Self Supervision for Attention Networks

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Abstract

In recent years, the attention mechanism has become a fairly popular concept and has proven to be successful in many machine learning applications. However, deep learning models do not employ supervision for these attention mechanisms which can improve the model's performance significantly. Therefore, in this paper, we tackle this limitation and propose a novel method to improve the attention mechanism by inducing "self-supervision". We devise a technique to generate desirable attention maps for any model that utilizes an attention module. This is achieved by examining the model's output for different regions sampled from the input and obtaining the attention probability distributions that enhance the proficiency of the model. The attention distributions thus obtained are used for supervision. We rely on the fact, that attenuation of the unimportant parts, allows a model to attend to more salient regions, thus strengthening the prediction accuracy. The quantitative and qualitative results published in this paper show that this method successfully improves the attention mechanism as well as the model's accuracy. In addition to the task of Visual Question Answering(VQA), we also show results on the task of Image classification and Text classification to prove that our method can be generalized to any vision and language model that uses an attention module.

1. Introduction

Humans beings have the ability to comprehend a scene by paying attention to selective parts of an image instead of processing the entire scene. This ability to intelligently pick where to look reduces the problem complexity as it allows us to focus on regions of interest and ignore the background clutter. The attention mechanism, inspired by such human behavior, has gained immense popularity among researchers. But even after commendable success in various tasks (like machine translation, object recognition, image captioning, visual question answering, etc) the attention modules that implicitly learn during training are not very accurate. They differ immensely from human attention (i.e. where human beings attend to while performing the same task) and this results in incorrect predictions by the model. Thus, adding supervision to the attention module can be beneficial as explored in previous research works of [20] [8] [23]. Das *et al.* in [8] depicted that there is a strong interdependence between focusing on the 'right regions' and obtaining better semantic understanding while solving a problem. They showed (in the context of visual question answering) that an attention model that correlates better with human attention has better reliability in predicting the correct output and introduced a dataset of human-like attention called VQA-HAT. However, obtaining such human-like attention maps for the supervision of each machine learning task is impractical and unrealistic, as annotations are time-consuming and require a lot of human resources.

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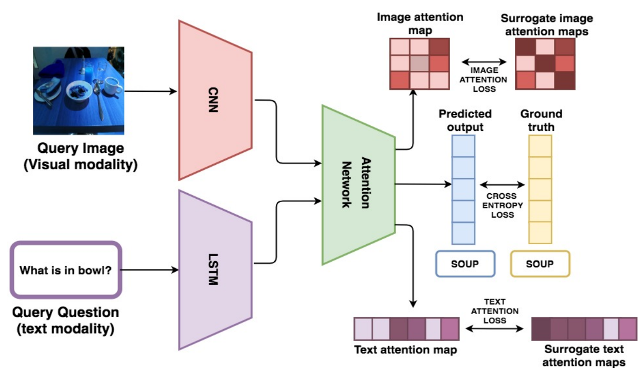


Figure 1. Supervision of attention module using surrogate attention maps in a multi-modal system taking VQA as the example.

To tackle this problem, in this paper we propose a novel method to provide "self-supervision" for an attention network without incorporating any external module or dataset. This method can be used with inputs of different modalities (text and image are analyzed in this paper) and can be generalized to any attention-based neural network. We generate desirable attention maps that act as the surrogate ground truth for the attention maps implicitly produced by a model.

These surrogate attention maps are generated by feeding the pre-trained baseline model with randomly masked versions of the inputs. The confidence of the model for prediction of the ground truth for each masked input is recorded. This way, we find out the input regions salient for the ground truth class prediction by analyzing the masked input and its corresponding confidence score for the ground truth prediction.

Figure 1 shows the supervision technique proposed in this paper. The architecture shown displays the multi-modal supervision technique. For the individual tasks of image attention supervision and text attention supervision, the basic architecture remains the same, however, only the corresponding input modality is present. We define this approach in detail and also explain the generation of surrogate attention maps used for supervision in section 3. The major contributions of this paper are as follows:

- We provide a novel technique to generate attention maps which are analogous to human attention, which are used as self-supervision for the attention model
- We show that the addition of supervision not only allows the model to generate better attention maps but also increases its prediction accuracy.
- We show the generality of our method by applying it to three distinct classification tasks employing different attention mechanisms.

2. Related Work

Attention: The main objective of the attention mechanism is to either highlight the important local information or address the issue of irrelevant noise brought by the global features. It is one of the most successful techniques used in deep learning for computer vision and natural language processing. Past work on attention include [12] [28] [31] [24] [30] [21]. Vaswani *et al.* [28], propose an architecture based solely on attention mechanism which performs well on the task of machine translation. Yang *et al.* [31] show that image question answering often requires multiple steps of reasoning and using multiple layers of attention leads to a better model. Xu *et al.*[30] show through visualization, how the model can automatically learn to fix its gaze on salient objects while generating caption. Hence, the ability of attention is enhanced by the fact that it can benefit a wide range of distinct problems. An interesting work by Fukui *et al.* [10], proposes an Attention Branch Network for CNN architecture and improves the model's performance by using an attention branch but differs with our method as we explicitly try to improve the attention mechanism which in turn improves the model's prediction capabilities and cannot our method can be generalized beyond CNN. Patro *et al.*[20] also try to obtain an improved attention for a visual question answering (VQA) task by employing an external explanation module and incorporating a discriminator that aims to bring distributions of attention maps and visual explanation closer. However, in our method instead of using explanation as supervision, we generate desirable attention maps implicitly from the existing pre-trained model.

Self-supervision: The concept of self-supervision was introduced to overcome the limitations of traditional supervision such as effort of producing new datasets, availability of vast amount of unlabelled data or difficulty in providing annotations. Some of the work which can be considered as self-supervised include [5], [26], [6], [21]. Patro *et al.* [21] proposed an exemplar base self-supervision method to improve attention for the Visual Question Answering task. However, this method uses a pre-trained model to get an exemplar image, which is not an exact method for self-supervision.

Self-Attention: The self-attention(also called intra-attention) module helps in finding out the relationship amongst different segments of an input to a model and where to pay more attention. This mechanism can also be used for a wide variety of tasks. Cheng *et al.* [7] correlate the previous sentence with the current word using self-attention and achieves good results for the task of machine reading. Xu *et al.* [30] has proposed a self-attention based method to generate proper descriptions of the contents depicted in an image.

In this paper for the purpose of attention in text, we choose the self-attention mechanism proposed by Lin *et al.* [18], although our proposed method can be extended to any attention mechanism in general. To provide a thorough analysis of our technique we apply our method to 3 tasks i.e. Image Classification, Text Classification, and VQA. The VQA task was first proposed by Malinowski *et al.* [19] and combines both textual and visual modalities. Past work on VQA include [2] [13] [29]. The analysis of our method for image and text classification is done on CIFAR-10 [16] and TREC-6 [1] datasets respectively. The randomized masking technique for images in our model resembles the work by Petsiuk *et al.* [22] in which this technique is used for obtaining visual explanation. We take inspiration from this and use the masking technique to get supervision for our attention model in images. In the case of text, we simulate masking by concealing two words at a time and feeding it to the classification model as input.

3. Method

The process of yielding supervision for attention involves two steps. The first step is to generate surrogate ground truth attention maps $\hat{Att}$ from the baseline model pre-trained on the required machine learning task. The second step involves re-training the model and supervising the attention maps produced by the model Att with $\hat{Att}$ which gives the model an additional supervision. The improved attention module helps the model to focus on the right regions, removes the noise from the input, and thus enhances the model's prediction capabilities. The first step of generating attention maps $\hat{Att}$ for image i.e. $\hat{Att}_I$ and for text i.e. $\hat{Att}_Q$ involves different methods which are explained in the subsequent sub-sections.

For the second step of supervision, we utilize a similar mechanism for image and text. The generated attention maps $\hat{Att}$ are considered to be the surrogate ground truth for Att produced by the model. We calculate the loss L_{att} between the $\hat{Att}$ and Att to introduce the supervision for attention mechanism as:-

$$L_{att} = loss(\hat{Att}, Att) \tag{1}$$

We use different variants of the $loss()$ function for calculating attention loss and present results with all the variants. The details of all four types of loss functions used are explained in section 4.3.

The attention Att produced by the model is applied over the input and non-linearities are then applied to the attended input to produce probabilities over the class labels. The classification loss is defined as:-

$$Loss_c = \frac{1}{K}\sum_{k=1}^{K} -logP(a_k|input) \tag{2}$$

Note that we average the log-likelihoods over all the correct answers $a_1, a_2, ..., a_K$ where K is the number of training samples. The final loss is calculated as $Loss_c + \gamma * Loss_{att}$ where γ is the scaling factor which brings both the losses to the same scale.

3.1. Generation of Surrogate Attention Supervision for Images

We first generate m random masks with values in the range [0,1] for each region. For each input, we apply the m generated masks and probe the model with all the masked versions of that input. Then we find out the attention map with the highest confidence in predicting the ground truth as shown in figure 2. The selector module shown in the diagram is a simple rule-based module that selects the attention map with the highest score for ground truth prediction. We choose a singular attention map with the highest prediction score for ground truth instead of considering the weighted sum of all the attention maps because during initial experiments we found that we get better results, both qualitatively and quantitatively with the former. This might be due to the fact that the weighted average method gives certain importance to regions corresponding to non-ground truth classes as well whereas the highest-scoring mask focuses almost entirely on regions important to the ground-truth class.

Let the image features obtained after passing through a CNN architecture such as ResNet or VGGNet be $X \in \mathcal{R}^{\mathcal{C}\times\mathcal{N}}$ where C represents the number of channels and $N = W * H$ represents the dimension of image features. Let M_i be a random mask with values of each region in the range of [0,1] and having it's dimensions the same as image regions i.e $W * H$. The masked versions of input are obtained by element-wise multiplication of the input with a mask and are represented as $X \odot M_i$ where M_i can be $M_0, M_1, \ldots, M_m$. A mask is applied to each channel of the image feature producing the masked input $X'_i = X \odot M_i \in \mathcal{R}^{\mathcal{C}\times\mathcal{N}}$. Let the ground truth class probability predicted by the pre-trained baseline model when probed with masked image be $f(X'_i)$. We find mask M_i with which we get the maximum value of $f(X'_i)$ and re-

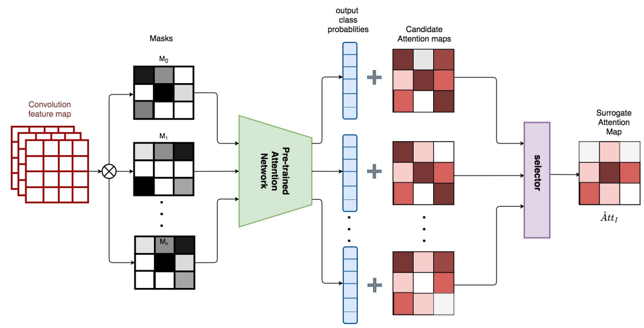


Figure 2. Generation of Surrogate Attention Maps for visual-attention based network.

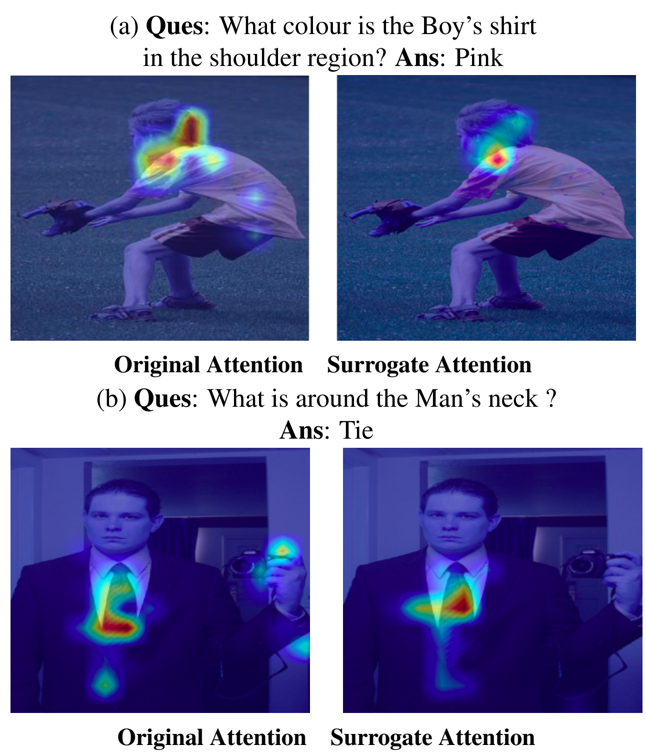


Figure 3. Comparison of Image Attention Maps with(right) and without(left) Masking for VQA.

trieve the attention map $\hat{Att}_I$ generated by the pre-trained model when for the corresponding input i.e. X_i'.

The image features for the task of VQA were extracted from layer 4 of ResNet-152 network, therefore the number of channels is $C = 2048$ and the number of regions $N = 14 \times 14$. The baseline model used for evaluation of our method on VQA is similar to the one proposed in [13] but slightly modified by including the self-attention module for text as well. This modification makes the model standard for comparison with our method for both image and text attention supervision. For image classification on CIFAR-10 we obtain image representation with $C = 32$ and $N = 8 \times 8$ for each image. We implement a CNN based classification code and apply the self-attention module to use as a baseline for classification on the CIFAR-10 dataset. The variation in the above feature dimensions for different tasks is intended to show that our method is independent of the number of channels and can be extended to any channel size.

Figure 3 shows the attention maps produced by the pre-trained baseline VQA model. It depicts the comparison between the attention map originally produced by the model and the attention map chosen i.e. $\hat{Att}_I$ after probing the model with masked inputs. It clearly shows that $\hat{Att}_I$ correlates better with human attention as masking helps in hiding the unimportant regions and enables the model to focus more accurately on the regions that are important for obtaining the ground truth answer.

3.2. Generation of Surrogate Attention Supervision for Text

To generate supervision for attention maps of text, we aim to find out the words which the model needs to attend to more, for predicting the output class correctly. Suppose we have a text T which has n words $(q_1, q_2, q_3, \ldots, q_n)$, we mask two words at a time and probe the classification model with the masked text T' for example , $T' = (t_1, t_2, 0, 0, \ldots, t_n)$. There are total $\binom{n}{2}$ possible combinations for T'. Let the ground truth class probability predicted by the model when probed with masked text be $f(T')$. We find the masked text T' with which we get the maximum value of $f(T')$, and retrieve the attention map $\hat{Att}_Q$ generated by the model when probed with T'. This method is depicted in figure 4. Similar to images, we choose one attention map instead of a weighted average of all for text as well. The self-attention model used for text classification on the TREC-6 dataset is [18] which provides the baseline for our experiments and results. We use the same baseline for the VQA task as defined in 3.1 but in this case, we supervise the attention module that attends to text. We get a better attention map $\hat{Att}_Q$ with the masked question as compared to the one generated with the unmasked question Att_Q, as shown in figure-5. This is again because the noise i.e. the unimportant regions are being hidden from the model and

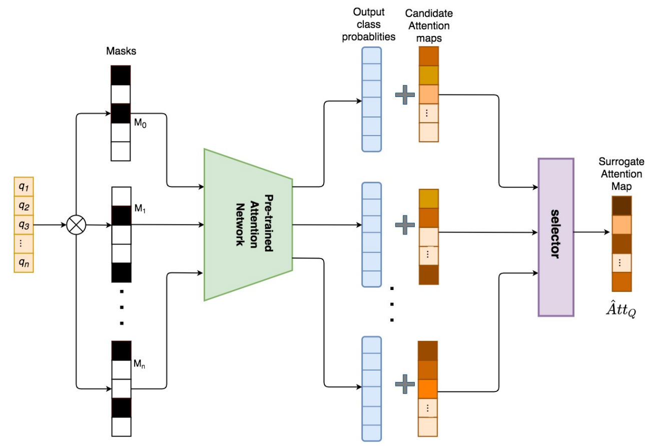


Figure 4. Generation of Surrogate Attention Maps for textual-attention based network.

thus the model focuses on the important regions.

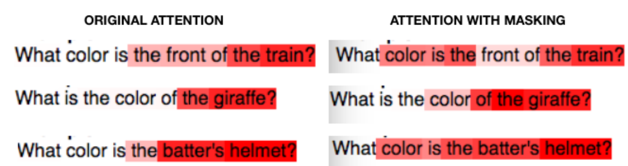


Figure 5. Comparison of text attention visualisation with(right) and without(left) masking for the task of VQA. Here, opacity of the red color is directly proportional to weight of the corresponding word in the attention map generated

3.3. Combined multimodal supervision

We also provide the method for supervision on both image and text combined as shown in fig. 1. This method is evaluated on VQA only, as it combines both these modalities. First, surrogate ground-truth attention maps are retrieved as explained in 3.1 and 3.2. The supervision is then done by minimizing $Loss = Loss_c + \gamma * Loss_{attI} + \beta * Loss_{attT}$ where $Loss_{attI}$ is the image attention loss, $Loss_{attT}$ is the text attention loss and γ, β are scaling factors. The baseline model used for comparison in VQA remains constant in this case as well and is the same as the one defined in 3.1. However, the difference in this case as expected is that we supervise both image and text attention modules.

4. Experiments

We evaluate our proposed method and provide both quantitative and qualitative analyses for the VQA task. VQA is a classification task in which we give an image and question as input and the output is one of 3000 possible answers. The baseline model used is VQA-SAN with self-attention introduced for text. Quantitative analysis includes i) evaluation of our proposed model against the baseline models ii) comparison of the attention map generated by our proposed model with the attention map generated by the baseline model for VQA task by calculating Rank Correlation (RC) score and Earth Mover Distance (EMD) [4] against VQA-HAT dataset [8] as shown in table 3. The qualitative analysis includes i) visualization of image attention maps generated by the baseline and our proposed model (fig 8), ii) visualisation of text attention maps for question(fig 9).

Further, we provide quantitative analysis for image and text classification. We show the accuracy comparison of the baseline model with our method. The baseline used for text classification is [18] and for image classification, we implement a basic CNN based classification model with a self-attention module. We also provide the code for our method on Text Classification task[1].

4.1. Dataset

We evaluate our method on three dataset , 1) VQA-v1 [3], 2) CIFAR-10[16] and 3) TREC-6[1]. For the VQA task we choose VQA-v1 [3] which consists of 204,721 images form the MS COCO dataset [17]. This evaluation is done on the real open-ended challenge which consists of 614,163 questions and 6,141,630 answers.

We choose VQA v1 dataset to evaluate our model because it allows us to compare the attention maps produced by our model against the VQA HAT dataset, which in turn, allows us to quantify whether our VQA model is "looking" at the same regions of the image as humans do to produce an answer. Furthermore, we are quantitatively able to prove that our model is able to achieve its ultimate goal that is to improve the attention maps produced by an attention-module-based deep learning model.

CIFAR-10[16] dataset is an image dataset that consists of 60000, 32×32 size color images. The train split consists of 50000 and the test split consists of the remaining 10000 images. There is a total of 10 class labels in which the images are classified.

TREC-6[1] is a dataset for text classification consisting of 5452 train and 500 test samples classified into 6 class labels. We evaluate our method on this dataset and provide results in section-4.6.

4.2. Training and Model Configuration

We train our model intending to minimize the total loss given by: $Loss_{total} = Loss_c + \gamma * Loss_{att}$ Where $Loss_c$ is cross-entropy classification loss, which signifies the difference between ground truth and prediction. The $Loss_{att}$ is the loss between surrogate attention maps and the attention maps predicted by the model. Apart from the adversarial loss, $Loss_{att}$ was also taken as CORAL[25] loss, Mean Square Error (MSE) loss, and maximum mean discrepancy (MMD)[27] loss for supervision loss for training our model to show the comparison between these losses. As shown by the results, the adversarial loss has the best performance.

We form the binary masks for images, by randomly assigning values of 0 and 1 to maps with dimensions $\frac{W}{s} * \frac{H}{s}$ and then using bilinear interpolation for creating maps of size $W * H$. Hence, each region has a corresponding value in the map between 0 and 1. We take the value of 's' as 6 for VQA dataset and 2 for CIFAR-10 dataset after extensive experimentation and a total number of masks as 500 for each image. We also include a mask with all values as 1 i.e., the entire image is sent without masking any region. This was done because in some cases sending the whole image gave the best result and so this case needed to be considered as well. In the case of text, we do not mask randomly, instead, we calculate the importance of each word in the text itself by masking two words at a time as discussed in section 3.2.

[1]The code is available at https://github.com/Anonymous1207/Self_Supervsion_for_Attention_Networks

4.3. Loss Functions

Adversarial Loss: For this variant, we formulate the supervision task as a zero-sum adversarial game between two players ($\hat{A}tt$,Att), with one set of players being a Generator (G) network and the other being a discriminator (D) network. The solution for a zero-sum game is called a min-max solution, where the min-max [11] objective is defined as:-

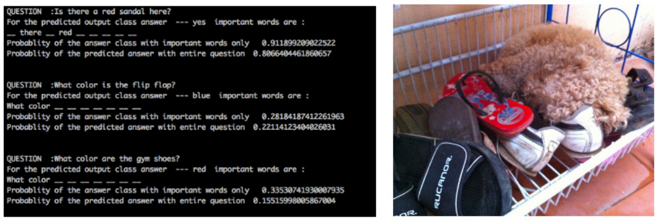
$$\min_G \max_D L_{att}(G, D) = E_{g_{Att} \sim G_{Att}(x_i)}[\log D(g_{Att}/x_i)] + E_{g_{\hat{A}tt} \sim G_{\hat{A}tt}(x_i)}[\log(1 - D(G(g_{\hat{Att}}/x_i)))] \tag{3}$$

Maximum Mean Discrepancy (MMD) Net: In this variant, we minimize this distance using MMD [27] based standard distribution distance metric. We have computed this distance with respect to a representation $\psi(.)$. In our case, we obtain representation feature $\psi(\alpha)$ for attention & $\psi(\mu)$ for importance map for ground-truth class. Then we compute the distance vector between them

$$L_{MMD}(\mu, \alpha) = \Big|\Big|\frac{1}{\mu}\sum_{\mu_i \in \mu}\psi(\mu_i) - \frac{1}{\alpha}\sum_{\alpha_i \in \alpha}\psi(\alpha_i)\Big|\Big| \tag{4}$$

CORAL Net: In this variant, we minimize the distance between second-order statistics (co-variances) of attention and importance map using CORAL loss [25] based on standard distribution distance metric. Here, both (μ) and (α) are the d-dimensional deep layer activation feature for attention and importance map. We have computed feature co-variance matrix of attention feature and importance

(a) Example 1



(b) Example 2

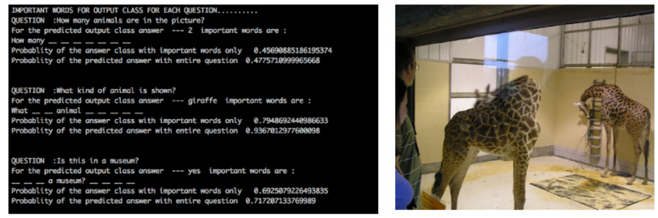


Figure 6. Right side of each example shows original image and left side shows importance of each words and corresponding answer prediction probability if only unmasked words are sent as questions.

map feature represented by $C(\alpha)$ and $C(\mu)$ respectively. Then we compute the distance between their second-order statistics(co-variance) using the following formula where $||.||_F$ is the square matrix Frobenius norm:

$$L_{Coral}(\mu, \alpha) = \frac{1}{4}||C(\mu) - C(\alpha)||_F^2 \tag{5}$$

MSE Net: In this variant, we minimize the Mean Square Error between the attention mask and importance map. The mean square loss is defined by :

$$L_{MSE}(\mu, \alpha) = \frac{1}{N}\sum_i (\mu_i - \alpha_i)^2 \tag{6}$$

We evaluate the above architectures for the method proposed in this paper although we advocate the use of adversarial loss as it shows the best result.

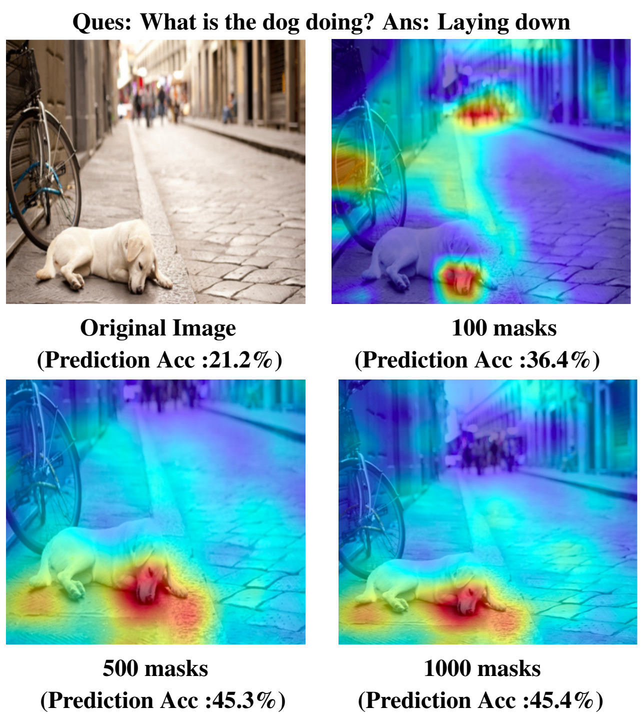


Figure 7. Comparison of surrogate attention maps taking different number of masks

4.4. Selection of masks for image attention

The number of masks was selected by conducting an experiment to determine the effect of the number of masks on the output probability for the ground truth while considering computation complexity as well. We experimented with 100, 500, and 1000 masks on a few images and visualized the results as shown by the example in figure 7. The experiment revealed that for most images the score for the ground truth increased significantly when the number of masks was increased from 100 to 500 whereas, for 1000 masks, the accuracy was either comparable or insignificantly improved to 500 masks. Hence the optimum number of masks was chosen to be 500.

4.5. Importance of text tokens

Although we generate self-supervision for attention in text by masking two words at a time, we conducted experiments to determine the importance of different words in text for the task of VQA as well. We first obtained the output probability of ground-truth answers by masking all except one word, similarly, we masked all words except two and so on. The results for masking all words except two are shown in 6. We send each text input with all text tokens (i.e. words) masked except two and extracted the two words that achieved the highest score in predicting the correct answer. The experiment revealed that in most cases, a high confidence score (close to the score obtained when the entire text input is used) for predicting ground-truth answers was achieved even when two words were given as input. In some cases, the masked input even outperformed the iteration where the entire unmasked text is given as input. This experiment further enforced that few tokens are more important than others in text inputs and few tokens even add noise that makes a model predict poorly. Hence, improvement in attention for text correlates to the enhancement of a model's accuracy.

4.6. Quantitative Results for Image and Text Classification

The tables 1 and 2 show the results of Text classification and Image classification on TREC-6 and CIFAR-10 datasets respectively. The results depict the comparison of

Model	Accuracy
Baseline Model	81.20
Text Supervision + Coral	81.89
Text Supervision + MSE	82.33
Text Supervision + MMD	84.80
Text Supervision + Adv	84.91

Table 1. Accuracy comparison on TREC-6 dataset for text attention supervision.

Models	Accuracy
Baseline Model	69.59
Image Supervision + Coral	69.83
Image Supervision + MSE	69.87
Image Supervision + MMD	70.80
Image Supervision + Adv	71.12

Table 2. Accuracy comparison on CIFAR-10 dataset for Image attention supervision.

our method with the baseline. Moreover, we train the model with self-supervision of attention, using different types of losses as defined in Section 4.3 and show the results. These results reinforce one of the claims in this paper that the proposed method can be extended to multiple models that are attention-based and improve the results. We are able to achieve a 3.7% improvement in accuracy over the baseline for text classification and 1.5% improvement over the baseline for image classification. Accuracies are shown for the test split of both the datasets. We advocate the use of Adversarial loss as it gives better results compared to other losses.

(a) **Ques** : What is in the bowl?
Ans: Soup

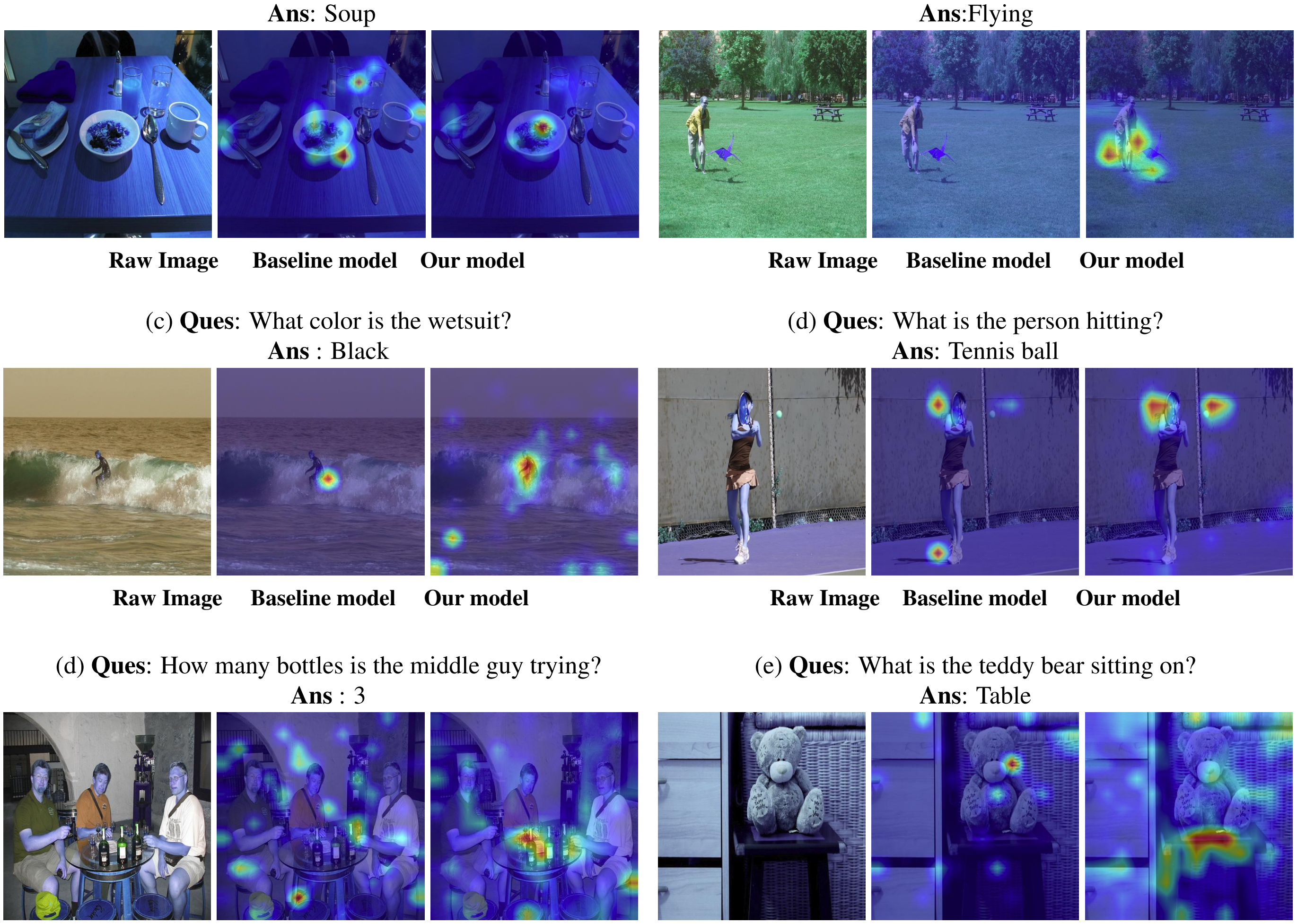
(b) **Ques**: What is the person doing to the kite?
Ans:Flying

(c) **Ques**: What color is the wetsuit?
Ans : Black

(d) **Ques**: What is the person hitting?
Ans: Tennis ball

(d) **Ques**: How many bottles is the middle guy trying?
Ans : 3

(e) **Ques**: What is the teddy bear sitting on?
Ans: Table



Raw Image **Baseline model** **Our model**

Figure 8. Comparison of the attention maps generated by the baseline VQA model and our proposed model. Using our self-supervision technique, our method focus on. more accurate as compare to baseline attention map.

4.7. Qualitative Analysis for VQA (Multimodal)

We compare the attention maps generated by the baseline model and our proposed technique and observe a significant improvement in our method. In figure 8 we can see how attention is improved as we go from the baseline model (SAN[32]) to the proposed model. For example, in the first illustration, the baseline is unable to focus on any specific portion of the image, but the proposed model is able to focus accurately on the bowl (indicated by intense orange color). The same can be observed for other illustrations. The comparison of text attention is also shown in the figure 9. It is shown that the method proposed in this paper can focus more clearly on words that are considered important by humans while answering such questions. For example, for the question "What is leaning against the house?", the baseline method does not attend well to "leaning" which is an important word to answer this question.

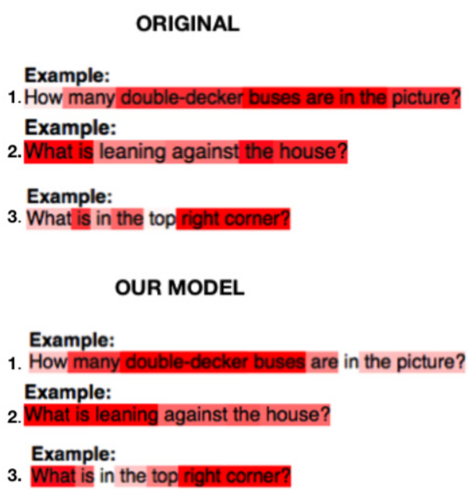


Figure 9. Comparison of self attention of text for baseline and our proposed method.

4.8. Quantitative results for VQA

We compare attention maps generated by our proposed method with the baseline VQA method (SAN[32]) based on rank correlation metric and EMD metric against the VQA-HAT dataset [8]. The results as shown in table 3 show the ability of our method to improve attention and correlate better with human attention. We also compare the results of the baseline model with our proposed method based on answer prediction accuracy using the VQA-v1[3] dataset, as shown in the table-4. We obtain an improvement of around 3.85% over the VQA baseline for the combined model with adversarial loss function used for calculating attention loss. Our proposed method with textual attention supervision improves by 2% and visual attention supervision improves by 3.7%. The accuracy improvement signifies that improving the attention also improves the prediction capability of the model. Our method can be extended to attention mechanisms other than (SAN) as well such as MCB [9], MLB [15] and BAN[14]. However, our objective is not to compare different attention modules but to propose a method to provide self-supervision for attention based deep learning models, so we select SAN which is relatively simpler and requires less computation.

Model	RC(↑)	EMD(↓)
Baseline	0.08	0.421
Ques + Coral	0.09	0.393
Ques + MSE	0.10	0.387
Ques + MMD	0.12	0.381
Ques + Adv	0.13	0.370
Image + Coral	0.10	0.381
Image + MSE	0.11	0.372
Image + MMD	0.13	0.369
Image + Adv	0.15	0.350
Both + Adv	0.15	0.352

Table 3. Rank Correlation and EMD between HAT attention and final generated attention masks from our model.

Models	All	Y/N	Num	Other
Baseline	58.08	76.7	35.2	44.2
Ques + Coral	58.17	76.03	36.3	45.2
Ques + MSE	58.85	76.8	36.9	45.6
Ques + MMD	59.29	77.0	37.04	46.0
Ques + Adv	60.11	77.5	37.5	46.7
Image + Coral	59.23	76.2	36.6	45.1
Image + MSE	60.42	77.07	37.21	45.7
Image + MMD	61.02	77.9	37.6	46.2
Image + Adv	61.76	78.3	38.2	47.0
Both + Adv	61.92	78.6	38.3	47.2

Table 4. Accuracy comparison on VQA-v1 dataset for VQA task.

5. Conclusion

In this chapter, we have proposed a method to obtain self-supervision for improving attention in both visual and textual modalities. Specifically, we consider the use of a random masking technique for obtaining attention supervision. Our method provides a means for obtaining surrogate supervision for attention. The proposed method also shows that improved attention indeed results in improved results for semantic classification tasks. In the future, we would like to investigate other such means for obtaining a higher correlation between human-like attention and a model's attention, and have an improved performance and higher interpretability for solving vision and language-based problems.

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