

# An Iterative Closest Point Method for Unsupervised Word Translation

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## Abstract

Unsupervised word translation from non-parallel inter-lingual corpora has attracted much research interest. Very recently, neural network methods trained with adversarial loss functions achieved high accuracy on this task. Despite the impressive success of the recent techniques, they suffer from the typical drawbacks of generative adversarial models: sensitivity to hyper-parameters, long training time and lack of interpretability. In this paper, we make the observation that two sufficiently similar distributions can be aligned correctly with iterative matching methods. We present a novel method that first aligns the second moment of the word distributions of the two languages and then iteratively refines the alignment. Our simple linear method is able to achieve better performance than recent state-of-the-art deep adversarial approaches and is competitive with the supervised baseline. Our method is also efficient, easy to parallelize on CPU and interpretable.

## 1 Introduction

Inferring word translations between languages is a long-standing research task. Earliest efforts concentrated on finding parallel corpora in a pair of languages and inferring a dictionary by force alignment of words between the two languages. An early example of this approach is the translation achieved using the Rosetta stone.

However, if most languages share the same expressive power and are used to describe similar human experiences across cultures, they should share similar statistical properties. Exploiting statistical properties of letters has been successfully employed by substitution crypto-analysis since at least the 9th century. It seems likely that one can learn to map between languages statistically, by considering the word distributions. As one specific example, it is likely that the set of elements

described by the most common words in one language would greatly overlap with those described in a second language.

Another support for the plausibility of unsupervised word translation came with the realization that when words are represented as vectors that encode co-occurrences, the mapping between two languages is well captured by an affine transformation (Mikolov et al., 2013b). In other words, not only that one can expect the most frequent words to be shared, one can also expect the representations of these words to be similar up to a linear transformation.

A major recent trend in unsupervised learning is the usage of Generative Adversarial Networks (GANs) presented by Goodfellow et al. (2014), in which two networks provide mutual training signals to each other: the generator and the discriminator. The discriminator plays an adversarial role to a generative model and is trained to distinguish between two distributions. Typically, these distributions are labeled as “real” and “fake”, where “fake” denotes the generated samples.

In the context of unsupervised translation (Conneau et al., 2017; Zhang et al., 2017a,b), when learning from a source language to a target language, the “real” distribution is the distribution of the target language and the “fake” one is the mapping of the source distribution using the learned mapping. Such approaches have been shown recently to be very effective when employed on top of modern vector representations of words.

In this work we ask whether GANs are necessary for achieving the level of success displayed by recent work on the task of unsupervised word translation. Given that the learned mapping is simple and that the concepts described by the two languages are similar, we suggest to directly map every word in one language to the closest word in the other. While one cannot expect that all words

would match correctly for a random initialization, some would match and could help refine the affine transformation. Once an improved affine transformation is recovered, the matching process can repeat.

Naturally, such an iterative approach relies on a good initialization. For this purpose we employ two methods. First, an initial mapping is obtained by matching the means and covariances of the two distributions. Second, multiple solutions, which are obtained stochastically, are employed.

Using multiple stochastic solutions is crucial for languages that are more distant, e.g., more stochastic solutions are required for learning to translate between English and Arabic, in comparison to English and French. Evaluating multiple solutions relies on the ability to automatically identify the true matching without supervision and we present two methods for achieving this. The first considers the matching cost and the second considers the number of words  $x$  that are translated to words  $y$  in the other language that are translated back to the same word  $x$ .

Our presented approach is linear, has very few hyper-parameters, and is trivial to parallelize. It is also easily interpretable, since every step of the method has a clear goal and a clear success metric, which can also be evaluated without the ground truth bilingual lexicon. An extensive set of experiments shows that our much simpler and more efficient method is more effective than the state-of-the-art GAN based method.

## 2 Related Work

The earlier contributions in the field of word translation without parallel corpora were limited to finding matches between a small set of carefully selected words and its translation, and relied on co-occurrence statistics (Rapp, 1995) or on similarity in the variability of the context before and after the word (Fung, 1995). Finding translations of larger sets of words was made possible in follow-up work by incorporating a seed set of matching words that is either given explicitly or inferred based on words that appear in both languages or are similar in edit distance due to a shared etymology (Fung and Yee, 1998; Rapp, 1999; Schafer and Yarowsky, 2002; Koehn and Knight, 2002; Haghighi et al., 2008; Irvine and Callison-Burch, 2013; Xia et al., 2016; Artetxe et al., 2017).

For example, Koehn and Knight (2002)

matched English with German. Multiple heuristics were suggested based on hand crafted rules, including similarity in spelling and word frequency. A weighted linear combination is employed to combine the heuristics and the matching words are identified one by one, in a greedy manner. Haghighi et al. (2008) modeled the problem of matching words across independent corpora as a generative model, in which cross-lingual links are represented by latent variables, and employed an iterative EM method.

Another example that employs iterations was recently presented by Artetxe et al. (2017). Similarly to our method, this method relies on word vector embeddings, in their case the word2vec method (Mikolov et al., 2013a). Unlike our method, their method is initialized using seed matches.

Our core method incorporates a circularity term, which is also used in (Xia et al., 2016) for the task of NMT and later on in multiple contributions in the field of image synthesis (Kim et al., 2017; Zhu et al., 2017; Yi et al., 2017). This term is employed when learning bidirectional transformations to encourages samples from either domain to be mapped back to exactly the same sample when translated to the other domain and back. Since our transformations are linear, this is highly related to employing orthogonality as done in (Xing et al., 2015; Smith et al., 2017; Conneau et al., 2017) for the task of weakly or unsupervised word vector space alignment. Conneau et al. (2017) also employ a circularity term, but unlike our use of it as part of the optimization’s energy term, there it is used for validating the solution and selecting hyperparameters. In a similar vein, one of the two methods we use for model selection measures reciprocity.

Very recently, Zhang et al. (2017a,b); Conneau et al. (2017) have proposed completely unsupervised solutions. All three solutions are based on GANs. The methods differ in the details of the adversarial training, in the way that model selection is employed to select the best configuration and in the way in which matching is done after the distributions are aligned by the learned transformation.

Due to the min-max property of GANs, methods which rely on GANs are harder to interpret, since, for example, the discriminator  $D$  could focus on a combination of local differences between the distributions. The reliance on a discriminator

also means that complex weight dependent metrics are implicitly used, and that these metrics evolve dynamically during training.

Our method does not employ GANs. Alternatives to GANs are also emerging in other domains. For example, generative methods were trained by iteratively fitting random (“noise”) vectors by [Bojanowski et al. \(2017\)](#); In the recent images translation work of [Chen and Koltun \(2017\)](#), distinguishability between distribution of images was measured using activations of pretrained networks, a practice that is referred to as the “perceptual loss” ([Johnson et al., 2016](#)).

### 3 Non-Adversarial Word Translation

We present an approach for unsupervised word translation consisting of multiple parts: (i) Transforming the word vectors into a space in which the two languages are more closely aligned, (ii) Mini-Batch Cycle iterative alignment. There is an optional final stage of batch finetuning of the alignment.

Let us define two languages  $X$  and  $Y$ , each containing a set of  $N_X$  and  $N_Y$  words represented by the feature vectors  $x_1..x_{N_X}$  and  $y_1..y_{N_Y}$  respectively. Our objective is to find the correspondence function  $f(n)$  such that for every  $x_n$ ,  $f(n)$  yields the index of the  $Y$  word that corresponds to the word  $x_n$ . If a set of possible correspondences is available for a given input word, our objective is to predict one member of this set. In this unsupervised setting, no training examples of  $f(n)$  are given.

#### 3.1 Approximate Distribution Alignment with PCA

Each language consists of a set of words each parameterized by word vectors. A popular example of a word embedding method is FastText ([Bojanowski et al., 2016](#)), which uses the internal word co-occurrence statistics for each language. These word vectors are typically not expected to be aligned between languages and since the alignment method we employ is iterative, a good initialization is key.

Let us motivate our approach by a method commonly used in 3D point cloud matching. Let  $A$  be a set of 3D points and  $TA$  be the same set of points with a rotated coordinate system. Assuming non-isotropic distributions of points, transforming each set of points to its principle axes of variations

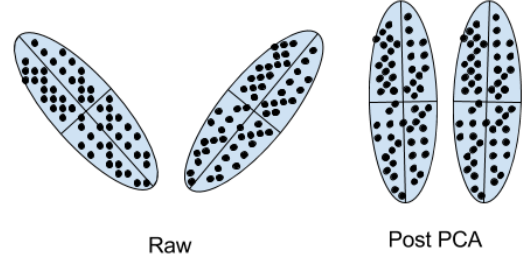


Figure 1: An illustration of distribution alignment by PCA

(using PCA) will align the two point clouds, see Fig. 1 for a 2D illustration. As noted by [Daras et al. \(2012\)](#), PCA-based alignment is very popular in the literature of point cloud matching.

Word distributions are quite different from 3D point clouds: They are much higher dimensional, and it is not obvious apriori that different languages present different “views” of the same “object” and share exactly the same axes of variation. The success of previous results, e.g. ([Conneau et al., 2017](#)), to align word vectors between languages using an orthonormal transformation does give credence to this approach. Our method relies on the assumption that many language pairs share some principle axes of variation. The empirical success of PCA initialization in this work supports this assumption.

For each language  $[X, Y]$ , we first select the  $N$  most frequent word vectors. In our implementation, we use  $N = 5000$  and employ FastText vectors of dimension  $D = 300$ . We consider the  $N \times D$  matrix  $L_l$  that contains these vectors for language  $l$  and project it, after centering the data, to the top  $p$  principle components (we use  $p = 50$ ). We denote the projected language representation as  $P_l \in \mathbb{R}^{N \times p}$ .

#### 3.2 Mini-Batch Cycle Iterative Closest Point

Although projecting to the top principle axes of variation would perfectly align a rotated non-isotropic point cloud, it does not do so in the general case. This is due to languages not having exactly the same word distributions, having different components of variation between languages and due to the limitations of low dimensional linear modeling.

We therefore attempt to find a transformation  $T$  that will align every word  $x_i$  from language  $X$  to a word  $y_{f(i)}$  in language  $Y$ . The objective is there-

fore to minimize:

$$\arg \min_T \sum_j \min_{f(i)} \|y_{f(i)} - Tx_j\| \quad (1)$$

Eq. 1 is difficult to optimize directly and various techniques have been proposed for its optimization. One popular method used in 3D point cloud alignment is Iterative Closest Point (ICP). ICP solves Eq. 1 iteratively in two steps.

1. For each  $y_j$ , find the nearest  $Tx_i$ . We denote its index by  $f_y(j) = i$
2. Optimize for  $T$  in  $\sum_j \|y_j - Tx_{f_y(j)}\|$

In this work, we use a modified version of ICP which we call Mini-Batch Cycle ICP (MBC-ICP). MBC-ICP learns transformations  $T_{XY}$  for  $X \rightarrow Y$  and  $T_{YX}$  for  $Y \rightarrow X$ . We include cycle-constraints ensuring that a word  $x$  transformed to the  $Y$  domain and back is unchanged (and similarly for every  $Y \rightarrow X \rightarrow Y$  transformation). The strength of the cycle constraints is parameterized by  $\lambda$  (we have  $\lambda = 0.1$ ). We compute the nearest neighbor matches at the beginning of each epoch, and then optimize transformations  $T_{YX}$  and  $T_{XY}$  using mini-batch SGD with mini-batch size 128. The mini-batch rather than full-batch optimization greatly increases the success of the method. Experimental comparisons can be seen in the results section. Note we only compute the nearest neighbors at the beginning of each epoch, rather than for each mini-batch due to the computational expense.

Every iteration of the final MBC-ICP algorithm therefore becomes:

1. For each  $y_j$ , find the nearest  $T_{xy}x_i$ . We denote its index by  $f_y(j)$
2. For each  $x_i$ , find the nearest  $T_{yx}y_j$ . We denote its index by  $f_x(i)$
3. For all mini-batches of  $\{x_i\}$  and  $\{y_j\}$  in epoch, iteratively optimize  $T_{xy}$  and  $T_{yx}$  on:

$$\sum_j \|y_j - T_{xy}x_{f_y(j)}\| + \sum_i \|x_i - T_{yx}y_{f_x(i)}\| + \lambda \sum_i \|x_i - T_{yx}T_{xy}x_i\| + \lambda \sum_j \|y_j - T_{xy}T_{yx}y_j\|$$

A good initialization is important for ICP-type methods. We therefore begin with the projected data in which the transformation is assumed to be relatively small and initialize transformations  $T_{xy}$  and  $T_{yx}$  with the identity matrix.

Once MBC-ICP has generated the correspondences functions  $f_x(i)$  and  $f_y(j)$ , we run a second MBC-ICP with the original 300D word vectors (no PCA). In the first iteration of this second run, we skip steps 1 and 2, and instead use the  $f_x(i)$  and  $f_y(j)$  learned before. At the end of this stage, we recover transformations  $\bar{T}_{xy}$  and  $\bar{T}_{yx}$  that transform the 300D word vectors from  $X \rightarrow Y$  and  $Y \rightarrow X$  respectively.

*Reciprocal pairs:* After several iterations of MBC-ICP, the estimated transformation becomes quite reliable. We can therefore use this transformation to identify the pairs that are likely to be correct matches. We use the reciprocity heuristic: For every word  $y \in Y$  we find the nearest transformed word from the set  $\{T_{xy}x | x \in X\}$ . We also find the nearest neighbors for the  $Y \rightarrow X$  transformation. If a pair of words is matched in both  $X \rightarrow Y$  and  $Y \rightarrow X$  directions, the pair is denoted reciprocal. We have obtained significant increases in accuracy by including a third MBC-ICP stage which is trained only on pairs that are reciprocal. This stage is initialized with the transformations  $\bar{T}_{xy}$  and  $\bar{T}_{yx}$  learned in the previous iterations. As typically only a portion of the vocabulary has reciprocal matches, we use a slightly larger vocabulary of 7.5k words for this stage.

In summary: we first run MBC-ICP on the 5k most frequent words after transformation to principle components. The resulting correspondences  $f_x(i)$  and  $f_y(j)$  are used to initialize a second MBC-ICP on the raw 300D data (rather than PCA). The resulting translation matrices  $T_{xy}$  and  $T_{yx}$  are used to initialize a third MBC-ICP now operating only on reciprocal pairs and on a vocabulary of 7.5k words. The output of the method are transformation matrices  $T_{xy}$  and  $T_{yx}$ .

### 3.3 Fine-tuning

The PCA initialization and MBC-ICP iterative alignment are able to generate a good solution for the affine transformation  $T$  between the two languages. In accordance with previous works (Conneau et al., 2017; Hoshen and Wolf, 2018), we found that once a good solution is found, further fine-tuning can obtain some improvements in accuracy (1-2%). Fine-tuning is performed by running the Procrustes method on the full vocabulary of 200k words. The Procrustes method, which was first used for weakly-supervised translation by (Xing et al., 2015), solves a supervised equa-



tion of the form  $\min_W \|WX - Y\|$ , where  $W$  is orthonormal. Let us define the SVD decomposition of  $YX^T$  as  $USV^T$ . The optimal  $W$  given by the Procrustes method is recovered by  $UV^T$ . In our case, the method is initialized with matches from MBC-ICP.

### 3.4 Matching Metrics

Although we optimize the nearest neighbor metric, we found that in accordance with (Conneau et al., 2017), neighborhood retrieval methods such as Inverted Soft-Max (ISF) (Smith et al., 2017) and Cross-domain Similarity Local Scaling (CSLS) improve final retrieval performance. We therefore evaluate using CSLS. The similarity between a word  $x \in X$  and a word  $y \in Y$  is computed as  $2 \cos(T_{xy}x, y) - r(T_{xy}x) - r(y)$ , where  $r(\cdot)$  is the average distance between the word and its 10-NN.

## 4 Multiple Stochastic Solutions

Our approach utilizes multiple stochastic solutions, to provide a good initialization for the MBC-ICP algorithm. There are two sources of stochasticity in our system: (i) The randomized nature of the PCA algorithm (it uses random matrices (Liberty et al., 2007)) (ii) The order of the training samples (the mini-batches) when training the transformations.

The main issue faced by unsupervised learning in the case of multiple solutions, is (i) choosing the best solution in case of a fixed parallel run budget, or (ii) finding a good stopping criterion if attempting to minimize the number of runs serially.

We use two unsupervised metrics for measuring convergence of MBC-ICP:

**Reconstruction Cost:** We measure how closely every  $x \in X$  and  $y \in Y$  is reconstructed by a transformed word from the other domain.

$$\sum_j \|y_j - T_{xy}x_{f_y(j)}\| + \sum_i \|x_i - T_{yx}y_{f_x(i)}\| \quad (2)$$

Although in isotropic distributions this has many degenerate solutions, empirically we find that values that are significantly lower than the median almost always correspond to a good solution.

**Reciprocity:** The number of reciprocal pairs, as defined in Sec. 3, was found to be a good measure of convergence.

The optimization profile of MBC-ICP is very predictable and easily lends itself for choosing effective termination criteria. The optimiza-

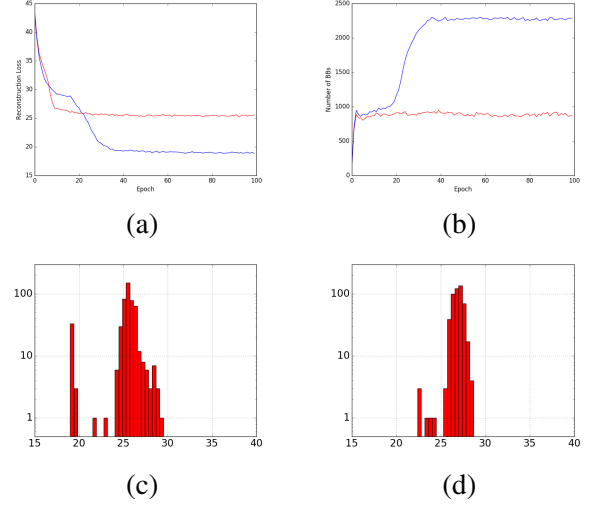


Figure 2: Examples of ICP convergence. (a) Evolution as a function of epoch number of Reconstruction loss for a successful (Blue) and unsuccessful run (Red). (b) Reciprocity per epoch for the same two runs. (c) The final reconstruction loss distribution for En-Fr. (d) A similar histogram for En-Ar.

tion profile of a successfully converged and non-converging runs are presented in Fig. 2(a,b). Both the reconstruction loss and reciprocity metrics are shown. Both move in sync and clearly distinguish between the converged and non-converging runs. Fig. 2(c,d) presents the distribution of final reconstruction costs for 500 different runs for *EN-Fr* and *En-Ar*.

When all ICP runs are evaluated in parallel we can select the run with the lowest Reconstruction metric and highest Reciprocity metric. The translation matrix from the best run will then be used for the refinement stages. In case the ICP runs are performed sequentially, a termination criterion is required. Such a criterion will also be useful in the parallel case if we would like to determine if our best run has in fact converged. We recommend using the Median Absolute Deviations (MAD) criterion on one of our metrics (Reconstruction loss or Reciprocity), obtaining a z-score for each run. As can be seen from the histograms in Fig. 2(c,d), the converged runs lie quite far away from the main non-convergent peak (we found  $z \leq -6$  to work well).

## 5 Experiments

### 5.1 Comparison to Prior Supervised and Unsupervised Methods

We evaluated our method extensively to ensure that it is indeed able to effectively and efficiently perform unsupervised word translation. To ensure comparability to previous methods we used the code and datasets from the MUSE repository by [Conneau et al. \(2017\)](#)<sup>1</sup>.

The evaluation concentrated on two aspects of the translation: (i) Word Translation Accuracy measured by the fraction of words translated to a correct meaning in the target language, and (ii) Runtime of the method.

We have evaluated our method against the best methods from ([Conneau et al., 2017](#)). The supervised baseline method learns an alignment from 5k supervised matches using the Procrustes method. The mapping is then refined using the Procrustes method and CSLS matching on 200k unsupervised word vectors in the source and target languages. The unsupervised method proposed by ([Conneau et al., 2017](#)), uses generative adversarial domain mapping between the word vectors of the 50k most common words in each language. The mapping is then refined using the same procedure that is used in the supervised baseline.

Where possible, we used the numbers from the original paper. Not all numbers for En-It and En-Ar were available in ([Conneau et al., 2017](#)) and were recomputed using the authors’ GitHub repository. The finetuned supervised baseline was recomputed so that it uses the full 200k unsupervised vocabulary rather than just 5k in the original paper (improving its performance).

A comparison of the word translation accuracies before finetuning can be seen in Tab. 1. Our method significantly outperforms the method of ([Conneau et al., 2017](#)) on all of the evaluated language pairs. Additionally we can see that our method performs comparably to the supervised baseline on all pairs except En-Ru for which supervision seems particularly useful. The same trends are apparent for simple nearest neighbors and CSLS although CSLS always performs better.

We present a comparison between the methods after finetuning and using the CSLS metric in Tab. 2. All methods underwent the same finetuning procedure. We can see that our method still

Table 1: Comparison of word translation accuracy (%) - without finetuning

Pair	Method					
	Supervised		GAN		Ours	
	nn	csls	nn	csls	nn	csls
En-Es	77.4	<b>81.4</b>	69.8	75.7	75.9	<u>81.1</u>
Es-En	77.3	<b>82.9</b>	71.3	79.7	76.0	<u>82.1</u>
En-Fr	74.9	<u>81.1</u>	70.4	77.8	74.8	<b>81.5</b>
Fr-En	76.1	<b>82.4</b>	61.9	71.2	75.0	<u>81.3</u>
En-De	68.4	<u>73.5</u>	63.1	70.1	66.9	<b>73.7</b>
De-En	67.7	<u>72.4</u>	59.6	66.4	67.1	<b>72.7</b>
En-Ru	47.0	<b>51.7</b>	29.1	37.2	36.8	<u>44.4</u>
Ru-En	58.2	<b>63.7</b>	41.5	48.1	48.4	<u>55.6</u>
En-It	75.7	<b>77.3</b>	54.3	65.1	71.1	<u>77.0</u>
It-En	73.9	<b>76.9</b>	55.0	64.0	70.4	<u>76.6</u>
En-Ar	31.3	<b>36.5</b>	18.9	23.5	26.9	<u>33.3</u>
Ar-En	45.0	<b>49.5</b>	*	*	39.8	<u>45.5</u>

\* Failed to converge

outperforms the GAN method and is comparable to the supervised baseline.

Another observation is that on most language pairs, finetuning only makes a small difference for our method (1-2%). An unaligned vocabulary of 7.5k is sufficient to achieve most of the accuracy. This is in contrast with the GAN, that benefits greatly from finetuning on 200k words.

We also compare the different methods in terms of training time required by the method. We emphasize that our method is trivially parallelizable, simply by splitting the random initializations between workers. The run time of each solution of MBC-ICP is 47 seconds on CPU. The run time of all solutions can therefore be as low as a single run, at linear increase in compute resources. As it runs on CPU, parallelization is not expensive. The average number of runs required for convergence depends on the language pair (see below, Fig. 2). We note that our method learns translations for both languages at the same time.

The current state-of-the-art method by ([Conneau et al., 2017](#)) requires around 3000 seconds on the GPU. It is not obvious how to parallelize such a method efficiently. It therefore requires about 30 times longer to train than our method (with parallelization) and is not practical on a multi-CPU platform. All methods use the optional refinement

<sup>1</sup><https://github.com/facebookresearch/MUSE>

Table 2: Comparison of word translation accuracy (%) - after finetuning and using CSLS

Pair	Method		
	Supervised	GAN	Ours
En-Es	<b>82.4</b>	81.7	<u>82.1</u>
Es-En	<u>83.9</u>	83.3	<b>84.1</b>
En-Fr	<b>82.3</b>	<b>82.3</b>	<b>82.3</b>
Fr-En	<b>83.2</b>	82.1	<u>82.9</u>
En-De	<b>75.3</b>	74.0	<u>74.7</u>
De-En	<u>72.7</u>	72.2	<b>73.0</b>
En-Ru	<b>50.7</b>	44.0	<u>47.5</u>
Ru-En	<b>63.5</b>	59.1	<u>61.8</u>
En-It	<b>78.1</b>	76.9	<u>77.9</u>
It-En	<b>78.1</b>	76.7	<u>77.5</u>
En-Ar	34.5	<b>35.3</b>	<u>35.1</u>
Ar-En	<u>49.7</u>	*	<b>50.6</b>

\* Failed to converge

step (for refinement each iteration requires about 100 seconds). The performance increases of refinement for our method are typically quite modest and can be skipped at the cost of 1-2% in accuracy, the GAN however requires finetuning to obtain competitive results. Another obvious advantage is that our method does not require a GPU.

*Implementation:* We used (100, 100, 5) iterations for the three MBC-ICP stages. Unsupervised reconstruction was used for stopping. Results were typically not sensitive to hyper-parameter choice.

## 5.2 Ablation Analyses

In the following we analyze the reasons for our method’s superior performance.

There are three important steps essential for the convergence of the ICP step: (i) PCA ii) Dimensionality reduction, (iii) Multiple stochastic solutions. In Tab. 3 we present the ablation results on the En-Es pair with PCA and no dimensionality reduction, with only the top 50 PCs and without PCA at all (best run out of 500 chosen using the unsupervised reconstruction loss). We can observe that the convergence rate without PCA and with PCA but without dimensionality reduction is much lower than with PCA, the best run without PCA has not succeeded in obtaining a good translation. This provides evidence that both PCA and dimensionality reduction are essential for the suc-

Table 3: En-Es accuracy with and without PCA

Method	En-Es	Es-En
No PCA	0.0%	0.0%
With 300 PCs	0.0%	0.0%
With 50 PCs	<b>82.2%</b>	<b>83.8%</b>

Table 4: Fraction of converging En-Es and En-Ar runs with different randomization strategies

Method	En-Es	En-Ar
No randomization	0.0%	0.0%
Randomized Ordering	0.0%	0.0%
Randomized PCA	9.8%	0.0%
Randomized Ordering + PCA	<b>16.8%</b>	<b>1.2%</b>

cess of the method.

We also experiment with the different factors of randomness between runs, to understand which aspect of the multiple solutions provides the diversity allowing for convergence in the more challenging language pairs (such as En-Ar). We therefore perform the following four experiments: i. Fixing PCA and Batch Ordering. ii. Fixing all data batches to have the same ordering in all runs, iii. Fix the PCA bases of all runs, iv. Let both PCA and batch ordering vary between runs.

Tab. 4 compares the results on En-Es for the experiments described above. From looking at the results we can observe that using both sources of stochasticity is usually better. Although there is some probability the PCA will result in aligned principle components between the two languages, this usually does not happen and therefore using stochastic PCA is highly beneficial.

## 5.3 Convergence Statistics

In Fig. 3 we present the statistics for all language pairs with Procrustes-ICP (P-ICP) vs MBC-ICP. In P-ICP, we first calculate the matches for the vocabulary, and then perform a batch estimate of the transformation using the P-ICP method (starting from PCA word vectors and  $T_{xy}$  initialized at identity). The only source of stochasticity in P-ICP is the PCA where in MBC-ICP the order of mini-batches provides further stochasticity. Adding random noise to the mapping initialization was not found to help. Each plot shows the histogram in log space for the number of runs that achieved unsupervised reconstruction loss within

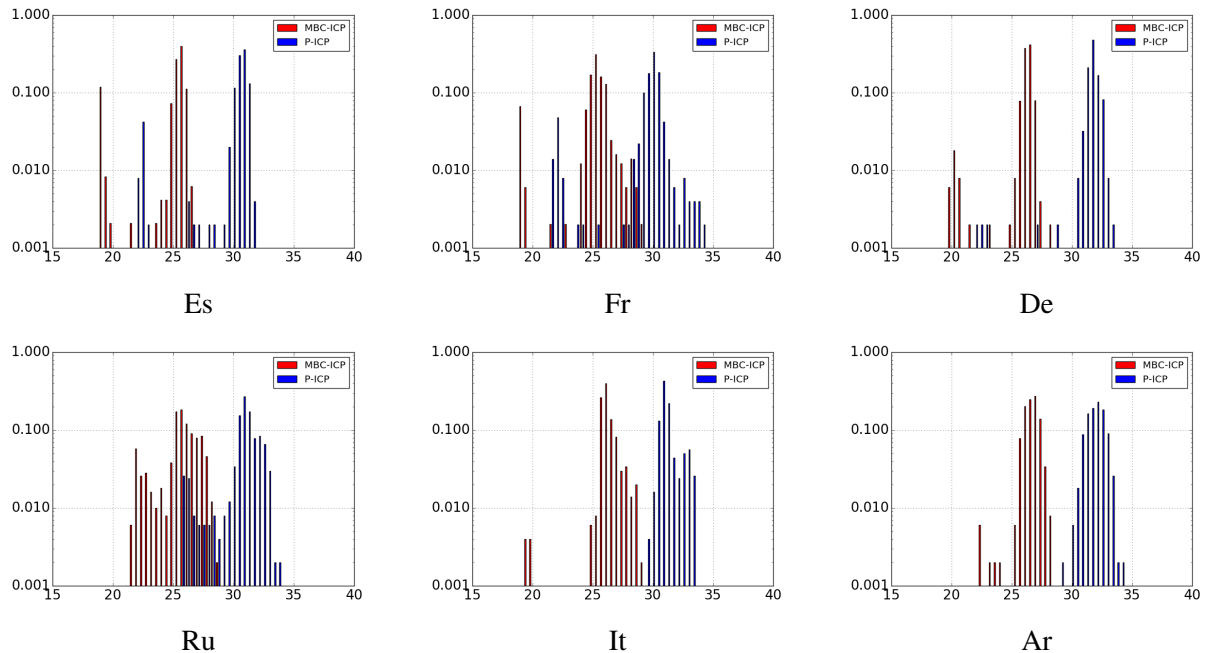


Figure 3: Histograms of the Reconstruction metric across 500 ICP runs for MBC-ICP (Red) and P-ICP (Blue). The comparison is shown for En-Es, En-Fr, En-De, En-Ru, En-It, En-Ar. On average MBC-ICP converges to much better minima. We can observe that MBC-ICP has many more converging runs than P-ICP. In fact for En-It and En-Ar, P-ICP does not converge even once in 500 runs.

the range of the bin. The converged runs with lower reconstruction values typically form a peak which is quite distinct from the non-converged runs allowing for easy detection of converged runs.

An interesting aspect of the convergence statistics is the fact that they measure the ease of translation between the two languages and generally correlate with our intuition (En-Ar converged much worse than En-Fr) but not always (En-Es converged better than En-De). As the statistics are potentially influenced by the dataset used to train the word vectors, further study is needed.

MBC-ICP converged much better than P-ICP: For the languages pairs with a wide convergence range (En-Es, En-Fr, En-Ru) we can see that MBC-ICP converged on many more runs than P-ICP. For the languages with a narrow convergence range (En-Ar, En-It), P-ICP was not able to converge at all. We therefore conclude that the mini-batch update and batch-ordering stochasticity increase the convergence range and is important for effective unsupervised matching.

## 6 Conclusions

We have presented an effective technique for unsupervised word-to-word translation. Our method

is linear and non-adversarial. We have empirically shown that our method outperforms current state-of-the-art GAN methods in terms of pre and post finetuning word translation accuracy. Our method runs on CPU and is much faster than current methods when using parallelization. The proposed method is interpretable, i.e. every stage has an intuitive loss function with an easy to understand objective.

With the growing popularity of GANs, attempts are made to introduce this powerful technique into many fields. However, looking at the body of accumulated work, it seems that most of the success is in image generation, where CNN-based discriminators are extremely effective in pointing to perceptual differences while training, and in unsupervised domain adaptation, where gradient reversal (Ganin et al., 2016) is effective in the recovery of invariant features. At this point in time, the jury on the current success of the GAN technique in other domains, e.g. in NLP and voice, could still be out.

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