"Let me convince you to buy my product ... "

A Case Study of an Automated Persuasive System for Fashion Products

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ABSTRACT

Persuasiveness is a creative art aimed at making people believe in certain set of beliefs. Many a times, such creativity is about adapting richness of one domain into another to strike a chord with the target audience. In this research, we present PersuAIDE! - A persuasive system based on linguistic creativity to transform given sentence to generate various forms of persuading sentences. These various forms cover multiple focus of persuasion such as memorability and sentiment. For a given simple product line, the algorithm is composed of several steps including: (i) select an appropriate well-known expression for the target domain to add memorability, (ii) identify keywords and entities in the given sentence and expression and transform it to produce creative persuading sentence, and (iii) adding positive or negative sentiment for further persuasion. The persuasive conversion were manually verified using qualitative results and the effectiveness of the proposed approach is empirically discussed.

CCS CONCEPTS

• Computing methodologies → Cognitive science; Learning latent representations;

KEYWORDS

creative AI, persuasive system, fashion

1 INTRODUCTION

Consider the following question, "I want to buy a blue gown for wearing to an evening party?". The cognitive search systems, could find and retrieve all the relevant "blue gown" dresses that are popularly voted as a suitable fashion wear for an "evening party". The state-of-art systems could summarize content from various source and present in a much readable manner. The summarized response from Google’s search is shown in Figure 1. More so, the systems could even point to the most relevant e-commerce websites where the dress could be purchased. Figure 2 shows the results from a personalized mobile assistant, Google’s Allo, where each image is an hyperlink to it’s corresponding e-commerce website. Existing question-answering systems and conversation systems are well trained for resolving the facts from the input query and finding semantic similarity with respect to a huge corpus of background dataset.

Figure 1: Summarized results obtained from the Google search for an input query, "I want to buy a blue gown for wearing to an evening party".
Figure 2: Personalized results obtained from the Google’s assistant, Allo for an input query, “I want to buy a blue gown for wearing to an evening party”.

(1) Memorability [4]: Plain descriptions and bland facts do not tend to be attract the consumers. To increase the memorability of such descriptions, popular slogans, movie titles/double, poetry, catchy-phrases could be adopted to suit the product’s description.

(2) Sentiment [9]: Addition of positive sentiments in the description could influence the consumer’s inclination towards the product. One such way of adding sentiments into sentences could be to add enhancing adjectives to noun-phrases in the sentence. For example, a description such as “Blue Embroidered Net Semi-Stitched Anarkali Gown” could be enhanced as "Dazzling Blue Embroidered Net Semi-Stitched Anarkali Gracious Gown”

In the rest of the paper, Section 2 briefs the closely related literature work, Section 3 explains the proposed approach, Section 4 discusses the obtained results, Section 5 details some of the future extensions of this work, and Section 6 concludes our research.

2 LITERATURE STUDY

Usage of linguistic creativity in the past have been looked into for poetry generation. [11] proposed a poetry generation system that uses morphological analysis to identify substitutable words for the given topic to generate variants of poem. Recently, there is lot of focus on creative text generation based on lexical substitution. [5] discussed about slanting an original expression to more positive or negative version by adding or subtracting a word. [6] discussed about identifying various topic in the news and choosing the right expression that captures them. [8] proposed an extensible framework that allows users to force multiple words to appear in the expression. Given keywords, the framework comes up with an expression that includes them. More recently, [2] proposed a system that blends expression with best matching evolving news. [3] proposed a creative system that generates a news headlines based on best matching expression. Almost all of these work could be considered as catering to memorability aspect of persuasion alone as they rely on popular expression, quote, poem etc. and their input text are fairly expressive text like headline which are fairly easy to persuade compared to product description which are blunt statements. Also none of them discussed about transforming sentences to include complex persuasive features like argumentation, sentiment etc in the target domain.

3 PERSUAIDE!: PROPOSED APPROACH

In this section, we discuss the details of the proposed persuasive system. Figure 3 shows an overview of the proposed system. Further explanation of multi-step transformation process is as follows,

Step 1: From a large corpus of text data, capture fashion domain knowledge in terms of dependency relationship between different words commonly used in fashion. In order to create this domain knowledge, we collected a large corpus of fashion related text from some of the leading fashion magazines: Chictopia1 and Vogue fashion 2. From these blog posts and magazine articles, we extracted about 425,000 text sentences. This dataset is appended with a list

1http://www.chictopia.com/
2http://www.vogue.in/fashion/
of popular slogans, cliches, movie dialogs, quotations [2] to find the prominent dependency relations in fashion domain. We use the Stanford’s dependency parser [1] to get the dependency relation in each sentence of the training corpus and store the frequency of each such relation. We obtained a dependency relationship matrix whose rows and columns are the words in vocabulary and the integer in each cell $f(a, b)$ denotes the frequency of a relation (between row words and the column word) in the entire corpus. In our dataset, we had a vocabulary size of 51,000 words and 4,600,000 dependency relations.

**Step 2:** This step is to improve the memorability of the product description. Once the dependency relations are captured, we get to the process of sentence transformation. Given a sentence, we now transform it into another form by making use of quotations, slogans, etc while taking into consideration the domain dependency relations. For a given product description, we find the most similar auxiliary sentence from the quotations, slogans, movie dialogs corpus with the help of an LSTM based text similarity algorithm.

**Step 3:** Once the auxiliary sentence is identified, the sentence transformation can happen in two ways. Either by substituting few words in the product description sentence using the words in the auxiliary sentence or introducing new words into the auxiliary sentence from the words in the product description sentence.

**Step 4:** For word substitution, we capture all the nouns, verbs, adjectives and adverbs in the input and auxiliary sentences. For each of the selected word from the auxiliary sentence, we find its derivationally related forms with the help of wordnet. These derivationally related forms are bucketed into four categories (nouns, verbs, adjectives, adverbs) based on their POS tags. Now, for each of the selected word from input sentence, we choose the best substituting word from one of the created buckets. The bucket is chosen based on the POS tag of the input word. In the chosen bucket, we find the best word by making use of the following procedure.

- Find all the dependency relations from the input sentence which involves the chosen word ‘w’.
- For each word ‘k’in the chosen bucket, we find the matching score to replace the word w. The matching score is defined as below.

$$score(R, w, k) = \exp \left( \sum_{a \in w} \frac{\log f(a, b)}{|R \ni w|} \right)$$  \hspace{1cm} (1)

where, $R$ denotes the dependency relations in the input sentence and $f(a, b)$ denotes the frequency of the dependency relation $a \rightarrow b$ in the training corpus, and $R \ni w$ denotes the set of all relations containing the word w. If w is child in the dependency relation r then, $a = \text{parent in the relation } r$ and $b = k$. If w is parent in the dependency relation r then, $a = k$ and $b = \text{parent in the relation } r$. For each selected word in the input sentence, we select k which has maximum matching score and replace the word w.

**Step 5:** For word addition, we select word from a list of positive sense adjectives like wonderful, wonderful, dazzling, etc. For each noun in the input sentence, we check the possibility of introducing a suitable adjective. In fashion text, we observed that most of the nouns are colors, garments (outfits), jewelry, etc. Based on the type of noun, we select a suitable adjective to add.

## 4 SYSTEM

While this is a work-in-progress, we show some initial results in Table 1, listing the input sentence, selected quotation and the transformed outputs (with and without sentiment). For input sentence, the best matching quotation is selected from the quotations corpus using the Siamese adoption of LSTM networks [7]. Next, suitable word replacements are identified by extracting all the nouns, verbs, adjectives, adverbs using Stanford CoreNLP parser from both the input sentence and the quote. For each selected word in the quotation, the derivationally related forms are found using the wordnet and bucketed using their POS tags (nouns, verbs, adjectives, adverbs). For example, pink#adjective, pink#noun, pinkify#verb, wear#verb, wear#noun, etc. Next, for each of the selected word in the input sentence, the best suitable word is selected from the bucket of derivationally related forms having same POS tag as the input word. The criterion for selecting the best matching word is matching score (discussed in the previous section). It might so happen that multiple words in the fashion sentence may match with some in the slogan, in this case, the pair which has the maximum score is selected. Using this process, we generate the transformed sentence, shown in the third row of the table. Further, to enhance the transformation, suitable adjectives are added to the nouns. For this purpose, from a list of positive adjectives, those suitable to be used in the fashion domain were hand picked. Based on the noun in the input sentence, an appropriate adjective from the selected list is chosen and introduced into the previously transformed sentence.

## 5 FUTURE WORKS

In the current work, we only make use of the auxiliary information like slogans, etc to enhance the sentences related to fashion. In our observation, the fashion related sentences are tougher to deal with when compared to any news article based work predominantly
Table 1: Qualitative examples illustrating the proposed approach by transforming some fashion description statements to make it more persuasive.

| Fashion Description | Matching Quotation | Transformed text | Transformed text + sentiment |
|---------------------|--------------------|-----------------|-----------------------------|
| Think pink but don’t wear it | Comes with a matching slip | Think pink but don’t match it | Think gleaming pink but don’t match it |
| Jewelry maybe is more expensive than clothes, but clothes are more important than jewelry | Accentuate the outfit with a sling bag and a bracelet | Jewelry maybe is more expensive than outfit, but clothes are more important than jewelry | Jewelry maybe is more expensive than outfit, but stylish clothes are more important than jewelry |

6 CONCLUSION

In this paper, we presented a system called PersuAIDE which aims to generate persuasive text for input product description. We demonstrated the work in fashion domain where popular expressions were used to generate creative sentences covering memorability aspects of persuasion. Further, based on the type of sentence, sentiment features were added to slant the generated sentence. Our study can be considered as a novel attempt to blend well known expressions with non expressive product lines in a linguistically motivated framework that accounts for syntagmatic and paradigmatic aspects of language.

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