Predicting Directionality in Causal Relations in Text

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Abstract

In this work, we test the performance of two bidirectional transformer-based language models, BERT and SpanBERT, on predicting directionality in causal pairs in the textual content. Our preliminary results show that predicting direction for inter-sentence and implicit causal relations is more challenging. And, SpanBERT performs better than BERT on causal samples with longer span length. We also introduce CREST which is a framework for unifying a collection of scattered datasets of causal relations.

1 Introduction

Causal relations play a major role in many tasks in Natural Language Understanding (NLU) (Girju, 2003) and discourse analysis (Mulder, 2008; Kuperberg et al., 2011). The relation between X and Y is considered causal when X makes Y happen or exist, or vice versa, where X and Y can be an event, state, or object. For example, in “The river had now turned into full flood after the deluge of rain a few days ago.”, deluge of rain is the cause of flood which happens when there is an overflow of water.

Automatic extraction of causal relations is a challenging task in Natural Language Processing (NLP). Previous work on identifying causal relations is mainly focused on classifying pairs as causal/non-causal without necessarily considering direction in the pairs. These lines of research either assume a fixed direction between spans in a pair or do not directly test models in predicting the direction in a causal pair. For example, (Gao et al., 2019a; Liu et al., 2020) focus only on identifying causal pairs in context and not specifying the direction in the pairs, namely which entity caused the other. The knowledge-oriented CNN (K-CNN) model for causal relation extraction model (Li and Mao, 2019) attempts at finding sentences that include a causal relation only by feeding a pair of spans and a sentence as input to the model. On the other hand, (Dunietz et al., 2018) indirectly addresses the direction prediction problem by finding cause and effect spans associated with only explicit causal connectives in context. They adopt a syntactic perspective.

The cappuccino's climate change impact depends on whether the cafe is double-glazed, the decisions the staff and I take to get there, the diet of the methane-producing cow that produced the milk and the source of power for the espresso machine.

Figure 1: A golden non-causal relation that can be Causal if we change the direction between spans.

Direction between spans in a relation may play an important role in the classification of some instances of causal relations. For example, in the non-causal relation shown in Figure 1, from a commonsense perspective, we know that milk cannot produce a cow but a cow can produce milk and be the reason for milk to be produced. Thus, if we treat causal relation classification here simply as a pair classification task with no direction provided, we will have a pair that can be marked as both causal and non-causal while the gold label for the pair is non-causal. We then ask a question here: RQ) how well can a model tell the difference between cause and effect in a causal relation?

In the rest of the paper, first, we discuss the scatteredness of causal relation datasets and introduce a simple framework to unify a collection of well-known datasets of causal relations (§2). Then we explain the preprocessing steps on datasets we chose from this collection for our experiments (§3). We report our experiments on predicting direction
in causal relations (§4) along with some preliminary results and qualitative error analysis (§5). We conclude this paper with reviewing the related work (§6) and discussing next steps (§7).

2 Unifying Causal Relation datasets

Data resources of causal relations are rather scattered and do not often follow the same schematic or machine-readable format. Such an incompatibility among resources is not a new problem and it has been slowing down the progress in the classification of semantic relations including causal relations (Hendrickx et al., 2010). That is why we decided to unify a collection of widely used resources of causal/non-causal relations to make them easier for the research community to use.

In this step, we focused on publicly available datasets in which the context associated with a causal relation is available, and we excluded data resources in which a relation is only a pair of words/tokens without any given context such as (Luo et al., 2016). The main reason is that causal relation/pair classification is mainly a context-dependent task. We also excluded data resources that only contain context and a label (binary or multi-label) without annotating the spans/arguments of a relation such as (Yu et al., 2019). It is worth pointing out that these excluded resources can fit in the format we define and they were just not our focus for now. It is also important to mention that some resources are not publicly available—which itself is another challenge in addition to the incompatibility of schemes—such as Penn Discourse Treebank (PDTB) (Prasad et al., 2008), and some others such as the corpus of Temporal-Causal relations (Bethard et al., 2008) and BECauSE (Dunietz et al., 2017) only share their annotation.

By comparing a wide range of well-known and widely-used datasets of causal relations, we identified the largest common set of features and annotations among them to define CREST. In Table 1, we listed all these features. We call the process of converting relations to CREST as CRESTing a dataset.

3 Data and preprocessing

We chose two datasets that follow the definition of causal relations from a commonsense perspective to use in our experiments. Compared to other datasets of causal relations such as (Do et al., 2011; Mirza et al., 2014; Mostafazadeh et al., 2016; Dunietz et al., 2017), these datasets have enough causal relations to allow us to create fairly balanced train and test splits. In the following, we briefly introduce each of them:

Penn Discourse Treebank 3.0 (PDTB3) (Prasad et al., 2008) contains annotated samples of discourse connectives, implicit and explicit, and their arguments. These discourse connectives are taken to be the predicates of binary discourse relations including causal relations. There are four coarse-grained discourse relation types at Level-1 including Contingency in PDTB3. And Contingency relation itself contains the finer-grained Cause relations at Level-2. We use all Level-3 relations in PDTB3 with Level-2 classes: Cause, Cause+Belief, and Cause+SpeechAct. We excluded the Level-3 NegResult relations since in these relations one argument does not cause but prevents the effects mentioned in the other argument. EventStoryLine (ESL) v1.5 is created by crowd-
sourcing causal relations between events in news articles (Caselli and Inel, 2018). EventStoryline’s crowd-sourcing approaches and experiments follow a commonsense reasoning perspective of causality. Causality in EventStoryLine refers to the broader notion of contingent relations rather than a strict causal relation. We extract all PLOT_LINK tags of the two following classes from EventStoryLine: 1) PRECONDITION, events which enable or cause another event, or 2) FALLING_ACTION that mark speculations or consequences.

### 3.1 Converting relations to sequences

When we use relation, we mean a pair of span, in a context, where span is a sequence of one or more tokens and context can be one or more sentences. Direction of a relation can be either span1 ⇒ span2 or span1 ⇐ span2. In a causal relation, the starting span is always cause and the ending span is always effect. Span1 and span2 in a relation do not always appear in the same order in context.

As shown in Figure 2, we convert relations to input sequences. For specifying spans in a sequence, we add the special [unused*] tokens from BERT vocabulary\(^3\) to the start and end of each span in the context. It is very important to notice that the order in which [unused*] tokens appear in a sequence is always the same, no matter if a relation is cause-effect or effect-cause. As a result, we do not feed the direction between spans to the models and models will not know the span type or direction at test time.

\(^3\)For models with a different vocabulary than BERT, the [unused*] tokens can be replaced by the special tokens in that vocabulary.

### 4 Experiments

**Task:** For a causal relation, given a context, two spans of text, namely span1 and span2, this task is a binary classification of the relation between the two spans into either cause-effect or effect-cause. The goal in this task is to predict the direction in a causal relation.

We chose two transformer-based language representation models including BERT (Devlin et al., 2018) and SpanBERT (Joshi et al., 2020), their base and cased version. BERT is one of the first transformer-based language models that achieved a promising performance across a diverse range of NLP tasks and later inspired the architecture of some other language models (Liu et al., 2019; Lan et al., 2019). SpanBERT is an improved pre-training model, with the same format as BERT, designed to better predict spans of text. In our experiments, we use HuggingFace’s BertForSequenceClassification which is a BERT model with a sequence classification head on top (Wolf et al., 2019) implemented in PyTorch (Paszke et al., 2019). In all experiments, we use 4 different random seeds when fine-tuning our models and report the average result.

### 4.1 Data splits

In all our experiments, we divide our data into train, development (dev), and test splits with 80:10:10 ratio. Information about data splits is shown in Table 2.

**Checking context overlaps:** There is a possibility that causal relations in a dataset share the exact or similar context. For example, there are two causal relations, (cause, effect) pairs, annotated in the following context: "A major earthquake struck south-
The <s1>inflammation</s1> is caused by the <s2>growth</s2> of unusual bacteria, which usually results from antibiotic use.

[CLS] The [unused1] inflammation [unused2] is caused by the [unused3] growth [unused4] of unusual bacteria, which usually results from antibiotic use. [SEP]

Financial <s1>stress</s1> is one of the main causes of <s2>divorce</s2>.

[CLS] Financial [unused1] stress [unused2] is one of the main causes of [unused3] divorce [unused4] [SEP]

Figure 2: Converting an input example to an input sequence with and without direction, for the BertForSequenceClassification model.

| Data | Source | Train | Dev | Test |
|------|--------|-------|-----|------|
| $D_1$ | PDTB3  | 5,692 | 727 | 729  |
| $D_2$ | ESL    | 1,095 | 169 | 224  |

Table 2: Number of samples in data splits.

ern Haiti on Tuesday, knocking down buildings and power lines”; (“struck”, “knocking”) and (“earthquake”, “knocking”). Even though these relations are annotated in the same context, they are stored as two separate relations. And when splitting the data into train, dev, and test sets, there is a chance that one of these relations be put in train and another one in test set, respectively. When creating splits, we check to make sure there is no such context overlap, full or partial between: 1) train+dev and test, and 2) train and dev, since we want our models not to be tested on classifying relations in a context they have already seen and were fine-tuned on.

5 Results

Results of experiments are reported in Table 3. One interesting point to notice is that on PDTB3 where the length of spans is way longer compared to ESL, SpanBERT performs better than BERT. And on ESL where the majority of spans contain one or two tokens, BERT outperforms SpanBERT. Another point to consider is that even though the average performance of best-performing models on $D_2$ is not too low and is higher than random classification (if we consider random as baseline here,) not all models could converge well on $D_2$. The small size of training data we use for fine-tuning our models on $D_2$ to a certain degree may explain models’ convergence problem. It is worth thinking how we can leverage some recent datasets of causal relations such as GLUCOSE (Mostafazadeh et al., 2020) to address this problem or focus on methods that require a lesser number of golden annotated samples. Our results here can also be seen as a baseline for future experiments.

5.1 Qualitative error analysis

For error analysis and for each language model, we looked at all samples misclassified by all models we fine-tuned and tested with different random seeds on each dataset. We observed two main reasons for errors: 1) inter-sentence relations in which two spans of a relation appear in two different sentences and far from one another in context, and 2) implicit relations, as we expected. As mentioned earlier, in PDTB3, spans are relatively longer and contain more tokens. It will be interesting to see if we can find a better way to put a model’s attention in an input sequence on the main tokens in a long span, for example, by adjusting the start and end tokens for each span ([unused*] tokens, in our case) or adding an encoding vector of span boundaries in input sequences to the models.

| Data | Model  | P   | R   | F1   |
|------|--------|-----|-----|------|
| $D_1$ | Random | 0.54| 0.5 | 0.52 |
|      | BERT   | 0.83| 0.82| 0.83 |
|      | SpanBERT | 0.86| 0.85| 0.86 |
| $D_2$ | Random | 0.5 | 0.47| 0.48 |
|      | BERT   | 0.8 | 0.78| 0.79 |
|      | SpanBERT | 0.76| 0.67| 0.71 |

Table 3: Precision, Recall, and F1 of evaluating BERT and SpanBERT models on predicting direction in a causal relation.
6 Related work

Work on automatic extraction of causal relations started around the late 80s and early 90s with a focus on rule-based methods with a substantial amount of manual work (Joskowicz et al., 1989; Kaplan and Berry-Rogghe, 1991; Garcia et al., 1997; Khoo et al., 1998). Starting 2000, a combination of learning-based and rule-based methods were employed to improve the quality of automatic causality extraction in text (Girju, 2003; Chang and Choi, 2004, 2006; Blanco et al., 2008; Do et al., 2011; Hashimoto et al., 2012; Hidey and McKeown, 2016). More recently, word-embedding and language representation models started to emerge in work around causal relation classification (Dunietz et al., 2018; Pennington et al., 2014; Dasgupta et al., 2018; Gao et al., 2019b).

To the best of our knowledge, the closest study to ours is (Bhagat et al., 2007) where LEDIR is introduced as a method to predict directionality in inference rules.

7 Conclusion

In this work, we evaluated the performance of two bidirectional transformer-based language models on predicting the direction in causal relations in text. Our preliminary results show that finding directionality of inter-sentence and implicit causal pairs is more challenging and SpanBERT performs better than BERT on classifying causal relations with longer span length. We also introduced a framework, CREST, for unifying a collection of scattered causal relation datasets. As our next steps, we will work on different methods of feeding input sequences to our causal relation classification models such that boundaries of spans in context are less latent. And, we will continue unifying new datasets of causal relations and add counterfactual relations to our unified collection as well.

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As can be seen in Figures 5, 6, models fine-tuned on $D_2$ (EventStoryLine v1.5) could not converge well in the majority of cases which to a certain degree can be explained by the small set of causal relations we use for fine-tuning our models.

Figure 3: Accuracy and evaluation loss of BERT model on $D_1$’s development set.

Figure 4: Accuracy and evaluation loss of SpanBERT model on $D_1$’s development set.

We fine-tuned our models with sequence length of 128 and the following hyperparameter values: Batch size: 16, learning rate: 2e-5, and number of epochs: 10. All experiments were run on an Amazon AWS p3.2xlarge EC2 instance with one Tesla V100 GPU.

A Experiments

Accuracy and evaluation loss plots for our experiments on dev set are shown in Figures 3, 4, 5, and 6.
Figure 5: Accuracy and evaluation loss of BERT model on $D_2$’s development set.

Figure 6: Accuracy and evaluation loss of SpanBERT model on $D_2$’s development set.

Table 4: List of CRESTed datasets. Signal refers to signal words/tokens or markers annotated for a relation.

| ID | Dataset               | Signal | Causal |
|----|-----------------------|--------|--------|
| 1  | Semeval-2007 task 4   | ✗      | 114    |
| 2  | Semeval-2010 task 8   | ✗      | 1,331  |
| 3  | EventCausality        | ✗      | 485    |
| 4  | Causal-TimeBank       | ✓      | 318    |
| 5  | EventStoryLine v1.5   | ✓      | 2,608  |
| 6  | CaTeRS                | ✗      | 308    |
| 7  | BECauSE v2.1          | ✓      | 554    |
| 8  | COPA                  | ✓      | 1,000  |
| 9  | PDTB3                 | ✓      | 7,991  |

Table 4: List of CRESTed datasets. Signal refers to signal words/tokens or markers annotated for a relation.

B CRESTed Datasets

In this section, we briefly introduce datasets we have aggregated and CRESTed so far. Some statistics related to these datasets are shown in Table 4. **Semeval-2007 task 4** contains samples of different semantic relations between nominals in text (Girju et al., 2007). Cause-Effect is one of these semantic relations. Nominal in this dataset is defined as a noun or base noun phrase excluding named entities. Samples in Semeval-2007 task 4 are initially extracted based on predefined patterns and then manually annotated for the final label. **Semeval-2010 task 8** (Hendrickx et al., 2010) is very similar to the Semeval-2007 task 4 dataset and mainly follows the same schema. The main goal in creating Semeval-2010 task 8 was to have a standard benchmark dataset for multi-way semantic relation classification in context.

**EventCausality** is a dataset created for evaluation purposes using news articles (Do et al., 2011). There are two types of relations annotated in this dataset including causality and relatedness, C and R, respectively. Causality relations in EventCausality are manually annotated for pairs of events based on two rules: 1) Cause event should temporally precede the Effect event and 2) Effect event occurs because the Cause event occurs.

**Choice of Plausible Alternatives (COPA)** is a tool for evaluating models’ performance in commonsense causal reasoning (Roemmele et al., 2011). COPA consists of 1000 questions, split equally into development and test sets. Each question is composed of a premise of and two alternatives where premise is either cause/effect and one of the alternatives more plausibly has a causal relation with the premise. When CRESTing COPA, we also store pairs of premises and their less plausible alternatives.

**Causal-TimeBank** contains explicit causal relations between event pairs in a sentence (Mirza et al., 2014). For annotating causal relations, C-LINKs, expressions containing affect verbs, link verbs, causative conjunctions, and prepositions are used in addition to basic construction for CAUSE, ENABLE, and PREVENT categories of causation and periphrastic causatives. In Causal-TimeBank,

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4Since the existence of causality in Relatedness relations is debatable, we excluded these relations when converting relations from EventCausality.
polarity, factuality, and certainty are annotated for events involved in a causal relation. Signals of causality for CLINKs are annotated in Causal-TimeBank as well.

**CaTeRS** has annotations of explicit and implicit causal relations between events from a collection of stories (Mostafazadeh et al., 2016). In CaTeRS, causal relations between events are annotated more from a commonsense reasoning perspective than based on the presence of causal markers. Moreover, annotated relations are either in a sentence or across sentences in a story which makes CaTeRS a proper dataset especially for evaluating the performance of models on identifying inter-sentence causal relations.

**EventStoryLine v1.5** EventStoryLine is created by crowd-sourcing causal relations between events in news articles (Caselli and Inel, 2018). EventStoryLine’s crowd-sourcing approaches and experiments follow a commonsense reasoning perspective of causality, the approach adopted by CaTeRs as well. Causality in EventStoryLine refers to the broader notion of contingent relations rather than a strict causal relation. When converting EventStoryLine relations to CREST, we extract all `PLOT_LINK` tags of the two following classes: 1) **PRECONDITION**, events which enable or cause another event, or 2) **FALLING_ACTION** that mark speculations or consequences.

**BECauSE** is a bank of effects and causes that are explicitly stated in the context. BECauSE uses a variety of constructions to express causal relations. Causal relations in this dataset are not necessarily relations that hold from a philosophical perspective in the real-world but relations that are expressed in context as causal (Dunietz et al., 2017). Every relation in BECauSE has a signal word associated with it.

**Penn Discourse Treebank (PDTB3)** (Prasad et al., 2008) contains annotated samples of discourse connectives, implicit and explicit, and their arguments. These discourse connectives are taken to be the predicates of binary discourse relations including causal relations. There are four coarse-grained discourse relation types at Level-1 including **Contingency** in PDTB3. And Contingency relation itself contains the finer-grained **Cause** relations at Level-2. We use all Level-3 relations in PDTB3 with Level-2 classes: **Cause**, **Cause+Belief**, and **Cause+SpeechAct**. We excluded the Level-3 **NegResult** relations since in these relations one argument does not cause but *prevents* the effects mentioned in the other argument.