Abstract

We introduce the task of cross-lingual semantic parsing: mapping content provided in a source language into a meaning representation based on a target language. We present: (1) a meaning representation designed to allow systems to target varying levels of structural complexity (shallow to deep analysis), (2) an evaluation metric to measure the similarity between system output and reference meaning representations, (3) an end-to-end model with a novel copy mechanism that supports intra-sentential coreference, and (4) an evaluation dataset where experiments show our model outperforms strong baselines by at least 1.18 \( F_1 \) score.

1 Introduction

We are concerned here with representing the semantics of multiple natural languages in a single meaning representation. Renewed interest in meaning representations has led to a surge of proposed new frameworks, e.g., GMB (Basile et al., 2012), AMR (Banarescu et al., 2013), UCCA (Abend and Rappoport, 2013), and UDS (White et al., 2016), as well as further calls to attend to existing representations, e.g., Episodic Logic (EL) (Schubert and Hwang, 2000; Schubert, 2000; Hwang and Schubert, 1994; Schubert, 2014), or Discourse Representation Theory (DRT) (Kamp, 1981; Heim, 1988).

Many of these efforts are limited to the analysis of English, but with a number of exceptions, e.g., recent efforts by Bos et al. (2017), ongoing efforts in Minimal Recursion Semantics (MRS) (Copes-take et al., 1995), multilingual FrameNet annotation and parsing (Fung and Chen, 2004; Pado and Lapata, 2005), among others. For many languages, semantic analysis can not be performed directly, owing to a lack of training data. While there is active work in the community focused on rapid construction of resources for low resource languages (Strassel and Tracey, 2016), it remains an expensive and perhaps infeasible solution to assume in-language annotated resources for developing semantic parsing technologies. In contrast, bitext is easier to get: it occurs often without researcher involvement, and even when not available, it may be easier to find bilingual speakers that can translate a text, than it is to find experts that will create in-language semantic annotations. In addition, we are simply further along in being able to automatically understand English than we are other languages, resulting from the bias in investment in English-rooted resources.

Therefore, we propose the task of cross-lingual semantic parsing, which aims at transducing a sentence in the source language (e.g., Chinese sen-
tence in Fig. 1) into a meaning representation derived from English examples, via bitext. Our contributions are four-fold:

1. We present a meaning representation, which allows systems to target varying levels of structural complexity (shallow to deep analysis).

2. We design an evaluation metric to measure the similarity between system output and reference meaning representations.

3. We propose an encoder-decoder model to learn end-to-end cross-lingual semantic parsing. With a copying mechanism, the model is able to solve intra-sentential coreference explicitly.

4. We release the first evaluation dataset for cross-lingual semantic parsing. Experiments show that our proposed model achieves an \( F_1 \) score of 38.38, which outperforms several strong baselines.

2 Related Work

Our work synthesizes two strands of research, meaning representation and cross-lingual learning.

The meaning representation targeted in this work is akin to that of Hobbs (2003), but our eventual goal is to transduce texts from arbitrary human languages into a “…broad, language-like, inference-enabling [semantic representation] in the spirit of Montague…” (Schubert, 2015). Unlike efforts such as by Schubert and colleagues that directly target such a representation, we are pursuing a strategy that incrementally increases the complexity of the target representation in accordance with our ability to fashion models capable of producing it.\(^2\) Embracing underspecification in the name of tractability is exemplified by MRS (Copestake et al., 2005; Copestake, 2009), the so-called slacker semantics, and we draw inspiration from that work. Representations such as AMR (Banarescu et al., 2013) also make use of underspecification, but usually this is only implicit: certain aspects of meaning are simply not annotated. Unlike AMR, but akin to decisions made in PropBank (Palmer et al., 2005) (which forms the majority of the AMR ontological backbone), we target a representation with a close correspondence to natural language syntax. Unlike interlingua (Mitamura et al., 1991; Dorr and Habash, 2002) that maps the source language into an intermediate representation, and then maps it into the target language, we are not concerned with generating text from the meaning representation. Substantial prior work on meaning representations exists, including HPSG-based representations (Copestake et al., 2005), CCG-based representations (Steedman, 2000; Baldridge and Kruijff, 2002; Bos et al., 2004), and Universal Dependencies based representations (White et al., 2016; Reddy et al., 2017). See (Schubert, 2015; Abend and Rappoport, 2017) for further discussion.

Cross-lingual learning has previously been applied to various NLP tasks. Yarowsky et al. (2001); Padó and Lapata (2009); Evang and Bos (2016); Faruqui and Kumar (2015) focused on projecting existing annotations on source-language text to the target language. Zeman and Resnik (2008); Ganchev et al. (2009); McDonnell et al. (2011); Naseem et al. (2012); Wang and Manning (2014) enabled model transfer by sharing features or model parameters for different languages. Sudo et al. (2004); Zhang et al. (2017a) worked on cross-lingual information extraction and demonstrated the advantages of end-to-end learning approaches. In this work, we explore end-to-end learning for cross-lingual semantic parsing, as discussed in Section 6.

3 Meaning Representation

The goal of cross-lingual semantic parsing is to provide a meaning representation which can be used for various types of deep and shallow analysis on the target language side. Many meaning representations potentially suitable for this goal, e.g., AMR (Banarescu et al., 2013), UCCA (Abend and Rappoport, 2013), UDS (White et al., 2016), and UDEPLAMBADA (Reddy et al., 2017). In this work, we choose the representation used as a scaffold by UDS, namely the PredPatt meaning representation. Other meaning representations may also be feasible.

PredPatt is a framework which defines a set of patterns for shallow semantic parsing. The reasons for choosing PredPatt meaning representation are three-fold: (1) Compatibility: The PredPatt meaning representation relates to Robust Minimal Recursion Semantics (RMRS) (Copestake, 2007), aiming for a maximal degree of semantic compatibility. With such a meaning representation, shallow analysis, such as predicate-argument extraction (Zhang et al., 2017a), can be regarded as producing a semantics which is underspecified.
and reusable with respect to deeper analysis, such as lexical semantics and inference (White et al., 2016). (2) **Robustness and Speed**: Patterns defined in PredPatt for producing this meaning representation are non-lexical and linguistically well-founded, and PredPatt has been shown to be fast and accurate enough to process large volumes of text (Zhang et al., 2017b). (3) **Cross-lingual validity**: Patterns in PredPatt are purely based on Universal Dependencies, which is designed to be cross-linguistically consistent.

In the following sections, we describe three forms of PredPatt meaning representation (Fig. 2). They are created for different purposes, and are inter-convertible. In this work, the graph representation is used for evaluation, and the linearized representation is used for learning cross-lingual semantic parsing.

### 3.1 Flat Representation

The non-recursive or “flat” representation can be viewed as a Parson-style (Parsons, 1990) and underspecified version of neo-Davidsonianized RMRS (Copestake, 2007). As shown in Fig. 2(a), the flat representation is a tuple \( F = (P, A) \) where \( P \) is a bag of predicates that are all maximally unary, and \( A \) is a bag of arguments represented by separate binary relations.

**Predicate**: Predicates in PredPatt representation are referred as complex predicates: they are open-class predicates represented in the target language. Scope and lexical information in the predicates are left unresolved, yet can be recovered incrementally in deep semantic parsing. From the perspective of RMRS, complex predicates are conjunctions of underspecified elementary predications (Copestake et al., 2005) where handles are ignored, but syntax properties from Universal Dependencies are retained. For instance, in Fig. 2(a), the subscript “h” in the predicate “\( \langle \text{were reported}_h \rangle \)” indicates that “reported” is a syntactic head in the predicate.

**Argument Relation**: The Parson-style flat representation makes arguments first-class predications \( \text{ARG}(\cdot, \cdot) \). Using this style allows incremental addition of arguments, which is useful in shallow semantics where the arity of open-class predicate and the argument indexation are underspecified. They can be recovered when lexicon is available in deep analysis (Dowty, 1989; Copestake, 2007).

### 3.2 Graph Representation

The graph representation as shown in Fig. 2(b) is developed to improve ease of readability, parser evaluation, and integration with lexical semantics. The structure of the graph representation is a triple \( G = (V, I, R) \): a set of variables \( V \) (e.g., \( e_1 \) and \( x \)), a mapping \( I \) from each variable to its instance in the target language (e.g., the dotted arrows in Fig. 2(b)), and a mapping \( R \) from each pair of variables to their argument relation (e.g., the solid arrows in Fig. 2(b)). The graph representation can be viewed as an underspecified version of Dependency Minimal Recursion Semantics (DMRS) (Copestake, 2009) due to the underspecification of scope. Different from DMRS, the graph representation can be linked cleanly to the syntax of Universal Dependencies in PredPatt.
3.3 Linearized Representation

The linearized representation aims to facilitate learning of cross-lingual semantic parsing. Recently parsers based on recurrent neural networks that make use of linearized representation have achieved state-of-the-art performance in constituency parsing (Vinyals et al., 2015), logical form prediction (Dong and Lapata, 2016; Jia and Liang, 2016), cross-lingual open information extraction (Zhang et al., 2017a), and AMR parsing (Barzdins and Gosko, 2016; Peng et al., 2017).

An example of PredPatt linearized representation is shown in Fig. 2(c): Starting at the root node of the dependency tree (i.e., “reported_h”), we take an in-order traversal of its spanning tree. As the tree is expanded, brackets are inserted to denote the beginning or end of a predicate span, and parentheses are inserted to denote the beginning or end of an argument span. The subscript “h” indicates the syntactic head of each span. Intra-sentential coreference occurs when an argument refers to one of its preceding nodes, where we replace the argument with a special symbol “•” and add a coreference link between “•” and its antecedent. Such a linearized representation can be viewed as a sequence of tokens accompanied by a list of coreference links. Brackets, parentheses, syntactic heads, and the special symbol “•” are all considered as tokens in this representation.

4 Evaluation Metric \( S_{(\phi,\psi)} \)

In cross-lingual semantic parsing, meaning representation for the target language can be represented in three forms as shown in Fig. 2. Evaluation of such forms is crucial to the development of algorithms for cross-lingual semantic parsing. However, there is no method directly available for evaluation. Related methods come from semantic parsing, whose results are mainly evaluated in three ways: (1) task correctness (Tang and Mooney, 2001), which evaluates on a specific NLP task that uses the parsing results; (2) whole-parsing correctness (Zettlemoyer and Collins, 2005), which counts the number of parsing results that are completely correct; and (3) Smatch (Cai and Knight, 2013), which computes the similarity between two semantic structures.

Nevertheless, in cross-lingual semantic parsing where instances of predicates are represented in the target language, we need an evaluate metric that can be used regardless of specific tasks or domains, and is able to differentiate two parsing results that have not only similar structures but also similar predicate instances. We design an evaluation metric \( S_{(\phi,\psi)} \) that computes the similarity between two argument relations. These scores are normalized to \([0, 1]\).

As described in Section 3.2, the graph representation consists of three types of information \( G = (V, I, R) \). For two graphs \( G_1 = (V_1, I_1, R_1) \) and \( G_2 = (V_2, I_2, R_2) \), we define the score \( S_{(\phi,\psi)} \) to measure the similarity of \( G_1 \) against \( G_2 \):

\[
S_{(\phi,\psi)}(G_1, G_2) = \max_{m \in M} \left[ \sum_{v_i \in V_1} \phi(I_1(v_i), I_2(m(v_i))) + \sum_{(v_i, v_j) \in U(R_1)} \psi(R_1(v_i, v_j), R_2(m(v_i), m(v_j))) \right]
\]

where \( m \) is a mapping from variables in \( V_1 \) to variables in \( V_2 \). \( U(R_1) \) is the domain of \( R_1 \), i.e., all argument edges in \( G_1 \). \( S_{(\phi,\psi)} \) computes the highest similarity score among all possible mappings \( M \).

The precision and recall are computed by

\[
\text{Precision} = \frac{S_{(\phi,\psi)}(G_1, G_2)}{|U(I_1)| + |U(R_1)|}
\]

\[
\text{Recall} = \frac{S_{(\phi,\psi)}(G_1, G_2)}{|U(I_2)| + |U(R_2)|}
\]

where \(|U(I_1)|\) is the number of instances in \( G_1 \), \(|U(R_1)|\) is the number of argument relations in \( G_1 \).

In this work, we set \( \phi = \text{BLEU} \) (Papineni et al., 2002) and \( \psi = \delta \), the Kronecker delta. BLEU is a widely-used metric in machine translation, and here it gives partial credits to instance similarity in \( S_{(\phi,\psi)} \). Finding an optimal variable mapping \( m \) that yields the highest similarity score \( S_{(\phi,\psi)} \) is NP-complete. We instead adopt a strategy used in Smatch (Cai and Knight, 2013) that does a hill-climbing search with smart initialization plus 4 random restarts, and has been shown to give the best trade-off between accuracy and speed. Smatch for evaluating semantic structures can be considered as a special case of \( S_{(\phi,\psi)} \), where \( \phi = \delta \) and \( \psi = \delta \). We show an example of evaluating two similar graphs using \( S_{(\phi,\psi)} \) in the supplemental material.
5 Task

We formulate the task of cross-lingual semantic parsing as a joint problem of sequence-to-sequence learning and coreference resolution. The input is a sentence \( X \) in the source language, e.g., the Chinese sentence in Fig. 1. The output is a linearized meaning representation as shown in Fig. 2(c): it contains a sequence of tokens \( Y \) in the target language as well as coreference assignments \( \mathcal{A} \) for each special symbol “*” in \( Y \).

Formally, let the input be a sequence of tokens \( X = x_1, \ldots, x_N \), and let the output be a sequence of tokens \( Y = y_1, \ldots, y_M \) and a list of coreference assignments \( \mathcal{A} = [a_1, \ldots, a_M] \), where \( a_t \) is the coreference assignment for \( y_t \). The set of possible assignments for \( y_t \) is \( \mathcal{A}(t) = \{\epsilon, y_1, \ldots, y_{t-1}\} \), a dummy antecedent \( \epsilon \) and all preceding tokens. The dummy antecedent \( \epsilon \) represents a scenario where the token is not a special symbol “*” and should be assigned to none of the preceding tokens. \( N \) is the length of the input sentence, and \( M \), the length of the output sentence.

6 Model

The goal for cross-lingual semantic parsing is to learn a conditional probability distribution \( P(Y, A \mid X) \) whose most likely configuration, given the input sentence, outputs the true linearized meaning representation. While the standard encoder-decoder framework shows the state-of-the-art performance in sequence-to-sequence learning (Vinyals et al., 2015; Jia and Liang, 2016; Barzdins and Gosko, 2016), it can not directly solve intra-sentential coreference in cross-lingual semantic parsing. To achieve this goal, we propose an encoder-decoder architecture incorporated with a copying mechanism. As illustrated in Fig. 3, Encoder transforms the input sequence into hidden states; Decoder reads the hidden states, and then at each time step decides whether to generate a token or copy a preceding token.

6.1 Encoder

The encoder employs a bidirectional recurrent neural network (Schuster and Paliwal, 1997) to encode the input \( X = x_1, \ldots, x_N \) into a sequence of hidden states \( h = h_1, \ldots, h_N \). Each hidden state \( h_i \) is a concatenation of a left-to-right hidden state \( \overrightarrow{h}_i \) and a right-to-left hidden state \( \overleftarrow{h}_i \),

\[
\hat{h}_i = \left[ \begin{array}{c} \overrightarrow{h}_i \\ \overleftarrow{h}_i \end{array} \right] = \left[ \begin{array}{c} f(x_i, \overrightarrow{h}_{i+1}) \\ f(x_i, \overleftarrow{h}_{i-1}) \end{array} \right], \tag{1}
\]

where \( f \) and \( \overrightarrow{f} \) are \( L \)-layer stacked LSTM units (Hochreiter and Schmidhuber, 1997). The encoder hidden states are zero-initialized.

6.2 Copying-Enabled Decoder

Given the encoder hidden states, the decoder predicts meaning representation according to the conditional probability \( P(Y, A \mid X) \) which can be decomposed as a product of the decoding probabilities at each time step \( t \):

\[
P(Y, A \mid X) = \prod_{t=1}^{M} P(y_t, a_t \mid y_{<t}, a_{<t}, X) \tag{2}
\]

where \( y_{<t} \) and \( a_{<t} \) are the preceding tokens and the coreference assignments. We omit \( y_{<t} \) and \( a_{<t} \) from the notation when the context is unambiguous. The decoding probability at each time step \( t \) is defined as

\[
P(y_t, a_t) = \begin{cases} P_g(y_t), & \text{if } a_t = \epsilon \\
P_c(y_t), & \text{otherwise} \end{cases} \tag{3}
\]

where \( P_g \) is the generating probability, and \( P_c \) is the copying probability. If the dummy antecedent \( \epsilon \) is assigned to \( y_t \), the decoder generates a token for \( y_t \), otherwise the decoder copies a token from the preceding tokens.

Generation: If the decoder decides to generate a token at time step \( t \), the probability distribution of the generated token \( y_t \) is defined as

\[
P_g(y_t) = \text{softmax}(\text{FFNN}_g(s_t, c_t)) \tag{4}
\]

where \( \text{FFNN}_g \) is a two-layer feed-forward neural network over the decoder hidden state \( s_t \) and the context vector \( c_t \). The decoder hidden state \( s_t \) is computed by

\[
s_t = \text{RNN}(y_{t-1}, s_{t-1}) \tag{5}
\]

where \( \text{RNN} \) is a recurrent neural network using \( L \)-layer stacked LSTM, and \( s_0 \) is initialized by the last encoder left-to-right hidden state \( \overrightarrow{h}_N \). The context vector \( c_t \) is computed by Attention Mechanism (Bahdanau et al., 2014; Luong et al., 2015).
Figure 3: Illustration of the model architecture. At the current decoding step, the decoder takes a token “I” as input, and decides to copy a preceding head token “block_h” via the coping mechanism, instead of generating a token via the attention mechanism.

as illustrated in Fig. 3,

\[ c_t = \sum_{i=1}^{N} \alpha_{t,i} h_i, \]
\[ \alpha_{t,i} = \frac{\exp(s^\top_t \left(W^\alpha h_i + b^\alpha\right))}{\sum_{j=1}^{N} \exp(s^\top_t \left(W^\alpha h_j + b^\alpha\right))}, \]

where \( W^\alpha \) is a transform matrix and \( b^\alpha \) is a bias.

**Copying Mechanism:** If the decoder at time step \( t \) decides to copy a token from the preceding tokens as shown in Fig. 3, the probability of \( y_t \) being a copy of the preceding token \( y_k \) is defined as

\[ P_c(y_t = y_k) = \frac{\exp \left( \text{SCORE}(y_t, y_k) \right)}{\sum_{y_k' \in A(t)} \exp \left( \text{SCORE}(y_t, y_k') \right)}, \]

where \( A(t) = \{ \epsilon, y_1, \ldots, y_{t-1} \} \) is the set of possible coreference assignments for \( y_t \) defined in Section 5. \( \text{SCORE}(y_t, y_k) \) is a pairwise score for a coreference link between \( y_t \) and \( y_k \). There are three terms in this pairwise coreference score, which is akin to Lee et al. (2017): (1) whether \( y_t \) should be a copy of a preceding token, (2) whether \( y_k \) should be a candidate source of such a copy, and (3) whether \( y_k \) is an antecedent of \( y_t \).

\[ \text{SCORE}(y_t, y_k) = s_c(y_t) + s_p(y_k) + s_a(y_t, y_k) \]

Here \( s_c(y_t) \) is a unary score for \( y_t \) being a copy of a preceding token, \( s_p(y_k) \) is a unary score for \( y_k \) being a candidate source of such a copy, and \( s_a(y_t, y_k) \) a pairwise score for \( y_k \) being an antecedent of \( y_t \).

Fig. 4 shows the details of the scoring architecture in the copy mechanism. At the core of the three factors are vector representations \( \gamma(y_t) \) for each token \( y_t \), which is described in detail in the following section. Given the currently considered token \( y_t \) and a preceding token \( y_k \), the scoring functions above are computed via standard feed-forward neural networks:

\[ s_c(y_t) = w_c \cdot \text{FFNN}_c(\gamma(y_t)) \]
\[ s_p(y_k) = w_p \cdot \text{FFNN}_p(\gamma(y_k)) \]
\[ s_a(y_t, y_k) = w_a \cdot \text{FFNN}_a(\gamma(y_t), \gamma(y_k)), \]

where \( \cdot \) denotes dot product, \( \circ \) denotes element-wise multiplication, and FFNN denotes a two-layer feed-forward neural network over the input. The in-
put of FFNN_a is a concatenation of vector representations \( \gamma(y_t) \) and \( \gamma(y_k) \), and their explicit element-wise similarity \( \gamma(y_t) \odot \gamma(y_k) \).

**Token representations:** To accurately predict conference scores, we consider three types of information in each token representation \( \gamma(y_t) \): (1) the token itself \( y_t \), (2) on the decoder side, the preceding context \( y_{t-1} \), and (3) on the encoder side, the input sequence \( X = x_1, \ldots, x_N \).

The lexical information of the token itself \( y_t \) is represented by its word embedding \( e(y_t) \). The preceding context \( y_{t-1} \) is encoded by the decoder RNN in Equation (5). We use the decoder hidden state \( s_t \) to represent the preceding context information.

The encode-side context is also crucial to predicting coreference: if \( y_t \) and \( y_k \) pay attention to the same context on the encoder side, they are likely to refer the same entity. Therefore, we use the context vector \( o_t \) computed by an attention mechanism to represent the encoder side context information for \( y_t \):

\[
o_t = \sum_i^N \beta_{t,i} h_i, \quad (13)
\]

\[
\beta_{t,i} = \frac{\exp (s_t^T W_{\beta} h_i)}{\sum_{j=1}^N \exp (s_t^T W_{\beta} h_j)}, \quad (14)
\]

where \( h_i \) is the encoder hidden state computed by Equation (1), \( s_t \) is the decoder hidden state computed by Equation (5), and \( W_{\beta} \) is a transform matrix.

All the above information is concatenated to produce the final token representation \( \gamma(y_t) \):

\[
\gamma(y_t) = [e(y_t), o_t] \quad (15)
\]

### 6.3 Learning

In the training objective, we consider both the copying accuracy as well as the generating accuracy. Given the input sentence \( X \), the output sequence of tokens \( Y \), and the coreference assignments \( A \), the objective is to minimize the negative log-likelihood:

\[
\mathcal{L} = -\frac{1}{|D|} \sum_{(X,Y,A) \in D} \log P(Y, A | X)
\]

\[
= -\frac{1}{|D|} \sum_{(X,Y,A) \in D} \sum_{t=1}^M \left[ P_{\gamma}(y_t) + \mu P_{\epsilon}(y_t) \right]
\]

To increase the convergence rate, we pretrain the model by setting \( \mu = 0 \) to only optimize the generating accuracy. After the model converges, we set \( \mu \) back to 1 and continue training. Since most tokens in the output are not copied from their preceding tokens, and are therefore assigned the dummy antecedent \( \epsilon \), the training of the copy mechanism is heavily unbalanced. To alleviate the balance problem, we consider coreference assignments of syntactic head tokens in optimization.

### 7 Experiments

We now describe the evaluation data, baselines, and experimental results. Hyperparameter settings are reported in the supplemental material.

**Data:** We choose Chinese as the source language and English as the target language. For testing, we sampled 2,258 sentences from Universal Dependencies (UD) English Treebank (Silveira et al., 2014), which is taken from five genres of web media: weblogs, newsgroups, emails, reviews, and Yahoo answers. We then created PredPatt meaning representations for these sentences based on the gold UD annotations. Meanwhile, the Chinese translations of these sentences were created by crowdworkers on Amazon Mechanical Turk. The test dataset will be released upon publication. For training, we first collected about 1.8M Chinese-English sentence bitexts from the GALE project (Cohen, 2007), then tokenized Chinese sentences with Stanford Word Segmenter (Andor et al., 2016). We created PredPatt meaning representations for English sentences based on automatic UD annotations generated by SyntaxNet Parser (Andor et al., 2016). We hold out 10K training sentences for validation. The dataset statistics are reported in Table 1.

| No. sentences | Source     |
|---------------|------------|
| Train         | 1,889,172  | GALE       |
| Validation    | 10,000     | GALE       |
| Test          | 2,258      | UD Treebank|

Table 1: Statistics of the evaluation data.

**Comparisons:** We evaluate 4 approaches in the experiments: (1) SEQ2SEQ+COPY is our proposed approach, described in Section 6. (2) SEQ2SEQ+HEURISTIC preprocesses the data by replacing the special symbol ‘*’ with the syntactic head of its antecedent. During training and testing, it replaces the copying mechanism with a heuristic that solves coreference by randomly choosing an antecedent among preceding arguments which have the same syntactic head. (3)
The translation system (Klein et al., 2017) and are then first translated into English by a neural machine translation system. We also include a comparison to random predictions, which only predict coreference via the copying mechanism, the heuristic baseline, or the random baseline. We report the precision, recall, and F₁ for the standard MUC, B₁, and CEAF metrics using the official coreference scorer of the CoNLL-2011/2012 shared tasks (Pradhan et al., 2014).

Table 2 shows the evaluation results. Since coreference in our setup occurs at the sentence level, the proposed copying mechanism achieves high scores in all three metrics, and the average F₁ is 97.82. The heuristic baseline, which solves coreference only based on syntactic heads, also achieves a relatively high average F₁ of 81.94. Under the MUC metric, the copying mechanism performs significantly better than the heuristic baseline. The random baseline limits the choice of coreference to preceding syntactic heads, ignoring all other tokens, achieving scores much lower than the other two approaches in all three metrics.

8 Conclusions

We introduce the task of cross-lingual semantic parsing, which maps content provided in a source language into a meaning representation based on a target language. We present: the PredPatt meaning representation as the target semantic interface, the S(φ,ψ) metric for evaluation, and the Chinese-English semantic parsing dataset. We propose an end-to-end learning approach with a copying mechanism which outperforms two strong baselines in this task. The PredPatt meaning representation, the evaluation metric S(φ,ψ), and the evaluation dataset provided in this work will be beneficial to the increasing interests in meaning representations and cross-lingual applications.

Table 3: Precision, recall, and F₁ scores for the evaluation metric S(φ,ψ) on the test dataset.

|          | Prec. | Rec. | F₁   |
|----------|-------|------|------|
| SEQ2SEQ+COPY | 49.72 | 31.25 | 38.38 |
| SEQ2SEQ+HEURISTIC | 46.76 | 30.88 | 37.20 |
| SEQ2SEQ+RANDOM | 42.86 | 30.74 | 35.80 |
| PIPELINE   | 28.50 | 20.65 | 23.95 |

SEQ2SEQ+RANDOM replaces the copying mechanism by randomly choosing an antecedent among all preceding arguments. (4) We also include a PIPELINE approach where Chinese sentences are first translated into English by a neural machine translation system (Klein et al., 2017) and are then annotated by a UD parser (Andor et al., 2016). The final meaning representations of PIPELINE are created based on the automatic UD annotations.

Results: Table 3 reports the test set results based on the evaluation metric S(φ,ψ) defined in Section 4. Overall, our proposed approach, SEQ2SEQ+COPY, achieves the best precision, recall, and F₁. The two baselines, SEQ2SEQ+HEURISTIC and SEQ2SEQ+RANDOM also achieve reasonable results. These two baselines both employ sequence-to-sequence models to predict meaning representations, which can be considered a replica of state-of-the-art approaches for structured prediction (Vinyals et al., 2015; Barzdins and Gosko, 2016; Peng et al., 2017).

Our proposed approach outperforms these two strong baselines: the copying mechanism, aiming for solving coreference in cross-lingual semantic parsing, results in both precision and recall gains. The detailed gains achieved by the copying mechanism are discussed in the following section. In the PIPELINE approach, each component is trained independently. During testing, residual errors from each component are propagated through the pipeline. As expected, PIPELINE shows a significant performance drop compared to the other end-to-end learning approaches.

Coreference occurs 5,755 times in the test data. To evaluate the coreference accuracy of these end-to-end learning approaches, we force each approach to generate the gold target sequence, and only predict coreference via the COPYING mechanism, the HEURISTIC baseline, or the RANDOM baseline. We report the precision, recall, and F₁ for the standard MUC, B₁, and CEAF metrics using the official coreference scorer of the CoNLL-2011/2012 shared tasks (Pradhan et al., 2014).

Table 2 shows the evaluation results. Since coreference in our setup occurs at the sentence level, the proposed copying mechanism achieves high scores in all three metrics, and the average F₁ is 97.82. The heuristic baseline, which solves coreference only based on syntactic heads, also achieves a relatively high average F₁ of 81.94. Under the MUC metric, the copying mechanism performs significantly better than the heuristic baseline. The random baseline limits the choice of coreference to preceding syntactic heads, ignoring all other tokens, achieving scores much lower than the other two approaches in all three metrics.

8 Conclusions

We introduce the task of cross-lingual semantic parsing, which maps content provided in a source language into a meaning representation based on a target language. We present: the PredPatt meaning representation as the target semantic interface, the S(φ,ψ) metric for evaluation, and the Chinese-English semantic parsing dataset. We propose an end-to-end learning approach with a copying mechanism which outperforms two strong baselines in this task. The PredPatt meaning representation, the evaluation metric S(φ,ψ), and the evaluation dataset provided in this work will be beneficial to the increasing interests in meaning representations and cross-lingual applications.
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