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LIPI at FinCausal 2022: Mining Causes and Effects from Financial Texts

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Abstract

While reading financial documents, investors need to know the causes and their effects. This empowers them to make data-driven decisions. Thus, there is a need to develop an automated system for extracting causes and their effects from financial texts using Natural Language Processing. In this paper, we present the approach our team LIPI followed while participating in the FinCausal 2022 shared task. This approach is based on the winning solution of the first edition of FinCausal held in the year 2020.

Keywords: Financial Texts, Causality Extraction, Natural Language Processing

1. Introduction

Recently, investors refer to financial content available online to educate themselves. Identifying causes and their effects help them in understanding financial markets better. For making investment-related decisions, they tend to strategize based on the causes and their effects. However, manually identifying causes and effects is extremely tedious and time-consuming. This paper proposes an approach for automating this. We pictorially represent such a scenario in Figure 1. This approaches consists of a BERT-base model fine-tuned for the task of token classification using BIO (Begin, Inside, Outside) tags. Subsequently, it uses Viterbi decoder (Forney, 1973) for finding out the best sentence.

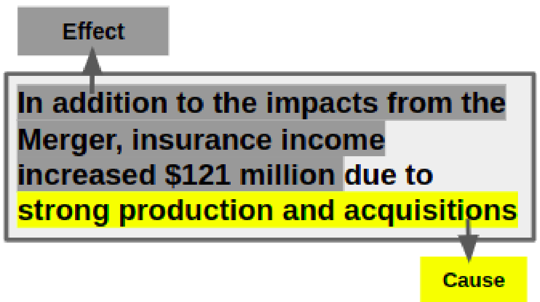

Figure 1: Extraction of a cause and it's effect.

2. Related Works

Relation extraction from documents has been one of the trending areas of research. Several SemEval (Hendrickx et al., 2010), (Gábor et al., 2018) shared task have been organized relating to this. FinCausal is a shared task that deals with extracting causes and effects specific to the financial domain. Its inaugural edition was held in the year 2020 (Mariko et al., 2020) and team NTUNLPL (Kao et al., 2020) secured the first position. They used BIO tagging and fine-tuned a BERT (Devlin et al., 2019) based pre-trained model for the task of token classification. The second edition of FinCausal (Mariko et al., 2021) was held in the following year. Team NUS-IDS (Tan and Ng, 2021) won the competition by leveraging Graph Neural Networks over the solution open-sourced by team NTUNLPL (Kao et al., 2020). We participated in the third edition of this shared task. We narrate our approach in the subsequent sections.

3. System Description

Our best performing system is the same as the one developed by team NTUNLPL (Kao et al., 2020) while participating in FinCausal-2020. It consists of three parts. They are:

1. Tagging each token of the input text using the BIO scheme. For causes (C) and effects (E) additional tags C and E are added.
2. Fine-tuning BERT-base model for the task of token classification
3. Using Viterbi decoder to select the best output sentence.

This is presented in Figure 2. The codebase has been open-sourced [1] We trained a BERT-base model on the full labelled dataset using the architecture proposed by team NTUNLPL (Kao et al., 2020). This dataset included the newly released labelled set for FinCausal 2022. Additionally, we scored the model released by team NTUNLPL (Kao et al., 2020) on the evaluation set of 2022. Finally, we ensembled the predictions by considering outputs from the former model when the one described latter was unable to generate predictions ('effects').

[1]`https://github.com/sohomghosh/FinCausal-2020_2022`.

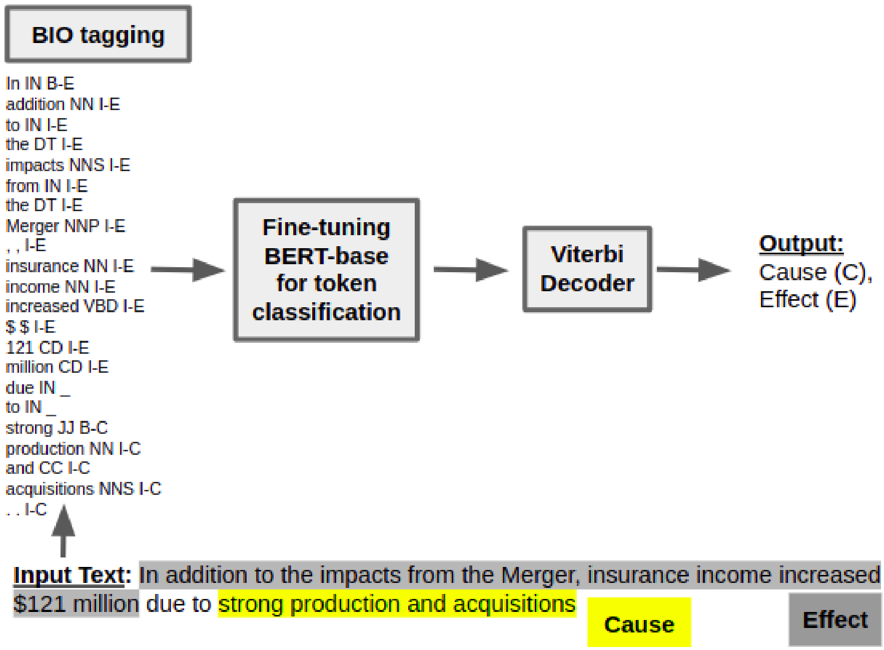

Figure 2: Cause and Effect extraction system

4. Experiments and Results

We present the results obtained from CodaLab[2] in Table 1.

We initiated our experiments by implementing two of the state of the art approaches (Nayak et al., 2022) and (Kao et al., 2020). Since the winning solution of FinCausal-2020 (Kao et al., 2020) is similar to that of FinCausal-2021 (Tan and Ng, 2021), we chose to move ahead with the former. We trained the CEPN (Nayak et al., 2022) architecture proposed by Nayak et al. separately on FinCausal-2020 and FinCausal-2021 datasets and evaluated them on the FinCausal-2022 data set. Subsequently, we combined the entire labelled dataset available till 2022 and re-trained the same architecture (Sl. No. 1). We experimented with both base and the large variant of BERT (Devlin et al., 2019). Furthermore, we replaced BERT embeddings with SEC-BERT-BASE (Loukas et al., 2022) embeddings which are specific to the financial domain (Sl. No. 2). For each of these cases, we maintained a train validation split of 80 to 20. For simplicity, we have modified the scoring logic slightly thereby generating only one set of cause and effect for each of the given texts. These codes are available in `https://github.com/sohomghosh/CEPN`.

After this, we started to experiment with the architecture presented by Kao et al. (team NTUNLPL) (Kao et al., 2020). Firstly, we scored their model on the evaluation set shared by organizers of FinCausal 2022 (Sl. No. 3). Subsequently, we re-trained it using the labelled dataset from all the three editions of FinCausal (Sl. No. 4). We also replaced the underlying BERT-base model with the one shared by Kao et al. (Kao et al., 2020) and fine-tuned it further for the task of token classification using the combined dataset mentioned above (Sl, No. 5).

Finally, combining ensembling results as discussed in the section 3 gave us the best results (Sl. No. 6).

Most of the systems were trained on Google Colab[3] using GPU as the hardware accelerator.

5. Future Works

In future, we would like to explore knowledge graphs for extracting chains of causes and their effects from financial documents. Moreover, we want to develop a tool for mining causes and effects in real-time.

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[2] `https://codalab.lisn.upsaclay.fr/competitions/3802`

[3] `https://colab.research.google.com/`

Sl. No.	Base Model	Model Architecture	F1	Recall	Precision	Exact Match
1	BERT-large (re-train)	CEPN (simplified)	0.77	0.75	0.84	0.66
2	BERT-SEC (re-train)	CEPN (simplified)	0.74	0.72	0.81	0.58
3	BERT-NTUNLPL (scoring only)	NTUNLPL	**0.92**	**0.92**	0.92	0.78
4	BERT-base (re-train)	NTUNLPL	0.86	0.86	0.86	0.68
5	BERT-NTUNLPL (re-train)	NTUNLPL	0.30	0.38	0.25	0.00
6	Ensemble(3,4)	NTUNLPL	**0.92**	**0.92**	**0.93**	**0.79**

Table 1: Results after training on the labelled dataset available till 2022

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