

# Exploiting Semantic Product Descriptions for Recommender Systems

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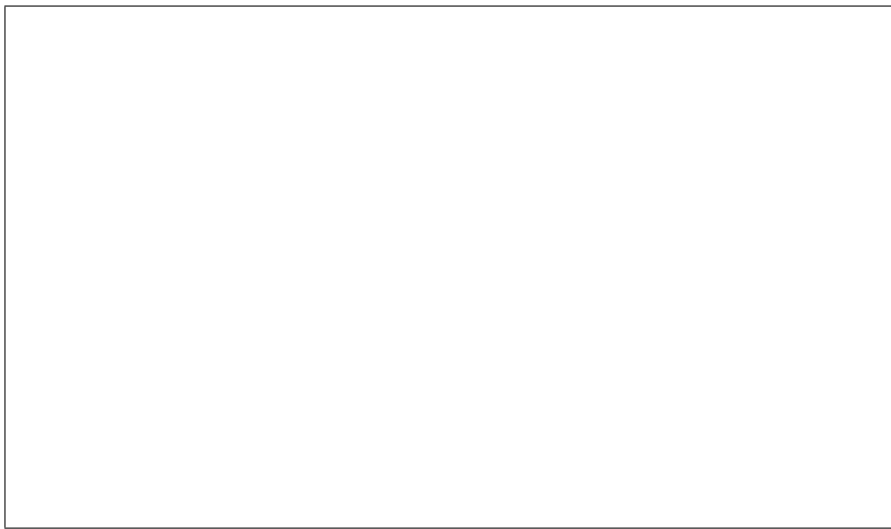
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blessings provided by recommender systems.

We intend to alleviate the information sparsity issue by exploiting those before-mentioned product classification taxonomies as powerful background knowledge. Hereby, our hybrid information filtering approach permits properly inferring profile similarity between two given users though both agents might not have rated any products in common. Making use of the “collaboration via content” paradigm [23],

of dimensionality  $|B|$ , but by vectors of interest scores assigned to *topics* taken from taxonomy  $C$  over product categories  $d \in D$ .



Relevance  $w_i(b_k)$  of product  $b_k$  for the active user  $a_i$  is then defined as follows:

$$w_i(b_k) = \frac{q \cdot c_b(a_i, b_k) \cdot \sum_{a_j \in A_i(b_k)} c(a_i, a_j)}{|A_i(b_k)| + R}, \quad (7)$$

where

$$A_i(b_k) = \{a_j \mid \text{clique}(a_i) / b_k \cap R_j\}$$

and

$$q = q$$

procedure diversify (*P*)

$$w_i(b_k) = \frac{c(a_i, a_j)}{\sum_{a_j \in A_i(b_k)} c(a_i, a_j)} \quad (8)$$

Hereby, we measure user similarity  $c(a_i, a_j)$  according to Pearson correlation, introduced in Section 3.3.1. Profile vectors  $v_i, v_j$  for agents  $a_i, a_j$ , respectively, represent implicit ratings for every product  $b_k \in B$ , hence  $v_i, v_j \in \{0, 1\}^{|B|}$ .

#### 4.2.1.3 Hybrid Recommender Approach.

The third competing system exploits both collaborative and content-based filtering facilities, hence its hybrid nature. The algorithmic clockwork mimics Pazzani's "collaboration via content" proposal [23], representing user profiles  $v_i$  through





14	1.37057472	0.17335063	2.41760397	1.60240506
15	1.39215949	0.18358535	2.44001489	1.65442854
16	1.40580331	0.19158667	2.44087139	1.70458443
17	1.38639753	0.18093777	2.54088386	1.72781798
18	1.3813139	0.18297222	2.5909104	1.77596723
19	1.37089092	0.19004361	2.57706446	1.7171881
20	1.34556085	0.1827844	2.61306722	1.76000474
21	1.41032046	0.18140914	2.68021622	1.84471085
22	1.39184461	0.19165824	2.69981036	1.91931885
23	1.40053345	0.20192565	2.70627937	1.89828101
24	1.39420985	0.16253384	2.73844159	1.9214737

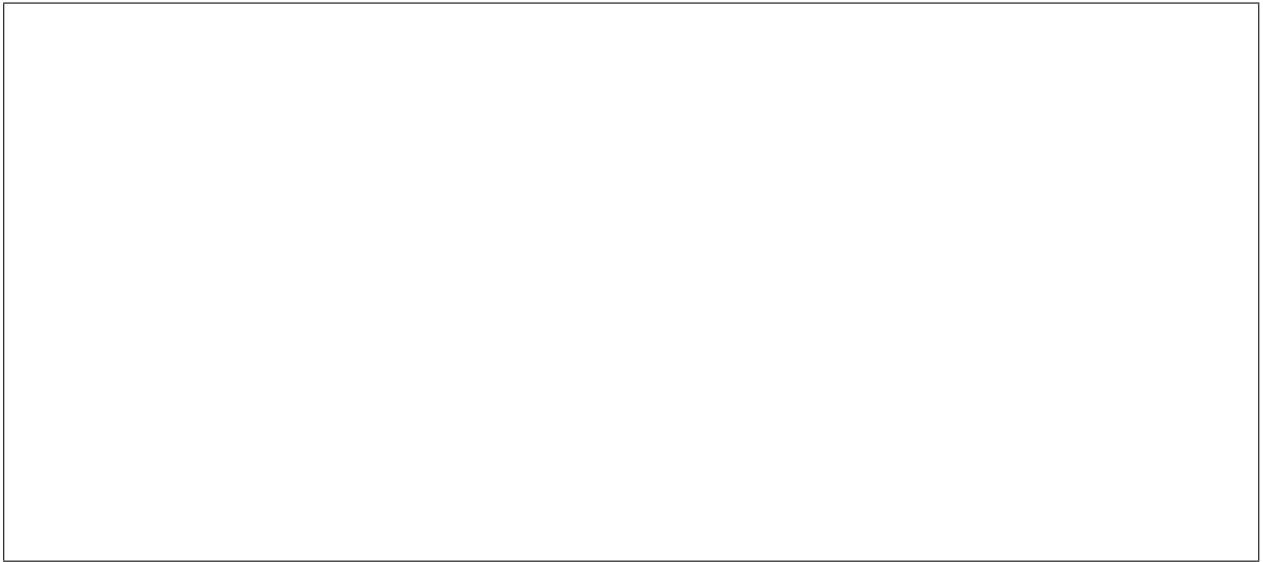


Figure 4: Results obtained from online evaluation

participating users. In both cases, the taxonomy-driven system performed best and the purely collaborative worst.

Second, we counted all those raters perceiving one specific system as best. Again, comparison was based upon the overall verdict and average recommendation, likewise. In order to guarantee fairness, we discarded users not having rated all three systems for each metric. The right chart of Figure 4 shows that the appreciation of the taxonomy-driven method significantly prevailed.

Eventually, we may conclude that results obtained from the online analysis back offline evaluation results. In both

*Workshop on Personalization and Recommendation in E-Commerce*  
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