**Positive Effects of Negative Publicity: When Negative Reviews Increase Sales**

The purpose of this paper is to show how even negative tweets about a product can increase its sales based on the current awareness and accessibility of that product among the users. To prove this, point the authors had carried out three studies: (1) New York Times Book reviews: the authors made the users of New York Times to give reviews about the books by authors who had published one or fewer books, authors who had published between two and nine books and authors who had published 10 or more books. The strong point about handling the user reviews was they approximated the average subjective reading in the population, so the results are not biased. Results which they obtained aligned with their predictions that negative reviews increased the sales of unknown authors by 45% where-as decreased the sales of well-known authors. (2) The Role of time: the authors also argued that the results from the previous study is also time dependent and that users might just consider buying a product in spite of it having bad reviews after some time because the valence of publicity for unknown products may be forgotten. This study was done by making users read second one being the same and the first one being either positive or negative. Their result was the reviews of a previously negatively rated product became more positive after a certain period of time. (3) Increasing Product Awareness: in this study the authors made the same users to review the same product after a certain time interval and the results which they obtained was that the review prior to the increased awareness was negative and after the awareness was positive. Future research work can be done on how other factors such as word of mouth affects the sales of a product.

**Twitter Sentiment Classification using Distant Supervision**

The purpose of this paper is to perform sentiment analysis on tweets using Distant Supervision technique. The authors removed emoticons from the tweet because it allowed the algorithm to learn from other features such as unigrams and bigrams. The authors also replaced the username in the tweets by replacing the words starting with ‘@’ with an appropriate username class label. They replaced the URL’s with their corresponding class label. They replaced repeated letters with those 2 exact letters. The authors then point out that features like bigrams and phrases can be added to Maximum entropy without worrying about the overlapping of features, and this cant be done in Naïve Bayes. To speed up the SVM algorithm the authors used a feature presence technique instead of a count technique. To filter out their data the authors did the following: (1)They removed a pre-defined set of emoticons from the tweet.(2) They removed tweets that consist of both positive and negative emoticons. (3)They only considered unique tweets by removing re-tweets. (4)Tweets with “:P” were removed because it usually does not imply a negative sentiment. They used both unigrams and bigrams as features. Compared to unigram features the accuracy improved for Naïve Bayes from 81.3 to 82.7% and maximum entropy from 80.5 to 82.7. However there was a decline in SVM from 82.2 to 81.6%. The authors also used parts of speech tagging so that they can find out the correct meaning of the word in that sentence. The authors also suggested that techniques which can be used to increase their results: (1)Use of Semantics role labeler to indicate which noun is associated with which verb. (2)To limit the tweets to a specific domain. (3)To not only focus on tweets written in English language. (4)To utilize emoticons in the test set to improve accuracy.