iLab at FinCausal 2022: Enhancing Causality Detection with an External Cause-Effect Knowledge Graph

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OUTLINES

I. Task Description @ FinCausal 2022

Initial Task: to detect the cause span and effect span from given sentences

After applying BIO scheme on given sentences:

Changes in foreign currency exchange rates unfavorably impacted net sales by 23million, or 223 million, or 2%.

B-C I-C I-C I-C I-C I-C B-E I-E I-E I-E I-E I-E I-E I-E

Beginning / Inner of Cause

Beginning / Inner of Effect

Practical Task: to classify tokens from given sentences

General methodology

- train a token classifier to distinguish the 5 labels for given text.

Scope focus

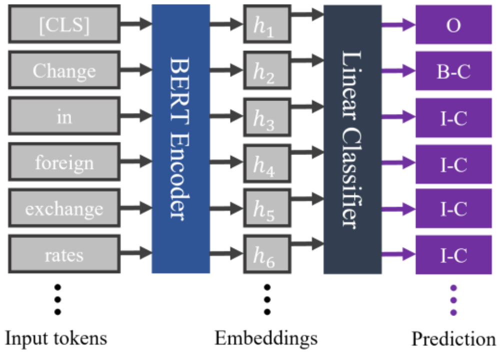
- apply the pre-trained language models, i.e. BERT, is more beneficial to reflect semantic/syntactic relations between text

II. Literature Review

1. General way

- BertForTokenClassification in HuggingFace [Devlin et al., 2018]

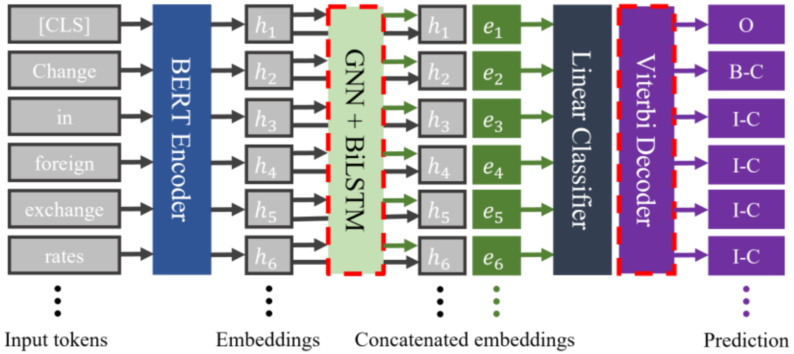
1.



2. Winner of Fincausal2021 --- DTGNN [Tan and Ng, 2021]

- concatenate embedding of <u>GNN</u> to Bert embedding
- apply <u>Viterbi Decoder</u> to guarantee the prediction of ***Inner*** *Tag* is followed by the ***Beginning Tag*** [Kao et al., 2020]

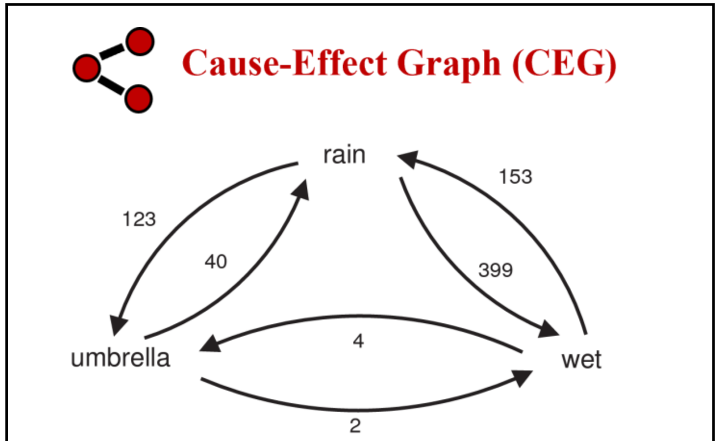
2.



3. External Knowledge Graph

- Cause-Effect Graph(CEG) is constructed based on 89M lexical pairs extracted from causal contexts, weighted by co-occurrence frequency [Li at al., 2021]

3.

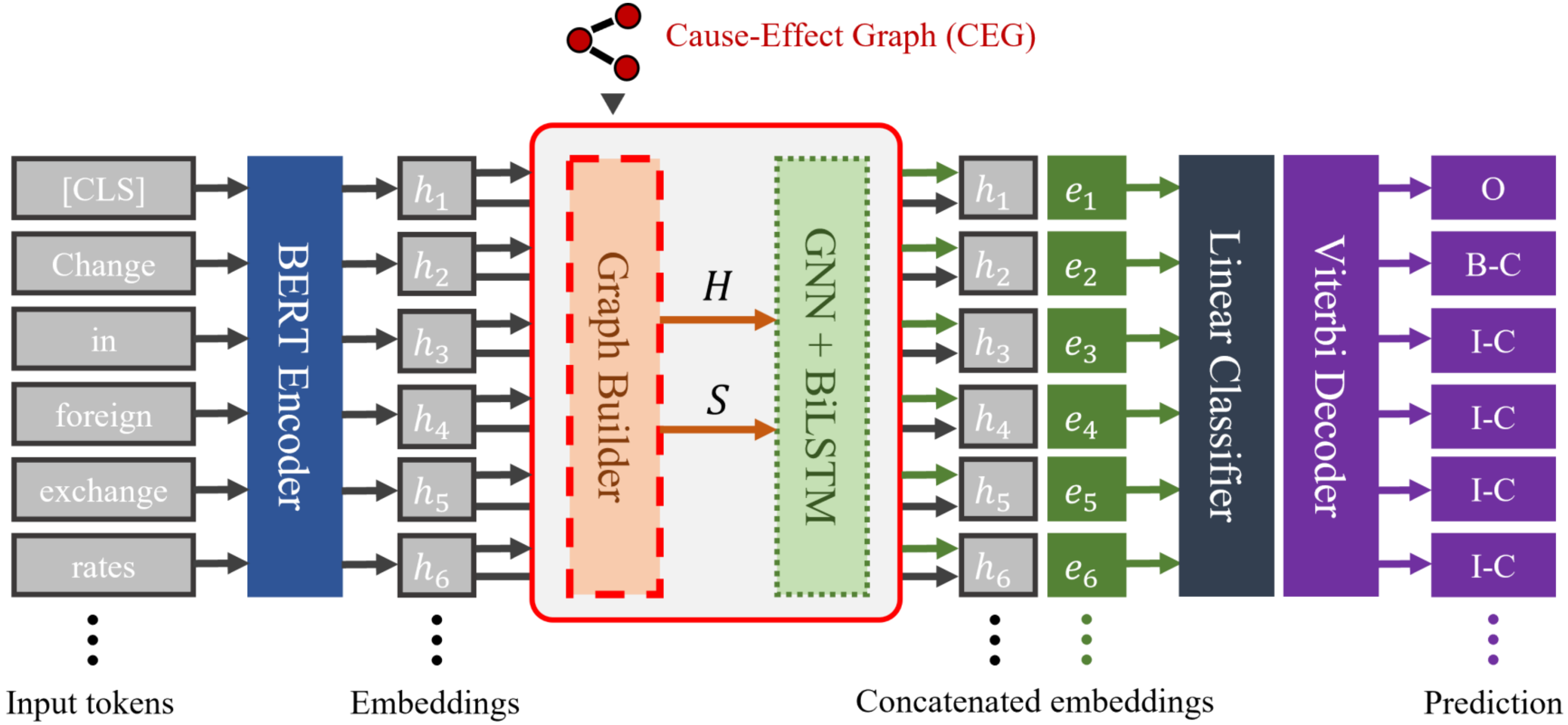


Extracted from Figure1 in [Luo et al., 2016]

III. Proposals

1 **(Graph Builder)** propose a new way to build the subgraph according to causality features

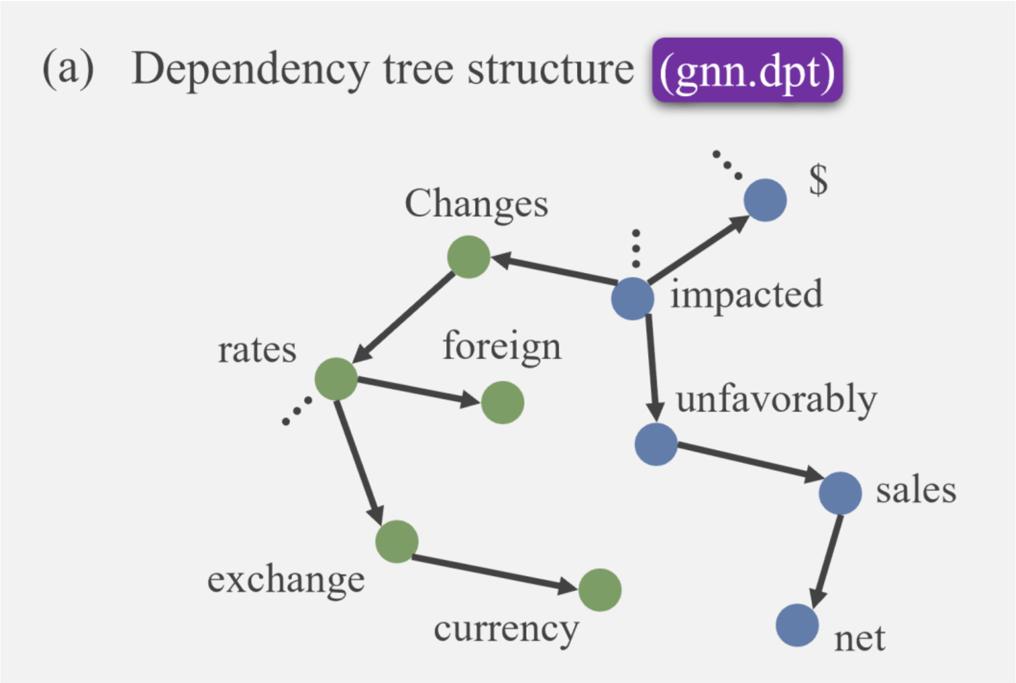
2 **(Knowledge Injection)** inject the causality knowledge to the all kinds of subgraphs



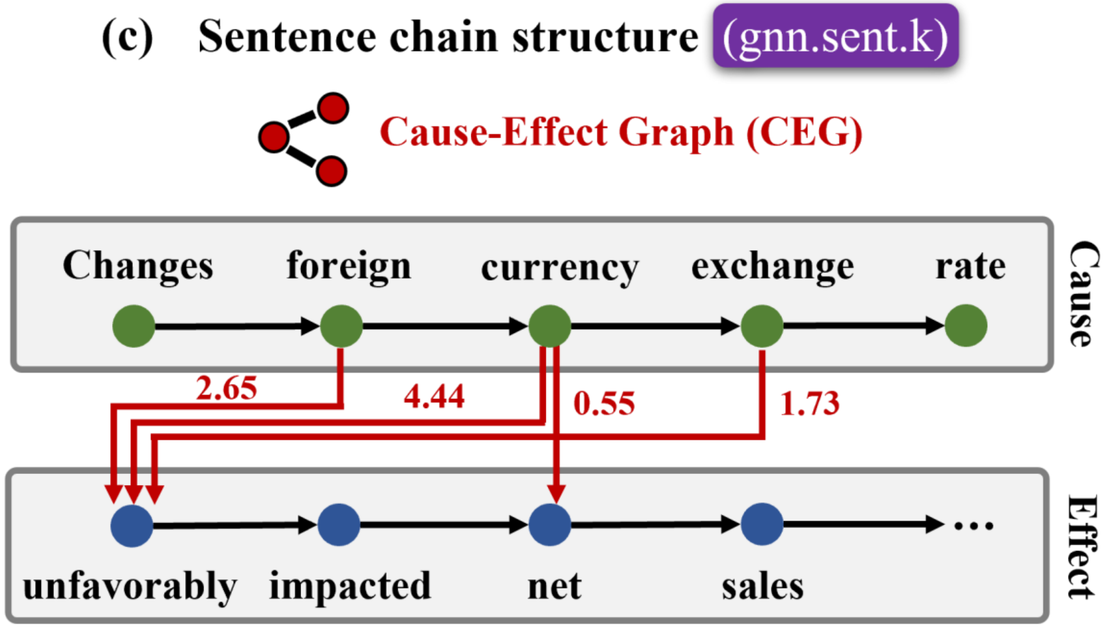
III. Proposals

1 Graph builder

Example: Changes in foreign currency exchange rates unfavorably impacted net sales by 23million, or 223 million, or 2%.



DTGNN's idea

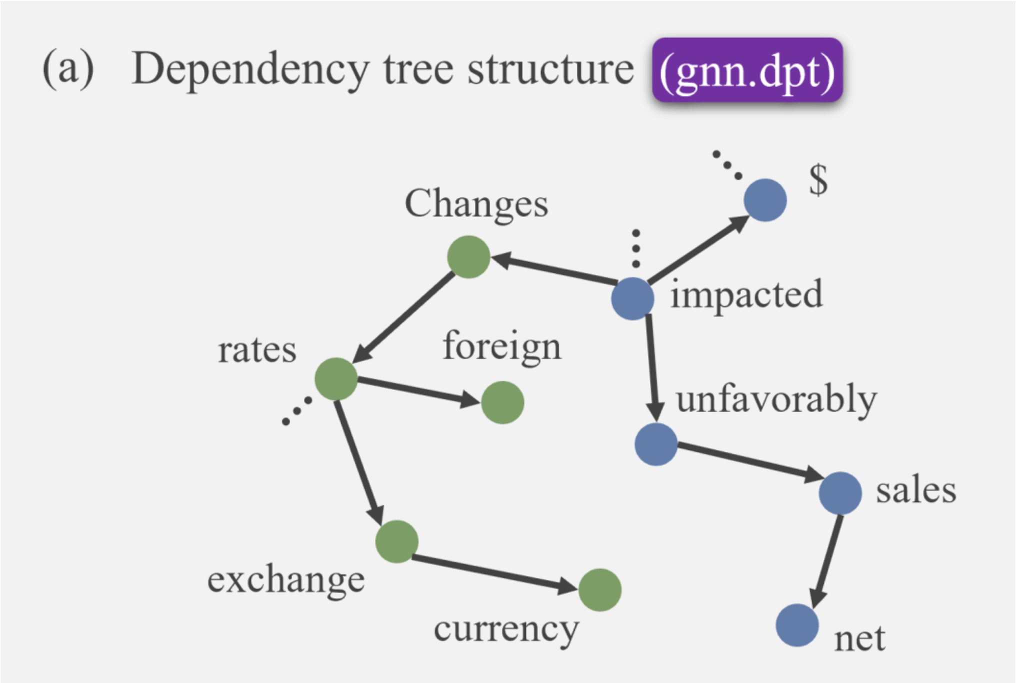


Our graph builder

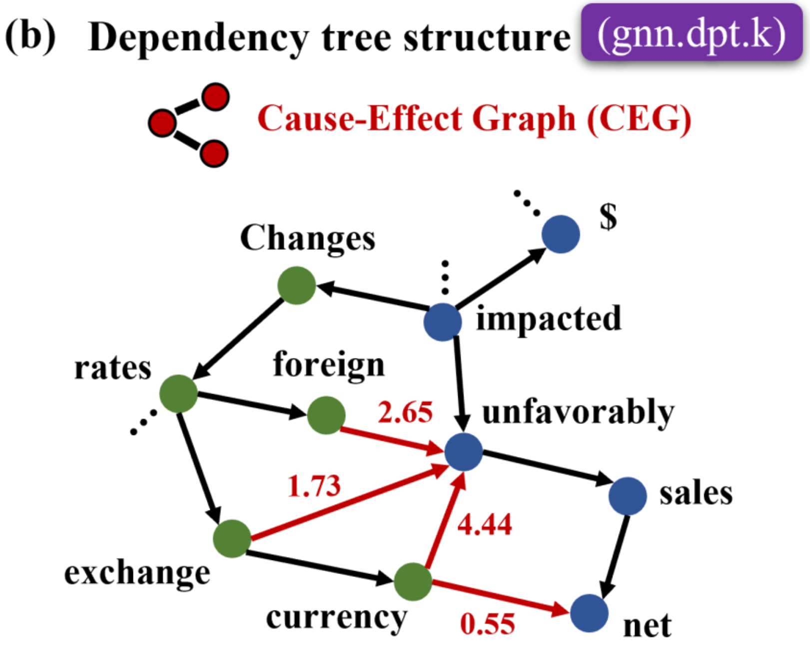
III. Proposals

2 Knowledge Injection

Example: **Changes in foreign currency exchange rates unfavorably impacted net sales by 23million, or 223 million, or 2%.**



DTGNN's idea



Knowledge injection on exiting structure

IV. Performance Evaluation

Datasets

merging the data releases* of 2020, 2021 and 2022, then we have:

- 2,290 samples for training
- 255 samples for validation
- 933 samples for blind test

**https://github.com/yseop/YseopLab*

Results							
#	User	Entries	Date of Last Entry	F1 ▲	Recall ▲	Precision ▲	Exact match ▲
1	spock	17	04/20/22	0.95 (1)	0.95 (1)	0.95 (1)	0.86 (1)
2	ilab	40	04/20/22	0.94 (2)	0.94 (2)	0.94 (2)	0.83 (2)
3	jlee24282	42	04/21/22	0.92 (5)	0.92 (5)	0.92 (5)	0.79 (3)
4	sohomghosh	32	04/21/22	0.92 (4)	0.92 (4)	0.93 (4)	0.79 (3)
5	joydeb	74	04/21/22	0.90 (6)	0.90 (6)	0.91 (6)	0.71 (4)
6	Chenyang_Lyu	23	04/12/22	0.93 (3)	0.93 (3)	0.93 (3)	0.69 (5)

Competition Results in Colab (we ranked as 2nd)

	F1	Recall	Precision	EM
gnn.dpt	93.58	93.56	93.66	82.53
gnn.dpt.k	93.41	93.37	93.50	81.99
gnn.sent.k	93.90	93.89	93.95	82.64

Table 1: The best scores achieved on blind test set.

	F1	Recall	Precision	EM
gnn.dpt	89.70	89.66	89.77	73.38
gnn.dpt.k	88.38	88.36	88.42	73.02
gnn.sent.k	90.22	90.20	90.25	75.90

Table 2: The best scores achieved on our validation set.

Experiment Result

- Our model achieved slightly improvement than the winner of Fincausal2021

- The proposed knowledge injection approach fits better on **sentence chain structure(gnn.sent.k)**, compared to dependency tree structure (gnn.dpt/ gnn.dpt.k).

V. References:

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

- Kao, P.-W., Chen, C.-C., Huang, H.-H., and Chen, H.-H. (2020). NTUNLPL at FinCausal 2020, task 2:improving causality detection using Viterbi decoder. *In Proceedings of the 1st Joint Workshop on Financial Narrative Processing and MultiLing Financial Summarisation*, pages 69–73, Barcelona, Spain (Online), December. COLING.

- Tan, F. A. and Ng, S.-K. (2021). NUS-IDS at FinCausal 2021: Dependency tree in graph neural network for better cause-effect span detection. In *Proceedings of the 3rd Financial Narrative Processing Workshop*, pages 37–43, Lancaster, United Kingdom, 15-16 September. Association for Computational Linguistics.

- Luo, Z., Sha, Y., Zhu, K. Q., Hwang, S. W., & Wang, Z. (2016, March). Commonsense causal reasoning between short texts. In *Fifteenth International Conference on the Principles of Knowledge Representation and Reasoning*.

- Li, Z., Ding, X., Liu, T., Hu, J. E., & Van Durme, B. (2021, January). Guided generation of cause and effect. In *Proceedings of the Twenty-Ninth International Conference on International Joint Conferences on Artificial Intelligence* (pp. 3629-3636).

Thanks for your listening.