FONDAZIONE
BRUNO KESSLER

Predicting Persuasiveness in Political Discourses

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Intro

- Persuasion is becoming a hot topic in NLP.
- Past works on persuasion and NLP have focused mainly on text generation using knowledge-based approaches.

Scope of the work

- In political speeches, the audience tends to react or resonate to signals of persuasive communication
- Automatically predicting the impact of such discourses is a challenging task
- It can be useful to have a measure for testing the persuasiveness of what we retrieve or possibly of what we want to publish on Web
- We exploit a corpus of political discourses, tagged with audience reactions, such as applause, as indicators of persuasive expressions
- We explore differences between Democratic and Republican speeches, experiment the resulting classifiers in grading some of the discourses in the Obama-McCain presidential campaign available on the Web.

Resources

- We want to explore persuasive expression mining techniques as a component for persuasive NLP systems in an unrestricted domain.

- In order to automatically produce and analyze persuasive communication, specific resources and methodologies are needed.

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typologies & resources

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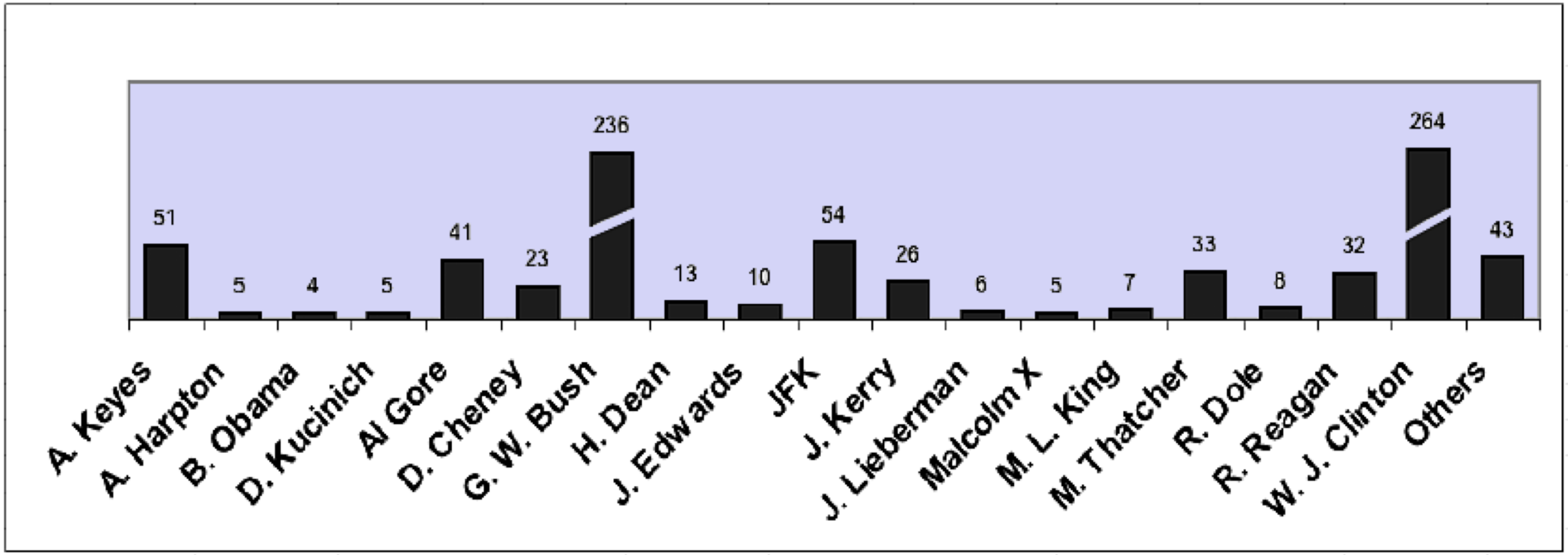
CORPS

Characteristics

- About 900 tagged speeches (from the Web) in the corpus and about 2.2 millions words.



Characteristics (cont'd)

- **Hypothesis**: *tags* about audience reaction, such as **APPLAUSE**, are indicators of hot-spots, where persuasion attempts succeeded.
- Semi-automatic conversion of tags names to make them homogeneous

Tags List

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 r placed: "cries" "shouts" "whistles" etc.
{BOOING}	In this case, the act of showing displeasure by loud yelling "Boo" Tags replaced: "hissing"
{TAG1 ; TAG2 ; ...}	In case of multiple tagging, tags are divided by semicolo Usually there are at most two tags.

Special tags	Note
{AUDIENCE-MEMBER} [text] {/AUDIENCE-MEMBER}	Tag used to signal a single audience member's interve tion such as claques speaking.
{OTHER-SPEAK} [text] {/OTHER-SPEAK}	Tag used to signal speakers other than the subject (li journalists, chairmen, etc.)
{AUDIENCE} [text] {/AUDIENCE}	Tag used to signal audience's intervention.

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  - **Ironical**: Indicate the use of ironical devices in persuasion. Tags considered: {LAUGHTER}

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- We considered:
  - Windows of different width *wn* of terms preceding audience reactions tags.
  - The typology of audience reaction.

An example: Fragment from JFK

Freedom has many difficulties and democracy is not perfect. But we have never had to put a wall up to keep our people in, to prevent them from leaving us. {APPLAUSE ; CHEERS} I want to say on behalf of my countrymen who live many miles away on the other side of the Atlantic, who are far distant from you, that they take the greatest pride, that they have been able to share with you, even from a distance, the story of the last 18 years. I know of no town, no city, that has been besieged for 18 years that still lives with the vitality and the force, and the hope, and the determination of the city of West Berlin. {APPLAUSE ; CHEERS}

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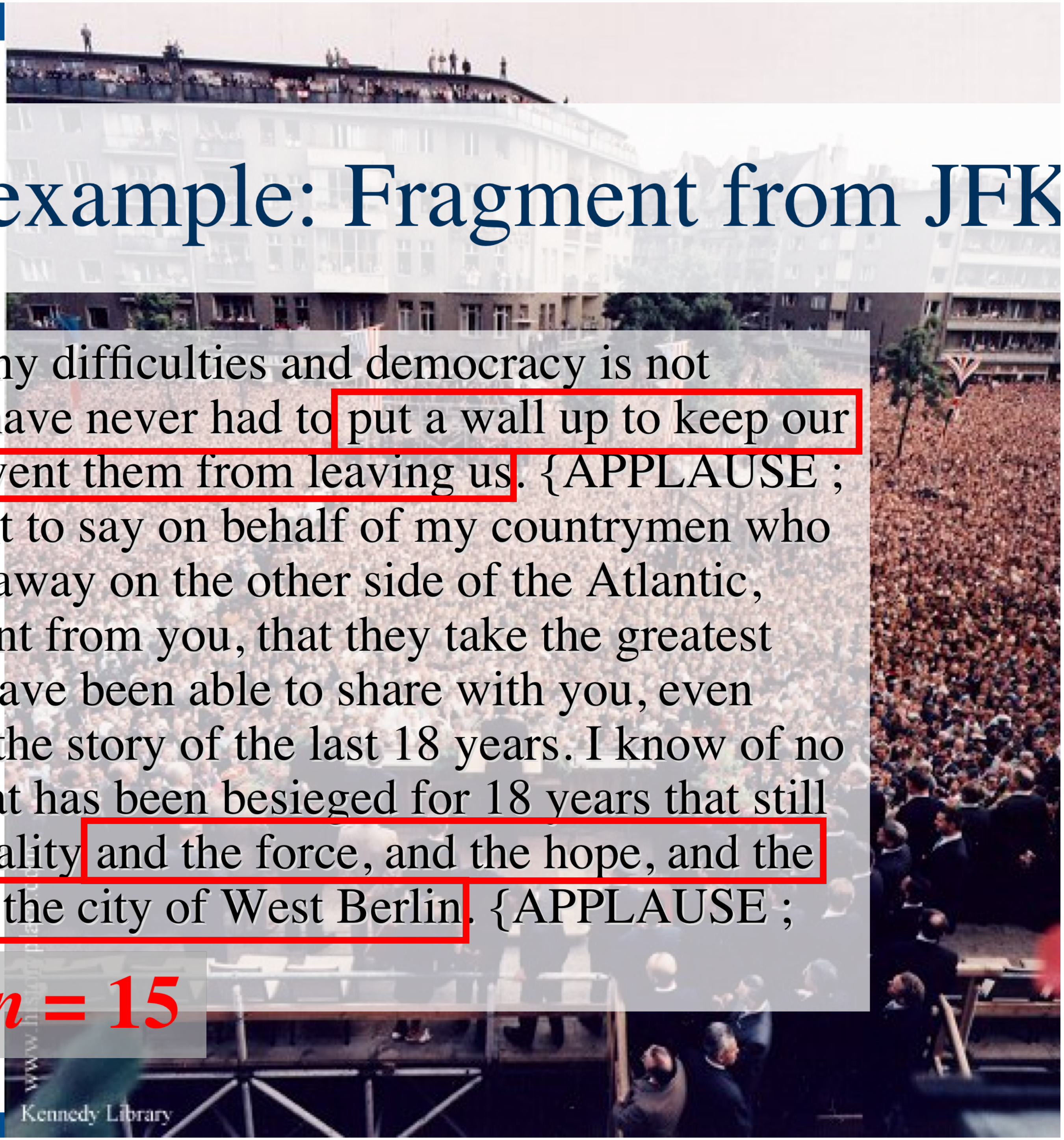

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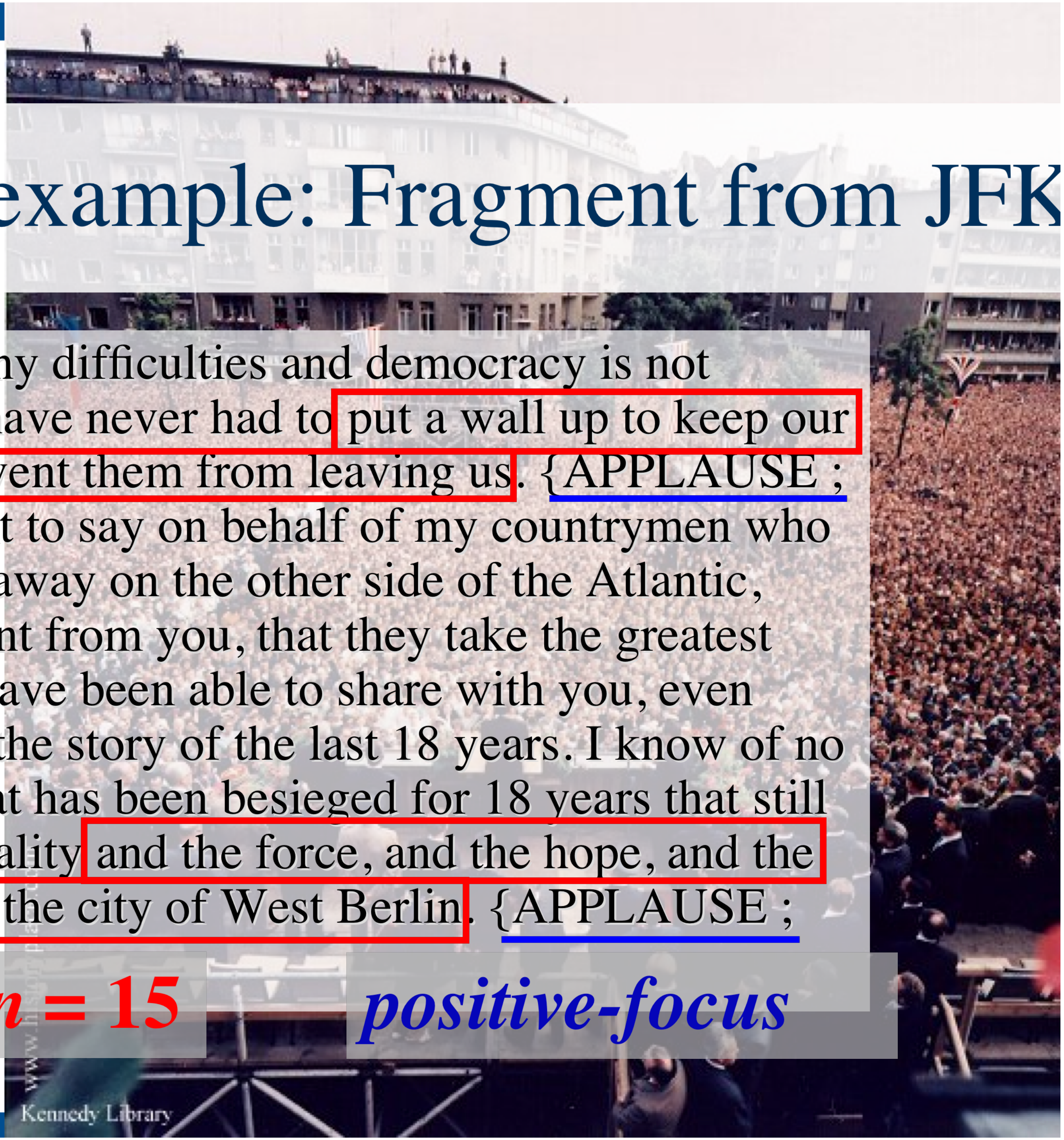
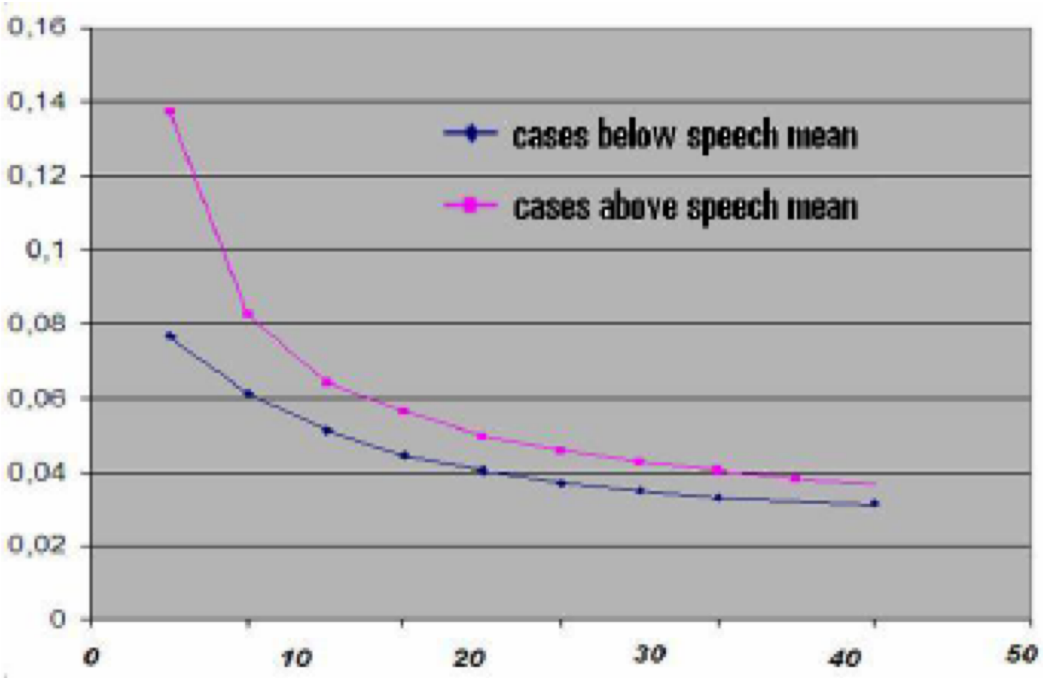
positive-focus



Valence and persuasion relation

the phase that leads to audience reaction, if it presents valence dynamics, is characterized by a valence *crescendo*

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



Words persuasive impact

- We extracted "persuasive words" by using a coefficient of **persuasive impact** (*pi*) based on a weighted tf-idf (*pi* = *tf* × *idf*).

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

Topmost 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

Advantages

- For persuasive political communication the approach using the *persuasive impact* *(pi)* of words is much more effective than simple word count.

Examples of Use (1)

- *What can be said of the lexical choices of a specific speaker that obtains a certain characteristic pattern of public reaction*? Many qualitative researches on Ronald Reagan's (aka "the great communicator") rhetorics, e.g. conversational style, use of irony.

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  - **Use of irony**: Density of ironical tags in Reagan's speeches almost double as compared to the whole corpus (t-test; $\alpha < 0.001$). In Reagan's speeches the *mean ironical-tags ratio* (*mtri*) is about 7.5 times greater than the *mtri* of the whole corpus (t-test; $\alpha < 0.001$).

Examples of Use (1)

- Mean ironical-tags ratio *mtr* - the mean of the ratio of ironical tags to positive-focus and negative-focus tags per speech.

$$mtr_i = \sum \frac{|ironical\text{-}tags|}{|positive\text{-}focus| + |negative\text{-}focus|}$$

- In Reagan's speeches the *mtr* is about 7.5 times greater than the *mtr* of the whole corpus
- That is to say, while normally there is one tags of LAUGHTER every two other tags such as APPLAUSE, in Reagan's speeches there is one tag such as APPLAUSE out of three, four tags of LAUGHTER.

Examples of Use (2)

- *How do political speeches change after key historical events*?
  Bush's speeches before and after 9/11 (70 + 70 speeches)
  - while the positive valence mean remains totally unvaried, the negative increases by 15% (t-test; $\alpha < 0.001$).
  - Words counts only partially reflects word impact…

Examples of Use (2) – Cont'd

Lemma	***pi* before**	***pi* after**	**Occur before**	**Occur after**
win#v	112	7	27	52
justice#n	x	9	15	111
military#n	**197**	**36**	**23**	**29**
defeat#v	x	16	1	44
right#r	**x**	**25**	**94**	**55**
victory#n	826	65	9	26
evil#a	-	129	0	44
death#n	4	450	65	32
war#n	**36**	**x**	**80**	**258**
soldier#n	70	296	20	47
tax#n	**x**	**93**	**702**	**81**
drug-free#a	87	x	9	3
leadership#n	81	261	40	75
future#n	**83**	**394**	**54**	**51**
dream#n	99	321	77	30

Examples of Use (3)

- *Persuasive lexical choice NLG microplanning*:
  given a synset and an affective/persuasive goal use the lists of words to choose the lemma that maximizes the impact of the msg.

- The candidate with highest ranking (*pi*) selected.
  – "elephantine#a#1 gargantuan#a#1 giant#a#1 jumbo#a#1" → "giant"

- Approach Implemented in *Valentino* (VALENced Text INOculator)

For more details see:
Guerini, Strapparava, Stock
"CORPS: A corpus of tagged political speeches for persuasive communication processing".
Journal of Information Technology & Politics.

Predicting Audience Reaction

- Using machine learning for predicting the persuasive impact of novel discourse
  - Predicting the passages that trigger a positive audience reaction
  - Distinguishing Democrats from Republicans
  - Cross classification (training made on adverse party speeches, and test on the others)

Machine Learning Setting

- For all experiment we used Support Vector machine framework (SVM-light)
- Preprocessing:
  - all corpus pos-tagged
  - we considered lemmata in the form *lemma#POS*
  - all the tokens - no frequency cut-off

Democrats vs. Republicans

- Considering the corpus as 4-sentences chunks
- About 38,000 chunks, random splitting 80%/20% training and test
- Baseline 50% for all the experiments

	Precision	*Recall*	*F1*
Democrats	0.842	0.756	0.797
Republicans	0.773	0.854	0.811
micro	0.804	0.804	0.804

Positive vs. Neutral

- Positive-Ironical chunks vs. Neutral chunks
- Neutral: no audience reaction labels
- Positive-Ironical: all positive audience reaction tags
- Baseline 0.50

	Precision	*Recall*	*F1*
Positive-Ironical	0.646	0.683	0.664
Neutral	0.676	0.641	0.658
Micro average	0.660	0.660	0.660

Cross-Classification

- Training on Democrats, Test on Republicans

	Precision	*Recall*	*F1*
Positive-Ironical	0.642	0.632	0.637
Neutral	0.579	0.599	0.589
Micro average	0.612	0.612	0.612

- Training on Republicans, Test on Democrats

	Precision	*Recall*	*F1*
Positive-Ironical	0.625	0.660	0.642
Neutral	0.658	0.626	0.641
Micro average	0.641	0.641	0.641

Further Testing

- Testing on typical non-persuasive texts
- ~ 8000 four-sentences chunks from BNC (form A00 to A0H texts)
- Supposing that all chunks are neutral
- F1 measure: 0.891

Obama vs. McCaine

- Speeches from the last presidential campaign
- ~ 2400 four-sentences chunks
- Who was more persuasive (according to the classifier) ?

	Obama	*McCain*
Positive-Ironical	2372	2360
Neutral	68	80
Total chunks	2440	2440

Conclusions

- We have presented a resource and some approaches for persuasive NLP:
  - a Corpus of tagged Political Speeches (CORPS) and a method for extracting persuasive words.
  - a measure of persuasive impacts of words

  ⇨ Experiments about prediction of audience reaction
- Future work: consider also persuasive rhetorical pattern extraction from CORPS.