

# GENERATING IMAGES FROM CAPTIONS WITH ATTENTION

**Elman Mansimov\*, Emilio Parisotto\*, Jimmy Lei Ba & Ruslan Salakhutdinov**

Department of Computer Science

University of Toronto

Toronto, Ontario, Canada

{emansim, eparisotto, rsalakhu}@cs.toronto.edu, jimmy@psi.utoronto.ca

## ABSTRACT

At the end.

## 1 INTRODUCTION

Generating realistic images from their descriptions is a very hard task that combines together two challenging problems of language modelling and image generation. Generating images from captions is a significantly harder problem than a reverse problem of generating captions from images which has recently attracted a lot of attention. The model has to capture the semantic knowledge expressed in the description and then use it to generate the values of RGB channels of each pixel in the image ...

## 2 RELATED WORK

Deep Neural Networks have achieved a remarkable performance in various tasks such as image recognition (Krizhevsky et al., 2012), speech transcription (Graves et al., 2013) and etc. While most of the recent success has been achieved by discriminative models, the generative models have not yet enjoyed the same level of success. Most of the previous work in generative models has been focused on variants of Boltzmann Machines (Smolensky, 1986), (Salakhutdinov & Hinton, 2009) and Deep Belief Networks (Hinton & Salakhutdinov, 2006). While these models are very powerful, each iteration of training requires a computationally costly step of MCMC to approximate an intractable normalization constant that makes it hard to scale them to large datasets.

Kingma & Welling (2013) have introduced the Variational Auto-Encoder (VAE) which can be seen as a neural network with continuous latent variables. The encoder is used to approximate posterior distribution and the decoder is used to stochastically reconstruct the data from latent variables. The model performs an efficient inference and learning that allows it to scale to large datasets. Gregor et al. (2015) have introduced Deep Recurrent Attention Writer (DRAW), where they have incorporated a novel differentiable attention mechanism into the VAE which significantly improved its performance as well as quality of generated samples. While most of the samples of VAE and DRAW resemble a clear structure of objects, the generated images are blurry most of the time.

Generative Adversarial Networks (GANs) (Goodfellow et al., 2014) are another type of generative models that use noise-contrastive estimation (Gutmann & Hyvärinen, 2010) to avoid calculating intractable normalization constant. The model consists of generator that generates samples from uniform distribution and discriminator that discriminates between real and generated images. Both networks are playing the game, where generator tries to produce samples that look real and discriminator tries not to be fooled by generator. Recently, Denton et al. (2015) have scaled those models, by training GANs at each level of Laplacian pyramid of images. While their model has generated sharp looking samples, the generated images have lacked a clear structure. Compared to other mentioned generative models, GANs are more unstable and are harder to train.

---

\*Equal Contribution

While all of the previous work has been focused on unconditional models or models conditioned on labels, to the best of our knowledge this paper is the first to introduce the generative model of images conditioned on captions.

### 3 MODEL

Our proposed model can be seen as a part of sequence-to-sequence framework (Sutskever et al., 2014), (Cho et al., 2014), (Srivastava et al., 2015) where captions are represented as a sequence of consecutive words and images are represented as a sequence of patches drawn on canvas over time  $t = 1, \dots, T$ . Let  $y$  be the input caption, consisting of  $N$  words  $y_1, y_2, \dots, y_n$  and  $x$  be the image corresponding to that caption.

#### 3.1 ENCODER

The encoder is a deterministic Bidirectional LSTM that encodes the variable size sentences into the vector representation  $s$ . Bidirectional LSTM consists of one Forward LSTM and Backward LSTM which combine information from past and future respectively. The Forward LSTM computes the sequence of forward hidden states  $[\vec{h}_1^{lang}, \vec{h}_2^{lang}, \dots, \vec{h}_N^{lang}]$ , whereas the Backward LSTM computes the sequence of backward hidden states  $[\overleftarrow{h}_1^{lang}, \overleftarrow{h}_2^{lang}, \dots, \overleftarrow{h}_N^{lang}]$ . Then these hidden states are concatenated together into the sequence  $[h_1^{lang}, h_2^{lang}, \dots, h_N^{lang}]$ , where  $h_n^{lang} = [\vec{h}_n^{lang}, \overleftarrow{h}_n^{lang}]$ ,  $1 \leq n \leq N$ .

The final representation of the sentence is calculated as follows:

$$s_t = \alpha_1 h_1^{lang} + \alpha_2 h_2^{lang} + \dots + \alpha_N h_N^{lang} \quad (1)$$

where  $h_0^{lang}$  is initialized to the learned bias. Setting  $\alpha_{1 \dots N}$  to  $\frac{1}{N}$  turns the encoder into the vanilla model introduced in (Cho et al., 2014) without the attention. We will describe how  $\alpha_{1 \dots N}$  are calculated in the next section.

#### 3.2 DECODER

The decoder is a DRAW model, which is a stochastic recurrent neural network that consists of Inference LSTM that infers the distribution of latent variables of image  $x$  given  $y$  and then the Generator LSTM that uses the inferred latent variables in order to reconstruct the image  $x$  given  $y$ . Formally, the decoder iteratively computes the following equations for  $t = 1, \dots, T$

$$\hat{x}_t = x - \sigma(c_{t-1}) \quad (2)$$

$$r_t = read(x_t, \hat{x}_t, h_{t-1}^{dec}) \quad (3)$$

$$h_t^{enc} = LSTM^{enc}(h_{t-1}^{enc}, [r_t, h_{t-1}^{dec}]) \quad (4)$$

$$z_t \sim Q(Z_t | h_t^{enc}) \quad (5)$$

$$h_t^{dec} = LSTM^{dec}(h_{t-1}^{dec}, z_t, s_{t-1}) \quad (6)$$

$$s_t = align(h_{t-1}^{dec}, \mathbf{h}^{lang}) \quad (7)$$

$$c_t = c_{t-1} + write(h_t^{dec}) \quad (8)$$

where *read* and *write* are the same attention operators as in (Gregor et al., 2015),  $\mathbf{h}^{lang} = [h_1^{lang}, h_2^{lang}, \dots, h_n^{lang}]$  and  $c_0, h_0^{dec}, h_0^{enc}$  are initialized to the learned biases.

The *align* function introduced by Bahdanau et al. (2015) is used to compute probabilities  $\alpha_{1 \dots n}$  by first computing the energies  $e_{t,0}, e_{t,1}, \dots, e_{t,n}$  and then rescaling them to the probability distribution  $\alpha_1, \alpha_2, \dots, \alpha_n$

$$e_{tj} = v^T \tanh(Uh_j^{lang} + Wh_t^{dec}) \quad (9)$$

$$\alpha_j = softmax(e_{tj}) \quad (10)$$

where  $softmax(e_{tj}) = \frac{\exp(e_{tj})}{\sum_{j=1}^N \exp(e_{tj})}$

### 3.3 LEARNING

The model is learned by the modified version of Stochastic Gradient Variation Bayes (SGVB) algorithm introduced by Kingma & Welling (2013). The model is trained to maximize the marginal likelihood  $\mathcal{L}$  of the correct image  $x$  given the input caption  $y$ . The  $\mathcal{L}$  is decomposed into the latent loss  $\mathcal{L}^z$  and the reconstruction loss  $\mathcal{L}^x$ .

The reconstruction loss  $\mathcal{L}^x$  equals to  $\frac{1}{L} \sum_{l=1}^L (\log p(x_l|y, z))$  where  $L$  is the number of samples used during training, which was set to 1 in our experiments.

The latent loss is a negative sum of Kullback–Leibler divergence terms between distribution  $Q(Z_t|h_t^{enc})$  and some prior distribution  $P(Z_t)$  over time  $t = 1, \dots, T$ , which can be seen as a regularization term. Since the patches drawn on canvas over time are not independent of each other, naturally the sufficient statistics of the prior distribution at time  $t$  should be dependent on the sufficient statistics of the prior distribution at time  $t - 1$ . Therefore, instead of setting  $P(Z_1), \dots, P(Z_T)$  to be independent unit gaussian distributions, the mean and variance of  $P(Z_t)$  depends on the  $h_{t-1}^{dec}$ , as in (Bachman & Precup, 2015), where

$$\mu_t^{prior} = \tanh(W_{mu}h_{t-1}^{dec}) \quad (11)$$

$$\sigma_t^{prior} = \exp(\tanh(W_{\sigma}h_{t-1}^{dec})) \quad (12)$$

Overall, the likelihood  $\mathcal{L}$  is calculated as follows:

$$\begin{aligned} \mathcal{L} &= - \sum_{t=1}^T D_{KL}(Q(Z_t|h_t^{enc}, s_{t-1}) || P(Z_t)) + \frac{1}{L} \sum_{l=1}^L \log p(x_l|y, z) \\ &= \frac{1}{2} \sum_{t=1}^T (1 - 2 \log \sigma_t^{prior} + 2 \log \sigma_t - \frac{\exp(2 \log \sigma_t) + (\mu_t - \mu_t^{prior})^2}{\exp(2 \log \sigma_t^{prior})}) + \frac{1}{L} \sum_{l=1}^L \log p(x_l|y, z) \end{aligned} \quad (13)$$

### 3.4 IMAGE GENERATION

During the image generation step, we throw away the Inference LSTM from the Decoder and instead sample from the prior distribution. Due to the samples from DRAW model being blurry, we do an additional post processing step, where we use adversarial net ...

## 4 EXPERIMENTS

### REFERENCES

- Bachman, Philip and Precup, Doina. Data generation as sequential decision making. *CoRR*, abs/1506.03504, 2015. URL <http://arxiv.org/abs/1506.03504>.
- Bahdanau, D., Cho, K., and Bengio, Y. Neural machine translation by jointly learning to align and translate. *ICLR*, 2015.
- Cho, Kyunghyun, van Merriënboer, Bart, Gülçehre, Çağlar, Bahdanau, Dzmitry, Bougares, Fethi, Schwenk, Holger, and Bengio, Yoshua. Learning phrase representations using RNN encoder-decoder for statistical machine translation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, EMNLP 2014*, pp. 1724–1734, 2014.
- Denton, Emily L., Chintala, Soumith, Szlam, Arthur, and Fergus, Robert. Deep generative image models using a laplacian pyramid of adversarial networks. *CoRR*, abs/1506.05751, 2015. URL <http://arxiv.org/abs/1506.05751>.
- Goodfellow, Ian J., Pouget-Abadie, Jean, Mirza, Mehdi, Xu, Bing, Warde-Farley, David, Ozair, Sherjil, Courville, Aaron C., and Bengio, Yoshua. Generative adversarial nets. In *Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada*, pp. 2672–2680, 2014. URL <http://papers.nips.cc/paper/5423-generative-adversarial-nets>.

- Graves, A., Jaitly, N., and Mohamed, A.-r. Hybrid speech recognition with deep bidirectional LSTM. In *2013 IEEE Workshop on Automatic Speech Recognition and Understanding*, pp. 273–278, 2013.
- Gregor, Karol, Danihelka, Ivo, Graves, Alex, and Wierstra, Daan. DRAW: A recurrent neural network for image generation. *CoRR*, abs/1502.04623, 2015.
- Gutmann, Michael and Hyvärinen, Aapo. Noise-contrastive estimation: A new estimation principle for unnormalized statistical models. In *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics, AISTATS 2010, Chia Laguna Resort, Sardinia, Italy, May 13-15, 2010*, pp. 297–304, 2010. URL <http://www.jmlr.org/proceedings/papers/v9/gutmann10a.html>.
- Hinton, Geoffrey and Salakhutdinov, Ruslan. Reducing the dimensionality of data with neural networks. *Science*, Vol. 313:504–507, 2006.
- Kingma, Diederik P. and Welling, Max. Auto-encoding variational bayes. *CoRR*, abs/1312.6114, 2013. URL <http://arxiv.org/abs/1312.6114>.
- Krizhevsky, Alex, Sutskever, Ilya, and Hinton, Geoffrey E. Imagenet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems 25: 26th Annual Conference on Neural Information Processing Systems 2012. Proceedings of a meeting held December 3-6, 2012, Lake Tahoe, Nevada, United States.*, pp. 1106–1114, 2012.
- Salakhutdinov, Ruslan and Hinton, Geoffrey E. Deep boltzmann machines. In *Proceedings of the Twelfth International Conference on Artificial Intelligence and Statistics, AISTATS 2009, Clearwater Beach, Florida, USA, April 16-18, 2009*, pp. 448–455, 2009. URL <http://www.jmlr.org/proceedings/papers/v5/salakhutdinov09a.html>.
- Smolensky, Paul. Information processing in dynamical systems: foundations of harmony theory. *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, 1986.
- Srivastava, Nitish, Mansimov, Elman, and Salakhutdinov, Ruslan. Unsupervised learning of video representations using LSTMs. *ICML*, 2015.
- Sutskever, Ilya, Vinyals, Oriol, and Le, Quoc V. V. Sequence to sequence learning with neural networks. In *Advances in Neural Information Processing Systems 27*, pp. 3104–3112. 2014.