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Adversarial Noise Benchmarking On Image Caption

Bachelor Thesis

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Abstract

TODO Abstract

1 Introduction

The image caption generation task is at the cross-section between Computer Vision (CV) and Natural Language Processing (NLP). It requires the computer to understand a visual scene and describe it into a grammatically correct natural sentence. Practical use cases vary from automated describing of images to visually impaired people (Mazzoni, 2019) to context based image retrieval.

Show Attend and Tell (S.A.T.) proposed by K. Xu et al. is an end-to-end deep learning approach that tries to solve the image caption generation problem. It combines an attention mechanism with LSTM to generate sentences that describe the given image. An example output from S.A.T can be seen in figure 1 Achieving good BLEU scores on Flickr8K, Flickr30K(Hodosh, Young & Hockenmaier, n.d.) and COCO(Lin et al., 2015) datasets. Although the scores are not state-of-the-art(Stefanini et al., 2021) anymore. This model is chosen because it is small and thus can be run locally, and has publicly available implementations (Sgrvinod, n.d.).

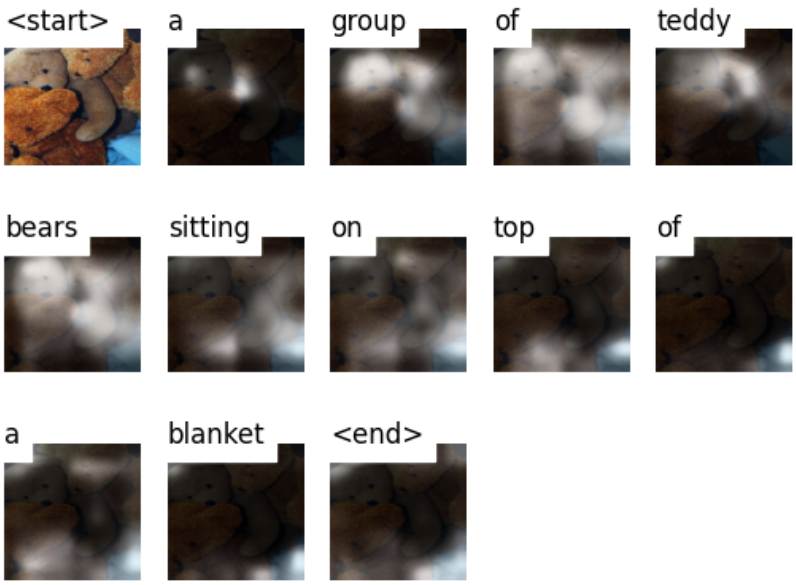

Figure 1: Prediction by Show Attend and Tell on a clean image.
Top left picture is the input image. The highlighted areas in white are the visualization of the attention per predicted word.

Machine learning models can be very susceptible to noise where small changes to the input can lead to radically different outcomes. As shown by Goodfellow, Shlens and Szegedy adding a specific (small) noise layer to an image can alter a correct prediction to a very confident wrong prediction. As can be seen in figure 2. Because the generation of the adversarial examples is not that computational expansive, they can be generated during training making the model more robust. It is also shown that these adversarial examples act as regularizes during training.

Reducing the change of overfitting. Kurakin, Goodfellow and Bengio expands on generating adversarial examples showing that one can also steer the model towards a specific classification.

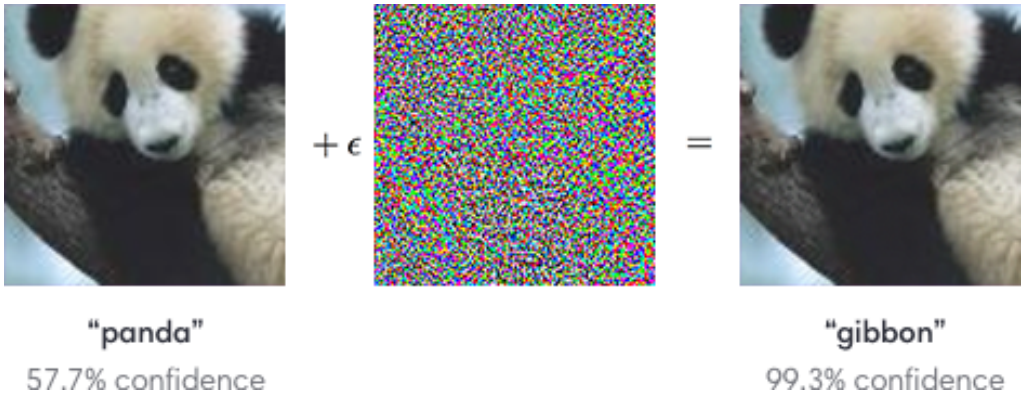

Figure 2: Adversarial noise example from (Goodfellow et al., 2015). Where $\epsilon = 0.07$.

Combining these previous findings, S.A.T. can be used to find adversarial examples for image captioning models. These adversarial images can then be used to either improve current datasets by providing hard samples, or in a more malicious way. The latter being especially true when one can specify the output sentence for which an adversarial sample should be created. An additional benefit to adversarial samples that can be cheaply generated is that they can be generated during training of models and act as regularizes. Improving the robustness of the model. However, this is only viable if generating the adversarial samples is not computational expensive. Analyzing the successful and failed adversarial samples can also give a better insight in the strengths and weaknesses of S.A.T.

1.1 Motivation and Related Work

In the last few years research in the direction of generating adversarial samples for gradient based models has been published (Goodfellow et al., 2015; Kurakin et al., 2016a) as well as research showing the usefulness of such adversarial samples(Ilyas et al., 2019). The latter stating: "Adversarial vulnerability is a direct result of our models' sensitivity to well-generalizing features in the data." However, these generalizing features are only true for most samples, as models are optimized to do well in the average case. Inserting adversarial examples in training help regularize these non-robust features(Kurakin, Goodfellow & Bengio, 2016b). The Fast Gradient Sign Method was originally designed for classification task, however it (and variations) have been successfully adopted to other tasks such as object detection (Bose & Aarabi, 2018; Liu et al., 2020; Zhang & Wang, 2019), and most notably for this research on image captioning(Chen, Zhang, Chen, Yi & Hsieh, 2017). Chen et al.'s method Show-and-Fool successfully and robustly is able to attack Show-and-Tell(Vinyals, Toshev, Bengio & Erhan, 2014) (predecessor of Show Attend and Tell (S.A.T.)). Achieving a success rate of 95.8% however it takes about 38 seconds to generate a single adversarial sample. Making it less useable during training.

Adversarial Methods

Over the last few years variations of the Fast Gradient Sign Method by (Goodfellow et al., 2015) have been designed. The Iterative Fast Gradient Method by Kurakin et al. applies the Fast Gradient Sign Method multiple times. Which is further improved by using various optimization techniques such as momentum (J. Xu, 2020), and in the case of Show-and-Fool the well known Adam(Kingma & Ba, 2017) optimizer. Carlini and Wagner also directly include a distance metric in their optimization instead of clipping. However, all these methods are iterative and therefore take non-negligible time and are thus less useful during training.

1.2 Research Questions

This research investigates the susceptibility of S.A.T. against adversarial samples that are visually close but generate completely different descriptions as output.

- Is S.A.T. susceptible to adversarial attacks using noise?
- Can the noise be crafted in such a way that it can steer the output.

2 Methodology

2.1 Dataset and Model

2.2 Generating Adversarial Samples

Randomly sampling the noise field to find samples close to a certain image would be time-consuming and inefficient. Luckily generating adversarial input images can be done by using the Fast Method (EQ. 1) proposed by Goodfellow et al..

$$X^{adv} = clip(X + \epsilon * sign(\nabla_x J(X, y_{true})), 0, 1) \tag{1}$$

With X being the input image, ϵ a hyperparameter determining much the original image can be perpetrated and $J(X, y_{true})$ the loss function which to, in the adversarial case, maximize. Finally, the image is clipped ensuring the vector stays within the 0 to 1 input range. As can be seen in Figure 3 (and bigger size in appendix A), using this method images up to and including $\epsilon = 0.04$ are nearly indistinguishable and up to $\epsilon = 0.16$ very recognizable to humans.

ϵ=0.000 ϵ=0.005 ϵ=0.010 ϵ=0.020 ϵ=0.040 ϵ=0.080 ϵ=0.160 ϵ=0.320

Figure 3: Adversarial images for varying values of epsilon.

Steering Adversarial Samples

To steer the network towards a specific output we can adjust the equation 1 to minimize a loss function with a given target y.

$$X^{steer} = clip(X - \epsilon * sign(\nabla_x J(X, y_{target}))) \tag{2}$$

Where y_{target} can be determined to be anything.

Evaluation

To determine if the model is indeed susceptible the BLEU scores will be calculated for different values of ϵ. Furthermore, to also investigate if the semantic meaning of the sentence is significantly affected, the cosine similarity of the original and adversarial output will be calculated using universal sentence embedding proposed by Cer et al.. To see if the model can also be steered the BLEU score and cosine similarity are calculated with respect to the y_{target}.

Figure 4: Prediction by Show Attend and Tell on a normal image

Figure 5: Prediction on an adversarial image with $\epsilon = 0.2$ (roughly 5% of original range)

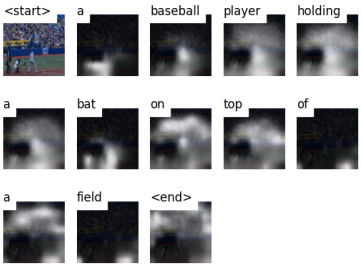

Figure 6: Prediction by Show Attend and Tell on a normal image

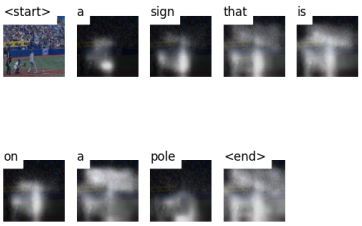

Figure 7: Prediction on an adversarial image with $\epsilon = 0.2$ (roughly 5% of original range)

3 Results

Although I currently don't have complete results. I do have some initial samples that worked. I am still in the process of calculating the BLEU score and cosine similarity over the whole datasets. Preliminary results images:

Figure 8: Prediction by Show Attend and Tell on a normal image

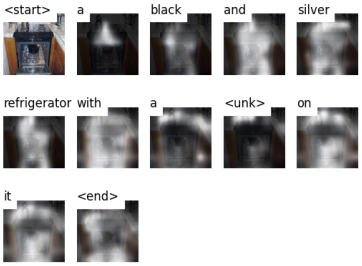

Figure 9: Prediction on an adversarial image with $\epsilon = 0.2$ (roughly 5% of original range)

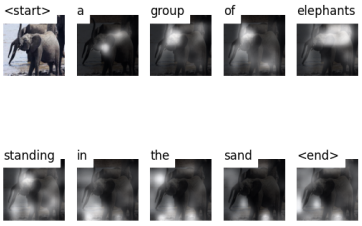

Figure 10: Prediction by Show Attend and Tell on a normal image

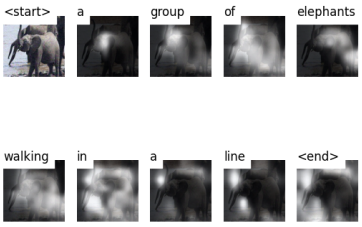

Figure 11: Prediction on an adversarial image with $\epsilon = 0.2$ (roughly 5% of original range)

4 Conclusions

Preliminary conclusion: It is possible

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A Bigger adversarial images

Clean image
Prediction by S.A.T.: A group of people standing around a tennis court.

Adversarial Image with $\epsilon = 0.005$
Prediction by S.A.T.: A group of people sitting in a room with a bunch of different colored vases.

Clean image
Prediction by S.A.T.: A group of people standing around a tennis court.

Adversarial Image with $\epsilon = 0.010$
Prediction by S.A.T.: A group of vases sitting on top of a table.

Clean image
Prediction by S.A.T.: A group of people standing around a tennis court.

Adversarial Image with $\epsilon = 0.020$
Prediction by S.A.T.: A group of vases sitting on top of a table.

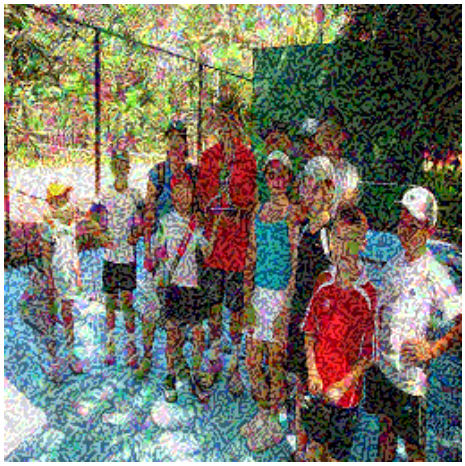
Clean image
Prediction by S.A.T.: A group of people standing around a tennis court.

Adversarial Image with $\epsilon = 0.040$
Prediction by S.A.T.: A large glass vase with a bunch of flowers on it.

Clean image
Prediction by S.A.T.: A group of people standing around a tennis court.

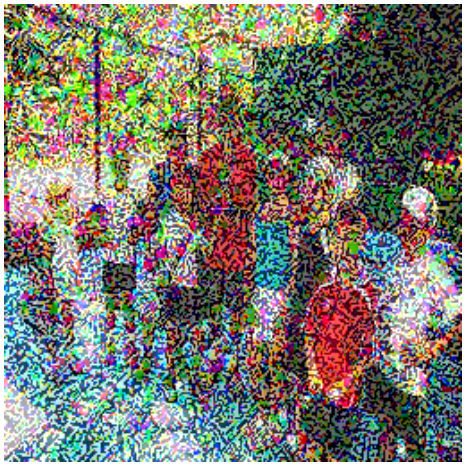
Adversarial Image with $\epsilon = 0.080$
Prediction by S.A.T.: A bathroom with a toilet and a sink.

Clean image
Prediction by S.A.T.: A group of people standing around a tennis court.



Adversarial Image with $\epsilon = 0.160$
Prediction by S.A.T.: A red wall with a red and white design.

Clean image
Prediction by S.A.T.: A group of people standing around a tennis court.



Adversarial Image with $\epsilon = 0.320$
Prediction by S.A.T.: A large red object with a red and white background.