# IELM: An Open Information Extraction Benchmark for Pre-Trained Language Models 

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#### Abstract

We introduce a new open information extraction (OIE) benchmark for pre-trained language models (LM). Recent studies have demonstrated that pre-trained LMs, such as BERT and GPT, may store linguistic and relational knowledge. In particular, LMs are able to answer "fill-in-the-blank" questions when given a pre-defined relation category. Instead of focusing on pre-defined relations, we create an OIE benchmark aiming to fully examine the open relational information present in the pretrained LMs. We accomplish this by turning pre-trained LMs into zero-shot OIE systems. Surprisingly, pre-trained LMs are able to obtain competitive performance on both standard OIE datasets (CaRB and Re-OIE2016) and two new large-scale factual OIE datasets (TAC KBP-OIE and Wikidata-OIE) that we establish via distant supervision. For instance, the zeroshot pre-trained LMs outperform the F1 score of the state-of-the-art supervised OIE methods on our factual OIE datasets without needing to use any training sets. ${ }^{1}$


## 1 Introduction

Pre-trained language models (LM), such as BERT (Devlin et al., 2018) and GPT-3 (Brown et al., 2020), have revolutionized NLP over the last several years and advanced the state-of-theart results in a wide set of downstream NLP tasks. Recent studies show that a considerable amount of linguistic (Hewitt and Manning, 2019; Clark et al., 2019) and relational knowledge (Petroni et al., 2019; Talmor et al., 2019; Jiang et al., 2020; Petroni et al., 2020) has been captured by the pretrained LMs via pre-training on large-scale textual corpora. These approaches often design "fill-in-theblank" questions based on pre-defined relations. For example, a question "Bob Dylan was born in

[^0]_" is manually created for the LMs to answer the "birthplace" relation of "Bob Dylan".

Most existing approaches that evaluate what pretrained LMs have learned are based on benchmarks with pre-defined relation categories. Yet, the benchmarks present two limitations. First, most benchmarks only cover a limited number of pre-defined relations. Therefore, it is unclear whether the pretrained LMs have stored general open relation information. For example, the Google-RE in LAMA benchmark (Petroni et al., 2019) includes only three relations (i.e., "birthplace", "birthdate", and "deathplace"), while there are hundreds of relations available in the real world scenario. Second, a majority of benchmarks evaluate LMs in a close manner. This means that the gold relation is given to the models. For example, "was born in" is given as the model's input. Besides, the existing benchmarks often provide a single gold relation for each input sentence. However, an input sentence may indicate multiple relations, e.g., containing both "birthplace" and "birthdate" information about an argument or entity. We are curious: instead of the limited relational information, can we systematically benchmark the general information stored in the pre-trained LMs?

In this work, we set up a new open information extraction (OIE) benchmark, called IELM, towards testing the general and open relational information stored in pre-trained LMs. We refer to OIE as it is a task that is designed to extract open relations from massive corpora without requiring a pre-defined relation category. As shown in Figure 1, we successfully convert pre-trained LMs to zero-shot OIE systems. We apply them to two standard OIE datasets, including CaRB (Bhardwaj et al., 2019) and ReOIE2016 (Stanovsky and Dagan, 2016; Zhan and Zhao, 2020), as well as two new large-scale factual OIE datasets in our IELM benchmark. We show that the zero-shot pre-trained LMs outperform the fully supervised state-of-the-arts on fac-


Figure 1: Summary of our approach. The zero-shot open information extraction system takes a noun phrase (NP) chunked sentence as input, and outputs a set of triples. The approach first conducts argument extraction by encoding NPs as argument pairs, then performs predicate extraction via decoding using the parameters (i.e., attention scores) of the pre-trained language models. The output extractions are then evaluated on our IELM benchmark.
tual OIE datasets. Standard OIE datasets rely on human annotations and often consist of thousands of gold triples and sentences. Unlike those datasets, we create two large-scale OIE datasets, namely TAC KBP-OIE and Wikidata-OIE, via distant supervision from knowledge graphs. For example, Wikidata-OIE is constructed via aligning English Wikipedia to Wikidata triples, resulting in millions of triples and documents. The design of zero-shot LMs for OIE is important: by encoding the noun chunks as arguments in the input, we only make use of the parameters of pre-trained LMs to decode the predicates (or relations) between the arguments. To the best of our knowledge, this is the first attempt to systematically evaluate pre-trained LMs in a zero-shot OIE setting. To summarize, our key contributions are the following.

1. We benchmark the general relational information in pre-trained LMs on our IELM benchmark. Besides two standard OIE datasets (CaRB and Re-OIE2016), we also create two largescale factual OIE datasets for our benchmark. The two new OIE datasets are called TAC KBPOIE and Wikidata-OIE, which are constructed via distant supervision from two knowledge graphs (TAC KBP and Wikidata). Our benchmark is a general OIE benchmark, helping the development of future OIE systems.
2. We enable the zero-shot capabilities of pretrained LMs for OIE by encoding the arguments
in the input and decoding predicates using the parameters of pre-trained LMs. The pre-trained LMs are particularly good at recovering factual arguments and predicates.
3. We test the OIE performance of 6 pre-trained LMs (BERT and GPT-2 (Radford et al., 2019) families) and 14 OIE systems on IELM benchmark. The zero-shot LMs achieve state-of-theart OIE performance on TAC KBP-OIE and Wikidata-OIE, even outperforming fully supervised OIE systems.

## 2 Language Models as Zero-Shot Information Extractors

For open information extraction (OIE), we take an input as a NP-chunked sentence and output a set of triples. Below is an example.

Input Dylan $_{\mathrm{NP}}$ was born in MinnesotanP, and was awarded Nobel Prize ${ }_{\text {NP }}$.
Output (Dylan; born in; Minnesota), (Dylan; awarded; Nobel Prize).

NP denotes the noun phrase.

### 2.1 Argument Extraction

Follow traditional linguistic OIE systems such as Stanford OpenIE (Angeli et al., 2015) and OpenIE5 (Saha et al., 2017, 2018), we treat each NP pair as an argument pair (e.g., "Dylan" and "Minnesota"). We then utilize the parameters of LMs to extract the predicates (e.g., "born in") between the pair in the input as below.

### 2.2 Predicate Extraction

The predicate extraction problem is formulated as extracting a set of sequences in the input that are associated with an argument pair. We particularly use the attention scores in a pre-trained LM to measure the relevance between a sequence and the argument pair. We frame the process as a search problem. Given an argument pair, we aim to search for the sequences with the largest attention scores connecting the pair. To compute a score for every possible sequence is computationally expensive especially when the sequence length is large, the exhaustive search is therefore intractable. We adapt beam search as an approximate strategy to efficiently explore the search space. Beam search maintains the $k$-best candidates. This means the time cost of beam search does not depend on the sequence length, but on the size of the beam and

Step 0 Sylan

| Step | Action | Partial candidate | Total score |
| :--- | :--- | :--- | :--- |
| 0 | START | (Dylan; | 0 |
| 1 | YIELD | (Dylan; born | 0.2 |
| 2 | YIELD | (Dylan; born in; | 0.5 |
| 3 | STOP | (Dylan; born in; Minnesota) | 0.7 |

(a) Predicate extraction example.

(b) Attention matrix.

Figure 2: Illustration of predicate extraction with a pre-trained language model (LM). The upper part of (a) represents the general search steps of producing the triple (Dylan; born in; Minnesota) from the input "Dylan ${ }_{\mathrm{NP}}$ was born in Minnesota ${ }_{\mathrm{NP}}$ " encoded with argument noun phrases (NP). The lower portion shows the corresponding step-by-step process. (b) shows the attention scores generated through the forward pass of the LM over the corresponding input.
the average length of the candidates. In general, the beam search starts with the first argument (e.g., "Dylan"). At each step, beam search simply selects top- $k$ next tokens with the largest attention scores, and just keeps $k$ partial candidates with the highest scores, where $k$ is the beam size. When a candidate produces the second argument (e.g., "Minnesota"), the candidate is complete.

We show a running example as follows. Let's first consider the search from left to right with beam size equal to 1 . An example search process is shown in Figure 2. Given an argument pair "Dylan" and "Minnesota", at each step, the search performs one of the following actions:

- START the search from first argument. The first argument is added as an initial candidate into the beam. In Figure 2(a), at step 0, "Dylan" is added into the beam. The total attention score is initialized to 0 .
- YIELD a new partial candidate in the beam if the current candidate has not reached the second argument. This action conducts the following: The next largest attended token is appended to the end of the current candidate to yield the new candidate. The total score is increased by the associated attention score. At step 1 of Figure 2(a), "born" is appended to the current candidate to yield the partial candidate, since "born" has the largest attention score ( 0.2 as highlighted in Figure 2(b)) with "Dylan" in the attention matrix. The total score becomes 0.2 . Note that we only consider the single head attention in this example for simplicity. "x" in Figure 2(b) marks the tokens (prior to the current token) that are not considered in the search to prevent searching
backward. Step 2 takes the same action, and the score becomes 0.5 .
- STOP the search step if the candidate has reached the second argument, then add the candidate as a valid triple into the beam. As beam size equals to 1, (Dylan; born in; Minnesota) is returned for the given pair. The final score of the triple is 0.7 .

We also notice triples are often in reverse order in the sentence, thus enabling bidirectionality by running the algorithm in both directions (left to right and right to left). We merge the subwords as words, and only consider word-level attention. The beam search is implemented by the breadth-first search, which is efficient as the time complexity is $O(k \cdot d) . d$ is the maximum depth of the search tree.

## 3 The IELM Benchmark

### 3.1 Datasets

### 3.1.1 Standard OIE

We adopt two standard OIE datasets below.
CaRB CaRB (Bhardwaj et al., 2019) is a crowdsourced OIE dataset, where the input sentences are from the OIE2016 (Stanovsky and Dagan, 2016).

Re-OIE2016 Re-OIE2016 (Zhan and Zhao, 2020) is also generated based on the input sentences in the OIE2016, and is further enhanced by human annotations.

### 3.1.2 Factual OIE

In addition, we introduce two large-scale factual OIE datasets based on knowledge graphs (KG).

| Method | AIDA |  |
| :--- | :---: | :---: |
|  | dev | test |
| Spitkovsky and Chang 2012 | 26.0 | 28.2 |
| Kolitsas et al. 2018* | - | 82.4 |
| Ours | 63.8 | 64.5 |

Table 1: Evaluation of unsupervised entity linking of Wikidata-OIE on AIDA benchmark. An asterisk (*) indicates a supervised method.

TAC KBP-OIE TAC Knowledge Base Population (KBP) Slot Filling is a task to search a document collection to fill in a target entity for predefined relations (slots) with a given entity in a reference KG. We adapt the dataset as an OIE dataset. In particular, we use a document sub-collection of the TAC KBP 2013 task (Surdeanu, 2013) as the input, and use the official human annotations regarding the documents as gold extractions.

Wikidata-OIE Besides TAC KBP-OIE, we create a larger factual OIE dataset based on the English Wikipedia. Different from TAC KBP, there are no gold triple annotations for Wikipedia. Since a large amount of Wikidata triples are from English Wikipedia, we create the dataset using distant supervision (Zhang et al., 2017) by aligning Wikidata triples to Wikipedia text. We employ an unsupervised entity linker based on a pre-built mention-to-entity dictionary (Spitkovsky and Chang, 2012) to extract potential gold arguments for scalability considerations. The entity linker links an arbitrary entity mention in a sentence to a Wikipedia anchor, which is further linked to a Wikidata entity. For each sentence in Wikipedia articles containing two linked arguments, if there is a Wikidata triple describing a relation holding the two arguments, we denote the Wikidata triple as a gold extraction.

Unlike TAC KBP-OIE which is built based on human annotations, Wikidata-OIE is derived from automatic annotations. Therefore, we evaluate our unsupervised entity linker on the standard AIDA benchmark (Hoffart et al., 2011) consisting of Wikipedia entities. Table 1 shows that it significantly improves the unsupervised performance (Spitkovsky and Chang, 2012) and reaches competitiveness with a supervised method (Kolitsas et al., 2018). Given the scale of Wikidata-OIE, we sacrifice acceptable effectiveness for efficiency.

The statistics of the datasets are shown in Table 2. For CaRB and Re-OIE2016, we report the statistics of the corresponding test sets. We include a dataset

| Dataset | \# of triples | \# of arguments | \# of predicates | \# of documents |
| :--- | :---: | :---: | :---: | :---: |
| Re-OIE2016 | 1,508 | 3,328 | 1,506 | 595 |
| CaRB | 2,715 | 6,226 | 2,715 | 641 |
| TAC KBP-OIE | 27,655 | 39,661 | 41 | $3,877,207$ |
| Wikidata-OIE | $27,368,562$ | $6,047,494$ | 1,156 | $6,047,494$ |

Table 2: Dataset statistics of the IELM benchmark.
comparison in Appendix A.3.

### 3.2 Pre-Trained Language Models for OIE

Unidirectional Language Models Given an input sequence $\mathbf{x}=\left\{x_{1}, x_{2}, \ldots, x_{N}\right\}$, unidirectional LMs assign a joint probability to the sequence by factorizing it as $p(\mathbf{x})=\prod_{t} p\left(x_{t} \mid x_{t-1}, \ldots, x_{1}\right)$, where $p\left(x_{t} \mid x_{t-1}, \ldots, x_{1}\right)=\sigma\left(\mathbf{W h}_{t}+\mathbf{b}\right) . \mathbf{h}_{t}$ is the output vector of a neural network at position $t$.

We consider GPT-2 (Radford et al., 2019), where $\mathbf{h}_{t}$ is produced by Transformer decoders (Vaswani et al., 2017). GPT-2 is pre-trained on WebText containing 40 GB of text. We explore all four pretrained GPT-2s with different model sizes: GPT$2(117 \mathrm{M})$, GPT- $2_{\text {MEDIUM }}(345 \mathrm{M})$, GPT- $2_{\text {LARGE }}$ (774M), and GPT-2XL (1558M).

Bidirectional Language Models Different from unidirectional LMs that predict the next word given the previous words, bidirectional LMs take both left and right context of the target word into consideration, formally, $p\left(x_{t}\right)=$ $p\left(x_{t} \mid x_{1}, \ldots, x_{t-1}, x_{t+1}, \ldots, x_{N}\right)$.

We use BERT (Devlin et al., 2018) that enables bidirectional context modeling via a masked LM objective and utilizing the Transformer architecture. BERT is pre-trained on BooksCorpus and English Wikipedia. We use both its pre-trained settings: BERT $_{\text {BASE }}(109 \mathrm{M})$ and BERT LARGE (335M).

### 3.3 Comparison Methods

We compare our method with a wide set of OIE systems including both neural and traditional linguistic OIE systems. Most OIE systems are based on supervised learning, which are indicated with asterisks $(*)$ in Table 3. We provide details of the comparison systems in Appendix A.5.

### 3.4 Evaluation Method

### 3.4.1 Standard OIE

On CaRB and Re-OIE2016, we follow the original evaluation proposed in (Bhardwaj et al., 2019) and (Stanovsky and Dagan, 2016; Zhan and Zhao, 2020), and report precision, recall, F1, area under the curve (AUC) for compared OIE systems. AUC
is calculated from a plot of the precision and recall values for all potential confidence thresholds. The F1 is the maximum value among the precisionrecall pairs. We follow the matching function proposed for each dataset, i.e., lexical match for ReOIE2016, and tuple match for CaRB. The CaRB evaluation function is stricter as it penalizes long extractions.

### 3.4.2 Factual OIE

We report precision, recall, and F1 of the OIE systems on two large-scale factual OIE datasets: TAC KBP-OIE and Wikidata-OIE. We introduce exact match as the matching function for them as below.

Matching Function The matching functions for standard OIE datasets are generally flexible. For example, the lexical match of Re-OIE2016 judges an argument or predicate as correct if and only if it includes the syntactic head of the gold argument or predicate. Unlike these matching functions, our exact matching function requires both arguments and predicates are linked to the gold extractions.

For TAC KBP-OIE, we judge an argument to be correct if and only if it matches the name of the gold argument and the span position of the gold argument in the sentence. The main challenge is how to properly link a predicate, since there are often many ways to express it. We follow Stanford OpenIE (Angeli et al., 2015) to produce the predicate mapping between the OIE relations and TAC KBP predicates. A predicate is correct if the pair of OIE relation and gold predicate exists in the predicate mapping. The predicate mapping is constructed in two steps. First, a collection of predicate mappings was constructed by a single annotator in approximately a day. Second, predicate mappings were finalized through the following learning procedure. This process matches OIE relations to the TAC KBP predicates by searching for co-occurrent relations in a large distantly-labeled corpus, and decides pairs of OIE relations and TAC KBP predicates that have a high $\mathrm{PMI}^{2}$. The basic idea is that the more often the argument pairs of the triples and TAC KBP triples are linked, the more likely the corresponding relations or predicates are linked to each other. Example predicate mappings are shown in Appendix A.4.

For Wikidata-OIE, we link an argument based on the entity linker used in Wikidata-OIE construction (Sec. 3.1). An argument is correct if the linked argument matches the name of the gold argument and
the span position of the gold argument in the sentence. The predicate mapping is bootstrapped from TAC KBP-OIE's mapping. In addition, we normalize each predicate phrase of the triples by lemmatization, and removing inflection, auxiliary verbs, adjectives, adverbs. One author manually filters out the bad predicate pairs. This process takes approximately a day. A predicate is correct if the OIE to gold predicate pair exists in the bootstrapped predicate mapping. An annotator randomly subsampled and checked 100 aligned triple-sentence pairs and concluded with a $93 \%$ accuracy of extracted triples.

Metrics We use the official scorer of TAC KBP Slot Filling 2013 to calculate precision, recall, and F1 for TAC KBP-OIE. Besides, like previous OIE systems, for LMs, we adopt two constraints from ReVerb (Fader et al., 2011), the antecessor of OpenIE5: (i) the frequency of predicates must be above a threshold aiming to avoid triples to be overspecified, and (ii) a predicate must be a contiguous sequence in the sentence avoiding predicates that have no meaningful interpretation. We set these parameters according to Sec. 4.4.

We only report precision, recall, and F1 based on the parameter study in Sec. 4.4 for pre-trained LMs on the IELM benchmark. We do not compute AUC as pre-trained LMs are treated as zeroshot OIE systems. We therefore do not tune the results with respect to different confidence. Our main focus is to benchmark the OIE performance of the LMs under a unified setting. Another reason is that it is computationally expensive to get the AUC on the two large-scale datasets: TAC KBPOIE and Wikidata-OIE. We also do not report AUC for the compared OIE systems on TAC KBP-OIE and Wikidata-OIE. Instead, we use the confidence threshold that obtains the best F1 on Re-OIE2016 to compute the scores.

## 4 Results

In this section, we show that pre-trained LMs are effective zero-shot OIE systems, and exceed the previous state-of-the-art OIE systems on our largescale factual OIE datasets in IELM benchmark. To keep our evaluation as simple as possible, the hyperparameters and settings are shared across datasets. More experimental details are described in the appendix.

| Method | \#Params | CaRB |  |  |  | Re-OIE2016 |  |  |  | TAC KBP-OIE |  |  | Wikidata-OIE |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | P | R | F1 | AUC | P | R | F1 | AUC | P | R | F1 | P | R | F1 |
| MinIE (Gashteovski et al., 2017) | - | - | - | 41.9 |  | 48.2 | 71.1 | 57.5 | 47.2 | - | - |  | - | - |  |
| ClausIE (Del Corro and Gemulla, 2013) | - | - | - | 44.9 | 22.4 | - | - | 64.2 | 46.4 | - | - | - | - | - | - |
| OLLIE (Schmitz et al., 2012) | - | - | - | 41.1 | 22.4 |  | - | 49.5 | 31.3 | - | - | - | - | - |  |
| PropS (Stanovsky et al., 2016) | - | - | - | 31.9 | 12.6 |  | - | 64.2 | 43.3 | - | - | - | - | - | - |
| OpenIE4 (Christensen et al., 2011) | - | - | - | 48.8 | 27.2 | - | - | 68.3 | 50.9 | 52.9 | 14.2 | 22.4 | 30.6 | 14.0 | 19.2 |
| OpenIE5 (Saha et al., 2017, 2018) | - | - | - | 48.0 | 25.0 | 61.1 | 76.5 | 67.9 | 45.8 | 57.0 | 14.6 | 23.2 | 26.3 | 14.4 | 18.6 |
| Stanford OpenIE* (Angeli et al., 2015) | - | - | - | 23.0 | 13.4 | - | - | 16.7 | 11.5 | 61.6 | 17.4 | 27.1 | 23.3 | 13.1 | 16.8 |
|  | ${ }^{6} \overline{4} 0 \overline{\mathrm{~K}}$ |  | - | 28.2 | - | - | - |  | -- | -- |  |  |  |  |  |
| SpanOIE* (Zhan and Zhao, 2020) | 963K | 60.9 | 41.6 | 49.4 | 30.0 | 79.7 | 74.5 | 77.0 | 65.8 | - | - | - | - | - |  |
| NeuralOIE* (Cui et al., 2018) | 5M | - | - | 51.6 | 32.8 | 79.2 | 77.5 | 78.4 | 73.0 | - | - | - | - | - |  |
| Multi ${ }^{2}$ OIE* (Ro et al., 2020) | 110M | 60.9 | 45.8 | 52.3 | 32.6 | 86.9 | 81.0 | 83.9 | 74.6 |  | - | - | - | - | - |
| RnnOIE* (Stanovsky et al., 2018) | 965K | 55.6 | 40.2 | 46.7 | 26.8 | 84.2 | 73.9 | 78.7 | 68.3 | 50.0 | 14.6 | 22.6 | 29.9 | 15.9 | 20.7 |
| IMOJIE* (Kolluru et al., 2020b) | 110M | 64.7 | 45.6 | 53.5 | 33.3 | 88.1 | 67.1 | 76.2 | 63.1 | 58.2 | 14.9 | 23.8 | 31.2 | 16.2 | 21.3 |
| OpenIE6* (Kolluru et al., 2020a) | 220M | - | - | 54.0 | 35.7 | 75.3 | 78.2 | 76.7 | 73.8 | 60.0 | 14.9 | 23.9 | 29.8 | 15.3 | 20.3 |
|  | ${ }^{-109} 9 \mathrm{M}$ | $\overline{2} 1.2$ | 18.3 | 19.7 |  | 25.9 | 34.0 | 29.4 |  | $\overline{6} 1.6$ | 18.8 | 28.8 | 32. ${ }^{\text {a }}$ | $\overline{1} \overline{8} . \overline{9}$ | $\overline{2} \overline{3} \cdot \overline{7}$ |
| BERT ${ }_{\text {LARGE }}$ (zero-shot) (ours) | 335M | 22.4 | 20.2 | 21.2 | - | 30.7 | 38.5 | 34.1 | - | 61.7 | 19.0 | 29.1 | 32.3 | 19.1 | 24.0 |
| GPT-2 (zero-shot) (ours) | 117M | 23.1 | 19.8 | 21.3 |  | 25.1 | 38.3 | 30.3 | - | 61.6 | 18.2 | 28.1 | 32.4 | 18.1 | 23.2 |
| GPT-2 ${ }_{\text {MEDIUM }}$ (zero-shot) (ours) | 345M | 23.7 | 20.0 | 21.7 | - | 26.8 | 39.9 | 32.0 | - | 62.1 | 18.7 | 28.7 | 33.1 | 18.2 | 23.5 |
| GPT-2 LARGE (zero-shot) (ours) | 774M | 24.2 | 20.5 | 22.2 | - | 27.4 | 41.6 | 33.0 | - | 62.4 | 19.0 | 29.1 | 34.2 | 18.3 | 23.8 |
| GPT-2 ${ }^{\text {XL }}$ (zero-shot) (ours) | 1558M | 24.5 | 21.0 | 22.7 | - | 29.3 | 43.4 | 35.0 | - | 62.7 | 19.5 | 29.7 | 35.7 | 18.5 | 24.4 |

Table 3: Compare the quality of different OIE systems. An asterisk (*) indicates a supervised method.

### 4.1 OIE Results

Table 3 shows the results. While zero-shot OIE systems synthesized by pre-trained LMs obtain notably lower scores compared to previous OIE systems on standard OIE datasets, they outperform the previous OIE systems on factual OIE datasets. We also find that larger LMs obtain improved results on all datasets. For example, BERT LARGE outperforms BERT $_{\text {BASE }}$ due to its larger model size. GPT-2s share similar trends. This is because larger LMs store richer relational information. This finding is consistent with previous studies (Petroni et al., 2019, 2020).

### 4.1.1 Standard OIE

The main reasons for the degraded performance of pre-trained LMs on standard OIE datasets are three-fold. First, the comparison methods mainly involve supervised systems that are trained on OIE datasets, which are denoted with asterisks (*) in Table 3. Besides the supervised systems, the remaining comparison systems all require human involvement, such as providing linguistic patterns for the extraction. In contrast, the pre-trained LMs are used as zero-shot OIE systems without using any training sets. Second, the zero-shot OIE modules still have room to improve. For example, approximately $30.0 \%$ of the argument extraction errors are due to the spaCy noun chunker. $16.9 \%$ of the gold extractions contain predicates outside the argument pairs. The current predicate extraction only allows searching between the arguments, and thus cannot handle such cases. Third, standard OIE benchmarks
such as CaRB and Re-OIE2016 mainly examine the general information extraction capability. The zero-shot approach is not able to recall the information of interest in LMs. We might need a specific module (e.g., ranking) to locate such information. Interestingly, pre-trained LMs achieve comparable performance with supervised Stanford OpenIE. The result indicates pre-trained LMs contain informative patterns that are useful for OIE.

### 4.1.2 Factual OIE

As shown in Table 3, the best zero-shot OIE system based on GPT- $2_{\text {XL }}$ obtains a $+2.6 \%$ and $a+3.1 \%$ absolute F1 improvement on TAC KBP-OIE and Wikidata-OIE respectively over the previous supervised state-of-the-art. Due to the computation cost of OIE systems (Sec. 4.3), we only select several best performed OIE systems on the standard OIE datasets for the large-scale OIE experiments including: linguistic OIE systems (OpenIE4, OpenIE5, Stanford OpenIE) and neural OIE systems (RnnOIE, IMOJIE, OpenIE6).

Compared to the results on standard OIE datasets, pre-trained LMs consistently achieve state-of-the-art performance on both datasets. Both datasets emphasize measuring factual arguments and predicates in the reference KGs. Previous studies (Petroni et al., 2019, 2020) show that LMs have stored a considerable amount of factual information via pre-training on large-scale text. We draw the same conclusion. To the best of our knowledge, our IELM benchmark is the first benchmark that includes factual OIE datasets. More importantly, both

| Method | MinIE | ClausIE | OLLIE | PropS | OpenIE 4 | OpenIE 5 | Stanford OpenIE | SpanOIE | RnnOIE |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Sentences/sec. | 8.9 | 4.0 | 14.5 | 4.6 | 20.1 | 3.1 |  | 2.5 | 19.4 | 149.2 |
| Method | NeuralOIE | IMOJIE | Multi $^{2}$ OIE | OpenIE 6 | BERT $_{\text {BASE }}$ | BERT $_{\text {LARGE }}$ | GPT-2 | GPT-2 MEDIUM | GPT-2 LARGE | GPT-2 2 XL |
| Sentences/sec. | 11.5 | 2.6 | 21.2 | 142.0 | 16.2 | 11.9 | 13.9 | 12.7 | 11.5 | 11.0 |

Table 4: Runtime on Re-OIE2016.
linguistic and neural OIE systems are derived from manually designed linguistic patterns or learned patterns. The result shows that the pre-trained attention weights capture a more flexible set of factual patterns. The result also suggests that our approach is capable of using such patterns. In order to scale our approach to large-scale datasets, the argument and predicate extraction are both efficient by design. In particular, the beam search for predicate extraction is efficient in exploring the relational sequences in the input sentence. Besides, the attention scores used in the beam search are produced via a single forward pass of the pre-trained LM over the input sentence without fine-tuning.

Moreover, we find that BERT LMs outperform GPT-2 LMs under similar model sizes. On both datasets, BERT BASE performs better than GPT- 2 in F 1 , and BERT LARGE outperforms GPT- $2_{\text {MEDIUM }}$ in F1. This is mainly because the recall of BERT LMs is higher than that of corresponding GPT-2 LMs. The result indicates that the Cloze-style loss function (i.e., masked LM) of BERT is more effective and flexible in recovering information than the autoregressive LM objective. We also notice that the precision of GPT-2 LMs is higher than that of BERT LMs. The reason is that the autoregressive LM objective captures more accurate information than Cloze-style loss does by preventing extra noise (e.g., masked tokens) in pre-training.

Pre-trained LMs achieve competitive precision, e.g., the precision is greater than $60 \%$ on TAC KBPOIE. However, only moderate recalls are obtained. Therefore, improving recall is clearly the future direction. We find that both argument and predicate extraction can be further improved. For example, the main cause of the moderate recall is the incorrect arguments caused by spaCy noun chunks as summarized in Sec. 4.2. Besides, we can incorporate predicates that are not between the argument pairs into the extractions, as we observe a number of gold triples are in inverted sentences. We also notice that the F1 gain over previous state-of-the-arts on TAC KBP-OIE is smaller compared to that on Wikidata-OIE. A larger text corpus, e.g.,

Wikipedia, provides more information. We could improve the recall by running on larger corpora such as WebText2 and Common Crawl (Raffel et al., 2019; Brown et al., 2020) to collect more triples.

### 4.2 Error Analysis

There is still significant room to improve the results. We argue that we are measuring a lower bound for what LMs know. To further understand the shortcomings of the current method, we conduct an error analysis of the errors in precision on all datasets. We choose BERT $_{\text {LARGE }}$ for the study. We sample 100 documents from the Wikidata-OIE dataset, and manually check the reasons for the errors. We find $33.1 \%$ of the errors are caused by incorrect arguments, while the predicate phrases are correct. The errors are due to the incorrect noun chunks detected by the spaCy. $18.3 \%$ of the errors are due to the missing pairs in predicate mapping. We also note that approximately $23.8 \%$ of the errors are actually correct triples that are not covered by Wikidata. For example, (Bob_Dylan, residence, Nashville) does not exist in Wikidata, but it is a correct triple. The rest of the errors made by $\mathrm{BERT}_{\text {LARGE }}$ are incorrect predicate phrases, such as uninformative phrases. We find similar errors are made by $\mathrm{BERT}_{\text {LARGE }}$ on other datasets. Based on the above analysis, enhancing argument detection and predicate mapping is helpful to further improve the results.

### 4.3 Runtime Analysis

The runtime of OIE systems is crucial in practice. We test the runtime of different OIE systems on Re-OIE2016. The results are in Table 4. We find ours is competitive in terms of efficiency given the size of the models.

### 4.4 Parameter Study

We study the effects of the key parameters using BERT $_{\text {BASE }}$ on TAC KBP-OIE as shown in Figure 3 . We randomly sample $20 \%$ of the oracle query entities (provided by TAC KBP) as a hold-out


Figure 3: Parameter study with BERT $_{\text {BASE }}$ on TAC KBP-OIE hold-out subset.
dataset to tune the parameters, and use the best parameter setting achieved for all experiments. When studying the effect of a certain parameter, we keep the remaining parameters as default. We use F1 to measure the effects. Additional details are described in Appendix A.2.3.

## 5 Related Work

Pre-trained language models (LM), e.g., BERT (Devlin et al., 2018), GPT (Radford et al., 2018, 2019), and large LMs over 100B parameters (Brown et al., 2020; Chowdhery et al., 2022; Zeng et al., 2022) contain growing amount of linguistic and factual knowledge obtained via pre-training on large-scale corpora. To evaluate their abilities, researchers have created many knowledge benchmarks. LAMA leverages manually created prompts (Petroni et al., 2019, 2020). Recent studies have also developed soft prompts (Liu et al., 2021; Zhong et al., 2021)) for fact retrieval. KILT (Petroni et al., 2021) proposes a knowledge-intensive benchmark concerning several downstream tasks to evaluate LMs' ability in capturing knowledge. Wang et al. (2022) have utilized a set of knowledge-intensive structure prediction tasks to evaluate the knowledge in pre-trained LMs. Shen et al. (2022) have adapted KG completion as a benchmark to evaluate LMs. Besides relational knowledge, closedbook OpenQA (Roberts et al., 2020) benchmarks (in which LMs answer the open-domain questions without retrieving contexts) have also been adopted as a way to evaluate LMs' knowledge. While the existing benchmarks evaluate LMs in an implicit
way, the main difference is that our benchmark explicitly and interpretably evaluates triples from the textual corpora extracted using model parameters (e.g. attentions). In the field of neural network interpretation (Linzen et al., 2016; Adi et al., 2016; Tenney et al., 2019), in particular the pre-trained deep LM analysis, substantial recent work focuses on both visualizing and analyzing the attention (Vig, 2019; Jain and Wallace, 2019; Clark et al., 2019; Michel et al., 2019; Ramsauer et al., 2020). Instead of analyzing or visualizing, our benchmark quantitatively evaluates the relational information with respect to open information extraction.

Open information extraction systems, e.g., OLLIE (Schmitz et al., 2012), Reverb (Fader et al., 2011), Stanford OpenIE (Angeli et al., 2015), OpenIE 5 (Saha et al., 2017, 2018), RnnOIE (Stanovsky et al., 2018), and OpenIE 6 (Kolluru et al., 2020a) aim to extract triples from web corpora for open schema KGs. Besides, NELL (Carlson et al., 2010), DeepDive (Niu et al., 2012), Knowledge Vault (Dong et al., 2014) extract information based on a fixed schema or ontology, where humans help improve the accuracy of the extractions. Probase (Wu et al., 2012) produces taxonomies instead of rich typed relations in general KGs. Our benchmark first evaluates LMs' unsupervised information extraction ability on common open information extraction datasets such as CaRB (Bhardwaj et al., 2019) and Re-OIE2016 (Zhan and Zhao, 2020), and then aligns the extracted triples to KG triples for large-scale knowledge extraction benchmark construction. Our algorithm is similar to
the generation algorithm in DeepEx (Wang et al., 2021). The focus of this work is to benchmark the zero-shot OIE performance of pre-trained LMs on both standard and factual OIE datasets. To further improve the OIE performance, the ranking module in DeepEx can be useful. The structure pre-training proposed in (Wang et al., 2022) can also be helpful.

## 6 Conclusion

We benchmark the general relational information in pre-trained language models (LM) in an open information extraction (OIE) setup. We find that the pretrained LMs contain a considerable amount of open relational information through large-scale evaluation on both standard OIE datasets and newly created large-scale factual OIE datasets in our IELM benchmark. We are able to turn pre-training LMs into zero-shot OIE systems to efficiently deliver the benchmark results. The reach of this result is broad and has potential downstream utility for deep neural network interpretation, information extraction, and knowledge graph construction. Although the results are promising, we argue that our results just indicate a lower bound about what the LMs have. We hope our results will foster further research in the LM OIE benchmark direction.

## 7 Limitations

For the limitations of our method, the argument extraction module of our algorithm relies on a thirdparty noun chunker. As reported, the noun chunker introduces the majority of the errors in our extraction results. A limitation in our benchmark is that we have not conducted a large-scale manual evaluation of our factual OIE datasets (TAC KBP-OIE and Wikidata-OIE). The main focus of our study is to provide a large-scale OIE benchmark. As a result, this makes our benchmark more challenging to be used than standard OIE datasets in terms of computation costs and infrastructure. Finally, we have only benchmarked BERT and GPT-2 on our datasets. Future work could include testing a wide range of language models on our benchmark.

## 8 Ethical Considerations

We hereby acknowledge that all of the co-authors of this work are aware of the provided ACM Code of Ethics and honor the code of conduct. This work is about benchmarking the zero-shot OIE capability of pre-trained language models including BERT and GPT. Our ethical considerations and the work's
underlying future impacts are discussed in the following perspectives. Language models are known to present potential risks and limitations (Brown et al., 2020), and the corpus used in pre-training (such as Wikipedia) may introduce unwanted biases and toxicity. We do not anticipate the production of harmful outputs after using our method or datasets, especially for vulnerable populations.

## 9 Environmental Impact

We adopt the pre-trained language models BERT (Devlin et al., 2018) and GPT-2 series (Radford et al., 2019) in our IELM benchmark. The models' carbon footprints are estimated to be 22-28 kilograms (Gibney, 2022). Additionally, The focus of this study is to test the zero-shot OIE ability of pre-trained language models. We do not train language models on massive datasets. Instead, we only do inference on a few evaluation datasets. This cost is less than $0.1 \%$ energy than that of their pre-training. This demonstrates that developing proper zero-shot learning strategies for large language models can not only deepen our understanding of their latent mechanisms, but also further reduce the energy consumption and environmental impacts that language models with ever-growing size may cause.

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## A The IELM Benchmark Details

Additional details of our open information extraction (OIE) benchmark IELM are described in this section.

## A. 1 Wikidata-OIE

In this section, we describe some technical details regarding the construction and evaluation of Wikidata-OIE.

## A.1.1 Entity Linking

We use an unsupervised entity linker for both Wikidata-OIE dataset construction and OIE evaluation. The entity linker is originally developed in (Spitkovsky and Chang, 2012), which is based on a mention-to-entity dictionary. We build an enhanced dictionary as follows: we add new Wikipedia anchors to the dictionary which results in 26 million entries compared to the original 21 million entries. Then a Wikipedia anchor to the Wikidata item dictionary is used to further link the entities (or arguments) to Wikidata. If an argument is a pronoun, we further use neuralcoref ${ }^{2}$ for coreference resolution.

## A.1.2 Predicate Mapping

The predicate mapping of Wikidata-OIE is constructed offline using the method in Sec. 3.4. In more detail, we randomly sampled a hold-out dataset including 2,000 documents from English Wikipedia for the bootstrapped predicate mapping construction based on the TAC KBP mapping (Angeli et al., 2015). To filter out the wrong predicate pairs, we manually check whether the top predicate phrases are true.

## A.1.3 Gold Triples

For gold triples in Wikidata-OIE, we only preserve those triples describing predicates between arguments that can be linked to corresponding Wikipedia anchors. We rule out triples of attributes about arguments and triples of auxiliary predicates (such as topic's main category.P901) and finally result in 27,368,562 gold triple extractions.

## A.1.4 Evaluation

Given the large number of source sentences and gold triples in Wikidata-OIE, a MongoDB database is maintained to store the gold triples to enable an efficient evaluation.

## A. 2 Zero-Shot Language Model Based Open Information Extraction

In this section, we introduce additional details about how we adapt pre-trained language models (LM) as zero-shot OIE systems.

## A.2.1 Argument Extraction

We use spaCy noun chunker ${ }^{3}$ to annotate the noun phrases in the sentences.

[^1]```
Algorithm 1 Beam search with attention scores.
Input: Argument pair \(\left(\arg g_{0}, \arg g_{1}\right)\), sentence \(s\), attention
    matrix \(\mathbf{A}_{\mathbf{s}}\), action manager \(\mathcal{O}=\{\) START, YIELD, STOP \(\}\),
    beam size \(k\)
Output: Triples \(T_{\left(\text {arg }_{0}, \text { arg }_{1}\right)}\)
    1: \(T_{\left(\arg _{0}, \arg _{1}\right)} \leftarrow\left\{\operatorname{START}\left(\arg _{0}\right)\right\} \triangleright\) Start by adding the
    first argument as a candidate in the beam
    while \(\exists c \in T_{\left(\text {arg }_{0}, \arg _{1}\right)}[\mathcal{O}(c)=\) YIELD \(]\) do
        \(\widetilde{T}_{\left(\text {arg }_{0}, \arg _{1}\right)} \leftarrow \emptyset \quad \triangleright\) Initialize a new beam
        for each \(c \in T_{\left(\text {argo }_{0}, \text { arg }_{1}\right)}\) do
            if \(\mathcal{O}(c)=\) YIELD then
                \(\widetilde{T}_{\left(\text {arg }_{0}, \text { arg }_{1}\right)} \leftarrow \quad \widetilde{T}_{\left(\arg _{0}, \text { arg }_{1}\right)} \cup\)
    \(\left\{\operatorname{YIELD}\left(c, s, \mathbf{A}_{s}\right)\right\} \triangleright\) Yield a new candidate if not reached
    the second argument
            else
                            \(\widetilde{T}_{\left(\arg _{0}, \arg _{1}\right)} \leftarrow \widetilde{T}_{\left(\arg _{0}, \arg _{1}\right)} \cup\{\operatorname{STOP}(c, t)\}\)
    \(\triangleright\) Stop then produce a valid triple if reached the second
    argument
                end if
        end for
        \(T_{\left(a^{2} g_{0}, a r g_{1}\right)} \leftarrow \operatorname{TOP}\left(k, \widetilde{T}_{\left(\arg _{0}, \arg _{1}\right)}\right) \quad \triangleright\) Maintain
    \(k\)-best candidates in the beam
    end while
    return \(T_{\left(\arg _{0}, \text { arg }_{1}\right)}\)
```


## A.2.2 Predicate Extraction

We first describe predicate extraction introduced in Sec. 2.2 in detail.

- Beam Search. The inputs of the search algorithm are an argument pair $\left(a r g_{0}, a r g_{1}\right)$, a sentence $s$, an attention matrix $\mathbf{A}_{s}$ of $s$. Both $\arg _{0}$ and $\arg _{1}$ are identified by the noun chunker in $s . \mathbf{A}_{s}$ is the attention matrix associated with $s$ from the forward pass of an LM without fine-tuning. The search gets started by adding the first argument $\arg _{0}$ as the initial candidate in the beam. While there are still new candidates waiting to be yielded, the search continues, and the top $k$ candidates sorted by the attention scores are maintained in the beam. The details of the proposed beam search are described in Algorithm 1. In practice, we implement an action manager $\mathcal{O}$ to decide which action to take at each step. Given a candidate $c$ in the beam, $\mathcal{O}(c)=$ START always happens at the beginning of the search. If $c$ has not reached the second argument $\arg g_{1}$ yet, $\mathcal{O}(c)=$ YIELD. Otherwise, $\mathcal{O}(c)=$ STOP.
- Implementation Details. For Wikidata-OIE, we randomly split the English Wikipedia data into 20 partitions, and map the data partitions to 20 distributed servers to run. Each server is configured with four Tesla K80 12Gs. We set the max sequence length to 256 , and batch size as 32 for BERT $_{\text {LARGE }}$ and 4 for GPT- $2_{\text {XL }}$. We use implementations of pre-trained LMs in the

Transformers package ${ }^{4}$. We use spaCy sentencizer ${ }^{5}$ to segment the documents into sentences. BERT LARGE takes approximately 48 hours, and GPT- $2_{\text {xL }}$ costs around 96 hours. The resulting triples from the 20 servers are then reduced to a data server. The batch sizes of BERT BASE , GPT2 , GPT- $2_{\text {MEDIUM }}$, GPT- $2_{\text {LARGE }}$ are $64,32,16$, 8 respectively.

## A.2.3 Parameter Settings

We then discuss the parameter setup of our OIE systems as below.

The parameter settings are shared across all OIE datasets. All the choices are based on the parameter study in Sec. 4.4. The beam size of Algorithm 1 is set to 6 . The attention score threshold is set to 0.005 , and the number of relation/predicate frequencies is set to 10 . To generate the attention weight matrix $\mathbf{A}_{s}$ of a sentence, we reduce the weights of every attention head in the last layer of pre-trained LMs using the mean operator. We analyze the effects of various parameters below.

Figure 3(a) illustrates the effects of various beam sizes in Algorithm 1. We find that in general, the larger the beam size is, the better F1 the setting achieves. This is because our method is able to reserve more potentially correct triples when more candidates are allowed. However, F1 improvement gradually becomes subtle, while the computation costs increase more significantly. For efficiency consideration, we do not explore larger beam sizes. We set the beam size as 6 .

Figure 3(b) compares the effect of different thresholds of the total score. We set the threshold as 0.005 since it achieves the best result. Note that the summed attention score is normalized by the length of the triple to penalize the cumbersome triples. The threshold is effective. This is mainly because of the relational information contained in the self-attention matrix: the score in the attention matrix is representing the chance of the triples to be the true triples based on the stored information. Figure 3(c) shows the impact of the predicate frequency threshold in identifying common predicates. The best result is achieved when it equals 10 . This shows that while our method mostly identifies frequent predicates, it is also able to capture some rare predicates.

Figure 3(d) shows the comparison between the attention weights of the last layer and the mean of

[^2]all layers. The attention weights of the last layer perform better. This is due to the attention weights in lower layers being low-level linguistic knowledge according to (Clark et al., 2019; Ramsauer et al., 2020), which are less relevant to the relational information. Figure 3(e) compares the impact of different attention reductions, i.e., mean, max, over the attention heads of the last layer. We find the "mean" performs better. The reason is that the token often intensively attends to several specific tokens in the sequence (Michel et al., 2019), and the "mean" operator is less sensitive to such biases.

## A. 3 The Number of Predicates of Standard and Factual OIE Datasets

Note that there are more predicates in standard OIE datasets than that in factual datasets. This is because, for standard OIE, predicates are open and not attached to a certain schema. These predicates were extracted from the input sentences and are usually natural language utterances. For factual OIE, the predicates are unified into a fixed KG schema. For example, for a person's birthplace, there are multiple natural language expressions like "was born in" or "gave birth" in standard OIE datasets, while only a single "birth_place" predicate exists in the factual OIE sets.

## A. 4 Predicate Mapping Examples

We show example predicate mappings in a dictionary below.

- per:city_of_birth: born in, born at, born, birth city, hometown.
- org: founded_by: established by, founded by, founded, founder, co-founder of.
where the keys are KG predicates, e.g., per:city_of_birth and org:founded_by. The values are the corresponding OIE relations.


## A. 5 Comparison Systems

We compare our zero-shot OIE systems with the following OIE systems.

## A.5.1 Neural OIE Systems

The following neural network based systems are selected.

- SenseOIE (Roy et al., 2019) ${ }^{6}$ learns to ensemble various previous unsupervised OIE systems' ex-

[^3]tractions using supervised learning to combine their strengths.

- SpanOIE (Zhan and Zhao, 2020) ${ }^{7}$ presents the Re-OIE2016 datasets for a more rigorous evaluation and a span-based (instead of sequence labeling) extraction model.
- RnnOIE (Stanovsky et al., 2018) ${ }^{8}$ is one of the state-of-the-art OIE systems. It uses LSTM to model the OIE problem as a sequence tagging problem, and is trained on a large-scale OIE training set.
- NeuralOIE (Cui et al., 2018) ${ }^{9}$ is an encoderdecoder based architecture that adopts the copy mechanism to conduct OIE.
- IMOJIE (Kolluru et al., 2020b) ${ }^{10}$ is a sequence generation based OIE model that uses BERT at encoding time.
- Multi ${ }^{2}$ OIE (Ro et al., 2020) ${ }^{11}$ models OIE as a sequence labeling problem that combines BERT with multi-head attention blocks.
- OpenIE6 (Kolluru et al., 2020a) ${ }^{12}$ is one of the state-of-the-art OIE systems. It treats OIE as a 2-D grid labeling task, and trains a BERT family architecture for the task.

Note that while our methods are zero-shot without needing to use the specific training sets, all the neural OIE systems are supervised on corresponding training sets.

## A.5.2 Linguistic OIE Systems

We also compare our systems with the following linguistic pattern based systems developed prior to the use of neural networks.

- MinIE (Gashteovski et al., 2017) ${ }^{13}$ proposes to minimize facts in OIE by representing information by annotations rather than extraction and removing redundant specific information.
- ClausIE (Del Corro and Gemulla, 2013) ${ }^{14}$ is a clause-based approach by first identifying lin-

[^4]guistic structure and then their information and attributes.

- OLLIE (Schmitz et al., 2012) ${ }^{15}$ uses contextual sentence decomposition to conduct OIE.
- PropS (Stanovsky et al., 2016) ${ }^{16}$ proposes proposition structure which is implied from syntax using dependency trees.
- OpenIE4 (Christensen et al., 2011) ${ }^{17}$ is the successor to OLLIE using similar argument and relation expansion heuristics to create OIE extractions from semantic role labeling frames.
- OpenIE5 (Saha et al., 2017, 2018) ${ }^{18}$ is one of the state-of-the-art OIE systems, which is the successor to OLLIE, and it improves extractions from noun relations, numerical sentences, and conjunctive sentences depending on the linguistic patterns.
- Stanford OpenIE (Angeli et al., 2015) ${ }^{19}$ leverages POS tag and dependency parser, and generates self-contained clauses from long sentences to extract the triples.


## B The TAC KBP-OIE and Wikidata-OIE Datasets

We show samples of our zero-shot OIE extractions and the gold triples on both TAC KBP-OIE and Wikidata-OIE datasets.

## B. 1 TAC KBP-OIE

OIE Extractions and Gold Extractions We randomly sample 100 documents from the TAC KBP-OIE corpus, then sample sentences from those documents. The uncurated triples and the corresponding gold triples of the sampled sentences based on our best methods BERT $_{\text {LARGE }}$ and GPT- $2_{\text {xL }}$ are shown in Figure 4 and Figure 5 respectively. We also randomly sample sentences in which BERT ${ }_{\text {LARGE }}$ differs from GPT- $2_{\mathrm{XL}}$ in the resulting triples for comparison, which are illustrated in Figure 6. In each table, "ID" represents the document ID of a sampled sentence in the TAC KBP-OIE corpus. "Sentence" indicates the sampled sentence. "Triples to gold triples" column contains the extraction triples (on the left side of

[^5]$" \rightarrow$ ") and their corresponding gold triples (on the right side of " $\rightarrow$ ").

## B. 2 Wikidata-OIE

OIE Extractions and Gold Extractions Similar to TAC KBP-OIE, we randomly sample 100 documents from the Wikidata-OIE corpus (i.e., English Wikipedia), then sample sentences from those documents. Similar to TAC KBP-OIE, Figure 7 and Figure 8 show the uncurated triples and the corresponding gold triples of the sampled sentences based on our zero-shot systems BERT LARGE and GPT- $2_{\text {XL }}$ respectively. Figure 9 illustrates the randomly sampled sentences in which BERT $_{\text {LARGE }}$ extracts different triples compared to that from GPT-2 XL . In each table, "ID" represents the Wikipedia page's title of the sampled sentence. "Sentence" indicates the sampled sentence. "Triples to gold triples" column contains the triples (on the left side of " $\rightarrow$ ") and their corresponding gold triples (on the right side of " $\rightarrow$ ").

| In |
| :--- | :--- |

Figure 4: BERT $_{\text {LARGE }}$ on TAC KBP-OIE.

| II |  |  |
| :---: | :---: | :---: |
| 13.15 ENGOOH | Butins |  |
|  |  |  |
| ${ }_{\text {SFIS_ENG_007 }}$ |  |  |
|  |  | verity) |
| SFI3-ENG_OM9 | Hc look fificc in 2006 b by detataing long | (Lorgsin |
| SFI |  |  |
|  | Marshall is charged with grand lacceny and frad d and faces 4 p 1025 y cars in prison if 6 | larshall, with, Fraud) $\rightarrow$ (An) |
| SFI]_ENG_OII | Marshall, a Tony Award-winning Broadway producer and former U.S. diplomat, sat stonelike as the jury forewoman read each verdict aloud, the word "guilty" clearly resonating in the otherwise silent courtroom. |  |
| STI3-ENG_OIT |  | grandlar |
|  | dad |  |
| chisenconil | But Marshalis som, Philp, told a aifierern st |  |
| ${ }^{\text {Pr }}$ 3-ENG_O12 |  | (Adam Gidahh, also kown, Azzam) $\rightarrow$ (Addam Giadan, perailermate_n |
| SFI3 E.ENG.012 | Gadatn, also known as A Azam the American, was bom in 1 1978. |  |
| SFl3_ENG_O12 | Gadahn grew up in California and converted to Islam before he moved to Pakistan in 1998 and attended an al-Qaida training camp media reports. |  |
| SFI3_ENG_OM2 |  |  |
|  | asa tanalator and |  |
| Sfiseng_oit |  |  |
| SFIS ENG_OIS |  |  |
| ${ }^{\text {a }}$ |  |  |
|  |  |  |
| SFI3-ENG_(20) |  |  |
|  |  | (Peenerer by his broher, John) $\rightarrow$ (Mike Penerer. pers.shlings, John) |
|  |  |  |
| ${ }^{\text {Pri3 ENG } 025}$ | Michijan native Nancy Kisel Was sonvicted of murder and seneneced in Hong Kongs H High Court in Scplember 2005. | (Michigan Native Nancy K Kisel, convicted of, Murter) $\rightarrow$ (Nimey Ki |
|  | aremeremer |  |
| 3_EN | In 1953, she married Roald and other tales for children. |  |
| ENG | Osar-wiming yerress Patac |  |
|  | Hakim's son. Ammaral.hakim, |  |
| ENG | A-Hakim is the cead of Supreme lraq isd | (A1-Hakim, of, Supreme Iraqi Islamic Councill) |
| SFI3_ENG_ |  |  |
| SF13-ENG_(028 |  the next Billy Mays, his son Billy Mays III. | The Next Bily Mays, his son, Bily Mays iii) $\rightarrow$ (Billy Mays, per:hilden, Billy Mays III) |
| \% 129 |  |  |
|  |  |  |
|  | Alan Trammell at shortstop, Lou Whitaker at second base, Kirk Gibson in the outfield and Jack Morris on the pitching staff. |  |
| SFI3-ENG_I30 |  | (Anderson, is survived by his sons, Lee) $\rightarrow$ (Sparky Anderson, percribilden, Lec) |
| SFI3_ENG_331 | Blakce Edurds a w | (Blalke Edwards, writer) $\rightarrow$ (Blake Edwurds. peritic, witer) |
|  |  |  |
| ${ }^{\text {SFI3_ENG_332 }}$ |  | five. Scoul) $\rightarrow$ (Hwang Jang.-Yop. Pr |
| SFI3,ENG_035 |  academics. |  |
| SFI3 ENEGOU36 |  |  |
| SFI3.ENG_336 |  |  |
| SFI3, ENG. 036 |  |  |
| SFI3-ENG_(136 | Koirala was born in 1925 in Bihar of India at the time when his father Krishna Prasad Koirala along with his family was exiled by |  |
| ${ }_{\text {SFI3_ENG_037 }}$ |  |  |
|  |  |  |
| Sfliseng (338 | ${ }^{\text {The }}$ |  |
| ENC |  |  |
| NG 039 |  |  |
| ENG_(041 |  Wcanesdy | (Don Hewit., The chs Newsman) $\rightarrow$ (Don Hewit, perituc, newsman) |
| SFI3-ENG_(94) | He was the consummat celevision ney | (Don Hewitl, execeutive) $\rightarrow$ (Don Hewitit perfille e exceutive) |
| , | Minutes news program, told Recues. |  |
| ENG |  |  |
| ${ }_{\text {SFIS }}$ ENG 0103 |  |  |
| 3.ENG_O44 |  family to Stair Galleries in Hudson, N.Y., which will auction them Nov. 20 |  |
|  |  | (Chares Gwathey, , architect) $\rightarrow$ (Charies Gwalthey, prituc, architect) |
| Stiz |  |  |
|  | he worked for BM M in New I | $\rightarrow$ (Ben |
|  |  | Dt. percemployecoor_member_of , IBM) |
|  |  |  |
|  |  |  |
| Fl3_ENG_S66 | "Its ani iscut for evershody in. |  |
| $\mathrm{SFP13}^{\text {a }}$ | "We'll be mecting with scientists, university and science policy officials to explore praticical opportunitics for exchange and colliab- | (The Aasas President, , Agre) $\rightarrow$ (American A |
| SFI3 ENNG_(600 |  |  |
|  |  | orgtop memberss.employeses, Ala |
|  |  |  |
|  | ment of Science: Roger Martin, dean of the Reomman School of Managecment: Brian O Neill, a fomer president of the Insurance |  |
| SFI3EENG_062 |  |  |
| SFIT EVGG.064 |  |  |
|  |  | orgtop_members_ cmployes, Bates Sill) |
| Sti3_ENG_064 |  |  |
|  | and have more and more sophisticated means of violence, are becoming bigger and bigger challenges to the international system," said Bates Gill, director of the Stockholm International Peace Rescarch Institute | Instiute, org_top_members_ _mployeces, Bates Gill) |
|  |  | (The Indoor Timming Asscocition, dircector of, John Ovestrect) $\rightarrow$ (Indoor Timning |
|  | said in a statement Saturay. |  |
| SFI3 ENGGO.076 |  |  |
| 6.076 | The majority of voters in Switzerland, which manages more than 25 percent of the world's foreign-held private wealth, support banking secrecy, according to a survey published last month by the Swiss Bankers Association in Basel. |  |
| SFI3 ENG_O78 | "Americans have a right to know the truth - Elam is a religion of imolicrance and violecce," said Richard Thompson, Icgal dircetor |  |
|  |  |  |
| ${ }^{\text {SFITSEN }}$ |  | son) |
| SFI3_ENG_(SS4 |  |  |
|  | Obama campaign lats cerr |  |
| Sfiseng _us |  | (The China |
| SFI3-ENG_(899 | RIA Novosti and Incerfax cite Anatoly lsikikin, head of Rosoboronoxxport, as ssying Thursday " noching is blocking He continuation |  |
|  |  |  |
| SFI3EENG_(091 | With his wife, Cornelie, Middelhoff invested money in 2000 and 2001 with Esch in funds that were formed to buy five properties from KarstadtQuelle, as Arcandor was then known, and leased back to the department store chain before Middelhoff joined the |  |
|  |  |  |
|  |  |  |

Figure 5: GPT-2xL on TAC KBP-OIE.


Figure 6: BERT $_{\text {LARGE }}$ vs. GPT- $2_{\mathrm{xL}}$ on TAC KBP-OIE.

| II |
| :--- | :--- | :--- |

Figure 7: BERT $_{\text {LARGE }}$ on Wikidata-OIE.


Figure 8: GPT- $2_{\text {xL }}$ on Wikidata-OIE.

| id | Sentence | Ter $\quad$ Triples togold triples |  |
| :---: | :---: | :---: | :---: |
| Andy_Hibert | In the same cesason he was climectoff wivers by her Pitsburgh Penguis on March | Larce |  |
| Bob, Diplan. 0392 |  |  |  |
|  | n |  | (ily |
| Bones_Hilman | During the hiatus of Midnight Oil, Hillman returned to New Zealand, working as studio and live musician with Dave Dobbyn and recorded the alb |  |  |
| Brent-Hinds | Hinds continest to concentrate on Mastodon, with he |  |  |
| Buch Vivig |  |  |  |
|  | sand cerrificd double platinum in the UK. Unitcd S Sates and Aus |  |  |
| C-Kan | In addition tobeing known as arppere, C-Kan is as alo k kown tor |  | (Marijuana, in, México) $\rightarrow$ (c-kan.Q27734073, country_of_citizenship.P27, mex- |
| harcs_Ginat | Cratiod dicdod fat stroke inst. Louis. | (Gratiot, died, St. Louis) $\rightarrow$ (charles_gratiot_sr..Q2959257, place_of_death.P20,st._louis.Q38022) |  |
|  |  |  |  |
| CherylChan | Cheryl Chan Cheryl Chan Wei Ling, PBM, isas Singuperan politician | (Cheryl Chan Wei Ling, is, A Singaporean Politician) $\rightarrow$ (cheryl_chan.Q22003605, |  |
| Cyba_Aud |  |  |  |
| Doughas_LCmat | He is a Fellow of the AAAS , AAA1, and Cognitive Science Society, and an editor of the J. Automated Reasoning , J. Learning Sciences, and J . Applied Ontology . |  |  |
| Doughas Lenat |  |  |  |
|  |  |  |  |
|  | Despite managing for 39 years he only ever took charge of two clubs, Stockport County and Cardiff City, and he holds the record for longest serving manager in the County and Cardiff City <br> istory of both clubs. |  |  |
| Felix_Tinco | Bom Felix Manuel de Jessisis Tanco y Bosmenicl, in Bogotí, Colombia , he arrived |  |  |
| Gary_Ablet]s. | He also won his second Brownlow Medal, becoming the first Gold Coast player to win the award and the 14 th player in VFL/AFL history to win it twice. win the award and the 14th player in VFL/AFL history to win it twice | (He, also won, His Second Brownlow Medal) $\rightarrow$ (gary_ablett_jr..Q3098509.award_received.P166, leigh_mathews_trophy.Q6519632); (He, also won, His |  |
| Gecto Mongol | After mecting his would - be tag team partner, Bepo Mongol, Tattrie returned to the WWWF as Geto Mongol and The Mongols were brought to the United States in 1968 |  |  |
| Plek |  |  |  |
| roady |  |  |  |
|  |  |  |  |
| Honce_Rawins | Rawlins dict on 22 January 10355 in a nursising home in Recuing, Berkshire. | $\underset{\substack{\text { (Rawlins, died, Reading) } \\ \text { ing__berkshire.Q161491) }}}{\text { (horacac_rawlins.Q4436711, place_of_death.P20, read- }}$ |  |
| Honace_Rawlins | fritesional event at Stanmorec Coiff Club in June 1894 but fnish |  |  |
| Hugowinctralater | Winterhalter remained with RCA Victor until 1963 , at which time he moved to Kapp; that same year, he also penned the main title theme for the film. "Diamond Kapp, |  |  |
| Ioanis TSTiainos | He compectd in the men $\leqslant 4 \times 100$ metess relay at the 1924 Summer Olympics. |  |  |
|  |  |  | (Their Way, in, France) $\rightarrow$ (jaan_of_france._duchess_of_ bery. Q236220, coun- |
| hymardKecyec | John Maynard Keynes John Maynard Keynes , Ist Baron Keynes, was a British economist, whose ideas fundamentally changed the theory and practice of macroe |  |  |
| Jonathan_Cullcr |  |  |  |
|  | chl Univesily |  |  |
| Jordi_Cainas-Percz |  | (The Province, of, Barcelona) $\rightarrow \underset{\text { (jordi_can̄as_pérez_Q557693, }}{ }$ (spanish political_party).Q1393123) |  |
| Jules.Diligny | He conpected in the freesyle lighwe ight event at the 1920 Summer olympics. |  |  |
| L3-Mcreger |  |  |  |
|  | for leading South African newspapers such as the "Sunday Times" and the "Rand Daily Mail " | (Liz Mcgregor, is, A Journalist) $\rightarrow$ (iiz_mcgregor.Q23541069, occupation.P106,journalist.Q1930187) |  |
| Louis_ Shrophirc | The granddaughter of slaves. Louise Shropshire was bom Louise darett on February 15. 1913 in Coffec County Albuma 15, 1913 in Coffee County, Alabama. |  | $\begin{array}{lcccc} \hline \text { (Louise } & \text { Shropshire, was, } & \text { Woffee } & \text { County, } & \text { Alabama) } \\ \text { (louise_shropshire.Q15430857, } & \text { place_of_birth.P19, } & \overrightarrow{\text { cof- }} \end{array}$ |
| Macit_Giridal | He compected in the men 's sournamentat the 1952 Summer Olympics. |  |  |
| Markus Prioll | At the begiming of his carect, Pronll became atarge of some ridicult becausc his |  |  |
| - | name" Proill licrealy means something like" lout" in German. |  |  |
| Monde_Hactec | Their Round Four match against the saw Hadebe score the first senior try of his career in a $27-10$ victory, and the Sharks XV again finished top of the Southern career in a 2 |  |  |
| Nerille_Southall | He moved on to Everton for $£ 150,000$ in 1981 and established himself as the club's first-choice goalkeeper by the $1983-84$ scason. |  |  |
| Olsa_Semenov_Tyan-Shanklaya | diedin | (She, died, Leningrad) $\rightarrow$ (olga_sermenova_tyan-shanskaya_(23922240, place_of_death.P20, saint_petersburg.Q656) |  |
| Parathy_Rathecsh | Parvathy Ratheesh made her film acting debut in 2015 similar to that of her younger brother, Padmaraj through - Fireman | (Her Film, that of her younger brother, Padmaraj Ratheesh) $\rightarrow$ (parvathy_ratheesh.Q19895785, sibling.P3373, padmaraj_ratheesh.Q19895782) |  |
| talla, | In 1993, he ws inducted into he Canadian Fooball Hall of Fime. |  |  |
| Picre_ Dincm | Unlike many former historians, who denigrated the Middle Ages, he endeavored to its most fruitful periods. |  | (The Roman Catholic Church, had, Foster Western Science) (pierre_duhem.Q314172, field_of_work.P101, philosophy_of_science.Q59115) |
| Afrel_A Aradio_Bernal_Supelino | He then served as bishop of the Roman Catholic Diocese of Arauca, Colombia, Com l990 to 2003 and as bishop |  | (The Roman $\quad$ Catholic (rafael_arcadio_bernal_supelano.Q2126904, country_of_citizenship.P27, bia.Q739) |
| Rajchwar_Dayal |  |  |  |
| Ray_Johnson_(American_Focotall) | Ray Johnson Raymond Robert Johnson was an American football defensive back who played three seasons in the National Football League with the Cleveland Rams and Chicago Cardinal | (The National Football League, back who played, Raymond Robert Johnson) $\rightarrow$ (ray_johnson_(american_football).Q21077889, sport.P641, ameri |  |
| Scan_Hmish | Sean Hanish Sean Hanish is an American film writer, producer and director best known for "Saint Judy ", | (Sean Hanish, is, An American Film Writer) $\rightarrow$ (sean_hanish.Q19867622, coun- <br>  |  |
| Schluplum | Bom in Edmonton, Plum played professionally for Chartlon Athlectic, Chelsea and |  |  |
| Scti_Plum | Plum received dis only cap for England atage 23 while playing for Charlton Athletic .starting and playing the full 100 minutes in a $4-1$ win over France on 10 May 1923 |  |  |
| Stanislav_Neckikv |  |  |  |
| Stiliyan Pectov |  |  |  |
|  | me stace |  |  |
| mand | Player of the Year |  |  |
| Thomas_A. Dunn | He graduated from Depaul University College of Law in 1971. |  |  |
| Thomas_Scot_(Commentuter) | In 1803 , Scott left the Lock Hospital to become Rector of Aston Sandford in Buckighamshire where he remained until his death in 1821 | (His Death, he remained until, Aston $\begin{aligned} & \text { Sandford) } \\ & \text { (thomas_scott_(commentator).Q7793831, }\end{aligned}$$\begin{aligned} & \text { ton_sandford.Q3088093) }\end{aligned}$ |  |
| Thor_Hegeratat |  |  |  |
| Venkatest_Kulukani | His first novel, "Naked in Deccan ", won the 1984 American Book Award of the Before Columbus Foundation and was listed among the top ten novels of the decade | (His First Novel, won, The $\quad \begin{gathered}\text { 1984 American Book } \\ \text { (venkatesh_kulkari.Q7920091, }\end{gathered}$$\rightarrow \quad \begin{gathered}\text { Award) } \\ \text { amard_received.P166, }\end{gathered}$ameri- |  |
| Viror_Casto DC_Sosouza | Vitor Castro de Souza Vitor Castro de Souza , or simply Vitor Castro, is a Brazilian strike |  | (Vítor Castro De Souza, is, A Brazilian Striker) $\rightarrow$ (vi- tor_castro_de_souza_Q5604876, position_played_on_team_/_speciality.P413, forward_(association_football)_Q280658) |
| $V_{\text {yaxhesav_Tsaryov }}$ | he Sowict Top Leagye in | (He, for, Fc Dynamo Moscow) $\rightarrow$ (vyachestav_Lsaryov. $Q 45013307$, member_of_sports_team.PS4, fc_dynamo_moscow.Q.Q17497] ber_of_spors_t_tam.P54, kk_ _rabotnicki.02603345) |  |
| Zare_Markovsi | Zure Markovski as player played in KK Rabowicki and MLT Skopje. |  |  |
|  |  |  |  |

Figure 9: BERT $_{\text {LARGE }}$ vs. GPT- $2_{\text {XL }}$ on Wikidata-OIE.


[^0]:    ${ }^{1}$ Our code and datasets are available at https://github. com/cgraywang/IELM.

[^1]:    ${ }^{2}$ https://github.com/huggingface/neuralcoref
    3 https://spacy.io/usage/linguistic-features/\#noun-chunks

[^2]:    ${ }_{5}^{4}$ https://github.com/huggingface/transformers
    5 https://spacy.io/api/sentencizer

[^3]:    ${ }^{6}$ The code is not available.

[^4]:    ${ }^{7}$ https://github.com/zhanjunlang/Span_OIE
    ${ }^{8}$ https://github.com/gabrielStanovsky/supervised-oie
    ${ }^{9}$ We use the BERT implementation available at https://github.com/dair-iitd/ imojie.
    10
    ${ }^{10}$ https://github.com/dair-iitd/imojie
    11 https://github.com/youngbin-ro/Multi20IE
    $12 \mathrm{https}: / /$ github.com/dair-iitd/openie6
    13 https://github.com/uma-pi1/minie
    14 https://www.mpi-inf.mpg.de/departments/

[^5]:    15 https://github.com/knowitall/ollie
    16 https://github.com/gabrielStanovsky/props
    17 https://github.com/allenai/openie-standalone
    18 https://github.com/dair-iitd/OpenIE-standalone
    19 https://nlp.stanford.edu/software/openie.html

