# **UniCausal: Unified Benchmark and Model for Causal Text Mining**

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#### **Abstract**

Current causal text mining datasets vary in objectives, data coverage, and annotation schemes. These inconsistent efforts prevented modeling capabilities and fair comparisons of model performance. Few datasets include cause-effect span annotations, which are needed for end-to-end causal extraction. Therefore, we proposed UniCausal, a unified benchmark for causal text mining across three tasks: Causal Sequence Classification, Cause-Effect Span Detection and Causal Pair Classification. We consolidated and aligned annotations of six high quality human-annotated corpus, resulting in a total of 58,720, 12,144 and 69,165 examples for each task respectively. Since the definition of causality can be subjective, our framework was designed to allow researchers to work on some or all datasets and tasks. As an initial benchmark, we adapted BERT pre-trained models to our task and generated baseline scores. We achieved 70.10% Binary F1 score for Sequence Classification, 52.42% Macro F1 score for Span Detection, and 84.68% Binary F1 score for Pair Classification.

#### 1 Introduction

Causal text mining relates to the extraction of causal information from text. Given an input text, we are interested to know if and where causal information occurs. After extracting causal information from text, researchers can use these information as a knowledge base (Heindorf et al., 2020; Luo et al., 2016; Li et al., 2020), for summarization, or prediction (Radinsky et al., 2012; Radinsky and Horvitz, 2013). Since causality is an important part of human cognition, causal text mining also has important downstream natural language understanding use-cases, like in question answering (Jain, 2016; Verberne, 2006; Verberne et al., 2006; Jo et al., 2021; Verberne et al., 2008, 2010; Girju, 2003; Dalal et al., 2021; Stasaski et al., 2021; Dunietz

et al., 2020). Figure 1 illustrates three popular causal text mining tasks (Sequence Classification, Span Detection and Pair Classification<sup>1</sup>) and their expected output.

At the moment, causal text mining corpora are limited (Asghar, 2016), and annotation guidelines vary (Yang et al., 2022). This hinders both modeling capabilities and fair comparisons between models. Additionally, working on independent tasks and datasets runs the risk of training task-specialized and dataset-specific models that are not generalizable.

Similar to information extraction, all causal text mining tasks 'can be modeled as text-to-structure transformations' (Lu et al., 2022), except that each has slightly different end goals. At the crux of it, models must be able to perform spotting (Argument identification) and association (Connecting spans to relations). For causal text mining, this means that models should be able to identify cause-effect arguments, and tie them together. Therefore, a unified model working on various causal text mining tasks, which can collaboratively learn from various objectives and knowledge sources, should be more universally adaptable and generalizable to unseen examples.

The contributions of UniCausal are as follows:

- To our knowledge, we are the first to produce a unified benchmark for causal text mining tasks across six datasets and three tasks. We employed BERT-based neural network models to create baselines for all three tasks.
- Our framework<sup>2</sup> provides a seamless way for researchers to design individual or joint models, while bench-marking their performance

<sup>&</sup>lt;sup>1</sup>Pair Classification with event-based arguments is commonly referred to as Event Causality Identification (Zuo et al., 2021a,b, 2020a,b; Cao et al., 2021).

<sup>&</sup>lt;sup>2</sup>Our repository is at https://github.com/tanfiona/CausalNewsCorpus.

against clearly defined test sets across some or all the processed corpora.

#### 2 Related Work

## 2.1 Causal Text Mining

#### 2.1.1 Tasks

Causal relation extraction can be done by extracting causal relations and assessing the validity of the extract relations directly (Khoo, 1995; Khoo et al., 1998; Garcia, 1997; Girju and Moldovan, 2002; Girju, 2003; Wu et al., 2012; Agrawal and Srikant, 1994; Ittoo and Bouma, 2011, 2013). Alternatively, a two-stepped approach would also return the same outcome: After the successful identification of causal sequences (Causal Classification), detection of the cause-effect spans can be conducted on the positive sequences (Cause-effect Span Detection). This step-wise approach to causal relation extraction is employed in shared tasks like FinCausal 2020<sup>3</sup> (Mariko et al., 2020) and Causal News Corpus Shared Task 2022<sup>4</sup> (Tan et al., 2022).

#### 2.1.2 Datasets

Research in causal text mining has been limited by data deficiency issues (Yang et al., 2022). The lack of standardized datasets also hinders comparisons in performance across models (Asghar, 2016). Different corpora have slightly different agendas. Penn Discourse TreeBank (Prasad et al., 2008; Webber et al., 2019; Prasad et al., 2006) is a corpus working on discourse relations between clauses, where causality is one out of the many relations they annotated. Meanwhile, event-based corpora like EventStoryLine (Caselli and Vossen, 2017) and CausalTimeBank (Mirza et al., 2014; Mirza and Tonelli, 2014) annotated head words of events as arguments. Table 1 delineates the differences in terms of data source, sentence lengths, linguistic expression and definition of arguments across the six corpora we studied. Since causal datasets have different annotation schemes and coverage, direct comparisons of model performance across datasets is unfair. Furthermore, some corpora are unsuitable for supervised end-to-end causal extraction.

## 2.2 Unified Causal Text Mining

We propose UniCausal, a large consolidated resource of annotated texts for causal text mining. We relied on six high quality human-annotated corpora and aligned each corpus' definitions, where possible, to cater to the three causal text mining tasks. Although some large corpora or knowledge bases (KBs) that include causal relations already exists<sup>5</sup>, they are typically annotated in a semi-supervised manner and constructed using rule-based methods. Such causal examples are of a lower quality and have less linguistic variation. These resources are useful databases for commonsense causal relations, however, they are unsuitable for training and testing supervised causal text mining models. Our consolidated corpus serves as an extensive resource for causal text mining modeling. By training an effective text mining model on our combined corpus, researchers can potentially create an even larger causal KB by extracting more relations compared to rule-based methods.

There is an on-going attempt, known as CREST<sup>6</sup>, that consolidated and formatted causal, counterfactual and commonsense resources. Since they excluded *Non-causal* examples from many datasets, many of such datasets are unsuitable for Classification tasks. CREST also did not index the examples in a manner that recognizes that one sequence can have multiple cause-effect relations.

## 3 Methodology

#### 3.1 Benchmark

## 3.1.1 Causal Text Mining Datasets

We combined six popular datasets used for causal text mining: AltLex (Hidey and McKeown, 2016), BECAUSE 2.0 (Dunietz et al., 2017b), CausalTime-Bank (CTB) (Mirza et al., 2014; Mirza and Tonelli, 2014), EventStoryLine V1.0 (ESL) (Caselli and Vossen, 2017), Penn Discourse Treebank V3.0 (PDTB) (Webber et al., 2019) and SemEval 2010 Task 8 (SemEval) (Hendrickx et al., 2010). Appendix Table A.6 illustrates one *Causal* example per dataset.

<sup>3</sup>https://competitions.codalab.org/com
petitions/23748

https://codalab.lisn.upsaclay.fr/com petitions/2299

<sup>&</sup>lt;sup>5</sup>Some examples of available causal corpora: Bootstrapped versions of AltLex (Hidey and McKeown, 2016) and SCITE (Li et al., 2021); Causal KBs: CauseNet (Heindorf et al., 2020), CausalNet (Luo et al., 2016) and CausalBank (Li et al., 2020); Semantic KBs that include causal relations: FrameNet (Ruppenhofer et al., 2016) and ConceptNet (Speer et al., 2017)

<sup>&</sup>lt;sup>6</sup>https://github.com/phosseini/CREST

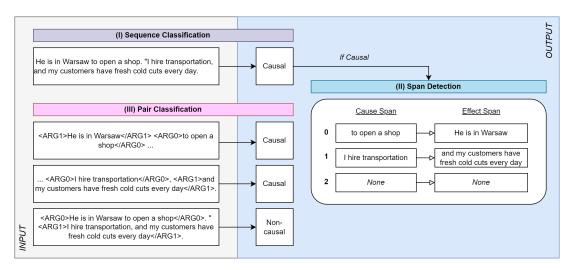


Figure 1: A two-sentence example (from PDTB-3) that contains causal relations. (I) Sequence Classification aims to return a *Causal* label. (II) Span Detection identifies the text related to the Cause-Effect spans and we focus on up to three causal relations in our work. This example also contains three annotated relation pairs, of which, two are labeled *Causal* and one is labeled *Non-causal*. These are target labels of the (III) Pair Classification task.

Corpus	Source	Inter-sent	Linguistic	Arguments
AltLex (Hidey and McKeown, 2016)	News		AltLex	Words before/after signal
BECAUSE 2.0 (Dunietz et al., 2017b)	News, Congress Hearings		Explicit	Phrases
CausalTimeBank (CTB) (Mirza et al., 2014)	News	$\checkmark$	All	Event head word(s)
EventStoryLine V1.0 (ESL) (Caselli and Vossen, 2017)	News	$\checkmark$	All	Event head word(s)
Penn Discourse Treebank V3.0 (PDTB) (Webber et al., 2019)	News	$\checkmark$	All	Clauses
SemEval 2010 Task 8 (SemEval) (Hendrickx et al., 2010)	Web		All	Noun phrases

Table 1: Six popular causal corpora and their annotation coverage in terms of: data source, sentence lengths, linguistic construction and argument types.

#### 3.1.2 Causal Text Mining Tasks

There are three causal text mining tasks that we focused on, corresponding to the tasks shown in Figure 1:

- (I) Sequence Classification: Given an example, does it contain any causal relations?
- (II) Span Detection: Given a causal example, which words in the sentence correspond to the Cause and Effect arguments? Identify up to three causal relations and their spans.
- (III) Pair Classification: Given the marked argument or entity pair, are they causally related such that the first argument (ARG0) causes the second argument (ARG1)?

From our literature review, we believe these tasks are general enough to cover a broad range of causal datasets. Additionally, accurate Sequence Classification followed by Span Detection equates to end-to-end causal relation extraction. Pair Classification separately investigates presence of causality given argument prompts.

#### 3.1.3 Preprocessing

For every dataset, we retained examples that were of  $\leq 3$  sentence length. For each example, we kept sentences that contained the arguments<sup>7,8</sup>. We split the dataset into train and test sets based on previous works' recommendations, or if not, randomly. Finally, we processed each dataset to fit into the format required for our three tasks described below.

Let a unique sequence of text be represented by a vector  $\vec{w} = w_1, w_2, ..., w_N$  of N word tokens. Each sentence has a binary sequence label s of either 0 or 1, representing *Non-causal* or *Causal* respectively.

(I) Sequence Classification: Worked on both *Causal* and *Non-causal* texts. Each example text was unique with a target label, s.

 $<sup>^7</sup>$ In an example with three sentences [a,b,c], if ARG0 was in Sentence a while ARG1 was in Sentence c, the example text was only a concatenation of Sentences a and c. If ARG1 spanned across both Sentences b and c, then the example text was comprised of all three sentences.

 $<sup>^8</sup>$ This step is less relevant now since we worked with examples of <=3 sentence length. For longer document-level applications in the future, it helps to shorten the input text to the most relevant portions.

- (II) Span Detection: Worked on only *Causal* texts. Each example text was unique, and we allowed up to three cause-effect relations per example. To generate the target labels, the annotated spans in the texts were converted to BIO-format (Begin (B), Inside (I), Outside (O)) (Ramshaw and Marcus, 1995) for two types (Cause (C), Effect (E)). Therefore, there were five possible labels per word: B-C, I-C, B-E, I-E and O. The corresponding target token vector will be  $\vec{t} = t_1, t_2, ..., t_N$ , where each  $t_n$  represents one of the five labels. For examples with multiple relations, we sorted them based on the location of the B-C, followed by B-E if tied. This means that an earlier occurring Cause span was assigned a lower index number. See Figure 1's spans for example. For multiple relations,  $\vec{w}$  has multiple token vectors  $\vec{t^v}$  where v = 0, 1, 2, since we permitted up to three causal relations per unique text<sup>9</sup>.
- (III) Pair Classification: Worked on both *Causal* and *Non-causal* texts. Each example text was unique after taking into account of where special tokens ARG0 and ARG1 are located. For a sequence of text with N word tokens, we included  $2 \cdot a$  special beginning and end tokens 10 such that the input word vector  $\vec{u}$  is now of length  $N+2 \cdot a$ . a represents the number of arguments in the example. Notice that  $\vec{w}$  can have multiple versions of  $\vec{u}$ , depending on the location of the special tokens. For example, in Figure 1, we had three Pair Classification examples for one Sequence Classification example.

The final data sizes used for modeling is reflected in Table 2. The number of Span Detection example tally with the positive instances of Sequence Classification examples because span examples are grouped by unique text as described above. Therefore, multiple cause-effect relation spans (i.e.  $t^{\vec{0}}$ ,  $t^{\vec{1}}$  and  $t^{\vec{2}}$ ) were consolidated together into a unique example (i.e. same  $\vec{w}$ ). For ungrouped span example counts (i.e. to regard each  $t^{\vec{v}}$  as an individual example), refer to Appendix Table A.9. At evaluation, performance metrics were calculated

		(1	I)	(II)	(I)	II)			
		Se	eq	Span	Pair				
Corpus	Split	Non-	Causal	Causal	Non-	Causal			
		causal			causal				
AltLex	Train	277	300	300	296	315			
	Test	286	115	115	289	127			
BEC-	Train	183	716	716	266	902			
AUSE	Test	10	41	41	14	46			
CTB	Train	1,651	234	-	3,047	270			
	Test	274	42	-	444	48			
ESL	Train	957	1,043	-	-	-			
	Test	119	113	-	-	-			
PDTB	Train	24,901	8,917	8,917	32,587	9,809			
	Test	5,796	2,055	2,055	7,694	2,294			
Sem-	Train	6,976	999	-	6,997	1,003			
Eval	Test	2,387	328	-	2,389	328			
Tot	al	43,817	14,903	12,144	54,023	15,142			

Table 2: Sizes of final train and test datasets per task. "-" indicates tasks not applicable to the corpus.

at the ungrouped level so that every target token vector is evaluated against equally. Appendix A.1.2 discusses data pre-processing steps per dataset in detail.

## 3.2 Modeling

As an initial benchmark, we experimented with baseline models that performed the Span Detection, Sequence Classification and Pair Classification task independently from Huggingface (Wolf et al., 2020). For the Span Detection task, we utilized the BertForTokenClassification model on the ungrouped span dataset. For the two Classification tasks, we utilized the BertForSequenceClassification model on the sequence and pair datasets separately. The models are detailed further below. From here on, we refer to these baseline models as "Individual".

## 3.2.1 BERT Embeddings

Transformer-based pre-trained language models are the latest state-of-the-art in NLP. Likewise, we employed the popular Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019) to tokenize our sentences and obtain our token embeddings  $(\vec{r_n})$ . For the Pair Classification task only, we added four special tokens to the vocabulary to represent the boundaries of the two arguments. The BERT encoder is not frozen and thus can fine-tune to our tasks.

#### 3.2.2 Sequence and Pair Classification

For each classification task, we pooled the token embeddings into a sequence embedding by extracting the embedding on the [CLS] token. The se-

 $<sup>^9</sup>$ For datasets compatible for Span Detection, we removed examples with >3 causal relations to simplify our study.

<sup>&</sup>lt;sup>10</sup>(<ARG0>, </ARG0>) marks the boundaries of a Cause span, while (<ARG1>, </ARG1>) marks the boundaries of a corresponding Effect span.

	(I) S	Sequence	Classific	ation	(II)	Span Dete	ection	(I	(III) Pair Classification			
Test Set	P	R	F1	Acc	P	R	F1	P	R	F1	Acc	
All	71.13	69.14	70.10	86.27	46.33	60.35	52.42	85.44	83.93	84.68	93.68	
	$\pm 0.80$	$\pm 1.60$	$\pm 0.58$	$\pm 0.15$	±1.22	$\pm 0.30$	$\pm 0.90$	$\pm 0.96$	$\pm 0.44$	$\pm 0.27$	$\pm 0.16$	
AltLex	50.76	63.48	56.37	71.87	27.74	42.99	33.72	82.60	87.09	84.76	90.43	
	±1.61	$\pm 4.60$	$\pm 2.49$	±1.19	±1.20	$\pm 0.85$	±1.12	±1.99	±1.53	$\pm 0.66$	$\pm 0.55$	
BECAUSE	92.32	70.24	79.77	71.37	32.51	44.30	37.47	87.93	94.78	91.21	86.00	
	±1.69	$\pm 2.04$	$\pm 1.68$	$\pm 2.24$	$\pm 2.82$	$\pm 2.33$	$\pm 2.57$	$\pm 1.73$	$\pm 1.94$	±1.18	$\pm 1.90$	
CTB	42.37	66.19	51.58	83.48	-	-	-	75.66	72.50	73.94	95.04	
	$\pm 2.11$	±4.26	$\pm 1.82$	±1.21				$\pm 3.61$	±6.81	$\pm 4.68$	$\pm 0.78$	
ESL	76.11	67.43	71.45	73.79	-	-	-	-	-	-	-	
	$\pm 2.04$	±3.45	±1.89	±1.34								
PDTB	72.59	66.34	69.31	84.63	47.77	61.54	53.78	84.56	82.04	83.28	92.43	
	±0.61	±1.63	$\pm 0.70$	$\pm 0.17$	±1.22	±0.29	$\pm 0.88$	±1.17	$\pm 0.46$	±0.36	±0.23	
SemEval	73.39	89.51	80.64	94.81	-	-	-	93.38	96.10	94.71	98.70	
	±1.18	±1.59	±0.46	±0.16				±0.88	±0.59	±0.23	±0.07	

Table 3: Performance metrics for different test sets across the three tasks. All models were trained on all six datasets, where applicable. Tasks that are not applicable to the dataset are indicated by "-". Scores are reported in percentages (%).

quence embeddings was then fed into a sequence classifier g(.) to predict logits for the two labels: Causal and Non-causal.

$$\hat{y} = g(\vec{r_{[CLS]}}) \tag{1}$$

The logits produced were compared against the true sequence label y to calculate Cross-Entropy (CE) Loss for learning.

$$\mathcal{L}_{seq} = -y \cdot \log(\hat{y}) - (1 - y) \cdot \log(1 - \hat{y}) \quad (2)$$

#### 3.2.3 Span Detection

We fed the token embeddings into a token classifier (f(.)). The classifier returns predicted logits for the five BIO-CE token labels, which aims to predict the cause-effect span in the input sentence, obtained via argmax. Note that given the current simple set up, the Span Detection model can only predict one cause-effect relation per input sequence.

$$\hat{t_n} = f(\vec{r_n}) \tag{3}$$

Again, the logits produced were compared against the true token vector  $\vec{t^v}$  to calculate CE Loss.

$$\mathcal{L}_{token} = -\sum_{n=1}^{N} \sum_{i=1}^{C} t_{n,i} \cdot \log(\hat{t_{n,i}})$$
 (4)

#### 3.2.4 Evaluation Metrics

For the two Classification tasks, we calculated the Accuracy (Acc), Precision (P), Recall (R) and F1

scores per experiment. For the Span Detection, we referred to evaluation metrics from text chunking (Tjong Kim Sang and Buchholz, 2000) and Cause-Effect Span Detection (Mariko et al., 2020, 2021; Tan et al., 2022) shared tasks, and used the Macro P, R and F1 metrics. The token classification evaluation scheme by seqeval (Nakayama, 2018; Ramshaw and Marcus, 1995) reverts the BIOformatted labels to the original form (i.e. Cause (C) and Effect (E)) for evaluation. Our default evaluation scripts report metrics for all and each corpus.

In the next section, we present the average and standard deviation scores obtained from multiple runs using five random seeds. For model hyperparameters and further experimental details, refer to Appendix Section A.2.

#### 4 Experiments

#### 4.1 Baseline Performance

In Table 3, we present the performance of the baseline BERT models when trained on all datasets, and tested on all and each dataset. Across all test sets, baseline models achieved 70.10% Binary F1 score for Sequence Classification, 52.42% Macro F1 score for Span Detection, and 84.68% Binary F1 score for Pair Classification. Refer to Appendix Section A.4 for F1 scores across training epochs when testing on all datasets.

Overall, we noticed that regardless of the dataset, performance for Pair Classification is always better than Sequence Classification. F1 scores for Span Detection is generally poor in comparison

	Source	Features	Model	P	R	F1	Acc
	Hidey and McKeown (2016)	Lexical	SVM		58.51		
	Ours (All)	BERT	BERT+LR		63.48		
	Ours (AltLex)	BERT	BERT+LR		53.57		
BEC-	Zuo et al. (2020b)§‡	Discourse, self-attention embed-	PSAN	-	-	81.70	
AUSE	( ) ) ) }	dings					
	Ours (All)	BERT Embeddings	BERT+LR	92,32	70.24	79.77	71.3
	Ours (BECAUSE)	BERT Embeddings	BERT+LR		96.01		
СТВ	Kyriakakis et al. (2019)	n-gram	LR		22.22		
		word2vec	BIGRUATT		73.89		
		ELMO	BIGRUATT		70.28		
		BERT	BERT+LR		93.33		
		BERT	BERT+BIGRUATT		86.94		
	Ours (All)	BERT	BERT+LR		66.19		
	Ours (CTB)	BERT	BERT+LR		58.57		
ESL	Kyriakakis et al. (2019)^	n-gram	LR		27.27		
LoL	Teyriakakis et al. (2017)	word2vec	BIGRUATT		60.91		
		ELMO	BIGRUATT		59.09		
		BERT	BERT+LR		87.17		
		BERT	BERT+BIGRUATT		83.64		
	Ours (All)	BERT	BERT+LR		67.43		
	Ours (ESL)	BERT	BERT+LR		87.79		
PDTB	Ponti and Korhonen (2017)‡	Lexical	Shallow CNN	39.8	75.29		
ГОТЬ	Tonu and Romonen (2017) <sub>‡</sub>	Lexical	FFNN		71.74		
		Lexical Lexical, positional, event-related	FFNN		76.45		
	Zuo et al. (2020b)§‡	Discourse, self-attention embed-	PSAN	42.37	7 <b>0.4</b> 3	76.60	
	Zuo et al. (20200)3‡		FSAN	-	-	70.00	-
	707 at al. (2022)§	dings	DEDT I D			74.45	
	Tan et al. (2022)§	BERT BERT	BERT+LR BERT+LR	72.50	66.34		
	Ours (All)						
0	Ours (PDTB)	BERT	BERT+LR	73.54	67.35		
Sem-	Niki et al. (2019)	n-gram	Random Forest	-	-	52.80	
Eval		n-gram	LR	-	-	81.90	
		n-gram	SVM	-	-	77.90	
		word2vec	LSTM . Salf Attacking	-	-	85.60	
	V	word2vec	LSTM + Self-Attention	- 00 (7	-	86.90	
	Kyriakakis et al. (2019) <sup>^</sup>	n-gram	LR		66.83		
		word2vec	BIGRUATT		87.59		
		ELMO	BIGRUATT		91.26		
		BERT	BERT+LR	86.62	97.09	91.55	
		DEDE	DEDT. DICDIIATE	06.00	06.62	01 45	
	0 (410)	BERT	BERT+BIGRUATT		96.63		-
	Ours (All)	BERT	BERT+LR	73.39	89.51	80.64	- 94.8
	Ours (All) Ours (SemEval)			73.39		80.64	- 94.8
(III) Dai	Ours (SemEval)	BERT	BERT+LR	73.39	89.51	80.64	- 94.8
	Ours (SemEval)	BERT BERT	BERT+LR BERT+LR	73.39 87.84	89.51 91.40	80.64 89.58	94.8 <b>97.</b> 4
Corpus	Ours (SemEval) ir Classification Source	BERT BERT Features	BERT+LR BERT+LR Model	73.39 87.84	89.51 91.40	80.64 89.58 F1	94.8 <b>97.</b> 4
(III) Pai Corpus CTB	Ours (SemEval)	BERT BERT Features Rule-based	BERT+LR BERT+LR Model Rule-based	73.39 87.84 P 36.79	89.51 91.40 R 12.26	80.64 89.58 F1 18.40	94.8 <b>97.</b> 4
Corpus	Ours (SemEval)  ir Classification Source  Mirza and Tonelli (2014)§	BERT BERT Features Rule-based Rule-based	BERT+LR BERT+LR Model Rule-based SVM	73.39 87.84 P 36.79 67.29	89.51 91.40 R 12.26 22.64	80.64 89.58 F1 18.40 33.88	94.8 97.4 Acc
Corpus	ours (SemEval)  ir Classification Source Mirza and Tonelli (2014)§ Zuo et al. (2020a)§	Features Rule-based Rule-based Lexical, causal commonsense, BERT	BERT+LR BERT+LR  Model Rule-based SVM KnowDis	73.39 87.84 P 36.79 67.29 42.30	89.51 91.40 R 12.26 22.64 60.50	80.64 89.58 F1 18.40 33.88 49.80	- 94.8 <b>97.</b> 4 Acc
Corpus	Ours (SemEval)  ir Classification Source  Mirza and Tonelli (2014)§	Features Rule-based Rule-based Lexical, causal commonsense,	BERT+LR BERT+LR Model Rule-based SVM	73.39 87.84 P 36.79 67.29 42.30	89.51 91.40 R 12.26 22.64	80.64 89.58 F1 18.40 33.88 49.80	- 94.: <b>97.</b> - -
Corpus	ours (SemEval)  ir Classification Source Mirza and Tonelli (2014)§ Zuo et al. (2020a)§	Features Rule-based Rule-based Lexical, causal commonsense, BERT	BERT+LR BERT+LR  Model Rule-based SVM KnowDis  Contrastive Representation	P 36.79 67.29 42.30 43.60	89.51 91.40 R 12.26 22.64 60.50	F1 18.40 33.88 49.80 43.20	- 94.: 97.: Acc
Corpus	Ours (SemEval)  ir Classification Source Mirza and Tonelli (2014)§  Zuo et al. (2020a)§  Zuo et al. (2021a)§	Features Rule-based Rule-based Lexical, causal commonsense, BERT BERT, causal knowledge	BERT+LR BERT+LR  Model Rule-based SVM KnowDis  Contrastive Learning Representation	P 36.79 67.29 42.30 43.60	R 12.26 22.64 60.50 68.10	F1 18.40 33.88 49.80 43.20	94.: 97.: Acc
Corpus	Ours (SemEval)  ir Classification Source Mirza and Tonelli (2014)§  Zuo et al. (2020a)§  Zuo et al. (2021a)§  Zuo et al. (2021b)§	Features Rule-based Rule-based Lexical, causal commonsense, BERT BERT, causal knowledge BERT, causal knowledge	BERT+LR BERT+LR  Model Rule-based SVM KnowDis  Contrastive Learning LearnDA  Representation	P 36.79 67.29 42.30 43.60 41.90 75.66	R 12.26 22.64 60.50 68.10	F1 18.40 33.88 49.80 43.20 51.90 <b>73.94</b>	94. 97.
COTPUS CTB	Ours (SemEval)  ir Classification Source  Mirza and Tonelli (2014)§  Zuo et al. (2020a)§  Zuo et al. (2021a)§  Zuo et al. (2021b)§  Ours (All)  Ours (CTB)	BERT BERT  Features  Rule-based Rule-based Lexical, causal commonsense, BERT BERT, causal knowledge  BERT, causal knowledge BERT BERT	BERT+LR BERT+LR  Model Rule-based SVM KnowDis  Contrastive Learning LearnDA BERT+LR BERT+LR	P 36.79 67.29 42.30 43.60 41.90 75.66	R 12.26 22.64 60.50 68.10 68.00 72.5	F1 18.40 33.88 49.80 43.20 51.90 <b>73.94</b> 73.29	94. 97. Acc
Corpus CTB	Ours (SemEval)  ir Classification Source  Mirza and Tonelli (2014)§  Zuo et al. (2020a)§  Zuo et al. (2021a)§  Zuo et al. (2021b)§  Ours (All)	Features Rule-based Rule-based Lexical, causal commonsense, BERT BERT, causal knowledge BERT, causal knowledge BERT BERT Lexical, semantic, dependency	BERT+LR BERT+LR  Model Rule-based SVM KnowDis  Contrastive Representation Learning LearnDA BERT+LR BERT+LR Bayesian Classifier	P 36.79 67.29 42.30 43.60 41.90 75.66 82.18	R 12.26 22.64 60.50 68.10 68.00 72.5	F1 18.40 33.88 49.80 43.20 51.90 73.94 73.29 66.00	94. 97. Acc 95. 95. 93.
Corpus CTB	Ours (SemEval)  ir Classification Source  Mirza and Tonelli (2014)§  Zuo et al. (2020a)§  Zuo et al. (2021a)§  Zuo et al. (2021b)§  Ours (All)  Ours (CTB)	BERT BERT  Features  Rule-based Rule-based Lexical, causal commonsense, BERT BERT, causal knowledge  BERT, causal knowledge  BERT BERT Lexical, semantic, dependency word2vec	BERT+LR BERT+LR  Model Rule-based SVM KnowDis  Contrastive Representation Learning LearnDA BERT+LR BERT+LR Bayesian Classifier CNN	P 36.79 67.29 42.30 43.60 41.90 75.66 82.18	R 12.26 22.64 60.50 68.10 68.00 72.5 67.08	F1 18.40 33.88 49.80 43.20 51.90 73.94 73.29 66.00 66.00	94.: 97 Acc 95.: 93.: 88.
Corpus	Ours (SemEval)  ir Classification Source  Mirza and Tonelli (2014)§  Zuo et al. (2020a)§  Zuo et al. (2021a)§  Zuo et al. (2021b)§  Ours (All)  Ours (CTB)  Ayyanar et al. (2019)	BERT BERT  Features  Rule-based Rule-based Lexical, causal commonsense, BERT BERT, causal knowledge  BERT, causal knowledge  BERT Lexical, semantic, dependency word2vec GrammarTags	BERT+LR BERT+LR  Model Rule-based SVM KnowDis  Contrastive Representation Learning LearnDA BERT+LR BERT+LR Bayesian Classifier CNN CNN	73.39 87.84 P 36.79 67.29 42.30 43.60 41.90 75.66 82.18	R 12.26 22.64 60.50 68.10 68.00 72.5 67.08	F1 18.40 33.88 49.80 43.20 51.90 73.94 73.29 66.00 66.00 86.60	94.3 97.4 Acc - - - 95.4 93.4 88.6 93.9
Corpus CTB	Ours (SemEval)  ir Classification Source  Mirza and Tonelli (2014)§  Zuo et al. (2020a)§  Zuo et al. (2021a)§  Zuo et al. (2021b)§  Ours (All)  Ours (CTB)	BERT BERT  Features  Rule-based Rule-based Lexical, causal commonsense, BERT BERT, causal knowledge  BERT, causal knowledge  BERT BERT Lexical, semantic, dependency word2vec	BERT+LR BERT+LR  Model Rule-based SVM KnowDis  Contrastive Representation Learning LearnDA BERT+LR BERT+LR Bayesian Classifier CNN	73.39 87.84 P 36.79 67.29 42.30 43.60 41.90 75.66 <b>82.18</b> - - - 93.38	R 12.26 22.64 60.50 68.10 68.00 72.5 67.08	F1 18.40 33.88 49.80 43.20 51.90 73.94 73.29 66.00 66.00 86.60 94.71	- 94 97 95 95 93 88 93 98

Table 4: Evaluation metrics for each dataset in the literature review compared to our benchmark (Ours). We do not cover methods that rely on the connectives as features for Classification tasks. Notations: ^ Rebalanced the dataset, § Evaluated on k-folds or different folds, ‡ Slightly different definitions for class labels. Abbreviations: Logistic Regression (LR), Bidirectional GRU + Self-Attention (BIGRUATT), Feed-forward neural network (FFNN), Support Vector Machine (SVM), Causal Contrastive Representation Learning (CauseRL), Pyramid Salient Aware Network (PSAN).

## (I) Sequence Classification

				Test Set			
Training Set	All	AltLex	BECAUSE	CTB	ESL	PDTB	SemEval
All	70.10	56.37	79.77	51.58	71.45	69.31	80.64
	$\pm 0.58$	$\pm 2.49$	±1.68	±1.82	±1.89	$\pm 0.70$	±0.46
AltLex	32.93	51.85	36.47	38.21	53.30	22.91	55.83
	±3.57**	* ±2.53	±11.18***	±6.20*	±8.37**	±5.79***	±6.68***
BECAUSE	39.15	47.02	90.77	25.17	63.49	42.49	23.71
	±0.99**	* ±1.52**	±2.22***	±1.34**	* ±1.94**	±0.68***	±1.93***
CTB	33.49	55.91	54.73	63.65	33.26	25.97	51.76
	±5.48**	* ±7.63	±9.40**	±5.55**	±15.44*	* ±3.73***	±13.85**
ESL	39.62	46.29	90.12	30.84	81.21	42.55	26.15
	±0.89**	* ±1.15**	±1.05***	±1.35**	* ±2.35**	*±1.25***	±2.62***
PDTB	60.99	48.94	69.61	39.54	38.71	70.31	19.75
	±0.76**	* ±1.88**	±2.16**	±1.88**	* ±3.15**	* ±0.56*	±3.35***
SemEval	28.25	28.95	16.91	38.51	45.95	10.11	89.58
	±0.86**	* ±1.74**	* ±3.40***	±3.44**	±3.50***	* ±1.61***	±0.71***

## (II) Span Detection

	Test Set							
Training Set	All	AltLex	BECAUSE	PDTB				
All	52.42	33.72	37.47	53.78				
	$\pm 0.90$	±1.12	±2.57	$\pm 0.88$				
AltLex	6.20	21.45	11.51	5.47				
	±0.74**	** ±1.87**	* ±1.63***	±0.76***				
BECAUSE	12.74	7.38	37.79	12.60				
	±0.35**	** ±2.19**	* ±5.77	±0.34***				
PDTB	51.97	6.73	35.84	55.02				
	$\pm 0.48$	±0.94**	* ±2.42	±0.38*				

## (III) Pair Classification

			Test	Set		
Training Set	All	AltLex	BECAUSE	CTB	PDTB	SemEval
All	84.68	84.76	91.21	73.94	83.28	94.71
	$\pm 0.27$	±0.66	±1.18	±4.68	±0.36	±0.23
AltLex	31.83	80.57	48.44	20.06	25.11	57.72
	±3.93**	* ±2.48*	±20.00**	±7.14**	* ±8.75**	* ±14.52**
BECAUSE	36.40	47.99	90.01	23.58	38.39	25.23
	±0.64**	* ±1.33***	* ±1.95	±1.52**	* ±0.37**	* ±2.02***
CTB	20.17	19.16	22.00	73.29	7.02	63.69
	±5.78**	* ±15.64*	* <b>±</b> 10.92***	±6.14	±6.06**	* ±5.65***
PDTB	68.13	40.34	82.59	26.74	83.70	33.64
	±0.88**	* ±1.52**	* ±2.17***	±2.42**	* ±0.34	±1.76***
SemEval	26.66	37.07	25.70	50.63	8.08	94.80
	±1.86**	* ±6.58**	* ±11.46***	±1.74**	* ±3.20**	* ±0.28

Table 5: F1 score across different training and test set combinations. Panels I, II, III reflect F1 scores in each of the three tasks. The top score per column per sub-panel is bolded. Tasks that are not applicable to the dataset are indicated by "-". Scores are reported in percentages (%). Paired T-test of the models was conducted against the first row per panel, where all datasets were used for training, with statistical significance indicated by: \*\*\*< 0.001, \*\*< 0.01, \*\*< 0.05. Refer to extended Table A.10 in Appendix for Precision, Recall and Accuracy performance metrics.

to the Classification tasks. This finding correlates with the difficulty of each task: For Pair Classification, since the prompts that already identifies the arguments are provided, it is arguably a simpler task than Sequence Classification. For Span Detection, it is much more challenging than both Classification tasks because it involves accurate identification of the words that corresponds to the cause and effect, not just the mere identification that they exist. Furthermore, the baseline token classification set-up was too simplistic, and unable to handle multiple cause-effect span relations in the same sentence. For each input text, only one pair of Cause and Effect will be predicted. Thus, if multiple relation exists, only one pair can be predicted correctly at best.

In Table 4, we consolidated the models and evaluation metrics for each of the six datasets based on previous works. Since most papers differed in the alignment of labels per corpus and also used different data splits for testing, comparisons based off this table will not be directly reflective of model superiority. We indicated the data differences using notations ( $\hat{}$ ,  $\S$ ,  $\ddagger$ ) to the best of our knowledge. For datasets like AltLex and SemEval, the development set is predefined, and comparisons between previous work and ours can be made concretely. For Sequence Classification with AltLex, (Hidey and McKeown, 2016)'s handcrafted lexical features fed through a Support Vector Machine (SVM) surpassed our baseline F1 score, achieving 60.19%. For Sequence Classification with SemEval, our BERT-based model scored an F1 score of 89.58% at best, surpassing methods covered by (Niki et al., 2019) which at best achieved 86.90% using word2vec embeddings fed through a Long-Short Term Memory (LSTM) Self-Attention network. Finally, for Pair Classification with SemEval, our BERT-based model consistently surpasses Bayesian Classifier and Convolutional Neural Network (CNN) methods explored by (Ayyanar et al., 2019).

All in all, our baseline model is simple but competitive. Therefore, we hope that the scores presented in Table 3 will serve as the universal baseline score for the Causal Text Mining community to beat.

#### 4.2 Impact of Datasets

In Table 5, we present the F1 scores when training and testing on different corpus. This table reflects

how compatible each corpus is to one another.

When testing on all the datasets, we noticed that training on all datasets returned the best performance across all tasks by a large margin. Training on any one dataset was unable to achieve similar performance. Meanwhile, the generalized model trained on all datasets did not always return the best performance for each corpus. Given the differences in definitions and linguistic coverage of each dataset, it is expected that for some datasets, specializing on its own data distributions leads to better performance. However, such specialized models are more likely to overfit and lack generalizability. Thus, good performance on one dataset but not others should be handled with caution.

#### 5 Conclusion

We proposed UniCausal, a unified benchmark for causal text mining. This includes a consolidated repository of diverse human-annotated corpora for three causal text mining tasks. Since the definition of causality can be subjective, researchers might not always agree on some datasets' definition. Therefore, our codes were designed to allow researchers to work on some or all datasets and tasks, while still comparing their performance fairly against us or others. Researchers are also able to incorporate new corpora into their train or test sets with our framework.

We also provided detailed evaluation metrics per dataset as an initial benchmark for future researchers to compete against. In terms of modelling, we believe a joint model that is able to concurrently learn from multiple tasks and datasets might be the next key step to perform Causal Text Mining.

In the upcoming release of our UniCausal repository, we intend to include more datasets relevant to causal text mining, like the Temporal Eval-3 dataset (Mirza and Tonelli, 2016), Son Facebook dataset (Son et al., 2018), FinCausal (Mariko et al., 2020), and Causal News Corpus (Tan et al., 2022). There is also interest in the community to detect causal connectives or signals (Dunietz et al., 2017a), which is a fourth task we wish to add. We also intend to implement K-folds for evaluation, especially for smaller datasets like BECAUSE, ESL, and CTB.

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## **A** Appendices

#### A.1 Datasets

#### A.1.1 Examples

A *Causal* example from each of the six corpora is presented in Table A.6.

## A.1.2 Pre-processing

This section expands on the discussion about data pre-processing in Section 3.1.3. As mentioned, we limited our study to examples of up to 3 sentences. For examples where a Cause and Effect argument spans within one sentence, we only retained the sentences containing the argument spans, even if they are not consecutive (i.e. "extended contexts" are not taken as inputs). This means that in most cases, each example comprises of 1 or 2 sentences. In some datasets (E.g. PDTB-3), the argument itself can span across multiple sentences. For such cases, the examples can comprise of up to 3 sentences. Table A.7 reflects counts from the raw data, where the last column reflects the number of examples we essentially drop from the final consolidated dataset. Subsequently, we perform train-test split, with the data distributions shown in Table A.8. For datasets compatible with the Span Detection task, we also removed examples with more than 3 causal relations to simplify our current stage of modeling. The final data counts are available in Table 2.

The subsequent paragraphs describes each corpus and the pre-processing steps further:

AltLex (Hidey and McKeown, 2016)<sup>11</sup> AltLex is a corpus that focuses specifically on causal relations with AltLex connectives in single sentences. According to PDTB (Webber et al., 2019), alternative lexicalizations (AltLex) refer to an open-class of markers that has varied linguistic constructions. Example causal AltLexes are "so (close) that" and "This may help explain why". For the corpus, we used the development and gold datasets that have been annotated by graduate students and crowd workers respectively. Although additional distantly labeled data was made available in their repository, we wish to focus on a high-quality dataset

<sup>11</sup>https://github.com/chridey/altlex

Corpus	Causal Example
AltLex	<arg0>In the Philippines , Washi</arg0> caused <arg1>at least 1,268 deaths .</arg1>
<b>BECAUSE</b>	<arg0>Having only a Republican measure</arg0> makes <arg1>the task harder</arg1> .
CTB	Iraq said it <arg1>invaded</arg1> Kuwait because of <arg0>disputes</arg0> over oil and money.
ESL	Ten <arg1>dead</arg1> in southern Iran <arg0>quake</arg0> .
PDTB	<arg1>And the firms are stretching their nets far and wide</arg1> <arg0>to do it</arg0> .
SemEval	The front <arg0>wheels</arg0> are making a <arg1>grinding noise</arg1> .

Table A.6: Causal examples from each corpus. (<ARG0>, </ARG0>) marks the boundaries of a Cause span, while (<ARG1>, </ARG1>) marks the boundaries of a corresponding Effect span.

Corpus	N	Number of Sentences						
Corpus	1	2	3	>3	Total			
AltLex	1,027	-	-	-	1,027			
<b>BECAUSE</b>	1,245	-	-	-	1,245			
CTB	3,043	578	188	390	4,199			
ESL	7,140	6,487	5,754	19,753	39,134			
PDTB	28,088	22,945	1,468	1,175	53,676			
SemEval	10,717	-	-	-	10,717			
Total	51,260	30,010	7,410	21,318	109,998			

Table A.7: Sizes of raw datasets by sentence length.

Corpus	Split	Numb	er of Sent	ences	Total
Corpus	Spiit	1	2	3	10141
AltLex	Train	611	-	-	611
	Test	416	-	-	416
BECAUSE	Train	1,185	-	-	1,185
	Test	60	-	-	60
СТВ	Train	2,671	496	150	3,317
	Test	372	82	38	492
ESL	Train	6,447	5,873	5,094	17,414
	Test	693	614	660	1,967
PDTB	Train	22,598	18,671	1,190	42,459
	Test	5,490	4,274	278	10,042
SemEval	Train	8,000	-	-	8,000
	Test	2,717	-	-	2,717
Total	•	51,260	30,010	7,410	88,680

Table A.8: Sizes of train and test datasets by sentence length. We only retain examples with <= 3 sentence length for our study.

Corpus	Split	Span
AltLex	Train	315
	Test	127
BECAUSE	Train	919
	Test	46
PDTB	Train	9,854
	Test	2,329
Total		13,590

Table A.9: Sizes of final train and test datasets available for Span Detection task. These numbers are the ungrouped version corresponding to the grouped ones in Table 2.

and therefore, incorporated only human-annotated subsets. Additionally, only the human-annotated datasets include labels with REASON and RESULT, which we can use to help discern the Cause and Effect arguments. REASON and RESULT sentences were regarded as causal, while sentences with the label NONE were treated as Non-causal. REA-SON examples were in the order of Effect-Signal-Cause, while RESULT had the format of Cause-Signal-Effect. Equipped with this template, we could convert the causal labels into Cause and Effect spans around the marked signal words. For train-test splits, the development set was used for testing, while the gold set was used for training. The AltLex corpus is suitable for all three tasks: For Span Detection, we had 415 examples; For sequence classification, we had 415 causal and 563 non-causal examples; For pair classification, we had access to 442 causal and 585 non-causal examples.

BECAUSE 2.0 (Dunietz et al., 2017b)<sup>12</sup> BE-CAUSE 2.0 corpus contains annotations for causal language in single sentences. They annotated texts that expresses causation corresponding to Cause, Effect or Connective based on principles of Construction Grammar. Documents and articles were selected from four data sources: Congressional Hearings from 2014 NLP Unshared Task in Poli-Informatics (CHRG), Penn Treebank (PTB) (Marcus et al., 1994), Manually Annotated Sub-Corpus (MASC) (Ide et al., 2010), and the New York Times Annotated Corpus (NYT) (Sandhaus, 2008). PTB is a paid resource which we had access to. We did not have access to the raw files of the NYT which requires subscription, and missed out on annotations for the 59 randomly selected articles. We will work on obtaining this resource to be included in our dataset in the future.

Interestingly, in BECAUSE 2.0, there are a few sentences where the Effect is annotated with no corresponding Cause<sup>13</sup> Such examples are treated as *Non-causal* in our consolidated corpus because we require both Cause and Effect spans to be present within each example for them to be considered *Causal*. On top of this treatment, BECAUSE 2.0

itself also contains some *Non-causal* examples. All in all, we obtained 965 *Causal* pairs and 280 *Non-causal* pairs.

To fit our framework of creating a fixed subset for train-test split for easier bench-marking, we randomly set 10% of the documents as test sets.<sup>14</sup> For PTB files, we followed the development and test splits recommended by PDTB V2.0 (Prasad et al., 2008), mentioned later below.

CausalTimeBank (CTB) (Mirza et al., 2014; Mirza and Tonelli, 2014)<sup>15</sup> This corpus contained 184 documents, 6,813 events, and 318 causal event pairs. It covers annotations both intra- and intersentential causal relations between events. After processing, we obtained 318 causal event pairs and 3,881 non-causal event pairs from 183 documents. After filtering to examples with  $\leq 3$  sentence length, we ended up with 318 causal and 3,491 non-causal examples for pair classification, and 276 causal and 1,925 non-causal examples for sequence classification. To fit our framework of creating a fixed subset for train-test split for easier bench-marking, we randomly set 10% of the documents as test sets. <sup>16</sup> For files that tapped onto PTB, we followed the development and test splits recommended by PDTB V2.0 (Prasad et al., 2008) which is described later below. Previous works (Zuo et al., 2021a; Mirza and Tonelli, 2014) evaluated models using 10-fold cross-validation or to use an external Temporal Eval-3 dataset (Mirza and Tonelli, 2016). Our method essentially only evaluates on one of the ten folds. Researchers can process the dataset to perform the other nine folds if needed. For Temporal Eval-3, we will work on including this dataset in the next release.

**EventStoryLine (ESL)** (Caselli and Vossen, 2017)<sup>17</sup> We utilised the V1.0 expert annotations because it is the more updated version according to Caselli and Vossen<sup>18</sup>. This corpus contains contains 258 documents, and includes anno-

<sup>12</sup>https://github.com/duncanka/BECAUSE/
tree/2.0

<sup>&</sup>lt;sup>13</sup>An example sentence from BECAUSE 2.0 where the Effect is annotated with no corresponding cause is: "However, the lower prices these retail chains are now expected to bring should make it easier for managers to raise the necessary capital and pay back the resulting <effect>debt</effect>.".

<sup>&</sup>lt;sup>14</sup>Test set: 'Article247\_327.ann'

<sup>15</sup>https://github.com/paramitamirza/Cau sal-TimeBank

<sup>&</sup>lt;sup>16</sup>Test set: 'ea980120.1830.0456.tml', 'APW19980227.0494.tml', 'PRI19980306.2000.1675.tml', 'APW19980213.1320.tml', 'APW19980501.0480.tml', 'PRI19980205.2000.1998.tml'

 $<sup>^{17} \</sup>rm https://github.com/tommasoc80/EventS$  toryLine

<sup>&</sup>lt;sup>18</sup>Compared to V0.9, V1.0 includes additional data curation checks to ensure consistency of TimeX3 normalisation, TLINK annotation and event annotation, plus removes some wrong event tokens.

tations both intra- and inter-sentential causal relations between events. For events, we only consider markables tagged as actions or negative actions. All PLOT\_LINK relations are treated as Causal. 19 To generate Non-causal examples, for every head event, we defined all tails unidentified by PLOT LINK as Non-causal. Because ESL does not mark out the causal direction of their events, we were unable to use this dataset for Pair Classification. ESL is only suitable for Sequence Classification, of which after filtering to keep only examples with  $\leq$  3 sentences, we obtained 2,232 examples in total. The last two topics were used as test set,<sup>20</sup> while the remaining 20 topics were used for training, as suggested by Gao et al. (2019).

Penn Discourse Treebank V3.0 (PDTB) (Webber et al., 2019)<sup>21</sup> PDTB is a corpus that annotates discourse relations between arguments, expressed either explicitly, implicitly or in AltLex forms (Prasad et al., 2008; Webber et al., 2019; Prasad et al., 2006). We worked on the third release of PDTB. One of the senses annotated involve is the CONTINGENCY<sup>22</sup> type, which is often treated as a positive example of causal relations by previous reseachers (Ponti and Korhonen, 2017; Dunietz et al., 2017b). Dunietz et al. (2017b) argued for the exclusion of evidentiary uses of causal language.<sup>23</sup> We felt that two sub-senses under CONTINGENCY, namely the BELIEF<sup>24</sup> and SPEECHACT<sup>25</sup> types were similar to evidential types. Therefore, we treated them as negative examples. This treatment is consistent with the approach by Tan et al. (2022). For PDTB, since the direction of the arguments are marked, we could retrace the Cause and Effect arguments in place. For five sub-senses, <sup>26</sup> the first argument is the Cause, while the second argument is the Effect. For four sub-senses, <sup>27</sup> the reverse. Examples with all other senses were treated as Non-causal. The PDTB corpus is suitable for all three tasks, of which after filtering to examples with  $\leq 3$  sentences and  $\leq 3$  causal relations, we had 10,972 Span Detection, 41,669 Sequence Classification and 52,384 Pair Classification examples. For train-test split, we used the development and test set recommended by PDTB V2.0 (Prasad et al., 2008),<sup>28</sup> while the remaining was used for training. Unless explicitly specified otherwise, we refer to the final test set as the combination of the development and test set.

SemEval 2010 Task 8 (SemEval) (Hendrickx et al., 2010)<sup>29</sup> SemEval is a corpus annotated for the purpose of semantic relations classification. They accepted only noun phrases with commonnoun heads as relation arguments, labelling 10,717 examples with ten relations. We regarded the Cause-Effect relation as Causal, while all other relations were treated as Non-causal. Since the arguments annotated were short, SemEval is not compatible for Span Detection. Therefore, we only formatted SemEval for the Sequence Classification and Pair Classification task, of which, we obtained 10,690 and 10,717 examples respectively. We used their test set for testing, while all other examples were used for training.

#### **Model Details A.2**

For the **BERT** model, we used bert-base-cased from Huggingface (Wolf et al., 2020). Sequence output dimension from the BERT encoder is the default at 768. The token classifier had output dimensions of 5, while

<sup>&</sup>lt;sup>19</sup>We ignore markables tagged as location, time or time date. TLINK relations that have time related entities, like "May 02" or "Thursday" are not particularly challenging to classify as Non-causal. Therefore, we have excluded them from our corpus.

<sup>&</sup>lt;sup>20</sup>Test set: T37, T41

<sup>21</sup>https://catalog.ldc.upenn.edu/LDC201

<sup>&</sup>lt;sup>22</sup>Definition of CONTINGENCY relations: "one argument provides the reason, explanation or justification for the situation described by the other". (Webber et al., 2019)

<sup>&</sup>lt;sup>23</sup>E.g. "We went to war based on bad intelligence." (Dunietz et al., 2017b)

<sup>&</sup>lt;sup>24</sup>BELIEF: One argument gives the evidence justifying the claim in the other argument. E.g. "Kellogg suspended work on a \$1 billion cereal plant, indicating a pessimistic outlook by the cereal maker, which has been losing market share." (Webber et al., 2019)

<sup>&</sup>lt;sup>25</sup>SPEECHACT: One argument provides the reason for the speaker uttering the speech act in the other argument. E.g. "Maybe I'm a little stuffy, but I wouldn't sell them,..." (Webber et al., 2019)

<sup>&</sup>lt;sup>26</sup>The first argument is Cause span for: CONTIN-GENCY.CAUSE.RESULT, CONTINGENCY.PURPOSE.ARG1-CONTINGENCY. CONDITION. ARG1-AS-AS-GOAL, CONTINGENCY. NEGATIVE-CONDITION. ARG1-COND. AS-NEGCOND, and CONTINGENCY. NEGATIVE-CAUSE.NEGRESULT

<sup>&</sup>lt;sup>27</sup>The second argument is Cause span for: CONTIN-GENCY. CAUSE. REASON, CONTINGENCY. PURPOSE. ARG2-AS-GOAL, CONTINGENCY. CONDITION. ARG2-AS-COND, CONTINGENCY. NEGATIVE-CONDITION. ARG2-AS-NEGCOND

<sup>&</sup>lt;sup>28</sup>Dev set: wsj\_00, wsj\_01, wsj\_24; Test set: wsj\_22,

wsj\_23

29
https://drive.google.com/file/d/0B\_j tOWY1ZDMwY2U4YjFk/view?sort=name&layout= list&num=50&resourcekey=0-k00TSIGrF9UAc rTFfInlrw

the sequence classifiers output dimension was 2. The classifiers' input dimension was the BERT embedding at 768. To train our model, we used the AdamW optimizer (Loshchilov and Hutter, 2019) with  $\beta 1=0.9,\,\beta 2=0.999.$  Learning rate was set at 2e-05 with linear decay. GPU train batch size was 128. Maximum sequence length was variable according to the longest sequence per batch. 20 epochs were ran per experiment.

Following previous works (Akbik et al., 2019; Peters et al., 2017; Chiu and Nichols, 2016), we repeated each experiment 5 times with different random seeds.<sup>30</sup> We reported mean and standard deviation performance in the results section. We also performed Paired T-test when comparing models with one another (E.g. UniCausal ( $\alpha = 1$ ) vs. Individual) to calculate statistical significance of difference in means.

For a complete run to train and test on all six datasets, the Individual models for Sequence Classification, Span Detection, and Pair classification took 1h6m38s, 34m21s, and 1h1m27s to run in total. In terms of memory, each model requires approximately 20000MiB GPU space. In terms of storage, each saved model is about 420MB in size.

#### A.3 Experiments

#### **A.4** Performance Across Epochs

Figure 2 presented the F1 scores of both each of the Individual models for each of the three tasks across training epochs. Span Detection observed the largest F1 score improvements in the first few epochs. All three tasks generally plateaued in their F1 improvements towards the second half of training.

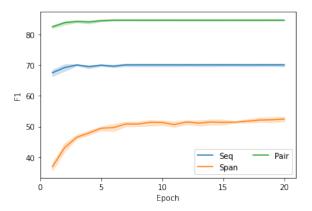


Figure 2: F1 scores for all datasets across three models over training epochs: Sequence Classification Binary F1 in Blue, Pair Classification Binary F1 in Green, and Span Detection Macro F1 in Orange. The shaded regions reflect confidence intervals.

<sup>&</sup>lt;sup>30</sup>The random seeds used were: 42, 975, 106, 239, and 303.

		(П)	Sequence	Classific	cation	(П)	Span Det	ection	<i>(</i> 11	I) Pair C	lassificat	tion
Test Set	Training Set		R	F1	Acc	P	R	F1	P	R	F1	Acc
All	All	71.13	69.14	70.10	86.27	46.33	60.35	52.42	85.44	83.93	84.68	93.68
		$\pm 0.80$	±1.60	±0.58	±0.15	±1.22	$\pm 0.30$	±0.90	±0.96	±0.44	$\pm 0.27$	±0.16
	AltLex	39.77	29.03	32.93	72.90	4.29	11.21	6.20	31.68	44.64	31.83	61.94
												**±17.68*
	BECAUSE	24.74	94.25	39.15	31.62	10.35	16.57	12.74	22.64	93.11	36.40	32.27
	CTD											**±4.28**
	CTB	66.88 ±3.05*	22.66	33.49 **+5.48**	79.30 **±0.36*	- **	-	-	73.66 ±6.50*	11.83	20.17 **+5 78*	80.78 **±0.61***
	ESL	28.48	65.37	39.62	53.52	_	_	_	-	±3.77	-5.76	-0.01
	LUL		**±3.09*		**±3.61*	**						
	PDTB	63.30	58.85	60.99	82.47	45.88	59.92	51.97	59.46	79.86	68.13	84.45
			**±1.29*		**±0.26*	**±0.65	±0.27*	* ±0.48	±2.15*			**±0.88***
	SemEval	52.00	19.44	28.25	77.02	-	-	-	61.08	17.23	26.66	80.37
			**±1.12**				10.00					**±0.65**
AltLex	All	50.76	63.48	56.37	71.87	27.74	42.99	33.72	82.60	87.09	84.76	90.43
	AltLex	<b>±1.61</b> 50.58	±4.60 53.57	<b>±2.49</b> 51.85	±1.19 71.52	<b>±1.20</b> 16.06	±0.85 32.28	<b>±1.12</b> 21.45	±1.99 <b>88.70</b>	±1.53 74.17	<b>±0.66</b> 80.57	<b>±0.55</b> 89.04
	AILLEX	±3.35	±5.17*		±1.99		**±2.71*				* ±2.48*	
	BECAUSE	31.69	91.83	47.02	40.40	5.65	10.71	7.38	32.14	94.80	47.99	37.21
	220.1022											**±3.34***
	CTB	63.35	51.65	55.91	77.36	-	-	-	84.28	12.60	19.16	71.83
			* ±13.15		±1.13*	*			±18.29	$\pm 13.35$	* <b>≝</b> 15.64	** <b>±</b> 1.64***
	ESL	30.83	93.57	46.29	37.66	_	-	-	-	-	-	-
	DDED		**±6.81*				0.06	6.70	26.72	02.20	10.24	25.02
	PDTB	48.02 ±2.10	49.91	48.94 * ±1.88*	70.12	5.36	9.06	6.73	26.73 **±0.89**	82.20	40.34	25.82 **±1.14***
	SemEval	55.23	±2.00*** 19.65	28.95	72.37	±0.81***	- -	-±0.94**	72.07	25.35	±1.32** 37.07	74.13
	Schievar	±2.44*		*生1.74*		_	_	-				**±0.91***
BEC-	All	92.32	70.24	79.77	71.37	32.51	44.30	37.47	87.93	94.78	91.21	86.00
AUSE		±1.69	±2.04	±1.68	±2.24	±2.82	±2.33	±2.57	±1.73	±1.94	±1.18	±1.90
	AltLex	98.67	22.93	36.47	37.65	8.30	18.92	11.51	80.49	37.83	48.44	45.00
		±2.98*					**±2.10**					**±12.19**
	BECAUSE	86.20	96.10	90.77	84.31	31.15	48.17	37.79	83.37	97.83	90.01	83.33
	CTD		* ±5.06**				±5.66	±5.77	±2.33*	±2.17	±1.95	±3.33
	CTB	97.87 ±2.94*	38.54	54.73 * +0.40**	49.80 * ±6.59*	- *	-	-	84.90	13.04	22.00 **±10.02	31.67 **±4.86***
	ESL	83.42	98.05	90.12	82.75	_	_	_	- 11.92	±1.51 -	- 10.92	± <del>4</del> .00
	LUL		**±2.67*			*						
	PDTB	89.33	57.07	69.61	60.00	32.50	40.00	35.84	77.99	87.83	82.59	71.67
		±1.57*	±2.78*		* ±2.24*	* ±2.77	$\pm 1.92$	$\pm 2.42$	±1.47*	**±3.95*		**±3.12***
	SemEval	100.00		16.91	27.06	-	-	-	98.18	15.22	25.70	34.67
			**±2.04**			**						** <u>±</u> 5.32***
CTB	All	42.37	66.19	51.58	83.48	-	-	-	75.66	72.50	73.94	95.04
	AltLex	±2.11 40.43	±4.26 39.05	±1.82 38.21	±1.21 83.80				±3.61 20.48	±6.81 35.42	±4.68 20.06	±0.78 74.84
	AILLEX	±6.72		\$6.21*		-	-	-				**±14.26*
	BECAUSE	14.45	98.10	25.17	22.15	_	_	_	13.42	97.50	23.58	38.09
	BEC.10 BE		**±1.99*			**						**±5.14***
	CTB	71.46	58.57	63.65	91.27	-	-	-	82.18	67.08	73.29	95.28
		±4.90*	* <b>±</b> 10.59		* ±0.62*	**			±7.47	±9.93	±6.14	±0.96
	ESL	18.48	93.33	30.84	44.30	-	-	-	-	-	-	-
	DDED		**±4.58**			**			16.07	64.17	26.71	65.00
	PDTB	33.36	48.57 * ±2.71*	39.54	80.25 **: 0.86*	-	-	-	16.97	64.17	26.74	65.98 ** <del>±</del> 3.86***
	SemEval	±1.77* 49.19	31.90	38.51	86.52				±1.20*** 46.94	55.42	±2.42** 50.63	89.43
	Senievai		±4.33*			-	-	-				**±1.09***
ESL	All	76.11	67.43	71.45	73.79		-	-	-	-		-
<del></del>		±2.04	±3.45	±1.89	±1.34							
	AltLex	45.40	65.84	53.30	45.60	-	-	-	-	-	-	-
			**±18.33		* ±3.77*	**						
	BECAUSE	48.17	93.27	63.49	47.84	-	-	-	-	-	-	-
	CED		**±5.89*			**						
	CTB	92.10	21.42	33.26	60.69 **: 4.70*:	- *	-	-	-	-	-	-
	ESL	±7.32* 75.90	±12.01 <sup>3</sup>	™±15.44° <b>81.21</b>	**±4.70* <b>80.17</b>		_	_	_	_	_	_
	LUL	±5.08			*生3.00*	*	-	-	-	-	-	-
		±5.00	_5.00		-5.00							

	PDTB	68.44	27.26	38.71	58.10	-	-	-	-	-	-	-	
		$\pm 8.81$	8.81 ±3.39***±3.15***±2.16***										
	SemEval	42.91	49.56	45.95	43.45	-	-	-	-	-	-	-	
		±1.95***±5.70***±3.50****±1.86***											
PDTB	All	72.59	66.34	69.31	84.63	47.77	61.54	53.78	84.56	82.04	83.28	92.43	
		$\pm 0.61$	$\pm 1.63$	$\pm 0.70$	$\pm 0.17$	±1.22	$\pm 0.29$	$\pm 0.88$	$\pm 1.17$	$\pm 0.46$	$\pm 0.36$	$\pm 0.23$	
	AltLex	34.38	17.92	22.91	69.49	3.77	9.97	5.47	24.08	39.15	25.11	54.18	
		±2.46***±6.86***±5.79***±1.84***±0.60***±1.04***±0.76***±3.84***±28.09* ±8.75***±20.53*											
	BECAUSE	27.49	93.87	42.49	33.39	10.28	16.28	12.60	24.24	92.47	38.39	31.81	
		±0.92** <b>±4.32**±</b> 0.68** <b>±</b> 4.95** <b>±</b> 0.28** <b>±</b> 0.58** <b>±</b> 0.34** <b>±</b> 0.52** <b>*±4.46**±</b> 0.37** <b>*±</b> 3.78***											
	CTB	66.42	16.30	25.97	75.87	-	-	-	83.73	3.77	7.02	77.74	
		±3.44*	* ±3.22**	*±3.73**	**±0.09**	*			$\pm 8.27$	±3.43**	**±6.06	**±0.65***	
	ESL	33.97	57.18	42.55	59.58	-	-	-	-	-	-	-	
		±1.57*	±1.57***±3.51** ±1.25***±2.58***										
	PDTB	73.54	67.35	70.31	85.11	48.89	62.92	55.02	86.28	81.27	83.70	92.73	
		$\pm 0.37*$	$\pm 0.90$	±0.56*	±0.22**	\$ ±0.54	±0.27**	*±0.38*	$\pm 0.38$	±0.36**	£0.34	$\pm 0.15$	
	SemEval	27.47	6.24	10.11	71.13	-	-	-	29.32	4.80	8.08	75.46	
		±0.84***±1.24***±1.61***±0.65*** ±3.92***±2.19***±3.20***										**±0.86***	
Sem- Eval	All	73.39	89.51	80.64	94.81	-	-	-	93.38	96.10	94.71	98.70	
		$\pm 1.18$	±1.59	$\pm 0.46$	$\pm 0.16$				$\pm 0.88$	$\pm 0.59$	$\pm 0.23$	$\pm 0.07$	
	AltLex	44.85	76.89	55.83	84.68	-	-	-	50.83	73.90	57.72	84.33	
		±9.44** ±5.62* ±6.68***±5.49* ±19.73**±5.42** ±14.52**±12.18											
	BECAUSE	13.52	97.13	23.71	23.91	-	-	-	14.56	95.61	25.23	31.00	
		±1.28*	**±2.20**	* <b>±</b> 1.93**	**±8.67**	**			±1.40**	*±2.53	±2.02**	**±8.75***	
	CTB	63.55	46.16	51.76	90.27	-	-	-	68.73	59.63	63.69	91.79	
		±4.28** ±16.86**±13.85**±1.03***									**±1.36***		
	ESL	15.33	91.40	26.15	36.57	-	-	-					
		±1.93*	**±7.82	±2.62**	**±12.82*	***							
	PDTB	18.60	21.16	19.75	79.40	-	-	-	22.25	70.24	33.64	66.60	
		±2.29***±4.87***±3.35***±0.51***										**±4.06***	
	SemEval	87.84	91.40	89.58	97.43	-	-	-	93.96	95.67	94.80	98.73	
		±1.49*	* <b>±</b> 0.26*	±0.71*	* <b>*</b> 10.20**	**			±0.49	±0.59	$\pm 0.28$	$\pm 0.07$	

Table A.10: Performance metrics for different test datasets across the three tasks using Individual models. The top score for each metric per test set is bolded. Tasks that are not applicable to the dataset are indicated by "-". Scores are reported in percentages (%). Paired T-test of the models was conducted against setting where all datasets were used for training, with statistical significance indicated by: \*\*\*< 0.001, \*\*< 0.01, \*< 0.05. For each test set, the first row (i.e. when training set is "All") is consolidated and corresponds to Table 3. The F1 scores of this table also corresponds to the values consolidated in Table 5.