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AN ANALYSIS

ON

WHAT MAKES US LAUGH? INVESTIGATIONS INTO AUTOMATIC HUMOR CLASSIFICATION

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By

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Main Idea

This paper demonstrates the adaptability and shows the ability to componentize the model, and that a host of classification techniques can be used to overcome the challenging problem of distinguishing between various categories and subcategories of jokes.

Introduction

Humor has been studied for several years in computational linguistics in terms of both humor generation and detection, but no such work has been done to create a classification of humor. Classification of humor is a very difficult task because even theoretically there is not much consensus among theorists regarding what exactly humor is and what the fine line is for example what can be considered as humor and what cannot be.

Proposal

This paper discusses the Script Semantic Theory of Humor(SSTH) and General Verbal Theory of Humor(GVTH) in detail.

According to SSTH, Each concept expressed by a word which is internalized by the native speaker of a language, is related to a semantic script via some cognitive architecture to all the surrounding pieces of information and Humor is evoked when a trigger at the end of the joke, the punch line, causes the audience to abruptly shift its understanding from the primary (or more obvious) script to the secondary, opposing script.

The key idea behind GVTH are the 6 levels of independent Knowledge Resources (KRs) defined by Attardo and Raskin, 1991. These KRs could be used to model individual jokes and act as the distinguishing factors in order to determine the similarity or differences between types of jokes.

For the dataset, the data collected was a set of nearly 40,000 one liners. They had recognized three major marked characteristics which are reflected across all types of jokes: Mode, theme, and topic. Each joke is characterized by the before mentioned types. For example, Sarcastic, Exaggeration/Hyperbole, Phonetics Assisted, Semantic Opposites, Secondary Meaning come under ‘Mode’. Dark Joke, Gross Joke, Adult/Sexual Joke, Insults come under ‘Theme’ and Animal, Food, Money, Fat etc., come under ‘Topic’.

Experiments

Various experiments were done on the dataset. Topic detection was done using LDA, Naïve Bayes and SVM. Logistic Regression and SVM were used to distinguish between sarcastic jokes from non-sarcastic jokes. Individual sentiment score of every token is calculated for finding specific phrases in a sentence that lead to exaggeration. For example, as mentioned in the paper, considering the sentence “Your Grandma is as old as the mountains”, the phrase “as old as” causes exaggeration in that sentence and that is exactly what they’re trying to detect. For phonetic features, they used the CMU’s pronunciation dictionary to detect rhyming words. For example, as mentioned in the paper, considering the sentence “Coca Cola went to town, Diet Pepsi shot him down, Dr. Pepper fixed him up, now we are drinking 7up” the words town and down, up and 7up are rhyming and words like these play an important rhetoric in wordplay jokes. For secondary meaning, they used a knowledge base called Concept-Net which consists of words and phrases that people use and the usual relation between them. For example, considering the joke “Those who like the sport fishing can really get hooked", the words "fish" and "hook" are create a comical effect. Coming to Dark Humor they used Sentiment Scores, Logistic Regression and SVM to classify the dark humor jokes. For detecting Adult Slangs, they used a slang dictionary called "Slang SD" in combination with Logistic Regression and SVM. Using a list of 100 gross words selecting them by their TF-IDF score, they used SVM and Logistic Regression to detect Gross Jokes. Finally, for "insults", they created a list of 100 insulting words going by their TF-IDF score, and used Sentiment Scores, Naïve Bayes classifier and SVM to classify insult jokes.

Analysis

We see that SVM has a better accuracy in all the cases than Naive Bayes and Logistic Regression. In the case of Topic Detection, Proper noun boosting increases the accuracy furthermore. In the case of sarcasm detection, we see the sentiment scores as well as unigrams and bigrams given to an SVM gave the best possible result. In the case of detection of dark humor, we see that there is significant increase in accuracy as sentiment values are introduced. In case of adult slang detection, we are getting a very good accuracy as soon as a slang dictionary is introduced. In detection of gross jokes, the accuracy is increased as soon as sentiment and common gross words are introduced.

We can understand from this work that the whole framework largely depends on data. So, addition of more and diverse data will make the framework more robust and accurate. This also makes it possible to add a greater number of subcategories of jokes. In future, this can be extended to not only a particular instance but also a classification of humorous events (like a small moment between two people), and non-humorous events, thereby opening the possibilities for broader range of media.