Exploring Show, Attend, Tell Attention Mechanisms for Image Captioning

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Introduction



[Figure 3]

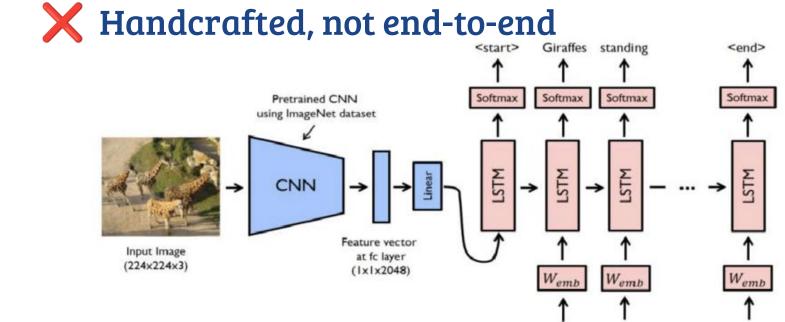
Hundreds of determined runners push forward at the start of a vibrant city marathon, each athlete focused on the road ahead under a bright, sunny sky.

- Image captioning is complex requires understanding objects/relationships in images
- Reproducing the Show, Attend, Tell captioning model, training on Flickr-8k & optimizing for METEOR

Background & Motivation

Prior Approaches

- CNN \rightarrow Single Vector \rightarrow RNN (Vinyals et al., 2014)
 - X Loses spatial **and** contextual detail
- CRF + Object Detectors (Fang et al., 2014)



[Figure 4]

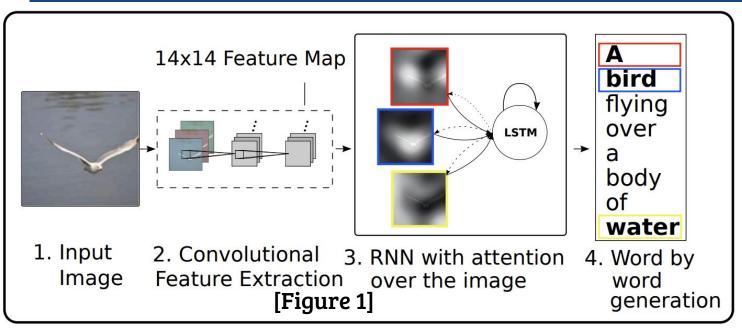
Encoder-Decoder Architecture for Captioning

Solution: Attention-Based Models

- Dynamically **focuses** on relevant image regions during captioning
- Mimics <u>human visual</u> attention to salient features; interpretable



Methods



ResNet CNN, LSTM with Attention



Attention

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

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

Soft Attention



[Figure 5]

Weighted sum over **image** regions at each timestep; fully differentiable

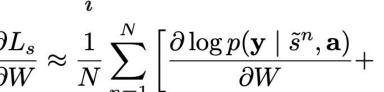
$$\mathbb{E}_{p(s_t|a)}[\hat{\mathbf{z}}_t] = \sum_{i=1}^L lpha_{t,i} \mathbf{a}_i$$

Doubly Stochastic Attention

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

Selects **one** region to focus on per timestep; non-differentiable and trained with REINFORCE

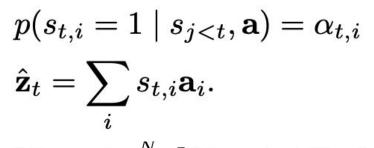
$$p(s_{t,i} = 1 \mid s_{j < t}, \mathbf{a}) = \alpha_{t,i}$$
 $\hat{\mathbf{z}}_t = \sum_i s_{t,i} \mathbf{a}_i.$



$$\lambda_r(\log p(\mathbf{y} \mid \tilde{s}^n, \mathbf{a}) - b) \frac{\partial \log p(\tilde{s}^n \mid \mathbf{a})}{\partial W} + \lambda_e \frac{\partial H[\tilde{s}^n]}{\partial W}$$

Moving baseline and entropy term for estimator variance reduction

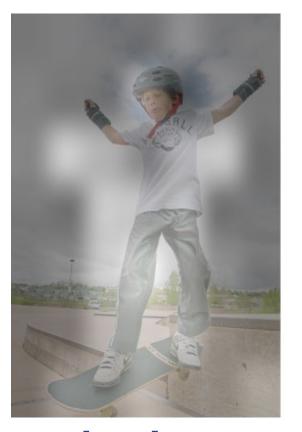
Hard Attention



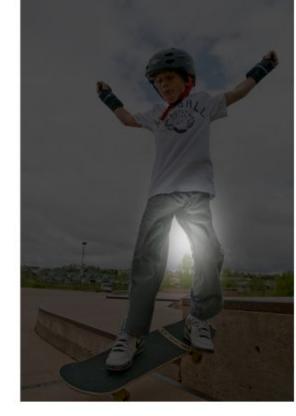
[Figure 6]

$$(\log p(\mathbf{y} \mid \tilde{s}^n, \mathbf{a}) - b) \frac{\partial \log p(\tilde{s}^n \mid \mathbf{a})}{\partial W} + \lambda_e \frac{\partial H[\tilde{s}^n]}{\partial W}]$$

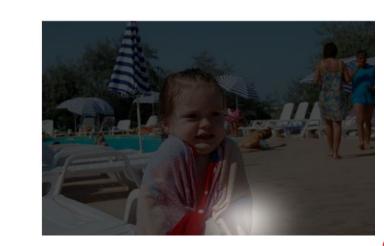
Where is the Model "Looking?"



A <u>boy</u> does a skateboard trick.



A child in a green and white shirt and black pants skateboarding.

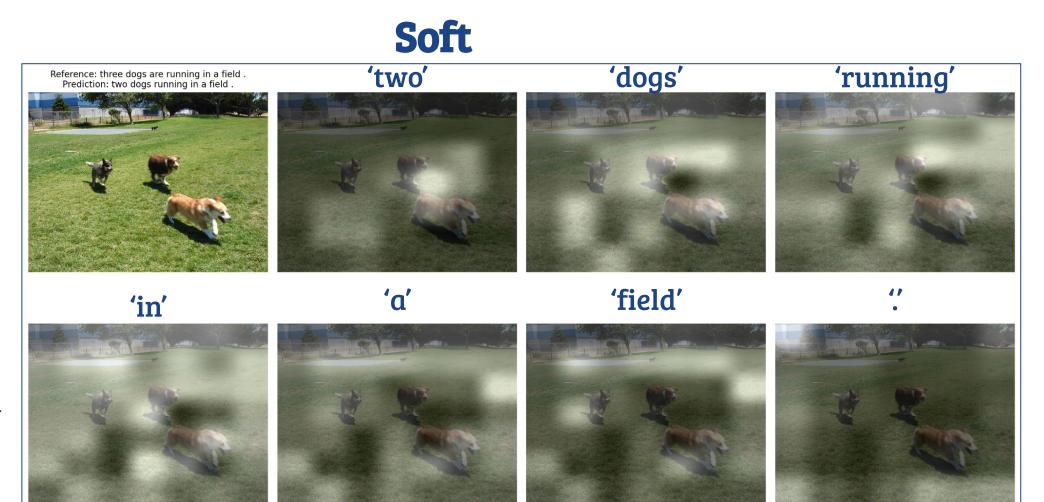


A girl in a red <u>striped</u> shirt.

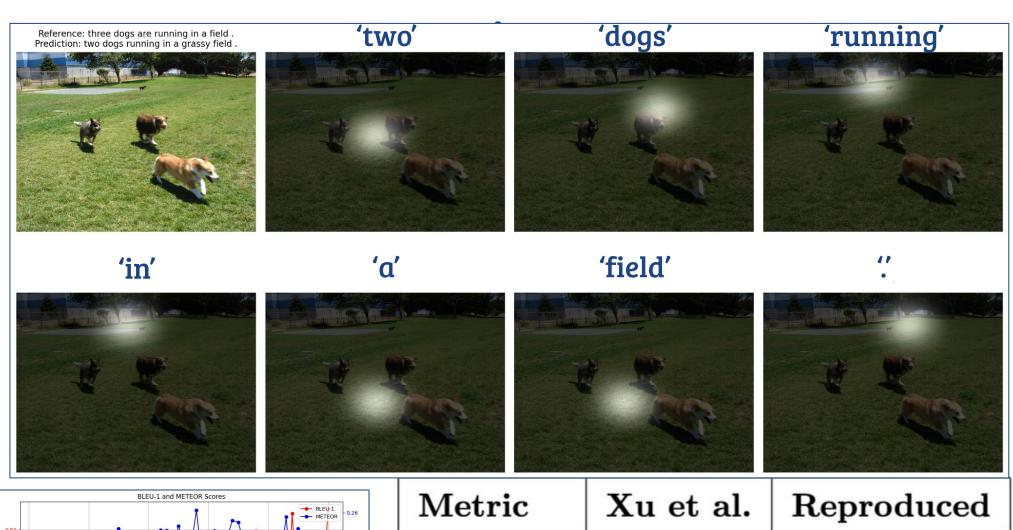


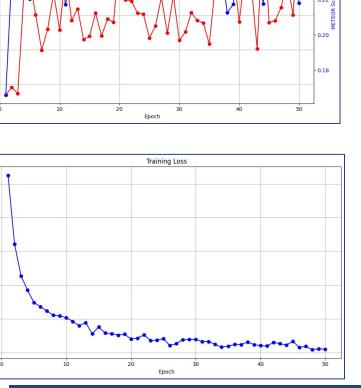
Two men skiing down a snowy

Results



Hard



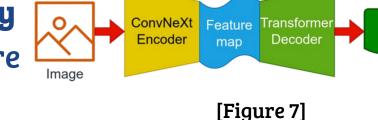


Soft Attention		
BLEU-1	67.0	45.9
METEOR	18.93	18.96
Hard Attention		
BLEU-1	67.0	43.2
METEOR	20.30	20.75

Train Loss/Validation Meteor Curves, METEOR/BLEU-1 Inference

Conclusion

- Attention-based models improve caption quality and interpretability
- Soft and hard attention guide where the model "looks" when generating



Outperformed paper METEOR results