Sentence Meta-Embeddings for Unsupervised Semantic Textual Similarity

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Abstract

We address the task of unsupervised Semantic Textual Similarity (STS) by ensembling diverse pre-trained sentence encoders into sentence meta-embeddings. We apply and extend different meta-embedding methods from the word embedding literature, including dimensionality reduction (Yin and Schütze, 2016), generalized Canonical Correlation Analysis (Rastogi et al., 2015) and cross-view auto-encoders (Bollegala and Bao, 2018). We set a new unsupervised State of The Art (SoTA) on the STS Benchmark and on the STS12–STS16 datasets, with gains of between 3.7% and 6.4% Pearson’s r over single-source systems.

1 Introduction

Word meta-embeddings have been shown to exceed single-source word embeddings on word-level semantic benchmarks (Yin and Schütze, 2016; Bollegala and Bao, 2018). Presumably, this is because they combine the complementary strengths of their components.

There has been recent interest in pre-trained “universal” sentence encoders, i.e., functions that encode diverse semantic features of sentences into fixed-size vectors (Conneau et al., 2017). Since these sentence encoders differ in terms of their architecture and training data, we hypothesize that their strengths are also complementary and that they can benefit from meta-embeddings.

To test this hypothesis, we adapt different meta-embedding methods from the word embedding literature. These include dimensionality reduction (Yin and Schütze, 2016), cross-view auto-encoders (Bollegala and Bao, 2018) and Generalized Canonical Correlation Analysis (GCCA) (Rastogi et al., 2015). The latter method was also used by Poerner and Schütze (2019) for domain-specific Duplicate Question Detection.

Our sentence encoder ensemble includes three models from the recent literature: Sentence-BERT (Reimers and Gurevych, 2019), the Universal Sentence Encoder (Cer et al., 2017) and averaged ParaNMT vectors (Wieting and Gimpel, 2018). Our meta-embeddings outperform every one of their constituent single-source embeddings on STS12–16 (Agirre et al., 2016) and on the STS Benchmark (Cer et al., 2017). Crucially, since our meta-embeddings are agnostic to the size and specifics of their ensemble, future improvements may be possible by adding new encoders.

2 Related work

Word embeddings are functions that map word types to vectors. They are typically trained on unlabeled corpora and capture word semantics (e.g., Mikolov et al. (2013); Pennington et al. (2014)).

Word meta-embeddings combine ensembles of word embeddings by various operations: Yin and Schütze (2016) use concatenation, SVD and linear projection, Coates and Bollegala (2018) show that averaging word embeddings has properties similar to concatenation, Rastogi et al. (2015) apply generalized canonical correlation analysis (GCCA) to an ensemble of word vectors. Bollegala and Bao (2018) learn word meta-embeddings using autoencoder architectures. Neill and Bollegala (2018) evaluate several loss functions for autoencoder word meta-embeddings.

Sentence embeddings are methods that produce one vector per sentence. They can be grouped into two categories:

(a) Word embedding average sentence encoders take a (potentially weighted) average of pre-trained word embeddings. Despite their inability to understand word order, they are surprisingly effective on sentence similarity tasks (Arora et al., 2017; Wieting and Gimpel, 2018;
Sentence meta-embeddings are less frequently explored than their word-level counterparts. Kiela et al. (2018) create meta-embeddings by training an LSTM sentence encoder on top of a set of dynamically combined word embeddings. Since this approach requires labeled data, it is not applicable to unsupervised STS.

Tang and de Sa (2019) train a Recurrent Neural Network (RNN) and a word embedding average encoder jointly on a large corpus to predict similar representations for neighboring sentences. Their approach trains both encoders from scratch, i.e., it cannot be used to combine existing encoders.

Poerner and Schütze (2019) propose a GCCA-based sentence meta-embedding that combines domain-specific and generic sentence encoders for unsupervised Duplicate Question Detection. In this paper, we extend their approach by exploring a wider range of meta-embedding methods and an ensemble that is more suited to STS.

Semantic Textual Similarity (STS) is the task of rating the similarity of two natural language sentences. Related applications are semantic search, duplicate detection and sentence clustering. Supervised SoTA systems for STS typically apply cross-sentence attention (Devlin et al., 2019; Wang et al., 2019). This means that they are unable to cache embeddings, making them impractical for many downstream applications. Supervised “siamese” models (Reimers and Gurevych, 2019) are not competitive with cross-sentence attention, but they can cache embeddings. Our meta-embeddings are also cacheable (and hence efficient), but we do not need supervision.

3 Sentence Meta-Embeddings

Below, we assume access to an ensemble of pre-trained sentence encoders, denoted $F_1 \ldots F_J$. Every $F_j$ maps from a finite vocabulary of word types to a fixed-size $d_j$-dimensional vector.

Word meta-embeddings are usually learned from a finite vocabulary of word types (Yin and Schütze, 2016). Sentence embeddings lack such a “vocabulary”, as they can encode any member of $S$. Therefore, we train on a sample $S \subset \mathbb{S}$.

**Naive meta-embeddings.** We create naive sentence meta-embeddings by concatenating (Yin and Schütze, 2016) or averaging1 (Coates and Bollegala, 2018) length-normalized sentence embeddings (where $\bar{x} = x/||x||_2$):

$$F^{\text{avg}}(s') = \sum_j \hat{F}_j(s') / J$$

**SVD.** Yin and Schütze (2016) use Singular Value Decomposition (SVD) to compactify concatenated word embedding matrices. The method can easily be extended to sentence meta-embeddings: Let $X \in \mathbb{R}^{N \times \sum_j d_j}$ with $x_n = F^{\text{conc}}(s_n) - \mathbb{E}_{s \in S}[F^{\text{conc}}(s)]$, and let $USV^T \approx X$ be its $d$-truncated SVD. The meta-embedding of a new sentence $s'$ is:

$$F^{\text{svd}}(s') = V^T(F^{\text{conc}}(s') - \mathbb{E}_{s \in S}[F^{\text{conc}}(s)])$$

**GCCA.** Given random vectors $x_1, x_2$, Canonical Correlation Analysis (CCA) finds linear projections such that $\theta^T_1 x_1$ and $\theta^T_2 x_2$ are maximally correlated. Generalized CCA (GCCA) extends CCA to three or more random vectors. Bach and Jordan (2002) show that a variant of GCCA reduces to a generalized eigenvalue problem on block matrices:

$$\rho \begin{bmatrix} \Sigma_{1,1} & 0 & 0 \\ 0 & \Sigma_{2,2} & \ldots \\ 0 & 0 & \Sigma_{J,J} \end{bmatrix} \begin{bmatrix} \theta_1 \\ \ldots \\ \theta_J \end{bmatrix} = \begin{bmatrix} 0 & \Sigma_{1,1} & \ldots \\ \Sigma_{2,2} & 0 & \ldots \\ \Sigma_{J,J} & \ldots & 0 \end{bmatrix} \begin{bmatrix} \theta_1 \\ \ldots \\ \theta_J \end{bmatrix}$$

where $\Sigma$ are (cross-)covariance matrices of $F_1 \ldots F_J$ estimated on $S$. For stability, we add $\tau \mathbb{E}_{i=1}^d[\text{diag}(\Sigma_{j,j})]_i$ to $\text{diag}(\Sigma_{j,j})$, where $\tau$ is a hyperparameter. Given the top-$d$ eigenvectors $\Theta_j \in \mathbb{R}^{d_j \times d}$, the meta-embedding of sentence $s'$ is:

$$F^{\text{gcc}}(s') = \sum_{j=1}^J \Theta_j^T(F_j(s') - \mathbb{E}_{s \in S}[F_j(s)])$$

$F^{\text{gcc}}$ corresponds to MV-DASE in Poerner and Schütze (2019).

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1Shorter embeddings are zero-padded before averaging.
### Table 1: Hyperparameter search on STS Benchmark development set for AE (top) and GCCA (bottom). Pearson’s $r \times 100$ / Spearman’s $\rho \times 100$.

| Loss function | MSE | MAE | KLD | (1-COS)$^2$ |
|---------------|-----|-----|-----|-------------|
| hidden layers | 0   | 83.0/84.2 | 84.2/85.1 | 83.0/84.2 | 82.4/83.5 |
|               | 1   | 82.7/83.9 | 83.8/84.6 | **85.1/85.5** | 83.3/83.4 |
|               | 2   | 82.5/82.8 | 81.3/82.1 | 83.3/83.4 | 82.3/82.3 |

$\tau = 10^{-2}$, $\tau = 10^{-1}$, $\tau = 10^{0}$, $\tau = 10^{1}$, $\tau = 10^{2}$

84.2/84.1, 84.8/84.7, 85.5/85.7, **85.5/86.1**, 84.9/85.9

Our training objective is to reconstruct every embedding $x_j$ from every $E_j(x_j)$. This results in $j^2$ loss terms: $L(x_1 \ldots x_j) = \sum_{j'j} l(x_j', D_j'(E_j(x_j)))$. Neill and Bollegala (2018) propose different reconstruction loss functions for $l$: Mean Squared Error (MSE), Mean Absolute Error (MAE), KL-Divergence (KLD) or squared cosine distance (1-COS)$^2$.  

### 4 Experiments

#### Data

We train on all sentences of length $< 60$ from the first file (news.en-00001-of-00100) of the tokenized, lowcased Billion Word Corpus (Chelba et al., 2014) (~302K sentences). We evaluate on STS12–16 (Agirre et al., 2016) and the unsupervised STS Benchmark test set (Cer et al., 2017). These datasets consist of triples $(s_1, s_2, y)$, where $s_1, s_2$ are sentences and $y$ is their ground truth semantic similarity. The task is to predict similarity scores $\hat{y}$ that correlate well with $y$. We predict $\hat{y} = \cos(F(s_1), F(s_2))$.

#### Metrics

Previous work on STS differs with respect to (a) the correlation metric and (b) how to aggregate the sub-testsets of STS12–16. To maximize comparability, we report both Pearson’s $r$ and Spearman’s $\rho$. On STS12–16, we aggregate by a non-weighted average, which diverges from the original shared tasks (Agirre et al., 2016) but ensures comparability with more recent baselines (Wieting and Gimpel, 2018; Ethayarajh, 2018). Results for individual STS12–16 subtestsets can be found in the Appendix.

#### Ensemble

Our ensemble contains three sentence encoders: Universal Sentence Encoder (USE) (Cer et al., 2018), Sentence-BERT (SBERT) (Reimers and Gurevych, 2019) and ParaNMT (Wieting and Gimpel, 2018). SBERT is a pre-trained BERT Transformer (Devlin et al., 2019) finetuned on Natural Language Inference. USE is a Transformer trained on skip-thought, conversation response prediction and Natural Language Inference. ParaNMT averages word and 3-gram vectors trained on synthetic similar sentence pairs generated by Machine Translation.

#### Hyperparameters

We set $d = 1024$ in all experiments, which corresponds to the embedding size of SBERT. The value of $\tau$ (GCCA), as well as the autoencoder depth and loss function are tuned on the development set (Table 1). We train the autoencoder for a fixed number of 500 epochs with a batch size of 10,000 and the Adam optimizer (Kingma and Ba, 2014).

#### Efficiency

All meta-embeddings are efficient to train, either because they have closed-form solutions (GCCA and SVD) or because they are lightweight FFNs (autoencoder). The underlying sentence encoders are more complex and slow, but since we do not train them, we can cache and reuse their outputs. At inference time, our meta-embeddings are cacheable, i.e., scalable. For instance, to calculate the pairwise similarities of $N$ sentences, systems that use cross-sentence attention – such as the current STS SoTA by Wang et al. (2019) – have to compute $N^2$ sentence pair embeddings, while we – like Reimers and Gurevych (2019) – compute $N$ sentence embeddings and $N^2$ pairwise cosines.

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1 We use The large-ml-1-mean-tokens model, which was not finetuned on STS.
Table 2: Results on STS12–16 and STS Benchmark test set. STS12–16: mean Pearson’s $r \times 100$ / Spearman’s $\rho \times 100$. STS Benchmark: overall Pearson’s $r \times 100$ / Spearman’s $\rho \times 100$. **Boldface:** best in column (except supervised). Underlined: best component of ensemble. *Random projections averaged over 10 seeds. †Unweighted average computed from Table 8. ‡Paper reports Spearman’s $\rho = 86.15\%$, but the best published model achieves Spearman’s $\rho = 85.29\%$. There is no supervised SoTA on STS12–16, as they are unsupervised benchmarks.

| Method                          | $d$ (dim) | STS12 | STS13 | STS14 | STS15 | STS16 | STS-B |
|--------------------------------|-----------|-------|-------|-------|-------|-------|-------|
| single:ParaNMT                  | $d = 600$ | 67.5/66.3 | 62.7/62.8 | 77.3/74.9 | 80.3/80.8 | 78.3/79.1 | 79.8/78.9 |
| single:USE                      | $d = 512$ | 62.6/63.8 | 57.3/57.8 | 69.5/66.0 | 74.8/77.1 | 73.7/76.4 | 76.2/74.6 |
| single:SBERT                    | $d = 1024$ | 66.9/66.8 | 63.2/64.8 | 74.2/74.3 | 77.3/78.3 | 72.8/75.7 | 76.2/79.2 |
| single:ParaNMT – random projection* | $d = 1024$ | 67.3/66.2 | 62.1/62.4 | 77.1/74.7 | 79.7/80.2 | 79.7/78.7 | 79.5/78.6 |
| single:USE – random projection*  | $d = 1024$ | 62.4/63.7 | 57.0/57.5 | 69.4/65.9 | 74.7/77.1 | 73.6/76.3 | 76.0/74.5 |
| meta:conc                      | $d = 2436$ | 72.7/77.1 | 68.4/68.6 | 81.0/79.0 | 84.1/85.5 | **82.0/83.8** | **82.8/83.4** |
| meta:avg                       | $d = 1024$ | 72.5/71.2 | 68.1/68.3 | 80.8/78.8 | 83.7/85.1 | 81.9/83.6 | 82.5/83.2 |
| meta:svd                       | $d = 1024$ | 71.9/70.8 | 68.3/68.3 | 80.6/78.6 | 83.8/85.1 | **81.9/83.6** | **83.4/83.8** |
| meta:gcca                      | $d = 1024$ | **72.8/71.6** | **69.6/69.4** | **81.7/79.5** | **84.2/85.5** | **81.3/83.3** | **83.9/84.4** |
| meta:ae                        | $d = 1024$ | 71.5/70.6 | 68.5/68.4 | 80.1/78.5 | 82.5/83.1 | **80.4/81.9** | 82.1/83.3 |

| Method                          | $d$ (dim) | STS12 | STS13 | STS14 | STS15 | STS16 | STS-B |
|--------------------------------|-----------|-------|-------|-------|-------|-------|-------|
| Ethayarajh (2018) (unsupervised) | 68.3/- | 66.1/- | 78.4/- | 79.0/- | -/- | 79.5/- |
| Wieting and Gimpel (2018) (unsupervised) | 68.0/- | 62.8/- | 77.5/- | 80.3/- | 78.3/- | 79.9/- |
| Tang and de Sa (2019) (unsupervised meta) | 64.0/- | 61.7/- | 73.7/- | 77.2/- | -/- | 76.7/- |
| Hassan et al. (2019)† (unsupervised meta) | 67.7/- | 64.6/- | 75.6/- | 80.3/- | 79.3/- | 77.7/- |
| Poerner and Schütze (2019) (unsupervised meta) | -/- | -/- | -/- | -/- | -/- | -/- |
| Reimers and Gurevych (2019)‡ (sup. siamese SoTA) | -/- | -/- | -/- | -/- | -/- | -86.2 |
| Wang et al. (2019) (supervised SoTA) | -/- | -/- | -/- | -/- | -/- | 92.8/92.4 |

Table 3: Ablation study on STS Benchmark development set. Pearson’s $r \times 100$ / Spearman’s $\rho \times 100$.

| Method                             | $d$ (dim) | STS12 | STS13 | STS14 | STS15 | STS16 | STS-B |
|-----------------------------------|-----------|-------|-------|-------|-------|-------|-------|
| meta:gcca                         | 85.5/86.1 | 84.9/84.8 | 83.8/83.8 | 85.4/85.4 |

**Baselines.** Our main baselines are our single-source embeddings. Wieting and Kiel (2019) warn that high-dimensional sentence embeddings can have an advantage over low-dimensional ones. To exclude this possibility, we also up-project smaller embeddings by a random $d \times d_j$ matrix sampled from $[-a_j^{-0.5}, d_j^{-0.5}]$. Since the up-projected embeddings perform slightly worse than their originals (see Table 2, rows 4–5), we are confident that performance gains by our meta-embeddings are due to content rather than size.

**Discussion.** Table 2 shows that even the worst of our meta-embeddings consistently outperforms its single-source components. This underlines the overall usefulness of ensembling sentence encoders, irrespective of the meta-embedding method. GCCA is the most successful meta-embedding method, beating the other methods on five out of six STS datasets. By contrast, SVD and the autoencoder fail to improve over naive concatenation or averaging. Note that concatenation is not directly comparable to the other meta-embeddings due to dimensionality.

To the best of our knowledge, our GCCA meta-embeddings set a new unsupervised SoTA on the STS Benchmark and on STS12–16. We close the gap between unsupervised systems and the supervised siamese SoTA of Reimers and Gurevych (2019), from 7% down to 2% Spearman’s $\rho$ on the STS Benchmarks.

**Ablation.** Table 3 shows that all single-source embeddings contribute positively to the GCCA meta-embedding, which supports their hypothesized complementarity. The result suggests that further improvements may be possible by extending the ensemble.

5 Conclusion

Inspired by success on word meta-embeddings, we have shown how to apply different meta-embedding techniques to ensembles of sentence encoders. We have shown that all meta-embeddings consistently outperform their individual single-source components on the STS Benchmarks and the STS–16 datasets, with a new unsupervised SoTA set by our GCCA meta-embeddings. Because sentence meta-embeddings are agnostic to the size and specifics of their ensemble, we hope that this performance can improve further when we add new sentence encoders.
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| Method         | dimensionality: | single-source embeddings | meta-embeddings |
|---------------|-----------------|--------------------------|-----------------|
|               |                 |                          | conc  | avg  | svd  | gcca | ae  |
|               |                 |                          | d = 600 | d = 1024 | d = 512 | d = 2136 | d = 1024 | d = 1024 | d = 1024 |
| STS12         |                 |                          | 60.13/60.53 | 58.90/59.71 | 59.56/60.24 | **62.79/63.90** | 61.64/63.57 |           |
| MSRpar        | d = 600         |                          | 58.51/59.31 | 59.56/60.24 | 62.79/63.90 | 61.64/63.57 |           |           |
| MSRvid        | d = 1024        |                          | 89.12/90.75 | 89.12/90.75 | 89.12/90.75 |           |           |           |
| SMTeuroparl1  | d = 512         |                          |           |           |           |           |           |           |
| OnWN          |                 |                          | 80.13/81.13 | 80.13/81.13 | 80.13/81.13 |           |           |           |
| SMTnews       |                 |                          | 74.85/66.53 | 74.85/66.53 | 74.85/66.53 | 75.75/67.31 | 74.91/64.76 |           |
| STS13         |                 |                          | 86.44/68.10 | 86.44/68.10 | 86.44/68.10 |           |           |           |
| FNWN          |                 |                          | 79.52/79.30 | 79.52/79.30 | 79.52/79.30 |           |           |           |
| OnWN          |                 |                          | 80.84/81.13 | 80.84/81.13 | 80.84/81.13 |           |           |           |
| SMT           |                 |                          | 47.46/46.89 | 47.46/46.89 | 47.46/46.89 |           |           |           |
| headlines     |                 |                          | 81.13/83.48 | 81.13/83.48 | 81.13/83.48 |           |           |           |
| STS14         |                 |                          | 89.01/89.01 | 89.01/89.01 | 89.01/89.01 |           |           |           |
| OnWN          |                 |                          | 81.72/79.04 | 81.72/79.04 | 81.72/79.04 |           |           |           |
| deft-forum    |                 |                          | 78.85/76.98 | 78.85/76.98 | 78.85/76.98 |           |           |           |
| deft-news     |                 |                          | 79.64/79.93 | 79.64/79.93 | 79.64/79.93 |           |           |           |
| headlines     |                 |                          | 80.13/81.13 | 80.13/81.13 | 80.13/81.13 |           |           |           |
| images        |                 |                          | 89.52/85.68 | 89.52/85.68 | 89.52/85.68 |           |           |           |
| tweet-news    |                 |                          | 82.50/76.50 | 82.50/76.50 | 82.50/76.50 |           |           |           |
| STS15         |                 |                          | 83.03/83.56 | 83.03/83.56 | 83.03/83.56 |           |           |           |
| answers-forums|                 |                          | 89.38/76.82 | 89.38/76.82 | 89.38/76.82 |           |           |           |
| answers-students|               |                          | 86.14/80.63 | 86.14/80.63 | 86.14/80.63 |           |           |           |
| belief         |                 |                          | 83.20/86.03 | 83.20/86.03 | 83.20/86.03 |           |           |           |
| headlines     |                 |                          | 84.38/86.72 | 84.38/86.72 | 84.38/86.72 |           |           |           |
| images        |                 |                          | 90.92/91.95 | 90.92/91.95 | 90.92/91.95 |           |           |           |
| STS16         |                 |                          |           |           |           |           |           |           |
| answer-answer  |                 |                          | 79.65/79.89 | 79.65/79.89 | 79.65/79.89 |           |           |           |
| headlines     |                 |                          | 80.97/84.95 | 80.97/84.95 | 80.97/84.95 |           |           |           |
| plagiarism     |                 |                          | 85.86/87.17 | 85.86/87.17 | 85.86/87.17 |           |           |           |
| postediting    |                 |                          | 88.18/90.76 | 88.18/90.76 | 88.18/90.76 |           |           |           |
| question-question|               |                          | 75.49/77.42 | 75.49/77.42 | 75.49/77.42 |           |           |           |

Table 4: Pearson’s $r$ / Spearman’s $\rho$ on individual sub-testsets of STS12–STS16. **Boldface**: best method in row.