Modeling Human Mental States with an Entity-based Narrative Graph

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Abstract

This paper proposes an Entity-based Narrative Graph (ENG) to model the internal-states of characters in a story. We explicitly model entities, their interactions and the context in which they appear, and learn rich representations for them. We experiment with different task-adaptive-pretraining objectives, in-domain training, and symbolic inference to capture dependencies between different decisions in the output space. We evaluate our model on two narrative understanding tasks: predicting character mental states, and desire fulfillment, and conduct a qualitative analysis.

1 Introduction

Understanding narrative text requires modeling the motivations, goals and internal states of the characters described in it. These elements can help explain intentional behavior and capture causal connections between the characters' actions and their goals. While this is straightforward for humans, machine readers often struggle as a correct analysis relies on making long range common-sense inferences over the narrative text. Providing the appropriate narrative representation for making such inferences is therefore a key component. In this paper we suggest a novel narrative representation and evaluate it on two narrative understanding tasks, analyzing the characters' mental states and motivation (Abdul-Mageed and Ungar, 2017; Rashkin et al., 2018), and desire fulfillment (Chaturvedi et al., 2016; Rahimtoroghi et al., 2017).

We follow the observation that narrative understanding requires an expressive representation capturing the context in which events appear and the interactions between characters' states. To clarify, consider the short story in Fig. 1. The desire expression appears early in the story and provides the context explaining the protagonist's actions. Evaluating the fulfilment status of this expression, which tends to appear towards the end of the story,

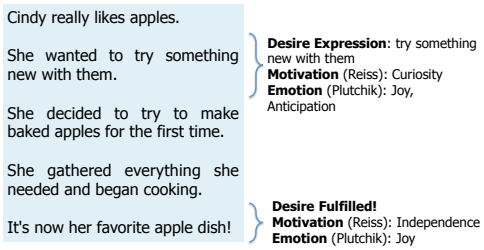


Figure 1: Narrative Example

requires models that can reason over the desire expression (*"trying something new"*), its target (*"apples"*) and the outcome of the protagonist's actions (*"it's now her favorite apple dish!"*). Capturing the interaction between the *motivation* underlying the desire expression (in Fig. 1, CURIOSITY) and the *emotions* (in Fig. 1, ANTICIPATION) likely to be invoked by the motivation can help ensure the consistency of this analysis and improve its quality.

To meet this challenge we suggest a graph-contextualized representation for entity states. Similar to contextualized word representations (Peters et al., 2018; Devlin et al., 2019), we suggest learning an entity-based representation which captures the narrative it is a part of. For example, in *"She decided to try to make baked apples for the first time"* the mental state of "she" would be represented differently given a different context, such as a different motivation for the action (*"Her mother asked her to make an apple dish for a dinner party"*). In this case, the contextualized representation would capture the different emotion associated with it (e.g., FEAR of disappointing her mother). Unlike contextualized word embedding models, our challenging settings require dealing with complex internal event structure (associations between the predicate and the entities, and their semantic roles), long narrative text, often beyond the length that can be effectively represented using these models. Furthermore, we exploit the event structure, and incorporate constraints ensuring consistency between

the mental state attributes of the characters.

We begin by generating an Entity-based Narrative Graph (ENG) representation of the text. Unlike other graph-based narrative representations (Lehnert, 1981; Goyal et al., 2010; Elson, 2012) which require intensive human annotation, we emphasize simplicity and shift the focus from symbolic graph representations of nuanced information to their learned embedding. In our representation nodes correspond to events and edges represent observed relations between events. These relations capture the sequential order of event occurrence, represented using the **Next** relationship. Events sharing a coreferenced entity are connected via the **CNext** relationship. We also represent discourse relations corresponding to six relations defined in the Penn Discourse Tree Bank (PDTB) (Prasad et al., 2007), which include **Before, After, Sync., Contrast, Reason** and **Result**.

We define the contextualized event embedding over this graph, by using a Relational Graph Convolution Network (R-GCN) (Schlichtkrull et al., 2018), a relational variant of the Graph Convolution Network architecture (GCN) (Kipf and Welling, 2016), which creates contextualized node representations by unfolding the graph structure recursively into a tree structure and learning a composition function. This architecture allows us to take into account the narrative structure and the different discourse relations connecting events when embedding the event node.

We first define a self-supervised pre-training process for embedding the narrative graph, by learning to recover removed edges and capture incorrect associations between event nodes and edges. We apply our the learned graph representation to two challenging narrative analysis tasks, predicting characters' psychological states (Rashkin et al., 2018) and desire fulfilment (Rahimtoroghi et al., 2017) and show that our model can outperform competitive transformer-based representations of the narrative text. Our code and trained models will be publicly available in the camera-ready version.

2 Related Work

Tracking entities and modeling their properties has proven successful in a wide range of tasks, including language modeling (Ji et al., 2017), question answering (Henaff et al., 2017) and text generation (Bosselut et al., 2018). In an effort to model complex story dynamics in text, Rashkin et al. (2018) released a dataset for tracking emotional reactions of characters in stories. In their dataset, each character mention is annotated with three types of mental state descriptors: Maslow's "hierarchy of needs" (Maslow, 1943), Reiss' "basic motives" (Reiss, 2004), that provide a more informative range of motivations, and Plutchik's "wheel of emotions" (Plutchik, 1980), comprised of eight basic emotional dimensions (e.g. joy, sadness, etc). In their paper, they showed that neural models with explicit or latent entity representations achieve promising results on this task. Paul and Frank (2019) approached this task by extracting multi-hop relational paths from ConceptNet, while Gaonkar et al. (2020) leveraged semantics of the emotional states by embedding their textual description and modeling the co-relation between different entity states. Rahimtoroghi et al. (2017) introduced a dataset for the task of desire fulfillment. They identified desire expressions in first-person narratives and annotated their fulfillment status. They showed that models that capture the flow of the narrative perform well on this task.

Representing the narrative flow of stories using graph structures and multi-relational embeddings has been studied in the context of script learning (Li et al., 2018; Lee and Goldwasser, 2019; Lee et al., 2020). In these cases, the nodes represent predicate-centric events, and entity mentions are added as context to the events. In this paper, we use an entity-centric narrative graph, where nodes are defined by entity mentions and their textual context. We encode the textual information in the nodes using pre-trained language models (Devlin et al., 2019; Liu et al., 2019), and the graph structure with a relational graph neural network (Schlichtkrull et al., 2018). To learn the representation, we incorporate a task-adaptive pre-training phase. Gururangan et al. (2020) showed that further specializing large pre-trained language models to domains and tasks within those domains is effective.

3 Entity-based Narrative Graph

3.1 Framework Overview

Many NLU applications require understanding entity states in order to make sophisticated inferences (Sap et al., 2018; Bosselut et al., 2019; Rashkin et al., 2018). In this work, we propose a learning framework that includes task-adaptive pretraining (TAPT) and downstream task training to train an entity-based narrative graph (ENG), a

graph neural model designed to capture implicit states and interactions between entities. We extend the narrative graph proposed by Lee et al. (2020), which models event relationships, and adapt it for entity mentions. Although ENG has the flexibility to be applied in various entity-based tasks, we demonstrate and explain it through a target downstream task, StoryCommonsense (Rashkin et al., 2018).

Our framework consists of four main components: Node Encoder, Graph Encoder, Learning Objectives, and Symbolic Inference, outlined in Figure 2. The node encoder is a function used to extract local information about the target entity mention corresponding to the uncontextualized node representation. The graph encoder uses a graph neural network to contextualize the node representations within a document, generating entity-context-aware representations. The learning objectives use this representation for several learning tasks, such as node classification, link prediction, and document classification. Finally, we include a symbolic inference procedure to capture dependencies between output decisions.

We introduce a training pipeline, containing pretraining and downstream training, following recent evidence suggesting that task-adaptive pretraining is potentially useful for many NLU tasks (Gururangan et al., 2020). We experiment with three pretraining setups, including the common whole-word-masking pretraining (Liu et al., 2019), and two newly proposed unsupervised pretraining objectives based on ENG. We then evaluate two downstream tasks: StoryCommonsense and DesireDB (Rahimtoroghi et al., 2017). StoryCommonsense aims at predicting three sets of mental states based on psychological theories (Maslow, 1943; Reiss, 2004; Plutchik, 1980), while DesireDB's goal is to identify whether a target desire is satisfied or not. Solving these tasks requires understanding entities' mental states and their interactions.

3.2 Node Encoder

Each node in our graph captures the local context of a specific entity mention (or character mention). Following Gaonkar et al. (2020), we format the input information to feed into a pretrained language model. For a given character c and sentence s, the inputs to the node encoder consist of three components $(s, ctx(c), L)$, where s is the sentence in which c appears, $ctx(c)$ is the context of c (all the sentences that the character appears in), and L is a label sentence. The label sentence is an artificial sentence of the form "[entity name] is [label 1], [label 2], ..., [label k]." The k labels correspond to the targets in the downstream task. For example, in StoryCommonsense, the Plutchik state prediction task has eight labels characterizing human emotions, such *joy*, *trust*, and *anger*. Gaonkar et al. (2020) show that self-attention is an effective way to let the model take label semantics into account, and improve performance[1].

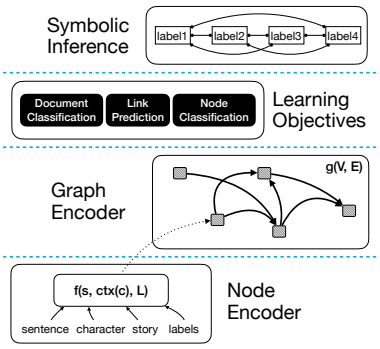


Figure 2: Overview of the ENG framework.

Our best model uses RoBERTa (Liu et al., 2019), a highly-optimized version of BERT (Devlin et al., 2019), to encode nodes. We convert the node input $(s, ctx(c), L)$ to RoBERTa's two-sentence input format by treating s as the first sentence, and the concatenation of $ctx(c)$ and L as the second sentence. After forward propagation, we take the pooled sentence representation (i.e., <*s*>for RoBERTa, *CLS* for BERT), as the node representation v. This is formulated as $v = f_{roberta}(s, ctx(c), L)$.

3.3 Graph Encoder

The ENG is defined as $ENG = (V, E)$, where V is the set of encoded nodes in a document and E is the set of edges capturing relationships between nodes. Each edge $e \in E$ is a triplet $(v1, r, v2)$, where $v1, v2 \in V$ and r is an edge type ($r \in R$). Following Lee et al. (2020), we use eight relation types ($|R| = 8$) that have been shown to be useful for modeling narratives. NEXT denotes if two nodes appear in neighboring sentences. CNEXT expresses the next occurrence of a specific entity following its co-reference chain. Six discourse relation types, used in (Lee et al., 2020) and defined in Penn Discourse Tree Bank (PDTB) (Prasad et al., 2007), are also used in this work, including BE-

[1]Our preliminary experiments also confirm this.

FORE, AFTER, SYNC., CONTRAST, REASON, RESULT. Their corresponding definition in PDTB and can be found in Appendix A. Following Lee et al. (2020), we use the Stanford CoreNLP pipeline[2] (Manning et al., 2014) to obtain co-reference links and dependency trees. We use them as heuristics to extract the above relations and identify entities for TAPT[3]. Details of this procedure can be found in (Lee et al., 2020). Note that although we share the same relation definitions, our nodes are defined over entities, instead of predicates.

For encoding the graph, we use a Relational Graph Convolution Network (R-GCN) (Schlichtkrull et al., 2018), which is designed for Knowledge Base Completion. This architecture is capable of modeling typed edges and is resilient to noise. R-GCN is defined as:

$$h_i^{l+1} = ReLU\left(\sum_{r\in R}\sum_{u\in U_r(v_i)}\frac{1}{z_{i,r}}W_r^l h_u^l\right), \quad (1)$$

where h_i^l is the hidden representation for the i-th node at layer l and $h_i^0 = v_i$ (output of the node encoder); $U_r(v_i)$ represents v_i's neighboring nodes connected by the relation type r; $z_{i,r}$ is for normalization; and W_r^l represents trainable parameters.

Our implementation of R-GCN propagates messages between entity nodes, emulating the interactions between their psychological states, and thus enriching node representations with context. Note that our framework is flexible, and alternative node and graph encoders could be used.

3.4 Output Layers and Learning Objectives

We explore three learning problem types.

Node Classification For node classification, we use the contextualized node embeddings coming from the graph encoder, and plug in a k-layer feed-forward neural network on top ($k = 2$ in our case). The learning objectives could be either multi-class or multi-label. For multi-class classification, we use the weighted cross-entropy loss (CE). For multi-label classification, we use the binary cross-entropy (BCE) loss for each label[4]:

$$CE = -\frac{1}{N}\sum_{i=1}^{N}\alpha_i y_i \log(S(g(f(x_i)))), \quad (2)$$

where $S(.)$ is the Softmax function, $f(.)$ is the graph encoder, $g(.)$ is the node encoder, x_i is the input including the target node i ($(s, ctx(c), L)$) and all other nodes in the same document (or ENG), y_i is the label, and α_i is the weight.

Link Prediction This objective tries to recover missing links in a given ENG. We remove a small portion of edges (20% in our case) and learn to predict them. To obtain negative examples, we sample edges by truncating either end of the positive edges, based on the relation type distribution given in Table 3, taken from the training set. Following Schlichtkrull et al. (2018), we score each edge sample with DistMult (Chang et al., 2014):

$$D(i, r, j) = h_i^T W_r h_j, \quad (3)$$

where W_r is a relation-specific trainable matrix (non-diagonal) and h_i and h_j are node embeddings coming from the graph encoder. A higher score indicates that the edge is more likely to be active. To learn this, we reward positive samples and penalize negative ones, using an adapted CE loss:

$$L = -\frac{1}{T}\sum_{(i,r,j,y)\in T} y\log(\sigma(\epsilon_r D(i, r, j))) + (1-y)\log(1-\sigma(\epsilon_r D(i, r, j))), \quad (4)$$

T is the sampled edges set, $y = \{0, 1\}$, $\sigma(.)$ is the Sigmoid function, and ϵ_r is the edge type weight, based on the edge sampling rate (Append. A).

Document Classification For such tasks, such as DesireDB, we aggregate the node representations from the entire ENG to form a single representation. To leverage the relative importance of each node, we add a node attention layer. We calculate the attention weight for each node by attending on a target embedding. In DesireDB, we use the sentence embedding for the desire expression.

$$a_i = ReLU(W_a[h_i; h_t] + b_a)$$
$$z_i = exp(a_i)$$
$$\alpha_i = \frac{z_i}{\sum_k z_k} \quad ; \quad h_d = \sum_i \alpha_i h_i \quad (5)$$

, where h_i is the i-th node representation, h_t is the target embedding (e.g, the desire expression), W_a and b_a are trainable parameters, and h_d is the final document representation. We then feed h_d to a two-hidden-layer classifier to make predictions. We use the loss function specified in Eq. 2.

[2]Stanford CoreNLP v4.0 with default annotators.

[3]For StoryCommonsense, since the entity names are annotated, we simply use them.

[4]We tried weighted an unweighted BCE, and selected the unweighted one for our final model.

3.5 Task-Adaptive Pretraining

Recent studies demonstrate that downstream tasks performance can be improved by applying the self-supervised pretraining task on the text of the target domain (Gururangan et al., 2020), we refer to this step as Task-Adaptive Pre-Training (TAPT). We investigate whether different TAPT objectives can provide different insights for the target task. We empirically set our target task as StoryCommonsense, and since StoryCommonsense is based on RocStories (Mostafazadeh et al., 2016), we run TAPT on all the RocStories text (not including the validation and testing sets). We use the learning parameters suggested by Gururangan et al. (2020) and explore three different TAPT settings:

Whole-Word Masking: Randomly masks a subset of words and asks the model to recover them from their context (Radford et al., 2019; Liu et al., 2019). We perform this task over RoBERTa, initialized with *roberta-base*.

ENG LinK Prediction: Weakly-supervised TAPT over the ENG. The setup follows Sec. 3.4(Link Prediction) to learn a model that can recover missing edges in the ENG.

ENG Node Sentiment Classification: Performs weakly-supervised sentiment TAPT. We use the Vader sentiment analysis (Hutto and Gilbert, 2014) tool to annotate the sentiment polarity for each node in the ENG, based on its sentence. The setup follows Sec. 3.4 (Node Classification).

3.6 Symbolic Inference

In addition to modeling the narrative structure in the embedding space, we add a symbolic inference procedure to capture structural dependencies in the output space for the StoryCommonsense task. To model these dependencies, we use DRaiL (Pacheco and Goldwasser, 2020), a neural-symbolic framework that allows for defining probabilistic logical rules on top of neural network potentials.

Decisions in DRaiL are modeled using rules, which can be weighted (i.e., soft constraints), or unweighted (i.e., hard constraints). Rules are formatted as horn clauses: A $\Rightarrow$ B, where A is a conjunction of observations and predicted values, and B is the output to be predicted. Weighted rules are associated with a neural architecture, used to learn the rule weights. The collection of rules represents the global decision, and the solution is obtained by performing MAP inference. In DRaiL, parameters are trained using the structured hinge loss.

We used feed-forward networks over the node embeddings obtained by the objectives outlined in Sec. 3.4 and 3.5, without back-propagating to the full graph. We model the following rules:

Weighted rules We score each state, as well as *state transitions* to capture the progression in a character's mental state throughout the story.

$$\texttt{Entity}(\texttt{e}_\texttt{i}) \Rightarrow \texttt{State}(\texttt{e}_\texttt{i}, \texttt{l}_\texttt{i})$$
$$\texttt{State}(\texttt{e}_\texttt{i}, \texttt{l}_\texttt{i}) \wedge \texttt{HasNext}(\texttt{e}_\texttt{i}, \texttt{e}_\texttt{j}) \Rightarrow \texttt{State}(\texttt{e}_\texttt{j}, \texttt{l}_\texttt{j})$$

Where e_i and e_j are two different mentions of the same character, and `HasNext` is a relation between consecutive sentences. `State` can be either `Maslow`, `Reiss` or `Plutchik`.

Unweighted rules There is a dependency between Maslow's "hierarchy of needs' and Reiss "basic motives" (Rashkin et al., 2018). We introduce logical constraints to disallow mismatches in the Maslow and Reiss prediction for a given mention e_i. In addition to this, we model positive and negative sentiment correlations between Plutchik labels. To do this, we group labels into positive (e.g. joy, trust), and negative (e.g. fear, sadness). We refer to this set of rules as *inter-label dependencies*.

$$\texttt{Maslow}(\texttt{e}_\texttt{i}, \texttt{m}_\texttt{i}) \wedge \neg\texttt{Align}(\texttt{m}_\texttt{i}, \texttt{r}_\texttt{i}) \Rightarrow \neg\texttt{Reiss}(\texttt{e}_\texttt{i}, \texttt{r}_\texttt{i})$$
$$\texttt{Reiss}(\texttt{e}_\texttt{i}, \texttt{r}_\texttt{i}) \wedge \neg\texttt{Align}(\texttt{m}_\texttt{i}, \texttt{r}_\texttt{i}) \Rightarrow \neg\texttt{Maslow}(\texttt{e}_\texttt{i}, \texttt{m}_\texttt{i})$$
$$\texttt{Plut}(\texttt{e}_\texttt{i}, \texttt{p}_\texttt{i}) \wedge \texttt{Pos}(\texttt{p}_\texttt{i}) \wedge \neg\texttt{Pos}(\texttt{p}_\texttt{j}) \Rightarrow \neg\texttt{Plut}(\texttt{e}_\texttt{i}, \texttt{p}_\texttt{j})$$

Given that the DesireDB task requires a single prediction for each narrative graph, we do not employ symbolic inference for this task.

4 Evaluations

Our evaluation includes two downstream tasks and a qualitative analysis. We report the results for different TAPT schemes and symbolic inference on StoryCommonsense. For the qualitative analysis, we visualize and compare the contextualized graph embeddings and contextualized word embeddings.

4.1 Data and Experiment Settings

For TAPT, we use RocStories, as it has a decent amount of documents (90K after excluding the validation and testing sets) that share the text style of StoryCommonsense. For all tasks, we use the train/dev/test splits used in previous work.

All the RoBERTa models used in this paper are initialized with *roberta-base*, and the BERT models with *bert-base-uncased*. The maximum sequence length for the language models is 160; for large

Group	Models	Maslow			Reiss			Plutchik		
		Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
G1	**RANDOM**	7.45	49.99	12.96	1.76	50.02	3.40	10.35	50.00	17.15
	TF-IDF	29.79	34.56	32.00	20.55	24.81	22.48	22.71	25.24	23.91
	GLOVE	27.02	37.00	31.23	16.99	26.08	20.58	19.47	46.65	27.48
	LSTM	30.34	40.12	34.55	21.38	28.70	24.51	25.31	33.44	28.81
	CNN	29.30	44.18	35.23	17.87	37.52	24.21	24.47	38.87	30.04
	REN	26.85	44.78	33.57	16.73	26.55	20.53	25.30	37.30	30.15
	NPN	26.60	39.17	31.69	15.75	20.34	17.75	24.33	40.10	30.29
G2	**SA-ELMo**	34.91	32.16	33.48	21.23	16.53	18.59	47.33	40.86	43.86
	SA-RBERT	43.58	30.03	35.55	24.75	18.00	20.84	46.51	45.45	45.97
	LC-BERT	43.05	41.31	42.16	29.46	28.67	29.06	49.36	52.09	50.69
	LC-RBERT	43.25	47.17	45.13	39.62	29.75	33.98	47.87	53.41	50.49
G3	**ENG**	43.87	51.13	47.22	37.66	36.20	36.92	48.96	56.07	52.27
	ENG+Mask	44.27	53.54	**48.47**	39.29	33.93	36.41	49.64	56.93	**53.03**
	ENG+Link	43.47	52.80	47.68	37.17	37.18	**37.18**	50.62	54.48	52.48
	ENG+Sent	45.29	50.89	47.93	36.69	36.14	36.41	49.48	57.12	**53.03**
G4	**ENG+IL**	40.90	58.03	47.98	31.67	41.19	35.81	49.93	74.95	59.93
	ENG+IL+ST	40.47	58.43	47.82	31.80	40.58	35.66	51.19	72.60	**60.04**

Table 1: Results for the StoryCommonsense task, including three multi-label tasks (Maslow, Reiss, and Plutchik), for predicting human's mental states of motivations or emotions.

ENGs, we set the maximum number of nodes to 60; all the hidden layer have 128 hidden units; and the number of layers for R-GCN is 2.

For learning parameters in TAPT, we set the batch size to 256 through gradient accumulations; the optimizer is Adam (Kingma and Ba, 2014) with an initial learning rate of $1e-4$, $\epsilon = 1e-6$, $\beta = (0.9, 0.98)$, weight decay 0.01, and warm-up proportion 0.06. We run TAPT for 100 epochs. For the downstream tasks, we conduct a grid search of Adam's initial learning rate from $\{2e-3, 2e-4, 2e-5, 2e-6\}$, 5000 warm-up steps, and stop patience of 10. Model selection is done on the validation set. We report results for the best model. For learning the potentials for symbolic inference with DRaiL (Pacheco and Goldwasser, 2020), we use local normalization with a learning rate of 1e-3, and represent neural potentials using 2-layer Feed-Forward Networks over the ENG node embeddings. All hidden layers consist of 128 units. The parameters are learned using SGD with a patience of 5, tested against the validation set. For more details, refer to (Pacheco and Goldwasser, 2020). Note that while it would be possible to back-propagate to the whole graph, this is a computationally expensive procedure. We leave this exploration for future work.

4.2 Task: StoryCommonsense

StoryCommonsense consists of three subtasks: Maslow, Reiss, and Plutchik, introduced in Sec. 2. For each task, for each sentence-character pair in a given story, conduct multi-label classifications for each subtask. Each story was annotated by three annotators and the final labels were determined through a majority vote. For Maslow and Reiss, the vote is count-based, (i.e., if two out of three annotators flag a label, then it is an active label). For Plutchik, the vote is rating-based, where each label has an annotated rating, ranging from $\{0, 5\}$. If the averaged rating is larger or equal to 2, then it is an active label. This is the set-up given in the original paper (Rashkin et al., 2018). Some papers (Gaonkar et al., 2020) report results using the count-based majority vote, resulting in scores that are not comparable to ours. Therefore, we re-implement two recent strong models proposed for this task–the Label Correlation model (LC (Gaonkar et al., 2020)) and the Self-Attention model (SA (Paul and Frank, 2019)) and evaluate them under the same set of hyper-parameters and model selection strategies as our models.

We briefly explain all the baselines, as well as our model variants shown in Table 1. The first group (G1) are the baselines proposed in the task paper. **TF-IDF** uses TF-IDF features, trained on RocStories, to represent the target sentence s and character context $ctx(c)$, and uses a Feed-Forward Net (FFN) classifier; **GloVe** encodes the sentences with the pretrained GloVe embeddings and learns uses a FFN; **CNN** (Kim, 2014) replaces the FFN with a Convolutional Neural Network; **LSTM** is

a two-layer bi-directional LSTM; **REN** (Henaff et al., 2017) is a recurrent entity network that learns to encode information for memory cells; and **NPN** (Bosselut et al., 2018) is an **REN** variant that includes a neural process network.

The second group (G2) of baselines are based on two recent publications–**LC** and **SA**–that showed strong performance on this task. We re-implement them and run the evaluation under the same setting as our proposed models. They originally use BERT and ELMo, respectively. To provide a fair comparisons, we also train a RoBERTa variant for them (LC-RBERT and SA-RBERT).

The third (G3) and fourth (G4) groups are our model variants. **ENG** is the model without TAPT; **ENG+Mask**, **ENG+Link**, and **ENG+Sent** are the models with Whole-Word-Masking (WM), Link Prediction (LP), and Node Sentiment (NS) TAPT, respectively. In the last group, **ENG(Best) + IL** and **ENG(Best) + IL + ST** are based on our best ENG model with TAPT and adding inter-label dependencies (IL) and state transitions (ST) using symbolic inference, described in Sec. 3.6.

Table 1 reports all the results. We can see that Group 2 generally performs better than Group 1 on all three subtasks, suggesting that our implementation is reasonable. Even without TAPT, **ENG** outperforms all baselines, rendering $2-3\%$ absolute F1-score improvement. With TAPT, the performance is further strengthened. Moreover, we find that different TAPT tasks offer different levels of improvement for each subtask. The WM helps the most in Maslow and Plutchik, while the LP and NS excel in Reiss and Plutchik, respectively. This means that different TAPTs embed different information needed for solving the subtask. For example, the ability to add potential edges can be key to do motivation reasoning (Reiss), while identifying sentiment polarities (NS) can help in emotion analysis (Plutchik). This observation suggests a direction of connecting different related tasks in a joint pipeline. We leave this for future work.

Lastly, we evaluate the impact of symbolic inference. We perform joint inference over the rules defined in Sec. 3.6. On Table 1, we can appreciate the advantage of modeling these dependencies for predicting Plutchik labels. However, the same is not true for the other two subtasks, where symbolic inference increases recall at the expense of precision, resulting in no F1 improvement. Note that labels for Maslow and Reiss are sparser, accounting for 55% and 42% of the nodes, respectively. In contrast, Plutchik labels are present in 68% of the nodes.

4.3 Task: DesireDB

DesireDB (Rahimtoroghi et al., 2017) is the task of predicting whether a given desire expression is fulfilled or not, given its prior and post context. It requires aggregating information from multiple parts of the document. If a target desire is "I want to be rich", and the character's mental changed from "sad" to "happy" along the text, we can infer that their desire is likely to be fulfilled.

We use the baseline systems described in (Rahimtoroghi et al., 2017), based on SkipThought (ST) and Logistic Regression (LR), with manually engineered lexical and discourse features. We train a stronger baseline by encoding the prior and post contexts, as well as the desire using BERT. Then, we add an attention layer (Eq. 5) for the two contexts over the desire expression. The resulting three representations (the weighted prior and post representations, and the desire representation) are then concatenated. For ENG, we add an attention layer over the nodes to form the ENG document representation. We compare BERT and BERT+ENG document representations by feeding each of them in to a two-layer FFN for classfications, as described in Sec. 3.4 (Doc. Classification).

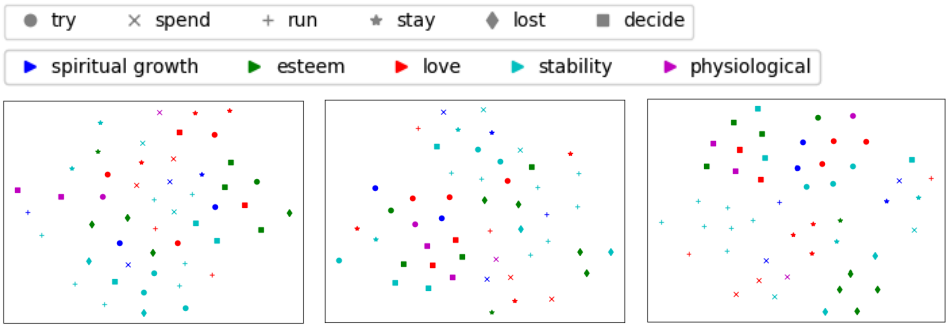
Table 2 shows the result. The BERT baseline outperforms other baselines with a large gap, 4.27% absolute increase in the averaged F1-score. Furthermore, BERT+ENG forms a better document summary for the target desire, which further increase another absolute 3.23% on the avg. F1-score, which illustrates that ENG can be used in various settings for modeling entity information.

4.4 Qualitative Analysis

We conduct qualitative analysis by measuring and visualizing distances between event nodes corresponding to six verbs and their Maslow labels. We project the node embeddings, based on different encoders, to a 2-D space using t-SNE (Maaten and Hinton, 2008). We use shapes to represent verbs and colors to represent labels. In Fig. 3b and 3c, RoBERTa, pretrained on Whole-Word-Masking TAPT, was used. Node are word-contextualized, receiving the whole story (W-CTX-STORY) or the target sentence (W-CTX-SENT) as context. In these two cases, event nodes with the same verb (shape) tend to be closer. In Fig. 3a, we use ENG as the

Models	Fulfilled			Unfulfilled			Average		
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
ST-BOW	78.00	78.00	78.00	57.00	56.00	57.00	67.50	67.00	67.50
ST-ALL	78.00	79.00	79.00	58.00	56.00	57.00	68.0	67.50	68.00
ST-DISC	80.00	79.00	80.00	58.00	56.00	57.00	68.00	67.50	68.00
LR-BOW	69.00	65.00	67.00	53.00	57.00	55.00	61.00	61.00	61.00
LR-ALL	79.00	70.00	74.00	52.00	64.00	58.00	65.50	67.00	66.00
LR-DISC	75.00	84.00	80.00	60.00	45.00	52.00	67.50	64.50	66.00
BERT	81.75	75.90	78.72	57.95	66.23	61.82	69.85	71.06	70.27
BERT+ENG	81.99	83.06	**82.52**	65.33	63.64	**64.47**	73.66	73.35	**73.50**

Table 2: Results for the DesireDB task: identifying if a desire described in the document is fulfilled or not.



(a) ENG-CTX (b) W-CTX-STORY (c) W-CTX-SENT

Figure 3: t-SNE visualization of embeddings based on ENG and RoBERTa.

encoder to generate graph-contextualized embeddings (ENG-CTX). We observe that nodes with the same label (color) tend to be closer. In all cases, the embedding was trained using only the TAPT tasks, without task specific data. The ENG embedding are better at capturing entities' mental states, rather than verb information, as the graph structure is entity-driven.

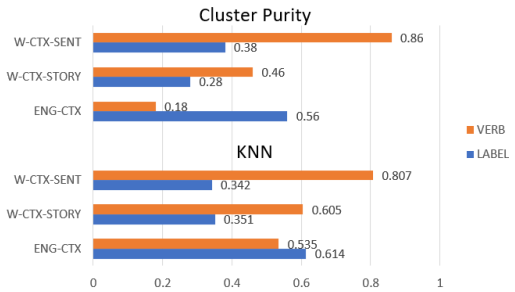


Figure 4: Cluster Purity and KNN Classification results for graph- and word-contextualized embeddings.

Figure 4 makes this point quantitatively. We use 10-fold cross validation and report averaged results. The proximity between verbs and between labels are measured in two ways: cluster purity and KNN classification. For the cluster purity (Manning et al., 2008), we cluster the events using K-Means ($K = 5$), and calculate the averaged cluster purity, defined in Appendix B. For the graph contextualization, we can see that the labels have higher cluster purity than the verbs, while for the word contextualization, the verbs have higher cluster purity. This result aligns with our visualization. The KNN classification uses the learned embedding as a distance function. The KNN classifier performs better when classifying labels using the graph-contextualized embeddings, and the vice-versa when classifying verbs, demonstrating that ENG helps capture entities' states better.

5 Conclusions

We propose a ENG model that can capture the implicit states of entities by multi-relational graph contextualization. We study three types of weakly-supervised TAPTs for ENG and their impact to downstream tasks. The evaluation includes two psychological commonsense inference tasks. The results shows that ENG can outperform other strong baselines, and can be benefit from different types of TAPT for different tasks. In future work, we want to connect different TAPT schemes and downstream tasks, and explore constrained representations.

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A Event Relation Types and PDTB Relations

See Table 3.

Abbrev.	PDTB	Distr.
NEXT	–	50%
CNEXT	–	20%
BEFORE	Temporal.Async.Precedence	5%
AFTER	Temporal.Async.Succession	5%
SYNC.	Temporal.Synchrony	5%
CONTRAST	Comparison.Contrast	5%
REASON	Contingency.Cause.Reason	5%
RESULT	Contingency.Cause.Result	5%

Table 3: Alignment between PDTB relations and the abbreviations used in this paper. The third column in the sampling distribution.

B Cluster Purity

$$\frac{1}{N} \sum_{c \in C} \max_{d \in D} |c \cap d|, \tag{6}$$

where C is the set of clusters and D is either the set of labels or verbs.