Question-Conditioned Counterfactual Image Generation for VQA

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Abstract

While Visual Question Answering (VQA) [2] models continue to push the state-of-the-art forward, they largely remain black-boxes – failing to provide insight into how or why an answer is generated. In this ongoing work, we propose addressing this shortcoming by learning to generate counterfactual images for a VQA model – i.e. given a question-image pair, we wish to generate a new image such that i) the VQA model outputs a different answer, ii) the new image is minimally different from the original, and iii) the new image is realistic. Our hope is that providing such counterfactual examples allows users to investigate and understand the VQA model's internal mechanisms.

1. Introduction

While VQA models have steadily improved over the years, they are still prone to making somewhat silly errors that can leave human users baffled. In these situations, a user might ask for an explanation as to why the model answered as it did rather than with some alternative response for a given image and question. One way to respond to this request for discriminative explanation is through counterfactuals – that is, to present the user with other images for which the model produces the requested alternative response given the original question. But to be most instructive, these images ought to be as similar to the original as possible. In this ongoing work, we explore learning to generate such question-conditioned counterfactual images.

Counterfactual Visual Explanations. While there is extensive work on generating explanations for deep models [13, 3, 1], only a few works have addressed counterfactual based visual explanations [6, 9]. Unlike our work which generates images, [6] and [9] operate in feature rather than pixel space and apply to the context of image classification rather than language-conditioned settings.

Language-Conditioned Image Generation. Critically, counterfactual explanations for VQA must be conditioned on the question, *e.g.* while changing the color of a skateboard wheel is an excellent counterfactual for "What color

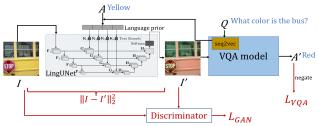


Figure 1: We learn to generate counterfactual visual explanations for VQA models. For example, to explain why a model predicted the bus to be in yellow color in the example above, we want to generate a new image I' that is similar to the original but results in a different answer (white in this case) so the user can see what the most important factors are in the decision¹.

is the wheel?" the same edit would be irrelevant to a question about the board's deck. As such, recent work on generating images based on natural language captions [14] or dialogs [12] about the image is closely related. However, our setting lacks explicit target images and must generate images such that a VQA model changes its decision.

2. Method

Given a VQA model $f\colon (I,Q)\to \hat{A}$ and a dataset of image-question-answer tuples $\{(I_i,Q_i,A_i)\}_{i=1}^N$, our goal is to learn a model $g\colon (I,Q,A)\to I'$ that observes the image I_i , question Q_i , and ground-truth answer A_i and then generates a counterfactual image I_i' such that the answer for the new image is different than that for the old, *i.e.* $f(I,Q)\neq f(I',Q)$. Further, we require the differences between I_i and I_i' to be minimal and for I_i' to be visually realistic.

Language-Conditioned Image Editing. The general architecture of our model is shown in Fig. 1. We instantiate the counterfactual generator $g\colon (I,Q,A)\to I'$ as a LingUNet [8] architecture that maps conditioning language to key intermediate filter weights in the popular pixel-to-pixel UNet model [10]. For language conditioning, we encode the question based on the VQA model's language encod-

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¹The way VQA v2.0 [5] was collected shares the 'minimal edit' notion, where human were asked to pick nearest neighbor images s.t. one question can be applied to multiple images with minimal difference.

ing and the final logit weight vector for the VQA model's answer. These are concatenated and passed through a fully-connected layer before being passed to LingUNet.

Constraining Image Generation. We train the counter-factual generator under three losses, each corresponding to one of our desired traits. First, the generated image should change the VQA model's response so we train with the negated cross-entropy from the VQA model with the original answer A as the target, *i.e.* we train for any answer other than A. Second, we want edits to be minimal so we add an ℓ_2 loss between the original and generated image, *i.e.* $||I,I'||_2$. Finally, we introduce a discriminator (as in GAN training [4]) that penalizes unrealistic generated images.

3. Experiments & Results

Dataset. We apply our approach to the VQAv1 [2] dataset and use a pre-trained MLB model [7] as the VQA model.

Training. We warm up LingUNet using only the ℓ_2 loss for reconstruction before adding in the question-answer inputs. We then add question-answer conditioning and train with all three losses for 6 epochs. We use the Adam optimizer, gradient clipping, and soft-labels for the discriminator [11].

3.1. Results

We explore our counterfactual image generation algorithm under three criteria: (a) change of semantics, (b) sensitivity to language-conditioning, and (c) realism.

Change of semantics. Ideally, the counterfactual images generated will change the semantics of the image based on the question and original answer - resulting in a different answer for both the VQA system and human observers. We find VQA accuracy on the validation set drops from 64.33% to 57.64% when using our generated examples. Moreover, we find a significantly larger effect for "what color" questions, 72.64% to 34.02%. This means that a large portion of generated counterfactual images have successfully changed semantics that are observable by the VQA system. Fig. 2 shows some qualitative results of our approach. We can see that for color questions (Q_1) the image regions in question are shifting color to an alternative that both the VQA and human annotator can identify. However, for other question types (Q_2 and Q_3 in Fig. 2), our approach is either ineffective at changing the VQA model's answer or does so in a way that is not human perceptible, leading to disagreement as in Q_2 in Fig. 2b. Another failure mode is over-editing of irrelevant objects as in the woman's shirt for Q_1 in Fig. 2c.

Sensitivity to language-conditioning. As we can see from Fig. 2, the model does learn to produce different image edits for different input questions-answer pairs. However, the resulting edits for non-color questions don't seem to be modifying the image significantly.

Realism. In most cases, our model does not generate obvi-

	Q ₁ : What color is the frosting on the doughnut?	Q ₂ : What is next to the doughnut?	Q ₃ : Is this a healthy dish?
Original Answer	Pink	Bag	No
New Answer (VQA)	White	Plate	No
New Answer (human)	White	Bag	No
			I_3'
(a)			
	Q ₁ : What color is the skateboard wheel?	Q ₂ : Is this skateboard made of plastic?	Q ₃ : Are the wheels the same size?
Original Answer	Green	No	No
New Answer (VQA)	Blue	Yes	No
New Answer (human)	Blue	No	No
			1/3
(b)			
	Q ₁ : What color is the old man's shirt?	Q_2 What is made of wood?	Q ₃ : Where are the women and man in the picture?
Original Answer	Red	UNK	Kitchen
New Answer (VQA)	Yellow	UNK	Kitchen
New Answer (human)	Yellow	UNK	Kitchen
		I'2	1/3

Figure 2: Examples of generated images and answer to them given by VQA model and human.

(c)

ous artifacts; however, there remain light checkerboard patterns in some output images (visible in Fig. 2a). Achieving even this level of realism required significant fine-tuning of the discriminator training regime to avoid the introduction of adversarial "deep dream" style artifacts like superimposing dog faces into the images to fool the VQA model.

4. Discussion

Our current experiments have shown our proposed model effective for language-conditioned counterfactual image generation in the context of color questions, but has yet to show promise with larger semantic edits (e.g. changing wheel size in Fig. 2b, I_3'). This may be due to our ℓ_2 loss that may be overly constraining for larger scale edits. We are exploring different configurations to train a better discriminator (i.e., converged to Nash Equilibrium) so that we can loosen ℓ_2 constraint for larger semantic edits.

Further, our model seems to make color edits on all relevant areas (both the man and woman's shirts in Fig. 2c). Shifting to a model which predicts not only edits but a spatial mask for where to apply them may resolve both these issues – localizing edits and allowing for a minimum edit loss to be applied to the mask rather than individual pixels.

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