Constructing a Knowledge Graph from Unstructured Documents without External Alignment

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Abstract
Knowledge graphs (KGs) are relevant to many NLP tasks, but building a reliable domain-specific KG is time-consuming and expensive. A number of methods for constructing KGs with minimized human intervention have been proposed, but still require a process to align into the human-annotated knowledge base. To overcome this issue, we propose a novel method to automatically construct a KG from unstructured documents that does not require external alignment and explore its use to extract desired information. To summarize our approach, we first extract knowledge tuples in their surface form from unstructured documents, encode them using a pre-trained language model, and link the surface-entities via the encoding to form the graph structure. We perform experiments with benchmark datasets such as WikiMovies and MetaQA. The experimental results show that our method can successfully create and search a KG with 18K documents and achieve 69.7% hits@10 (close to an oracle model) on a query retrieval task.

1 Introduction
Knowledge graphs (KGs) have been a key component of question-answering (QA) systems (Hao et al., 2017; Chen et al., 2019; Deng et al., 2019; Sun et al., 2019). Given a query, a QA system will typically first retrieve relevant triples by traversing the KG, and then form an answer from the retrieved information. The KG structure not only enables the system to do multi-hop reasoning, but also provides a nice interpretability mechanism to inform users about how an answer is extracted.

However, creating a human-annotated KG is expensive, typically requiring large amounts of expert labor. While there exists large general-purpose knowledge bases such as FreeBase (Bollacker et al., 2008), human knowledge is continually expanding so knowledge bases need continuous refinement or will tend to become outdated. To overcome this issue, many approaches have attempted to build KGs automatically (Dong et al., 2014; Bosselut et al., 2019), but the steps required to align extracted knowledge with prior existing knowledge sources are necessary, so expert labor is still required.

Given these issues, it is attractive for a QA system to use only unstructured documents (Chen et al., 2017; Wang et al., 2018; Clark and Gardner, 2018), since this approach has the potential to exclude the need for human labor. However, it loses the nice properties of the KG structure. In addition, most recent work in this direction (Feldman and El-Yaniv, 2019; Karpukhin et al., 2020) still relies on an existing KB.

In this work, we aim to build a system combining advantages from both worlds, by building a virtual KG from unstructured documents. Our approach has the following features: (1) It does not rely on any expert labor or existing knowledge base. (2) It does not rely on labeled training data (e.g. QA pairs). (3) By structuring documents as a KG, we enable a mechanism for interpretability during multi-hop reasoning.

2 Approach
Task Setup: Our approach first builds a knowledge graph (KG) from a set of unstructured documents \( \{D_1, \ldots, D_M\} \), where each document \( D \) is a sequence of sentences \( \{S^D_1, \ldots, S^D_M\} \). Note that in the formulations we assume each document consists of \( M \) sentences just for notation convenience. Given a query \( q \) that is in the form of a natural language question, our system will traverse the KG, and the final output will be a retrieval of the top-k most relevant paths (We will define the notion of
| Sentence: The Goonies is an American film directed by Richard Donner. |
|---|---|---|
| The Goonies | is | an American film |
| directed | by | Richard Donner |

Table 1: An example of the transformation from raw text to entity-relation triples by OpenIE. In the table “sf” stands for “surface”.

a path in Section 2.2). Finally we judge the system’s performance by checking whether the reference answer is included in any of the retrieved paths.

Our framework is roughly composed of three phases: (1) Build a KG from a potentially large number of unstructured documents. (2) Given a query, traverse the KG. (3) Retrieve the top-k most relevant paths. In the following sections, we describe each phase in more detail.

2.1 Building a Knowledge Graph from Unstructured Documents

Creating a graph from raw text is at the core of this work. We use a three-step process to do this: conversion, encoding, and surface-entity linking.

*Conversion:* We start by applying OpenIE\(^1\) to every sentence \(S\) to generate a list of entity-relation triples. We will use the terms “surface-entities” (se) and “surface-relation” (sr), because they are not predefined entities/relations. For each document \(D\), we merge all triples extracted from each sentence into a list \(\{(se_1^i, sr_i, se_2^i)\}\). Note that OpenIE extraction is imperfect: In Table 1, for example, “by Richard Donner” is extracted instead of the correct entity “Richard Donner”. More importantly, different surface-entities could refer to the same underlying entity. We address these problems in the next two steps.

*Encoding:* In the second step we utilize the BERT model (Devlin et al., 2019) to encode each surface-entity or surface-relation from sentence \(S\). We first form word-level embeddings by adding the associated word-piece embeddings from the model. Then challenge is to incorporate contextualized information into the encoding (e.g. the word “Apple” has different meanings in different contexts). Inspired by (Clark et al., 2019), we adopt the “weighted embedding” technique, where the encoding of each surface-entity / relation is a simple weighted summation of the word embeddings and the output embedding of the final [CLS] token when \(S\) is fed into the BERT model. We refer readers to the Spacy-transformer toolkit for details\(^2\). We denote the resulting encoding of \(se\) as \(se^{enc}\).

*Surface-entity Linking:* The third and final KG building step performs surface-entity linking, which creates a graph structure out of the extracted entity-relation triples in a document \(D\). The goal is to link entities with the same underlying concept together, for example from Table 1, a new surface-entity “the film” could be referring to “the Goonies” in some follow-up sentence, so the relations with “the film” should also be applied to “the Goonies”. In this work, we use an adaptive threshold on the cosine distance between the encodings of surface-entities to compute their similarity. The intuition is that if there exists an \(se_j\) that has high similarity to \(se_i\), then the acceptable similarity threshold for \(se_j\) should be higher.

We denote the set of surface-entities linked to \(se_i\) as \(Link(se_i)\), which is formulated below:

\[
Link(se_i) = \{se_j : \cos(se_i^{enc}, se_j^{enc}) \geq \lambda \ast \max_{l \in E^D} (\cos(se_l^{enc}, se_i^{enc}))\} \tag{1}
\]

Note that \(E^D\) denotes the set of all surface-entities existing in document \(D\). \(\lambda\) is a hyper-parameter controlling the adaptive threshold, and we found that a setting of 0.6 works well in our experiments.

To summarize, after the above three steps, for each document we have a list of extracted entity-relation triples \(\{(se_1^i, sr_i, se_2^i)\}\), and each surface-entity/relation has a contextualized encoding. Within every document, each surface-entity \(se_i\) is linked to \(Link(se_i)\).

2.2 Multi-hop KG Traversal and Retrieval

In this stage, we will traverse the constructed KG to find relevant information to a given query \(q\). To start the traversal, we first select a set of seed surface-entities in the virtual graph as the start points of our traversal. In most cases, we simply use the set of surface-entities that exist in the query \(q\). If that set is empty, we encode \(q\) with the BERT as \(q^{enc}\), and use the surface-entity whose encoding has the largest cosine-similarity with \(q^{enc}\) as the seed entity.

Starting with the seed surface-entities, we adopt an expand-and-prune strategy that is similar in

\(^1\)https://openie.allenai.org/

\(^2\)https://explosion.ai/
spirit to breath-first search. For each hop, we expand the current set of paths first via the surface-entity linking, and then via the entity-relations triples. The detailed traversal algorithm is shown in Algorithm 1 and we provide an illustration in Figure 1.

Since the number of active paths could grow exponentially during this expansion, we design an importance score to rate and prune the paths. For each path $p$, we concatenate its surface-entities/relations with a period between each triple, and feed it to the BERT model to get an encoding of this path $p^{enc}$. We use the cosine-similarity between $p^{enc}$ and $q^{enc}$ as the importance score. After the expansion of each hop, we only keep $B$ most relevant paths. In our experiments, we find that we only need to set $B$ to 10 to achieve good performance.

The product of the traversal stage will be a set of paths. We use the list of the surface-entities/relations traversed to represent a path: For example, $p = [se_1, sr_1, se_2, sr_2, se_3]$ is a two-hop path. Finally, we use the cosine-similarity between $p^{enc}$ and $q^{enc}$ to select the final top-$k$ paths as the output.

3 Experimental Results

To quantitatively evaluate our model, we adopt two popular QA benchmark datasets: WikiMovies\(^3\) (Miller et al., 2016), and MetaQA\(^4\) (Zhang et al., 2018). Since these datasets consist of pairs of questions and answers and related Wikipedia articles, we can leverage the entire set of articles in the dataset to build a knowledge graph and use our system to find the information that contains the correct answer to a given question. WikiMovies and MetaQA use the same 18,128 movie domain Wikipedia articles, but have different types of questions. Since our framework does not need training, we do not use training data. We search the hyperparameter space using WikiMovies dev data (10K), and evaluate the model with the test data. The test data consists of 9,952/14,872/14,274 QA pairs that require 1-hop (WikiMovies), 2-hop, and 3-hop (MetaQA) inference, respectively.

Finding a baseline to compare the performance of our model is not straightforward because our system is different from conventional approaches in several ways: (1) Unlike existing automatic knowledge building methods that obtain results using external knowledge, we do not require exter-

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3 https://research.fb.com/downloads/  
4 https://github.com/yuyuz/MetaQA
We present the main results in Table 2, which shows that our model obtains reasonable performance considering that we did not rely on any existing KB or additional training data. We achieve 69.67 / 49.71 / 38.53 hits@10 for each 1-hop QA (WikiMovies), 2-hop, and 3-hop QA (MetaQA). Hit@k (Bordes et al., 2013) is the accuracy of top-k predicted paths containing the answer. In most cases, our performance comes close to the oracle model, and in the case of MetaQA (2-hop), our model outperforms the oracle. As expected, performance is better when the number of hops to navigate the graph is more than the hops needed to find the answer. Example predictions are shown in Table 3. One interesting observation is that in a significant number of failure cases, our model actually has the right answer, but is deemed wrong because the reference label is incomplete. Therefore, we believe that the performance of our model is being underestimated.

4 Related Work

Automatic knowledge graph construction: In most research to create knowledge graphs from unstructured text without human intervention, the popular approach is to develop a pipeline of NLP operations such as named entity recognition, entity linking and relationship extraction (Wu et al., 2019). These approaches require a predefined knowledge base to align the extracted entities or relationships (Lin et al., 2016; Zhou et al., 2016; Zhang et al., 2019; Cao et al., 2020). Unlike existing methods, our model can directly handle these tasks with extracted surface forms from unstructured documents.

Graph based multi-hop retrievers: In order to reason over documents and extract the desired information, it is necessary to extract information from multiple sentences or documents. To achieve this, Sun et al. (2019) builds a question-relevant sub-graph from the knowledge base or text corpus to gather all the relevant information. This is similar to our approach in that it creates question-related sub-graphs, but differs from us in that it creates graphs using a predefined KB. Das et al. (2019); Asai et al. (2019) construct a Wikipedia graph using hyperlinks within the article to extract paragraphs related to the query. Therefore, their method contrasts with ours in that a human-annotated hyperlink is essential and the minimum unit of information to be searched is a paragraph.

5 Conclusion

We propose a novel method to automatically build a knowledge graph from unstructured documents, without having to align resulting entities with external information. Our method successfully constructs a KG from 18K documents. The perfor-
formance of our system is a 69.7 hits@10, which is close to an oracle model. In the future, we plan to improve multi-hop / multi-documents retrieval by introducing a trainable re-ranking module.

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