

One-Shot Learning for Language Modelling

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Abstract

Humans can infer a great deal about the meaning of a word, using the syntax and semantics of surrounding words even if it is their first time reading or hearing it. We can also generalise the learned concept of the word to new tasks. Despite great progress in achieving human-level performance in certain tasks (Silver et al., 2016), learning from one or few examples remains a key challenge in machine learning, and has not thoroughly been explored in Natural Language Processing (NLP). In this work we tackle the problem of one-shot learning for an NLP task by employing ideas from recent developments in machine learning: embeddings, attention mechanisms (softmax) and similarity measures (cosine, Euclidean, Poincare, and Minkowski). We adapt the framework suggested in matching networks (Vinyals et al., 2016), and explore the effectiveness of the aforementioned methods in one, two and three-shot learning problems on the task of predicting missing word explored in (Vinyals et al., 2016) by using the WikiText-2 dataset.

Our work contributes in two ways: Our first contribution is that we explore the effectiveness of different distance metrics on k-shot learning, and show that there is no single best distance metric for k-shot learning, which challenges common belief. We found that the performance of a distance metric depends on the number of shots used during training. The second contribution of our work is that we establish a benchmark for one, two, and three-shot learning on a language task with a publicly available dataset that can be used to benchmark against in future research.

1 Introduction

In the last few years, there has been great progress in the applications of deep neural networks, especially in speech (Hinton and N, 2012), computer vision (CV) (Krizhevsky et al., 2012) and

NLP (Mikolov et al., 2010). Their success has mostly relied on the availability of large datasets and powerful hardware (TPU, GPU). Despite their success, these networks are still not good at generalising concepts from few samples, and require re-training on new data and for new tasks. This is mainly due to the parametric nature of these models, in which one needs large datasets to generalise better. However, non-parametric alternatives such as k-Nearest Neighbour (k-NN) avoid this problem, and incorporate new data better i.e. one can use a k-NN to classify a new class without having to do any optimisation, but its performance depends on the chosen metric such as L2 distance (Atkeson et al., 1997). One solution would be training a fully end-to-end nearest neighbour classifier.

Hence, the shortcomings of the current state of the art neural networks and possible advantages of non-parametric models make us wonder: Can we do better? Can we build networks that can learn from few examples? This question motivates “one-shot” learning through training a fully end-to-end nearest neighbour classifier. We define one-shot learning as learning a class from a single labelled example. We use the Matching Networks of (Vinyals et al., 2016) as our basic model to incorporate different similarity measures, embeddings, and attention mechanisms to improve generalisation from few examples.

Our contribution is twofold: at the modelling level, and at the benchmarking level. Firstly, we explore new similarity metrics in the context of one-shot learning and how they match up with different embedding schemes. Secondly, due to the exploratory nature of our work, we believe that it can be used to benchmark other approaches on language modelling using WikiText-2 dataset.

We have organised this report by first defining and explaining our architecture in Section 2. Then,

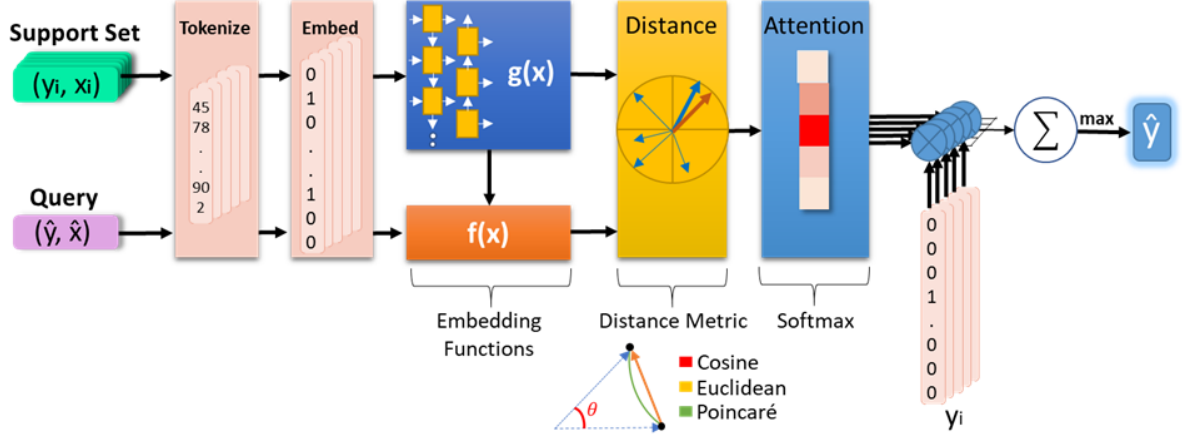


Figure 1: **Architecture:** Embedding + Distance Metric + Attention

in Section 3, we briefly discuss some of the related work to the task and our model. In Section 4, we describe our setup and the experiments we performed, demonstrating strong results in one-shot learning for language modelling in matching the old baseline set by (Vinyals et al., 2016). In Section 5, we present and analyse our findings. Finally, in Section 6, we conclude with a summary of our research outcomes, as well as future research directions one might take.

2 Model & Methods

Our approach to one-shot learning has multiple aspects. First, our architecture follows matching networks (Vinyals et al., 2016), in which we use embedding layers to encode sentences, distance metrics to measure similarity, and an attention scheme that uses softmax. Secondly, our training approach is different than traditional supervised learning routines. One-shot learning is easier if the network is specifically trained to do one-shot learning. Therefore, we want the training-time protocol to be exactly the same as the test-time protocol. In this case, given a support set, S (N classes with k examples each, where $k=1,2$, or 3), the model matches new samples to one of N classes.

2.1 Model Architecture

We describe our model as a differentiable nearest neighbor. This analogy becomes clear through the equation that we use to compute the target \hat{y} for a test sample \hat{x} :

$$\hat{y} = \sum_{i=1}^k a(\hat{x}, x_i) y_i \quad (1)$$

where we are assigning label of \hat{x} , based on its similarity to training examples x_1, \dots, x_k by using kernel $a(\cdot)$ to get a weighted average of labels y_i of the training examples. In this case, x_i represents the embedding of a sentence, and y_i is a one-hot vector of the size of the vocabulary.

2.2 Embedding & Attention

We embed both the training examples x_i and the test example \hat{x} . We use a distance metric such as cosine similarity to decide how similar the test sample is to each of the training samples. We pass these similarity measurements through a softmax to get normalized weights:

$$a(\hat{x}, x_i) = \frac{e^{c(f(\hat{x}), g(x_i))}}{\sum_{j=1}^k e^{c(f(\hat{x}), g(x_j))}} \quad (2)$$

where $c()$ is the cosine distance, but we will later discuss using other distance metrics. The important thing to note here is that we compute the embedding using both the test sample and the support set S together so that the embedding is learned through the relationship between the test and training samples.

2.2.1 Pre-Embedding

We have two-level embeddings. In the first level of embedding, or pre-embedding, we embed each sentence using max-pooling sentence embedding. This establishes our baseline. But, we might want to replace max-pooling with any other embedding method such as BERT, or word2vec in a future work. Since each method introduces differently sized embedded vectors, we standardise the interface between the first and second level embedding

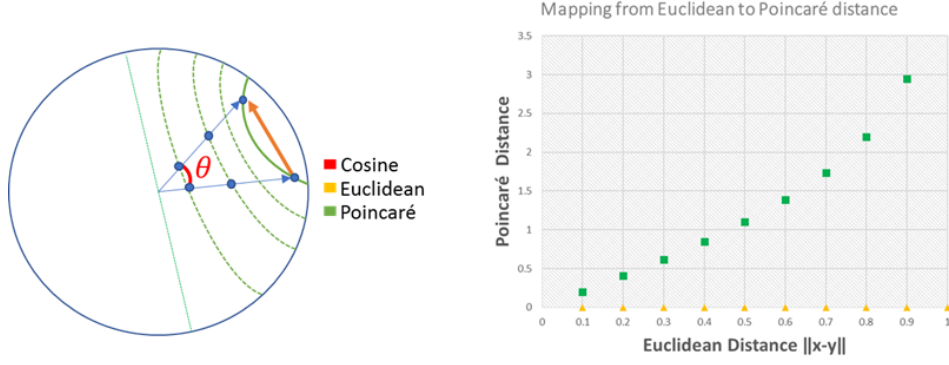


Figure 2: **Comparing distance metrics:** Cosine, Euclidean, and Poincaré

by using a linear network to reduce the dimension of the sentence embedding to 64 just before the second level embedding. The second level embedding is known as a Full Context Embedding (FCE) as was introduced by (Vinyals et al., 2016).

2.2.2 Full Context Embedding

Figure-1 shows two embedding functions $f(x)$ and $g(x)$. Function $f(x)$ is used to embed the test sample into a vector while $g(x)$ embeds each training example into a vector. $g(x)$ is a bidirectional LSTM over the examples:

$$g(x_i, S) = \vec{h}_i + \overleftarrow{h}_i + g'(x_i)$$

$$\vec{h}_i, \vec{c}_i = \text{LSTM}(g'(x_i), \vec{h}_{i-1}, \vec{c}_{i-1})$$

$$\overleftarrow{h}_i, \overleftarrow{c}_i = \text{LSTM}(g'(x_i), \overleftarrow{h}_{i-1}, \overleftarrow{c}_{i-1})$$

where the encoding of the i 'th example x_i is a function of its pre-embedding $g'(x_i)$ (g' might seem confusing but is common in the literature) and the embedding of other examples in set S . The relationship between examples is built through the bidirectional network's hidden states. In this way, each training example becomes a function of itself as well as other samples in the set. This particular feature is what separates the Matching Network from typical nearest neighbour methods since nearest neighbour does not change the representation of a sample based on other data points in the training set. Also, it is important to note that since each sample in set S is randomly picked, there is no particular order in which we feed them to the bidirectional LSTMs. So, it is possible that

we would get different embeddings if we permute the examples, which is something left to do as a future work.

$f(x)$ is used to embed the test example. We use support set, S , to affect the encoding of test sample, so $f(\hat{x})$ is actually $f(\hat{x}, S)$ i.e. a function of test and training samples. Specifically, $f(\hat{x}, S)$ is a vanilla LSTM with an attention mechanism that unfolds over K steps:

$$f(\hat{x}, S) = \text{attLSTM}(f'(\hat{x}), g(S), K) \quad (3)$$

It processes K -time steps to attend over the examples in the training set. The encoding is the last hidden state of the LSTM:

$$\hat{h}_k, c_k = \text{LSTM}(f'(\hat{x}), [h_{k-1}, r_{k-1}], c_{k-1}) \quad (4)$$

$$h_k = \hat{h}_k + f'(\hat{x}) \quad (5)$$

$$r_k = \sum_{i=1}^{|S|} a(h_{k-1}, g(x_i))g(x_i) \quad (6)$$

$$a(h_{k-1}, g(x_i)) = \text{softmax}(h_{k-1}^T g(x_i)) \quad (7)$$

We should note that the hidden state is a function of the previous hidden state as well as a vector r , which is computed by attending over the encoded training examples i.e. the output of the aforementioned $g(x)$ function. In this way, the encoding of the test sample becomes a function of the training samples.

2.3 Distance Metrics

The original work of (Vinyals et al., 2016) uses the cosine distance as a similarity measures, and does not explore other possibilities. Since we are using a kernel as a weighting on labels, performance of this model partly depends on the

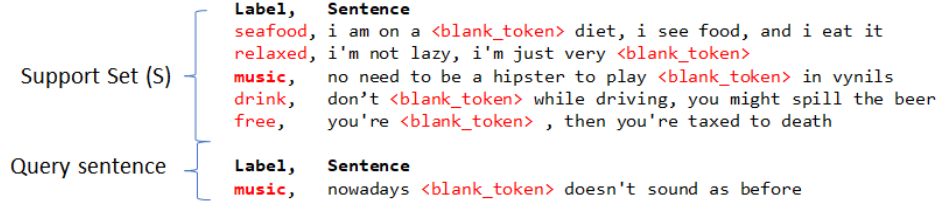


Figure 3: One-shot learning task

choice of distance metric, though see the results and discussion. Hence, we explored four possible options among others to compare their effect on performance: cosine, Euclidean, Poincaré, and Minkowski ($p=1,3$).

Figure-2 shows what each distance metric means in terms of relating two embeddings. The cosine distance finds the cosine of the angle between the two embeddings so it is thus a judgement of orientation and not magnitude: two vectors with the same orientation have a cosine similarity of 1 while orthogonal vectors have a similarity of 0, regardless of their magnitude. However, the Euclidean distance between two points is the length of the path connecting them. The Minkowski distance is a generalised metric form of Euclidean distance and Manhattan distance. Different metrics arise from the Minkowski general formula:

$$\left(\sum_{i=1}^n |x_i - y_i|^p \right)^{1/p}$$

where

- $p = 1$ is Manhattan distance, L1-Norm
- $p = 2$ is Euclidean distance, L2-Norm
- $p = \infty$ is Chebyshev distance, Lmax-Norm

We are using $p=1$, and 3 in our experiments. Lastly, the Poincaré distance is shown to be successful in predicting links in graphs where they outperform Euclidean embeddings in terms of representation capacity and in terms of generalisation ability (Nickel and Kiela, 2017). The Poincaré distance between points $u, v \in B^d$ is:

$$d(\mathbf{v}, \mathbf{u}) = \text{arcosh}\left(1 + 2 \frac{\|\mathbf{u} - \mathbf{v}\|^2}{(1 - \|\mathbf{u}\|^2)(1 - \|\mathbf{v}\|^2)}\right) \quad (8)$$

where $B^d = \{x \in R^d \mid \|x\| < 1\}$ is a d -dimensional unit ball, the Poincaré ball. We

can see that the distance within the Poincaré ball changes smoothly with respect to the location of u and v . We observed that, during training, this smoothness manifested itself as loss going down more smoothly (i.e. less spiky) than other distance metrics and there was less variance on the validation error between batches. Moreover, (Krioukov et al., 2010) modelled complex networks using hyperbolic spaces and discussed how typical properties such as strong clustering emerges by assuming an underlying hyperbolic geometry. This was appealing to us since our underlying model can be considered a clustering method.

2.4 Training

We want the test-time protocol to exactly match the training time protocol. Our task is as follows: given N classes (words) with k sentences each ($k = 1, 2$ or 3), predict a new label from one of N classes. We do this in two steps:

- Sample a task T from the training data by selecting N labels ($N=5, 20$), and k sentences per label ($k=1, 2$, or 3).
- Generate an episode by sampling a label set L (i.e. "music", "dogs"...) and then use L to sample the support set S and a batch B of examples to evaluate the loss on.

Let θ be the parameters of the model, and P_θ a probability distribution. Then the matching net is trained to minimise the error predicting P 's labels, conditioned on S with the following training objective:

$$\theta = \underset{\theta}{\operatorname{argmax}} E_{L \sim T} [E_{S \sim L, P \sim L} [K]] \quad (9)$$

,where

$$K = \sum_{(x,y) \in P} \log P_\theta(y \mid x, S) \quad (10)$$

where symbols in red are added for meta-learning in addition to the supervised learning objective.

	Model-based	Metric-based	Optimization-based
Key idea	RNN, memory	Embeddings, distance metric	Training optimization
How is $P(y x)$ modeled?	$f(y, \mathcal{S})$	$\sum_i k(x, x_i) y_i$	$P(y x)$

Table 1: Summary of different approaches to Few-Shot Learning

Figure-3 shows examples of training and test samples for a 5-way, one-shot learning task. Meta-learning is another term for the training and testing paradigm used here and was discussed in more detail in our previous report.

3 Related Work

With the recent resurgence of deep learning, a new body of work on one-shot, and few-shot learning has started to emerge. There are three main approaches to one-shot, and few-shot learning:

- a) **Metric-based.** Focuses on distance metrics (Koch et al., 2015; Vinyals et al., 2016; Snell et al., 2017; Sung et al., 2018)
- b) **Model-based.** Uses recurrent networks with attention as well as external or internal memory (Santoro et al., 2016; Munkhdalai and Yu, 2017)
- c) **Optimization-based.** Optimizes the model parameters explicitly (Ravi and Larochelle, 2017; Finn et al., 2017; Nichol et al., 2018).

Table 1 summarises these observations.

Our work is mostly influenced by metric-based models, which combine ideas such as attention, and embeddings.

(Koch et al., 2015) proposed a method to use the Siamese Neural Network (SNN) to do one-shot learning in vision. The model is trained to predict whether two input images are in the same class. During test time, it processes all the image pairs between a test image and every image in the support set, and makes a prediction using the class of the support image with the highest probability. One of the shortcomings of this work is that it heavily depends on a pre-trained model, whose advantage decreases when the new task diverges from the original task that the model was trained on.

(Sung et al., 2018) proposed Relation Networks, which is similar to SNN but with a few differences: Firstly, the relationship between images is captured by a CNN classifier instead of using the

L1 norm distance metric. Secondly, they use the mean-square-error loss as the objective function instead of the cross-entropy since their network focuses on predicting relation scores rather than binary classification.

The Prototypical Networks of (Snell et al., 2017) use some of the same insights as in Matching Networks (Vinyals et al., 2016) and simplifies Matching Networks. One major difference between the two approaches is the distance metric: Prototypical Networks uses the Euclidean distance instead of the cosine similarity. However, both are equivalent in the case of one-shot learning since they can be reduced to k-nearest neighbours (k-NN).

Although each aforementioned work offers a new idea, they are mostly designed for vision tasks. Among them, only the Matching Network has tried to solve a language task, and made an attempt to establish a benchmark, though not on a publically available dataset as we do. Moreover, each fails to explore and compare the effectiveness of other distance metrics. Lastly, since their publication, there have been new developments on word and sentence embeddings such as BERT, and Poincaré embeddings (Nickel and Kiela, 2017), which enable researchers to build more expressive language models.

4 Experiments

For our experiments, we define an N-way k-shot learning task as following: Given k (1,2, or 3) labelled examples for a support set of sentences (N=5, or 20), in which each has a missing word and a corresponding 1-hot label, and is not previously trained on, choose the label from the support set that best matches the query sentence. Sentences are taken from the WikiText-2 dataset.

On each trial, the support set and batches are populated with non-overlapping sentences. Thus, we do not use infrequent words since if there is only a single sentence for a given word it would not work since the sentence would need to be in both the set and the batch.

Distance Metric	5 Class			20 Class	
	1-Shot	2-Shot	3-Shot	1-Shot	5-Shot
Cosine	28.6%	32.8%	34.1%	10.7%	14.7%
Euclidean	30.1%	31.0%	35.4%		
Poincare	28.1%	30.6%	35%		
Minkowski (p=1)	27.5%	30.5%	37.7%		
Minkowski (p=3)	29.1%	32.0%	35.5%		
Matching Networks	32.4 ± 0.2%	36.1 ± 0.1%	38.2 ± 0.2%		

Table 2: Accuracy results of different distance metrics on One, Two, and Three-Shot models for the WikiText-2 dataset. ‘FCE’ enabled in all cases, and all are trained with ‘5’ processing steps on the ‘attLSTM’ layer. The final row in bold is for the results for the same task in (Vinyals et al., 2016).

Each trial consisted of a 5-way choice between the classes available in the set. We used a batch size of 20 throughout the sentence matching task and varied the set size across $k=1,2$, and 3. We made sure that the same number of sentences were available for each class in the set. We split the words into a randomly sampled 9000 for training, 1000 for cross-validation and 1000 for testing. Our results are based on the test set. Thus, words and sentences used during test time were not trained on during training.

Baseline: We use Matching Networks as our baseline model, in which we use:

- Max-pooling sentence embedding
- Cosine similarity
- Full context embedding enabled

We build on this baseline by exploring different distance metrics. Table 2 compares results for our experiments and the original Matching Network.

5 Results and Discussion

In this section, we present the results of our experiments with similarity metrics and embeddings. As mentioned before, all the experiments followed the pattern of an N -way k -shot learning task.

Table 2 shows the accuracy of trials with different distance metrics, and compares against results of the original Matching Network (Vinyals et al., 2016). Our first experiment was to reproduce the results of the original Matching Networks with a simple embedding scheme. Compared to the original paper, we managed to achieve very similar accuracy in each of the tests with results ranging from 30.1% for 5-class 1-shot learning to 37.7% for 5-class 3-shot. Ju

Exploration of different metrics introduced to our model has shown some insights. To list a few, we will use 5-Class k -shot learning results:

- Euclidean distance did better than Cosine across in 1, and 3-shot learning, while performed worse in 2-shot learning. This challenged the findings of Prototypical Networks (Snell et al., 2017), where the claim was that Euclidean was much better as a similarity measure.
- Accuracy of all metrics increases with increased number of samples (i.e. shots).
- Although Euclidean distance outperformed others in 1-shot learning, Cosine was best in 2-shot learning. The biggest performance gain is achieved using Minkowski ($p=1$) i.e. Manhattan distance in 3-shot learning. This is somewhat surprising since it shows that there is no single best metric, and the performance of a distance metric depends on number of examples (shots) used. This challenges some of the claims made by other authors, where the claim was superiority of one distance metric over others.
- Poincare distance did not perform well. This poor performance is mainly due to the basic embedding scheme we used. We believe that if we used embeddings learned with Poincare distance this would boost its performance. This remains as future work.

Although the accuracy achieved for the 5-Class k -shot task was very positive in terms of matching past research, we have noticed very low accuracy for all the models performing 20-class k -shot learning. As a result we have completely

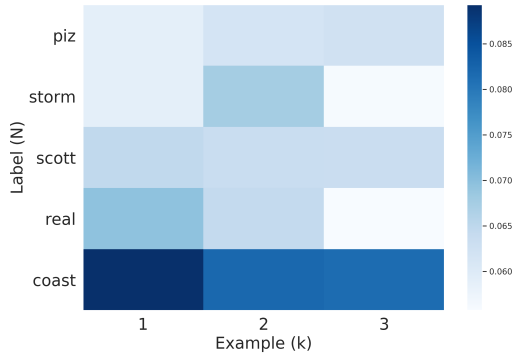


Figure 4: Attention map for target label *coast* with Euclidean distance

dropped the 20-way k -shot learning task and focused on 5-way k -shot. This also made us realise why (Vinyals et al., 2016) most likely did not report findings using more than 5 classes.

To further investigate the similarity performance we have plotted an attention map for the support set and target label (See figure 4). In the plot the x -axis was assigned to the k number of example sentences and the y -axis to the N number of labels in support set. Although Euclidean distance was not the best choice of similarity metrics for 5-way 3-shot learning, it can be clearly seen that the model performs matching correctly. The target word was *coast* and it was accurately allocated with the highest attention to all three example sentences from support set.

Moreover, in Figure 5, it can be observed that the correct example labels have been clustered near the target label proving accurate performance of the embedding process between target and support sets. However, one issue noticed during the experiments was related to embedding different examples of the same label. To illustrate, in figure 5, some examples of the same support set label are not appropriately clustered, as the distances between them should be relatively short (for instance *storm* label examples). The overall accuracy of the process could perhaps be improved by introducing a different embedding, for instance BERT (Devlin et al., 2018), and word2vec. We did generate Bert embeddings at the end of our project but ran out of time to finish training.

A few concerns: During our work, we came to realise a few weaknesses of our approach:

- In bidirectional LSTMs, we feed sets of training examples to encode them, but, the order

is random. Depending on which order we choose, we get a different encoding for the same support set. This could be resolved by using a recurrent attentional mechanism instead (Vinyals et al., 2015)

- This approach also gets quite a bit slower as the number of training examples grow. So we think that for larger datasets, parametric approaches could be more suitable for this task.
- Another weakness of this approach is that we use a specific number of examples, e.g. 5-20 during training, which forces us to use the same number at test time. This is problematic if we want the size of our training set to grow online. This would require retraining the network because the encoder LSTM for the training data is not "used to" seeing inputs of more examples. This could be resolved by iteratively sub-sampling the training data, doing multiple inference passes and averaging. Moreover, the attention mechanism LSTM might have problems with attending over many more examples. An interesting experiment to try would be to disable FCE and try to use up to 1000 training examples, and compare it with the case where we train on up to 25 examples (with and without FCE).
- Another candidate baseline that we could have chosen to compare to would be SVM, but this is left as a future work.
- Performance of each distance metric was limited by the fact that we used relatively simple max-pooling embedding. And we feel that we maxed out the performance. To do better, one needs to use more expressive embeddings such as BERT. Also, we believe that the best performance would be gained through using sentence embedding that was acquired using same similarity measure that is being used to compare distances. In our case, we can consider max-pooling embedding as being more friendly to Euclidean measures, but not so much to Poincare. One of future direction in this work is to explore Poincare further by using Poincare embeddings.

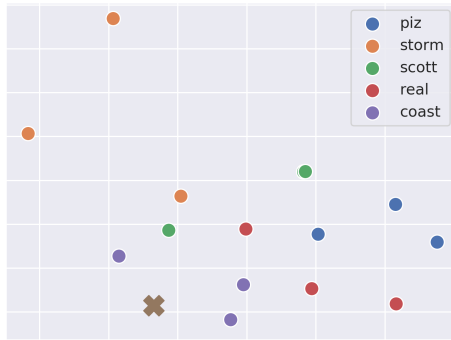


Figure 5: Clustering of example labels’ embeddings in relation to *coast* target label

6 Conclusion

We explored the effectiveness of different embedding schemes and distance metrics in one-shot learning for a language modelling task. We used Matching Networks, a differentiable nearest neighbor model, as our starting point, and trained it end-to-end. We contributed towards improving one-shot learning problem in an NLP task by exploring distance metrics, and establishing a benchmark for future research. What remains to be done in near future is exploring the same problem by using more powerful sentence embeddings, and achieving state-of-the-art result in this task. Our code can be found in this [GitHub repository](#)¹

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References

- C Atkeson, A Moore, and S Schaal. 1997. [Locally weighted learning](#). Artificial Intelligence Review.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. BERT: pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805.

¹<https://github.com/adriangonz/statistical-nlp-17>

- Chelsea Finn, Pieter Abbeel, and Sergey Levine. 2017. [Model-agnostic meta-learning for fast adaptation of deep networks](#). In *Proceedings of the 34th International Conference on Machine Learning*, volume 70 of *Proceedings of Machine Learning Research*, pages 1126–1135, International Convention Centre, Sydney, Australia. PMLR.
- Deng Li Yu Dong Dahl George E Mohamed Abdelrahman Jaitly Navdeep Senior Andrew Vanhoucke Vincent Nguyen Patrick Sainath Hinton, Geoffrey and Tara N. 2012. [Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups](#). page 29(6):82–97. Signal Processing Magazine.
- Gregory Koch, Richard Zemel, and Ruslan Salakhutdinov. 2015. Siamese neural networks for one-shot image recognition.
- D. Krioukov, F. Papadopoulos, and M Kitsak. 2010. [Hyperbolic geometry of complex networks](#). page 6338–6347. Physical Review.
- A. Krizhevsky, I. Sutskever, and G. Hinton. 2012. [Imagenet classification with deep convolutional neural networks](#). NIPS.
- T Mikolov, M Karafiát, L Burget, J Cernocky, and J. Khudanpur. 2010. [Recurrent neural network based language ‘model](#). INTERSPEECH.
- Tsendsuren Munkhdalai and Hong Yu. 2017. [Meta networks](#). In *Proceedings of the 34th International Conference on Machine Learning*, volume 70 of *Proceedings of Machine Learning Research*, pages 2554–2563, International Convention Centre, Sydney, Australia. PMLR.
- Alex Nichol, Joshua Achiam, and John Schulman. 2018. On first-order meta-learning algorithms. *CoRR*, abs/1803.02999.
- M. Nickel and D. Kiela. 2017. [Poincaré embeddings for learning hierarchical representations](#). page 6338–6347.
- Sachin Ravi and Hugo Larochelle. 2017. Optimization as a model for few-shot learning. In *ICLR*.
- Sebastian Ruder. 2018. [A review of the neural history of natural language processing](#). Last accessed: 17/02/2019.
- Adam Santoro, Sergey Bartunov, Matthew Botvinick, Daan Wierstra, and Timothy Lillicrap. 2016. [Meta-learning with memory-augmented neural networks](#). In *Proceedings of The 33rd International Conference on Machine Learning*, volume 48 of *Proceedings of Machine Learning Research*, pages 1842–1850, New York, New York, USA. PMLR.
- David Silver, Aja Huang, Chris J. Maddison, Arthur Guez, Laurent Sifre, George van den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Sander Dieleman Marc Lanctot, Dominik Grewe, John Nham, Nal Kalchbrenner, Ilya

Sutskever, Timothy Lillicrap, Madeleine Leach, Koray Kavukcuoglu, Thore Graepel, , and Demis Hassabis. 2016. Mastering the game of go with deep neural networks and tree search. In *Nature*.

Jake Snell, Kevin Swersky, and Richard S. Zemel. 2017. Prototypical networks for few-shot learning. In *NIPS*, pages 4080–4090.

Flood Sung, Yongxin Yang, Li Zhang, Tao Xiang, Philip HS Torr, and Timothy M Hospedales. 2018. Learning to compare: Relation network for few-shot learning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*.

O. Vinyals, S. Bengio, and M. Kudlur. 2015. [Order matters: Sequence to sequence for sets](#).

Oriol Vinyals, Charles Blundell, Timothy Lillicrap, koray kavukcuoglu, and Daan Wierstra. 2016. [Matching networks for one shot learning](#). In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, editors, *Advances in Neural Information Processing Systems 29*, pages 3630–3638. Curran Associates, Inc.

Lilian Weng. 2018. [Meta-learning: Learning to learn fast](#). Last accessed: 17/02/2019.