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and
Dr Ales Novak
Conference Co-Chairs

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Contents

Preface

These Proceedings represent the work of contributors to the 9th European Conference on Management Leadership and Governance held this year in Klagenfurt, Austria, on the 14-15 November 2013. The Conference Co-Chairs are Dr Ales Novak from the University of Maribor, Faculty of Organizational Sciences, Slovenia and Dr. Maria Th. Semmelrock-Picej, Austria.

The conference will be opened with a keynote address by Dr Julia Sloan, from Sloan International Inc., USA on the topic of *Learning to Think Strategically: A Leadership Imperative for the 21st Century*. The second day will be opened by Prof. Vlado Dimovski from the University of Ljubljana, Faculty of Economics in Slovenia with a presentation on the topic of *Authentic Leadership*.

The Conference offers an opportunity for scholars and practitioners interested in the issues related to Management, Leadership and Governance to share their thinking and research findings. These fields of study are broadly described as including issues related to the management of the organisations' resources, the interface between senior management and the formal governance of the organisation. This Conference provides a forum for discussion, collaboration and intellectual exchange for all those interested in any of these fields of research or practice.

With an initial submission of 145 abstracts, after the double blind, peer review process there are 46 academic papers, 12 Phd Papers, 1 Work in Progress paperin these Conference Proceedings. These papers reflect the truly global nature of research in the area with contributions from Australia, Austria, Belgium, Croatia, Cyprus, Czech Republic, Finland, Germany, Greece, India, Indonesia, Iran, Lithuania, Malaysia, Morocco, New Zealand, Nigeria, Pakistan, Philippines, Romania, Slovakia, Slovenia, South Africa, The Netherlands, UK, United Arab Emirates, and the USA.

We wish you a most interesting conference.

Dr. Maria Th. Semmelrock-Picej and Dr Ales Novak

Conference Co-Chairs

November 2013

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Getting Inside the Minds of the Customers: Automated Sentiment Analysis

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Abstract: Sentiment analysis and opinion mining is being perceived as one of the major trends of the nearest future. This issue follows up on the spontaneous and massive expansion of new media (esp. social networks). The amount of the user-generated content published on social networks significantly increases every day and becomes an important source of information for potential customers. More than 75 % of the users confirm that customer's reviews have a significant influence on their purchase and they are willing to pay more for a product with better customer reviews. Furthermore one third of the users has posted an online review or rating regarding a product or service and thus became an influencer himself. Using sentiment analysis, company can take advantage to get insight from (social) media, recognize company or product reputation or develop marketing strategy responding to the negative sentiment and positively impact consumer's perception. Moreover, top influencers and opinion makers can be identified for further cooperation. Even though social media monitoring is commonly carried out automatically (by tracking selected channel or by crawling the web and searching for given keywords) the analysis and interpretation of retrieved data is still often performed manually. Such unsystematic approach is then prone to subjective error and is dependent on the experience and skills of the person performing the analysis. Thus there is a strong call for automated methods (based on computer-based processing and modeling) which would be able to classify expressed sentiment automatically. Good results can be obtained with supervised learning models (i.e. support vector machine models). However, for a good performance a good training set is needed. Such approaches also often work with lexical databases (i.e. WordNet) or sentiment vocabularies (identifying polarity keywords with the sentiment clearly distinguished i.e. "horrible", "bad", "worst"). These models do not work very well when the training set comes from different domain than the testing data and also not many studies have addressed sentiment analysis issue for morphologically rich languages, i.e. Arabic, Hebrew, Turkish or Czech. This experiment tries to develop and evaluate a sentiment analysis model for Czech language (which is morphologically rich) which is not dependent on any prior information (lexical databases or sentiment vocabularies which are not available for Czech language) and works well on different domains. As training set data from Czech-Slovak Film Database were used. The support vector machine based classification model has been then tested on different domain (data from an e-shop selling a wide range of products from electronics to clothing or drugstore goods). With a good results (accuracy around 80 %), the model has been also tested on other languages, including Amazon customer reviews in English (Amazon.com, Amazon.co.uk), German (Amazon.de), Italian (Amazon.it) and French (Amazon.fr). Even on other languages, the model still provided a good performance ranging from 70 to 80 %. This may not sound impressive but there are studies reporting that human raters typically agree about 80 % of the time. Thus if an automated systems were absolutely correct about sentiment classification, humans would still disagree with the results about 20 % of the time (since they disagree at this level about any answer).

Keywords: sentiment analysis, opinion mining, automated model, morphologically rich languages, support vector machine

1. Introduction

Sentiment analysis is becoming a buzzword these days. With the spontaneous and massive expansion of new media (esp. social networks), this issue is being considered as one of the major trends for the nearest future (King, 2011). Google Trends (showing how often a particular term has been searched across various regions of the world and in various languages) reports more than a fivefold increase of search queries since 2007. Over 7 000 research articles have been written addressing this issue in recent years; many startup companies are developing system solutions and also many major statistical packages (SAS, SPSS) include dedicated sentiment analysis modules (Feldman, 2013).

However opinion mining and sentiment analysis is not only a recent phenomenon related to the expansion of modern technologies. A long time before the www service was born; people's attitudes and decisions had been influenced by their relatives or friends around them (Anderson, 1998, Goldenberg, Libai et al., 2001). As we specialize and narrow our focus, the more frequently we need additional information about certain fields. Thus we have been looking for specialists or professionals with (life) experience who are able to share their opinion or advice. A car enthusiast whom we know could recommend a mechanic or a garage, a respectable person we appreciate could help us with the decision for whom to vote in the local election, or a colleague might provide a reference about a job applicant we would like to hire for our company (Pang and Lee, 2008).

The online environment made it further possible to find out what others are thinking or experiencing, no matter if those are our personal contacts or well know professionals. In 2008, Pew Internet & American Life Project Report (focused on online shopping behavior) discovered that more than 80 percent of US internet users have previously done online research about a product. Twenty percent do so commonly. More than 75 % of online-hooked customers confirm that reviews have a significant influence on their purchase and they are willing to pay more for a product with better customer reviews. In addition, one third of users has posted an online review or rating regarding a product or a service and thus became an influencer themselves (Horrigan, 2008).

Therefore continuous and systematic new media monitoring became an integral part of company processes. The aim of such activities is to recognize whether and (if so) in which context the media speaks about the company, hence companies can adjust their strategies and react in advance according to public opinions or attitudes (Pak and Paroubek, 2010). Moreover, top influencers and opinion makers can be identified.

The introduction of WWW in 1990s brought revolutionary changes on the media monitoring. Almost all media are now digitalized and available online. New monitoring companies offer a computer-based processing where country borders or national languages do not matter anymore. CyberAlert – the world press clipping service – monitors 55 000+ online news sources in 250+ national languages 24 hours a day. Many new websites spontaneously emerge, change and disappear every single day. A common user is not only a “content consumer”, but also contributes as an author. Users write product reviews, post comments in discussion forums or on social networks or even have their personal online blogs. Such fragmented and unofficial information is a significant source of word-of-mouth or “buzz” about companies and their products. Many of today’s most influential blogs (i.e. The Huffington Post, Techcrunch, Engadget, Mashable) began just few years ago as one-man-show, quickly growing into internationally recognized and respected media (Aldred, Astell et al., 2008). However, recognizing sentiment and finding out about people’s attitudes still remains a challenge. Even these days when the data are collected automatically, companies mostly interpret them manually. Such an approach is then susceptible to subjective error and is dependent on the experience and skills of the persons performing the analysis. Nevertheless, computer-based processing and modeling allows for automated sentiment analysis. Automated systems are repeatedly able to determine the sentiment (whether positive or negative) with 70–80 % accuracy (Grimes, 2010). If automated systems were absolutely correct about sentiment classification, humans would still disagree with the results about 20 % of the time which is in no contrast to the level of agreement between raters they reached in human-rated analyses (Ogneva, 2010).

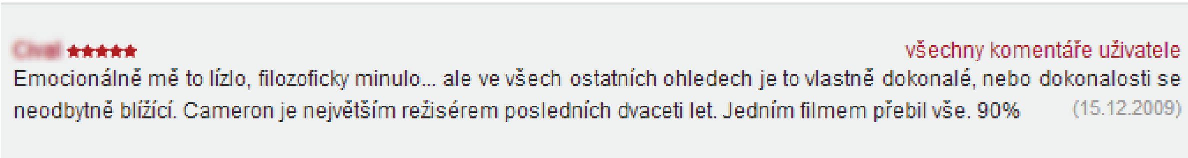
The sentiment analysis is a Natural Language Processing task. The literature highlights two main approaches to this issue (Balahur, 2013, Zhang, Ghosh et al., 2011). The first approach uses a dictionary of words (opinion lexicon) to recognize the sentiment orientation (positive, negative or neutral). Thus such approaches are so called lexicon-based (Feldman, 2013, Taboada, Brooke et al., 2011). Dictionaries for lexicon-based approaches are created manually, or automatically (expanding the word list using seed words) (Banea, Mihalcea et al., 2013, Zagibalov and Carroll, 2008). Then each word in the document is compared against the dictionary, rated with sentiment polarity score and its polarity score is added to the total polarity score of the document. The total polarity score determines the sentiment of the document (Annett and Kondrak, 2008). The weakness of the lexicon-based approach often lies in the absence of preselected opinion words (i.e. slang, typos or new trendy, fashion words). Furthermore, the polarity of the words might be domain dependent and the analysis is obviously limited just to the language of the lexicon (Zhang, Ghosh et al., 2011).

The second group of approaches to sentiment analysis is based on (supervised) machine learning methods (Pang, Lee et al., 2002). First, the classifier is trained to distinguish between text elements with positive and negative sentiment. Machine classifiers use not only unigrams or bigrams, but also longer parts of the text, although the most successful document features are simple unigrams(Wiegand, Klenner et al., 2013). As a training set, Amazon customer’s reviews or IMDB movie fans reviews are often used (since these sources are publicly available and contain large data). However, it is well known that classifiers trained on one specific domain do not perform very well on other domains (Aue and Gamon, 2005). The most common algorithms used to perform the sentiment analysis are Naïve Bayes, Maximum Entropy or Support Vector Machines (Pang, Lee et al., 2002). Some authors propose hybrid approaches utilizing both approaches – the lexicon-based and machine learning together, i.e. to create the training set for supervised learning (Wiebe and Riloff, 2005). Others (Godbole, Srinivasaiah et al., 2007) use the Wordnet (a lexical database where nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms) and there is also a specialized lexical resource for opinion mining called SentiWordnet (available just for some languages). Not many studies also have addressed sentiment analysis issue for morphologically rich languages, i.e. Arabic, Hebrew, Turkish or Czech (Tsarfaty, Seddah et al., 2010).

2. Experiment design

The first experiment was designed to verify, whether the approaches used commonly for English language could be utilized also for the Czech language. Since there are only few lexical resources for Czech language (i.e. stemming tools or Czech Wordnet) available (and those that are available are mostly paid), we decided to employ machine learning methods. All experiments were performed in RapidMiner software (http://rapid-i.com/), which is available for free and contains most methods used in machine learning based sentiment analysis (i.e. Naïve Bayes or Support Vector Machines).

As a training set, we used data from Czech-Slovak Film Database (http://www.csfd.cz/) which is the Czech alternative for International Movie Database (IMDB). An automated crawler downloaded and parsed several million comments. The sentiment in CSFD is expressed not only with unstructured text (a fan's comment about the movie), but also with stars assigned. The star scale goes from 0 (really bad movie) to 5 (great movie). Figure 1 displays an example of user evaluation at the CSFD website.



Source: CSFD website, evaluation of the Avatar movie, available at: *http://www.csfd.cz/film/228329-avatar/*

Figure 1: An example of CSFD user evaluation (the Avatar movie)

The initial set of experiments focused on which machine learning approach works the best for the specified domain (movies) in Czech language. Support Vector Machines (SVM) gave best overall performance and was the fastest among tested methods. This result is consistent with some previous studies (Boiy and Moens, 2009). For all experiments, the accuracy (what percent of the predictions were correct), precision (what percent of positive predictions were correct) and recall (what percent of positive cases has been caught) was computed. Thus if the results are arranged as in Table 1

Table 1: A confusion table (pred = predictive, pos = positive, neg = negative)

	true neg	true pos
pred neg	tn	fn
pred pos	fp	tp

the accuracy, precision and recall is then computed as

$$accuracy = \frac{tp+tn}{tp+tn+fp+fn},\ precision = \frac{tp}{tp+fp},\ recall = \frac{tp}{tp+fn}$$

To train the model, 1756 positive and 1575 negative comments have been selected (comments with 4 or 5 stars were considered as positive, comments with 0, 1 or 2 stars as negative; 3-star comments were considered as neutral and thus omitted from the training). Data preprocess included transformation into lower-case tokenization (tokens separated by spaces and stop-words filtering (filtering based on built-in of Czech stopwords). The model is shown in Figure 2 (the grey areas represent a sub-setting and sub-items of given object).

The SVM algorithm was set as C-SVC type with linear kernel. To estimate the statistical performance of the model the 10-fold cross-validation has been used.

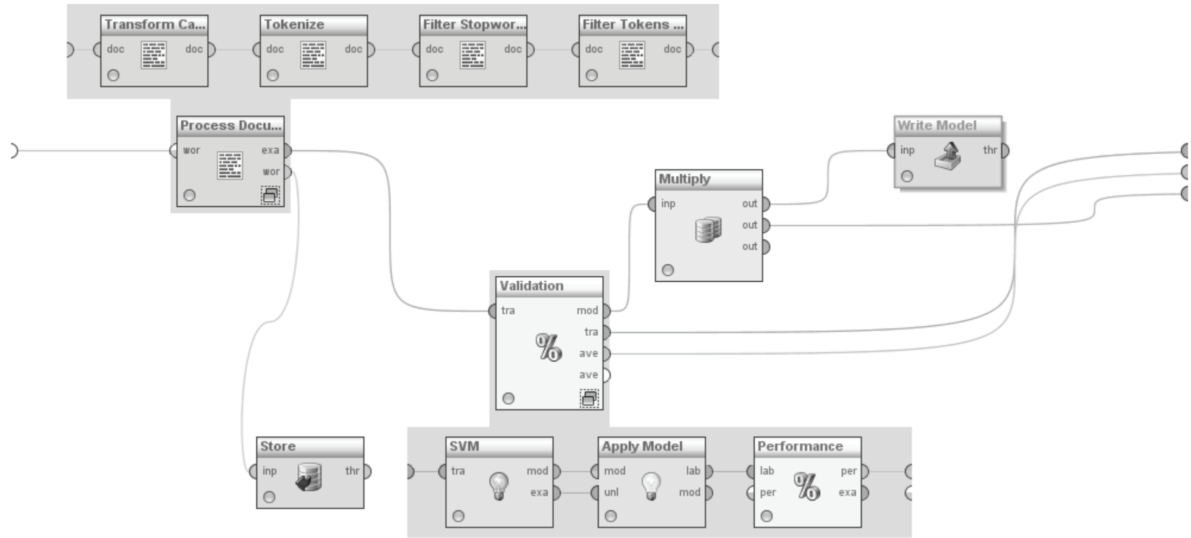


Figure 2: A classification model in RapidMiner Software

3. Results

Table 2 depicts the results of training process. The accuracy of the training procedure was almost 80 % (precision and recall reached similar values).

Table 2: Results of the first experiment

	true neg	true pos	class precision
pred neg	1161	319	78.45%
pred pos	414	1437	77.63%
class recall	73.71%	81.83%	

Accuracy: 77.99 %, precision: 77.63 %, recall: 81.84 %

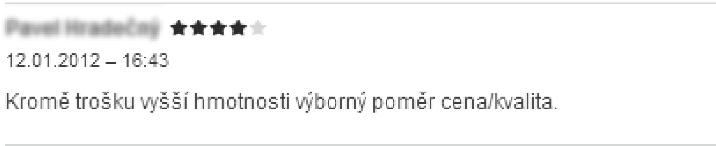
Then we used the testing set of another 12 000 randomly selected CSFD comments (2 000 from each "star rating class") to evaluate the model. The star-rating has been removed. The model established in first experiment has been then used to classify the unstructured data. Table 3 depicts the key finding. The first column displays the rating of the comments; the second/third column then represents the share of comments (with given star rating) classified as negative/positive. For polarized movie fans opinion, the share of correctly classified comments outreached 80 %.

Table 3: Model performance summary (same domain as training set)

star-rating	neg	pos
0	80,40%	19,60%
1	78,65%	21,35%
2	67,50%	32,50%
3	41,90%	58,10%
4	18,45%	81,55%
5	15,35%	84,65%

Accuracy: 75.14 %, precision: 75.33 %, recall: 74.77 % (0-2-stars as negative; 3-5 stars as positive)

Thus, for morphologically rich language like Czech, even a simple SVM model worked very well. However it still remains a question, whether the model performs well only in specific domain. Movie evaluations contain a lot of specific terms and expressions, which don't appear anywhere else. Therefore we decided to verify the model on another domain. An automated crawler downloaded and parsed tens of thousands of comments from the largest Czech e-shop mall.cz (http://www.mall.cz/). The e-shop sells a wide range of products from electronics to clothing or drugstore goods.



Source: mall.cz website, evaluation of Sencor hand mixer, available at: http://www.mall.cz/tycove-mixery/sencor-shb-4355:ranking

Figure 3: An example of mall.cz user evaluation (Sencor hand mixer)

The testing set contained thousand randomly selected comments from each rating class (1-5 star rating). The comments evaluated a variety of products. Table 4 summarizes the model performance. The accuracy of classification differs among comments with different star-rating. The classification is more precise for more polarized opinions. The neutral sentiment is classified partially as positive and partially as negative, but using human evaluators would not give a better results (Ogneva, 2010).

Table 4: Model performance summary (different domain from training set)

star-rating	neg	pos
1	78,60%	21,40%
2	73,80%	26,20%
3	56,20%	43,80%
4	39,50%	60,50%
5	20,80%	79,20%

Accuracy: 73.03 %, precision: 74.59 %, recall: 69.85 % (1-2-stars as negative; 4-5 stars as positive)

The first column represents the rating of comments, whereas the second/third column displays how many comments was classified negative/positive from each rating class. Even on completely different (and moreover heterogeneous) domain the model performed well. Since many companies are established on more than one market, there might be a good question whether suggested model delivers good and stable result also in other languages. As a training set, we decided to use Amazon data. Amazon is available not only in English, but also in Chinese, French, German, Indian, Italian, Japanese and Spanish languages. As a product we chose the novel Fifty Shades of Grey by E. L. James. This product has enough reviews in more languages and the customer's reviews are also very polarized (see summary on Figure 4).

Source: Amazon.com website, evaluation of the novel Fifty Shades of Grey by E. L. James, available at: http://www.amazon.com/Fifty-Shades-of-Grey-book/dp/B007L3BMGA/

Figure 4: The user evaluation summary of the novel Fifty Shades of Grey by E. L. James (Amazon.com)

The experiment was also limited to languages written in the Latin alphabet only. Data preprocess included tokenization (into words), transformation into lower-case and stop-words filtering (see Figure 2). The SVM algorithm was set as C-SVC type with linear kernel. To estimate the statistical performance of the model the 10-fold cross-validation has been used. The set contained 2884 positive (4-5 stars) and 2247 negative (1-2 stars) reviews. Table 5 displays the result for English.

Table 5: Results of the experiment with Amazon data (English language)

	true neg	true pos	class precision
pred neg	2066	157	92.94%
pred pos	181	2727	93.78%
class recall	91.94%	94.56%	

Accuracy: 93.41 %, precision: 93.80 %, recall: 94.56 %

From Amazon.de, the crawler extracted 1535 positive (4-5 stars) and 854 negative (1-2 stars) reviews. Table 6 displays the result for German language.

Table 6: Results of the experiment with Amazon data (German language)

	true neg	true pos	class precision
pred neg	752	64	92.16%
pred pos	102	1471	93.52%
class recall	88.06%	95.83%	

Accuracy: 93.05 %, precision: 93.57 %, recall: 95.83 %

From Amazon.fr, the crawler extracted 399 positive (4-5 stars) and 167 negative (1-2 stars) reviews. Table 7 displays the result for French language.

Table 7: Results of the experiment with Amazon data (French language)

	true neg	true pos	class precision
pred neg	118	16	88.06%
pred pos	49	383	88.66%
class recall	70.66%	95.99%	

Accuracy: 88.51 %, precision: 88.78 %, recall: 96.01 %

From Amazon.it, the crawler extracted 88 positive (4-5 stars) and 162 negative (1-2 stars) reviews. Table 8 displays the result for Italian language.

Table 8: Results of the experiment with Amazon data (Italian language)

	true neg	true pos	class precision
pred neg	159	34	82.38%
pred pos	3	54	94.74%
class recall	98.15%	61.36%	

Accuracy: 85.20 %, precision: 94.90 %, recall: 61.53 %

Thus, the model performed well also on other languages and was able to reach the accuracy over 80 %. Other Amazon websites (in the Latin alphabet) did not contain selected product or enough comments to perform the experiment.

4. Conclusion

The experiment confirmed a good performance of the model on morphologically rich language (Czech) and even on multiple domains (when the testing and training set doesn't come from the same domain). The model also performed well on Amazon data from different languages. The suggested model is very simple and easy to implement, with no lexical databases or sentiment keywords added and thus might be a good start for companies which consider sentiment analysis to get deeper inside the minds of the customers.

Automated sentiment analysis became an integral part of market research activities in companies such as Kia Motors, Best Buy, Deutsche Bank, Southwest Airlines or Paramount Pictures. Even for morphologically rich languages, (supervised) machine learning methods can provide satisfying results not limited to a specific domain or given language. Although the analysis cannot provide a hundred percent certainty, it can definitely offer important insights (King, 2011). It could be used to gain understanding of customer experience, recognize competitive dangers or discover emerging market opportunities. Opinions floating around the cyberspace begin to represent vox populi to the degree, in which most market segments participate in online discussions. Automated sentiment analysis might be a good way how to deal with cluttered online environment and how to get insight into the mind of a new millennial consumer.

5. Discussion and limitations

The performance of the model could be even better since there are stemmers available for some languages (i.e. English, German) and thus the number of features in the analysis could be lowered. Some studies also suggest to utilize word or character n-grams to improve the performance of the model (Abbasi, Chen et al., 2008). The model will be tested on more domains and with different settings to improve the performance. Still, the main goal is to keep the model simple and thus easy to implement and find an acceptable balance between the complexity of the model and "good enough" performance.

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