

Towards Open-Text Semantic Parsing via Multi-Task Learning of Structured Embeddings

Antoine Bordes^(1,2), Xavier Glorot⁽²⁾, Jason Weston⁽³⁾, Yoshua Bengio⁽²⁾

(1) Heudiasyc, Université de Technologie de Compiègne, Compiègne, France

(2) Dept. IRO, Université de Montréal, Montréal, QC, Canada

(3) Google, 111 8th Avenue, New York, NY, USA

Abstract

Open-text (or open-domain) semantic parsers are designed to interpret any statement in natural language by inferring a corresponding *meaning representation* (MR). Unfortunately, large scale systems cannot be easily machine-learned due to lack of directly supervised data. We propose here a method that learns to assign MRs to a wide range of text (using a dictionary of more than 70,000 words, which are mapped to more than 40,000 entities) thanks to a training scheme that combines learning from WordNet and ConceptNet with learning from raw text. The model learns structured embeddings of words, entities and MRs via a multi-task training process operating on these diverse sources of data that integrates all the learnt knowledge into a single system. This work ends up combining methods for knowledge acquisition, semantic parsing, and word-sense disambiguation. Experiments on various tasks indicate that our approach is indeed successful and can form a basis for future more sophisticated systems.

1 Introduction

A key ambition of AI has always been to render computers able to read text and express its meaning in a formal representation in order to bring about a major improvement in human-computer interfacing, question answering or knowledge acquisition. Semantic parsing [25] precisely aims at building such systems to interpret statements expressed in natural language. The purpose of the semantic parser is to analyze the structure of sentence meaning and, formally, this consists of mapping a natural language sentence into a logical *meaning representation* (MR). This task seems too daunting to carry out manually (because of the vast quantity of knowledge engineering that would be required) so machine learning seems an appealing avenue. On the other hand, machine learning models usually require many labeled examples, which can also be costly to gather, especially when labeling properly requires the expertise of a linguist.

Hence, research in semantic parsing can be roughly divided in two tracks. The first one, which could be termed *in-domain*, aims at learning to build highly evolved and

Corresponding author: Antoine Bordes – antoine.bordes@utc.fr .

comprehensive MRs [16, 38, 21]. Since this requires advanced training data, such approaches have to be applied to text from a specific domain with restricted vocabulary (a few hundred words). Alternatively, a second line of research, which could be termed *open-domain*, works towards learning to associate a MR to any kind of natural language sentence [31, 17, 28]. In this case, the supervision is much weaker because it is unrealistic and infeasible to label data for large-scale, open-domain semantic parsing. As a result, models usually infer simpler MRs; this is sometimes referred to as *shallow* semantic parsing.

In this paper, we propose a novel method directed towards the open-domain category with the aim of automatically inducing meaning representations out of free text, by exploiting existing resources such as WordNet to bootstrap and anchor the process. For a given sentence, the proposed approach infers a MR in two stages: (1) a semantic role labeling (SRL) step predicts the semantic structure, and (2) a disambiguation step assigns a corresponding entity to each relevant word, so as to minimize an energy given to the whole input.

This paper considers simple MR structures and relies on an existing method to perform SRL because its focus is on step (2). Indeed, in order to go open-domain, a large number of entities must be considered. For this reason, the set of entities considered is defined from WordNet [24]. This results in a dictionary of more than 70,000 words that can be mapped to more than 40,000 possible entities. For each word, WordNet provides a list of candidate senses so step (2) reduces to detecting the correct one and can be seen as a challenging all-words word-sense disambiguation (WSD) step.

The model used here builds upon the *structured embedding framework*, defined in [6], in which each entity of a knowledge base (such as WordNet) is encoded into a low dimensional embedding vector space preserving the original data structure. The training procedure is based on multi-task learning across different knowledge sources including WordNet, ConceptNet [22] and raw text. In this way MRs induced from raw text and MRs for WordNet entities are embedded (and hence integrated) in the same space. This allows us to learn to perform disambiguation on raw text with *little direct and much indirect supervision*. The model can learn to use WordNet and ConceptNet knowledge (such as relations between entities) to help choose the correct sense of a particular word, and then label the words from the raw text with the WordNet sense. At the same time, MR prediction can also be seen as knowledge extraction. In addition to extracting MRs from raw text, the model proposed here has the potential to enrich WordNet with the extracted MRs. The proposed method is evaluated on different criteria to reflect its different properties. Thus, presented results illustrate MR inference, word-sense disambiguation, WordNet encoding and enrichment.

The paper is organized as follows. Section 2 describes our framework to perform semantic parsing. Section 3 introduces our model based on structured embeddings and Section 4 the multi-task training process we used to learn it. Section 5 discusses some related work. Finally our experiments are presented in Section 6.

2 Semantic Parsing Framework

2.1 Definitions

The MRs considered in semantic parsing are simple logical expressions of the form $REL(A_0, \dots, A_n)$. REL is the relation symbol, and A_0, \dots, A_n are its arguments. Note that several forms can be recursively constructed to form more complex structures. Because this work is oriented towards raw text, a wide range of possible relation types and arguments must be considered.

Hence, WordNet [24] is used for defining the arguments and some relation types as proposed in [31]. WordNet encompasses comprehensive knowledge within its graph structure, whose nodes (termed *synsets*) correspond to senses, and edges (which can have different types) define relations between those senses. Each synset is associated with a set of words sharing that sense. They are usually identified by 8-digit codes, however, for clarity reasons, we indicate a synset by the concatenation of one of its words, its part-of-speech tag and a number indicating which sense it refers to (in the case of polysemous words). For example, *_score_NN_1* refers to the synset representing the first sense of the word “score” and also contains the words “mark” and “grade”, whereas *_score_NN_2* refers to the second meaning (i.e. a written form of a musical composition).

We denote instances of relations from WordNet using triplets (lhs, rel, rhs) , where lhs depicts the left-hand side of the relation, rel its type and rhs its right-hand side. Examples are $(_score_NN_1, _hypernym, _evaluation_NN_1)$ or $(_score_NN_2, _has_part, _musical_notation_NN_1)$. In this work we filter out the synsets appearing in less than 15 triplets, as well as relation types appearing in less than 5000 triplets. We obtain a graph with the following statistics: 41,024 synsets and 18 relations types; a total of 70,116 different words belong to these synsets.

2.2 Methodology

MR structure inference (and preprocessing) The first stage consists in preprocessing the text and inferring the structure of the MR. Using the SENNA software¹ [12], we performed part-of-speech (POS) tagging, chunking, lemmatization² and semantic role labeling (SRL). The SRL step consists in labeling, for each proposition, each semantic argument associated with a verb with its grammatical role. Each argument is specified by a tuple of lemmas. It is crucial because it will be used to infer the *structure* of the MR. In this restricted setting, the structure of the MR follows that of the sentence.

We only consider sentences that match the following template: $(subject, verb, direct\ object)$. Here, each of the three elements of the template is associated with a tuple of lemmatized words or synsets (when the words are disambiguated). SRL is used to structure the sentence into the $(lhs = subject, rel = verb, rhs = object)$ template, note that the order is not necessarily subject / verb / direct object in the raw text. The semantic match energy function is used to predict appropriate synsets or answer questions by choosing those corresponding to low-energy synset configurations.

¹Freely available from ml.nec-labs.com/senna/.

²lemmatization is not carried out with SENNA but with the NLTK toolkit, nltk.org.

Clearly, the subject-verb-object structure causes the resulting MRs to have a straightforward structure (with a single relation), but this pattern is the most common and a good choice to test our ideas at scale. Learning to infer more elaborate grammatical patterns is left as future work. In this work we chose to focus on handling the large scale of the set of entities.

As an illustration, to parse the sentence: “A musical score accompanies a television program or a film.”, the SRL step will produce as output the following triplet (*_musical_JJ* *_score_NN*, *_accompany_VB*, *_television_program_NN* *_film_NN*). In the following, we call the concatenation of a lemmatized word and POS tag (such as NN, VB, etc.) a *lemma*. Note the absence of an integer suffix, which distinguishes a lemma from a synset: a lemma is allowed to be semantically ambiguous. To summarize, this step starts from a sentence and either rejects it or outputs a triplet of lemma tuples, one for the subject, one for the relation or verb, and one for the direct object.

Detection of MR entities This second step aims at identifying each semantic entity expressed in a sentence. Given a relation triplet ($lhs^{lem}, rel^{lem}, rhs^{lem}$) where each element of the triplet is associated with a tuple of lemmas, a corresponding triplet ($lhs^{syn}, rel^{syn}, rhs^{syn}$) is produced, where the lemmas are replaced by synsets. Depending on the lemmas, this can be either straightforward (some lemmas such as *_television_program_NN* or *_world_war_ii_NN* correspond to a single synset) or very challenging (*_run_VB* can be mapped to 41 different synsets and *_run_NN* to 16). Hence, in the proposed semantic parsing framework, MRs correspond to triplets of synsets ($lhs^{syn}, rel^{syn}, rhs^{syn}$). For the example from the previous section, the associated MR is (*_musical_JJ_I*, *_score_NN_2*, *_accompany_VB_I*, (*_television_program_NN_I*, *_film_NN_I*)).

This step can be seen as particular form of all-words word-sense disambiguation. This is achieved by an approximate search for a set of synsets that are compatible with the observed lemmas and that also minimize a semantic matching energy function, using the model described in the next section.

Since the model is structured around relation triplets, MRs and WordNet relations are cast into the same scheme. For example, the WordNet relation (*_score_NN_2*, *_has_part*, *_musical_notation_NN_I*) fits the same pattern as our MRs, with the relation type *_has_part* playing the role of the verb.

3 Structured Embeddings

Inspired by the framework introduced by Bordes *et al.* [6] as well as by recent work of L. Bottou [8], the main idea behind our structural embedding model is the following.

- Named symbolic entities (including WordNet synsets and relation types and lemmas) are associated with a d -dimensional vector space, termed the “embedding space”, following previous work in neural language models (see [3] for a review). The i^{th} entity is assigned a vector $E_i \in \mathbb{R}^d$. Note that if a lemma is unambiguous because it maps to a single synset, its embedding and the embedding of this synset are shared.

- The semantic energy function value associated with a particular triplet (lhs, rel, rhs) is computed by a parametrized function \mathcal{E} that starts by mapping all of the symbols to their embeddings. Note that in our case \mathcal{E} must be able to handle variable-size arguments, since for example there could be multiple lemmas in the subject part of the sentence.
- The energy function \mathcal{E} is optimized to be lower for training examples than for other possible configurations of symbols. Hence the semantic energy function can distinguish plausible combinations of entities from implausible ones, to choose the most likely sense for a lemma, or to answer questions, e.g. corresponding to a tuple $(lhs, rel, ?)$ with a missing rhs entry “?”.

3.1 Training Objective

Let us now more formally define the training criterion for the semantic match energy function. Let \mathcal{C} denote the dictionary which includes all entities (lemmas **and** synsets) and relation types of interest, and let \mathcal{C}^* denote the set of tuples (or sequences) whose elements are taken in \mathcal{C} . Let $\mathcal{R} \subset \mathcal{C}$ be the subset of entities which are relation types (\mathcal{R}^* is defined similarly as \mathcal{C}^*). We are given a training set \mathcal{D} containing m triplets of the form $x = (x_{lhs}, x_{rel}, x_{rhs})$, where $x_{lhs} \in \mathcal{C}^*$, $x_{rel} \in \mathcal{R}^*$, and $x_{rhs} \in \mathcal{C}^*$. We define the energy as $\mathcal{E}(x) = \mathcal{E}(x_{lhs}, x_{rel}, x_{rhs})$. Ideally, we would like to perform maximum likelihood over $P(x) \propto e^{-\mathcal{E}(x)}$ but this is intractable. The approach we follow here has already been used successfully in ranking settings [11, 35, 34] and corresponds to performing two approximations. First, like in pseudo-likelihood we only consider one input given the others. Second, instead of sampling a negative example from the model posterior, we use a ranking criterion (that is based on uniformly sampling a negative example).

If one of the elements of a given triplet were missing, then we would like the model to be able to predict the correct entity. For example, this would allow us to answer questions like “what is part of a car?” or “what does a score accompany?”. The objective is to learn a real-valued semantic energy function \mathcal{E} such that it can successfully rank the training samples below all other possible triplets:

$$\mathcal{E}(x) < \mathcal{E}(i, x_{rel}, x_{rhs}) \quad \forall i \in \mathcal{C}^* : (i, x_{rel}, x_{rhs}) \notin \mathcal{D} \quad (1)$$

$$\mathcal{E}(x) < \mathcal{E}(x_{lhs}, k, x_{rhs}) \quad \forall k \in \mathcal{R}^* : (x_{lhs}, k, x_{rhs}) \notin \mathcal{D} \quad (2)$$

$$\mathcal{E}(x) < \mathcal{E}(x_{lhs}, x_{rel}, j) \quad \forall j \in \mathcal{C}^* : (x_{lhs}, x_{rel}, j) \notin \mathcal{D} \quad (3)$$

In practice the following stochastic criterion is minimized:

$$\sum_{x \in \mathcal{D}} \sum_{\tilde{x} \sim Q(\tilde{x}|x)} \max(\mathcal{E}(x) - \mathcal{E}(\tilde{x}) + 1, 0) \quad (4)$$

where $Q(\tilde{x}|x)$ is a corruption process that transforms a training example x into a corrupted *negative example*. In the experiments Q only changes one of the three members of the triplet, by changing only one of the lemmas, synsets or relation type in it, by sampling it uniformly from \mathcal{C} (not actually checking if the negative example is in \mathcal{D}).

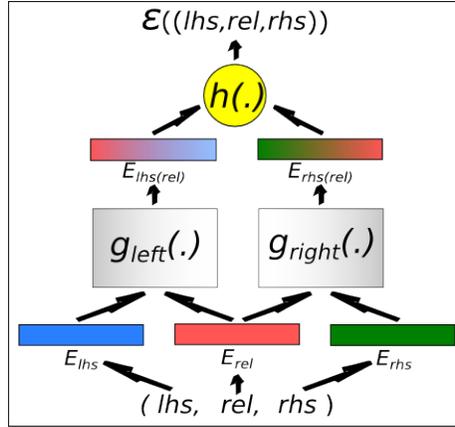


Figure 1: **Semantic matching energy function.** A triple of tuples (lhs, rel, rhs) is first mapped to its embeddings E_{lhs} , E_{lhs} and E_{lhs} (using an aggregating function for tuples involving more than one symbol). Then E_{lhs} and E_{rel} are combined using $g_{left}(\cdot)$ to output $E_{lhs(rel)}$ (similarly $E_{rhs(rel)} = g_{right}(E_{rhs}, E_{rel})$). Finally the energy $\mathcal{E}((lhs, rel, rhs))$ is obtained by merging $E_{lhs(rel)}$ and $E_{rhs(rel)}$ with the $h(\cdot)$ function.

3.2 Parametrization of the Semantic Matching Energy Function

Many parametrizations are possible for the semantic matching energy function but we have explored only a few. Let the input triplet be $x = ((lhs_1, lhs_2, \dots), (rel_1, rel_2, \dots), (rhs_1, rhs_2, \dots))$. In all of the experiments, the energy function is structured as follows, based on the intuition that the relation type should first be used to extract relevant components from each argument’s embedding, and put them in a space where they can then be compared (see Figure 1 for an illustration).

- (1) Each symbol i in the input tuples is mapped to its embedding $E_i \in \mathbb{R}^d$.
- (2) The embeddings associated with all the symbols within the same tuple are aggregated by a pooling function π (we only used the mean in the experiments but other plausible candidates include the sum, the max, and combinations of several such elementwise statistics):

$$\begin{aligned} E_{lhs} &= \pi(E_{lhs_1}, E_{lhs_2}, \dots), \\ E_{rel} &= \pi(E_{rel_1}, E_{rel_2}, \dots), \\ E_{rhs} &= \pi(E_{rhs_1}, E_{rhs_2}, \dots), \end{aligned}$$

where lhs_i denotes the i -th individual element of the left-hand side tuple, etc.

- (3) The embeddings E_{lhs} and E_{rel} respectively associated with the lhs and rel arguments are used to construct a new relation-dependent embedding $E_{lhs(rel)}$ for the lhs in the context of the relation type represented by E_{rel} , and similarly

for the *rhs*: $E_{lhs(rel)} = g_{left}(E_{lhs}, E_{rel})$ and $E_{rhs(rel)} = g_{right}(E_{rhs}, E_{rel})$, where g_{left} and g_{right} are parametrized functions whose parameters are tuned during training. See more details in the experiments section.

- (4) The energy is computed from the transformed embeddings of the left-hand side and right-hand side: $\mathcal{E}(x) = h(E_{lhs(rel)}, E_{rhs(rel)})$, where h is a parametrized function whose parameters are tuned during training. More details are given in the experiments section.

3.3 Disambiguation Process

Our semantic matching energy function is used for raw text semantic to perform stage 2 of the protocol described in Section 2.2, that is to carry out the word-sense disambiguation step.

We label a triplet of lemmas $((lhs_1^{lem}, lhs_2^{lem}, \dots), (rel_1^{lem}, \dots), (rhs_1^{lem}, \dots))$ with synsets in a greedy fashion, one lemma at a time. For labeling lhs_2^{lem} for instance, we fix all the remaining elements of the triplet to their lemma and select the synset leading to the lowest energy:

$$lhs_2^{syn} = \operatorname{argmin}_{S \in \mathcal{C}(syn|lem)} \mathcal{E}((lhs_1^{lem}, S, \dots), (rel_1^{lem}, \dots), (rhs_1^{lem}, \dots)) \quad (5)$$

with $\mathcal{C}(syn|len)$ the set of allowed synsets to which lhs_2^{lem} can be mapped. We repeat that for all lemmas. We always use lemmas as context, and never the already assigned synsets. This process is interesting because it is efficient as it only requires to compute a low number of energies, equal to the number of senses for a lemma. However, it requires to have good representations (i.e. good embedding vectors) for synsets and lemmas. That is the reason why the multi-task training presented in next section, takes good care of learning both properly.

4 Multi-Task Training

4.1 Multiple Data Resources

In order to encode as much common-sense knowledge as possible in the model, the following heterogeneous data sources are combined.

WordNet v3.0 (WN). Described in Section 2.1, this is the main resource, defining the dictionary of entities. The 18 relation types and 40,989 synsets retained are composed to form a total of 221,017 triplets. We randomly extracted from them a validation and a test set with 5,000 triplets each.

WordNet contains only relations between synsets. However, the disambiguation process needs embeddings for synsets and for lemmas. Following [19], we created two other versions of this dataset to leverage WN in order to also learn lemma embeddings: “Ambiguated” WN and “Bridge” WN. In “Ambiguated” WN both synset entities of each triplet are replaced by one of their corresponding lemmas. “Bridge”

WN is designed to teach the model about the connection between synset and lemma embeddings, thus in its relations the *lhs* or *rhs* synset is replaced by a corresponding lemma. Sampling training examples from WN involves actually sampling from one of its three versions, resulting in a triplet involving synsets, lemmas or both.

ConceptNet v2.1 (CN). CN [22] is a common-sense knowledge base in which lemmas or groups of lemmas are linked together with rich semantic relations as, for example, (*_kitchen_table_NN, _used_for, _eat_VB _breakfast_NN*). It is based on *lemmas* and not synsets, and it does not make distinctions between different senses of a word. Only triplets containing lemmas from the WN dictionary are kept, to finally obtain a total of 11,332 training lemma triplets.

Wikipedia (Wk). This resource is simply raw text meant to provide knowledge to the model in an unsupervised fashion. In this work 50,000 Wikipedia articles were considered, although many more could be used. Using the protocol of the first paragraph of Section 2.2, we created a total of 1,484,966 triplets of lemmas. Imperfect training triplets (containing a mix of lemmas and synsets) are produced by performing the disambiguation step of Section 3.3 on one of the lemmas. This is equivalent to MAP (Maximum A Posteriori) training, i.e., we replace an unobserved latent variable by its mode according to a posterior distribution (i.e. to the minimum of the energy function, given the observed variables). We have used the 50,000 articles to generate more than 3M examples.

EXtended WordNet (XWN) and Unambiguous Wikipedia (Wku). XWN[18] is built from WordNet *glosses*, syntactically parsed and with content words semantically linked to WN synsets. Using the protocol of Section 2.2, we processed these sentences and collected 47,957 lemma triplets for which the synset MRs were known. We removed 5,000 of these examples to use them as an evaluation set for the MR entity detection/word-sense disambiguation task. With the remaining 42,957 examples, we created unambiguous training triplets to help the performance of the disambiguation algorithm described in Section 3.3: for each lemma in each triplet, a new triplet is created by replacing the lemma by its true corresponding synset and by keeping the other members of the triplet in lemma form (to serve as examples of lemma-based context). This led to a total of 786,105 training triplets, from which we removed 10,000 examples to build a validation set.

We added to this training set some triplets extracted from the Wikipedia corpus which were modified with the following trick: if one of its lemmas corresponds unambiguously to a synset, and if this synset maps to other ambiguous lemmas, we create a new triplet by replacing the unambiguous lemma by an ambiguous one. Hence, we know the true synset in that ambiguous context. This allowed to create 981,841 additional triplets with supervision, and we named this data set Unambiguous Wikipedia.

4.2 Training Procedure

To train the parameters of the energy function \mathcal{E} we loop over all of the training data resources and use stochastic gradient descent (SGD) [30]. That is, we iterate the following steps:

1. Select a positive training triplet x_i at random (composed of synsets, of lemmas or both) from one of the above sources of examples.
2. Select at random resp. constraint (1), (2) or (3).
3. Create a negative triplet \tilde{x} by sampling an entity from \mathcal{C} to replace resp. lhs_i , rel_i or rhs_i .
4. If $\mathcal{E}(x_i) > \mathcal{E}(\tilde{x}) - 1$, make a stochastic gradient step to minimize the criterion (4).
5. Enforce the constraint that each embedding vector is normalized, $\|E_i\| = 1, \forall i$.

The constant 1 in step 4 is the **margin** as is commonly used in many margin-based models such as SVMs [7]. The gradient step requires a learning rate of λ . The normalization in step 5 helps remove scaling freedoms from the model.

The above algorithm was used for all the data sources except XWN and Wku. In that case, positive triplets are composed of lemmas (as context) and of a disambiguated lemma replaced by its synset. Unlike for Wikipedia, this is labeled data, so we are certain that this synset is the true sense. Hence, to increase training efficiency and yield a more discriminant disambiguation, in step 3 with probability $\frac{1}{2}$ we either sample randomly from \mathcal{C} or we sample randomly from the set of remaining candidate synsets corresponding to this disambiguated lemma (i.e. the set of its other meanings).

The matrix E which contains the representations of the entities is thus learnt via a complex *multi-task learning* procedure because a single embedding matrix is used for all relations and all data sources (each really corresponding to a different distribution of symbol tuples, i.e., a different task). As a result, the embedding of an entity contains factorized information coming from all the relations in which the entity is involved as *lhs*, *rhs* or even *rel* (for verbs). For each entity, the model is forced to learn how it interacts with other entities in many different ways.

5 Related Work

Our approach is original by the way that it connects many tasks and many training resources within the same framework. However, it is highly related with many previous works. Shi and Mihalcea [31] proposed a rule-based system for open-text semantic parsing using WordNet and FrameNet [2] while Giuglea and Moschitti [17] proposed a model to connect WordNet, VerbNet and PropBank [20] for semantic parsing using tree kernels. Poon and Domingos [28, 29] recently introduced a method based on Markov-Logic Networks for unsupervised semantic parsing that can be also used for information acquisition. However, instead of connecting MRs to an existing ontology the proposed method does, it constructs a new one and does not leverage pre-existing

knowledge. Automatic information extraction is the topic of many models and demos [32, 37, 36, 33] but none of them relies on a joint embedding model. In that trend, some approaches have been directly targeting to enrich existing resources, as we do here with WordNet, [1, 14, 10] but these never use learning. Finally, several previous works have targeted to improve WSD by using extra-knowledge by either automatically acquiring examples [23] or by connecting different knowledge bases [19].

Our model is related to earlier approaches (e.g. [4, 11, 26, 9]) and is similar to but more convenient than the approach of Bordes *et al.* [6], where the embeddings for the left/right-hand side arguments i and j are d -vectors and the embedding for relation k is a pair of $d \times d$ matrices. The disadvantage of embedding each relation type into a pair of matrices is that it gives relation types a different status (they cannot appear as left-hand side or right-hand side) and many more parameters.

6 Experiments

6.1 Experimental Setting

Experiments were performed with three different types of parametrizations (linear, bilinear and non-linear) for the g functions. We selected the hyper-parameter values w.r.t. the WN validation set. We only present in this section results with the bilinear parametrization for g and with a dot product for the output h function, $h(a, b) = a \cdot b$, because this combination achieved the best performance in validation. The bilinear function for the left side (and similarly for the right side) is as follows:

$$g_{left}(E_{lhs}, E_{rel})^l = \sum_{i,j,k} (W_{3left}^{kl} * (W_{1left}^{ik} * E_{lhs}^i + b_{1left}^k) * (W_{2left}^{jk} * E_{rel}^j + b_{2left}^k) + b_{3left}^l)$$

where i denotes indices of the elements of the embedding E_{lhs} , j of the relation embedding E_{rel} , k of the latent representation, and l of the output of the g function (that will be fed into the dot product). We hypothesize that the success of the bilinear parametrization comes from its natural ability to encode AND relationships between the *lhs* (or *rhs*) and the *rel* embeddings.

To assess the performance w.r.t. choices made with that architecture, the multi-task training and the diverse data sources, we evaluated models trained with several combinations of data sources. **WN** denotes models trained on WordNet, “Ambiguated” WordNet and “Bridge” WordNet, **WN+CN+Wk** models also trained on CN and Wk datasets, and **All** models are trained on all sources.

6.2 WordNet Encoding

The WN encoding is measured with the mean predicted rank and the prediction at top 10 (top-10), calculated with the following procedure. For each test WordNet triplet, the left entity is removed and replaced by each of the 41,024 synsets of the dictionary in turn. Energies of those degraded triplets are computed by the model and sorted by ascending order and the rank of the correct synset is stored. That is done for both the left-hand and right-hand arguments of the relation. The mean predicted rank is the average of those predicted ranks and top-10 is the proportion of ranks within 1 and 10.

Table 1: **WordNet encoding and Word Sense Disambiguation results.** MFS is just using the Most Frequent Sense. **All+MFS** is our best system, combining all sources of information. **Random** chooses uniformly among allowed synsets. (*)Results of **StructEmbed**, copied from [6], were obtained with a different version of WordNet and are presented here as indication only.

Model	WordNet rank	WordNet top-10	F1 XWN	F1 Senseval3
All+MFS	–	–	72.35%	70.19%
All	139.3	34.71%	67.52%	51.44%
WN+CN+Wk	95.9	46.02%	34.80%	34.13%
WN	72.1	58.87%	29.55%	28.36%
MFS	–	–	67.17%	67.79%
Gamble [15]	–	–	–	66.41%
StructEmbed [6]	140.1*	74.20%*	–	–
Random	20512	0.024%	26.71%	29.55%

The left side of Table 1 presents the comparative results, together with previous performance of [6] (**StructEmbed**). We obtain better predicted rank but lower top-10. However, the difference can be caused by the fact that the dictionaries of synsets are slightly different between [6] and the setting presented here (different preprocessing of WordNet). Training with other data sources (**All**) still allows to encode well WordNet knowledge, even if it is slightly worse than with WordNet alone (**WN**).

6.3 Word Sense Disambiguation

Performance on WSD is assessed on two test sets: the XWN test set and a subset of English All-words WSD task of SenseEval-3.³ For the latter, we processed the original data using the protocol of Section 2.2 and obtained a total of 208 words to disambiguate (out of ≈ 2000 originally). The performance of the most frequent sense (**MFS**) based on WordNet frequencies is also evaluated. Finally, we also report the results of **Gamble** [15], winner of Senseval-3, on our subset of its data.

F1 scores are presented in Table 1 (right). The difference between **All** and **WN+CN+Wk** indicates that, even without direct supervision, the model can disambiguate some words (**WN+CN+Wk** is significantly above **Random**), that the information from XWN and Wku is crucial (+30%) and yields performance better than **MFS** (a strong baseline in WSD) on the XWN test set.

However, performance can be greatly improved by combining the **All** sources model and the MFS score. To do so, we converted the frequency information into an energy by taking minus the log frequency and used it as an extra energy term. The total energy function is used for disambiguation. This yields the results denoted by **All+MFS** which achieves the best performance of all the methods tried.

³www.senseval.org/senseval3.

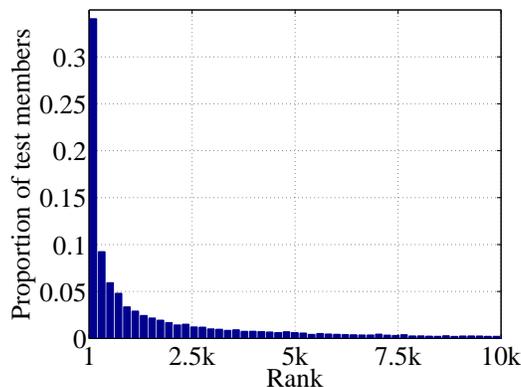


Figure 2: **MR ranking with respect to the model energy on the XWN test set.** On a total of 41,024 synset entities, the median/mean rank is 640/3012 whereas with WordNet::Similarity we obtained 13,200/13,800.

6.4 Meaning Representations

Assessing the quality of the obtained MRs is difficult as there is no benchmark for open-text semantic parsing. Yet, we intend to give an insight of how well the model represents language information by measuring and ranking the energy function of MRs. We measure the ranks of the predicted and the correct MRs obtained from the XWN test set, like WordNet triplets were treated in Section 6.2: we replace each lemma of a triplet by all the 41,024 synsets to rank (by energy) both correct and predicted synsets (according to **All+MFS**). In both cases we obtain comparable median (mean) ranks: 640 (3012)/41,024 for the correct representation and 516 (2443)/41,024 for the prediction. Figure 2 shows a histogram of the ranks of each correct MR of the test set for **All+MFS**. These low ranks indicates that the model has learnt to give lower energies to plausible MRs, i.e. has integrated higher level information about how synsets and lemmas can form sentences in language.

Interestingly, the WordNet::Similarity package [27] can also be used to rank MRs because it is designed to compute a similarity between synsets using the WordNet graph. We used the package’s second order co-occurrence vector of synset definitions to compute similarity, which gave the best results. This leads to 13,500 (14,000)/41,024 median (mean) ranks for the correct representations. Even though, these ranks are above chance, they are far worse than those of our model. This is mainly caused by the fact that WordNet::Similarity only knows about relations between language entities through the WordNet graph, for which the number of relation type is very low (≈ 20). For instance, it has no clue that a noun and a verb can (and how they can) be related, contrary to our model that learns that through its multi-task training on raw text.

	Model (All)	TextRunner
<i>lhs</i>	._army_NN_1	army
<i>rel</i>	._attack_VB_1	attacked
top ranked <i>rhs</i>	._troop_NN_4 ._armed_service_NN_1 ._ship_NN_1 ._territory_NN_1 ._military_unit_NN_1	Israel the village another army the city the fort
top ranked <i>lhs</i>	._business_firm_NN_1 ._person_NN_1 ._family_NN_1 ._payoff_NN_3 ._card_game_NN_1	People Players one Students business
<i>rel</i>	._earn_VB_1	earn
<i>rhs</i>	._money_NN_1	money

Table 2: **Lists of entities** reported by our system and by TextRunner.

6.5 WordNet Enrichment

WordNet and ConceptNet use a limited number of relation types. Thanks to its multi-task training and its unified representation for MRs and WordNet/ConceptNet relations, our model is able to learn rich relationships between synsets and lemmas and can even enrich those knowledge bases since it sees every verb as a potential relation type. Therefore our model is able to learn richer relationships between synsets and lemmas entities. As illustration, predicted lists for relation types that do not exist in the two knowledge bases are given in Table 2. We also compare with lists returned by TextRunner [37] (an information extraction tool having extracted information from 100M webpages, to be compared with our 50k Wikipedia articles). Lists from both systems truly reflect common-sense. However, contrary to our system, TextRunner does not disambiguate different senses of a lemma, and thus it cannot connect its knowledge to an existing resource to enrich it.

7 Conclusion

In this work we developed a large-scale system for semantic parsing from raw text to disambiguated meaning representations. The generalization ability of our method crucially centers upon scoring triplets of relations between ambiguous lemmas and unambiguous concepts (synsets) both using a single structured embedding energy function. Multi-tasking the learning of such a function over several resources we effectively learn to build disambiguated meaning representations from raw text with little direct supervision.

The final system can potentially capture the deep semantics of sentences in the structured embedding energy function by generalizing the knowledge learnt across the multiple resources (e.g. common-sense knowledge from ConceptNet and relations be-

tween concepts from WordNet) and linking it to raw text (from Wikipedia). We obtained positive experimental results on several semantic tasks that appear to support this assertion, but future work should explore the capabilities of such systems further including other semantic tasks, and utilizing more evolved grammars, e.g. by using FrameNet [2] (see e.g. [13]).

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