Trusting Politicians' Words (for Persuasive NLP)

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Abstract. This paper presents resources and lexical strategies for persuasive natural language processing. After the introduction of a specifically tagged corpus of political speeches, some forms of affective language processing in persuasive communication and prospects for application scenarios are provided. In particular *Valentino*, a prototype for valence shifting of existing texts, is described.

1 Introduction

In order to automatically produce and analyze persuasive communication, specific resources and methodologies are needed. For persuasive NLP we built a resource called CORPS that contains political speeches tagged with audience reactions. A key role in persuasive communication is played by affects: we have focused on lexical choice and we present here a tool for modifying existing textual expressions towards more positively or negatively valenced versions, as an element of a persuasive system.

The paper is structured as follows: Section 2 gives an overview of key concepts connected to persuasion and briefly describes the state of the art in related areas. Section 3 describes the resources we built for statistical acquisition of persuasive expressions. Finally, Section 4 describes how this approach can be used for various persuasive NLP tasks, while Section 5 presents the *Valentino* prototype, built upon the resources we presented.

2 Persuasion, Affect and NLP

According to Perelman and Olbrechts-Tyteca [1], persuasion is a skill that human beings use - in communication - in order to make their partners perform certain actions or collaborate in various activities. Here below we introduce some related key concepts.

Argumentation and Persuasion. In AI the main approaches focus on the argumentative aspects of persuasion. Still, argumentation is considered as a process that involves "rational elements", while persuasion includes also elements like emotions. In our view, a better distinction can be drawn considering their different foci of attention: while the former focuses on message correctness (its being a valid argument) the latter is concerned with its effectiveness.

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Natural Argumentation. The recent area of natural argumentation [2] tries to bridge argumentation and persuasion by focusing, for example, on the problem of the adequacy - effectiveness - of the message.

Emotions and Persuasion. Since persuasion includes non-rational elements as well, it is a “superset” of argumentation, but this does not rule out that there is a role for emotion within argumentation (Miceli *et al.* [3]): through arousal of emotions or through appeal to expected emotions. Indeed, emotional communication has become of increasing interest for Persuasive NL Generation.

Rhetorics. The study of how language can be used effectively. This area of studies concerns the linguistic means of persuasion (one of the main means, but not the only one). This is the area we are focusing on in this paper.

Irony. It refers to the practice of saying one thing whilst meaning another. Irony occurs when a word or phrase has a surface meaning, but another contradictory meaning beneath the surface. Irony is a widely used rhetorical artifice, especially in advertisement.

Past works on persuasion and NLP has focused mainly on text generation (a notable exception being *Araucaria* [4]). Persuasive text generation deals with the production of texts that are meant to affect the behavior of the receiver. For example STOP, one of the best known NLG systems [5], uses domain specific rules, based on expert knowledge acquisition for the clinical smoking domain [6]. *Promoter* instead [7] uses strategies gathered from different persuasive theories and subsumed in a general planning framework. Other persuasive NLG systems are more argumentation oriented. In these cases “theoretical expert knowledge” is used (e.g. Toulmin [8], Perelman and Olbrechts-Tyteca [1], Walton [9]). NAC [10], for example, is concerned with the abstract form of the unfolding of the argument - strategic planning -. The system presented by Reed *et. al.* [11] uses two modules, Argument Structure (strategic planning) and Eloquence Generation (tactical planning), leaving the problem of message effectiveness to the latter module. The PORTIA [12] and ARGUER [13] systems focuses on dialogical aspects of argumentation. PORTIA uses Walton’s argumentation schemata, extended to formalize a-rational aspects of persuasion. ARGUER is also based on argumentation schemata to detect attack or support relations among participants’ moves.

Since emotional reasoning is usually performed in order to modify/increase the impact of the message, affective NLP is strictly connected to persuasive NLP. An annotated bibliography on affective NL generation can be found in [14]. de Rosis and Grasso [15] focus on the technological aspects for an affectively “richer” NL production. Their model uses plan operators - for text structuring - combined with rule based heuristics for revising both strategic and tactic planning. Carofiglio and de Rosis [16] instead use a dynamic belief network for modeling activations of emotional states during dialogical interactions. This model of emotional activation is inserted in an argumentation framework.

Opinion mining is a topic at the crossroads of information retrieval and computational linguistics concerned with the opinions expressed in a document. Recent research has tried to automatically identify whether a term has a positive or a negative connotation (see for example [17] and [18]). In [17] a method for feature extraction that draws on an existing unsupervised method is introduced. The work in [18] presents methodologies that use a wide range of features, including new syntactic features, for opinion recognition. Opinions, once extracted, must be summarized (in case) and presented to the user. In [19] the authors argue that an effective method for summarizing evaluative arguments must synthesize sentence extraction-based approaches and language generation-based approaches. Even though opinion mining deals with texts that are meant to persuade its focus is on polarity (valence) recognition for evaluative language retrieval. Instead persuasive expression mining deals with the extraction of pieces of text that are meant to persuade, regardless of their possible evaluative use.

3 Aims and Resources

Authors such as Radev and McKeown [20] rely on automatic acquisition of sentences mapped on their functional description, to overcome the problem of simple canned texts extraction. In this paper we adopt persuasive expression mining techniques and refinement as a component for persuasive NLP systems in an unrestricted domain. As for emotions, we restrict our focus on valenced expressions (i.e. those that have a positive or negative connotation). For us the task of producing affective expressions, as a component of persuasive systems, involves changing appropriately the valence of existing expressions. We collected specific resources aimed at persuasion[1]:

- A CORpus of tagged Political Speeches (CORPS), as examples of long and elaborated persuasive texts
- A Corpus of labeled advertising or political slogans (*SloGun*), as examples of short, high impact, sentences
- A resource containing terms gathered by semantic similarity and ordered by valence (Ordered Vectors of Valenced Terms - OVVT).

The resources we focus on in this paper are CORPS and OVVTs.

3.1 CORPS

In collecting this corpus we relied on the hypothesis that tags about public reaction, such as `APPLAUSE`, are indicators of hot-spots, where persuasion attempts succeeded (or, at least, a persuasive attempt has been recognized by

[1] In fact, it is difficult to state if a text is persuasive per se: let us consider the following inform sentence: "Monte Bondone is half an hour by car from Trento". It can be considered as a persuasive utterance if emitted as a reply to the sentence: "I'm in Trento and I have a spare afternoon. I'd like to go skiing".

Table 1. List of main tags

Tag	Note
{APPLAUSE}	Main tag in speech transcription.
{SPONTANEOUS-DEMONSTRATION}	Tags replaced: "reaction" "audience interruption"
{STANDING-OVATION}	-
{SUSTAINED APPLAUSE}	Tags replaced: "big applause" "loud applause" etc.
{CHEERS}	Cries or shouts of approval from the audience. Tags replaced: "cries" "shouts" "whistles" etc.
{BOOING}	In this case, the act of showing displeasure by loudly yelling "Boo" Tags replaced: "hissing"
{TAG1 ; TAG2 ; ...}	In case of multiple tagging, tags are divided by semicolon. Usually there are at most two tags.
Special tags	**Note**
{AUDIENCE-MEMBER} [text] {/AUDIENCE-MEMBER}	Tag used to signal a single audience member's intervention such as claques speaking.
{OTHER-SPEAK} [text] {/OTHER-SPEAK}	Tag used to signal speakers other than the subject (like journalists, chairmen, etc.)
{AUDIENCE} [text] {/AUDIENCE}	Tag used to signal audience's intervention.

the audience; on this point see the bibliography on mistimed applause in political speeches [21]). We can then perform specific analyses - and extractions - of persuasive linguistic material that causes the audience reaction.

At present, there are about 900 speeches in the corpus and about 2.2 millions words (see Figure 1 for a survey on main speakers' number of speeches). These speeches have been collected from internet, and an automatic conversion of tags - to make them homogeneous in formalism and labelling - has been performed (see Table 1 for a summary of the tags and their conversion). Given that the tags represent audience reactions this is the case in which there is an "evident" high inter-annotators agreement. Metadata regarding the speech has also been added (title, event, speaker, date, description).

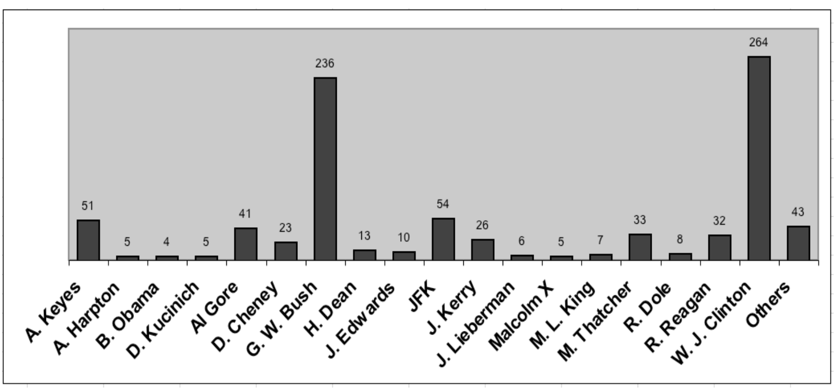

Fig. 1. Number of speeches per speaker

3.2 OVVTs

We drove a preliminary study with human subjects to understand how people perform the task of modifying the valence of existing texts. The insight gained from the study showed that (a) people usually modify single words, (b) sometimes use paraphrases (c) sometimes add or subtract words that play the role of down toners or intensifiers.

We also found that in point (a) there are different classes of valenced terms that are addressed, like adjectives, adverbs, quantifiers, terms indicating strength of belief, etc. We built a resource that gathers these terms in vectors (OVVTs). We used the WordNet `antonymy` relation as an indicator of terms that can be "graded". We built four groups of terms that can be potentially used (one group for each POS). Moreover, we populated the vectors using other specific WN relations (`similar_to` relation for adjectives, `hyponym` relation for verbs and nouns). Finally the valence of WN synsets (taken from SentiWordNet[2] scores [22]) was added to the corresponding lemmata. Thus, an OVVT is composed of several "terms" (lemmata) with similar semantic reference (e.g. beauty) but different valence (see Figure 2, each entry in the OVVTs takes the form `lemma#pos#sense-number`).

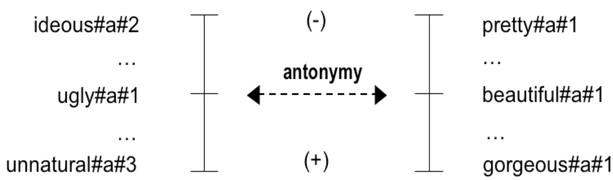

Fig. 2. An example of OVVT

4 Exploiting the Corpus

CORPS has been used both for analysis and generation (the latter use will be briefly discussed in Section 5).

We considered: (a) windows of different width wn (where wn is the number of tokens considered) of terms preceding tags; and (b) the typology of persuasive communication. We individuate three main groups of tags according to the characteristics of the reaction induced in the audience:

- *Positive-Focus*: this group indicates a persuasive attempt that sets a positive focus in the audience. Tags considered (about 16 thousand): {`APPLAUSE`}, {`SPONTANEOUS-DEMONSTRATION`}, {`STANDING-OVATION`}, {`SUSTAINED APPLAUSE`}, {`AUDIENCE INTERVENTION`}, {`CHEERING`}.

[2] SentiWordNet is a lexical resource in which each WordNet synset is associated to three numerical scores: Obj(s), Pos(s) and Neg(s). These scores represent the objective, positive and negative valence of the synset.

– *Negative-Focus*: It indicates a persuasive attempt that sets a negative focus in the audience. Note that the negative focus is set towards the object of the speech and not on the speaker herself (e.g. "Do we want more taxes?") Tags considered (about 1 hundred): {BOOING}, {AUDIENCE} No! {/AUDIENCE}.
– *Ironical*: Indicate the use of ironical devices in persuasion. Tags considered (about 4 thousand): {LAUGHTER}[3].

We conducted a preliminary analysis of the corpus focusing on the relation between valence and persuasion: the phase that leads to audience reaction (e.g. APPLAUSE), if it presents valence dynamics, is characterized by a valence crescendo. That is to say: not necessarily persuasion is achieved via modification of valence intensity, but, when this is the case, it is by means of an increasing in the valence of the fragment of speech.

To come to this result we calculated, for every window, its mean valence ($\overline{w}$), and subtracted the mean valence of the corresponding speech ($\overline{s}$). In this way we obtained two classes of windows:

– Windows with mean-valence above the mean-valence of the speech ($\overline{w} > \overline{s}$)
– Windows with mean-valence below the mean-valence of the speech ($\overline{s} > \overline{w}$)

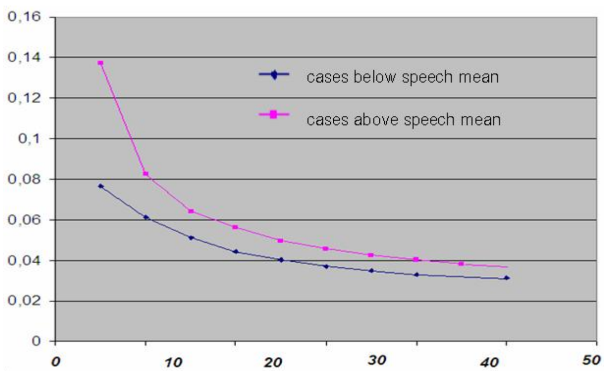

Fig. 3. Relation between valence and persuasion

We then summed up all the values for the two classes and normalized the results by dividing it for the total number of cases in the class (n_c). We repeated the procedure for various window widths ($5 < wn < 40$), see Figure 3 and Formula 1. The results show that cases above the speech mean are fewer but far stronger. We are planning to have a finer grained analysis by means of cluster-based approaches and variable window width.

$$y = \frac{\sum abs\,|\overline{w} > \overline{s}|}{n_c} \qquad x = wn \tag{1}$$

[3] If LAUGHTER appears in a multiple tag (e.g. together with APPLAUSE) by default this tag is associated to the ironical group. This is not the case for BOOING that occurs always alone.

Analysis of public reaction can substantiate intuitions about the speakers' rhetorical style; for example:

How do political speeches change after key historical events? Analyzing the speeches of George W. Bush before and after 9/11 (70 speeches before and 70 after, from 12 months before to 16 months after) at the lexical level we found that: while the positive valence mean remains totally unvaried, the negative increases by 15% (t-test; $\alpha < 0.001$).

What can be said of the lexical choices of a specific speaker that obtains a certain characteristic pattern of public reaction? By considering 30 of Ronald Reagan's (also know as "the great communicator") speeches we found that the mean tag density of this collection was 1/2 of the mean tag density of the whole corpus (t-test; $\alpha < 0.001$). Interestingly, focusing only on the subgroup of ironical tags we found that the density in Reagan's speeches is almost double as compared to the whole corpus (t-test; $\alpha < 0.001$).

How does the perception of the enemy change in different historical moments? A specific analysis on the valence of the lexical context surrounding named entities that elicit negative-focus audience reactions in different period of times can provide interesting insights.

Persuasive Opinion Mining. Not all the opinions expressed in speeches or texts have the same persuasive impact. "Successful" opinions (for example G. W. Bush speaking about W. J. Clinton) can be extracted considering those followed by a reaction of the audience. The role of rhetorical constructs will be taken into account in future research.

We extracted "persuasive words" by using a weighted tf-idf (see Formula 2).

$$tf_i = \frac{n_i \times \sum_{n_i} s_i}{\sum_k n_k} \qquad idf_i = \log \frac{|D|}{|\{d : d \ni t_i\}|} \tag{2}$$

To calculate the tf-idf weight, we created a "virtual document" by unifying all the terms inside all the windows (of dimension wn) preceding the tags, and considering the number of documents in the corpus as coincident to the number of speeches plus one (the virtual document). Obviously from the speeches we subtracted those pieces of text that were used to form the virtual documents. Given this premise we can now define the terms in Formula 2:

- n_i = number of times the term ti appears in the virtual document
- $\sum_{n_i} s_i$ = sum of the scores of the term (the closer to the tag the higher the score)
- $\sum_k n_k$ = the number of occurrences of all terms = $wn \times |tags\, number|$
- $|D|$ = total number of speeches in the corpus
- $|\{d : d \ni t_i\}|$ = number of documents where the term ti appears (we made an hypothesis of equidistribution).

Four lists of words were created according to the group of tags they refer to (positive-focus-words, negative-focus-words, ironical-words and a persuasive-words list - computed by considering all tags together). Analyzing the 100 top words of these lists we found that the negative valence mean of positive-focus and negative-focus groups is the same, while for the the negative-focus group the positive valence mean is about 1/4 with regard to the positive-focus group (t-test; $\alpha < 0.01$). In Table 2 a comparison between the positive-focus and negative-focus top 50 most persuasive words is given (note that named entities have not been discarded).

Table 2. List of top most persuasive words

Positive-focus words	**Negative-focus words**
bless#v deserve#v victory#n justice#n fine#a relief#n November#n win#v help#n thanks#n glad#a stop#v better#r congressman#n lady#n regime#n fabulous#a uniform#n military#a wrong#a soul#n lawsuit#n welcome#v appreciate#v Bush#n behind#r grateful#a 21st#a defend#v responsible#a safe#a terror#n cause#n bridge#n prevail#v choose#v hand#n love#v frivolous#a sir#n honor#n defeat#v end#v fight#n no#r Joe#n ready#a wear#v future#a direction#n foreign#a death#n single#a democratic#a	horrible#a criticize#v waste#n opponent#n timidity#n shuttle#n erode#v torpor#n Soviets#n invasion#n scout#n violation#n Castro#n troop#n authority#n Guevara#n Kaufman#n Sachs#n Goldman#n ferociously#r solvent#n page#n front#a international#a direction#n monstrosity#n Cambodia#n unbearable#a drilling#n Soviet#a increase#v intelligence-gathering#a Carolina#n Gerald#n trusted#a drift#n operation#n WTO#n entry#n mcgovern#v coward#n household#n Neill#n

For lexical choice in text generation micro-planning, there are approaches (e.g. Jing [23]) which use corpus and domain information for choosing appropriate lemmata inside synsets. For persuasive NLG, the lists of words we collected allow us to decide, given a synset and an affective/persuasive goal, which lemma to choose inside which list, to maximize the impact of the message.

With a similar approach we also extracted chunks of persuasive sentences. In this case the window width was based on the number of sentences instead of the number of tokens. We plan to use these chunks in two different ways: for extracting linguistic/rhetorical patterns and rhetorical relations pattern among sentences.

5 The *Valentino* Prototype

In this section we present *Valentino* (VALENced Text INOculator) a tool for modifying existing textual expressions toward more positively or negatively valenced versions as an element of a persuasive system. For instance a strategic planner may decide to intervene on a draft text with the goal of "coloring" it emotionally. When applied to a text, the changes invoked by a strategic level may be uniformly negative or positive; they can smooth all emotional peaks; or they can be introduced in combination with deeper rhetorical structure analysis, resulting in different types of changes for key parts of the texts. Valentino is meant to be an easily pluggable component. The only information it requires in input is a coefficient (included between 1 and -1) that represents the designed valence for the final expression.

At the current stage of implementation only a simple POS analysis (together with named entity recognition and morphological analysis) without contextual information is performed. For this task we used the TextPro package (see [24,25]). Various strategies have been implemented, mimicking those performed by humans.

Paraphrase: if a lemma has only one sense, then the gloss of the word is inserted in the text. The gloss is then valenced, but no more paraphrases are allowed. This augments (a) variety in the output text and (b) the possibility of further valencing the original text (see Table 3 for an example).

Table 3. An example of paraphrase

Original expression	Selected gloss	Shifted Output
likely he would go ...	with considerable certainty	*with* {*wide*} {*certitude*} He would go

Use of OVVTs considering only the most frequent senses: for every lemma the candidate substitutes are chosen by searching in the OVVTs up to the third sense of that lemma (e.g. given `big#a` it is first searched `big#a#1`, in case of failure `big#a#2` and eventually `big#a#3`).

Candidate lemmas selection: After these two steps there is the necessity to choose among the candidates lemmas. This choice is performed by using the lists of persuasive words that we collected from CORPS. If the shifting is toward positive (negative) valence the list on positive (negative) focus words is accessed first and the candidate with highest ranking is selected.

Strengthening/weakening by modifying adjectives grade: if the chosen lemma is "too weak" (e.g. the output valence should be -1 but the most valenced candidate for substitution is -0.125), the superlative form is used. Also the opposite situation is considered: if the chosen lemma should be in the superlative form (according to the morphology of the substituted term), but the output valence is already met, then the superlative is discarded.

Morphology synthesis: As a final step the chosen lemma is synthesized according to the chosen morphology (either the morphology of the original lemma, or the modified morphology as defined in the aforementioned strategy).

Named entity blocking: Named entities are not valenced to prevent cases like "*Super* Bowl" shifting to "*Giant* Bowl".

In Table 4 various examples of valence shifting of the sentence "He is absolutely the best guy" are given; lemmata chosen from OVVTs are between curly brackets and adjectives that underwent grade modification are between parentheses.

5.1 Advantages and Limits

Even though there are missing scores in SentiWordNet (i.e. words that should be -clearly- valenced that are not, words that are too much valenced) *Valentino* performs reasonably well.

Table 4. An example of Valentino shifting capabilities

CF 1.0	He is {absolutely} (a superb) {hunk}
CF 0.5	He is {highly} the {redeemingest} {signor}
CF 0.0	He is {highly} (a well-behaved) {sir}
CF -0.5	He is {nearly} (a well-behaved) {beau}
CF -1.0	He is {pretty} (an acceptable) {eunuch}

The advantages of using only the most frequent senses of words can be appreciated starting from the sentence "he was a *great* singer":

1. without taking into account the senses frequencies order: "he was a *pregnant*[4] singer"
2. by searching among most frequent senses (1^{st} to 3^{rd}): "he was a *giant* singer"

A strategy based on LSA similarity techniques will further improve the performances of our system, preventing cases like "newspaper *article*" that is (negatively) shifted to "newspaper *lemon*" because "article" is taken in the primary sense of "artifact". Another filter (still using LSA techniques) can rule out cases of incongruence between adjacent words once chosen. For example "toughest eunuch" is a correct but incongruent realization (with coefficient -1) of "tough guy".

The Advantages of using the list of persuasive words can be seen considering the word "giant". It has been chosen from the following bunch of candidate lemmas (score 0.375): `elephantine#a#1 - gargantuan#a#1 - giant#a#1 - jumbo#a#1`

For the second stage of implementation -insertion or deletion of words by considering context- we plan to use WordNet and machine learning techniques to build connections between, for example, semantic typology of verbs and associated adverbs for VP valence modification. E.g. from "He is convinced" to "He is *firmly* convinced".

5.2 Application Scenarios

There are several application scenarios: edutainment systems that should adapt the output to the audience, news agencies wishing to deliver valenced information, conflict management systems that adapt the messages according to the stage of the conflict (fostering escalation or de-escalation) and so on.

An interesting technological scenario is for Embodied Conversational Agents' applications. Often these applications rely on canned, pre-compiled text. Different emotion intensity realizations of the same message are obtained via facial expression (see for example [7]). With *Valentino* the text can be automatically valenced according to emotion intensity, producing a more effective output.

[4] Here "pregnant" is in the secondary sense of "significant" which is correct but sounds odd.

6 Conclusions

We have presented some resources (in particular the corpus CORPS, that we plan to put freely available for research purposes) and techniques for statistical acquisition of persuasive expressions with a view of contributing to various persuasive NLP tasks. Affective expressions are of paramount importance.

We implemented a prototype named *Valentino* that uses a term extraction and transformation approach: given a term in the text to be modified, the system accesses the OVVT containing that term and chooses the most appropriate transformation in agreement with the valence shift for the persuasive goal.

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