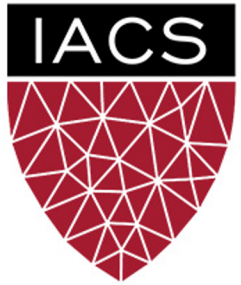
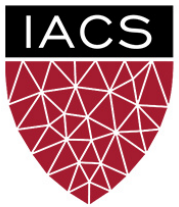
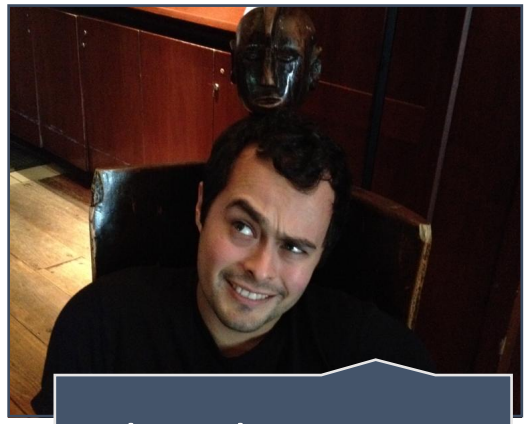


Show, Attend and Tell: Neural Image Caption Generation with Visual Attention

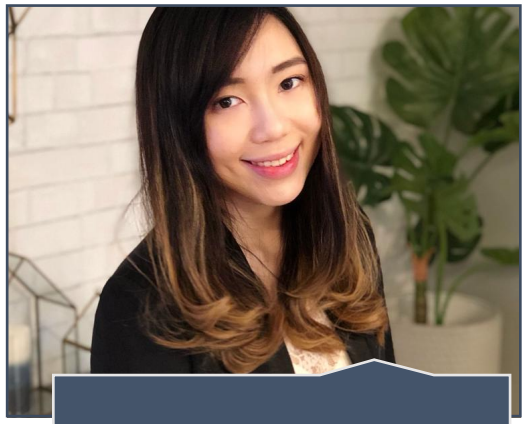
$\alpha\beta normal$ Distriβution
AC295/CS115



$\alpha\beta normal$ Distriβution



Eduardo Peynetti

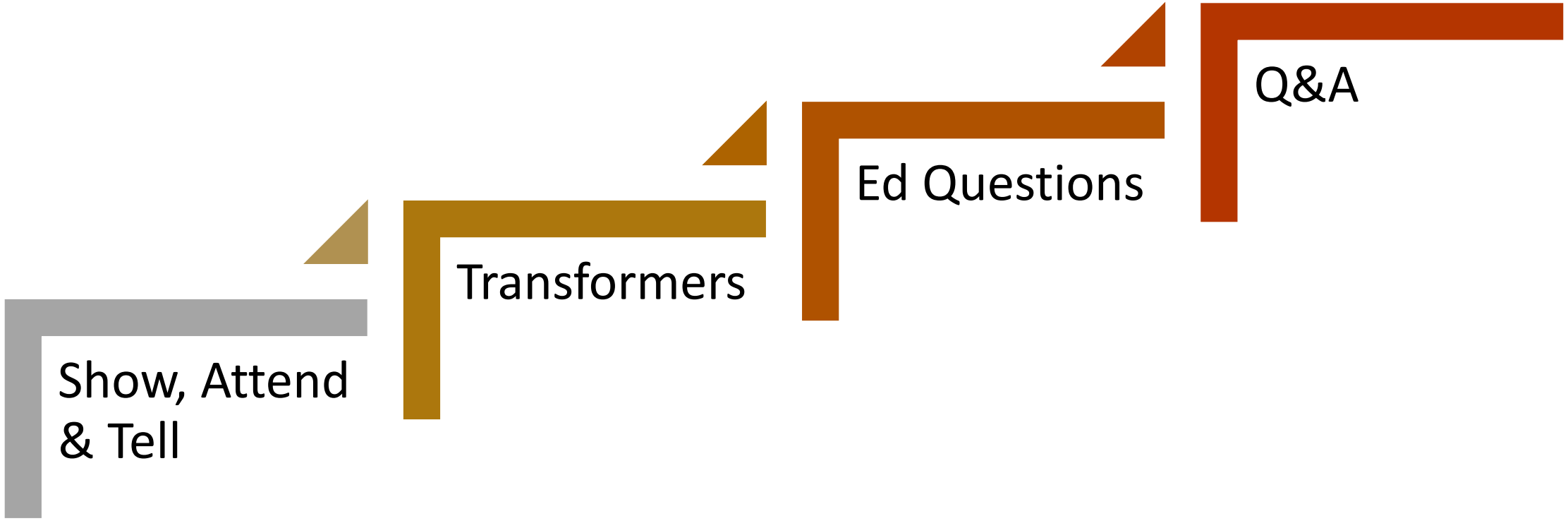


Jessica Wijaya

Rohit Beri

Stuart Neilson

Contents



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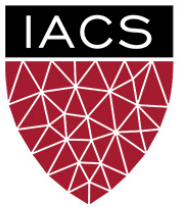
Show, Attend and Tell

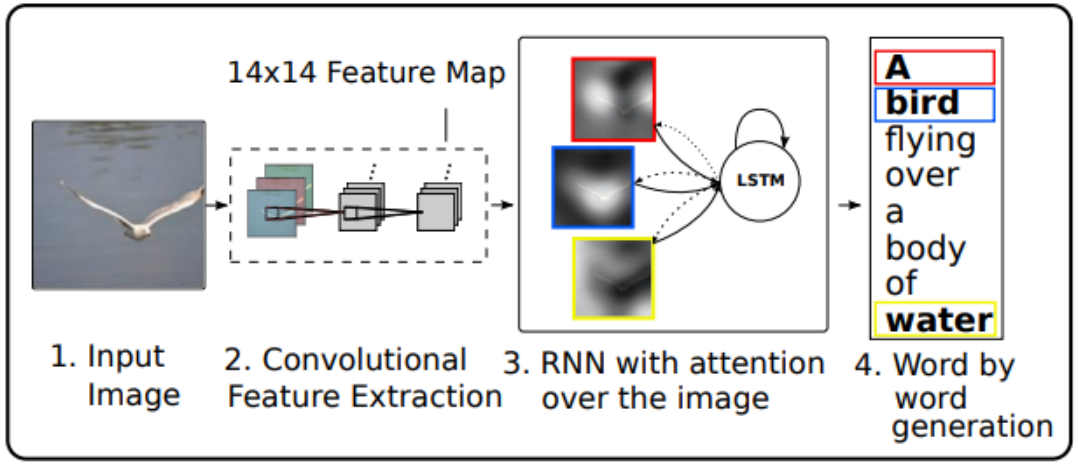
Neural Image Caption Generation with Visual Attention



Show, Attend and Tell

Attention-based Model

- Automatically learns to describe the content of the images
- Two ways to train the model
- State-of-the-art performance on three different datasets



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Automatic Caption Generation

- At the heart of scene understanding
- One of the primary goals of computer vision
- Express relationships of objects in a natural language
- Mimicking human ability to compress visual information into descriptive language

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

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

Attention

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

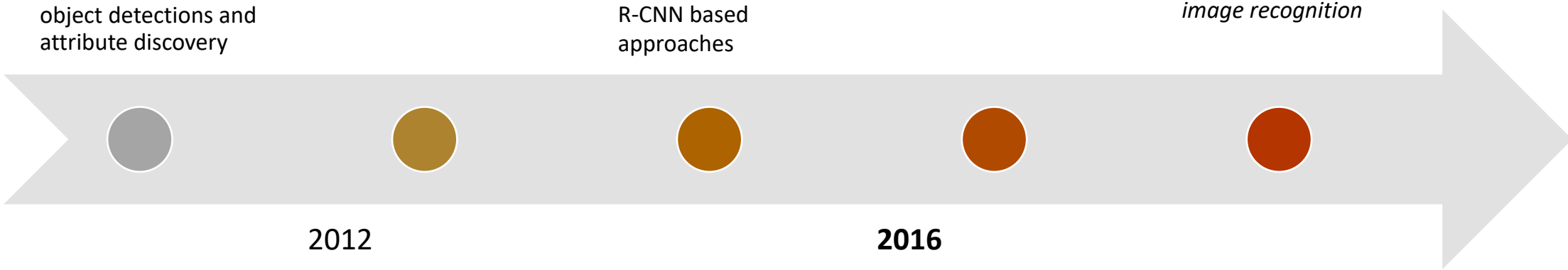
Top-layer representations distill information to most salient objects

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

Two attention-based image caption generators

- Soft deterministic attention
- Hard stochastic attention

Timeline – Image Captioning/Visual Attention



2011

- Generating caption templates which were filled in based on the results of object detections and attribute discovery

2012

- First retrieving similar captioned images for a large dataset and then modifying these retrieved captions to fit the query

2014

- Flurry of Neural Networks based approaches
- FFNN, RNN, LSTM & R-CNN based approaches

2016

- **Show, Attend and Tell**
- **Neural image caption generation with visual attention**

2020

- *An Image is worth 16 x 16 words*
- *Transformer based architecture for image recognition*

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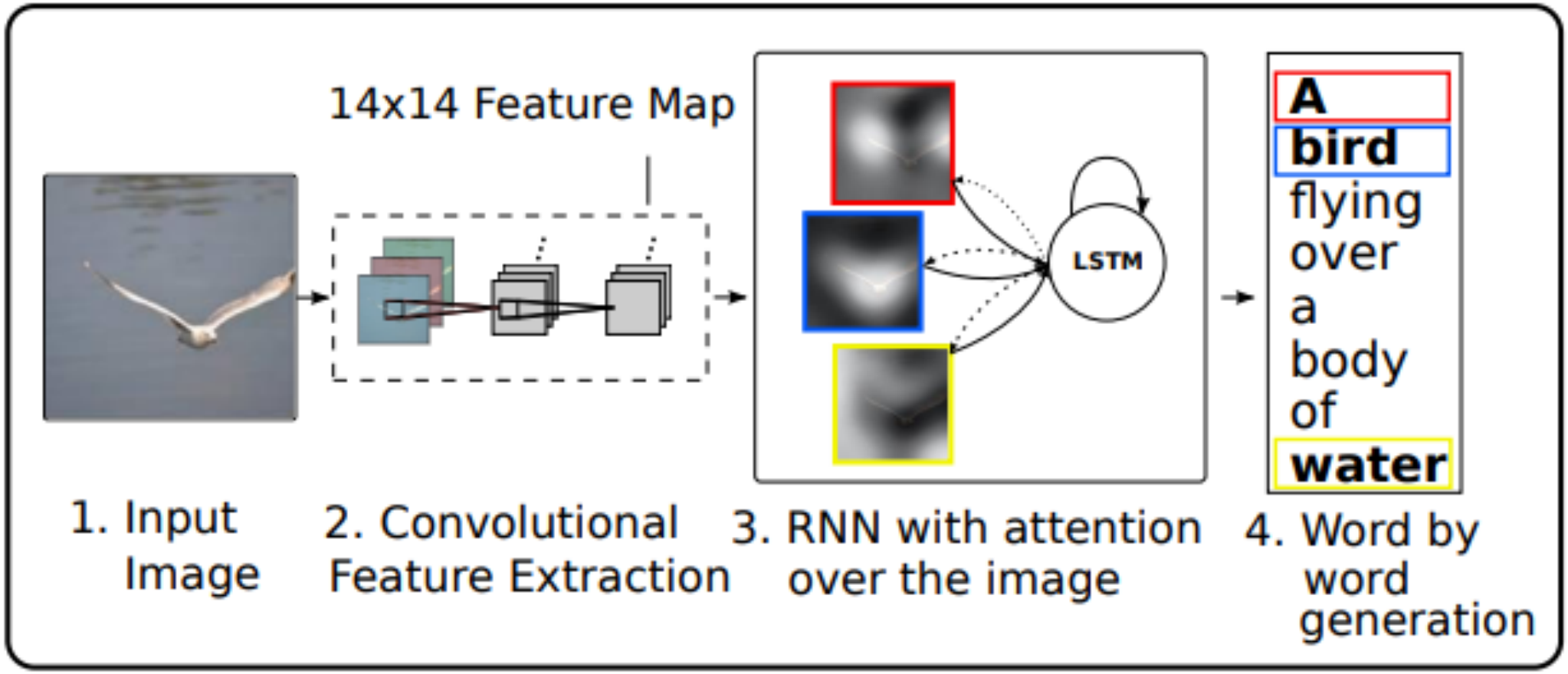
Image Caption Generation – Model Overview



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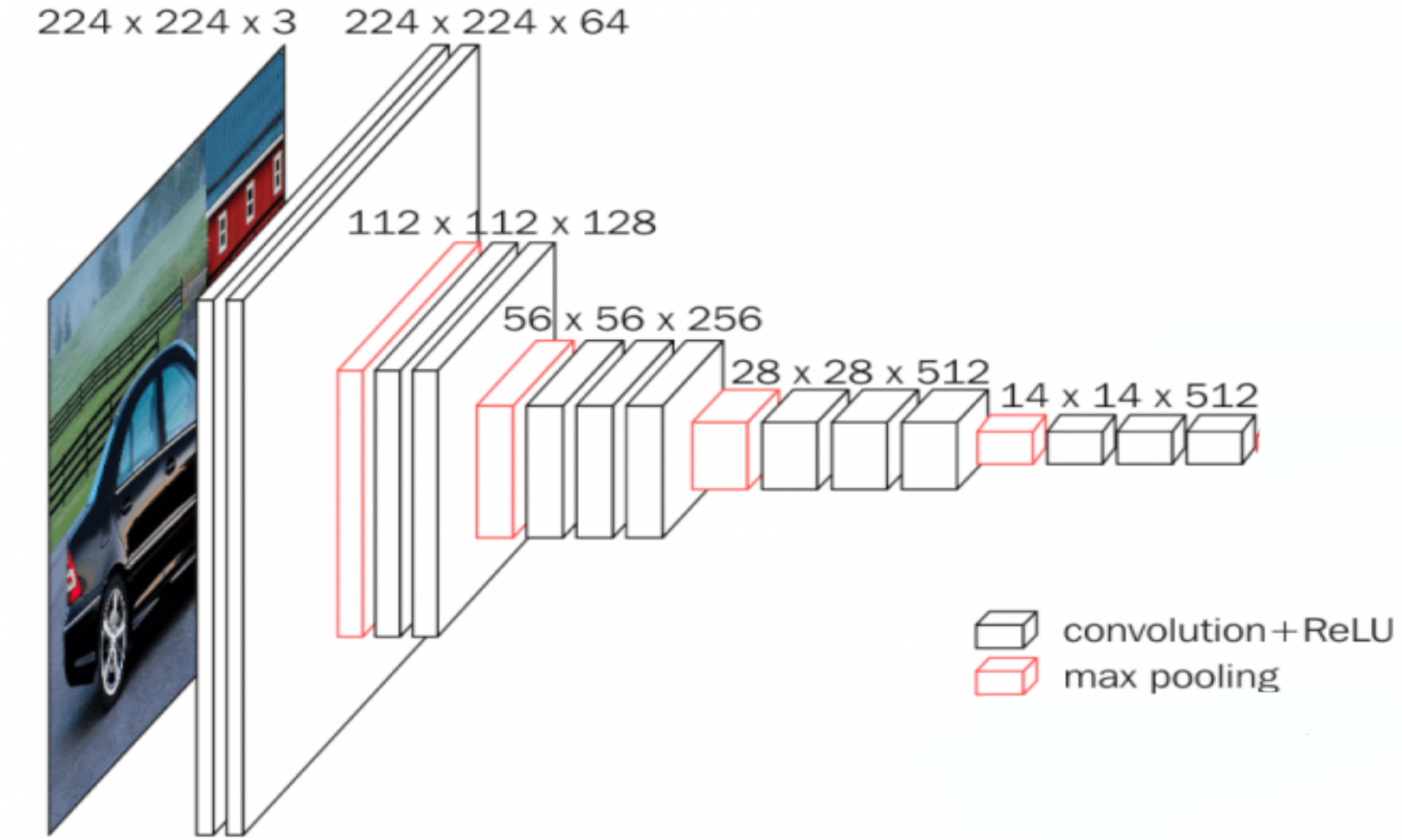
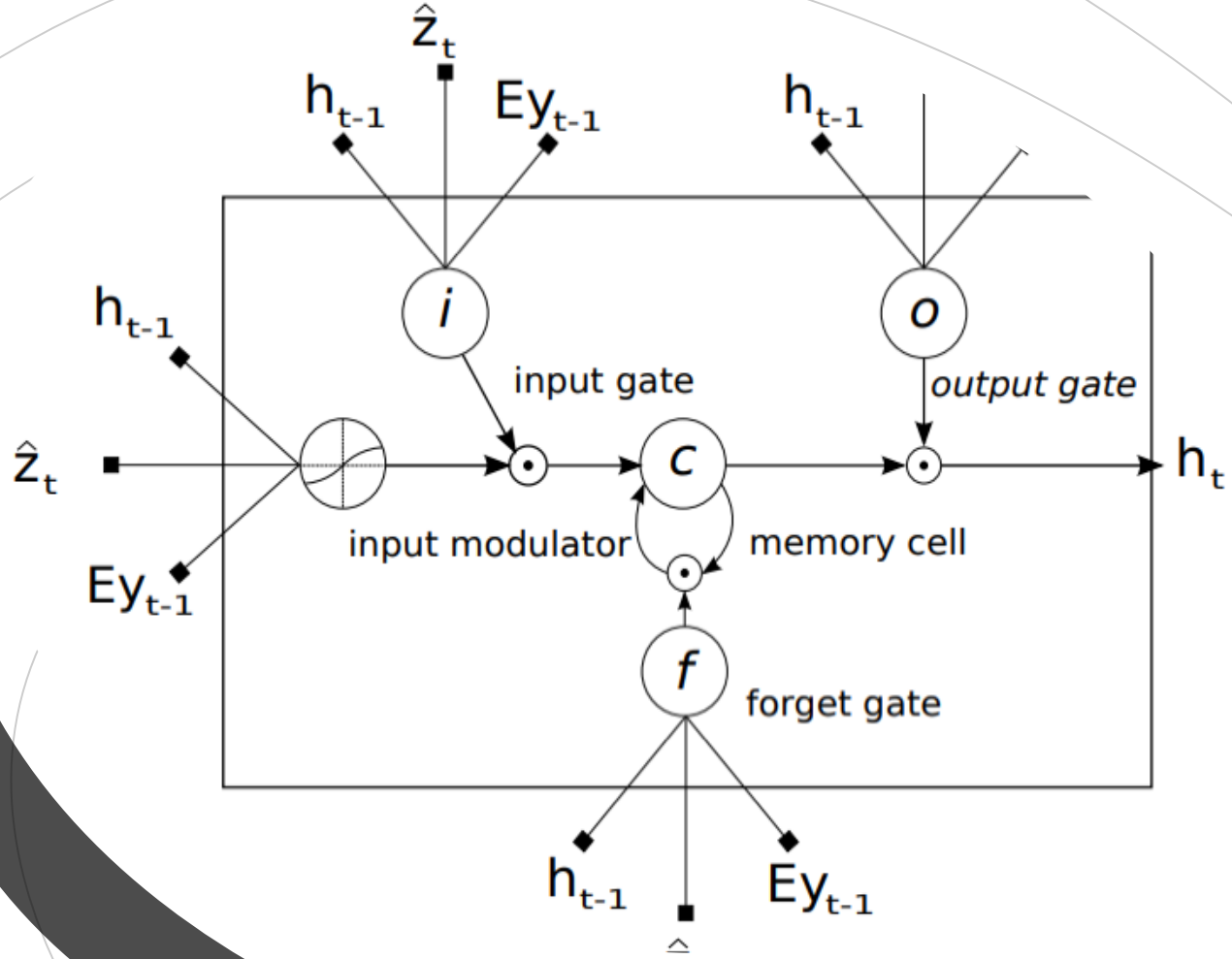
Encoder – Oxford VGG





Decoder – LSTM with Attention

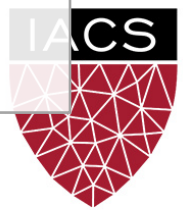
Decoder – LSTM with Attention

LSTM generates one word at every time step, ***conditioned on***:

- Context vector z_t
- Previous hidden state h_{t-1}
- Previously generated word y_{t-1}

LSTM

- $\begin{pmatrix} i_t \\ f_t \\ o_t \\ g_t \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ tanh \end{pmatrix} T_{D+m+n,\,n} \begin{pmatrix} Ey_{t-1} \\ h_{t-1} \\ \hat{z}_t \end{pmatrix}$
- $c_t = f_t \odot c_{t-1} + i_t \odot g_t$
- $h_t = o_t \odot \tanh(c_{t-1})$



Decoder – LSTM with Attention

Initial Memory State and Hidden State

- Average of the Annotation Vectors

$$c_0 = f_{init,c}\left(\frac{1}{L}\sum_i^L a_i\right)$$

$$h_0 = f_{init,h}\left(\frac{1}{L}\sum_i^L a_i\right)$$

Weight α_i of each Annotation Vector a_i

- Computed by the attention model f_{att}
  - MLP conditioned on the h_{t-1}.

$$e_{ti} = f_{att}\left(a_i, h_{t-1}\right)$$

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

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Decoder – LSTM with Attention

Context Vector: $\hat{z}_t$

- Dynamic representation of the relevant part of the image at time t

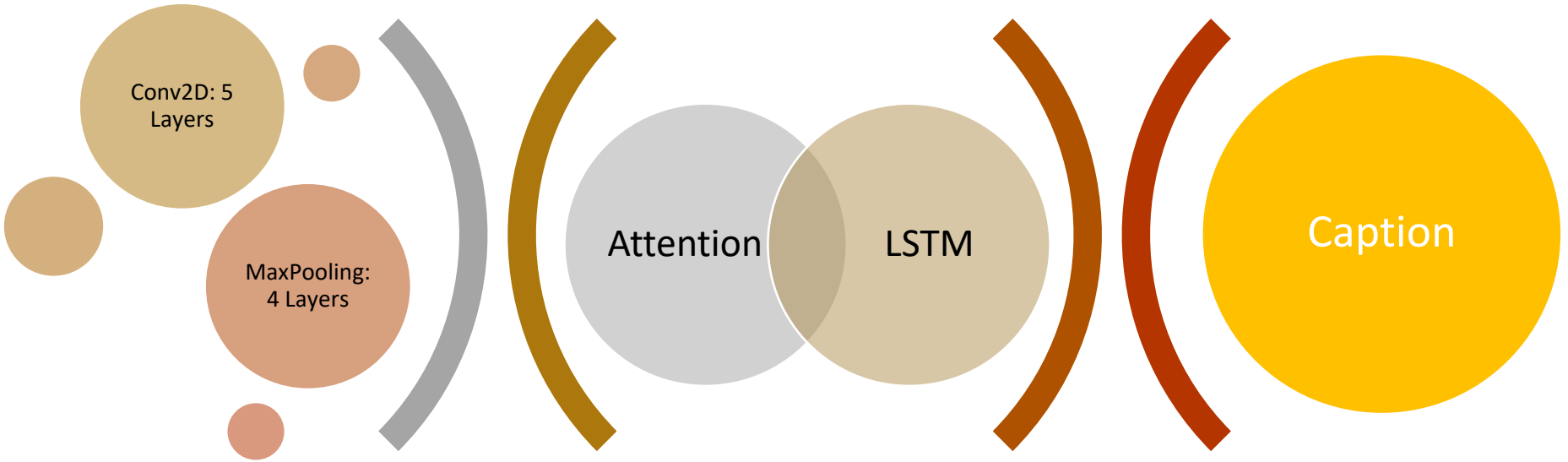
Mechanism: ϕ

- $\hat{z}_t = \phi(\{a_i\}, \{\alpha_i\})$
  - Meaning of α_i
    - Probability: Hard attention
    - Relative Importance: Soft attention

Deep output layer

- $p(y_t | a, y_1^{t-1}) \propto e^{(L_0(E y_{t-1} + L_h h_t + L_z \hat{z}_t))}$
  - Probability of the output word
  - Where: $L_0 \in \mathbb{R}^{K \times m}, L_h \in \mathbb{R}^{m \times n}, L_z \in \mathbb{R}^{m \times D}$, and E are learned parameters

Show, Attend & Tell – Architecture



Encoder - Oxford VGG

Decoder

Prediction

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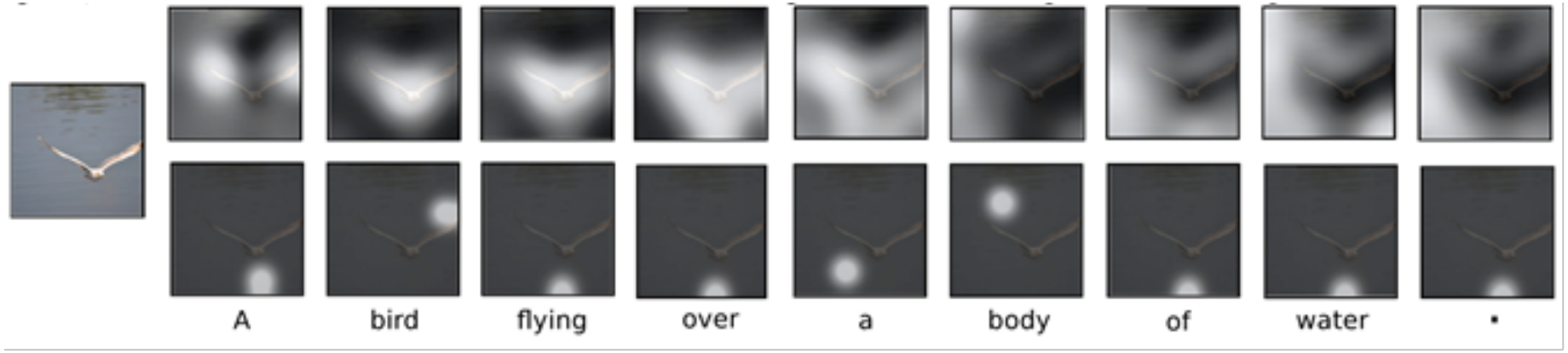
Soft vs Hard Attention



Soft Attention

ϕ returns the expectation of the context vector

Differentiable and amenable to standard backpropagation

Hard Attention

ϕ returns a_i at every time step using multinouilli distribution sampling

Monte-Carlo based sampling to compute the gradient

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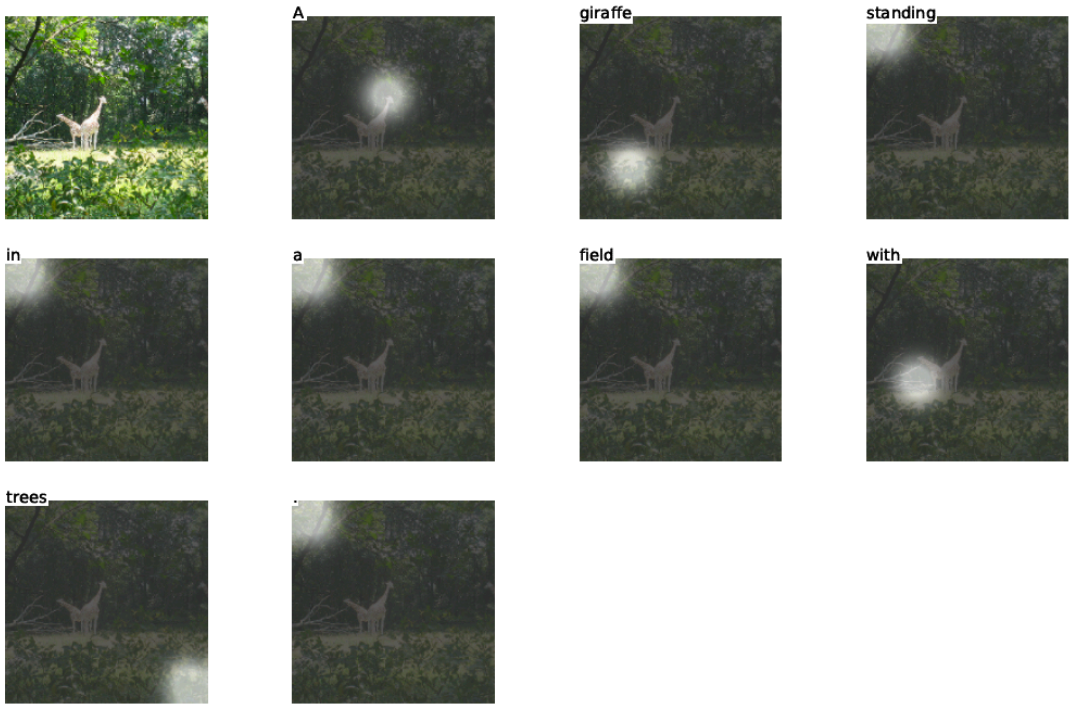
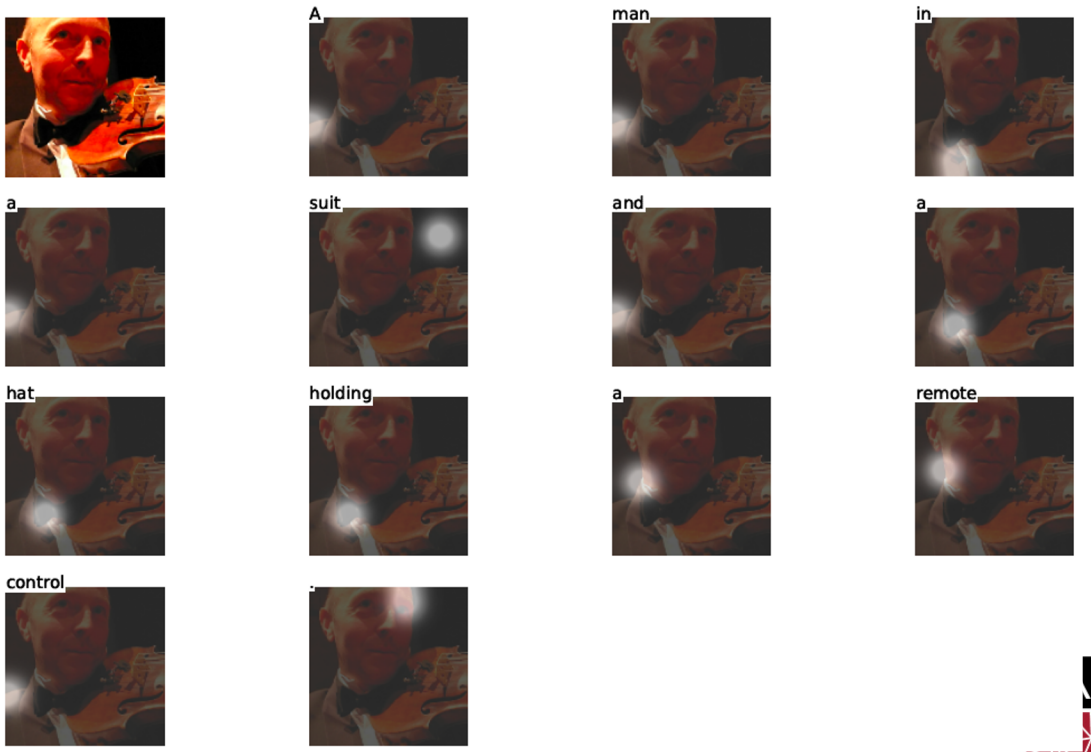
Hard (Stochastic) Attention

Correct Captioning



Incorrect Captioning



Hard (Stochastic) Attention

Objective function: L_s

- $\log p(y|a)$
  - Likelihood of observing words *y* given image feature *a*
- Hard to compute
  - Optimize the variational lower bound instead

$$L_s = \sum_s p(s|a) \log p(y|s,a)$$
$$\leq \log \sum_s p(s|a)\, p(y|s,a)$$
$$= \log p(y|a)$$

Latent Variable: s_t

- Location where the model focuses on when generating the t^{th} word

$$\tilde{s} \sim Multinouilli_L(\{\alpha_i\})$$
$$p(s_{t,i} = 1 | s_{j<t}, a) = \alpha_{t,i}$$
$$\hat{z_t} = \sum s_{t,i}\, a_i$$

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Hard (Stochastic) Attention

Optimize L_s

$$L_s = \log p(y|a)$$

Function not **differentiable**

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

Sampling Based Approximation

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

Variance Reduction & Regularization

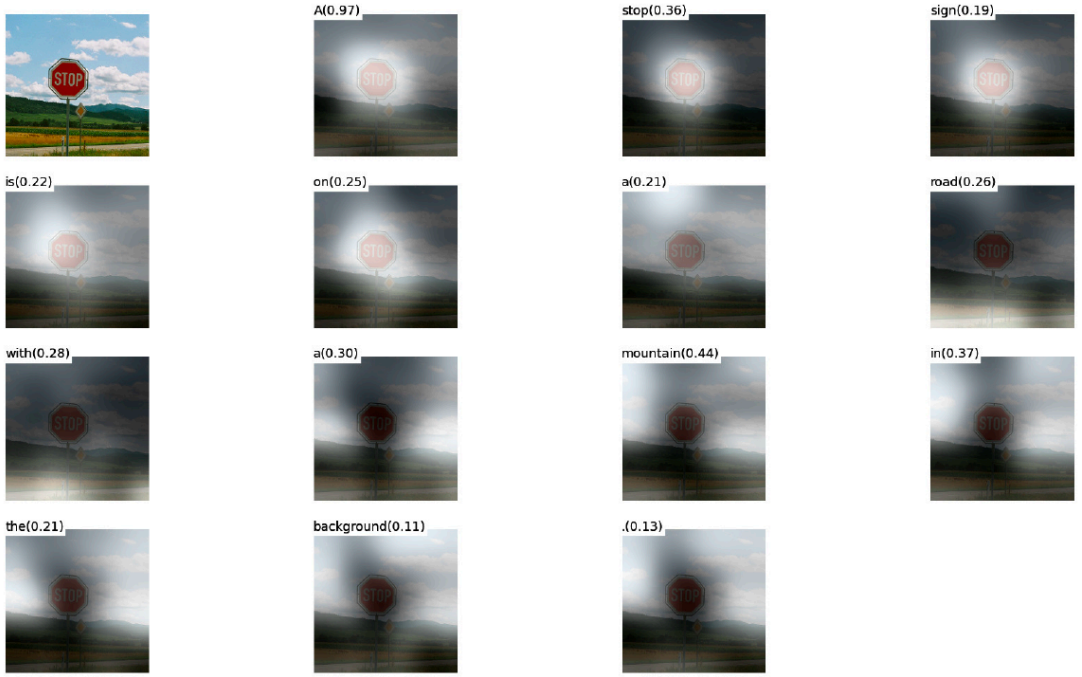
- **Use a moving average baseline**
- **Add an entropy term H[s]**

Final Learning Rule – REINFORCE Learning

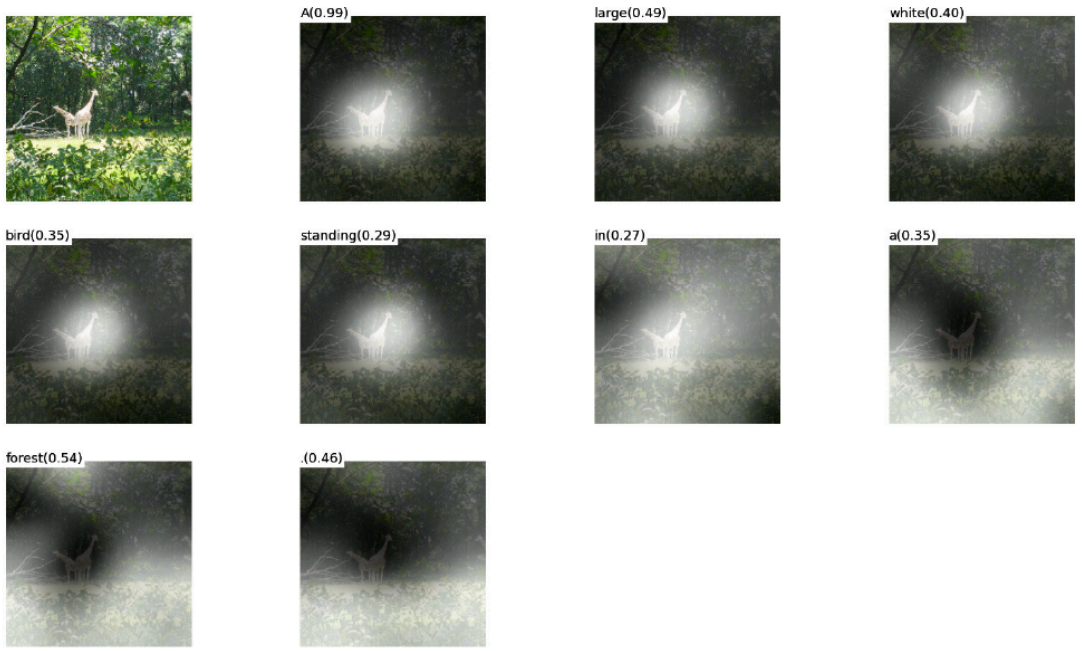
$$\frac{\partial L_s}{\partial W} \approx \frac{1}{N}\sum_{n=1}^{N}\left[\frac{\partial \log p(y|\tilde{s}^n,a)}{\partial W} + \lambda_r(\log p(y|\tilde{s}^n,a) - b)\,\frac{\partial \log p(\tilde{s}^n|a)}{\partial W} + \lambda_e\frac{\partial H[\tilde{s}^n]}{\partial W}\right]$$

Soft (Deterministic) Attention

Correct Captioning



Incorrect Captioning



Soft (Deterministic) Attention

Objective function: L_s

- $\log p(y|a)$
  - Likelihood of observing words *y* given image feature *a*
- Model is differentiable and amenable to backpropagation

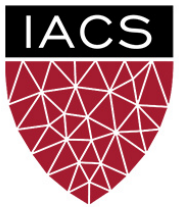
$$L_s = \log p(y|a)$$

Context Vector: $\hat{z}_t$

- Directly computes the expectation of the context vector

$$\hat{z}_t = \phi(\{a_i\}, \{\alpha_i\})$$

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



Soft (Deterministic) Attention

Doubly Stochastic Regularization

- Forces algorithm to pay equal attention to every part of the image over the course of caption generation

$$Encourage \sum_t \alpha_{ti} \approx 1 \; in \; addition \; to \sum_i \alpha_{ti} = 1$$

Model also predicts β

- Predicted from previous hidden state h_{t-1} at each time-step t
- Emphasis objects in image

$$\hat{z}_t = \phi(\{a_i\}, \{\alpha_i\}) = \beta_t \sum_{i=1}^{L} \alpha_{t,i} \, a_i$$

$$\beta_t = \sigma(f_\beta(h_{t-1}))$$

Final Objective Function

- *Minimize penalized* negative log-likelihood

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

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Datasets

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 >5 reference sentences

Training

Optimizers

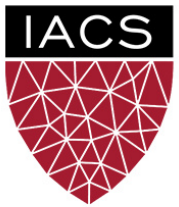
- Flickr8k
  - RMSProp
- Flickr30k & MS COCO
  - ADAM

BLEU

- Early stopping on BLEU
- Corr. breakdown between log-likelihood and BLEU
- BLEU for model selection

Computing Efficiency

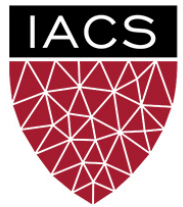
- Mini batches of equal length captions to improve speed
- Randomly selected caption length



Quantitative Evaluation

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 - Visualization

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.

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Conclusion & Future of Image Captioning

Conclusion

Alignments correspond well to human intuition

"Attention" can help with the model interpretation

Future

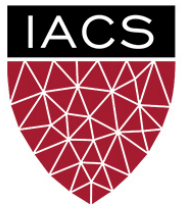
Transformers

Can we replace CNNs and LSTMs with Transformers?

An Image is worth 16 x 16 words

Transformers for Image Recognition at Scale

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).



State of the Art

Natural Language Processing

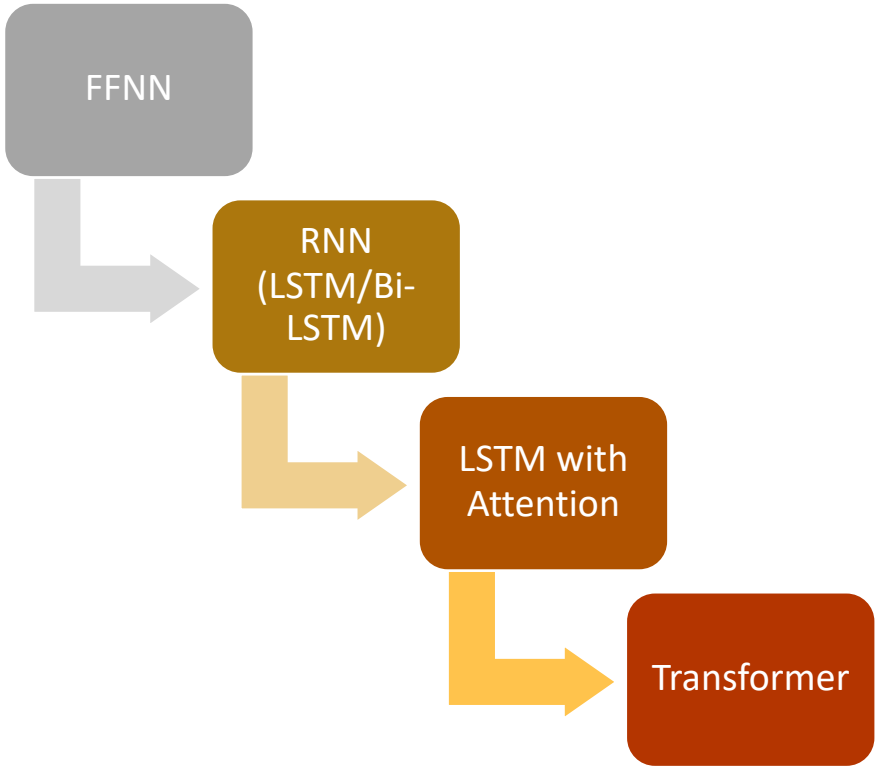
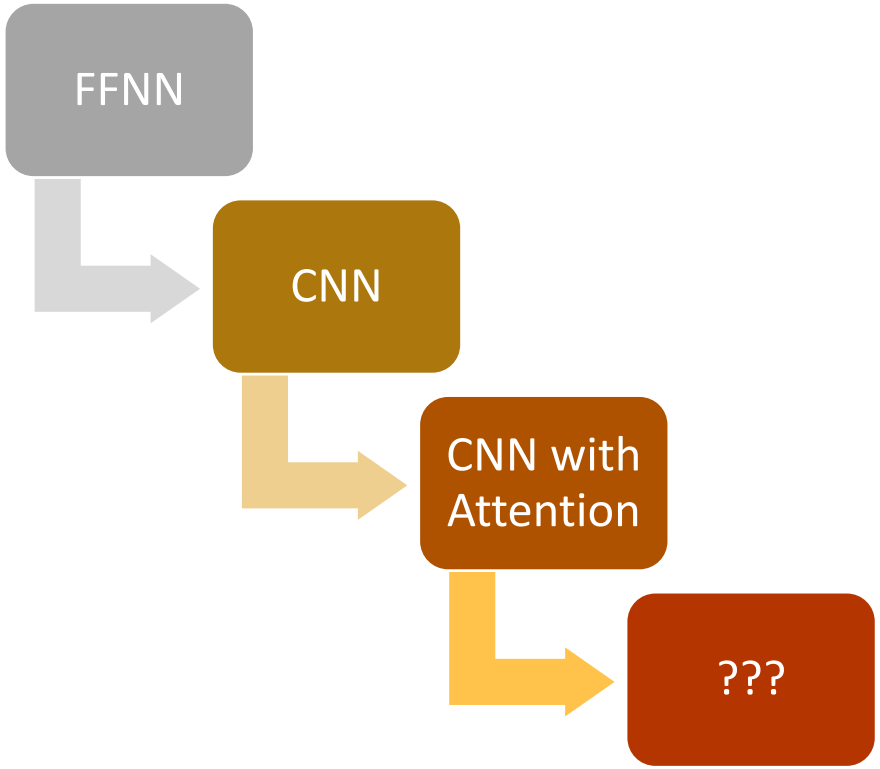


Image Recognition



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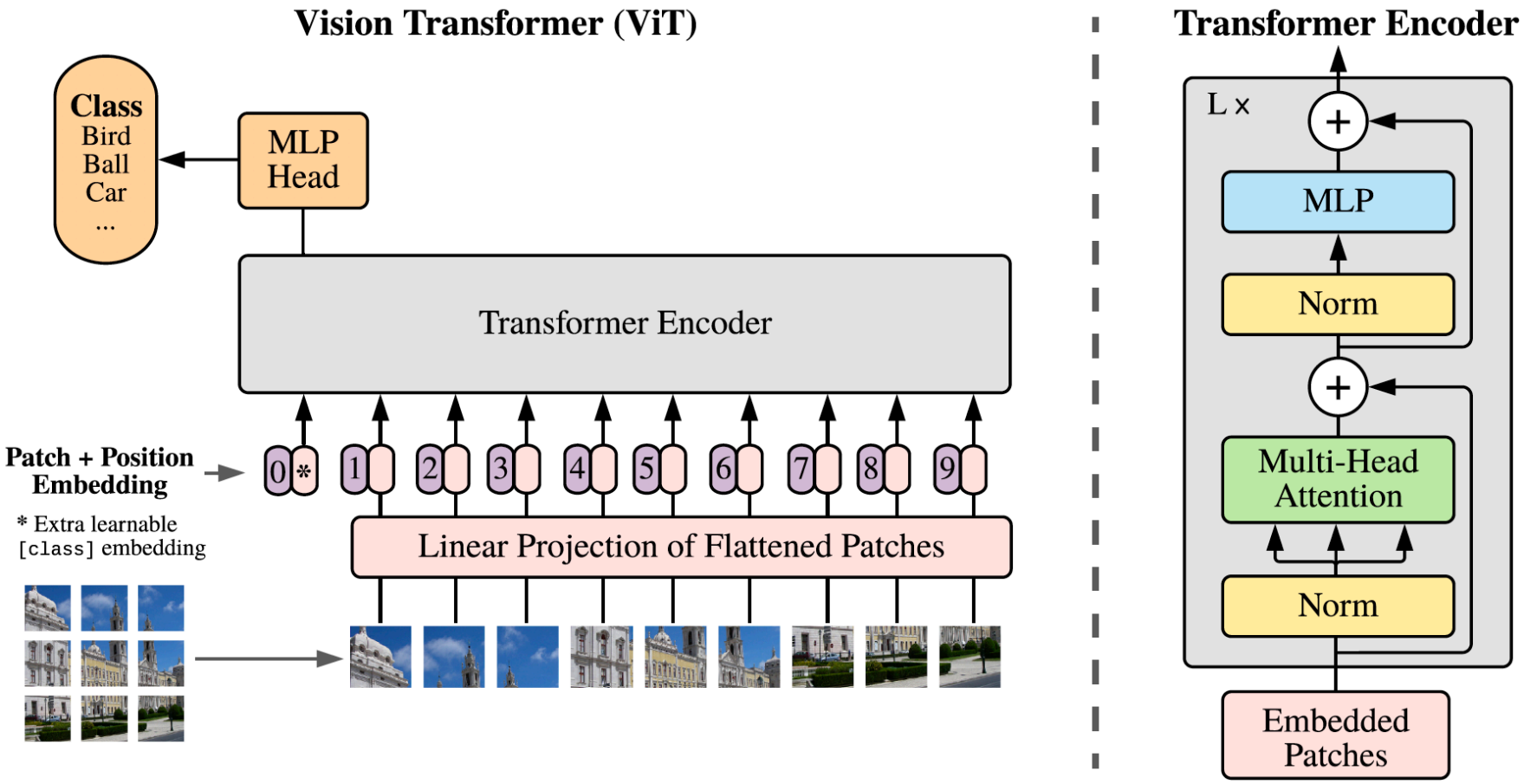
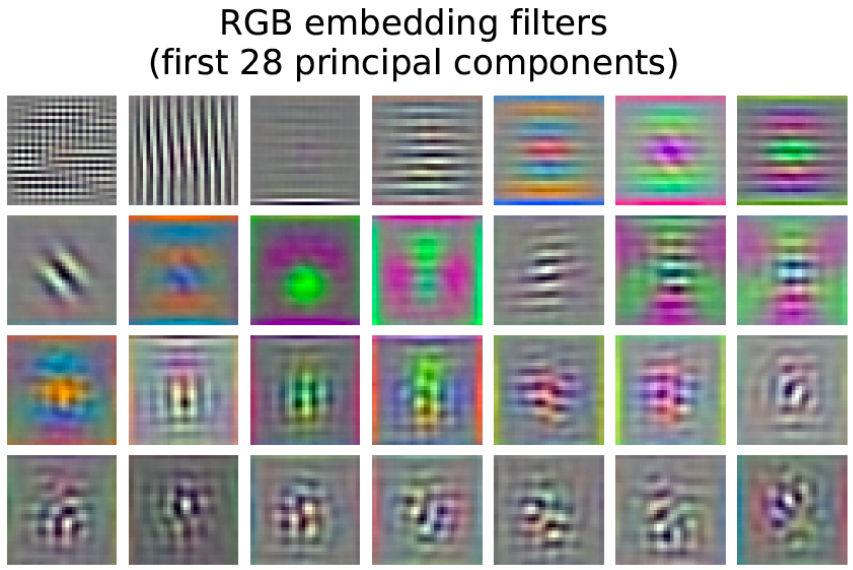
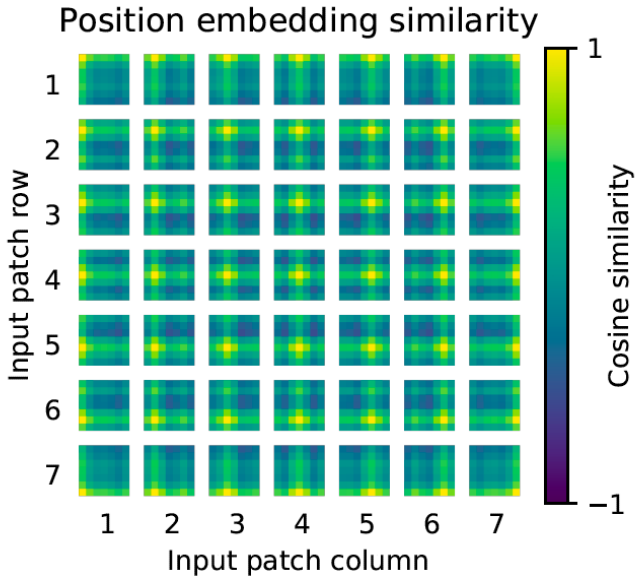
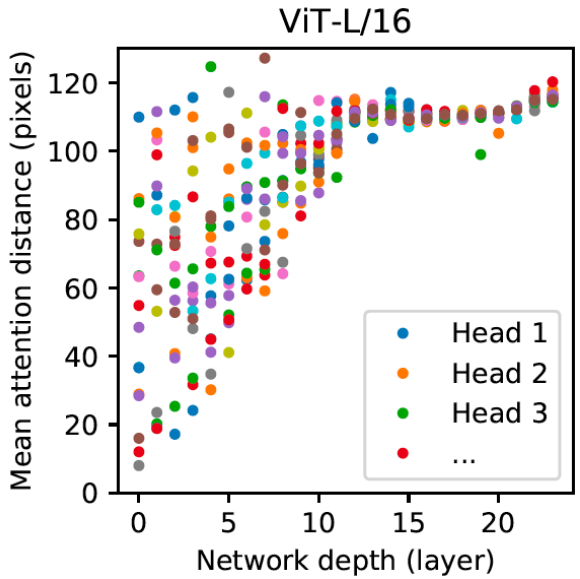
Vision Transformer (ViT)



ViT: Learning similar features as CNN







ViT vs SOTA - Performance

	Ours-JFT (ViT-H/14)	Ours-JFT (ViT-L/16)	Ours-I21K (ViT-L/16)	BiT-L (ResNet152x4)	Noisy Student (EfficientNet-L2)
ImageNet	**88.55** ± 0.04	87.76 ± 0.03	85.30 ± 0.02	87.54 ± 0.02	88.4/88.5*
ImageNet ReaL	**90.72** ± 0.05	90.54 ± 0.03	88.62 ± 0.05	90.54	90.55
CIFAR-10	**99.50** ± 0.06	99.42 ± 0.03	99.15 ± 0.03	99.37 ± 0.06	–
CIFAR-100	**94.55** ± 0.04	93.90 ± 0.05	93.25 ± 0.05	93.51 ± 0.08	–
Oxford-IIIT Pets	**97.56** ± 0.03	97.32 ± 0.11	94.67 ± 0.15	96.62 ± 0.23	–
Oxford Flowers-102	99.68 ± 0.02	**99.74** ± 0.00	99.61 ± 0.02	99.63 ± 0.03	–
VTAB (19 tasks)	**77.63** ± 0.23	76.28 ± 0.46	72.72 ± 0.21	76.29 ± 1.70	–
TPUv3-core-days	2.5k	0.68k	0.23k	9.9k	12.3k

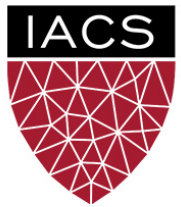
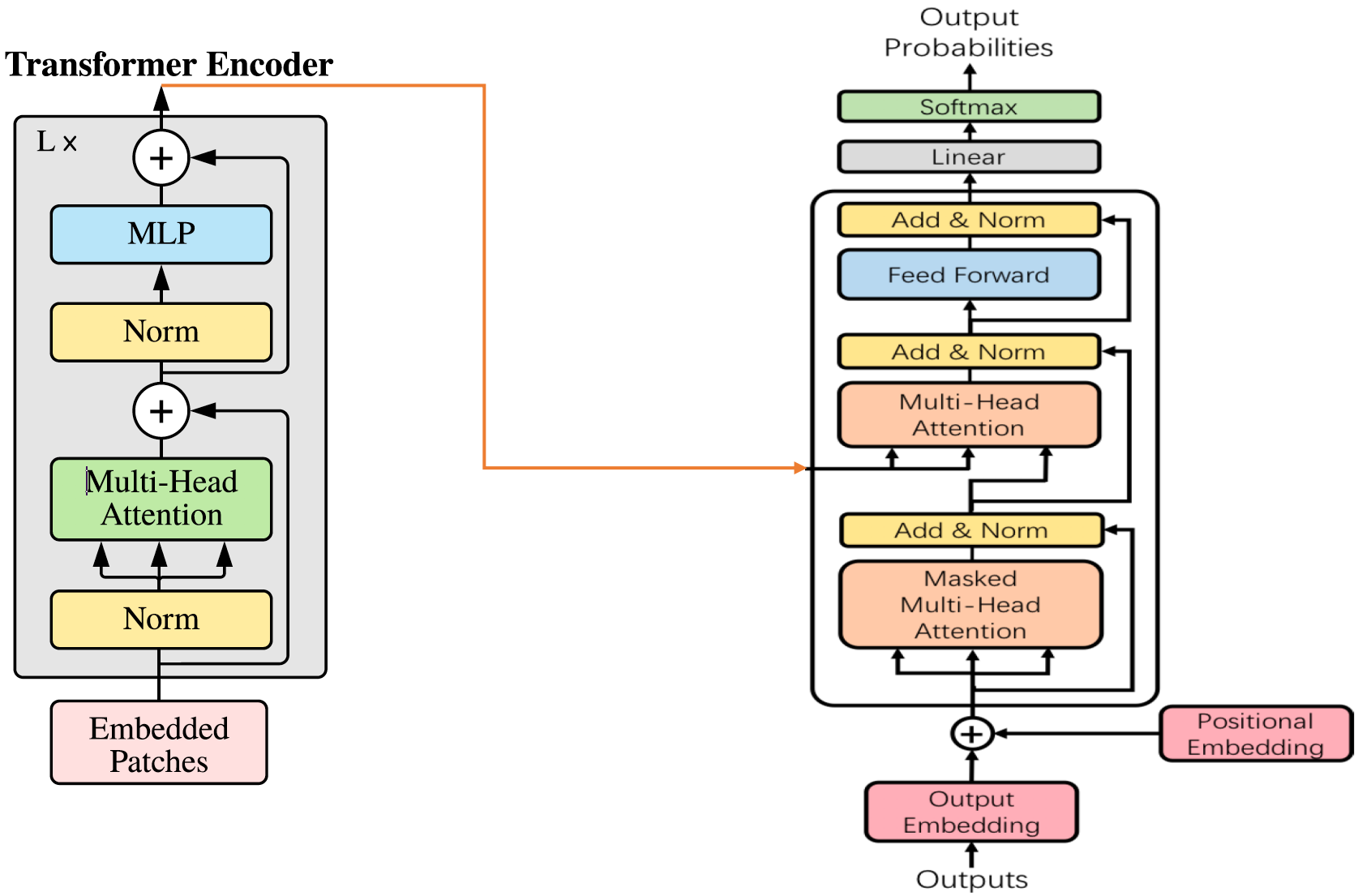
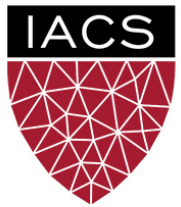


Image Captioning with Transformers?



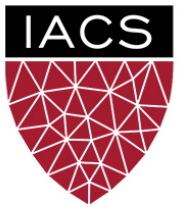
Ed Questions



Cost Function

It's not very clear what kind of cost function is used to evaluate the performance, would be nice to elaborate that.

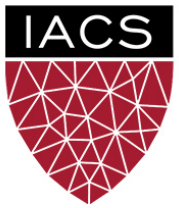
- There is a difference between cost function and the performance evaluation
- Cost Function is used for Training is $L_d = -\log\big(P(y|x)\big) + \lambda \sum_i^L (1 - \sum_t^C \alpha_{ti})^2$
- For Performance Evaluation, authors use 2-different measures:
  - BLEU: Bilingual Evaluation Understudy
    - Uses a modified form of precision to compare a translation against multiple reference translations
  - METEOR: Metric for Evaluation of Translation with Explicit Ordering
    - Based on the harmonic mean of unigram precision and recall, with recall weighted higher than precision



Data Splits

How would you handle/standardize the differences between dataset splits?

- Authors use the predefined splits of Flickr8k
- For Flickr30k and MS COCO, authors use publicly available splits used in previous work i.e. Karpathy & Li, 2014
- Other splits can be generated, and as per authors, are unlikely to impact the performance scores

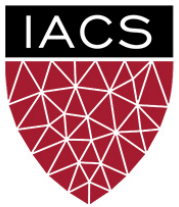


Data Preprocessing

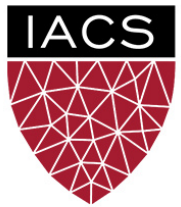
How to input and train with text data and image data at the same time? What are the preprocessing needed for constructing data pipeline?

```
train_captions = []
img_name_vector = []

for image_path in train_image_paths:
  caption_list = image_path_to_caption[image_path]
  train_captions.extend(caption_list)
  img_name_vector.extend([image_path] * len(caption_list))
```



Questions Please!



Thanks!