

Entropy-based Sampling for Abstractive Multi-document Summarization in Low-resource Settings

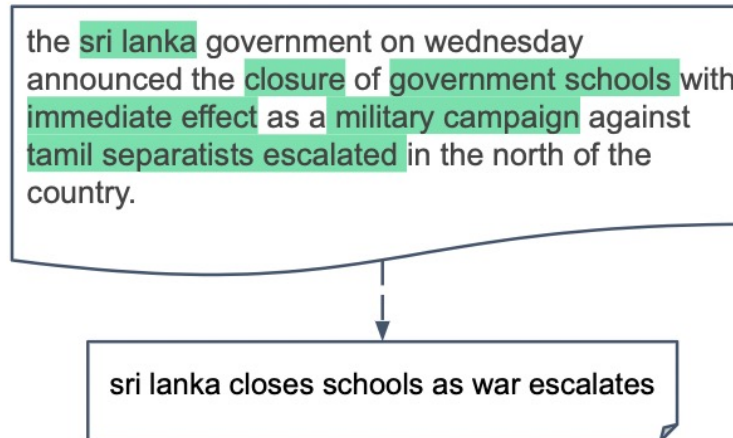
Laura Mascarell, Ribin Chalumattu, and Julien Heitmann

Introduction and Background

Abstractive Multi-document Summarization (MDS)



Abstractive Summarization



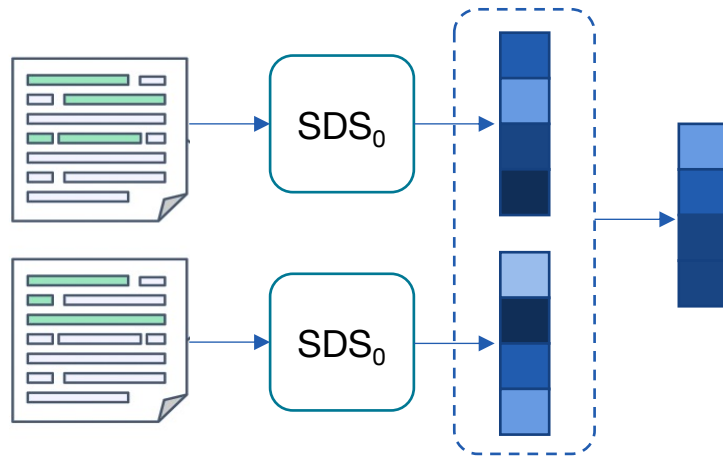
→ Research in MDS mostly focuses on English and MDS training data

Introduction and Background

Abstractive Multi-document Summarization (MDS)

Single-document summarization (SDS) models for MDS task

→ Dynamic ensemble (Hokamp et al., 2020)



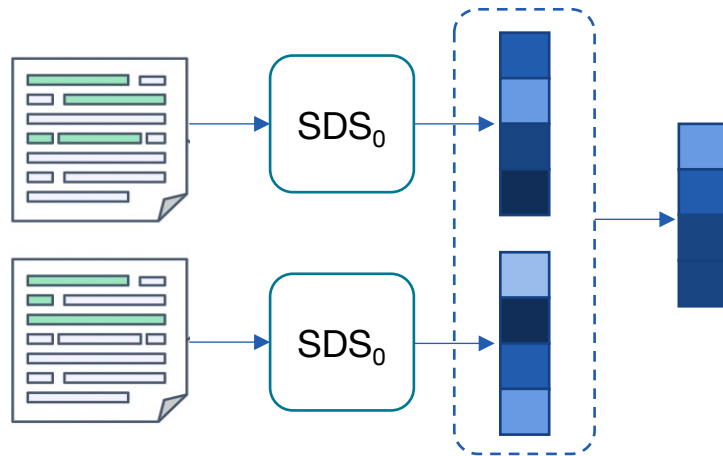
$$p_{\theta}(y_t|\mathcal{X}) = \frac{1}{|\mathcal{X}|} \sum_{\mathbf{x}_i \in \mathcal{X}} p_{\theta}(y_t|\mathbf{x}_i; \mathbf{y}_{0:t-1})$$

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Contributions

- Entropy-based sampling approaches for the MDS task
- German MDS test set for abstractive MDS

Entropy-based Decoding

1. Minimum Entropy

$$H(X) = - \sum_{i=1}^n p(x_i) \log p(x_i)$$

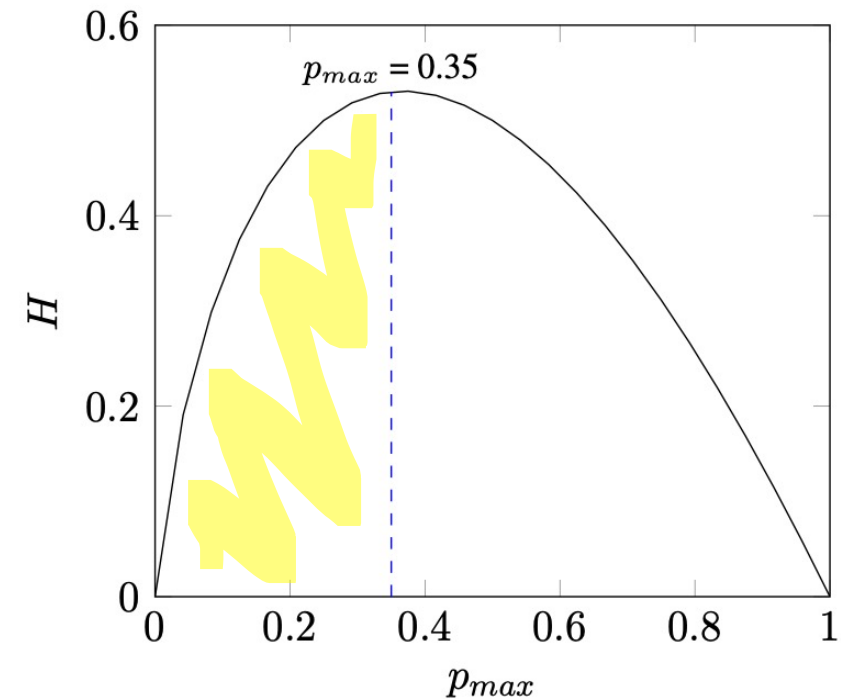
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$$H(X) = -p_{max} \log p_{max}$$



Entropy-based Decoding

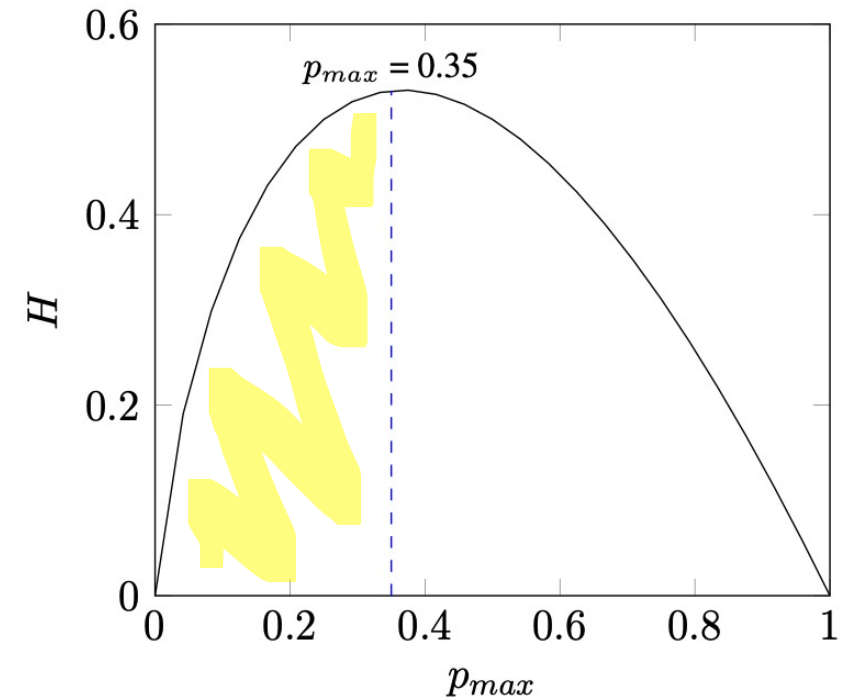
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- b) $p_{max} < 0.35$: average log-probabilities



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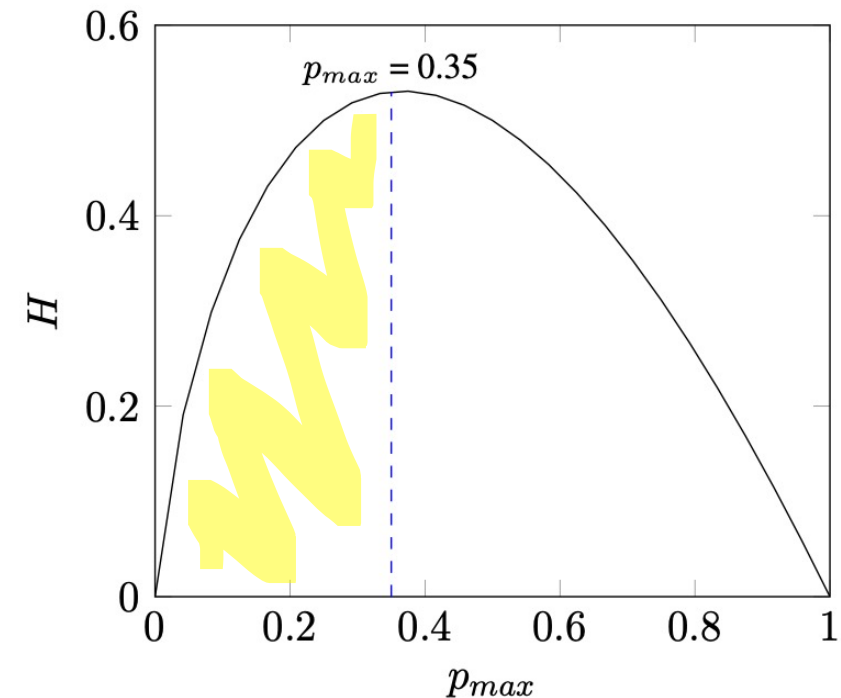
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3. Pointwise Mutual Information

$$p(y|x) = \log p(y|x) - \log p(y)$$



Multi-GeNews

German Abstractive MDS Test Set

Data collection

1. Obtain clusters of related articles from SRF news portal.¹
2. Generate summary by combining their lead paragraphs.
3. Filter salient summary sentences using mBertExt

Final test set

- 402 clusters of articles + summary
- 2 to 6 related articles per cluster

1. <https://www.srf.ch/news>

Chaos am Flughafen Zürich

«Plötzlich war einfach der Bildschirm schwarz»

Gestrandete Passagiere sprechen über die bangen Stunden am Flughafen Zürich während der Luftraumsperrung.

Mittwoch, 15.06.2022, 13:00 Uhr

Mehr zum Thema



Problem bei Skyguide gelöst

Luftraumsperrung aufgehoben: Flug ab Zürich und Genf wieder möglich

15.06.2022 · Mit Video



Grounding an zwei Flughäfen

Skyguide-Ausfall: «Sowas darf nicht passieren»

15.06.2022 · Mit Video

Experimental Setting

Models

- mBART (Liu et al., 2020) fine-tuned on:
 1. 20m (Rios et al., 2021)
 2. auto-hMDS (Zopf, 2018)
- GPT-2 (Radford et al., 2019)

Approaches

- H_{min} - minimum entropy
- H_{th} - max-predicted probability threshold
- H_{pmi} - pointwise mutual information
- *concat* - articles are concatenated into a single input
- *DynE* - dynamic ensemble (Hokamp et al., 2020)

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| Method | 100 words | | | |
|---------------------|-------------|------------|-------------|----------|
| | R1↑ | R2↑ | RL↑ | ρ ↓ |
| mBART concat | 23.0 | 6.0 | 14.8 | 9.23 |
| mBART + <i>DynE</i> | 22.2 | 4.8 | 14.9 | 1.5 |
| mBART + H_{min} | 23.4 | 5.6 | 15.0 | 2.46 |
| mBART + H_{th} | 24.5 | 6.2 | 15.6 | 2.72 |
| mBART + H_{pmi} | 23.9 | 7.2 | 16.1 | 2.78 |

Table 1: Performance on Multi-GeNews test set. MBart fine-tuned on the 20m dataset.

Manual Evaluation

German Abstractive MDS

Manual Evaluation Tasks

1. Summary Ranking Task
 - relative quality of the summaries
2. Faithfulness Annotation Task
 - summary text spans (Krishna et al., 2023)

Evaluation on 20 instances of Multi-GeNews

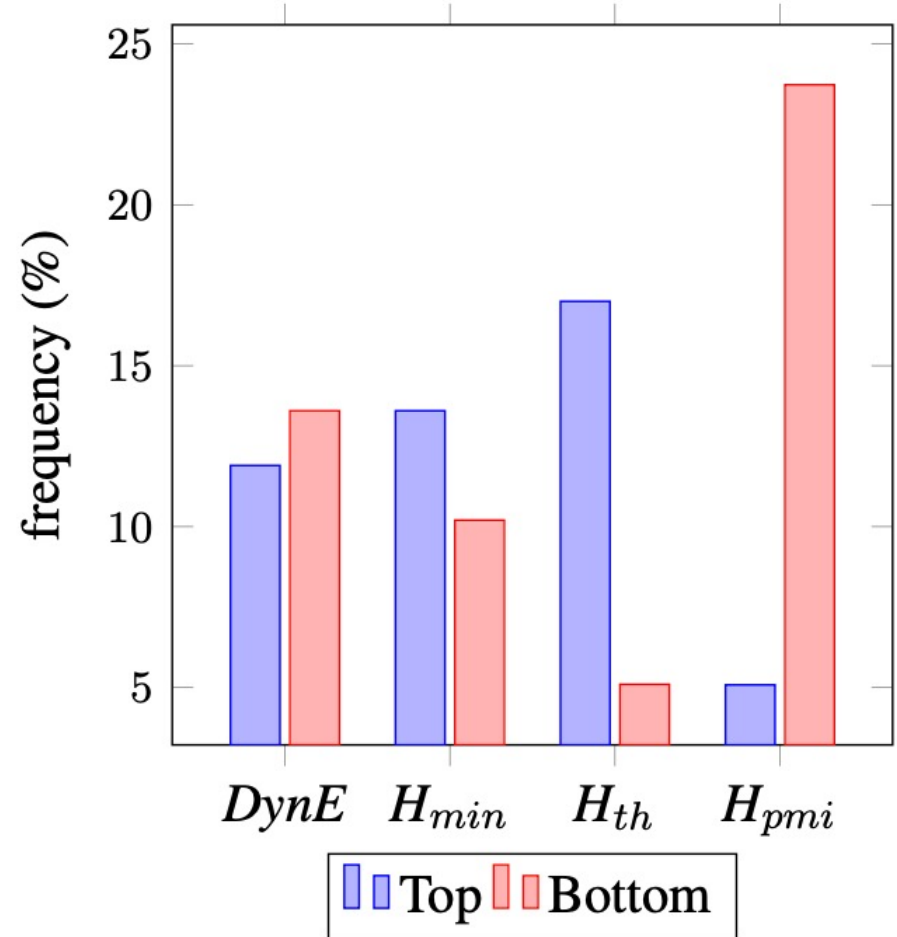
- 3 source articles
- Lexical differences between summaries
 - Token-level edit distance between 5 and 10

Manual Evaluation

German Abstractive MDS

Summary Ranking Task - majority agreement

- DynE mixed ratings
- H_{th} consistently ranked top (1st- 2nd rank)
- H_{pmi} consistently ranked bottom (3rd-4th rank)



Manual Evaluation

German Abstractive MDS

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H_{th}

Donald Trump hielt sich in der Nacht auf Mittwoch in den beiden Kammern des US-Kongresses seine dritte Rede ab.
[Donald Trump delivered his third speech to both chambers of the U.S. Congress on Wednesday night.]

H_{pmi}

Donald Trump hielt sich in den USA nicht an die Corona-Regeln.
[Donald Trump did not follow the Covid rules in the USA.]

Manual Evaluation

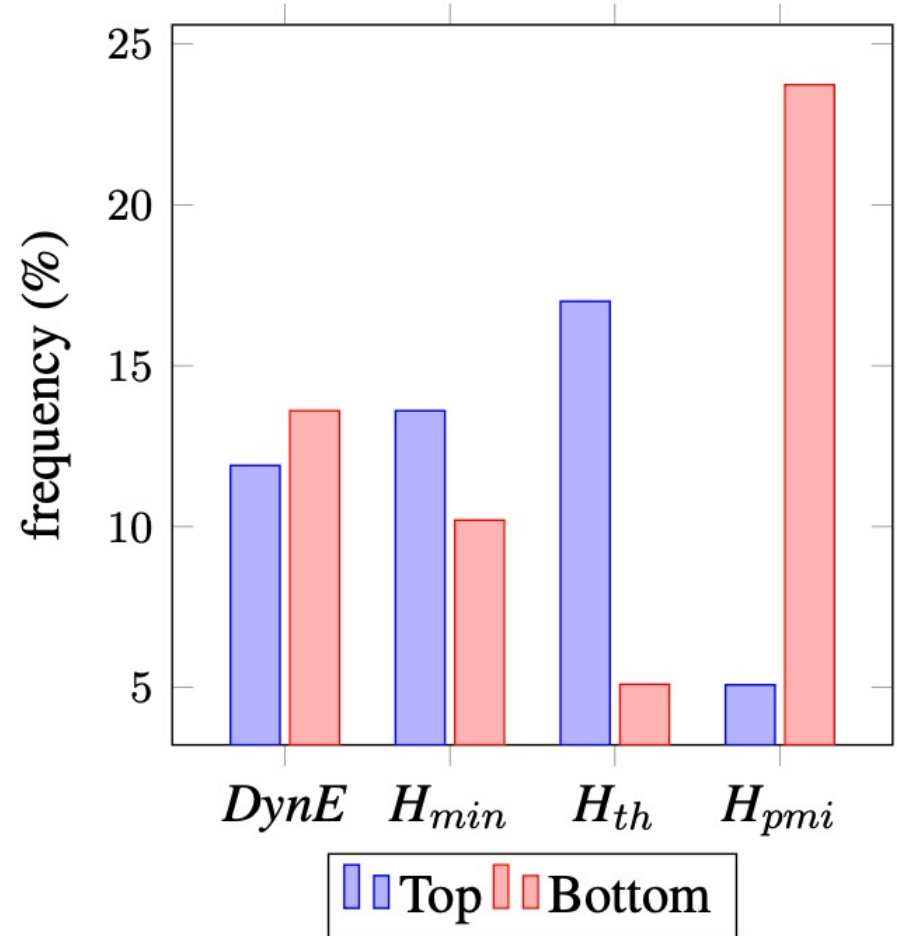
German Abstractive MDS

Summary Ranking Task - majority agreement

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Faithfulness Annotation Task

- Overall, lots of hallucinations
- No significant improvement with H_{pmi}
 - 36.2% (H_{pmi}) vs. 33.3% (H_{th})



Conclusions

Abstractive MDS of German text

- Explore multiple entropy-based approaches
- Build and release a test set on the news domain

Future work

- Important to tackle hallucination
- MDS with Large Language Models

Thank you!

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Link to paper

