User-Oriented Document Summarization through Vision-Based Eye-Tracking

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Motivation I

So many articles, so long an article, so little time!

Summarization

There's no argument.

Motivation II

Personalized Summarization

- I just need what I am interested

- Attention time (AT) reflects the user interest
  - AT = attention time spent by a user on a certain word of the article (browsing, reading, …)

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System Overview

- Acquiring the user AT through an eye-tracking interface on each word and sentence while reading an article.

- Analyzing the user's interest on each part of the article implicitly reflected by the attention time.

- Re-rank all the sentences in the article according to the predicted user's AT on them.

- Pick up sentences with top AT as the summary.

- Assumption: a user shall have more or less the same amount of interest towards similar text.

Organization of the Talk

- Related work
- Acquisition of eye-tracking samples
- Prediction of user's interest on sentences
- User-oriented text summarization
- Experiment results
- Future work

Related Work

- Text Summarization
  - A comprehensive list of published research papers and tools on the web page http://www.summarization.com/

  - Popular tools:
    - "AutoSummarize" functionality in Microsoft Word
    - MEAD - *A platform for multidocument multilingual text summarization*
    - LexRank: *Graph-based lexical centrality as salience in text summarization*

Related Work II

- Eye-tracking Strategy
  - E. H. Chi, M. Gumbrecht, and L. Hong. Visual foraging of highlighted text: An eye-tracking study. In HCII '07: Proceedings of HCI International Conference, pages 589–598, 2007.

  - A. Bulling, D. Roggen, and G. Troster. It's in your eyes: towards context-awareness and mobile HCI using wearable EOG Goggles. In UbiComp '08: Proceedings of the 10th International Conference on Ubiquitous Computing, pages 84–93, New York, NY, USA, 2008. ACM.

  - *R. W. Reeder, P. Pirolli, and S. K. Card. Webeyemapper and weblogger: tools for analyzing eye tracking data collected in web-use studies. In* CHI '01: CHI '01 Extended Abstracts on Human Factors in Computing Systems*, pages 19–20, New York, NY, USA, 2001. ACM.*

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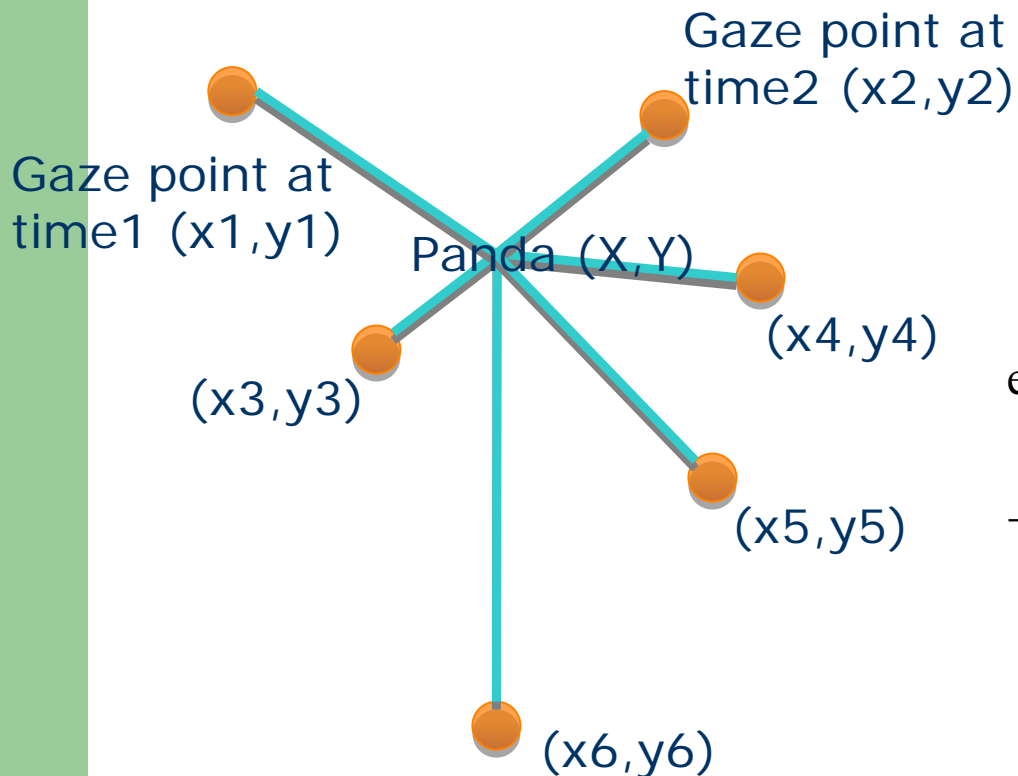
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Web Camera

- Eye-tracking with web camera
  - *P. Zielinski. Opengazer: open-source gaze tracker for ordinary webcams (software), Samsung and The Gatsby Charitable Foundation. http://www.inference.phy.cam.ac.uk/opengazer/, last visited on December 11 2008.*

Gathering AT for Each Word

Gaze point at time2 (x2,y2)

Gaze point at time1 (x1,y1)

Panda (X,Y)

(x4,y4)

(x3,y3)

(x5,y5)

(x6,y6)
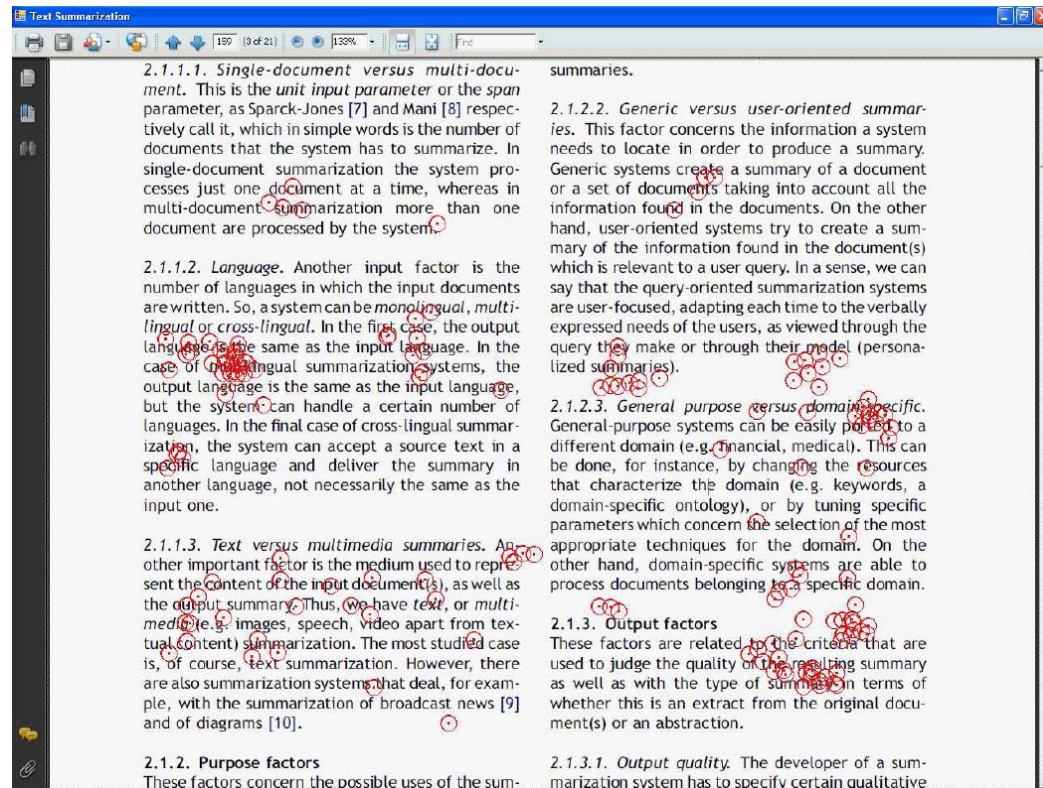
In this example, gaze points has been next to the word "Panda" for 6 times.

$$AT(\text{"Panda"}) =$$

$$\exp\left(-\frac{(x1-X)^2}{2a^2} - \frac{(y1-Y)^2}{2b^2}\right) + \ldots$$

$$+ \exp\left(-\frac{(x6-X)^2}{2a^2} - \frac{(y6-Y)^2}{2b^2}\right)$$

NOTE: AT(w) - user attention time on the word w

A Snapshot of the Eye-tracking User Interface

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Essential Concept

- Prediction based on the content similarity of text.

- We assume if two words are sufficiently similar, then a user shall have more or less the same amount of interest towards either of them.

Estimating Word Similarities

- A good estimation of text similarity plays a critical role in user's interest prediction.

- We utilize the method in the paper
  - *Y. Li, Z. A. Bandar, and D. Mclean. An approach for measuring semantic similarity between words using multiple information sources.* IEEE Transactions on Knowledge and Data Engineering, *15(4):871–882, 2003.*

Predict AT on Words

$$AT(w, U_j) = \frac{\sum_{i=1}^{k} \left(AT(w_i, U_j) Sim(w_i, w) \rho(w_i, w) \right)}{\sum_{i=1}^{k} \left(Sim(w_i, w) \rho(w_i, w) \right) + \epsilon}$$

$$\rho(w_i, w) = \begin{cases} 1 & \text{If } Sim(w_i, w) > 0.1 \\ 0 & \text{Otherwise.} \end{cases}$$

The AT on every word in the article is determined by all the words that have sampled AT and the semantic similarities between these words.

Predict AT on Sentences

$$AT(s, U_j) = \sum_{w_i \in s} AT(w_i, U_j)\delta(w_i, U_j)$$

The AT on every sentence in the article is the sum of AT on all the distinct words in that sentence.

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User-oriented Summarization (I)

- For an article, *c%* sentences are reserved as its summarization result.

- At first, get the summary generated by a traditional semantic text summarization algorithm with a compression rate of c%.
  - MEAD
  - Microsoft Word "AutoSummarize"

User-oriented Summarization (II)

- Increase the predicted AT of a sentence if it appears in the summary generated by MEAD.

  - AT on a sentence is adjusted as,

$$AT_{offset}(s_i, U_j) \triangleq (1 - \kappa) \max_{k=1}^{n} \{AT(s_k, U_j)\} \widehat{\delta}(s_i, U_j)$$

- Offset is 0 if the sentence is not in the summary by MEAD; otherwise, offset is set as the maximum AT over all the sentences.

- k is a user-tunable parameter. When k = 0, it performs completely the same as MEAD. When k = 1, the summary is fully determined by user AT.

User-oriented Summarization (III)

$$AT_{cal}(s_i, U_j) \triangleq AT(s_i, U_j) + AT_{offset}(s_i, U_j)$$

- The top c% sentences according the adjusted AT are extracted as the summary of the article.

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Evaluating the Summarization Result

- Two dataset of articles for experiments, each of which has 60 randomly selected articles
  - Data set 1: articles from the journal "Science"
  - Data set 2: articles about leisure things on New York Times

Article set	I	II	I + II
Articles in the set	60	60	120
Words per article	979.0	942.3	960.7
Sentences per article	37.6	53.2	45.4
Paragraphs per article	9.1	11.3	10.2
Sentences per manual summary	12.4	14.7	13.6
Manual compression rate	33.0%	27.6%	29.8%

Measurements

- Three measurements — Recall (R), Precision (P) and F-rate (F)—are introduced to evaluate the machine summarization quality against the human expected summary result.

$$P \triangleq \frac{\text{Number of common sentences in } SU_e \text{ and } SU}{\text{Number of sentences in } SU}$$

$$R \triangleq \frac{\text{Number of common sentences in } SU_e \text{ and } SU}{\text{Number of sentences in } SU_e}$$

$$F \triangleq \frac{2PR}{P+R}.$$

Comparison with Popular Summarization Tools

Summarization Algorithm	Compression Rate								
	10%			20%			30%		
	Recall	Precision	F-rate	Recall	Precision	F-rate	Recall	Precision	F-rate
MS Word AutoSummarize	0.13	0.25	0.17	0.20	0.27	0.23	0.23	0.27	0.25
MEAD	0.18	0.47	0.26	0.25	0.44	0.32	0.30	0.42	0.35
Our Algorithm	0.28	0.64	0.39	0.42	0.60	0.49	0.53	0.58	0.55

(a) Algorithm performance statistics for article set I

Summarization Algorithm	Compression Rate								
	10%			20%			30%		
	Recall	Precision	F-rate	Recall	Precision	F-rate	Recall	Precision	F-rate
MS Word AutoSummarize	0.16	0.23	0.19	0.21	0.28	0.24	0.23	0.30	0.26
MEAD	0.18	0.36	0.24	0.26	0.45	0.33	0.29	0.60	0.39
Our Algorithm	0.25	0.70	0.37	0.44	0.64	0.52	0.56	0.61	0.58

(b) Algorithm performance statistics for article set II

Summarization Algorithm	Compression Rate								
	10%			20%			30%		
	Recall	Precision	F-rate	Recall	Precision	F-rate	Recall	Precision	F-rate
MS Word AutoSummarize	0.15	0.24	0.18	0.20	0.27	0.23	0.23	0.29	0.26
MEAD	0.18	0.41	0.25	0.25	0.44	0.32	0.30	0.51	0.37
Our Algorithm	0.27	0.67	0.38	0.43	0.62	0.50	0.54	0.59	0.57

(c) Algorithm performance statistics for both article sets

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Conclusion & Future Work

- Experiment shows the excellent performance of our algorithm.

- Achieving an optimal balance between document summarization following the traditional discourse analysis approach and our learning based approach.

- Generating personalized summary for any future article that has not been read.

Q & A

Thank you!

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Performance under different parameter settings

Measurement	κ				
	0.00	0.25	0.50	0.75	1.00
Recall	0.33	0.41	0.53	0.58	0.61
Precision	0.35	0.44	0.58	0.65	0.70
F-rate	0.34	0.42	0.55	0.61	0.63

(a) Performance measurement statistics for article set I

Measurement	κ				
	0.00	0.25	0.50	0.75	1.00
Recall	0.39	0.44	0.56	0.56	0.46
Precision	0.42	0.48	0.61	0.60	0.50
F-rate	0.40	0.45	0.58	0.58	0.47

(b) Performance measurement statistics for article set II

Measurement	κ				
	0.00	0.25	0.50	0.75	1.00
Recall	0.36	0.42	0.54	0.57	0.54
Precision	0.38	0.46	0.59	0.62	0.60
F-rate	0.37	0.44	0.57	0.60	0.55

(c) Performance measurement statistics for both article sets

The compression rate is 30%.

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Future Work

- Achieving an optimal balance between document summarization following the traditional discourse analysis approach and our learning based approach.

- Generating personalized summary for any future article that has not been read.

- Improve the text content similarity metrics.