Argument Mining with Customized and Feature-Injected Large Language Models

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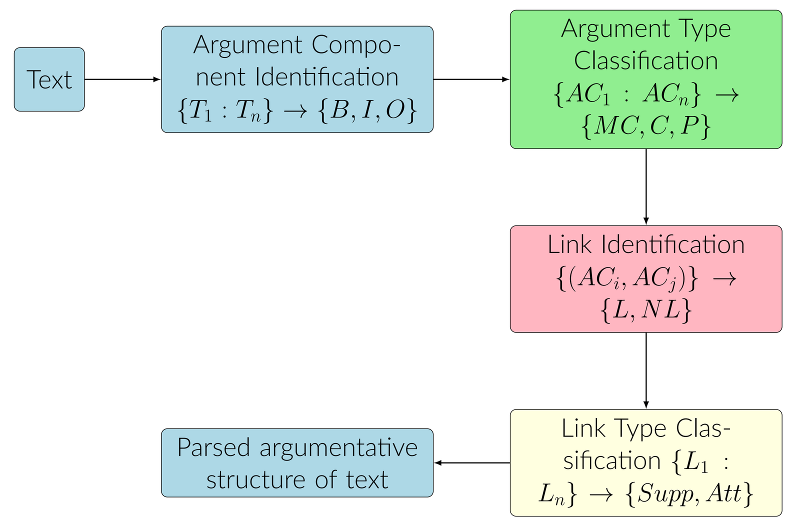
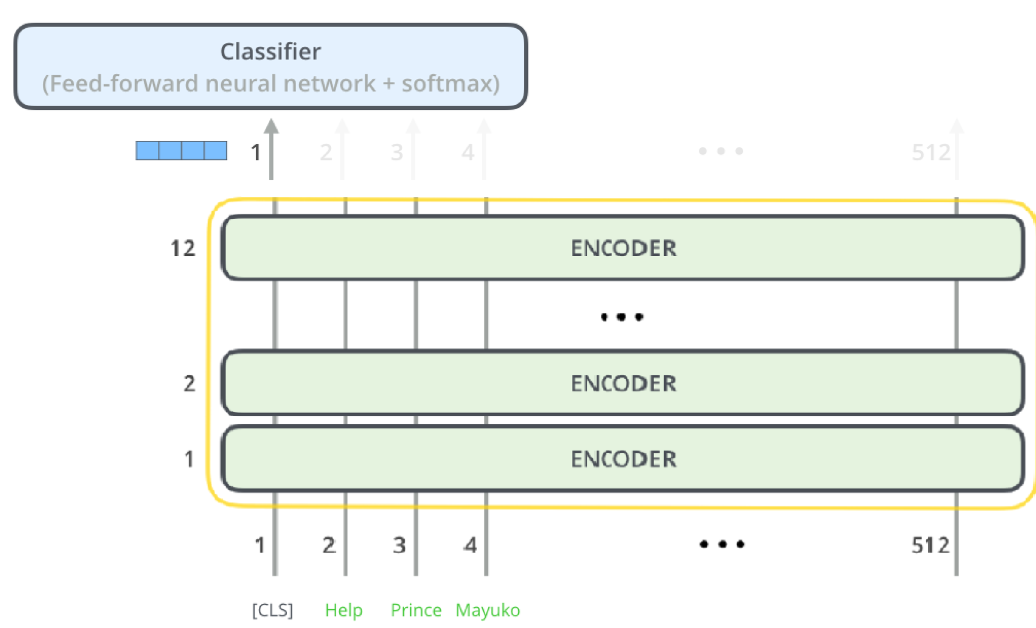
Argument Mining

- Automated detection and parsing of argumentational structure in text.



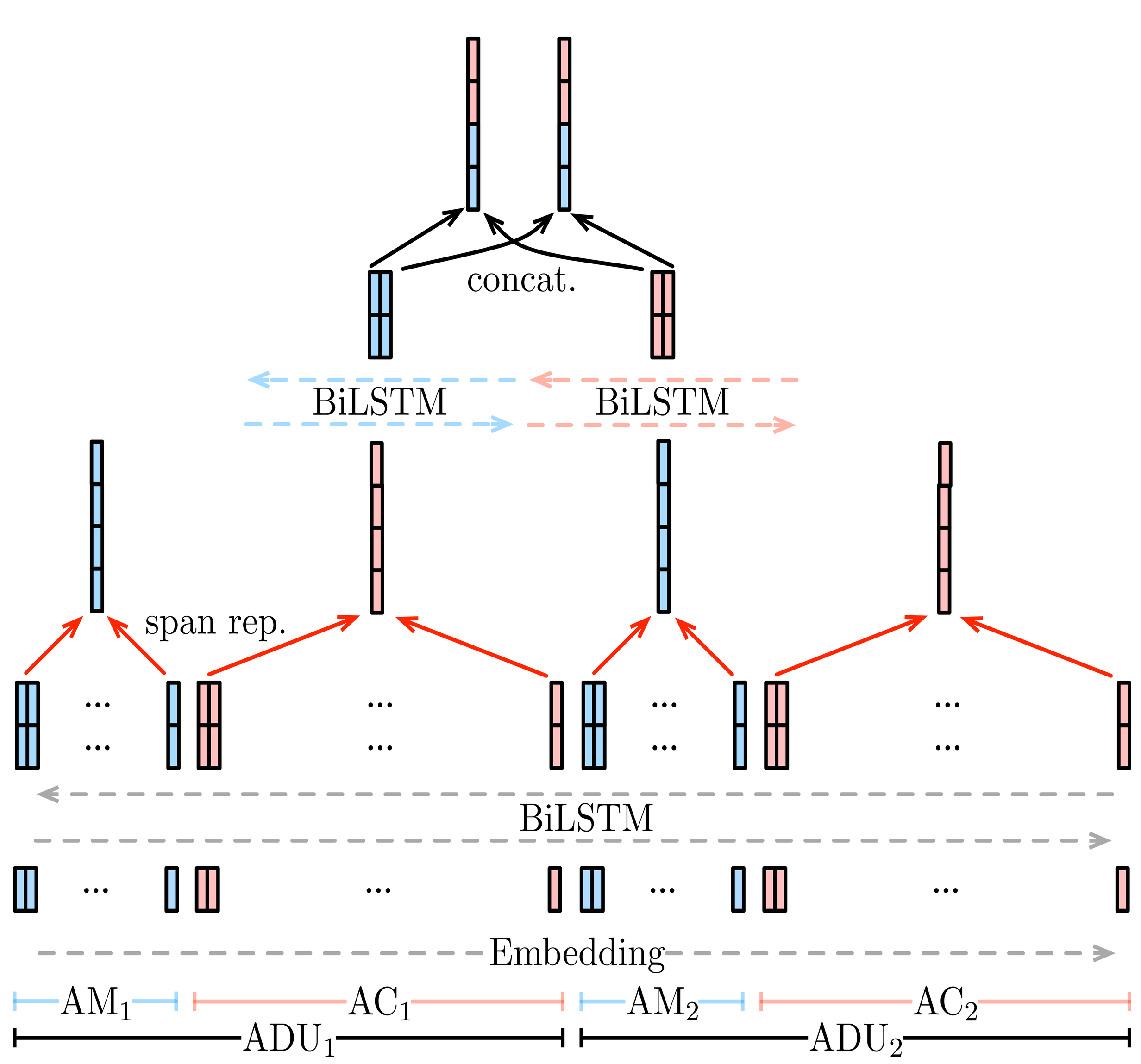
BERT Model

- Transformer-based Large Language Model (LLM).
- Pre-trained on huge data corpus, supervised fine-tuning on downstream task.



LSTM-Minus Span Representation

- Text span representation based on BiLSTM hidden states [1].



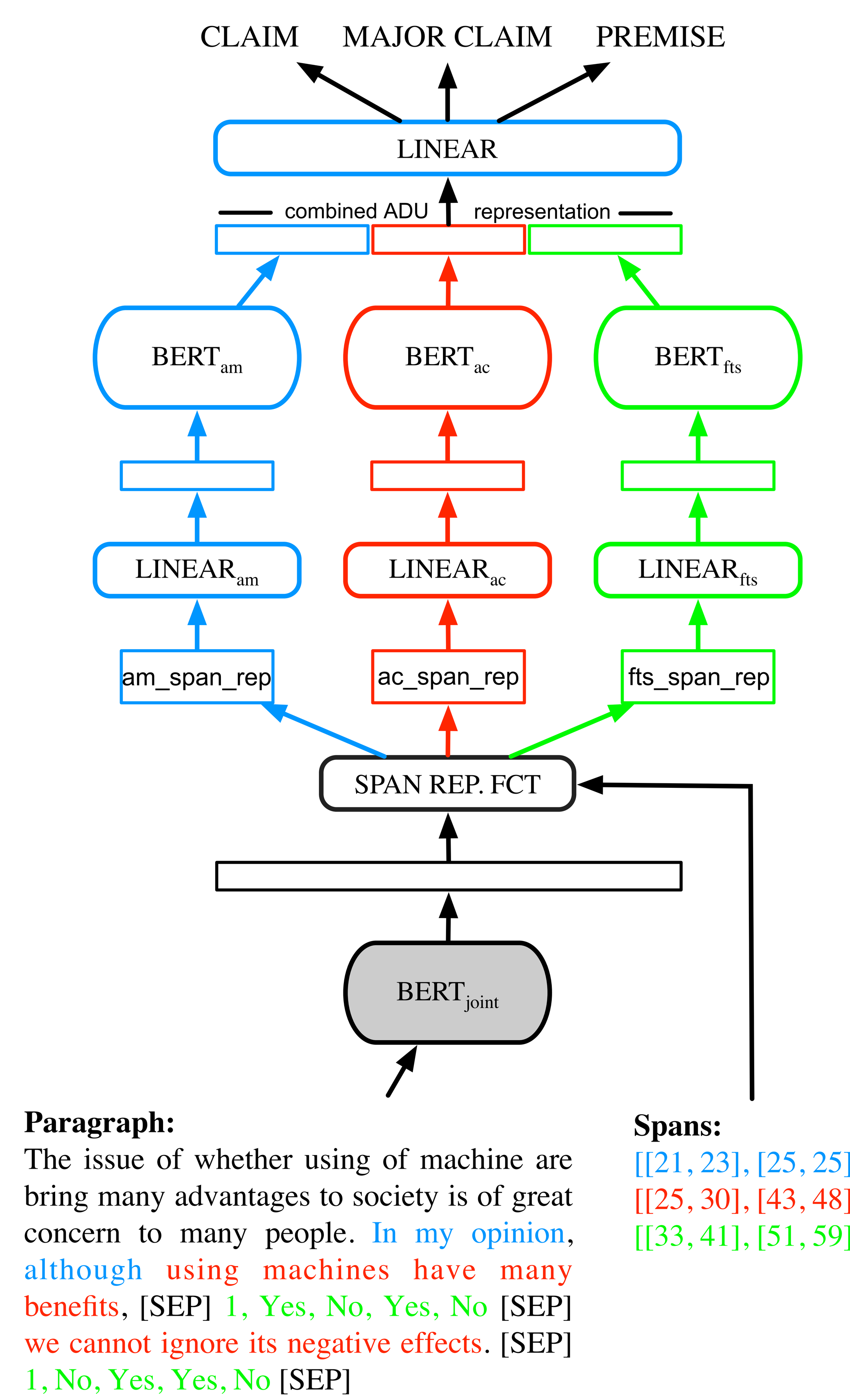
Our Idea

- **Observation:** with BERT, text of ACs alone does not suffice for accurate argument role prediction.
- **FeaTxt:** inject contextual, structural and syntactic features into BERT - *as text* (LIFT [2]).
- **BERT span representations:** define span representations based on BERT hidden states: AM span + AC span + FeaTxt span = ADU embedding.
- **BERT-Minus model:** distinct BERT modules to contextualize the three spans, then combine them to form an enriched ADU representation.
- **Transfer Learning:** sequential approach to TL between AM sub-tasks.

BERT-FeaTxt

[Topic: Society should ban all forms of advertising. Sentence: Ads will keep us well informed about new products and services, but we should also bear in mind that ***advertising cigarettes and alcohol will definitely affect our children in negative way.*** *]$_{contextual}$ [Paragraph Number: Five. Is in introduction: No. Is in conclusion: Yes. Is first in paragraph: No. Is last in paragraph: Yes.]$_{structural}$ [Part of Speech tags: VERB, NOUN, CCONJ, NOUN, VERB, ADV, VERB, DET, NOUN, ADP, ADJ, NOUN]$_{syntactic}$*

BERT-MINUS Model



Experiments

- **Datasets:** Persuasive Essays (PE), Yes We Can! (YWC), Change My Views (CMV).
- **Tasks:** Argument Type Classification (ATC), Link Identification (LI).
- **Transfer Learning:** instead of pre-trained BERT, use BERT fine-tuned on ATC/LI as the joint module.
- **Model Configurations:** comparison with classical BERT, various feature combinations, with/without FeaTxt, with/without Transfer Learning.

Results

- BERT-FeaTxt vs BERT on ATC:

Dataset	Numerical features				Features as Text (FeaTxt)			
	MC	C	P	F1	MC	C	P	F1
PE	0.82	0.57	0.90	0.76	0.86	0.68	0.91	**0.81**
YWC	-	0.70	0.65	0.67	-	0.69	0.65	**0.69**
CMV	-	0.70	0.76	0.73	-	0.76	0.80	**0.78**

- BERT-FeaTxt fine-tune on ATC:

Sent. representation	PE				YWC			CMV		
	MC	C	P	F1	C	P	F1	C	P	F1
component only	0.49	0.41	0.81	0.57	0.71	0.68	**0.69**	0.74	0.79	0.76
sent+strct	0.85	0.68	0.91	0.81	0.70	0.68	**0.69**	0.75	0.84	**0.79**
top+sent+strct+synt	0.86	0.71	0.91	**0.82**	0.71	0.62	0.67	0.76	0.78	0.77

- BERT-FeaTxt-Minus on LI:

Models	**L**	**NL**	**F1**
BERT	0.216	0.833	0.524
BERT–FeaTxt	0.585	0.877	0.731
BERT–MINUS	0.721	0.826	0.773
BERT–MINUS–FeaTxt–TL	0.778	0.850	**0.814**

Conclusions and Insights

- BERT-FeaTxt improves on standalone BERT, outperforms BERT plus binary/numerical features.
- BERT-Minus improves on BERT-FeaTxt, enables Transfer Learning between ATC and LI.
- LLMs are able to leverage non-textual data given textually.
- Future Work: Towards Prompt-based learning for end-to-end Argument Mining using Generative AI.

References

[1] Kuribayashi et. al. An Empirical Study of Span Representations in Argumentation Structure Parsing, 2019.

[2] Tuan Dinh et. al. LIFT: Language-Interfaced Fine-Tuning for Non-Language Machine Learning Tasks, 2022.

[3] Umer Mushtaq and Jérémie Cabessa. Argument classification with BERT plus contextual, structural and syntactic features as text, 2022.

[4] Umer Mushtaq and Jérémie Cabessa. Argument mining with modular BERT and transfer learning, 2023.