A Generative Approach for Financial Causality Extraction

Tapas Nayak
tnk02.05@gmail.com
IIT Kharagpur
India

Soumya Sharma
soumyasharma20@gmail.com
IIT Kharagpur
India

Yash Butala
butalayash99@gmail.com
IIT Kharagpur
India

Koustuv Dasgupta
Koustuv.x.Dasgupta@gs.com
Goldman Sachs
India

Pawan Goyal
pawang@cse.iitkgp.ac.in
IIT Kharagpur
India

Niloy Ganguly
niloy@cse.iitkgp.ac.in
IIT Kharagpur
India

Leibniz University, Germany

ABSTRACT
Causality represents the foremost relation between events in financial documents such as financial news articles, financial reports. Each financial causality contains a cause span and an effect span. Previous works proposed sequence labeling approaches to solve this task. But sequence labeling models find it difficult to extract multiple causalities and overlapping causalities from the text segments. In this paper, we explore a generative approach for causality extraction using the encoder-decoder framework and pointer networks. We use a causality dataset from the financial domain, FinCausal, for our experiments and our proposed framework achieves very competitive performance on this dataset.

CCS CONCEPTS
- Deep learning → Generative models
- Natural language processing → Information extraction
- Event extraction → causality extraction

KEYWORDS
financial information extraction, financial causality extraction, generative models, pointer networks

ACM Reference Format:
Tapas Nayak, Soumya Sharma, Yash Butala, Koustuv Dasgupta, Pawan Goyal, and Niloy Ganguly. 2022. A Generative Approach for Financial Causality Extraction. In Companion Proceedings of the Web Conference 2022 (WWW ’22 Companion), April 25–29, 2022, Virtual Event, Lyon, France. ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/3487553.3524633

1 INTRODUCTION
Causality extraction from financial text is an important task for the analysis of financial documents such as financial news articles, financial reports. Previously, sequence labeling models [1, 5, 6] were proposed to solve this task and they assign ‘BIO’ tags for cause and effect span to each token in the text. Although these models perform quite well in this task, they are not modeled to handle the challenges of multiple and overlapping causalities present in the financial text. In this paper, we explore a generative approach using an encoder-decoder framework for causality extraction. We incorporate pointer networks into our decoding framework for structured prediction of the cause and effect spans in the text. The encoder-decoder approach extracts the causalities in a sequence thus the challenges of variable-length causality extraction and overlapping causalities extraction are solved. The pointer network-based decoding identifies the cause and effect spans using the start and end positional index in the text. So the cause and effect spans of different lengths are modeled uniformly in this approach. We use FinCausal [7], a dataset containing text segments from financial news articles, for our experiments. Our proposed model achieves very competitive performance in this dataset. We release our code and data for future research at https://github.com/nayakt/CEPN.

2 THE CEPN FRAMEWORK
We present CEPN, a Causality Extraction framework using Pointer Network-based encoder-decoder model. To formally define this task, given a text segment $S = \{w_1, w_2, \ldots, w_n\}$ with $n$ tokens, the goal is to extract a set of causalities $T = \{y_1, y_2, \ldots, y_{m-1}\}$ where $y_t = (c^t, e^t, c^t_{\text{b}}, e^t_{\text{b}}, c^t_{\text{e}}, e^t_{\text{e}})$ is the $t^{th}$ causality, $m - 1$ is the number of causalities. $c^t_{\text{b}}$ and $e^t_{\text{b}}$ represent the positions of the start and end tokens of the cause and effect span of the $t^{th}$ causality in the text segment $S$, respectively. In Fig 1, we give an overview of our proposed model which is inspired from the models proposed in similar structure prediction tasks such as joint entity-relation extraction [9] and aspect-sentiment triplet extraction [8].

We use a pre-trained BERT model [3] to encode the source text. We concatenate the part-of-speech tag embeddings of the tokens with the BERT vectors to obtain the encoder hidden states $h^e \in \mathbb{R}^{d_h}$. We add a special token ‘[unused0]’ at the front of the text and use its positional index ‘0’ to stop the decoding process. We use BERT_Base_Cased of dimension 768 and BERT_Large_Cased of dimension 1,024 model for encoding, and we refer them as CEPN_Base and CEPN_Large. We set the dimension of the part-of-speech tag embeddings at 32, and initialize them randomly. The hidden dimension $d_0$ of encoder for CEPN_Base and CEPN_Large model is $768 + 32 = 800$ and $1,024 + 32 = 1,056$, respectively.

We consider the causalities as a sequence $T = \{y_1, y_2, \ldots, y_{m-1}\}$. We use two special tuples to model this task as a sequence generation problem. We start the sequence generation process with a special tuple $y_0$, and we mark the end of this generation process with another special tuple, $y_m = (0, -1, -1, -1)$. Here, only $c^t_{\text{e}} = 0$
We use the FinCausal 2020 and FinCausal 2021 datasets in Table 1. We see that our CF and EF versions of the model perform almost equally on both of these datasets. Compare to GBe_Large model, our CEPN_Large_EF model achieves 1.4% higher token-level F1 score and 3.3% higher exact match-based F1 score on the FinCausal 2020 dataset. On the FinCausal 2021 dataset, compare to GBe_Large model, our CEPN_Large_CF model achieves 0.9% higher token-level F1 score and 1.4% higher exact match-based F1 score in this dataset. We also perform a statistical significance test (two-tailed and paired) between CEPN_Large_CF model and GBe_Large model on the FinCausal 2020 and 2021 datasets and find that our model is statistically significant with $p < 0.001$ (achieves a 1.1% higher mean token-level F1 score on both datasets).

| Model               | FinCausal 2020 | FinCausal 2021 |
|---------------------|----------------|----------------|
| UPB_Base [4]        | 0.689          | -              |
| DOMINO_Base [2]     | 0.796          | -              |
| PAMNet_Large* [10]  | 0.767          | 0.485          |
| GBe_Large* [1]      | 0.860          | 0.710          |
| NTUNLPL_Base [5]    | 0.869          | 0.703          |
| CEPN_Base_CF        | 0.866          | 0.733          |
| CEPN_Base_EF        | 0.857          | 0.722          |
| CEPN_Large_CF       | 0.870          | 0.739          |
| CEPN_Large_EF       | 0.874          | 0.743          |

Table 1: Performance comparison of CEPN model on the FinCausal datasets against the previous SOTA models. * marked baseline scores are reproduced by us. The remaining baseline scores are taken from their papers. 'Base' and 'Large' refer to the use of BERT_Base and BERT_Large models for source encoding. We report the average of the 5-folds in a cross-validation setting.

4 CONCLUSION

In this paper, we explore a generative approach for causality extraction in financial text using the encoder-decoder framework and pointer networks. Our model is designed to handle different challenges in this task such as extracting unknown variable-length causalities, identifying text with no causality, and extracting overlapping causalities from the text in an end-to-end architecture. Experimental results on the FinCausal datasets show the effectiveness of our proposed framework on financial causality extraction.

ACKNOWLEDGMENTS

This research was partially supported by Goldman Sachs under the research grant FTHS (FinTalk: Research towards creating a platform for highlight generation and summarization of financial documents while taking into account user feedback).
REFERENCES

[1] Guillaume Becquin. 2020. GBe at FinCausal 2020, Task 2: Span-based Causality Extraction for Financial Documents. In Proceedings of the 1st Joint Workshop on Financial Narrative Processing and MultiLing Financial Summarisation.

[2] Sharanya Chakravarthy, Tushar Kanakagiri, Karthik Radhakrishnan, and Anjana Umamaheswari. 2020. Domino at FinCausal 2020, Task 1 and 2: Causal Extraction System. In Proceedings of the 1st Joint Workshop on Financial Narrative Processing and MultiLing Financial Summarisation. https://aclanthology.org/2020.fnp-1.15

[3] Jacob Devin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In NAACL.

[4] Marius Ionescu, Andrei Marius Arram, George-Andrei Dima, Dumitru-Clementin Cercel, and Mihai Dascalu. 2020. UPB at FinCausal-2020, Tasks 1 & 2: Causality Analysis in Financial Documents using Pretrained Language Models. In Proceedings of the 1st Joint Workshop on Financial Narrative Processing and MultiLing Financial Summarisation. https://aclanthology.org/2020.fnp-1.8

[5] Pei-Wei Kao, Chung-Chi Chen, Hen-Hsen Huang, and Hsin-Hsi Chen. 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.

[6] Zhaoning Li, Qi Li, Xiaotian Zou, and Jianguo Ren. 2021. Causality Extraction based on Self-Attentive BiLSTM-CRF with Transferred Embeddings. Neurocomputing.

[7] Dominique Mariko, Hanna Abi Akl, Estelle Lahidjer, Stephane Durfort, Hugues De Mazancourt, and Mahmoud El-Haj. 2020. Financial Document Causality Detection Shared Task (FinCausal 2020). arXiv preprint arXiv:2012.02505 (2020).

[8] Rajdeep Mukherjee, Tapas Nayak, Yash Butala, Sourangshu Bhattacharya, and Pawan Goyal. 2021. PASTE: A Tagging-Free Decoding Framework Using Pointer Networks for Aspect Sentiment Triplet Extraction. In EMNLP.

[9] Tapas Nayak and Hwee Tou Ng. 2020. Effective modeling of encoder-decoder architecture for joint entity and relation extraction. In AAAI.

[10] Zsolt Szántó and Gábor Berend. 2020. ProsperAMnet at FinCausal 2020, Task 1 & 2: Modeling causality in financial texts using multi-headed transformers. In Proceedings of the 1st Joint Workshop on Financial Narrative Processing and MultiLing Financial Summarisation.