

Ontology-Based News Recommendation

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Outline

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Introduction

Motivation

Problem

- ▶ Stock prices are sensitive to news
- ▶ News overload (different sources, different topics)
- ▶ Difficult to find the news of interest
- ▶ ... need for an intelligent solution to support news-based decision processes

Partial solution

- ▶ RSS feeds
- ▶ Broad categories (business, cars, entertainment, etc.)

Introduction

Motivation

Solutions

- ▶ News querying systems (intrusive)
- ▶ News recommender systems (non-intrusive)

Recommender systems:

- ▶ Content-based (Traditional)
- ▶ Collaborative filtering (Users-based)
- ▶ Semantics-based (Our focus here)
- ▶ Hybrid

Introduction

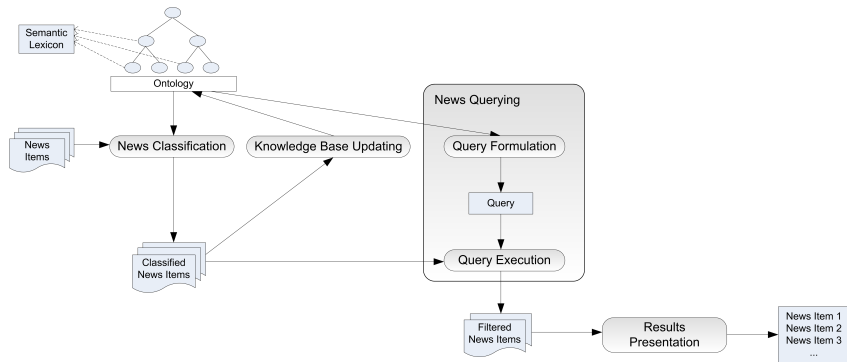
Related Work

- ▶ Content-based
 - ▶ Based on TF-IDF for representing articles and the user profile
 - ▶ Cosine similarity between new article and the user profile
 - ▶ Performance of cosine similarity decreases as the length of the article increases
 - ▶ Tools: YourNews, News Dude
- ▶ Semantics-based
 - ▶ Based on is-a relationships
 - ▶ Semantic relatedness as a similarity measure
 - ▶ Uses concepts instead of terms for the vector representation (improves precision)
 - ▶ Considers concepts related to the ones appearing in news items (improves recall)
 - ▶ Tools: PersoNews, (Getahun et al., 2009)

Hermes: News Personalization Service Framework

- ▶ Input:
 - ▶ News items from RSS feeds
 - ▶ Domain ontology linked to a semantic lexicon (e.g., WordNet)
 - ▶ User query
- ▶ Output:
 - ▶ News items as answers to the user query
- ▶ Four phases:
 1. News Classification
 - ▶ Relate news items to ontology concepts
 2. Knowledge Base Updating
 - ▶ Update the knowledge base with news information
 3. News Querying
 - ▶ Allow the user to express his concepts of interest and the temporal constraints
 4. Results Presentation
 - ▶ Present the news items that match users query

Hermes: News Personalization Service Architecture



Athena: News Recommendation Service Framework

- ▶ Input:
 - ▶ News items from RSS feeds
 - ▶ Domain ontology linked to a semantic lexicon (e.g., WordNet)
 - ▶ User items of interest
- ▶ Output:
 - ▶ List of other news items of interest (possibly ranked)
- ▶ Five similarity measures (alternatives):
 - ▶ Concept Equivalence
 - ▶ Binary Cosine
 - ▶ Jaccard
 - ▶ Semantic Relatedness (adaptation of (Getahun et al., 2009))
 - ▶ Ranked Semantic Relatedness (our contribution)

Athena: News Recommendation Service

Preliminary Definitions

Ontology

$$C = \{c_1, c_2, c_3, \dots, c_n\} . \quad (1)$$

User Profile

$$U = \{c_1^u, c_2^u, c_3^u, \dots, c_p^u\} , \text{ where } c_i^u \in C . \quad (2)$$

News Article

$$A = \{c_1^a, c_2^a, c_3^a, \dots, c_q^a\} , \text{ where } c_j^a \in C . \quad (3)$$

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Similarity Measures

Concept Equivalence

$$\text{Similarity}(U, A) = \begin{cases} 1 & \text{if } |U \cap A| > 0 \\ 0 & \text{otherwise} \end{cases} . \quad (4)$$

- ▶ Concept Equivalence does not consider consider the number of user profile concepts found in a news article

Binary Cosine

$$B(U, A) = \frac{|U \cap A|}{|U| \times |A|} . \quad (5)$$

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Similarity Measures

Jaccard

$$J(U, A) = \frac{|U \cap A|}{|U \cup A|}. \quad (6)$$

- ▶ Binary Cosine and Jaccard do not consider the number of occurrences of a concept in an article
- ▶ Binary Cosine and Jaccard do not consider the concepts related to the ones found in an article

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Similarity Measures

Semantic Relatedness

Semantic Neighbourhood

$$N(c_i) = \{c_1^i, c_2^i, \dots, c_n^i\} . \quad (7)$$

Vector Representation for 2 News Articles

$$V_l = (w_1^l, w_2^l, \dots, w_p^l) , \quad (8)$$

where

- ▶ $l \in \{i, j\}$, the two news articles t_i and t_j
- ▶ w_i represents the weight of c_i (number of occurrences of c_i)
- ▶ $p = |CS_i \cup CS_j|$ is the number of distinct concepts in CS_i and CS_j

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Similarity Measures

Semantic Relatedness

Vector Representation for 2 News Articles

$$w_i = \begin{cases} 1 & \text{if freq}(c_i \text{ in } CS_j) > 0 \\ \max_j(\text{ES}(c_i, c_j)) & \text{otherwise} \end{cases} \quad (9)$$

where the enclosure similarity is defined as

$$\text{ES}(c_i, c_j) = \frac{|N(c_i) \cap N(c_j)|}{|N(c_i)|} . \quad (10)$$

$$\text{SemRel}(t_i, t_j) = \cos(V_i, V_j) = \frac{V_i \cdot V_j}{\|V_i\| \cdot \|V_j\|} \in [0, 1] , \quad (11)$$

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Similarity Measures

Ranked Semantic Relatedness

Extended User Profile

- ▶ The set of related concepts to concept c_i is

$$r(c_i) = \{c_1^i, c_2^i, \dots, c_k^i\} . \quad (12)$$

- ▶ The set of related concepts to the concepts in the user profile is

$$R = \bigcup_{u_i \in U} r(u_i) . \quad (13)$$

- ▶ The extended user profile is

$$U_R = U \cup R . \quad (14)$$

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Similarity Measures

Ranked Semantic Relatedness

Rank Matrix

	e_1	e_2	\dots	e_q
u_1	r_{11}	r_{12}	\dots	r_{1q}
u_2	r_{21}	r_{22}	\dots	r_{2q}
\vdots	\vdots	\vdots	\vdots	\vdots
u_m	r_{m1}	r_{m2}	\dots	r_{mq}

where the ranks from the rank matrix are:

$$r_{i,j} = w_i \times \begin{cases} +1.0 & \text{if } e_j = u_i \\ +0.5 & \text{if } e_j \neq u_i, e_j \in r(u_i) \\ -0.1 & \text{otherwise} \end{cases} . \quad (15)$$

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Similarity Measures

Ranked Semantic Relatedness

Rank Matrix

- ▶ The weight w_i is the number of articles the user has read about concept u_i .
- ▶ The elements of the rank vector V_U for the extended profile concepts are:

$$\text{Rank}(e_j) = \sum_{i=1}^m r_{ij} . \quad (16)$$

- ▶ The normalization of the rank vector V_U is:

$$V_U[v_i] = \frac{v_i - \min(v_u)}{\max(v_u) - \min(v_u)} . \quad (17)$$

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Similarity Measures

Ranked Semantic Relatedness

- ▶ A new article is a set of concepts

$$A = \{a_1, a_2, \dots, a_t\} . \quad (18)$$

- ▶ The rank vector of the article is

$$V_A = (s_1, s_2, \dots, s_t) , \quad (19)$$

where

$$s_j = \begin{cases} \text{Rank}(e_j) & \text{if } e_j \in A \\ 0 & \text{if } e_j \notin A \end{cases} . \quad (20)$$

$$\text{RankedSemanticSimilarity}(V_A, V_U) = \frac{\sum_{v_a \in V_A} v_a}{\sum_{v_u \in V_U} v_u} . \quad (21)$$

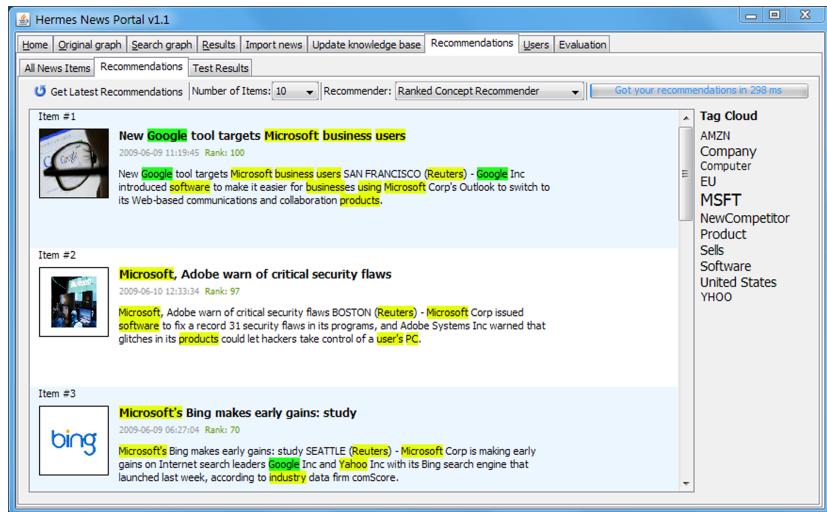
Athena Implementation

Athena as HNP Plugin

- ▶ Hermes News Portal (HNP) is the implementation of Hermes
- ▶ Athena is a plugin for HNP
- ▶ Athena has three tabs:
 - ▶ Browser for all news items
 - ▶ Recommendations
 - ▶ Evaluation
- ▶ Implements all five recommenders
- ▶ Double clicking means the news item is added to the profile

Athena Implementation

Athena Plugin



The screenshot displays the Hermes News Portal v1.1 interface. At the top, there is a navigation bar with tabs: Home, Original graph, Search graph, Results, Import news, Update knowledge base, Recommendations, Users, and Evaluation. Below this, there are sub-tabs: All News Items, Recommendations, and Test Results. A control bar includes a refresh icon, the text "Get Latest Recommendations", a "Number of Items:" dropdown set to 10, a "Recommender:" dropdown set to "Ranked Concept Recommender", and a status indicator "Got your recommendations in 298 ms".

The main content area lists three news items:

- Item #1:** **New Google tool targets Microsoft business users**
2009-06-09 11:19:45 Rank: 100
New Google tool targets Microsoft business users SAN FRANCISCO (Reuters) - Google Inc introduced software to make it easier for businesses using Microsoft Corp's Outlook to switch to its Web-based communications and collaboration products.
- Item #2:** **Microsoft, Adobe warn of critical security flaws**
2009-06-10 12:33:34 Rank: 97
Microsoft, Adobe warn of critical security flaws BOSTON (Reuters) - Microsoft Corp issued software to fix a record 31 security flaws in its programs, and Adobe Systems Inc warned that glitches in its products could let hackers take control of a user's PC.
- Item #3:** **Microsoft's Bing makes early gains: study**
2009-06-09 06:27:04 Rank: 70
Microsoft's Bing makes early gains: study SEATTLE (Reuters) - Microsoft Corp is making early gains on Internet search leaders Google Inc and Yahoo Inc with its Bing search engine that launched last week, according to industry data firm comScore.

On the right side, there is a **Tag Cloud** with the following tags: AMZN, Company, Computer, EU, MSFT, NewCompetitor, Product, Sells, Software, United States, and YHO0.

Athena Implementation

HNP/Athena Implementation Tools

- ▶ Programming Language: Java
- ▶ Ontology Language: OWL
- ▶ Query Language: tSPARQL
- ▶ Semantic Web Framework: Jena
- ▶ Semantic Lexicon: WordNet
- ▶ Natural Language Processing: GATE
- ▶ Visualization: Prefuse
- ▶ Stemmer: Krovetz

Evaluation

Evaluation Setup

- ▶ 300 news items
- ▶ 5 users
- ▶ Each user has different interests
- ▶ All news items are marked as interesting/non-interesting by the users
- ▶ News items randomly split into two different sets:
 - ▶ Training set (60% of news items)
 - ▶ Validation set (40% of news items)
 - ▶ Similarity cut-off value: 0.5

Evaluation

Evaluation Results

Method	Accuracy	Precision
TF-IDF	90%	90%
Concept Equivalence	44%	22%
Binary Cosine	47%	23%
Jaccard	93%	92%
Semantic Relatedness	57%	26%
Ranked	94%	93%

Method	Recall	Specificity
TF-IDF	45%	99%
Concept Equivalence	98%	32%
Binary Cosine	95%	36%
Jaccard	58%	99%
Semantic Relatedness	92%	47%
Ranked	62%	99%

Evaluation

Evaluation Results

- ▶ Ranked Semantic Recommender scores better than TF-IDF for accuracy, precision, and recall, and the same for specificity
- ▶ Ranked Semantic Recommender scores best for accuracy and precision (closely followed by Jaccard)
- ▶ Ranked Semantic Recommender has a lower recall than Concept Equivalence, Binary Cosine, and Semantic Relatedness
- ▶ Concept Equivalence scores the best for recall

Conclusions and Future Work

Conclusions

- ▶ Athena: News Recommendation Service
- ▶ Athena implementation: HNP plugin
- ▶ Semantic recommenders are superior to traditional recommenders
- ▶ Ranked Semantic Recommender performs best for accuracy and precision

Conclusions and Future Work

Future Work

- ▶ Perform statistical significance tests
- ▶ Improve the recall of the Ranked Semantic Recommender by considering also the concepts related to the ones found in a new article
- ▶ Consider the indirect concepts in the semantic neighbourhood of a concept
- ▶ Refine the concept importance in an article: consider also the place appearance (title or/and body) in addition to number of occurrences

Ranked Semantic Recommender

Example

- ▶ The user profile is:

$$U = \{\text{Yahoo!}, \text{Obama}, \text{China}\} .$$

- ▶ The weights W (number of articles) for the corresponding user profile concepts are:

$$W = (4, 3, 2) .$$

- ▶ The sets of related concepts for each concept in the profile are as follows:

$$r(\text{Yahoo!}) = \{\text{Google}, \text{Apple}\} ,$$

$$r(\text{Obama}) = \{\text{USA}\} ,$$

$$r(\text{China}) = \{\text{USA}\} .$$

Ranked Semantic Recommender

Example

- ▶ The set of related concepts to the user profile concepts is:

$$\begin{aligned} R &= r(\text{Yahoo!}) \cup r(\text{Obama}) \cup r(\text{China}) \\ &= \{\text{Google, Apple, USA}\}. \end{aligned}$$

- ▶ The extended user profile is:

$$U_R = \{\text{Yahoo!, Obama, China, Google, Apple, USA}\}.$$

- ▶ The rank matrix is:

	Yahoo!	Obama	China	Google	Apple	USA
Yahoo!	4	-0.4	-0.4	2	2	-0.4
Obama	-0.3	3	-0.3	-0.3	-0.3	1.5
China	-0.2	-0.2	2	-0.2	-0.2	1
Rank	3.5	2.4	1.3	1.5	1.5	2.1

Ranked Semantic Recommender

Example

- ▶ The normalized rank vector V_U is:

$$V_U = (1, 0.5, 0, 0.091, 0.091, 0.364) .$$

- ▶ Two new news articles:

$$A_1 = \{\text{Google, USA, Vitamins}\}$$

$$A_2 = \{\text{Yahoo!, USA}\} .$$

- ▶ The vector representations of these two articles:

$$V_{A_1} = (0.091, 0.364, 0.0)$$

$$V_{A_2} = (1, 0.364) .$$

Ranked Semantic Recommender

Example

- ▶ The ranked semantic similarities of these two news items to the extended user profile:

$$\begin{aligned} \text{RankedSemSim}_{A_1} &= \frac{0.091 + 0.364}{1 + 0.5 + 0 + 0.091 + 0.091 + 0.364} \\ &= 0.222 \end{aligned}$$

$$\begin{aligned} \text{RankedSemSim}_{A_2} &= \frac{1 + 0.364}{1 + 0.5 + 0 + 0.091 + 0.091 + 0.364} \\ &= 0.667. \end{aligned}$$

- ▶ For a cut-off value of 0.5 only A_2 is recommended
- ▶ NB: Both A_1 and A_2 share only 1 concept with the user profile

Key Issues

- ▶ How to improve the recall for the Ranked Semantic Recommender?
- ▶ How to compute the importance of a concept in an article?