

Robust Explanations for Visual Question Answering

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Abstract

In this paper, we propose a method to obtain robust explanations for visual question answering (VQA) that correlate well with the answers. Our model explains the answers obtained through a VQA model by providing visual and textual explanations. The main challenges that we address are i) Answers and textual explanations obtained by current methods are not well correlated and ii) Current methods for visual explanation do not focus on the right location for explaining the answer. We address both these challenges by using a collaborative correlated module which ensures that even if we do not train for noise based attacks, the enhanced correlation ensures that the right explanation and answer can be generated. We further show that this also aids in improving the generated visual and textual explanations. The use of the correlated module can be thought of as a robust method to verify if the answer and explanations are coherent. We evaluate this model using VQA-X dataset. We observe that the proposed method yields better textual and visual justification that supports the decision. We showcase the robustness of the model against a noise-based perturbation attack using corresponding visual and textual explanations. A detailed empirical analysis is shown.

1. Introduction

In this paper, we solve for obtaining robust explanations for visual question answering. Visual question answering is a semantic task that aims to answer questions based on an image. The practical implication for this task is that of an agent answering questions asked by, for instance, a visually impaired person that wants to know answers. An important aspect related to this model is the ability to reason whether the model is able to really understand and provide explanations for its answer. This aspect was investigated, for instance, by a recent method by [20], where the authors proposed a method to generate textual explanations and also provide localizations that contribute to the explanation for their answer. This was obtained by their approach which generates explanations based on the answer attention. How-

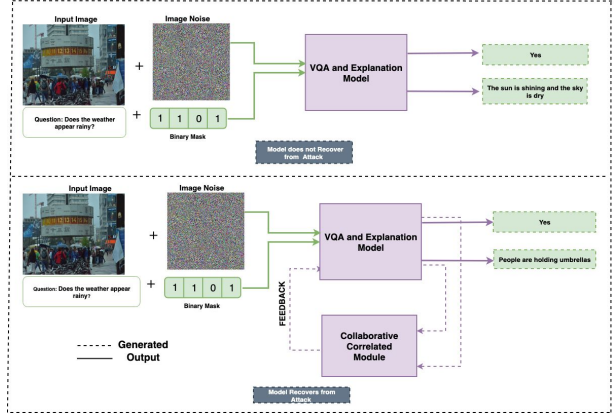


Figure 1: Illustration of proposed method: In case coherence of explanation and answer generation of VQA network is not enforced, a noise based perturbation will result in diverse answer and explanation being generated. This is shown in first row. In second row we illustrate that the proposed method ensures coherence and therefore is able to be robust to noise based perturbation.

ever, one drawback we observe for such an approach is that the explanation need not be correct. For instance, using a noise based perturbation on the image, we can have instances of answer and explanation being different. We solve this by jointly generating the answer and explanation. We further improve over this method by proposing a novel method that enhances the correlation by verifying that the answer and explanation do agree with each other. This is obtained through a collaborative correlated network. This concept is illustrated in figure 1 where we show that current methods can generate answers and explanations. However, these may diverge for an image corrupted using noise based perturbation. Our proposed method aids in generating robust explanations that are tolerant of such perturbation though our methods are not trained using such noise at the time of training.

We investigate various other ablations of the system, such as verifying whether the answer is correct or the explanation is correct or separately verifying that the answer and explanations are correct. These variations are illustrated in figure 2. We observe that jointly verifying that the answer and explanations are correct and agree with each other is

better than all the other variations. This is termed as a collaborative correlation module as the answer and explanation collaboratively are checked. This module not only aids in generating better textual explanations but also helps to generate better localization for the visual explanation. It also ensures the coherence of answer and explanation generation.

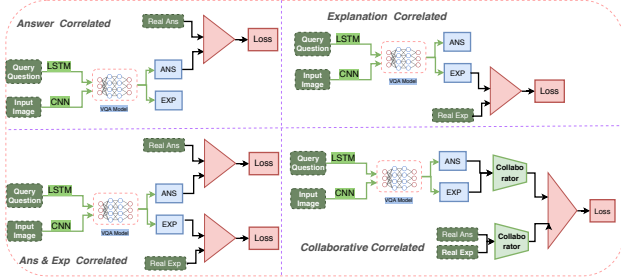


Figure 2: This figure shows variations of our methods. Answer Correlated only corrects the altered answers. Explanation Correlated only corrects the altered explanations. Answer and Explanation Correlated corrects answer and explanation separately. Collaborative Correlated Module jointly corrects both altered answer and explanation.

To summarize, through this paper we provide the following contributions:

- We investigate the tolerance of VQA systems against noise based perturbation and propose a method that is robust to such perturbation.
- We propose joint explanation and answer generation systems that are improved using a novel collaborative correlated network that ensures that the answer and explanations are coherent and correct.
- We illustrate the role of the correlated networks by providing corresponding attention maps that correlate well with human annotated attention maps.
- A detailed empirical analysis of variants of our model provides quantitative evidence of improvements over the current state of the art methods in terms of improved answers being tolerant to adversarial attacks and generating coherent textual and visual explanations.

2. Related Work

Extensive work has been done in the Vision and Language domain for solving image captioning [4, 12, 24, 47, 51, 23, 53, 11, 6, 22, 54], Visual Question Answering (VQA) [33, 30, 1, 44, 32, 36], Visual Question Generation (VQG) [35, 21, 40] and Visual Dialog [7, 2, 49, 50, 55]. Malinowski et al. [33] has proposed Visual question answering task, which answer natural language question based on the image. [1, 17] generalize this task with a large bias free dataset. Joint

embedding approach was proposed by [1, 30, 1, 44, 32, 36] where they combine image features with question features to predict answers. Attention-based approach comprises image-based attention, question-based attention and both image and question based attention. Recent work from [60, 14, 15, 52, 31, 45, 27, 38, 41] considers region-based image attention.

Explanation: Early textual explanation models spanned a variety of applications such as medicine [46], feedback for teaching [25] and were generally template based. Some methods find discriminative visual patches [9], [5] whereas others aim to understand intermediate features which are important for the end decisions [57], [10], [59]. Recently, the author [41] has proposed a new paradigm of providing visual explanation using uncertainty based class activation map. Furthermore, a variety of works proposed methods to visually explain decisions. The method that is closest to our work is the recent work by [20]. Their work aims at generating explanations and also providing visual justification for their answer. None of the methods checks robustness. To the best of our knowledge, we are raising a new novel issue related to the robustness of the prediction and explanation that has not been previously considered in the literature. Our work is inspired by this effort and aims to provide a more robust and coherent explanation generation, which is verified experimentally.

Adversarial Methods: Generative adversarial networks (GAN) [16] is an adversarial methods that consists of a generative model, G, which captures the data distribution, and a discriminative model, D, which estimates the probability of a sample as to whether it came from the training data or not. GANs are widely used to explain data distribution and various other tasks in vision domain [34, 42]. Also, there has been a lot of work on GANs in the field of natural language processing [34, 58, 19, 56, 18, 28]. Reed *et al.* [43] have proposed a model which combines vision with language to generate image from text. Li *et al.* [26] has proposed an advanced method to generate sequence of conversation about an image. Patro *et al.* [39] have proposed an adversarial method to improve explanation and attention using surrogate supervision method.

In this work, we propose a collaborative correlated module to generate both answer and textual explanation of that answer which will be tightly correlated with each other. We show that this module ensures that even if we do not train for noise based attacks, the enhanced correlation can ensure that the right explanation and answer can be generated.

3. Method

Interpretability of models through explanation does not consider the robustness and consistency of the provided explanations. While providing interpretability for understanding models is important, ensuring that the same are robust and consistent is also crucially important. We are specifically

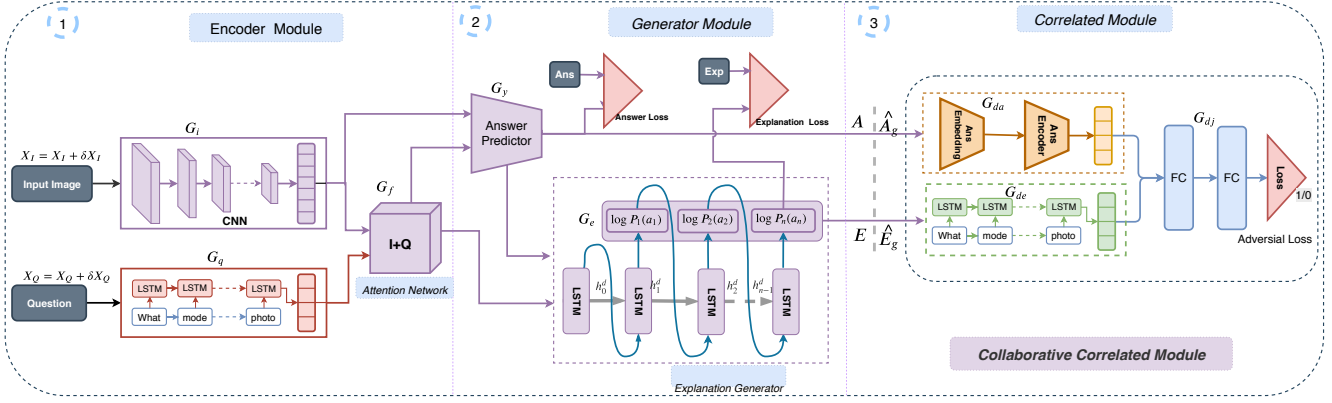


Figure 3: Illustration of Collaborative Correlated Model (CCM). The model receives input image feature and its question feature using CNN and LSTM respectively. then the model predict answer and generate explanation for the predicted answer. During training we ensure that the model collaborates with both answer and explanation features and learns jointly using adversarial fashion.

investigating this problem and provide a simple framework to solve for the same. The main focus of our approach is to ensure correctness and correlation in visual question answering (VQA). We propose a correlated network that learns joint embedding by collaborating with textual explanation and answer embedding. The key difference between our architecture and other existing VQA architectures is in the use of a mutually collaborating module for explanation and answering blocks in a joint adversarial mechanism. This is illustrated in figure 3. The other aspects of VQA and explanation are retained as it is. In particular, we adopt a classification based approach for solving VQA where an image embedding is combined with the question embedding to solve for the answer. This is done using a softmax function in a multiple choice setting:

$$\hat{A} = \underset{A \in \Omega}{\operatorname{argmax}} P(A|I, Q; \theta)$$

where Ω is a set of all possible answers, I and Q are image and question respectively and θ represents the parameters in the network. Also we adopt generation based approaches for explanation generation

$$\hat{E} = \underset{\hat{E} \in \Omega_e}{\operatorname{argmax}} P(e_t|(I, Q), A, e_0, \dots, e_{t-1}; \theta_e)$$

where Ω_e is the explanation vocabulary.

We provide four variants of our model, as shown in figure 2. Correlated Answer Module (CAM) only corrects altered answers, Correlated Explanation Module (CEM) only corrects altered explanations, Answer and Explanation Correlated Module (AECM) corrects answers and explanations separately and Collaborative Correlated Module (CCM) corrects both answers and explanations jointly.

CCM comprises of three modules: Encoder Module, Generator Module, and Correlated Module. The Encoder Module encodes images and questions using CNN and LSTM. We combine these two using an attention mechanism to obtain

an attention feature. Using the attention feature, the generator module predicts answers and explanations that justify the predicted answer. The Correlated module defends the model against perturbations in the input, which facilitates the model to predict correct answers even under perturbation though we do not perturb the input at the time of training. Details of each module are as follows:

3.1. Encoder Module

Given an input image X_i , we obtain an embedding $g_i \in \mathcal{R}^{W \times H \times C}$ using CNN which is parameterized by a function $G_i(X_i, \theta_i)$, where θ_i represents the weights for the image embedding module. Similarly, for the query question X_Q , we obtain question feature embedding g_q after passing it through an LSTM, which is parameterized using a function $G_q(X_q, \theta_q)$, where θ_q represents the weights for the question embedding module. The image embedding g_i and question embedding g_q are used in an attention network, which is parameterized using a function $G_f(g_i, g_q, \theta_f)$ where θ_f are the parameters of the attention network that combines the image and question embeddings with a weighted softmax function and produces an output attention weighted vector g_f . The corresponding attention expressions are as follows:

$$\begin{aligned} f_j &= \tanh(\theta_i g_i \odot \theta_q g_q) \\ f_s &= ||(\operatorname{signed_sqrt}(f_j))||_2 \\ \alpha &= \operatorname{softmax}(\theta_{a1} \sigma(\theta_a f_s + b_a)) \\ g_f &= (\alpha * g_i) \odot f_q \end{aligned} \quad (1)$$

where \odot represents element-wise multiplication and $\sigma(\cdot)$ represents the sigmoid operator.

3.2. Generator Module

Our generator module aims to predict an answer and generate an explanation. Both the answer prediction and textual explanation rely on the attention feature g_f . Answer generation is through a classifier network G_y using a fully

connected network. Our generator module aims to predict answer and generate explanation. First, it helps to obtain the probability of the predicted answer class with the help of a softmax classifier. The answer prediction relies on the attention feature g_f . g_f is projected into V_a dimensional answer space using a fully connected layer. Answer classifier network is defined as follows: $g_y = h(\theta_{y1}, h(\theta_{y2}, g_f))$

$$g_y = h(\theta_{y1}, h(\theta_{y2}, g_f)) \quad (2)$$

where h is the ReLU activation function, $\theta_{y1} \in \mathcal{R}^{V_a \times l1}$ and $\theta_{y2} \in \mathcal{R}^{l1 \times l_f}$. At training time, we minimize the cross entropy loss between the predicted and the ground truth answers.

$$L_y(\theta_f, \theta_y) = L_y(G_y(G_f(g_i, g_q)); y) \quad (3)$$

For generating textual explanation, we condition attention feature g_f on answer embedding g_y . This is generated using an LSTM based sequence generator for generating textual explanation g_e . At training time, we generate meaningful explanations by minimizing the cross entropy loss between generated explanation and ground truth explanation.

$$L_e(\theta_f, \theta_y, \theta_e) = L(G_e(G_y, G_f); e) \quad (4)$$

3.3. Correlated Module

We introduce an Adversarial Correlated Network. Using the adversarial mechanism, we develop a Collaborative Correlated Module which simultaneously checks whether the predicted answer and the corresponding explanation are correct or not. Each time the model predicts a wrong answer, the correlated module tries to correct it by comparing it with the real answer and the corresponding real explanation. Our correlated module includes Correlated Answer Module, Correlated Explanation Module and Collaborative Correlated Module. Each of the correlated modules are explained as follows:

Correlated Answer Module: We use a V_a dimensional one-hot vector representation for every answer word and transform it into a real valued word representation f_{da} by matrix $\theta_{aw} \in \mathcal{R}^{l_{aw} \times v_a}$. We pass the obtained l_{aw} dimensional word embedding through a fully connected layer to obtain l_a dimensional answer encoding g_{da} . g_{da} is represented as follows: $g_{da} = h(\theta_{da}, h(\theta_{aw}, A))$, where h is a nonlinear function ReLU.

Correlated Explanation Module : For explanation, we obtain representation g_{de} using an LSTM. The hidden state representation of the last word of the LSTM network provides a semantic representation of the whole sentence conditioned on all the previously generated words e_0, e_1, \dots, e_t . The model can be represented as $g_{de} = LSTM(E)$

Collaborative Correlated Module: We design a collaborative network by concatenating the answer and explanation

Algorithm 1 Training CCM

- 1: **Input:** Image X_I , Question X_Q
 - 2: **Output:** Answer y , Explanation e
 - 3: **repeat**
 - 4: Answer Generator $G_y(X_I, X_Q) \leftarrow g_y$
 - 5: Explanation Generator $G_e(X_I, X_Q) \leftarrow g_e$
 - 6: Ans cross entropy $L_{ans} \leftarrow \text{loss}(\hat{y}, y)$
 - 7: Exp cross entropy $L_{exp} \leftarrow \text{loss}(\hat{e}, e)$
 - 8: **repeat**
 - 9: *Sample mini batch of fake Ans and Exp:*
 $y_f^1 \dots y_f^m \text{ and } e_f^1 \dots e_f^m$
 - 10: *Sample mini batch of real Ans and Exp:*
 $y_r^1 \dots y_r^m \text{ and } e_r^1 \dots e_r^m$
 - 11: Discriminator: $D_j(D_y(y_r^i), D_e(e_r^i)) \leftarrow D(Y, E)$
 - 12: Update the discriminator using stochastic gradient ascent
 $\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^m [\log D(Y, E) + \log(1 - D(G_y, G_e))]$
 - 13: **until** $k = 1 : K$
 - 14: *Sample mini batch of Real Ans and Exp:*
 $y_f^1 \dots y_f^m \text{ and } e_f^1 \dots e_f^m$
 - 15: Update the Generator by descending its stochastic gradient: $\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^m \log(1 - D(G_y, G_e))$
 - 16: **until** Number of iterations
-

embeddings to obtain a joint embedding. The collaborative module is trained in an adversarial setting to correct the misclassified answers. Given answer embedding g_{da} and explanation embedding g_{de} , we obtain a joint feature g_{dj} by concatenating both of them and passing it through a fully connected layer to obtain final feature embedding which is as follows:

$$g_{dj} = \theta_{dj} \tanh(\theta_{da} g_{da}; \theta_{de} g_{de})$$

where ; indicates the concatenation of two modules. The complete scheme is shown in figure 3. We use these modules to make variants of our model, as shown in figure 2. We train the discriminator in an adversarial manner between the generated and ground truth embedding. The adversarial cost function is given by:

$$\min_G \max_D L_c(G, D) = E_{y \sim Y, e \sim E} [\log D(Y, E)] + E_{g_y \sim G_y, g_e \sim G_e} [\log(1 - D(G_y, G_e))]$$

The final cost function for CCM can be formulated as follows:

$$L = L_y + L_e - \eta L_c$$

where L_y is the loss of answer generator module, L_e is the loss of explanation generator module, L_c is the loss of collaborative correlated module and η is a hyper-parameter. We trained our model by optimizing this cost function with model parameters $(\theta_f, \theta_e, \theta_y, \theta_d)$ to deliver a saddle point

Model	BLEU-1	BLEU-2	BLEU-3	BLEU-4	METEOR	ROUGE-L	CIDEr	SPICE
Baseline	54.7	38.1	26.8	19.1	18.0	42.9	66.1	14.0
CAM	55.0	38.3	26.8	19.0	18.3	43.1	69.2	15.2
CEM	54.5	38.3	27.2	19.6	18.4	43.1	68.2	15.1
AECM	55.5	38.9	27.4	19.3	18.3	43.4	67.9	14.8
CCM	56.7	40.8	29.2	21.1	19.7	44.9	73.9	16.2

Table 1: Ablation Analysis of Our Model. We achieve improvements in all the metrics.

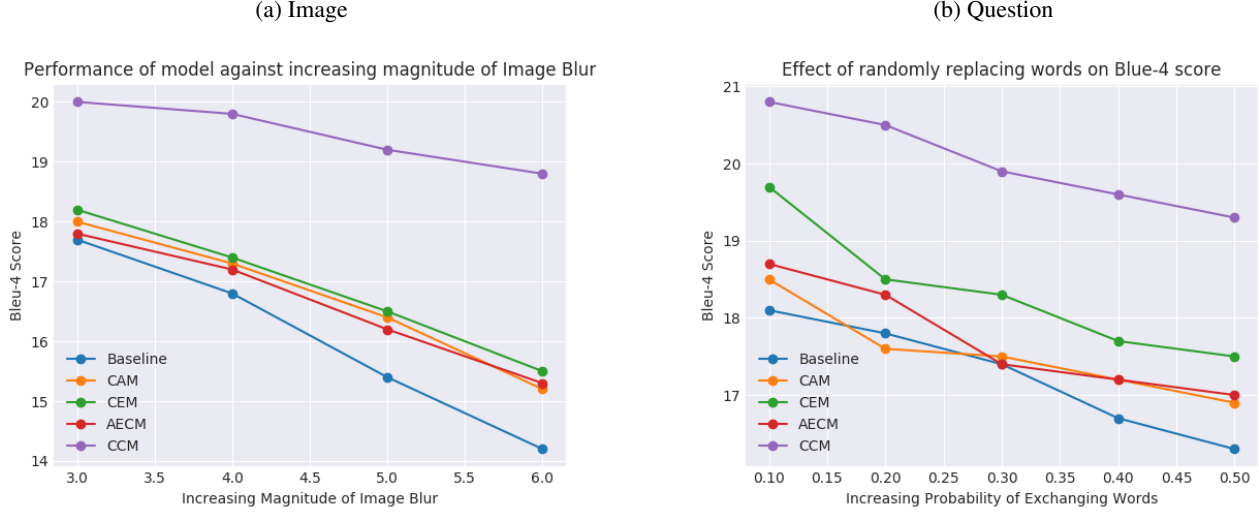


Figure 4: (a)**Blurring Images**: BLUE-4 score of our variants of model vs increasing blur in validation images. Slope with which CCM’s score decreases is less as compared to other models and hence it is robust to blur in images. (b)**Replacing Words**: BLUE-4 score of our variants of models vs increasing random exchange of question words with question vocabulary words. Slope with which CCM’s score decreases is less as compared to other models and hence it is robust to replaced question words.

function as follows:

$$\begin{aligned}
 (\hat{\theta}_f, \hat{\theta}_e, \hat{\theta}_y) &= \arg \max_{\theta_f, \theta_e, \theta_y} (C(\theta_f, \theta_e, \theta_y, \hat{\theta}_d)) \\
 (\hat{\theta}_d) &= \arg \min_{\theta_d} (C(\hat{\theta}_f, \hat{\theta}_e, \hat{\theta}_y, \theta_d))
 \end{aligned} \tag{5}$$

4. Experiments

We evaluate our proposed CCM method using quantitative and qualitative analysis. The quantitative evaluation is conducted using standard metrics like BLEU [37], METEOR [3], ROUGE [29] and CIDEr [48]. We evaluate our attention maps using rank correlation [38]. We further consider the statistical significance for the many ablations as well as the state-of-the-art models. In qualitative analysis, we show the word statistics of generated explanation with a Sunburst plot in figure 7. We provide gradual improvement in visualization of attention maps for a few images as we move from our base model to CCM model. We perform ablation analysis based on various samples of noise.

4.1. Dataset

We evaluate our proposed model on VQA Explanation Dataset (VQA-X) [20] which contains human annotated explanations for open-ended question answer(QA) pairs. QA

Model	RC
Random Point [20]	+0.0017
Uniform [20]	+0.0003
Answering [20]	+0.2211
ME [20]	+0.3423
Baseline (ME)	+0.3425
CAM (ours)	+0.3483
CEM (ours)	+0.3589
AECM (ours)	+0.3595
CCM (ours)	+0.3679

Table 2: Ablation and State of the art comparison with our models for Rank Correlation(higher is better)

pairs are taken from Visual Question Answering (VQA) dataset [1]. VQA-X consists of one explanation per QA pair in train split and three explanations per QA pair in validation and test split with a total of 31,536 explanations in training split, 4,377 explanations in validation split and 5904 explanations in test split. VQA-X also consists of human annotated visual justification collected from Amazon Mechanical Turk.

Model	Combination	BLEU-4	METEOR	ROU-L	CIDEr	SPICE
ME1 [20]	+ Ans + Att + Des	6.1	12.8	26.4	36.2	12.1
ME2 [20]	- Ans - Att + Des	5.9	12.6	26.3	35.2	11.9
ME3 [20]	- Ans - Att + Exp	18.0	17.3	42.1	63.6	13.8
ME4 [20]	+ Ans - Att + Exp	18.0	17.6	42.4	66.3	14.3
ME5 [20]	- Ans + Att + Exp	19.5	18.2	43.4	71.3	15.1
ME6 [20]	+ Ans + Att + Exp	19.8	18.6	44.0	73.4	15.4
Baseline	- Ans + Att + Exp	19.1	18.0	42.9	66.1	14.0
Our (CCM)	+ Ans + Att + Exp	21.1	19.7	44.9	73.9	16.2

Table 3: Comparison with State of the Art models on VQA-X dataset. Ans denotes use of ground truth answers for explanation generation, Att denotes answer attention and Exp denotes explanation attention. After using all three, our model outperforms all the other models.



Figure 5: This figure shows visual and textual explanation for images picked from validation set. The 1st, 3rd, 5th and 7th columns contain original image and its question. 2nd, 4th, 6th and 8th column provide predicted answer, visual explanation mask and textual explanation.

4.2. Ablation Analysis

We provide comparisons of our models with the prevalent baselines. We compare our model on textual and visual explanations. We add noise during inference time to test the robustness of models. As the methods were not intended or designed to be robust to noise, normal methods perturbed more as compared to our models.

4.2.1 Analysis on Textual Explanations

For textual explanations, we consider different variations of our method and various ways to obtain collaborating embedding as mentioned in section 3.3. Table 1 shows the performance of variants of our model on different metrics for the VQA-X test set. It is clear that CCM outperforms all the other variants. There is a trend of increasing scores as we move from baseline to CCM. We achieve an improvement of about 2% in BLEU-4, 1.7% in METEOR, 2% in ROUGE-L,

7% in CIDEr and 2.1% in SPICE.

4.2.2 Analysis on Visual Explanation

We measure the similarity between our explanation and ground truth explanation by rank correlation and its results are shown in table 2. We start with the rank correlation of the baseline model and then we compare with different variants such as CAM, CEM, AECM and CCM. We achieve an improvement of about 2.56% when we move from state of the art(ME) to CCM.

4.2.3 Statistical Significance Analysis

We analyze Statistical Significance [8] of our model(CCM) against the variants mentioned in section 3. The Critical Difference(CD) for Nemenyi [13] test depends on given confidence level α (0.05 in our case) for average ranks and number of tested datasets N. Low difference in ranks between

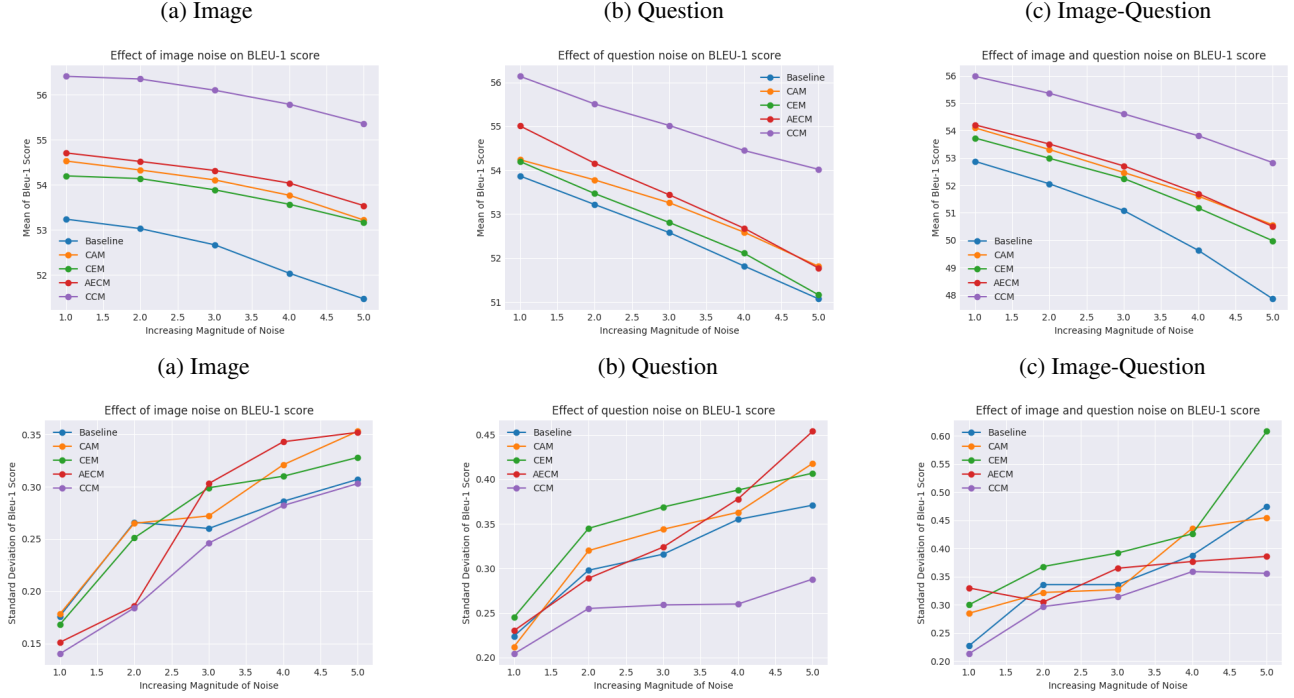


Figure 6: **Effect of Image and Question Noise** : First row, First Column shows variation of Mean of Bleu-1 score for image noise, second column shows mean of Bleu-1 score for question noise and third column shows mean of Bleu-1 score for image and question noise combined. We add noise in image features by introducing gaussian noise with increasing noise intensity. Noise in questions is added by randomly masking question words with increasing probability of masking shown in column-2. Finally we add noise in image features and question with increasing intensity/probability shown in column-3. Purple line shows performance of our model(CCM). It can be observed that our model perturbs least as compared to other models and hence it is robust as compared to other models. Similarly second row provides the variation of Standard Deviation of Bleu-1 score for image noise, question noise and combined noise(image and question).

two models implies that they are significantly less different and vice versa. Figure 8 visualizes the post hoc analysis using the CD diagram. It is clear that CCM is significantly different from other methods.

Model	Mean	Std Dev	Actual	Abs. Dif
Baseline	51.9	0.235	53.60	1.720
CAM	53.9	0.254	54.42	0.520
CEM	53.7	0.360	54.36	0.660
AECM	54.3	0.257	54.39	0.093
CCM	56.7	0.187	56.70	0.007

Table 4: Performance of models against image and question noise(on BLUE-1 score)

4.3. Analysis on Robustness of Model

We analyze the behavior of our model against increasing noise in figure 6. We sample the noise 50 times and report mean and standard deviation. Note that the model has not been trained with this noise, rather we only use it in the test time. Since Bleu-1 score varies the most(among all the scores), we choose Bleu-1 so that we can get proper estimates of standard deviation(Bleu-4 score deviates much less). First, we add gaussian noise to image features. Mean of the noise is same as that of the image features and the standard

deviation is $\alpha \times (\text{standard deviation})$ of the image features where $\alpha \in 1, \dots, 5$. We observe that our model has the highest mean, lowest standard deviation and lowest slope for mean and standard deviation. Second, we randomly mask words in questions during validation time. We mask words with increasing probabilities of 0.05, 0.1, 0.15, 0.2, 0.25. Humans are robust to such noise since we can extract the semantic meaning of a sentence even if some words are masked or missing. So we test our model on this noise and observe that our model follows the previous trend. Then, we add both image and question noise with increasing magnitude. We again observe that our model outperforms all other models and it perturbs least.

In figure 4(a), we analyze the effect of blurring the input images and extracting features from these noisy images. We observe that our model again outperforms other models along with deviating less w.r.t. the input. In figure 4(b), we analyze the effect of replacing words in question from question vocabulary. Humans are not much affected by these since we can extract the meaning of a sentence based on the neighboring words. Again, our model outperforms all other models and perturbs the least. Since our model is learning joint distribution from two inputs(answers and explanations), it

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