Neural Baselines for Word Alignment

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Abstract

Word alignments identify translational correspondences between words in a parallel sentence pair and is used, for instance, to learn bilingual dictionaries, to train statistical machine translation systems, or to perform quality estimation. In most areas of natural language processing, neural network models nowadays constitute the preferred approach, a situation that might also apply to word alignment models. In this work, we study and comprehensively evaluate neural models for unsupervised word alignment for four language pairs, contrasting several variants of neural models. We show that in most settings, neural versions of the IBM-1 and hidden Markov models vastly outperform their discrete counterparts. We also analyze typical alignment errors of the baselines that our models overcome to illustrate the benefits — and the limitations — of these new models for morphologically rich languages.

1. Introduction

Word alignment is one of basic tasks in multilingual Natural Language Processing (NLP) and is used to learn bilingual dictionaries, to train statistical machine translation (SMT) systems, or to perform quality estimation. In most areas of natural language processing, neural network models nowadays constitute the preferred approach, a situation that might also apply to word alignment models. In this work, we study and comprehensively evaluate neural models for unsupervised word alignment for four language pairs, contrasting several variants of neural models. We show that in most settings, neural versions of the IBM-1 and hidden Markov models vastly outperform their discrete counterparts. We also analyze typical alignment errors of the baselines that our models overcome to illustrate the benefits — and the limitations — of these new models for morphologically rich languages.

2. Neural Word alignment models

2.1. Statistical Word alignment

The standard approach to statistical alignment [2] is to consider asymmetric models associating each word in a source sentence \( f_1^t = f_1 \ldots f_J \) of \( J \) words with exactly one word from the target sentence \( e_1^t = e_0 \ldots e_I \) of \( I + 1 \) words. This relationship can be modeled as:

\[
P(f_1^t | e_1^t) = \sum_{a_1^t} P(f_1^t | a_1^t) P(a_1^t | e_1^t)
\]

\[
= \sum_{a_1^t} \prod_{j=1}^J p(f_j | f_{j-1}, a_j^t, e_j^t) \times p(a_j | f_{j-1}, a_{j-1}, e_j^t)
\]

where \( a_1^t = a_1 \ldots a_J \) are the latent alignment variables, with \( a_j \in [0 \ldots J] \). The two terms in the inner product in equation (1) are referred to respectively as the translation model and the alignment model.

2.2. Neural Translation Models

Both IBM-1 and HMM make the simplifying assumption that \( p(f_j | f_{j-1}, a_j^t, e_j^t) \) simplifies to \( p(f_j | e_j) \). Analogous to these models, we propose two baseline neural variants IBM-1+NN and HMM+NN, where we implement the translation component with a neural network. As explained below, we then develop several additional versions, all relying on a simple and computationally efficient feed-forward architecture.

As is custom, the target sentences is completed with a “null” symbol, conventionally at index 0. Our implementation is slightly more complex (see details in Section 2.3).
2.2.1. A Baseline neural model

Our first neural model only modifies the translation model, keeping the transition model unchanged with respect to the corresponding baseline. Both the IBM-1+NN and HMM+NN use a simple feed-forward architecture which computes a distribution over possible source words \( f_j \) from an input target word \( e \). This is implemented as a single linear layer, followed by a softmax layer. In this architecture, a fixed size target vocabulary has to be specified to compute the softmax.

\[
\text{po}(f_j | f_1^{-1}, a_1^j, e_1^j) = \text{po}(f_j | e_a^j)
\]  

(2)

In this framework, EM also applies [17, 18]: during the (E) step, alignment posteriors are computed as usual using the Baum-Welch algorithm; in the (M) step, the main change is that the NN parameters have to be optimized numerically, e.g. via gradient descent.

2.2.2. A Contextual translation model

A first variant adds some context around the target word. As the target words are fully observed, this modification has no impact on the computations needed to implement the model. We use a sliding window of size \((2 * h + 1)\) to represent word contexts and model \(p(f_j | f_1^{-1}, a_1^j, e_1^j) \) as \( p(f_j | a_{j+1}^h, e_{a_j}^h) \). For this variant, we compare two approaches to combine the embeddings of words in the context window:

- Concatenation (NN+CtxCC): we concatenate all word embeddings inside a window of size \( h \) and use a feed-forward layer for combination. We consider that the context of the null “word” is made of null tokens, similarly to [12].
- Convolution (NN+CtxCnn): we use a convolution filter of size \((2 * h + 1, 2 * h + 1)\) to combine context words. We use a simpler approach for the null model by performing a convolution over a window of null tokens.

2.2.3. Character-based representations

We consider ways to use character-based representations to improve or even replace word embeddings, so as to accommodate arbitrary vocabularies in source and target. We apply a Bi-LSTM model to encode all characters in a target word \( e \) respectively in the forward \( h_e \) and backward \( h_e^{-1} \) direction. We concatenate the resulting two hidden states \([h_e^{-1}, h_e]\) to represent each target word. Again, three variants are considered:

- Pure character-based representations on the target side NNCharTgt:
- Combined character-based and word-based representations on the target side NNCharWord, where we simply concatenate both representations;
- Pure character-based representation on both sides NNCharBoth. While the first two variant only amount to changing the target embeddings, this latter model is more challenging as we modify the source embeddings that are used in output layer. While we keep a fixed size target vocabulary in the softmax computation during training, we are in a position to compute the association of any source with any target word, known or unknown, during testing.

2.3. Alignment models

2.3.1. Baseline: a jump model

We mostly follow the assumptions of [2] to design our alignment models. Only first-order dependencies are taken into account; furthermore, alignment positions only depend on the jump width and not on the absolute index positions:

\[
p(a_j | f_1^{-1}, a_1^j, e_1^j) = p(\Delta_{a_j})
\]  

(3)

where \( \Delta_{a_j} = a_j - a_j-1 \).

Note that we associate a specific null token to every target word, which allows us to faithfully model jumps from and to null tokens. The probability to transition to an empty word is governed by one single parameter \( p_0 \). Constraints for transitioning into and out of empty words follow the proposal of [2]. For all variants of IBM-1, we thus use a uniform transition distribution \( p(a_j | a_{j-1}) = \frac{1}{2I} \).

2.3.2. Neural alignment models

Our alignment models used in the HMM also rely on MLPs to compute the multinomial distribution in (3); they further combine character-based representations for the word embeddings, as well as contextual word representations. Two variants are considered, where we only take the source, or the source and the target into account.

- Character-based representation on the target side NNJumpTgt: here the jump value only depends on target words. We use the same character-based representations as above to represent words and also use a Bi-LSTM to encode target word contexts. Therefore, the alignment probability becomes:

\[
p(a_j | f_1^{-1}, a_1^j, e_1^j) = p(\Delta_{a_j} | h_{a_j-1})
\]  

(4)

where \( h_{a_j-1} \) combines the forward and backward LSTM states computed for target word \( e_{a_j-1} \), effectively encoding the full context around \( e_{a_j-1} \).

- Character-based representations on both sides NNJumpBoth: we consider a more complex alignment model, which in addition takes into account the source side. Using the same representations as for the target side, we make the jump value also depend on the previously aligned source word. The source and target representations are concatenated before being passed through the MLP.

\[
p(a_j | f_1^{-1}, a_1^j, e_1^j) = p(\Delta_{a_j} | [h_{a_j-1}, h_{j-1}])
\]  

(5)

where \( h_{j-1} \) is a context-dependent representation of the source word \( f_{j-1} \).

Again, as source and target words are fully observed, these modifications have no impact on the computations used to compute the various quantities required for the estimation of our models. Finally note that in our implementation, the alignment and the translation models do not share any parameter.

2.4. Training neural HMMs with EM

Our training algorithm mostly follows [18], where expectation-maximization (EM) is combined with back-propagation to train the neural network(s) models. For a number of training epochs, we repeat the following procedure:

\( ^2 \)We restrict ourselves to jump values in the interval \([-K, +K] \) where \( K \) is a parameter of our model. For each sentence, the remaining probability mass corresponding to jumps greater than \( K \) or lower than \(-K \) is uniformly divided among those valid offsets [19]. This means that we parameterize alignments using a multinomial distribution over \((2K + 3)\) buckets.
1. For each batch:
   (a) Compute the posterior probability of each possible alignment link and the auxiliary function of the EM algorithm;
   (b) Improve the auxiliary function by performing one gradient update of the neural network parameters.
2. After a fixed number of batches, collect and store the entire translation model and jump width distribution for all sentences in the corpus; update the jump distribution.

The initial parameter values are either random (for IBM-1) or are initialized with the parameter values of the corresponding IBM-1 models (for the HMM models).

3. Experiments

3.1. Set-ups and evaluation protocol

3.1.1. Implementation
Our neural translation models are based on a simple architecture composed of a word embedding layer (64 units), feed-forward layers (each comprising 64 units) with activation function bnl1h [12], followed by a drop-out layer and a softmax layer. The contextual models use a context window of size $b = 1$, based on the experiments reported in [13]. For the convolutional models, we apply one small filter of size (3,3) to combine context word embeddings. For the character-based models, the bi-LSTM model also contains 64 units in the embedding layers and in the hidden layers.

In the alignment model, we consider jump values in the interval $[-5, +5]$. In the neural alignment models, the character embeddings are also 64 dimensional; the hidden layer of the MLP contains 80 cells. In all cases, our optimizer is Adam [20] with an initial learning rate of 0.001; the batch size is set to 100 sentences.
We use all sentences of length lower than 50 and a 50K word vocabulary for both the source and target languages; in our experiments with character-based models, the source and/or vocabulary is not constrained. However, training still requires to compute a softmax layer, which we approximate when needed by defining “batch specific” vocabularies of 5K words containing all the words in the batch plus the remaining most frequent words.
All parameters of the Giza++ and Fastalign baselines are set to their default values. Note that the baselines use a complete vocabulary for training, which is much larger than the vocabulary size of the neural models, and gives the discrete models a small edge over their neural counterpart. We train all models for 10 EM iterations.

3.1.2. Datasets
Our experiments consider several language pairs all having English on one side. For consistency, our training sets are mostly made of sentences from Europarl [21]: this is the case for French, German and Romanian (in the latter case, we also use the SETIMES corpus used in WMT'16 MT evaluation); for Czech we use the parallel data from News Commentary V11 to reproduce another “small data” condition. Testing use standard test sets when applicable:

In our initial experiments with En:Ro, we found that using a larger number of cells (128 or 256) did significantly improve the AER score after 10 iterations. As for the other meta-parameters, we decided to stick with these baseline values; we assume that the relative differences between models observed in our setting would carry-over, albeit with slightly different values, for larger models.

Arguably, larger training datasets exist for French and Romanian but we use data from the 2003 word alignment challenge [22]; the German test data is also Europarl, while for Czech we use the corpus described in [23].

Basic statistics for these corpora are in Table 1. En-Fr and En-De training data is much larger than for En-Ro and En-Cz (∼260K and ∼190K respectively). As expected, the vocabulary sizes of the German, Romanian and Czech corpora are substantially greater than the corresponding English, which contains a smaller number of inflected variants. These differences of size are thus a factor considered in the evaluation section.

### Table 1: Basic statistics for the training data

| Corpus  | # sentence pairs | vocabulary |
|---------|-----------------|------------|
| En-Fr   | ~1.9M           | 122580     |
| En-De   | ~1.7M           | 113037     |
| En-Ro   | ~260K           | 77361      |
| En-Cz   | ~190K           | 74504      |

### Table 2: Basic statistics for the test data

| Corpus  | # sent. | # tokens | # non-null links |
|---------|---------|----------|------------------|
| En-Fr   | 447     | 7020     | 17438            |
| En-De   | 509     | 10413    | 10533            |
| En-Ro   | 246     | 5455     | 5991             |
| En-Cz   | 2501    | 39724    | 67423            |

We use Alignment Error Rate (AER) [24] as a measure of performance. AER is based on a comparison of predicted alignment links with a human reference alignments including sure (S) and possible (P) links, and is defined as an average of the recall and precision taking into account P and S links. Formally, the AER score is defined as:

$$AER = 1 - \frac{|A \cap S| + |A \cap P|}{|A| + |S|}$$

where $A$ is the set of predicted alignments. Out of the four datasets, only Romanian/English does not contain Possible links.

3.2. Results
Table 3 reports the AER scores of our four baselines (IBM-1, HMM, IBM-4 implemented in Giza++ and Fastalign). These are systematically contrasted to our neural network models (IBM-1+NN, IBM+NN and their variants). A first general observation is that almost all neural network models outperform their discrete counterpart, with our best HMM models even outperforming IBM-4 for some language pairs.

Most of the improvement is already achieved by the vanilla NN model, which improves over the baseline for all languages, sometimes for a very large margin, eg. ∼89 AER for the neural IBM-1 for the pair Ro:En in both directions. The corresponding gains for the basic neural HMM model are not as large, our best improvement being observed for the Cz:En language pair. The improvements are overall lesser for German: on the one hand, the issues with unknown words are not as bad as for Czech, owing to a larger training set; on the other hand all our NN architectures fail to improve the modeling of alignments of German compounds which typically yield...
many-to-one alignment links that are poorly predicted; word order
differences with English are another area where our models do not
help much (see Section 4.3).
Regarding contextual variants, a first observation is that the differ-
ence between concatenation and convolutions is limited, typically in
the order of 1 AER point; the latter approach seems to be on average
the best choice. Comparison with the neural IBM-1 baselines re-
veal that the contextual version is not always better than the default.
The largest gains are observed in small data conditions (Ro:En and
Cz:En) when English is on the target side: in this case, the context
helps to disambiguate alignment links for English words by improv-
ing the translation distribution \( p(f_j | \alpha_j, c_{a_j-k}^{a_j+h}) \). For instance, we
found that the context vastly improved the precision (from 0.58 to
0.74) as well as the recall (from 0.5 to 0.54) in the Ro:En data; in
the other direction the change is insignificant. This effect is less
clear for the HMM model, where contextual models are almost al-
ways outperformed by character-based variants.
Models using character-based in the target (with or without word
information) also yield significant and consistent gains, especially
also in small data conditions. Comparing the two conditions, we
see that combining word and character information is not always
the best approach, as the pure character-based approach is some-
times even better. Our claim is that this approach should be pre-
ferred given a sufficient large dataset (as in the Fr:En condition);
when this is not the case, word information, which is easier to train,
can also prove helpful. With respect to the neural baseline, the gains
are maximal when the morphologically rich language is on the tar-
get side: in this situation, character-based representations help to
differentiate the translation model for the rare words, which in the
baseline versions all correspond to the same UNK symbol.\(^5\) The
use of character models in the target did not enable us to improve
these results.
Regarding alignment models, we see a gain in using a neuralized
version of the jump model in the cases where character-based mod-
els are already helping, i.e. for the large data conditions (Fr:En and
Ge:En). For the other languages, we do not find any improvements
in our setting, probably because the small data condition makes
character-based models less effective.
All in all, using our best models, we obtain symmetrized align-
ments\(^6\) that greatly outperform their corresponding baselines, by 5/6
AER point for Cz:En and Ro:En. Even better scores are obtained
when symmetrization uses the best model in each direction: doing
so in Ro:En with our best HMM models brings us an additional im-
provement of about +1 AER (24.93 instead of 25.89). Finally note
that all these results were obtained using a limited vocabulary of
50k words for each language; increasing the vocabulary size would
be another (computationally expensive) way to further boost align-
ment quality.

### 4. Error Analysis

In this section, we perform a detailed analysis of the quantitative
results presented above, focusing mostly on the differences between
discrete and neural versions of the HMM and IBM model. Our goal
in this section is to better understand the improvements brought by
the neural models, but also to highlight the problems that remain
difficult for alignment models. To this end, we study the error types
of each translation model, broken down by link category, where we
distinguish links joining frequent vs rare words or unknown words,
null links, etc. We also study the difference between the inferred
distribution of jumps wrt. the actual jump distribution.

#### 4.1. Issues with unaligned words

We study the accuracy of alignment models. Figure 1 compares
our 17 models for the task of aligning Czech words with their En-

\(^5\)Remember that the neural models, contrarily to the discrete
models, use a limited vocabulary of 50K words.

\(^6\)Using the grow-diag-final heuristic proposed in [25].

\(^7\)Cases where a Czech word is aligned with the dummy null En-
lish word. In this analysis, null links for English words are not taken
into account.
display a different pattern: (a) they make less predictions (and less errors) for non-null links; (b) they tend to predict a large number of null links, with only a small portion of them being actually correct. About half of the remaining errors of our best models concern null links, in this case the prediction of a link for a word that should have stayed unaligned. Null links are often due to deep syntactic divergences between languages and are quite hard to predict based on the sole source (or target) word. This is mostly a modeling issue, for which the transition from discrete to neural models is of little help. Similar trends were observed for the other language pairs / directions.

4.2. Issues with rare words and part of speech

A similar view emerges from the analysis of recall: for this, we consider all the En:Cz links that actually exist in the reference, including null-links (or equivalently, non aligned words) and study the alignment patterns that are not present in the model’s predictions. We break down the results in two categories: null links and non-null links. The former number correspond to words that should be left unaligned, yet are aligned by the model; the latter correspond to non-null links that are missed in our predictions. In the case of unknown target words (Figure 2), we see the clear benefits of using neural translation models: both IBM-1 variants and IBM variants yield a clear reduction of errors, specially null links.

The most important gains is obtained with character-based models. We then categorize target word into two groups of Part-of-Speeches (PoS): content words include noun, verb, adjective and adverb and function words. For the remaining PoS (Figure 3), we observe this problem, we collect errors corresponding to non-null words should with high probability align to rare targets [29]. To observe this problem, we collect errors corresponding to non-null links between a rare target word and a more frequent source. On the source side, we distinguish into three groups: highly frequent word (accounting overall for 90% of the training tokens), less frequent words (accounting for 10% of the tokens), and unknown words, (never seen in training). On the target side, we define the rare words group as accounting for 1% of the training data. These errors are reported in table 4 for the regular IBM-1 model and the IBM-1+NN. As can be observed, the number of errors due to rare target words aligning with more frequent source words is much lower for the neural model, suggesting that it provides a remedy to this problem.

This is also illustrated by the example of the French rare word “liquid” (found only 8 times in the training set), which is mis-aligned by IBM-1 to common English words such as “had”, “see”, “taken”, “over” and “result”. When using IBM-1+NN, “liquid” is misaligned only to the English “see”.

| Model         | IBM-1 | Giza++ | IBM-1+NN |
|---------------|-------|--------|----------|
| Source        | Target| %      | %        | %        |
| 90%           | 131   | 90     | 74       |
| 10%           | 312   | 167    | 37       |
| 0%            | 37    | 46     | 0        |

Table 4: Incorrect non-null links between rare and frequent words (see text for comments).

5. Related work

With the rapid dissemination of attention-based Neural Translation architectures, which dispenses with the word/phrase alignment step, only a small number of studies have considered this task. Early work on neural alignment model is in [12], which considers a feed-forward network to replace (and generalize) conventional count-based translation model in a HMM model. This line of work is continued by [13] who show an improvement by using recurrent neural network. Their works aim to improve the alignment quality for a phrase-based translation system by using non-probabilistic scores. [30] tackles the problem differently by directly extracting word alignment matrix without using any underlying probabilistic model; this simple symmetrical approach has also proven useful for phrase-par cleaning [31]. All these works report AER scores and show improvements with respect to standard models, but lack a detailed analysis of the benefits of neural models in alignments.

A much more productive line of research tries to exploit the conceptual similarity between word alignments and attention [32] with the goal to improve NMT. This can be achieved in several ways: [33] modify the attention component to integrate some structural bias that have proved useful for alignments, such as a preference for monotonic alignments, for reduced fertilities, etc; they also propose, following [19], to enforce symmetrization constraints, an idea also explored in [34]; the same general methodology is explored in [10, 35] with the objective to introduce dependencies between adjacent alignment vectors.

The work of [14, 15] takes a different path, and explore ways to explicitly model alignments in NMT, revisiting with novel tools early word-based translation systems; in their approach, they study various neuralizations, some very similar to our word-based models, of the standard alignment models, and also consider effective training strategies also exploiting weak supervision from count-based models. This line of research is pursued by [36], where attention vectors are (duely) processed as latent variables in NMT. The work of [37] also exploits neural versions of conventional alignment (IBM-1/2) models, with the goal to improve word representations in low resource contexts; contrarily to most work focusing on NMT, some
scores for most languages pairs, with the higher gains observed of and discuss how neural network overcomes alignment difficulties serve the performance of our models in word alignment for four lan-
tion, word noise detection and also machine translation. We ob-
maintain neural networks, notably contextual models and character-
conditions count-based translation and alignment models with several
In this paper, we have studied alignment models, replacing the tra-
language pairs (say, En:Fr), and pairs that include more distant lan-
progress still needs to be made in the prediction of null words on
due to a decrease of non-null link errors. Moreover, our analysis
for Czech and Romanian, two morphologically rich languages, in
AER scores are reported, which are mostly in line with our baseline neural IBM-1.

6. Conclusion and outlook

In this paper, we have studied alignment models, replacing the tradi-
tional count-based translation and alignment models with several
variants neural networks, notably contextual models and character-
based models. We concentrate on word alignment which provides
the base for translation lexicon induction, word sense disambigua-
tion, word noise detection and also machine translation. We ob-
serve the performance of our models in word alignment for four lan-
guage pairs (English versus French, German, Czech and Romanian)
and discuss how neural network overcomes alignment difficulties of Giza++ and Fastalign. One important observation is that
neural models can help achieve remarkable improvements in AER
scores for most languages pairs, with the higher gains observed
for Czech and Romanian, two morphologically rich languages, in
a small data condition. We also show that most of these gains are
due to a decrease of non-null link errors. Moreover, our analysis
suggests that the alignment problem is still far from solved, and that
progress still needs to be made in the prediction of null words on
the one hand, and in a more fine grained prediction of jumps on
the other hand. We intend to keep working in this direction, trying
to close the remaining gap that we observe between well aligned
language pairs (say, En:Fr), and pairs that include more distant lan-
guages, one of them possibly morphologically complex. One ob-
vious way to progress in this direction is to use better embeddings
on the target side or embeddings that are pre-trained on very large
monolingual corpora.

Another area where we intend to develop our work is to revisit and
improve models that yield symmetrical or near symmetrical align-
ments [19]: in this area, we intend to investigate recent proposals
based on variational autoencoders [38], that have proven effective
in various other unsupervised learning tasks.
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