

Emotion-Based Recommender System for Overcoming the Problem of Information Overload

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Motivation

With the technological advance registered in the last decades, there has been an **exponential growth of the textual information available** (Bawden et al., 1999)



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Personal Assistant Agents (PAAs) can help humans to cope with the task of filtering out irrelevant information

PAAs should consider not only the user's **preferences**, but also their **context** and **intentions** when **recommending a new piece of information**



Main Goal

Help humans with the **Information Overload** problem



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Develop a Emotion-Based News Recommender System
using a Multiagent Approach



Background Knowledge

Natural Language Processing (NLP)

Affective Computing (AC)

Multiagent Systems (MAS)

Recommender Systems (RS)



NLP & AC

Natural Language Processing

(Jurafsky and Martin, 2009)

understand the language

Information Extraction (IE)

*automatically extract structured
information from unstructured
natural language resources*

Information Retrieval (IR)

*locate specific information in
natural language resources*



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Affective Computing

(Picard, 1997)

simulate human affect

Detect Affective States

explicitly or implicitly

Affective Interaction

*make emotional experiences
available for reflection*



MAS & RS

Multiagent Systems

(Wooldridge, 2009)

work in dynamic environments

Agents

*multiple, independent,
autonomous and goal-oriented*



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Recommender Systems

(Jannach et al., 2011)

filter information

Approaches

*Collaborative Filtering,
Content-Based, Hybrid*



Tasks

Collect

Extract

Represent

Share

Deliver



Tasks

Collect information from different sources (Paliouras et al., 2008)

Extract

Represent

Share

Deliver



Tasks

Collect

Extract information from the news (Ritter et al., 2011; Li et al., 2011)

Represent

Share

Deliver



Tasks

Collect

Extract

Represent the extracted information into a structured representation
(Sacco and Bothorel, 2010; IJntema et al., 2010)

Share

Deliver



Tasks

Collect

Extract

Represent

Share information between users, such as users' preferences and emotional features (González et al., 2002; Stickel et al., 2009; Yu et al., 2011)

Deliver



Tasks

Collect

Extract

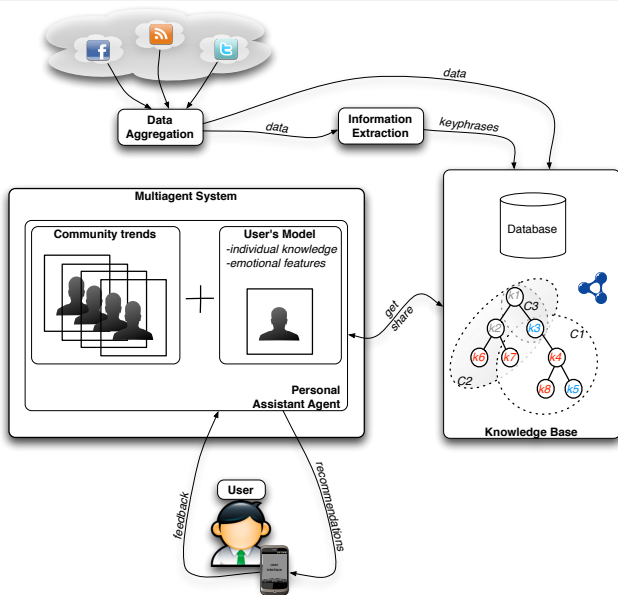
Represent

Share

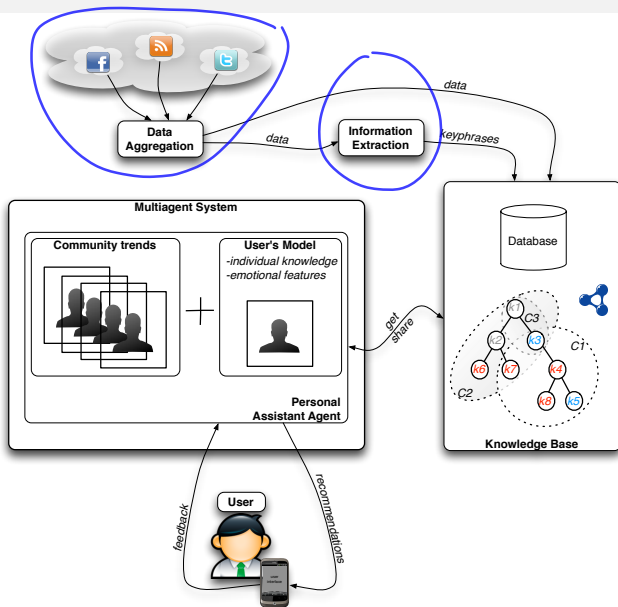
Deliver information based on the learned preferences and expected human's intentions (Knijnenburg et al., 2011; Lops et al., 2011; Costa et al., 2012)



Approach



Emotion-Based News RS's Architecture



Data Aggregation and Extraction

Data Aggregation

- ▶ capable of gathering information from a wide number of Web sources
- ▶ responsible for the information's quantity and quality

¹ http://dmir.inesc-id.pt/project/SentiLex-PT_02

² <http://ontopt.dei.uc.pt>

³ <http://dbpedia.org>



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- ▶ terms polarity, e.g., ML algorithms and SentiLex¹

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pre-filter

keyphrase extraction algorithm
post-filter

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pre-filter

stopwords, POS tagger or grammars (Costa, 2010)

keyphrase extraction algorithm

post-filter

e.g., discard verbs and rate the keyphrases (Onto.PT² and DBpedia³)

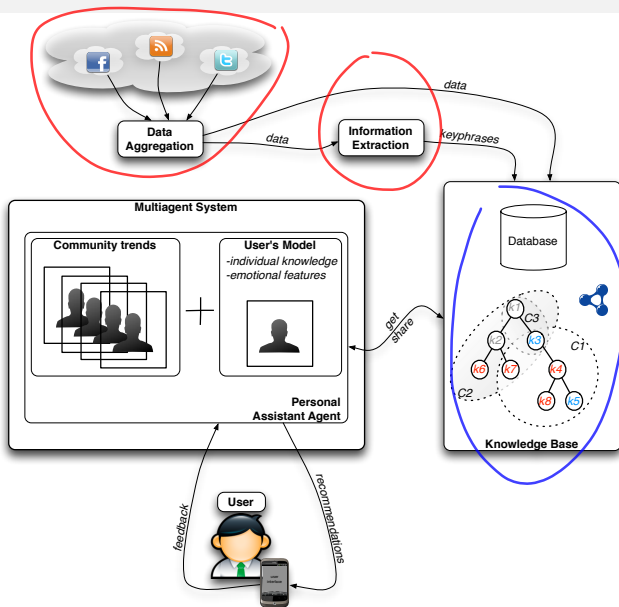
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Emotion-Based News RS's Architecture



Knowledge Base

Traditional Database

Ontology



Knowledge Base

Traditional Database

- ▶ store
 - ★ the gathered information
 - ★ users' feedback
 - ★ community trends
- ▶ perform
 - ★ tests
 - ★ debug

Ontology



Knowledge Base

Traditional Database

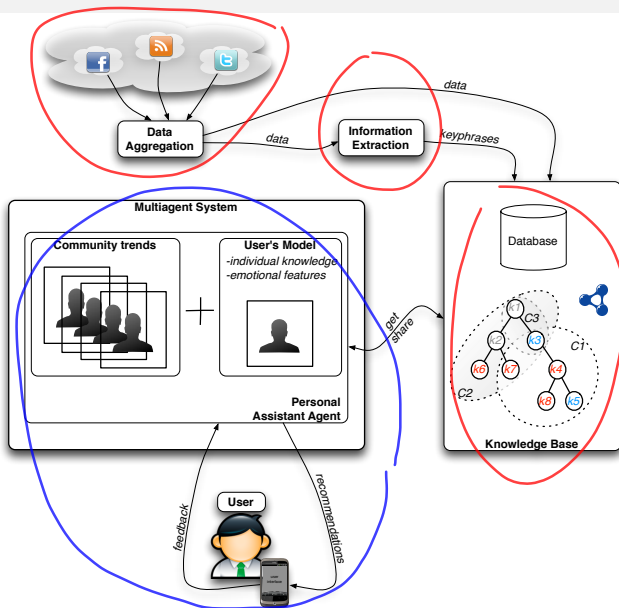
- ▶ store
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Ontology

- ▶ represent structured information, i.e., keyphrases and their relations
- ▶ infer new knowledge, e.g., main topics by using clustering algorithms (to reduce the cold-start problem (Schein et al., 2002))

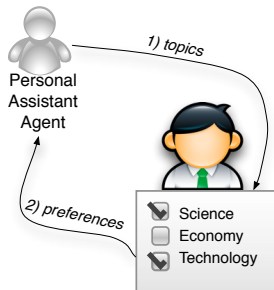


Emotion-Based News RS's Architecture



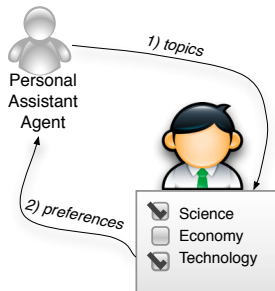
Personal Assistant Agents

User's preferences

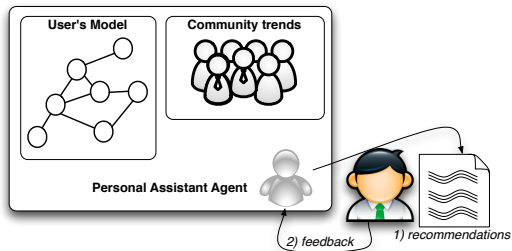


Personal Assistant Agents

User's preferences



User's feedback



Validation

Knowledge Extracted

System's Recommendations



Extraction Methods and Knowledge Extracted

Manual Evaluation

- ▶ using a reliable sample size



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Manual Evaluation

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Information Retrieval Methods

- ▶ quality
 - ★ amount of keyphrases that are correctly identified (precision)
- ▶ quantity
 - ★ amount of keyphrases among those that should have been extracted (recall)



Recommender's Evaluation

Quality and Quantity

Performance

Usability



Recommender's Evaluation

Quality and Quantity

- ▶ users' feedback
- ▶ IR methods, e.g., precision, recall and F_1

Performance

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Performance

- ▶ time the system consumes while executing the expected tasks
- ▶ system scales and keeps responding under different circumstances

Usability



Recommender's Evaluation

Quality and Quantity

- ▶ users' feedback
- ▶ IR methods, e.g., precision, recall and F_1

Performance

- ▶ time the system consumes while executing the expected tasks
- ▶ system scales and keeps responding under different circumstances

Usability

- ▶ questionnaires to identify interface needs and assess the users' satisfaction



Expected Contributions

Make a comparative view of the most common **algorithms** used to identify **keyphrases** and **clusters**



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Study the most suitable **metrics** to quantify and quality the **information extracted**



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Study the most suitable **metrics** to quantify and quality the **information extracted**

Define **dynamic users' models** to work in real-time



Expected Contributions

Study the impact of **sharing information** among the users

Does the introduction of collaborative recommendations improve the users' trust and usage?



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Does the introduction of collaborative recommendations improve the users' trust and usage?

[Make freely available](#)

the Knowledge Base, as well as the final Application



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Make freely available

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Analyse if the **affect-based PAA** avoid their human owners from receiving irrelevant or emotionless information



Deployment and Advertisement

Collect Feedback

- ▶ ResearchGate⁴, Forum-LP⁵, Corpora List⁶, Linguist List⁷

⁴ <https://www.researchgate.net>

⁵ forum-lp@di.fct.unl.pt

⁶ corpora@uib.no

⁷ linguistlinguistlist.org



Deployment and Advertisement

Collect Feedback

- ▶ ResearchGate⁴, Forum-LP⁵, Corpora List⁶, Linguist List⁷

Website

- ▶ get information about the project
- ▶ download the Application
- ▶ browse and search the Knowledge Base
- ▶ provide feedback

⁴ <https://www.researchgate.net>

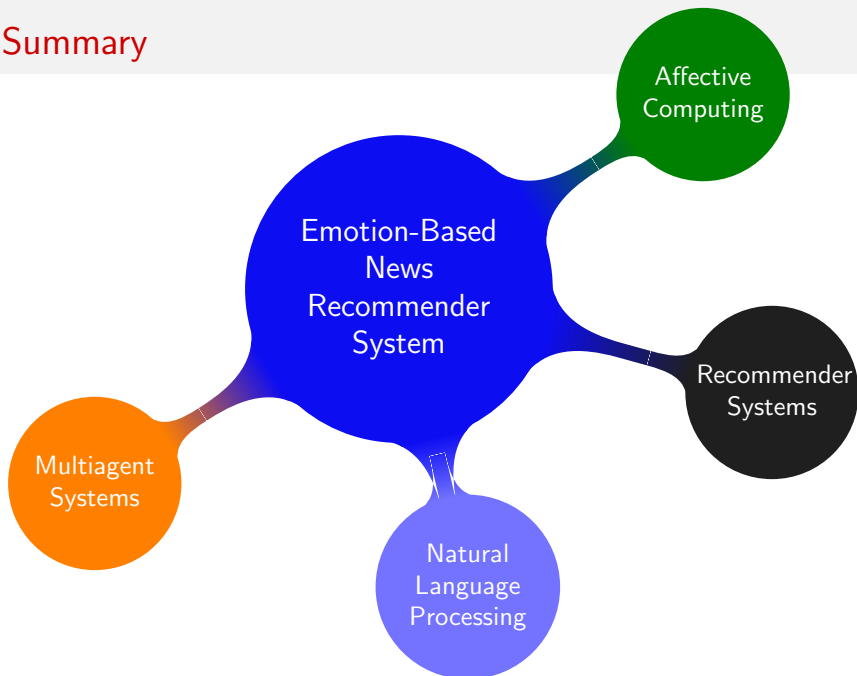
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Summary



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