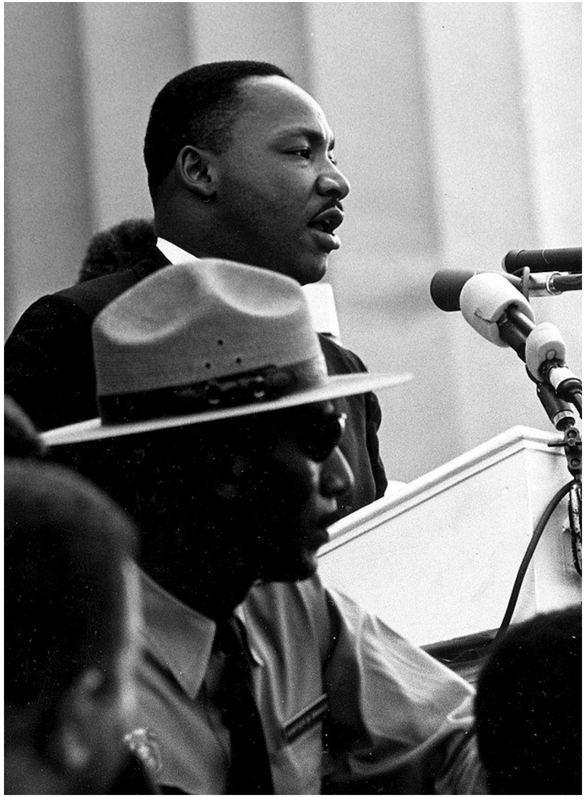
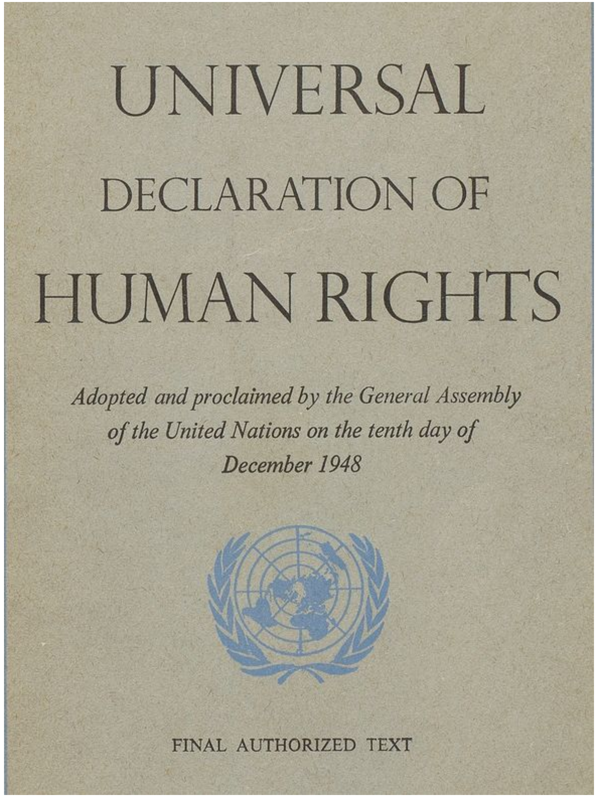
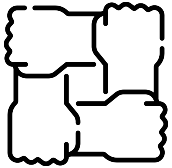
Data Innovation Lab | Team faktual

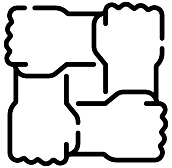
Using NLP for Adaptive Fact Extraction and Text Summarization

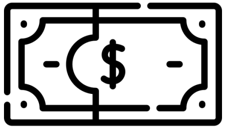
Afag Hasanli, Anelia Petrova, Benedikt Anselment, Marc Schneider and Sergii Poluektov | 31.07.2020

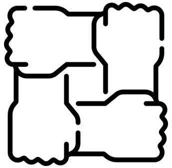


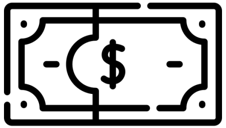

UNIVERSAL
DECLARATION OF
HUMAN RIGHTS
Adopted and proclaimed by the General Assembly
of the United Nations on the tenth day of
December 1948
FINAL AUTHORIZED TEXT



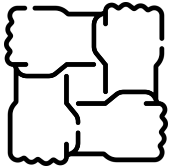


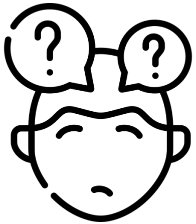


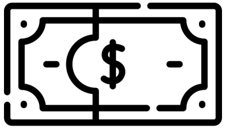



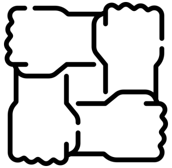


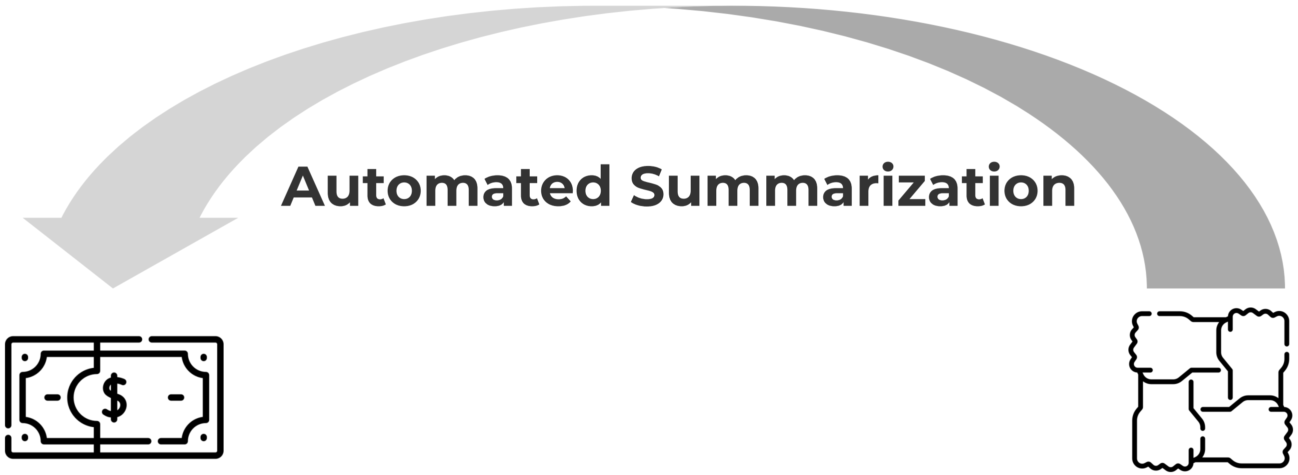

NEWS
FAKE!










Automated Summarization

Team Introduction

Afag Hasanli
Data Engineering and Analytics

Anelia Petrova
Informatics

Benedikt Anselment
Management & Technology

Marc Schneider
Student of teaching (Mathematics & Informatics)

Sergii Poluektov
Robotics, Cognition, Intelligence

Agenda

Data → Methodology → Models → Use cases → Conclusion

Agenda

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Data → Methodology → Models → Use cases → Conclusion

Acquisition

Pipeline

Exploration

Session Protocols

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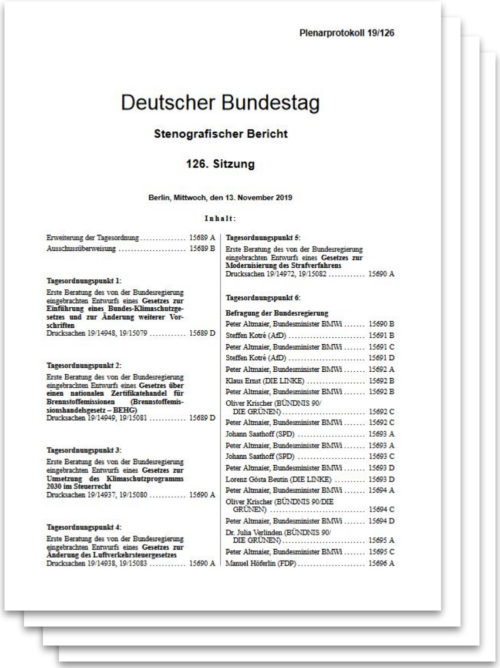


Plenarprotokoll 19/126

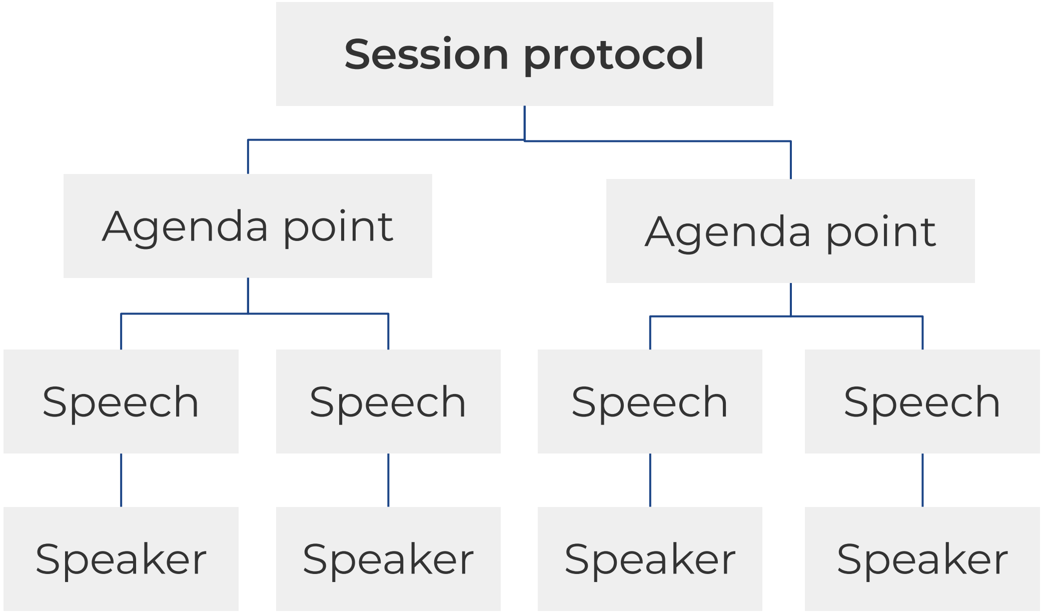
Deutscher Bundestag

Stenografischer Bericht

126. Sitzung

Berlin, Mittwoch, den 13. November 2019

Inhalt:



Approximately 100 pages

Drucksachen

Deutscher Bundestag
19. Wahlperiode

Druckache 19/20920
08.07.2020

Gesetzentwurf
der Bundesregierung

**Entwurf eines Gesetzes
zu dem Protokoll vom 10. Oktober 2018
zur Änderung des Übereinkommens vom 28. Januar 1981
zum Schutz des Menschen
bei der automatischen Verarbeitung
personenbezogener Daten**

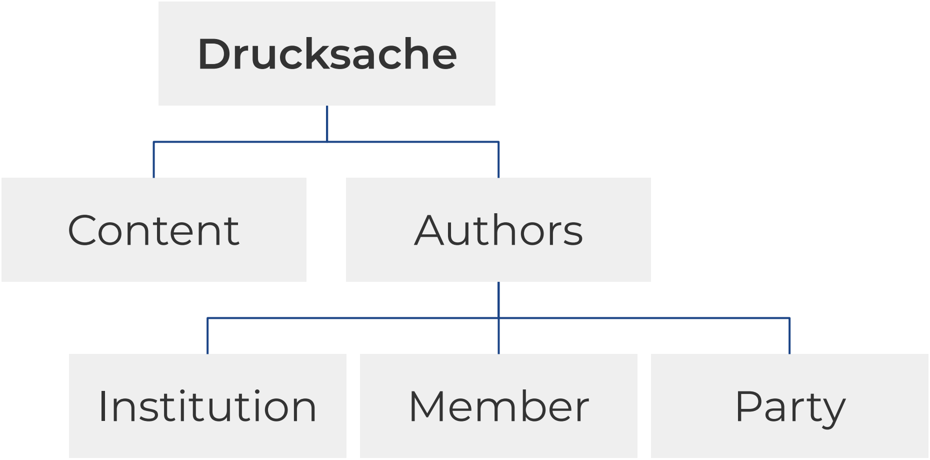
A. Problem und Ziel

Das Übereinkommen vom 28. Januar 1981 zum Schutz des Menschen bei der automatischen Verarbeitung personenbezogener Daten (BGBl. 1985 II S. 538, 539) war das erste rechtsverbindliche zwischenstaatliche Übereinkommen zum Datenschutz. Nach mehrjährigen Verhandlungen haben sich die Konventionsstaaten im Jahr 2018 auf ein Änderungsprotokoll geeinigt, das die Konvention 108 modernisiert (Protokoll vom 10. Oktober 2018 zur Änderung des Übereinkommens vom 28. Januar 1981 zum Schutz des Menschen bei der automatischen Verarbeitung personenbezogener Daten). So werden etwa die Betroffenenrechte gestärkt und eine Meldepflicht für Verantwortliche bei Verletzungen des Datenschutzes an die Aufsichtsbehörde eingeführt. Die Schaffung einer unabhängigen Aufsichtsbehörde wird für alle Konventionsstaaten verpflichtend.

Der Rat der Europäischen Union hat die Mitgliedstaaten der Europäischen Union ermächtigt, das Änderungsprotokoll zu ratifizieren.

Nach Artikel 59 Absatz 2 Satz 1 des Grundgesetzes ist die Zustimmung der gesetzgebenden Körperschaften zu dem Änderungsprotokoll Voraussetzung für dessen Ratifikation.

Vorabfassung - wird durch die lektorierte Fassung ersetzt.



Approximately 15 pages

Available Data

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Legislative Period	Years	Protocol count	Drucksache count
14	1998 - 2002	253	10005
15	2002 - 2005	187	6016
16	2005 - 2009	233	14163
17	2009 - 2013	253	14839
18	2013 - 2017	245	13706
19	2017 -	152+	21069+
14 - 19	**1998 - 2020**	**1323+**	**79798+**

Agenda

Data

Methodology

Models

Use cases

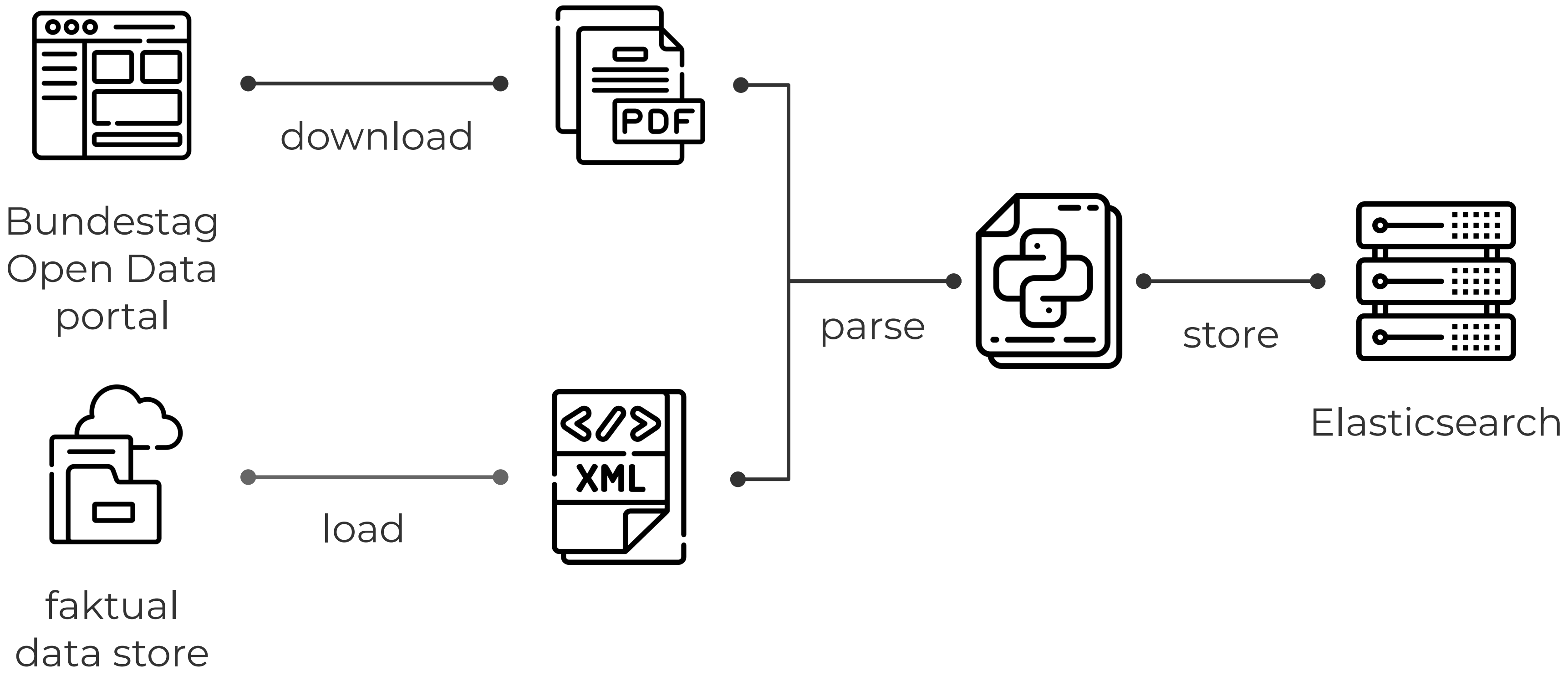
Outlook

Acquisition

Pipeline

Exploration

Data Acquisition



Agenda

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Data | Methodology | Models | Use cases | Conclusion

- Acquisition
- Pipeline
- **Exploration**

Character Length Distribution

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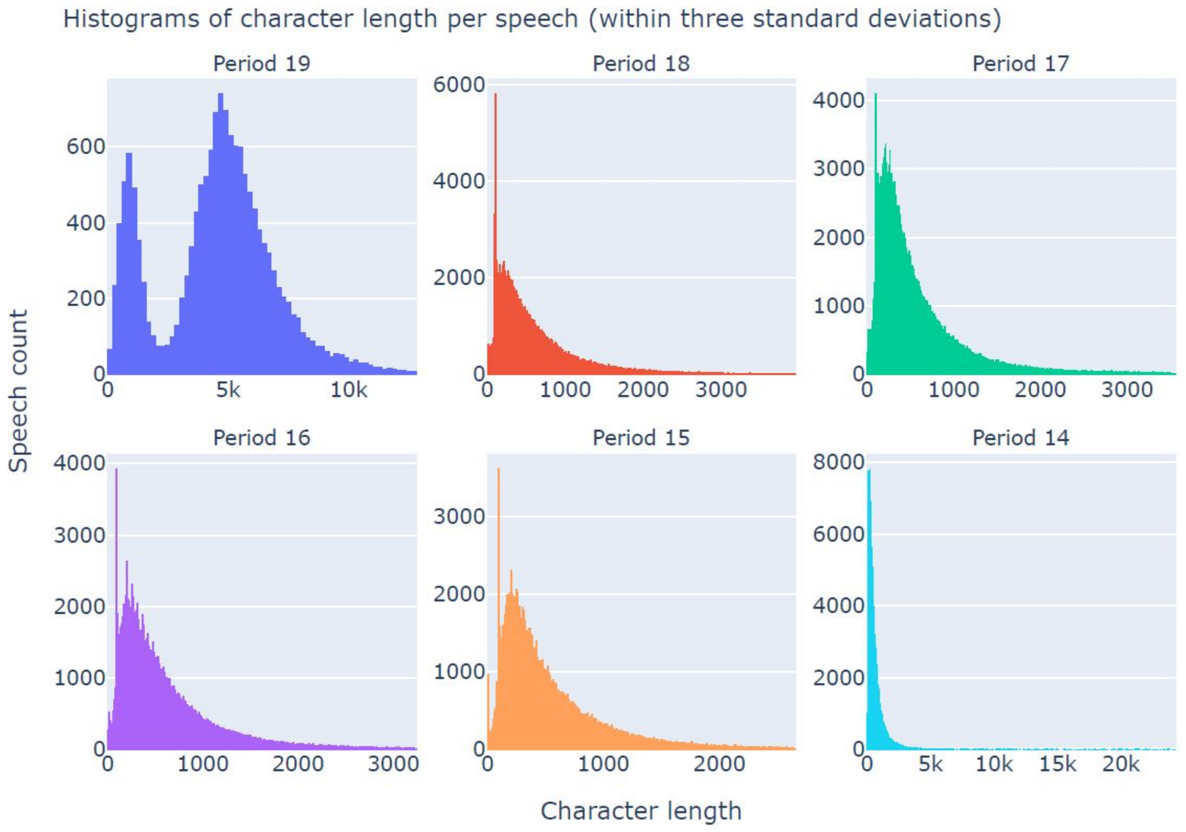
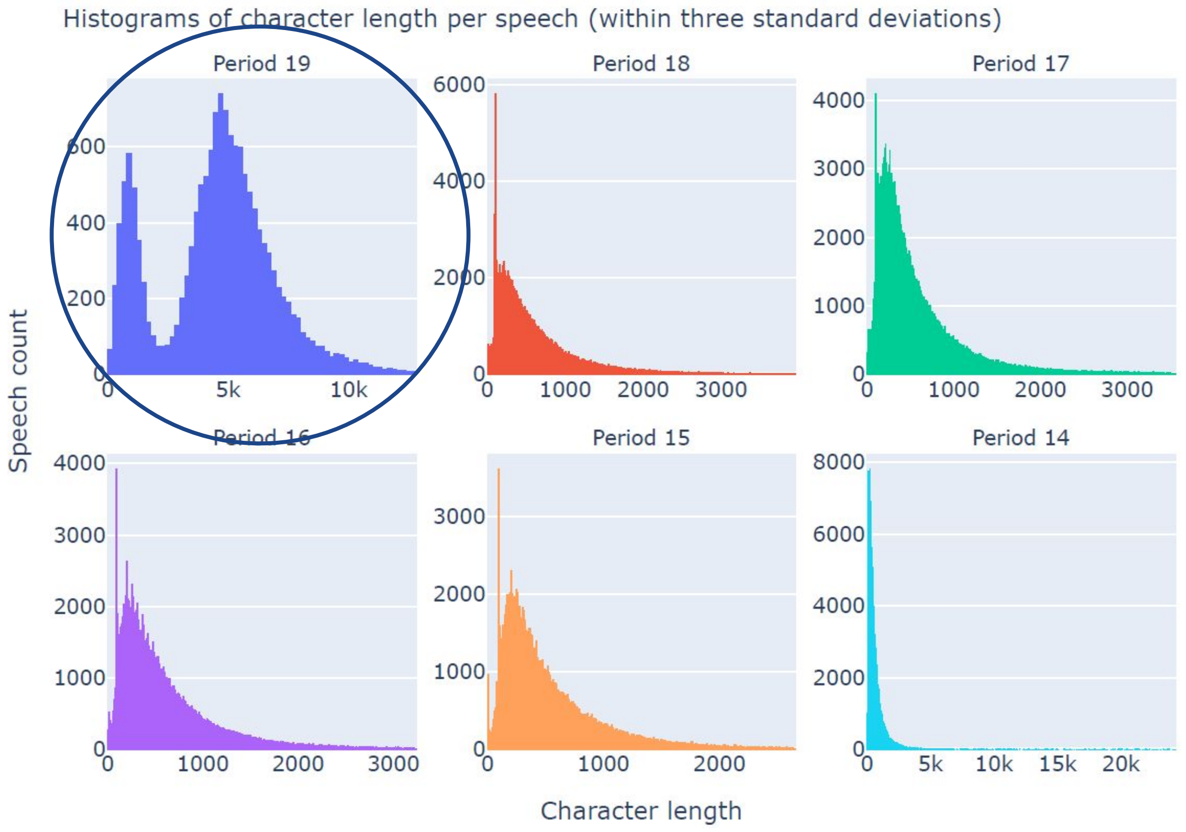
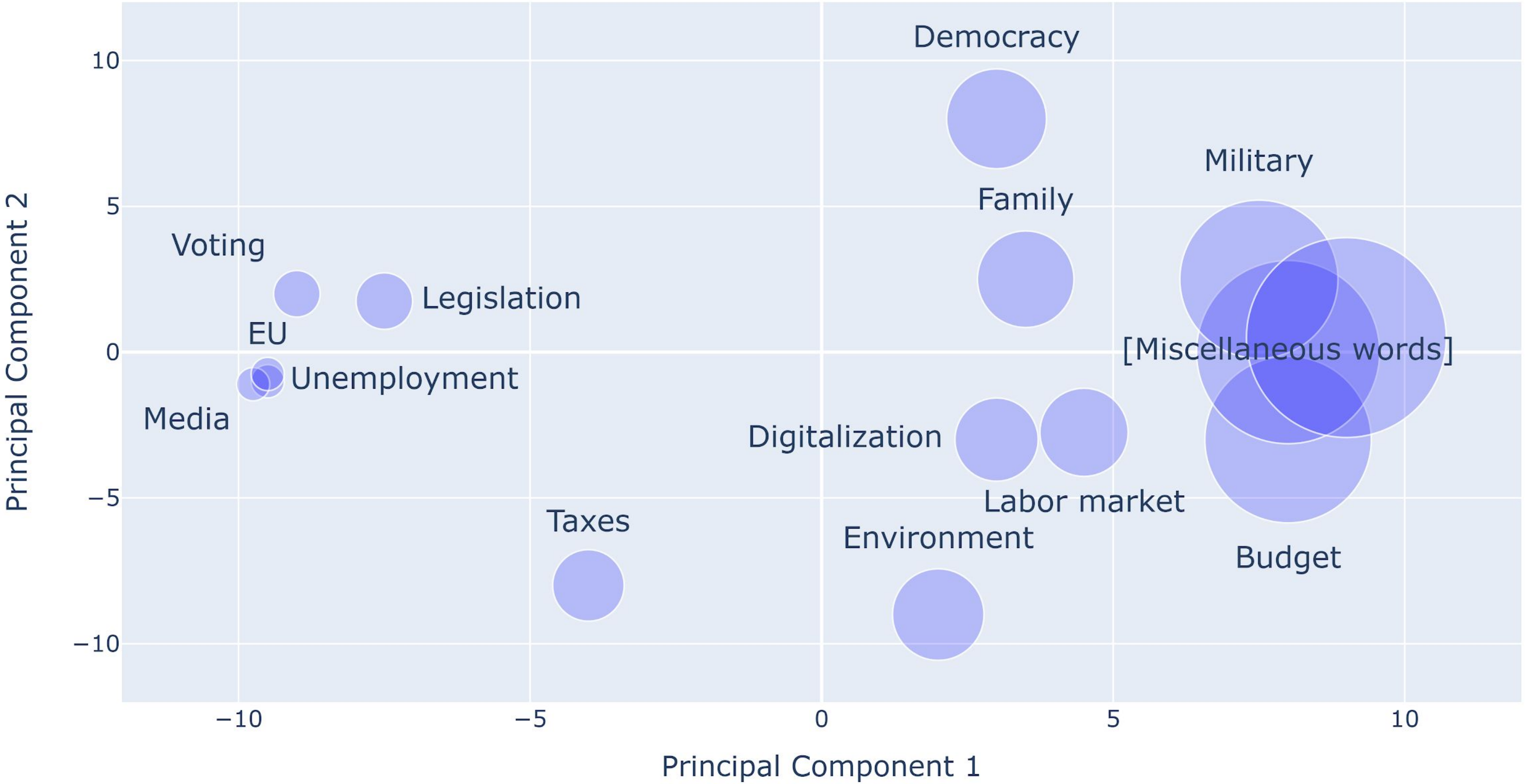


Character Length Distribution



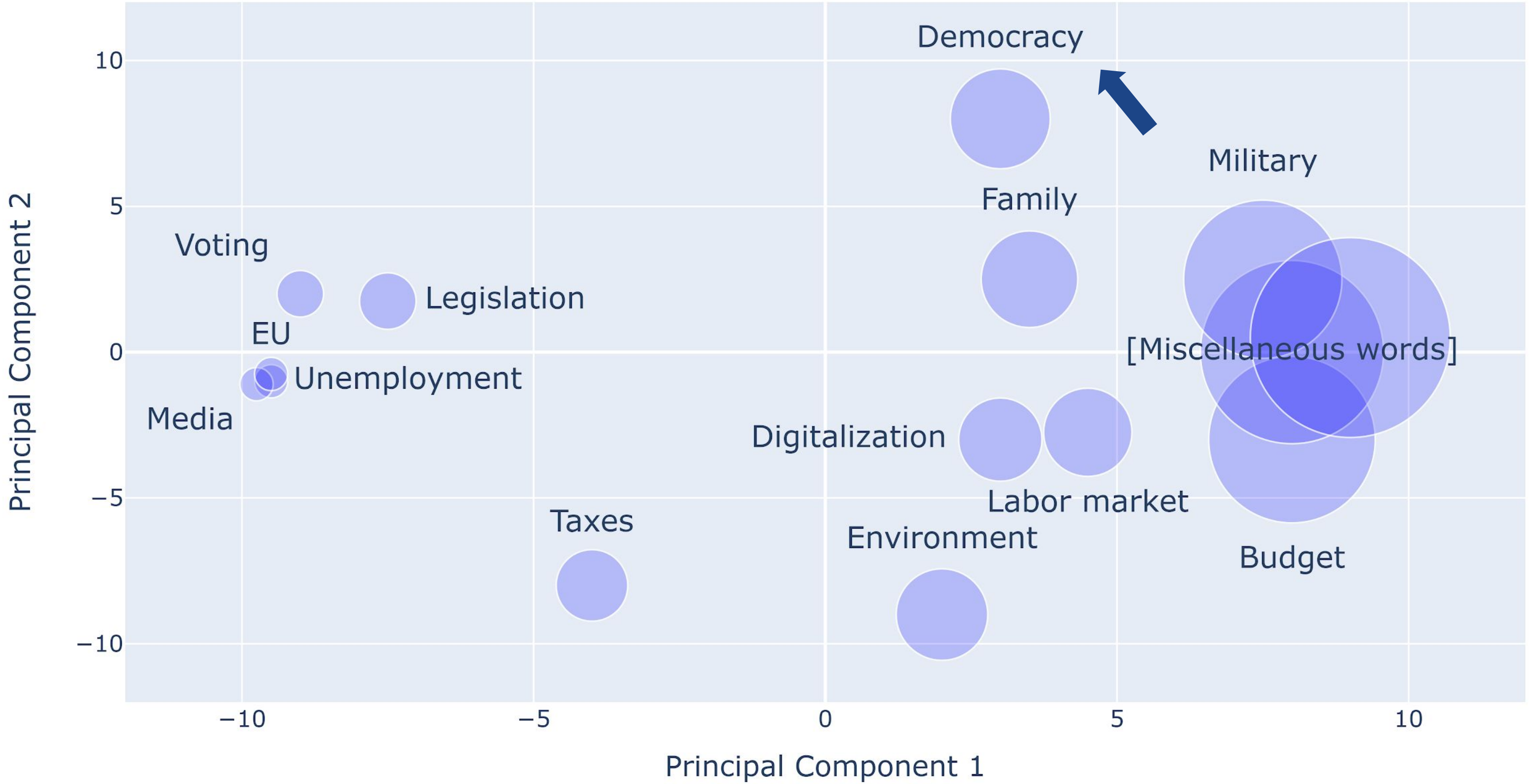
Topic Distribution in Period 19

faktual & TUM

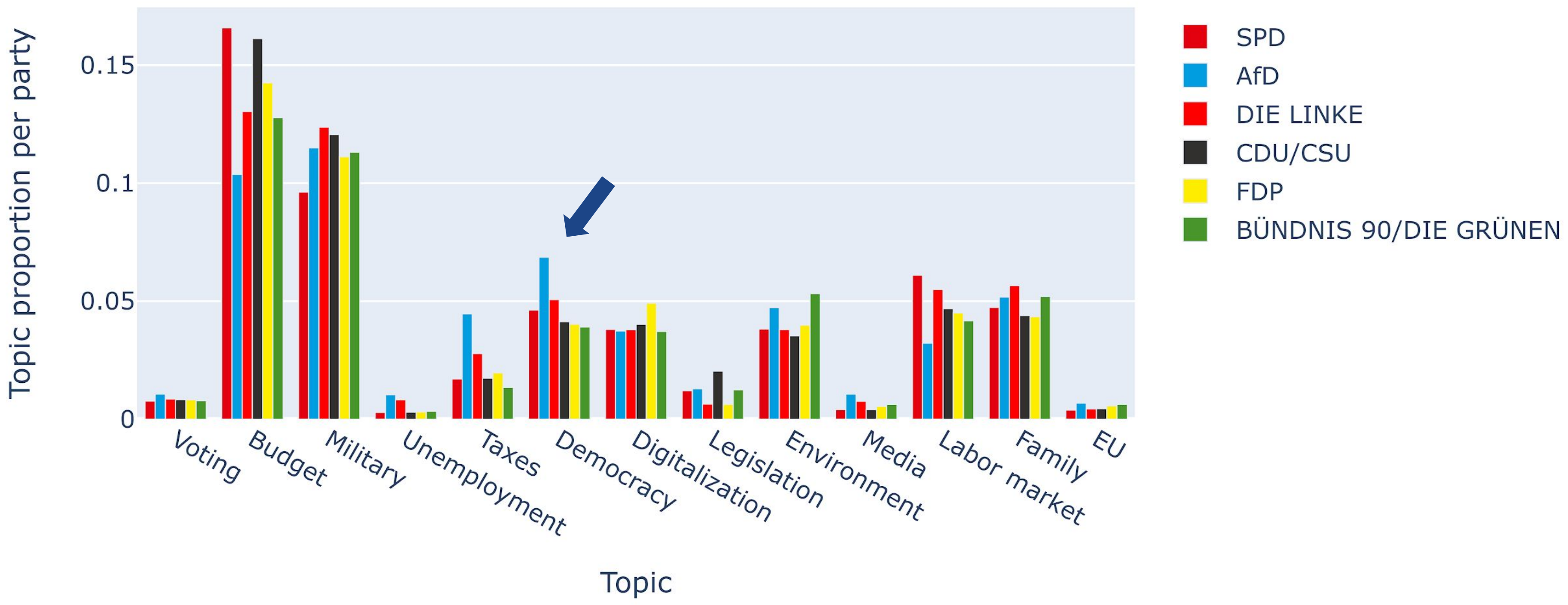


Topic Distribution in Period 19

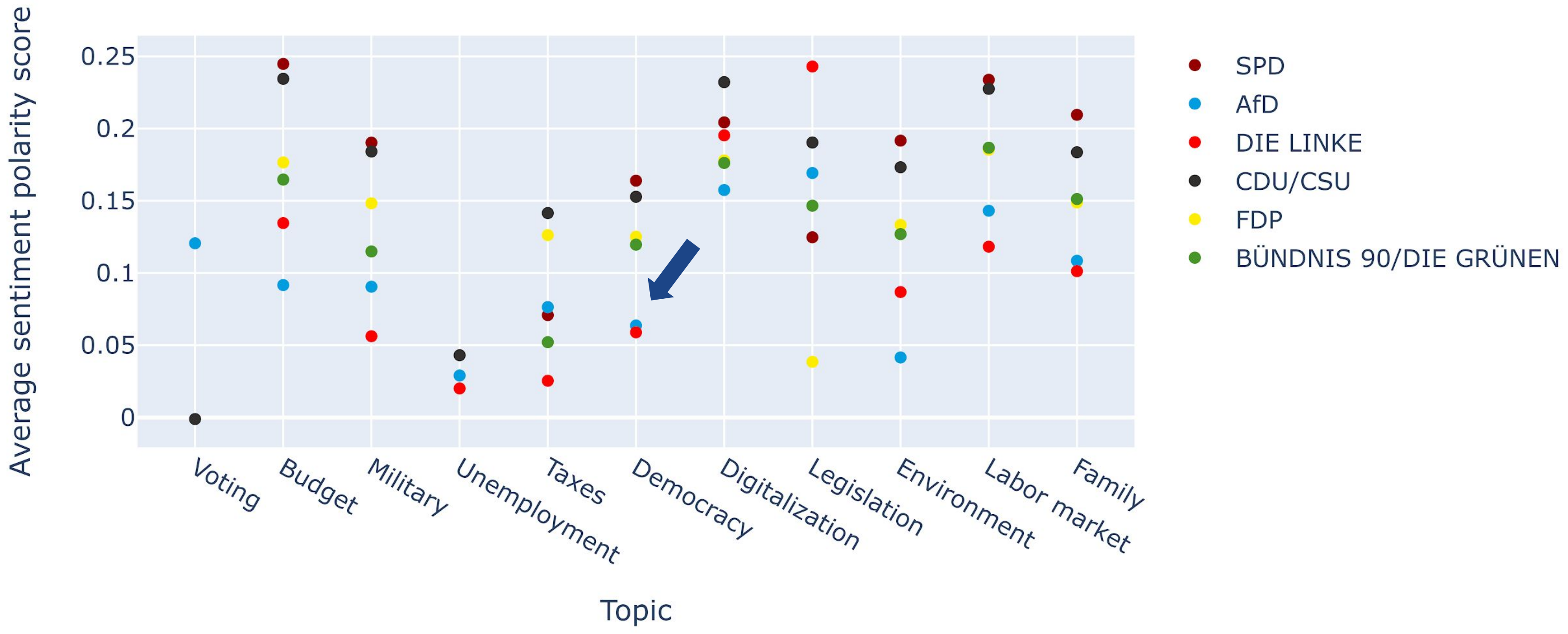
faktual & TUM



Topic Distribution per Party in Period 19



Sentiment Analysis per Topic in Period 19



Agenda

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Data

Methodology

Models

Use cases

Conclusion

Model selection

Evaluation

The two main categories in summarization

Extractive summarization

"This is an example text. The two main model-categories in automated summarization are extractive and abstractive summarization. Thank you for reading."

Abstractive summarization

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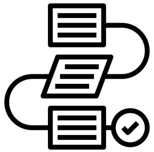

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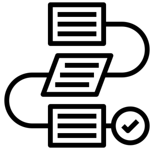

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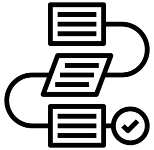

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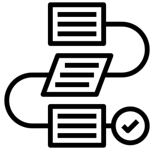

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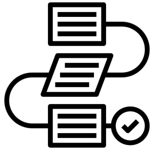


“The field of automated text summarization can be divided in an extractive and an abstractive domain.”

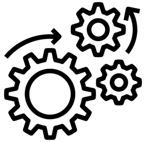
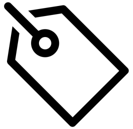
Our model-choosing approach

Abstractive summarization

Approach from scratch			
Unsupervised approach (MeanSum)			
German pretrained approach (BERT)			
English pretrained approach (BART)			

Our model-choosing approach

Abstractive summarization

			
Approach from scratch			
Unsupervised approach (MeanSum)			
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Our model-choosing approach

faktual & TUM

Abstractive summarization

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	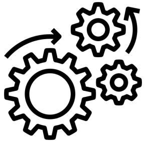	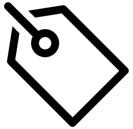	
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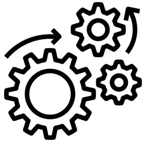
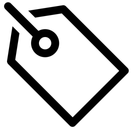
Our model-choosing approach

faktual & TUM

Abstractive summarization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Agenda

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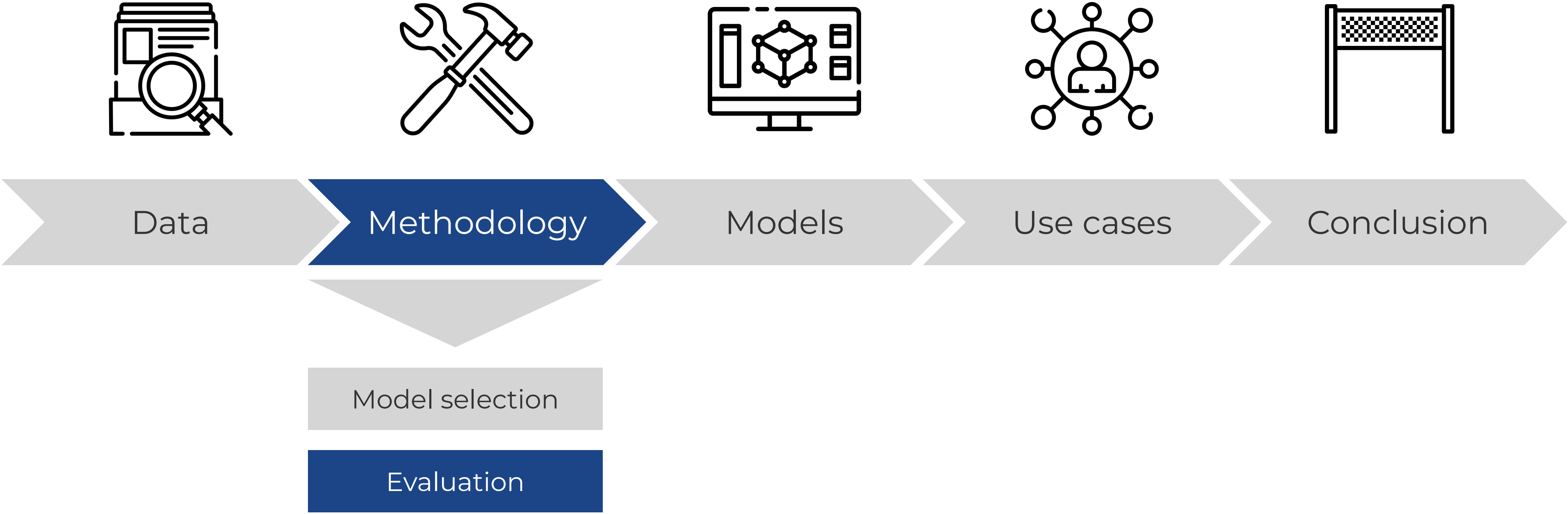

Quantitative evaluation

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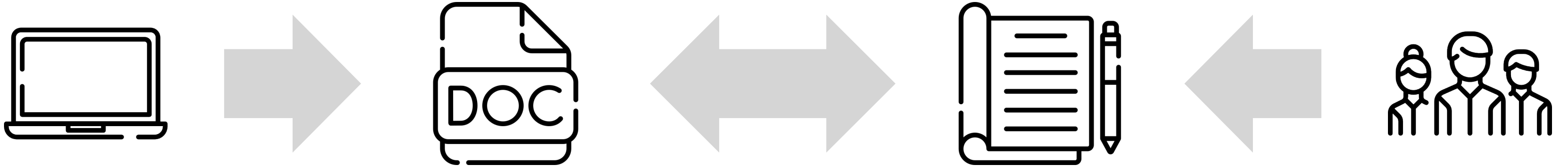

System summary

Reference summary

ROUGE

Measures n-gram overlap

Computational effort

Abstraction capturing

BERTscore

Compares sentence embeddings

Computational effort

Abstraction capturing

Quantitative evaluation

faktual & TUM

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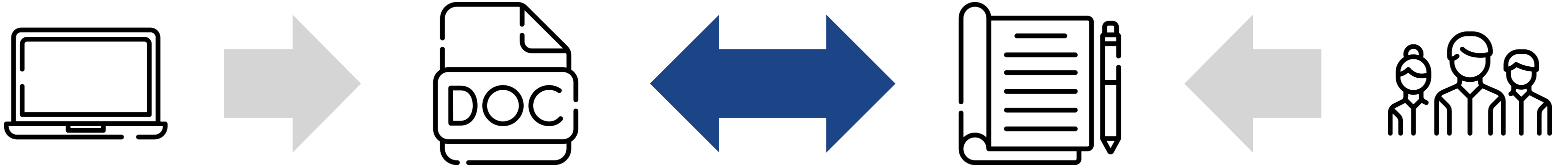

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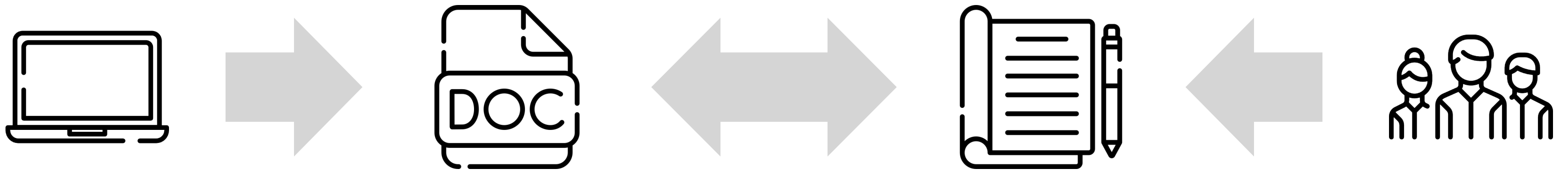
faktual & TUM



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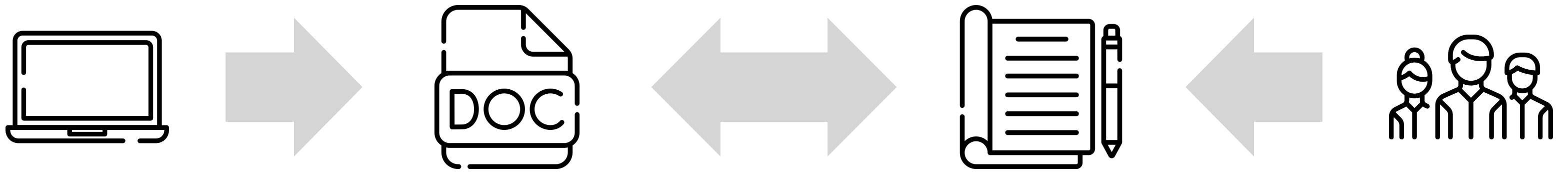

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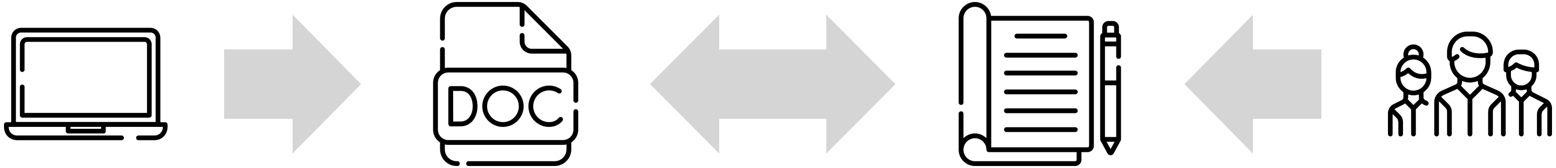

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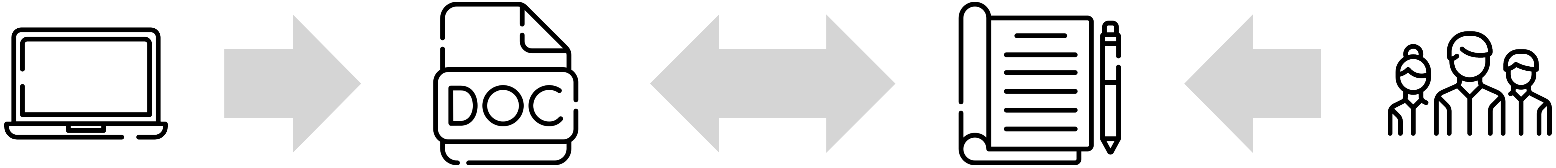

System summary

Reference summary

ROUGE	BERTscore
Measures n-gram overlap	Compares sentence embeddings
Computational effort	Computational effort
Abstraction capturing	Abstraction capturing

Qualitative evaluation

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Language-related questions

1. Grammatical correctness
2. Reading-fluency

Content-related questions

3. Key-point capturing
4. Content mix-up
5. Misleading information added

Agenda

Data · Methodology · **Models** · Use cases · Conclusion

- **Model from scratch**
- MeanSum
- BERT & BART
- Overall comparison

Our model from scratch

Dataset

Architecture

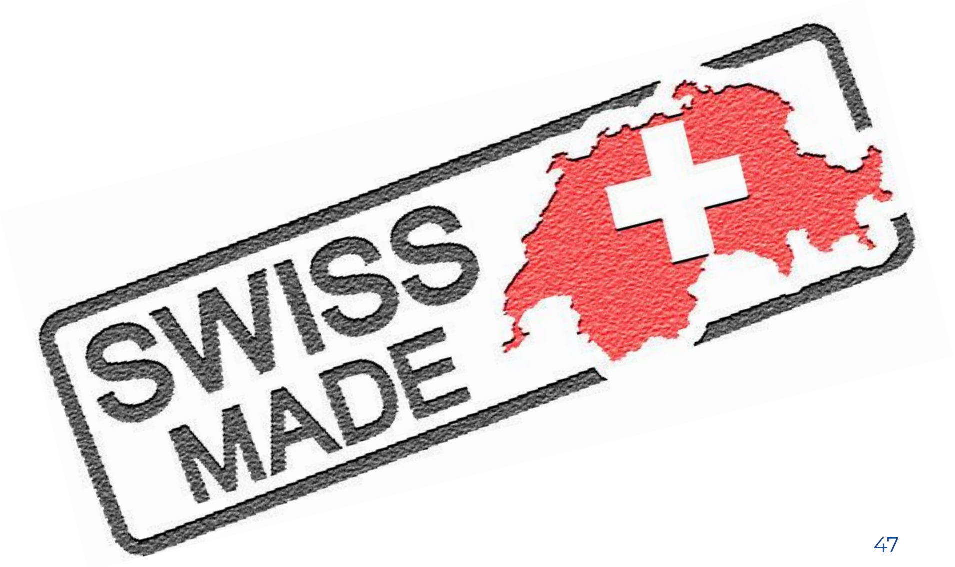
Evaluation

Benchmark

The “SwissText”-dataset

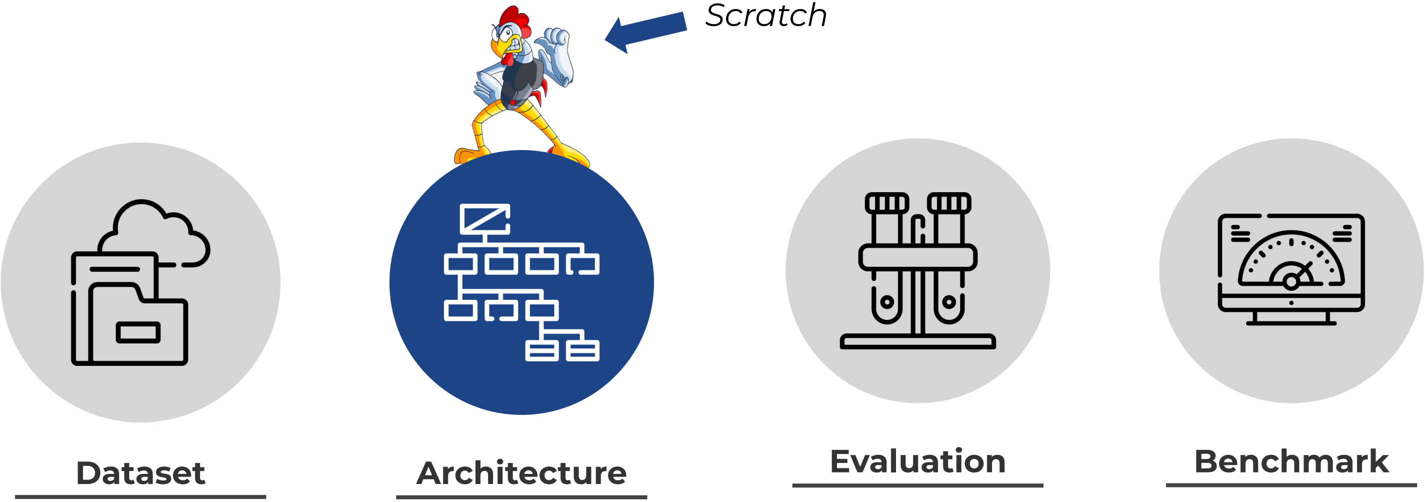
Created for “German text summarization challenge 2019” by researchers from UA Zurich

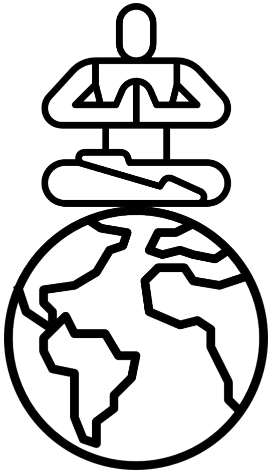
100,000 texts with corresponding reference summaries extracted from Wikipedia



Our approach from scratch

faktual & TUM

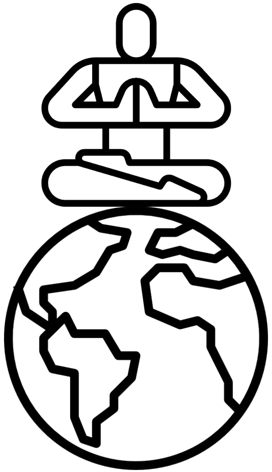




Attention Layer

Encoder-Decoder

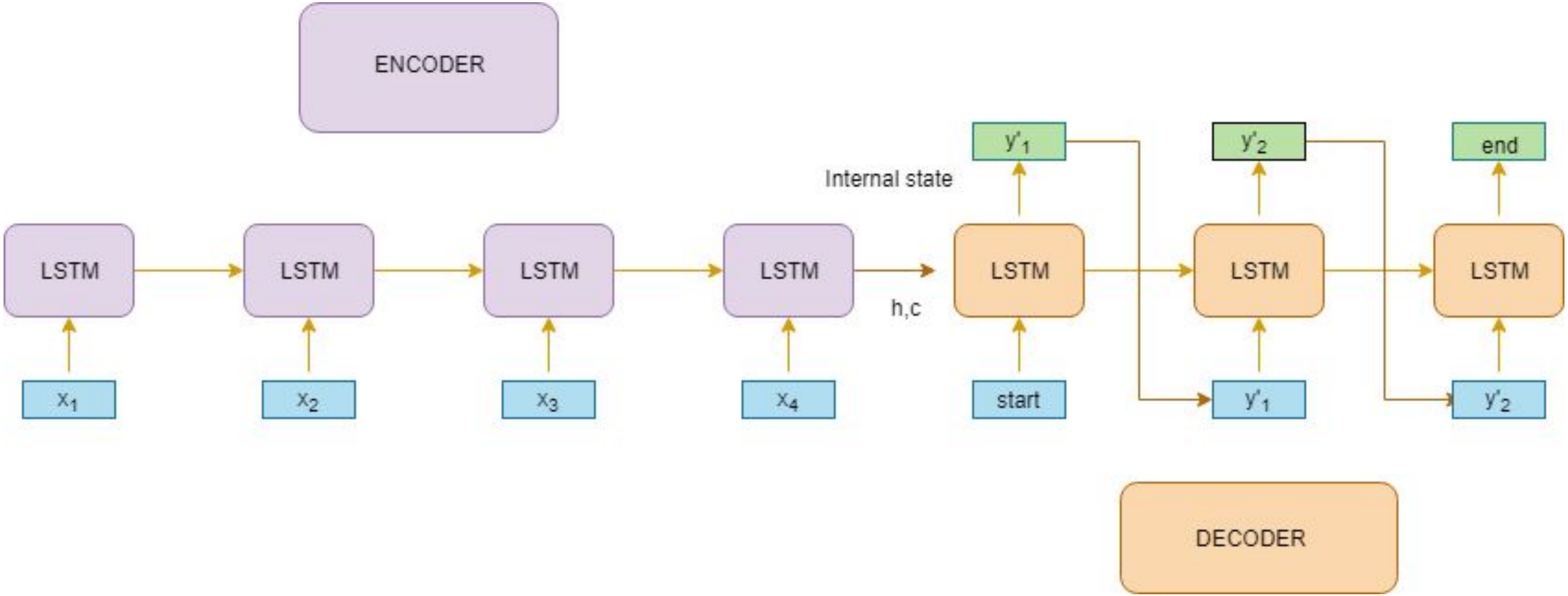
Architecture



Attention Layer → Attention layer implemented in keras package

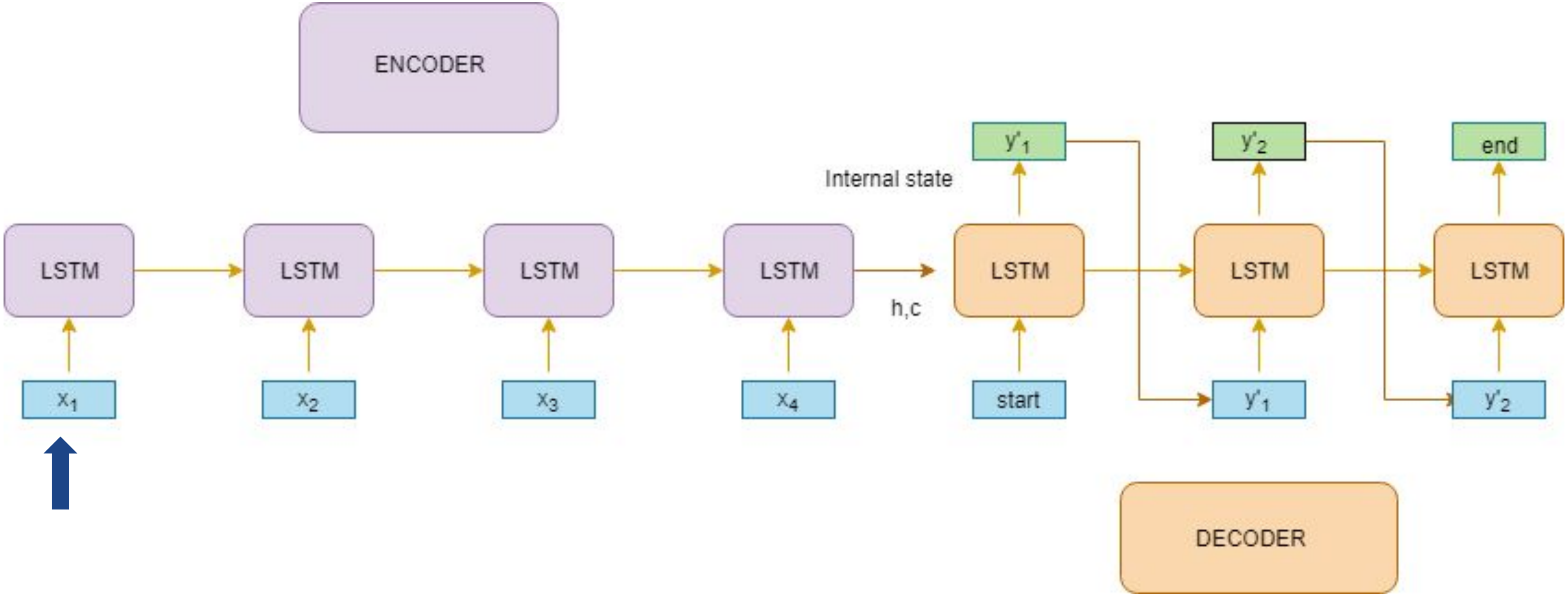
Encoder-Decoder → Stacked LSTM layers

Encoder-Decoder Architecture



LSTM-Architecture of our model built from scratch [1]

Encoder-Decoder Architecture



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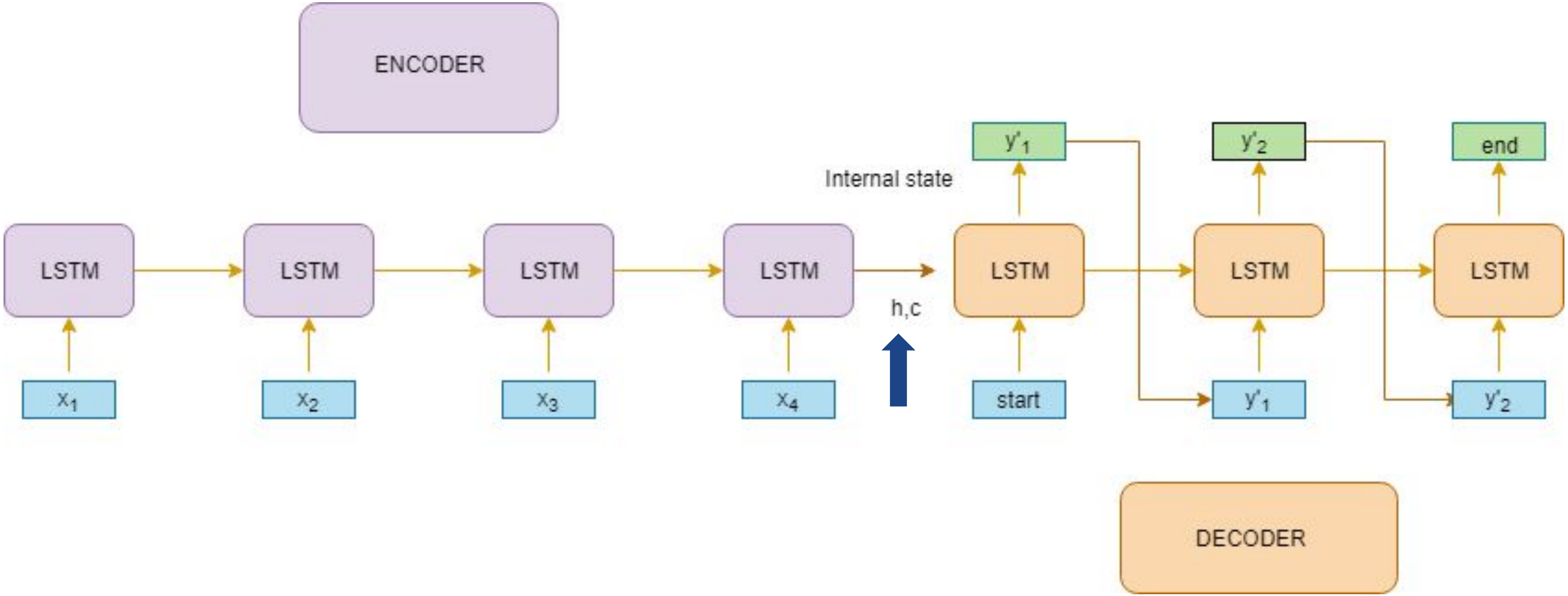


LSTM-Architecture of our model built from scratch [1]

Architecture

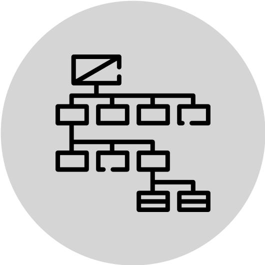
Attention Layer → Attention layer implemented in keras package

Encoder-Decoder → Stacked LSTM layers

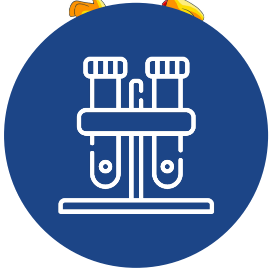
380 020 868 trainable parameters.

Our approach from scratch

Dataset



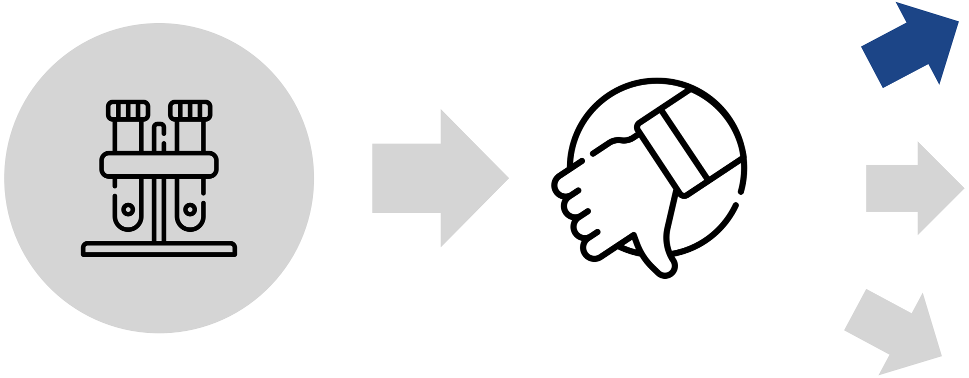
Architecture



Evaluation

Benchmark

Evaluation and Results



few number of epochs

small training sample size

model does not scale for larger amount of text

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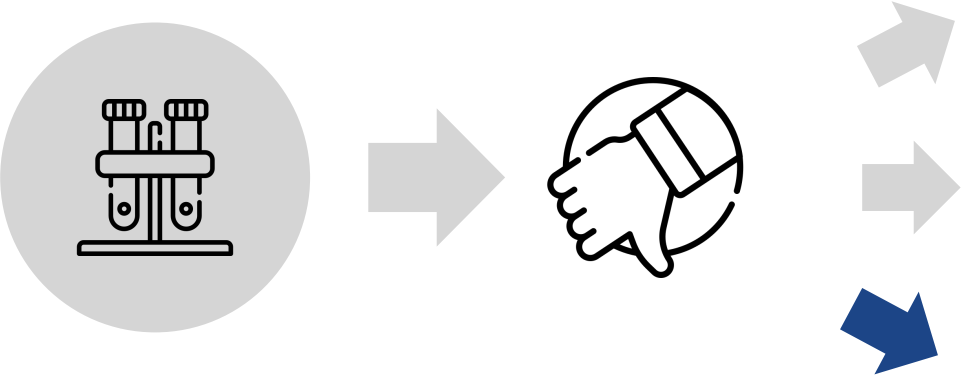

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sample size

model does not scale for
larger amount of text

Our approach from scratch

Dataset

Architecture

Training

Benchmark

Our benchmark speech

Speech given by Hermann Färber (CDU/CSU) on 11th of November 2019

Bundestag is discussing an agricultural bill regarding financial support for sheep and goat farmers

Hermann Färber (CDU/CSU)

Our benchmark speech

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Bundestag is discussing an agricultural bill regarding financial support for sheep and goat farmers

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Benchmark summary

faktual & TUM

“vereins vereins vereins vereins verbandsfreie verbands-freie verbandsfreie ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer rat-meyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyerratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer rat-meyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer”

Evaluation

Benchmark summary

“vereins vereins vereins vereins verbandsfreie verbands-freie verbandsfreie ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer rat-meyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyerratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer rat-meyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer”

Evaluation

Agenda

Data

Methodology

Models

- Model from scratch
- **MeanSum**
- BERT & BART
- Overall comparison

Use cases

Conclusion

Our unsupervised approach

Dataset

Architecture

Evaluation

Benchmark

Our unsupervised approach

faktual & TUM

MeanSum : A Neural Model for Unsupervised Multi-Document Abstractive Summarization

Eric Chu [*†1] Peter J. Liu [*2]

Abstract

Abstractive summarization has been studied using neural sequence transduction methods with datasets of large, paired document-summary examples. However, such datasets are rare and the models trained from them do not generalize to other domains. Recently, some progress has been made in learning sequence-to-sequence mappings with only unpaired examples. In our work, we consider the setting where there are only documents (product or business reviews) with no summaries provided, and propose an end-to-end, neural model architecture to perform unsupervised abstractive summarization. Our proposed model consists of an auto-encoder where the mean of the representations of the input reviews decodes to a reasonable summary-review while not relying on any review-specific features. We consider variants of the proposed architecture and perform an ablation study to show the importance of specific components. We show through automated metrics and human evaluation that the generated summaries are highly abstractive, fluent, relevant, and representative of the average sentiment of the input reviews. Finally, we collect a reference evaluation dataset and show that our model outperforms a strong extractive baseline.

or recognition of short utterances, for which there is an abundance of parallel data. The application of such models to longer sequences (multi-sentence documents or long audio) works reasonably well in production systems because the sequences can be naturally decomposed into the shorter ones the models are trained on and thus sequence-transduction can be done piece-meal.

Similar neural models have also been applied to abstractive summarization, where large numbers of document-summary pairs are used to generate news headlines (Rush et al., 2015) or bullet-points (Nallapati et al., 2016; See et al., 2017). Work in this vein has been extended by Liu et al. (2018) to the multi-document[1] case to produce Wikipedia article text from references documents.

However, unlike translation or speech recognition, adapting such summarization models to different types of documents without re-training is much less reasonable; for example, in general documents do not decompose into parts that look like news articles, nor can we expect our idea of saliency or desired writing style to correspond with that of particular news publishers. Re-training or at least fine-tuning such models on many in-domain document-summary pairs should be expected to get desirable performance. Unfortunately, it is very expensive to create a large parallel summarization corpus and the most common case in our experience is that we have many documents to summarize, but have few or no examples of summaries.

[3] Eric Chu and Peter Liu (2019)

Multi-document summarization model

Summarizes multiple Yelp reviews of the same business

Our unsupervised approach

faktual & TUM

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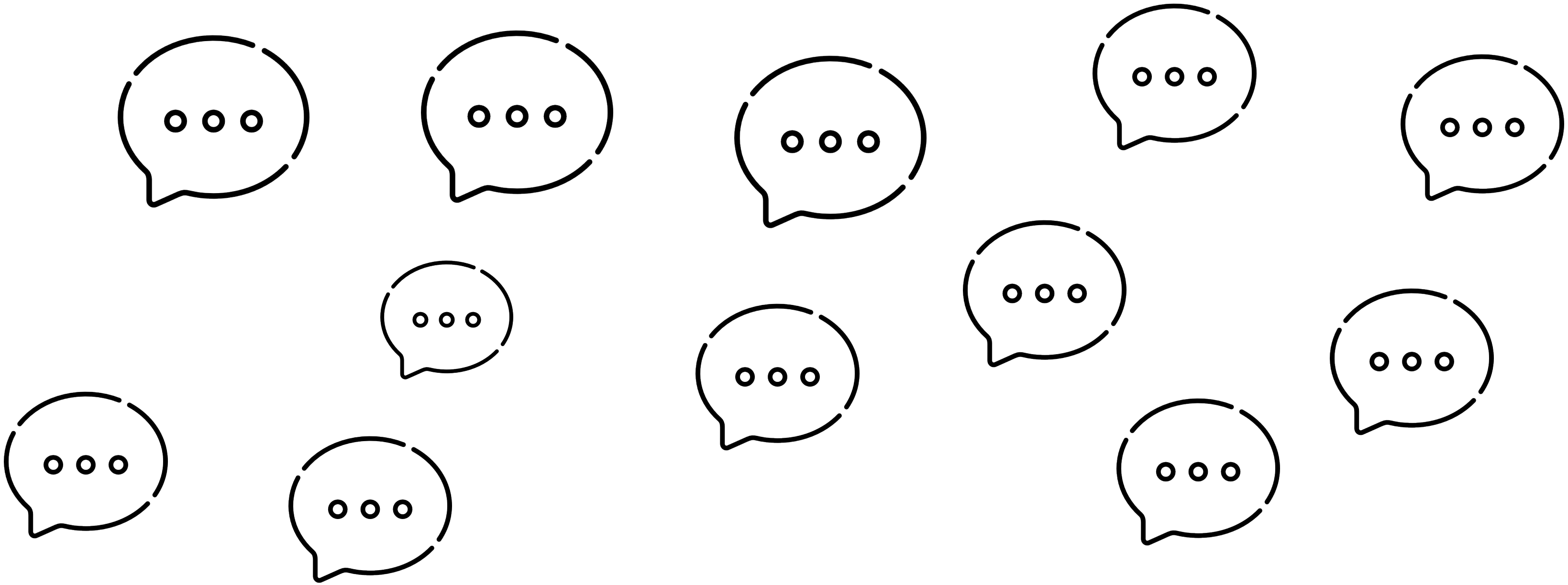
Creating a compatible dataset

faktual & TUM

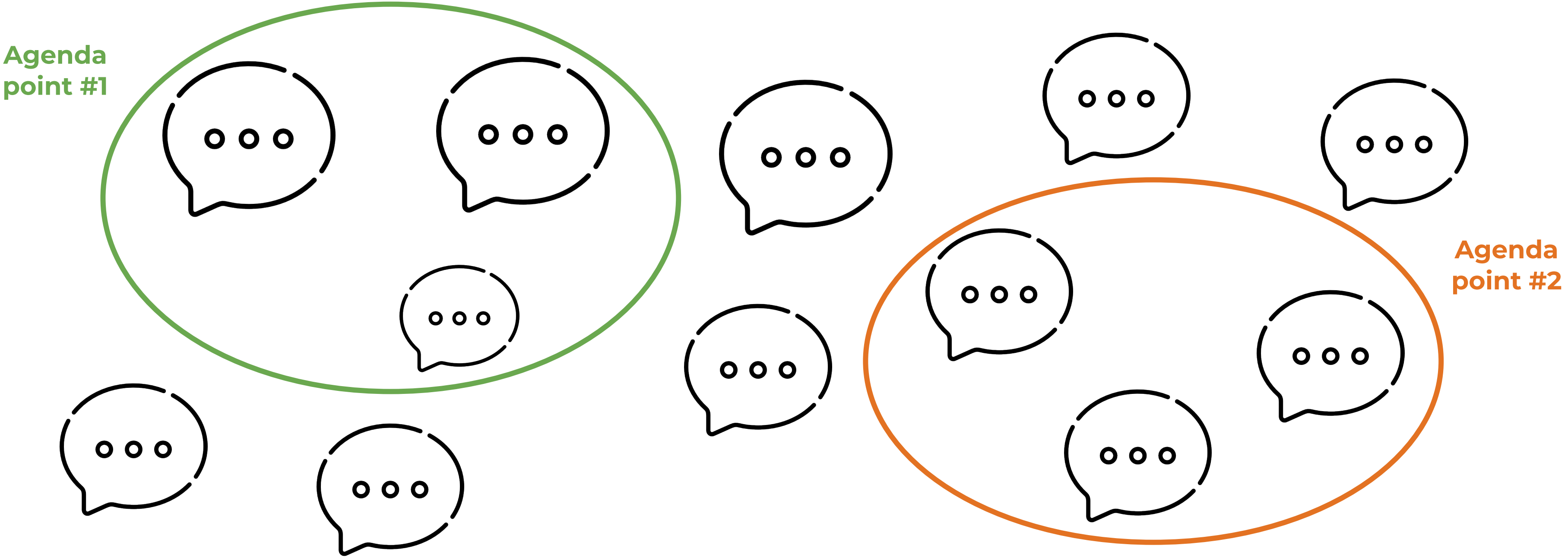


Cluster PP19-speeches by agenda point

1289 agenda points

22 speeches on average

Creating a compatible dataset



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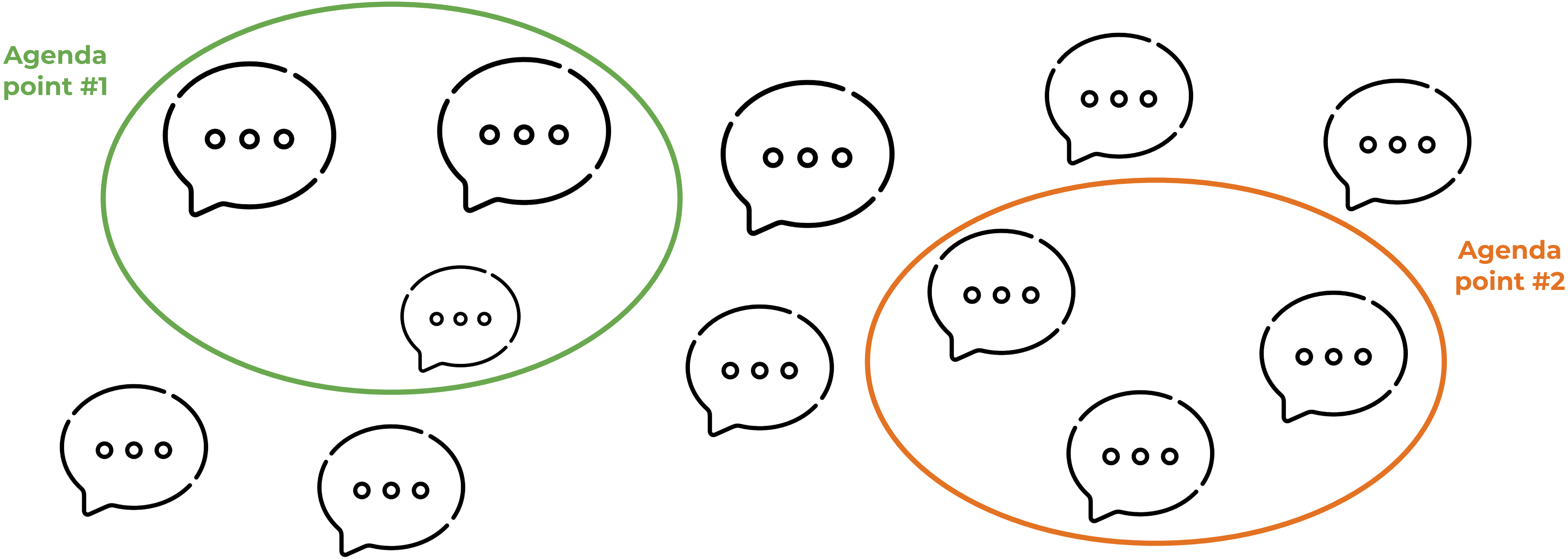

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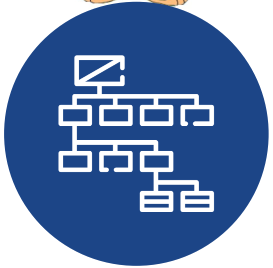
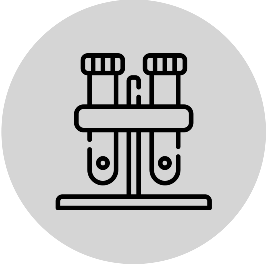
Unsupervised approach

MeanSum

Dataset



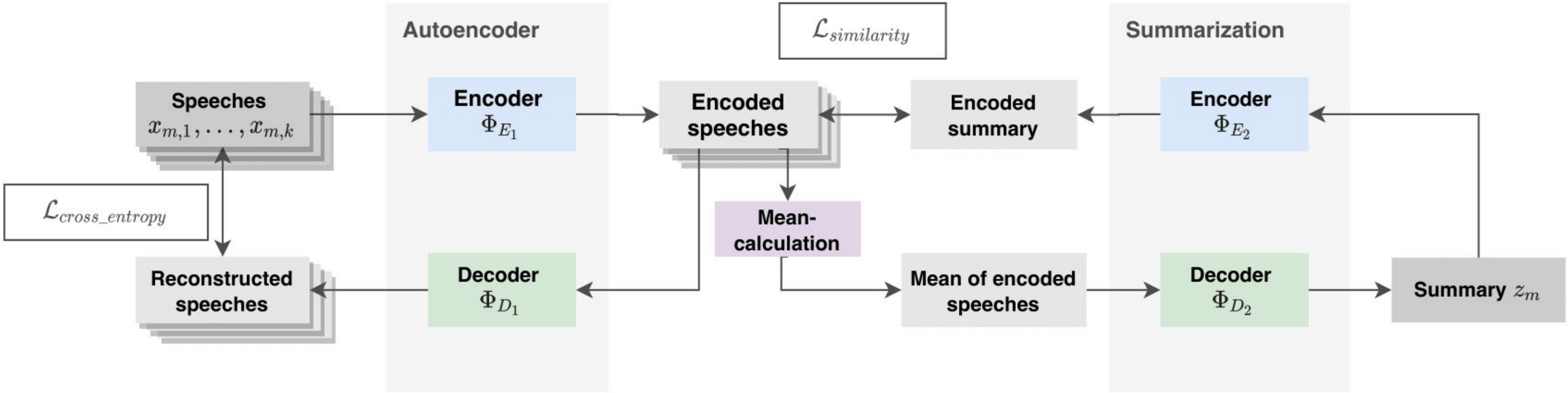
Architecture



Evaluation

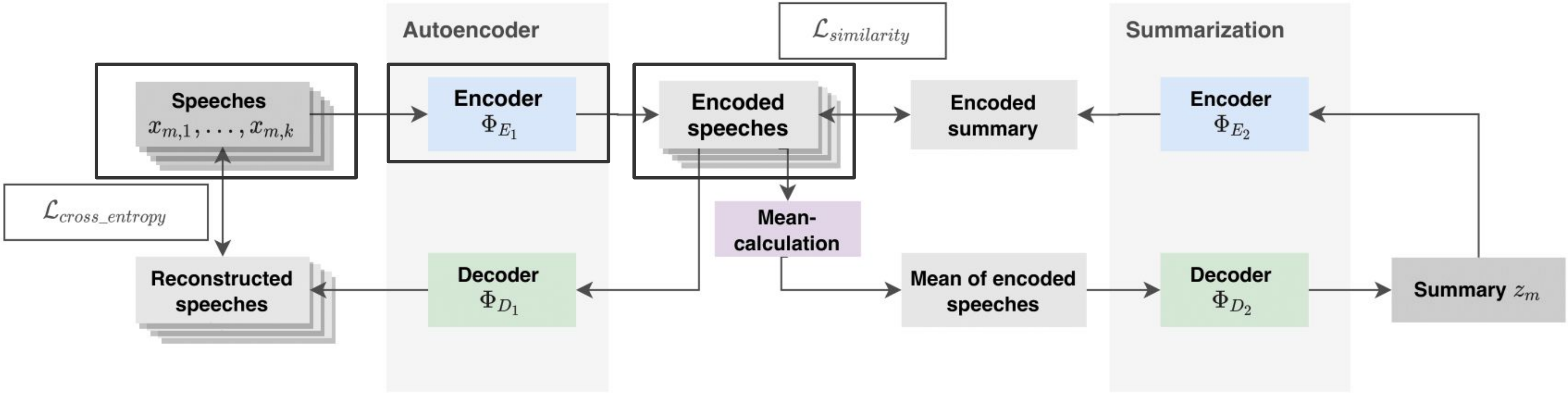
Benchmark

Model architecture



Model architecture

faktual & TUM



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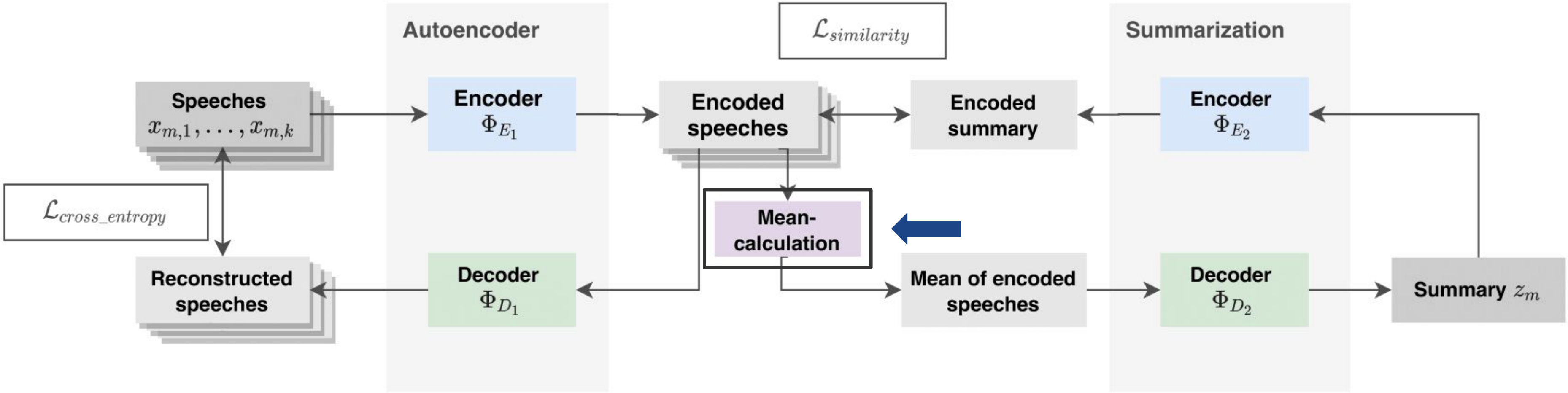

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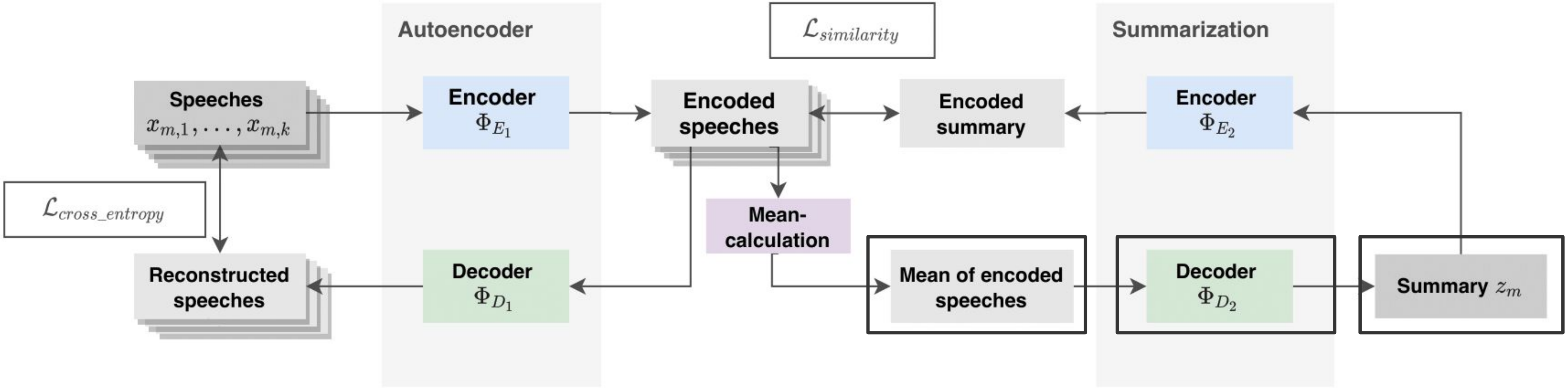

Our unsupervised approach

Dataset

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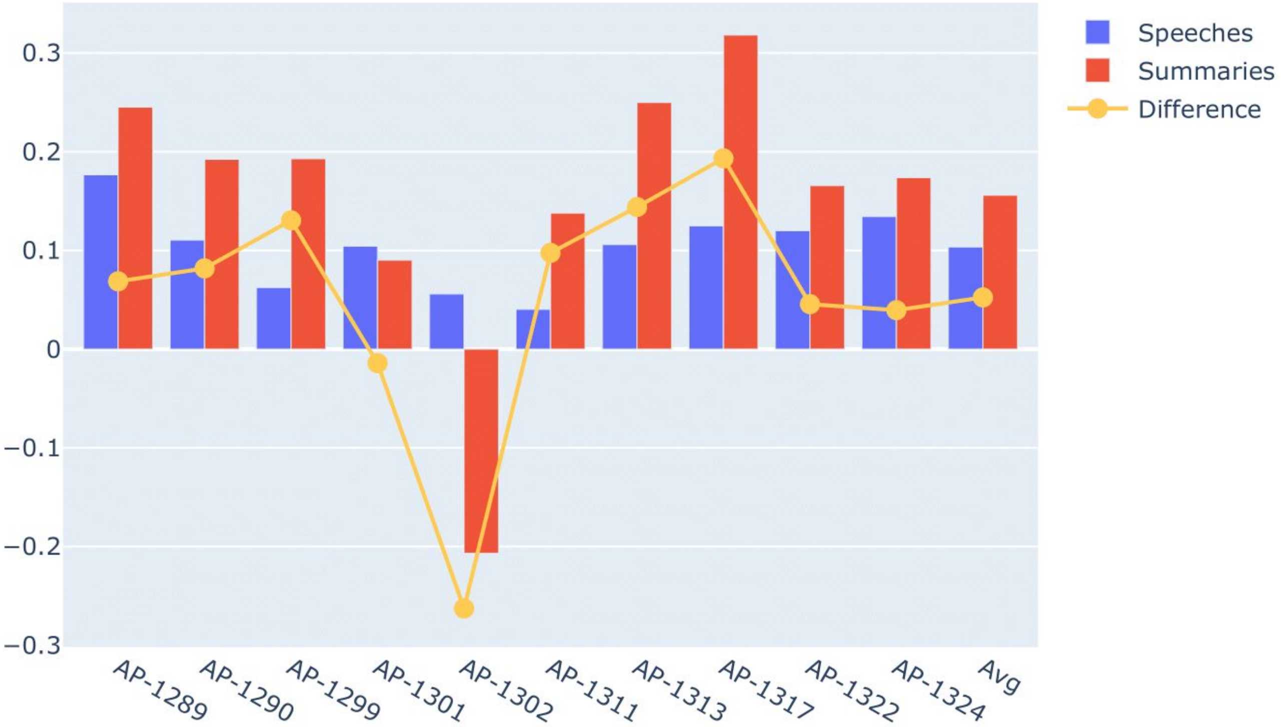
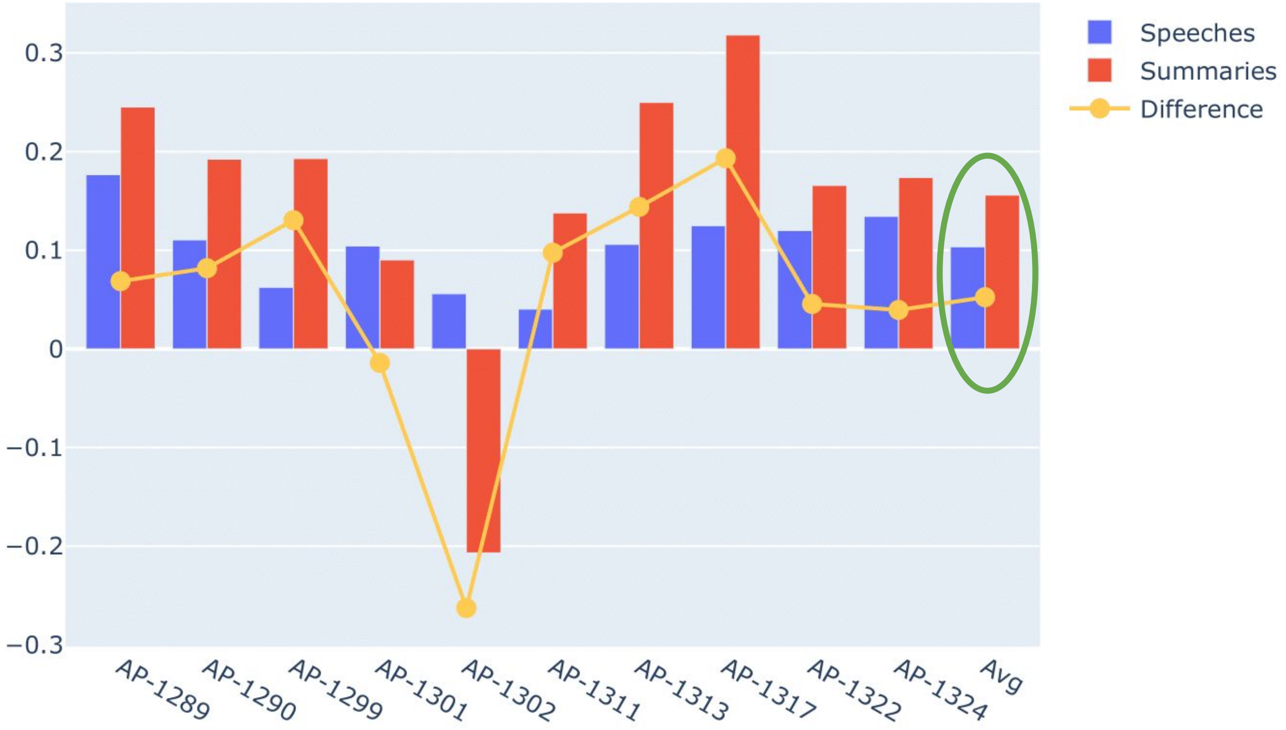
Quantitative evaluation

faktual & TUM



Sentiment analysis

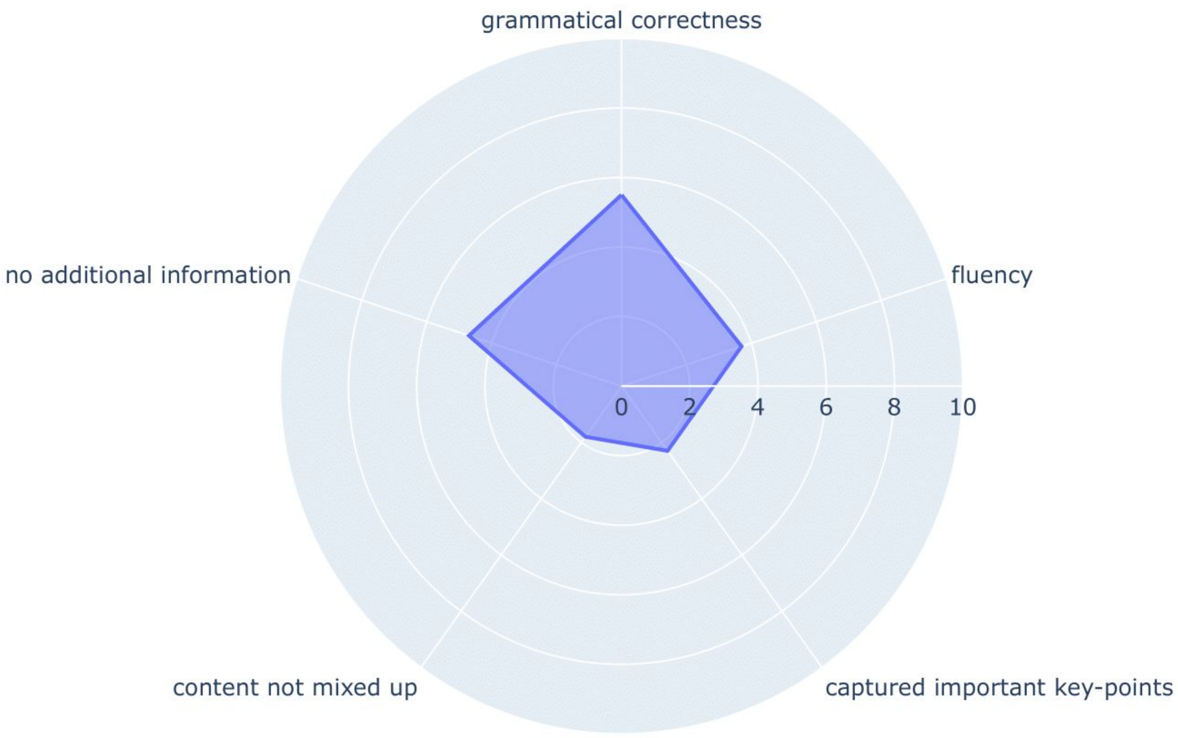
Quantitative evaluation



Sentiment analysis

Qualitative evaluation

faktual & TUM



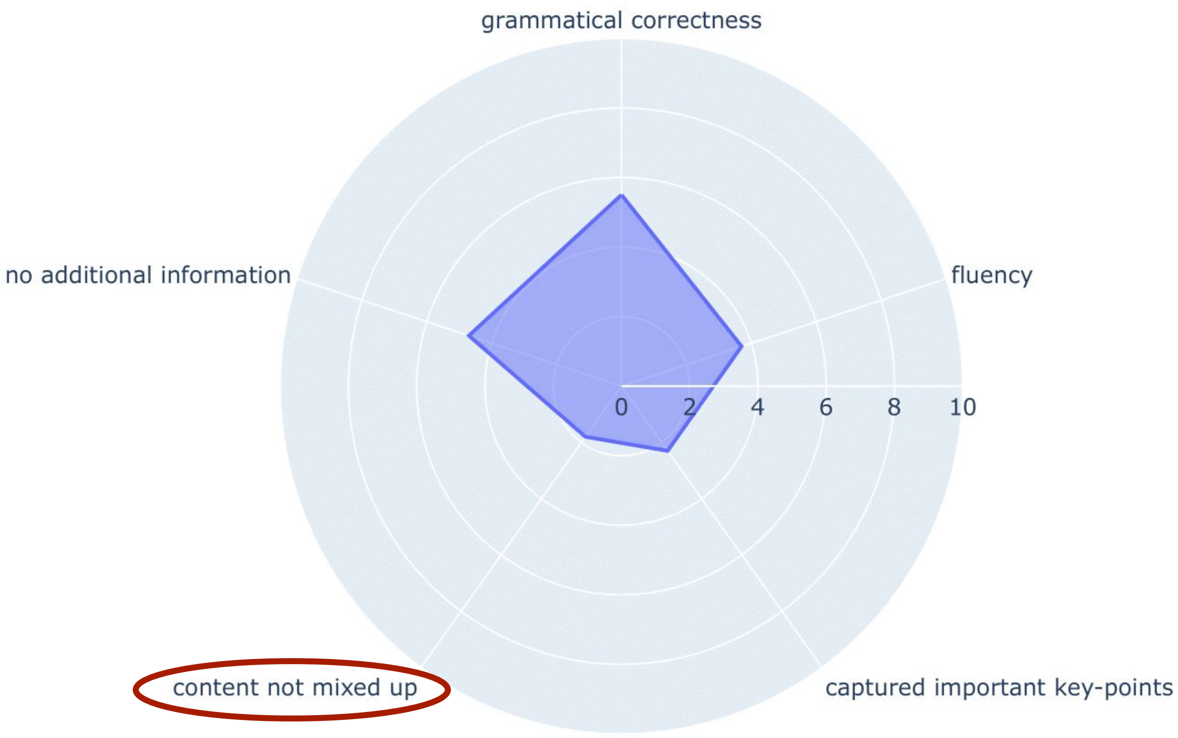
Questionnaire results

Model not designed for long input-sequences

Attention-mechanism likely to improve model

Qualitative evaluation

faktual & TUM



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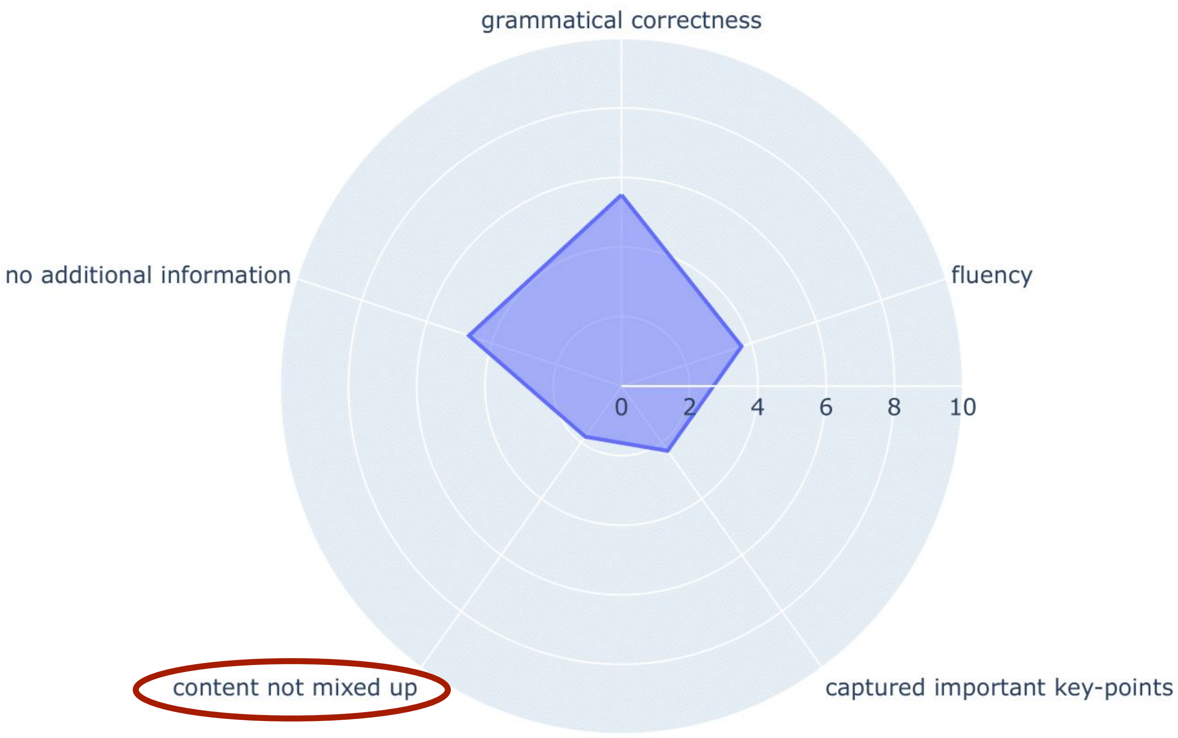

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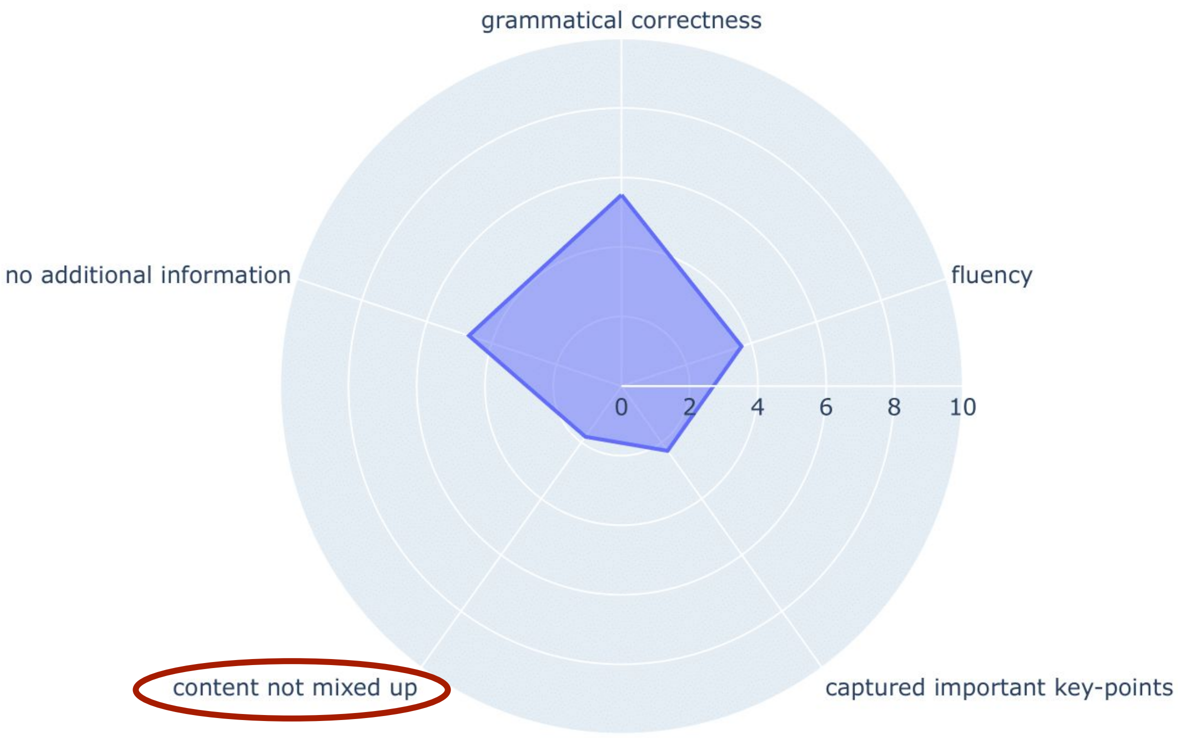

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Our unsupervised approach

Dataset

Architecture

Evaluation

Benchmark

Benchmark summary

faktual & TUM

“Hallo, liebe Kollegen! Liebe Gäste! Es geht darum, die Landwirtschaft zu fördern, auch wenn man sich das Ganze in einem Biergarten ansieht, der jetzt genutzt wird. Dies ist das Ergebnis der Bundesregierung und 2020. Meine Damen und Herren, meine Damen und Herren, lassen Sie uns auf die Erde gehen. Wir sind mitten im Budget. Dies ist ein großer Schritt nach vorne. Das kann man nicht einfach essen. Sie können auch darüber sprechen. Sie fordern das Steuerprivileg des EEG-Zuschlags, zum Beispiel für ein Video von 418 Millionen, das dann natürlich von der Regierung finanziert wird. Dies ist ein sehr wichtiger Schritt in Richtung Weltklima- und Umweltpolitik.”

Evaluation

Benchmark summary

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Evaluation

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faktual & TUM

Data

Methodology

Models

Use cases

Conclusion

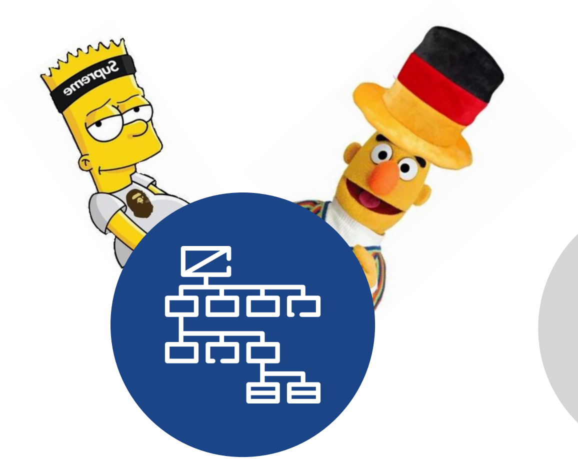
Model from scratch

MeanSum

BERT & BART

Overall comparison

BERT and BART

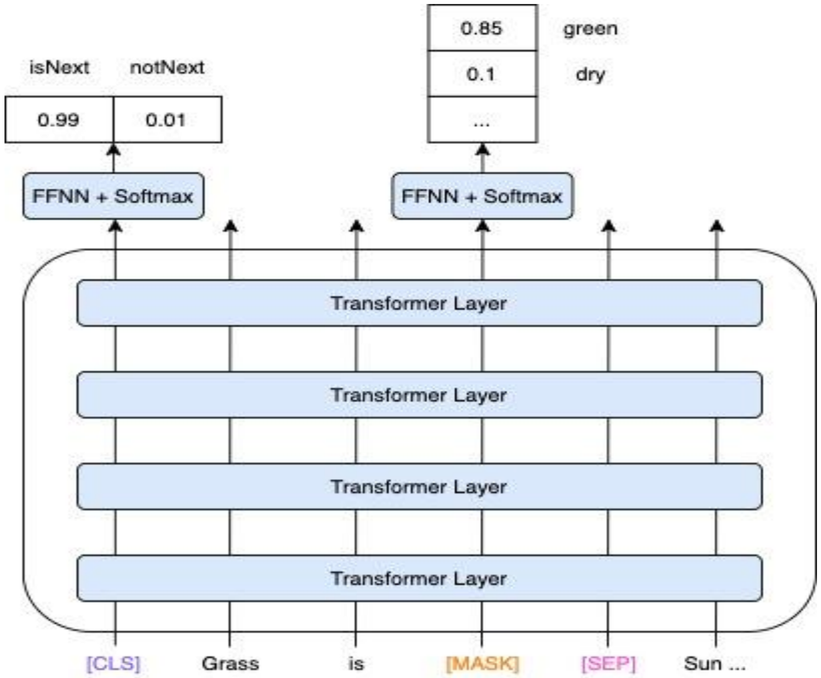


Architecture

Evaluation

Dataset

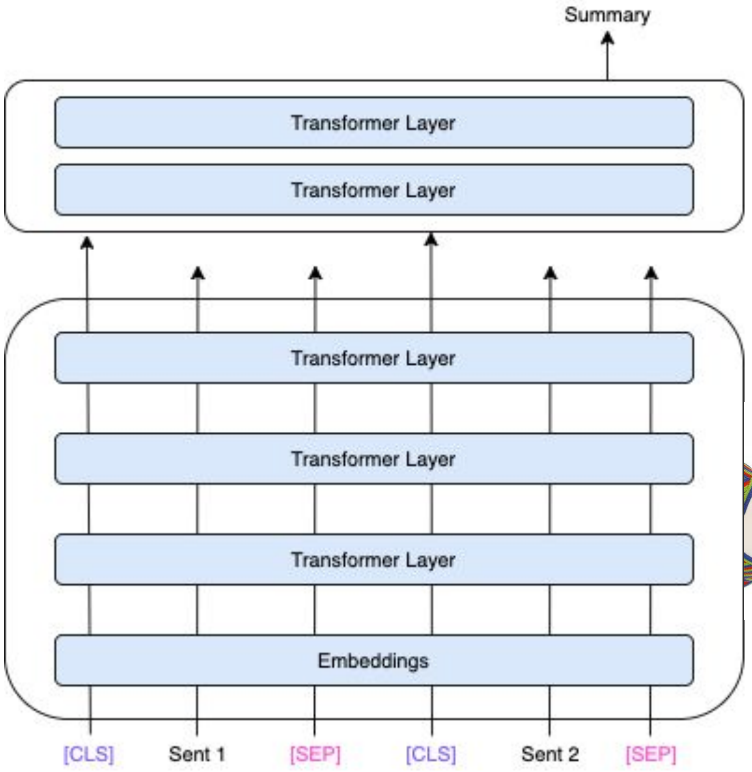
BERTSumAbs using German BERT



Bert

Bidirectional **E**ncoder **R**epresentations from **T**ransformers [2]

BERTSumAbs using German BERT



BERTSumAbs architecture [4]

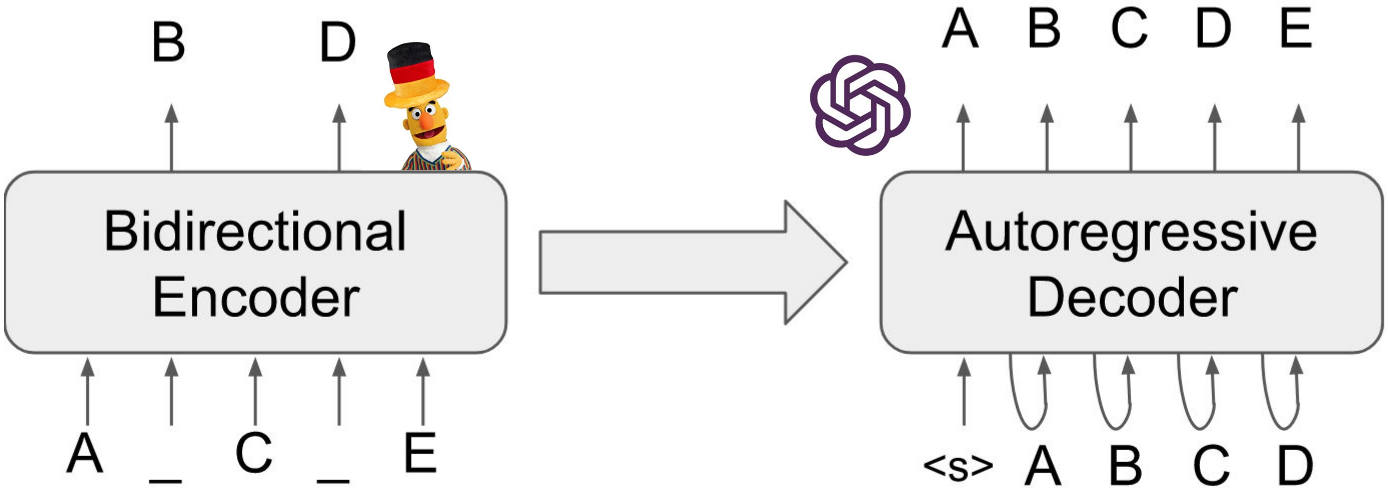
Benchmark summary

faktual & TUM

“Die Simmulation ist ein Verfahren zurückragung, bei der für die für die für die führte. Das Verfahren ist in der Regel für das Verfahrenzurückragung der Regel führt der Regel führte das Verfahren zurückragungen vonder Regel führte - und das Verfahren zurührt - das Verfahren zur Verfügung derRegel führt der Regel fürt - Änderung der Regel führte das Verfahren der Regelfuhrte.”

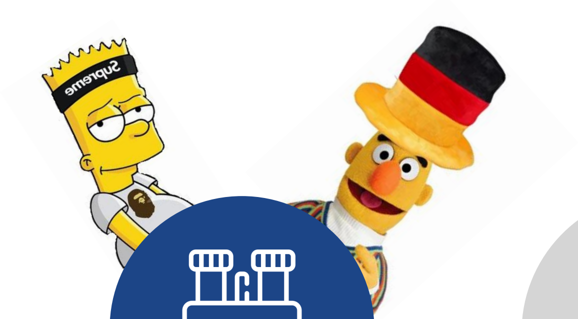
Evaluation


Supreme
Supreme



Bidirectional **A**uto**R**egressive **T**ransformer [5]

BERT and BART



Architecture

Evaluation

Dataset

Comparison BART and BERT

Model	R1-score	R2-score	RL-score	BERT-score	precision
BART	0.2024 (0.07)	0.0456 (0.04)	0.1955 (0.07)	**0.6251 (0.05)**	0.7274
BERTSumAbs	**0.2222 (0.12)**	**0.0801 (0.10)**	**0.2479 (0.13)**	0.6224 (0.08)	0.4454
lead-sum	0.1882 (0.08)	0.0412 (0.05)	0.1777 (0.07)	0.6112 (0.05)	**1.0**
english-lead-sum	0.1782 (0.07)	0.0341 (0.04)	0.1682 (0.06)	0.6049 (0.04)	0.7317

SwissText-Dataset

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faktual & TUM

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SwissText-Dataset

Benchmark summary

faktual & TUM

“Die AfD debattiert über das Gesetz zur Umsetzung von Direktzahlungen und die einmalige Erhöhung der Umschichtung um 1,5 Prozentpunkte. Dies entspricht einer Steigerung von 4,50 EUR pro Hektar von der ersten zur zweiten Säule der Agrarumweltprogramme. Die Gruppen Die Linke und Bündnis 90 / DieGrünen erkennen in ihrer Bewerbung zu Recht, dass die Schafzüchter mit ihrer Arbeit uns qualitativ hochwertige Produkte in der Bevölkerung liefern.”

Evaluation

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SwissText-Dataset

BART is highly extractive

BERT uses patterns

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SwissText-Dataset

BART is highly extractive

BERT uses patterns

Will BERT generalize?

BERT and BART

Architecture

Evaluation

Dataset

“Heute im Bundestag”-dataset

faktual & TUM

Deutscher Bundestag
19. Wahlperiode

Druckache 19/20920
08.07.2020

Gesetzentwurf
der Bundesregierung

**Entwurf eines Gesetzes
zu dem Protokoll vom 10. Oktober 2018
zur Änderung des Übereinkommens vom 28. Januar 1981
zum Schutz des Menschen
bei der automatischen Verarbeitung
personenbezogener Daten**

A. Problem und Ziel

Das Übereinkommen vom 28. Januar 1981 zum Schutz des Menschen bei der automatischen Verarbeitung personenbezogener Daten (BGBl. 1985 II S. 538, 539) war das erste rechtsverbindliche zwischenstaatliche Übereinkommen zum Datenschutz. Nach mehrjährigen Verhandlungen haben sich die Konventionsstaaten im Jahr 2018 auf ein Änderungsprotokoll geeinigt, das die Konvention 108 modernisiert (Protokoll vom 10. Oktober 2018 zur Änderung des Übereinkommens vom 28. Januar 1981 zum Schutz des Menschen bei der automatischen Verarbeitung personenbezogener Daten). So werden etwa die Betroffenenrechte gestärkt und eine Meldepflicht für Verantwortliche bei Verletzungen des Datenschutzes an die Aufsichtsbehörde eingeführt. Die Schaffung einer unabhängigen Aufsichtsbehörde wird für alle Konventionsstaaten verpflichtend.

Der Rat der Europäischen Union hat die Mitgliedstaaten der Europäischen Union ermächtigt, das Änderungsprotokoll zu ratifizieren.

Nach Artikel 59 Absatz 2 Satz 1 des Grundgesetzes ist die Zustimmung der gesetzgebenden Körperschaften zu dem Änderungsprotokoll Voraussetzung für dessen Ratifikation.

Vorabfassung - wird durch die lektorierte Fassung ersetzt.

Breitband soll Universaldienst werden

Verkehr und digitale Infrastruktur/Antrag - 08.07.2020 (hib 735/2020)

Berlin: (hib/SCR) Die Fraktion Bündnis 90/Die Grünen will einen "Rechtsanspruch auf einen schnellen Breitband-Internetanschluss" festschreiben. Ein solcher Anschluss sei "eine wichtige Voraussetzung für die gleichberechtigte Teilhabe am gesellschaftlichen, wirtschaftlichen und kulturellen Leben", führen die Grünen aus und weisen auf entsprechende Versorgungsprobleme gerade im ländlichen Raum hin. In einem Antrag (19/20786) fordert die Fraktion die Bundesregierung unter anderem auf, die Bundesnetzagentur zum Handeln zu bewegen. Die Bundesnetzagentur soll nach Vorstellung der Grünen auf Grundlage der Regelungen zum Universaldienst im Telekommunikationsgesetz (§ 78 ff.) "den Bedarf der Breitband-Universaldienstleistung bei den Endnutzerinnen und Endnutzern formal" feststellen, "insbesondere hinsichtlich der geographischen Versorgung". In unterversorgten Gebieten soll die Netzagentur die Erbringung des Breitband-Universaldienstes ausschreiben.

Zudem wollen die Grünen die Internetdienstanbieter stärker hinsichtlich der zugesicherten Bandbreite in die Pflicht nehmen. Verbraucher sollen laut Antrag ein Sonderkündigungsrecht beziehungsweise ein Recht auf Tarifanpassung erhalten, wenn die angepriesene und die tatsächlich gemessene Leistung erheblich, kontinuierlich und wiederkehrend voneinander abweichen. Zudem fordern die Grünen erweiterte Sanktionsmöglichkeiten für die Bundesnetzagentur. Sie soll laut Antrag "umsatzbezogene Bußgelder von bis zu vier Prozent des in Deutschland im betreffenden Geschäftsbereich erzielten Jahresumsatzes" des Vorjahres verhängen können.

Drucksachen

50 suitable press releases

Comparison BART and BERT

Model	R1-score	R2-score	RL-score	BERT
BART	0.1275	0.0288	0.1383	**0.5994**
distil-BERTSumAbs	0.0983	0.0053	0.0784	0.4867
rand-sum	**0.2300**	**0.0338**	**0.1833**	0.5863
lead-sum	0.0123	0	0.174	0.4713

Heute im Bundestag-Dataset

BART is highly extractive

BERT uses patterns

Will BERT generalize?

Comparison BART and BERT

faktual & TUM

Model	R1-score	R2-score	RL-score	BERT
BART	0.1275	0.0288	0.1383	**0.5994** ✓
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rand-sum	**0.2300**	**0.0338**	**0.1833**	0.5863
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Heute im Bundestag-Dataset

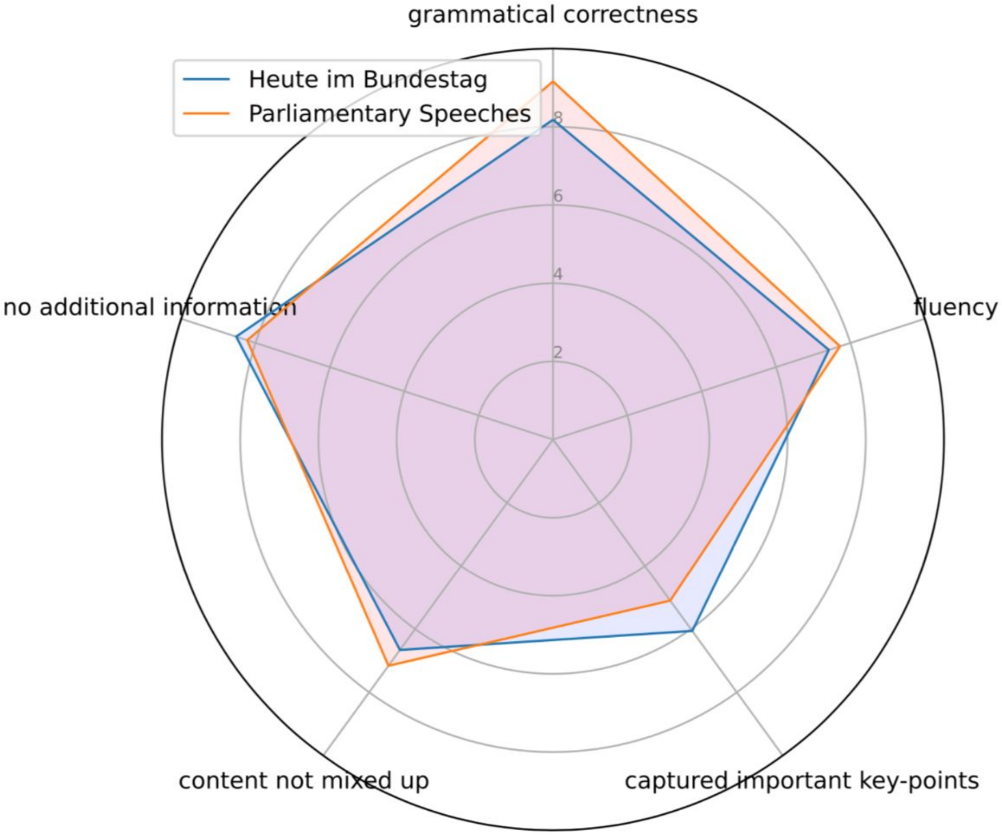
BART is highly extractive

BERT uses patterns

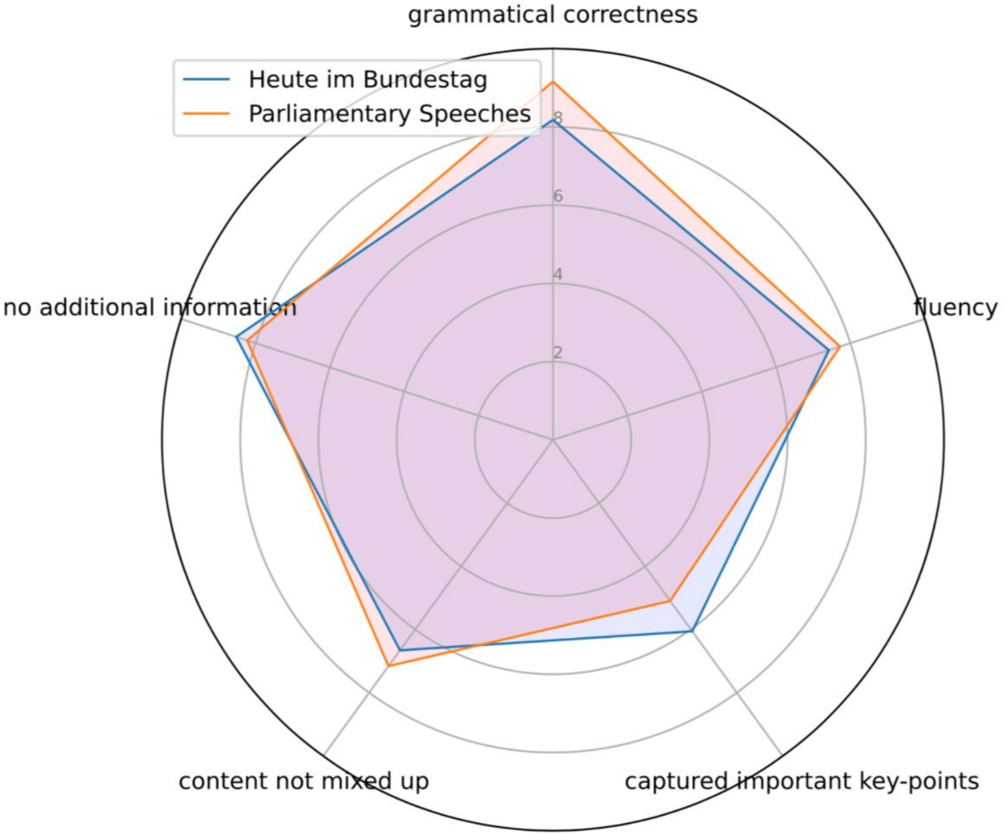
BART generalizes

BERT does not

Qualitative evaluation of BART



Qualitative evaluation of BART

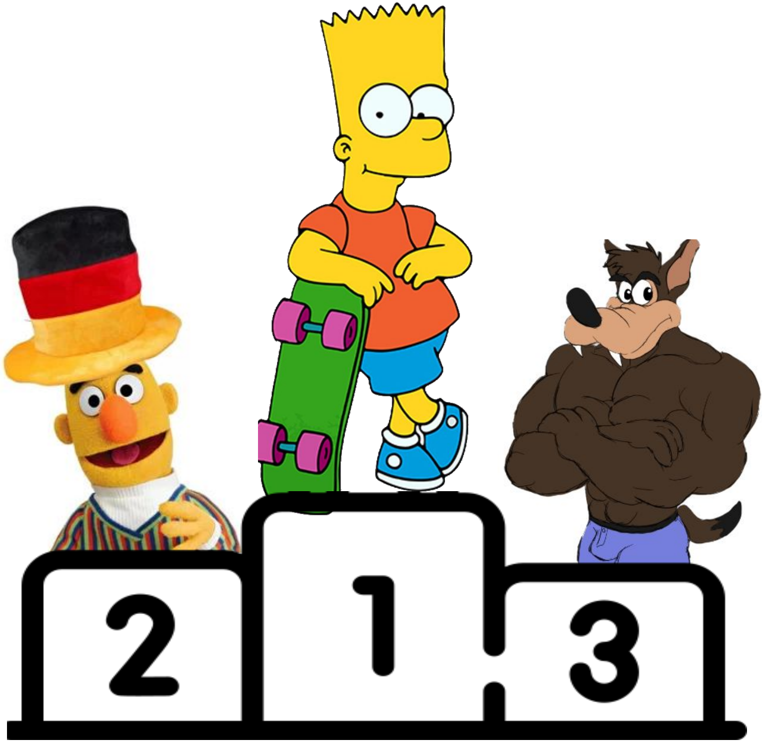


Agenda

Data | Methodology | **Models** | Use cases | Conclusion

- Model from scratch
- MeanSum
- BERT & BART
- **Overall comparison**

Our approaches



Agenda

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Data

Methodology

Models

Use cases

Conclusion

Journalism

MVP

Application in journalism

When writing articles, journalists face a vast amount of session protocols and Drucksachen

An easy way to retrieve key points would facilitate the life of journalists considerably

To cover the Bundestag, speed and accuracy are key

Meinolf Ellers | CDO @ DPA

Application in journalism

faktual & TUM

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Agenda

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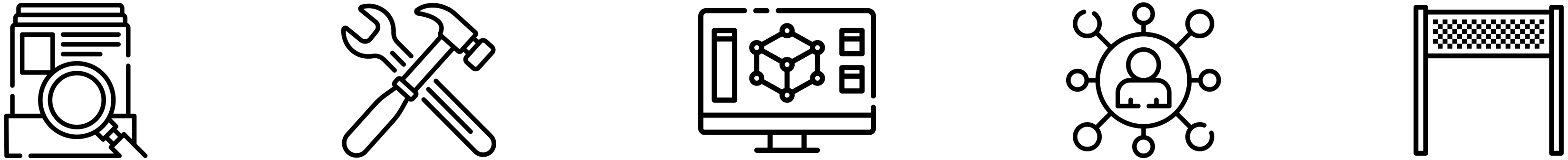

Data → Methodology → Models → **Use cases** → Conclusion

- Journalism
- **MVP**

Our minimum viable product

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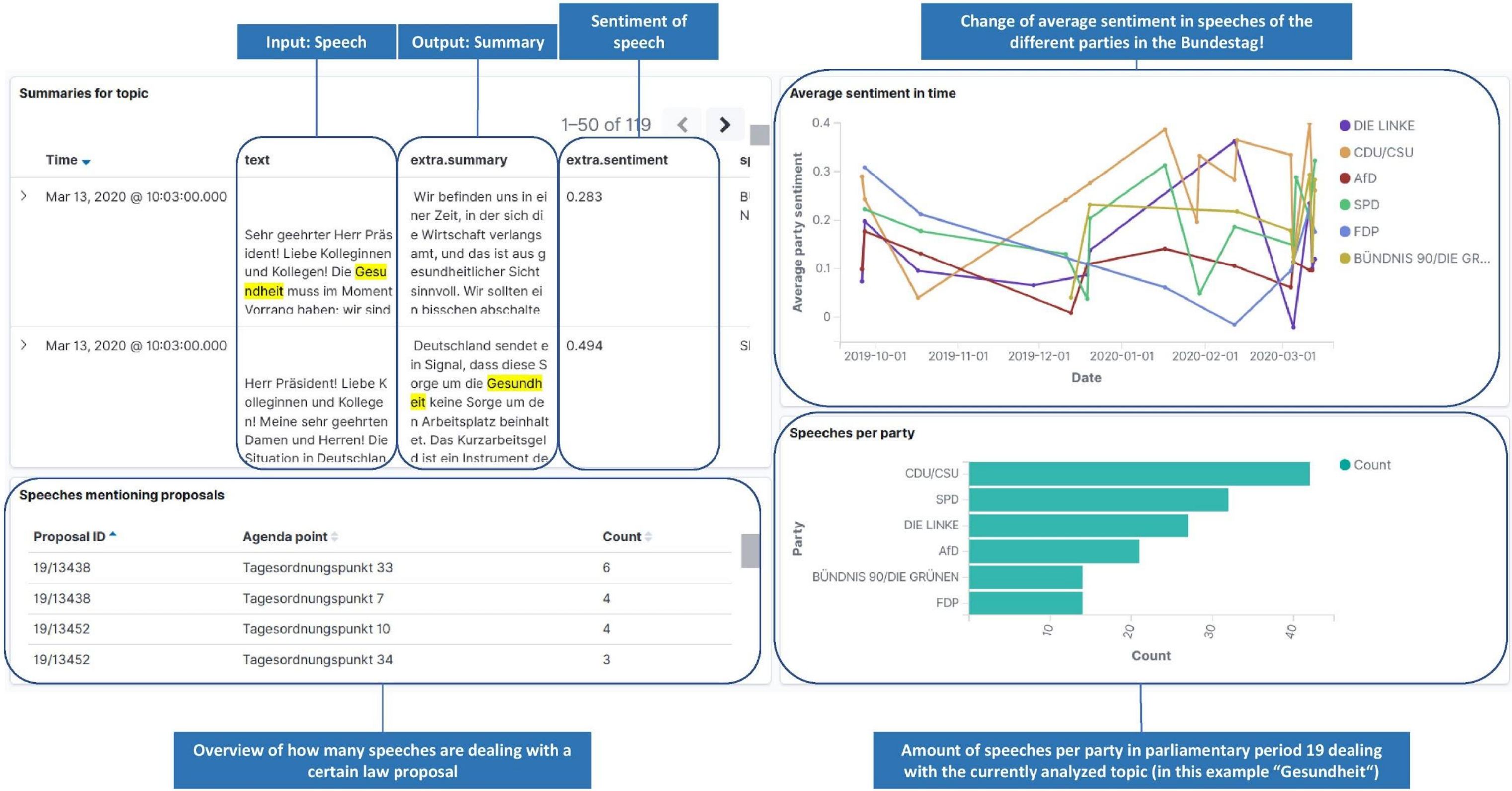

Agenda

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Data

Methodology

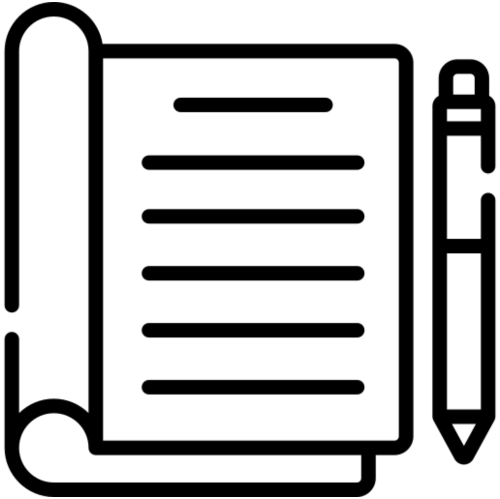
Models

Use cases

Conclusion

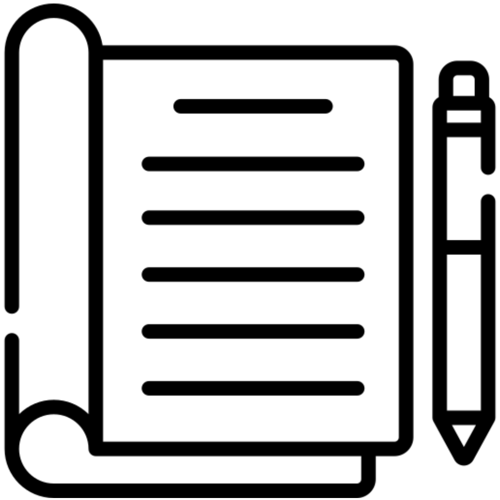
Our recommendations to faktual

faktual & TUM



1. Use pretrained models
2. Use supervised approaches
3. Use English-based models

Our recommendations to faktual



1. Use pretrained models
2. Use supervised approaches
3. Use English-based models

Our recommendations to faktual

1. Use pretrained models
2. Use supervised approaches
3. **Use English-based models**

Thank you for your support throughout our project!

References

[1] Pai, A. (2019). Comprehensive Guide to Text Summarization using Deep Learning in Python. Retrieved from https://www.analyticsvidhya.com/blog/2019/06/comprehensive-guide-text-summarization-using-deep-learning-python/ .

[2] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

[3] Chu, E., & Liu, P. (2019, May). MeanSum: a neural model for unsupervised multi-document abstractive summarization. In International Conference on Machine Learning (pp. 1223-1232).

[4] Liu, Y., & Lapata, M. (2019). Text summarization with pretrained encoders. arXiv preprint arXiv:1908.08345.

[5] Lewis, M., Liu, Y., Goyal, N., Ghazvininejad, M., Mohamed, A., Levy, O., ... & Zettlemoyer, L. (2019). Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. arXiv preprint arXiv:1910.13461.

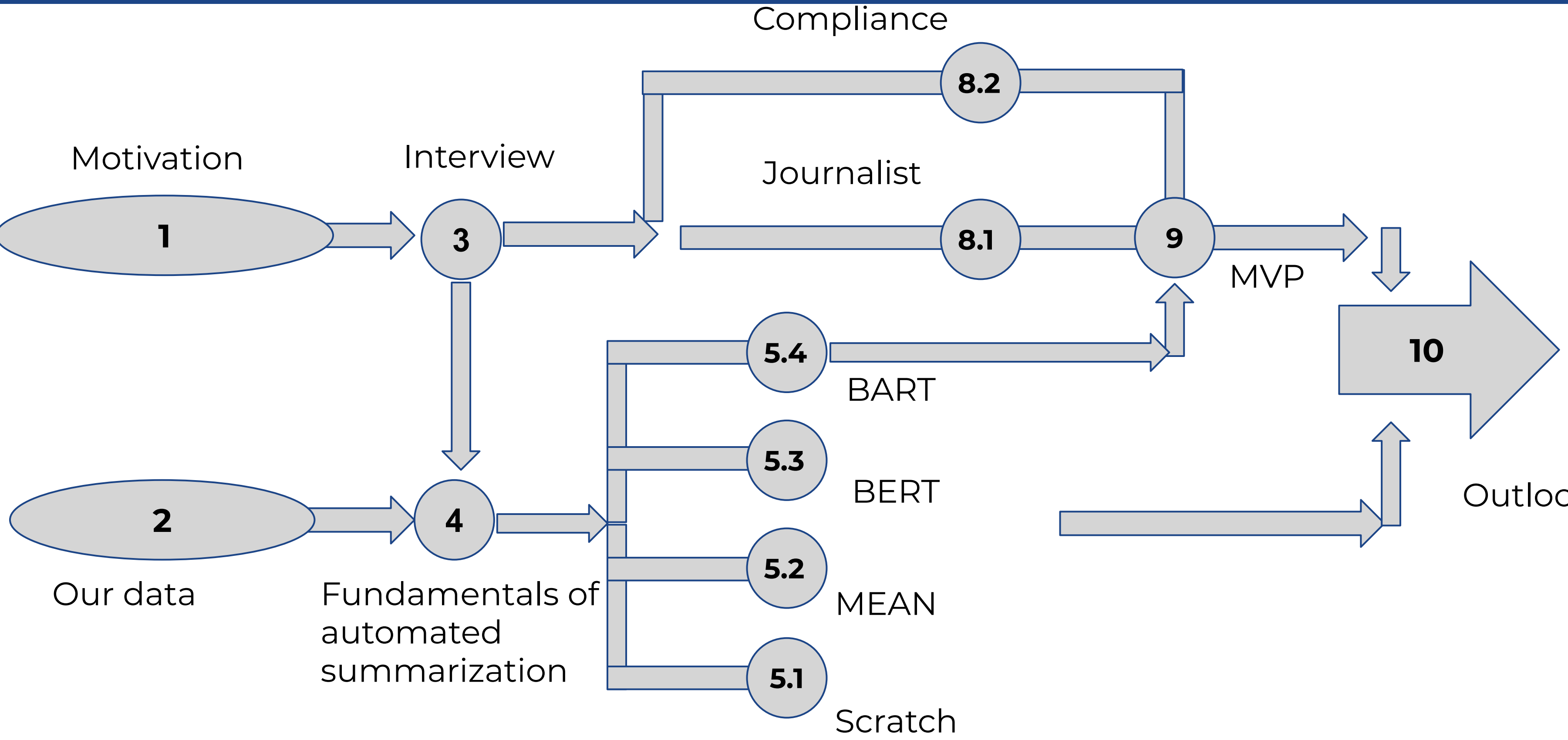
Attributions

All icons made by Freepik from www.flaticon.com

BART images adapted from
https://www.goodfon.com/download/multfilm-shou-simpsons-personazh-bart-art-risunok-multseri-2/1920x1080/
and https://www.pinterest.de/pin/680676931152976911/
GermanBERT from https://deepset.ai/german-bert
HuggingFace logo from https://huggingface.co/
OpenAI Logo from http://allvectorlogo.com/openai-logo/
Logo “abstraction captioning” https://creativemarket.com/eucalyp

Back-up

Overview of our project



Storing of our data

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MongoDB-storage

Established text indexing for fast searching capabilities

Able to accesss additional metadata for all Bundestag members from 1940 to 2020

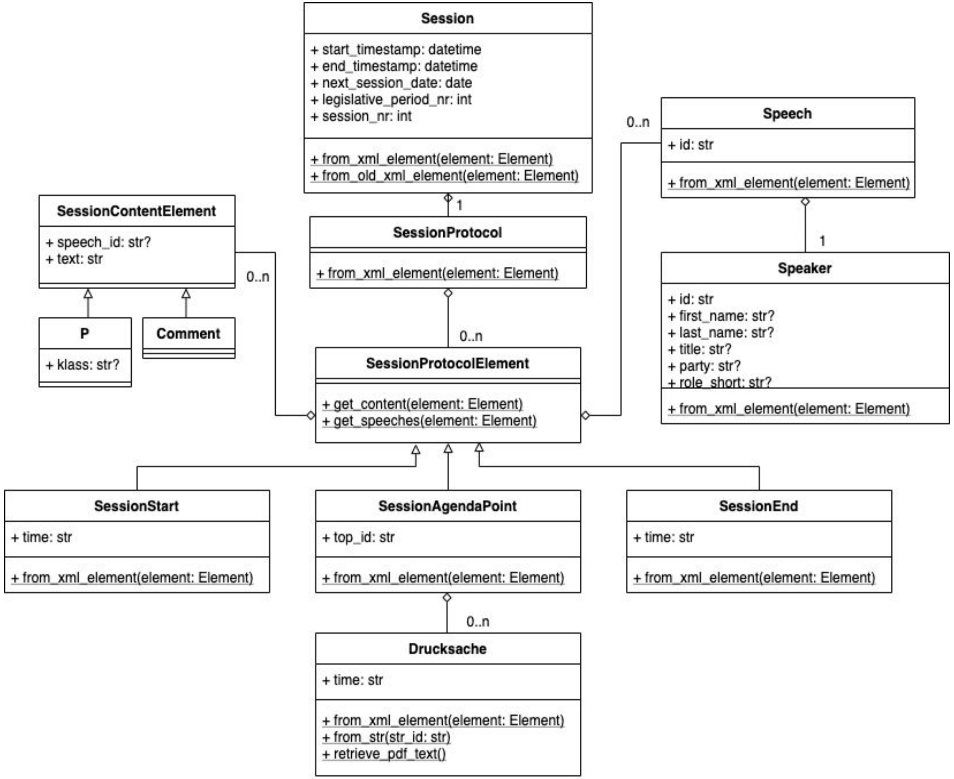

```
_id: "19/1"
start_timestamp: 2017-10-24T11:00:00.000+00:00
end_timestamp: 2017-10-24T17:03:00.000+00:00
next_session_date: 2017-11-22T00:00:00.000+00:00
legislative_period_nr: 19
session_nr: 1
v agenda_points: Object
  v 1: Object
    > introduction: Array
    v speech: Object
      v ID19100100: Object
          _id: "ID19100100"
        v speaker: Object
            _id: "11002190"
            first_name: "Alterspräsident Dr. Hermann"
            last_name: "Otto Solms"
            title: null
            role_short: "Alterspräsident"
            role_long: "Alterspräsident"
            location: null
            party: null
        > speech_elements: Array
      > ID19100200: Object
  > 2: Object
  > 3: Object
```

UML-diagram

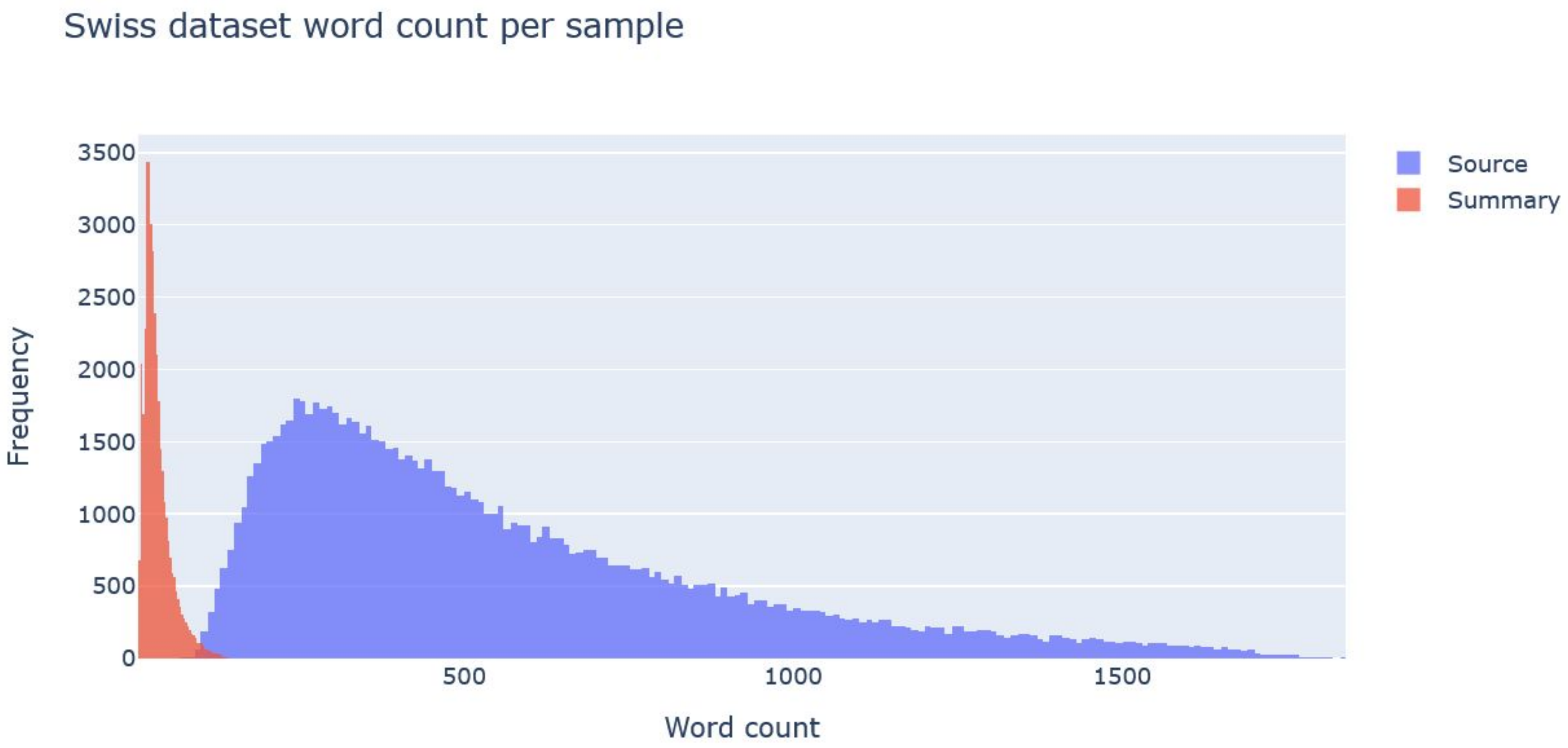
Able to access data from pp14 to pp18 in the same way as the data from pp19

Established automatic extraction of Drucksachen mentioned in protocol text

Created interface for downloading and extracting current Drucksachen from Bundestag website



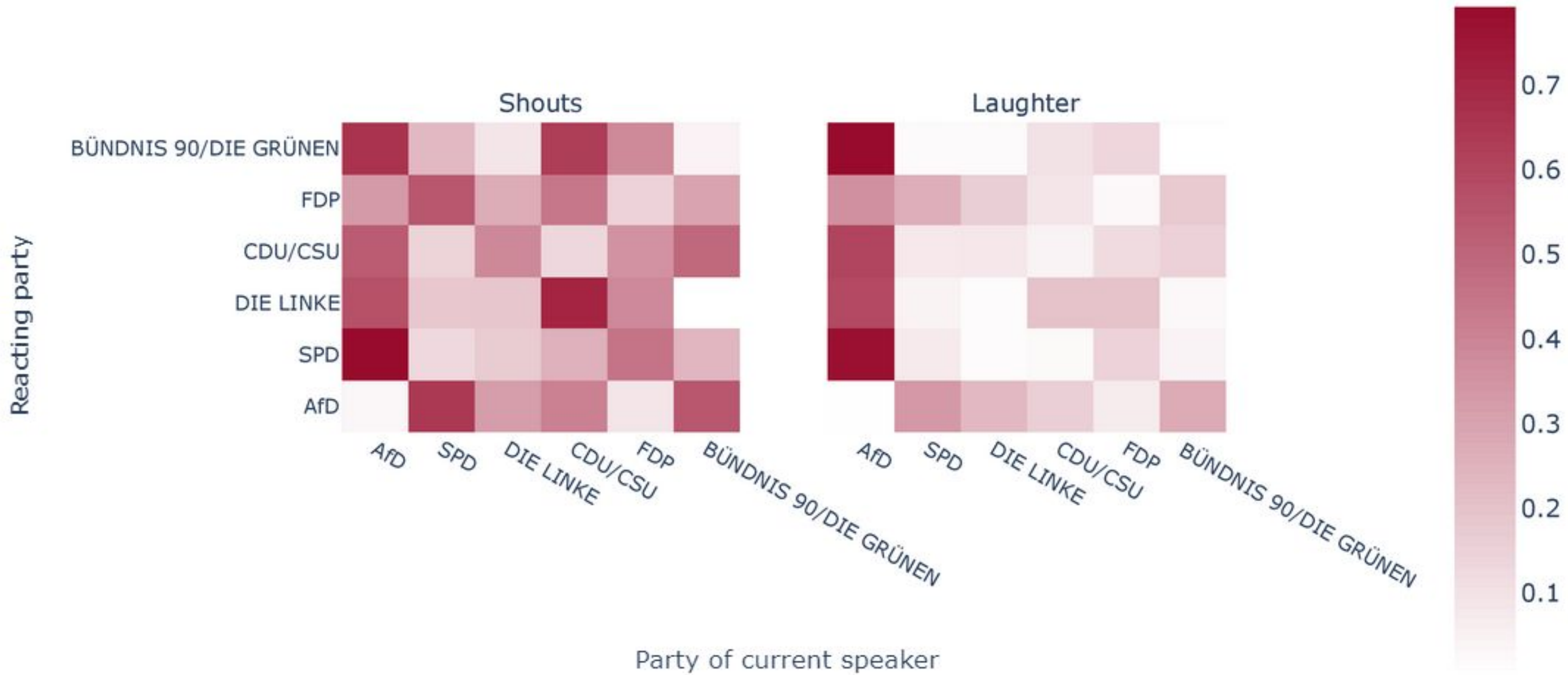
The "SwissText"-dataset



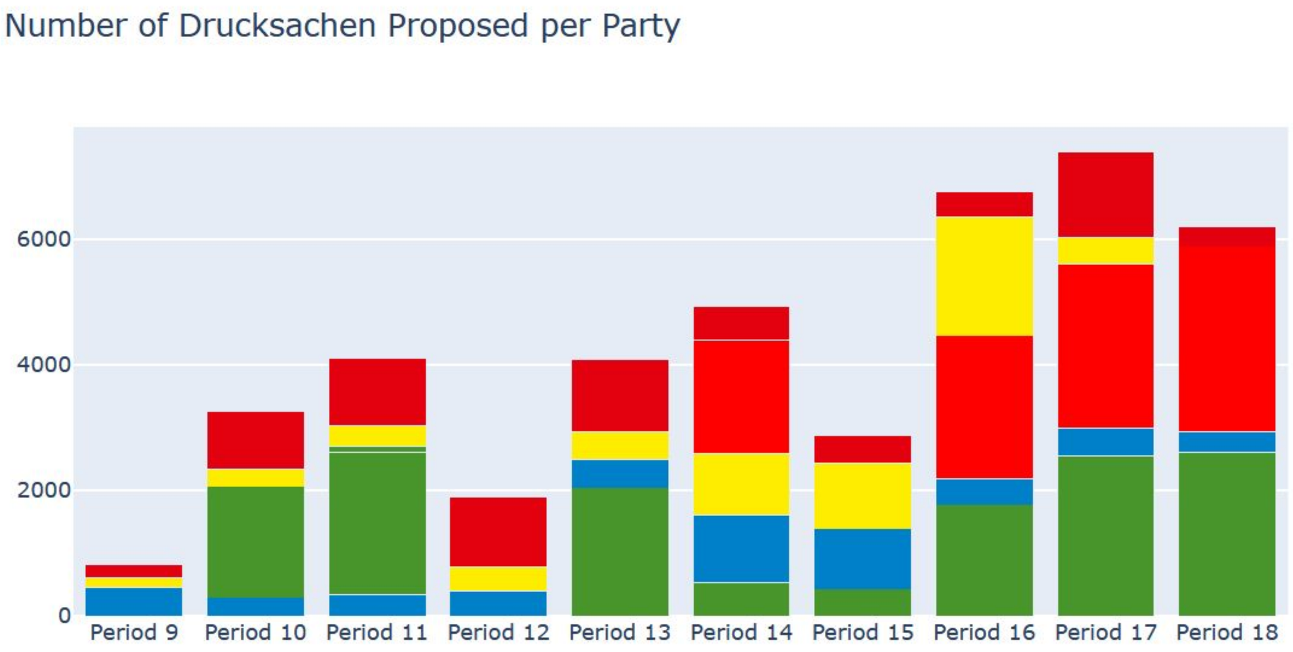
Frequent Terms

Legislative Period	Years	Words
14	1998-2002	Kuba, Stammzellen, Öcalan
15	2002-2005	Moldau, HIV, Ukraine, Baukultur
16	2005-2009	Cannabis, Roma/Sinti, Sri Lanka
17	2009-2013	Glyphosat, Westsahara, Honig
18	2013-2017	Europol, Isis, Substanzen
19	2017-...	Gigawatt, Adoption, LKWs

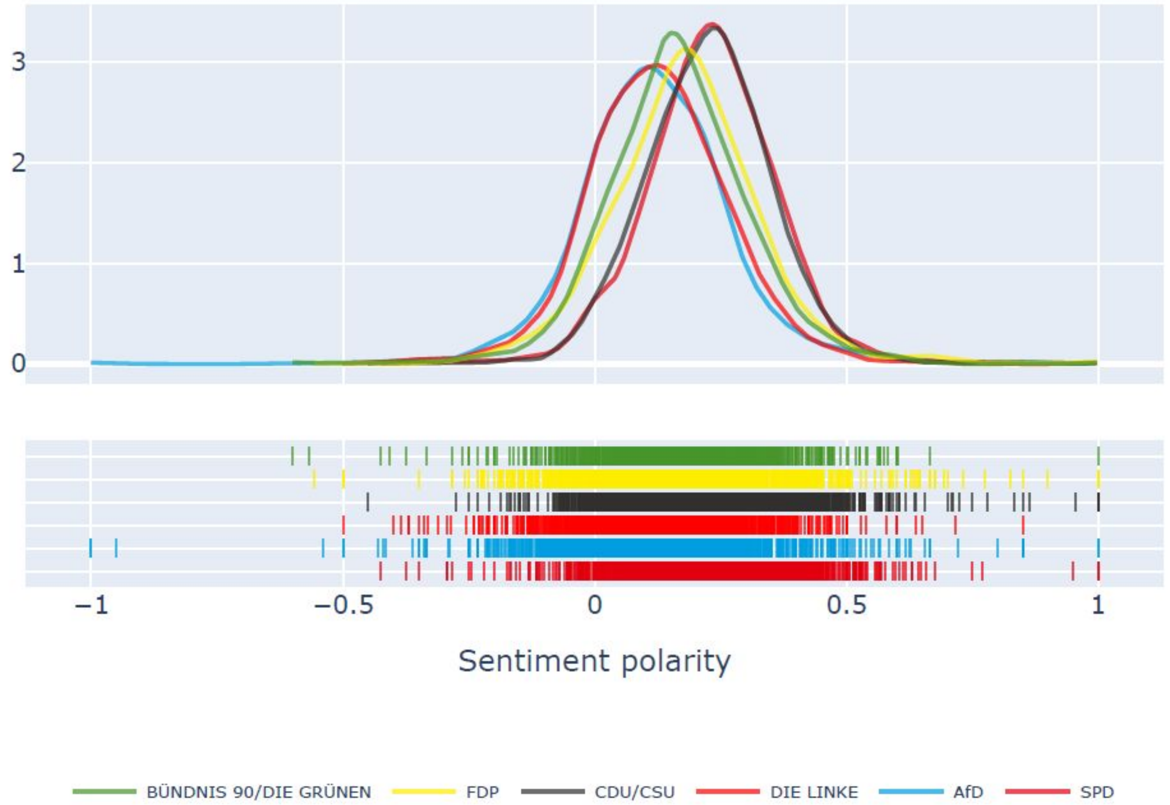
Speech Reactions in Period 19



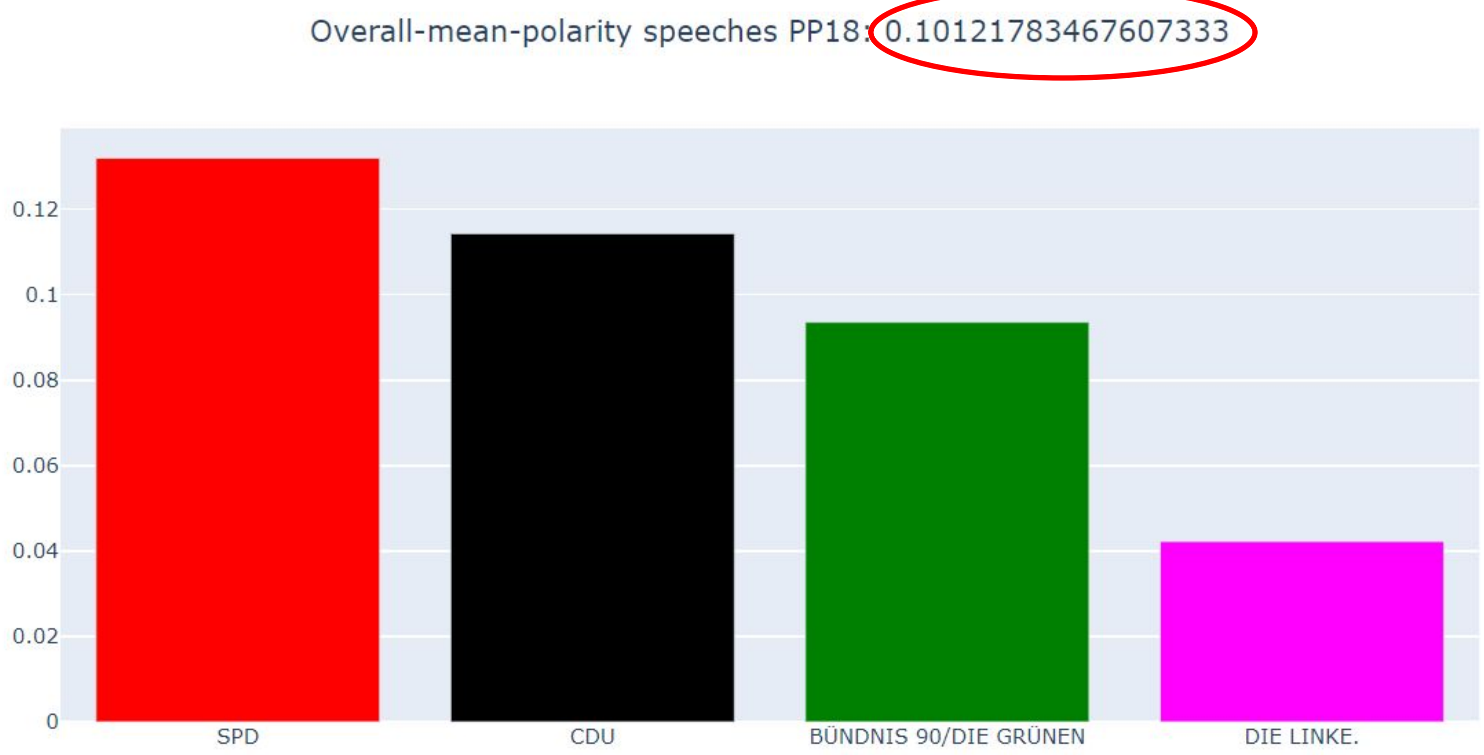
Proposed Drucksachen



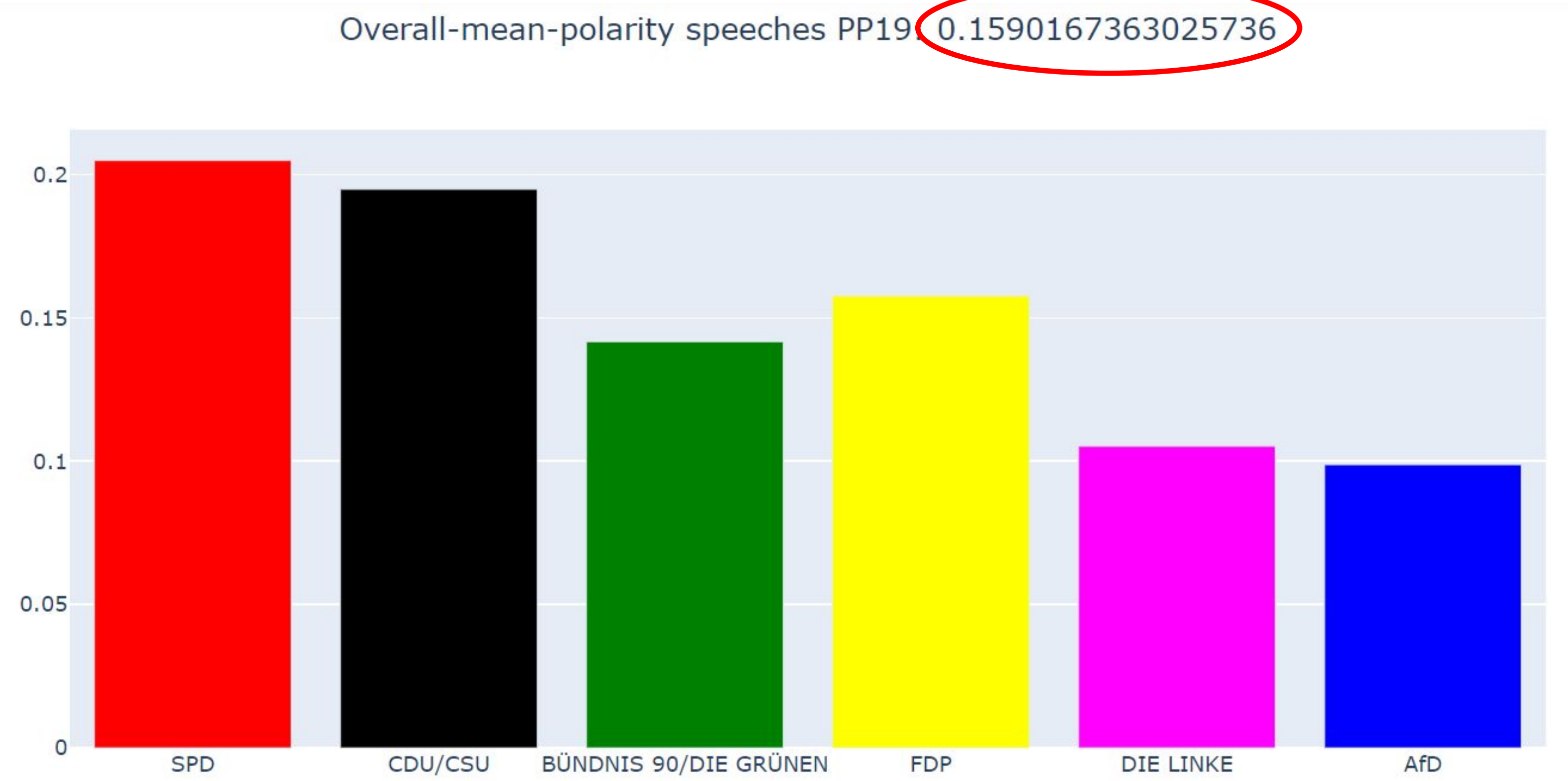
Sentiment Analysis per Party in Period 19



Sentiment analysis of speeches in PP18



Sentiment analysis of speeches in PP19



Named Entity Recognition

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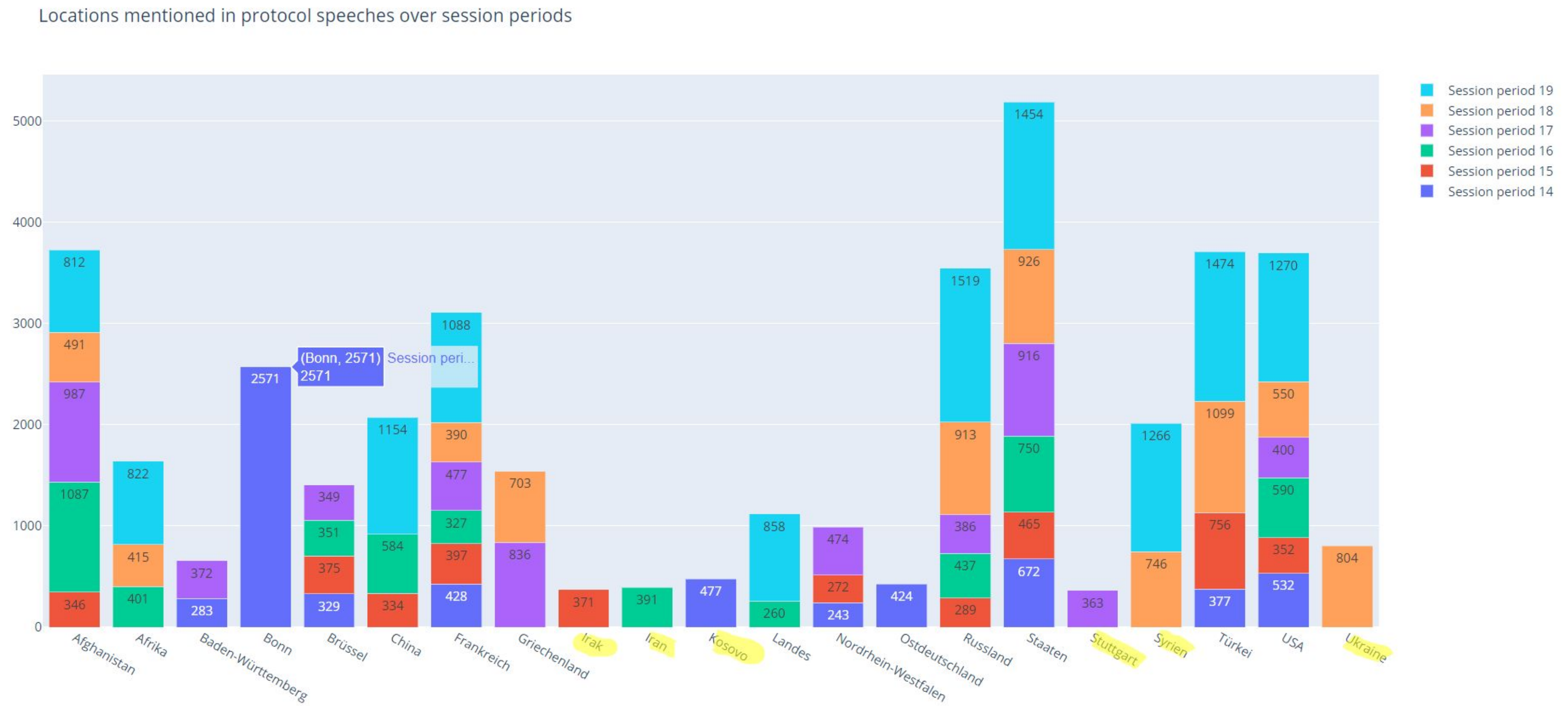


Quantitative evaluation

faktual & TUM

ROUGE

Intuition

Recall:

$$\frac{\textit{number of overlapping n-grams}}{\textit{total n-grams in reference summary}}$$

Precision:

$$\frac{\textit{number of overlapping n-grams}}{\textit{total n-grams in system summary}}$$

F1-Score:

$$\frac{2}{1/Recall + 1/Precision}$$

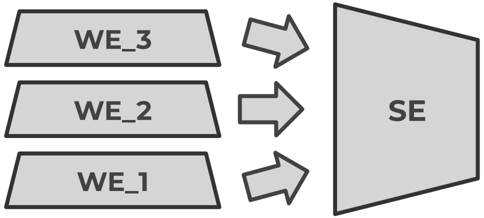
Pro & Contra

- Computational effort
- Number of variants
- Abstraction capturing

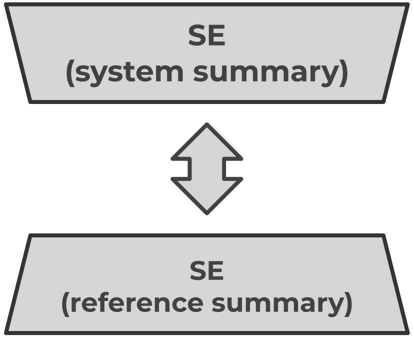
BERTscore

Intuition

1 Sentence embedding



2 Vector similarity



Pro & Contra

Computational effort

Number of variants

Abstraction capturing

Cosine distance

faktual & TUM

$$similarity(A,B) = \frac{A \cdot B}{\|A\| \times \|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}}$$

Full Questionnaire

1. On a scale from 0 *(miserable)* to 10 *(excellent)*, evaluate the **grammatical correctness** of the machine-generated summary.
2. On a scale from 0 *(miserable)* to 10 *(excellent)*, evaluate the **fluency** of the machine-generated summary.
3. On a scale from 0 *(no key points captured)* to 10 *(all key points captured)*, evaluate if the machine-generated summary has **captured all important key-points of the input-text.**
4. On a scale from 0 *(content is so mixed-up, that meaning is changed fundamentally)* to 10 *(content is not mixed up at all)*, evaluate if the machine-generated summary has **mixed up the content of the input-text.**
5. On a scale from 0 *(summary talks about smth completely different)* to 10 *(summary didn't add any misleading information)*, evaluate if the machine-generated summary has **added misleading information compared with the input-text.**

Complex model, longer texts

20 000 samples with batch size 150

1 epoch: 9-10 hours

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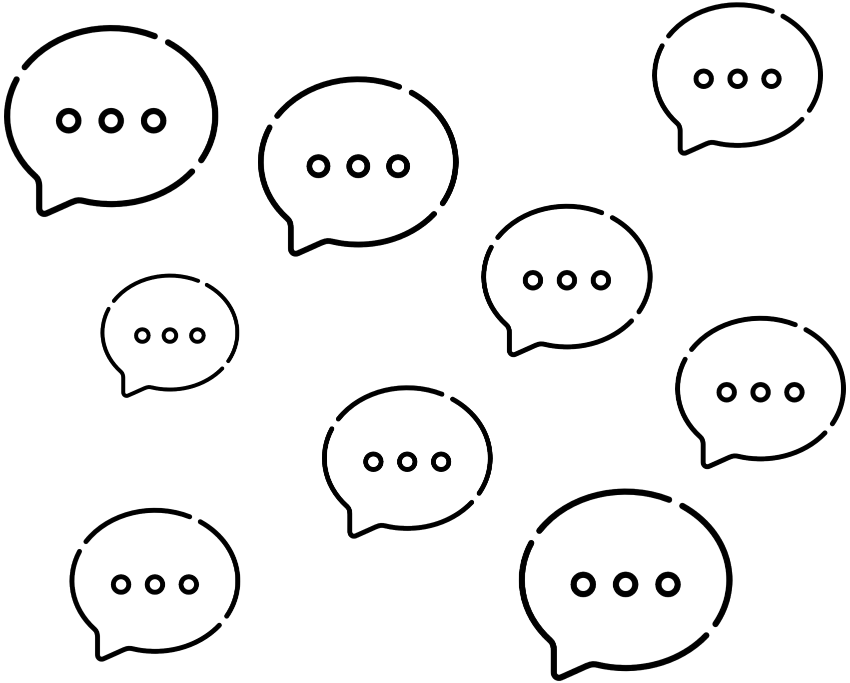
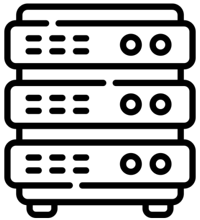
Multi-document summarization



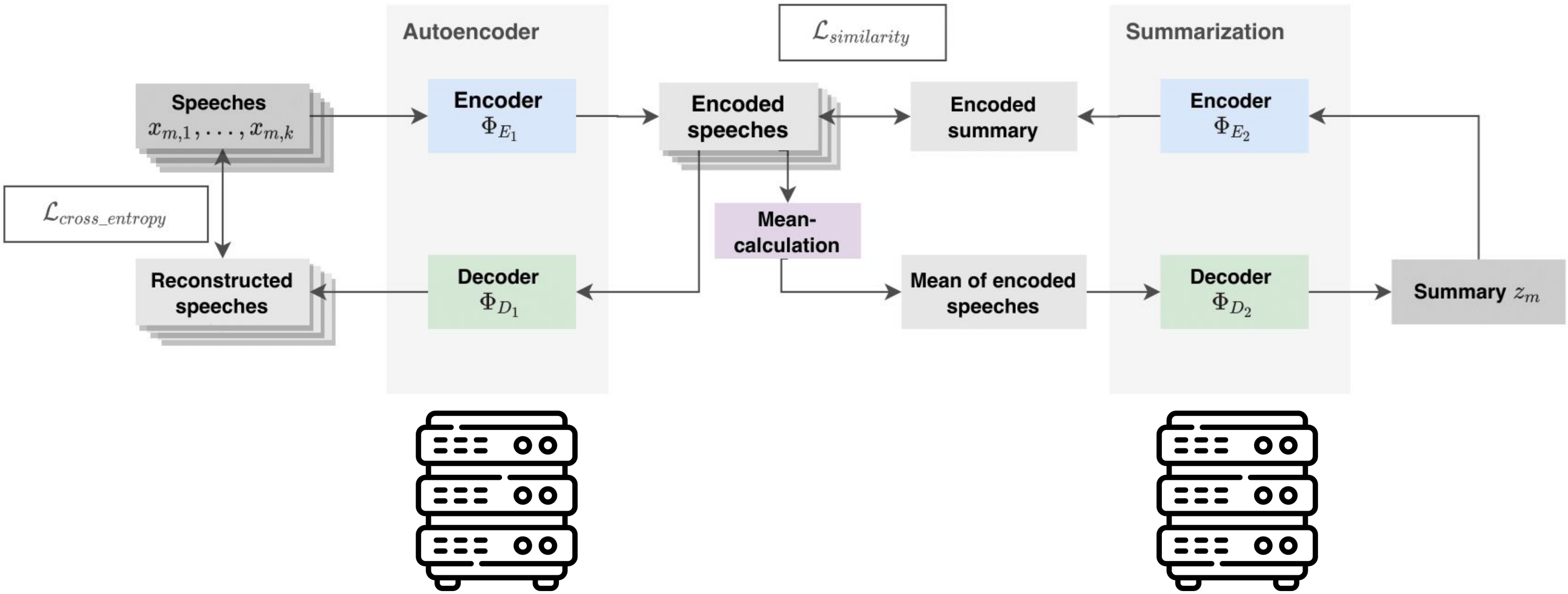
Translation-approach

MeanSum based on pretrained english language model



Translate speeches to english and translate obtained summaries back

Model architecture



Quantitative evaluation

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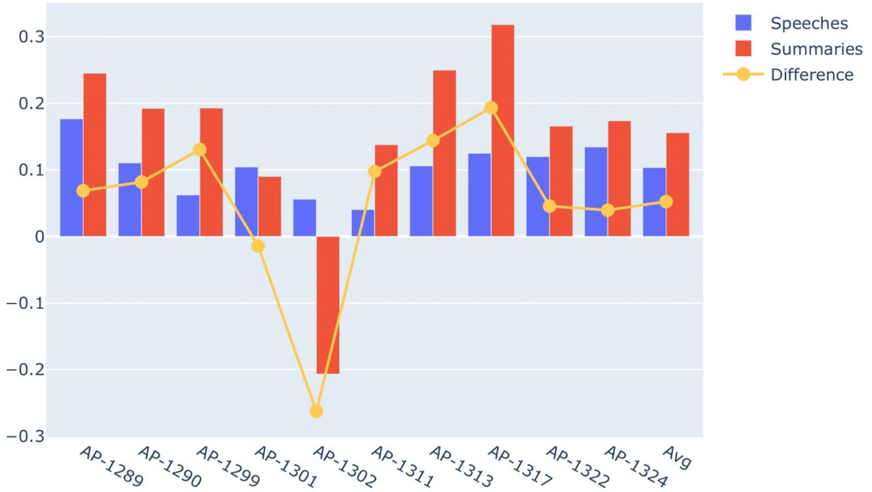
Rouge-scores

R1-Score	R2-Score	RL-Score
0.201	0.043	0.108

High abstraction

Sentiment analysis



Comparison BART and BERT

faktual & TUM

Model	R1-score	R2-score	RL-score	BERT-score	precision
BART	0.2024 (0.07)	0.0456 (0.04)	0.1955 (0.07)	**0.6251 (0.05)**	0.7274
BERTSumAbs	**0.2222 (0.12)**	**0.0801 (0.10)**	**0.2479 (0.13)**	0.6224 (0.08)	0.4454
lead-sum	0.1882 (0.08)	0.0412 (0.05)	0.1777 (0.07)	0.6112 (0.05)	**1.0**
english-lead-sum	0.1782 (0.07)	0.0341 (0.04)	0.1682 (0.06)	0.6049 (0.04)	0.7317

SwissText-Dataset

Model	R1-score	R2-score	RL-score	BERT
BART	0.1275	0.0288	0.1383	**0.5994**
distil-BERTSumAbs	0.0983	0.0053	0.0784	0.4867
rand-sum	**0.2300**	**0.0338**	**0.1833**	0.5863
lead-sum	0.0123	0	0.174	0.4713

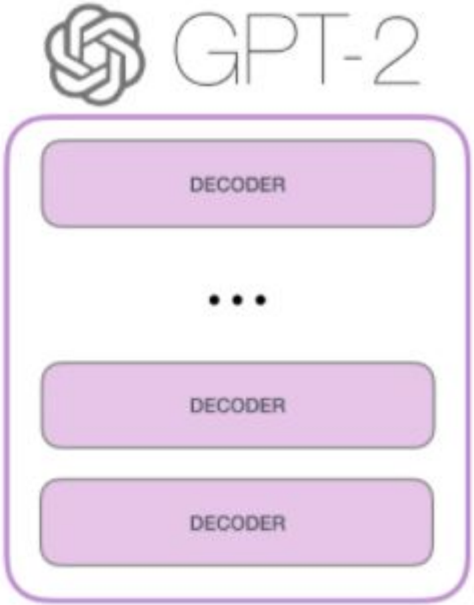
Heute im Bundestag-Dataset

Takeaways:

- BERT uses patterns
- BART is highly extractive

- HiB contains patterns
- BART generalizes best

Overview



Source:[http://jalammar.github.io/illustrated-gpt2]

Utilized the 345M German GPT-2 model trained on a 27Gb twitter + wikipedia + heise + parole corpus. http://zamia-speech.org/

Fine-tuning for Summarization: <source> + <tldr> + <summarization>

Inference: <source> + <tldr> => generated tokens is the summarization

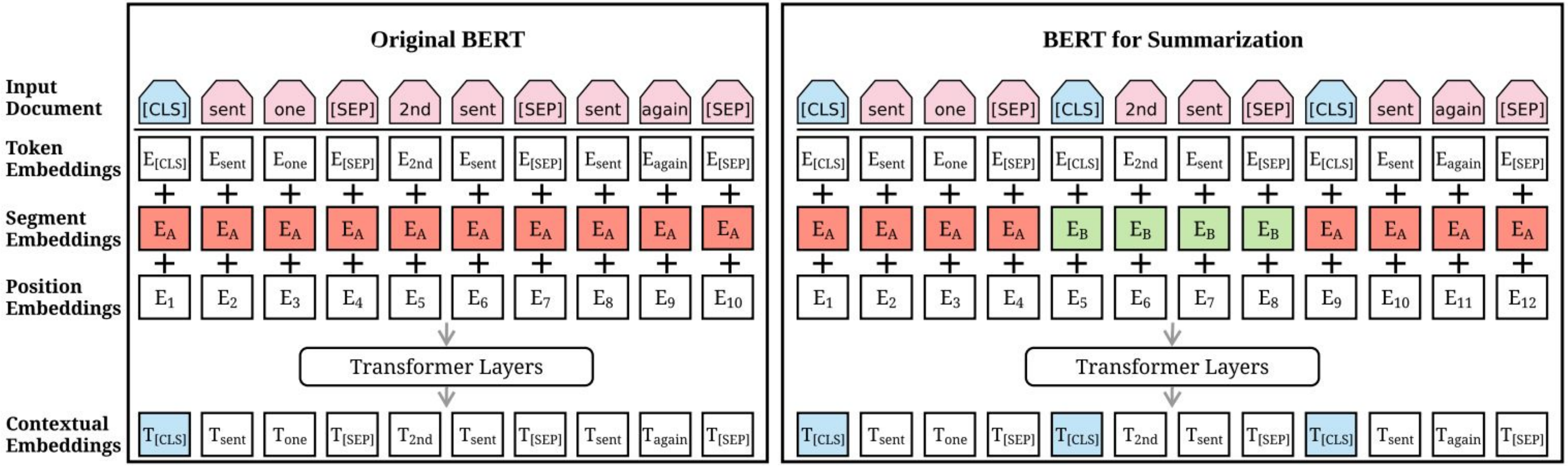
BERTSumAbs using German BERT

German BERT

Hugging Face

German Distil-BERT

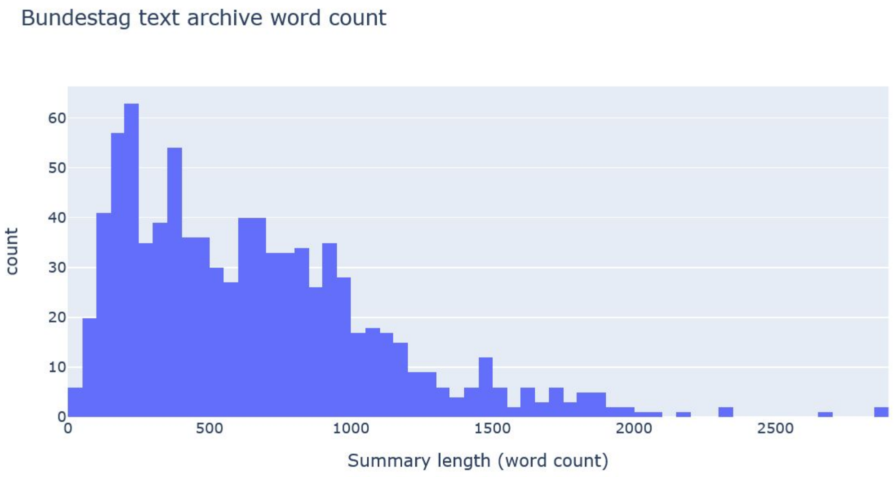
BertSum [4]

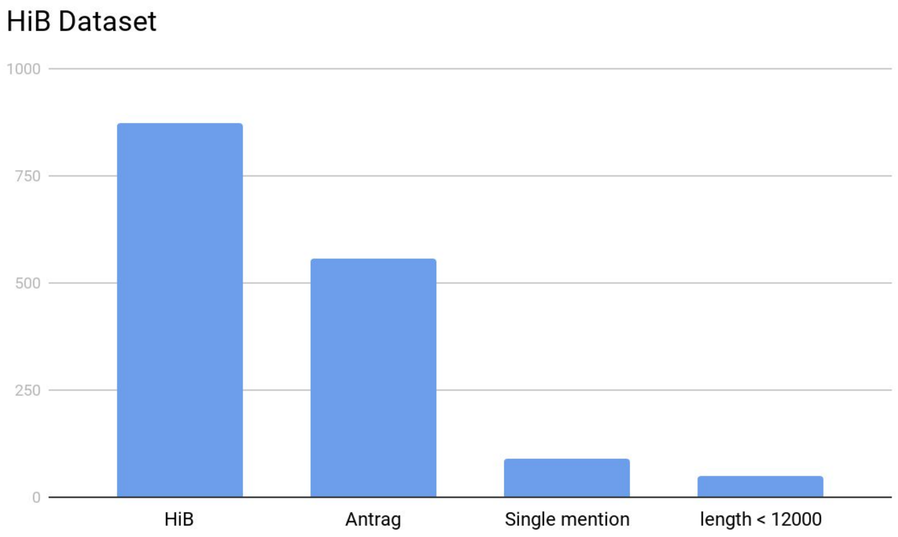


Utilized German Bert and Huggingface Transformers library

Trained on 80k samples from Swiss dataset

Heute im Bundestag





lead_sum

Takes first three sentences of source as summary

```
[29]
def lead_sum(text:str) -> str:
    first_three = text.split(".")[0:3]
    return ".".join(first_three)+"."
```

rand_sum: How can we mimic overfitting models?

In our case overfitting means that the model
- ignores the input
- returns some summary it has seen during the training process

```
[-]
def rand_sum(text:str) -> str:
    return random.choice(summaries_in_trainingset)
```

Comparison BART and BERT

faktual & TUM

John Stewart war ein US - amerikanischer Politiker . Zwischen 1823 und 1823 vertrat er den Bundesstaat Pennsylvania im US - Repraesentantenhaus.
William Brown war ein US - amerikanischer Politiker . Zwischen 1847 und 1823 vertrat er den Bundesstaat Virginia im US - Repraesentantenhaus.
Samuel Flander war ein US - amerikanischer Politiker . Zwischen 1847 und 1823 vertrat er den Bundesstaat New York im US - Repraesentantenhaus.

John Stewart war ein US-amerikanischer Politiker. Zwischen 1843 und 1845 vertrat er den zweiten Wahlbezirk des Bundesstaates Connecticut im US-Repräsentantenhaus.

- Wikipedia: *https://de.wikipedia.org/wiki/John_Stewart_(Politiker,_1795)*

Our benchmark speech

faktual & TUM

Context

Speech given by Hermann Färber (CDU/CSU) on 11th of November 2019

Bundestag is discussing an agricultural bill

Key points

Providing direct payments of 4.50€ per hectare grazing land for sheep and goat farmers

Ensuring legal and financial security for farmers participating in agri-environmental programs

Increasing demand for products from sheep and goat farmers

Hermann Färber (CDU/CSU)

Overview summaries for benchmark-speech

faktual & TUM

From scratch:
“vereins vereins vereins vereins verbandsfreie verbands-freie verbandsfreie ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer rat-meyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyerratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer rat-meyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer ratmeyer”

MeanSum:
“Hallo, liebe Kollegen! Liebe Gäste! Es geht darum, die Landwirtschaft zu fördern, auch wenn man sich das Ganze in einem Biergarten ansieht, der jetzt genutzt wird. Dies ist das Ergebnis der Bundesregierung und 2020. Meine Damenund Herren, meine Damen und Herren, lassen Sie uns auf die Erde gehen. Wir sind mitten im Budget. Dies ist ein großer Schritt nach vorne. Das kann man nicht einfach essen. Sie können auch darüber sprechen. Sie fordern das Steuerprivileg des EEG-Zuschlags, zum Beispiel für ein Video von 418 Millionen, das dann natürlich von der Regierung finanziert wird. Dies ist ein sehr wichtiger Schritt in Richtung Weltklima- und Umweltpolitik.”

BERT:
“Die Simmulation ist ein Verfahren zurückragung, bei der für die für die für die führte. Das Verfahren ist in der Regel für das Verfahrenzurückragung der Regel führt der Regel führte das Verfahren zurückragungen vonder Regel führte - und das Verfahren zurührt - das Verfahren zur Verfügung derRegel führt der Regel fürt - Änderung der Regel führte das Verfahren der Regelführte.”

lead-sum:
“Sehr geehrter Herr Präsident! Meine Damen und Herren! Wir debattieren heute das Direktzahlungen-Durchführungsgesetz und damit die einmalige Erhöhung der Umschichtung um 1,5 Prozentpunkte – das entspricht einer Erhöhungum 4,50 Euro pro Hektar – aus der ersten in die zweite Säule.”

BART:
“Die AfD debattiert über das Gesetz zur Umsetzung von Direktzahlungen und die einmalige Erhöhung der Umschichtung um 1,5 Prozentpunkte. Dies entspricht einer Steigerung von 4,50 EUR pro Hektar von der ersten zur zweiten Säule der Agrarumweltprogramme. Die Gruppen Die Linke und Bündnis 90 / DieGrünen erkennen in ihrer Bewerbung zu Recht, dass die Schafzüchter mit ihrer Arbeit uns qualitativ hochwertige Produkte in der Bevölkerung liefern.”

gerBart:
“Wir debattieren heute das Direktzahlungen-Durchführungsgesetz und damit die einmalige Erhöhung der Umschichtung um 1,5 Prozentpunkte. Wir erwarten jedoch, das entspricht Erhöhung um 4,50 Euro pro Hektar – ausschließlichan die landwirtschaftliche Mittelvergabe.”

Example

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Speech:

Herr Präsident! Liebe Kolleginnen und Kollegen! In dieser Krise zeigt sich eine gewisse Doppelgesichtigkeit: Auf der einen Seite beweisen der Sozialstaat und die Sozialversicherungen in diesen Monaten, dass sie selbst in der jetzigen Extremsituation mit Milliardeneinsatz in der Lage sind, in der Krise ein gewisses Maß an Sicherheit zu geben. Auf der anderen Seite zeigt das umwälzende Ausmaß der Krise auch, dass all diese Gegenmaßnahmen die Erschütterungen durch Arbeitslosigkeit, Existenzverlust und Bildungsmangel nicht vollständig auffangen können.Tiefe Gräben tun sich auf. Es sind gerade die Verwundbarsten und die ärmsten Gruppen, die ohnehin am Rande der Gesellschaft stehen, die nun umso mehr den Anschluss verlieren: Menschen, bei denen das Kurzarbeitergeld nicht reicht, Familien, die Covid-19 vor fast unlösbare Probleme stellt, Frauen, die den größten Teil der Sorgearbeit leisten müssen, Wohnungslose ohne jede Unterstützung oder Studierende...

Summary bart:

Durch die Pandemie fühlen sich viele Menschen einsam, überwältigt und sogar verzweifelt. Die Koronakrise ist daher auch eine Krise des sozialen und sozialen Zusammenhalts. Materielle Unterstützung allein reicht nicht aus. Was benötigt wird, ist eine Strategie, die alle dabei unterstützt, besser mit bevorstehenden Unsicherheiten umzugehen, die durch all die anderen Krisen verursacht werden, die wir noch haben.

Summary bertsum:

die franzosische organisation , die in den vereinigten staaten in der vereinigten staaten , ist . sie ist in der vereinigte staaten . ist die grundlage der franzosischen staaten . sie wurde im jahr 2010 in den usa . wurde sie in den jahren von der vereinigten konigreich gegrundet . gehort zu den grossten staaten , die sich im jahre . der grundlage ist die grossten staaten . die entwicklung der grundung der grundlage der grundung des computerspielen . der entwicklung der grundmandate . sie ist sie die sie in der grund die grundung

Application in compliance

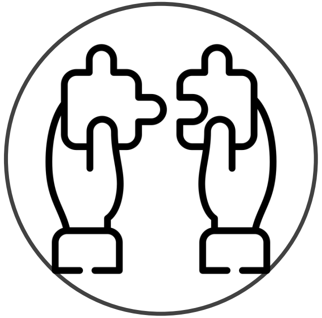
I need to analyze Drucksachen to understand the intentions of certain laws

Unfortunately, there is no convenient way to search for specific law proposals

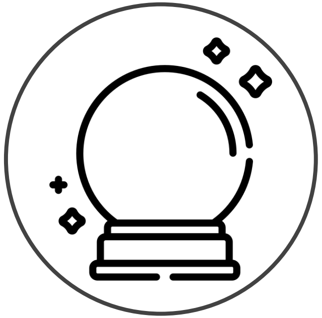
Therefore, I often rely on Blogposts and other secondary sources of information

Tobias Gumpp | Law student

Extended take-aways



- **MODELS:**
  - Model from scratch, BART, BertSUM, MeanSum
- **SIDE-PRODUCTS:**
  - Parsers
  - Translation Pipeline
  - Dataset
- **USE-CASES:**
  - Talked to experienced people in the journalism field



- More sophisticated pretrained language models are released every year
- Our parsing tools can facilitate the creation of German parliamentary data.
- Our translation pipeline can be used to create English summarization models
- Approaches can be extended for query-based or topic-based summarization and generation of summaries of user-defined length

Our Journey

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Challenges

- Remote team communication
- Different schedules
- Different levels of expertise
- Lack of meeting structure

Improvements

- Regular meetings (2x-3x per week)
- Version control rules
- Team code reviews and mentoring
- Meeting agendas & time keeping