SENTIMENT VARIATIONS IN TEXT FOR PERSUASION TECHNOLOGY

A Summary of the Paper published by Lorenzo Gatti, Marco Guerini, Oliviero Stock & Carlo Stapparava

By Ethiraj Srinivasan, Naitik Shukla, Raghavan Kalyanasundaram, Shobhit Jaipurkar, Sindhu Rumesh Kumar and Suya Hao.

Introduction:

The inspiration behind the paper published is the importance of accurate wording in persuasive verbal communication. The subtleties in persuasive communication are almost an art, and we can see it in our day-to-day activities with sales representatives trying to sell us their product, or by subliminal brand marketing. We are however, not interested in understanding the closed-door tactics of persuasion, but rather interested in diving into the field of Natural Language Generation (NLG) of persuasive messages. More specifically, we are going to focus on the affective NLG, and modifying existing text to change their overall sentiment and rendering them towards a particular sentiment based on our desired persuasive effect. Let us begin.

The Role of Emotions in Persuasive Systems:

There is an observed effect of Emotional Load on message effectiveness. We shall focus on the four dimensions of emotional elements that affect the message persuasiveness. They are:

a) The Current Emotional State of the Persuadee.
b) The Current Emotional State of the Persuader.
c) The Emotional State Expressed by the Persuader.
d) The Emotional State possibly produced in the Persuadee.

For the purposes of this paper, we shall concentrate on just the third point. This includes the chosen wording and word order of the persuader. There have been similar works in the same domain by various prominent researchers where the focus of the study was on ***believability***, rather than on ***effectiveness*** of natural communication. Other works include Multi Agent Platforms to Simulate Emotional Reactions among Groups of Agents, Affective Language Generation and Adapting Messages to Users' Profiles. However, none of them focused directly on persuasion or the kind of study implemented in this paper.

Persuasion and Sentiment-Based Text Variations:

The key aspect to understand about emotional persuasion is- the distinct role of ***sentiment*** and ***arousal*** in textual corpora. The sentiment is just the polarity of an emotion, whether positive or negative, while the arousal quantifies the level of effectiveness in the given text.

For the purposes of this study, we shall use a tool called *VALENTINO* to modify existing textual expressions towards more positively/negatively valenced versions of itself. This kind of automatic variation introduced in text can smooth all emotional peaks, or can bring about different types of changes in key parts of the text. The applications of the aforementioned methods find themselves in several fields such as branding, marketing, slogan design, advertising, etc.

An Architecture for Sentiment Text Variations:

The primary objective associated with the task of Text Sentiment Variation is retaining the core meaning of the statement while modifying the intermittent sentiment contained in it. This is the task of Text Sentiment Variation. To carry this out, we use a combination of specific rules that classifies into High Level Rules and Low Level Rules.

To put it simply, High Level Rules decide which parts of the text should be modified, while Low Level Rules take care of the single parts of the message in accordance to the indications specified by the High Level Rules. When these rules work together, they are able to insert or delete sentiment-bearing words. Valentino, the software we shall be using, does a good job at quantifying sentiment from text.

The architecture of Valentino is specifically built to work on an open domain without any lexical restrictions. Being built from large-scale corpora and English lexical repositories such as GoogleWeb n-grams and WordNet, Valentino offers us exactly what we need to carry out our desired task. The slanting procedure used can be divided into two steps, namely – ***Analysis*** and ***Modification.***

Analysis:

In the analysis phase, the input text is analysed and enriched with information regarding Part Of Speech, Morphology, Syntax, Rhetoric and Affective Weight. We may break up the analysis phase into three main tasks, namely – ***Constituent and Dependency Identification***, ***Semantic Reasoning*** and ***Rhetorical Analysis***

Constituent & Dependency Identification:

Context is a key feature in analysing sentiment related text data. For this reason, text dependencies must be taken into account so that the language models can be properly queried. To do this, the text is POS tagged, morphologically analysed and divided into sentence constituents using the TextPro package. The dependences and co-reference relations are then reconstructed using the Stanford CoreNLP suite.

- *Constituents* are important, as we need to know the grammatically correct position to append a word for the pertinent query. For example, an adjective can only be appended to the article or a noun.
- In the case of non-adjacent phrases, we use a method called *Parsing* where, we locate the argument of an adjectival constituent.
- For example, in the sentence – “My house in Bukit Batok is very spacious”, we need to parse the sentence to analyse for dependencies so that we know that the adjective ‘very spacious’ is a dependency of ‘My house’.
- Similarly, for more complex text samples, where adjectives are co-referenced in adjacent sentences, it is imperative to incorporate *Anaphora Resolution* to locate dependencies across the co-referenced words.
- For example, in the sentence – “I love my dog. Everyone says he is very friendly”, we know that ‘very friendly’ refers to ‘my dog’ by projecting the proper NP to the ADJ, through pronouns.

Semantic Reasoning:

In cases where we choose modifiers with a similar form, but a different semantic function, it is necessary to distinguish the instances according to their meaning. These cases are dealt with using the Semafor parser. For example, the model must learn to recognize the difference in the meaning of the given two sentences based on their semantic implications.

We went on vacation with friends **vs** *We went on vacation with enthusiasm*

Rhetorical Analysis:

The rhetoric of the given sample is also important as it can impose constraints in the modification phase and be exploited to obtain subtle variations. The Hilda Rhetoric parser is used to generate rhetorical contrasts between sentences as shown below.

I love my new phone but it is a bit slow.

Modifications:

1. High Level Rules:

The model implements three kinds of High Level Rules:

- *Selective Modification*. For example, in statements of the form X_{NP} <be> Y_{ADJP}, it leaves the NP part untouched while modifying the adjective chunk.
- *Sentence Re-Ordering*. These rules move text spans in contrasting sets of sentence such that the second conjunct has a good recency effect that makes the entire statement sound more positive.
- *Score Constraining*. These rules mitigate the valence in the sentence to preserve the overall grammatical correctness of the statement.

2. Low Level Rules:

As observed from the above examples, a big chunk of the reasoning in Valentino is done on constituents and their relations. They follow these basic Low Level Rules:

- Constituents are slanted to a target constraint, which limits the variation in the model.
- Hierarchical modification is done considering the first dependents from Left to Right, and then possibly the head. This is in the idea that, in a constituent, as we move from the head outward, the variation is less prominent. It also ensures the variation in meaning is minimized, and reduces the ambiguity in recognition for the user.

Both high and low level rules are implemented in GBBOpen, an open blackboard system that schedules rules accordingly.

3. Language Models & Resources:

In addition to successful modification, we must also verify the grammatical quality of the output. For example, we cannot describe a house as delicious, or a dish as spacious. We used a language model that provides the co-occurrences of words in a language use.

4. Metrics & Language Models:

Metrics used in this model are divided into three major groups:

a) *Linguistic Usage:* This is used to add more relevance to common terms/modifiers specific to the term of interest. ***N-gram frequency*** or ***Pointwise Mutual Information (PMI)*** is used.

b) *Valence:* Used to define the arousal of a particular word.
For Example: Fine < Good < Exquisite

c) *Persuasiveness:* Sometimes, there exist words with similar valence scores, PMI and frequency. In this case, we choose a word for modification based on how persuasive that particular word is. For eg: ***Delicious*** is more persuasive than ***Exquisite.***

In addition to the existing frameworks, we also used an extended version of NgramQuery that integrated WordNet with GoogleWeb 1T 5-Grams, and added SentiWordNet information. This provides us with a set of substitutes matching the target score and simultaneously fit within the context.

Evaluation Challenges:

A challenge with the study is the testing of said model. The success of the model is defined by three criteria, namely- *Output Quality*, *Output Consistency* and *Output Effectiveness*. These three criteria mark the first step at the prototyping stage. The Output Quality evaluates the grammatical correctness and awkwardness of the output. The Output Consistency checks whether the target score is met effectively, and the Effectiveness measures whether the output has an impact on the emotions of the persuadee.

Existing methods are known to assess for either long-term behavioural changes, or short-term effects. In the first case, it is hard to ascertain whether said changes are solely caused by the experiment, whereas the second case poses a challenge in quantifying the miniscule reactions. In addition, some well-crafted exercises may also fail due to inability to measure said miniscule changes, or just overall lack of enthusiasm by the candidates. There are two possible solutions for these problems.

1. Mechanical Turk (Partial Solution):

Here, the subjects are willingly undergoing a process of being tested on their skills using pre-conceived questionnaires or forms. However, this method is just a partial solution as the fact that the candidates are paid for undertaking the task, and the existence of a 'gold standard' to assess contributors' reliability, dampen the integrity of the output.

2. Targeted Ads (Advanced Solution):

Targeted Ads check all the boxes of a perfect solution as they are automatically performed by the system, highly targeted to unaware users who fit the required cohort, and operate on a virtually infinite pool of users across the internet.

For the experiment, a methodology using AdWords was devised for the evaluation of short promotional expressions, suitable to work in combination with Valentino. It was to check whether different wordings of an ad influences audiences in an A/B testing scenario. Using metrics like Click-Through Rate, it is possible to quantify the success of that particular ad.

Conclusion & Scope for Future Work:

This study focussed on subtle sentiment variations of short expressions. The goal was to develop technology for automating the task of bringing sentiment-based variation into textual chunks of data without losing the readability. As for evaluating the output of this experiment, we described the method developed as an optimal match for Valentino such that a final user who may want to check the persuasiveness of the expressions produced by the system can also use the same.

Future works in this domain may extend to various features such as More Variation Rules, Increased Linguistic Flexibility and Adaptive Target Profile Metrics.

THE POSSIBILITIES FOR INNOVATIVE METHODS IN THIS FIELD IS BOTTOMLESS, AND WE HOPE TO OFFER NOVEL SOLUTIONS FOR EVERYONE WHO WISHES TO INDULGE IN LANGUAGE-BASED PERSUASIVE TECHNOLOGY.