Joint Optimization of User-desired Content in MDS by Learning from User Feedback
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Overview

Motivation:
- No one best summary for all needs
- Low k of content selection
- Automatic methods produce low quality summaries compared to humans

Objective:
- Creation of user-desired summaries using interactive learning methods.

Contributions:
- Interactive loop to integrate feedback
- AL and joint optimization techniques to collect user feedback

Applications:
- Journalistic aid, Interactive annotation tool

Interactive Models

Baseline Model*: \( \max \sum w_i c_i \)

Novel User Feedback Models

Accept Model: (ACCEPT)
\[
\forall i \in I_1, \quad w_i = \text{MAX} \\
\forall i \in Q_0 - I_1, \quad w_i = 0
\]

Accepted concepts + Ignored concepts

Joint ILP Model: (JOINT)

Explore concepts lacking feedback

\[
\max \sum w_i c_i - \sum w_i c_i
\]

Lacking feedback = Received feedback

Active Learning Uncertainty Model: (AL)

Explore concepts with high uncertainty

\[
\max \sum w_i c_i
\]

Uncertainty

Active Learning Certainty Model: (AL+)

Explore concepts based on positive prediction of acceptance of a concept

\[
\max \sum w_i c_i (1 - w_i) c_i
\]

Prediction

Certainty

Feature Function

Concept Feature Vector

*SOA ICSI system (Boudin et al. (2015))

Interactive Personalized Summarization

Presidential Elections in France

What are Macron’s policies?

What were the causes of Le Pen’s loss?

What Macron’s win means for Africa?

Generic summaries cannot satisfy all needs

Documents

Interactive Personalized Summarization

Learning from user feedback

Summary

Best of both the worlds: Automatic (System) and Manual (Human) Summarization

Experiments & Analysis

Evaluate: The coverage of the user-desired content in the summary

\( = \) Evaluate: To reach the upper bound for a user’s reference summary

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Conclusions

- Interactively collecting feedback steers a general summary to a personalized summary.
- JOINT model consistently converges to the upper bound with minimal feedback.
- AL model balances well the trade-off between faster convergence and amount of feedback.
- AL+ model performs well when there is sufficient amount of feedback.
- Future work: Sampling strategies using AL and propagation methodologies.

Try it out, get in touch
Code and data: [https://github.com/UKPLab/ac2017-interactive_summarizer](https://github.com/UKPLab/ac2017-interactive_summarizer)
Questions or comments: avinesh@ai.phes.tu-darmstadt.de

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