Optimising sentiment analysis in commercial context

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Summary

The proposed paper is about data analysis of consumer reviews of Argos products. The objective behind the paper is to use the review data to produce insight for Argos managers so that they can reduce the rate of returns for products they sell to customers. Methodological innovation for the purpose of this research assignment is to improve on the sentiment analysis model used currently, including an attempt to detect and interpret irony. Furthermore, this study aims at a systematic identification of best solutions for making data summaries as insightful and as easy to interpret as practicable.

KEYWORDS: sentiment analysis; Argos; product reviews

1. Introduction

This study is to help Argos improve the quality of analysis for the product reviews submitted by customers. Product reviews are a critical source of information for Argos product category managers to know whether and how Argos products meet customer expectations. This study is expected to make it easy for the managers to access insight from product reviews, and in consequence help them cut operational costs by reducing the percentage of product returns on the total sales volume. Sentiment analysis, an analysis of attitudes expressed in text, is the most appropriate general approach for the task of automatically identifying what customers think about products from the textual data of product reviews.

2. Possible research designs for sentiment analysis

There is a range of possible approaches for carrying out sentiment analysis to learn about opinions of authors of texts. Broadly speaking, sentiment analysis requires a training set of data – a list of words or lists of words that are processed using statistical tools to automatically identify which sentences from

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the text data being analysed are to be associated with negative comments, which ones with positive comments and which ones with neutral comments in relation to a given subject (Balahur et al. 2014). Methodological innovation can involve changes to how the training sets of data are built (e.g. Balahur et al. 2012; Duric & Song 2012) and used (e.g. Kennington & Schlangen 2014; Tang et al. 2009). Sentiment analysis can be carried out on individual words or symbols such as emoticons (Ptaszynski et al. 2014) and on colocations of words (Balahur et al. 2014) within documents or within sentences.

Product reviews used in this study include messages of about 6 sentences long and star ratings of a product and its select attributes such as quality or value for money. The data will be analysed for comparison of results using different techniques. The current data analysis method used in Argos to process these product reviews and the star ratings will be compared with other data analysis approaches (see Table 1) so as to identify the best solution. The current approach identifies positive or negative sentiments of less than 50% of text reviews. Moreover, the added value that comes from data analysis is restricted because the insight produced is not widely used and implemented, possibly due to failures in how the data is summarised or visualised. This study will search for a solution with:

- the highest percentage of success in assigning sentiments to text
- a strong fit between sentiment analysis outcomes and star ratings of products
- a high level of acceptance among the end users of the analyses, who would judge the methods based on the usefulness of the produced insight

Table 1 Possible research approaches and their descriptions

Approach	Description
Support Vector Machines and/or Naïve Bayes theorem	Both methods are frequently used for text analysis (Barhan & Shakhomirov 2012). Bayesian algorithm is simpler to use with short messages, but at the cost of efficiency (Barhan & Shakhomirov 2012). They can be used to analyse data through classifying a set of textual data into sentiment categories automatically, or by relying on a previously provided lexicon with coded sentiment readings (Barhan & Shakhomirov 2012). Other researchers, e.g. Carstens (Carstens 2011), have also modified and improved on those commonly used techniques.
Markov Logic Networks	A statistical method with high potential to analyse data within its thematic context. This statistical method can automatically adapt sentiment analysis to its particular context in which it takes place (Kennington & Schlangen 2014).
Topic modelling	The text can be analysed to find out the dominant topics that pervade through the comments about certain products. It is possible to get a quick glimpse of customers' thoughts about the product this way (Blei 2012). Potentially, the content ascribed to each identified topic could be further analysed with sentiment analysis.
Combining product review data with other data types	Amazon, a competitor of Argos, uses both formal product reviews from the media and individual customers' reviews from the Amazon website to predict sales. The two types of reviews influence each other as well as sales levels (Bao & Chang 2014). It is not certain yet, however, if correlations can be found between product returns and the sentiment readings from data types other than product reviews.
Different methods combined	It is possible to triangulate the results of different methodological approaches in sentiment analysis to cut out misleading bits of text from

	analysis. The analysis may become more accurate through exclusion of misleading fragments of text (Tang et al. 2009).
Irony detection	Irony detection also has potential to be used in analysing customer reviews. Ironical comments are known for their potential to have both negative and positive consequences for sales (Reyes & Rosso 2012). So far, however, the most widely used methods have tended to exclude or misclassify ironical comments in the analysis (ibid.). Irony detection and analysis will be used in this study together with sentiment analysis to produce more a robust insight for Argos-based decision-makers.

3. Data representation of sentiment analysis

Representation of sentiment analysis output has not been specifically discussed in any published works reviewed on sentiment analysis so far. There are notable examples of good practice, however (see figures 1 and 2). Interesting examples can also be found in other sciences, such as spatial data analysis, where projects like DataShine convert hard-to-process census data into interactive maps (Cheshire & O'Brien n.d.). Furthermore, there are also very good visualisation tools available, such as Plotly (www.plotly.ly) – an online tool that makes data visualisations interactive. Part of this research is to verify which data visualisation methods would be most effective in an authentic commercial context. The visualisation tools must adapt to the challenges of time scarcity and valuable insight generation that is easy to access.

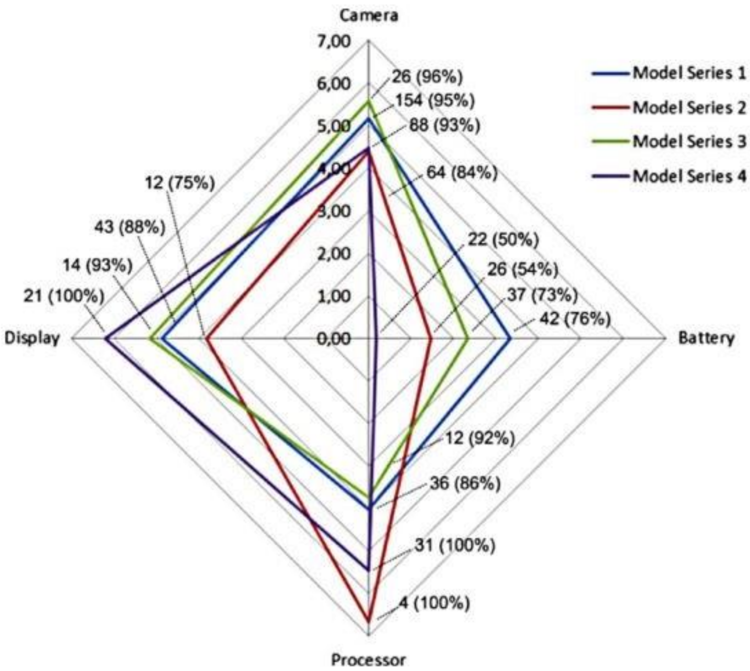

Figure 1 Sentiment scores for product attributes of similar products, in this case smartphones (Kontopoulos et al. 2013).

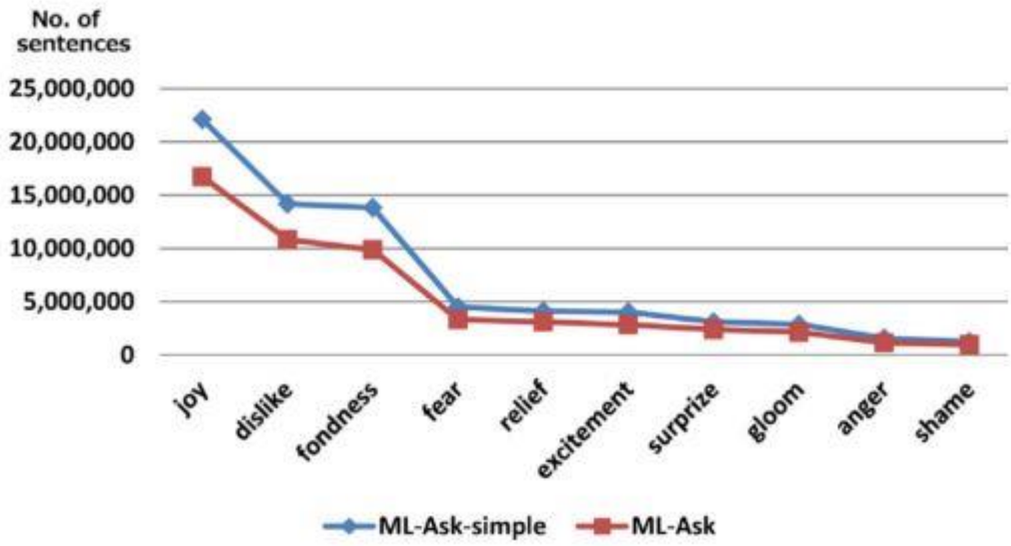

Figure 2 Graphical visualisation of sentence level emotion class annotations done using two techniques, ML-ask and ML-ask-simple (Ptaszynski et al. 2014).

4. Conclusion

This study tackles the problem of improving sentiment analysis through an innovative use of available methodological approaches. Furthermore, the study attempts to systematically identify the most valuable forms of expression to the users of insight. After all, a statistical robustness of a statistical model or a seemingly effective form of representation may not necessarily always coincide with user preferences. Sentiment analysis, when applied in a business context, needs to strike a balance between the need for accuracy and simplicity.

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4. Biography

Radoslaw Kowalski joined UCL in September 2014 to contribute to research into how unstructured data can be analysed automatically. Radoslaw’s research interests lie in the analysis of social media and other spontaneously created texts to learn about personal characteristics of writers without reference to other data types.

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