Dense-ATOMIC: Construction of Densely-connected and Multi-hop Commonsense Knowledge Graph upon ATOMIC

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Abstract

ATOMIC is a large-scale commonsense knowledge graph (CSKG) containing everyday if-then knowledge triplets, i.e., \{head event, relation, tail event\}. The one-hop annotation manner made ATOMIC a set of independent bipartite graphs, which ignored the numerous missing links between events in different bipartite graphs and consequently caused shortcomings in knowledge coverage and multi-hop reasoning. To address these issues, we propose a CSKG completion approach by training a relation prediction model based on a set of existing triplets, and infer the missing links on ATOMIC. On this basis, we construct Dense-ATOMIC, a densely-connected and multi-hop commonsense knowledge graph. The experimental results on an annotated dense subgraph demonstrate the effectiveness of our CSKG completion approach upon ATOMIC. The evaluation on a downstream commonsense reasoning task also proves the advantage of Dense-ATOMIC against conventional ATOMIC.

1 Introduction

ATOMIC is a large-scale human-annotated commonsense knowledge graph focusing on the inferential knowledge in social life. It consists of nine if-then relation types describing the causes, effects, agent, static, and theme of an event. The research on ATOMIC has drawn more and more attention in recent years. An increasing number of downstream tasks, including commonsense reasoning (Bosselut et al., 2019), storytelling (Ammanabrolu et al., 2021), conversational emotion identification (Ghosal et al., 2020), dialog generation (Majumder et al., 2020), etc., have improved their performances by acquiring and utilizing the commonsense knowledge from ATOMIC.

Currently, ATOMIC was constructed under one-hop annotations. It began with 24,000 pre-defined base events and nine relation types. For each base event and each relation, the annotators were asked to write a possible tail event based on one-hop reasoning. As shown in Figure 1, given the base event “PersonX asks PersonY to marry”, the tail events can be “loving”, “smiles” and “says yes”, under the relations of “xAttr”, “xEffect” and “oEffect”, respectively.

In such a one-hop annotation manner, each base event and its related tail events shape a bipartite graph, which contains only connections between base events and annotated tail events. The whole graph of ATOMIC can be viewed a set of subgraphs, and the subgraphs with respect to different base events are independent of each other.

However, the links between events in different bipartite graphs were ignored. The missing links can be classified into four categories: B-to-A, B-to-B, A-to-B and A-to-A, where B denotes the Base event and A denotes the Annotated tail event. In Figure 1, the dashed lines illustrate such missing links in ATOMIC, e.g., the A-to-B missing link between the annotated tail event “in front of PersonY” and an external base event “PersonX asks PersonY to marry” (relation: “xIntent”), the A-to-A missing link between two annotated tail events “loving” and “happy” (relation: “oPersona”), etc.

The link-missing problem leads to two shortcomings of ATOMIC. Firstly, it is difficult for ATOMIC to support multi-hop reasoning directly. Secondly, the knowledge graph in ATOMIC is sparse, and the knowledge coverage is unsatisfactory. The two shortcomings limit the potential of ATOMIC. Intuitively, a CSKG applicable on various downstream tasks should cover as many events as possible. Moreover, the multi-hop reasoning capacity is also crucial for machines to capture the evolution of events.

In this work, we aim to construct Dense-ATOMIC, a densely-connected and multi-hop CSKG upon ATOMIC, via inferring missing links between existing nodes in ATOMIC. We formalize
it as a commonsense knowledge graph completion problem.

To the best of our knowledge, the CSKG completion problem upon ATOMIC has not been sufficiently explored. Only a few studies have been carried out in this direction, following the mainstream method in conventional knowledge graph completion. For example, Malaviya et al. (2020) formalized the CSKG completion problem as a tail node prediction given the head node and a specified relation. It utilized a graph convolutional network (GCN) to encode the graph embeddings of nodes, whose performance is unsatisfactory, since the sparsity of ATOMIC restricts the information propagation on the GCN.

In contrast, in this work, we regard the CSKG completion task as a relation prediction problem given the head event and the tail event, and propose a corresponding method called Rel-CSKGC to conduct CSKG completion upon ATOMIC. It consists of three main steps: Node Homogenization, Training a Relation Prediction Model and Inferring Missing Links. In node homogenization, nodes in ATOMIC are converted to a uniform pattern (“Subject + Verb + Object”). Specific relations are also grouped to mitigate the ambiguity. We then train a relation prediction model based on a set of existing triplets in ATOMIC, and infer the missing links on ATOMIC. On this basis, we construct Dense-ATOMIC, a densely-connected and multi-hop CSKG.

Figure 1 illustrates main differences between ATOMIC and Dense-ATOMIC. Firstly, Dense-ATOMIC completes many missing links in ATOMIC, including B-to-A, B-to-B, A-to-B and A-to-A links. Secondly, Dense-ATOMIC supports multi-hop reasoning. For example, by adding a link between two tail events “PersonY says yes” and “PersonX smiles”, we can obtain a two-hop path, “PersonX asks PersonY to marry” → “PersonY says yes” → “PersonX smiles”.

To evaluate the effectiveness of Rel-CSKGC, we sample a small subgraph from ATOMIC and annotate all pairs of head events and tail events with the most reasonable relation. We experiment with different strategies of Rel-CSKGC and achieve the best precision of 0.68 on the annotated subgraph.

We further evaluate Dense-ATOMIC on a commonsense reasoning task based on COMET by utilizing ATOMIC as the external commonsense knowledge. The results also prove the advantage of Dense-ATOMIC against conventional ATOMIC.

We will make Dense-ATOMIC and the source code of Rel-CSKGC publicly available on Github.

# 2 Approach

In this work, we aim to construct Dense-ATOMIC, a densely-connected and multi-hop CSKG. Figure 2 illustrates the procedure of constructing Dense-ATOMIC, consisting of three main steps: Node Homogenization, Training a Relation Prediction Model, and Inferring Missing Links.

Node homogenization converts annotated tail events in ATOMIC to a uniform pattern (“Subject + Verb + Object”), the same as that of base events. The homogenized ATOMIC is then decomposed
into independent triplets. We train a relation prediction model based on these existing triplets to infer the missing links on ATOMIC. During the inference, we first adopt an intra-and-inter cluster completion strategy to sample a subgraph. Rel-CSKGC is then applied on the missing link completion of the sampled subgraph.

2.1 Node Homogenization

The goal of node homogenization is to convert annotations in ATOMIC to the same pattern of base events. For each base event, ATOMIC is constructed by writing down annotated tail events based on one-step reasoning, thus containing only base-event-to-annotation (B-to-A) triplets. Completing only B-to-A links in ATOMIC is trivial, since B-to-A triplets have been extensively explored during the annotation process.

Nevertheless, as seen in Figure 1, the base events and annotations have different patterns. A CSKG completion model optimized with B-to-A triplets is inappropriate for inferring B-to-B, A-to-A and A-to-B links, e.g., the missing A-to-A link between the annotated tail event “propose marriage” and “delightful”, which are however extremely under-explored and fundamental for multi-hop reasoning. Only by eliminating patterns in annotations can a model optimized with B-to-A triplets be able to predict B-to-B, A-to-A and A-to-B links. It is essential for missing link prediction and multi-hop reasoning.

To this end, we design an algorithm to perform node homogenization, including subject removal, third person singular form conjugation, subject recovery, and relation grouping. The comparison between human annotations and homogenized annotations is illustrated in Table 1.

Table 1: Comparison of human annotations and homogenized annotations given the base event “PersonX has a ball”.

| Relation   | Human Anno. | Homogenized Andno. |
|------------|-------------|---------------------|
| xEffect    | loses it    | PersonX loses it    |
| xWant      | to play basketball | PersonX plays basketball |
| xNeed      | to acquire the ball | PersonX acquires the ball |
| xIntent    | to have fun | PersonX has fun |
| xAttr      | skillful   | PersonX is skillful |
| xReact     | ready to play | PersonX is ready to play |
| oEffect    | takes the ball | PersonY takes the ball |
| oWant      | to win the game | PersonY wins the game |
| oReact     | jealous    | PersonY is jealous |

Subject Removal. Annotations are basically phrases or adjectives. However, there exist some annotations being complete sentences. For these annotations, we perform dependency tree parsing and part-of-speech tagging with Corenlp, and remove subjects based on the two kinds of structure patterns.

Third Person Singular Form Conjugation. As seen in Table 1, phrases under specific relations start with “to”, e.g., “to play basketball” under relation “xWant”. In our experiment, a CSKG completion model is prone to always correlate these phrases to relations such as “xWant”, “xIntent”, etc.
etc. To alleviate the problem, we leverage WordNet to acquire the verb root, and add the suffix (-s, -es, etc.) according to English grammar.

**Subject Recovery.** Till now, annotations are either phrases with verbs in third person singular form or adjectives. We add subjects to annotations according to different types of relations. For example, given relation “oReact” in Table 1, the added subject is “PersonY is”.

**Relation Grouping.** After node homogenization on ATOMIC, specific relations may lead to ambiguity. For example, in Table 1, differences between “oEffect” and “oWant” can be distinguished based on “to” in human annotations, but not in homogenized annotations, since both of them are events likely to happen next. To this end, We perform relation grouping to mitigate the ambiguity. “xEffect” and “xWant” form “xAfter” describing what PersonX will do. “oEffect” and “oWant” form “oAfter” describing what PersonY will do. “xAttr” and “xReact” form “xPersona” describing how PersonX feels or is described.

Due to the space limitation, we leave the pseudocode of Node Homogenization to the Appendix A of the paper.

### 2.2 Training a Relation Prediction Model

Commonsense knowledge graph completion aims to infer missing links over existing links in CSKGs. There has been little work targeting the completion of ATOMIC. Following the main-stream method in conventional knowledge graph completion, Malaviya et al. (2020) proposed to score all candidate tail events given the head event and the relation. A GCN was employed to encode graph embeddings of nodes, which resulted in two shortcomings: 1) it is difficult for a GCN to propagate information due to the sparse graph structure of ATOMIC; 2) it did not sufficiently utilize semantic information on nodes.

To make full use of semantic information on nodes and resolve the sparsity issue, we propose Rel-CSKGC. The overall architecture of Rel-CSKGC is illustrated in Figure 3. Specifically, we regard ATOMIC as a series of independent triplets, and Rel-CSKGC predicts the relation given the head event and the tail event. Consequently, the sparsity issue is resolved since the graph structure is completely irrelevant. Additionally, encoding both the head event and the tail event with the pretrained language model successfully takes advantage of semantic information on nodes.

**Problem Formulation.** Given a commonsense knowledge graph $G = (N, V)$, where $N$ is the set of nodes and $V$ is the set of edges, we consider a single training instance as a triplet $v_i = (h, r, t)$ with the head event $h$, relation type $r$ and the tail event $t$. Here, $r \in V$ and $h, t \in N$. The objective of Rel-CSKGC is to maximize the probability of the most reasonable $r$ given $h$ and $t$.

**Rel-CSKGC.** As is illustrated in Figure 3, we utilize RoBERTa (Liu et al., 2019) to encode contextual representations of free-form texts on nodes. The input is the concatenation of $h$ and $t$. We acquire the embedding matrix of $h$ and $t$ by:

$$[H; T] = \text{RoBERTa}([h; t])$$  \hspace{1cm} (1)

where $H \in \mathbb{R}^{N \times D}$ and $T \in \mathbb{R}^{N \times D}$. $|N|$ is the number of tokens in the node, and $D$ is the dimensionality of representation. We experiment with two pooling strategies for $H$ and $T$ to acquire sentence embeddings $e_h$ and $e_t$: Computing the mean of $H$ and $T$, and computing the maximum of $H$ and $T$. We also explore two feature combination strategies: Concatenating $e_h$ and $e_t$ directly, and applying the cross attention before concatenation. The objective function can be defined with trainable weights $W_t \in \mathbb{R}^{1 \times D}$ and $W_e \in \mathbb{R}^{K \times 2D}$:

$$o = \text{sigmoid}(W_t e_{\text{CLS}}) + \text{softmax}(W_e(e_h, e_t))$$  \hspace{1cm} (2)

where $K$ is the number of labels and $e_{\text{CLS}}$ the embedding of CLS-token used as an indicator for whether $h$ and $t$ are related.

\[\text{To keep ATOMIC simple, we only predict the most reasonable relation here.}\]
Negative Sampling. Rel-CSKGC needs negative samples so as to predict unlinkable links. We consider the following two strategies to construct negative samples:

- Random negative sampling. For each gold triplet, we select a random event in homogenized ATOMIC as the new tail event to replace the original tail event.

- Persona negative sampling. Triplets under relations of “xPersona” and “oPersona” follow the pattern of “Subject + is + Adjective” and account for a large part in ATOMIC. Models tend to always predict “xPersona” or “oPersona” when the given tail event follows the pattern of “Subject + is + Adjective”. To alleviate this problem, we specifically create negative samples by replacing the head event of triplets under relations of “xPersona” and “oPersona” with a randomly-chosen event in homogenized ATOMIC.

2.3 Inferring Missing Links
This section introduces two strategies of applying optimized Rel-CSKGC on completion of ATOMIC, including threshold-based link prediction, intra-and-inter cluster completion strategy and uniform sampling completion strategy.

Threshold-based Link Prediction. We adopt threshold-based link prediction (TLP), a heuristic strategy to decide whether a relation is acceptable according to the probability output by Rel-CSKGC. Different thresholds are specifically set for different relations. The model predicts the relation only if the final probability is above the corresponding threshold. TLP is used in all our models as the last step for the link acceptance decision.

Intra-and-inter Cluster Completion Strategy. Inference on ATOMIC with Rel-CSKGC requires iterating over all pairs of head events and tail events, which is computationally-expensive. We adopt an intra-and-inter cluster completion strategy to trade off between the completion scale and the time complexity.

In Figure 1, we consider each base event and its annotations as a cluster. Intra-cluster completion aims to infer missing links inside a cluster. Annotations in one cluster are provided based on the same base event. Intuitively, these annotations are highly-related and in great need of mining A-to-A and A-to-B links. Inter-cluster completion is to infer missing links between two different clusters. Annotations in different clusters are provided based on different base events independently without considering the semantic similarity, thus B-to-A, B-to-B, A-to-A and A-to-B links between two different clusters are under-explored. Inter-cluster completion targets for predicting these links.

3 Evaluation
In this section, we present our experimental results on the evaluation of Rel-CSKGC.

3.1 Experimental Setup
Following Sap et al. (2019), we split ATOMIC into the training split, the validation split and the test split. Following negative sampling strategies introduced in 2.2, negative triplets are randomly sampled on the training split. We combine sampled negative triplets and the training split to construct the training set for Rel-CSKGC. The statistics of the training set are illustrated in Table 2.

| ATOMIC | Rand. Neg. Samples | Per. Neg. Samples |
|--------|--------------------|-------------------|
| 463,264| 1,890,350          | 756,140           |

Table 2: Statistics of training set for Rel-CSKGC.

Rel-CSKGC is a relation classification-based commonsense knowledge graph completion model, which predicts the relation given the head event and tail event. Unlike query-based methods in commonsense knowledge graph completion (Malaviya et al., 2020) using ranking metrics (HITS and Mean Reciprocal Rank), we use precision for the purpose of evaluation, since we value precision more than recall on commonsense knowledge graph completion.

We use RoBERTa-base to acquire sentence representations. Adam optimizer is adopted and the batch size is set to 128. The learning for RoBERTa and MLP are set to 2e-5 and 1e-4, respectively. We train all models for 5 epochs.

3.2 Ground-truth Subgraph Annotation
To test the performance of commonsense knowledge graph completion on ATOMIC, we construct a ground-truth subgraph by randomly sampling three clusters from the test split and annotating all pairs of head events and tail events with the most reasonable relation. The statistic of the annotated ground-truth subgraph is shown in Table 3.
### 3.3 Main Results

Experimental results of Rel-CSKGC with different strategies on the annotated subgraph are reported in Table 4. TLP thresholds of different models are specifically adjusted for better performance.

Among all strategies, Rel-CSKGC with max pooling strategy achieves the best performance. We can observe from the experimental results of all strategies that the precision of intra-cluster completion is significantly higher than that of inter-cluster completion in all strategies. This demonstrates that annotated tail events based on the same base event are highly related to each other and easier for Rel-CSKGC to predict relations, while the prediction for inter-cluster events is more challenging.

### 3.4 Ablation Study

To validate the effectiveness of negative sampling, we report experimental results without random and persona negative sampling in Table 5. The performance of Rel-CSKGC drops dramatically without any of the negative sampling strategies, demonstrating the effectiveness of negative sampling.

We further experiment with different random negative sampling ratios and report the experimental results in Figure 4. The precision of Rel-CSKGC increases as we use more negative triples for training.

Upon observing model predictions, we note that some triplets could be reasonable while the annotated graph doesn’t cover it. Consequently, we do the human evaluation to check whether a predicted triplet is meaningful and report the results in Figure 4. Rel-CSKGC achieves better performance.

### 3.5 Human Evaluation

To further demonstrate the effectiveness of Rel-CSKGC, we design a strategy to compare Rel-CSKGC with previous methods on completion of ATOMIC, e.g., SynLink (Malaviya et al., 2020) and InductivE (Wang et al., 2021). Since SynLink and InductivE experiment with BERT embeddings, RoBERTa is replaced with BERT in Rel-CSKGC. We utilize Rel-CSKGC to predict relation on 500 triplets randomly sampled from the test set of SynLink and InductivE. For SynLink and InductivE, the threshold is set for hit@1 score, and a tail event is accepted only when the score is above the threshold. We adjust the threshold to ensure the number of triplets inferred by Rel-CSKGC, SynLink and InductivE close. Rel-CSKGC, SynLink and InductivE predict 174, 133 and 132 triplets, respectively. We then perform the human evaluation to judge whether a predicted triple is meaningful and report the number of meaningful triplets in Table 6. Rel-CSKGC outperforms SynLink and InductivE by a large margin.

### Table 3: Statistics of the annotated ground-truth subgraph.

| Relation | Intra-and-Inter | Intra-Cluster | Inter-Cluster |
|----------|-----------------|---------------|--------------|
| xAfter   | 243             | 186           | 57           |
| xNeed    | 66              | 64            | 2            |
| xIntent  | 72              | 51            | 21           |
| xPersona | 291             | 226           | 65           |
| oAfter   | 262             | 174           | 88           |
| oPersona | 114             | 70            | 44           |
| NoLink   | 4234            | 2303          | 1931         |

### Table 4: Precision of Rel-CSKGC on the annotated subgraph.

| Method                  | Intra-and-Inter | Intra-Cluster | Inter-Cluster |
|-------------------------|-----------------|---------------|--------------|
| Mean Pooling            | 0.676           | 0.777         | 0.500        |
| Max Pooling             | 0.680           | 0.780         | 0.507        |
| Mean Pooling + Att.     | 0.642           | 0.741         | 0.468        |
| Max Pooling + Att.      | 0.510           | 0.605         | 0.333        |

### Table 5: Precision of Rel-CSKGC without negative sampling strategies.

| Method                  | Intra-and-Inter | Intra-Cluster | Inter-Cluster |
|-------------------------|-----------------|---------------|--------------|
| Max Pooling             | 0.680           | 0.780         | 0.507        |
| w/o random              | 0.357           | 0.454         | 0.216        |
| w/o persona             | 0.581           | 0.658         | 0.436        |

### Figure 4: Precision of different random negative sampling ratio on the annotated subgraph by automatic and human evaluation.

### Table 6: Human evaluation on randomly sampled 500 triplets from test set.

| Method       | # Predicted | # Meaningful | Ratio |
|--------------|-------------|--------------|-------|
| SynLink_adpt | 133         | 93           | 0.70  |
| InductivE_adpt | 132   | 106          | 0.80  |
| Rel-CSKGC    | 174         | 152          | 0.87  |
we temporarily provide the results of 100 tail event
we make inference on the entire graph of A
4.1 Construction of Dense-A

4 Construction and Evaluation of
Dense-Atomic

4.2 Density: Atomic vs. Dense-Atomic

Table 7: Example of Multi-hop paths in Dense-Atomic.

| 2-hop paths                  |
|------------------------------|
| PersonX contributes to PersonY’s understanding $\rightarrow$ PersonX continues to teach PersonY $\rightarrow$ PersonY thanks PersonX |
| PersonX takes a breath $\rightarrow$ PersonX becomes sleepy $\rightarrow$ PersonX goes back to their own bed |
| PersonX misses PersonY opportunity $\rightarrow$ PersonX goes home sad $\rightarrow$ PersonX is melancholy |
| PersonX gets near PersonY $\rightarrow$ PersonX walks over to PersonY $\rightarrow$ PersonY nods |

| 3-hop paths                  |
|------------------------------|
| PersonX gets an accident $\rightarrow$ PersonX asks for medical help $\rightarrow$ PersonY helps PersonX feel better |
| PersonX plays a role in the development $\rightarrow$ PersonX receives an award $\rightarrow$ PersonX gets compliments $\rightarrow$ PersonX smiles |
| PersonX says bye $\rightarrow$ PersonX goes home sad $\rightarrow$ PersonX takes some rest $\rightarrow$ PersonX quiets the turmoil in their life |
| PersonX makes an appointment $\rightarrow$ PersonX sits in the waiting room $\rightarrow$ PersonX grows tired $\rightarrow$ PersonX takes a nap due being tired |

Table 8: Comparison of Atomic and Dense-Atomic.

|            | # Nodes | # 1-hop | # 2-hop | # 3-hop |
|------------|---------|---------|---------|---------|
| Atomic     | 299068  | 696321  | 19231   | 509     |
| Dense-Atomic | 283435 | 1967373 | 10658242 | 67888373 |

We furthermore evaluate our Dense-Atomic on commonsense reasoning, which utilizes Atomic as the external knowledge to improve the performance. Commonsense transformer COMET is an encoder-decoder model based on GPT (Radford et al., 2018). Given a triple \{head event, relation, tail event\} from Atomic, COMET is trained to generate the tail event according to the concatenation of head event and relation. Empirical results demonstrate that COMET frequently produces novel high-quality commonsense knowledge.

Although Dense-Atomic contains 1,271,052 newly-predicted triplets, the relation distribution of newly-predicted triplets is long-tailed. We randomly sample 262,678 triplets from newly-predicted triplets and recover the grouped relations to their original relations by following the relation distribution of the training set of Atomic.

With more training samples, COMET is able to generate more diversified tail events given the same head event and relation. We design a strategy to evaluate the diversity of generated tail events manually. We randomly sample 10 head events under each relation from the test set. For each sample consisting of a head event and a relation, 10 candidates are generated using beam search. For each generated tail event, we give a score of 0, 1 or 2, representing “unreasonable”, “plausible”, “reasonable”, respectively. We then merge candidates of similar semantics into a group and calculate the average score. The final score of 10 candidates is the sum of the average scores of different groups.

We report the perplexity and the diversity score in Table 9. COMET ours outperforms COMET. An example of the diversity evaluation is illustrated in Table 10.
Table 9: Results of COMET and COMET\textsubscript{ours}.

|        | PPL  | Diversity Score |
|--------|------|-----------------|
| COMET  | 11.14| 9.16            |
| COMET\textsubscript{ours} | 11.11| 10.77           |

Table 10: Results of COMET and COMET\textsubscript{ours} given the base event “PersonX needs a good grade”. Candidates in the same color are semantically similar and in the same group.

5 Related Work

The development of CSKGs is central to for tasks requiring understanding and reasoning the underlying causes and effects of events, such as question answering (Lv et al., 2020; Yasunaga et al., 2021), commonsense reasoning (Bosselut et al., 2019; Xu et al., 2021; Du et al., 2021; Lourie et al., 2021), dialog generation (Ghosal et al., 2020; Majumder et al., 2020), storytelling (Guan et al., 2020; Brahman and Chaturvedi, 2020; Ammanabrolu et al., 2021), etc.

ConceptNet (Speer et al., 2017) is a large-scale CSKG merging different sources of knowledge bases, e.g., DBPedia, WordNet, etc. ASER (Zhang et al., 2020b, 2022; He et al., 2022) contains the selectional preference knowledge extracted from more than 11-billion-token unstructured textual data. TransOMCS (Zhang et al., 2020a) utilizes linguistic graphs to convert ASER into the same representation as ConceptNet. DISCOS (Fang et al., 2021b) aggregates the neighboring information with GraphSAGE (Hamilton et al., 2017) to distill the commonsense knowledge in ASER. Fang et al. (2021a) performed commonsense knowledge graphs population on four CSKGs. Hao et al. (2022) harvested knowledge graphs from pretrained language models.

Different from (semi-)automatically-constructed CSKGs, recent years have brought about a number of crowdsourced CSKGs aiming to provide high-quality commonsense knowledge triplets. Sap et al. (2019) released ATOMIC consisting of if-then knowledge triplets mainly about daily events. Hwang et al. (2021) augmented ATOMIC with event-centered and physical-entity triplets to cover knowledge not readily available in pretrained language models. GLUCOSE (Mostafazadeh et al., 2020) grounds the implicit commonsense knowledge about everyday situations in a narrative context, thus containing richer inferential content.

Similar to conventional knowledge graphs, CSKGs also have missing links. Prior work on CSKG completion performed binary classification by scoring BiLSTM-encoded tuple (Li et al., 2016; Saito et al., 2018; Jastrzębski et al., 2018). Techniques proposed for conventional knowledge graph completion mainly base on the query-based paradigm (Dettmers et al., 2018; Shang et al., 2019; Meilicke et al., 2019; Qu et al., 2021; Zhang et al., 2021; Lovelace et al., 2021). Recently, there have been work on CSKG completion following the query-based paradigm. Malaviya et al. (2020) first discovered the sparsity problem induced by applying the query-based paradigm on CSKG completion. They proposed to densify the CSKG based on BERT similarity and achieve the promising results. Inspired by Malaviya et al. (2020), Wang et al. (2021) designed heuristic rules to add edges for nodes with fewer neighbors. Moghimifar et al. (2021) presented a neural-symbolic reasoner to learn logic rules during the training, making the CSKG completion process interpretable.

Our work differs from them in that we utilize pretrained language models to predict the relation given the head event and the tail event. Similar relation classification methods targeting at the conventional knowledge graph completion have been proposed (Socher et al., 2013; Yao et al., 2019; Cao et al., 2020). To our best knowledge, we are the first to explore the relation classification method on CSKG completion.

6 Conclusion and Future Work

In this paper, we construct Dense-ATOMIC, a densely-connected and multi-hop commonsense knowledge graph upon ATOMIC. We propose a CSKG completion approach, named Rel-CSKGC, to train a relation prediction model and infer the missing links in ATOMIC. The experimental results illustrate the effectiveness of Rel-CSKGC for CSKG completion upon ATOMIC. We also evaluate Dense-ATOMIC on a downstream commonsense reasoning task based on COMET, which proves the
advantage of Dense-ATOMIC against conventional ATOMIC.

In future work, we plan to further improve the inference efficiency and apply Dense-ATOMIC on more downstream tasks requiring multi-hop reasoning.

Limitations

Our approach for constructing Dense-ATOMIC still has two limitations: 1) the quality of Dense-ATOMIC is inevitably declines when the scale of completion increases; 2) to keep Dense-ATOMIC simple, we only consider the most reasonable relation in this paper, while the relation between two events can be complex and diversified. We will address the two issues in our future work. Finally, as we have mentioned in Section 4.1, the sampling size is relatively small due to limited computing resource and time. We will release versions of Dense-ATOMIC with larger sampling sizes soon.

Ethics Statement

We would like to thank the Allen Institute for AI for their valuable work on ATOMIC. The ATOMIC is licensed under a licence of CC BY, which allows remix, transform, and build upon the material for any purpose. We will also make our Dense-ATOMIC publicly available later.

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A Node Homogenization

Algorithm 1 presents the pseudo-code of the Node Homogenization algorithm in Section 2.1.
Algorithm 1 Node Homogenization

Input: A set of annotations $A$ and relations $R$

Output: A set of sentences in present tense $FA$

1: Remove annotations with underscores or none, and get a series of filtered annotations $FA$
2: for each $fa \in FA, r \in R$ do
3: Obtain the dependency tree $dep$ and POS tagging result $pos$ of $fa$
4: Find sub node with POS $prp$ and edge $subj$ connected directly to it
5: if Position of $sub$ is at the start of $fa$ then
6: Remove $sub$ in $fa$
7: end if
8: Find node $verb$ with POS $vb$ in $fa$
9: if $r \in [xIntent, xWant, xNeed, oWant]$ AND the first word of $fa$ is to then
10: Remove the first to of $fa$
11: end if
12: Transform node $verb$ in $fa$ to its root form
13: Append $suf \in [-s, -es, -ies, ...]$ to $verb$ based on English grammar
14: if $r \in [xAttr, xReact]$ then
15: Insert $PersonX$ is to the start of $fa$
16: else if $r$ is $oReact$ then
17: Insert $PersonY$ is to the start of $fa$
18: else if $r \in [oWant, oEffect]$ then
19: Insert $PersonY$ to the start of $fa$
20: else
21: Insert $PersonX$ to the start of $fa$
22: end if
23: end for
24: Return $FA$