Improved Image Captioning with Adversarial Semantic Alignment

Pierre L. Dognin\*  Igor Melnyk\*  Youssef Mroueh\*  Jarret Ross\*  Tom Sercu\*
IBM Research  IBM Research  IBM Research  IBM Research  IBM Research

Abstract

We study image captioning as a conditional GAN training, proposing both a context-aware LSTM captioner and co-attentive discriminator, which enforces semantic alignment between images and captions. We empirically study the viability of two training methods: Self-critical Sequence Training (SCST) and Gumbel Straight-Through (ST). We show that, surprisingly, SCST (a policy gradient method) shows more stable gradient behavior and improved results over Gumbel ST, even without accessing the discriminator gradients directly. We also address the open question of automatic evaluation for these models and introduce a new semantic score and demonstrate its strong correlation to human judgement. As an evaluation paradigm, we suggest that an important criterion is the ability of a captioner to generalize to compositions between objects that do not usually occur together, for which we introduce a captioned Out of Context (OOC) test set. The OOC dataset combined with our semantic score is a new benchmark for the captioning community. Under this OOC benchmark, and the traditional MSCOCO dataset, we show that SCST has a strong performance in both semantic score and human evaluation.

1 Introduction

Significant progress has been made on the task of generating image descriptions using neural image captioning [1–3]. Early models optimized the cross-entropy of the generated words. More recently, evaluations metrics such as CIDEr [4], BLEU4 [5] and SPICE [6] were optimized using reinforcement learning techniques [7, 8, 6]. Despite those advances, image captioning is far from being a solved task. A lot remains to be done in order to bridge the semantic gap and produce diverse, creative, human-like captions. Another important issue is dataset bias: common objects co-occurring in common context. Captioning systems need to be able to generalize to objects appearing in unseen contexts.

Optimizing automatic NLP metrics misses an essential part of the alignment between the image visual cues and the caption. Recently GANs [9] were applied to the captioning problem [10, 11] where, using a conditional GAN, the discriminator gives a strong signal on the alignment between the image and the generated sentence. This alignment score, produced by the discriminator and used as a reward for training the captioner, is learned along with the captioner in a min/max game.

Results in [10, 11] are encouraging but rely on a complex and computationally expensive setup. Evaluation in [10, 11] with respect to generalization and capturing the semantic alignment with the image remains unclear. In this paper, we address the image captioning problem in the GAN framework with three main objectives: 1) Enabling language composition and compositional alignment of image and text (Section 3.1). 2) Light-weight training of discrete GANs for text generation (Section 3.2). 3) Generalization to out of context scenes and a quantitative evaluation of semantic alignment across GAN models (Section 4).

\*Equal Contribution. Correspondence with authors: pdognin@us.ibm.com, igor.melnyk@ibm.com, mroueh@us.ibm.com, rossja@us.ibm.com, tom.sercu1@ibm.com.

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2 Related Work

Image captioning systems modeled as recurrent networks are traditionally trained using cross-entropy (CE) minimization \([1,3]\). Lately, efforts to train captioners using NLP metrics such as CIDEr, BLEU4, or SPICE have used policy gradient methods such as REINFORCE as in \([7,6,8]\) introduced Self-critical Sequence Training, a variant of REINFORCE with the baseline being the reward of the policy under the decoding algorithm. SCST produced state of the art results using CIDEr as an optimization metric.

As discussed in the introduction, automatic NLP metrics are based on consensus and \(n\)-grams matching and do not carry any semantic alignment between the image and the caption. Furthermore they do not provide a way to promote naturalness of the language as measured by a Turing test, where machine generated text cannot be distinguished from text created by humans. More recently, image captioning has been explored in the GAN framework. \([10,11]\) have tackled the problem of diversity and naturalness using a conditional GAN. Neural generators of discrete sequences are challenging to train in the GAN framework. Reinforcement learning techniques were proposed in many recent works for training GAN for text generation \([10,12–15]\). The Gumbel Softmax relaxation \([16]\) has also been applied to GAN for text generation in \([11,17]\).

3 Adversarial Caption Generation

In this Section we present our captioner and discriminator models. We show how to train discrete GANs using a policy gradient method, namely SCST, and compare it with the approach based on the Gumbel trick. Our experiments (Section 5) show that, surprisingly, SCST obtains better results, even though it does not directly access the discriminator gradients.

3.1 Compositional Captioner and Discriminator

Here we introduce an image captioning model with attention that we call context aware captioning based on \([18]\). This allows the captioner to compose sentences based on fragments of observed visual scenes in the training. Furthermore, we introduce a discriminator that scores the alignment between images and captions based on a co-attention model \([19]\). This gives the generator a signal on the semantic alignment and the compositional nature of visual scenes and language. We show in Section 5 that we obtain better results across evaluation metrics when using this co-attentive discriminator.

Context Aware Captioner \(G_0\). For caption generation we use an LSTM with visual attention \([3,8]\) together with a visual sentinel \([18]\) to give the LSTM a choice to attend to visual or textual cues. While \([18]\) feeds at each step only an average image feature, we feed a mixture of image features and visual sentinel from the previous step to make the LSTM aware of the attention context used in the past (we call it Context Aware Attention). As shown in Appendix A in Table 5 this modification gives a significant boost in performance.

Co-attention Pooling Discriminator \(D_0\). The task of the discriminator is to score the similarity between an image and a caption. Previous works jointly embed the modalities at the similarity computation level, which we call late joint embedding, see Figure 1(a). Instead, we propose to jointly embed image and caption in earlier stages using a co-attention model \([19,20]\) and compute similarity on the attentive pooled representation. We call this a co-attention discriminator (Figure 1(b)) and provide architecture details below.

Given a sequence of words \((w_1, \ldots, w_T)\), the discriminator embeds them using the LSTM (state dimension \(m = 512\)) to get \(H = [h_1, \ldots, h_T]^T \in \mathbb{R}^{T \times m}\), where \(h_t, c_t = \text{LSTM}(h_{t-1}, c_{t-1}, w_t)\). The image features \((I_1, \ldots, I_C)\), \(C = 14 \times 14 = 196\) (number of crops), is also embedded as \(I = [WI_1, \ldots, WI_C]^T \in \mathbb{R}^{C \times m}\), where \(W \in \mathbb{R}^{m \times d I}\), and \(d_I = 2048\) is the image feature size. Following \([19]\), we then compute a correlation \(Y\) between image and text using bilinear projection \(Q \in \mathbb{R}^{m \times m}\), \(Y = \text{tanh}(IQH^T) \in \mathbb{R}^{C \times T}\). Matrix \(Y\) is used to compute co-attention weights \([19]\) of each modality conditioned on another:

\[
I_H = \text{tanh}(IW_I + YHW_Ih_I) \in \mathbb{R}^{C \times m}, \quad \alpha = \text{Softmax}(I_Hw_I + b_I) \in \mathbb{R}^{C}, \quad w_I \in \mathbb{R}^m, \quad b_I \in \mathbb{R},
\]
\[
H_I = \text{tanh}(HW_I + Y^T IW_Ih_I) \in \mathbb{R}^{T \times m}, \quad \beta = \text{Softmax}(H_Iw_h + b_h) \in \mathbb{R}^{T}, \quad w_h \in \mathbb{R}^m, \quad b_h \in \mathbb{R},
\]
When compared to other policy gradient methods used in the sequential GAN context, we note two main advantages for SCST: 1) The reward in SCST can be global at the sentence level and the training still succeeds. If using simpler policy gradient methods as in [10, 6], the reward needs to be defined at each word generation with the full sentence sampling, which means that the discriminator needs to relax its approach of [10, 11].

We describe here the details of the adversarial training of the discriminator and the captioner. The reward in SCST can be global at the sentence level and the training still succeeds. If using simpler policy gradient methods as in [10, 6], the reward needs to be defined at each word generation with the full sentence sampling, which means that the discriminator needs to relax its approach of [10, 11].

The generator is optimized to solve

\[ \max_{\theta} \mathcal{L}_{G}(\theta) \]

where \( \mathcal{L}_{G}(\theta) = \mathbb{E}_{I} \log D_{\eta}(I, G_{\theta}(I)) \).

The main difficulty is the discrete nature of the problem, making it non-differentiable. We solve this issue by adopting a variant of the policy gradient method, SCST [8], and compare it to Gumbel relaxation approaches of [16].

**3.2 Adversarial Training**

We describe here the details of the adversarial training of the discriminator and the captioner.

**Training** \( D_{\eta} \). Discriminator \( D_{\eta} \) is not only trained to distinguish real from fake (generated) captions, but also to classify images with random unrelated sentences as fake [10, 11], thus forcing it to focus on the semantic correlations between images and captions. Therefore, we solve the following optimization problem: \( \max_{\eta} \mathcal{L}_{D}(\eta) \), where the loss \( \mathcal{L}_{D}(\eta) \) has the form

\[
\mathcal{L}_{D}(\eta) = \mathbb{E}_{I,w} \log D_{\eta}(I, w) + \frac{1}{2} \mathbb{E}_{I,w^{*} \sim p_{0}(\cdot | I)} \log (1 - D_{\eta}(I, w^{*})) + \frac{1}{2} \mathbb{E}_{I,w^{*} \notin S(I)} \log (1 - D_{\eta}(I, w^{*}))
\]

and the sequence \( w^{*} \) is obtained by sampling from the generator \( G_{\theta} \) (fake caption).

**Training** \( G_{\theta} \). The generator is optimized to solve \( \max_{\theta} \mathcal{L}_{G}(\theta) \), where \( \mathcal{L}_{G}(\theta) = \mathbb{E}_{I} \log D_{\eta}(I, G_{\theta}(I)) \).

The main difficulty is the discrete nature of the problem, making it non-differentiable. We solve this issue by adopting a variant of the policy gradient method, SCST [8], and compare it to Gumbel relaxation approaches of [16].

**Training** \( G_{\theta} \) : \textbf{SCST} [8] is a light-weight REINFORCE variant that uses the reward under the decoding algorithm as baseline. In this work, the decoding algorithm is a “greedy max”, selecting at each step the most probable word \( \arg \max \log p_{\theta}(\cdot | h_{t}) \). For a given image, a single sample \( w^{*} \) of the generator is used to estimate the full sequence reward, \( \mathcal{L}_{G}(\theta) = \log (D_{\eta}(I, w^{*})) \) where \( w^{*} \sim p_{\theta}(\cdot | I) \).

Using SCST, the gradient is estimated as follows:

\[
\nabla_{\theta} \mathcal{L}_{G}(\theta) \approx \log D_{\eta}(I, w^{*}) - \log D_{\eta}(I, \hat{w}) \nabla_{\theta} \log p_{\theta}(w^{*}| I) = \left( \log \frac{D_{\eta}(I, w^{*})}{D_{\eta}(I, \hat{w})} \right) \nabla_{\theta} \log p_{\theta}(w^{*}| I),
\]

where \( \hat{w} \) is obtained using greedy max. The baseline does not change the expectation of gradient but reduces the variance of the estimate.

When compared to other policy gradient methods used in the sequential GAN context, we note two main advantages for SCST: 1) The reward in SCST can be global at the sentence level and the training still succeeds. If using simpler policy gradient methods as in [10, 6], the reward needs to be defined at each word generation with the full sentence sampling, which means that the discriminator needs to...
We experiment with Gumbel Soft and Gumbel ST variations in this paper. We present here an alternative way to deal with the discreteness of the generator using Gumbel Softmax re-parameterization [16]. In particular, in this work we adopt the Gumbel Straight-Through (Gumbel ST) approach, recently used in [11, 17]. Define the soft samples for the generator using Gumbel Softmax re-parameterization [16]. In particular, in this work we adopt the Gumbel ST approach, recently used in [11, 17].

\[ r(ws) = \log (D_\eta(I, (ws_1, \ldots, ws_T))) \]

\[ r(\hat{w}) = \log (D_\eta(I, (\hat{w}_1, \ldots, \hat{w}_T))) \]

\[ (r(ws) - r(\hat{w})) \nabla \theta \log p_\theta(ws^*) \]

Figure 2: SCST Training of GAN-captioning.

be evaluated \( T \) times (sentence of length \( T \)). 2) In [10] [14], many Monte-Carlo rollouts are needed to reduce variance of the gradients, requiring many forward-passes through the generator. In contrast, due to a strong baseline, only a single sample estimate is enough in SCST (see Figure 2).

It must be noted that we can also regularize the GAN training with any NLP metric \( r_{\text{NLP}} \) (such as CIDEr) and the gradient becomes:

\[ \left( \log \frac{D_\eta(I, ws)}{D_\eta(I, \hat{w})} + \lambda (r_{\text{NLP}}(ws) - r_{\text{NLP}}(\hat{w})) \right) \nabla \theta \log p_\theta(ws^* | I) \quad (2) \]

**Training \( G_\theta : \text{Gumbel Trick.}** We present here an alternative way to deal with the discreteness of the generator using Gumbel Softmax re-parameterization [16]. In particular, in this work we adopt the Gumbel Straight-Through (Gumbel ST) approach, recently used in [11, 17]. Define the soft samples \( y_t \), for \( t = 1, \ldots, T \) and \( j = 1, \ldots, K \) such that: \( y_t^j = \text{Softmax} \left( \frac{1}{\tau} \text{logits}_t(j | h_t, I + g_j) \right) \), where \( K \) is the vocabulary size, \( g_j \) are samples from the Gumbel distribution, \( \tau \) is a temperature parameter. We experiment with Gumbel Soft and Gumbel ST variations in this paper.

For **Gumbel soft**, we use the soft samples \( y_t \) as LSTM input \( w_{t+1}^s \) on the next time step and in \( D_\eta \):

\[ \nabla \theta \mathcal{L}_G^t(\theta) = \nabla \theta \log (D_\eta(I, (y_1, \ldots, y_T))) \]

For **Gumbel ST**, we define one-hot encodings \( O_t = \text{OneHot}(\arg \max_j y_t^j) \) and approximate the gradients \( \partial \mathcal{O}_t^j / \partial y_t^{j'} = \delta_{jj'} \). When we sample from \( G_\theta \), we use the hard \( O_t \) as LSTM input \( w_{t+1}^s \) on the next time step and in \( D_\eta \), hence the gradient becomes:

\[ \nabla \theta \mathcal{L}_G^t(\theta) = \nabla \theta \log (D_\eta(I, (O_1, \ldots, O_T))) \]

Note that in this case, the loss can be easily regularized with Feature Matching (FM) as follows:

\[ \mathcal{L}_G^t(\theta) = \log(D_\eta(I, (y_1, \ldots, y_T))) - \lambda_F^t \left( \left| \left| E_I(w_1^*, \ldots, w_T^*) - E_I(y_1, \ldots, y_T) \right| \right|^2 \right) 
- \lambda_S^{12} \left( \left| \left| E_S(w_1^*, \ldots, w_T^*) - E_S(y_1, \ldots, y_T) \right| \right|^2 \right), \quad (3) \]

where \( (w_1^*, \ldots, w_T^*) \) is the ground truth caption corresponding to image \( I \), and \( E_I \) and \( E_S \) are co-attention image and sentence embeddings (as defined in Section 3.1). Feature matching enables us to incorporate more granular information from discriminator representations of the ground truth caption, similar to how SCST reward can be regularized with CIDEr, computed with a set of baseline captions.

### 4 Evaluation: Semantic Score and Out of Context Image Set

**Semantic Score.** Established automatic language metrics such as CIDEr or BLEU4 are inadequate for evaluating GAN models. As an early alternative, both [10] [11] used the GAN discriminator score as a model comparison metric. We argue that this is not a fair evaluation across models since the GAN generator was trained to maximize the discriminator likelihood. In order to enable universal automatic evaluation across models we propose the **semantic score**. Analogous to the “Inception score” [21] for image generation which leverages a large pretrained classification network, the semantic score relies on a powerful model, trained with supervision, to heuristically evaluate caption quality and its alignment to the image. Across metrics, algorithms and test sets we show that our semantic score correlates well with human judgement (Section 5).

The semantic score is a CCA-based retrieval model [22] which brings the image into the scoring loop by training on the combination of COCO [23] and SBU [24] (~1M images), ensuring a larger
exposure of the score to diverse visual scenes and captions, and lowering the COCO dataset bias. In the retrieval context, the semantic score achieves state of the art performance [22]. The semantic score outputs a cosine similarity in CCA space based on a 15k dimension image embedding from resnet-101 [25], and a sentence embedding computed using a Hierarchical Kernel Sentence Embedding [22] based on word2vec [26], as given by Equation (4) in Appendix B. Using word2vec allows scores for captions with words falling outside of COCO vocabulary to be computed. The semantic score we use from [22] provides the likelihood of the image given the sentence while also penalizing wrong attributes and objects. See Table 4 in Appendix B for examples. Scripts and models for computing the semantic score will be publicly released.

**Out of Context Test Set (OOC).** A captioner's ability to generalize to objects out of their common contexts is an important evaluation criterion. In order to test the compositional and generalization properties to out of context scenes (see Figure 5), we expanded the "out of context objects" set of [27] into the "Out of Context" (OOC) dataset with captions. The original set [27] contained 256 images, to which we added 51 images for a total of 297 images in OOC. For each image, we collected 5 captions on Amazon MTurk. We evaluate standard NLP metrics as well as our proposed semantic score on the OOC set. We plan to release the OOC set and the code for evaluating semantic scores. Improving scores on the OOC set remains an open area for future work.

### 5 Experiments

**Experimental Setup.** We evaluate our proposed methods on the COCO dataset [23] using data splits from [2]: training set of 113k images with 5 captions each, 5k validation set, and 5k test set for offline evaluation. Our vocabulary size is 10096 after pruning words with counts less than 5. We also report performance on our OOC set (297 images). Each image is encoded by a resnet-101 [25] without rescaling or cropping, followed by a spatial adaptive max-pooling to ensure a fixed size of 14×14×2048. An attention mask is produced over the 14×14 spatial locations, resulting in a spatially averaged 2048-dimension representation. LSTM hidden state, image, word, and attention embedding dimensions are fixed to 512 for all models. All models are first trained with CE loss using ADAM with a learning rate of 3×10⁻⁴ with a weight decay of 0.0001. The initial learning rate for SCST and Gumbel ST is 10⁻³. We report standard NLP metrics, our introduced semantic score, and vocabulary coverage (percentage of vocabulary used at generation).

Table 1: Results for all models mentioned in this work. Scores are reported for both COCO and OOC sets. All results are averaged (± standard deviation) over 4 models trained with different random seeds. See Table 5 in Appendix C for a full set of results.

| COCO Test Set | OOC (Out of Context) |
|---------------|-----------------------|
|               | CIDEr METEOR Semantic Score Vocabulary Coverage | CIDEr METEOR Semantic Score Vocabulary Coverage |
| CE            | 101.6 ± 0.4 0.260 ± 0.001 0.146 ± 0.001 9.2 ± 0.1 | 101.6 ± 0.4 0.260 ± 0.001 0.146 ± 0.001 9.2 ± 0.1 |
| CE+e-RLL     | 116.1 ± 0.2 0.289 ± 0.001 0.184 ± 0.001 5.1 ± 0.1 | 116.1 ± 0.2 0.289 ± 0.001 0.184 ± 0.001 5.1 ± 0.1 |
| GAN*(SCST, Co-att, log(D)) | 97.5 ± 0.8 0.356 ± 0.001 0.190 ± 0.000 11.9 ± 0.1 | 97.5 ± 0.8 0.356 ± 0.001 0.190 ± 0.000 11.9 ± 0.1 |
| GAN*(SCST, Co-att, log(D) + 5×CIDEr) | 111.1 ± 0.7 0.271 ± 0.002 0.192 ± 0.000 7.3 ± 0.2 | 111.1 ± 0.7 0.271 ± 0.002 0.192 ± 0.000 7.3 ± 0.2 |
| GAN*(SCST, Joint-Emb, log(D)) | 97.1 ± 1.2 0.266 ± 0.002 0.180 ± 0.000 11.2 ± 0.1 | 97.1 ± 1.2 0.266 ± 0.002 0.180 ± 0.000 11.2 ± 0.1 |
| GAN*(SCST, Joint-Emb, log(D) + 5×CIDEr) | 108.2 ± 1.9 0.367 ± 0.004 0.190 ± 0.000 8.3 ± 0.1 | 108.2 ± 1.9 0.367 ± 0.004 0.190 ± 0.000 8.3 ± 0.1 |
| GAN*(Gumbel Soft, Co-att, log(D)) | 93.6 ± 0.3 0.253 ± 0.007 0.137 ± 0.002 11.1 ± 0.2 | 93.6 ± 0.3 0.253 ± 0.007 0.137 ± 0.002 11.1 ± 0.2 |
| GAN*(Gumbel Soft, Co-att, log(D) + 5×CIDEr) | 93.4 ± 0.1 0.249 ± 0.004 0.184 ± 0.003 10.1 ± 0.0 | 93.4 ± 0.1 0.249 ± 0.004 0.184 ± 0.003 10.1 ± 0.0 |
| GAN*(Gumbel ST, Co-att, log(D)) | 92.1 ± 0.4 0.243 ± 0.011 0.175 ± 0.006 8.6 ± 0.0 | 92.1 ± 0.4 0.243 ± 0.011 0.175 ± 0.006 8.6 ± 0.0 |
| GAN*(Gumbel ST, Co-att, log(D) + 5×CIDEr) | 93.7 ± 0.2 0.242 ± 0.001 0.175 ± 0.002 9.9 ± 0.0 | 93.7 ± 0.2 0.242 ± 0.001 0.175 ± 0.002 9.9 ± 0.0 |
| GAN*(SCST, Co-att, log(D)) | 87.6 ± 0.6 0.253 ± 0.006 0.173 ± 0.002 6.8 ± 0.0 | 87.6 ± 0.6 0.253 ± 0.006 0.173 ± 0.002 6.8 ± 0.0 |
| GAN*(SCST, Co-att, log(D) + 5×CIDEr) | 100.4 ± 0.7 0.253 ± 0.006 0.173 ± 0.002 6.8 ± 0.0 | 100.4 ± 0.7 0.253 ± 0.006 0.173 ± 0.002 6.8 ± 0.0 |
| GAN*(SCST, Joint-Emb, log(D)) | 98.7 ± 0.9 0.246 ± 0.001 0.184 ± 0.001 13.2 ± 0.2 | 98.7 ± 0.9 0.246 ± 0.001 0.184 ± 0.001 13.2 ± 0.2 |
| GAN*(SCST, Joint-Emb, log(D) + 5×CIDEr) | 103.5 ± 0.5 0.261 ± 0.001 0.185 ± 0.001 7.1 ± 0.2 | 103.5 ± 0.5 0.261 ± 0.001 0.185 ± 0.001 7.1 ± 0.2 |
| GAN*(SCST, Joint-Emb, log(D)) | 102.7 ± 0.4 0.260 ± 0.004 0.182 ± 0.001 7.7 ± 0.1 | 102.7 ± 0.4 0.260 ± 0.004 0.182 ± 0.001 7.7 ± 0.1 |
| GAN*(SCST, Joint-Emb, log(D) + 5×CIDEr) | 102.7 ± 0.4 0.260 ± 0.004 0.182 ± 0.001 7.7 ± 0.1 | 102.7 ± 0.4 0.260 ± 0.004 0.182 ± 0.001 7.7 ± 0.1 |
| G-GAN [10] from Table 1 | 79.5 ± 0.2 0.224 ± 0.000 0.184 ± 0.000 7.7 ± 0.1 | 79.5 ± 0.2 0.224 ± 0.000 0.184 ± 0.000 7.7 ± 0.1 |

**Experimental Results.** Table 1 presents results for both COCO and OOC datasets for two discriminator architectures (Co-att, Joint-Emb) for all training algorithms (SCST, Gumbel ST, and Gumbel Soft). We include results for our CE and CIDEr-RL conventional captioners, i.e. non-GANs, baseline models, as well as results from non-attentional captioners (models in rows below CE*). Our CE model is trained to maximize the cross-entropy of each word when generating a caption. CIDEr-RL starts from the CE model and is trained using SCST with a CIDEr reward over the whole caption. As already observed in [8], automatic metrics scores for CIDEr-RL are greatly improved compared to the CE model (from 101.6 to 116.1 CIDEr on COCO). Semantic scores remain close while vocabulary
coverage drops significantly from CE to CIDEr-RL model (from 9.2% to 5.1% for COCO). Improving CIDEr n-gram based metric impoverishes CIDEr-RL vocabulary coverage, revealing the vanilla, ubiquitous nature of the generated captions. On OOC, CIDEr-RL improves slightly on the CE model (CIDEr from 42.2 to 45.0), leading to a small drop in vocabulary coverage.

For GAN models $GAN_1, \ldots, GAN_4$, we use SCST with either Co-att or Joint-Emb discriminator. For both discriminators, we use ST with reward $\log(D)$, or $\log(D) + 5 \times $ CIDEr. Gumbel ST training without Feature Matching is used for $GAN_3$, while we use Gumbel ST training with and without Feature Matching, as defined in [10], for $GAN_4$ and $GAN_5$ respectively. SCST provides stable training of models across several runs, while Gumbel relaxation approaches often become unstable beyond 15 epochs. SCST GAN models outperform CE and CIDEr-RL captioners on semantic score and vocabulary coverage for both COCO and OOC sets. CIDEr and METEOR results for these models can be improved significantly using a CIDEr-regularized SCST GAN reward. It results also in a slight improvement of the semantic score (at the cost of some vocabulary coverage loss) as seen for $GAN_1$ vs. $GAN_2$ and $GAN_3$ vs. $GAN_4$. Our best semantic score model (0.192) is $GAN_2$ with CIDEr-regularized SCST. This $GAN_2$ model displays the best overall performance on COCO and OOC set. Note that on OOC, $GAN_2$ has the overall best CIDEr while recovering higher vocabulary coverage than CIDEr-RL. SCST GANs using our Co-att discriminator outperform their Joint-Emb [10] counterparts on every metric except vocabulary coverage (for COCO). On OOC, $GAN_4$ is tied with Co-att $GAN_2$ for best METEOR at 0.173 but behind for semantic score. Overall, Joint-Emb discriminators systematically achieve better vocabulary coverages compared to models with Co-att discriminators.

For $GAN_5, \ldots, GAN_7$, we use Gumbel training solely with our Co-att discriminator. They show mixed results. Gumbel Soft trained $GAN_7$ gives some slight improvements over CE and CIDEr-RL for semantic scores on both COCO and OOC, and good vocabulary coverage for OOC (3.3%). However, Gumbel trained GANs underperform on all other metrics compared to SCST GANs. We conclude that SCST is a better technique for training sequence GANs. For baselining, we reproduce results from [10] with non-attentional generators (same architecture as in [10]). Non-attentional models are behind in all metrics, except for one: vocabulary coverage for both datasets. Interestingly, Co-att discriminators still provide better semantic scores than their Joint-Emb counterparts despite non-attentional Generators. For reference, published results from [10] for their G-GAN (in Table 1) are also included in Table 1.

Figures 3 and 4 show semantic scores and vocabulary coverage evolutions during training for $GAN_1, \ldots, GAN_4$, CE, CIDEr-RL models compared to ground truth (GT) captions. Semantic scores increase steadily for all cost functions and discriminator architectures as the training sees more data. In Figure 3(a), GAN models improve steadily over CE and RL, ultimately surpassing both of them mid-training. Co-att GANs perform overall much better than Joint-Emb GANs. For CIDEr-regularized SCST GANs, the same trend is observed with a faster rate of improvement across epochs since the models start off worse than CE and RL. Again, Co-att GANs outperform Joint-Emb GANs. For OOC in Figure 3(b), previous trends are confirmed with Co-att GANs outperforming all other models. For COCO, GT semantic score is greater than any other models while the opposite is true for OOC. This may be caused by the vocabulary mismatch between OOC and the combination of COCO and SBU. Figures 3 and 4 show that semantic score improvements of GAN trained models correlate well with vocabulary coverage increase for both COCO and OOC.

**Ensemble Models.** Table 2 presents results for ensemble models. An ensemble caption is generated by averaging softmax scores from 4 different models before word selection. $Ens_{CE}$ and $Ens_{RL}$ ensemble CE and CIDEr-RL models. Similarly, $Ens_1, \ldots, Ens_7$ ensemble models from $GAN_1, \ldots, GAN_7$ respectively ($Ens_{ijk}$ denotes an ensemble of $GAN_i$, $GAN_j$, and $GAN_k$). Ensemble models show improved results on all metrics. Similar relative performance trends are observed among the models. Ensembling SCST GANs provides our best results, reinforcing the conclusion that SCST is a superior method for stable sequence GANs training.

**Gradient Analysis.** We established that SCST is a stable sequence GAN training technique. Gumbel relaxation based methods achieve worse performance overall. Figure 9 in Appendix F compares gradient behaviors of both techniques. Gradients from SCST training have smaller absolute gradient norm and variance across minibatches. This is a considerable advantage for SCST as a superior policy gradient technique providing low variance gradient estimates.
Table 2: Ensembling results for some GANs from Table 1 for COCO and OOC sets. See Table 6 in Appendix C for complete set of results including BLEU4, and ROUGEL.

| GAN (SCST, Joint-Emb, log(D)) | Semantic Score | Vocabulary Coverage |
|------------------------------|---------------|---------------------|
| GAN1 (SCST, Co-att, log(D))  | 0.1075        | 0.0500              |
| GAN2 (SCST, Co-att, log(D) + 5*CIDEr) | 0.1100        | 0.0525              |
| GAN3 (SCST, Joint-Emb, log(D)) | 0.185         | 0.0700              |
| GAN4 (SCST, Joint-Emb, log(D) + 5*CIDEr) | 0.190         | 0.0725              |
| CE                            | 0.195         | 0.0750              |
| RL                            | 0.200         | 0.0775              |
| GT                            | 0.205         | 0.0800              |

Human Evaluation. We evaluate image/caption pairs on Amazon MTurk where workers are asked for ratings (between 1 and 5 stars) and rankings for EnsCE, EnsRL, and ensemble GAN models (MTurk details are given in Appendix E). A Mean Opinion Score (MOS) is computed from these ratings. Figure 5(a) shows that GAN EnsCE model scored higher ratings than CE and CIDEr-RL on a majority vote of 5 workers. This confirms that GAN training improves the perceived quality of captioners significantly. Figure 5(b) gives Turing test results where workers are asked whether a caption is human or machine generated. GANs demonstrate a good capacity at fooling humans.
Figure 5 (c) shows that human evaluation MOS correlates well with our semantic score (See Table 7 in Appendix E for all scores). The semantic score captures semantic alignments pertinent to humans, validating its use as a proxy for human evaluation. Figure 6 gives examples of our models captions and illustrate the difficulty of captioning images from OOC. GT captions on OOC are clearly much longer than GT from COCO. Human captioners need more words to accurately describe these unusual images. This exemplifies the challenge of automatic captioning of OOC images.

Figure 6: Examples of captions for our proposed model for COCO Test and OOC datasets.

6 Conclusion

We conclude with three main messages from this study: 1) SCST training for sequence GAN surprisingly outperforms the Gumbel relaxation approach in terms of stability and overall performance. 2) The modeling part in captioning is crucial for generalization to out of context: we demonstrate that non-attention captioners and discriminators – while still widely used – fail at generalizing to out of context hinting at a memorization of the training set. Attentive captioners and discriminators succeed at composing on unseen visual scenes as demonstrated on our newly introduced OOC set. 3) Human evaluation is still the gold standard for assessing the quality of GAN captioning. Our introduced semantic score correlates well with human judgement, and can be used as a proxy for it.
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A  Context-Aware Attention Captioner Performance

Table 3: Performance of captioning systems given various attention mechanisms, Att2All [8], sentinel attention [10] and Context Aware Attention (this work). Models are compared using CIDEr scores on the validation set of COCO. Models are built using cross-entropy (‘CE’) and REINFORCE based SCST from [8] (‘RL’). Context aware attention brings large gains in CIDEr for both CE and RL trained models despite being a small architectural change from sentinel attention from [18].

| Attention Model          | CE  | RL  |
|--------------------------|-----|-----|
| Att2All [8]              | 98.5| 115.7|
| Sentinel [18]            | 99.7|     |
| Context Aware (ours)     | 103.3| 118.6|

B  Semantic Score

Semantic scores was first introduced in the context of image retrieval where it achieves state of the art performance [22]. The semantic score is a cosine similarity measure defined as:

$$s(x, y) = \frac{\langle \Sigma U^\top x, V^\top y \rangle}{\|\Sigma U^\top x\|_2 \|V^\top y\|_2},$$

where $x$ and $y$ are caption and image embedding vectors respectively. $U$, $\Sigma$, and $V$ are matrices obtained from CCA as described in details in [22]. Some examples of the properties of semantic scores are given in Table 4.

C  Experimental Results: Complete Tables

We report here CIDEr, BLEU4, ROUGEL, METEOR, semantic scores, and vocabulary coverage for all models mentioned in this work, both COCO and OOC sets. Table 5 presents all GAN results as average ($\pm$ standard deviation) over 4 models with different random seeds. Table 6 presents all our ensemble results.

D  Semantic and Discriminator Scores Correlation over Training Epochs

We are interested in the correlation between the semantic scores and discriminator scores of image captions as well as its evolution along the process of SCST GAN training. We provide scatter plots for the Joint-Embedding discriminator [10] across training in Figure 7. This GAN model was trained over 40 epochs with a discriminator pretrained on 15 epochs of data.

We compare semantic scores and discriminator scores over training epochs given the ground truth (GT) caption for each image in the COCO Test set (5K images). Each GT caption being fixed, we can observe the evolution of the semantic and discriminator score without any other effects. Figure 7 show the semantic score, discriminator score pairs for each image (one point per image) for the joint embedding discriminator. Since the GT captions are fixed, the semantic scores will be identical across epochs. From the first epoch, the joint embedding discriminator provides a wide range of scores with most scores close to the 0.0 and 1.0 min/max values. Quickly the points cluster into a 'sail' like shape in the lower right corner, away from the min/max edges. The color assigned to each point is directly linked to the semantic scores assigned at the first epoch of training. You can therefore have a small visual cue of the movement of these points from epoch to epoch and witness the discriminator learning how to distinguish real and fake captions.

E  Human Evaluation

In this section we present the details of our evaluation protocol for our captioning models on Amazon MTurk. All images are presented to 5 workers and aggregated in mean opinion score (MOS) or majority vote.
Table 4: Semantic scores for various captions given an image from COCO validation set. Set A is composed of the 5 ground truth captions provided by COCO. Semantic scores are in between .14 and .25 for a possible range of [-1,1] being a cosine distance. Set B is made of captions from another randomly selected image in the validation set. The scores are clearly much worse (smaller) when captions do not match the image visual cues. Set C is a one-word modification set of the first caption in Set A. Semantic scores are all lower compared to the original caption. In Set C, we want to see if the metric is solely sensitive the main visual cues and if it can pick up subtle differences like gender. Again, all the scores are still lower, even if closer to the original caption’s score. In Set E, we are trying to break the metric by narrowing down to only factual words and objects. The combined knowledge of visual and text correlation penalize simplistic descriptive list of words. This does not imply that the metric cannot be fooled, but it seems resilient to obvious gaming like repeating words of some visual cues.

| COCO validation image | Set   | Semantic Score | Captions                                                                 |
|-----------------------|-------|----------------|--------------------------------------------------------------------------|
|                       | A     | 0.181052       | female tennis player reaches back to swing at the ball                   |
|                       |       | 0.210224       | a woman on a court swinging a racket at a ball                           |
|                       |       | 0.181592       | a woman in a gray top is playing tennis                                  |
|                       |       | 0.251200       | the woman is playing tennis on the court                                 |
|                       |       | 0.145646       | a woman prepares to hit a tennis ball with a racket                      |
|                       | B     | 0.008990       | a clear refrigerator is stocked up with food                            |
|                       |       | 0.005519       | a store freezer is shown with food inside                               |
|                       |       | -0.014052      | a refrigerated display case is full of dairy groceries                   |
|                       |       | 0.011076       | a close up of a commercial refrigerator with food                        |
|                       |       | -0.029001      | a large cooler with glass doors containing mostly dairy products         |
|                       | C     | 0.054441       | a giraffe reaches back to swing at the ball                             |
|                       |       | 0.123822       | female tennis player reaches back to swing at the boat                   |
|                       |       | 0.152860       | male tennis player reaches back to swing at the ball                     |
|                       |       | 0.067289       | female football player reaches back to swing at the ball                 |
|                       | D     | 0.152860       | male tennis player reaches back to swing at the ball                     |
|                       |       | 0.164755       | female tennis player reaches back to swing at the ball                   |
|                       |       | 0.152524       | female tennis player looks back to swing at the ball                     |
|                       |       | 0.100098       | female flute player reaches back to swing at the ball                    |
|                       |       | 0.114010       | female tennis player swing ball                                         |
|                       |       | 0.031566       | female player swing ball                                                |
|                       |       | 0.084016       | tennis player swing ball                                                |
|                       |       | 0.115490       | tennis player ball                                                      |
|                       |       | 0.092226       | tennis player                                                           |
|                       |       | -0.044019      | tennis                                                                    |
|                       |       | -0.001948      | ball ball ball                                                           |

**Turing Test.** In this setting we give human evaluators an image with a sentence either generated from our GAN captioning models or the ground truth. We ask them whether the sentence is human generated or machine generated. Exact instructions are: “Is this image caption written by a human? Yes/No. The caption could be written by a human or by a computer, more or less 50-50 chance.”

**Fine Grained Evaluation and Model Comparison.** In this experiment we give human evaluators an image and a set of 3 captions: Generated by CE trained model, SCST CIDEr trained model, and a GAN model. We ask them to rate each sentence on a scale of one to five. After rating, the worker chooses the caption he/she thinks is best at describing the image. In Section 5, we provide results for Mean Opinion Score and Majority vote based of this interface (see Figure 8) and Table 7.

**F Gradient Analysis**

We established that SCST is a superior training procedure for GAN sequence such as captioner models. Gumbel relaxation based methods were capable of training stable models, but with worse performance overall. A simple investigation summarized in Figure 9 was conducted to compare the behaviors of gradients across the different generator training strategies. Clearly, the $L_2$ norms of the gradients w.r.t. the logits during the generator updates under SCST and Gumbel training display sharp differences. Gradients from SCST training have small absolute gradient norm and small variances.
Table 5: Collection of results for all models mentioned in this work. We provide commonly used CIDEr, BLEU4, ROUGEL, METEOR scores, as well as semantic scores, and percentage of vocabulary coverage for both COCO and OOC. Results are averaged from 4 models from independent trainings. We report mean and standard deviation for all metrics when available.

| Model                        | COCO Test Set       | OOC (Out of Context) |
|------------------------------|---------------------|----------------------|
|                              | CIDEr   | BLEU4  | ROUGEL | METEOR | Semantic Score | Vocabulary Coverage |
| CE   | 101.6 ± 0.4 | 0.312 ± 0.01 | 0.542 ± 0.01 | 0.260 ± 0.01 | 0.186 ± 0.01 | 9.2 ± 0.1 |
| GCE-RL |          |         |         |        |             |                     |
| GAN | 116.1 ± 0.2 | 0.350 ± 0.003 | 0.582 ± 0.01 | 0.269 ± 0.000 | 0.184 ± 0.001 | 5.1 ± 0.1 |
| (SCST, Co-att, log(D)) | 97.5 ± 0.8 | 0.294 ± 0.002 | 0.532 ± 0.001 | 0.256 ± 0.001 | 0.190 ± 0.000 | 11.0 ± 0.1 |
| (SCST, Co-att, log(D) + γ) | 111.1 ± 0.7 | 0.330 ± 0.004 | 0.555 ± 0.002 | 0.271 ± 0.002 | 0.192 ± 0.000 | 7.3 ± 0.2 |
| (SCST, Joint-Emb, log(D)) | 97.1 ± 1.2 | 0.287 ± 0.005 | 0.530 ± 0.002 | 0.256 ± 0.002 | 0.188 ± 0.000 | 11.2 ± 0.1 |
| (SCST, Joint-Emb, log(D) + γ) | 108.2 ± 4.9 | 0.325 ± 0.017 | 0.551 ± 0.008 | 0.267 ± 0.004 | 0.190 ± 0.000 | 8.3 ± 1.6 |
| GAN(Gumbel Soft, Co-att, log(D)) | 93.6 ± 3.3 | 0.282 ± 0.015 | 0.524 ± 0.007 | 0.253 ± 0.007 | 0.187 ± 0.002 | 11.1 ± 1.2 |
| GAN(Gumbel ST, Co-att, log(D)) | 95.4 ± 1.5 | 0.298 ± 0.009 | 0.531 ± 0.005 | 0.249 ± 0.004 | 0.184 ± 0.003 | 10.1 ± 0.9 |
| GAN(Gumbel ST, Co-att, log(D) + FM) | 92.1 ± 5.4 | 0.269 ± 0.020 | 0.523 ± 0.015 | 0.243 ± 0.011 | 0.175 ± 0.006 | 8.6 ± 0.8 |

+GAN [10] from Table 1 | 79.5 ± 0.2 | 0.207 ± 0.01 | 0.475 ± 0.01 | 0.224 ± 0.01 | 0.224 ± 0.01 | 0.224 ± 0.01 |

CE - for non-attentional models | 87.6 ± 1.2 | 0.275 ± 0.003 | 0.516 ± 0.003 | 0.242 ± 0.001 | 0.175 ± 0.002 | 9.9 ± 0.8 |
| GCE-RL* | 100.4 ± 7.9 | 0.305 ± 0.018 | 0.536 ± 0.010 | 0.253 ± 0.006 | 0.173 ± 0.002 | 6.8 ± 1.4 |

GAN*(SCST, Co-att, log(D)) | 89.7 ± 0.9 | 0.276 ± 0.000 | 0.518 ± 0.001 | 0.246 ± 0.001 | 0.184 ± 0.001 | 13.2 ± 0.2 |
| GAN*(SCST, Co-att, log(D) + γ) | 103.1 ± 0.5 | 0.311 ± 0.003 | 0.542 ± 0.001 | 0.261 ± 0.001 | 0.183 ± 0.001 | 7.1 ± 0.2 |
| GAN*(SCST, Joint-Emb, log(D)) | 90.7 ± 0.1 | 0.277 ± 0.002 | 0.520 ± 0.000 | 0.248 ± 0.001 | 0.181 ± 0.001 | 12.9 ± 0.1 |
| GAN*(SCST, Joint-Emb, log(D) + γ) | 102.7 ± 0.4 | 0.315 ± 0.000 | 0.542 ± 0.000 | 0.260 ± 0.001 | 0.182 ± 0.001 | 7.7 ± 0.1 |

as well. This is a considerable advantage for SCST in GAN training as superior RL techniques in policy gradients are the ones who provide low variances for the gradients estimate. This confirms the superiority of SCST at training sequence GAN models over other alternatives.

G Examples of Generated Captions

In this section we present several examples of captions generated from our model. In particular, Figure 11 and Figure 12 show captions for randomly picked images (from COCO and OOC respectively) which provide a good description of the image content. We do the opposite in Figure 12 and Figure 13 where examples of bad captions are provided for COCO and OOC respectively.
Table 6: Collection of ensembling results for GAN models from Table 1. We provide commonly used CIDEr, BLEU4, ROUGEL, METEOR scores, as well as semantic scores, and percentage of vocabulary coverage for both COCO and OOC.

| COCO Test Set | CIDEr     | BLEU4   | ROUGEL  | METEOR  | Semantic Score | Vocabulary Coverage |
|---------------|-----------|---------|---------|---------|----------------|---------------------|
| (CE and RL Baselines) | | | | | | |
| EnsCE(CE)     | 105.8     | 0.327   | 0.553   | 0.266   | 0.189          | 8.4                 |
| EnsRL(CIDEr-RL) | **118.9** | **0.359** | **0.568** | 0.273   | 0.186          | 5.0                 |
| (SCST, Co-att, *) | | | | | | |
| Ens1(GAN1)    | 102.6     | 0.314   | 0.543   | 0.262   | **0.195**      | 9.9                 |
| Ens2(GAN2)    | 115.1     | 0.347   | 0.566   | 0.277   | 0.194          | 7.0                 |
| Ens12(GAN1,GAN2) | 113.2     | 0.344   | 0.564   | 0.274   | **0.195**      | 7.3                 |
| (SCST, Joint-Emb, *) | | | | | | |
| Ens2(GAN1)    | 109.8     | 0.331   | 0.556   | 0.270   | 0.193          | 8.5                 |
| Ens3(GAN1)    | 113.0     | 0.343   | 0.562   | 0.274   | 0.193          | 7.6                 |
| Ens12(GAN1,GAN2) | 111.1     | 0.335   | 0.558   | 0.271   | 0.193          | 8.1                 |
| (Gumbel *, Co-att, *) | | | | | | |
| Ens2(GAN1)    | 100.1     | 0.307   | 0.538   | 0.259   | 0.191          | **10.0**            |
| Ens3(GAN1)    | 99.6      | 0.313   | 0.541   | 0.253   | 0.187          | 9.3                 |
| Ens12(GAN1,GAN2) | 100.2     | 0.321   | 0.543   | 0.254   | 0.180          | 7.8                 |
| (SCST+Gumbel Soft, Co-att, *) | | | | | | |
| Ens12(GAN1,GAN2) | **113.2** | **0.344** | **0.564** | 0.274   | 0.193          | 7.3                 |

| OOC (Out of Context) | CIDEr     | BLEU4   | ROUGEL  | METEOR  | Semantic Score | Vocabulary Coverage |
|-----------------------|-----------|---------|---------|---------|----------------|---------------------|
| (CE and RL Baselines) | | | | | | |
| EnsCE(CE)             | 44.8      | 0.177   | 0.423   | 0.172   | 0.122          | 2.6                 |
| EnsRL(CE)             | **48.8**  | **0.198** | **0.427** | 0.175   | 0.122          | 2.1                 |
| (SCST, Co-att, *)     | | | | | | |
| Ens1(GAN1)            | 44.8      | 0.175   | 0.422   | 0.172   | **0.129**      | **3.0**             |
| Ens2(GAN1)            | 48.3      | 0.189   | 0.429   | 0.176   | 0.127          | 2.7                 |
| Ens12(GAN1+4×GAN2)    | 49.9      | 0.197   | **0.437** | 0.178   | **0.129**      | **2.6**             |
| (SCST, Joint-Emb, *)  | | | | | | |
| Ens1(GAN1)            | **48.5**  | **0.198** | **0.429** | 0.175   | 0.127          | 2.8                 |
| Ens2(GAN1)            | 48.0      | 0.185   | 0.432   | 0.178   | 0.127          | 2.7                 |
| Ens12(GAN1+4×GAN2)    | **50.1**  | **0.195** | **0.435** | 0.177   | 0.127          | 2.8                 |
| (Gumbel *, Co-att, *) | | | | | | |
| Ens2(GAN1)            | 43.1      | 0.169   | 0.420   | 0.170   | 0.127          | **3.0**             |
| Ens3(GAN1)            | 41.0      | 0.155   | 0.420   | 0.165   | 0.128          | 2.8                 |
| Ens4(GAN1)            | 38.9      | 0.166   | 0.413   | 0.164   | 0.113          | 2.3                 |
| Ens12(GAN1,GAN2,GAN3) | 41.8      | 0.167   | 0.418   | 0.164   | 0.121          | 2.7                 |
| (SCST+Gumbel Soft, Co-att, *) | | | | | | |
| Ens12(GAN1,GAN2,GAN3) | **49.8**  | **0.198** | **0.436** | 0.179   | **0.129**      | **2.7**             |

Table 7: MOS and semantic scores collected from Amazon MTurk.

| COCO Test | OOC | Semantic Score | MOS | Semantic Score | MOS |
|-----------|-----|----------------|-----|----------------|-----|
| EnsCE(CE) |     | 0.189          | 3.222 | 0.122          | 3.065 |
| EnsRL(CIDEr-RL) | | 0.186 | 3.297 | 0.122 | 3.097 |
| Ens1(SCST, Co-att, log(D)) | | **0.195** | 3.398 | – | – |
| Ens2(SCST, Co-att, log(D) + 5 × CIDEr) | | 0.194 | **3.442** | 0.127 | 3.107 |
| Ens3(SCST, Joint-Emb, log(D)) | | 0.193 | 3.286 | – | – |
| Ens2(Gumbel Soft, Co-Att,log(D)) | | 0.191 | 3.138 | – | – |
| Ens2(Gumbel ST, Co-Att, log(D) + FM) | | 0.180 | 3.235 | – | – |
Figure 7: Semantic vs. Discriminator scores across 40 training epochs for ground truth captions using the joint embedding discriminator [10].
Figure 8: The interface of “Fine Grained Evaluation”.

Figure 9: $L_2$ norm of the gradient with respect to the logits during training of $G_\theta$ with different training strategies. We plot the minibatch-mean during training, while the variance between minibatches gives a good idea of the gradient stability. We see that SCST with pure discriminator reward has the lowest gradient norm.
Figure 10: Cherry-picked examples on the COCO validation set.
Figure 11: Cherry-picked examples on the Out of Context (OOC) set.
Figure 12: Lime-picked examples on the COCO test set.
Figure 13: Lime-picked examples on the Out of Context (OOC) set.