# Concatenated p-mean Word Embeddings as Universal Cross-Lingual Sentence Representations

Andreas Rücklé<sup>†</sup>, Steffen Eger<sup>†</sup>, Maxime Peyrard<sup>†‡</sup>, Iryna Gurevych<sup>†‡</sup>

†Ubiquitous Knowledge Processing Lab (UKP)

‡Research Training Group AIPHES

Department of Computer Science, Technische Universität Darmstadt

† www.ukp.tu-darmstadt.de

‡ www.aiphes.tu-darmstadt.de

# Abstract

Average word embeddings are a common baseline for more sophisticated sentence embedding techniques. An important advantage of average word embeddings is their computational and conceptual simplicity. However, they typically fall short of the performances of more complex models such as InferSent (Conneau et al., 2017). Here, we generalize the concept of average word embeddings to p-mean word embeddings, which are (almost) as efficiently computable. We show that the concatenation of different types of p-mean word embeddings considerably closes the gap to stateof-the-art methods such as InferSent monolingually and substantially outperforms these more complex techniques cross-lingually. In addition, our proposed method outperforms different recently proposed baselines such as SIF and Sent2Vec by a solid margin, thus constituting a much harder-to-beat monolingual baseline for a wide variety of transfer tasks. Our data and code are publicly available.<sup>1</sup>

#### 1 Introduction

Sentence embeddings are dense vector representations that summarize different properties of a sentence (e.g. its meaning), thereby extending the very popular concept of word embeddings (Mikolov et al., 2013a; Pennington et al., 2014) to the sentence level.

Universal sentence embeddings have recently gained considerable attention due to their wide range of possible applications in downstream tasks. In contrast to task-specific representations, such as the ones trained specifically for tasks like textual entailment or sentiment (Tai et al., 2015; Lin et al., 2017), they are trained in a task-agnostic manner on large datasets. As a consequence, they often

perform better when little labeled data is available from which it is difficult to induce adequate taskspecific representations.

To a certain degree, the history of sentence embeddings parallels that of word embeddings, but on a faster scale: early word embeddings models were complex and often took months to train (Bengio et al., 2003; Collobert and Weston, 2008; Turian et al., 2010) before Mikolov et al. (2013a) presented a much simpler method that could train substantially faster and therefore on much more data, leading to significantly better results. Likewise, sentence embeddings originated from the rather resource-intensive 'Skip-thought' encoder-decoder model of Kiros et al. (2015), before successively less demanding models (Hill et al., 2016; Kenter et al., 2016; Arora et al., 2017) were proposed that are much faster at train and/or test time.

The current state of the art is the so-called InferSent model (Conneau et al., 2017), which learns sentence embeddings with a rather simple architecture in single day (on a GPU), but on very high quality data, namely, Natural Language Inference data (Bowman et al., 2015). Following previous work (e.g. Kiros et al. 2015), InferSent has also set the standards in measuring the usefulness of sentence embeddings, in particular, by requiring the embeddings to be "universal" in the sense that they must yield stable and high-performing results on a wide variety of so-called "transfer tasks".

We follow both of these trends and posit that sentence embeddings should be simple, on the one hand, and universal, on the other. We extend universality to the cross-lingual case: universal sentence embeddings should perform well across multiple tasks and across natural languages.

The arguably simplest possible sentence embedding technique is to average individual word embeddings. This so-called mean word embedding is the starting point of our extensions.

Ihttps://github.com/UKPLab/
arxiv2018-xling-sentence-embeddings

First, we observe that average word embeddings have partly been treated unfairly in previous work such as Conneau et al. (2017) because the newly proposed methods yield sentence embeddings of rather large size (e.g., d = 4096) while they have been compared to much smaller average word embeddings (e.g., d = 300). Increasing the size of individual—and thus average—word embeddings is likely to improve the quality of average word embeddings, but with an inherent limitation: there is (practically) only a finite number of words in natural languages, so that the additional dimensions will not be used to store additional information, beyond a certain threshold. To remedy, we instead propose to concatenate diverse word embeddings that store different kinds of information, such as syntactic, semantic or sentiment information; concatenation is a simple but effective technique and has been applied in different setups before (Zhang et al., 2016).

Secondly, and more importantly, we posit that the concept of 'mean' has been defined too narrowly by the corresponding NLP community. Standard mean word embeddings stack the word vectors of a sentence in a matrix and compute perdimension *arithmetic* means on this matrix. We perceive this mean as a summary of all the entries in a dimension. In this work, we instead focus on so-called *power means* (Hardy et al., 1952) which naturally generalize the arithmetic mean: other special cases are the quadratic mean as well as minand max-pooling. While *p*-means are (nearly) as computationally efficient as standard means, they contain complementary information.

Finally, we combine concatenation of word embeddings with different *p*-means and show that our sentence embeddings satisfy our requirement of universality: they substantially outperform different other strong baselines across a number of tasks monolingually, and substantially outperform all other approaches we compared to cross-lingually.

Our contributions (i) We show that concatenated p-mean word embeddings considerably narrow the gap to more complex models compared to standard average word embeddings. (ii) In particular, we show that they perform well crosslingually and outperform cross-lingual extensions of InferSent. (iii) We also provide new mono- and cross-lingual sentence classification datasets, partly from different (namely, argumentation mining) domains.

## 2 Related Work

Monolingual word embeddings are typically learned to predict context words in fixed windows (Mikolov et al., 2013a; Pennington et al., 2014). Extensions predict contexts given by dependency trees (Levy and Goldberg, 2014) or combinations of windows and dependency context (Komninos and Manandhar, 2016), leading to more syntactically oriented word embeddings. Fasttext (Bojanowski et al., 2017) represents words as the sum of their n-gram representations trained with a skipgram model. Attract-repel (Mrkšić et al., 2017) uses synonymy and antonymy constraints from lexical resources to fine tune word embeddings with linguistic information. Vulić et al. (2017) morph-fit word embeddings using language-specific rules so that derivational antonyms ("expensive" vs. "inexpensive") move far away in vector space.

**Cross-lingual word embeddings** originate from the idea that not only monolingually but also crosslingually similar words should be close in vector space. Common practice is to learn a mapping between two monolingual word embedding spaces (Faruqui and Dyer, 2014; Artetxe et al., 2016). Other approaches predict mono- and bilingual context using word alignment information as an extension to the standard skip-gram model (Luong et al., 2015) or inject cross-lingual synonymy and antonymy constraints similar as in the monolingual setting (Mrkšić et al., 2017). As with monolingual embeddings, there exists a veritable zoo of different approaches, but they have been reported to nonetheless often perform similarly in applications (Upadhyay et al., 2016).

In this work, we train one of the simplest approaches: BIVCD (Vulić and Moens, 2015). This creates bilingual word embeddings from aligned bilingual documents by concatenating parallel document pairs and shuffling the words in them before running a standard word embedding technique.

Monolingual sentence embeddings usually built on top of existing word embeddings, and different approaches focus on computing sentence embeddings by composition of word embeddings. Wieting et al. (2015) learned paraphrastic sentence embeddings by fine-tuning skip-gram word vectors while using additive composition to obtain representations for short phrases. SIF (Arora et al., 2017) computes sentence embeddings by taking weighted averages of word embeddings

and then modifying them via SVD. Sent2vec (Pagliardini et al., 2017) learns n-gram embeddings and averages them. Siamese-CBOW (Kenter et al., 2016) trains word embeddings that, when averaged, should yield good representations of sentences. However, even non-optimized average word embeddings can encode valuable information about the sentence, such as its length and word content (Adi et al., 2017).

Other approaches consider sentences as additional tokens whose embeddings are learned jointly with words (Le and Mikolov, 2014), use autoencoders (Hill et al., 2016), or mimick the skipgram model (Mikolov et al., 2013a) by predicting surrounding sentences (Kiros et al., 2015).

Recently, InferSent (Conneau et al., 2017) achieved state-of-the-art results across a wide range of different transfer tasks. Their model uses bidirectional LSTMs and was trained on the SNLI (Bowman et al., 2015) and MultiNLI (Williams et al., 2017) corpora. This is novel in that previous work, which likewise used LSTMs to learn sentence embeddings but trained on other tasks (i.e. identifying paraphrase pairs), usually did not achieve significant improvements compared to simple word averaging models (Wieting et al., 2016).

Cross-lingual sentence embeddings have received comparatively less attention. Hermann and Blunsom (2014) learn cross-lingual word embeddings and infer document-level representations with simple composition of unigrams or bigrams, finding that added word embeddings perform on par with the more complex bigram model. Several authors proposed to extend ParagraphVec (Le and Mikolov, 2014) to the cross-lingual case: Pham et al. (2015) add a bilingual constraint to learn cross-lingual representations using aligned sentences; Mogadala and Rettinger (2016) add a general cross-lingual regularization term to ParagraphVec; Zhou et al. (2016) train task-specific representations for sentiment analysis based on ParagraphVec by minimizing the distance between paragraph embeddings of translations. Finally, Chandar et al. (2013) train a cross-lingual auto-encoder to learn representations that allow reconstructing sentences and documents in different languages, and Schwenk and Douze (2017) use representations learned by an NMT model for translation retrieval.

To our best knowledge, all of these cross-lingual works evaluate on few individual datasets, and none focuses on *universal* cross-lingual sentence embed-

dings that perform well across a wide range of different tasks.

## 3 Concatenated p-mean Embeddings

#### 3.1 p-means

Our core idea is to generalize average word embeddings, which summarize a sequence of word embeddings  $\mathbf{w}_1,...,\mathbf{w}_n \in \mathbb{R}^d$  by taking componentwise arithmetic averages:

$$\forall i = 1, \dots, d: \frac{w_{1i} + \dots + w_{ni}}{n}$$

This operation summarizes the 'time-series'  $(w_{1i}, \ldots, w_{ni})$  of variable length n by their arithmetic mean. Of course, then, we might also compute other statistics on these time-series such as standard deviation, skewness (and further moments), Fourier transformations, etc., in order to capture different information from the sequence.

For simplicity and to focus on only one type of extension, we consider in this work so-called *power means* (Hardy et al., 1952), defined as:

$$\left(\frac{x_1^p + \dots + x_n^p}{n}\right)^{1/p}; \quad p \in \mathbb{R} \cup \{\pm \infty\}$$

for a sequence of numbers  $(x_1,\ldots,x_n)$ . This generalized form retrieves many well-known means such as the arithmetic mean (p=1), the geometric mean (p=0), and the harmonic mean (p=-1). In the extreme cases, when p equals  $\pm \infty$ , the power mean specializes to the minimum  $(p=-\infty)$  and maximum  $(p=+\infty)$  of the sequence.<sup>2</sup>

#### 3.2 Concatenation

For a sequence of vectors  $\mathbf{w}_1, \dots, \mathbf{w}_n$ , concisely written as a matrix  $\mathbf{W} = [\mathbf{w}_1, \dots, \mathbf{w}_n] \in \mathbb{R}^{n \times d}$ , we let  $H_p(\mathbf{W})$  stand for the vector in  $\mathbb{R}^d$  whose d components are the p-means of the sequences  $(w_{1i}, \dots, w_{ni})$ , for all  $i = 1, \dots, d$ .

Given a sentence  $s=w_1\cdots w_n$  we first look up the embeddings  $\mathbf{W}^{(i)}=[\mathbf{w}_1^{(i)},\ldots,\mathbf{w}_n^{(i)}]\in\mathbb{R}^{n\times d_i}$  of its words from some embedding space  $\mathbb{E}^i$ . To get summary statistics of the sentence, we then compute K p-mean summaries of s and concatenate

 $<sup>^2</sup>$ It must be noted that p-means, for arbitrary p, are defined for positive real numbers  $x_1,\ldots,x_n$ . When some of the  $x_i$  are negative, problems arise, particularly (but not exclusively) for  $0 , because in this case <math>x_i^p$  is a complex number c = a + bi. This can be resolved by identifying the complex number  $c \in \mathbb{C}$  by the two real numbers  $a,b \in \mathbb{R}$  that define it. For reasons relating to embedding size, however, we drop the imaginary part and only retain a in our experiments.

them:

$$\mathbf{s}^{(i)} = H_{p_1}(\mathbf{W}^{(i)}) \oplus \cdots \oplus H_{p_K}(\mathbf{W}^{(i)})$$

where  $\oplus$  stands for concatenation and  $p_1, \ldots, p_K$  are K different power mean values. Note that our resulting sentence representation, which we denote as  $\mathbf{s}^{(i)} = \mathbf{s}^{(i)}(p_1, \ldots, p_k)$ , lies in  $\mathbb{R}^{d_i \cdot K}$ .

To get further representational power from different word embeddings, we concatenate different p-mean sentence representations  $\mathbf{s}^{(i)}(p_1,\ldots,p_k)$  obtained from different embedding spaces  $\mathbb{E}^i$ :

$$\bigoplus_{i} \mathbf{s}^{(i)} \tag{1}$$

The dimensionality of this representation is  $K\sum_i d_i$ . When all embedding spaces have the same dimensionality d, this becomes  $K \cdot L \cdot d$ , where L is the number of spaces we consider.

# 4 Monolingual Experiments

## 4.1 Experimental Setup

**Tasks** The goal of universal sentence embeddings is to yield good results across a wide range of so-called transfer tasks. To measure whether our sentence embeddings satisfy this criterion, we replicate the setup of Conneau et al. (2017) and evaluate on the six transfer tasks listed in their table 1.

Noting that their selection of tasks is somewhat biased towards sentiment analysis, we add three additional tasks: AM, an argumentation mining task based on Stab and Gurevych (2017) where sentences are classified into the categories major claim, claim, premise, and non-argumentative; AC, a further argumentation mining task with very few data points based on Peldszus and Stede (2015) in which the goal is to classify sentences as to whether they contain a claim or not (Daxenberger et al., 2017); and CLS, a task based on Prettenhofer and Stein (2010) to identify *individual sentences* as being part of a positive or negative book review.<sup>3</sup>

We summarize properties of the different tasks in Table 1.

Word embeddings We use four diverse, potentially complementary types of word embeddings as basis for our sentence representation techniques: GloVe embeddings (GV) (Pennington et al., 2014) trained on Common Crawl; Word2Vec (Mikolov et al., 2013b) trained on GoogleNews

(GN); Attract-Repel (AR) (Mrkšić et al., 2017), which are designed to differentiate between antonyms; and MorphSpecialized (MS) (Vulić et al., 2017), which are designed to differentiate between inflectional forms and derivational antonyms.

We use pre-trained word embeddings except for Attract-Repel where we use the retrofitting code provided by the authors to tune the embeddings of Komninos and Manandhar (2016).

**Evaluated approaches** For each type of word embedding, we evaluate the standard average (p = 1) as sentence embedding as well as different p-mean concatenations. We also evaluate concatenations of embeddings  $\mathbf{s}^{(i)}(1,\pm\infty)$ , where i ranges over the word embeddings mentioned above. We motivate the choice of our p-mean values in §6.

We compare against the following four sentence embedding approaches: SIF (Arora et al., 2017), a weighted average technique, applied to GloVe vectors; average Siamese-CBOW embeddings (Kenter et al., 2016) based on the Toronto Book Corpus, which are tuned for averaging; Sent2Vec (Pagliardini et al., 2017), a method based on n-gram features, and InferSent, which constitutes the recent state-of-the-art approach (Conneau et al., 2017).

While SIF (d=300), average Siamese-CBOW (d=300), and Sent2Vec (d=700) embeddings are relatively low-dimensional, InferSent embeddings are high-dimensional (d=4096). In all our experiments the maximum dimensionality of our concatenated p-mean sentence embeddings does not exceed  $d=4\cdot3\cdot300=3600$ .

**Evaluation procedure** We train a simple logistic regression classifier on top of sentence embeddings *for our newly added tasks* and use random subsample validation with 50 runs for each model to mitigate the effects of different random initializations. We use SGD with the Adam optimizer (Kingma and Ba, 2015) and tune the learning rate on the validation set.

In contrast, for a direct comparison against previously published results, we use SentEval (Conneau et al., 2017) to evaluate MR, CR, SUBJ, MPQA, TREC, and SST. For most tasks, this approach likewise uses logistic regression with cross validation.

We report macro F1 performance for AM, AC,

<sup>&</sup>lt;sup>3</sup>In contrast, the original CLS dataset was built for *document* classification.

 $<sup>^4</sup>$ Monolingually, we limit our experiments to the three named p-means to not exceed the dimensionality of InferSent.

Task	Type	Size	X-Ling	C	(X-Ling) Example
AM	Argumentation	7k	HT <sup>†</sup>	4	Viele der technologischen Fortschritte helfen der Umwelt sehr. (claim)
AC	Argumentation	450	$HT^\dagger$	2	Too many promises have not been kept. (none)
CLS	Product-reviews	6k	HT	2	En tout cas on ne s'ennuie pas à la lecture de cet ouvrage! (pos)
MR	Sentiment	11k	MT	2	Dunkel und verstörend, aber auch überraschend witzig. (pos)
CR	Product-reviews	4k	MT	2	This camera has a major design flaw. (neg)
SUBJ	Subjectivity	10k	MT	2	On leur raconte l'histoire de la chambre des secrets. (obj)
MPQA	Opinion-polarity	11k	MT	2	sind eifrig (pos)   nicht zu unterstützen (neg)
TREC	Question-types	6k	MT	6	What's the Olympic Motto? (desc)
SST	Sentiment	70k	MT	2	Holm incarne le personnage avec un charisme regal [] (pos)

Table 1: Evaluation tasks with examples from our transfer languages. The first three tasks include human-generated cross-lingual data (HT), the last 6 tasks contain machine translated sentences (MT). C is the number of classes. † indicates that a dataset contains machine translations for French.

and CLS to account for imbalanced classes, and accuracy for all tasks evaluated using SentEval.

#### 4.2 Results

Table 2 compares models across all 9 transfer tasks. The results show that we can substantially improve sentence embeddings when concatenating multiple word embedding types. All four embedding types concatenated achieve 2pp improvement over the best individual embeddings (GV). Incorporating further p-means also substantially improve performances. GV improves by 0.6pp on average, GN by 1.9pp, MS by 2.1pp and AR by 3.7pp when concatenating  $p = \pm \infty$  to the standard value p = 1(dimensionality increases to 900). The combination of concatenation of embedding types and p-means gives an average improvement of 3pp over the individually best embedding type. This reduces the gap to InferSent from 4.6pp to 1.6pp (or 60%), while still having a lower dimensionality (3600 vs 4096).

In addition, we consistently outperform the lower-dimensional SIF, Siamese-CBOW, and Sent2Vec embeddings. We conjecture that these methods underperform as universal sentence embeddings<sup>5</sup> because they each discard important information. For instance, SIF assigns low weight to common words such as discourse markers, while Siamese-CBOW similarly tends to assign low vector norm to function words (Kenter et al., 2016). However, depending on the task, function words may have crucial signaling value. For instance, in AM, words like "thus" indicate argumentativeness.

While the representations learned by Siamese-CBOW, SIF, and Sent2Vec are indeed lower-dimensional than both our own representations as well as those of InferSent, we find it remark-

able that they all perform below the (likewise low-dimensional) GV baseline on average, thus challenging their status as hard-to-beat baselines when evaluated on many different transfer tasks.

We further note that our concatenated *p*-mean word embeddings outperform much more resource-intensive approaches such as Skip-thought in 4 out of 6 common tasks reported in Conneau et al. (2017) as well as the neural MT (en-fr) system reported there in 5 of 5 common tasks.

# **5** Cross-Lingual Experiments

In the monolingual evaluation we only measured one aspect of universal sentence embeddings, namely, performance across transfer tasks. We now extend this evaluation to cross-lingual transfer.

#### 5.1 Experimental Setup

**Tasks** We obtained German (de) and French (fr) translations of all sentences in our 9 transfer tasks.

Sentences in AC are already parallel (en, de), having been (semi-)professionally translated by humans from the original English. For AM, we have access to student translations from the original English into German. CLS (en, de, fr) is also available bilingually. In addition, we created machine translated versions of all remaining datasets using Google Translate for the directions en-de and en-fr.

**Word embeddings** Since our monolingual embeddings are not all available cross-lingually, we use alternatives where necessary:

• We train en-de and en-fr BIVCD (BV) embeddings on aligned sentences from the Europarl (Koehn, 2005) and the UN corpus (Ziemski et al., 2016), respectively, using word2vec (Mikolov et al., 2013b);

<sup>&</sup>lt;sup>5</sup>SIF and others were originally only evaluated in textual similarity tasks.

Model	Σ	AM	AC	CLS	MR	CR	SUBJ	MPQA	SST	TREC
Arithmetic mean										
GloVe (GV)	77.2	50.0	70.3	76.6	77.1	78.3	91.3	87.9	80.2	83.4
GoogleNews (GN)	76.1	50.6	69.4	75.2	76.3	74.6	89.7	88.2	79.9	81.0
Morph Specialized (MS)	73.5	47.1	64.6	74.1	73.0	73.1	86.9	88.8	78.3	76.0
Attract-Repel (AR)	74.1	50.3	63.8	75.3	73.7	72.4	88.0	89.1	78.3	76.0
$GV \oplus GN$	78.3	52.8	71.0	76.8	77.9	78.6	91.6	88.6	81.5	86.2
$GV \oplus GN \oplus MS$	78.7	53.5	70.9	77.0	77.9	79.6	91.9	88.9	81.6	86.6
$GV \oplus GN \oplus MS \oplus AR$	79.1	53.9	71.1	77.2	<b>78.2</b>	<b>79.8</b>	91.8	89.1	82.8	87.6
p-mean [p-values]										
$GV\left[-\infty,1,\infty\right]$	77.9	54.4	69.5	76.4	76.9	78.6	92.1	87.4	80.3	85.6
GN $[-\infty, 1, \infty]$	77.9	55.6	71.4	75.8	76.4	78.0	90.4	88.4	80.0	85.2
$MS[-\infty,1,\infty]$	75.8	52.1	66.6	73.9	73.1	75.8	89.7	87.1	79.1	84.8
$AR[-\infty,1,\infty]$	77.6	55.6	68.2	75.1	74.7	77.5	89.5	88.2	80.3	89.6
$GV \oplus GN \oplus MS \oplus AR [-\infty, 1, \infty]$	80.1	58.4	71.5	77.0	<b>78.4</b>	80.4	<u>93.1</u>	88.9	83.0	<u>90.6</u>
Baselines										
GloVe + SIF	76.1	45.6	72.2	75.4	77.3	78.6	90.5	87.0	80.7	78.0
Siamese-CBOW	60.7	42.6	45.1	66.4	61.8	63.8	75.8	71.7	61.9	56.8
Sent2Vec	76.8	52.4	72.7	75.9	76.3	80.3	91.1	86.6	77.7	78.2
InferSent	<u>81.7</u>	<u>60.9</u>	72.4	<u>78.0</u>	<u>81.2</u>	<u>86.7</u>	92.6	<u>90.6</u>	<u>85.0</u>	88.2

Table 2: Monolingual results. Brackets show the different p-means that were applied to all individual embeddings.

- Attract-Repel (AR) (Mrkšić et al., 2017) provide pre-trained cross-lingual word embeddings for en-de and en-fr;
- Monolingual Fasttext (FT) word embeddings (Bojanowski et al., 2017) of multiple languages trained on Wikipedia, which we map into shared vector space with a non-linear projection method similar to the ones proposed in Wieting et al. (2015), but with necessary modifications to account for the cross-lingual setting. (technical details of this method are given in Appendix A.1).

We also re-map the BV and AR embeddings using our technique. Even though BV performances were not affected by this projection, AR embeddings were greatly improved by it.

All our cross-lingual word embeddings have dimensionality d=300.

**Evaluated approaches** Similar to the monolingual case, we evaluate standard averages (p=1) for all embedding types, as well as different concatenations of word embedding types and p-means. Since we have only three rather than four base embeddings here, we additionally report results for p=3. Again, we motiviate our choice of p in  $\S 6$ .

We also evaluate bilingual SIF embeddings, i.e., SIF applied to bilingual word embeddings, the CVM-add of Hermann and Blunsom (2014) with dimensionality d=1000 which we trained using

sentences from Europarl and the UN corpus,<sup>6</sup> and three novel cross-lingual variants of InferSent:

- (1) InferSent MT: We translated all 569K sentences in the SNLI corpus (Bowman et al., 2015) to German and French using Google Translate. To train, e.g., en-de InferSent, we consider all 4 possible language combinations over each sentence pair in the SNLI corpus. Therefore, our new SNLI corpus is four times as large as the original.
- (2) InferSent TD: We train the InferSent model on a different task where it has to differentiate between translations and unrelated sentences (translation detection), i.e., the model has two output classes but has otherwise the same architecture. To obtain translations, we use sentence translation pairs from Europarl (en-de) and the UN corpus (en-fr); unrelated sentences were randomly sampled from the respective corpora. We limited the number of training samples to the size of the SNLI corpus to keep the training time reasonable.<sup>7</sup>
- (3) InferSent MT+TD: This is a combination of the two previous approaches where we merge translation detection data with cross-lingual SNLI. The two label sets are combined, resulting

 $<sup>^6</sup>$ We observed that d=1000 performs slightly better than higher-dimensional CVM-add embeddings of d=1500 and much better than the standard configuration with d=128. This is in line with our assumption that single-type embeddings become better with higher dimension, but will not generate additional information beyond a certain threshold, cf.  $\S1$ .

<sup>&</sup>lt;sup>7</sup>Also, adding twice as much translation data did not improve performances.

in 5 different classes.

We trained all InferSent adaptations using the best-performing word embeddings as input (the ones that achieved the highest performance in our evaluations) to provide 'best case' performances.

We do not consider cross-lingual adaptations of ParagraphVec and NMT approaches in our evaluation because they already underperform simple word averaging models monolingually (Conneau et al., 2017).

**Evaluation procedure** In the bilingual setup we replicate the same evaluation procedure as in the monolingual one and train the classifiers on English sentence embeddings. However, we then measure the transfer performance on German and French sentences (en $\rightarrow$ de, en $\rightarrow$ fr).

#### 5.2 Results

For ease of consideration, we report average results over  $en \rightarrow de$  and  $en \rightarrow fr$  in Table 3. Per-language scores can be found in Appendix A.2.

As in the monolingual case, we observe substantial improvements when concatenating different types of word embeddings of  $\sim\!2pp$  on average. However, when adding FT embeddings to the already strong concatenation  $BV\oplus AR$ , the performance only slightly improves on average.

Conversely, using different *p*-means is more effective, considerably improving performance values compared to arithmetic mean word embeddings. On average, concatenation of word embedding types plus different power means beats the best individual word embeddings by 4.4pp crosslingually (dimensionality of 3600), from 69.2% for AR to 73.6%.

We not only beat all our InferSent adaptations by more than 2pp on average cross-lingually, our concatenated *p*-mean embeddings also outperform the more complex InferSent adaptations in almost all individual transfer tasks (8 out of 9).

Further, we observe that we perform on par with InferSent already with dimensionality d=900, either using the concatenation of our three crosslingual word embeddings or using AR with three power means  $(p=1,\pm\infty)$ . In contrast, CVD-add and AR+SIF stay below InferSent, and, as in the monolingual case, even underperform relative to the best individual cross-lingual average word embedding baseline (AR), indicating that they are not suitable as universal feature representations.

# 6 Analysis

**Machine translations** To test the validity of our evaluations that are mostly based on machine translations, we compared performance scores when evaluating on machine (MT) and human translations (HT) of our two parallel AM and AC datasets.

We re-evaluated the same 14 methods as in Table 3 using MT target data. We find a Spearman correlation of  $\rho=96.5\%$  and a Pearson correlation of  $\tau=98.4\%$  between HT and MT for AM. For AC we find a  $\rho$  value of 83.7% and a  $\tau$  value of 89.9%. While the latter correlations are lower, we note that the AC scores are rather close in the direction en $\rightarrow$ de, so small changes (which may also be due to chance, given the dataset's small size) can lead to rank differences. Overall, this indicates that our MT experiments yield reliable rankings and that they strongly correlate to performance values measured on HT. Indeed, introspecting the Google Translate translations, we observed that these were of very high perceived quality.

**Different** *p*-values We performed additional cross-lingual experiments based on the concatenation of BV  $\oplus$  AR  $\oplus$  FT with additional *p*-mean values. In particular, we test (i) if some *p*-means are more effective than others, and (ii) if using more *p*-means, and thus increasing the dimensionality of the embeddings, further increases performances.

We chose several intuitive choices for p in addition to the ones already tried out, namely p=-1 (harmonic mean), p=0.5, p=2 (quadratic mean), and p=3 (cubic mean). Table 4 reports the average performances over all tasks. We notice that p=3 is the most effective p-mean here and p=-1 is (by far) least effective. We discuss below why p=-1 hurts performances in this case. For all cases with p>0, the addition of multiple means tends to further improve the results, but with decreasing marginal returns. These results also means that improvements are not merely due to additional dimensions (indeed, adding p=-1 hurts performances) but due to addition of complementary, useful information.

# 7 Discussion

Why is it useful to concatenate p-means? The average of word embeddings is a summary that discards a lot of information because different sentences can be represented by similar averages. The concatenation of p-mean summaries yields a more

Model	Σ	AM	AC	CLS	MR	CR	SUBJ	MPQA	SST	TREC
Arithmetic mean										
BIVCD (BV)	67.3	40.5	67.6	66.3	64.4	71.7	81.1	81.6	65.7	67.0
	(3.7)	(5.6)	(3.1)	(4.0)	(1.9)	(0.6)	(3.5)	(3.1)	(3.8)	(7.7)
Attract-Repel (AR)	69.2	38.6	68.8	68.9	68.2	73.9	82.8	84.4	72.5	64.5
	(3.6)	(4.8)	(0.8)	(4.3)	(3.4)	(2.1)	(3.0)	(1.8)	(3.4)	(9.2)
FastText (FT)	68.3	38.4	63.4	70.0	69.1	73.1	85.1	81.5	69.3	65.1
DV & AD	(5.6)	(8.5)	(2.9)	(4.1)	(4.1)	(2.5)	(3.6)	(4.5)	(8.6)	(11.7)
$BV \oplus AR$	71.1	41.5	68.8	70.1	68.9	75.9	84.0	84.7	74.1	71.9
	(4.2)	(8.6)	(3.1)	(3.8)	(3.4)	(0.7)	(3.4)	(2.8)	(4.1)	(7.5)
$BV \oplus AR \oplus FT$	71.2	40.0	67.7	<u>71.6</u>	70.3	<u>76.8</u>	86.2	84.7	73.3	70.5
	(5.9)	(11.8)	(3.3)	(3.6)	(5.1)	(1.4)	(3.8)	(3.3)	(6.8)	(13.9)
p-mean [p-values]										
BV $[-\infty, 1, \infty]$	68.7	48.0	68.8	65.8	63.7	72.2	82.5	81.3	66.9	69.5
	(4.3)	(4.7)	(1.5)	(4.9)	(3.5)	(1.4)	(3.7)	(3.6)	(3.9)	(11.1)
$AR[-\infty,1,\infty]$	71.1	44.2	67.8	68.7	68.8	75.5	84.3	84.4	73.0	73.5
	(4.5)	(8.1)	(1.2)	(5.0)	(3.8)	(2.8)	(3.1)	(2.5)	(4.9)	(8.8)
$FT\left[-\infty,1,\infty\right]$	69.4	43.9	64.2	69.4	67.6	73.4	85.8	81.4	73.2	65.5
	(6.2)	(9.7)	(2.5)	(4.4)	(5.8)	(3.0)	(3.7)	(5.1)	(5.3)	(16.4)
$BV \oplus AR \oplus FT [-\infty, 1, \infty]$	73.2	50.2	69.3	71.5	70.4	<b>76.7</b>	86.7	84.5	75.2	74.3
	(5.0)	(6.8)	(1.5)	(3.8)	(5.0)	(2.4)	(4.1)	(3.8)	(5.9)	(12.0)
$BV \oplus AR \oplus FT [-\infty, 1, 3, \infty]$	<u>73.6</u>	<u>52.5</u>	69.1	71.1	<u>70.6</u>	76.7	<u>87.5</u>	<u>84.9</u>	<u>75.5</u>	<u>74.8</u>
	(5.0)	(5.7)	(1.6)	(4.3)	(5.2)	(2.7)	(4.0)	(3.3)	(5.1)	(12.8)
Baselines										
AR + SIF	68.1	38.4	67.7	69.1	67.7	73.8	81.6	81.7	70.0	63.2
	(3.5)	(3.8)	(2.6)	(3.0)	(4.2)	(1.9)	(2.9)	(3.1)	(6.2)	(3.5)
CVM-add	67.4	47.8	68.9	64.2	63.4	70.3	79.5	79.3	70.2	67.8
	(5.7)	(5.7)	(-0.1)	(5.9)	(4.5)	(5.5)	(6.8)	(4.5)	(6.8)	(12.1)
InferSent MT	71.0	49.3	69.8	67.9	69.2	76.3	84.6	76.4	73.4	72.3
	(7.4)	(8.5)	(2.7)	(7.3)	(5.1)	(4.5)	(3.8)	(11.7)	(6.4)	(16.5)
InferSent TD	71.0	51.1	<u>72.0</u>	67.9	68.9	74.7	84.3	76.8	72.7	71.0
	(6.9)	(8.3)	(1.2)	(7.3)	(5.2)	(4.2)	(4.0)	(10.5)	(6.1)	(15.0)
InferSent MT+TD	71.3	50.2	71.3	67.7	69.6	76.2	84.4	77.0	72.1	73.2
	(7.5)	(8.3)	(2.2)	(8.2)	(5.4)	(5.1)	(4.3)	(11.1)	(7.1)	(15.9)

Table 3: Cross-lingual results averaged over en $\rightarrow$ de and en $\rightarrow$ fr. Numbers in parentheses are the in-language results minus the given cross-language value.

p-values	$\Sigma$ X-Ling	$\Sigma$ In-Language
$p=1,\pm\infty$	73.2	78.2
$p = 1, \pm \infty, -1$	59.9	61.6
$p=1,\pm\infty,0.5$	73.0	78.6
$p=1,\pm\infty,2$	73.4	78.5
$p=1,\pm\infty,3$	73.6	78.6
$p = 1, \pm \infty, 2, 3$	73.7	78.7
$p = 1, \pm \infty, 0.5, 2, 3$	73.6	78.9

Table 4: Average scores (en $\rightarrow$ de and en $\rightarrow$ fr) for additional p-means (based on BV  $\oplus$  AR  $\oplus$  FT).

precise representation because fewer sentences exhibit similar p-means (for several p's). For example, knowing the min and the max guarantees that words of the sentence are all within certain ranges. Thus, concatenating p-means reduces uncertainty about the semantic variation within a sentence.

Which p-means promise to be beneficial? Large |p| quickly converge to min  $(p = -\infty)$  and

 $\max\ (p=\infty).$  Hence, besides min and  $\max$ , further good p-values are typically small numbers, e.g., |p|<10. If they are integral, then odd numbers are preferable over even ones because even p-means lose sign information. Further, positive p-means are preferable over negative ones (see results in Table 4) because negative p-means are in a fundamental sense discontinuous when input numbers are negative: they have multiple poles (p-mean value tends toward  $\pm\infty)$  and different signs around the poles, depending on the direction from which one approaches the pole.

Cross-lingual performance decrease For all models and tasks we observed decreased performances in the cross-lingual evaluation compared to the in-language evaluation. Most importantly, we observe a substantial difference between the performance decreases of our best model (5pp) and our best cross-lingual InferSent adaptation (7.5pp).

Two reasons may explain these observations.

First, InferSent is a complex approach based on a bidirectional LSTM. In the same vein as Wieting et al. (2016), we hypothesize that embeddings learned from complex approaches transfer less well across domains compared to embeddings derived from simpler methods such as *p*-mean embeddings. In our case, we transfer across languages, which is a pronounced form of domain change, and it is perceivable that this affects InferSent embeddings more drastically.

Second, InferSent typically requires large amounts of high-quality training data. In the crosslingual case we rely on translated sentences for training. Even though we found these translation to be of high quality, they can still introduce noise because some aspects of meaning in languages can only be approximately captured by translations. This effect could increase with more distance between two languages. In particular, we observe a higher cross-language drop for the language transfer en $\rightarrow$ fr than for en $\rightarrow$ de. Furthermore, this difference is less pronounced for our p-mean embeddings than it is for InferSent, potentially supporting this assumption (see Table 6 of Appendix A.2 for individual cross-language results).

Applications for cross-lingual embeddings A fruitful application scenario of cross-lingual sentence embeddings are cases in which we do not have access to labeled target language training data. Even though we could, in theory, machine translate sentences from the target language into English and apply a monolingual classifier, state-of-the-art MT systems like Google Translate currently only cover

a small fraction of the world's  $\sim$ 7000 languages.

Using cross-lingual sentence embeddings, however, we can train a classifier on English and then directly apply it to low-resource target language sentences. This so-called direct transfer approach (McDonald et al., 2011; Zhang et al., 2016) on the sentence-level can be beneficial in scenarios where labeled data is scarce, because sentence-level approaches typically outperform task-specific sentence representations induced from word-level models in this case.

Importantly, simple methods such as our concatenated *p*-mean word embeddings have clear advantages over more complex methods such as InferSent: while it is possible to train and project word embeddings for many low-resource languages (e.g., using the Bible), we cannot easily obtain

cross-lingual SNLI variants for those languages.

## 8 Conclusion

We proposed concatenated p-mean word embeddings, a conceptually and computationally simple method for inducing sentence embeddings using two ingredients: (i) the concatenation of diverse word embeddings, which injects complementary information in the resulting representations; (ii) the use of p-means to perform different types of summarizations over word embedding dimensions.

Our proposed method significantly narrows the monolingual gap to the current state-of-the-art supervised method InferSent while substantially outperforming our cross-lingual adaptations of this approach in the cross-lingual scenario.

We believe that our generalizations can be widely extended and that we have merely laid the conceptual ground-work: automatically learning p-values is likely to result in further improved sentence embeddings as we have observed that some p-values are more suitable than others; using different p-values for different embedding dimensions could introduce much more diversity; and lastly, many further compressions besides the p-means considered here can be taken into account, including non-symmetric ones that are sensitive to word-order as well as ones that measure correlations between embedding 'time-series'.

Furthermore, by providing a number of new cross-lingual datasets for evaluation as well as translated variants of SNLI, we hope to facilitate future research in the area of universal cross-lingual sentence embeddings.

Finally, we believe that even in monolingual scenarios, future work should consider (concatenated) *p*-mean embeddings as a challenging and truly hard-to-beat baseline across a wide array of transfer tasks.

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# **A** Supplemental Material

# A.1 Details on our Projection Method

Here we describe the necessary conceptual and technical details to reproduce the results of our non-linear projection method that we use to map word embeddings of two languages into a shared embedding space (cf. §5).

**Formalization** We learn a projection of two embedding spaces  $\mathbb{E}^l$  and  $\mathbb{E}^k$  with dimensionality e and f, respectively, into a shared space of dimensionality d using two non-linear transformations:

$$f_l(\mathbf{x}_l) = \tanh(\mathbf{W}_l \mathbf{x}_l + \mathbf{b}_l)$$
  
 $f_k(\mathbf{x}_k) = \tanh(\mathbf{W}_k \mathbf{x}_k + \mathbf{b}_k)$ 

where  $\mathbf{x}_l \in \mathbb{R}^e$ ,  $\mathbf{x}_k \in \mathbb{R}^f$  are original input embeddings and  $\mathbf{W}_l \in \mathbb{R}^{d \times e}$ ,  $\mathbf{W}_k \in \mathbb{R}^{d \times f}$ ,  $\mathbf{b}_l \in \mathbb{R}^d$ ,  $\mathbf{b}_k \in \mathbb{R}^d$  are parameters to be learned. Here  $\mathbf{x}_l$  and  $\mathbf{x}_k$  are monolingual representations.

For each sentence s and its translation t we randomly sample one unrelated sentence u from our data and obtain sentence representations  $\mathbf{r}_s = f_l(\mathbf{x}_s)$ ,  $\mathbf{r}_t = f_k(\mathbf{x}_t)$ , and  $\mathbf{r}_u = f_k(\mathbf{x}_u)$ . We then optimize the following max-margin hinge loss:

$$\mathcal{L} = \max(0, m - \text{sim}(\mathbf{r}_s, \mathbf{r}_t) + \text{sim}(\mathbf{r}_s, \mathbf{r}_u))$$

where sim is cosine similarity and m is the margin parameter. This objective moves embeddings of translations closer to and embeddings of random cross-lingual sentences further away from each other.

**Training** We use minibatched SGD with the Adam optimizer (Kingma and Ba, 2015) for training. We train on >130K bilingually aligned sentence pairs from the TED corpus (Hermann and Blunsom, 2014), which consists of translated transcripts from TED talks. Each sentence s is represented by its average (monolingual) word embedding, i.e.,  $H_1$ .

We set the margin parameter to m=0.5 as we have observed that higher values lead to a faster convergence. We furthermore randomly set 50% of the input embedding dimensions to zero during training (dropout).

Training of one epoch usually takes less than a minute in our TensorFlow implementation (on CPU), and convergence is usually achieved after less than 100 epochs.

Model	∑ X-Ling	∑ In-Language
FT (monolingual)	-	80.8
FT (CCA <sup>‡</sup> )	71.1	79.3
FT (our projection)	74.6	79.7
BV (orig)	70.9	75.8
BV (our projection)	71.0	74.6
AR (orig)	61.8	79.3
AR (our projection)	74.5	77.9

Table 5: The performance of our average word embeddings with our projection method in comparison to other approaches. <sup>‡</sup>We trained CCA on word-alignments extracted from TED transcripts using fast\_align (i.e., CCA uses the same data source as our method).

**Application** Even though we learn our nonlinear projection on the sentence level, we later apply it on the word level, i.e., we map individual word embeddings from each of two languages via  $f_{\psi}(\mathbf{x}_{\psi})$  where  $\psi=l,k$ . This is valid because average word embeddings live in the same space as individual word embeddings. The reason for doing so is that otherwise we would have to learn individual transformations for each of our power means, not only the average  $(=H_1)$ , which would be too costly particularly when incorporating many different p-values. Working on the word-level, in general, also allows us to resort to word-level projection techniques using, e.g., word-alignments rather than sentence alignments.

However, in preliminary experiments, we found that our suggested approach produces considerably better cross-lingual word embeddings in our setup. Results are shown in Table 5, where we report the performance of average word embeddings for cross-lingual en→de task transfer (averaged over MR, CR, SUBJ, MPQA, SST, TREC). Compared to the word-level projection method CCA we obtain substantially better cross-lingual sentence embeddings, and even stronger improvements when re-mapping AR embeddings, even though these are already bilingual.

# A.2 Individual Language-Transfer Results

We report results for the individual language transfer across  $en \rightarrow de$  and  $en \rightarrow fr$  in Table 6.

Model	Ω	$\Sigma$ de	$\Sigma$ fr	AM	1	AC	-	CLS	-	MR	-  -	CR		SUB	_	MPC	A A	SS	L	TR	EC
Transfer Language				de	fr	de	fr	de	fr	de	fr	de	fr	de fr	fr	de fr	fr	de 1	fr	de	de fr
Arithmetic mean																					
BIVCD (BV)	67.3	65.5	68.1	39.2		6.89	66.4	65.0	67.7	62.2	66.5	70.6	72.9	8.62	82.4	79.8	83.3	61.2	70.2	72.2	61.8
	(3.7)	(3.9)	(3.6)	(7.0)		(1.5)	(4.7)	(4.3)	(3.7)	(2.3)	(1.5)	(1.1)	(0.1)	(3.8)	(3.2)	(3.9)	(2.4)	(7.2)	(0.3)	(3.6)	(11.8)
Attract-Repel (AR)	69.2	69.4	6.89	39.0		71.1	66.5	67.4	70.4	9.99	2.69	73.7	74.0	81.8	83.8	84.0	84.8	71.3	73.6	9.69	59.4
	(3.6)	(3.4)	(3.8)	(4.7)		(0.4)	(1.3)	(5.8)	(2.8)	(4.7)	(2.2)	(1.9)	(2.4)	(3.2)	(2.7)	(2.1)	(1.5)	(4.4)	(2.4)	(3.8)	(14.6)
FastText (FT)	68.4	2.89	0.89	36.9		63.8	67.9	70.1	70.0	68.3	6.69	73.9	72.3	86.3	84.0	81.7	81.3	69.5	69.2	8.79	62.4
	(5.6)	(5.5)	(5.7)	(10.5)		(4.0)	(1.8)	(4.2)	(4.0)	(5.2)	(3.0)	(2.0)	(3.1)	(2.4)	(4.8)	(4.5)	(4.5)	(8.8)	(8.5)	(8.2)	(15.2)
$\mathbf{BV} \oplus \mathbf{AR}$	71.1	6.07	71.3	40.8		70.0	9.79	69.4	70.9	67.2	70.5	75.4	76.5	83.3	84.8	84.1	85.4	72.5	75.6	75.8	0.89
	(4.2)	(4.2)	(4.1)	(6.7)		(2.2)	(3.9)	(4.6)	(2.9)	(4.7)	(2.1)	(1.1)	(0.4)	(3.8)	(3.1)	(3.3)	(2.5)	(5.3)	(3.0)	(3.4)	(11.6)
$\mathbf{BV} \oplus \mathbf{AR} \oplus \mathbf{FT}$	71.2	71.9	9.07	39.2	40.7	71.0	64.5	71.2	72.1	8.69	20.8	9.9/	76.9	8.98	85.7	84.6	84.9	71.8	74.7	75.8	65.2
	(5.9)	(5.4)	(6.4)	(12.9)	_	(1.5)	(5.0)	(3.8)	(3.4)	(6.1)	(4.0)	(1.6)	(1.2)	(3.2)	(4.4)	(3.3)	(3.3)	(8.5)	(5.1)	(7.8)	(20.0)
p-mean [p-values]																					
$\mathbf{BV}\left[-\infty,1,\infty\right]$	68.7	0.89	69.5	48.0	_	70.7	8.99		67.3	60.5	8.99	71.1	73.3	81.1	83.9	79.9	82.7	64.4	69.4	72.0	67.0
	(4.3)	(4.1)	(4.4)	(4.1)		(0.8)	(2.3)		(4.2)	(4.2)	(2.7)	(2.2)	(9.0)	(4.4)	(2.9)	(3.9)	(3.3)	(3.1)	(4.7)	(8.4)	(13.8)
$AR~[-\infty,1,\infty]$	71.1	71.3	71.0	45.7		70.5	65.1		70.3	67.4	70.2	75.3	75.7	83.7	84.9	84.0	84.8	71.2	74.9	9.92	70.4
	(4.5)	(4.4)	(4.5)	(6.7)		(-0.1)	(5.6)		(3.5)	(5.2)	(2.3)	(3.5)	(2.1)	(3.2)	(3.1)	(2.7)	(2.3)	(9.9)	(3.2)	(5.6)	(12.0)
$\mathrm{FT}\left[-\infty,1,\infty\right]$	69.4	70.2	68.5	42.7		67.1	61.3		69.2	68.3	0.79	73.4	73.4	86.7	84.9	81.6	81.2	74.4	72.0	68.2	62.8
	(6.2)	(5.4)	(7.0)	(11.1)		(1.3)	(3.7)		(4.6)	(4.9)	(9.9)	(3.0)	(3.0)	(2.7)	(4.7)	(5.2)	(5.0)	(4.0)	(6.7)	(12.0)	(20.8)
$BV \oplus AR \oplus FT [-\infty, 1, \infty]$	73.2	73.7	72.7	50.8		72.0	9.99		72.0	70.6	70.2	77.3	76.1	9.98	8.98	84.1	84.9	73.4	77.0	9.77	71.0
	(5.0)	(4.6)	(5.5)	(5.6)		(0.3)	(2.8)		(3.4)	(4.7)	(5.2)	(2.3)	(2.5)	(4.2)	(4.0)	(3.9)	(3.6)	(8.1)	(3.7)	(7.8)	(16.8)
$BV \oplus AR \oplus FT \left[ -\infty, 1, 3, \infty \right]$	73.6	74.0	73.3	51.4	53.6	72.0		70.8	71.5	70.5	70.7	77.1	76.2	2.7	<u>87.3</u>	84.2 2.3 9.0	85.6 85.6	74.1	76.9	78.4 5	$\frac{71.2}{67.9}$
Baselines	(6:6)			(2:0)	-	(20)			-   -   -	(2:2)			- (G.i.)	(6:5)		(6:5)	- (6:3)	(2.0)	(6:6)	(7:)	(6.71)
AR + SIF	1 89	5 2 5	7 89	40.2	-	70.3	65.1	7 7 7	70.4	699	69.7	73.7	73.8	0 08	83.7	82.0	80.5	0.89	71.9	58.4	0.89
	(3.5)	(4.3)	(2.7)	(2.3)		(1.8)	(3.4)	(4.5)	(1.5)	(5.5)	(3.0)	(2.3)	(1.6)	(3.8)	(2.0)	(2.0)	(4.1)	(8.8)	(3.7)	(7.4)	(-0.4)
CVM-Add	67.4	65.3	69.4	45.6		9.69	68.1	62.3	66.0	60.7	66.1	68.6	72.0	9.9/	82.3	76.1	82.5	62.7	67.7	65.2	70.4
	(5.7)	(9.9)	(4.8)	(7.7)		(-0.7)	(-0.1)	(6.3)	(5.5)	(4.9)	(4.0)	(6.5)	(4.5)	(8.5)	(5.0)	(5.7)	(3.3)	(7.7)	(5.9)	(13.2)	(11.0)
InferSent MT	71.0	71.8	70.2	50.3		70.9	68.7	0.79	6.89	69.3	69.2	7.97	75.8	4.4	84.9	77.9	74.9	72.5	74.3	77.4	67.2
£	(7.4)	(6.7)	(8.2)	(8.2)		(1.2)	(4.2)	(8.5)	(6.1)	(5.2)	(4.9)	(3.5)	(5.5)	(3.7)	(3.8)	(10.2)	(13.3)	(7.4)	(5.5)	(12.2)	(20.8)
InterSent TD	0.17	7.7	0.0/	27.7		73.4	/0.6	8.99	1.69	9.89	2.69	/4.9	4.4	84.3 5.4	2.4.2	4.//	/6.3	77.5	7.78	7.8/	63.8
InferSent MT+TD	(6.9) <b>7</b>	(5.9) <b>7.2</b> 4	(2.5) (2.5)	(7.0)	(10.0)	(1.7) 7.85	(0.7)	(8.9)	(5.7) 68.8	(4.7) 50 5	(5.8)	(3.8)	(4.6)	(3.7) <b>24</b> 7	(4.3)	(9.7) 78.3	(11.3)	(5.9)	(6.3)	(4.7 (4.8 (4.8)	(22.6) 67.6
	3 (	t (	1 6	5.7		<u> </u>	7:00	0.00	0.00	3 6	•	t 6	2	<b>;</b> 3	7:+5	. 6 . 6		1 6	1 6	0,0	0.79
	(6.7)	(0.0)	(8.4)	(0.7)	-	(1.4)	(3.0)	(9.6)	(0.8)	(2.2)	(0.0)	(4.8)	(5.5)	(4.7)	(4.4)	(7.7)	(12.4)	(Y.I)	(0.7)	(10.8)	(0.12)

Table 6: Individual cross-lingual results for the language transfer en $\rightarrow$ de and en $\rightarrow$ fr. Numbers in parentheses are the in-language results minus the given cross-language value..  $\oplus$  denotes the concatenation of different embeddings (or p-means), brackets show the different p-means of the model.