Effective Products Categorization with Importance Scores and Morphological Analysis of the Titles

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E-commerce

• Large growth rate:
  – E-commerce share of retail sales worldwide (2015): 7.4%.
  – E-commerce share of retail sales worldwide (2018): 11.9%.
  – Predicted E-commerce share of retail sales worldwide (2021): 17.5%¹

• The related research problems have been rendered increasingly important.

• Effective and efficient management, processing, and mining of products data are examples of such problems.

Products Categorization

• One of the most important problems in the area.
• Given a product and a set of categories, it is required that we determine the category where the product belongs to.
• It leads to numerous novel applications:
  – Query expansion and rewriting.
  – Relevant/Similar products retrieval.
  – Personalized recommendations etc.
Attributes or not?

• Relevant work is divided into two categories:
  – those which are based on the products titles only and
  – those which take into consideration additional properties of the product (brand name, attributes, technical characteristics, etc).

• However, such metadata is not always present; even if it is present, it is frequently incomplete, ambiguous, inconsistent, or incorrect.

• The proposed method belongs to the first category and operates by accessing the titles only.
Theoretical Background

• Let $Y$ be the set of all categories.
• The categories are usually organized into a tree structure with parent and leaf categories.
• A product can only be assigned one leaf category in the aforementioned tree.
• Each product is described by its title $\tau$.
• The title has the words $(w_1, w_2, \ldots, w_{lx})$. 
N-grams vs. words

• The proposed method performs morphological analysis of the titles and extracts n-grams of variable sizes.
• The reason of employing n-grams is that a n-gram is less ambiguous than single words.
• For instance, a brand name (e.g. Apple) may be correlated with multiple diverse categories (mobile phones, tablets, computers, etc).
• However, the bigram Apple iPhone is much more specific.
Tokens and Ambiguity

• We collectively refer to all n-grams and words as tokens.

• Each token has its own level of ambiguity.
  – Ambiguous tokens are not tightly correlated with a single category; they can be connected with multiple categories.

• Or, each token is of different importance.

• According to the previous example, longer tokens are less ambiguous, that is, more important.
Importance Scores

• Furthermore, a token is more important if it has been correlated with only a few categories.

• Based on these notifications, we introduce the following importance score for a token $t$.

$$I_t = l_t \log \frac{|Y|}{f_t}$$

− $|Y|$: the total number of categories,
− $f_t$: the frequency of $t$, i.e. the number of the categories which have been correlated with $t$, and
− $l_t$: the length (in words) of $t$. 
Categorization Model: Training Phase

• The training phase builds a lexicon $L$ for the tokens. Each entry in the lexicon stores:
  • The token $t$,
  • Its frequency $f_t$,
  • Its importance score $I_t$,
  • A relevance description vector (RDV) which for each token-category relationship, includes a pair in the form $(y, f_{t,y})$, where $y$ is a category and $f_{t,y}$ is another frequency value that reflects how many times $t$ has been correlated with the category $y$. 

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Model Training Algorithm

Algorithm 1: Model training algorithm

1. initialize the lexicon $L$;
2. for each product $x$ in the training set do
   3. retrieve the category $y$;
   4. extract the title $T$;
   5. perform linguistic processing of $T$;
   6. for each $n \in [1, N]$ do
      7. compute all tokens $T_n$ of length $n$;
      8. for each token $t \in T_n$ do
         9. if $L\.search(t) == false$ then
            10. $L\.insert(i)$;
            11. set $f_t \leftarrow 1$;
            12. $L\.insertRDV(t,y)$;
            13. set $f_{t,y} \leftarrow 1$;
         14. else
            15. if $L\.searchRDV(t,y) == false$ then
               16. set $f_t \leftarrow f_t + 1$;
               17. $L\.insertRDV(t,y)$;
               18. set $f_{t,y} \leftarrow 1$;
            19. else
               20. set $f_{t,y} \leftarrow f_{t,y} + 1$;
            21. end
         22. end
      23. end
   24. end
25. for each token $t \in L$ do
26. set $I_t \leftarrow I_t \log(|Y|/f_t)$;
27. sort RDV of $t$ in decreasing $f_{t,y}$ order;
28. end
Categorization Model: Testing Phase

- The testing phase is based on the lexicon $L$ of the previous phase.
- Initially, an empty candidates list $Y'$ is created.
- In the sequel, for each token $t$ of each product $p$, we perform a search in $L$.
- In case it is successful, we retrieve the RDV, $f_t$ and $I_t$ of $t$. Then, we traverse the RDV and for each entry $y$ we update the candidates list $Y'$. 
Candidates Scoring

- The score $S_{t,y}$ of each candidate category is expressed as linear combination of the importance score of the token and a quantity $Q_{t,y}$:

$$S_{t,y} = k_1 I_t + k_2 Q_{t,y}$$

$$Q_{t,y} = \log f_{t,y} \log \frac{|Y|}{f_t}$$

- Finally, the candidates are sorted in decreasing $S_{t,y}$ order and the top candidate is selected as a category for the product.
Algorithm 2: Categorization algorithm

1. for each product $x$ in the test set do
2. initialize candidates list $Y'$;
3. extract the title $\tau$;
4. perform linguistic processing of $\tau$;
5. for each $n \in [1, N]$ do
6. compute all tokens $T_n$ of length $n$;
7. for each token $t \in T_n$ do
8. if $L.\text{search}(t) == \text{true}$ then
9. for each pair $(y, f_{t,y})$ in the RDV of $t$
10. do
11. if $Y'.\text{search}(y) == \text{false}$ then
12. $Y'.\text{insert}(y)$;
13. set $S_y \leftarrow f(I_{t,y}, Q_{t,y})$
14. else
15. set $S_y \leftarrow S_y + I_{t,y}$
16. end
17. end
18. end
19. end
20. sort $Y'$ in decreasing $S_y$ order;
21. set $y \leftarrow Y'[0]$;
Model Pruning

• We may decrease the size of the lexicon $L$ by preserving only the tokens whose importance score exceeds a threshold $C$:

$$C = T \max_{t,y} I_{t,y}$$

• We will demonstrate experimentally that this choice combines a significant reduction of the size of $L$, with infinitesimal losses in the accuracy of the algorithm.
Experimental Setup

• Dataset: 313,706 products & 230 (191 leaf) categories from shopmania.com.
• Training/Test Set sizes: 60%/40%.
• Four scenarios for the extracted n-grams:
  – N=1: Extract unigrams (single words) only.
  – N=2: Extract unigrams & bigrams.
  – N=3: Extract unigrams, bigrams, & trigrams.
  – N=4: Extract 1-, 2-, 3-, and 4-grams.
• $0.0 < T < 1.0$ with steps of 0.1.
Examined Methods

• SPC – Supervised Products Classifier – the proposed algorithm.
• LogReg – Logistic Regression.
• RanFor – Random Forests.
Accuracy Evaluation

Highest Accuracy: 95.1% for N=3, T=0.

Interesting Measurement: Accuracy 93% for N=3, T=0.7.

Fig. 1. Comparison of the classification performance of SPC against Logistic Regression (LogReg) and Random Forests (RanFor). Accuracy fluctuation with respect to the value of the cut-off threshold $T$ for: i) $N = 1$ (top left), ii) $N = 2$ (top right), iii) $N = 3$ (bottom left), and iv) $N = 4$ (bottom right).
Recall: For N=3, T=0.7, accuracy 93% with 47% fewer tokens and 54% fewer RDV entries.
Conclusions

• We presented a supervised learning algorithm for products categorization.
• It trains a classification model based on:
  – The morphological analysis of the titles,
  – The extraction of n-grams of variable sizes,
  – The assignment of importance scores to each token.
• The method achieves ~95% classification accuracy.
• It also embodies a self-pruning strategy.
• The experiments have demonstrated that this strategy leads to a reduction of about 50% in the size of the model combined with small losses in the classifier performance.
Thank You

Any Questions?