AdaVQA: Overcoming Language Priors with Adapted Margin Cosine Loss∗

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Abstract

A number of studies point out that current Visual Question Answering (VQA) models are severely affected by the language prior problem, which refers to blindly making predictions based on the language shortcut. Some efforts have been devoted to overcoming this issue with delicate models. However, there is no research to address it from the angle of the answer feature space learning, despite of the fact that existing VQA methods all cast VQA as a classification task. Inspired by this, in this work, we attempt to tackle the language prior problem from the viewpoint of the feature space learning. To this end, an adapted margin cosine loss is designed to discriminate the frequent and the sparse answer feature space under each question type properly. As a result, the limited patterns within the language modality are largely reduced, thereby less language priors would be introduced by our method. We apply this loss function to several baseline models and evaluate its effectiveness on two VQA-CP benchmarks. Experimental results demonstrate that our adapted margin cosine loss can greatly enhance the baseline models with an absolute performance gain of 15% on average, strongly verifying the potential of tackling the language prior problem in VQA from the angle of the answer feature space learning.

1 Introduction

Visual Question Answering (VQA) targets at accurately answering natural language questions regarding a visual scene. Perceived as a more ‘AI-complete’ task, VQA has received critical attention from both computer vision and natural language processing communities. Recently, several large-scale benchmarks [Antol et al., 2015; Goyal et al., 2017] have been constructed to facilitate the advancement of VQA, followed by a number of elaborately designed visual reasoning models [Kazemi and Elqursh, 2017; Anderson et al., 2018; Zhang et al., 2018].

Despite its flourishing development, there still exits a major issue in VQA, i.e., most VQA models tend to make predictions by taking the language shortcut between questions (or more specifically, question types1) and answers. For example, 2 takes large proportions of the answers to questions initiated with how many in the train set. And then the model leverages these language priors and directly yields answer 2 to how many questions when testing, regardless of both the remaining question words and the given image. As a result, the visual signal is largely under-explored, making the visual reasoning in VQA deteriorate into a pure language matching problem without the consideration of ‘V’. Obviously, it is a contradiction to the initial motivation of this vision-and-language task.

Many research efforts have been devoted to overcoming this arduous problem, which can be roughly classified into two groups: 1) balancing the biased dataset; and 2) correcting VQA models for alleviating the effects of language priors. In detail, the first category of methods contribute to either enlarging [Goyal et al., 2017] or re-splitting [Agrawal et al., 2018] the existing biased datasets. Notably, [Agrawal et al., 2018] curated a diagnostic dataset - VQA-CP, wherein the answer distributions of per question type are significantly distinct between the train and test sets. It thus provides a favorable test-bed for estimating the language prior effect the VQA model encounters. Based on this dataset, some pioneering work has been conducted to correct the advanced VQA models for alleviating language prior problem [Ramakrishnan et al., 2018; Chen et al., 2020; Guo et al., 2020]. A typical design of this category of methods is to attach an additional question-only branch, whereby the language prior is intentionally captured and further suppressed by the orthodox question-image branch.

Due to the fact that the answers in most VQA datasets are composed of a few words, existing VQA models often cast VQA as a classification task, i.e., classifying the answer class rather than progressively generating answer words to achieve better visual reasoning capability. However, what attracts our attention is that, there has been no research diving into investigating the learned feature space that each answer/class engages. We argue that the feature space learned from the

1We refer question type in VQA to the first few words in the given question.
biased dataset cannot distinguish the answers distinctly and is the key to alleviate the language prior effect. Inspired by this thought, we empirically visualize the 2-D embedding features of the answers to the question type how many in Fig 1b. One can see that different answers of the baseline are actually intertwined with each other in the two kinds of feature spaces. On the basis of this phenomenon, we make a further assumption: is it beneficial for overcoming the language prior problem if we properly separate the answers via manipulating their learned feature space?

To address this question, we propose to revisit the language prior problem from the viewpoint of the answer feature space learning. The primary goal of this work is to introduce an adapted margin for different answers in the angular space under the corresponding question type, which can effectively separate the answer embeddings. Towards this end, we firstly reformulate the softmax loss function as a cosine loss by $L_2$ normalizing both answer features $x$ and weight vectors $W_i$ [Liu et al., 2017; Wang et al., 2018a]. Consequently, the decision boundary can be computed through the cosine function of the angle $\theta_i$ between $x$ and $W_i$, i.e., $W_i^T x = \|W_i\|_2 \cdot \|x\|_2 \cdot \cos \theta_i = \cos \theta_i$, s.t. $\|W_i\|_2 = 1$ and $\|x\|_2 = 1$. Thereafter, an adapted margin $m_i$ is employed to separate the answer features, i.e., $\cos \theta_i - m_i$, where $m_i$ is computed based on the train set statistics of answer $a_i$ under the corresponding question type. In the ideal scenario, for each given question and its corresponding question type, frequent answers would span broader in the angular space with a smaller margin, while sparse answers span tighter in the angular space with a larger margin (see Fig. 1c). The intuition behind this is that frequent answers under certain question types often go with more training samples, and thus a smaller margin is required to control a broader space to sufficiently include these answers. In contrast, the number of sparse answers is relatively small, requiring a more tighter feature space. Moreover, we find that the answer embeddings in the Euclidean space become more discriminative, and further benefit the reducing of the language prior effect.

In a nutshell, the proposed adapted margin cosine loss is beneficial in overcoming the language prior problem in VQA, making itself being model-agnostic and easy to implement. Besides, it introduces NO incremental parameters or computational cost when testing. To the best of our knowledge, this is the first attempt to directly optimize the feature space learning to attack this problem. Additionally, we apply this loss function over three baseline methods, verifying its effectiveness on two VQA-CP benchmarks. The experimental results demonstrate that the baselines equipped with our loss achieve an absolute gain of over 15% averagely. The code is released for the re-implementation of this work.

2 Related Work

In recent years, a considerable literature has thrived around the task of VQA [Malinowski et al., 2018; Antol et al., 2015; Goyal et al., 2017; Wang et al., 2018b; Zhang et al., 2018]. From the very beginning, researchers proposed to encode the question and image into a common latent space, based on which the accurate answers can be identified through classification [Antol et al., 2015; Malinowski et al., 2015].

https://github.com/guoyang9/AdaVQA.
With the prevailing advent of the attention mechanism, different contributions of each image region [Yang et al., 2016; Fukui et al., 2016; Kazemi and Elqursh, 2017; Anderson et al., 2018] or each question word [Lu et al., 2016; Yu et al., 2017] for the answer prediction have been taken into consideration. Some studies have also explored the modular structure of questions for more explicit reasoning [Andreas et al., 2016]. Nevertheless, questions in real world often require reasoning beyond what is in the image. To better handle such situation, FVQA [Wang et al., 2018b] and OK-VQA [Marino et al., 2019] develop new benchmarks as well as insightful approaches to incorporate structured and unstructured knowledge in VQA, respectively.

It is noted that many VQA models are influenced by the language prior problem [Agrawal et al., 2018; Guo et al., 2019]. Therefore, some efforts have been devoted to the bias-based dataset balancing. For instance, VQA v2 [Goyal et al., 2017] adds complementary samples to the original VQA v1 dataset [Antol et al., 2015] such that for each sample <v,q,a>, another one with the same v, similar q yet a different a is generated. VQA-CP [Agrawal et al., 2018] re-splits the VQA v1 and v2 datasets that the answer distribution of per question type is distinct between the train and test sets. In addition to the studies on the dataset side, methods devised for tackling this problem mostly try to diminish the answer prediction influence from the question encoding layer [Selvaraju et al., 2019; Wu and Mooney, 2019; KV and Mittal, 2020; Jing et al., 2020]. One popular solution essentially involves a new question-only training branch, wherein the answers are predicted based solely on the question input [Ramakrishnan et al., 2018; Cadene et al., 2019; Clark et al., 2019; Chen et al., 2020]. The answer prediction from this branch is further suppressed by the original question-image one.

3 Proposed Method

3.1 Problem Definition

Following the prevalent formulation, we consider the VQA task as a multi-label classification problem. That is, for a textual question \( Q \) regarding an image \( I \), the objective function is given by:

\[
\hat{a} = \arg \max_{a \in \Omega} \log p(a|Q, I; \Theta),
\]

where \( \Omega \) and \( \Theta \) denote the answer set and the model parameters, respectively. Note that there can be multiple correct answers for each instance. The negative log likelihood loss function is then formulated as\(^3\):

\[
L_2 = \sum_{i=1}^{[\Omega]} -a_i \log p_i
\]

\[
= \sum_{i=1}^{[\Omega]} -a_i \log \frac{\exp(W_i^T x)}{\sum_{j=1}^{[\Omega]} \exp(W_j^T x)},
\]

where \( W \) and \( x \) denote the weight matrix and feature vector directly adjacent to the answer prediction, respectively;

\(^3\)The individual loss is considered instead of the total instances throughout this paper due to the space limitation.

\( a_i \in [0, 1] \) represents the corresponding answer label. Besides, we remove the bias vector for simplicity as we also found it contributes little to the final model performance.

3.2 Method Intuition

To date, most VQA methods tackling the language prior problem present to confront the prediction from a question-only branch. Nevertheless, there is no literature exploring the answer/class embedding in the learned feature space. Therefore, in this work, we adopt a new viewpoint to overcome this problem, and validate its effectiveness in what follows. Specifically, we propose to place an adapted margin to separate the answer embeddings in the angular space properly based upon the train set statistics. Compared to the Euclidean space, the angular space is less complicated to manipulate, as the margin range reduces from \((-\infty, +\infty)\) to \([-1, 1]\). In the light of this, we firstly leverage the \( L_2 \) normalization on weight vector \( W_i \) and feature vector \( x \) to ensure the posterior probability to be determined by the angle \( \theta_i \) between \( W_i \) and \( x \) (the answer feature space is converted from the Euclidean space to the angular space), i.e., \( \|W_i\|_2 = 1 \) and \( \|x\|_2 = 1 \). Accordingly, a modified normalized SoftMax loss (NSL) [Wang et al., 2018a] can be obtained by,

\[
L_{ns} = \sum_{i=1}^{[\Omega]} -a_i \log \frac{\exp s \cos \theta_i}{\sum_{j=1}^{[\Omega]} \exp s \cos \theta_j},
\]

where \( s \) is a scale factor for more stable computation. In order to achieve a more discriminative classification boundary, LMLC [Wang et al., 2018a] introduces a fixed cosine margin to NSL,

\[
L_{lmc} = \sum_{i=1}^{[\Omega]} -a_i \log \frac{\exp s(\cos \theta_i - m)}{\sum_{j \neq i} \exp s(\cos \theta_j + \exp s(\cos \theta_i - m))},
\]

where \( m \) implies the fixed cosine margin.

However, applying a fixed cosine margin cannot obtain satisfactory results as observed in our experiments. For this situation, the key reason is that the answer distribution of each question type is highly biased, resulting in the incapability of learning a sufficient representation with a fixed margin in the angular space. In the next subsection, we will introduce a more sophisticated adapted margin cosine loss to overcome this issue.

3.3 AdaVQA Formulation

The results in our experiments (see Sect. 4.2) explicitly demonstrate that a fixed cosine margin yields limited improvements or even deteriorates the model performance. The results in this subsection, we will introduce a more sophisticated adapted margin cosine loss to overcome this issue.

\[
\begin{align*}
L_{AdaVQA} &= \sum_{i=1}^{[\Omega]} -a_i \log \frac{\exp s(\cos \theta_i - m)}{\sum_{j=1}^{[\Omega]} \exp s(\cos \theta_j - m)}, \\
mm &= 1 - \frac{m}{m}, \\
mm &= \frac{n_{i,j} + \epsilon}{\sum_{j=1}^{[\Omega]} n_{i,j} + \epsilon},
\end{align*}
\]
How many kites are in the trees?

CNNs RNNs visual attention loss computation feature space for answers

![Diagram]

Figure 2: The training pipeline of AdaVQA. The input image and question is consumed via pre-trained convolutional neural networks (CNNs) and recurrent neural networks (RNNs), respectively. A visual attention module is then prefixed for identifying salient image regions pertaining to the given question. After normalizing the weight and feature vectors, an adapted cosine margin is introduced to produce suitable decision boundaries.

where \( m_i \) is the adapted margin for answer \( i \) based on the given question type, \( n_i^k \) denotes the number of answer \( i \) under the question type \( q_k \) in the train set, \( \epsilon = 10^{-6} \) is a hyperparameter for avoiding computational overflow. The intuition behind this is that, for the current given question and its corresponding question type, the frequent answers span broader in the angular space (smaller margin), while sparse answers span tighter (larger margin). In other words, frequent answers imply more training samples, which require a broader feature space to sufficiently include these answers. On the contrast, a tighter feature space is acceptable for sparse answers as the number of training samples is much smaller. This setting enables the VQA models to place a more proper cosine margin in the angular answer feature space. Taking Fig. 1a as an example, answer 2 is more frequent than the other two answers (1 and 100) in the train set, which results in a larger feature space as we expect. In particular, Fig. 2 provides a general training pipeline of AdaVQA, where the feature space for the three answers (1, 2, 100) is learned based on the proposed loss function.

However, one may concern that such a margin restriction might damage the inter-type discrimination, i.e., the answer decision boundary among different question types becomes less discriminative. We therefore obtain the answer embeddings with respect to its question type and visualize them in Fig. 1a. From this figure, an obvious decision boundary pertaining to question types can be observed. One possible reason to this situation is that the cosine margin of each answer is computed according to the train set statistic under the given question type, while other answers outside this question type are kept untouched. This empirical setting inherently equip the model with the discrimination capability among different question types.

**Entropy Threshold.** One major problem has yet to be addressed, i.e., not all questions within their corresponding question type would cause the language prior problem. Different from previous methods handling all questions without differentiation, we propose to employ an entropy threshold over each question type. In particular, the questions whose question type entropy is greater than the threshold should be considered for regularization. Specifically, the entropy for each question type is defined as:

\[
e_{q_t} = - \sum_{i=1}^{[|T|]} \tilde{m}_i^k \log_2 \tilde{m}_i^k,
\]

where \( \tilde{m}_i^k \) is actually the occurrence probability of answer \( i \) under the question type \( q_k \) in the train set.

**Partial Derivatives.** We further provide the partial derivatives of the weight vector \( W_i \) and feature vector \( x \) from our loss function. Let \( p_i = s(\cos \theta_i - m_i) = s(\frac{W_i^T x}{||W_i||_2} \cdot \frac{x}{||x||_2} - m_i) \), and \( \hat{p}_i = \frac{\exp p_i}{\sum_{j=1}^{m} \exp p_j} \). The partial derivatives are obtained via,

\[
\frac{\partial L_{AdaVQA}}{\partial x} = \sum_{i=1}^{[|T|]} (\sum_{j=1}^{[|T|]} a_j \hat{p}_i - a_i) \cdot \frac{s \cdot ||x||_2 \cdot 1 - xx^T}{||x||_2^2} \cdot W_i,
\]

and

\[
\frac{\partial L_{AdaVQA}}{\partial W_i} = \sum_{i=1}^{[|T|]} (\sum_{j=1}^{[|T|]} a_j \hat{p}_i - a_i) \cdot s \cdot \frac{W_i \cdot 1 - W_i \cdot W_i^T \cdot x}{||W_i||_2^2}. \]

**Lower Bound for \( s \).** The scale factor \( s \) is critical for the final answer feature learning. A too small \( s \) leads to an insufficient convergence as it limits the feature space span (as we found in our experiments that the loss goes 'nan' with a small \( s \)). In view of this, a lower bound for \( s \) should be prescribed. Without loss of generality, let \( P_i \) denote the expected minimum of the answer class \( i \). Therefore, we have,

\[
s \geq - \frac{\ln(P_i) - 1}{2 - m_i - \sum_{j=1}^{[|T|]} m_j \cdot \frac{1}{||x||_2^2}}. \]

### 3.4 Comparison with Different Loss Functions

We consider the binary-class scenario for intuitively illustrating the decision boundary from different loss functions. As can be seen from Fig. 3, the decision boundary can be negative of the plain SoftMax one, which is enlarged to be equal to zero of the NSL loss [Wang et al., 2018a]. The LMLC [Wang et al., 2018a] defines a fixed margin for different classes, which is not suitable in our case for overcoming the language prior problem. Regarding our AdaVQA, the sparser answer (green one) engages a smaller feature space while the more frequent answer (orange one) engages a larger feature space.

### 4 Experiments

#### 4.1 Experimental Setup

**Datasets.** To validate the effectiveness of the proposed loss function, we conducted extensive experiments on the two VQA-CP datasets: VQA-CP v2 and VQA-CP v1 [Agrawal...
et al., 2018], which are two public benchmarks for estimating the models’ capability of overcoming the language prior problem in VQA.

**Evaluation Metric.** The standard metric in VQA is adopted for evaluation [Antol et al., 2015]. That is, for each predicted answer $a$, the accuracy is computed as,

$$\text{Acc}_a = \min(1, \frac{\# \text{humans that provide answer } a}{3}).$$ (10)

Note that each question is answered by ten annotators, and this metric takes the disagreement in human answers into consideration [Antol et al., 2015; Goyal et al., 2017]. In addition, the answers are divided into three categories: yes/no, number and other.

**Implementation Details.** We empirically applied our AdaVQA to three baselines: Strong-BL [Kazemi and Elqursh, 2017], Counter [Zhang et al., 2018] and UpDn [Anderson et al., 2018]. The prevailing visual attention (i.e., focusing on salient image regions with respect to given questions) is employed by these methods. And UpDn is a popular backbone for estimating the alleviation effect of language priors from the existing methods. Different from most prior methods overcoming the language prior problem in VQA, for all the three baselines, we simply replaced the original loss with our AdaVQA and did not change any other settings, such as embedding size, learning rate, optimizer, and batch size.

### 4.2 Experimental Results

**Overall Accuracy**

We conducted extensive experiments on two VQA-CP datasets, i.e., VQA-CP v2 and VQA-CP v1, and illustrated the results in Tab. 1 and Tab. 2, respectively. The main observations from these two tables are as follows:

- Our method achieves the best on the two benchmark datasets except for the Other answer category (SCR [Chen et al., 2018] and LMH [Clark et al., 2019] outperform ours on VQA-CP v2 and VQA-CP v1, respectively). One possible reason for this is that most questions under this answer category are starting with 'what ...', and the answers are therefore much more diverse than other categories. Accordingly, less language prior would be introduced under this category since the answers are less biased.

- For all the three baselines, i.e., Strong-BL, Counter and UpDn, when applying our loss function, a significant performance improvement (15% on average) can be observed. For example, on the VQA-CP v2 dataset, Counter+Ours

| Method                      | Y/N       | Num.     | Other     | All       |
|-----------------------------|-----------|----------|-----------|-----------|
| Question-Only [2015]        | 35.09     | 11.63    | 07.11     | 15.95     |
| SAN [2016]                  | 38.35     | 11.14    | 21.74     | 24.96     |
| NMN [2016]                  | 38.94     | 11.92    | 25.72     | 27.47     |
| MCB [2016]                  | 41.01     | 11.96    | 40.57     | 36.33     |
| Strong-BL+Ours [2017]       | 40.04     | 12.01    | 37.60     | 34.41     |
| HAN [2018]                  | 52.25     | 13.79    | 20.33     | 28.65     |
| Counter+Ours [2018]         | 41.01     | 12.98    | 42.69     | 37.67     |
| UpDn [2018]                 | 42.27     | 11.93    | 46.05     | 39.74     |
| UpDn†[2018]                 | 49.78     | 14.07    | 43.42     | 40.79     |
| GVQA [2018]                 | 57.99     | 13.68    | 22.14     | 31.30     |
| AdvReg [2018]               | 65.49     | 15.48    | 35.48     | 41.17     |
| Rubi [2019]                 | 68.65     | 20.28    | 43.18     | 47.11     |
| LMH [2019]                  | -         | -        | -         | 52.05     |
| LMH†[2019]                  | 70.29     | 44.10    | 44.86     | 52.15     |
| HINT [2019]                 | 67.27     | 10.61    | 45.88     | 46.73     |
| SCR [2019]                  | 72.36     | 10.93    | 48.02     | 49.45     |
| VGQE [2020]                 | 66.35     | 27.08    | 46.77     | 50.11     |
| CSS [2020]                  | 43.96     | 12.78    | 47.48     | 41.16     |
| Decomp-LR [2020]           | 70.99     | 18.72    | 45.57     | 48.87     |
| Strong-BL+Ours              | 62.70     | 21.64    | 35.33     | 41.21     |
| Counter+Ours                | 61.00     | 53.22    | 43.17     | 49.90     |
| UpDn+Ours                   | **72.47** | **53.81**| **45.58** | **54.67** |

| Method                     | Y/N       | Num.     | Other     | All       |
|-----------------------------|-----------|----------|-----------|-----------|
| Question-only [2015]        | 35.72     | 11.07    | 08.34     | 20.16     |
| SAN [2016]                  | 35.34     | 11.34    | 24.70     | 26.88     |
| NMN [2016]                  | 38.85     | 11.23    | 27.88     | 29.64     |
| MCB [2016]                  | 37.96     | 11.80    | 39.90     | 34.39     |
| Strong-BL†[2017]            | 40.04     | 12.01    | 37.60     | 34.41     |
| Counter†[2018]              | 41.01     | 12.98    | 42.69     | 37.67     |
| UpDn†[2018]                 | 43.76     | 12.49    | 42.57     | 38.02     |
| GVQA [2018]                 | 64.72     | 11.87    | 24.86     | 39.23     |
| AdvReg [2018]               | 74.16     | 12.44    | 25.32     | 43.43     |
| LMH†[2019]                  | 76.61     | 29.05    | 43.38     | 54.76     |
| Strong-BL+Ours              | 72.64     | 27.61    | 36.11     | 49.84     |
| Counter+Ours                | 72.01     | **49.28**| 42.60     | 55.92     |
| UpDn+Ours                   | **91.17** | 41.34    | 39.38     | **61.20** |
Table 3: Effectiveness validation of the proposed loss function on three baselines over the VQA-CP v2 dataset.

| Model     | Margin | Strong-BL | Counter | UpDn  |
|-----------|--------|-----------|---------|-------|
| Baseline  | -      | 34.41     | 37.67   | 40.79 |
| NSL       | -      | 31.89     | 49.08   | 40.97 |
| Fixed Margin | 0.1   | 34.42     | 38.03   | 40.62 |
|           | 0.3    | 34.38     | 38.21   | 40.68 |
|           | 0.5    | 34.29     | 38.07   | 40.88 |
|           | 0.7    | 34.22     | 38.15   | 40.98 |
|           | 0.9    | 34.38     | 38.10   | 41.02 |
| Adapted Margin | adapted | 41.21 | 49.90 | 54.67 |

achieves an absolute performance gain of 12.23% compared with Counter; and on the VQA-CP v1 dataset, UpDn+Ours outperforms the baseline UpDn with 23.18%.

- Compared with other methods whose backbone model is also UpDn on the VQA-CP v2 dataset, our method (UpDn+Ours) surpasses them with a large margin, especially for the three newly accepted approaches VGQE, CSS and Decomp-LR.

Ablation Study

For a deeper understanding of our AdaVQA, we further provided the detailed ablation study on the VQA-CP v2 dataset. From the results in Tab. 3 and Fig. 4, we can see that:

- As shown in Tab. 3, when using the $L2$ normalization on both the weight vector and the feature vector, the de facto NSL, the results are inconsistent amongst different methods. For example, the Counter with NSL surpasses the baseline with 11.41%, while Strong-BL with NSL even leads to a little bit deterioration of the performance.

- We then leveraged the fixed margin to yield effective feature discrimination, where the margins are tuned from 0.1 to 0.9 with a step size of 0.2. However, the results are not favorable (the improvement is limited), which validates the evidence that a fixed margin is not suitable for overcoming the language prior problem. In contrast, when replacing the fixed margin with our adapted one, the model can substantially outperform the one equipped with fixed margins, which additionally proves the superiority of AdaVQA.

- We investigated the different influence of the question type entropy and scales in Fig. 4. From this figure, we found that 1) an appropriate entropy should be considered, since a very large one will not bring more gains or even cause performance degradation; and 2) too small scales are not sufficient for learning the feature space, while too large ones will also lead to unsatisfactory results.

Case Study

Finally, we visualized two successful cases from our method and illustrated them in Fig. 5. Regarding the first case, as the answer 2 takes large proportion under the question type *how many* in the train set, the baseline model thus yields an answer 2 to this question. In contrast, our AdaVQA corrects this mistake, producing a more reasonable attention map (focusing on the elephant object). As for the second case, the baseline model wrongly predicting the answer *white* mainly attribute to *white* being more frequent under the question type *what color* in the train set. Besides, too much attention has been paid to the cat region, which contributes another reason to the incorrect answer, as the fur of the cat is white and black. On the contrary, our AdaVQA can guide the model to pay more attention to the target object - luggage, leading to the correct answer *red*.

5 Conclusion

We propose to tackle the language prior problem in VQA from the angle of the answer feature space learning, which has not been explored in previous studies. To achieve this goal, we design an adapted margin cosine loss to discriminate the answers via properly characterizing the answer feature space. Concretely, for the given question, the frequent and sparse answers with respect to the corresponding question type are learned to span broader and tighter on the angular space, respectively. Extensive experiments over two benchmarks validate the effectiveness of the proposed loss function on three baselines.

Nevertheless, this work does not present an advanced model for pursuing the SOTA results in VQA. We instead expect that, with this adapted margin cosine loss, future research can focus more on the enhancement of the visual rea-
soning capability without too much influence of the language prior problem.

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AdaVQA: Overcoming Language Priors with Adapted Margin Cosine Loss
-Supplementary Material-

1 Proposed AdaVQA
1.1 Formulation of Partial Derivatives

Let \( p_i = s(\cos \theta_i - m_i) \) and \( \hat{p}_i = \frac{\exp p_i}{\sum_{i=1}^{\Omega} \exp p_j} \). According to the derivative of the softmax function, we have,

\[
\frac{\partial \hat{p}_i}{\partial p_i} = \begin{cases} p_i(1 - \hat{p}_j), & \text{if } i = j \\ -\hat{p}_i \hat{p}_j, & \text{otherwise.} \end{cases}
\] (1)

Consequently,

\[
\frac{\partial L_{AdaVQA}}{\partial p_i} = -\sum_{i=1}^{\Omega} a_i \frac{\partial \log \hat{p}_i}{\partial p_i} = -\sum_{i=1}^{\Omega} a_i \frac{1}{\hat{p}_i} \frac{\partial \hat{p}_i}{\partial p_i} = a_i(\hat{p}_i - 1) + \sum_{j \neq i}^{\Omega} a_j \hat{p}_i = \sum_{j=1}^{\Omega} a_j \hat{p}_i - a_i. \] (2)

In addition, the derivative of vector norms is given by,

\[
\frac{\partial \|x\|_2}{\partial x} = \frac{xx^T}{\|x\|_2^2},
\] (3)

which gives,

\[
\frac{\partial L_{AdaVQA}}{\partial \mathbf{x}} = \sum_{i=1}^{\Omega} \frac{\partial L_{AdaVQA}}{\partial p_i} \frac{\partial p_i}{\partial \mathbf{x}} = \sum_{i=1}^{\Omega} \left( \sum_{j=1}^{\Omega} a_j \hat{p}_i - a_i \right) \cdot s \cdot \frac{\|x\|_2^2}{\|x\|_2^2} \mathbf{W}_i \mathbf{W}_i^T \mathbf{x}.
\] (4)

Similarly, the partial derivative for weight vector \( \mathbf{W}_i \) can be obtained by,

\[
\frac{\partial L_{AdaVQA}}{\partial \mathbf{W}_i} = \sum_{i=1}^{\Omega} \frac{\partial L_{AdaVQA}}{\partial p_i} \frac{\partial p_i}{\partial \mathbf{W}_i} = \sum_{i=1}^{\Omega} \left( \sum_{j=1}^{\Omega} a_j \hat{p}_i - a_i \right) \cdot s \cdot \frac{\|\mathbf{W}_i\|_2^2}{\|\mathbf{W}_i\|_2^2} \mathbf{W}_i^T \mathbf{x}.
\] (5)

Based on this, the partial derivatives of other parameters can also be deduced through the chain rule.

1.2 Proof for the Scaling Factor \( s \)

Without loss of generality, let \( P_i \) denotes the expected minimum of the answer class \( i \). In the ideal formulation, the \( \theta_i \) between answer \( i \) and weight vector \( \mathbf{W}_i \) should be 0, while that for others answers should be 180. We then have:

\[
\frac{\exp s(1 - m_i)}{\sum_{j \neq i} \exp s(-1 - m_j) + \exp s(1 - m_i)} \geq P_i,
\]

\[
1 + \frac{\sum_{j \neq i} \exp s(-1 - m_j)}{\exp s(1 - m_i)} \leq \frac{1}{P_i},
\]

\[
1 + \frac{\sum_{j \neq i} \exp s(m_j)}{\exp s(2 - m_i)} \leq \frac{1}{P_i}. \]

On the basis of Jensen’s inequality,

\[
\sum_{j \neq i} \exp s(m_j) = \frac{\Omega - 1}{\Omega - 1} \sum_{j \neq i} \exp s(m_j),
\]

\[
\geq (\Omega - 1) \exp s\left(\frac{\sum_{j \neq i} m_j}{\Omega - 1}\right). \]

Accordingly, we obtain,

\[
1 + \frac{(\Omega - 1) \exp s\left(\frac{\sum_{j \neq i} m_j}{\Omega - 1}\right)}{\exp s(2 - m_i)} \leq \frac{1}{P_i},
\]

\[
\exp s\left(\frac{\sum_{j \neq i} m_j}{\Omega - 1} + m_i - 2\right) \leq \frac{1}{P_i} - 1.
\]

Finally, we have,

\[
s \geq \frac{-\ln\left(\frac{1}{P_i} - 1\right)}{2 - m_i - \sum_{j \neq i} m_j}. \] (6)

2 Experimental Settings
2.1 Datasets

We validated the effectiveness of our proposed loss function on the two VQA-CP datasets: VQA-CP v2 and VQA-CP v1 [Agrawal et al., 2018], which are two public benchmarks for estimating the models’ capability of overcoming
the language prior problem in VQA and are the unbiased splits of the traditional VQA datasets [Antol et al., 2015; Goyal et al., 2017]. The VQA-CP v2 and VQA-CP v1 datasets consist of ∼122K images, ∼658K questions and ∼6.6M answers, and ∼122K images, ∼370K questions and ∼3.7M answers, respectively. And each question is answered by ten annotators. Moreover, the answer distribution of each question type is significantly different between the training and the testing sets in the VQA-CP datasets. For example, in VQA-CP v1, 1 and 3 take about 50% of the answers under the question type how many in the training set, while 2 and 4 hold around 75% in the testing set.

2.2 Baselines

We mainly tested our method over the following three baselines: Strong-BL [Kazemi and Elqursh, 2017], Counter [Chen et al., 2020] and UpDn [Anderson et al., 2018]. Thereinto, Strong-BL utilizes the pre-trained grid-based image features directly produced from CNNs [He et al., 2016], while Counter and UpDn use the pre-trained region-based image features from faster-RCNN [Ren et al., 2015].

Strong-BL [Kazemi and Elqursh, 2017] first leverages two stacked convolutional layers to obtain the attention weights for each equal-sized image grid. Afterwards, it fuses the attentive image features with the question features from RNNs [Cho et al., 2014] in a vector additive fashion. Counter [Zhang et al., 2018] is an upgraded model of the Strong-BL, introducing a counting module to enable robust counting from object proposals. UpDn [Anderson et al., 2018] firstly leverages the pre-trained object detection networks to obtain salient object features for VQA. And then it employs a simple attention network to focus on the most important objects which are highly related with the given question.

3 Experimental Results

Ablation Study.

The detailed analysis of the margin on the VQA-CP v1 is provided in Fig. 1 and Tab. 1. We also demonstrate the elaborate ACC results with respect to both question type entropy and number of scales in Fig. 2.

Answer Manifold Embedding.

The answer embedding results from two more question types, i.e., is this and what color is the are shown in Fig. 3 and Fig. 4, respectively.

Case Study.

More attention map cases can be found at Fig. 5.

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Figure 2: Test set accuracy with respect to different question type entropy as well as different scales on the VQA-CP v2 dataset.

Figure 3: Answer manifold embedding of *is this* question type in Euclidean and angular spaces from the baseline.

(a) Answer manifold embedding of *is this* question type in Euclidean and angular spaces from our method.

(b) Answer embedding of *what color is the* question type in Euclidean and angular spaces from the baseline.

Figure 4: Answer embedding of *what color is the* question type.
Figure 5: Visualization of the baselines method (UpDn) with and without our proposed loss function. The key answer distributions under the question’s corresponding question type are illustrated on the second row, followed by the attention maps from baseline and ours on the last two rows.
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