Recommending POIs based on the User's Context and Intentions

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Introduction

With the technological advance registered in the last decades

- there has been an exponential growth of the information available
- e.g., location-based services (van Setten et al., 2004)

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Personal Assistant Agents (PAAs) can help humans to cope with the task of selecting the relevant information (Costa et al., 2012)

PAAs 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)

i.e., traditional RS consider only two types of entities, users and items

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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...

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

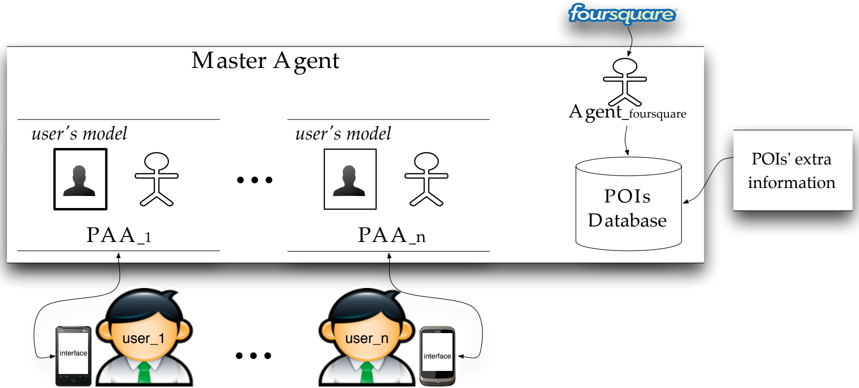
Introduction

approach

$$\text{Recommender System (RS)} + \text{Multiagent System (MAS)}$$
$$\Downarrow$$

contextualised and intention-aware recommendations of Points of Interest (POIs)

System's Architecture



Set-Up

Agent Foursquare

- retrieved POIs from Foursquare API[2]

Extra Information for 365 POIs

- dayOff, timetable, average price
- as well as some of the attributes missing in the API

Area of Work

- Coimbra's Downtown

[2] https://developer.foursquare.com

Set-Up

main attributes used to defined the context

- POI
  - category
  - dayOff
  - latitude
  - longitude
  - price
  - timetable
- Interface
  - currentTime
  - distanceToPOI
- User
  - budget
  - intention
  - dayOfWeek
  - timeOfDay
  - latitude
  - longitude

Set-Up

definition of Run

Run is a combination of

a) POI's Context

b) User's Context

c) User's Intention/Goal

d) All the POIs within a radius of 350m

Set-Up

definition of Run

Run is a combination of

a) POI's Context

  i) category `e.g., SandwichShop, Vegetarian and WineBar` (≈60)
  ii) price ⟨`cheap, average or expensive`⟩
  iii) timetable ⟨`morning, afternoon, night, or combinations`⟩
  iv) day off ⟨`a day of the week or combinations`⟩

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b) User's Context
   i) proximity related to a specific POI
      ⟨near$\leq 200m >$average$\leq 300m >$far⟩
   ii) current time of day ⟨morning, afternoon or night⟩
   iii) current day of the week

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c) User's Intention/Goal
   i) coffee, lunch, dinner or go party

d) All the POIs within a radius of 350m

Set-Up

user stereotypes and their datasets

User stereotypes

- u_1
  - distance=near
  - price=cheap
- u_2
  - distance=near
- u_3
  - price=expensive

Set-Up

user stereotypes and their datasets

Rules used to create the three user stereotypes

(to resolve the cold-start problem (Schein et al., 2002))

$$R(Goal(u_n)) = \begin{cases} \forall Goal(u_1)\ if\ (distance \leq 200m\ \&\& \\ \qquad\qquad price = cheap), \quad R(u_1) = 1 \\ \forall Goal(u_2)\ if\ (distance \leq 200m), \quad R(u_2) = 1 \\ \forall Goal(u_3)\ \underline{if\ (price = expensive),\ R(u_3) = 1} \\ \qquad otherwise, \qquad\qquad R(u_n) = \emptyset \end{cases}$$

Goal

Verify how different Machine Learning[a] (ML) algorithms perform the task of predicting the user's preferences, while taking his context and intentions into account

[a] BayesNet; Naïve Bayes; J48 pruned; J48 unpruned

Results Analysis Outline

1. Cross validation
2. Manual evaluation
3. Manual evaluation vs. PAAs' recommendations

Results Analysis

cross validation's statistics for user stereotypes u_1

	$\mathbf{u_1}$			
	BN	**J48$_p$**	**J48$_u$**	**NB**
Correctly classified instances (%)	99.14	98.57	100	99.43
Total number of instances	350			

Caption

BN = BayesNet

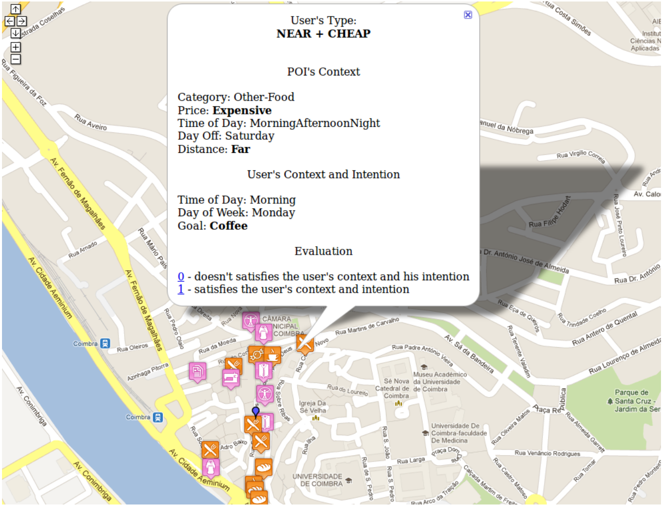
$J48_p$ = J48 pruned

$J48_u$ = J48 unpruned

NB = Naïve Bayes

Results Analysis

manual evaluation



Results Analysis

manual evaluation

Nine human judges ($\mathtt{H}$), divided into three groups

$\mathtt{G}_1 = \langle u_{1\rightarrow}\ \mathtt{H}_1, \mathtt{H}_2, \mathtt{H}_3 \rangle$
$\mathtt{G}_2 = \langle u_{2\rightarrow}\ \mathtt{H}_4, \mathtt{H}_5, \mathtt{H}_6 \rangle$
$\mathtt{G}_3 = \langle u_{3\rightarrow}\ \mathtt{H}_7, \mathtt{H}_8, \mathtt{H}_9 \rangle$
each $\mathtt{H}$ give their personal opinion[3] for a list of scenarios (15 runs)

Exact Agreement

$\mathtt{G}_1 = 94.4\%$
$\mathtt{G}_2 = 100\%$
$\mathtt{G}_3 = 99.4\%$

[3] never contradicting the user's profile s/he was evaluating

Results Analysis

e.g., of some F_1 results (%) for the three user stereotypes, using the EA of each group

	BN	$J48_p$	$J48_u$	NB
$\mathbf{r_3} \rightarrow u_1$	76.19	76.19	76.19	76.19
$\mathbf{r_4} \rightarrow u_2$	78.57	78.57	78.57	78.57
$\mathbf{r_{11}} \rightarrow u_3$	87.50	87.50	87.50	87.50

Caption

$r_3 = \texttt{lunch}$

$r_4 = \texttt{dinner}$

$r_{11} = \texttt{coffee}$

Conclusions

PAAs

- context and intentions in the recommendation process

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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 PAAs

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ML can be a powerful tool to be used in location-based services

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ML 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

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- use new information sources
- take into account new attributes (e.g., POI's quality)
- analyse other users' profiles

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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.

Costa, H., Furtado, B., Pires, D., Macedo, L., and Cardoso, A. (2012). Context and Intention-Awareness in POIs Recommender Systems. In *6th ACM Conf. on RS, 4th Workshop on Context-Aware Recommender Systems*. ACM.

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.

Schein, A., Popescul, A., Ungar, L., and Pennock, D. (2002). Methods and Metrics for Cold-Start Recommendations. In *25th Int. ACM SIGIR Conf. on Research and Development in Information Retrieval*, pages 253–260, NY, USA. ACM.

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.

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.


Recommender Systems
Location-Based Services
Points of Interest
User Modeling
Machine Learning
J48 unpruned
Cross-Validation
Recall
Collaborative Filtering
Precision
Algorithms
F-Measure
Coimbra
J48 pruned
Context
Content-Based
Validation
BayesNet
Information Overload
Ubiquitous Computing
Naïve Bayes
Evaluation
Personal Assistant Agents
Multiagent Systems
Artificial Intelligence
Intentions
Preferences