A Latent Semantic Pattern Recognition Strategy for an Untrivial Targeted Advertising

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Outline

INTRODUCTION

BEHAVIORAL TARGETING

- ✓ *Behavioral targeting* is the strategy used to identify sets of users who share common properties
- ✓ Classic partitioning algorithms (e.g.,*k-means*) cannot take in account the semantic of the user behavior (*Gong et al.* [2])

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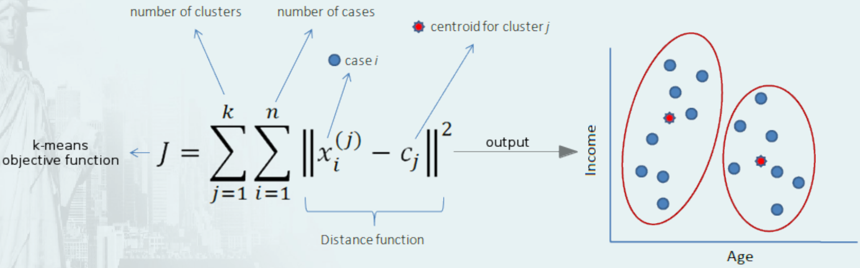

RELATED WORK AND OPEN PROBLEMS

- ✓ In the literature strategies that take into account the semantic aspect have been proposed:
  - ✓ *Tu and Lu* [5], based on query semantic analysis
  - ✓ *Gong et al.* [2], based on queries and clicks analysis
- ✓ However, some problems remain open:
  1. The **reliability** of a semantic query analysis (*Spink et al.* [4])
     - ✓ Nearly 50% of the times users reformulate their queries
  2. The **interpretability** of the segments (*Nairn and Bottomley* [3])
     - ✓ A segmentation is either trivial or too complex to analyze (too many features involved)
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PROPOSED SOLUTION

- ✓ Semantic analysis of the description of the items positively evaluated by the users
  - ✓ This solve the **reliability** of the semantic query analysis problem (*step 1*)
- ✓ Definition of novel binary filters that describe which terms (Wordnet[1] synsets) characterize each class of items
  - ✓ This solves the segments **interpretability** problem (*steps 2 and 3*)
- ✓ Matching between the user profiles and the binary filters, in order to detect non trivial user segments
  - ✓ This solves the problem related to the **preference stability** (*steps 4 and 5*)

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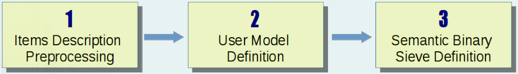

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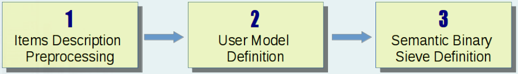

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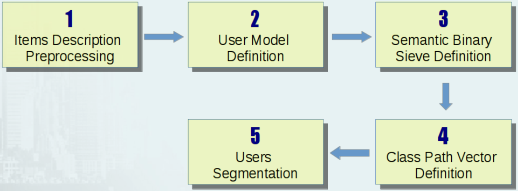

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IMPLEMENTATION

1. ITEMS DESCRIPTION PREPROCESSING

- ✓ We preprocess the textual description of each item, to remove the useless elements (i.e., punctuation marks and stop-words)
- ✓ We determine the lemma of each word (e.g., use *good* instead of *better*, and *walk* instead of *walking*)
- ✓ We assign to them the best sense (i.e., **1**=noun, **2**=verb)

Input

In the near future, a computer hacker named Neo discovers that all life on Earth may be nothing more than an elaborate illusion

Output

future/**1** computer/**1** hacker/**1** nam/**2** neo/**1** discover/**2** life/**1** earth/**1** illusion/**1**

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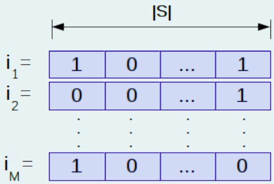
2. USER MODEL DEFINITION

$$m_u[w] = \begin{cases} 1, & \textit{if } ds_i[w] = 1 \\ m_u[w], & \textit{otherwise} \end{cases}$$

- ✓ For each user $u \in U$, we consider the set of items I_u she/he likes



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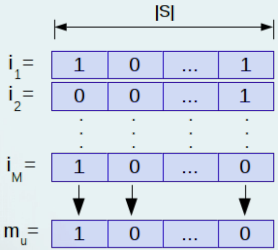
- ✓ Then build a model m_u that describes which synsets[2] appear in the semantic description ds_i of each item i



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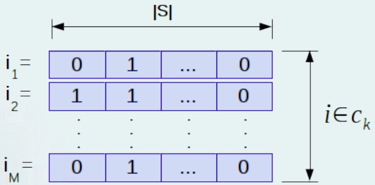
$$b_k[w] = \begin{cases} 1, & \textit{if } ds_i[w] = 1 \wedge i \in c_k \\ b_k[w], & \textit{otherwise} \end{cases}$$

- ✓ For each class $c \in C$, we create a binary vector that reports which synsets are relevant for that class



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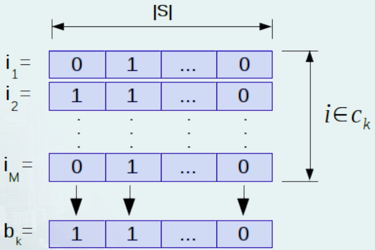
- ✓ For each class $c \in C$, we create a binary vector that reports which synsets are relevant for that class
- ✓ Then we stored each vector b_k in a set $B = \{b_1, \ldots, b_K\}$ (note that $|B| = |C|$)



4. CLASS PATH VECTOR DEFINITION

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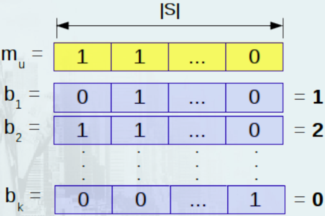
- ✓ We compare ($\ominus$ operator) the *user models* $M = \{m_1, \ldots, m_N\}$ and the *SBS* vectors $B = \{b_1, \ldots, b_K\}$



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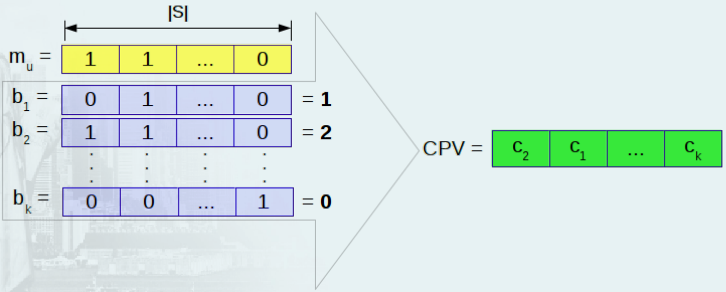
- ✓ Then build a *Class Path Vector* (*CPV*) for each user, which contains the class relevance in decreasing order



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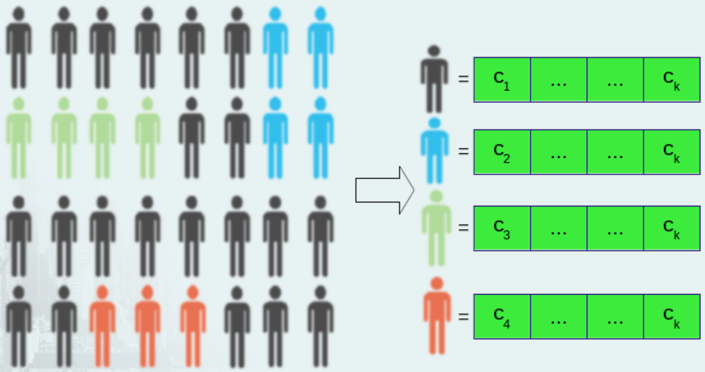
- ✓ Then place each user in the class with the highest value of relevance score



EXPERIMENTS

FRAMEWORK

- ✓ The experiments were performed using 2 real-world datasets: the *Yahoo! Webscope Movie (R4)*[3], and the *Movielens 10M*[4]
- ✓ We compare our strategy with:
  - ✓ the k-means approach
  - ✓ the *native classification* of the items, obtained by selecting for each user the most preferred class in the real dataset
- ✓ The aim is to study the *users distribution* (i.e., the ability to group the users in a non-trivial way) and the *segments composition* (i.e., the ability to group the users in a pertinent way)

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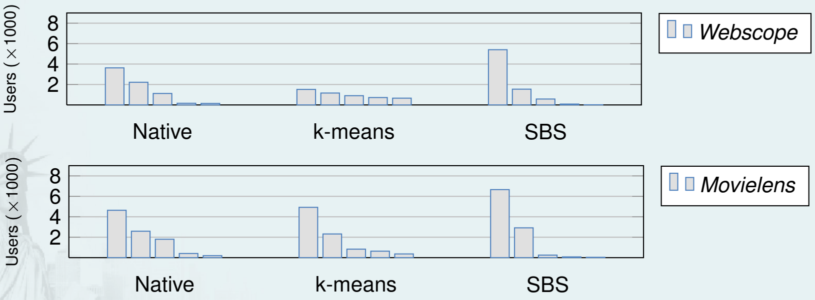
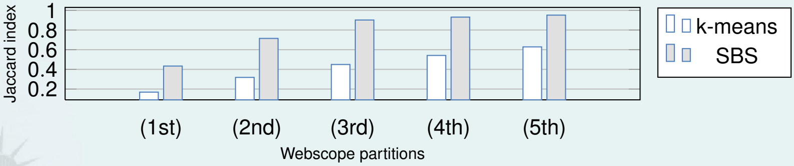
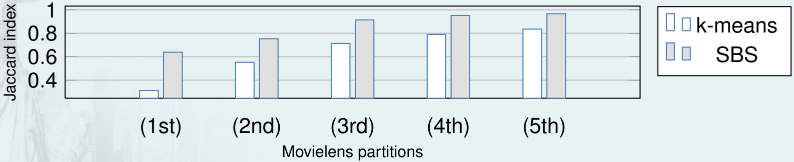


The results show that *k-means* segments the users in a quite uniform way (*Webscope*), or like the native classification (*Movielens*), since it is not able to discover any implicit preferences, differently from our approach

SEGMENTS COMPOSITION





The relevance of our partitioning is proved by the strong overlap between with the users in the native classification, differently from those classified by *k-means*

CONCLUSIONS

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- ✓ This approach allows us to perform group recommendations, by suggesting items to groups of “semantically related” users
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Questions and Answers

THANK YOU