Outline

1. Witty language
   - Humor generation
   - Humor recognition
2. Affective Text
   - Lexical resources
   - Annotation of emotions in text
   - Colors of emotions in texts
   - Dancing with words
3. Persuasive NLP
   - Analyzing political speeches along with audience reactions (e.g. applauses)
   - How to evaluate persuasive language ?
4. Deceptive Language recognition
   - Is it possible to recognize when people are lying, just using the produced text ?

Emotion and texts: motivation

- Future of HCI is in themes such as entertainment, emotions, aesthetic pleasure, motivation, attention, engagement, etc.
- Automatically produce what human graphic designers sometime manually do for TV/Web presentations (e.g. advertisements, news titles, …)
- Studying the relation between natural language and affective information and dealing with its computational treatment is becoming crucial.

Affective lexical resources

- What an emotion is ?
  - ⇨ Notoriously it is a difficult problem.
    Many approaches: facial expressions (Ekman), action tendencies (Frijda), physiological activity (Ax), …
- Emotions, of course, are not linguistic things
- However the most convenient access we have to them is *through the language*
- *Ortony et al. (1987)* introduced the problem
  => an analysis of 500 words taken form literature on emotions. The words are then organized in a taxonomy.

Some affective lexical resources

- General Inquirer (Stone et al.)
- SentiWordNet (Esuli and Sebastiani)
- Affective Norms for English Words (ANEW) (Bradley and Lang)
- WordNet Affect (Strapparava and Valitutti)

Affective semantic similarity

- All words can potentially convey affective meaning
- Even those not directly related to emotions can evoke pleasant or painful experiences
- Some of them are related to the individual story
- But for many others the affective power is part of the collective imagination (e.g. **`mum`**, **`ghost`**, **`war`**, …)
- cfr. Ortony & Clore

⇨ C. Strapparava and A. Valitutti and O. Stock *"The Affective Weight of Lexicon"* Proceedings of LREC 2006

Affective words

- *Direct affective words* that refer directly to emotional states (e.g. **`fear`**, **`love`**, …)
- *Indirect affective words* that have an indirect reference (e.g. **`monster`**, **`cry`**, …)
- Many words can potentially convey affective meaning
- For the second group of words the affective power can be induced automatically form large corpora of texts (e.g. British National Corpus, ~ 100 millions of words)

WordNet Affect

- We built an affective lexical resource, essential for affective computing, computational humor, text analysis, etc.
- It is a lexical repository of the *direct affective words*
- The resource, named WordNet-Affect, started from WordNet, through selection and labeling of synsets representing affective concepts.

Analogy with WordNet domains

- In WordNet Domains each synset has been annotated with a *domain label* (e.g. **`Sport`**, **`Medicine`**, **`Politics`**) selected form a set of 200 labels hierarchically organized
- In WordNet-Affect we have an additional hierarchy of *affective domain labels* (independent from the domain labels) with which the synsets representing affective concepts are annotated

A-Labels and some examples

A-Label	*Examples of Synsets*
EMOTION	noun "anger#1", verb "fear#1"
MOOD	noun "animosity#1", adjective "amiable#1"
TRAIT	noun "aggressiveness#1", adjective "competitive#1"
COGNITIVE STATE	noun "confusion#2", adjective "dazed#2"
PHYSICAL STATE	noun "illness#1", adjective "all_in#1"
HEDONIC SIGNAL	noun "hurt#3", noun "suffering#4"
EMOTION-ELICITING SITUATION	noun "awkwardness#3", adjective "out_of_danger#1"
EMOTIONAL RESPONSE	noun "cold_sweat#1", verb "tremble#2"
BEHAVIOUR	noun "offense#1", adjective "inhibited#1"
ATTITUDE	noun "intolerance#1", noun "defensive#1"
SENSATION	noun "coldness#1", verb "feel#3"

Freely available (for research purposes) at
`http://wndomains.itc.it`

New extensions of WN-affect

- *Specialization of the Emotional Hierarchy*.
  For the present work we provide a specialization of the a-label **Emotion**
- *Stative/Causative tagging*.
  Concerning mainly the adjectival interpretation
- *Valence Tagging*.
  Positive/Negative dimension

Emotional hierarchy

- With respect to WN-Affect, we provided some additional a-labels, hierarchically organized starting form the a-label *Emotion*
- About 1637 words / 918 synsets

Synset	*A-Path*
joy, joyousness, joyfulness	EMOTION → POSITIVE → GENERAL-JOY → JOY
scare, panic_attack	EMOTION → NEGATIVE → NEGATIVE-FEAR → SCARE
surprise	EMOTION → AMBIGUOUS → SURPRISE
indifference	EMOTION → NEUTRAL → NEUTRAL-UNCONCERN → INDIFFERENCE

Valence tagging

- Distinguishing synsets according to emotional valence
- *Positive* emotions (**`joy#1`**, **`enthusiasm#1`**),
- *Negative* emotions (**`fear#1`**, **`horror#1`**),
- *Ambiguous*, when the valence depends on the context (**`surprise#1`**) ,
- *Neutral*, when the synset is considered affective but not characterized by valence (**`indifference#1`**)

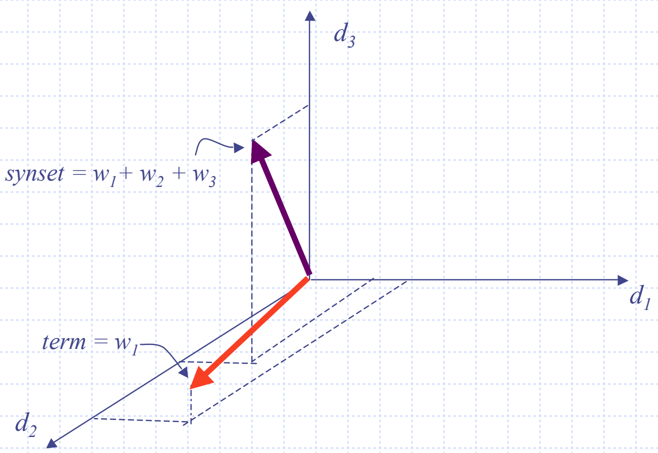
Affective semantic similarity

- We needed a technique for evaluating the affective weight of *indirect affective words*
- The mechanism is based on *similarity* between *generic terms* and *affective lexical concepts*
- We estimated term similarity from a large scale corpus (BNC ~ 100 millions of words)
- Latent Semantic Analysis => dimensionality reduction operated by Singular Value Decomposition on the term-by-documents matrix

Homogeneous representations

- In the Latent Semantic Space, we can represent in a homogeneous way
  - Words
  - Texts
  - Synsets
- Each text (and synsets) can be represented in the LSA space exploiting a variation of the *pseudo-document* methodology
  => summing up the normalized LSA vectors of all the terms contained in it

LSA space



- Similarity: *cosine* among vectors

Affective synset representation

- Thus an affective synset (and then an emotional category) can be represented in the Latent Semantic Space
- We can compute a similarity measure among terms and affective categories
- Ex. the term "*gift*" is highly related (in BNC) with the emotional categories:
  - **`Love`** (with positive valence)
  - **`Compassion`** (with negative valence)
  - **`Surprise`** (with ambiguous valence)
  - **`Indifference`** (with neutral valence)

Affective weight

- We defined the *affective weight* the similarity value between an emotional vector and an input term vector
- Given a term (i.e. university), ask for related terms that have a positive affective valence, possibly according to some emotional category
- Given two terms, check if they are semantically related, with respect to some emotional category

An example: *university*

Related emotional terms	*Positive emotional category*
university	Enthusiasm
professor	Sympathy
scholarship	Devotion
achievement	Encouragement

Related emotional terms	*Negative emotional category*
university	Downheartedness
professor	Antipathy
study	Isolation
scholarship	Melancholy

Affective synset similarity

- The adjective **terrific#a** is polisemous
  - a sense of {**fantastic**, **howling**, **marvelous**, **rattling**, **terrific**, **tremendous** **wonderful**} - *extraordinarily good*:
    - most similar to the positive emotion **Joy**
  - a sense of {**terrific**, **terrifying**} - *causing extreme terror*:
    - most similar to the negative emotion **Distress**

News titles

- E.g. the affective weight of some news titles

News titles (Google-news)	*Emotion*	*Word with highest affective weight*
Review: `King Kong' a giant pleasure	**Joy**	`pleasure#n`
Romania: helicopter crash kills four people	**Fear**	`crash#v`
Record sales suffer steep decline	**Sadness**	`suffer#v`
Dead whale in Greenpeace protest	**Anger**	`protest#v`

Possible Applications

- Computer Assisted Creativity
  - Automatic personalized advertisement, Computational Humor, persuasive communication
- Verbal Expressivity of Embodied Conversational Agents
  - Intelligent dynamic word selection for appropriate conversation
- Sentiment Analysis
  - Text categorization according to affective relevance, opinion analysis

Summing up

1. WordNet-Affect provides the representation of *direct affective terms*
2. LSA from the BNC gives a measure of the similarity between direct affective terms and generic terms

Summing up

- Some resources and functionalities for dealing with affective evaluative terms
- An affective hierarchy as an extension of WordNet-Affect lexical database, including emotion, causative/stative and valence tagging
- A semantic similarity mechanism acquired in an unsupervised way from a large corpus, providing relations among concepts and emotional categories

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Annotation of emotions in text

- Semeval 2007 task
- Emotion classification of news headlines
- Headlines typically consist of few words and often written to "provoke" emotions (e.g. to attract reader's attention)

⇨ Affective/emotional features probably present

- Suitable for use in automatic emotion recognition

C. Strapparava and R. Mihalcea.
"Learning to identify emotions in text".
In Proceedings of the 23rd Annual ACM Symposium on Applied Computing, 2008

Data and objective

- **Corpus**
  - News titles from the web sites Google News, CNN, New York Times, BBC over a period of time of 3 months
  - Development set of 250 headlines
  - Test set of 1,000 annotated headlines

Thailand attacks kill three, injure 70

Women face greatest threat of violence at home, study finds

Prehistoric lovers found locked in eternal embrace

Male sweat boosts women's hormone levels

Data and objective

- **Objective**
  - Provided a set of predefined six emotion labels (*Anger*, *Disgust*, *Fear*, *Joy*, *Sadness*, *Surprise*) classify the titles with
    - the appropriate emotion label and/or
    - a positive/negative valence indication
  - Emotion labeling and valence classification are seen as independent tasks
  - The task was carried out in an unsupervised setting
  - We want to emphasize emotion lexical semantics, avoid biasing towards simple text categorization

Data and objective

- **Other Data**
  - Participants were free to use any resources they want
  - We provide a set of words extracted from WordNet-Affect (Strapparava and Valitutti, 2004), relevant to the six emotions of interest
  - Links to other possibly useful resources on the Web - e.g. SentiWordNet (Esuli and Sebastiani, 2006)

Data annotation

- We developed a web-based annotation interface:
  - One headline at time, six slide bars for emotions and one slide bar for valence
  - Interval for emotion annotations [0,100], while [-100, 100] for valence annotations (0 means neutral)

  ⇨ Finer-grained scale than typical 0/1 annotations

Data annotation

- Six annotators
- Presence of words or phrases with emotional content, as well the overall feeling invoke by the headline
- Inter-annotator agreement: Pearson correlation measure

Emotions	
Anger	49.55
Disgust	44.51
Fear	63.81
Joy	59.91
Sadness	68.19
Surprise	36.07
Valence	
Valence	78.01

Evaluations

- Fine-grained evaluation
  - Pearson between system scores and gold standard, averaged over all the headlines in the data set
- Coarse-grained evaluation
  - Each emotion annotation was mapped in a 0/1 classification 0= [0,50) and 1=[50,100], and valence annotation into -1/0/1 -1=[-100,-50] 0=(-50,50) 1=[50,100]
  - Then accuracy, precision and recall wrt the possible classes

Participating systems

- Five teams with
  - Five systems for valence classification
  - Three systems for emotion labeling

Teams/Contact	Emotion Labeling	Valence Classification
Concordia University - Alina Andreevskaia		- CLaC - CLaC-NaïveBayes
Swedish Institute of Computer Science - Magnus Sahlgren		- SICS
Swarthmore College - Phil Katz	- SWAT	- SWAT
University Paris 7 - Francois-Regis Chaumartin	- UPAR7	- UPAR7
University of Alicante - Zornitsa Kozareva	- UA	

Participant Systems

System	Approach	Main Resources
- CLaC	Unsupervised knowledge-based system	- Sentiment words - Valence shifters - set of rules
- CLaC-NaïveBayes	Supervised corpus-based	- additional corpus manually annotated
- SICS	Word space model + seed words	- LA times corpus
- SWAT	Supervised	- Roget Thesaurus - additional 1000 headlines manually annotated
- UPAR7	Rule-based system with linguistic approach	- Stanford parser - SentiWordNet - WordNet-Affect
- UA	Point-wise Mutual Information	- search engines

Results

	Fine	Coarse			
	r	Acc.	Prec.	Rec.	F1
CLaC	**47.70**	**55.10**	**61.42**	9.20	16.00
UPAR7	36.96	55.00	57.54	8.78	15.24
SWAT	35.25	53.20	45.71	3.42	6.36
CLaC-NB	25.41	31.20	31.18	**66.38**	**42.43**
SICS	20.68	29.00	28.41	60.17	38.60

System results for valence annotations

	Fine	Coarse			
	r	Acc.	Prec.	Rec.	F1
Anger					
SWAT	24.51	92.10	12.00	5.00	7.06
UA	23.20	86.40	12.74	**21.6**	**16.03**
UPAR7	**32.33**	**93.60**	**16.67**	1.66	3.02
Disgust					
SWAT	**18.55**	97.20	0.00	0.00	-
UA	16.21	**97.30**	0.00	0.00	-
UPAR7	12.85	95.30	0.00	0.00	-
Fear					
SWAT	32.52	84.80	25.00	14.40	18.27
UA	23.15	75.30	16.23	**26.27**	**20.06**
UPAR7	**44.92**	**87.90**	**33.33**	2.54	4.72
Joy					
SWAT	**26.11**	80.60	35.41	**9.44**	**14.91**
UA	2.35	81.80	40.00	2.22	4.21
UPAR7	22.49	**82.20**	**54.54**	6.66	11.87
Sadness					
SWAT	38.98	87.70	32.50	11.92	17.44
UA	12.28	88.90	25.00	0.91	1.76
UPAR7	**40.98**	**89.00**	**48.97**	**22.02**	**30.38**
Surprise					
SWAT	11.82	**89.10**	11.86	10.93	11.78
UA	7.75	84.60	**13.70**	**16.56**	**15.00**
UPAR7	**16.71**	88.60	12.12	1.25	2.27

System results for emotion labeling

Affective Texts

- The task reveals itself as difficult but interesting !
- The gap between annotator agreement and system results suggest there are room for future improvements

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The Color of Emotions in Texts

- Similarity between Colors and Emotions in texts
- Emotions: Affective analysis of text is a relatively new area of research
  - Important for many NLP applications
    - Opinion mining
    - Market analysis
    - Affective user interfaces
    - E-learning environments
- Colors: in everyday speeches using colors for increasing expressiveness by invoking different emotions

C. Strapparava & G. Ozbal
"The Color of emotions in Texts".
COLING Workshop on Cognitive Aspects of the Lexicon - 2010

Colors and Emotions

- Technique for measuring affective semantic similarity
  - Representing *emotions* from large text corpora

- Color emotion in psychology: emotions arousing in people when they percept a color

⇨ Correlation between results from psychological and NLP affective similarity experiments

Color and emotion

- "Colour can have a profound effect on an individual's moods and feelings, and designers exploit these to provide acceptable spaces in which we can live with minimal visual stress and optimal visual comfort," (Hutchings, 2006, p. 87)

Color Emotion in psychology

- Considerable interest on impact of colors on emotions
  - Children vs. adults color preferences (Zentner, 2001)
  - Color as feedback on emotion expression in music (Bresin, 2005)
  - Color/emotion associations (Gao et al. 2007) - also cross-language (Adams and Osgood, 1973)
  - Color emotional response in the field of marketing and advertisement (Madden et al. 2000, Alt 2008)

Psychological reference

- M. Alt "*Emotional response to color associated with an advertisement*" (2008)
- Focus on advertisement
- Subjects were required to view an advertisement with dominant color, and then to select a specific emotional response
- More than 150 subjects, equally partitioned by gender
- Colors:
  - Blue, Red, Green, Orange, Purple, Yellow
- Emotions:
  - Anger, Aversion/disgust, Fear, Joy, Sadness

Psychological reference

- Emotions ranked by colors from psycholinguistic experiments

Color	*Ranking of Emotions*				
	Anger	Aversion/ Disgust	Fear	Joy	Sadness
Blue	5	2	4	1	3
Red	1	4	2	3	5
Green	5	2	3	1	4
Orange	4	2	3	1	5
Purple	5	2	4	1	3
Yellow	5	2	4	1	3

Experiments

- For emotion representation we followed (Strapparava and Mihalcea, 2008)
- LSA space acquired from British National Corpus
- To represent emotional categories, we use the setting `Emotion synset' that proved to give the best results in term of fine-grained emotion sensing (dataset Semeval-2007 - affective text)
- The synsets of direct emotion words (taken from WordNet Affect), are considered

⇨ We compare the similarities among the representation of *colors* and *emotions* in the latent semantic space

Results

- Emotion ranked by similarity with colors

Color	*Ranking Emotions using Similarity with Colors*				
	Anger	Aversion/ Disgust	Fear	Joy	Sadness
Blue	4	2	3	1	5
Red	4	3	2	1	5
Green	4	2	3	1	5
Orange	4	2	3	1	5
Purple	5	2	3	1	4
Yellow	4	2	3	1	5

Correlation

Color	*Correlation*
Blue	0.7
Red	0.3
Green	0.9
Orange	1.0
Purple	0.9
Yellow	0.7
Total	0.75

- We use Spearman correlation coefficient
- The global correlation is good (0.75)
- In particular it is
  - very high for Orange, Green and Purple (≥ 0.9)
  - good for Blue and Yellow (≥ 0.7)
  - not so high for Red (maybe Red is quite ambiguous with respect to emotions)

Some considerations

- There are emotional and symbolic associations with different colors
- The goal of this study was exploring this association by employing a corpus-based approach for affective sensing
- We adopted a psycholinguistic experiments as a reference
- The results are quite correlated

Future developments

- Perception of colors in different languages and cultures, e.g.
  - In Islam, green has religious significance
  - Turquoise is the national color of Persia.
    Ancient Persians trusted it to ward off the evil eye
  - …
- Exploiting the technique in visual information about object and events
- Dynamic visualization of text (e.g. kinetic typography)
- Employing in designing applications (advertisement, marketing, e-learning environments,…)

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Dancing with Words

- Through *automatic* detection of the affective meaning of texts, it is possible to *animate* the words that compose them
- Idea: linking the automatic creation of text animation to the lexical semantic content (in particular to the affective meaning)

⇨ NLP techniques to recognize the affective content (semantic similarity mechanism)

⇨ Automatic text animation (using tools of kinetic typography)

=> C. Strapparava, A. Valitutti, O. Stock *"Dancing with Words"* Proceedings of IJCAI 2007

Emotion and texts

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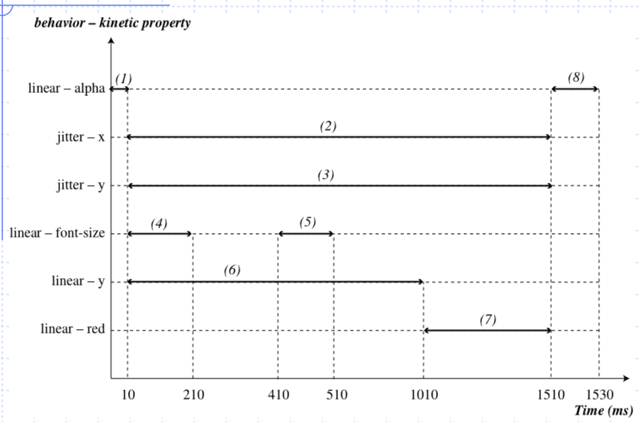
Text Animation

- *Kinetic typography*: texts that use movements or other perceptual changes over time
- It adds a further communicative dimension to simple text
- We want to exploit a link between lexical semantics of texts and some kinetic properties for animating them

Text animation

- We used as a starting point the *kinetic typography engine* [Lee et al. 2002]
- We built a development environment and a *scripting language* for dynamical creation of text animations
- Composing (e.g. joining, adding in parallel, …) elementary animations as building blocks
- Elementary animations: **`linear`**, **`oscillate`**, **`pulse`**, **`jitter`**, etc.

Kinetic behavior: e.g. "anger"



We annotated each emotion category in Wordnet-affect with an appropriate kinetic behavior

Emotional kinetic behaviors

- E.g. Imitating human responses

- Joy: a sequence of hops
- Fear: palpitations
- Anger: strong tremble and blush
- Surprise: sudden swelling of text
- Sadness: text deflation and squashing

Affective text animation

- ✓ News headlines (taken form Google-News)

- Two main steps: (i) emotion recognition and (ii) kinetic animation assembling

1. Recognize the emotional category of the headline
2. Mark the words that are closer to that emotion
3. Assign the proper affective animation to each word
4. Assemble a comprehensive animation script, and display the animated title

Examples

- Some sample text animations related to the following emotions:
  - anger
  - fear
  - joy
  - sadness
  - surprise

anger

fear

joy

sadness

surprise

Evaluation

- We conducted a preliminary evaluation:
- ten people on three dimensions: (i) pleasantness, (ii) agreement with annotation and (iii) memorization of headlines
- Pleasantness: 80% of users really liked the animated headlines
- Agreement with the automatic annotation: 72%

Evaluation (2)

- Memorization:
  - we showed to each subject five static headlines in a serial manner,
  - After some minutes we asked the subject to recognize the five headlines among a list of 50 news titles
  - we repeated this experiment with five animated headlines (of course with a different set of news titles)

  ⇒ People recognize faster animated headlines with respect to static titles (about 50% less time)

- "Inconsistent" animations: memorization performance worse than with static headlines

Summing up

- We developed a technique for giving life to texts automatically, exploiting a link between lexical semantics processing (in particular emotion recognition) and text animation
- Possible applications
  - Automatic personalized advertisements
  - Computational humor (e.g. irony)
  - Persuasive communication
  - Electronic newspapers
  - Computer assisted creativity
  - Edutainment
  - …

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