LOME: Large Ontology Multilingual Extraction

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Abstract

We present LOME, a system for performing multilingual information extraction. Given a text document as input, our core system identifies spans of textual entity and event mentions with a FrameNet (Baker et al., 1998) parser. It subsequently performs coreference resolution, fine-grained entity typing, and temporal relation prediction between events. By doing so, the system constructs an event and entity focused knowledge graph. We can further apply third-party modules for other types of annotation, like relation extraction. Our (multilingual) first-party modules either outperform or are competitive with the (monolingual) state-of-the-art. We achieve this through the use of multilingual encoders like XLM-R (Conneau et al., 2020) and leveraging multilingual training data. LOME is available as a Docker container on Docker Hub. In addition, a lightweight version of the system is accessible as a web demo\textsuperscript{1}.

1 Introduction

As information extraction capabilities continue to improve due to advances in modeling, encoders, and data collection, we can now look (back) toward making richer predictions at the document-level, with a large ontology, and across multiple languages. Recently, Li et al. (2020) noted that despite a growth of open-source NLP software in general, there is still a lack of available software for knowledge extraction. We wish to provide a starting point that allows others to build increasingly comprehensive document-level knowledge graphs of events and entities from text in many languages.

In Figure 1, we follow a multilingual input example. A sentence-level parser can identify both INGESTION events and their arguments. To connect these events cross-sententially, we can cluster coreferent mentions and predict the temporal relations between the events. We can also augment the entities with fine-grained entity types, like the rabbit entity with LIVING\_THING/ANIMAL.

Several prior packages have also used advances in state-of-the-art models to build comprehensive information extraction systems. Li et al. (2019) present an event, relation, and entity extraction and coreference system for three languages: English, Russian, and Ukrainian. Li et al. (2020, GAIA) extend that work to support cross-media documents. However, neither of these are truly multilingual: they are limited to three languages and rely on language-specific models to operate on monolingual documents. On the other hand, works focused on multilinguality is limited in their scope for extraction (Akbik and Li, 2016; Pan et al., 2017). Like prior work, LOME is focused on extracting entities and events from raw text documents. However, LOME is language-agnostic; all components prioritize multilinguality. Using XLM-R (Conneau et al., 2020) as the underlying encoder paves the way for both training on multilingual data (where it exists) and inference in many languages.\textsuperscript{2} Our pipeline includes a full FrameNet parser for events and their arguments, neural coreference resolution, an entity typing model over large ontologies, and temporal resolution between events.

Our system is designed to be modular: each component is trained independently and tuned on task-specific data. To communicate between modules, we use CONCRETE (Ferraro et al., 2014), a data schema used in other text processing systems (Peng et al., 2015). One advantage of using a standardized data schema is that it enables modularization and extension. Unless there are annotation dependencies, individual modules can be inserted.

\footnote{\textsuperscript{2}XLM-R itself is trained on one hundred languages.}
Figure 1: Architecture of LOME. The system processes text documents as input and first uses a FrameNet parser to detect entities and events. Then, a suite of models enrich the entities and events with additional predictions. Each individual model can be trained and tuned independently, ensuring modularity of the pipeline. Annotations between models are transferred using CONCRETE, a data schema for NLP.

replaced, merged, or bypassed depending on the application. We discuss two example applications of our CONCRETE-based modules, one of which further extracts relations and the other performs cross-sentence argument linking for events.

2 Tasks

The overarching application of LOME is to extract an entity- and event-centric knowledge graph from a textual document. In particular, we are interested in using these graphs to support a multilingual schema induction task (KAIROS), for which data is currently being annotated by the LDC (Cieri et al., 2020). As a result, some parts of the system are designed for compatibility with the KAIROS event and entity ontology. Nonetheless, there is significant overlap with publicly available datasets, which we describe for those tasks.

Figure 1 presents the architecture of our pipeline. Besides the FrameNet parser, which is run first, the remaining modules can be run in any order, if at all. In addition, our use of a standardized data schema for communication allows for the integration of third-party systems. In this section, we will go into further detail for each task.

2.1 FrameNet Parsing

FrameNet parsing is a semantic role labeling style task. The goal is to find all the frames and their roles, as well as the trigger spans associated with them in a sentence. Frames are concepts, such as events or entities, in a sentence. Every frame is associated with some roles, and both of them are triggered by spans in the sentence.

Unlike most previous work (Yang and Mitchell, 2017; Peng et al., 2018; Swayamdipta et al., 2018), our system is not conditioned on the trigger spans or frames. We perform “full parsing” (Das et al., 2014), where the input is raw sentence, and the output is the complete structure predictions.

As the first model in the whole pipeline system, the trigger spans found by the FrameNet parser will be used as candidate spans for all other tasks.

2.2 Entity Coreference Resolution

In coreference resolution, the goal is to cluster mentions in the text that refer to the same entity. Neural models for doing so typically encode the text first before identifying possible mentions (Lee et al., 2017; Joshi et al., 2019, 2020). These mentions are scored pairwise to determine whether two mentions refer to each other. These scores then determine coreference clusters by decoding under a variety of strategies (Lee et al., 2018; Xu and Choi, 2020).

In this work, we choose a constant-memory variant of that model which also achieves high performance (Xia et al., 2020). The motivation here is robustness: we prioritize the ability to soundly run on all document lengths over slightly better performing but fragile systems. In addition, because this coreference resolution model is part of a broader entity-centric system, the module used in this system does not perform the mention detection
A portion of the AIDA entity type ontology.

Figure 2: A portion of the AIDA entity type ontology.

step (which is left to the FrameNet parser). Instead, both training and inference assumes given mentions, and the task is to therefore perform linking.

2.3 Entity Typing

Entity typing assigns a fine-grained semantic label to a span of text, where the span is a mention of some entity found in our previous span finder module. Traditionally, labels include PER, GPE, ORG, etc., but recent work in fine-grained entity typing seek to classify spans into types defined by hierarchical type ontologies (e.g. BBN (Weischedel and Brunstein, 2005), FIGER (Ling and Weld, 2012), UltraFine\(^3\) (Choi et al., 2018), COLLIE (Allen et al., 2020)). Such ontologies refine coarse types like PER to fine-grained types such as /person/artist/singer that sits on a type hierarchy. A portion of the AIDA (LDC2019E07) ontology is illustrated in Figure 2.

We employ a recent coarse-to-fine-decoding entity typing model (Chen et al., 2020a) that is specifically designed to assign types that are defined by hierarchical ontologies. We swap the underlying encoder from ELMo (Peters et al., 2018) to \textit{XLM-R} to be able to assign types over mentions in different languages using a single multilingual model, and to enable transfer between languages.

The base typing model in Chen et al. (2020a) supports entity typing on entity mentions. We extend this model to gain the ability to perform entity typing on entities, i.e. clusters of entity mentions. Since our decoder is coarse-to-fine and predicts a type at each level of the type hierarchy, we employ Borda voting on each level. Specifically, given a coreference chain comprising mentions \(m_1, \ldots, m_n\), and the score for mention \(m_i\) being typed as type \(t\) as \(s_{i,t}\), we perform Borda counting to select the most confident type \(t^* = \arg \max_t \sum_i r(i, t)\over all\ t's\ in\ a\ specific\ type\ level,\ where\ r(i, t) = 1/\text{rank}_{\text{rel}}(s_{i,t})\) is the ranking relevance score used in Borda counting.

2.4 Temporal Relation Extraction

The task of Temporal Relation Extraction focuses on finding the chronology of events (e.g., Before, After, Overlaps) in text. Extracting temporal relation is useful for various downstream tasks – curating structured clinical data (Savova et al., 2010; Soysal et al., 2018), text summarization (Glavas and Snajder, 2014; Kedzie et al., 2015), question-answering (Llorens et al., 2015; Zhou et al., 2019), etc. The task is most commonly viewed as a classification task where given a pair of events, and its textual context, the temporal relation between them needs to be identified.

The construction of the TimeBank corpus (Pustejovsky et al., 2003) largely spurred the research of temporal relation extraction. It included 14 temporal relation labels. Other corpora (Verhagen et al., 2007, 2010; Sun et al., 2013; Cassidy et al., 2014) reduced the number of labels to a smaller number owing to lower inter-annotator agreements and sparse annotations. Various types of models (Chambers et al., 2014; Cheng and Miyao, 2017; Leeuwenberg and Moens, 2017; Ning et al., 2019; Vashishtha et al., 2019; Zhou et al., 2020) have been used in the recent years to extract temporal relations from text.

In this work, we use Vashishtha et al. (2019)’s best model and retrain it using \textit{XLM-R}. We evaluate their model using the transfer learning approach described in their work and retrain it on TimeBank-Dense (TBD) (Cassidy et al., 2014). TBD uses a reduced set of 5 temporal relation labels – before, after, includes, is included, and vague.

3 System Design

3.1 Modularization

Our system is modularized into separate models and libraries that communicate with each other using \textit{CONCRETE}, a data format for richly annotating natural language documents (Ferraro et al., 2014). Each component is independent of each other, which allows for both inserting additional modules or deleting those provided in the default pipeline. We choose this loosely-affiliated design to enable both faster and independent prototyping.
of individual components, as well as better compartmentalization of our models.

We emphasize that the system is a pipeline: while individual modules can be further improved, the system is not designed to be trained end-to-end and benchmarking the richly-annotated output depends on the application and priorities. In this paper, we only benchmark individual components and describe a couple of applications.

### 3.2 System Inputs and Outputs

The system can consume, as input, either tokenized or untokenized text, which is first tokenized either by whitespace or with a multilingual tokenizer, PolyGlot.\(^4\) However, this tokenization is not necessarily used by all modules, which may choose to either operate on the raw text itself or on a Sentence-Piece (Kudo and Richardson, 2018) retokenization.

The system outputs a CONCRETE communication file for each input document. This output file contains annotations including entities, events, coreference, entity types, and temporal relations. This schema used is entirely self-contained and the well-documented library also contains tools for visualizing and inspecting CONCRETE files.\(^5\) For the web demo, the output is displayed in the browser.

### 4 Evaluation Benchmarks

#### 4.1 FrameNet Span Finding

The FrameNet parser is comprised of an XLM-R encoder, a BIO tagger, and a typing module. It encodes the input sentences into a list of vectors, used by both the BIO tagger and the typing module. The goal of BIO tagger is to find trigger spans, which are then labeled by the typing module. To parse a sentence, we run the model to find all frames, and then find their roles conditioned on the frames.

We train the FrameNet parser on the FrameNet v1.7 corpus following Das et al. (2014), with statistics in Table 1. We evaluate the results with exact matching as our metric,\(^6\) and get 63.91 labeled F1 or 69.01 unlabeled F1. Since we are not aware of previous work on both full parsing and a metric for its evaluation, we do not have a baseline. However, we can force the model to perform frame identification given the trigger span, like prior work. These results are shown in Table 2.

#### 4.2 Coreference Resolution

We retrain the model by Xia et al. (2020) with XLM-R (large) as the underlying encoder and with additional multilingual data. The model is a constant-memory variant of neural coreference resolution models. We refer the reader to Xia et al. (2020) for model and training details.

Unlike that work, we operate under the assumption that we are provided gold spans. This is motivated by the location of coreference in LOMe. In addition, while they use a frozen encoder, we found that finetuning improves performance.\(^7\) Finally, we train on the full OntoNotes 5.0 (Weischedel et al., 2013; Pradhan et al., 2013), a subset of SemEval 2010 Task 1 (Recasens et al., 2010), and two additional sources of Russian data, RuCor (Toldova et al., 2014) and AnCor (Budnikov et al., 2019).

We benchmark the performance of our model on each language. We report the average F1 of MUC (Vilain et al., 1995), B\(^3\) (Bagga and Baldwin, 1998), and CEAF\(_{φ}\) (Luo, 2005) by language in Table 3. We can compare the model’s performance to monolingual gold-only baselines, where they exist. For English, we can train an identical model but instead use SpanBERT (Joshi et al., 2020), an English-only encoder finetuned for English OntoNotes coreference. That model achieves 92.2 average (dev.) F1, compared to our 92.7. There is also a comparable system for Russian AnCor from Le et al. (2019), which achieves 79.9 F1 using the model from Lee et al. (2018) and RuBERT (Kuratov and Arkhipov, 2019). This shows that our single, multilingual model, can perform similarly to monolingual models, with the advantage that our model does not need to perform language ID. This finding mirrors prior findings showing multilingual encoders are

\(^4\)https://github.com/aboSamoor/polyglot

\(^5\)http://hltcoe.github.io/concrete/

\(^6\)A role is considered to be correctly predicted only when its frame is precisely predicted.

\(^7\)We use AdamW and a learning rate of $5 \times 10^{-6}$. 

| Model                  | Accuracy |
|------------------------|----------|
| Yang and Mitchell (2017)| 88.2     |
| Hermann et al. (2014)   | 88.4     |
| Peng et al. (2018)      | 90.0     |
| This work               | 95.6     |

Table 2: Result on frame identification

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|------------------------|----------|
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| Peng et al. (2018)      | 90.0     |
| This work               | 95.6     |

Table 1: Statistics of FrameNet v1.7

\[^4\]https://github.com/aboSamoor/polyglot

\[^5\]http://hltcoe.github.io/concrete/
4.3 Entity Typing

We retrain the coarse-to-fine entity typer by Chen et al. (2020a) with XLM-R as the underlying encoder, and using the AIDA ontology as the type label inventory. The dataset annotated from AIDA is relatively small. To make the model more robust, we pre-train the model using extra training data from GAIA (Li et al., 2020), where they obtained YAGO fine-grained types (Suchanek et al., 2008) from the results of Freebase entity linking, and mapped these types to the AIDA ontology. After pre-training, we fine-tune the model using the AIDA M18 and M36 data with 3-fold cross-validation, where each fold is distinct in the topics of these documents.

| Data source | Language | # of entities |
|-------------|----------|---------------|
| AIDA M18    | English  | 4,433         |
|             | Russian  | 4,826         |
| LDC2019E07  | Ukrainian| 4,261         |
| AIDA M36    | English  | 703           |
|             | Spanish  | 557           |
| LDC2020E29  | Russian  | 729           |
| GAIA        | English  | 42.8M         |
|             | Spanish  | 11.1M         |
|             | Russian  | 2.4M          |

Table 4: Statistics of various datasets for entity typing.

Our models perform well in these datasets. Using one third of the AIDA M36 data as dev, our method obtained 60.1% micro-F1 score with pre-training using GAIA extra data, we get 76.5%.

Our system can also be extended to support other commonly used fine-grained entity type ontologies. We report the results in micro-F1 in Table 5.

Table 3: Average F1 scores by language with gold mentions. The superscripts O indicates data from OntoNotes 5.0 (dev), S indicates data from SemEval 2010 Task 1 (dev), and A is the AnCor data (test).

4.4 Temporal Relation Extraction

We retrain Vashishtha et al. (2019)'s best fine-grained temporal relation model on UDS-T (Vashishtha et al., 2019) using XLM-R (large). We then use their transfer learning approach and train an SVM model on event-event relations in TimeBank-Dense to predict categorical temporal relation labels. With this approach, we see a micro-F1 score of 56 on the test set of TBD.

For better performance, we train the same model on additional TempEval3 (TE3) dataset (UzZaman et al., 2013). Since TE3 and TBD use a different set of temporal relations, we consider only those instances that are labeled with 4 temporal relations from both TE3 and TBD for joint training – before, after, includes (container), and is included (contained). We retrain Vashishtha et al. (2019)'s transfer learning model on the combined TE3 and TBD dataset considering only these 4 relations and evaluate on their combined test set. Results on the combined test set are reported in Table 6.

| Relation   | Precision | Recall | F1  |
|------------|-----------|--------|-----|
| before     | 68        | 89     | 77  |
| after      | 74        | 69     | 71  |
| includes   | 83        | 5      | 10  |
| is included| 44        | 15     | 22  |

Table 5: Performance of our hierarchical entity typing model across several typing ontologies.

Table 6: Result on the combined test set of TempEval3 and TimeBank-Dense when trained with just 4 temporal relation labels.

5 Extensions

5.1 Incorporating third-party systems

Besides the core components described above, we also discuss the viability of including additional modules that may not fit directly in the core pipeline but can be included depending on the downstream application. For example, the system described above does not predict any relation

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8 Please refer to Chen et al. (2020a) for the exact definitions of the evaluation metric.
information, which was needed for a motivating application of downstream schema inference. To do so, we wrote a CONCRETE and Docker wrapper around OneIE (Lin et al., 2020) and attached it at the end of the pipeline. With our CONCRETE based design, the integration of any third-party module can be done via implementing the AnnotateCommunicationService service interface, which can ensure compatibility between LOME and external modules. The OneIE wrapper is one example of an external module.

5.2 Mix and Match Modules: SM-KBP

As another example application, we reconfigured our pipeline for the NIST SM-KBP 2020 Task 1 evaluation, which aims to produce document-level knowledge graphs. Each given document may be in English, Russian, or Spanish. On a development set consisting solely of text-only documents, we started with initial predictions, through GAIA (Li et al., 2020), for entity clusters, entity types, events and relations. Our goal was to recluster and relabel the dataset for knowledge extraction.

Our pipeline consisted of multilingual coreference resolution (using predetermined mention spans), the hierarchical entity typing model, and a separate state-of-the-art argument linking model (Chen et al., 2020b). We found improved performance with entity coreference (from 29.1 F1 to 33.3 F1), especially in Russian (from 26.2 F1 to 33.3 F1), likely due to our use of multilingual data and encoders. The improved entity clusters also led to downstream improvements in entity typing and argument linking. This example highlights the ability to pick out subcomponents of LOME and customize according to the downstream task.

6 Usage

We present two methods to interact with the pipeline. The first is a Docker container which contains the libraries, code, and trained models of our pipeline. This is intended to run on batches of documents. As a lighter demo of some of the system capabilities, we also have a web demo intended to interactively run on shorter documents.

Docker Our Docker image consists of the four core modules: FrameNet parser, coreference resolution, entity typing, and temporal resolution. Furthermore, there are two options for entity typing: a fine-grained hierarchical model (with the AIDA typing ontology) and a coarse-grained model (with the KAIROS typing ontology). The container and documentation is available on Docker Hub.

As some modules depend on GPU libraries, the image also requires NVIDIA-Docker support. Since there is a high start-up (time) cost for using Docker and loading models, we recommend using this container for batch processing of documents. Further instructions for running can be found on the LOME Docker Hub page.

Web Demo We make a few changes for the web demo. To reduce latency, we preload the models into memory and we do not write the CONCRETE communications to disk. At the cost of modularity, this makes the demo lightweight and fast, allowing us to run it on a single 16GB CPU-only server. To present the predictions, our front-end uses AllenNLP-demo.

In addition, the web demo is currently limited to FrameNet parsing and coreference resolution, as other models will increase latency and may impede usability. The web demo is intended to highlight only some of the system’s capabilities, like its ability to process multilingual documents.

7 Conclusions

To facilitate increased interest in large-ontology, multilingual, document-level knowledge extraction, we create and demonstrate LOME, a system for event and entity knowledge graph creation. Given input text documents, LOME runs a full FrameNet parser, coreference resolution, fine-grained entity typing, and temporal relation prediction. Furthermore, each component uses XLM-R, allowing our system to support a broader set of languages than previous systems. The pipeline uses a standardized data schema, which invites extending the pipeline with additional modules. By releasing both a Docker image and presenting a lightweight web demo, we hope to enable the community to build on top of LOME for even more comprehensive information extraction.
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