A Survey on Using Gaze Behaviour for Natural Language Processing

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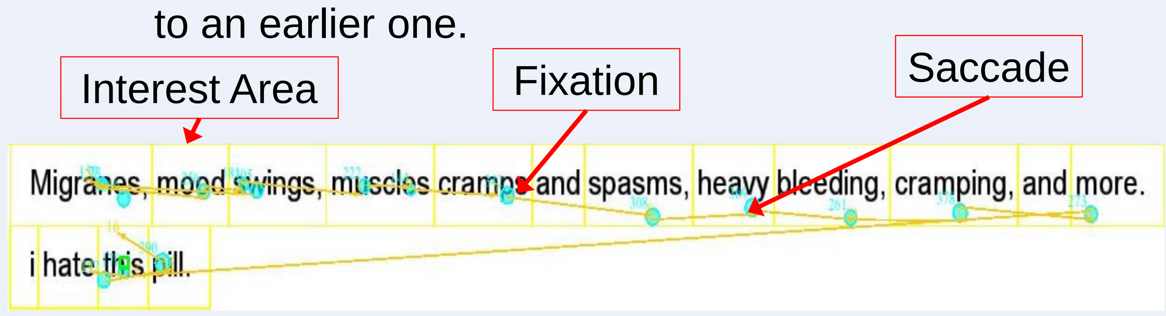
Eye-Tracking Motivation

- Eye-tracking is a means of using cognitive information for solving different language processing and understanding tasks that sometimes require interpretation of semantic and pragmatic aspects of language processing.
- Eye-tracking research is based on the Eye-Mind hypothesis :
  - "There is no appreciable lag between what is fixated and what is processed."
    - Just and Carpenter (1980)
- Example: Sarcasm Understandability (Mishra et al. (2017)

Eye-Tracking Terms

1. **Interest Area:** An interest area is the area of the screen which is of interest.
2. **Fixation:** An event where the eye focuses on a part of the screen.
3. **Saccade:** The movement of the eye from one fixation point to the next.
   – **Progression:** Saccade from the current interest area to a later one.
   – **Regression:** Saccade from the current interest area to an earlier one.



Eye-Tracking Corpora

Gaze behaviour corpora is available in multiple languages:

Dataset	Language	Stimulus	Subjects
Zang et al. (2018)	Chinese	90 sentences	35
Li et al. (2018)		15 documents	29
Cop et al. (2017)	Dutch	1 novel	33
Mak & Willems (2019)		3 stories	102
Kennedy et al. (2003)	French	20 documents	10
Nicenboim et al. (2016)	German	176 sentences	72
Kleigl et al. (2004)		144 sentences	55
Safavi et al. (2016)	Persian	136 sentences	40
Laurinavichuyte et al. (2017)	Russian	144 sentences	96
Nicenboim et al. (2017)	Spanish	212 sentences	79

And for solving multiple tasks (examples shown are in English):

Dataset	Task	Stimulus	Subj.
Joshi et al. (2014)	Sentiment Analysis	1059 sentences	5
Mishra et al. (2016)	Sarcasm Understanding	1000 Tweets	7
Cheri et al. (2016)	Coreference Resolution	22 documents	14
Mishra et al. (2017)	Reading Complexity	32 documents	16
Mathias et al. (2018)	Text Quality Prediction	30 documents	20

Collecting gaze behaviour data is expensive in terms of time and money. A solution is to **learn** gaze behaviour from existing corpora.

Learning Gaze Behaviour

- 2 learning approaches:
  - **Type aggregation** – For a given token (T), the value of the corresponding gaze behaviour feature's value (F) is the mean value of that feature for the token, across the corpus.
  - **Multi-Task Learning (MTL)** – Learning gaze behaviour features are auxiliary tasks while solving the NLP problem is the primary task.

Normalizing Gaze Behaviour

- Readers read at different speeds. So data must be normalized.
  - **Min-Max Normalization** – For a ***given reader***, normalize the feature values of each feature to the range of [0,1].
  - **Binning** – For a ***given reader***, assign the feature value to a given bin for each gaze behaviour feature.

Learning Gaze Behaviour for NLP Tasks

1. **Predicting Fixations While Reading**
   – Nilsson and Nivre (2009) detect fixated tokens using a transition-based approach.
   – Matthies and Sogaard (2013) use linear CRF model
2. **Predicting Grammatical Functions**
   – Barrett and Sogaard (2015) use logistic regression to learn gaze data to predict the grammatical functions of tokens in a sentence.
3. **Text Simplification**
   – Klerke et al. (2016) use a MTL approach to learn gaze behaviour and compress sentences.
4. **Part-of-Speech Tagging**
   – Barrett et al. (2016a) use type aggregation to learn gaze behaviour for PoS tagging.
   – Barrett et al. (2016b) do the same as Barrett et al. (2016a) but in a ***cross-lingual*** setup.
5. **Readability**
   – Gonzalez-Garduno and Sogaard (2018) predict readability using MTL, learning gaze behaviour from the Dundee Corpus (Kennedy et al. (2003).
6. **Sentiment Analysis**
   – Mishra et al. (2018) use MTL to learn gaze behaviour and PoS tagging as auxiliary tasks to aid in sentiment analysis.
7. **Sequence Classification**
   – Barrett et al. (2018) use MTL to learn gaze behaviour while solving sentiment analysis, grammar error detection, and hate speech detection.
8. **Named Entity Recognition**
   – Hollenstein and Zhang (2019) use type aggregation of gaze features from the Dundee Corpus to aid in named entity recognition.

Further Proposed Applications

1. **Complex Word Identification (CWI)**
   – Complex word identification is deciding whether a word / phrase is complex or not in the given context.
   – Fixation lengths will be longer for complex words, as compared to simple words.
   – Predicting the dwell time / fixation durations can help in identifying complex words.
2. **Automatic Essay Grading (AEG)**
   – Automatic essay grading is using a machine to assign a score to an essay written by a human.
   – Mathias et al. (2018) showed that using gaze data helps a lot for predicting the text quality rating given by a reader to the text.
   – Gaze behaviour can be learnt, using either type aggregation of multi-task learning, as an auxiliary task, and the learnt gaze behaviour would then be used to aid in automatically scoring the essay.

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