DISCOS: BRIDGING THE GAP BETWEEN DISCOURSE KNOWLEDGE AND COMMONSENSE KNOWLEDGE

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ABSTRACT

Commonsense knowledge is crucial for artificial intelligence systems to understand natural language. Previous commonsense knowledge acquisition approaches typically rely on human annotations (e.g., ATOMIC) or text generation models (e.g., COMET). Human annotation could provide high-quality commonsense knowledge, yet its high cost often results in relatively small scale and low coverage. On the other hand, generation models have the potential to automatically generate more knowledge. Nonetheless, machine learning models often fit the training data too well to generate novel knowledge in high quality, thus still suffering from coverage problems. To address the limitations of previous approaches, in this paper, we propose an alternative commonsense knowledge acquisition framework DISCOS (from DIScourse to COmmonSense), which automatically mines expensive complex commonsense knowledge from more affordable linguistic knowledge resources. Experiments demonstrate that we can successfully convert discourse knowledge over eventualities from ASER, a large-scale discourse knowledge graph, into inferential if-then commonsense knowledge defined in ATOMIC without any additional annotation effort. Further study suggests that DISCOS significantly outperforms previous supervised approaches in terms of novelty and diversity with comparable quality. In total, we can acquire 3.4M ATOMIC-like inferential commonsense knowledge by populating ATOMIC on the core part of ASER. Codes and data are available at https://github.com/HKUST-KnowComp/DISCOS-commonsense.

1 Introduction

Understanding commonsense knowledge has long been one of the ultimate goals of the artificial intelligence field. To achieve that goal, many efforts have been devoted to acquire commonsense knowledge. For example, ConceptNet [1] (originally known as Open Mind Common Sense (OMCS) [2]) and OpenCyc [3] leverage expert annotation and integration of existing knowledge bases to construct high-quality commonsense knowledge bases under human-defined relations. The majority of these relations are factoid commonsense such as isA, partOf, attributeOf, etc. Recently, the focus of events sequences and the social commonsense relating to them has drawn massive attention. ATOMIC [4] is such a knowledge base about inferential knowledge organized as typed if-then relations with variables being events and states. Different from traditional knowledge bases, events and states are usually more loosely-structured texts to handle diverse queries of commonsense represented by our natural language. Though being potentially useful for solving commonsense reasoning applications, such kind of commonsense knowledge also brings new challenges for machines to acquire new knowledge of the similar type and make inferences.

First, despite that various ways have been proposed for commonsense acquisition, they have several significant drawbacks. The knowledge acquired by ATOMIC are based on crowdsourcing, which are relatively more expensive than other automatic information extraction methods, and can be less comprehensive as human cannot enumerate all commonsense. To overcome this problem, COMET [4] is proposed to finetune a large pre-trained language
Figure 1: An illustration of DISCOS. Eventualities from ASER are connected by directed edges denoting the corresponding discourse relationships. DISCOS aims to transform the discourse edges in ASER to if-then commonsense edges. For example, an ASER edge (“I am hungry”, Result, “I have lunch”) will be transformed to (if “X be hungry”, then X Want to, “have lunch”) commonsense tuple.

A model (i.e., GPT [5]) with existing commonsense knowledge bases (e.g., ATOMIC) such that they can automatically generate reasonable commonsense knowledge. Even though COMET can generate high-quality complex commonsense knowledge with the supervised approach, it tends to fit the training data too well to generate novel concepts. This is usually referred to as a selection bias problem in statistical analysis [6, 7].

On the other hand, although information extraction may be also subject to reporting bias [8], where the frequencies may not truly reflect the relative likelihood in the real-world, it can provide a lot of candidate examples that can be evaluated by a machine learning model trained on human annotated data. For example, ASER [9] uses frequent syntactical patterns to extract eventualities (such as activities, events, and states) in a dependency parse of a sentence. Then it forms linguistic relations between eventualities based on discourse markers (such as “and”, “but”, etc.). Such an automatic extraction approach can easily scale up to two orders of magnitude larger than human annotations. However, it is not trivial to leverage such a knowledge resource. First, ASER and ATOMIC have different formats. As shown in Figure 1, the knowledge in ASER are mostly natural language, e.g., “I am hungry,” whereas in ATOMIC, person entities are mostly aggregated, e.g., “Person X be hungry.” Thus, aligning ATOMIC with ASER needs additional efforts on deeply exploring both knowledge bases. Second, while some discourse relations extracted in ASER can naturally reflect the if-then relations, they are not all valid for each of the if-then relations. For example, a Succession relation in ASER, which is usually extracted by connectives such as “after” and “once,” cannot be used as a candidate relation for the Stative relation in ATOMIC, because, by definition, the Stative represents the state of the agent at the same time or before the base event, which is opposite from the chronological order of Succession.

Last but not least, although it is widely accepted that the graph substructure can be useful for making predictions and inferences in entity-centric knowledge graphs [10], existing commonsense knowledge based models [4, 11] still treat the prediction as a translational problem for the triplets in the knowledge base and do not consider the subgraph structures. It is also not trivial to include graph structures in commonsense knowledge acquisition. First, there is no existing graph structure in ATOMIC, as the labeling procedure only considers the head, the tail, and their relations. There are few overlaps between heads and tails given both can be arbitrary texts. The heads and tails can form a bipartite graph but graph convolution in such a graph may not provide additional information compared to direct representation learning for nodes, because tails can be conditionally independent given a head. However, with ASER, which is a more structural knowledge graph, it is possible to perform more complicated reasoning over the substructures. Second, as we mentioned that heads and tails are loosely-structured texts in both ATOMIC and ASER, a contextualized representation model should be applied to them for better representations. As a result, when developing a graph-based model for commonsense acquisition, both the scalability and effectiveness should be carefully considered.
To address the above challenges, in this paper, we propose a new commonsense knowledge acquisition framework, DISCOS (from DIScourse knowledge to COmmonSense knowledge), which leverages the large-scale eventuality-centric discourse knowledge in ASER to enrich the inferential commonsense knowledge in ATOMIC. Figure 1 shows an example of the results. Different from existing mechanisms such as tail node prediction adopted in COMET [4] and link prediction in knowledge base completion tasks used by KG-BERT [12], we propose a knowledge base population approach for DISCOS. This can be done by firstly mapping ATOMIC nodes to ASER nodes, and then performing a transductive learning algorithm which is based on both contextualized text representation (i.e., BERT [13]) and a graph-related representation (i.e., graph neural networks [14]) to aggregate neighborhood information to jointly make decisions to decide whether we can populate the ATOMIC relations to a pair of ASER nodes. Experiments demonstrate that the proposed model inherits the advantage of both text and graph representation learning models. Compared with the learning method trained on ATOMIC only, we significantly improve the novelty and diversity of the acquired commonsense knowledge, with comparable accuracy. Extensive analysis are conducted to analyze the strengths and limitations of DISCOS.

Our contributions can be summarized as follows.

- We propose a novel framework, DISCOS, to populate the inferential if-then commonsense knowledge in ATOMIC to an eventuality-centric discourse knowledge graph ASER.
- We develop a model named BERTSAGE to jointly leverage the textual representation and graph representation to discriminate commonsense knowledge. It’s a general model that can be used flexibly in all tasks relevant to commonsense knowledge population.
- We not only systematically evaluate our framework with commonly used evaluation metrics such as novelty and accuracy using both benchmark dataset and human evaluations, but also thoroughly analyze our models and results as well as the patterns shown in both ATOMIC and ASER to demonstrate that incorporating information extraction results in ASER to enrich the if-then relations can indeed provide larger-scale qualified commonsense knowledge.

We organize the rest of this paper as follows. Section 2 provides a systematic review on commonsense knowledge bases and commonsense knowledge reasoning. Section 3 introduces the definition of our proposed framework, as well as basic knowledge about ASER and ATOMIC. The detailed methods of DISCOS are presented in Section 4. Section 5 presents the setup and results of the experiments. The corresponding analysis of results, ablations, and some case studies are illustrated in Section 6. Some discussions about the effects of ASER are presented in Section 7. Finally, the paper is concluded in Section 8.

2 Related Work

Commonsense knowledge spans a large range of human experience including spatial, physical, social, temporal, and psychological aspects of everyday life [2]. Commonsense knowledge has been shown to be crucial for many natural language understanding tasks including question answering [15, 16], understanding and generation of dialogues [17, 18, 19] and stories [20, 21, 22], and event prediction [23, 24].

To bridge the gap between world knowledge and natural language understanding (NLU) systems, several large-scale CommonSense Knowledge Bases (CSKB) are proposed [2, 1, 25]. The Open Mind Common Sense project (OMCS) [2] defined 20 commonsense relations (e.g., UsedFor, AtLocation) and manually annotate over 600K assertions. On top of that, ConceptNet 5.0 [1] extended it to 36 relations over 8M structured nodes and 21M edges by incorporating more knowledge from other resources like WordNet [26] and OpenCyc [3]. However, even with these great efforts, ConceptNet still cannot cover all commonsense knowledge. For example, ConceptNet is limited to entity-centric nodes and does not provide commonsense knowledge about daily events. To fill this gap, ATOMIC [25] is proposed to gather the everyday commonsense knowledge about events. Specifically, ATOMIC defined 9 relations and crowdsourced 880K assertions. The nodes in ATOMIC are eventuality-centric, i.e., they are verb phrases or a complete sentence, which is typically more complicated than ConceptNet and provides richer information about events.

One common limitation of these knowledge graphs is that the human annotation can be expensive and thus it is infeasible to further scale them up to cover all commonsense knowledge. To address the limitation of human annotation, many recent works tried to acquire commonsense knowledge automatically. For example, several recent works have been focusing on mining commonsense knowledge using pre-trained language models [27, 28]. LAMA [11] manually created cloze statements from CSKB, and predicted the clozes using the BERT model. They found that the pre-trained BERT itself contains much commonsense knowledge without fine-tuning. COMET [4] used unidirectional language model GPT [5] to generate new commonsense knowledge for ConceptNet and ATOMIC, showing good performance based on human evaluation. However, the ability of generating novel and diverse commonsense knowledge is limited due to the nature of encoder-decoder framework and beam search, as reported from experiments [4, 29]. Besides
Figure 2: ATOMIC relation definition. The relations are categorized based on chronological order and the subject of events. (1) cause_agent: What causes the agent (X) to do the events. (2) stative: What is the state of the agent (X). (3) effect_agent: What are the effects on the agent (X). (4) effect_theme: What are the effects on the theme (Others).

generation methods, TransOMCS [30] firstly formalized the task of mining commonsense knowledge from linguistic graphs. They automatically extracted patterns from ASER [9] using ConceptNet as seed commonsense knowledge, and retrieved high-quality commonsense tuples based on a ranking model. However, due to the limitation of pattern mining, TransOMCS can only deal with short, canonical phrases like the nodes in ConceptNet, and cannot be generalized to free-text and complicated linguistic patterns.

Besides automatically generating commonsense tuples, another line of work is treating commonsense acquisition as a knowledge base completion task [31]. Throughout the years, many techniques including LSTM and aggregation [31, 32], pre-trained encoders with graph neural networks [33], and inductive learning [34] have been proposed to model the commonsense relations between objects. Even though these models cannot be directly applied to generate novel objects, they can serve as good classification models to tell whether a new generated commonsense assertion is plausible or not. In this paper, to leverage the advantages of both the generation and classification models, we map ATOMIC with ASER to generate a large scale knowledge graph where the relations acquired by ATOMIC will be used as a supervision signal to train a graph representation learning model. Then the model is used to predict edges introduced in ASER to acquire more similar relations as ATOMIC. Our approach can be essentially regarded as a knowledge base population task [35]. Compared to the knowledge base completion task, which assumes the nodes in a knowledge base are fixed and only predict new edges, a knowledge base population task can introduce both new nodes and new edges to an existing knowledge base.

3 Preliminaries

The task of acquiring commonsense knowledge from linguistic graphs is defined as follows. Given a set of the seed commonsense knowledge base \( \mathcal{C} = \{(h, r, t) | h \in \mathcal{H}, r \in \mathcal{R}, t \in \mathcal{T}\} \), where \( \mathcal{H}, \mathcal{R}, \) and \( \mathcal{T} \) are the set of the heads, relations, and tails, respectively, and a discourse knowledge graph \( \mathcal{G} = (\mathcal{V}, \mathcal{E}) \), where \( \mathcal{V} \) is the set of all vertices and \( \mathcal{E} \) is the set of edges, storing the discourse relations among eventualities, the goal is to infer a new commonsense knowledge base \( \mathcal{C}^+ \) from \( \mathcal{G} \). In this work, we use ATOMIC as the seed commonsense knowledge base [25] because it contains rich complex commonsense knowledge, and ASER as the discourse knowledge graphs. Their details are as follows.
Figure 3: DISCOS overview. Firstly ATOMIC tuples are transformed to the format of ASER, to acquire candidate commonsense knowledge neighbors from the discourse edges in ASER. Then BERT-SAGE model is used to discriminate whether a \((h, r, t)\) tuple is plausible or not.

3.1 ATOMIC

We adopt ATOMIC \cite{zhang2021atomic} as the seed commonsense knowledge \(C\). ATOMIC consists of 880K tuples across nine relations about day-to-day if-then commonsense knowledge (e.g., if X feels hungry, then X wants to have lunch). Different from structured or canonical knowledge bases, the nodes in ATOMIC are in the form of free-text, which is more expressive in representing everyday commonsense but also makes the matching and generation harder. As shown in Figure 2, the nine relation types span over four categories, which are classified based on the order of time and subject of the events. Detailed illustrations can be found in Figure 2.

3.2 ASER

ASER \cite{Liu2021ASER}, a large-scale eventuality-centric knowledge graph that provides explicit discourse relationships between eventualities, is used as the source of linguistic knowledge \(G\). We use the core part of ASER, which consists of 15 discourse relation types, and 10M relation edges among 27M eventualities. As illustrated in Figure 1, the discourse relation (“I am hungry”, Result, “I have lunch”) can be potentially transformed to if-then commonsense knowledge, i.e., (“X be hungry”, X want to, “have lunch”).

4 DISCOS

The overall framework of DISCOS is shown in Figure 3. As illustrated in Figure 1, the subject of events in ATOMIC and ASER are quite different, where in ATOMIC the subjects are placeholders like “PersonX” and “PersonY”, while in ASER they are concrete personal pronouns like “she” and “he”. So, in order to align the two resources, we first map all heads and tails in \(C\) (ATOMIC) into \(G\) (ASER). Formally, we need a mapping function \(M(s)\) to map the input string \(s\) into the same format of nodes in \(G\), such that for each \((h, r, t)\) on \(C\), we can find corresponding \(M(h)\) and \(M(t)\) on \(G\). Next, we leverage a rule \(D(v, r), v \in \mathcal{V}, r \in \mathcal{R}\), to select candidate discourse edges in \(G\), given a node \(v = M(h)\), \(h \in \mathcal{C}\) and a commonsense relation \(r\). After finding all candidate discourse edges under relation \(r\), denoted as \(\mathcal{L}(r) = \{(v, u) | (v, u) \in \mathcal{E}\}\), we employ a novel commonsense knowledge population model, BERT-SAGE, to score the plausibility of the candidate commonsense tuple \((v, r, u)\). This framework is not restricted to the resource of ATOMIC and ASER, but can be well generalized to other resources, as one can change the mapping rules accordingly and use the BERT-SAGE model flexibly. Details about each steps are introduced as follows.
4.1 Mapping ATOMIC to ASER

In ATOMIC, the nodes are eventualities with “PersonX” and “PersonY” as subjects or objects. However, in ASER, the corresponding eventualities are nodes with concrete personal pronouns, e.g., I, she, Alex, and Bob. Also, as the tails in ATOMIC are written by human annotators, the formats can be arbitrary and sometimes subjects are missing in tails. To effectively align the information in ATOMIC and ASER, based on the above observations, we propose best-effort rules to convert ATOMIC nodes into the format of ASER, as shown in Table 1. Examples of the mapping process are shown in Figure 4.

After conducting the string substitution operations, we use the parser in ASER to parse the acquired text into standard ASER format. The mapping statistics are shown in Table 2, where the average percentage of ATOMIC nodes that can be detected in ASER, denoted as coverage, is 62.9%. It is worth noting that the relation with the highest coverage is xAttr, where the tails are mostly adjectives. By adding a personal pronoun and a be in front of the xAttr tail, we can find most stative eventualities in ASER.

We further study the dependency pattern distribution of ATOMIC heads. The head events of ATOMIC are extracted from various corpora, including Google Ngrams and Wiktionary idioms. The definitions of events [25] are similar with that in ASER. We examine the coverage of their dependency patterns using the parser defined in ASER. There are 13 eventuality dependency patterns defined in ASER, as suggested in the paper [2], e.g., s-v-o, s-v-o-p-o (‘v’ for normal verbs other than ‘be’, ‘n’ for nouns, ‘a’ for adjectives, and ‘p’ for prepositions.) The distribution of ATOMIC head patterns and ASER patterns is presented in Figure 5. The Pearson r between the distribution of ATOMIC pattern and ASER-core pattern is 0.8136, with p<0.01, showing consistency of ATOMIC and ASER. The syntactical patterns can be used to select eventualities when matching. For example, in “xAttr” relation, we restrict the candidate tails in ASER to be of syntactical patterns “s-v-a” and “s-v-o”.

4.2 Discourse Knowledge Extraction

We then introduce how to select candidate discourse edges from ASER. For a given node v and a relation r, we find the edges based on the rule $D(v, r)$. As we are studying if-then relations, the candidate discourse edges in ASER should be consistent with the order of time in the ATOMIC relation r. For example, for a commonsense tuple $(h, r, t)$ in the effect_agent category, the event t is an effect of h and thus t should happen at the same time or after the event h. To
retrieve ASER discourse edges with the same temporal logic, we first reconstruct an ASER subgraph by selecting specific edge types based on an ATOMIC relation \( r \) with rules illustrated in Figure 6.

We use the \textit{effect_agent} category as an example. For a given node \( u \in V \), we select the directed \((u,v)\) pairs from ASER, such that there exists either an edge \((u,v)\) \( \in E \) where the edge types are among discourse relations \textit{Precedence} and \textit{Result}, an edge \((v,u)\) \( \in E \) where the edge types are among \textit{Succession}, \textit{Condition}, and \textit{Reason}, or there exists an \( e \in \{(u,v),(v,u)\} \) such that the edge types of \( e \) is among \textit{Synchronization} and \textit{Conjunction}. In this way, all the selected directed tuples \((u,v)\) represent the same time order as in the ATOMIC relation \( r \).

In the next step, we need to distinguish the \textit{theme} categories from \textit{agent} categories. For relations under \textit{effect_theme}, only eventuality pairs \((u,v)\) with different personal pronouns are selected as candidate knowledge, while for other \textit{agent}-based categories we select eventuality pairs with the same personal pronouns. After this process, we collect all selected edges from \( G \) to form an ASER-induced directed graph \( G_r = (V_r, E_r) \), \( V_r \subseteq V \) for each relation, where edges \((u,v) \in E_r\) can be viewed as a candidate if \( u, \text{then} v \) relation under \( r \).

After that, we aggregate the nodes in \( G_r \) by conducting personal pronoun substitution. For the \textit{agent}-based relations, considering an edge \((u_r,v_r) \in E_r\), we replace the common personal pronouns in \( u_r \) and \( v_r \) as \textquote{PersonX}, to be consistent with the ATOMIC format. For other personal pronouns, we map them to \textquote{PersonY} and \textquote{PersonZ} according to the order of their occurrences. For the \textit{theme}-based relations, we replace the subject of \( u_r \) with \textquote{PersonX} and \( v_r \) with \textquote{PersonY}. After the personal pronoun substitution operation, we can acquire a unified discourse knowledge graph \( G^c_r = (V^c_r, E^c_r) \) in the same format as ATOMIC.

### 4.3 Commonsense Knowledge Population with BERTSAGE

The goal of this module is to classify whether a candidate discourse knowledge tuple \((u,v) \in E^c_r\) is a plausible \textit{if-then} commonsense knowledge under relation \( r \). We use the commonsense tuples provided by ATOMIC as the seed positive examples. For the negative examples, we explore several different sampling strategies:
1. **RAND (Random)**: Randomly sample two nodes \((u, v)\) from \(G^r\) such that \((u, v) \notin E^r\).

2. **O (Others)**: Randomly sample two nodes \((u, v)\) from other relations such that \((u, v) \in E^r, r' \in \mathcal{R}, r' \neq r\). These negative samples will help the model to distinguish different commonsense relations.

3. **I (Inversion)**: Randomly sample a tuple \((u, v)\) from \(E^r\) and add the inversion \((v, u)\) as negative samples. This is used to help the model understand the causal if-then relationships, when the input tuples have similar semantic meanings.

4. **S (Shuffling ATOMIC)**: Randomly select \(u\) from the set of ATOMIC heads, and \(v\) from the set of ATOMIC tails under relation \(r\). Add a negative sample if \((u, v)\) is not connected by an existing ATOMIC edge. This mechanism will prevent the model from assigning high scores only to nodes that have appeared in the ATOMIC training set.

To effectively encode both the semantic meaning of eventuality nodes and their neighbors on the overall graph, as shown in the right part of Figure 8 we propose a model BERTSAGE that contains two components: (1) a node encoder based on BERT that embeds the semantic meaning of nodes; (2) a graph encoder that learns and aggregate relational information from the discourse graph. The details are as follows.

- **Node encoder**: We use the pre-trained language representation mode BERT [13] to encode all the nodes in the dataset. For a node \(v = [w_1, w_2, \ldots, w_n]\) with \(n\) word tokens, we add a [CLS] token in the beginning of each sentence as \(w_0\) and a [SEP] token at the end of it as \(w_{n+1}\). We denote the contextualized representation provided by BERT as \([e_{w_0}, e_{w_1}, \ldots, e_{w_{n+1}}]\), \(e_{w_i} \in \mathbb{R}^d\), where \(d\) is the dimension of BERT embeddings, \(e_{w_0}\) and \(e_{w_{n+1}}\) are the embedding of [CLS] and [SEP] tokens, respectively. We then use the average pooling to acquire the final node representation as \(e_v = \sum_{i=0}^{n+1} e_{w_i}/(n + 2)\).

- **Graph encoder**: To effectively encode the semantics from neighbor events on the discourse graphs, we propose to use GraphSAGE [14] to aggregate the neighbor information of a given node \(v\).

Given a node \(v\), we first acquire its contextualized representation \(e_v\), and then calculate the embeddings of \(v\)'s neighbors in \(G^r\), which are denoted as \(\mathcal{N}(v)\). Here, \(\mathcal{N}(v)\) is a fixed size neighbor set uniformly sampled from all the neighbors of \(v\). The hidden representation after the GraphSAGE layer \(h_v\) is computed as follows:
We introduce the setups of all the experiments in this section. Similar with previous works, we adopt quality, novelty, and diversity as the evaluation metrics. Also we present the settings for the baseline models COMET.

5 Experiments

We introduce the setups of all the experiments in this section. Similar with previous works, we adopt quality, novelty, and diversity as the evaluation metrics. Also we present the settings for the baseline models COMET.

5.1 Setup

In this section, we compare DISCOS with the previous state-of-the-art model COMET \[4\] on ATOMIC. Similar with COMET, we use the training set of ATOMIC to train the classification model and the testing set for the evaluation, and propose to evaluate the acquired commonsense knowledge from three perspectives:

1. **Quality**: We evaluate the quality of acquired commonsense knowledge annotators from Amazon Mechanical Turk (AMT). For each relation in ATOMIC, we randomly sample 50 head events from the testing set and ask the annotators if they think the generated tuple makes sense. For COMET, we use beam 10 top 10 as the decoding mechanism to generate 10 commonsense knowledge for each head events. For DISCOS, we select the tuples ranked top 10 by the BERTSAGE model.

2. **Novelty**: We first evaluate the novelty of acquired commonsense knowledge with two novelty indicators, the proportion of generated tails that are novel (NT), and the proportion of novel tails in the set of all the unique generated tails (NU).

3. **Diversity**: Last but not least, considering that the novelty is evaluated based on string match, which cannot effectively distinguish whether a system is generating many different novel concepts or just similar but not identical concepts. Following previous works \[36,37\], we report diversity indicator dist-1 and dist-2, the proportion of distinct unigrams and bigrams among the total number of generated unigrams and bigrams. We evaluate the diversity of generated knowledge given the same head and relation and calculate the average among all the heads.

| Model         | oEffect | oReact | oWant | xAttr | xEffect | xIntent | xNeed | xReact | xWant |
|---------------|---------|--------|-------|-------|---------|---------|-------|--------|--------|
| COMET* (top 10) | 29.0    | 37.7   | 44.5  | 57.5  | 55.5    | 68.3    | 64.2  | 76.2   | 75.2   |
| COMET (top 10)  | 59.8    | 69.6   | 69.0  | 77.7* | 75.4*   | 86.2    | 80.7  | 75.6*  | 78.9*  |
| DISCOS (top 10) | 68.3*   | 67.1   | 69.9  | 66.7  | 60.9    | 87.8    | 84.9  | 68.4   | 73.4   |
| Human*         | 84.6    | 86.1   | 83.1  | 78.4  | 83.9    | 91.4    | 82.0  | 95.2   | 90.0   |

Table 3: Human evaluation on quality for the KBC setting (given \(h, r\) to predict \(t\)). COMET* represents the results provided by the original paper of COMET. In the last row, we report the human evaluation results of the gold ATOMIC knowledge given the same head and relation and calculate the average among all the heads.

| Model         | oEffect | oReact | oWant | xAttr | xEffect | xIntent | xNeed | xReact | xWant |
|---------------|---------|--------|-------|-------|---------|---------|-------|--------|--------|
| COMET @ 1     | 0.0     | 0.0    | 0.0   | 2.2   | 10.4    | 0.2     | 0.1   | 2.0    | 8.3    |
| DISCOS @ 1    | 61.2    | 65.0   | 15.5  | 36.3  | 43.2    | 56.7    | 6.8   | 17.2   | 45.3   |
| COMET @ 2     | 7.5     | 23.9   | 0.0   | 0.0   | 3.5     | 17.8    | 0.1   | 0.4    | 2.3    |
| DISCOS @ 2    | 58.4    | 65.9   | 13.7  | 33.8  | 45.1    | 63.0    | 7.1   | 20.1   | 45.3   |
| COMET @ 5     | 12.9    | 30.3   | 0.1   | 1.0   | 7.5     | 25.4    | 0.1   | 0.7    | 5.3    |
| DISCOS @ 5    | 59.9    | 72.8   | 16.5  | 38.8  | 49.9    | 69.6    | 8.9   | 25.8   | 50.2   |
| COMET @ 10    | 16.8    | 40.4   | 0.1   | 4.9   | 9.8     | 32.2    | 0.1   | 0.9    | 8.0    |
| DISCOS @ 10   | 62.9    | 76.2   | 22.5  | 50.4  | 55.8    | 75.4    | 12.0  | 30.4   | 54.5   |

Table 4: Novelty on the test set grouped by different relations. @ \(k\) means we evaluate the top \(k\) generation or retrieval for a given head \(h\). All the improvements by DISCOS are significant with z-test \(p < 0.05\).
The overall quality, novelty, and diversity of COMET and DISCOS are shown in Table 3, 4, and 5, respectively. From the results, we can make the following observations. Based on our crowd-sourcing results, DISCOS can achieve comparable or better quality on Effect_theme relations (oEffect, oReact, and oWant) and Cause_agent relations (xIntent and xNeed) among the nine relations. The results indicate that rich commonsense knowledge is indeed covered by the discourse graphs and the proposed DISCOS framework can effectively discover them. At the same time, we also notice that DISCOS can significantly outperform COMET in terms of the novelty. For example, for some relations like xAttr, oReact, and xReact, COMET hardly generate novel tails despite increasing the size of beam search while a large portion of the DISCOS knowledge is novel. One reason behind is that COMET fits the training data too well and the training set is similar to the test set. As a result, it tends to predict the concepts it has seen in the training set rather than something new. Last but not least, similar to the novelty, DISCOS also outperforms COMET in terms of the diversity, which is mainly due to the limitation of beam search as it often generates very similar sentences. As DISCOS is a classification model rather than a generation model, it does not suffer from that problem. To conclude, compared with COMET, DISCOS can acquire much more novel and diverse commonsense knowledge with the comparable quality.

To demonstrate that DISCOS has the potential to acquire the commonsense knowledge without the help of the head tuple, we evaluate it with a more challenging setting, where only the relation \( r \) is provided and the model is asked to retrieve the novel \((h, t)\) pairs from ASER. Specifically, we select the tuples scored higher than 0.5 by the BERT-SAGE model, and randomly sample 100 tuples from each relation for human evaluation. To make sure the acquired knowledge is not observed by the model, only novel concepts are evaluated.

From the results in Table 6, we can see the potential of DISCOS in directly mining high-quality and novel commonsense knowledge from the raw graph of ASER. For example, it achieves over 70% accuracy on three relations (i.e., “oEffect”, “xEffect”, and “xReact”). Following this experiment setting, we successfully convert ASER into a large scale commonsense knowledge graph DISCOS-ATOMIC, which contains 1.06 million complex commonsense knowledge in

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**Table 5:** Results of diversity grouped by all the relations. We report the diversity of top 10 generating or retrieval of COMET and DISCOS.

| relations  | dist-1      | dist-2      | COMET | DISCOS | COMET | DISCOS |
|-----------|-------------|-------------|-------|--------|-------|--------|
| oEffect   | 60.3        | 66.7        | 76.3  | 89.3   | 66.7  | 76.3   |
| oReact    | 35.5        | 33.5        | 13.5  | 35.9   | 33.5  | 13.5   |
| oWant     | 46.6        | 69.0        | 84.1  | 93.8   | 69.0  | 84.1   |
| xAttr     | 8.3         | 26.0        | 4.2   | 27.4   | 26.0  | 4.2    |
| xEffect   | 58.4        | 67.2        | 81.8  | 90.4   | 67.2  | 81.8   |
| xIntent   | 42.9        | 61.5        | 75.7  | 87.3   | 61.5  | 75.7   |
| xNeed     | 41.4        | 63.6        | 75.7  | 88.4   | 63.6  | 75.7   |
| xReact    | 27.1        | 29.3        | 12.1  | 32.9   | 29.3  | 12.1   |
| xWant     | 42.2        | 65.3        | 78.7  | 91.5   | 65.3  | 78.7   |
| Average   | 38.3        | 52.9        | 55.0  | 70.0   | 52.9  | 55.0   |

**Table 6:** Human annotation on quality for the challenging setting (given \( r \) to retrieve plausible \((h, t)\) pairs in DISCOS).

|               | oEffect | oReact | oWant | xAttr | xEffect | xIntent | xNeed | xReact | xWant |
|---------------|---------|--------|-------|-------|---------|---------|-------|--------|-------|
| DISCOS        | 70.2    | 63.2   | 59.4  | 69.2  | 78.2    | 65.8    | 67.8  | 80.0   | 49.2  |

Considering that \( G^e_c \) is much larger than ATOMIC, we restrict the size of \( G^c_r \) in the following ways. (1) We only select the subgraph of ASER which is induced by the one-hop neighbors of all the ATOMIC nodes. (2) For the subgraph acquired in the first step, we add two hop neighbors into the graph for the nodes whose degrees are less than a threshold \( k \). \( k \) is set to 20 in practice. We use bert-base-uncased [13] as the encoding layer for the classification model and the dimension of the hidden embeddings is 768. For the neighbor function \( N(u) \), we set the neighbor size to be four. The batch size is set to be 64. For COMET, we use the public available official implementation [2]. All the experimental settings are the same as in the original paper. Similar with the decoding mechanisms in the COMET paper, we use beam search top \( k \) to retrieve \( k \) generated tails.

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[13]: https://github.com/huggingface/transformers
[2]: https://github.com/atcbosselut/comet-commonsense
[3]: https://github.com/huggingface/transformers
[4]: https://github.com/atcbosselut/comet-commonsense
[5]: We present the original human annotation results from the ATOMIC paper as a reference. However, as we employ different annotators, they are not comparable with our results.
Table 7: Ablation study on different negative sampling methods under xWant relation, trained using BERTSAGE model. We report the accuracy of testing set here.

|       | Train | RAN| O20 | O20+I10 | O20+I10+S10 |
|-------|-------|----|-----|---------|-------------|
| RAND  | 94.40 | 93.65 | 93.50 | 90.88    |
| O20   | 87.46 | 91.16 | 90.93 | 89.12    |
| O20+I10 | 87.16 | 90.72 | 90.92 | 89.17    |
| O20+I10+S10 | 82.80 | 86.49 | 86.85 | 86.53    |

Table 8: Evaluations on the commonsense knowledge classification experiments. We report the accuracy here as the number of positive and negative samples in testing set are balanced. * after bold figures indicates that the improvement of BERTSAGE model is significant with z-test $p < 0.05$.

| Model   | oEffect | oReact | oWant | xAttr | xEffect | xIntent | xNeed | xReact | xWant |
|---------|---------|--------|-------|-------|---------|---------|-------|--------|-------|
| BERT    | 90.60   | 97.05  | 93.95 | 96.21 | 87.85   | 89.69   | 89.93 | 93.96  | 90.48  |
| BERTSAGE| 91.10*  | 97.29  | 94.21 | 96.33 | 89.49*  | 90.48*  | 91.10*| 94.02  | 90.91* |

6 Ablations and Analysis

In this section, we will present extensive analysis to show the effects of all components in our model.

6.1 Effects of Negative Sampling Strategy

As aforementioned, four different negative sampling strategies are employed in the DISCOS framework. In this subsection, we present the ablation study to show the contribution of these strategies. Specifically, we tried the following combinations:

1. **RAND**: All the negative examples are sampled randomly from the whole graph.
2. **O20**: 20% of the negative examples are sampled using the mechanism O.
3. **O20+I10**: 20% of the negative examples are sampled using the mechanism O and 10% from the mechanism I.
4. **O20+I10+S10**: 20% of the negative examples are sampled using the mechanism O, 10% from the mechanism I, and 10% from the mechanism S.

We tried to use aforementioned combinations to generate the negative examples for both the training and testing set of the classification task, and present the results on the test set in Table 7. We highlight the accuracy ranked highest on O20+I10+S10 test set, the hardest negative example set. From the result we can see that, even though the RAND achieves comparable performance on the simple test set RAND, it suffers a significant performance drop on the other harder ones. The reason behind is that the randomly selected negative examples can only help the model to distinguish the ATOMIC positive examples rather than distinguish the commonsense. This ablation study also demonstrates the importance of including more diverse negative example generation strategies to cover more signals we want the model to learn. In the end, we choose to use O20+I10 negative sampling for training in our final model.

6.2 Effects of BERTSAGE

To clearly show the contribution of the proposed BERTSAGE model, we compare it with a modified version of KG-BERT [12], denoted as BERT baseline for short, on the classification task. The only difference between BERTSAGE and BERT is that we incorporate the semantic about neighboring events to get the final representation in BERTSAGE. From the results in Table 8, we can see that adding a GraphSAGE layer over the BERT baseline will improve the classification

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We select the xWant relation as an example.
results on all relation types. These results prove our assumptions that adding information about the neighbor events on the discourse graph can help generate better event representations. Among nine relations, the improvement is significant with z-test $p < 0.05$ on five types. One interesting finding is that this improvement is in positive correlation with the graph complexity in Table 2. In general, GraphSAGE will contribute more to the performance when the graph is more complex.

### 7 Discussion on the Effects of ASER

As stated in the quality analysis in Section 5.2, the performance of DISCOS on effect_theme relations is better or comparable with the COMET baseline. This is because there are relatively fewer annotations for the effect_theme relations in ATOMIC. For oEffect, oReact, and oWant relations, the average number of ATOMIC tails per head are 1.5, 1.4, 2.2, respectively, compared with 4.2 tails per head for other agent(X)-driven relations. The performance of COMET drops on the theme(Other)-driven relations as there are fewer training data, which is consistent with the findings in COMET paper [4]. DISCOS can fill the gap of limited training data by finding explicit candidate discourse knowledge from ASER, thus resulting in better or comparable performance. Next, the performances on relations in cause_agent category are also improved compared to COMET. These relations require the tails to happen ahead of the base event. But under the if-then knowledge framework of COMET, a tail is generated after feeding the head and relation into the unidirectional language model, which is opposite from the definition of cause_agent in chronological order. From the case studies of xIntent and xNeed relations in Table 9, we could also see that the COMET model sometimes confuses the causes and effects, i.e., the generated tails are not the causes of the head events as they are supposed to be, but the

| Head | Model | Tail | Plau | Div |
|------|-------|------|------|-----|
| X gets the call (oEffect) | COMET | none | ☹ | ☑ |
|  |  | Y talks to X | ☑ | ☑ |
|  |  | Y hangs up | ☹ | ☑ |
|  |  | Y talk to X | ☑ | ☑ |
|  | DISCOS | Y get to sit | ☑ | ☑ |
|  |  | Y make contact with X | ☑ | ☑ |
|  |  | Y need X | ☑ | ☑ |
|  |  | Y feel better | ☑ | ☑ |
| X takes Y in Y’s arms (oWant) | COMET | none | ☹ | ☑ |
|  |  | Y to hug X | ☑ | ☑ |
|  |  | Y to hold X | ☑ | ☑ |
|  |  | Y to embrace X | ☑ | ☑ |
|  | DISCOS | Y kiss X | ☑ | ☑ |
|  |  | Y like it | ☑ | ☑ |
|  |  | Y reply softly | ☑ | ☑ |
|  |  | Y feel good | ☑ | ☑ |
| X bows X’s head (xIntent) | COMET | X to show respect | ☑ | ☑ |
|  |  | X to be respectful | ☑ | ☑ |
|  |  | X show respect | ☑ | ☑ |
|  |  | none | ☹ | ☑ |
|  | DISCOS | X love it | ☑ | ☑ |
|  |  | X look down | ☑ | ☑ |
|  |  | X eye sparkle | ☹ | ☑ |
|  |  | X close X’s eye | ☹ | ☑ |
| X want to sleep (xNeed) | COMET | X to go bed | ☹ | ☑ |
|  |  | X to close the eyes | ☹ | ☑ |
|  | DISCOS | X be tired | ☑ | ☑ |
|  |  | X take a shower | ☑ | ☑ |

Table 9: Case study. Plau. indicates the plausibility of the tuple, and Div. indicates whether the generated tail is a diverse generation. For example, the tail “Y talk to X” in the oEffect relation would not be considered as a diverse generation, as there exists a similar “Y talks to X” ahead of it.

As stated in the quality analysis in Section 5.2, the performance of DISCOS on effect_theme relations is better or comparable with the COMET baseline. This is because there are relatively fewer annotations for the effect_theme relations in ATOMIC. For oEffect, oReact, and oWant relations, the average number of ATOMIC tails per head are 1.5, 1.4, 2.2, respectively, compared with 4.2 tails per head for other agent(X)-driven relations. The performance of COMET drops on the theme(Other)-driven relations as there are fewer training data, which is consistent with the findings in COMET paper [4]. DISCOS can fill the gap of limited training data by finding explicit candidate discourse knowledge from ASER, thus resulting in better or comparable performance. Next, the performances on relations in cause_agent category are also improved compared to COMET. These relations require the tails to happen ahead of the base event. But under the if-then knowledge framework of COMET, a tail is generated after feeding the head and relation into the unidirectional language model, which is opposite from the definition of cause_agent in chronological order. From the case studies of xIntent and xNeed relations in Table 9, we could also see that the COMET model sometimes confuses the causes and effects, i.e., the generated tails are not the causes of the head events as they are supposed to be, but the
Table 10: Case study of the challenging setting of DISCOS where novel heads are produced. Two generated samples from DISCOS for each relations are presented.

effects. For example, for xNeed relation in Table 9, if “X want to sleep” then “X go to bed” is a plausible sentence, but is not a plausible xNeed commonsense knowledge, as “X go to bed” is the effect of the base event instead of the cause. DISCOS can handle this situation well by selecting ASER edges with exactly the same chronological order as the definition of each relations.

8 Conclusion

In this paper, we propose DISCOS, a novel commonsense acquisition framework that populates the inferential commonsense knowledge in ATOMIC to an eventuality-centric discourse knowledge graph ASER, which can overcome significant drawbacks of human annotation and neural text generation methods. Experimental results have shown that we can retrieve much more novel and diverse if-then commonsense knowledge from ASER with high quality comparable with neural text generation. This flexible approach is flexible and can be well generalized to other resources, showing promising future for converting cheap discourse knowledge into expensive commonsense knowledge.
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