Filtering

Ubiquitous Computing