Multi-Label Transfer Learning for Semantic Similarity

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Abstract

The semantic relations between two short texts can be defined in multiple ways. Yet, all the systems to date designed to capture such relations target one relation at a time. We propose a novel multi-label transfer learning approach to jointly learn the information provided by the multiple annotations, rather than treating them as separate tasks. Not only does this approach outperform the traditional multi-task learning approach, it also achieves state-of-the-art performance on the SICK Entailment task and all but one dimensions of the Human Activity Phrase dataset.

1 Introduction

Relating short texts in a semantic space – be those phrases, sentences or short paragraphs – is a task that requires systems to determine the degree of equivalence between the underlying semantics of the two texts. Although relatively easy for humans, this task remains one of the most difficult natural language understanding problems. The task has been receiving significant interest from the research community. For instance, between 2012 and 2017, the International Workshop on Semantic Evaluation (SemEval) has been holding a shared task, Semantic Textual Similarity (STS) (Agirre et al., 2012, 2013, 2014, 2015, 2016; Cer et al., 2017), dedicated to tackling this problem, with around 100 team submissions each year.

With the recent development and success of sentence encoders, which map sentences to fixed-length vectors, or sentence embeddings, one approach is to first compute the embedding of each sentence using a pre-trained model and then output the cosine similarity between the two embeddings as the predicted similarity (Wieting et al., 2015; Wieting and Gimpel, 2017; Cer et al., 2018). This approach has quickly gained popularity due to its advantage that the produced embeddings can be used in downstream tasks. Since these sentence encoders are trained on large corpora which are usually not in the domain of semantic similarity, transfer learning methodology is crucial to the performance of this approach (Zhang et al., 2018). While in some semantic similarity datasets, an example consists of a sentence pair and an annotated similarity score, in others, each sentence pair comes with multiple annotations. This is motivated by the fact that there can be different interpretations or dimensions of the similarity between two sentences, such as “are they paraphrases of each other?”, “are they under the same subject?”, and so on. Typically, these dimensions are treated as separate tasks, where a model trains and tests on one of them at a time and ignores the rest. However, we hypothesize that each dimension may contain useful information for the others, and thus training jointly on multiple dimensions may improve performance on one or more dimensions.

Targeting those semantic similarity datasets with multiple dimensions, we propose a joint multi-label transfer learning setting where the model is jointly trained on multiple dimensions by outputting predictions for multiple dimensions and aggregating the losses for back-propagation. This is different from the traditional multi-task learning setting where the model makes one prediction at a time, switching between the tasks. We treat the traditional setting and the single-task setting (i.e., a different model is learned for each dimension) as baselines, and show that the multi-label
setting outperform them in many cases, achieving state-of-the-art performance on the SICK Entailment task and all but one dimension of the Human Activity Phrase dataset.

2 Method

We introduce a multi-label setting specifically designed for transfer learning on semantic similarity tasks with multiple dimensions of annotations.

2.1 Architecture

We employ the “hard-parameter sharing” multi-task learning setting (Caruana, 1998; Ruder, 2017), where some hidden layers are shared across multiple tasks while each task has their own specific output layer. As shown in Figure 1 as an example of a semantic similarity dataset with two dimensions of annotations, a pair of sentences $s_L$ and $s_R$ are encoded as sentence embeddings $h_L$ and $h_R$. For each dimension that has been annotated with a ground-truth label, a dense layer takes the two embeddings as input and outputs a probability distribution across the range of possible scores, following the methods of Tai et al. (2015). Concretely, given a score for a sentence pair in the range $[1, K]$, where $K$ is an integer,

\[
\hat{y} = r^T \hat{p}_\theta, \\
W(x), W(+), b(h), W(p), b(p) \text{ are parameters of the layers, } r^T = [1, 2 \ldots K], \text{ and } \hat{y} \text{ is the predicted score.}
\]

where $m$ is the number of pairs in a batch and $k$ indicates the $k$-th sentence pair.

With two such dense layers, two losses $J_1$ and $J_2$ are calculated, one for each dimension. The total loss is calculated as $J_1 + J_2$ for back-propagation which updates all parameters in the sentence encoder and the dense layers.

2.2 Novelty

Multi-label learning is a subset of multi-task learning (Zhang and Yang, 2017), where the input data for all tasks are the same. The novelty of the multi-label setting that we propose lies in aggregating the losses for every dimension of annotations in a round of feed-forward and back-propagation. All existing multi-task learning settings in sentence representations (Hashimoto et al., 2016; Jernite et al., 2017) we know of only consider one task (dimension) during each round of feed-forward and back-propagation, that is, the dense output layers which do not correspond to the current task are not updated. The training examples belonging to different tasks are then fed to the model based on some curriculum. This is because it is typical for each training example in a task to have only a single annotation associated with it, but this is not the case for several semantic similarity datasets with multiple dimensions annotated per pair. We differentiate this traditional setting by referring to it as alternating multi-task and show later in this paper that our multi-label setting outperforms this in many cases.

Figure 1: Overview of the multi-label architecture.
3 Experiments

3.1 Datasets

We study three semantic similarity datasets with multiple dimensions of annotations, spanning phrases, sentences and short paragraphs.

Human Activity Phrase (Wilson and Mihalcea, 2017): a collection of pairs of phrases regarding human activities, annotated in four different dimensions: similarity (SIM), how much the two activity phrases describe the same thing, relatedness (REL), how much the activities are related to one another, motivational alignment (MA), how much the activities are typically done with similar motivations, and perceived actor congruence (PAC), how much the activities are expected to be done by the same type of person. The annotated scores range from 0 to 4 for SIM, REL and MA, and −2 to 2 for PAC, and evaluation is based on the Spearman’s ρ correlation coefficient between the systems’ predicted scores and the human annotations. There are 1000 pairs in the dataset. We use the 1373 pairs from Zhang et al. (2018) in which 1000 are randomly selected for training and the rest are for development. We then treat the original 1000 pairs as a held-out test set so that our results are directly comparable with those previously reported.

SICK (Marelli et al., 2014b,a): the Sentences Involving Compositional Knowledge benchmark, which includes a large number of sentence pairs that are rich in the lexical, syntactic and semantic phenomena. Each pair of sentences is annotated in two dimensions: relatedness and entailment. The relatedness score ranges from 1 to 5, and Pearson’s r is used for evaluation; the entailment relation is categorical, consisting of entailment, contradiction, and neutral. There are 4439 pairs in the train split, 495 in the development (trial) split and 4906 in the test split.

Typed-Similarity (Agirre et al., 2013): a collection of meta-data describing books, paintings, films, museum objects and archival records taken from Europeana3, presented as the pilot track in SemEval 2013 STS shared task. Typically, the items comprise title, subject, description, etc. describing a cultural heritage item and, sometimes, a thumbnail of the item itself. For the purpose of measuring semantic similarity, we only include the description, which is a short paragraph, as input, though the annotations might be informed of other aspects of the meta-data. Each pair of items is annotated in eight dimensions of similarity: general similarity, author, people involved, time, location, event or action involved, subject and description. However, some of these dimensions regard more information retrieval techniques than semantic similarity, such as people involved, time or location, hence we only consider general similarity (GS), event or action involved (EA), subject (SUBJ) and description (DES). There are 731 pairs in the train split and 721 in the test split; Pearson’s r is used for evaluation.

3.2 Model

We use InferSent (Conneau et al., 2017), a bi-directional LSTM with max-pooling trained on the Stanford Natural Language Inference corpus (Bowman et al., 2015) and Multi-Genre Natural Language Inference corpus (Williams et al., 2017), as the pre-trained sentence encoder to transfer to the semantic similarity tasks.

3.3 Baselines

We compare the multi-label setting with two baselines:

Single-task, where each dimension is treated as an individual task. For each dimension, a model with only one dense layer is trained and tested, ignoring all other dimensions of annotations. All parameters in the sentence encoder and the dense layer are updated.

Alternating multi-task, where only one dimension is involved during each round of feed-forward and back-propagation. For example, with a dataset of two dimensions A and B and a model with two corresponding dense layers, after a batch of sentence pairs are selected, the model first only makes use of annotations from dimension A and updates the parameters in dense layer A and the sentence encoder. Then, the same process is repeated for dimension B, updating the parameters in dense layer B and the sentence encoder, before moving on to the next batch.

3.4 Experimental Details

In each experiment, we use stochastic gradient descent as optimizer and a batch size of 64. We tune the learning rate over {0.1, 0.5, 1, 5} and train the model for 20 epochs. For each dataset in the rest of this paper, we tune these hyperparameters on

3http://www.europeana.eu/
Table 1: The performance of single-task baseline, multi-label transfer and alternating multi-task transfer on all dimensions of the datasets. The previous best results are restricted to those using transfer learning with sentence encoders for fair comparison. The P-value is for the significance test of multi-label transfer against the other settings. The performances of multi-label transfer which are significantly higher than those of single-task baseline are in bold font. Those which are significantly higher than those of alternating multi-task baseline are underlined.

|           | SIM | REL | MA  | PAC | SICK-E | SICK-R | GS  | EA  | SUBJ | DES |
|-----------|-----|-----|-----|-----|--------|--------|-----|-----|------|-----|
| Single    | .719| .717| .682| .555| 86.4   | .874   | .530| .531| .588 | .684|
| Alt.      | .683| .686| .651| .515| 86.2   | .870   | .559| .530| .564 | .674|
| Joint     | .720| .721| .682| .557| 86.7   | .882   | .559| .534| .568 | .680|
| Prev. best| .710| .715| .690| .549| 86.3   | .885   | -  | -  | -   | -   |

the development set if there is one or on the train set using 5-fold cross-validation otherwise. All other hyperparameters maintain their values from the original code. In the single-task setting, the model is trained and tested on each dimension, ignoring the annotations of other dimensions. In the multi-task settings, the model is trained and tested on all dimensions in a dataset. In the alternating multi-task setting, dimensions are presented to the model in the order they are listed in §3.1 within each batch.

4 Evaluation

The results are shown in Table 1. The P-values are calculated from results collected for 30 runs to conduct one-sided Student’s t-test of multi-label setting against single-task baseline and alternating multi-task setting, with a significance level of 0.05.

4.1 Comparison of Multi-Task Settings

For the Human Activity Phrase dataset, the single-task setting already achieves state-of-the-art performances on SIM, REL and PAC dimensions, surpassing the previous best results reported by Zhang et al. (2018). Using the multi-label setting, the model is able to gain a statistically significant improvement in the performance of REL, while maintaining performance in other dimensions. The traditional alternating multi-task setting, however, performs significantly worse than the other settings.

For the SICK dataset, the multi-label setting achieves state-of-the-art results on the entailment task, outperforming the single-task baseline and the previous best results also using InferSent (Conneau et al., 2017). The multi-label setting also has a statistically significant performance gain compared to the single-task setting in the relatedness task. Still, the traditional alternating multi-task setting underperforms the other settings.

For the Typed-Similarity dataset, of which we are unaware of any prior results using sentence encoders, the multi-label setting outperforms the single-task setting on general similarity and event or action involved, but underperforms it on subject and description. Moreover, this is the only dataset where the alternating multi-task setting is on par with the multi-label setting for every dimension.

4.2 Other Considerations

In the multi-label setting, we calculate the total loss by summing the loss from each dimension. We also explore weighting the loss by factors of 2, 5 and 10, but doing so hurts performance for all dimensions.

In the alternating multi-task setting, we attempt different ordering of the dimensions when presenting them to the model within a batch of examples, but the difference in performance is not statistically significant. Furthermore, the alternating multi-task setting takes about $n$ times longer to train than the multi-label setting, where $n$ is number of dimensions of annotations.

5 Conclusion

We present a multi-label transfer learning setting designed specifically for semantic similarity tasks with multiple dimensions of annotations. By experimenting with ten dimensions and three datasets, we show that the multi-label setting can outperform single-task and traditional multi-task settings in many cases. Future work includes exploring the performance of this setting on other sentence encoders, as well as multi-label datasets outside of the domain of semantic similarity.
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