Domain Knowledge Empowered Structured Neural Net for End-to-End Event Temporal Relation Extraction

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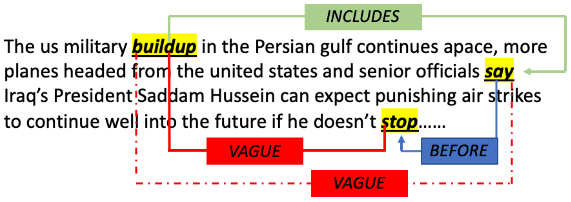
Abstract

Extracting event temporal relations is a critical task for information extraction and plays an important role in natural language understanding. Prior systems leverage deep learning and pre-trained language models to improve the performance of the task. However, these systems often suffer from two shortcomings: 1) when performing maximum a posteriori (MAP) inference based on neural models, previous systems only used structured knowledge that is assumed to be absolutely correct, i.e., *hard constraints*; 2) biased predictions on dominant temporal relations when training with a limited amount of data. To address these issues, we propose a framework that enhances deep neural network with *distributional constraints* constructed by probabilistic domain knowledge. We solve the constrained inference problem via Lagrangian Relaxation and apply it to end-to-end event temporal relation extraction tasks. Experimental results show our framework is able to improve the baseline neural network models with strong statistical significance on two widely used datasets in news and clinical domains.

1 Introduction

Extracting event temporal relations from raw text data has attracted surging attention in the NLP research community in recent years as it is a fundamental task for commonsense reasoning and natural language understanding. It facilitates various downstream applications, such as forecasting social events and tracking patients' medical history. Figure 1 shows an example of this task where an event extractor first needs to identify events (**buildup**, **say** and **stop**) in the input and then a relation classifier predicts all pairwise relations among them, resulting in a temporal ordering as illustrated in the figure. For example, **say** is *BEFORE* **stop**; **buildup** *INCLUDES* **say**; the temporal ordering between **buildup** and **stop** cannot be decided from the context, so the relation should be *VAGUE*.



The us military ***buildup*** in the Persian gulf continues apace, more planes headed from the united states and senior officials ***say*** Iraq's President Saddam Hussein can expect punishing air strikes to continue well into the future if he doesn't ***stop***......

	Overall	Type Pair (P)	Type Pair (G)
VAGUE	49.9%	55.1%	39.9%
INCLUDES	5.1%	0.0%	12.3%
Others	45.0%	44.9%	47.8%

Figure 1: An example of the event temporal ordering task. Text input is taken from the news dataset in our experiments. Solid lines / arrows between two highlighted events show their gold temporal relations, e.g. **say** *BEFORE* **stop** and **buildup** *INCLUDES* **say**, and the dash line shows a wrong prediction, i.e., the *VAGUE* relation between **buildup** and **say**. In the table, Column Overall shows the relation distribution over the entire training corpus; Column Type Pair (P) shows the *predicted* relation distribution condition on the event pairs having types `occurrence` and `reporting` (such as **buildup** and **say**); Column Type Pair (G) shows the *gold* relation distribution condition on event pairs having the same types. Biased predictions of *VAGUE* relation between **buildup** and **say** can be partially corrected by using the gold event type-relation statistics in Column Type Pair (G).

Predicting event temporal relations is inherently challenging as it requires the system to understand each event's beginning and end times. However, these time anchors are often hard to specify within a complicated context, even for humans. As a result, there is usually a large amount of *VAGUE* pairs (nearly 50% in the table of Figure 1) in an expert-annotated dataset, resulting in heavily class-imbalanced datasets. Moreover, expert annotations are often time-consuming to gather, so the sizes of existing datasets are relatively small. To cope

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with the class-imbalance problem and the small dataset issues, recent research efforts adopt *hard constraint*-enhanced deep learning methods and leverage pre-trained language models (Ning et al., 2018c; Han et al., 2019b) and are able to establish reasonable baselines for the task.

The *hard-constraints* used in the SOTA systems can only be constructed when they are nearly 100% correct and hence make the knowledge adoption restrictive. Temporal relation transitivity is a frequently used *hard constraint* that requires *if* **A** *BEFORE* **B** and **B** *BEFORE* **C**, it *must be* that **A** *BEFORE* **C**. However, constraints are usually not deterministic in real-world applications. For example, a clinical `treatment` and `test` are more *likely* to happen *AFTER* a medical `problem`, but not *always*. Such probabilistic constraints cannot be encoded with the *hard-constraints* as in the previous systems.

Furthermore, deep neural models have biased predictions on dominant classes, which is particularly concerning given the small and biased datasets in event temporal extraction. For example, in Figure 1, an event pair **headed** and **say** (with relation *INCLUDES*) is incorrectly predicted as *VAGUE* (Column Type Pair (P)) by our baseline neural model, partially due to dominant percentage of *VAGUE* label (Column Overall), and partially due to the complexity of the context. Using the domain knowledge that **headed** and **say** have event types of `occurrence` and `reporting`, respectively, we can find a new label probability distribution (Type Pair (G)) for this pair. The probability mass allocated to *VAGUE* would decrease by 10% and increase by 7.2% for *INCLUDES*, which significantly increases the chance for a correct label prediction.

We propose to improve deep structured neural networks by incorporating domain knowledge such as corpus statistics in the model inference, and by solving the constrained inference problem using Lagrangian Relaxation. This framework allows us to benefit from the strong contextual understanding of pre-trained language models while optimizing model outputs based on probabilistic structured knowledge that previous deep models fail to consider. Experimental results demonstrate the effectiveness of this framework.

We summarize our contributions below:

- We formulate the incorporation of probabilistic knowledge as a constrained inference problem and use it to optimize the outcomes from strong neural models.
- Novel applications of Lagrangian Relaxation on end-to-end temporal relation extraction task with event-type and relation constraints.
- Our framework significantly outperforms baseline systems without knowledge adoption and achieves new SOTA results on two datasets in news and clinical domains.

2 Problem Formulation

The problem we focus on is end-to-end event temporal relation extraction, which takes a raw text as input, first identifies all events, and then classifies temporal relations for all predicted event pairs. The left column of Figure 2 shows an example. An end-to-end system is practical in a real-world setting where events are not annotated in the input and challenging because temporal relations are harder to predict after noise is introduced during event extraction.

3 Method

In this section, we first describe the details of our deep neural networks for an end-to-end event temporal relation extraction system, then show how to formulate *domain-knowledge* between event types and relations as *distributional constraints* in Integer Linear Programming (ILP), and finally apply Lagrangian Relaxation to solve the constrained inference problem. Our base model is trained end-to-end with cross-entropy loss and multitask learning to obtain relation scores. We need to perform an additional inference step in order to incorporate *domain-knowledge* as *distributional constraints*.

3.1 End-to-end Event Relation Extraction

As illustrated in the left column in Figure 2, our end-to-end model shares a similar work-flow as the pipeline model in Han et al. (2019b), where multi-task learning with a shared feature extractor is used to train the pipeline model. Let $\mathcal{E}$, $\mathcal{EE}$ and $\mathcal{R}$ denote event, candidate event pairs and the feasible relations, respectively, in an input instance $\boldsymbol{x}^n$, where n is the instance index. The combined training loss is $\mathcal{L} = c_{\mathcal{E}}\mathcal{L}_{\mathcal{E}} + \mathcal{L}_{\mathcal{R}}$, where $\mathcal{L}_{\mathcal{E}}$ and $\mathcal{L}_{\mathcal{R}}$ are the losses for the event extractor and the relation module, respectively, and $c_{\mathcal{E}}$ is a hyper-parameter balancing the two losses.

Feature Encoder. Input instances are first sent to pre-trained language models such as BERT (Devlin

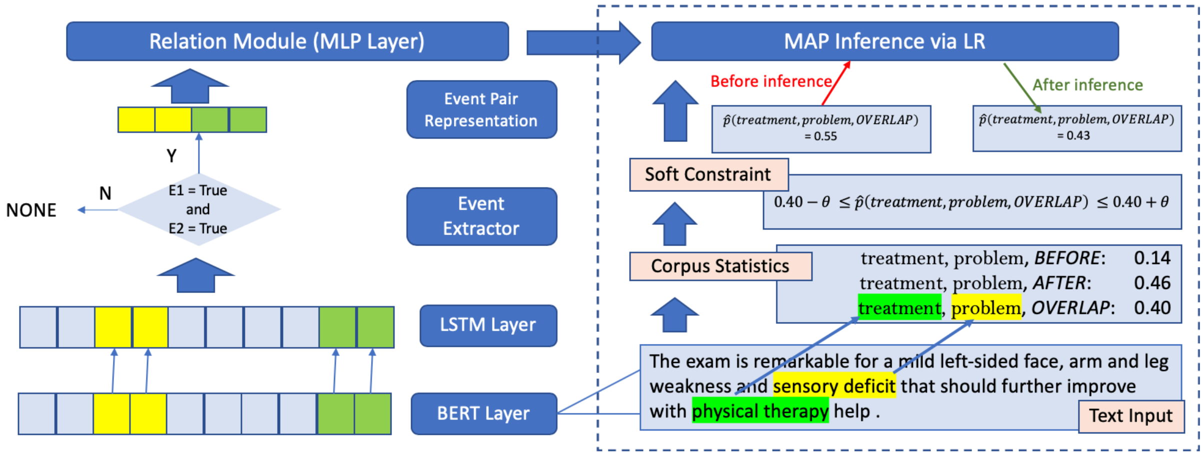
Relation Module (MLP Layer)
Event Pair Representation
Y
N
NONE
E1 = True and E2 = True
Event Extractor
LSTM Layer
BERT Layer
MAP Inference via LR
Before inference
After inference
p̂(treatment, problem, OVERLAP) = 0.55
p̂(treatment, problem, OVERLAP) = 0.43
Soft Constraint
0.40 − θ ≤ p̂(treatment, problem, OVERLAP) ≤ 0.40 + θ
Corpus Statistics
treatment, problem, BEFORE: 0.14
treatment, problem, AFTER: 0.46
treatment, problem, OVERLAP: 0.40
The exam is remarkable for a mild left-sided face, arm and leg weakness and sensory deficit that should further improve with physical therapy help .
Text Input

Figure 2: An overview of the proposed framework. The left column shows the end-to-end event temporal relation extraction workflow. The right column (in the dashed box) illustrates how we propose to enhance the end-to-end extraction system. The final MAP inference contains two components: scores from the relation module and *distributional constraints* constructed using domain knowledge and corpus statistics. The text input is a real example taken from the I2B2-TEMPORAL dataset. The MAP inference is able to push the predicted probability of the event type-relation triplet closer to the ground-truth (corpus statistics).

et al., 2018) and RoBERTa (Liu et al., 2019), then to a Bi-LSTM layer as in previous event temporal relation extraction work (Han et al., 2019a).

Encoded features will be used as inputs to the event extractor and the relation module below.

Event Extractor. The event extractor first predicts scores over event classes for each input token and then detects event spans based on these scores. If an event has over more than one tokens, its beginning and ending vectors are concatenated as the final event representation. The event score is defined as the predicted probability distribution over event classes. Pairs predicted to include non-events are automatically labeled as *NONE*, whereas valid candidate event pairs are fed into the relation module to obtain their relation scores.

Relation Module. The relation module's input is a pair of events, which share the same encoded features as the event extractor. We simply concatenate them before feeding them into the relation module to produce relation scores $S(y^r_{i,j}, \boldsymbol{x}^n)$, which are computed using the Softmax function where $y^r_{i,j}$ is a binary indicator of whether an event pair $(i, j) \in \mathcal{EE}$ has relation $r \in \mathcal{R}$.

3.2 Constrained Inference for Knowledge Incorporation

As shown in Figure 2, once the relation scores are computed via the relation module, a MAP inference is performed to incorporate *distributional constraints* so that the structured knowledge can be used to adjust neural baseline model scores and optimize the final model outputs. We formulate our MAP inference with *distributional constraints* as an LR problem and solve it with an iterative algorithm.

Next, we explain the details of each component in our MAP inference.

3.2.1 Distributional constraints

Much of the *domain-knowledge* required for real-world problems are probabilistic in nature. In the task of event relation extraction, *domain-knowledge* can be the prior probability of a specific event-pair's occurrence acquired from large corpora or knowledge base (Ning et al., 2018b); *domain-knowledge* can also be event-property and relation distribution obtained using corpus statistics, as we study in this work. Previous work mostly leverage *hard constraints* for inference (Yoshikawa et al., 2009; Ning et al., 2017; Leeuwenberg and Moens, 2017; Ning et al., 2018a; Han et al., 2019a,b), where constraints such as transitivity and event-relation consistency are assumed to be absolutely correct. As we discuss in Section 1, *hard constraints* are rigid and thus cannot be used to model probabilistic *domain-knowledge*.

The right column in Figure 2 illustrates how our work leverages corpus statistics to construct *distributional constraints*. Let P be a set of event properties such as clinical types (e.g. `treatment` or `problem`).

For the pair (P^m, P^n) and the triplet (P^m, P^n, r), where $P^n, P^m \in P$ and $r \in \mathcal{R}$, we can retrieve their counts in the training corpus as

$$C(P^m, P^n, r) = \sum_{i,j \in \mathcal{EE}} c(P_i = P^m; P_j = P^n; r_{i,j} = r)$$

and

$$C(P^m, P^n) = \sum_{i,j \in \mathcal{EE}} c(P_i = P^m; P_j = P^n).$$

Let $t = (P^m, P^n, r)$. The prior triplet probability can thus be defined as

$$p_t^* = \frac{C(P^m, P^n, r)}{C(P^m, P^n)}.$$

Let $\hat{p}_t$ denote the predicted triplet probability, *distributional constraints* require that,

$$p_t^* - \theta \leq \hat{p}_t \leq p_t^* + \theta \qquad (1)$$

where θ is the tolerance margin between the prior and predicted probabilities.

3.2.2 Integer Linear Programming with Distributional Constraints

We formulate our MAP inference as an ILP problem. Let $\mathcal{T}$ be a set of triplets whose predicted probabilities need to satisfy Equation 1. We can define our full ILP as

$$\mathcal{L} = \sum_{(i,j) \in \mathcal{EE}} \sum_{r \in \mathcal{R}} y_{i,j}^r S(y_{i,j}^r, \boldsymbol{x}) \qquad (2)$$

$$\textbf{s.t. } p_t^* - \theta \leq \hat{p}_t \leq p_t^* + \theta,\ \forall t \in \mathcal{T}, \text{ and}$$

$$y_{i,j}^r \in \{0, 1\},\ \sum_{r \in \mathcal{R}} y_{i,j}^r = 1,$$

where $S(y_{i,j}^r, \boldsymbol{x}), \forall r \in \mathcal{R}$ is the scoring function obtained from the relation module. For $t = (P^m, P^n, r)$, we have $\hat{p}_t = \frac{\sum_{(i:P^m, j:P^n)}^{\mathcal{EE}} y_{i,j}^r}{\sum_{(i:P^m, j:P^n)}^{\mathcal{EE}} \sum_{r'}^{\mathcal{R}} y_{i,j}^{r'}}$. The output of the MAP inference, $\hat{\mathbf{y}}$, is a collection of optimal label assignments for all relation candidates in an input instance $\boldsymbol{x}^n$. $\sum_{r \in \mathcal{R}} y_{i,j}^r = 1$ ensures that each event pair gets one label assignment and this is the only *hard constraint* we use.

To improve computational efficiency, we apply the heuristic to optimize only the equality constraints $p_t^* = \hat{p}_t, \forall t \in \mathcal{T}$. Our optimization algorithm terminates when $|p_t^* - \hat{p}_t| \leq \theta$. This heuristic has been shown to work efficiently without hurting inference performance (Meng et al., 2019). For each triplet t, its equality constraint can be rewritten as

$$F(t) = (1 - p_t^*) \sum_{(i:P^m, j:P^n)}^{\mathcal{EE}} y_{i,j}^r, \qquad (3)$$

$$-p_t^* \sum_{(i:P^m, j:P^n)}^{\mathcal{EE}} \sum_{r' \neq r}^{\mathcal{R}} y_{i,j}^{r'} = 0.$$

The goal is to maximize the objective function defined by Eq. (2) while satisfying the equality constraints.

Algorithm 1 Gradient Ascent for LR

```
procedure
    for $t \in \mathcal{T}$ do
        $\lambda_t^0 = 0$
    $k = 0$
    while $k < K$ do                                  ▷ $K$: max iteration
        $\hat{y}^{k+1} \leftarrow \arg\max \mathcal{L}(\boldsymbol{\lambda}^k)$
        for $t \in \mathcal{T}$ do
            $\Delta_t = p_t^* - \hat{p}_t$
            if $|\Delta_t| > \theta$ then
                $\lambda_t^{k+1} = \lambda_t^k + \alpha\Delta_t$
        if $\Delta_t \leq \theta, \forall t$ then
            break
        $k = k + 1$
        $\alpha = \gamma\alpha$                           ▷ $\gamma$: decay rate
```

3.2.3 Lagrangian Relaxation

Solving Eq. (2) is NP-hard. Thus, we reformulate it as a Lagrangian Relaxation problem by introducing Lagrangian multipliers λ_t for each *distributional constraint*. Lagrangian Relaxation has been applied in a variety NLP tasks, as described by Rush and Collins (2011, 2012) and Zhao et al. (2017).

The Lagrangian Relaxation problem can be written as

$$\mathcal{L}(\mathbf{y}, \boldsymbol{\lambda}) = \sum_{(i,j) \in \mathcal{EE}} \sum_{r \in \mathcal{R}} y_{i,j}^r S(y_{i,j}^r, \boldsymbol{x}) + \sum_{t \in \mathcal{T}} \lambda_t F(t). \qquad (4)$$

Initialize $\lambda_t = 0$. Eq. (4) can be solved with the following iterative algorithm (Algorithm 1).

1. At each iteration k, obtain the best relation assignments per MAP inference, $\hat{y}^k = \arg\max \mathcal{L}(\mathbf{y}, \boldsymbol{\lambda})$
2. Update the Lagrangian multiplier in order to bring the predicted probability closer to the prior. Specifically, for each $t \in \mathcal{T}$,
    - If $|p_t^* - \hat{p}_t| \leq \theta$, $\lambda_t^{k+1} = \lambda_t^k$
    - Otherwise, $\lambda_t^{k+1} = \lambda_t^k + \alpha(p_t^* - \hat{p}_t)$

α is the step size. We are solving a min-max problem: the first step chooses the maximum likelihood assignments by fixing $\boldsymbol{\lambda}$; the second step searches for $\boldsymbol{\lambda}$ values that minimize the objective function.

4 Constrained Inference Implementation

This section explains how to construct our *distributional constraints* and the implementation details for inference with LR.

Constraint Triplets	Count	%
occurrence, occurrence, *	124	19.7
occurrence, reporting, *	50	7.9
occurrence, action, *	44	7.0
reporting, occurrence, *	41	6.5
action, occurrence, *	40	6.4
action, action, *	20	3.2
reporting, reporting, *	18	2.9
action, reporting, *	18	2.9
reporting, action, *	17	2.7

Table 1: TimeBank-Dense: triplet prediction count and percentage in the development set (sample size = 629).

4.1 Distributional Constraint Selection

The selection of *distributional constraints* is crucial for our algorithm. If the probability of an event-type and relation triplet is unstable across different splits of data, we may over-correct the predicted probability. We use the following search algorithm with heuristic rules to ensure constraint stability.

4.1.1 TimeBank-Dense

For TimeBank-Dense, we first sort candidate constraints by their corresponding values of $C(P^m, P^n) = \sum_{\hat{r} \in \mathcal{R}} C(P^m, P^n, \hat{r})$. We list $C(P^m, P^n)$ with the largest prediction numbers and their percentages in the development set in Table 1.

Next, we set 3% as our threshold to include constraints for our main experimental results. We found this number to work relatively well for both TimeBank-Dense and I2B2-TEMPORAL. We will show the impact of relaxing this threshold in the discussion section. In Table 1, the constraints in the bottom block are filtered out. Moreover, Eq. 3 implies that a constraint defined on one triplet (P^m, P^n, r) has impact on all (P^m, P^n, r') for $r' \in \mathcal{R} \backslash r$. In other words, decreasing $\hat{p}_{(P^m, P^n, r)}$ is equivalent to increasing $\hat{p}_{(P^m, P^n, r')}$ and vice versa. Thus, we heuristically pick $(P^m, P^n, \textit{VAGUE})$ as our default constraint triplets.

Finally, we adopt a greedy search rule to select the final set of constraints. We start with the top constraint triplet in Table 1 and then keep adding the next one as long as it doesn't hurt the grid search[1] F_1 score on the development set. Eventually, four constraints triplets are selected, and they can be found in Table 3.

4.1.2 I2B2-TEMPORAL

Similar to TimeBank-Dense, we use the 3% threshold to select candidate constraints. However, it is computationally expensive to use the greedy search rule above by conducting grid search as the number of constraints that pass this threshold is large (15 of them), development set sample size is more than 3 times of TimeBank-Dense, and a large transformer is used for modeling, Therefore, we incorporate another two heuristic rules to directly select constraints,

1. We randomly split the train data into five subsets of equal size $\{s_1, s_2, s_3, s_4, s_5\}$. For triplet t to be selected, we must have $\frac{1}{5}\sum_{k=1}^{5} |p_{t,s_k} - p_t^*| < 0.001$.
2. $|\hat{p}_t - p_t^*| > 0.1$, where $\hat{p}_t$ is the predicted probability of t on the development set.

The first rule ensures that a constraint triplet is stable over a randomly split of data; the second one ensures that the probability gaps between the predicted and gold are large so that we will not over-correct them. Eventually, four constraints satisfy these rules, and they can be found in Table 9, and we run only one final grid search for these constraints.

4.2 Inference

The ILP component in Sec. 3.2.2 is implemented using an off-the-shelf solver provided by Gurobi optimizer. Hyper-parameters choices can be found in Table 6 in the Appendix.

5 Experimental Setup

This section describes the two event temporal relation datasets used in this paper and then explains the evaluation metrics.

5.1 Data

TimeBank-Dense. Temporal relation corpora such as TimeBank (Pustejovsky et al., 2003) and RED (O'Gorman et al., 2016) consist of expert annotations of news articles. The common issue of these corpora is missing annotations. Collecting densely annotated temporal relation corpora with all events and relations fully annotated is a challenging task as annotators could easily overlook some facts (Bethard et al., 2007; Cassidy et al., 2014; Chambers et al., 2014; Ning et al., 2017).

[1] Recall that our LR algorithm in Section 3.2.3 has three hyper-parameters: initial step size α, decay rate γ, and tolerance θ. We perform a grid search on the development set and use the best hyper-parameters on the test set.

	TimeBank-Dense				**2012 i2b2 Challenge** (I2B2-TEMPORAL)				
	Event	Relation			Event		Relation (TempEval Metrics)		
	F_1	R	P	F_1	Span F_1	Type Accuracy	R	P	F_1
Feature-based Benchmark	87.4	43.8	35.7	39.4	**90.1**	86.0	37.8	51.8	43.0
Han et al. (2019b)	**90.9**	52.6	46.5	49.4	-	-	73.4	76.3	74.8
End-to-end Baseline	90.3	51.5	45.9	48.5	87.8	**87.8**	73.3	79.9	76.5
End-to-end + Inference	90.3	**53.4**	**47.9**	**50.5**	87.8	**87.8**	**74.0**	**80.8**	**77.3**

Table 2: Overall experiment results: per MacNemar's test, the improvements against the end-to-end baseline models by adding inference with *distributional constraints* are both statistically significant for TimeBank-Dense (p-value < 0.005) and I2B2-TEMPORAL (p-value < 0.0005). For I2B2-TEMPORAL, our end-to-end system is optimized for the F_1 score of the gold pairs.

The TimeBank-Dense dataset mitigates this issue by forcing annotators to examine all pairs of events within the same or neighboring sentences, and this dataset has been widely evaluated on this task (Chambers et al., 2014; Ning et al., 2017; Cheng and Miyao, 2017; Meng and Rumshisky, 2018). Temporal relations consist of *BEFORE*, *AFTER*, *INCLUDES*, *INCLUDED*, *SIMULTANEOUS*, and *VAGUE*. Moreover, each event has several properties, e.g., **type**, **tense**, and **polarity**. Event types include `occurrence`, `action`, `reporting`, `state`, etc. Event pairs that are more than 2 sentences away are not annotated.

I2B2-TEMPORAL. In the clinical domain, one of the earliest event temporal datasets was provided in the 2012 Informatics for Integrating Biology and the Bedside (i2b2) Challenge on NLP for Clinical Records (Sun et al., 2013). Clinical events are categorized into 6 types: `treatment`, `problem`, `test`, `clinical-dept`, `occurrence`, and `evidential`. The final data used in the challenge contains three temporal relations: *BEFORE*, *AFTER*, and *OVERLAP*. The 2012 i2b2 challenge also had an end-to-end track, which we use as our feature-based system baseline. To mimic the input structure of TimeBank-Dense, we only consider event pairs that are within 3 consecutive sentences. Overall, 13% of the long-distance relations are excluded.[2]

5.2 Evaluation Metrics

To be consistent with previous work, we adopt two different evaluation metrics. For TimeBank-Dense, we use standard **micro-average** scores that are also used in the baseline system (Han et al., 2019b). Since the end-to-end system can predict the gold pair as *NONE*, we follow the convention of IE tasks and exclude them from the evaluation. For I2B2-TEMPORAL, we adopt the **TempEval** evaluation metrics used in the 2012 i2b2 challenge. These evaluation metrics differ from the standard F_1 in a way that it computes the graph closure for both gold and predictions labels. Since I2B2-TEMPORAL contains roughly six times more missing annotations than the gold pairs, we only evaluate the performance of the gold pairs.

Both datasets contain three types of entities: events, time expressions, and document time. In this work, we focus on **event-event** relations and exclude all other relations from the evaluation.

5.3 Baselines

Feature-based Systems. We use CAEVO[3] (Chambers et al., 2014), a hybrid system of rules and linguistic feature-based MaxEnt classifier, as our feature-based benchmark for TimeBank-Dense. Model implementation and performance are both provided by Han et al. (2019b). As for I2B2-TEMPORAL, we retrieve the predictions from the top end-to-end system provided by Yan et al. (2013) and report the performance according to the evaluation metrics specified in Section 5.2.

Neural Model Baselines. We use the end-to-end systems described by Han et al. (2019b) as our neural network model benchmarks (Row 2 of Table 2). For TimeBank-Dense, the best global structured model's performance is reported by Han et al. (2019b). For I2B2-TEMPORAL, we re-implement the pipeline joint model. [4] Note that this end-to-end model only predicts whether each token is an event as well as each pair of token's relation. Event

[2] Over 80% of these long-distance pairs are event coreference, i.e., simply predicting them as *OVERLAP* will achieve high performance.

[3] `https://www.usna.edu/Users/cs/nchamber/caevo/`

[4] `https://github.com/PlusLabNLP/JointEventTempRel`

spans are not predicted, so head-tokens are used to represent events; event types are also not predicted. Therefore, we do not report Span F_1 and Type Accuracy in this benchmark.

End-to-end Baseline. For the *TimeBank-Dense* dataset, we use the pipeline joint (local) model with no global constraints as presented by Han et al. (2019b). In contrast to the aforementioned neural baseline provided in the same paper, this end-to-end model does not use any inference techniques. Hence, it serves as a fair baseline for our method (with inference). For *TimeBank-Dense*, we build our framework based on this model[5].

For the I2B2-TEMPORAL dataset to be more comparable with the 2012 i2b2 challenge, we augment the event extractor illustrated in Figure 2 by allowing event type predictions; that is, for each input token, we not only predict whether it is an event or not, but also predict its event type. We follow the convention in the IE field by adding a "BIO" label to each token in the data. For example, the two tokens in "physical therapy" in Figure 2 will be labeled as B-`treatment` and I-`treatment`, respectively. To be consistent with the partial match method used in the 2012 i2b2 challenge, the event span detector looks for token predictions that start with either "B-" or "I-" and ensures that all tokens predicted within the same event span have only one event type.

RoBERTa-large is used as the base model, and cross-entropy loss is used to train the model. We fine-tune the base model and conduct a grid search on the random hold-out set to pick the best hyper-parameters such as $c_{\mathcal{E}}$ in the multitask learning loss and the weight, $w_{\mathcal{E}_{pos}}$ for positive event types (i.e. B- and I-). The best hyper-parameter choices can be found in Table 6 in the Appendix.

6 Results and Analysis

Table 2 contains our main results. We discuss model performances on TimeBank-Dense and I2B2-TEMPORAL in this section.

6.1 TimeBank-Dense

All neural models outperform the feature-based system by more than 10% per relation F_1 score. Our structured model outperforms the previous SOTA systems with *hard constraints* and **joint event and relation training** by 1.1%. Compared with the end-to-end baseline model with no constraints, our system achieves 2% absolute improvement, which is statistically significant with a p-value < 0.005 per MacNemar's test. This is strong evidence that leveraging Lagrangian Relaxation to incorporate domain knowledge can be extremely beneficial even for strong neural network models.

The ablation study in Table 3 shows how *distributional constraints* work and the constraints' individual contributions. The predicted probability gaps shrink by 0.15, 0.24, and 0.13 respectively for the three constraints chosen, while providing 0.91%, 0.65%, and 0.44% improvements to the final F_1 score for relation extraction. We also show the breakdown of the performance for each relation class in Table 4. The overall F_1 improvement is mainly driven by the recall scores in the positive relation classes (*BEFORE*, *AFTER*, and *INCLUDES*) that have much smaller sample size than *VAGUE*. These results are consistent with the ablation study in Table 3, where the end-to-end baseline model over-predicts on *VAGUE*, and the LR algorithm corrects it by assigning less confident predictions on *VAGUE* to positive and minority classes according to their relation scores.

6.2 I2B2-TEMPORAL

All neural models outperform the feature-based system by more than 30% per relation F_1 score. Our structured model with *distributional constraints* outperforms the neural pipeline joint models of Han et al. (2019b) by 2.5% per absolute scale. Compared with our end-to-end baseline model, our system achieves 0.77% absolute improvement on F_1 measure, which is statistically significant with a p-value < 0.0005 per MacNemar's test. This result also shows that adding inference with *distributional constraints* can be helpful for strong neural baseline models.

Table 9 in the Appendix Section C shows how *distributional constraints* work and their individual contributions. Predicted probability gaps shrink by 0.17, 0.16, 0.11, and 0.14, respectively, for the four constraints chosen, providing 0.19%, 0.25%, 0.22%, and 0.12% improvements to the final F_1 scores for relation extraction. We also have the breakdown performance for each relation class in Table 8. The performance gain is caused mostly by the increase of recall scores in *BEFORE* and *AFTER*. This is consistent with the results in Table 9 where the model over-predicts on the *OVERLAP*

[5] Code and data for TimeBank-Dense are published here: `https://github.com/rujunhan/EMNLP-2020`

Constraint Triplets	Prob. Gap	F_1
`occur.`, `occur.`, *VAGUE*	-0.15	+0.91%
`occur.`, `reporting`, *VAGUE*	-0.24	+0.65%
`action`, `occur.`, *VAGUE*	-0.13	+0.44%
`reporting`, `occur.`, *VAGUE**	0.0	0%
Combined F1 Improvement		2.0%

Table 3: TimeBank-Dense ablation study: gap shrinkage of predicted probability and F_1 contribution per constraint. * is selected per Sec. 4, but the probability gap is smaller than the tolerance in the test set, hence no impact to the F_1 score.

	End-to-end Baseline			**End-to-end Inference**		
	P	**R**	**F_1**	**P**	**R**	**F_1**
B	59.0	46.9	52.3	58.6	55.7	57.1
A	69.3	45.3	54.8	67.8	51.5	58.5
I	-	-	-	8.3	1.8	2.9
II	-	-	-	-	-	-
S	-	-	-	-	-	-
V	45.1	55.0	49.5	47.6	51.4	49.4
Avg	51.5	45.9	48.5	53.4	47.9	50.5

Table 4: Model performance breakdown for TimeBank-Dense. "-" indicates no predictions were made for that particular label, probably due to the small size of the training sample. *BEFORE* (**B**), *AFTER* (**A**), *INCLUDES* (**I**), *IS_INCLUDED* (**II**), *SIMULTANEOUS* (**S**), *VAGUE* (**V**)

class, possibly because of label imbalance. Inference is able to partially correct this mistake by leveraging *distributional constraints* constructed with event type and relation corpus statistics.

6.3 Qualitative Error Analysis

We can use the errors made by our structured neural model on TimeBank-Dense to guide potential directions for future research. There are 26 errors made by the structured model that are correctly predicted by the baseline model. In Table 5, we show the error breakdown by constraints. Our method works by leveraging corpus statistics to correct borderline errors made by the baseline model; however, when the baseline model makes borderline correct predictions, the inference could mistakenly change them to the wrong labels. This situation can happen when the context is complicated or when the event time interval is confusing.

For the constraint (`occur.`, `occur.`, *VAGUE*), nearly all errors are cross-sentence event pairs with long context information. In **ex.1**, the gold relation between **responded** and **use** is *VAGUE* because of the negation of **use**, but one could also argue that if **use** were to happen, **responded** is *BEFORE* **use**. This inherent annotation confusion can cause the baseline model to predict *VAGUE* marginally over *BEFORE*. When informed by the constraint statistics that **vague** is over-predicted, the inference algorithm revises the baseline prediction to *BEFORE*. Similarly, in **ex.2** and **ex.3**, one could make strong cases that both the relations between **delving** and **acknowledged**, and **opposed** and **expansion** are *BEFORE* rather than *VAGUE* from the context. This annotation ambiguity can contribute to the errors made by the proposed method.

`occurrence`, `occurrence`, *VAGUE* (57.7%)
ex.1 In a bit of television diplomacy, Iraq's deputy foreign minister responded from Baghdad in less than one hour, saying Washington would break international law by attacking without UN approval. The United States is not authorized to use force before going to the council.
`occurrence`, `reporting`, *VAGUE* (26.9%)
ex.2 A new Essex County task force began delving Thursday into the slayings of 14 black women over the last five years in the Newark area, as law-enforcement officials acknowledged that they needed to work harder...
`action`, `occurrence`, *VAGUE* (15.4%)
ex.3 The Russian leadership has staunchly opposed the western alliance's expansion into Eastern Europe.

Table 5: Error examples and breakdown by constraints.

Our analysis shows that besides the necessity to create high-quality data for event temporal relation extraction, it could be useful to incorporate additional information such as discourse relation (particularly for (`occur.`, `occur.`, *VAGUE*)) and other prior knowledge on event properties to resolve the ambiguity in event temporal reasoning.

7 Discussion

7.1 Constraint Selection

In Sec. 4, we use a 3% threshold when selecting candidate constraints. In this section, we show the impact of relaxing this threshold on TimeBank-Dense. Table 1 shows three constraints that miss the 3% bar by 0.1-0.3%. In Figure 3, we show F_1 scores on the development and test sets by including these constraints. Recall that only constraints that do not hurt development F_1 score are used. Therefore, **Top5** and **Top6** on the chart both correspond to the results in Table 2. **Top7** includes (`reporting`, `reporting`, *VAGUE*), **Top8** includes (`actioin`, `reporting`, *VAGUE*), and **Top9** includes (`reporting`, `actioin`, *VAGUE*).

We observe that F_1 score continues to improve over the development set, but on the test set, F_1 score eventually falls. This appears to support our hypothesis that when the triplet count is small, the ratio calculated based on that count is not so reliable as the ratio could vary drastically between development and test sets. Optimizing over the

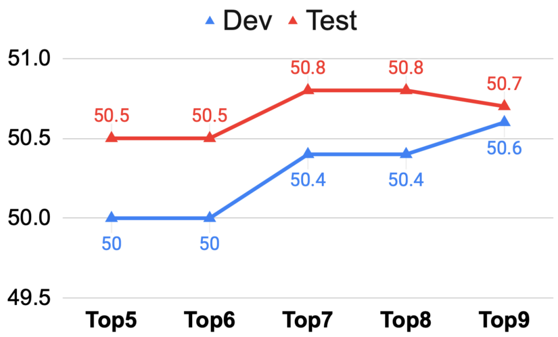

Figure 3: Dev v.s. Test sets performance (F_1 score) after relaxing the threshold of triplet count for selecting constraints. All numbers are percentages.

development set can be an over-correction for the test set, and hence results in a performance drop.

7.2 Event Type Prediction

As described in Sec 5.3, to ensure fair comparison with the previous SOTA system (Han et al., 2019b), our baseline model for TimeBank-Dense does not predict event types. That is, when counting the triplet $(P^m, P^n, \hat{r})$, we assume there is an oracle model that provides event types P^m, P^n for the predicted relation $\hat{r}$. One could potentially extend our work by training a similar multi-task learning model to predict both types and relations as our model does for the I2B2-TEMPORAL dataset. We leave this as a future research direction.

8 Related Work

News Domain. Early work on **temporal relation extraction** use local pair-wise classification with hand-engineered features (Mani et al., 2006; Verhagen et al., 2007; Chambers et al., 2007; Verhagen and Pustejovsky, 2008). Later efforts, such as ClearTK (Bethard, 2013), UTTime (Laokulrat et al., 2013), NavyTime (Chambers, 2013), and CAEVO (Chambers et al., 2014), improve earlier work with better linguistic and syntactic rules. Yoshikawa et al. (2009); Ning et al. (2017); Leeuwenberg and Moens (2017) explore structured learning for this task, and more recently, neural methods have also been shown effective (Tourille et al., 2017; Cheng and Miyao, 2017; Meng et al., 2017; Meng and Rumshisky, 2018). Ning et al. (2018c) and Han et al. (2019b) are the most recent work leveraging neural network and pre-trained language models to build an end-to-end system. Our work differs from these prior work in that we build a structured neural model with *distributional constraints* that combines both the benefits of both deep learning and *domain knowledge*.

Clinical Domain. The 2012 i2b2 Challenge ((Sun et al., 2013)) is one of the earliest efforts to advance event temporal relation extraction of clinical data. The challenge hosted three tasks on event (and event property) classification, temporal relation extraction, and the end-to-end track. Following this early effort, a series of clinical event temporal relation challenges were created in the following years ((Bethard et al., 2015, 2016, 2017)). However, data in these challenges are relatively hard to acquire, and therefore they are not used in this paper. As in the news data, traditional machine learning approaches (Lee et al., 2016; Chikka, 2016; Xu et al., 2013; Tang et al., 2013; Savova et al., 2010) that tackle the end-to-end event and temporal relation extraction problem require time-consuming feature engineering such as collecting lexical and syntax features. Some recent work (Dligach et al., 2017; Leeuwenberg and Moens, 2017; Galvan et al., 2018) apply neural network-based methods to model the temporal relations, but are not capable of incorporating prior knowledge about clinical events and temporal relations as proposed by our framework.

9 Conclusion

In conclusion, we propose a general framework that augments deep neural networks with *distributional constraints* constructed using probabilistic *domain knowledge*. We apply it in the setting of end-to-end temporal relation extraction task with event-type and relation constraints and show that the MAP inference with *distributional constraints* can significantly improve the final results.

We plan to apply the proposed framework on various event reasoning tasks and construct novel *distributional constraints* that could leverage *domain knowledge* beyond corpus statistics, such as the larger unlabeled data and rich information contained in knowledge bases.

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Appendix

A Hyper-parameters

B Data Summary

C I2B2-Temporal Results

We show the breakdown performance and contributions of individual constraints for I2B2-Temporal in Table 8 and Table 9 respectively.

	TimeBank-Dense	I2B2-Temporal
$c_{\mathcal{E}}$	-	1.0
$w_{\mathcal{E}_{pos}}$	-	5.0
lr	-	$2e^{-5}$
α	5.0	5.0
θ	0.05	0.02
γ	0.7	0.8

Table 6: Hyper-parameters chosen using development data. For TimeBank-Dense, end-to-end baseline model is provided by the Han et al. (2019b), so we do not train it from scratch.

	TimeBank-Dense	I2B2-Temporal
# of Documents		
Train	22	190
Dev	5	-
Test	9	120
# of Pairs		
Train	4032	11253
Dev	629	-
Test	1427	8794

Table 7: Data overview. Note that we exclude event pairs whose sentence distance longer than 3 in I2B2-Temporal, and there are 6 times more missing relations than the gold annotated ones in, which explains why number of pairs per documents are smaller in I2B2-Temporal than in TimeBank-Dense.

D Reproducibility List

- Data and code used for TimeBank-Dense can be found in project code base. However, due to user confidentiality agreement, we are not able to provide data and and data analysis code for I2B2-Temporal. Modeling code will be added to the project code base upon obtaining permission from the data owner.

- We use BERT-base-uncased and Roberta-large models implemented in Huggingface transformers. Additional parameters (such as LSTM and MLP) are negligible compared to those used in the pre-trained LMs;

- ILP is solved by an off-the-shelf solver provided by Gurobi optimizer;

- Range of grid-search. $c_{\mathcal{E}}$: (1.0, 2.0); $w_{\mathcal{E}_{pos}}$: (1.0, 2.0, 5.0, 10.0); lr: ($1e^{-5}$, $2e^{-5}$, $5e^{-5}$), α: (1.0, 2.0, 5.0, 10.0); θ: (0.2, 0.3, 0.5); γ: (0.7, 0.8, 0.9).

	End-to-end Baseline			End-to-end Inference		
	P	**R**	**F$_1$**	**P**	**R**	**F$_1$**
B	82.1	60.6	69.7	80.9	65.3	72.2
A	69.9	59.9	64.5	67.8	62.8	65.2
O	81.3	81.5	81.4	83.6	80.2	81.9
TempEval	73.3	79.9	76.5	74.0	80.8	77.3

Table 8: Model performance breakdown for I2B2-TEMPORAL. *BEFORE* (**B**), *AFTER* (**A**), *OVERLAP* (**O**).

Constraint Triplets	Prob. Gap	F$_1$
`occur.`, `problem`, *OVERLAP*	-0.17	+0.19%
`occur.`, `treatment`, *OVERLAP*	-0.16	+0.24%
`treatment`, `occur.`, *OVERLAP*	-0.11	+0.22%
`treatment`, `problem`, *OVERLAP*	-0.14	+0.12%
Combined F1 Improvement		0.77%

Table 9: I2B2-TEMPORAL ablation study: gap shrinkage of predicted probability and F$_1$ contribution per constraint.