

# Applying Automatic Text Summarization for Fake News Detection

LREC 2022 | Philipp Hartl & Udo Kruschwitz



# Challenge



VS



# Fake News Detection

## Content-based Identification [1, 2]

## Feedback-based Identification [3, 4]

## Intervention-based Solutions [5, 6]

[1] Zhou, X., Jain, A., Phoha, V. V., & Zafarani, R. (2020). Fake News Early Detection: A Theory-driven Model. *Digital Threats: Research and Practice*, 1(2), 1-25. <https://doi.org/10.1145/3377478>

[2] Zhou, X., Wu, J., & Zafarani, R. (2020). SAFE: Similarity-Aware Multi-modal Fake News Detection. In H. W. Lauw, R. C.-W. Wong, A. Ntoulas, E.-P. Lim, S.-K. Ng, & S. J. Pan (Eds.), *Advances in Knowledge Discovery and Data Mining* (pp. 354-367). Springer International Publishing. [https://doi.org/10.1007/978-3-030-47436-2\\_27](https://doi.org/10.1007/978-3-030-47436-2_27)

[3] Shu, K., Cui, L., Wang, S., Lee, D., & Liu, H. (2019). dEFEND: Explainable Fake News Detection. *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 395-405. <https://doi.org/10.1145/3292500.3330935>

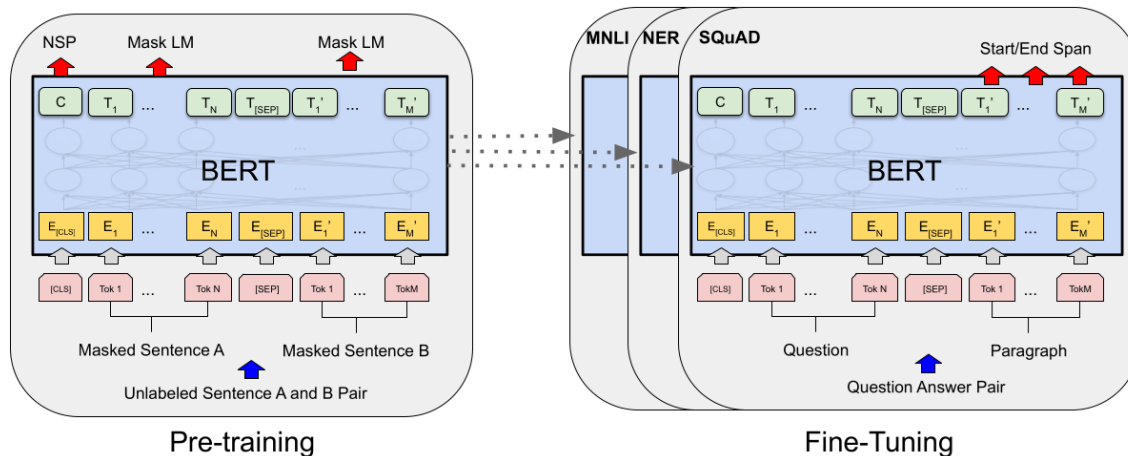
[4] Shu, K., Wang, S., & Liu, H. (2019). Beyond news contents: The role of social context for fake news detection. *WSDM 2019 - Proceedings of the 12th ACM International Conference on Web Search and Data Mining*, 312-320. <https://doi.org/10.1145/3289600.3290994>

[5] Jooyeon Kim, Behzad Tabibian, Alice Oh, Bernhard Schölkopf, and Manuel Gomez Rodriguez. 2018. Leveraging the Crowd to Detect and Reduce the Spread of Fake News and Misinformation. In *Proceedings of the 11th ACM International Conference on Web Search and Data Mining (WSDM 2018)*.

[6] Yiangos Papanastasiou. 2017. Fake news propagation and detection: A sequential model. *SSRN* (2017)



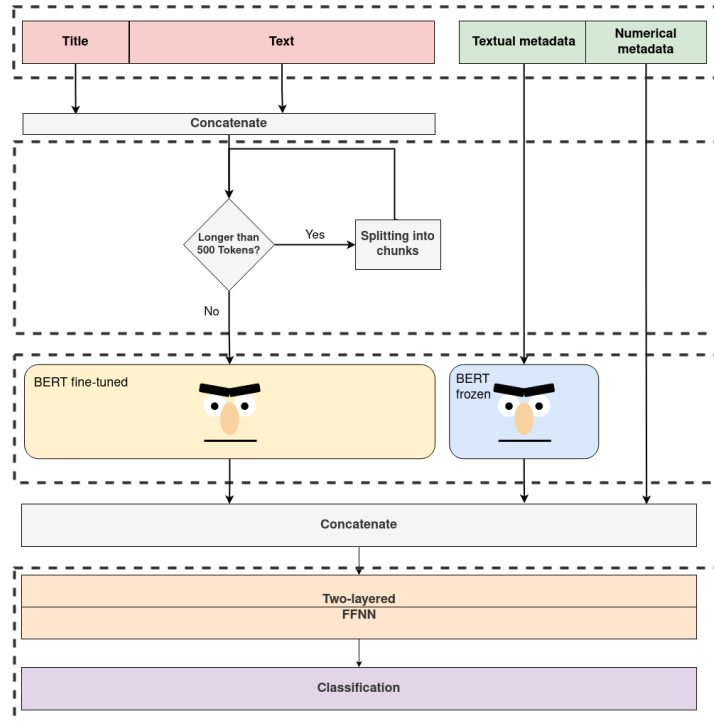
# Transfer Learning



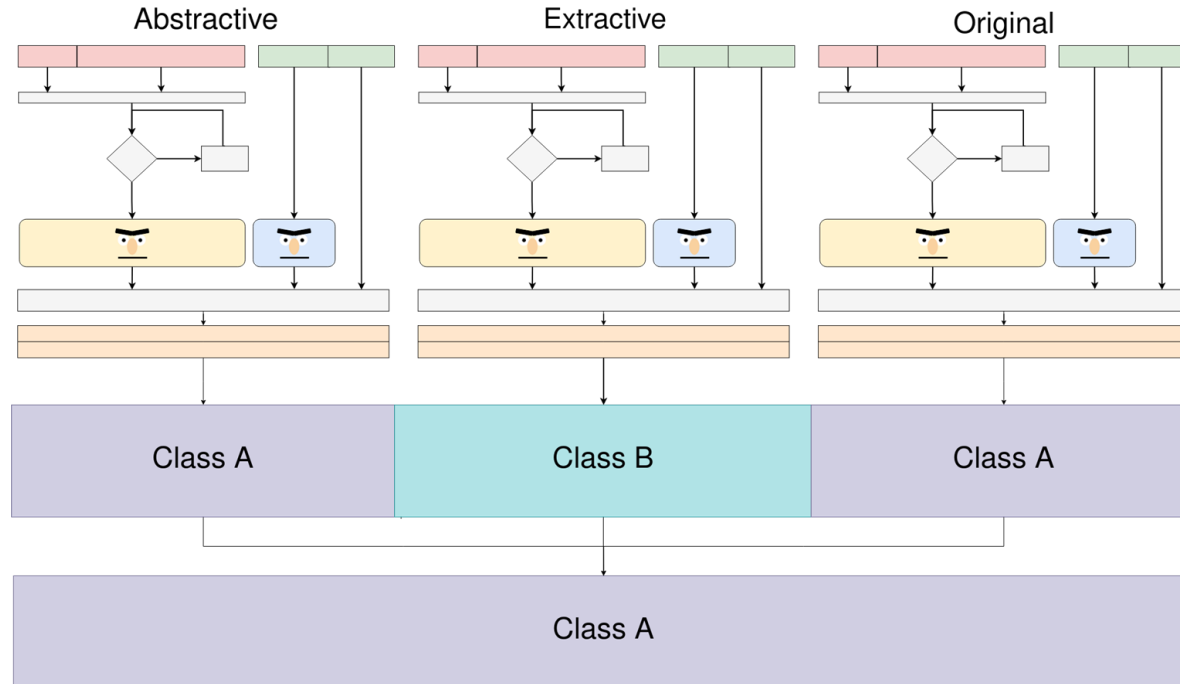
Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019, June). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1(Long and Short Papers)(pp. 4171-4186). Minneapolis, Minnesota: Association for Computational Linguistics.



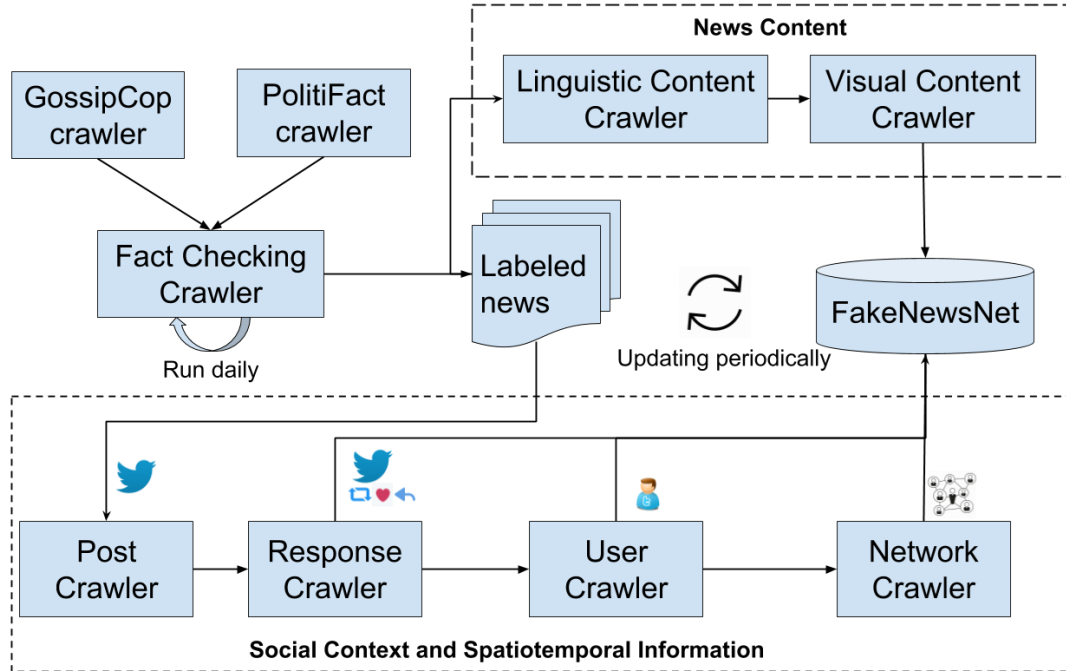
# CMTR-BERT



# CMTR-BERT Ensemble



# Datasets (1)



## Datasets (2)



CLEF 2021 BUCHAREST

# CLEF2021 - CheckThat! Lab

Detecting Check-Worthy Claims, Previously Fact-Checked Claims, and Fake News





## Performance (1)

Dataset	Metric	BERT	SAFE	dDEFEND	CMTR-BERT O	CMTR-BERT A	CMTR-BERT E	CMTR-BERT C	CMTR-BERT
Politifact	Accuracy	0.924	0.874	0.904	0.950	0.948	0.950	0.912	<b>0.956</b>
	Precision	0.934	0.889	0.902	0.953	0.945	0.941	<b>0.977</b>	0.958
	Recall	0.897	0.903	<b>0.956</b>	0.936	0.943	0.952	0.827	0.947
	F1	0.914	0.896	0.928	0.944	0.943	0.946	0.895	<b>0.952</b>
Gossipcop	Accuracy	0.863	0.838	0.808	0.960	0.956	0.958	0.957	<b>0.963</b>
	Precision	0.741	0.854	0.729	0.926	0.917	0.924	0.859	<b>0.936</b>
	Recall	0.666	0.937	0.782	0.908	0.898	0.899	<b>0.985</b>	0.910
	F1	0.701	0.895	0.755	0.917	0.907	0.911	0.918	<b>0.923</b>



## Performance (2)

Dataset	Metric	NoFake	NLP & IR@UNED	BERT-baseline	BERT	CMTR-BERT O w/o context	CMTR-BERT A w/o context	CMTR-BERT E w/o context
CT-FAN 21	Accuracy	<b>0.853</b>	0.528	0.316	0.453	0.461	0.441	0.480
	Precision	-	-	0.128	0.424	0.446	0.422	<b>0.467</b>
	Recall	-	-	0.251	0.402	0.414	0.384	<b>0.435</b>
	F1-macro	<b>0.838</b>	0.468	0.124	0.395	0.406	0.373	0.428



## Key findings

- CMTR-BERT is able to achieve state-of-the-art results
- Contextual information is a key aspect of Fake News
- Single text representations do not consistently bring advantage → Combination does the trick
- It remains unclear to what extent the input transformation influences the performance



**Thank you for your attention!**

