AUTOMATIC DYNAMIC PRODUCT CLASSIFICATION

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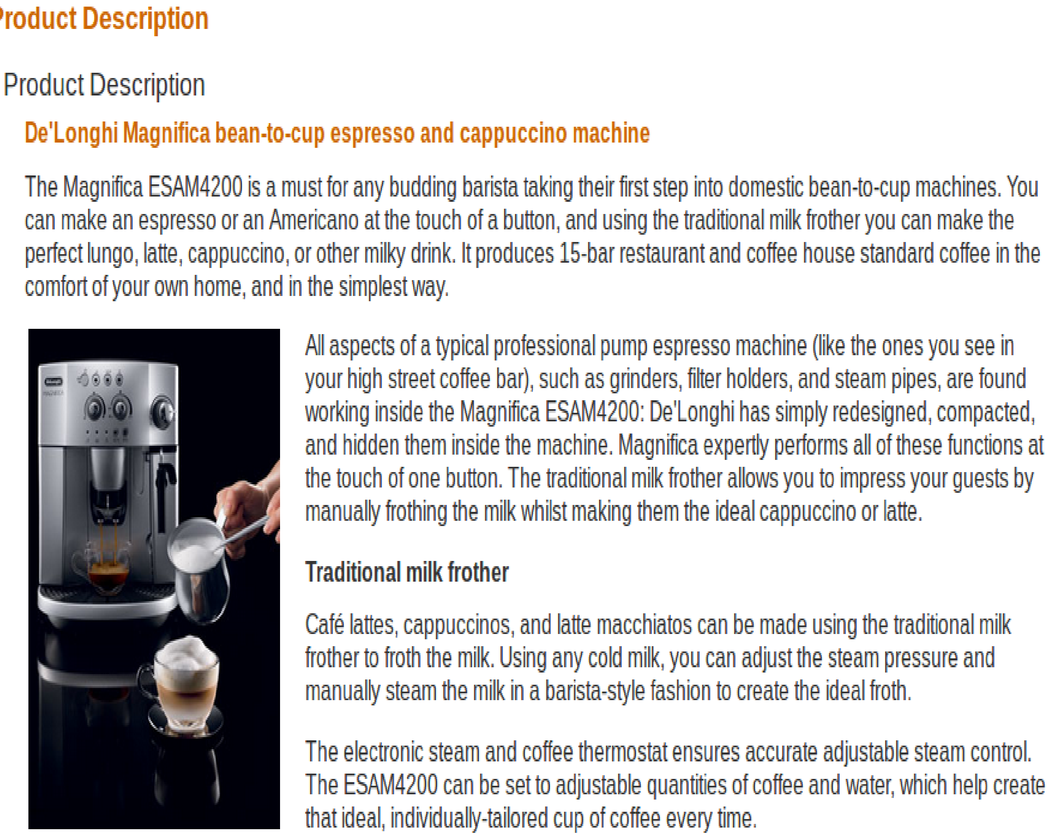
Abstract

- *Online shopping is part of our everyday experience. Nowadays, more and more people buy products via the internet.*
- *Consumers usually read the text description of a product of interest to gain an overview of its features.*
- *Classification of products based on text summaries of their product description is an increasing area of activity and a very important commercial application.*
- *The development of a stand-alone classification method that automatically classifies products in categories is a major challenge of today in Statistics.*

Introduction

- As shown in the figure below, the product description contains highly relevant information to provide the consumer with an overview of its features and performance.



- A very important part of online retail store analytics is the classification of products based on text product summaries.
- Current classification is done manually, which is time-consuming and prone to errors.
- The challenge at hand is to develop a stand-alone statistical classification model, which can be used to provide brands with quick and insightful product classifications.

Methods

- Before applying any classifier, the text of product summaries must be preprocessed. The **R** package **tm** is the most developed package for managing text documents ([1, 2]).
- Example of typical transformations: The initial product description is **PHILIPS HD8764/01 SAECO MINUTO. Coffee machine Expreso**
- Replace '/' with a space: **PHILIPS HD8764 01 SAECO MINUTO. Coffee machine Expreso**
- Conversion to lower case: **philips hd8764 01 saeco minuto. coffee machine expreso**
- Remove numbers: **philips hd saeco minuto. coffee machine expreso**
- Remove punctuation: **philips hd saeco minuto coffee machine expreso**

- In text mining, a *corpus* is a collection of n documents and can be represented as a *document-term matrix* (dtm).
- In a dtm, the rows are documents and the columns are words. Each entry in (i, j) is the frequency of the word t_j in document d_i:

$$X_{n\times p} = \begin{pmatrix} f(d_1,t_1) & \dots & f(d_1,t_p) \\ \vdots & \ddots & \vdots \\ f(d_n,t_1) & \dots & f(d_n,t_p) \end{pmatrix}$$

- In our case, the dtm is a matrix of n products and p words describing the products. The product categories are saved in a matrix $Y_{n\times 1}$ consisting of C categories.
- Each one of the n products is associated with one of the C classes.

- Existing reviews about statistical classification methods for automated text categorization indicate that dominant approaches are Naive Bayes, kNN and decision trees ([4, 5]).
- We propose to establish a comparison of all these methods, also analyzing the performance of multinomial logistic regression (maxent) and discriminant analysis.

Results in a first case study: Nestle Spain

- Extract of data for Nestle Spain.
- The texts with the products description are manipulated.
- The preprocessed texts are brought together in a dtm (33331×726).
- Every classifier is applied to a training, validation and test subsets of the dtm.
- Only those methods that have the smallest validation error rates will be used to get test error rates.
- For each category:
  1. Training data: Random selection of a half part of the products (the rows of the dtm) matching that category.
  2. Validation data: Random selection of a half part of the products not selected in the previous step.
  3. Test data: Remaining points.

Training dtm	Validation dtm	Test dtm
16667 (50%)	8335 (25%)	8329 (25%)

Method	**Error rates**	
	Validation error rate	**Test error rate**
kNN	0.38%	0.36%
MaxEnt.	0.35%	0.5%
LDA	2.98%	-
RF	0.65%	0.6%
NB	99.2% !!	-

- Extension of kNN to incorporate a probabilistic framework: Bayesian kNN ([3]) (new R function programmed). Its test error rate is very similar to the one returned by classical kNN.
- Taking advantage of the fact that the bayesian kNN returns probabilities for each category, just as maxent and random forests do, we can provide the customer with a classification in a number of top categories, for example, the top 3 categories, as shown in the tables below.
- Description of product 1 in the test set: *DOLCE GUSTO KRUPS MINI ME BLACK Coffee machine*. Category assigned by the three methods: *Electronics* (very suitable).

Products \ Categories	**Bayes KNN**		
	C1	C2	C3
P1	**Electronics (0.996)**	Babies (0.00038)	All sections

Products \ Categories	**Maxent**		
	C1	C2	C3
P1	**Electronics (0.953)**	All sections (0.0473)	Feeding (0.00013)

Products \ Categories	**Random Forests**		
	C1	C2	C3
P1	**Electronics (0.74)**	Feeding (0.146)	Small electr. appliance (0.114)

Conclusions

- The main objective of this work is to develop a statistical classification method to automatically classify products based on summaries of their product descriptions.
- Further goals: An extended hierarchical model which classifies products into hierarchical categories. A dynamic extension of the classifier to identify new categories.
- This project is in collaboration with the company Clavis Insight, which is providing us with data (http://clavisinsight.com/).

References

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