RepEval 2017

The 2nd Workshop on Evaluating Vector-Space Representations for NLP

Proceedings of the Workshop

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Introduction

This workshop deals with the evaluation of general-purpose vector representations for linguistic units (morphemes, words, phrases, sentences, etc). What distinguishes these representations (or embeddings) is that they are not trained with a specific application in mind, but rather to capture broadly useful features of the represented units. Another way to view their usage is through the lens of transfer learning: The embeddings are trained with one objective, but applied on others.

Evaluating general-purpose representation learning systems is fundamentally difficult. They can be trained on a variety of objectives, making simple intrinsic evaluations useless as a means of comparing methods. They are also meant to be applied to a variety of downstream tasks, which will place different demands on them, making no single extrinsic evaluation definitive. The best techniques for evaluating embedding methods in downstream tasks often require investing considerable time and resources in retraining large neural network models, making broad suites of downstream evaluations impractical. In many cases, especially for word-level embeddings, these constraints have led to the rise of dedicated evaluation tasks like similarity and analogy which are not directly related either to training objectives or to downstream tasks. Tasks like these can serve a valuable role in principle, but in practice performance on these tasks has not been highly predictive of downstream task performance.

This workshop aims foster discussion of these issues, and to support the search for high-quality general purpose representation learning techniques for NLP. The workshop will accept submissions through two tracks: a proposal track will showcase submitted proposals for new evaluation techniques, and a shared task will accept submissions of new general purpose sentence representation systems – for which standard evaluations are notably absent – which will be evaluated on a sentence understanding task.

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Torsten Zesch

Invited Speaker:

Yejin Choi, University of Washington
Kyunghyun Cho, New York University
Jakob Uszkoreit, Google

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Traversal-Free Word Vector Evaluation in Analogy Space

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Abstract

In this paper, we propose an alternative evaluating metric for word analogy questions (*A to B is as C to D*) in word vector evaluation. Different from the traditional method which predicts the fourth word by the given three, we measure the similarity directly on the "relations" of two pairs of given words, just as shifting the relation vectors into a new analogy space. Cosine and Euclidean distances are then calculated as measurements. Observation and experiments shows the proposed analogy space evaluation could offer a more comprehensive evaluating result on word vectors with word analogy questions. Meanwhile, computational complexity are remarkably reduced by avoiding traversing the vocabulary.

1 Introduction

In recent years, word vector, or addressed as word embedding or distributed vector representation of word, achieves high popularity in NLP (***Natural Language Processing***) applications. A word vector is a real-valued vector, which is quite low-dimensional when comparing with traditional one-hot representation of words. The theory behind is believed to be the early concept of distributional representation (Hinton, 1986), and modern word vector derives from the training process of neural language models (Bengio et al., 2003).

The usage of word vectors has been proven highly efficient and successful by various NLP tasks (Collobert et al., 2011), which further spurs the technical developments to achieve word vectors with better quality, such as Word2Vec (Mikolov et al., 2013a), GloVe (Pennington et al., 2014), Word2Vecf (Levy and Goldberg, 2014), LexVec (Salle et al., 2016), FastText (Bojanowski et al., 2016), *etc*.

However, discussion about how to evaluate the quality of word vectors remains open. Except for actual applications, most frequently used evaluation tasks are word similarity and word analogy. A word similarity task is to find the nearest word in the vector space of the given word, based on the theory that words with similar meanings should gather together. Although it is widely used, arguments are made to question its capability (Batchkarov et al., 2016; Faruqui et al., 2016).

While in a word analogy test, three words A, B and C are given and the goal is to find a fourth word D, which logically conforms "A to B is as C to D". Word analogy test has a long history of being used in examinations or IQ tests for human (McClelland, 1973; Sternberg, 1985) and is introduced into word vector evaluation by Mikolov *et al.* (2013b). After that, it has been widely applied.

Efforts are made to improve the original analogy metric, such as using PAIRDIRECTION to replace 3COSADD in calculation (Levy et al., 2014) or taking multiple word pairs into consideration (Drozd et al., 2016), but the goal is still to find word D from the vocabulary. Besides, Linzen (2016) made a thorough assessment of word analogy test, and the most prominent finding is that if not exclude three given words, the prediction of D would almost always be C (91%) or B (5%), especially when the lineal offset between words is small. This phenomenon would arouse the doubt, that whether we are searching for a word D which holds the same logic to C just as B to A, or actually searching for the nearest word of C? Furthermore, the general accuracy decline in reversed analogy also suggests the incertainty of current analogy evaluation metric.

In this paper, we would dig deeper into the limitations of current analogy evaluation metric in

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Table 1: Examples of Traditional Word Analogy Evaluation Result (Words in order of A, B, C & D)

Grammar-1	knowing		knew		selling		sold	
Predictions	thought	0.573	know	0.481	purchased	0.520	**sold**	**0.568**
	know	0.504	**knew**	**0.449**	resold	0.506	sell	0.535
	wanted	0.494	Knowing	0.441	**selling**	**0.486**	bought	0.528
	knowing	0.489	figured	0.404	sale	0.484	buying	0.486
Grammar-2	looking		looked		shrinking		shrank	
Predictions	look	0.540	**looked**	**0.536**	**shrinking**	**0.560**	shrunk	0.618
	looking	**0.526**	look	0.493	unexpectedly_shrank	0.478	**shrank**	**0.589**
	looks	0.521	looks	0.415	downwardly_revised	0.468	dwindled	0.498
	seemed	0.439	expecting	0.410	contraction	0.454	shrink	0.498

Section 2 and propose our simple alternative plan in Section 3, which is called "Analogy Space Evaluation". A significant difference of our approach is that we avoid traversing vocabulary from time to time. Experiments are presented in Section 4 and finally come the conclusion and discussion.

2 Limitations of Traditional Metric

In traditional word analogy evaluation, by given word pairs (A, B) and (C, D) with same syntactic or semantic relation, the goal is to find the nearest word to "$C+B-A$" in the vector space by Cosine similarity and check whether the word obtained is D. Practically some approaches use unit vector of A, B and C in "$C + B - A$", such as widely used Word2Vec. Anyway, the return value of such a word analogy question is in Boolean type.

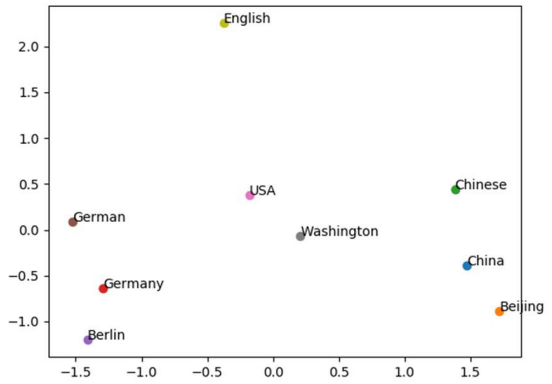
Generally, evaluating word vectors requires thousands of word analogy questions, which return thousands of Boolean values to calculate the accuracy from a macro perspective: how many supposed D have been successfully predicted. However, if we treat each question as an independent target in a micro aspect, result in Boolean type suffers an unneglectable information loss: true or false cannot quantitatively manifest the extent of how true or how false. For instance, it does not matter whether D is the 2nd nearest word to "$C + B - A$" or the 100th.

Another limitation of traditional metric is the deficiency in comprehensiveness. In a typical "A to B is as C to D" analogy, there are in fact 4 prediction choices, although in some analogies like "Nation-Currency" or "Nation-Language", available choices could drop to 2, since in reverse logic the answer is not unique. A single prediction on D is not enough to represent the quality of all 4 word vectors trained.

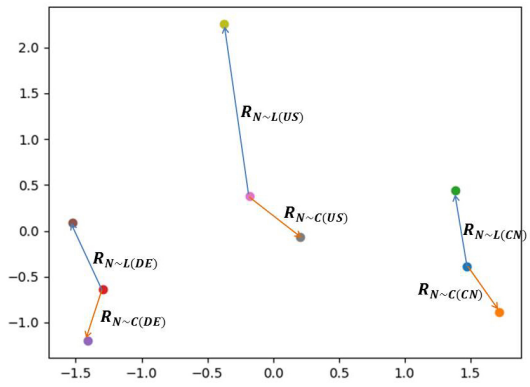
For better illustration, we run widely used "GoogleNews-vectors-negative300.bin" on default Word2Vec English analogy test and extract two examples to Table 1. All 4 words in example analogy questions are predicted and top 4 results are presented accordingly. From Table 1, it is clear that no matter with absolute value or average ranking of desired word in predictions, situation in Grammar-2 is apparently better than Grammar-1. However, because only word D is predicted by traditional metric, Grammar-1 would return a positive result while Grammar-2 is negative, which obviously fails to correctly represent the quality of corresponding word vectors trained.

In default Word2Vec analogy test, there is always another analogy question, which in fact predict word B of the original question. But there is no reverse logic prediction for A and C. So in final accuracy calculation, these two sets of words in Table 1 contribute the same precision of 0.5, which still cannot reflect the quality difference between these two sets of word vectors trained. Perhaps, 4 analogy questions are needed, but that would lead to another issue: higher complexity. Every time when searching for a nearest word, cosine similarity must be calculated with each word in the vocabulary. When the testing set is large, it may take quite a long time, and the time would be doubled if all 4 possible questions are included. Moreover, the majority of words in the vocabulary are actually unrelated with the prediction target. Calculating these words is simply wasting time.

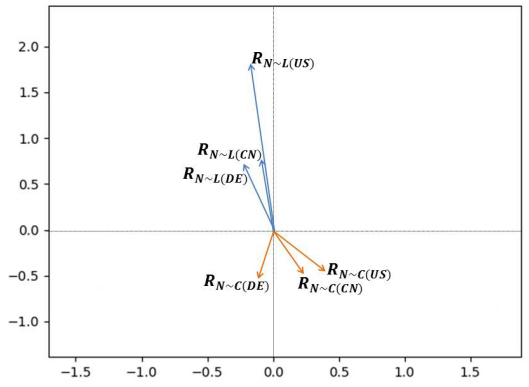
Based on all above reasons, we aim to offer an alternative metric for word analogy evaluation, by constructing a new analogy space based on the relation vectors achieved from analogy questions, in order to solve existing limitations in quantification, comprehensiveness and complexity.



(a) Orignial Word Vector Space



(b) Relation Vectors



(c) Final Analogy Space

Figure 1: Analogy Space Illustration

3 Analogy Space Evaluation

Proposed analogy space shares same dimensionality of original word vector space. For each analogy question, two relation vectors can be found in original word vector space, just as the definition of PAIRDIRECTION by Levy *et al.* (2014). Mathematically, the value of such a relation vector is the same as the position of the ending point if we take the starting point as the space origin. This is simply the new analogy space: shifting all relation vectors to the space origin, so each point in this new space represents a relation between a pair of words given in the analogy question. Figure 1 illustrates this process by several example words of "Nation-Capital" and "Nation-Language" analogies (*extracted from same test of Table 1, visualized by PCA*).

Table 2: Analogy Space Evaluation (Micro)

Analogy	Cos.	Euc.	N-Cos.	N-Euc.
Grammar-1	0.114	0.334	0.115	0.332
Grammar-2	0.324	0.410	0.320	0.415
NC: US-CN	0.310	0.380	0.314	0.356
NC: US-DE	0.367	0.423	0.376	0.411
NC: DE-CN	0.496	0.492	0.508	0.495
NL: US-CN	0.452	0.420	0.451	0.405
NL: US-DE	0.438	0.430	0.441	0.418
NL: DE-CN	0.712	0.617	0.714	0.619

Naturally, we expect relations with same or similar logic gather together in the analogy space. In order to quantitatively evaluate the similarity, we prepare four different measurements, based on Cosine similarity or Euclidean distance respectively. If we denote the vectors of word A, B, C and D as $\mathbf{a}$, $\mathbf{b}$, $\mathbf{c}$ and $\mathbf{d}$, then

$$Cos. = \frac{(\mathbf{b}-\mathbf{a})\cdot(\mathbf{d}-\mathbf{c})}{\|\mathbf{b}-\mathbf{a}\|\|\mathbf{d}-\mathbf{c}\|} \quad (1)$$

$$Euc. = 1 - \frac{\|(\mathbf{b}-\mathbf{a})-(\mathbf{d}-\mathbf{c})\|}{\|\mathbf{b}-\mathbf{a}\|+\|\mathbf{d}-\mathbf{c}\|} \quad (2)$$

while $Cos. \in [-1,1]$ and $Euc. \in [0,1]$. *N-Cos.* and *N-Euc.* have similar definitions, but using unit word vectors in calculation. Table 2 shows the result of examples mentioned in Table 1 and Figure 1. Among them, "NC:DE-CN" and "NL:DE-CN" succeed 2/2 in traditional nearest word evaluation, while all others achieve 1/2.

It's clear that proposed measurements could better represent the quality of these involved words or relations in a quantitative way. As already mentioned, words in Grammar-2 are considered better trained than Grammar-1, and this difference can be captured by proposed measurements only. And for NCs and NLs, traditional metric reports exactly the same accuracy, but as we can see, detailed similarities differ a lot. We believe these phenomena could help word analogy evaluation in the micro aspect.

Table 3: Analogy Space Evaluation (Macro)

WV Set	Voc.	Traditional		Proposed					SBD	
		Accu.	Time	Cos.	Euc.	N-Cos.	N-Euc.	Time	4C	2C
EN-w5-i5	1.8M	0.697	24'56"	0.325	0.419	0.325	0.420	0'38"	0.575	0.820
EN-w10-i10	1.8M	0.692	24'41"	0.314	0.414	0.315	0.415	0'37"	0.573	0.822
GoogleNews	3M	0.737	30'48"	0.352	0.431	0.352	0.431	1'09"	0.580	0.824
DE-w5-cbow	1.8M	0.465	92'39"	0.324	0.418	0.335	0.423	1'33"	–	–
DE-w5-sg	1.8M	0.434	92'09"	0.259	0.389	0.260	0.392	1'35"	–	–
DE-w10-cbow	1.8M	0.463	89'22"	0.318	0.416	0.331	0.422	1'37"	0.640	0.779
DE-w10-sg	1.8M	0.412	94'13"	0.251	0.385	0.254	0.389	1'34"	0.619	0.767

4 Macro Experiments

In this section, we would do some experiments on complete analogy question sets and discuss complexity. For English word vectors, we trained two sets on Wikipedia dump with different window size (w) and iteration (i) by Skip-Gram model, with same dimensionality of 300. They would further be compared with GoogleNews public set. We will evaluate these sets with proposed measurements, along with traditional analogy evaluation result and the performances of a downstream application: ***S**entence **B**oundary **D**etection (SBD)*. Details of SBD implementation can be found in references (Che et al., 2016a,b).

Beside of English test, we also conducted several tests in German. Leipzig dataset (Goldhahn et al., 2012) are used to training German word vectors with Word2Vec toolkit. Then the vectors with different training configurations are evaluated by a set of analogy questions, which contains 2834 semantic questions in 18 categories (*including some reverse logics*) and 77886 syntactic questions in 9 categories. We have uploaded these analogy questions in German for public access[1].

Table 3 shows the results and time expenditures of these experiments. It is clear that proposed measurements have same trend with traditional metric, which means once set X achieves better result than set Y in traditional test, it would also do better in proposed alternatives. Performances in downstream application SBD are also fit this trend in general. Meanwhile, proposed evaluation could significantly save time, approximately 95%. These facts prove that we can achieve same performance within way less time.

However, we also found some limitations. The absolute difference between different vector sets in proposed measurements is smaller, which make it difficult to distinguish, especially with *Euc.* and *N-Euc.* It is also unclear that which measurement from the four proposed could be the optimized option.

[1] https://drive.google.com/open?id=0B13Cc1a7ebTuaE83NEtyemM4aGM

5 Conclusion & Discussion

In this paper, we discuss some limitations of traditional word analogy evaluation metric in word vector evaluation, and then propose a simple alternative plan called "Analogy Space Evaluation", which directly measures the relation vectors between given pairs of words, instead of traversing the vocabulary to seek the nearest word of the target. Experiments shows that proposed approach serves as good as traditional metric in performance, but reduces the computational complexity significantly.

This effort can be simply applied on any existing word analogy tasks. Frankly speaking, we cannot claim that our method outperforms the original, except for the complexity part. But complexity does matter. Currently analogy tasks generally contain tens of thousands questions, so traditional traversal-based evaluation can still manage. However, we would definitely want to test higher portion of words in the vocabulary, and with the efforts from the whole community, we may have a "nearly optimized" test set someday with up to million words involved. At that time, traversal-free could be a highly desirable quality.

As far as we know, there is no widely acknowledged benchmark which can be used to test new evaluation methods, so our effort remains estimation. In the future, we would attempt to implement more real applications, just as SBD mentioned in this paper, and take their performances as feedbacks, in order to contribute in this dilemma of "Evaluation of Evaluation".

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Hypothesis Testing based Intrinsic Evaluation of Word Embeddings

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Abstract

We introduce the cross-match test - an exact, distribution free, high-dimensional hypothesis test as an intrinsic evaluation metric for word embeddings. We show that cross-match is an effective means of measuring distributional similarity between different vector representations and of evaluating the statistical significance of different vector embedding models. Additionally, we find that cross-match can be used to provide a quantitative measure of linguistic similarity for selecting bridge languages for machine translation. We demonstrate that the results of the hypothesis test align with our expectations and note that the framework of two sample hypothesis testing is not limited to word embeddings and can be extended to all vector representations.

1 Introduction

Word embeddings obtained via specialized models (Brown et al., 1992; Pennington et al., 2014; Mikolov et al., 2013a) or neural networks (Bengio et al., 2003) have been successfully used to address various natural language processing tasks (Vaswani et al., 2013; Soricut and Och, 2015). These embeddings provide a nuanced representation of words that can capture various syntactic and semantic properties of natural language (Mikolov et al., 2013b). Despite their effectiveness in downstream applications, embeddings have limited practical value as standalone items. Consequently, an intrinsic evaluation metric must provide insight on the downstream task the embeddings are designed for. In this work, we use Cross-match (Rosenbaum, 2005) - an exact, distribution free, high-dimensional hypothesis test to propose a novel approach for intrinsic evaluation of word embeddings, one that provides insight on tasks that depend on linguistic similarity.

Evaluating general purpose vector representations is difficult. They are trained using simple objectives and applied to a variety of downstream tasks, thus making no single extrinsic evaluation definitive. Often, due to computational constraints, direct downstream evaluations are also impractical. In the case of word embeddings, these constraints have led to the development of dedicated evaluation tasks like similarity and analogy (Rohde et al., 2006; Levy et al., 2015) which are not directly related to training objectives or to downstream tasks. Despite their ease of interpretability, Faruqui et al. (2016) have shown that these tasks do not correlate well with downstream performance. In related work, Tsvetkov et al. (2016) propose an evaluation measure QVEC-CCA that is shown to correlate well with downstream semantic tasks where the objective is to quantify the linguistic content of word embeddings by maximizing the correlation with a manually annotated linguistic resource.

In this work, we use the Cross-match hypothesis test (Rosenbaum, 2005) to measure distributional similarity between different word vector representations. Cross-match is an adjacency based test traditionally used in clinical settings where the goal is to assess no treatment effect on a high-dimensional outcome in a randomized experiment. In our setting, we assume there exists some unknown distribution W from which our constructed word embeddings $\{\mathbf{w_1}, \ldots, \mathbf{w_n}\}$ are "sampled" from. Given two sets of word embeddings, cross-match tests whether the underlying distribution from which the embeddings were "sampled" are identical or not. The test uses optimal non-bipartite matching to pair vectors from both sets of embeddings based on distance (e.g.

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a vector will be paired with it's nearest neighbor based on some distance metric). The cross-match test statistic C is the number of times that a vector from one set is paired with a vector from another. The null hypothesis assumes that the vectors were sampled from the same distribution and rejects for small values of C. Thus, a large number of cross-matches between two sets of word embeddings suggests that they are from the same embedding distribution.

Using cross-match, we propose two illustrative examples of intrinsic evaluation. First, we use pretrained word vectors (trained on Wikipedia using the skip-gram model in Bojanowski et al. (2016)) from Facebook's fastText library for several languages to calculate the cross-match statistic for several language pairs. We hypothesize that for linguistically similar languages, a larger statistic will be observed. Secondly, we use cross-match to assess the statistical significant of word embedding models. We consider several well known models trained on the same corpus and use cross-match to assess whether the respective word vector representations are statistically significantly different. We hypothesize that the number of cross-matches between two different embedding models is small, thus suggesting that they capture fundamentally different linguistic aspects of the corpus.

This paper is organized as follows: Section 2 introduces the cross-match test in detail. Experiments on embedding similarity and evaluation are described in Section 3. We discuss extensions and conclude in Section 4.

2 Cross-Match Test

The cross-match test (Rosenbaum, 2005) is a nonparametric goodness-of-fit test in arbitrary dimensions. It is an exact, distribution-free, two-sample hypothesis test that measures whether two distributions are equal or not. Formally, given two independent samples $w_1, \ldots, w_n \sim W$ and $v_1, \ldots, v_m \sim V$, cross-match tests the null hypothesis $H_0 : W = V$ versus the alternative hypothesis $H_1 : W \neq V$. The test has been traditionally used in clinical settings, where the goal is to assess no treatment effect on a high-dimensional outcome between control and treated subjects in a randomized experiment (Heller et al., 2010). In the case of word embeddings, the goal is to test whether two sets of word embedding vectors have been "sampled" from the same distribution.

2.1 Definition of the Cross-Match Statistic

Let W, V denote two word embedding distributions (distributions of word embedding vectors over a corpus), suppose we obtain two sets of word vectors $\{\mathbf{w_1}, \ldots, \mathbf{w_n}\} \sim W$ and $\{\mathbf{v_1}, \ldots, \mathbf{v_m}\} \sim V$. Assign the group labels 0 and 1 to indicate which sample the vectors are from such that the data are organized as follows: $\{(0, \mathbf{w_1}), \ldots, (0, \mathbf{w_n})\}$ and $\{(1, \mathbf{v_1}), \ldots (1, \mathbf{v_m})\}$.

The cross-match statistic C, is a function of the word vectors $D = \{\mathbf{w_1}, \ldots, \mathbf{w_n}, \mathbf{v_1}, \ldots, \mathbf{v_n}\}$ and the group labels $G = \{0, \ldots, 0, 1, \ldots, 1\}$. If $H_0 : W = V$ is true, then all the word vectors are i.i.d. "sampled" from W and the group labels are meaningless. It's as if the 0's and 1's were randomly assigned.

The cross-match test is performed as follows. For notational convenience ignore the group labels and treat the data as one sample $\{\mathbf{z_1}, \ldots, \mathbf{z_{n+m}}\}$ of size $n+m = N$ (assume for simplicity that N is even). We define a $N \times N$ symmetric distance matrix, with row k and column l giving the distance (any distance metric can be used) between $\mathbf{z_k}$ and $\mathbf{z_l}$. Compute the optimal non-bipartite matching of the $\mathbf{z}'\mathbf{s}$ (match the vectors into non-overlapping pairs) that minimizes the total distances between the points in each pair.

Formally, we find a permutation $\hat{\sigma}$ of $\{1, \ldots, N\}$ that minimizes

$$Match(\sigma) = \sum_{i=1}^{N} d(Z_i, Z_{\sigma(i)})$$

where $i \neq \sigma(i)$ and d is our chosen distance measure. The cross-match statistic C, is defined as the number of pairs that have group labels (0,1) or (1,0), the test rejects for small values of C.

If there is an odd number of word embedding vectors, then a psuedo-vector is added to the distance matrix at zero distance from everyone else. $\frac{N}{2}$ pairs are formed as before, and the pair containing the psuedo-vector is discarded (thus the least matchable word vector is discarded).

2.2 Null Distribution of the Cross-Match Statistic

One advantage of the cross-match test is that we can compute the exact distribution of the statistic C under the null hypothesis H_0. Given $\frac{N}{2}$ paired vectors, let c_0 denote the observed number of the

pairs with group labels (0,0), let c_1 denote the observed number of pairs with group labels (0,1) or (1,0) (this is our observed cross-match statistic) and finally let c_2 denote the observed number of pairs with group labels (1,1). The null distribution of C in closed form is:

$$f(c_1) = P(C = c_1) = \frac{2^{c_1} n!}{\binom{N}{n} c_0! c_1! c_2!}$$

where $\frac{N}{2} = c_0 + c_1 + c_2$. Having the null distribution in closed form also allows us to compute the exact p-value for our observed cross-match statistic. The resulting p-value is equal to $F(c_1)$ where

$$F(c_1) = P(C \leq c_1) = \sum_{c_1'=0}^{c_1} f(c_1')$$

A low p-value would suggests that we have evidence to reject the null hypothesis (at a given level of significance) that the word embedding vectors were "sampled" from the same distribution.

3 Experiments

In the following experiments, we demonstrate two different illustrative examples of the cross-match test. Our objective is to show the effectiveness of cross-match as a general tool for intrinsic evaluation of word embedding vectors.

3.1 Embedding Similarity

A bridge language (also referred to as a pivot language), is an artificial or natural language used as an intermediary for translation between two different languages. In machine translation, a bridge language is useful in low-resource situations where a good parallel corpora is not available for the target language. In such cases, a resource rich, linguistically similar language is used as a proxy in order to perform the required NLP task. For example in Tsvetkov and Dyer (2015) the authors use Arabic, Italian and French as bridge languages to perform Swahili-English, Maltese-English and Romanian-English translations respectively.

Assessing whether languages are linguistically similar is a reasonably difficult task and depends on the notion of similarity one uses (lexical, morphological etc.) In this experiment, we use cross-match to provide a quantitative measure to assess linguistic similarity between languages.

We use pre-trained word vectors (trained on Wikipedia using the skip-gram model in Bojanowski et al. (2016)) from Facebook's fastText library for several languages and calculate the cross-match statistic for several language pairs. Specifically, we randomly select 100,000 word vectors for each language (with the exception of Maltese and Swahili which have only 26,000 and 52,000 vectors respectively). Then for each language pair, we randomly sample 200 vectors and calculate the number of cross-matches between them using R's crossmatch package (`https://github.com/cran/crossmatch`). We repeat this 500 times for each language pair and report the average cross-match statistic.

Language Pair	Cross-Match
English-French	23.76
English-Italian	25.04
English-Spanish	23.36
English-Portuguese	18.44
English-Arabic	19.34
English-Maltese	7.84
English-Romanian	16.56
English-Swahili	17

Table 1: fastText vectors cross-match statistics for English-pair languages

Language Pair	Cross-Match
Maltese-English	7.84
Maltese-French	7.28
Maltese-Italian	9.20
Maltese-Spanish	6.76
Maltese-Portuguese	4.84
Maltese-Arabic	6.68
Maltese-Romanian	6.96
Maltese-Swahili	4.44

Table 2: fastText vectors cross-match statistics for Maltese-pair languages

Tables 1 and 2 present the results of calculating the average number of cross-matches between several English-pair and Maltese-pair languages. We note that with a sample of 400 vectors (200 from each language) the maximum possible number of cross-matches is 200. Given that are our reported statistics are considerably lower than 200 we can safely conclude that the distributions from which the word embedding vec-

tors were generated are different for different languages. In table 1 we note that the number of cross-matches between English and other romance languages (French, Italian, Spanish, Portuguese, Romanian) is noticeably higher than that between English and non-romance languages (Arabic, Maltese, Swahili). This corresponds with our notions of linguistic similarity between the languages, we certainly expect English to be more "similar" to French than to Maltese. We also note that in table 2, the Maltese-Italian pair has the highest cross-match statistic, thus supporting the choice of Italian as a bridge language for Maltese.

3.2 Embedding Evaluation

In this experiment, we use cross-match to assess the statistical significance of word embedding models. Despite the popularity of various different embedding models (Mikolov et al., 2013a,b; Pennington et al., 2014) it is not always clear whether one model represents a statistically significant improvement to other existing models (it maybe that all of them capture largely similar features of the text).

We consider four popular word embedding models: word2vec Skip-gram, word2vec CBOW, Glove and fastText all trained on the same English wikipedia corpus. Once again we take samples of size 200 from each method, caluclate the p-value between two pairs of methods using cross-match and then report the average p-value across 500 repeated iterations.

	Skip	CBOW	Glove	FastText
Skip	-	4.93e-26	2.39e-27	1.66e-23
CBOW	4.93e-26	-	9.42e-25	2.71e-22
Glove	2.39e-27	9.42e-25	-	1.13e-23
fastText	1.66e-23	2.71e-22	1.13e-23	-

Table 3: p-values calculated using Cross-match

The results in 3 show low p-values across all pairs of word embedding methods thus suggesting that they all seem to capture different aspects of the corpus they are modeling. In other words, using cross-match we have evidence to reject the null hypothesis that the vectors derived from any pair of models come from the same word embedding distribution.

Lastly, we note that there are at present some computational constraints in performing the cross-match test. There exists a bottleneck in the calculation of the optimal non-bipartite matching and this makes performing the test for larger sample sizes currently intractable. However, we feel confident that this software issue can be easily overcome by writing custom routines (as opposed to using existing open-source code) and parallelizing the problem. As a result of our limited sample size, we not that it is possible that the power of our hypothesis test is low and thus we may be making type I errors (falsely rejecting the null). Nonetheless our initial results seem promising and are in line with our expectations.

4 Conclusion

In this work we introduced the cross-match test, an exact, distribution free, high-dimensional hypothesis test as an intrinsic evaluation metric for word embeddings. We were able to demonstrate on two illustrative examples that the test performs reasonably in line with our expectations and can potentially be a useful tool in assessing bridge languages for machine translation. Despite the initially promising results, much further work remains to be done in order to confirm the efficacy of cross-match in the context of word embeddings.

We posit that our main contribution is the introduction of the hypothesis testing framework as a method for intrinsic evaluation of vector representations. We observe that there is nothing notable about word embeddings or the cross-match test and our experiments could be extended for other vector representations (sentence, phrase etc.) using other modern two-sample hypothesis tests such as the popular maximum mean discrepancy (Gretton et al., 2012). Given the rich literature on hypothesis testing in statistics, there is certainly much to be explored here.

For future work we aim to focus solely on the problem of bridge languages in machine translation. Our objective is to conduct a larger scale study that is able to definitively show a strong correlation between the results of a hypothesis test on word embedding vectors, and their subsequent performance on the downstream machine translation task.

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Evaluation of word embeddings against cognitive processes: primed reaction times in lexical decision and naming tasks

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Abstract

This work presents a framework for word similarity evaluation grounded on cognitive sciences experimental data. Word pair similarities are compared to reaction times of subjects in large scale lexical decision and naming tasks under semantic priming. Results show that GloVe embeddings lead to significantly higher correlation with experimental measurements than other controlled and off-the-shelf embeddings, and that the choice of a training corpus is less important than that of the algorithm. Comparison of rankings with other datasets shows that the cognitive phenomenon covers more aspects than simply word relatedness or similarity.

1 Introduction

Word representations have attracted a lot of interest in the community and led to very useful applications in a range of domains of natural language processing. Such representations are typically evaluated intrinsically on word similarity tasks and extrinsically on their impact on NLP systems performance (Schnabel et al., 2015; Lai et al., 2016; Ghannay et al., 2016).

A recent trend towards building more general representations has looked at how similarities in the representation space can predict the outcome of cognitive experiments, such as human reaction time in semantic priming experiments (Ettinger and Linzen, 2016) or relying on eye tracking and brain imaging data (Søgaard, 2016; Ruan et al., 2016). The idea is that ground truth from unconscious phenomena might be less prone to subjective factors of more traditional word similarity and relatedness datasets.

In this paper, we describe an evaluation framework based on comparing word embedding similarity against reaction times from the Semantic Priming Project (Hutchison et al., 2013). A set of word embeddings is evaluated by computing its Spearman rank correlation with average reaction times obtained by submitting a set of subjects to a prime (one word from the pair) and then perform one of two tasks: lexical decision (decide whether the second word is an existing word or not), and naming (read aloud the second word).

Extending the ideas developed in (Ettinger and Linzen, 2016), this paper describes the following contributions:

- we create and distribute a package[1] for word embedding evaluation based on the SPP primed reaction time data;
- in order to calibrate results from that evaluation framework, we look at the effect of training corpus on a set of word embeddings;
- we also look at the correlation between SPP reaction times and subjective similarity and relatedness ratings from existing datasets.

2 Related Work

Intrinsic and extrinsic approaches have been proposed for word embedding evaluation. The former typically consist in collecting human judgment of word similarity on a range of word pairs, and computing the rank correlation of their averaged value with the cosine similarity between the embeddings of the words in the pair. Word analogy is also evaluated but it has been proven to be equivalent to a linear combination between cosine similarities (Levy et al., 2014). In this work, we focus on

[1]Available at https://github.com/JomnTAL/spp-wordsim

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intrinsic evaluation, and therefore do not detail efforts for extrinsic evaluation of word embeddings. More pointers can be found in (Schnabel et al., 2015; Lai et al., 2016; Ghannay et al., 2016).

A number of datasets can be used to evaluate word similarity based on human judgment. Older datasets, such as RG (Rubenstein and Goodenough, 1965) and MC (Miller and Charles, 1991) shall not be used because differences between correlations are not significant due to their small size (Faruqui et al., 2016). While early datasets contained judgments collected in-house, such as WS-353 (Finkelstein et al., 2001; Agirre et al., 2009), most recent ones are created through crowd sourcing, with 10 to 20 annotations per word-pair, filtered for outliers: MTurk-287 (Radinsky et al., 2011), MTurk-771 (Halawi et al., 2012), MEN (Bruni et al., 2012), RW (Luong et al., 2013). Another trend is to address different syntactic categories than noun, such as YP-130 (Yang and Powers, 2006) and Verb (Baker et al., 2014) which focus on verbs. While past studies did not differentiate relatedness from semantic similarity, SimLex (Hill et al., 2016) and SimVerb (Gerz et al., 2016) explicitly promote the later. Embeddings can also be compared to lexical resources (Tsvetkov et al., 2015), but it is hard to balance the contribution of each linguistic phenomenon. Existing similarity ratings are subjective because they are the result of a conscious process while it seems desirable to directly evaluate embeddings against basic processes that support language in the brain.

In the cognitive sciences community, there has been efforts to explain how word associations are formed by introducing word embeddings in models. Pereira et al. (2016) look at how off-the-shelf word embeddings predict free associations (given a prime, say the first word that comes to your mind), a conscious process while we are interested in an unconscious process. The work by Hollis and Westbury (2016), among other experiments, compares word embedding principal components to unprimed reaction times from the English Lexicon Project (ELP) and British Lexicon Project (BLP). Both papers are interested in explaining cognitive behavior. There have also been efforts to evaluate word embeddings against fMRI recordings with the idea that embeddings can explain part of the neural activity (Søgaard, 2016).

The work by Ettinger and Linzen (2016) is particularly relevant to our study in that the authors also propose to evaluate embeddings against reaction time data from the SPP dataset. Our work differs in that we provide an evaluation setup which can be reused by other researchers, we propose a different evaluation metric based on rank correlation, and we perform an analysis in regard to different parameters, in particular the corpus used to train embeddings.

3 Semantic priming

There is an extensive psychological literature concerning the nature of semantic representations and the influence of semantic or associative context on word processing (McNamara, 2005). In this domain, the semantic priming paradigm is one of the most popular experimental tool to study these cognitive processes. In this task, participants are presented with a prime (stimulus) word (e.g., cat) immediately followed by either a related (e.g., dog) or an unrelated (e.g., truck) target word. A speeded response is expected on the target word (e.g., a lexical-decision, i.e., is it a word or not?) and a response time is recorded. Semantic priming refers to the finding that people respond faster to target words preceded by related, relative to unrelated, primes. This behavioral index therefore provides information about the influence of a semantic context (i.e., the prime word) on the processing of the target word and is suitable for the development of theories of semantic memory.

Due to the increasing precision of computational models of word processing, researchers are now testing models by using large-scale databases providing experimental data at the item level. The Semantic Priming Project (SPP) (Hutchison et al., 2013) is one of these recently collected databases. It provides response times from 768 participants in speeded naming (NT) and lexical decision (LDT) tasks for 1,661 target words following related and unrelated primes. The naming task consists in reading aloud the target, while the lexical decision task consists in pressing one of two buttons to specify if the target is a valid word or not. Aside from the relatedness between the prime and the target, the item data is also available for stimulus onset asynchronies (SOA) between the prime and target items of 200 and 1,200 ms. Stimulus onset asynchrony is the time between the end of showing the first (stimulus) word, and the target word in the reaction time experiments. Se-

mantic priming at shorter SOAs (e.g., under 300 ms) is thought to reflect automatic priming mechanisms, whereas priming at longer SOAs (e.g., over 300 ms) presumably reflects additional intentional strategies (Hutchison et al., 2001).

Reaction times observed in semantic priming experiments can be explained by a range of linguistic phenomena, such as relatedness, semantic similarity, syntactic traits, or morphology. Unlike Hill et al. (2016) who focus on one phenomenon, we assume that word representations should convey the full mixture of explaining factors observed in unplanned human behavior. Therefore we evaluate embeddings by computing the correlation between the cosine similarity of pairs of words and reaction times (RT). Shorter RT indicate more priming effect, leading to negative correlations. In addition, non linguistic factors such as frequency are known to influence RT measurements, so it is not expected that word embeddings explain the whole variance of the experiment.

The SPP data is significantly larger than word similarity datasets and consists of 6,637 word pairs. The RT for each pair is an average over the performance of 30 subjects. In addition to reaction times, the dataset contains demographics, proficiency and attention tests results.

4 Evaluation framework

Embeddings are evaluated by computing the cosine similarity between word pairs from the SPP project, and look at their Spearman rank correlation with the RT data. The results are given in term of negative correlation. Significance of the difference between correlations is calculated with the Steiger test (Steiger, 1980).

In this evaluation framework, the word pairs for the Lexical Decision Task (LDT) and Naming Task (NT) are split according to two partitions. The first one (P1), used here, consists of a development set of 1,328 pairs and a test set of 5,309 pairs. Parameters of the proposed approaches can be tuned on the development set and performance must be reported on the test set. Another partition (P2) is made available to also include data for training algorithms. The Train set consists of 3,981 pairs, the Dev has 1,328 pairs and the Test has 1,328 pairs. These partitions were obtained by using 10 folds which are also available. We didn't create them with a particular goal in mind but we made sure that the mean word frequency and the standard deviation (SD) of each fold was close to the mean word frequency and SD of the full dataset. By standardizing the data splits, we ensure that results presented in future work will be comparable.

Experiments In a first set of experiments, we benchmark a range of embeddings on the SPP data. Four conditions are considered: LDT-200, LDT-1200, NT-200, NT-1200 (for lexical decision task, and naming task, both with an onset of 200 ms and 1,200 ms). We compare two categories of embeddings: a controlled setting for which algorithms are trained on the same dataset, and a selection of pretrained embeddings available to the community. Due to space constraints, the pretrained embeddings considered[2] are limited to: W2V Skip-gram (Mikolov et al., 2013), GloVe (Pennington et al., 2014), Multilingual (Faruqui and Dyer, 2014), Dependency-based (Levy and Goldberg, 2014), and FastText (Bojanowski et al., 2016).

For the embeddings with controlled settings, we used two algorithms: W2V Skip-grams and GloVe. We used three different corpora to train these embeddings: Wikipedia 2013 (Wiki), Gigaword[3] (GW) and OpenSubtitles 2016 (OS). We used a centered window of size 10 and generated vectors with 100 dimensions for all 6 models.

From the experiment detailed in Table 1, it appears that GloVe leads to significantly larger negative correlation compared to other approaches, both on the controlled and pretrained settings. On the controlled setting, we notice that the choice of the corpora doesn't significantly affect the correlation. Even if the correlation seems to be higher with the NT-200 and NT-1200 datasets when using the OpenSubtitles corpus, the Steiger test shows that the difference in correlation when using the other corpora is not significant in most cases. However, the algorithms used do have a significant impact on the correlations. In the future, it would be interesting to look at the impact of various other settings such as the size and position of the window, or the dimension of the word vectors.

It can also noted that the correlations on the lexical decision tasks are higher than on the naming tasks which supports the idea that lexical decision

[2]URLs and descriptions available at https://github.com/JomnTAL/spp-wordsim.

[3]LDC2012T21

	Off-the-shelf embeddings					Embeddings with controlled settings					
	GloVe	W2V	Multilingual	Dependency	FastText	GloVe OS	GloVe Wiki	GloVe GW	W2V OS	W2V Wiki	W2V GW
LDT-200	**25.02**	15.35*	13.88*	5.48*	14.48*	23.61	23.06	**23.91**	17.77*	16.75*	16.86*
LDT-1200	**18.91**	11.21*	11.19*	3.76*	10.75*	17.65	17.88	**18.17**	12.86*	11.64*	11.35*
NT-200	**15.43**	5.70*	6.43*	-1.56*	3.73*	**15.37**	12.52*	13.67†	8.27*	6.30*	7.83*
NT-1200	**12.57**	8.86*	7.58*	4.68*	8.30*	**12.14**	10.36†	11.78	9.42*	9.23*	9.30*

Table 1: Spearman's correlation[4] between the test SPP datasets and word embedding models. Highest results are in bold. Significativity of the figures compared to the best results according to Steiger test is indicated by $^*(pval < 0.01)$ and $^\dagger(pval \in [0.01, 0.05[)$.

	Nb Pairs	LDT-200	LDT-1200	NT-200	NT-1200
WS-353-ALL	16	0.40	-0.30	0.26	-0.51
MTurk-771	26	-0.08	0.23	-0.23	-0.28
MEN-TR-3k	71	0.21	-0.20	0.04	-0.02
SimLex-999	101	-0.03	0.06	0.06	0.02

Table 2: Spearman's correlation between reaction times from the SPP datasets and relationship scores from other datasets (with more than 16 overlapping pairs).

seems to be a task less subject to variability from production of the response (pressing a button vs saying a word). Better correlations at an onset of 200 ms can be explained by the fact that subjects are allowed more time to build an intent, leading to more factors being involved. This also probably means that most word embedding models are better at capturing automatic priming mechanisms.

The second experiment detailed in Table 2 looks at the characteristics of the SPP data in regard to other available datasets. We calculated the correlation between the reaction times in the SPP datasets and the relationship scores in a set of existing datasets, using the pairs of words that are available in the two compared datasets (different pairs are compared for each dataset). We only show the results for datasets that have 16 or more pairs in common with the SPP dataset. The SimVerb dataset had 208 pairs in common but since the words used were only verbs whereas in the SPP dataset the part-of-speech wasn't specified, we couldn't really compare the two datasets. It can be observed that the correlations are low which probably means that evaluating on the SPP data could outline different phenomena than what is already covered by relatedness and similarity oriented datasets. Additional work has to be done to fully understand what factors are taken into account by the SPP data.

[4]For readability, correlations have been multiplied by -100

5 Discussion

It is not clear what cognitive processes lead to mental representations of words in the brain, and it is not clear how these processes relate to linguistic theories. However, reaction time in the context of semantic priming seems to be a good proxy for modeling word embeddings after cognitive processes. The proposed framework addresses some of the problems with word embedding evaluation exposed in (Faruqui et al., 2016)[5]: (2.1) subjectivity is addressed by looking at unconscious phenomena, (2.2) the lexical decision and naming tasks are very general but they are affected by other cognitive pipelines such as vision, (2.3) we provide standardized splits, and (2.5) the size of the dataset allows for significant differences between algorithms. However, we do not address the problem of low correlation with extrinsic evaluation (2.4), we do not account for frequency effects (2.6) and polysemy (2.7). These aspects are left for future work.

6 Conclusion

This work explores an evaluation target for word embeddings: reaction time in lexical decision and naming tasks from a semantic priming experiment. Experiments show that this setting is dominated by different factors than word relatedness or similarity, and that the choice of algorithm is a stronger predictor of correlation than the choice of training corpora. In future work, we will leverage the non-word data from the lexical decision task in order to evaluate character-based word embeddings.

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[5]According to their section numbers

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Playing with Embeddings : Evaluating embeddings for Robot Language Learning through MUD Games

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Abstract

Acquiring language provides a ubiquitous mode of communication, across humans and robots. To this effect, distributional representations of words based on co-occurrence statistics, have provided significant advancements ranging across machine translation to comprehension. In this paper, we study the suitability of using general purpose word-embeddings for language learning in robots. We propose using text-based games as a proxy to evaluating word embedding on real robots. Based in a risk-reward setting, we review the effectiveness of the embeddings in navigating tasks in fantasy games, as an approximation to their performance on more complex scenarios, like language assisted robot navigation.

1 Introduction

Language provides a natural interface for humans to communicate with robots. With their increasing public presence, from self-driving cars and rescue operations to warehouses, it is imperative to reduce this barrier of communication, by improving language learning in mobile robots. For instance, in search and rescue operations one might want to instruct the agents to "Reach the third floor of the blue building". Given the nature of the tasks, it is essential for the agent to accurately infer its current state and parse natural language instructions to corresponding actions.

In recent years, learning continuous representations of words and symbols have become central to dealing with several key problems in natural language understanding. Usually trained to maximize the likelihood of next utterance, these models effectively learn co-occurrence statistics based on corpora, motivated by the distributional hypothesis (Harris, 1954). This objective function, often organizes objects and actions with *similar* semantic information, to close neighborhoods in the corresponding embedding space. Here, the *similarity between words* is often defined by some metric for *similarity* of the word vectors.

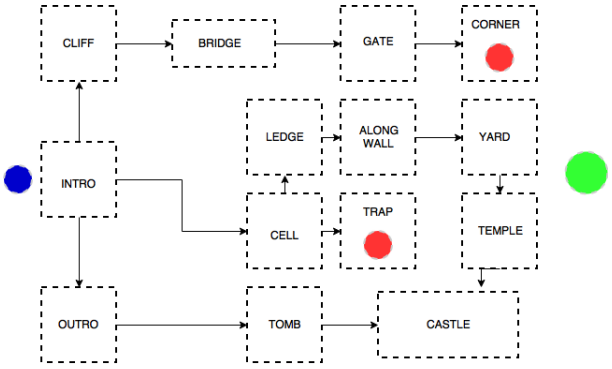

Figure 1: An example of environment generated in the MUD environment. While the blue blob denotes the start state, the red blobs denote deterministic intermediate negative rewards. The green blob on the right denotes positive reward on completion of quest.

Though evidently successful across several tasks, common general purpose word embeddings with fixed dimensions are often inadequate in their representation capacity. In recent works, (Gauthier and Mordatch, 2016; Lucy and Gauthier, 2017) argue that language learning grounded in perception, motion or actions, are important to learn meaningful representations corresponding to *consequences* of actions on objects. Specifically, in a scenario where robots are deployed in real world, it is important to distinguish even between

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Fantasy Environment You are standing very close to the bridges eastern foundation. If you go east you will be back on solid ground ... The bridge sways in the wind.
MARCO dataset (Chen and Mooney, 2011) face the octagon carpet. move until you see red brick floor to your right. turn and walk down the red brick until you get to an alley with grey floor. you should be two alleys away from a lamp and then an easel beyond that.

Table 1: Examples of instructions from MUD vs MARCO dataset for navigation.

similar actions based context and their effect in a given situation.

In this paper, we address this task of evaluating word embeddings for language learning in robots by introducing text-based MUD games (Curtis, 1992) as a proxy. Traditionally in robotics, elaborate simulators have been used to evaluate motor control policies of motion planning for the physical agents. In a similar spirit, MUD games provide a rich playground for define complex scenarios solely with textual descriptions. Based on these, the agents are required to take certain actions with the objective of clearing the quest. (Fig. 1)

To evaluate, we train a LSTM-DQN following (Narasimhan et al., 2015), in a reinforcement learning framework. The agent is trained to learn control policies, with the objective of maximizing the rewards obtained. We demonstrate that using general purpose embeddings improve on the average rewards per quest.

2 Multi-User Dungeon Games

A Multi-User Dungeon Game, as defined in (Curtis, 1992) *"is a network-accessible, multi-participant, user-extensible virtual reality whose user interface is entirely textual"*. In essence, it describes an elaborate environment with multiple characters and tasks for the player, the only constraint being that all interactions with the game are purely textual.

In (Amir and Doyle, 2002), the authors elaborately elucidate the richness of such environments, with insights specific to robotics. Primarily in our context of robot language learning, we make the following observations :

- The environment is partially observable, with stochasticity depending on the actions taken by the agent. This inherently allows us to cast the problem as an MDP, and studying it in the light of recent advances in Deep Reinforcement Learning.
- Intermediate rewards provide feedback to the agent, as proxy for a human in a real-life setting. This allows the agent to learn from consequences and formulating the problem in a risk-reward setting.
- Language based symbolic interface for interaction with the environment. Since language remains consistent across simulator and real world, we assume that the text-world is an accurate replica of the real environment.

Among others, the above characteristics suggest that MUD games provide an ideal sandbox for evaluating word-embeddings for robot language learning.

3 Dataset

We propose using text-based MUD games as proxy for evaluating language learning in robotics. As illustrated in (Table 1) the nature of instructions generated by the game environment are quite similar when compared to real datasets, in this case (Chen and Mooney, 2011).

In this work, we use the Evennia[1] game environment, an open-source library to build online textual MUD games. Evennia allows users to create complex environments with elaborate textural descriptions, by simply writing a batch file to describe the objects, actions and possible interactions in the environment. Compared to other available datasets for navigation, the MUD environment provides a risk-reward scenario, where the environment can also be designed to have deterministic negative feedback to represent undesirable outcomes.

To provide feedback on the action taken, the agents are provided positive/negative rewards depending on the state of the game. In case of quest completion, the agents are provided a large positive reward, while predefined bad intermediate checkpoints like colliding with walls, or falling off bridges are penalized with negative rewards. Building on extensive literature in reward shaping in the Deep Reinforcement Learning framework,

[1] http://www.evennia.com/

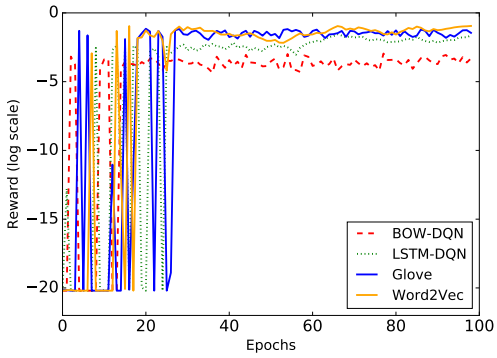

Figure 2: Evaluating agents trained across various embeddings based on average reward (log scale). Pretrained word-vectors outperform random initialized LSTM-DQN and BOW-DQN.

more complex environment can also be easily constructed to evaluate the generalizing capability of the embeddings.

4 Model Architecture

Formulating the problem in a reinforcement learning setting, we train the agent to learn a good Q-value function $Q(s, a)$, for all possible state-action pairs. More concretely the agent iteratively optimizes the Bellman objective

$$Q_{i+1}(s, a) = E[r + \gamma \max_{a'} Q_i(s', a')|s, a] \quad (1)$$

where, γ is the discount factor. With the changing distribution on Q-values the agent decides action a to maximize the future rewards.

In this regard, we follow the LSTM-DQN model by (Narasimhan et al., 2015) which builds on recent developments in Deep Q-Learning (Mnih et al., 2015).

4.1 LSTM-DQN

The input to the agent is the textual description of the current state of the environment. However, the model is required to keep a track over previous states, as well generate a compact representation for the same. Therefore we define a representation generator (ϕ_R), which is an LSTM module to keep a track of the current state of the environment. The individual time step rollouts are further aggregated (ϕ_A) to convert the textual description into compact vector representation (s).

Following the context, the model is required to choose an $action(a)$ to be taken, and an $object(o)$ on which the action is applied in the MUD environment. As a result, we define two Q-value functions $Q(s, a)$ and $Q(s, o)$, which share the same state, and generate distributions on actions and objects respectively. This (a, o) tuple, together defines the action executed by the game environment to update it's state. For detailed description of the model please refer (Narasimhan et al., 2015).

5 Evaluation

We experiment on the *Fantasy World* following the environment in (Narasimhan et al., 2015). The vocabulary consists of 1340 unique tokens, with 100 different descriptions for the room. Visiting the room provides random sequence of description as developed by the designers. Average length of descriptions in the rooms was 65 words per descriptions. The possible actions per state average to 222 per state. Please refer (Narasimhan et al., 2015) for elaborate game statistics.

To evaluate the performance of agents when using different word-embeddings, different metrics could be defined depending on the requirement of the task. In the particular case of evaluating the performance of the agent on navigation task, we follow common defined metrics as in (Narasimhan et al., 2015)

- cumulative reward per episode averaged over the number of episodes.
- fraction of quests successfully completed by the agent.

Considering the task as an downstream proxy for the actual environment, this does not evaluate the individual embeddings by similarity metrics, rather the generalization across environments. In this work we compare word2vec (Mikolov et al., 2013), GloVe (Pennington et al., 2014) general use embeddings against a BOW-DQN baseline and LSTM-DQN trained with random initialization (Fig 2). The baseline here (BOW-DQN) uses a simple bag-of-words model to represent the textual description.

We observe that using pre-trained embeddings generally improve the performance of the model. The rewards in our primary models have high variance due to the stochastic nature of the policy. In further work, we wish to build on recent advancements in Deep Reinforcement Learning literature, for training better models.

6 Discussion and Future Work

Using continuous vector representations of words for language learning in mobile robots poses the question of choice of embeddings which capture task specific semantics. In this work we propose using MUD games as proxy for this task, rather than elaborate testing on robotic platforms.

Similar to real world situation, all interactions between the agent and the environment are through language, without any other supervision. The rewards provide the models with required supervision of tuning the word embeddings to complete the quest. Preliminary evaluation on standard embeddings show that average rewards for pretrained embeddings are better than BOW models and randomly initialized LSTM embeddings.

In future work we wish to extensively evaluate the model on more standard word-embeddings and against real datasets to establish empirical correlation between the proposed proxy and actual task.

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Recognizing Textual Entailment in Twitter Using Word Embeddings

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Abstract

In this paper, we investigate the application of machine learning techniques and word embeddings to the task of Recognizing Textual Entailment (RTE) in Social Media. We look at a manually labeled dataset (Lendvai et al., 2016) consisting of user generated short texts posted on Twitter (tweets) and related to four recent media events (the Charlie Hebdo shooting, the Ottawa shooting, the Sydney Siege, and the German Wings crash) and test to what extent neural techniques and embeddings are able to distinguish between tweets that entail or contradict each other or that claim unrelated things. We obtain comparable results to the state of the art in a train-test setting, but we show that, due to the noisy aspect of the data, results plummet in an evaluation strategy crafted to better simulate a real-life train-test scenario.

1 Introduction

The ability to automatically deduce how the meaning of text flows from one sentence to the next is a central part of Natural Language Understanding (NLU) and highly important in many Natural Language Processing tasks (NLP). Recognizing Textual Entailment (RTE), started as a challenge in 2004 from this very need and reaching its 8th iteration in 2013 at SemEval[1], falls at the intersection between NLU, NLP, Information Extraction, and Information Retrieval (Dagan et al., 2006). Its goal is, given a pair of sentences dubbed *text* and *hypothesis*, to determine whether the meaning of either (traditionally, of the hypothesis) entails the meaning of the other, contradicts it, or whether nothing can be said of the relationship between the two sentences. Here, the notion of entailment and contradiction are not necessarily related to the linguistic notions, where entailment is always explained in contrast with presupposition and sometimes implicature(Sauerland, 2007), but are outlined in (de Marneffe et al., 2008).

Interest in this task was amplified with the creation of the SNLI corpus (Bowman et al., 2015) which lead to a few studies using Deep Neural Networks (DNN) (Wang and Jiang, 2016; Rocktäschel et al., 2015). Previous to this, the Excitement Open Platform [2] was considered the state-of-the-art model.

On the hand, interest in ways to represent text in order to improve performance in text classification (Lilleberg et al., 2015; Joulin et al., 2016), machine translation (Zou et al., 2013; Sulea et al., 2016) or question answering tasks (Sharp et al., 2016) has been rekindled with the introduction of the highly cited word2vec model (Mikolov et al., 2013) and the avenue of deep neural word embeddings (Palangi et al., 2016).

Our present research revolved around three questions:

- Can we apply state of the art neural methods created for large datasets or longer texts to small datasets containing very short texts?
- Will these methods work for fine grained contradictions?
- Can word embeddings, which were successfully used for word-level semantic tasks, improve performance in tasks pertaining to discourse level semantics?

[1] https://www.cs.york.ac.uk/semeval-2013/task7/

[2] http://hltfbk.github.io/Excitement-Open-Platform/

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2 Approach

In this paper we investigate the application of several state-of-the art approaches to the RTE task in the social media domain and investigate the use of word embeddings for what is essentially a discourse level semantic task. We use neural networks and compare our results with the results obtained previously using classical "feature engineering" methods.

2.1 Data

The data we used was presented in (Lendvai et al., 2016). It contains around 5000 Tweet pairs, distributed over four recent media events, reported in the press. These pairs were hand labeled as being either in a relationship of *entailment*, meaning that the underlying sense of each of the two text snippets was effectively the same, a relationship of *contradiction*, meaning that information in one of the tweets as minor as the number of victims or location of the event at hand contradicted the information expressed in the other tweet, or the two tweets were labeled to be in an *unknown* relationship, meaning that their underlying *stories* did not entail nor contradict each other, although they were referring to the same event. The dataset was slightly unbalanced, with the majority class pertaining to that of the *unknown* relationship and the minority class to the *contradiction* relationship.

Since the contradiction manifested between tweet pairs labeled was very fine grained, we expected bag of word models to perform poorly and confusion between entailment and contradiction to be high. Also, since, for each event, all three classes were represented, there was an expectation that BOW and similarity measures based on BOW would also fail, since pairs of tweets talking about the same event, but being in completely different relationships were abundant. Indeed, as can be seen from the results reported in (Lendvai et al., 2016), the f1 measure is slightly above the random baseline when using such features.

2.2 Classifier Implementation and Settings

For the implementation of the Multi Layer Perceptron classifier, we used the python library Keras [3] which wraps over the Deep Learning library for Python, Theano (Theano Development Team, 2016). The pre-trained word2vec model offered by Google was loaded into our system using the Gensim library (Řehůřek and Sojka, 2010). For the word-mover distance, we used pyemd [4], a Python wrapper for Pele and Werman's implementation of the Earth Mover's Distance metric (Pele and Werman, 2008).

The neural network was trained using several settings for the hyper-parameters (batch size and number of epochs) and we report the results for a batch size of 50 over 100 epochs. We also investigated several ways of representing the *t* and *h* text pairs.

2.3 Feature Representation

The first choice in representing the sentence pairs was to sum the 300-sized vector representation for each word in each of the two sentences separately and then concatenate the resulting 300-sized vectors into one. This lead to one 600-sized vectorial representation of the sentence pair. The second strategy lead to a 900-sized vector: the first 300 elements represented the sum of the vectors of words in the *t* text, the following 300 elements were 0s representing the separation vector, and the final 300 positions in the vector represented the sum of the vector for each word in the *h* text.

We also applied different similarity measures, including cosine and word mover's distance (Kusner et al., 2015), over the vectorial representations of the tweets. Ultimately, in terms of feature representation, we wanted to test two things:

- whether distance metrics between vectorial representations (weather one-hot or word2vec) of tweets are sufficient in predicting the RTE class
- whether inserting a *separation vector* between the two vectors for each of the texts in the pair leads to better results.

2.4 Event-based Cross Validation

In order to have a testing setup as close to a real-life scenario as possible, we employed the event-based cross validation, as proposed in (Lendvai et al., 2016). This effectively meant that, for each of the four events, we kept the tweets related to the other three events for training and used the tweets from the fourth event for testing. This meant that we had a 4-fold cross validation, where, for each *fold*, the train-test split was based on the event

[3] https://keras.io

[4] https://github.com/wmayner/pyemd

each pair belonged to. This in turn meant that, although the event label was never directly used as a feature or as the predicted label, it was indirectly used in cross-validation. This strategy was employed to simulate a real-life scenario where the end user of such an RTE system (e.g. a journalist trying to make sense of a large set of tweets on one event), would already have at their disposal a classification model pre-trained on other, possibly unrelated, events. We compared the results of event based cross-validation with typical train-test split results.

3 Results

Table 1 show the event-based cross validation results for the 3-way classification task when the features used are cosine distance between the sum of word2vec representation of the words in each tweet and word mover distance. More precisely, the cosine value and the word-mover distance value were concatenated to form a Nx2 feature matrix, where N was the number of input examples.

Model	Method	**P**	**R**	**F**
SVM	avg.	0.45	0.52	0.45
LR	avg.	0.46	0.52	0.45
Base	avg.	0.33	0.33	0.33
SVM	cont	0.38	0.49	0.40
LR	cont	0.43	0.53	0.46
Base	cont	0.26	0.31	0.28

Table 1: Event-based CV results using cosine similarity and word mover distance on the minority class and averaged

As can be seen from Figure 1, the distance metrics on occurrence vectors and word2vec summation vector are not good features to separate the three classes.

Logistic regression performed similar to Linear SVC when applied to the word2vec representation coupled with the word mover distance and averaging the event-based cross-validation results over all three classes. However, for the minority class contradiction, LR seemed to perform slightly better, although the standard deviation computed over each fold was higher.

For the 600 and 900 dimensional vector representation, the event-based CV results were slightly lower, as can be seen from Table 2.

Model	Method	**P**	**R**	**F**
MLP	avg.	0.41	0.34	0.30
LR	avg.	0.42	0.47	0.41
Dummy	avg.	0.35	0.35	0.35

Table 2: Event Based CV results for 900 dimensional vectors

Table 3 shows the train-test split results for the MLP and LR models over 900 dimensional vector

Model	Method	**P**	**R**	**F**
MLP	avg.	0.91	0.90	0.90
LR	avg.	0.78	0.78	0.78
Dummy	avg.	0.33	0.33	0.33
MLP	cont	0.87	0.77	0.82
LR	cont	0.62	0.60	0.61
Dummy	cont	0.26	0.26	0.26

Table 3: Train-Test Split results for LSTM and Logistic Regression

4 Conclusions and Future Work

In this paper we've investigated the use of current day classification tools for the task of recognizing textual entailment in Twitter data. We've shown that the same neural network models successfully used in the same task but on larger datasets perform similarly well (with only a small drop in performance) in a train-test split evaluation setting, but they perform as poorly as any other classifier in the event-based cross validation setting, a novel evaluation strategy, which was previously proposed to better simulate real life scenarios of RTE systems on Twitter.

We've also seen that using only the distance (cosine, word mover) between vector representations of the tweets, be those bow or sum of word2vec, was not enough to distinguish the minority class in the event-based cross validation setting and that using concatenation of word2vec leads to minor improvements in the same setting, but considerable in the train-test one.

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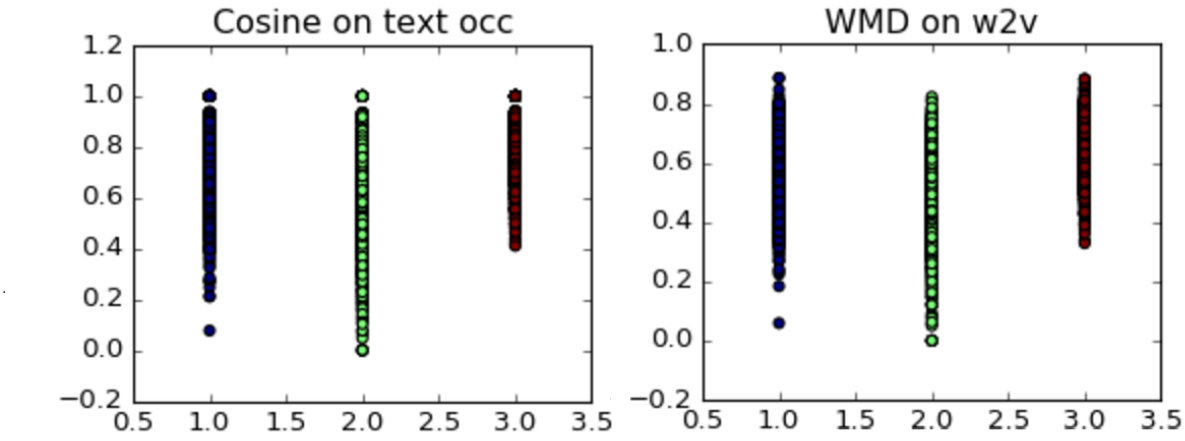

Figure 1: Plot of cosine distance on occurrence vector representation and word mover distance on word2vec summation representation for h and t; the horizontal axis represents the three classes and the vertical represents the distance values

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Recurrent Neural Network-Based Sentence Encoder with Gated Attention for Natural Language Inference

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Abstract

The RepEval 2017 Shared Task aims to evaluate natural language understanding models for sentence representation, in which a sentence is represented as a fixed-length vector with neural networks and the quality of the representation is tested with a natural language inference task. This paper describes our system (alpha) that is ranked among the top in the Shared Task, on both the in-domain test set (obtaining a 74.9% accuracy) and on the cross-domain test set (also attaining a 74.9% accuracy), demonstrating that the model generalizes well to the cross-domain data. Our model is equipped with intra-sentence gated-attention composition which helps achieve a better performance. In addition to submitting our model to the Shared Task, we have also tested it on the Stanford Natural Language Inference (SNLI) dataset. We obtain an accuracy of 85.5%, which is the best reported result on SNLI when cross-sentence attention is not allowed, the same condition enforced in RepEval 2017.

1 Introduction

The RepEval 2017 Shared Task aims to evaluate language understanding models for sentence representation with natural language inference (NLI) tasks, where a sentence is represented as a fixed-length vector.

Modeling inference in human language is very challenging but is a basic problem in natural language understanding. Specifically, NLI is concerned with determining whether a hypothesis sentence h can be inferred from a premise sentence p.

Most previous top-performing neural network models on NLI use attention models between a premise and its hypothesis, while how much information can be encoded in a fixed-length vector without such cross-sentence attention deserves some further understanding. In this paper, we describe the model we submitted to the RepEval 2017 Shared Task (Nangia et al., 2017), which achieves the top performance on both the in-domain and cross-domain test set.

2 Related Work

Natural language inference (NLI), also named recognizing textual entailment (RTE) includes a large bulk of early work on rather small datasets with more conventional methods (Dagan et al., 2005; MacCartney, 2009). More recently, the large datasets are available, which makes it possible to train natural language inference models based on neural networks (Bowman et al., 2015; Williams et al., 2017).

Natural language inference models based on neural networks are mainly separated into two kind of ways, sentence encoder-based models and cross-sentence attention-based models. Among them, Enhanced Sequential Inference Model (ESIM) with cross-sentence attention represents the state of the art (Chen et al., 2016b). However, in this paper we principally concentrate on

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sentence encoder-based model. Many researchers have studied sentence encoder-based model for natural language inference (Bowman et al., 2015; Vendrov et al., 2015; Mou et al., 2016; Bowman et al., 2016; Munkhdalai and Yu, 2016a,b; Liu et al., 2016; Lin et al., 2017). It is, however, not very clear if the potential of the sentence encoder-based model has been well exploited. In this paper, we demonstrate that proposed models based on gated-attention can achieve a new state-of-the-art performance for natural language inference.

3 Methods

We present here the proposed natural language inference networks which are composed of the following major components: word embedding, sequence encoder, composition layer, and the top-layer classifier. Figure 1 shows a view of the architecture of our neural language inference network.

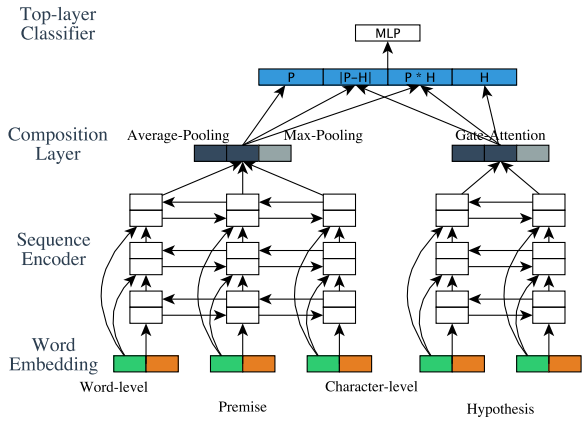

Figure 1: A view of our neural language inference network.

3.1 Word Embedding

In our notation, a sentence (premise or hypothesis) is indicated as $x = (x_1, \ldots, x_l)$, where l is the length of the sentence. We concatenate embeddings learned at two different levels to represent each word in the sentence: the character composition and holistic word-level embedding. The character composition feeds all characters of each word into a convolutional neural network (CNN) with max-pooling (Kim, 2014) to obtain representations $c = (c_1, \ldots, c_l)$. In addition, we also use the pre-trained GloVe vectors (Pennington et al., 2014) for each word as holistic word-level embedding $w = (w_1, \ldots, w_l)$. Therefore, each word is represented as a concatenation of the character-composition vector and word-level embedding $e = ([c_1; w_1], \ldots, [c_l; w_l])$. This is performed on both the premise and hypothesis, resulting into two matrices: the $e^p \in \mathbb{R}^{n \times d_w}$ for a premise and the $e^h \in \mathbb{R}^{m \times d_w}$ for a hypothesis, where n and m are the length of the premise and hypothesis respectively, and d_w is the embedding dimension.

3.2 Sequence Encoder

To represent words and their context in a premise and hypothesis, sentence pairs are fed into sentence encoders to obtain hidden vectors (h^p and h^h). We use stacked bidirectional LSTMs (BiLSTM) as the encoders. Shortcut connections are applied, which concatenate word embeddings and input hidden states at each layer in the stacked BiLSTM except for the bottom layer.

$$h^p = \text{BiLSTM}(e^p) \in \mathbb{R}^{n \times 2d} \quad (1)$$

$$h^h = \text{BiLSTM}(e^h) \in \mathbb{R}^{m \times 2d} \quad (2)$$

where d is the dimension of hidden states of LSTMs. A BiLSTM concatenate a forward and backward LSTM on a sequence $h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}]$, starting from the left and the right end, respectively. Hidden states of unidirectional LSTM ($\overrightarrow{h_t}$ or $\overleftarrow{h_t}$) are calculated as follows,

$$\begin{bmatrix} i_t \\ f_t \\ u_t \\ o_t \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \tanh \\ \sigma \end{bmatrix} (W x_t + U h_{t-1} + b) \quad (3)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot u_t \quad (4)$$

$$h_t = o_t \odot \tanh(c_t) \quad (5)$$

where σ is the sigmoid function, $\odot$ is the element-wise multiplication of two vectors, and $W \in \mathbb{R}^{4d \times d_w}$, $U \in \mathbb{R}^{4d \times d}$, $b \in \mathbb{R}^{4d \times 1}$ are weight matrices to be learned. For each input vector x_t at time step t, LSTM applies a set of gating functions—the input gate i_t, forget gate f_t, and output gate o_t, together with a memory cell c_t, to control message flow and track long-distance information (Hochreiter and Schmidhuber, 1997) and generate a hidden state h_t at each time step.

3.3 Composition Layer

To transform sentences into fixed-length vector representations and reason using those representations, we need to compose the hidden vectors obtained by the sequence encoder layer (h^p and h^h).

We propose intra-sentence gated-attention to obtain a fixed-length vector. Illustrated by the case of hidden states of premise h^p,

$$v_g^p = \sum_{t=1}^{n} \frac{\|i_t\|_2}{\sum_{j=1}^{n} \|i_j\|_2} h_t^p \quad (6)$$

$$\text{or } v_g^p = \sum_{t=1}^{n} \frac{\|1 - f_t\|_2}{\sum_{j=1}^{n} \|1 - f_j\|_2} h_t^p \quad (7)$$

$$\text{or } v_g^p = \sum_{t=1}^{n} \frac{\|o_t\|_2}{\sum_{j=1}^{n} \|o_j\|_2} h_t^p \quad (8)$$

where i_t, f_t, o_t are the input gate, forget gate, and output gate in the BiLSTM of the top layer. Note that the gates are concatenated by forward and backward LSTM, i.e., $i_t = [\overrightarrow{i_t}; \overleftarrow{i_t}]$, $f_t = [\overrightarrow{f_t}; \overleftarrow{f_t}]$, $o_t = [\overrightarrow{o_t}; \overleftarrow{o_t}]$. $\|*\|_2$ indicates l^2-norm, which converts vectors to scalars. The idea of gated-attention is inspired by the fact that human only remember important parts after they read sentences. (Liu et al., 2016; Lin et al., 2017) proposed a similar "inner-attention" mechanism but it's calculated by an extra MLP layer which would require more computation than us.

We also use average-pooling and max-pooling to obtain fixed-length vectors v_a and v_m as in Chen et al. (2016b). Then, the final fixed-length vector representation of premise is $v^p = [v_g^p; v_a^p; v_m^p]$. As for hidden states of hypothesis h^h, we can obtain v^h through similar calculation procedure. Consequently, both the premise and hypothesis are fed into the composition layer to obtain fixed-length vector representations respectively (v^p, v^h).

3.4 Top-layer Classifier

Our inference model feeds the resulting vectors obtained above to the final classifier to determine the overall inference relationship. In our models, we compute the absolute difference and the element-wise product for the tuple $[v^p, v^h]$. The absolute difference and element-wise product are then concatenated with the original vectors v^p and v^h (Mou et al., 2016).

$$v_{\text{inp}} = [v^p; v^h; |v^p - v^h|; v^p \odot v^h] \quad (9)$$

We then put the vector v_{inp} into a final multilayer perceptron (MLP) classifier. The MLP has 2 hidden layers with *ReLu* activation with shortcut connections and a *softmax* output layer in our experiments. The entire model (all four components described above) is trained end-to-end, and the cross-entropy loss of the training set is minimized.

4 Experimental Setup

Data RepEval 2017 use Multi-Genre NLI corpus (MultiNLI) (Williams et al., 2017), which focuses on three basic relationships between a premise and a potential hypothesis: the premise entails the hypothesis (*entailment*), they contradict each other (*contradiction*), or they are not related (*neutral*). The corpus has ten genres, such as fiction, letters, telephone speech and so on. Training set only has five genres of them, therefore there are in-domain and cross-domain development/test sets. SNLI (Bowman et al., 2015) corpus can be used as an additional training/development set, which includes content from the single genre of image captions. However, we don't use SNLI as an additional training/development data in our experiments.

Training We use the in-domain development set to select models for testing. To help replicate our results, we publish our code at `https://github.com/lukecq1231/enc_nli` (the core code is also used or adapted for a summarization (Chen et al., 2016a) and a question-answering task (Zhang et al., 2017)). We use the Adam (Kingma and Ba, 2014) for optimization. Stacked BiLSTM has 3 layers, and all hidden states of BiLSTMs and MLP have 600 dimensions. The character embedding has 15 dimensions, and CNN filters length is [1,3,5], each of those is 100 dimensions. We use pretrained *GloVe-840B-300D* vectors (Pennington et al., 2014) as our word-level embeddings and fix these embeddings during the training process. Out-of-vocabulary (OOV) words are initialized randomly with Gaussian samples.

5 Results

Table 1 shows the results of different models. The first group of models are copied from Williams et al. (2017). The first sentence encoder is based on continuous bag of words (CBOW), the second is based on BiLSTM, and the third model is Enhanced Sequential Inference Model (ESIM) (Chen et al., 2016b) reimplemented by Williams et al. (2017), which represents the state of the art on SNLI dataset. However, ESIM uses attention between sentence pairs, which is not a sentence-encoder based model.

Model	In	Cross
CBOW	64.8	64.5
BiLSTM	66.9	66.9
ESIM	72.3	72.1
TALP-UPC*	67.9	68.2
LCT-MALTA*	70.7	70.8
Rivercorners*	72.1	72.1
Rivercorners (ensemble)*	72.2	72.8
YixinNie-UNC-NLP*	74.5	73.5
Our ESIM	76.8	75.8
Single*	73.5	73.6
Ensembled*	74.9	74.9
Single (Input Gate)*	73.5	73.6
Single (Forget Gate)	72.9	73.1
Single (Output Gate)	73.7	73.4
Single - Gated-Att	72.8	73.6
Single - CharCNN	72.9	73.5
Single - Word Embedding	65.6	66.0
Single - AbsDiff/Product	69.7	69.2

Table 1: Accuracies of the models on MultiNLI. Note that * indicates that the model participate in the competition on June 15th, 2017.

The second group of models are the results of other teams which participate the RepEval 2017 Share Task competition (Nangia et al., 2017).

In addition, we also use our implementation of ESIM, which achieves an accuracy of 76.8% in the in-domain test set, and 75.8% in the cross-domain test set, which presents the state-of-the-art results. After removing the cross-sentence attention and adding our gated-attention model, we achieve accuracies of 73.5% and 73.6%, which ranks first in the cross-domain test set and ranks second in the in-domain test set among the single models. When ensembling our models, we obtain accuracies 74.9% and 74.9%, which ranks first in both test sets. Our ensembling is performed by averaging the five models trained with different parameter initialization.

We compare the performance of using different gate in gate-attention in the fourth group of Table 1. Note that we use attention based on input gate on all other experiments.

To understand the importance of the different elements of the proposed model, we remove some crucial elements from our single model. If we remove the gated-attention, the accuracies drop to 72.8% and 73.6%. If we remove character-composition vector, the accuracies drop to 72.9% and 73.5%. If we remove word-level embedding, the accuracies drop to 65.6% and 66.0%. If we remove absolute difference and element-wise product of the sentence representation vectors, the accuracies drop to 69.7% and 69.2%.

Model	Test
LSTM (Bowman et al., 2015)	80.6
GRU (Vendrov et al., 2015)	81.4
Tree CNN (Mou et al., 2016)	82.1
SPINN-PI (Bowman et al., 2016)	83.2
NTI (Munkhdalai and Yu, 2016b)	83.4
Intra-Att BiLSTM (Liu et al., 2016)	84.2
Self-Att BiLSTM (Lin et al., 2017)	84.2
NSE (Munkhdalai and Yu, 2016a)	84.6
Gated-Att BiLSTM	85.5

Table 2: Accuracies of the models on SNLI.

In addition to testing on this shared task, we have also applied our best single system (without ensembling) on the SNLI dataset; our model achieve an accuracy of 85.5%, which is best result reported on SNLI, outperforming all previous models when cross-sentence attention is not allowed. The previous state-of-the-art sentence encoder-based model (Munkhdalai and Yu, 2016b), called neural semantic encoders (NSE), only achieved an accuracy of 84.6% on SNLI. Table 2 shows the results of previous models and proposed model.

6 Summary and Future Work

We describe our system that encodes a sentence to a fixed-length vector for natural language inference, which achieves the top performances on both the RepEval-2017 and the SNLI dataset. The model is equipped with a novel intra-sentence gated-attention component. The model only uses a common stacked BiLSTM as the building block together with the intra-sentence gated-attention in order to compose the fixed-length representations. Our model could be used on other sentence encoding tasks. Future work on NLI includes exploring the usefulness of external resources such as WordNet and contrasting-meaning embedding (Chen et al., 2015).

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Shortcut-Stacked Sentence Encoders for Multi-Domain Inference

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Abstract

We present a simple sequential sentence encoder for multi-domain natural language inference. Our encoder is based on stacked bidirectional LSTM-RNNs with shortcut connections and fine-tuning of word embeddings. The overall supervised model uses the above encoder to encode two input sentences into two vectors, and then uses a classifier over the vector combination to label the relationship between these two sentences as that of entailment, contradiction, or neural. Our Shortcut-Stacked sentence encoders achieve strong improvements over existing encoders on matched and mismatched multi-domain natural language inference (top single-model result in the EMNLP RepEval 2017 Shared Task (Nangia et al., 2017)). Moreover, they achieve the new state-of-the-art encoding result on the original SNLI dataset (Bowman et al., 2015).

1 Introduction and Background

Natural language inference (NLI) or recognizing textual entailment (RTE) is a fundamental semantic task in the field of natural language processing. The problem is to determine whether a given hypothesis sentence can be logically inferred from a given premise sentence. Recently released datasets such as the Stanford Natural Language Inference Corpus (Bowman et al., 2015) (SNLI) and the Multi-Genre Natural Language Inference Corpus (Williams et al., 2017) (MultiNLI) have not only encouraged several end-to-end neural network approaches to NLI, but have also served as an evaluation resource for general representation learning of natural language.

Depending on whether a model will first encode a sentence into a fixed-length vector without any incorporating information from the other sentence, the several proposed models can be categorized into two groups: (1) encoding-based models (or sentence encoders), such as Tree-based CNN encoders (TBCNN) in Mou et al. (2015) or Stack-augmented Parser-Interpreter Neural Network (SPINN) in Bowman et al. (2016), and (2) joint, pairwise models that use cross-features between the two sentences to encode them, such as the Enhanced Sequential Inference Model (ESIM) in Chen et al. (2017) or the bilateral multi-perspective matching (BiMPM) model Wang et al. (2017). Moreover, common sentence encoders can again be classified into tree-based encoders such as SPINN in Bowman et al. (2016) which we mentioned before, or sequential encoders such as the biLSTM model by Bowman et al. (2015).

In this paper, we follow the former approach of encoding-based models, and propose a novel yet simple sequential sentence encoder for the MultiNLI problem. Our encoder does not require any syntactic information of the sentence. It also does not contain any attention or memory structure. It is basically a stacked (multi-layered) bidirectional LSTM-RNN with shortcut connections (feeding all previous layers' outputs and word embeddings to each layer) and word embedding fine-tuning. The overall supervised model uses these shortcut-stacked encoders to encode two input sentences into two vectors, and then we use a classifier over the vector combination to label the relationship between these two sentences as that of entailment, contradiction, or neural (similar to the classifier setup of Bowman et al. (2015) and Conneau et al. (2017)). Our simple shortcut-stacked encoders achieve strong improvements over existing encoders due to its multi-layered and shortcut-connected properties, on both matched and mis-

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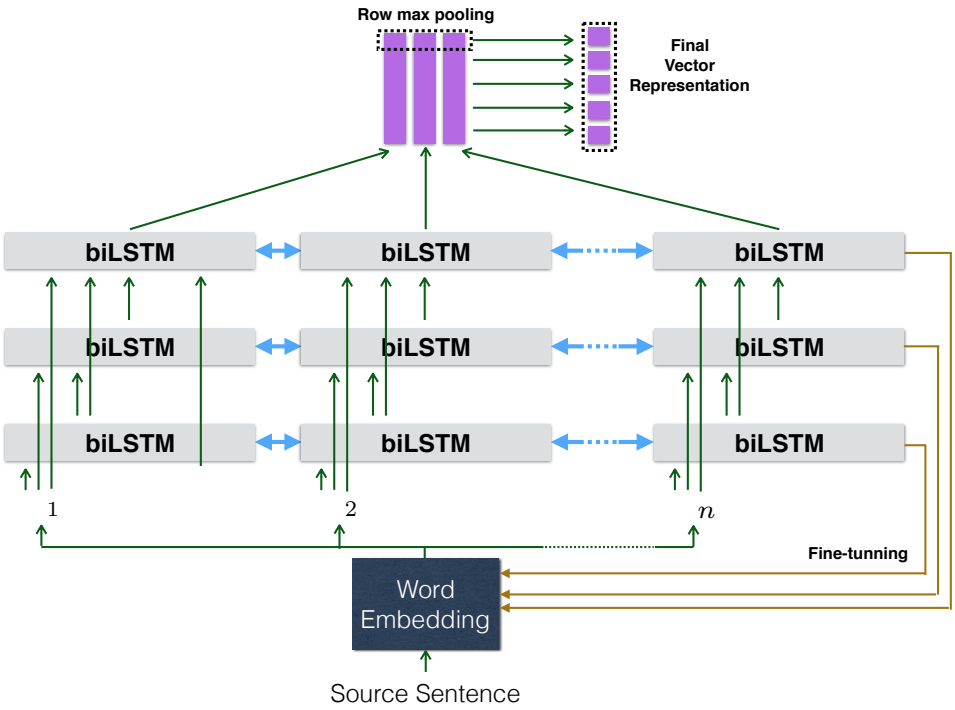

Figure 1: Our encoder's architecture: stacked biLSTM with shortcut connections and fine-tuning.

matched evaluation settings for multi-domain natural language inference, as well as on the original SNLI dataset. It is the top single-model (non-ensemble) result in the EMNLP RepEval 2017 Multi-NLI Shared Task (Nangia et al., 2017), and the new state-of-the-art for encoding-based results on the SNLI dataset (Bowman et al., 2015).

Github Code Link: `https://github.com/easonnie/multiNLI_encoder`

2 Model

Our model mainly consists of two separate components, a sentence encoder and an entailment classifier. The sentence encoder compresses each source sentence into a vector representation and the classifier makes a three-way classification based on the two vectors of the two source sentences. The model follows the 'encoding-based rule', i.e., the encoder will encode each source sentence into a fixed length vector without any information or function based on the other sentence (e.g., cross-attention or memory comparing the two sentences). In order to fully explore the generalization of the sentence encoder, the same encoder is applied to both the premise and the hypothesis with shared parameters projecting them into the same space. This setting follows the idea of Siamese Networks in Bromley et al. (1994). Figure 1 shows the overview of our encoding model (the standard classifier setup is not shown here; see Bowman et al. (2015) and Conneau et al. (2017) for that).

2.1 Sentence Encoder

Our sentence encoder is simply composed of multiple stacked bidirectional LSTM (biLSTM) layers with shortcut connections followed by a max pooling layer. Let bilstm^i represent the ith biLSTM layer, which is defined as:

$$h_t^i = \text{bilstm}^i(x_t^i, t), \forall t \in [1, 2, ..., n] \quad (1)$$

where h_t^i is the output of the ith biLSTM at time t over input sequence $(x_1^i, x_2^i, ..., x_n^i)$.

In a typical **stacked biLSTM** structure, the input of the next LSTM-RNN layer is simply the output sequence of the previous LSTM-RNN layer. In our settings, the input sequences for the ith biLSTM layer are the concatenated outputs of *all the previous layers*, plus the original word embedding sequence. This gives a **shortcut connection** style setup, related to the widely used idea of residual connections in CNNs for computer vision (He et al., 2016), highway networks for RNNs in speech processing (Zhang et al., 2016), and shortcut connections in hierarchical multitasking learning (Hashimoto et al., 2016); but in our case we feed in all the previous layers' output se-

quences as well as the word embedding sequence to every layer.

Let $W = (w_1, w_2, ..., w_n)$ represent words in the source sentence. We assume $w_i \in \mathbb{R}^d$ is a word embedding vector which are initialized using some pre-trained vector embeddings (and is then fine-tuned end-to-end via the NLI supervision). Then, the input of ith biLSTM layer at time t is defined as:

$$x_t^1 = w_t \quad (2)$$

$$x_t^i = [w_t, h_t^{i-1}, h_t^{i-2}, ...h_t^1] \quad (\text{for } i > 1) \quad (3)$$

where [] represents vector concatenation.

Then, assuming we have m layers of biLSTM, the final vector representation will be obtained by applying row-max-pool over the output of the last biLSTM layer, similar to Conneau et al. (2017). The final layer is defined as:

$$H^m = (h_1^m, h_2^m, ..., h_n^m) \quad (4)$$

$$v = max(H^m) \quad (5)$$

where $h_i^m, v \in \mathbb{R}^{2d_m}$, $H^m \in \mathbb{R}^{2d_m \times n}$, d_m is the dimension of the hidden state of the last forward and backward LSTM layers, and v is the final vector representation for the source sentence (which is later fed to the NLI classifier).

The closest encoder architecture to ours is that of Conneau et al. (2017), whose model consists of a single-layer biLSTM with a max-pooling layer, which we treat as our starting point. Our experiments (Section 4) demonstrate that our enhancements of the stacked-biRNN with shortcut connections provide significant gains on top of this baseline (for both SNLI and Multi-NLI).

2.2 Entailment Classifier

After we obtain the vector representation for the premise and hypothesis sentence, we apply three matching methods to the two vectors (i) concatenation (ii) element-wise distance and (iii) element-wise product for these two vectors and then concatenate these three match vectors (based on the heuristic matching presented in Mou et al. (2015)). Let v_p and v_h be the vector representations for premise and hypothesis, respectively. The matching vector is then defined as:

$$m = [v_p, v_h, |v_p - v_h|, v_p \otimes v_h] \quad (6)$$

At last, we feed this final concatenated result m into a MLP layer and use a softmax layer to make final classification.

Layers and Dimensions		Accuracy	
#layers	bilstm-dim	Matched	Mismatched
1	512	72.5	72.9
2	512 + 512	73.4	73.6
1	1024	72.9	72.9
2	512 + 1024	73.7	74.2
1	2048	73.0	73.5
2	512 + 2048	73.7	74.2
2	1024 + 2048	73.8	74.4
2	2048 + 2048	74.0	74.6
3	512 + 1024 + 2048	**74.2**	**74.7**

Table 1: Analysis of results for models with different # of biLSTM layers and their hidden state dimensions.

	Matched	Mismatched
without any shortcut connection	72.6	73.4
only word shortcut connection	74.2	74.6
full shortcut connection	**74.2**	**74.7**

Table 2: Ablation results with and without shortcut connections.

Word-Embedding	Matched	Mismatched
fixed	71.8	72.6
fine-tuned	**72.7**	**72.8**

Table 3: Ablation results with and without fine-tuning of word embeddings.

# of MLPs	Activation	Matched	Mismatched
1	tanh	73.7	74.1
2	tanh	73.5	73.6
1	relu	74.1	74.7
2	relu	**74.2**	**74.7**

Table 4: Ablation results for different MLP classifiers.

3 Experimental Setup

3.1 Datasets

As instructed in the RepEval Multi-NLI shared task, we use all of the training data in Multi-NLI combined with 15% randomly selected samples from the SNLI training set resampled at each epoch) as our final training set for all models; and we use both the cross-domain ('mismatched') and in-domain ('matched') Multi-NLI development sets for model selection. For the SNLI test results in Table 5, we train on only the SNLI training set (and we also verify that the tuning decisions hold true on the SNLI dev set).

3.2 Parameter Settings

We use cross-entropy loss as the training objective with Adam-based (Kingma and Ba, 2014) opti-

Model	Accuracy		
	SNLI	Multi-NLI Matched	Multi-NLI Mismatched
CBOW (Williams et al., 2017)	80.6	65.2	64.6
biLSTM Encoder (Williams et al., 2017)	81.5	67.5	67.1
300D Tree-CNN Encoder (Mou et al., 2015)	82.1	–	–
300D SPINN-PI Encoder (Bowman et al., 2016)	83.2	–	–
300D NSE Encoder (Munkhdalai and Yu, 2016)	84.6	–	–
biLSTM-Max Encoder (Conneau et al., 2017)	84.5	–	–
Our biLSTM-Max Encoder	85.2	71.7	71.2
Our Shortcut-Stacked Encoder	**86.1**	**74.6**	**73.6**

Table 5: Final Test Results on SNLI and Multi-NLI datasets.

mization with 32 batch size. The starting learning rate is 0.0002 with half decay every two epochs. The number of hidden units for MLP in classifier is 1600. Dropout layer is also applied on the output of each layer of MLP, with dropout rate set to 0.1. We used pre-trained 300D Glove 840B vectors (Pennington et al., 2014) to initialize the word embeddings. Tuning decisions for word embedding training strategy, the hyperparameters of dimension and number of layers for biLSTM, and the activation type and number of layers for MLP, are all explained in Section 4.

4 Results and Analysis

4.1 Ablation Analysis Results

We now investigate the effectiveness of each of the enhancement components in our overall model. These ablation results are shown in Tables 1, 2, 3 and 4, all based on the Multi-NLI development sets. Finally, Table 5 shows results for different encoders on SNLI and Multi-NLI test sets.

First, Table 1 shows the performance changes for different number of biLSTM layers and their varying dimension size. The dimension size of a biLSTM layer is referring to the dimension of the hidden state for both the forward and backward LSTM-RNNs. As shown, each added layer model improves the accuracy and we achieve a substantial improvement in accuracy (around 2%) on both matched and mismatched settings, compared to the single-layer biLSTM in Conneau et al. (2017). We only experimented with up to 3 layers with 512, 1024, 2048 dimensions each, so the model still has potential to improve the result further with a larger dimension and more layers.

Next, in Table 2, we show that the shortcut connections among the biLSTM layers is also an important contributor to accuracy improvement (around 1.5% on top of the full 3-layered stacked-RNN model). This demonstrates that simply stacking the biLSTM layers is not sufficient to handle a complex task like Multi-NLI and it is significantly better to have the higher layer connected to both the output and the original input of all the previous layers (note that Table 1 results are based on multi-layered models with shortcut connections).

Next, in Table 3, we show that fine-tuning the word embeddings also improves results, again for both the in-domain task and cross-domain tasks (the ablation results are based on a smaller model with a 128+256 2-layer biLSTM). Hence, all our models were trained with word embeddings being fine-tuned. The last ablation in Table 4 shows that a classifier with two layers of relu is preferable than other options. Thus, we use that setting for our strongest encoder.

4.2 Multi-NLI and SNLI Test Results

Finally, in Table 5, we report the test results for MNLI and SNLI. First for Multi-NLI, we improve substantially over the CBOW and biLSTM Encoder baselines reported in the dataset paper (Williams et al., 2017). We also show that our final shortcut-based stacked encoder achieves around 3% improvement as compared to the 1-layer biLSTM-Max Encoder in the second last row (using the exact same classifier and optimizer settings). Our shortcut-encoder was also the top singe-model (non-ensemble) result on the EMNLP RepEval Shared Task leaderboard.

Next, for SNLI, we compare our shortcut-stacked encoder with the current state-of-the-art encoders from the SNLI leaderboard (`https://nlp.stanford.edu/projects/snli/`). We also compare to the recent biLSTM-Max Encoder of Conneau et al. (2017), which served as our model's 1-layer starting point.[1] The results indicate that 'Our Shortcut-Stacked Encoder' sur-

[1]Note that the 'Our biLSTM-Max Encoder' results in the second-last row are obtained using our reimplementation of the Conneau et al. (2017) model; our version is 0.7% better, likely due to our classifier and optimizer settings.

passes all the previous state-of-the-art encoders, and achieves the new best encoding-based result on SNLI, suggesting the general effectiveness of simple shortcut-connected stacked layers in sentence encoders.

5 Conclusion

We explored various simple combinations and connections of biLSTM-RNN layered architectures and developed a Shortcut-Stacked Sentence Encoder for natural language inference. Our model is the top single result in the EMNLP RepEval 2017 Multi-NLI Shared Task, and it also surpasses the state-of-the-art encoders for the SNLI dataset. In future work, we are also evaluating the effectiveness of shortcut-stacked sentence encoders on several other semantic tasks.

Acknowledgments

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Character-level Intra Attention Network for Natural Language Inference

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Abstract

Natural language inference (NLI) is a central problem in language understanding. End-to-end artificial neural networks have reached state-of-the-art performance in NLI field recently.

In this paper, we propose Character-level Intra Attention Network (CIAN) for the NLI task. In our model, we use the character-level convolutional network to replace the standard word embedding layer, and we use the intra attention to capture the intra-sentence semantics. The proposed CIAN model provides improved results based on a newly published MNLI corpus.

1 Introduction

Natural language inference in natural language processing refers to the problem of determining a directional relation between two text fragments. Given a sentence pair (premise, hypothesis), the task is to predict whether hypothesis is entailed by premise, hypothesis is contradicted to premise, or whether the relation between premise and hypothesis is neutral.

Recently, the dominating trend of works in natural language processing is based on artificial neural networks, which aims at building deep and complex encoder to transform a sentence into encoded vectors. For instance, there are recurrent neural network (RNN) based encoders, which recursively concatenate each word with its previous memory, until the whole information of a sentence has been derived. The most common RNN encoders are Long Short-Term Memory Networks (LSTM; Hochreiter and Schmidhuber, 1997) and Gated Recurrent Unit (Chung et al., 2014). RNNs have surpassed the performance of traditional baselines in many NLP tasks (Dai and Le, 2015). There are also convolutional neural network (CNN; LeCun et al., 1989) based encoders, which concatenate the sentence information by applying multiple convolving filters over the sentence. CNNs have achieved state-of-the-art results on various NLP tasks (Collobert et al., 2011).

To evaluate the quality of the NLI model, the Stanford Natural Language Inference (SNLI; Bowman et al., 2015) corpus of 570K sentence pairs was introduced. It serves as a standard benchmark for NLI task. However, most of the sentences in SNLI corpus are short and simple, which limit the room for fine-grained comparisons between models. Currently, a more comprehensive Multi-Genre NLI corpus (MNLI; Williams et al., 2017) of 433K sentence pairs was released, aiming at evaluating large-scale NLI models. Authors gave out some baseline results accompanied by the publish of MNLI corpus, the BiLSTM model achieves an accuracy of 67.5, and the Enhanced Sequential Inference Model (Chen et al., 2016) achieves an accuracy of 72.4.

Among those encoders for NLI task, most of them use word-level embedding, and initialize the weight of the embedding layer with pre-trained word vectors such as GloVe (Pennington et al., 2014). The pre-trained word vectors helps the encoders to catch richer semantic information. However, it also has its downside. As the growth of vocabulary size in the modern corpus, there will be more and more out-of-vocabulary (OOV) words that are not presented in the pre-trained word embedding vector. As the word-level embedding is blind to subword information (e.g. morphemes), it leads to high perplexities for those OOV words.

In this paper, we use the BiLSTM model from (Williams et al., 2017) as the baseline model for the evaluation of the MNLI corpus. To augment the baseline model, firstly, a character-level

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convolutional neural network (CharCNN; Kim et al., 2016) is applied. We use the CharCNN to replace the word embedding layer in the baseline model, which will be computed from the characters of corresponding word. Secondly, the intra attention mechanism introduced by (Yang et al., 2016) will be applied, to enhance the model with a richer information of substructures of a sentence.

2 Model Development

2.1 BiLSTM Baseline

The baseline model we used here is introduced by (Williams et al., 2017) accompanied with the publication of MNLI corpus. It has a 5-layer structure which is shown in Figure 1.

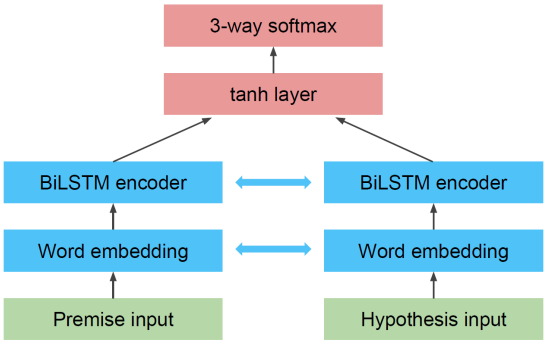

Figure 1: BiLSTM model architecture

In the baseline model, a word embedding layer initialized with pre-trained GloVe vectors (840B token version) is implemented to transform the input text into sequence of word vectors. OOV words are initialized randomly. Then, the sentence representation vector h is produced by implementing an average pooling over the BiLSTM hidden states $[h_0, h_1, \cdots, h_n]$. Finally, the concatenation of encoded premise and hypothesis representation vector is passed through a tanh layer followed by a three-way softmax classifier to attain the label prediction.

2.2 Character-level Convolutional Neural Network

In the baseline model, the input x_t to the BiLSTM encoder layer at time t is sequence of pre-trained word embeddings. Those pre-trained word embeddings can boost the performance of the model. However, it is limited to the finite-size of vocabulary. Here we replace the word embedding layer with a character-level convolutional neural network (CharCNN; Kim et al., 2016) for language modeling, which also achieved success in machine translation (Costa-Jussà and Fonollosa, 2016).

We define the text sentence input as vector $C^k \in R^{d \times l}$, where $k \in K$ is the k-th word in a sentence, d is the dimensionality of character embeddings, l is the length of characters in k-th word. Then a set of narrow convolutions between C^k and filter H is applied, followed with a max-over-time (max pooling) as shown in Equation 1-2.

$$f^k[i] = \tanh(\langle C^k[*, i : i + \omega - 1], H \rangle + b) \quad (1)$$

$$y^k = \max_i f^k[i] \quad (2)$$

The concatenation of those max pooling values y^k provides us with a representation vector y of each sentence. Then, a highway network is applied upon y, as shown in Equation 3, where g is a non-linear transformation, $t = \sigma(W_T y + b_T)$ is called the transform gate, and $(1 - t)$ is called the carry gate. Highway layers allow for training of deep networks by adaptively carrying some dimensions of the input y directly to the output z.

$$z = t \odot g(W_H y + b_H) + (1 - t) \odot y \quad (3)$$

Experiment conducted by (Kim et al., 2016) has shown that the CNN layer can extract the orthographic features of words (e.g. *German* and *Germany*). It has also been shown that highway layer is able to encode semantic features that are not discernable from orthography alone. For instance, after highway layers the nearest neighbor word of *you* is *we*, which is orthographically distinct from *you*.

2.3 Intra Attention Mechanism

In the baseline model, the BiLSTM encoder takes an average pooling over all its hidden states to produce a single representation vector of each sentence. However, this has its bottleneck as we intuitively know that not all words (hidden states) contribute equally to the sentence representation. To augment the performance of RNN based encoder, the concept of attention mechanism was introduced by (Bahdanau et al., 2014) for machine translation. Attention mechanism is a hidden layer which computes a categorical distribution to make a soft-selection over source elements (Kim et al., 2017). It has recently demonstrated success on tasks such as parsing text (Vinyals et al., 2015), sentence summarization (Rush et al., 2015) and

also on a wide range of NLP tasks (Cheng et al., 2016).

Here we implemented the Intra Attention mechanism introduced by (Yang et al., 2016) for document classification. We define the hidden states as the output of the BiLSTM encoder as $h_t \in [h_0, h_1, \cdots, h_n]$, the intra attention is applied upon the hidden states to get the sentence representation vector h, specifically,

$$u_t = \tanh(W_\omega h_t + b_\omega) \tag{4}$$

$$\alpha_t = \frac{exp(u_t^T u_\omega)}{\sum_t exp(u_t^T u_\omega)} \tag{5}$$

$$h = \sum_t \alpha_t h_t \tag{6}$$

It first feed all hidden states h_t through a nonlinearity to get u_t as the hidden representation of h_t. Then it uses a $softmax$ function to catch the normalized importance weight matrix α_t. After that, the sentence representation vector h is computed by a weighted sum of all hidden states h_t with the weight matrix α_t. The context vector u_ω can be seen as a high-level representation of the importance of informative words.

2.4 Character-level Intra Attention Network

The overall architecture of the Character-level Intra Attention Network (CIAN) is shown in Figure 2. The CIAN model is consisted with 7 layers, of which the first and the last layers are the same with our baseline model. The 4 layers in middle are our augmented layers that has been introduced in this section.

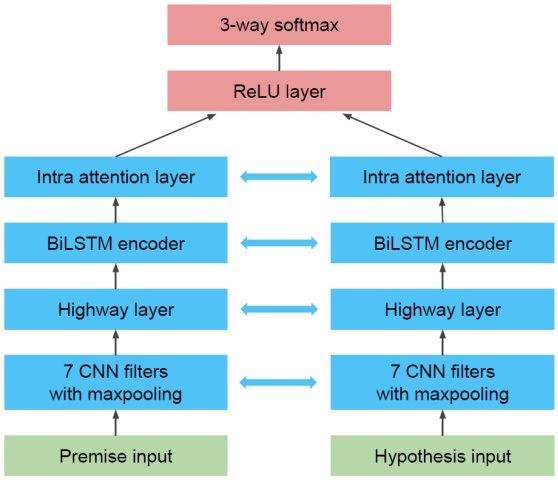

Figure 2: CIAN model architecture

The input text is firstly set to lowercase, then it is vectorized according to the tokenization list [abcdefghijklmnopqrstuvwxyz0123456789,;.!?:'"()[]{}]. Those characters not in the list are initialized with a vector of zero. After that we use 7 filters in CIAN model's CNN layer. The widths of the CNN filters are $w = [1, 2, 3, 4, 5, 6, 7]$, and the corresponding filters' size are $[\min\{200, 50 \cdot w\}]$. Two highway layers are implemented following the CNN layer. The attention layer uses weighted sum of all hidden states h_t with the attention weight matrix α_t to encode each sentence into a fixed-length sentence representation vector. Finally a ReLU layer and a three-way softmax classifier use those representation vectors to conduct the prediction.

3 Experiments

3.1 Data

We evaluated our approach on the Multi-Genre NLI (MNLI) corpus, as a shared task for RepEval 2017 workshop (Nangia et al., 2017). We train our CIAN model on a mixture of MNLI and SNLI corpus, by using a full MNLI training set and a randomly selected 20 percent of the SNLI training set at each epoch.

3.2 Hyper Parameters

The BiLSTM encoder layer use 300D hidden states, thus 600D as its a bidirectional encoder. Dropout (Srivastava et al., 2014) is implemented with a dropout rate of 0.2 to prevent the model from overfitting. Parameter weights for premise encoder and hypothesis encoder are shared using siamese architecture. The Adam optimizer (Kingma and Ba, 2014) is used for training with backpropagation.

The model has been implemented using Keras and we have released the code [1]. The training took approximately one hour for one epoch on GeForce GTX TITAN, and we stopped training after 40 epochs as an early stopping regularization.

3.3 Result

We compared the results of CIAN model with the results of BiLSTM model given by (Williams et al., 2017). Table 1 shows that the accuracy is improved by 0.9 percent in matched test set, and 0.6 percent in mismatched test set.

[1] https://github.com/yanghanxy/CIAN

Model	Matched	Mismatched
BiLSTM	67.0	67.6
CIAN	67.9	68.2

Table 1: Test set accuracies (%) on MNLI corpus.

	Matched		Mismatched	
Tag	**BiLSTM**	**CIAN**	**BiLSTM**	**CIAN**
CONDITIONAL	100	48	100	62
WORD_OVERLAP	50	79	57	62
NEGATION	71	71	69	70
ANTO	67	82	58	70
LONG_SENTENCE	50	68	55	63
TENCE_DIFFERNCE	64	65	71	72
ACTIVE/PASSIVE	75	87	82	90
PARAPHRASE	78	88	81	89
QUANTITY/TIME	50	47	46	44
COREF	84	67	80	72
QUANTIFIER	64	63	70	69
MODAL	66	66	64	70
BELIEF	74	71	73	70

Table 2: Accuracies (%) on matched and mismatched expert-tagged development data.

We conducted error analysis based on expert-tagged development data released by the organizers of RepEval 2017 shared task. The results are shown in Table 2. From the results, it can be seen that the accuracy for WORD_OVERLAP, LONG_SENTENCE, ACTIVE/PASSIVE and PARAPHRASE have been improved significantly in both matched and mismatched development set. While the accuracy for CONDITIONAL and COREF haven been decreased in both development set.

We also conducted visualization on the attention weights α_t of the intra attention layer. By doing so, we we can understand how the model judges the NLI relation between two sentences.

Figure 3 is visualizations of attention weights for 2 sentence pairs, with premise at left and hypothesis at right. Each word is attained with a color block. The darker the color, the greater the attention weight, which means the higher importance contributed to the sentence representation.

From the Visualization, it could be seen that the model has more attention on words with similar semantic meaning (e.g. *love* and *enjoy*), and the model applies more attention on overlapped words (e.g. *efficiencies* and *efficiencies*).

4 Conclusion

In this paper, we presented a Character-level Intra Attention Network (CIAN) for the task of natural language inference. Experimental results

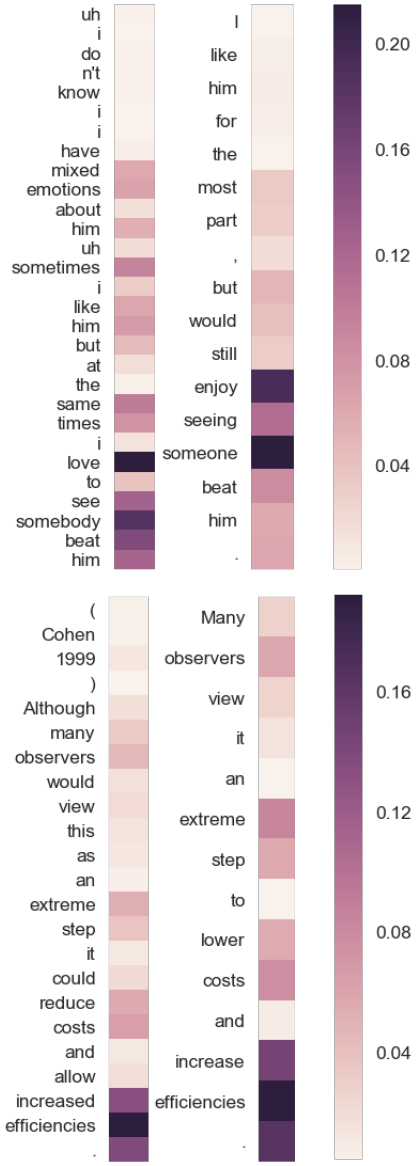

Figure 3: Visualization of attention weights of sentence pair 254941e (top) and 192997e (bottom)

demonstrate that our model slightly outperforms the baseline model upon the MultiNLI corpus. The CharCNN layers helps the model to capture rich semantic and orthographic features. The intra attention layer augment the model's ability to efficiently encode long sentences, and it enhances the models' interpretability by visualizing the attention weights.

In general, the model presented in this paper is a sequence encoder that do not need any specific pre-processing or outside data like pre-trained word embeddings. Thus, it can be easily applied to other autoencoder architecture tasks such as language modeling, sentiment analysis and question answering.

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Refining Raw Sentence Representations for Textual Entailment Recognition via Attention

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Abstract

In this paper we present the model used by the team Rivercorners for the 2017 RepEval shared task. First, our model separately encodes a pair of sentences into variable-length representations by using a bidirectional LSTM. Later, it creates fixed-length raw representations by means of simple aggregation functions, which are then refined using an attention mechanism. Finally it combines the refined representations of both sentences into a single vector to be used for classification. With this model we obtained test accuracies of 72.057% and 72.055% in the matched and mismatched evaluation tracks respectively, outperforming the LSTM baseline, and obtaining performances similar to a model that relies on shared information between sentences (ESIM). When using an ensemble both accuracies increased to 72.247% and 72.827% respectively.

1 Introduction

The task of Natural Language Inference (NLI) aims at characterizing the semantic concepts of entailment and contradiction, and is essential in tasks ranging from information retrieval to semantic parsing to commonsense reasoning, as both entailment and contradiction are central concepts in natural language meaning (Katz, 1972; van Benthem, 2008).

The aforementioned task has been addressed with a variety of techniques, including those based on symbolic logic, knowledge bases, and neural networks. With the advent of deep learning techniques, NLI has become an important testing ground for approaches that employ distributed word and phrase representations, which are typical of these models.

In this context, the Second Workshop on Evaluating Vector Space Representations for NLP (RepEval 2017) features a shared task meant to evaluate natural language understanding models based on sentence encoders by the means of NLI in the style of a three-class balanced classification problem over sentence pairs. The shared task includes two evaluations, a standard in-domain (matched) evaluation in which the training and test data are drawn from the same sources, and a cross-domain (mismatched) evaluation in which the training and test data differ substantially. This cross-domain evaluation is aimed at testing the ability of submitted systems to learn representations of sentence meaning that capture broadly useful features.

2 Proposed Model

Our work is related to intra-sentence attention models for sentence representation such as the ones described by Liu et al. (2016) and Lin et al. (2017). In particular, our model is based on the notion that, when reading a sentence, we usually need to re-read certain portions of it in order to obtain a comprehensive understanding. To model such phenomenon, we rely on an attention mechanism able to iteratively obtain a richer and more expressive version of a raw sentence representation. The model's architecture is described below:

Word Representation Layer: This layer is in charge of generating a comprehensive vector representation of each token for a given sentence. We construct this representation based on up to two basic components:

- Pre-trained word embeddings: We take pre-trained word embeddings and use them to generate a raw word representation. This can

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be seen as a simple lookup-layer that returns a word vector for each provided word index.

- Character embeddings: We generate a character-based representation of each word, which we concatenate to the word vectors as returned by the previous component. We start by generating a randomly initialized character embedding matrix C. Then, we split each word into its component characters, get their corresponding character embedding vectors from C and feed them into a unidirectional Long Short-Term Memory Network (LSTM) (Hochreiter and Schmidhuber, 1997). We then choose the last hidden state returned by the LSTM as the fixed-size character-based vector representation for each token. Our embedding matrix C is trained with the rest of the model (Wang et al., 2017).

Context Representation Layer: This layer complements the vectors generated by the Word Representation Layer by incorporating contextual information into them. To do this, we utilize a bidirectional LSTM that reads through the embedded sequence and returns the hidden states for each time step. These are context-aware representations focused on each position. Formally, let $\mathcal{S}$ be a sentence such as $\mathcal{S} = \{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n\}$, where each $\boldsymbol{x}_i$ is an embedded word vector as returned by the previous layer, then the context-rich word representation $\boldsymbol{h}_i$ is calculated as follows for each time step $i = 1, \ldots, n$:

$$\overrightarrow{\boldsymbol{h}}_i = LSTM(\boldsymbol{x}_i, \overrightarrow{\boldsymbol{h}}_{i-1}) \quad (1)$$

$$\overleftarrow{\boldsymbol{h}}_i = LSTM(\boldsymbol{x}_i, \overleftarrow{\boldsymbol{h}}_{i+1}) \quad (2)$$

$$\boldsymbol{h}_i = [\overrightarrow{\boldsymbol{h}}_i; \overleftarrow{\boldsymbol{h}}_i] \quad (3)$$

Where $\overrightarrow{\boldsymbol{h}}_i$ is the forward contextual vector representation of $\boldsymbol{x}_i$, $\overleftarrow{\boldsymbol{h}}_i$ the backward one, and $[\,\cdot\,;\,\cdot\,]$ represents the concatenation of two vectors. The output of this layer is a variable-length sentence representation for both the premise and hypothesis. We then define a pooling layer in charge of a generating a raw fixed-size representation of each sentence.

Pooling Layer: This layer is in charge of generating a crude sentence representation vector by reducing the sequence dimension using one of four simple operations, all of which are fed the context-aware token representations obtained previously:

$$\bar{\boldsymbol{h}} = \frac{1}{n}\sum_{i=1}^{n} \boldsymbol{h}_i \quad (4)$$

$$\bar{\boldsymbol{h}} = \sum_{i=1}^{n} \boldsymbol{h}_i \quad (5)$$

$$\bar{\boldsymbol{h}} = [\overrightarrow{\boldsymbol{h}}_n; \overleftarrow{\boldsymbol{h}}_1] \quad (6)$$

$$\bar{\boldsymbol{h}} = \max_{i=1\ldots n} \boldsymbol{h}_i \quad (7)$$

These operations correspond to the *mean* of the word representations (eq. 4), their *sum* (eq. 5), the concatenation of the *last* hidden state for each direction (eq. 6), and the *maximum* one (eq. 7).

Inner Attention Layer: To refine the representations generated by the pooling strategy, we use a global attention mechanism (Luong et al., 2015; Vinyals et al., 2015) that compares each context-aware token representation $\boldsymbol{h}_i$ with the raw sentence representation $\bar{\boldsymbol{h}}$. Formally,

$$u_i = \boldsymbol{v}^\top \tanh(W[\bar{\boldsymbol{h}}; \boldsymbol{h}_i]) \quad (8)$$

$$\alpha_i = \frac{\exp u_i}{\sum_{k=1}^{n} \exp u_k} \quad (9)$$

$$\bar{\boldsymbol{h}}' = \sum_{i=1}^{n} \alpha_i \boldsymbol{h}_i \quad (10)$$

Where both $\boldsymbol{v}$ and W are trainable parameters and $\bar{\boldsymbol{h}}'$ is the refined sentence representation[1].

Aggregation Layer: We apply two matching mechanisms to aggregate the refined sentence representations, which are directly aimed at extracting relationships between the premise and the hypothesis. Concretely, we concatenate the representations of the premise $\bar{\boldsymbol{h}}'_P$ and hypothesis $\bar{\boldsymbol{h}}'_H$ in addition to their element-wise product ($\odot$) and the absolute value ($|\cdot|$) of their difference, obtaining the vector $\boldsymbol{r}$. These last two operations, first proposed by Mou et al. (2015), can be seen as a sentence matching strategy.

$$\boldsymbol{h}_{mul} = \bar{\boldsymbol{h}}'_P \odot \bar{\boldsymbol{h}}'_H \quad (11)$$

$$\boldsymbol{h}_{dif} = |\bar{\boldsymbol{h}}'_P - \bar{\boldsymbol{h}}'_H| \quad (12)$$

$$\boldsymbol{r} = [\bar{\boldsymbol{h}}'_P; \bar{\boldsymbol{h}}'_H; \boldsymbol{h}_{mul}; \boldsymbol{h}_{dif}] \quad (13)$$

Dense Layer: Finally, $\boldsymbol{r}$ is fed to a fully-connected layer whose output is a vector containing the logits for each class, which are then fed to

[1]The refined sentence representation $\bar{\boldsymbol{h}}'$ for both premise and hypothesis is the final representation in which both are treated as separate entities. The representations produced by our best-performing model are available in https://zenodo.org/record/825946.

a softmax function for obtaining their probability distribution. The class with the highest probability is chosen as the predicted relationship between premise and hypothesis.

3 Experiments

To make our results comparable to the baselines reported in the Kaggle platform we randomly sampled 15% of the SNLI corpus (Bowman et al., 2015) and added it to the MultiNLI corpus.

We used the pre-trained 300-dimensional GloVe vectors trained on 840B tokens (Pennington et al., 2014). These embeddings were not fine-tuned during training and unknown word vectors were initialized by randomly sampling from the uniform distribution in $(-0.05, 0.05)$.

Each character embedding was initialized as a 20-dimensional vector and the character-level LSTM output dimension was set to 50. The word-level LSTM output dimension was set to 300, which means that after concatenating word-level and character-level representations the word vectors for each direction are 350-dimensional (i.e., $\boldsymbol{h}_i \in \mathbb{R}^{700}$).

For the Inner Attention Layer we defined the parameter W as a square matrix matching the dimension of the concatenated vector $[\bar{\boldsymbol{h}}; \boldsymbol{h}_i]$ (i.e., $W \in \mathbb{R}^{1400\times1400}$), and $\boldsymbol{v}$ as a vector matching the same dimension (i.e., $\boldsymbol{v} \in \mathbb{R}^{1400}$). Both W and $\boldsymbol{v}$ were initialized by randomly sampling from the uniform distribution on the interval $(-0.005, 0.005)$.

The final layer was created as a 3-layer MLP with 2000 hidden units each, and with ReLU activations.

Additionally, we used the Rmsprop optimizer with a learning rate of 0.001. We applied dropout of 0.25 only between the MLP layers of the Dense Layer.

Further, we found out that normalizing the capitalization of words by making all characters lowercase, and transforming numbers into a specific numeric token improved the model's performance while reducing the size of the embedding matrix. We also ignored the sentence pairs with a premise longer than 200 words during training (for improved memory stability), and those without a valid label ("-") both during training and validation.

Since one of the most conceptually important parts of our model was the raw sentence representation created in the Pooling Layer, we used four different methods for generating it (eqs. 4 – 7). Results are reported in Table 1.

We also tried using other architectures that rely on some sort of "inner" attention such as the *self-attentive* model proposed by Lin et al. (2017) and the *co-attentive* model by Xiong et al. (2016), but our preliminary results were not promising so we did not invest in fine-tuning them.

All the experiments were repeated without using character-level embeddings (i.e., $\boldsymbol{h}_i \in \mathbb{R}^{600}$).

4 Results

Table 1 presents the results of using different pooling strategies for generating a raw sentence representation vector from the word vectors. We can observe that that both the *mean* method, and picking the last hidden state for both directions performed slightly better than the two other strategies, however at 95% confidence we cannot assert that any of these methods is statistically different from one another.

This could be interpreted as if any of the four methods was good enough for capturing the overall meaning of the sentence, and the heavy lifting was done by the attention mechanism. It would be interesting to test these four strategies without the presence of attention to see whether it really plays an important role in this task or whether the predictive power lies within the sentence matching mechanism.

Method	**w/o. chars**	**w. chars**
mean	71.3 ± 1.2	71.3 ± 0.7
sum	70.7 ± 1.0	70.9 ± 0.8
last	70.9 ± 0.6	71.0 ± 1.2
max	70.6 ± 1.1	71.0 ± 1.1

Table 1: Mean matched validation accuracies (%) broken down by type of pooling method and presence or absence of character embeddings. Confidence intervals are calculated at 95% confidence over 10 runs for each method.

Another interesting result, as shown by Table 1 and Table 2, is that the model seemed to be insensitive to the usage of character embeddings, which was surprising because in our experiments with more complex models relying on shared information between premise and hypothesis, such as the one presented by Wang et al. (2017), the usage of character embeddings had a considerable impact

Method	w/o. chars	w. chars
mean	**72.3**	71.8
sum	71.6	71.6
last	71.4	**72.1**
max	71.1	71.6

Table 2: Best matched validation accuracies (%) obtained by each pooling method in presence and absence of character embeddings.

in model performance[2].

In Table 3 we report the accuracies obtained by our best model in both matched (first 5 genres) and mismatched (last 5 genres) development sets. We can observe that our implementation performed like ESIM overall, however ESIM relies on an attention mechanism that has access to both premise and hypothesis (Chen et al., 2017), while our model's treats each one separately. This supports the notion that inner attention is a powerful concept.

Genre	CBOW	ESIM	InnerAtt
Fiction	67.5	73.0	73.2
Government	67.5	74.8	75.2
Slate	60.6	67.9	67.2
Telephone	63.7	72.2	73.0
Travel	64.6	73.7	72.8
9/11	63.2	71.9	70.5
Face-to-face	66.3	71.2	74.5
Letters	68.3	74.7	75.4
Oup	62.8	71.7	71.5
Verbatim	62.7	71.9	69.5
MultiNLI Overall	**64.7**	**72.2**	**72.3**

Table 3: Validation accuracies (%) for our best model broken down by genre. Both CBOW and ESIM results are reported as in (Williams et al., 2017).

We picked the best model based on the best validation accuracy score obtained on the matched development set (72.257%). This model is as described in the previous section but without using character embeddings[3].

In addition, we created an ensemble by training 4 models as described earlier but initialized with different random seeds. The prediction is made by averaging the probability distributions returned by each model and then picking the class with the highest probability for each example. This improved our best test results, as reported by Kaggle, from 72.057% to 72.247% in the matched evaluation track, and from 72.055% to 72.827% in the mismatched evaluation track.

5 Conclusions and Future work

We presented the model used by the team Rivercorners in the 2017 RepEval shared task. Despite being conceptually simple and not relying on shared information between premise and hypothesis for encoding each sentence, nor on tree structures, our implementation achieved results as good as the ESIM model.

As future work we plan to incorporate part-of-speech embeddings to our implementation and concatenate them at the same level as we did with the character embeddings. We also plan to use pre-trained character embeddings to see whether they have any positive impact on performance.

Additionally, we think we could obtain better results by fine-tuning some hyperparameters such as the character embedding dimensions, the character-level LSTM encoder output dimension, and the Dense Layer architecture.

Further, we would like to see how different types of attention affect the overall performance. For this implementation we used the *concat* scoring scheme (eq. 8), as described by Luong et al. (2015), but there are several others that could provide better results.

Finally, we would like to exploit the structured nature of dependency parse trees by means of recursive neural networks (Tai et al., 2015) to enrich our initial sentence representations.

6 Resources

The code for replicating the results presented in this paper is available in the following link: `https://github.com/jabalazs/repeval_rivercorners`.

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[2]This type of models were not allowed in this competition which is why we do not report further on them.

[3]Without the use of character embeddings, the sentence representations are 600-dimensional.

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LCT-MALTA's Submission to RepEval 2017 Shared Task

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Abstract

We present in this paper our team LCT-MALTA's submission to the RepEval 2017 Shared Task on natural language inference. Our system is a simple system based on a standard BiLSTM architecture, using as input GloVe word embeddings augmented with further linguistic information. We use max pooling on the BiLSTM outputs to obtain embeddings for sentences. On both the matched and the mismatched test sets, our system clearly beats the shared task's BiLSTM baseline model.

1 Introduction

The RepEval 2017 Shared Task aims to evaluate fixed-length vector representations (or embeddings) of sentences on the basis of a natural language understanding task, viz. natural language inference (NLI), also known as recognising textual entailments. Given two sentences, the first being the premise and the second the hypothesis, the goal of NLI is to train a classifier to predict whether the relation of the hypothesis to the premise is one of entailment, contradiction or a neutral relation. The training and test data for this 3-way classification task at RepEval 2017 are drawn from the Multi-Genre NLI, or MultiNLI corpus (see Williams et al. (2017) for details). Task participants are provided with both training and development datasets, where parts of the development data match the training data in terms of genre, topic etc. (referred to as *matched* examples) and other parts do not (referred to as *mismatched* examples).

This paper presents Team LCT-MALTA's submission to the shared task. In line with previous research, we obtain a single vector which is the combined representation of both the premise and the hypothesis and feed it into a Multilayer Perceptron (MLP) for the actual 3-way classification.

2 Related Work

Various works in recent years have dealt with the creation of distributed sentence representations, typically based on existing word embeddings such as word2vec (Mikolov et al., 2013) or GloVe (Pennington et al., 2014). The baseline models at the shared task use GloVe vectors and present three approaches to obtaining sentence embeddings (Williams et al., 2017): a) taking the sum of the embeddings of all the words in the sentence (continous bag of words, CBOW); b) taking the average of the hidden state outputs of a bidirectional LSTM (BiLSTM; Hochreiter and Schmidhuber 1997) across all the words; and c) the Enhanced Sequential Inference Model (ESIM) by (Chen et al., 2017), which, however, relies on cross-sentence attention, which submissions to the shared task may not make use of.

Instead of the BiLSTM architecture, Tai et al. (2015) propose a tree-structured LSTM to capture the hierarchical structure of natural language sentences. Conneau et al. (2017) use BiLSTM with max pooling and achieve state-of-art results when testing their sentence representations on an NLI task based on the Stanford Natural Language Inference (SNLI) dataset (Bowman et al., 2015). Lin et al. (2017) introduce a self-attention mechanism with multiple hops of attention on top of BiLSTM, where the different hops attend to different parts of the input sentence. Their approach represents sentence embeddings as 2-D matrices instead of vectors.

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3 Our Approach

We present in our submission a simple BiLSTM-based approach related to the second baseline model. Crucially, however, we add the following alterations:

- Our input word vectors are enhanced with part-of-speech (POS), dependency and word character information.
- Instead of taking the average of the BiLSTM outputs across all words (mean pooling), we use max pooling.

3.1 Enhanced Word Embeddings

A central component of our approach is the enhancement of the pre-trained GloVe vectors with additional linguistic information. The main motivation is the following: BiLSTM proceeds linearly, processing an input sentence word by word. The structure of natural language sentences, however, is hierarchical in nature [1]. We wish to encode some information on linguistic structure while keeping the simple, standard BiLSTM architecture. Therefore, we attach such additional information to the representations of individual words.

In conrete terms, we initialise our model with 300-D pre-trained GloVe vectors (as is done in the BiLSTM baseline model) and enhance them with the following content:

3.1.1 POS-tag Embeddings

Part-of-speech (POS) tagging is a common first step in syntactic sentence processing. We postulate that explicit knowledge of a the input words' syntactic categories might help representing the meaning of the input sentence. Thus, using modules from UDPipe (Straka et al., 2016), we tokenise and tag input sentences with universal POS-tags. We then generate randomly-initialised, 20-D embeddings for all POS-tags.

3.1.2 Dependency Label Embeddings

Dependency parsing captures the binary dependency relation between words in a sentence and determines the central word of an input sentence (the head word of the sentence) (Kübler et al., 2009). In particular, it is enable to encode longer dependencies across multiple words. As such, dependency parsing provides vital information on the sentence's structure.

Hence, we apply UDPipe's (Straka et al., 2016) state-of-the-art dependency parser to the input sentence and subsequently equip each pre-trained word embedding with that word's dependency information, which in turn consists of the word's head word and its dependency relation to the head. In concrete terms, for each word w_i, we map the embedding of its head word w_j to a 50-D vector and generate a 50-D randomly initialised embedding for the dependency relation from w_i to its head. We then take the element-wise product between these two 50-D vectors to obtain the full dependency embedding for the word w_i. Formally, the dependency embedding w_{i_d} for any token w_i is computed as follows:

$$w_{i_d} = E_d[d_{ij}] \odot (W_d * w_j) \quad (1)$$

where d_{ij} is the dependency relation between token w_i and the head token w_j, E_d is the 50-D embedding of that dependency relation, W_d is a matrix of size 50x300 which maps w_j (originally a 300-D GloVe vector) to a 50-D vector, and $\odot$ is the element-wise product.

3.1.3 Character Embeddings

The usage of character embeddings is mainly inspired by various works which incorporate character-level embeddings into the distributed representation of words to yield improved word embeddings (Santos and Zadrozny, 2014; Bojanowski et al., 2016; Kim et al., 2016). For each token, we employ LSTMs to compute embeddings for each of its characters. The LSTM input at each time step is one character, i.e. one letter, and the output is a 100-D hidden state. The last 100-D hidden state vector is then considered the full character embedding for that token.

3.1.4 Final Input Word Embeddings

Finally, for each word, we concatenate its original GloVe embeddings with all of the above-mentioned additional linguistic information. Thus, our final embedding for each word, which we input to the BiLSTM to compute sentence embeddings, consists of the concatenation of the word's 300-D Glove embedding, its 20-D POS-tag embedding, its 50-D dependency embedding and 100-D character embedding. As mentioned, all of the embeddings except for the GloVe

[1] As mentioned in section 2, Tai et al. (2015) propose a *tree*-structured LSTM for similar reasons

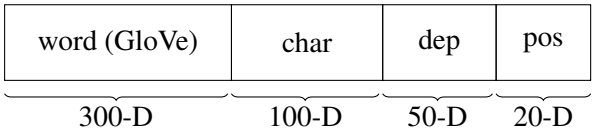

Figure 1: Our enhanced word embedding

word embeddings are randomly initialized. Figure 1 illustrates an instance of our final enhanced word embeddings.

3.2 BiLSTM Sentence Embedding with Max Pooling

The enhanced word embeddings described above are fed into a standard BiLSTM architecture, with a 100-D hidden state output vector for each unidirectional LSTM. Concatenating the forward ($\overrightarrow{h_t}$) and backward ($\overleftarrow{h_t}$) output vectors for each node, we obtain *n* hidden state vectors $\overrightarrow{h}$, where *n* is the number of words in the input sentence and $\overrightarrow{h}$ is a 200-D vector corresponding to one word.

$$\overrightarrow{h_t} = \overrightarrow{LSTM}(w_t, \overrightarrow{h_{t-1}}) \quad (2)$$

$$\overleftarrow{h_t} = \overleftarrow{LSTM}(w_t, \overleftarrow{h_{t-1}}) \quad (3)$$

Conneau et al. (2017) examine various supervised methods of obtaining general-purpose sentence embeddings, with their conclusion favouring a BiLSTM architecture combined with max pooling. We follow their findings and use max pooling on the *n* BiLSTM hidden outputs $\overrightarrow{h}$. Indeed, our own experiments shall show the superiority of max pooling over average pooling (see section 4). Hence, for each dimension *d* of the 200 dimensions, we take the maximum among the values of all hidden outputs at *d*. The result is a single 200-D vector embedding of the input sentence.

3.3 Combining Premise and Hypothesis Representations

We separately obtain the previously described sentence embeddings for the premise and the hypothesis. Mou et al. (2015) examine multiple heuristics for combining the same-length embeddings of two sentences in NLI tasks, including concatenating the two vectors and taking their element-wise difference or product. We use a combination of some of these heuristics. More specifically, we concatenate the two sentence embeddings, then further concatenate a) their element-wise maximum and b) their element-wise product

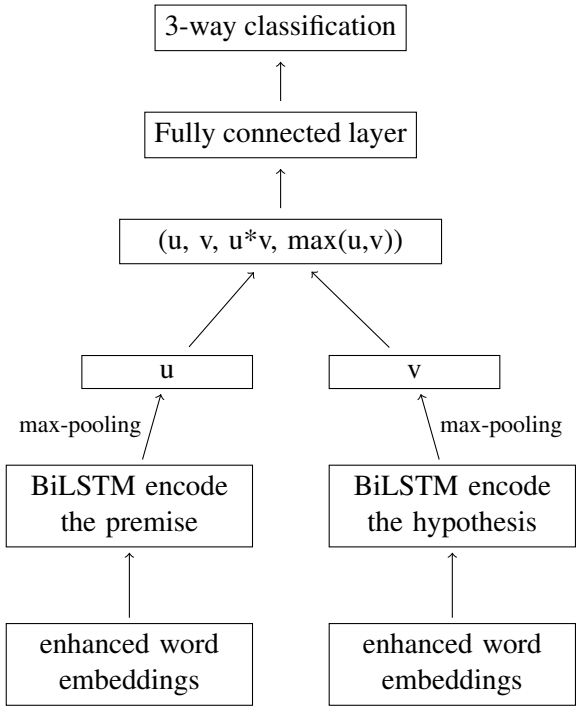

Figure 2: Architecture of our final submission

to the concatenation of the two sentence embeddings. Hence, we obtain as a result a single 800-D vector that is the combined representation of the premise and the hypothesis.

3.4 Classification

Finally, we feed the single vector representation of the two sentences to a *tanh* layer with a *softmax* layer on top of it to perform the 3-way classification to the classes *entailment*, *contradiction*, and *neutral*. Our complete model is illustrated in Figure 2.

4 Experiments & Results

We experimented with BiLSTM-based sentence encoders including and excluding our enhanced word embeddings as well as in combination with max pooling and average pooling. We use L2 regularization and set dropout rate to 0.1 to prevent overfitting. The models are trained in 10 epoches using Adam optimizer with learning rate 10^{-3}. The models having the best performance on development set are selected to evaluate on test set.

Furthermore, we implemented two systems presented in literature, viz. (Lin et al., 2017)'s self-attentive embeddings approach and (Kim, 2014)'s convolutional neural network (CNN) approach, and compared their performance with that of our

Method	Matched		Mismatched	
	Dev	Test	Dev	Test
BiLSTM + average pooling (baseline)	66.9	_	66.9	_
BiLSTM + max pooling	67.23	_	67.18	_
CNN (Kim, 2014)	67.3	_	68.0	_
Automatically learned self-attentive embeddings (Lin et al., 2017)	67.89	_	67.69	_
BiLSTM + enhanced embedding + average pooling	68.3	_	67.8	_
BiLSTM + enhanced embedding + max pooling	70.8	**70.7**	71.1	**70.8**

Table 1: System performances on MultiNLI dataset in order of ascending accuracy scores.

system. In their original work, Lin et al. (2017) use 30 hops of attention for each sentence. In our implementation of their algorithm, we deemed 10 hops to be sufficient due to the limited length of the sentences in our MultiNLI database.

The results of our experiments are shown in Table 1, in order of ascending accuracy scores. In our experiments, our final submission, i.e. the BiLSTM-encoder with enhanced word embeddings and max pooling, as described in section 3, performed best, obtaining accuracy scores of **70.8** and **71.1** on the matched and mismatched dev set, respectively. Its final results on the full shared task test set are **70.7** for matched and **70.8** for mismatched data.

5 Discussion

Our results favour max pooling over average pooling, which is in agreement with findings by Conneau et al. (2017). Moreover, our enhanced word embeddings are shown to be effective. Their addition alone produces the accuracy scores superior to what the incorporation of (Lin et al., 2017)'s automatically learned self-attention matrix yields. The combination of max pooling and enhanced word embeddings, which are extremely simple alterations to the BiLSTM baseline, yield results which clearly beat the baseline.

Thus, our submitted system to the RepEval 2017 shared task demonstrates that simple alterations to the standard BiLSTM architecture for computing sentence embeddings can obtain visible improvements. In particular, *linguistic* information is shown to be useful for the present NLI task. Therefore, with respect to distributed representations of sentence meaning, more sophisticated systems which take into account linguistic and grammatical relationships are worth further investigation.

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