

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

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ADAPTIVE PREPARATION OF INFORMATION FROM HETEROGENEOUS SOURCES



Overview

Motivation:

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

Objective:

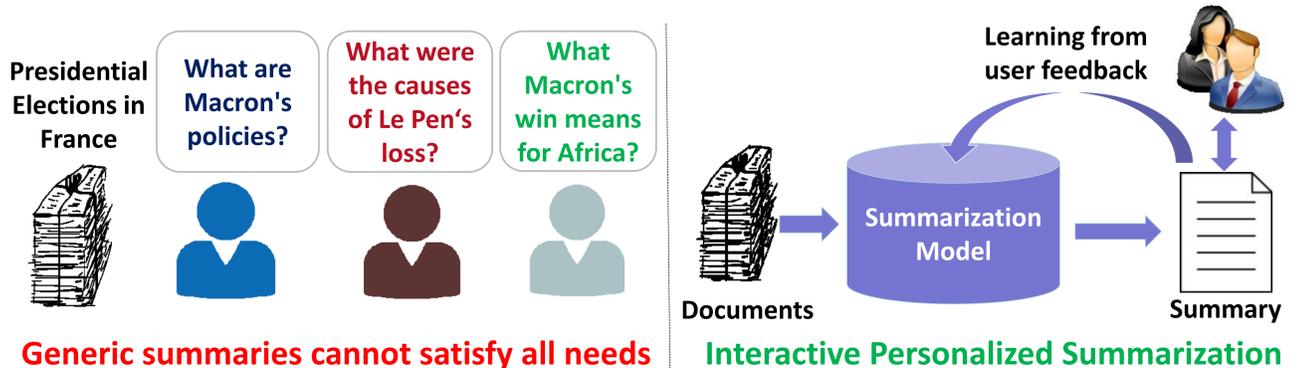
- Creation of **user-desired summaries** using interactive learning methods.

Contributions:

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

Applications: Journalistic aid, Interactive annotation tool

Interactive Personalized Summarization

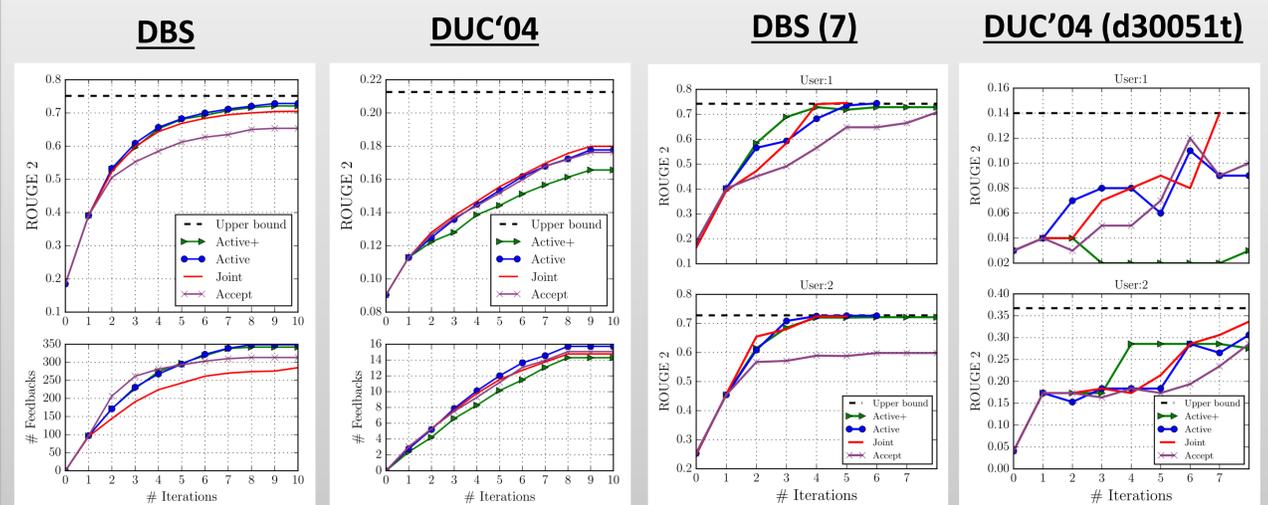


Best of both the worlds: Automatic (System) and Manual (Human) Summarization

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

| Datasets | ICSI | | | UB | | | Accept | | | JOINT | | | AL | | | AL+ | | |
|--------------------------------|------|------|------|------|------|------|--------|------|------|-------|------|------|------|------|------|------|------|------|
| | R1 | R2 | SU4 | R1 | R2 | SU4 | R1 | R2 | SU4 | R1 | R2 | SU4 | R1 | R2 | SU4 | R1 | R2 | SU4 |
| Concept Notion: Bigrams | | | | | | | | | | | | | | | | | | |
| DBS | .451 | .183 | .190 | .848 | .750 | .532 | .778 | .654 | .453 | .815 | .707 | .484 | .833 | .729 | .498 | .828 | .721 | .500 |
| DUC'04 | .374 | .090 | .118 | .470 | .212 | .185 | .442 | .176 | .165 | .444 | .180 | .166 | .440 | .178 | .160 | .427 | .166 | .154 |
| DUC'02 | .350 | .085 | .110 | .474 | .216 | .187 | .439 | .178 | .161 | .444 | .182 | .165 | .448 | .188 | .165 | .448 | .184 | .170 |
| DUC'01 | .333 | .073 | .105 | .450 | .213 | .181 | .414 | .171 | .156 | .418 | .167 | .149 | .435 | .186 | .163 | .426 | .181 | .158 |
| Concept Notion: Phrases | | | | | | | | | | | | | | | | | | |
| DBS | .403 | .135 | .154 | .848 | .750 | .532 | .691 | .531 | .430 | .742 | .597 | .419 | .776 | .652 | .448 | .767 | .629 | .440 |
| DUC'04 | .374 | .090 | .118 | .470 | .212 | .185 | .441 | .176 | .160 | .441 | .179 | .162 | .444 | .180 | .162 | .422 | .164 | .150 |
| DUC'02 | .350 | .085 | .110 | .474 | .216 | .187 | .436 | .181 | .162 | .444 | .183 | .165 | .446 | .185 | .168 | .442 | .182 | .162 |
| DUC'01 | .333 | .073 | .105 | .450 | .213 | .181 | .410 | .165 | .153 | .417 | .170 | .156 | .433 | .182 | .161 | .420 | .179 | .154 |



Interactive Models

Baseline Model*: $\max \sum_i w_i c_i$

Novel User Feedback Models

Accept Model: (ACCEPT)

$$\forall i \in I_0^t. \quad w_i = \text{MAX}$$

$$\forall i \in Q_0^t - I_0^t. \quad w_i = 0$$

Accepted concepts (blue) vs Ignored concepts (purple)

Joint ILP Model: (JOINT)

Explore concepts **lacking feedback**

$$\max \sum_{i \in Q_0^t} w_i c_i - \sum_{i \in Q_0^t} w_i c_i$$

Lacking feedback (blue) vs Received feedback (purple)

Active Learning Uncertainty Model: (AL)

Explore concepts with **high uncertainty**

$$\max \sum_{i \in Q_0^t} \mu_i w_i c_i$$

Uncertainty

Active Learning Certainty Model: (AL+)

Explore concepts based on **positive prediction of acceptance of a concept**

$$\max \sum_{i \in Q_0^t} l_i (1 - u_i) w_i c_i$$

Prediction (blue) vs Certainty (purple)

$$\text{Where } l_i = \begin{cases} 0 & \text{if } f^{(t)}(\Phi(\tilde{x}_i)) = -1 \\ 1 & \text{if } f^{(t)}(\Phi(\tilde{x}_i)) = 1 \end{cases}$$

Feature Function vs Concept Feature Vector

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

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/acl2017-interactive_summarizer
 Questions or comments: avinesh@aiphes.tu-darmstadt.de



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