Semantic Coherence-based User Profile Modeling in the Recommender Systems Context

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Outline

RECOMMENDER SYSTEMS

- A Recommender System (**RS**) produces personalized content for users in the form of suggestion of items
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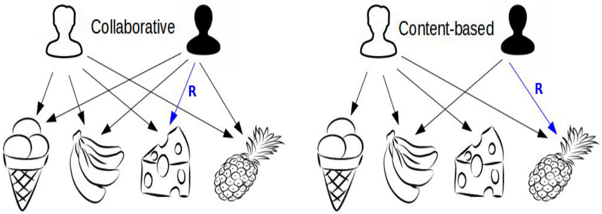

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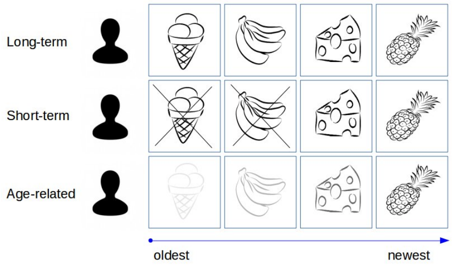

PROBLEM DEFINITION

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- We would like to define a strategy able to make the user profiles as adherent as possible to the real user tastes
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- There are several approaches designed to face this problem, but each of them usually is designed to operate within a precise context (e.g., news or goods)
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IMPLEMENTATION

- We use a *coherence-based* model to identify the *noise* in a user profile
- The idea is to measure the semantic similarity of each item with respect to remaining items (*Global Coherence*)
- The semantic similarity measures are performed exploiting WordNet (conceptual relations between synsets[1])

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DETECTION AND NOISE REMOVAL

- We remove an item **i** from the user profile when it meets two requirements:
  1. it is located in the oldest part **o** of the user interaction history;
  2. its semantic similarity $\mathbf{S_i}$ with the set of other items is below the mean value of the semantic similarity of all items $\overline{\mathbf{GS}}$ stored in the profile.
- Regarding both requirements, we can introduce an arbitrary tolerance value (α_1 and α_2)

$$Remove(i) = \begin{cases} yes, & \text{if } S_i < (\overline{GS} \mp \alpha_1) \text{ AND } Time(i) <= (o \mp \alpha_2) \\ no, & \text{otherwise} \end{cases}$$

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Questions and Answers

THANK YOU