Retrieval Augmentation to Improve Robustness and Interpretability of Deep Neural Networks

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Abstract—Deep neural network models have achieved state-of-the-art results in various tasks related to vision and/or language. Despite the use of large training data, most models are trained by iterating over single input-output pairs, discarding the remaining examples for the current prediction. In this work, we actively exploit the training data to improve the robustness and interpretability of deep neural networks, using the information from nearest training examples to aid the prediction both during training and testing. Specifically, the proposed approach uses the target of the nearest input example to initialize the memory state of an LSTM model or to guide attention mechanisms. We apply this approach to image captioning and sentiment analysis, conducting experiments with both image and text retrieval. Results show the effectiveness of the proposed models for the two tasks, on the widely used Flickr8 and IMDB datasets, respectively. Our code is publicly available.

Index Terms—deep learning, retrieval augmentation, nearest neighbors, LSTM, attention mechanism

I. INTRODUCTION

The most common methodology in deep learning involves the supervised training of a neural network with input-output pairs, so as to minimize a given loss function. In general, deep neural networks predict the output conditioned solely on the current input or, more recently, leveraging an attention mechanism that focuses only on parts of the input as well. This leaves the rest of the dataset examples unused for the current prediction, either during training or inference.

In this work, we leverage similar examples in the training set to improve the robustness and interpretability of deep neural networks, both at training and testing time. We propose an approach that retrieves the nearest training example to the one being processed and uses the corresponding target example together with the retrieved target, or (ii) to guide the attention mechanism of the neural network.

We show that the retrieved target can be easily incorporated in an LSTM model, making use of its initial memory state. In general, previous studies have given little consideration to the initialization of the LSTM’s memory state. Typically, the memory state is initialized simply with a vector of zeros. Even when it is initialized with the current context (e.g., the input text for machine translation tasks, or the input image in image captioning), it is just initialized in the same way as the hidden state: with a simple affine transformation of the same context. Our approach takes advantage of the initial memory state by encoding auxiliary information from training examples. We also present a new multi-level attention method that attends to the inputs, as well as to the target of the nearest example.

We evaluate the proposed approach on image captioning and sentiment analysis. In brief, image captioning involves generating a textual description of an image. The dominant framework involves using a CNN as an encoder that represents the image, and passes this representation to a RNN decoder that generates the respective caption, combined with neural-attention. The task of sentiment analysis aims to classify the sentiment of an input text. Within neural methods, RNNs and CNNs are commonly used for sentiment analysis, recently also combining attention mechanisms.

Our general aim is to show the robustness of our approach by applying it to different tasks (i.e., generation and classification) and by using a retrieval mechanism with different modalities (i.e., image and text retrieval).

II. PROPOSED APPROACH

The proposed approach consists of two steps. The first step involves retrieving the nearest training example given
the current input. The second step leverages the target of the nearest example, either by encoding it as the LSTM’s initial memory state or to guide the attention mechanism.

A. Retrieval Component

For retrieval, we use Facebook AI Similarity Search (FAISS) [9] to store the training examples as high-dimensional vectors, and search over the dataset. FAISS is an open source library for nearest-neighbor search, optimized for memory usage and speed, being able to quickly find similar high-dimensional vectors over a large pool of example vectors. To search over the stored vectors, FAISS uses as default the Euclidean distance, although it also supports the inner product distance. We use the default Euclidean distance to retrieve the nearest example $x_n$ given the current input $x_c$.

Note that, for the second stage, the target output of the nearest example is required, and not the nearest example itself. This can be retrieved with an auxiliary lookup table that maps the corresponding index of $x_n$ to its target $y_n$.

a) Image Retrieval: In image captioning, each training input image $x$ is stored as a D-dimensional vector using a pre-trained encoder network:

$$r_x = Enc(x) \in \mathbb{R}^D.$$  \hspace{1cm} (1)

In the previous expression, $r_x$ denotes the vector representation of the input, and $D$ its dimensionality. A CNN encoder $Enc$ extracts the images features $V$ via the last convolutional layer, followed by a global average pooling operation.

b) Text Retrieval: In Sentiment Analysis, each training input sentence $x$ is mapped to a vector representation $r_x$ using a pre-trained sentence representation model, denoted as $S$ in the following expression:

$$r_x = S(x) \in \mathbb{R}^D.$$  \hspace{1cm} (2)

In particular, we use a pre-trained sentence transformer to obtain the corresponding sentence representations [18], namely the paraphrase-distilroberta-base-v1\textsuperscript{2} model. This RoBERTa-based sentence representation model has been trained to produce meaningful sentence embeddings for similarity assessment and retrieval tasks.

B. Incorporating the Nearest Target in the LSTM

In the second step, we use the target of the nearest example to initialize the memory state of the LSTM or to guide the attention mechanism.

1) LSTM Initial Memory State: After retrieving the nearest input $x_n$ in the first step, the corresponding target $y_n$ is incorporated in the LSTM as the initial memory state. This can be accomplished as long as the target example is encoded into a continuous vector space with the same dimensionality of the LSTM. Our approach consists in mapping the retrieved target $y_n$ into a fixed-length representation and using an affine transformation to have the same dimensionality of the LSTM.

$$y_n = W_r f(y_n).$$  \hspace{1cm} (3)

In the previous expression, $W_r$ is a learned parameter that projects the vector representation of the retrieved target to the same dimensionality of the LSTM. For the image captioning and sentiment analysis tasks, we use the vector representations $f(y_n)$ produced through the procedures described next:

a) Image Captioning: We explore three alternative representations for the target caption of the nearest input image:

- **Average of static word embeddings**: Each word is represented with a pre-trained embedding, in particular using fastText [16], and then the word vectors are averaged to build the caption representation.

- **Weighted average of static word embeddings**: Taking the average of word vectors assumes that all words are of equal importance. To better capture the meaning of a caption, we will average the word embeddings weighted by their norms. Liu et al. [13] has shown that the norm of a word embedding can be used to define the importance of a word, with frequent words having smaller norms than rare words.

- **Contextual embeddings**: The aforementioned representations ignore word order and use static word embeddings not dependent on their left/right context within the sequence of words. To take this information into consideration, we encode the caption using the pre-trained sentence transformer paraphrase-distilroberta-base-v1\textsuperscript{2}.

b) Sentiment Analysis: In this task, the target of the nearest input sentence is either positive or negative. We suggest the following representations to encode the nearest target:

- **1s and -1s**: The nearest target is represented with a vector of 1s when positive or with a vector of -1s when negative. The rationale behind this choice relates to using opposite vectors with a cosine similarity of -1.

- **Average embeddings of positive/negative sentences**: When the nearest target is positive, we use a representation obtained from all the positive training sentences using the pre-trained fastText embeddings. This is done by averaging each word vector of each positive sentence and then averaging over all the positive sentences to obtain the final embedding that represents a positive target. The same idea is applied to a negative target (i.e. building a representation from the average embeddings of all negatives sentences). Essentially, we intend to provide the model with an overall memory of what resembles a positive/negative sentence.

- **Weighted average embeddings**: Similar to the previous formulation, but weighting each word by the norm of the word vectors.

- **Contextual embeddings**: Similar to the two aforementioned representations, but using paraphrase-distilroberta-base-v1\textsuperscript{2} to represent each sentence.

\[\text{http://github.com/UKPLab/sentence-transformers}\]
Fig. 1. Overview of the proposed approach. Typically, an LSTM model predicts the output based solely on the input, without leveraging auxiliary context from other training examples. Our approach retrieves the nearest training example \( x_n \) and incorporates its target \( y_n \) into the LSTM’s initial memory state \( m_0 \). We apply our approach to sentiment analysis (upper) and image captioning (down).

2) Guiding an Attention Mechanism: The target of the nearest input can also be included in an attention mechanism. We present a new multi-level attention method that attends to the inputs and also to the retrieved target, deciding which of those to focus on for the current prediction.

a) Image Captioning: First, a visual context vector \( c_t \) is computed with a typical additive attention \(^2\) given to the image features \( V \in \mathbb{R}^{D \times K} \) and the previous hidden state \( h_{t-1} \in \mathbb{R}^D \) of the LSTM:

\[
a_t = w^aT \tanh(W_aV + W_hh_{t-1}),
\]

\[
\alpha_t = \text{softmax}(a_t),
\]

\[
c_t = \sum_{i=1}^{K} \alpha_{i,t}v_i.
\]

In the previous expressions, \( W_a, W_h \) are parameters and \( \alpha_t \) are the attention weights. The attended image vector is defined as \( c_t \), the visual context vector.

Then, the multi-level context vector \( \hat{c}_t \) is obtained given the previous hidden state \( h_{t-1} \) and the concatenation of the visual context vector \( c_t \) with the retrieved target vector \( r_{y_n} \in \mathbb{R}^D \):

\[
\hat{a}_t = w^aT \tanh \left( W_m\text{concat}(c_t, r_{y_n}) + W_hh_{t-1} \right),
\]

\[
\hat{\alpha}_t = \text{softmax}(\hat{a}_t),
\]

\[
\hat{c}_t = \hat{\alpha}_{1,t}c_t + \hat{\alpha}_{2,t}r_{y_n}.
\]

In the previous expressions, \( W_m, w^aT \) are parameters to be learned, and \( \hat{\alpha}_t \) consists in \( \hat{\alpha}_{1,t} \), i.e. the weight given to the visual context vector, and \( \hat{\alpha}_{2,t} \), the weight given to the retrieved target, with \( \hat{\alpha}_{2,t} = 1 - \hat{\alpha}_{1,t} \). In this way, the proposed attention can decide to attend to the current image, or to focus on the nearest example.

b) Sentiment Analysis: The same attention mechanism described for image captioning is also applied here, with little modifications. In this case, attention is not calculated at each time-step of the LSTM, since the prediction only occurs at time-step T. Therefore, the previous hidden state \( h_{t-1} \) is replaced by the last hidden-state \( h_t \) and the visual features \( V \) are replaced by all the LSTM hidden-states \( H \).

III. IMPLEMENTATION DETAILS

We compare our two models, named Image Captioning through Retrieval (ICR) and Sentiment Analysis through Retrieval (SAR), against a vanilla encoder-decoder model with neural attention, and a vanilla attention-based LSTM, respectively. The differences between the baselines and our models are the aforementioned approaches: (i) the LSTM’s memory
state being initialized with the target of the nearest input, and (ii) the multi-level attention mechanism.

In image captioning, we use a pre-trained ResNet on ImageNet as the encoder, without finetuning, together with a standard LSTM as decoder, with one hidden layer and 512 units. For each input image, the ResNet encoder extracts the current image features \( V = [v_1, ..., v_k] \) (2048 x 146D) and performs average pooling to obtain the global image feature \( \bar{v} = \frac{1}{K} \sum_{i=1}^{K} v_i \) (that corresponds to \( r_x \)). The initial hidden state of the LSTM is then initialized with an affine transformation of the image feature \( h_0 = W_{ih} \bar{v} \) (512D). The initial memory state \( m_0 \) is also initialized in the same way, with \( m_0 = W_{im} \bar{v} \) for the baseline model. For the ICR model, \( m_0 \) is initialized with the retrieved target (Eq. 3), corresponding to the first reference caption of the retrieved nearest image. At each time-step \( t \), the LSTM receives as input the fastText embedding of the current word in the caption (300D), concatenated with the corresponding attention context vector (512D). The baseline model uses the visual context vector \( c_t \) and the ICR model uses the multi-level context vector \( \hat{c}_t \). In the particular case of the multi-level attention mechanism, the image features \( V \) receive an affine transformation before passing through Eq. 4 to ensure the same dimensionality of the retrieved target in order to compute Eq. 9. Finally, the current output word probability is computed with an affine transformation with dropout rate of 0.5, followed by a softmax layer.

In sentiment analysis, we also use an LSTM with one hidden layer and 512 units. We use a standard LSTM for coherence with image captioning, but note that the SAR model can also use a bi-directional model. As typically done in sentiment analysis, the baseline LSTM hidden states are initialized with a vector of zeros, whereas our SAR model initializes \( m_0 \) with the sentiment of the nearest review (Eq. 3). At each time step, the LSTM receives as input the current word embedding (based on pre-trained fastText embeddings). After processing the whole sequence, at the last time-step \( T \), attention is applied over the respective hidden states \( H \) and the last hidden state \( h_T \). Then, the corresponding context vector is passed through an affine transformation with dropout (0.5), followed by a sigmoid layer in order to obtain the positive sentiment probability.

The models are trained with the standard categorical and binary cross-entropy loss, respectively for image captioning and sentiment analysis. The batch size is set to 32 and we use the Adam optimizer with a learning rate of 4e-4 and 1e-3, for image captioning and sentiment analysis, respectively. As stopping criteria, we use early stopping to terminate if there is no improvement after 12 consecutive epochs on the validation set (over BLEU score for image captioning, and accuracy for sentiment analysis) and the learning rate is decayed after 5 consecutive epochs without improvement (shrink factor of 0.8). At testing time, we use greedy decoding in image captioning.

\[
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IV. EXPERIMENTS

This section presents the experimental evaluation of the proposed approach. We first describe the datasets and evaluation metrics, and then present and discuss the obtained results.

A. Datasets and Metrics

We report experimental results on commonly used datasets for image captioning and sentiment analysis, namely the Flickr8k dataset [7] and the IMDB dataset [15], respectively. The Flickr8k dataset has 8000 images with 5 reference captions per image. We use the publicly available splits of Karpathy [9] with 6000 images for training, 1000 images for validation and the remaining 1000 images for testing. The IMDB dataset contains 50000 movie reviews from IMDB, labeled as positive or negative. We use the publicly available train-test splits, with 25000 reviews each and we do a random split on the training set with 10% of the original training reviews for validation. For both datasets, the vocabulary consists of words that occur at least five times.

To evaluate caption quality, we use classic metrics in the literature such as BLEU, METEOR, ROUGE_L, CIDEr and SPICE [3]. All the aforementioned metrics were calculated through the implementation in the MS COCO caption evaluation package [4]. Additionally, we use the recent BERTRScore [21] metric which has a better correlation with human judgment. Regarding the evaluation of sentiment analysis, we also use established metrics, namely the F-score and the classification accuracy.

B. Image Captioning Results

In Table 1 we present the captioning results on the Flickr8k dataset. We compare the baseline model with the proposed ICR model, displaying the performance of the different representations suggested to encode the retrieved target caption, namely using average pre-trained embeddings (avg), weighted average (weighted) and RoBERTa sentence embeddings (RoBERTa). Results show that the ICR model outperforms the baseline, achieving a better performance on all metrics independently of the representation used. The best performance was achieved using the nearest target encoded with the weighted average, followed by simple average and then succeeded by RoBERTa embeddings, with all the three surpassing the baseline. We hypothesise that static fastText embeddings worked better than contextual RoBERTa embeddings in the representation of the retrieved target possibly due to the use of fastText embeddings for the input words in the captioning model as well, lying in the same representation space.

A representative example is shown in Figure 2 containing the captions generated by the aforementioned models, together with a visualization of our multi-level attention mechanism from the best model (ICR weighted). We provide more examples in Figure 3. These qualitative results further confirm that the ICR weighted model tends to produce better captions.

http://cs.stanford.edu/people/karpathy/deepimagesent/
http://github.com/tylin/coco-caption
TABLE I
IMAGE CAPTIONING PERFORMANCE ON THE FLICKR8K TEST SPLIT, WITH THE BEST RESULTS SHOWN IN BOLD.

| Models        | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | METEOR | ROUGE-L | CIDEr | SPICE | BERTScore |
|---------------|--------|--------|--------|--------|--------|---------|-------|-------|-----------|
| Baseline      | 0.5541 | 0.3848 | 0.2554 | 0.1691 | 0.1948 | 0.4421  | 0.4526| 0.1353| 0.4945    |
| ICR avg       | 0.6044 | 0.4199 | 0.2838 | 0.1921 | 0.1995 | 0.4537  | 0.4815| 0.1400| 0.5141    |
| ICR weighted  | 0.6080 | 0.4251 | 0.2857 | 0.1896 | 0.2002 | 0.4583  | 0.4897| 0.1364| 0.5250    |
| ICR RoBERTa   | 0.5831 | 0.4023 | 0.2689 | 0.1788 | 0.1992 | 0.4476  | 0.4643| 0.1373| 0.5064    |

TABLE II
IMAGE CAPTIONING ABLATION STUDY ON FLICKR8K TEST SPLIT. THE BASELINE IS COMPARED AGAINST THE USE OF THE RETRIEVED TARGET IN THE LSTM’S INITIAL MEMORY STATE (initialization $m_0$) AND IN THE ATTENTION MECHANISM (multi-level attention). THE BEST RESULTS ARE SHOWN IN BOLD AND THE SECOND-BEST ARE UNDERLINED.

| Models                                | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | METEOR | ROUGE-L | CIDEr | SPICE | BERTScore |
|---------------------------------------|--------|--------|--------|--------|--------|---------|-------|-------|-----------|
| Baseline                              | 0.5541 | 0.3848 | 0.2554 | 0.1691 | 0.1948 | 0.4421  | 0.4526| 0.1353| 0.4945    |
| ICR weighted initialization $m_0$     | 0.5971 | 0.4188 | 0.2817 | 0.1877 | 0.2016 | 0.4548  | 0.4822| 0.1377| 0.5263    |
| ICR weighted multi-level attention    | 0.5908 | 0.4134 | 0.2782 | 0.1873 | 0.2030 | 0.4534  | 0.4926| 0.1371| 0.5260    |
| ICR weighted (combined)               | 0.6080 | 0.4251 | 0.2857 | 0.1896 | 0.2002 | 0.4583  | 0.4897| 0.1364| 0.5260    |

Regarding the multi-level attention mechanism, in general, we noticed that the ICR weighted model tends to attend to the current input image in the beginning of the generation process and, after obtaining the current context, the model switches its attention to focus more on the semantics of the nearest caption. As observed in this example, the retrieved information can aid the prediction and it can also provide some evidence for the model’s decision. We thus argue that augmenting LSTM models with retrieved examples can also bring benefits in terms of model interpretability. We also provide some retrieved nearest examples in Figure 3. The encoder was pre-trained on the ImageNet dataset. This sometimes results in retrieved images that are not that similar to the given image or with some similar aspects but with different caption contexts (see the last row of the table). Better image representations could be achieved by fine-tuning the encoder on a task derived from the information associated to the captions (e.g. the nouns and adjectives of the captions, thus promoting similarity between images that correspond to similar captions).

Fig. 2. Upper: A visualization of our multi-level attention mechanism, showing how much attention the ICR weighted model pays to the current input image (blue bars) and to the retrieve target caption (orange bars). Bottom: the generated captions by the different models for the input image.

Fig. 3. Examples of retrieved images together with the corresponding target captions used in our ICR models. We also performed ablation studies, as shown in Table II to quantify the impact of each method we use in the ICR model: the retrieved target incorporated in the LSTM’s memory state (initialization $m_0$) and the multi-level attention mechanism (multi-level attention). Specifically we compare the baseline against the best performed model (ICR weighted), either including the former or the later method. Observing Table II, the baseline obtains the lowest scores across all metrics. The performance is improved using the retrieved information in the LSTM memory cell or in the attention, showing that the retrieved targets are effectively exploited in both methods. We also note that there are little gains from...
Fig. 4. Examples of test captions generated by the different models under analysis. The captioning quality tends to improve using the semantics of the retrieved target captions (highlighted in bold).

C. Sentiment Analysis Results

Table III presents the sentiment analysis results on the IMDB dataset. We contrast the baseline model against the proposed SAR model, comparing the performance of the different representations suggested to encode the retrieved target label, consisting in using vectors of -1s and 1s (-11s) to represent the negative and positive labels, respectively, or using the average of fastText embeddings (avg) of all the positive and negative training reviews, their weighted average (weighted) or RoBERTa sentence embeddings (RoBERTa). While the performance decreases with the SAR -11s model compared to the baseline, suggesting that this representation is not effective, the other SAR models slightly outperform the baseline, yielding a better performance on both accuracy and F-score. Our best result, using the SAR avg model, yields a 0.053 increase in accuracy compared to the baseline and a 0.052 increase in the F-score. We also conducted ablation studies with the proposed methods (i.e., initialization $m_0$ or multi-level attention), and observed that both outperformed the baseline, as can be seen in Table IV. It is to be noticed that the differences in performance are very small, but perhaps with a more challenging dataset or in another classification task the influence could be larger. For some retrieval examples please combining the two methods. Overall, the performance of both proposed methods is similar and each of the two can be used to capture the retrieved information.
see Table V. In most cases, the Text Retrieval is effective in finding a good neighbor but sometimes the neighbor can be the same movie with an opposite review as we can see in the last example.

**TABLE III**

| Models           | Accuracy | F-score |
|------------------|----------|---------|
| Baseline         | 0.8930   | 0.8929  |
| SAR -II          | 0.8914   | 0.8913  |
| SAR avg          | 0.8983   | 0.8981  |
| SAR weighted     | 0.8978   | 0.8976  |
| SAR RoBERTa      | 0.8963   | 0.8961  |

**TABLE IV**

| Models                        | Accuracy | F-score |
|-------------------------------|----------|---------|
| Baseline                      | 0.8930   | 0.8929  |
| SAR avg initialization \(\mu_0\) | 0.8935   | 0.8933  |
| SAR avg multi-level attention | 0.8949   | 0.8948  |
| SAR avg (combined)            | 0.8983   | 0.8981  |

### V. RELATED WORK

Our approach is closely related with those from some previous studies, in which models predict the output conditioned on retrieved examples [5] [19]. Hashimoto et al. [5] used an encoder-decoder model augmented by a learned retriever to generate source code. The authors suggest a retrieve-and-edit approach, in which the retriever finds the nearest input example and then that prototype is edited into an output pertinent to the input. In turn, Weston et al. [19] introduced a retriever for dialogue generation. The idea is to first retrieve the nearest response and then the generator, i.e. a seq-to-seq model, receives the current input concatenated with the retrieved response, separated with a special token. Our approach is similar, but rather than concatenating the input with the retrieved example, we make use of an LSTM’s memory cell state to incorporate the nearest training example. In our view, the retrieved examples should be considered as additional context, and not be treated as regular input. Also, unlike Hashimoto et al. [5], our retrieval component does not need to be trained.

Our retriever is, in fact, based on that from Khandelwal et al. [10]. In their work, a pre-trained Language Model (LM) is augmented with a nearest neighbors retrieval mechanism, in which the similar examples are computed using FAISS. The probabilities for the next word are computed by interpolating the LM’s output distribution with the nearest neighbor distribution. However, different from their work, we do not use the retriever just for inference, aiding the prediction both during training and testing time.

Retrieved examples have also been used to guide attention mechanisms. For instance Gu et al. [4] described an attention-based neural machine translation model that attends to the current source sentence as well to retrieved translation pairs. There are also other multi-level attention studies that attend to more than the input. Lu et al. [14] proposed an adaptive encoder-decoder framework that can choose when to rely on the image or the language model to generate the next word. Li et al. [12] proposed three attention structures, representing the attention to different image regions, to different words, and to vision and semantics. Our retrieval multi-level attention mechanism takes inspiration from these approaches. Note, however, that our attention mechanism is simpler and can be easily integrated on top of other attention modules. Our multi-level mechanism attends to the retrieved vector and to a given attention vector, which does not need to be the visual context vector that we used for image captioning or the context vector from the hidden states used for sentiment analysis. We can plug-in any context vector to be attended together with the retrieved target vector.

### VI. CONCLUSIONS AND FUTURE WORK

In this work, we proposed a new approach that can incorporate into any LSTM model, leveraging the information of similar examples in the training set, during training and test time. For a given input, we first retrieve the nearest training input example and then use the corresponding target as auxiliary context to the input of the neural network or to guide its attention mechanism. We showed that the retrieved target can be easily incorporated in an LSTM initial memory state and we also designed a multi-level attention mechanism that can attend both to the input and the target of the nearest example. We conducted a series of experiments, presenting alternative ways to represent the nearest examples for two different tasks, image captioning and sentiment analysis. Both the Image Captioning Retrieval model and our Sentiment Analysis Retrieval model yield better results than baselines without the retrieved information. Besides aiding to improve result quality, this retrieval approach also provides cues for the model’s decisions, and thus it can also be of help in terms of making models more interpretable.

Despite the interesting results, there are also many possible ideas for future work. For instance, further work could better explore our approach in terms of interpretability. Additionally, both models could be improved by receiving information from the top nearest examples, instead of relying on a single retrieved example. In the particular case of image captioning, it would be important to fine-tune the encoder used in the retrieval component for producing better image representations in order to ensure a more effective search of nearest examples. In addition, the selection of the retrieved target could also be improved. In this work, we simply select the first reference of the retrieved input image, when there are actually five possible references for the retrieved target. It would be interesting to select the most descriptive caption (i.e., in terms of length) or the most similar one between the five, or even try to combine the information of the five reference captions. Furthermore, the proposed multi-level attention mechanism could attend to the various words of the retrieved caption, as it does for the
image regions. Regarding sentiment analysis, our main priority involves conducting more experiments in more challenging datasets than the IMDB reviews to better assess the proposed approach. Moreover, we also plan to test with datasets that have more fine-grained labels than only positive or negative targets. We also note that, in movie reviews, neighbor inputs can have different targets but be similar, since they refer to the same movie. Therefore, exploring the proposed approach to the task of intent classification could be more effective since neighbor inputs usually have the same targets.

Therefore, exploring the proposed approach involves conducting more experiments in more challenging image regions. Regarding sentiment analysis, our main priority involves conducting more experiments in more challenging datasets than the IMDB reviews to better assess the proposed approach. Moreover, we also plan to test with datasets that have more fine-grained labels than only positive or negative targets. We also note that, in movie reviews, neighbor inputs can have different targets but be similar, since they refer to the same movie. Therefore, exploring the proposed approach to the task of intent classification could be more effective since neighbor inputs usually have the same targets.

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