# Show, Attend and Tell: Neural Image Caption Generation with Visual Attention

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## Abstract

An "Attention-based Model" that automatically learns to describe the content of the images:

- Two ways to train the model:
  - Stochastically: By maximizing variational lower bound
  - Deterministically: Using standard backpropagation techniques
- Visualization demonstrates the automatic learning of gaze fixing to generate corresponding words
- Use of attention on three datasets to demonstrate state-of-the-art performance

## Introduction

Automatically generating captions of an image is a task very close to the heart of scene understanding:

- One of the primary goals of computer vision
- Requires capability to capture and express relationships of the detected objects in a natural language
- Mimicking remarkable human ability to compress huge amounts of salient visual information into descriptive language

"Attention" is one of the most curious facets of human visual system:

- Allows for salient features to dynamically come to the forefront as needed
- Particularly important when there is lot of clutter

Top-layer representations distill information in image down to most salient objects:

- Leads to loss of information required for richer and more descriptive captions
- Low-level representations can help preserve this information

Two attention-based image caption generators under a common framework:

- Soft deterministic attention
- Hard stochastic attention

## Related Work

Prior to neural networks, two dominant approaches for image captioning:

- First: Generating caption templates which were filled in based on the results of object detections and attribute discovery – Li et al. (2011), Yang et al. (2011), Mitchell et al. (2012), Kulkarni et al. (2013), Elliot & Keller (2013)
- Second: First retrieving similar captioned images for a large dataset and then modifying these retrieved captions to fit the query – Kuznetsova et al. (2012, 2014)
- Involved intermediate generalization step to remove the specifics of a caption that are only relevant to the retrieved image

Neural networks-based approach to image captioning started in 2014:

- Image captioning is well suited to encoder-decoder framework of machine translation (sequence2sequence):
  - Analogous to translating an image to a sentence
- Kiros et al. (2014a & b) first proposed a multimodal log-bilinear model to be followed by a method to allow for ranking and generation
- Mao et al. (2014) took similar approach but replaced FFNN with RNN
- Vinyals et el. (2014) only showed image to RNN in the beginning in contrast to Kiros and Mao who used image at every time step of the output sequence
- Donahue et al. (2014) used LSTM and applied it to videos to generate video captions
- Karpathy & Li (2014) were the first to propose learning joint embedding space for ranking and generation to score sentence and image similarity using R-CNN object detection with bi-directional outputs of RNN
- Fang et al. (2014) proposed a three-step pipeline for generations by incorporating object detections

Long list of prior work incorporating "attention" in computer vision tasks:

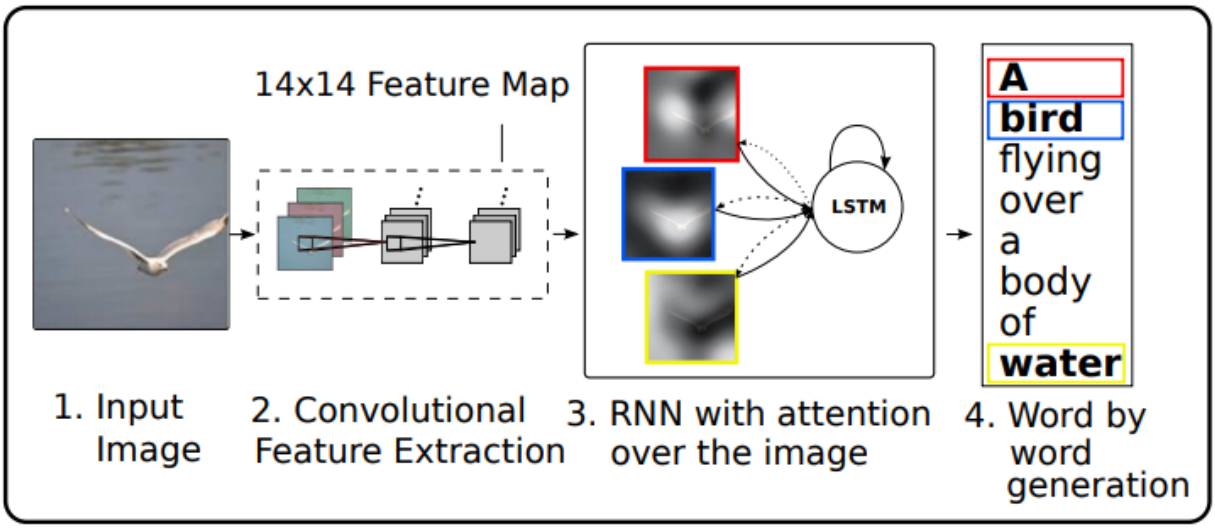
- Similar works in spirit include Larochelle & Hinton (2010), Denil et al. (2012), & Tang et al. (2014)
- Directly extents the works of Bahdanau et al. (2014), Mnih et al. (2014), & Ba et al. (2014)

## Image Caption Generation with Attention Mechanism

The proposed "attention" framework does not explicitly use object detection (unlike most prior works):

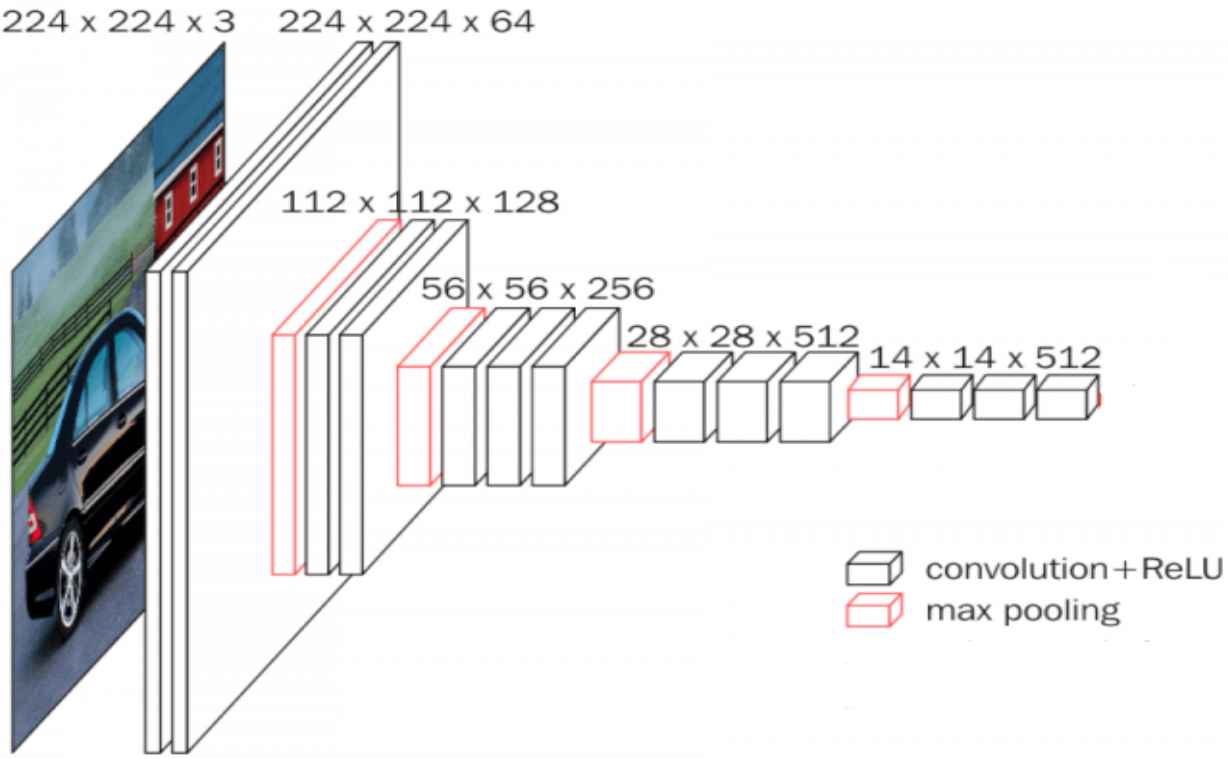
- Learns latent alignment from scratch
- Allows model to learn to attend to abstract concepts

### Model Details



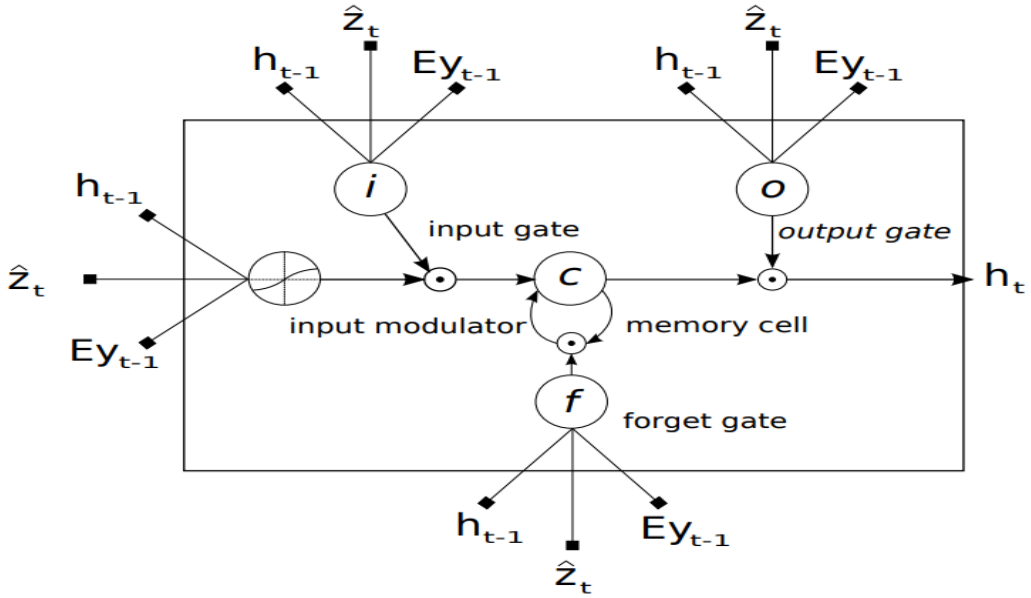

- Two variants of the attention-based model
  - The main difference is the definition of the ϕ function (soft and hard attention)
- Input is a single raw image
- Output is the caption y, encoded as a sequence of 1-of-K encoded words:
  - $y = \{y_1, \dots, y_C\}$, $y_i \in R^k$
  - where:
    - k is the size of the vocabulary, and
    - C is the length of the caption

## Encoder: Convolutional Features




- Uses convolutional neural network to extract a set of feature vectors, i.e., annotation vectors:
  - $a = \{a_1, \ldots, a_L\}$, $a_i \in R^D$
  - L – D-dimensional representation vectors corresponding to a part of the image
- Extract features from a lower convolutional layer
  - To obtain a correspondence between the feature vectors and portions of the 2-D image.
  - Allows the decoder to selectively focus on certain parts of an image by selecting a subset of all the feature vectors.
- Oxford VGGNet was used for "Encoder"
  - Pre-trained on ImageNet
  - Without fine-tuning
  - Used 14 x 14 x 512 feature map of 4$^{th}$ convolutional layer before MaxPooling
  - Flattened into 196 x 512 (i.e. L x D) encoding for Decoder

## Decoder: Long Short-Term Memory



- LSTM network is used to generate one word at every time step, ***conditioned on***:
  - a context vector $z_t$,
  - the previous hidden state $h_{t-1}$, and
  - the previously generated words $y_{t-1}$

$$\begin{pmatrix} \mathbf{i}_t \\ \mathbf{f}_t \\ \mathbf{o}_t \\ \mathbf{g}_t \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} T_{D+m+n,n} \begin{pmatrix} \mathbf{E}\mathbf{y}_{t-1} \\ \mathbf{h}_{t-1} \\ \hat{\mathbf{z}}_t \end{pmatrix}$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \mathbf{g}_t$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t).$$

  - where:
    - $i_t$ = input state
    - $g_t$ = input modulator
    - $f_t$ = forget state
    - $c_t$ = memory
    - $o_t$ = output
    - $h_t$ = hidden state
    - $z_t \in R^D$ = context vector, to capture the visual information associated with a particular input location
    - $E \in R^{m \times K}$ = embedding matrix of dimension m x K
    - $\sigma$ and $\odot$ be the logistic sigmoid activation & element-wise multiplication respectively

## Algorithm

- The initial memory state and hidden state of the LSTM are predicted by an average of the annotation vectors

$$\mathbf{c}_0 = f_{\text{init,c}}(\frac{1}{L}\sum_i^L \mathbf{a}_i)$$

$$\mathbf{h}_0 = f_{\text{init,h}}(\frac{1}{L}\sum_i^L \mathbf{a}_i)$$

- The weight $\alpha_i$ of each annotation vector $a_i$ is then computed by an attention model $f_{att}$ for which we use a multilayer perceptron conditioned on the previous hidden state $h_{t-1}$.

$$e_{ti} = f_{\text{att}}(\mathbf{a}_i, \mathbf{h}_{t-1})$$

$$\alpha_{ti} = \frac{\exp(e_{ti})}{\sum_{k=1}^{L} \exp(e_{tk})}$$

- For each location *i*, the mechanism generates a positive weight $\alpha_i$:
  - In hard attention: $\alpha_i$ is the probability that location *i* is the right place to focus for producing the next word
  - In soft attention: $\alpha_i$ is the relative importance to give to location *i* in blending the $\alpha_i$'s together.
- The mechanism $\phi$ will compute $z_t$ from the annotation vectors $a_i$ (corresponds to the features extracted at different image locations)

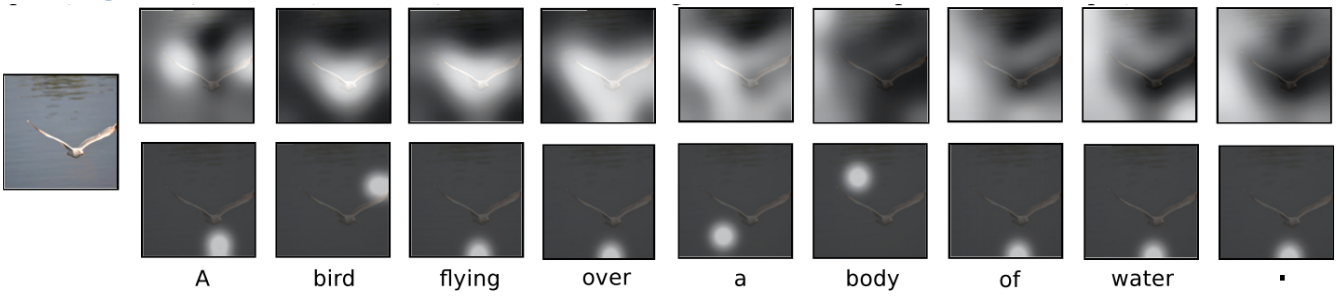
$$\hat{\mathbf{z}}_t = \phi\left(\{\mathbf{a}_i\}, \{\alpha_i\}\right)$$

- The context vector $z_t$ is a dynamic representation of the relevant part of the image input at time *t*
- The hidden state varies as the output RNN advances in its output sequence: "where" the network looks next depends on the sequence of words that has already been generated
- A deep output layer is then used to compute the output word probability given the LSTM hidden state, the context vector and the previous word

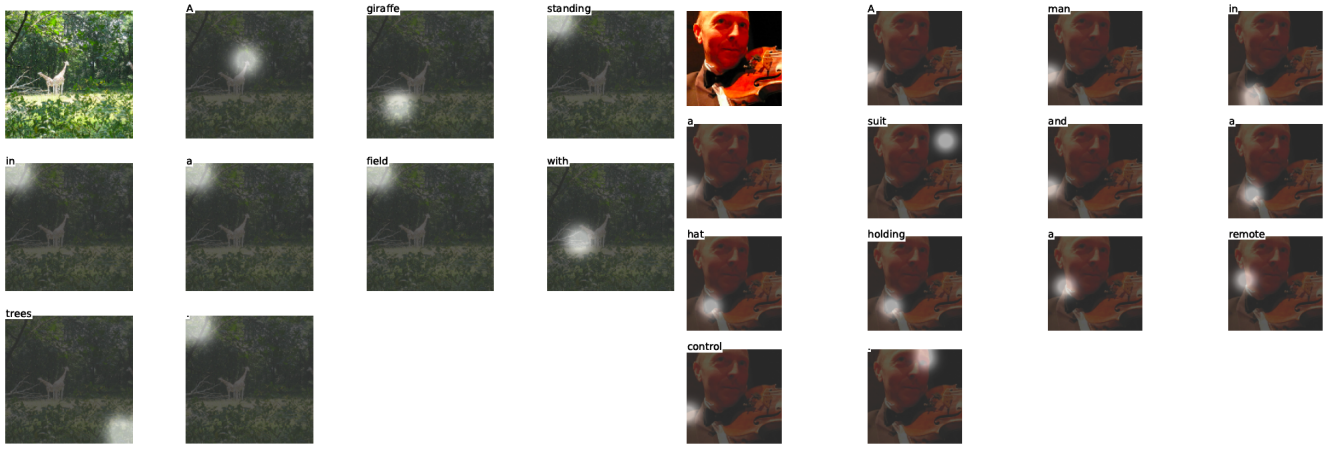
$$p(\mathbf{y}_t|\mathbf{a}, \mathbf{y}_1^{t-1}) \propto \exp(\mathbf{L}_o(\mathbf{E}\mathbf{y}_{t-1} + \mathbf{L}_h\mathbf{h}_t + \mathbf{L}_z\hat{\mathbf{z}}_t))$$

Where $\mathbf{L}_o \in \mathbb{R}^{K\times m}$, $\mathbf{L}_h \in \mathbb{R}^{m\times n}$, $\mathbf{L}_z \in \mathbb{R}^{m\times D}$, and $\mathbf{E}$ are learned parameters initialized randomly.

## Learning Stochastic "Hard" vs Deterministic "Soft" Attention




## Stochastic "Hard" Attention




- **"Hard Attention": ϕ returns a sampled $a_i$ at every timestep based on multinouilli distribution**
- $s_t$: The location where the model focuses on when generating the $t^{th}$ word
  - $s_{t,i}$: Indicator variable – 1 if the $i^{th}$ location is used to generate the $t^{th}$ word, 0 otherwise
- Attention locations are intermediate latent variables; $s_t$ and $z_t$ being randomly distributed as follows:
  - $t^{th}$ word focus will depend on the location that the previous words have already focused on

$$\tilde{s_t} \sim \text{Multinoulli}_L(\{\alpha_i\})$$
$$p(s_{t,i} = 1 \mid s_{j<t}, \mathbf{a}) = \alpha_{t,i}$$
$$\hat{\mathbf{z}}_t = \sum_i s_{t,i}\mathbf{a}_i.$$

- Objective function $L_s$ is a variational lower bound on marginal log-likelihood *log p(y|a)* of observing the sequences of words *y* given image feature *a*

$$\begin{aligned} L_s &= \sum_s p(s \mid \mathbf{a}) \log p(\mathbf{y} \mid s, \mathbf{a}) \\ &\leq \log \sum_s p(s \mid \mathbf{a}) p(\mathbf{y} \mid s, \mathbf{a}) \\ &= \log p(\mathbf{y} \mid \mathbf{a}) \end{aligned}$$

- The parameters *W* can be learned by optimizing $L_s$

$$\frac{\partial L_s}{\partial W} = \sum_s p(s \mid \mathbf{a}) \left[ \frac{\partial \log p(\mathbf{y} \mid s, \mathbf{a})}{\partial W} + \log p(\mathbf{y} \mid s, \mathbf{a}) \frac{\partial \log p(s \mid \mathbf{a})}{\partial W} \right]$$

- Parameters (W) are learned by computing gradient using Monte-Carlo based sampling approximations i.e., sampling the location $s_t$ from the multinouilli distribution

$$\frac{\partial L_s}{\partial W} \approx \frac{1}{N} \sum_{n=1}^{N} \left[ \frac{\partial \log p(\mathbf{y} \mid \tilde{s}^n, \mathbf{a})}{\partial W} + \log p(\mathbf{y} \mid \tilde{s}^n, \mathbf{a}) \frac{\partial \log p(\tilde{s}^n \mid \mathbf{a})}{\partial W} \right]$$

- Sampling based approximations might be problematic when the variance is large (estimation process takes longer to converge and is not efficient). Techniques to reduce variance:

- Use a moving average baseline (can be estimated as an accumulated sum of the previous log likelihoods with exponential decay)

$$b_k = 0.9 \times b_{k-1} + 0.1 \times \log p(\mathbf{y} \mid \tilde{s}_k, \mathbf{a})$$

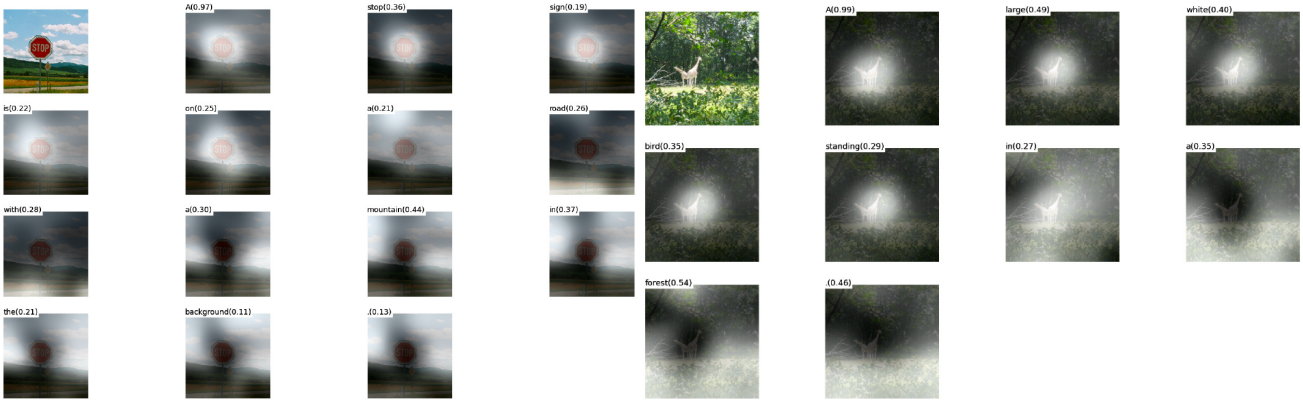
- Add an entropy term on the multinouilli distribution (H[s]).
- Also, with probability 0.5 for a given image, we set the sampled attention location s to its expected value α.

- The final learning rule for the model is equivalent to the REINFORCE Learning Rule – Reward for choosing a sequence of actions is proportional to log-likelihood of the target sentence

$$\frac{\partial L_s}{\partial W} \approx \frac{1}{N}\sum_{n=1}^{N}\left[\frac{\partial \log p(\mathbf{y} \mid \tilde{s}^n, \mathbf{a})}{\partial W} + \lambda_r(\log p(\mathbf{y} \mid \tilde{s}^n, \mathbf{a}) - b)\frac{\partial \log p(\tilde{s}^n \mid \mathbf{a})}{\partial W} + \lambda_e \frac{\partial H[\tilde{s}^n]}{\partial W}\right]$$

  - Where: $\lambda_r$ and $\lambda_e$ are two hyper-parameters set by cross-validation

## Deterministic "Soft" Attention




- **Unlike "Stochastic Hard Attention" which requires sampling the attention location $s_t$ each time, in of "Deterministic Soft Attention" we compute the expectation of the context vector directly**

$$\mathbb{E}_{p(s_t|a)}[\hat{\mathbf{z}}_t] = \sum_{i=1}^{L} \alpha_{t,i}\mathbf{a}_i$$

$$\phi\left(\{\mathbf{a}_i\}, \{\alpha_i\}\right) = \sum_i^L \alpha_i \mathbf{a}_i$$

- Unlike "Stochastic Hard Attention", this model is differentiable and amenable to standard backpropagation. Model here is optimizing the following equation:

$$\begin{aligned} L_s &= \sum_s p(s \mid \mathbf{a}) \log p(\mathbf{y} \mid s, \mathbf{a}) \\ &\leq \log \sum_s p(s \mid \mathbf{a}) p(\mathbf{y} \mid s, \mathbf{a}) \\ &= \log p(\mathbf{y} \mid \mathbf{a}) \end{aligned}$$

- Hidden activation $h_t$ is a linear projection of the context vector $z_t$ followed by *tanh* activation.
- Deterministic Attention model approximates the marginal likelihood over the attention locations.
- Normalized Weighted Geometric Mean for the softmax $k^{th}$ word prediction is given by:

$$\begin{aligned} NWGM[p(y_t = k \mid \mathbf{a})] &= \frac{\prod_i \exp(n_{t,k,i})^{p(s_{t,i}=1|a)}}{\sum_j \prod_i \exp(n_{t,j,i})^{p(s_{t,i}=1|a)}} \\ &= \frac{\exp(\mathbb{E}_{p(s_t|a)}[n_{t,k}])}{\sum_j \exp(\mathbb{E}_{p(s_t|a)}[n_{t,j}])} \end{aligned}$$

  - Where:

$$\begin{aligned} \mathbf{n}_t &= \mathbf{L}_o(\mathbf{E}\mathbf{y}_{t-1} + \mathbf{L}_h\mathbf{h}_t + \mathbf{L}_z\hat{\mathbf{z}}_t) \\ \mathbb{E}[\mathbf{n}_t] &= \mathbf{L}_o(\mathbf{E}\mathbf{y}_{t-1} + \mathbf{L}_h\mathbb{E}[\mathbf{h}_t] + \mathbf{L}_z\mathbb{E}[\hat{\mathbf{z}}_t]) \\ NWGM[p(y_t = k \mid \mathbf{a})] &\approx \mathbb{E}[p(y_t = k \mid \mathbf{a})] \end{aligned}$$

### Doubly Stochastic Attention

- By construction we have (softmax):

$$\sum_i \alpha_{ti} = 1$$

- Additional regularization for "Soft Attention":

$$\sum_t \alpha_{ti} \approx 1$$

- Regularization forces algorithm to pay equal attention to every part of the image over the course of caption generation
  - Quantitatively: leads to improvement in BLEU score
  - Qualitatively: leads to more rich and descriptive captions
- Additionally, the "Soft Attention" models predicts a scaler $\beta$ from previous hidden state $h_{t-1}$

$$\phi(\{\mathbf{a}_i\}, \{\alpha_i\}) = \beta \sum_i^L \alpha_i \mathbf{a}_i$$
$$\beta_t = \sigma(f_\beta(\mathbf{h}_{t-1}))$$

  - $\beta$ leads to attention weights being emphasized on objects in the images
- Model minimizes the penalized negative log-likelihood

$$L_d = -\log(P(\mathbf{y}|\mathbf{x})) + \lambda \sum_i^L (1 - \sum_t^C \alpha_{ti})^2$$

### Training Procedure

- Attention models (soft and hard) were trained with SGD using adaptive learning rate
  - Flickr8k dataset: RMSProp worked best
  - Flickr30k/MS COCO datasets: ADAM optimizer was used
- Implementation requires time proportional to the length of the longest sentence per update
  - Hence training on random group of captions of different sizes were computationally wasteful
  - Formed mini batches of size 64 with randomly selected equal length captions
    - Greatly improved convergence speed
  - MS COCO with soft attention took 3 days to train on NVIDIA Titan Black GPU
- Regularization
  - Dropout and early stopping on BLEU score was used
  - Breakdown in correlation between validation set log-likelihood and BLEU in later stages of training
  - Used BLEU for model selection
- Whetlab was used for hyperparameter tuning for Flickr8k using soft attention
  - Insights were useful for other datasets as well
- Theano was used for coding

## Experiments

5 different architectures are compared across 3 different datasets with 2 different performance measures. In total 63 different comparisons are made.

### Data

- Three different datasets are used in experiments:
  - Flickr8k – 8,000 images – 5 reference sentences per image
  - Flickr30k – 30,000 images – 5 reference sentences per image
  - Microsoft COCO – 82,783 images – some images have more than 5 reference sentences
- Basic tokenization was used for all three datasets for consistency
- Fixed vocabulary size of 10,000 words was used

## Evaluation Procedures

- Comparison is made against architectures which use GoogleNet or Oxford VGG
  - Google NIC (Vinyals et al., 2014)
  - Log Bilinear (Kiros et al., 2014a)
- Some additional models using AlexNet are also compared with METEOR
  - CMU/MS Research (Chen & Zitnick, 2014)
  - MS Research (Fang et al., 2014)
  - BRNN (Karpathy & Li, 2014)
- Ensembling is not used
- Used predefined splits or publicly available splits

## Quantitative Analysis

- State of the art performance on all three datasets without using ensemble
- Big Boost in METEOR performance is likely due to:
  - Regularization techniques
  - Use of lower-level representation

### BLEU

- Bilingual Evaluation Understudy (BLEU) is an algorithm for evaluating the quality of machine translation
- Ranges between 0 and 1 or 0% and 100%
- Uses a modified form of precision to compare a translation against multiple reference translations
- Frequently been reported as correlating well with human judgement
  - However, number of criticisms have been voiced

### METEOR

- Metric for Evaluation of Translation with Explicit Ordering (METEOR) is a metric for the evaluation of machine translation output
- Based on the harmonic mean of unigram precision and recall, with recall weighted higher than precision
- Produces good correlation with human judgement at the sentence or segment level
  - Results have been presented which give correlation of up to 0.964 with human judgement at the corpus level, compared to BLEU's achievement of 0.817
  - At the sentence level, the maximum correlation with human judgement achieved was 0.403

*Table 1.* BLEU-1,2,3,4/METEOR metrics compared to other methods, † indicates a different split, (—) indicates an unknown metric, ∘ indicates the authors kindly provided missing metrics by personal communication, Σ indicates an ensemble, $a$ indicates using AlexNet

| | | BLEU | | | | |
|---|---|---|---|---|---|---|
| Dataset | Model | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | METEOR |
| Flickr8k | Google NIC(Vinyals et al., 2014)$^{\dagger\Sigma}$ | 63 | 41 | 27 | — | — |
| | Log Bilinear (Kiros et al., 2014a)$^{\circ}$ | 65.6 | 42.4 | 27.7 | 17.7 | 17.31 |
| | Soft-Attention | **67** | 44.8 | 29.9 | 19.5 | 18.93 |
| | Hard-Attention | **67** | **45.7** | **31.4** | **21.3** | **20.30** |
| Flickr30k | Google NIC$^{\dagger\circ\Sigma}$ | 66.3 | 42.3 | 27.7 | 18.3 | — |
| | Log Bilinear | 60.0 | 38 | 25.4 | 17.1 | 16.88 |
| | Soft-Attention | 66.7 | 43.4 | 28.8 | 19.1 | **18.49** |
| | Hard-Attention | **66.9** | **43.9** | **29.6** | **19.9** | 18.46 |
| COCO | CMU/MS Research (Chen & Zitnick, 2014)$^{a}$ | — | — | — | — | 20.41 |
| | MS Research (Fang et al., 2014)$^{\dagger a}$ | — | — | — | — | 20.71 |
| | BRNN (Karpathy & Li, 2014)$^{\circ}$ | 64.2 | 45.1 | 30.4 | 20.3 | — |
| | Google NIC$^{\dagger\circ\Sigma}$ | 66.6 | 46.1 | 32.9 | 24.6 | — |
| | Log Bilinear$^{\circ}$ | 70.8 | 48.9 | 34.4 | 24.3 | 20.03 |
| | Soft-Attention | 70.7 | 49.2 | 34.4 | 24.3 | **23.90** |
| | Hard-Attention | **71.8** | **50.4** | **35.7** | **25.0** | 23.04 |

## Qualitative Analysis: Learning to attend

- Visualizing the attention component adds an extra layer of interpretability
- Model learns alignment that corresponds to human intuition
- Possible to exploit visualizations to get an intuition of the reasons for mistakes by algorithm

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.


A stop sign is on a road with a mountain in the background.

A little girl sitting on a bed with a teddy bear.

A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

## Conclusion

"Attention-based" approach given state-of-the-art performance on the three datasets.

- Learned "attention" can be exploited to give more interpretation for the model's generation process
- Learned alignments correspond very well to human intuition

# Bonus Article:
# An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale

Authors: Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, Neil Houlsby

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**SUMMARY BY: EDUARDO PEYNETTI, JESSICA WIJAYA, ROHIT BERI, STUART NEILSON**

For Natural Language Processing, we have seen the evolution RNN -> RNN with Attention -> Transformer Only

For image processing, the previous article similarly shows the progression from CNN -> CNN with Attention -> Can we also go to Transformer only for images?

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This new article shows that the answer is yes.

A conference paper for the 2021 ICLR conference, published on ArXiv last week (an earlier version in which the author names were redacted for blind review was up a few weeks earlier).

It introduces the ViT (Vision Transformer) model.

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Challenges with using Attention for images:

- Attention relates every pixel to every other pixel
    - Computational complexity $O(n^2)$ where n is the number of pixels ($n^4$ if you think of n as the image width)
    - Using Convolutional layers reduced this to a reasonable size by making a more compact latent representation

How this article handles this challenge: divide the image into “patches” of 16x16 = 256 pixels

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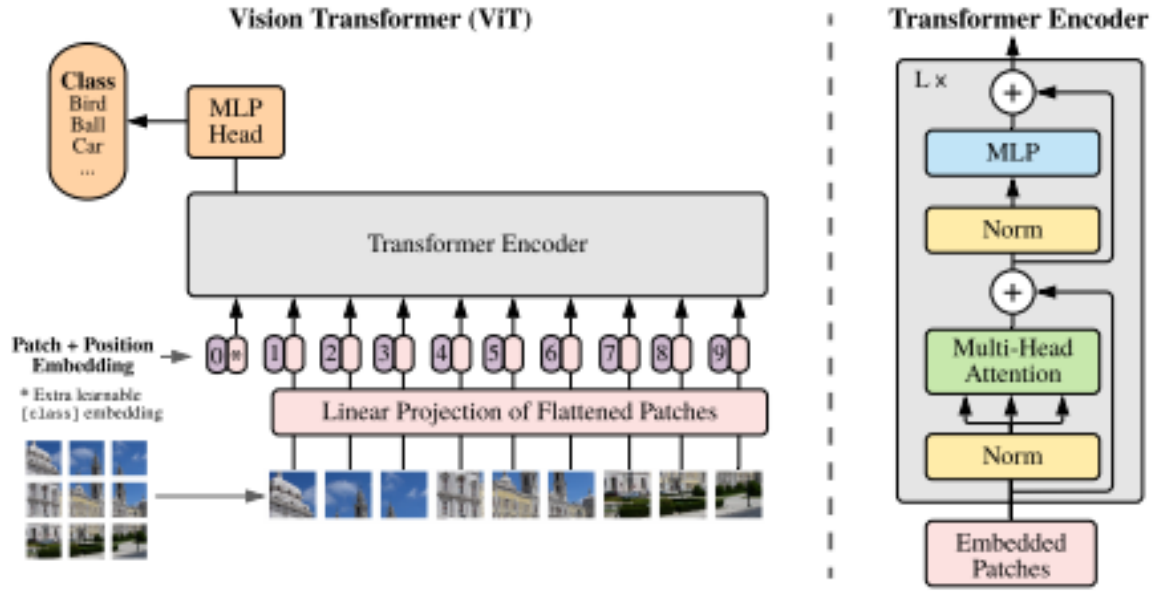


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The patches are flattened, then combined with a “position embedding” which is trainable (you can also see an extra zero position component on the left-hand side – which is analogous to the “cls” tag in BERT).

This is then passed into a standard “off-the-shelf" transformer.

Then finally, it goes through a Feed Forward Network to get to a classification prediction (the authors use the terminology MLP – Multi-Layer Perceptron).

This architecture can take advantage of parallelization in the calculations.

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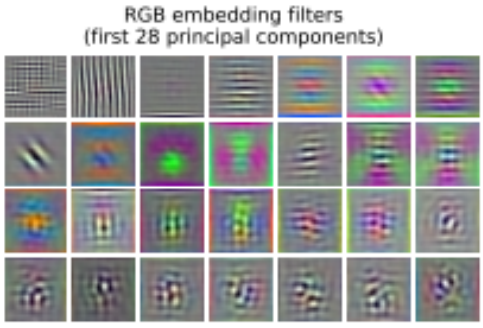
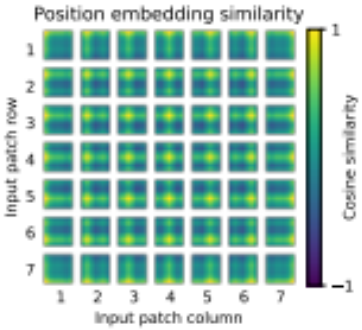
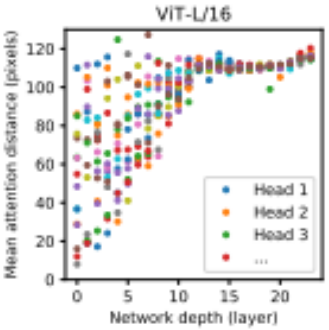
Visualization of their embedding filters indicates that they exhibit a learning process quite similar to Convolutional filters.

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The model achieves state-of-the-art performance in image classification
(it is the blue bars)

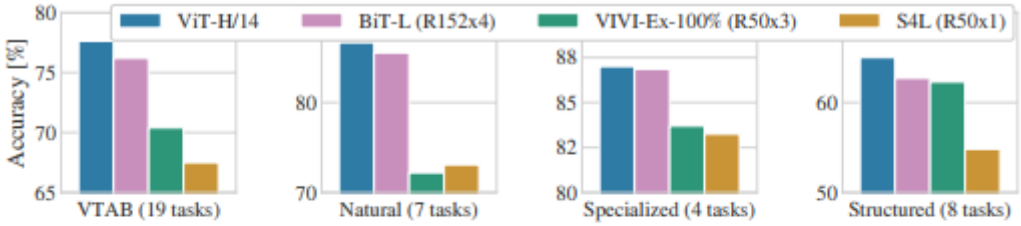
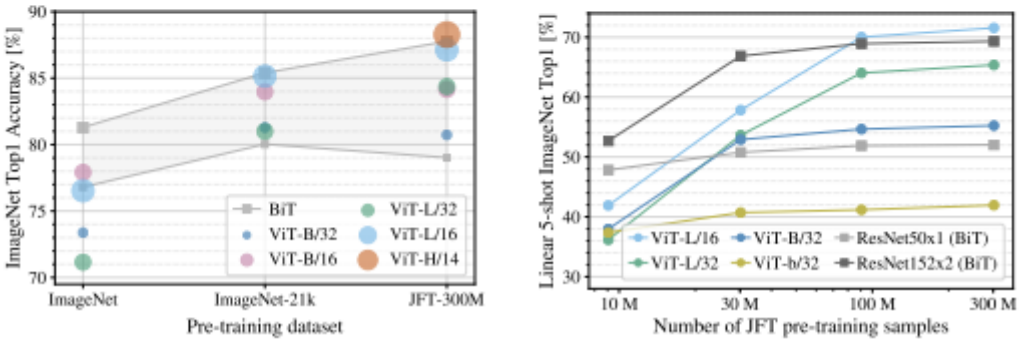



Figure 2: Breakdown of VTAB performance in *Natural*, *Specialized*, and *Structured* task groups.

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Question:

- Can such an approach be extended from image classification to caption generation as was done in the previous article?
    - Recall that the previous article fully reruns its attention process after each word in the generated caption – would a transformer for image captioning also want to do the same?

## Abstract

## Introduction

## Related Work

## Method

### Vision Transformer (TF)

### Hybrid Architecture