Mining Commonsense Facts from the Physical World

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Abstract

Textual descriptions of the physical world implicitly mention commonsense facts, while the commonsense knowledge bases explicitly represent such facts as triples. Compared to dramatically increased text data, the coverage of existing knowledge bases is far away from completion. Most of the prior studies on populating knowledge bases mainly focus on Freebase. To automatically complete commonsense knowledge bases to improve their coverage is under-explored. In this paper, we propose a new task of mining commonsense facts from the raw text that describes the physical world. We build an effective new model that fuses information from both sequence text and existing knowledge base resource. Then we create two large annotated datasets each with approximate 200k instances for commonsense knowledge base completion. Empirical results demonstrate that our model significantly outperforms baselines.

1 Introduction

Various knowledge bases are made publicly available, including Freebase (Bollacker et al., 2008), DBPedia (Auer et al., 2007), YAGO (Suchanek et al., 2007) and ConceptNet (Speer et al., 2017), which are paramount resources to many applications in Natural Language Processing committee, such as question answering (Yang and Mitchell, 2017; Zou and Lu, 2019b,c,e,d) and conversation generation (Zhou et al., 2018). Though such existing knowledge bases are impressively large, their coverage is still far from completion. Many prior studies on improving the coverage of knowledge bases mainly focus on Freebase (Bordes et al., 2013) and DBPedia (Yang et al., 2019), where nodes are entities. However, completing commonsense knowledge bases, such as ConceptNet containing arbitrary phrases as nodes, is under-explored. In this work, we focus on improving the coverage of ConceptNet. Table 1 lists several commonsense triples from ConceptNet.

Initially, commonsense facts were built via manual annotations (Lenat and Guha, 1989; Speer and Havasi, 2012) or games with a purpose (von Ahn et al., 2006). Works of (Gordon, 2014; Angeli and Manning, 2014) also inferred the commonsense knowledge from patterns in raw text. However, it would be difficult to obtain widely-covered patterns to mine commonsense facts for the rapidly changing physical world. Recent research progresses (Li et al., 2016; Saito et al., 2018) show the effectiveness of neural models on this task. Their approaches made predictions over structured commonsense triples comprising two phrases and their relation, where textual information is not considered.

Given a partial textual description of a physical world or a scene of a video, people can reason about what would happen next. Unlike machines, people is capable to bring a large body of implicit knowledge about the physical world to the given information to make inference. Such im-
explicit knowledge is commonsense knowledge. Exemplified by Table 1, given the description of a video scene as “A soldier carries a heavy machine gun on his shoulder,” people might know the content of the next scene that is described by “As police cars escort more military vehicles through the military throne.” One possible reason is that such two scenes essentially describe the same physical world, so that people can reason about the situation with commonsense reasoning. Conversely, given two textual descriptions or two consecutive video scenes that describe that same physical world, it is possible to mine commonsense facts from them. Considering the running example in Table 1, given two consecutive video captions that describe the same physical world, it would be possible to mine commonsense triples from such text. Specifically, the caption for the first scene contains phrase nodes in ConceptNet, including “soldier”, “machine gun” denoted as Phrase 1, and the second contains “cars”, “military vehicles” and “military”, indicated as Phrase 2. Then we are able to find out four commonsense triples that are implicitly mentioned in the text.

Based on the above observations, we propose to automatically mine unseen commonsense facts from raw text to complete ConceptNet. With today’s deep learning machinery, the first step is to create large-scale annotated datasets that is crucial to train a high-capacity neural model. We thus introduce two datasets, STORY244K and SWAG190K, which are built from textual corpora describing a real physical world. Then we propose a novel neural model that allows to collect evidence from textual source and existing knowledge bases to make mining decisions. Our major contributions made in this paper can be summarized as follows:

- We propose a new task of mining commonsense facts from the raw text that describes a real physical world with implicitly mentioned commonsense knowledge.
- We build a novel neural model that fuses sequence architecture extracting contextual evidence and graph architecture capturing information from the existing knowledge bases.
- We create two large datasets, STORY244K and SWAG190K, which support to train a high-capacity neural model in a supervised manner.¹

2 Methodology

In this section, we first define the task that aims to mine commonsense faces to complete the commonsense knowledge bases. Then we introduce the architecture of the proposed neural model to accomplish such a task.

2.1 Problem Definition

Textual descriptions for the same physical world, such as captions for two consecutive video scenes, contain two sentences consisting of sequences of words $s_1 = \{w_1^1, w_2^1, \ldots, w_{N_1}^1\}$ and $s_2 = \{w_1^2, w_2^2, \ldots, w_{N_2}^2\}$, where $N_1$ and $N_2$ are the length of two word sequences, respectively. Two lists of phrases residing in two sentences are $P_1 = \{p_1^1, p_2^1, \ldots, p_{M_1}^1\}$ and $P_2 = \{p_1^2, p_2^2, \ldots, p_{M_2}^2\}$, where the sizes of two phrase lists are $M_1$ and $M_2$. Each element of a phrase list $p_j^i = \{w_1^j, w_2^j, \ldots, w_{k}^j\}$ is a contiguous word sequence from sentence $s_j$, which contains $k \in [1, N_j)$ words ($j=1,2$), describing a concept in the physical world. A phrase can be a node in the commonsense knowledge base. To improve the coverage of the commonsense knowledge base, the goal is to extract the relation of two given phrases from two sentences separately. In this work, we focus on 34 types of relations consisting of 33 types from ConceptNet, like “HasContext”, “HasSubevent”, “RelatedTo”, and the negative relation “None”. Under such settings, the proposed task is essentially a relation classification problem.

Figure 1 illustrates the overall architecture of the proposed neural model for mining relations of two arbitrary phrases to extend the coverage of the commonsense knowledge bases. The model comprises of four main components: the input embedding layer, the contextual layer, the knowledge layer and the final output layer.

2.2 Embedding Layer

Unlike studies of (Wang et al., 2014; Ji et al., 2015) which learn the embeddings of entities and their relations from scratch based on the topological features, however, nodes in the commonsense knowledge base are arbitrary phrases, i.e., sequences of words. The commonsense knowledge graph can be very sparse. Therefore, we apply pretrained word embeddings which boost performance of many existing NLP models (Pennington

¹We put our code and datasets in the supplementary material for review.
is the concatenation of the two given sentences. The input to the embedding layer for the input word sequence \( s \) is the dimension of the word vector and \( \text{layer} \) is denoted as \( x \). state from time step \( t \) in. Given the embedding of the input sequence \( d \) ence from the context where the phrases reside on top of the embedding layer to collect evi-

(\text{BiLSTM}) (Graves et al., 2013) is adopted here bidirectional Long Short Term Memory Network To mine commonsense facts from raw text, the

2.3 Contextual Layer

To mine commonsense facts from raw text, the bidirectional Long Short Term Memory Network (BiLSTM) (Graves et al., 2013) is adopted here on top of the embedding layer to collect evidence from the context where the phrases reside in. Given the embedding of the input sequence \( x \), in the forward direction, the recurrent transition state from time step \( t - 1 \) to \( t \) can be calculated as follows:

\[
\begin{align*}
i_t &= \sigma(\vec{W}_i \cdot [\vec{h}_{t-1}; \vec{x}_t] + \vec{b}_i) \\
f_t &= \sigma(\vec{W}_f \cdot [\vec{h}_{t-1}; \vec{x}_t] + \vec{b}_f) \\
o_t &= \sigma(\vec{W}_o \cdot [\vec{h}_{t-1}; \vec{x}_t] + \vec{b}_o) \\
g_t &= \tanh(\vec{W}_g \cdot [\vec{h}_{t-1}; \vec{x}_t] + \vec{b}_g) \\
\vec{c}_t &= f_t \times \vec{c}_{t-1} + i_t \times g_t \\
\vec{h}_t &= o_t \times \tanh(\vec{c}_t)
\end{align*}
\]

where \( i_t, f_t, o_t \) are the input gate, forget gate and output gate, respectively; \( \sigma \) is the sigmoid activation function; \( \vec{W}_i, \vec{W}_f, \vec{W}_o, \vec{W}_g \in \mathbb{R}^{d \times (d + d_v)} \) and \( \vec{b}_i, \vec{b}_f, \vec{b}_o, \vec{b}_g \in \mathbb{R}^d \) and \( d \) is the dimension size of hidden states. The backward hidden state \( \vec{h}_t \) can be obtained in the same way but in a backward direction. Then we get the output \( h_t = [\vec{h}_t; \vec{c}_t] \in \mathbb{R}^{2d} \) for each word by concatenating hidden states from both directions.

By feeding the embedding sequence \( x = \{x_1, x_2, \cdots , x_{(N_1+N_2)}\} \) to the BiLSTM network, we are allowed to capture the contextual evidence for each word from the word sequence \( s = [s_1; s_2] \). For each element in the two phrase lists \( P_1 \) and \( P_2 \), the corresponding representation can be obtained by simply concatenating the hidden state of each word. For instance, one phrase \( p_i^1 \) from the phrase list \( P_1 \) for the first sentence \( s_1 \) is \( \{w_{i_1}^1, w_{i_2}^1, \cdots , w_{i_k}^1\} \). The corresponding representation is:

\[
R_{p_i^1} = [h_{i_1}; h_{i_2}; \cdots ; h_{i_k}]
\]

where \( i_k \in [1, N_1) \), and \( N_1 \) is the length of the first sentence.

Similarly, the representation of the phrase \( p_j^2 = \{w_{j_1}^2, w_{j_2}^2, \cdots , w_{j_k}^2\} \) from phrase list \( P_2 \) for the
second sentence \(s_2\) can also be obtained as:

\[
R_{p_j^2} = [h_{j_1+N_1}, h_{j_2+N_1}, \ldots, h_{j_k+N_1}]
\]

where \(j_k \in [1, N_2]\) and \(N_2\) is the length of the second sentence \(s_2\).

The BiLSTM is able to capture the global contextual evidence from the whole input word sequence comprising of two sentences that describe the same physical world. On the other hand, each individual sentence may depict a different concepts of the same world. In other words, there exists world knowledge specifically conveyed by different sentences separately. Exemplified by Table 1, natural language descriptions of two consecutive video scenes characterize the same world, they pay attention to different concepts. Motivated by such observation, we propose to collect local evidence for each phrase from the specific sentence where it resides in.

On top of the representations generated by the BiLSTM networks, we apply the convolution neural networks (CNNs) (LeCun et al., 1999; Krizhevsky et al., 2012) to capture the local correlations within a given word window consisting of the target phrase and its surrounding words residing in the same sentence. Previous studies have shown the efficacy of CNNs on NLP applications, especially on the classification tasks (Kim, 2014; Nguyen and Grishman, 2015). CNNs in NLP are applied to a sequence of vectors representing words. Therefore, they are typically one dimensional (Strubell et al., 2017; Lin et al., 2018). With such a property, a CNN layer is equivalent to applying a non-linear affine transformation. For each word \(x_t \in \mathbb{R}\), a convolution filter can be applied to it as:

\[
c_t = W_c \bigoplus_{i=1}^h x_{t+i} + b_c
\]

where \(\bigoplus\) is the vector concatenation operation, \(W_c\) is the convolution filter with width \(h\), \(b_c\) is a bias term and \(c_t\) is the output after convolutions.

To be specific, in this work, we employ the dilated Convolution Neural Network (CNN) (Yu and Koltun, 2015) over the word windows to capture concept-specific information that implicitly mentioned in individual sentence. Dilation is a widely-used mechanism for semantic segmentation in computer vision (Yu and Koltun, 2015) and has proven effective in NLP tasks (Kalchbrenner et al., 2016; Lin et al., 2018). The dilated convolutions take the same operation as the CNNs but over a wider input width by skipping over \(\delta\) inputs at a time, where the \(\delta\) is the dilation width. The dilation operator can be defined as:

\[
c_t = W_c \bigoplus_{i=1}^h x_{t+i\delta} + b_c
\]

A dilated convolution is the same as a simple convolution when \(\delta\) is equal to 1. A dilated convolution with \(\delta > 1\) allows to incorporate broader dependency among words in the given word window input than a simple convolution. We denote that the dilated convolution over a given input sequence as DCNN.

To capture high-level representation of a target phrase, we form a word window consisting of the target phrase and its surrounding \(l\) words:

\[
\text{Wind}_{p_1^1} = [h_{i_1-1}^{1}, h_{i_1}^{1}, \ldots, h_{i_1+l}^{1}]
\]

\[
\text{Wind}_{p_2^1} = [h_{j_1+N_1-1}^{1}, h_{j_1+N_1}, \ldots, h_{j_1+N_1+l}^{1}]
\]

where \(h_i^1\) represents the concatenation of hidden states \(h_{i_1}, h_{i_1+1}, \ldots, h_{i_1+l}\). The output by dilated CNN of the two target phrases are:

\[
L_{p_1^1} = DCNN(\text{Wind}_{p_1^1})
\]

\[
L_{p_2^1} = DCNN(\text{Wind}_{p_2^1})
\]

where \(L_{p_1^1}, L_{p_2^1} \in \mathbb{R}^{d_c}\).

### 2.4 Knowledge Layer

We also collects information from the existing knowledge bases, such as ConceptNet (Speer et al., 2017). The ConceptNet is essentially a graph \(G = (V, E)\) where \(V\) is a set of \(|V|\) vertices representing arbitrary phrases and \(E\) is a set of edges containing both directed and undirected edges. The Graph Convolution Networks (GCN) (Kipf and Welling, 2016) can be adopted to conduct convolutions over a graph structure. We also employ pretrained word embeddings to represent each vertex. For a phrase \(v = \{v_1, v_2, \ldots, v_k\}\) where \(k\) is the number of words in the phrase, we employ the embedding layer to map each word \(v_i\) into a high dimensional vector \(e_i \in \mathbb{R}^{d_e}\). The representation of the phrase is then defined as:

\[
x_v = \frac{1}{k} \sum_{i=1}^k e_i
\]

We then can perform convolution operations over such a graph. It is worth noting that we use the
held-out ConceptNet. All edges appearing in our dataset are removed from the ConceptNet when we use it as external resources.

The output hidden representation of a node $v$ after a single convolution layer can be obtained by considering only the immediate neighbors of $v$:

$$h_v = f\left(\sum_{u \in \mathcal{N}(v)} (W_{gc}x_u + b_{gc})\right), \forall v \in \mathcal{V}$$

where $W_{gc} \in \mathbb{R}^{d_{gc} \times d_v}$ and $b_{gc} \in \mathbb{R}^{d_{gc}}$ are model parameters; $\mathcal{N}(v)$ is the set of immediate neighbors of the node $v$; $f$ is a non-linear activation function. We use ReLU in this work. A multi-layer GCN can be stacked to capture information from multi-hop neighbors. The output of $k$th layer can be formulated as:

$$h_v^{k+1} = f\left(\sum_{u \in \mathcal{N}(v)} (W_{gc}^{k}h_u^{k} + b_{gc}^{k})\right), \forall v \in \mathcal{V}$$

where $W_{gc}^{k}, b_{gc}^{k}$ are parameters for $k$th layer GCN.

The edges in $\mathcal{E}$ from ConceptNet are with different labels, each of which represents a type of relation. Not every type of edge contributes equally to make correct predictions, while some of them may lead to erroneous. We thus incorporate edge importance to give higher importance to relevant edges and subdue the noisy ones. The label $l(u, v)$ of two nodes $u$ and $v$ is assigned a weight $w_{l(u,v)}$ which can be learned. At $k$th layer, the output is defined as:

$$h_v^{k+1} = f\left(\sum_{u \in \mathcal{N}(v)} w_{l(u,v)}(W_{gc}^{k}h_u^{k} + b_{gc}^{k})\right)$$

We use GCN$^{k}$ to represent the graph convolution network with $k$ layers. The representation of phrases $p_{i1}^{j}$ and $p_{i2}^{j}$ are:

$$K_{p_{i1}^{j}} = GCN^{k}(p_{i1}^{j})$$

$$K_{p_{i2}^{j}} = GCN^{k}(p_{i2}^{j})$$

where $K_{p_{i1}^{j}}, K_{p_{i2}^{j}} \in \mathbb{R}^{d_{gc}}$ are information collected from the knowledge base. Then the output are fed into a highway layer (Srivastava et al., 2015) which maps the input into different semantic spaces.

### 2.5 Output Layer

In the output layer, we concatenate the contextual evidence and knowledge information to get the final feature representation $F \in \mathbb{R}^{(2d_{c}+2d_{gc})}$. Such feature vector is then fed into a softmax layer to make final decisions.

$$F = [L_{p_{1}^{j}}; L_{p_{2}^{j}}; K_{p_{1}^{j}}; K_{p_{2}^{j}}]$$

$$p = \text{softmax}(W_{p} \times F + b_{p})$$

where $p \in \mathbb{R}^{C}$ is the probability distribution over the possible relation set with size of $C$, and $W_{p} \in \mathbb{R}^{C \times (2d_{c}+2d_{gc})}$ and $b_{p} \in \mathbb{R}^{C}$ are model parameters.

#### 2.6 Model Training

The proposed model is trained with a cross-entropy loss over a set of gold instances $G_{i}$:

$$\mathcal{L} = -\sum_{i=1}^{|G|} \log p(y_{i}|s_{i}, p_{i1}^{j}, p_{i2}^{j}, \Theta)$$

where $s_{i}$ is the $i$th instance from the training set consisting of two sentences $\{s_{i1}^{1}, s_{i2}^{2}\}$, $p_{i1}^{j}$ is the $j$th phrase from the first sentence $s_{i1}^{1}$, $p_{i2}^{j}$ is the $k$th phrase from the second sentence $s_{i2}^{2}$, $y_{i}$ is the corresponding gold relation of the two phrases $p_{i1}^{j}$ and $p_{i2}^{j}$, $\Theta$ is the model parameters, $|G|$ is the size of the training set. Standard gradient descent methods can be applied as optimizer to update model parameters, such as Stochastic Gradient Descent (Bottou, 1991) and Adam (Kingma and Ba, 2014). The model with parameters $\Theta$ that yields the best performance on the dev set are adopted as the final model to be evaluated on the test set.

### 3 Datasets

Mining commonsense facts from text to complete commonsense knowledge base is data hungry. To the best of our knowledge, ConceptNet 100K (Li et al., 2016) is the only publicly available large-scale datasets for commonsense knowledge base completion. It covers 34 types of relations in ConceptNet and consists of purely structured commonsense triples where no textual information is included. Recently, Xu et al. (2018) released a dataset for extracting commonsense facts from text with 5000 instances in total. However, such a dataset only focuses on one type of relation LocatedNear. Today’s deep neural mechanism always necessitate large-scale data with annotations to train high-capacity models. Moreover, to improve the coverage of commonsense knowledge bases, a dataset should cover various types of relations. Therefore, we introduce two newly-created
datasets for extracting commonsense triples from raw text that satisfies such two requirements.

**Data Collection.** A sequence of consecutive scenes from a video depicts the same physical world with a cohesive sequence of events through time. The textual captions of each scene literally describe the physical concepts of the world, where commonsense facts could be implicitly mentioned. A commonsense fact typically consists of two phrases and a relation where each phrase consists of a word sequence. The phrases and the relation of them are nodes and edge in the commonsense knowledge bases.

Motivated by the above observations, we are allowed to construct training instances from video captions. In this work, our focus is on completing the ConceptNet which is one of the largest commonsense knowledge bases. Thus, we make use of the triples from ConceptNet to make annotations.

SWAG (Zellers et al., 2018) is a newly-released dataset with multiple choice questions for grounded commonsense inference. Each instance comprises a starting sentence giving a partial description of the world, and four possible endings. The goal is to find the most possible end sentence that describe the same world as the starting description. According to their annotations, we extract the gold endings $s_2$ for each starting sentence $s_1$ to construct the text data serving our task. Then we make use of ConceptNet to extract phrases residing in the text and make annotations for relations. To be specific, if two phrases $p_1$ and $p_2$ are nodes in ConceptNet, and they appear in the two sentences $s_1$ and $s_2$, separately, then we treat the tuple $(s_1, s_2, p_1, p_2, r)$ as an instance. If $p_1$ and $p_2$ are connected by an edge with a relation in the ConceptNet, the $r$ is the corresponding relation. Otherwise $r$ is “None” and the instance is regarded as a negative example. Since a phrase can contain arbitrarily many words, there might exist exponentially many phrases appearing in a sentence. In this work, we focus on single word node and leave the phrase with multiple words as future work. Moreover, we discard stop words appearing in the text, such as “the”, “an”, etc. Following the above procedures, we construct an annotated dataset with 190,947 instances, denoted as SWAG190K.

A sequence of images depicts a cohesive narrative of events through time, which shows a set of physical world. The visual storytelling dataset (Huang et al., 2016) comprises textual descriptions (i.e., a short story) each paired with a sequence of images. We extract consecutive sentence pairs from each story and follow the same procedures as SWAG to make a new dataset with 244,857 instances from this corpus, denoted as STORY244K.

**Comparisons.** We compare our datasets with previous ones as listed in Table 2. Our datasets contain more examples covering more than 30 relation types. The dataset with such a scale is able to train a high-capacity neural model to mine commonsense facts from raw text. Table 3 demonstrates detailed data statistics for training, dev and test.

### 4 Experiments

#### 4.1 Baseline Models

**GCN.** Without considering the text information, we first implement a one layer GCN to collect the knowledge evidence of two given phrases from their immediate neighbors in ConceptNet. The outputs from GCN for two phrases are concatenated and then fed into a fully-connected layer followed by a softmax layer for classification. Here we use the held-out ConceptNet, where we remove edges appearing in our corpus.

**CNN.** The two phrase and their surrounding $L$ words are extracted to form a new word sequence, where $L = 2$ in this case. Then we cast the relation classification task as a sentence classification task. A CNN classifier following the work of (Kim, 2014) is implemented to make predictions.

**CNN-GCN.** The outputs of GCN and CNN are concatenated in this case and fed to the classifier.

| Dataset         | # Rel. | # Ex.     | % Neg. |
|-----------------|--------|-----------|--------|
| (Li et al., 2016) | 34     | 103,600   | 50.00% |
| (Xu et al., 2018) | 1      | 5,000     | 44.92% |
| STORY244K       | 34     | 244,857   | 17.00% |
| SWAG190K        | 33     | 190,947   | 54.23% |

Table 2: A comparison of existing datasets for commonsense knowledge base completion and our proposed two datasets. % Neg. refers to the percentage of negative examples (no relation).

| Data Split     | STORY244K | SWAG190K |
|----------------|-----------|-----------|
| Train          | 195,891   | 152,758   |
| Dev            | 24,486    | 19,096    |
| Test           | 24,480    | 19,093    |

Table 3: Statistics on two newly-built datasets: number of examples for training, dev and test.
4.2 Empirical Results

We evaluate our model on the two newly-created datasets. We train the model over the training set, and perform early stopping using the dev set. The model achieves the highest $F_1$ score on the dev set is selected as the final model and is evaluate on the test set. Since the dataset contains negative examples, we report precision, recall and $F_1$ scores on dev and test sets, respectively. The figures are listed in Table 4.\footnote{We also evaluate the popular models of entity-relation knowledge base completion for entity-relation triples on the two datasets, including TransE (Bordes et al., 2013), TransH (Wang et al., 2014), TransD (Ji et al., 2015), TransR (Lin et al., 2015b). However, preliminary empirical results show that they did not performed well on this task.} We observe that our proposed model including globally local contextual features and knowledge evidence from the existing knowledge bases significantly outperforms all baselines over two datasets. Four baseline models obtain results in the same level. RNN model is generally better than convolution-based models, including GCN, CNN and CNN-GCN. The GCN model which collects evidence from the existing knowledge base can obtain almost the same $F_1$ scores compared to CNN and RNN which extract knowledge from text. This demonstrates the effectiveness of knowledge bases on this task.

## 4.3 Analysis

### Ablation Test

We conduct ablation test to investigate the effectiveness of each component of our proposed model, as listed in Table 5. The GCN together with highway layer and label importance contributes around absolute 11 and 21 $F_1$ score on STORY244K and SWAG190K which proves efficacy of the evidence from knowledge bases. On top of the underlying Bi-LSTM model, the CNN layer aims to capture local features from the target phrase and its surrounding words. Such a component leads to approximate 5 and 3 absolute $F_1$ score on two datasets separately, which shows that surrounding words around the target phrase are beneficial to mining commonsense facts.

### Effects of the Number of Neighbors

We also investigate the effects of different number of neighbors of the target phrase that are considered by the GCN when collecting evidence from the ConceptNet. We evaluate the GCN model with different number of neighbors that are randomly selected from all immediately connected nodes over two datasets. We consider a list of values \{50, 100, 150, 200, 300, 400\}. The $F_1$ score of dev and test sets of two datasets are depicted in Figure 2. It is expected that there exists a bottleneck. The performance is not always growing linearly.

| Model          | STORY244K | SWAG190K |
|----------------|-----------|----------|
| Full Model     | 89.97     | 86.38    |
| - CNN          | 85.02     | 83.51    |
| - Label Importance | 84.24  | 76.13    |
| - Highway      | 73.59     | 65.67    |
| - GCN          | 72.06     | 63.52    |
|               | 89.43     | 85.39    |
|               | 84.71     | 82.98    |
|               | 82.97     | 78.58    |
|               | 72.02     | 65.96    |
|               | 70.40     | 64.41    |

Table 5: An ablation test of our model evaluated on both STORY244K and SWAG190K datasets. (P: Precision (%), R.: Recall (%), $F_1$: $F_1$ score (%))
to the number of randomly selected neighbors. As to STORY244K, we reach highest $F_1$ score with 300 neighbors randomly selected, while for SWAG190K, it is 200. After the peak point, the $F_1$ score tends to decline.

5 Related Work

5.1 Knowledge Base Completion

Knowledge base completion for entity-relation triples. An entity-relation triple consists of three elements: head/tail entity, and the relation. One line of studies on this topic is structured-base methods, including Bilinear Model (Sutskever et al., 2009), Neural Tensor Network (Socher et al., 2013) and Single Layer Model (Socher et al., 2013). The transition-based approaches are also popular, including TransE (Bordes et al., 2013) and its variants like TransH (Wang et al., 2014), TransD (Ji et al., 2015), TransR (Lin et al., 2015b). Such transition-based approaches aim to learn low-dimension embeddings for entities and relations by using the topological features. Recently, many systems are proposed to learn better representations of knowledge graphs by considering additional information, such as path information and logic rules (Lin et al., 2015a; Toutanova et al., 2016) as well as entity descriptions and word embeddings (Wang et al., 2014; Zhong et al., 2015; Xie et al., 2016; An et al., 2018).

Knowledge base completion for commonsense triples. To build the commonsense facts, researchers designed hand curated resources of commonsense knowledge via manual annotations (Lenat and Guha, 1989; Speer and Havasi, 2012) or games with a purpose (Von Ahn et al., 2006). Works of (Gordon et al., 2010; Gordon, 2014; Angeli and Manning, 2014) also inferred the commonsense knowledge from patterns in raw text.

Recently, research progresses improved the coverage of ConceptNet by casting the problem as a knowledge base completion task and designed neural-based solutions (Li et al., 2016; Saito et al., 2018; Xu et al., 2018). Li et al. (2016) proposed a simple LSTM architecture to predict the most probable tail entity given the head entity and one type of relation as query. Saito et al. (2018) proposed a new task, named commonsense knowledge generation. They further designed a joint model that incorporates both completion and generation jointly. The training data of such two studies are given as structured commonsense triples. Xu et al. (2018) developed systems to extract commonsense facts from text. However, they only worked on one type of relation, LocatedNear. In this work, we focus on 34 types of relations.

5.2 Open Information Extraction

The goal of open information extraction is to extract subject-relation-object triples from raw text (Fader et al., 2011; Schmitz et al., 2012). Different for ours, the subject and object are typically entities. Neural models are applied to conduct relation extraction, such as convolution neural networks (CNNs) (Zeng et al., 2014; Nguyen and Grishman, 2015), recurrent neural networks (RNNs) (Zhang et al., 2017; Zhang and Wang, 2015), combination of CNNs and RNNs (Vu et al., 2016; Wang et al., 2016), and graph neural networks (GNNs) (Zhang et al., 2018; Song et al., 2018). Similar to this work, the above models are trained on sentence-level data. Song et al. (2018) also address the relation extraction cross several sentences.

6 Conclusion

In this work, we propose a new task of mining commonsense facts from raw text to complete commonsense knowledge bases. We create two large-scale datasets that can be used to train high-capacity neural models. We design a novel neural system that incorporates contextual information from text and commonsense features from the existing knowledge base. In the future, we would like to extend this work to support open-world completion task where phrases that do not exist in the current knowledge bases can be handled.
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