Predicting Readers' Sarcasm Understandability by Modeling Gaze Behavior

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Central Idea

- Sarcasm understanding demands carefully orchestrated sequences of complicated cognitive activities in the brain (Shamay et al., 2005).
- Understanding textual sarcasm depends on readers' language proficiency, social knowledge, mental state and attentiveness.
- Can machines predict whether a reader has understood the intended meaning of a sarcastic text? We refer to this problem as *Sarcasm Understandability Prediction*.
- *Our proposed system takes readers' eye-gaze parameters as input along with textual features to determine whether the reader has understood the underlying sarcasm or not.*

Utility Scenario

The Mountain Three Wolf Moon Short Sleeve Tee

Review: *Unfortunately I already had this exact picture tattooed on my chest, but this shirt is very useful in colder weather.*

1: Online review analysis and management.
2: Second Language learning
3: Attentiveness testing
4: Mental health monitoring

Availability of mobile eye-trackers (like Samsung, Cogisen)

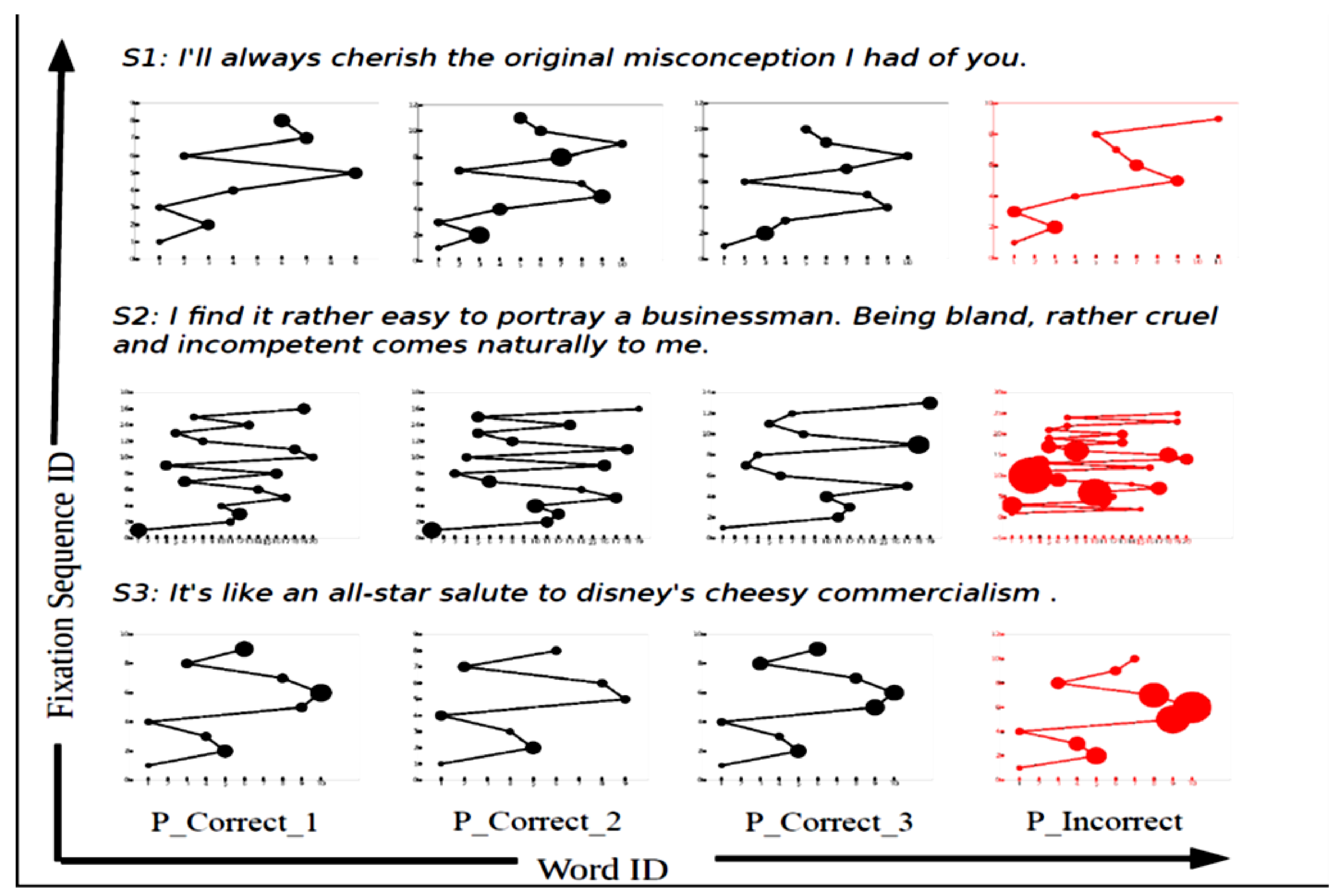
Creation of Eye-movement Database

- **Document Description:** 1000 short texts – Movie reviews, tweets and quotes , 350 sarcastic 650 non-sarcastic
- Ground truth verified by linguists. Grammatical mistakes corrected to avoid reading difficulties.
- **Participant Description:** 7 graduates from Engineering and Science background.
- **Task Description:** Texts annotated with sentiment polarity labels. Gaze data collected using *Eye-link 1000 plus* tracker following standard norms (Holmqvist et al. 2011)
- **Annotation Accuracy:** Highest- **90.29%**, Lowest- **72.57%**, Average- **84.64**% (Domain wise: Movie: **83.27%**, Quote: **83.6%**, Twitter: **84.88%)**

Sarcasm, Cognition and Eye-movement

- Sarcasm often emanates from **context incongruity** (Campbell and Katz 2012), which, possibly, surprises the reader and enforces a re-analysis of the text.
- In the absence of any information, human brain would start processing the text in a sequential manner, with the aim of comprehending the literal meaning.
- When incongruity is perceived, the brain initiates a re-analysis to reason out such disparity (Kutas et al.,1980).

Hypothesis: Incongruity may affect the way eye-gaze moves through the text. Hence, distinctive eye-movement patterns may be observed when sarcasm is understood in contrast to an unsuccessful attempt.



Circles: Fixations. Radii of Circles: Fixation Duration, X:Word Position Y: Temporal Fixation Sequence

Analysis of Eye-movement Data

- **Variation in Basic Gaze attributes:** Average Fixation Duration and Number of Regressive Saccades significantly higher ($p<0.0001$ and $p<0.01$) when sarcasm is not understood than when it is.
- **Variation in Scanpaths:** For two incongruous phrases *A* and *B,* Regressive Saccades often seen from *B to A* when sarcasm is successfully realized. Moreover, Fixation duration is more on *B* than *A*.
- **Qualitative observations from Scanpaths:** Sarcasm not understood due to: (i) Lack of attention (ii) Lack of realization of context incongruity

Correct labeling of polarity -> Sarcasm Understood

Predictive Features

Textual Features

(1) # of interjections
(2) # of punctuations
(3) # of discourse connectors
(4) # of flips in word polarity
(5) Length of the Largest Pos/Neg Subsequence
(6) # of Positive words
(7) # of Negative words
(8) Flecsh's reading ease score
(9) Number of Words

Gaze Features

(1) Avg. Fixation Duration (AFD)
(2) Avg. Fixation Count
(3) Avg. Saccade Length
(4) # of Regressions
(5) # of words skipped
(6) AFD on the 1st half of the text
(7) AFD on the 2nd half of the text
(8) # of regressions from the 2nd half to the 1st half
(9) Position of the word from which the longest regression happens.
(10) Scanpath Complexity

Experiment and Results

- **Classifier:** Multi-instance Logistic Regression (Xu and Frank 2004). Each training example corresponds to one sentence. Each example "bags" a maximum of 7 instances, one for each participant. Each instance is a combination of Gaze and Textual Features.

Class	sarcasm_miss			sarcasm_hit			Weighted Avg.			Kappa
	P	R	F	P	R	F	P	R	F	Avg.
	Baseline1: Classification based on class frequency									
All	16.1	15.5	15.7	86.5	87	86.7	85.9	86.71	86.3	0.014
	Baseline2: MILR Classifier considering time taken to read + textual features									
All	23.6	86.9	78.2	11.5	94.1	82.7	15.4	90.4	80	0.0707
	Our approach: MILR Classifier considering only gaze features									
All	82.6	36	50	89.9	98.7	94.1	88.8	89.4	87.5	0.4517
	Our approach: MILR Classifier considering gaze + textual features									
Quote	68.1	47.5	56.0	91.8	96.3	94.0	88.4	89.4	88.6	0.5016
Movie	42.9	36.6	39.5	88.6	91.0	89.8	81.4	82.5	81.9	0.293
Twitter	63.0	61.7	62.4	94.4	94.7	94.6	90.4	90.5	90.5	0.5695
All	**87.8**	**61**	**72**	**94.1**	**98.6**	**96.3**	**93.2**	**93.5**	**93**	**0.6845**

Future work

- Output real valued scores instead of binary classes.
- Propose similar methods for general text-understandability.
- Test the current and future systems on mobile eye-trackers.

References:

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URL: http://www.cfilt.iitb.ac.in/cognitive-nlp