

# Describing images and videos in natural language

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# Intro - Captioning



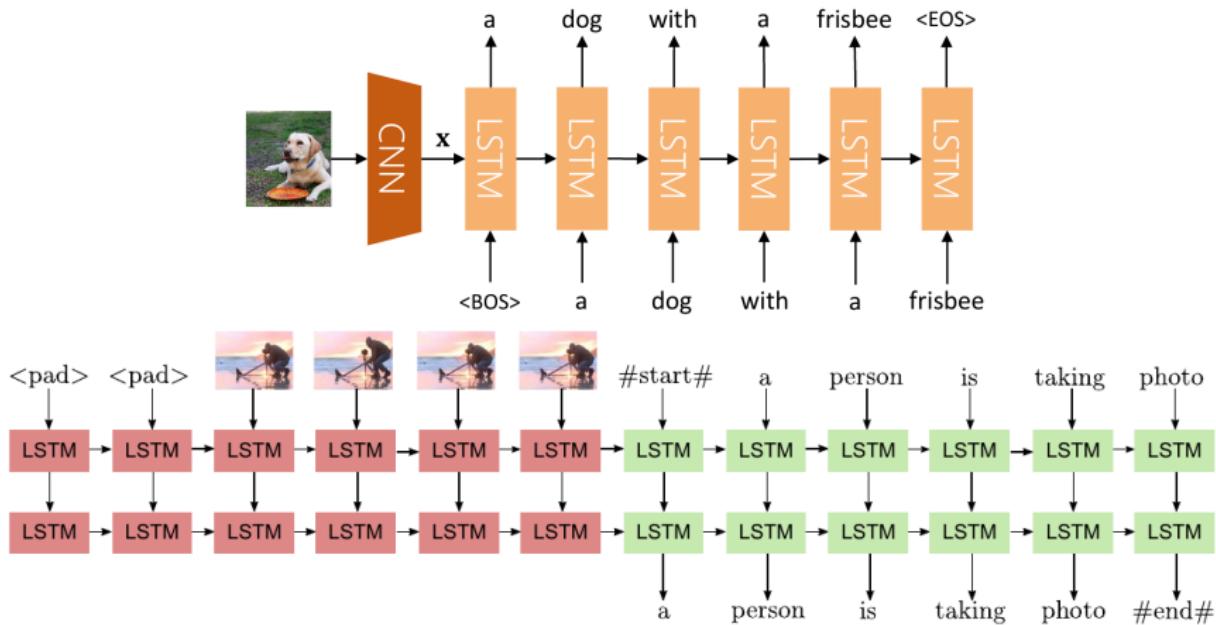
**Ours** : A bird is standing on a rock in the water.



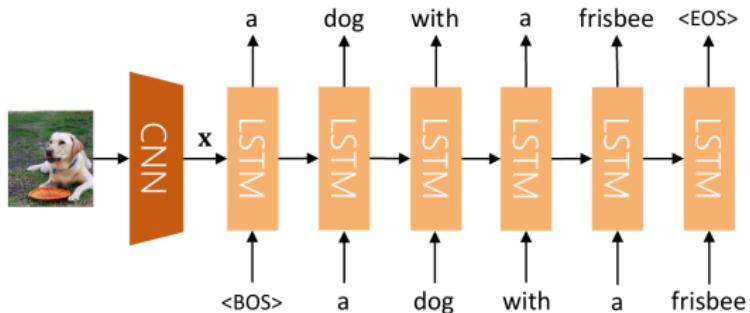
**GT** : The sun sets behind the watery horizon as the foursome continues along the shore toward a distant resort.

**Ours** : The sun shines as the sun sets to the horizon.

# Baseline Architectures



# Baseline Architectures



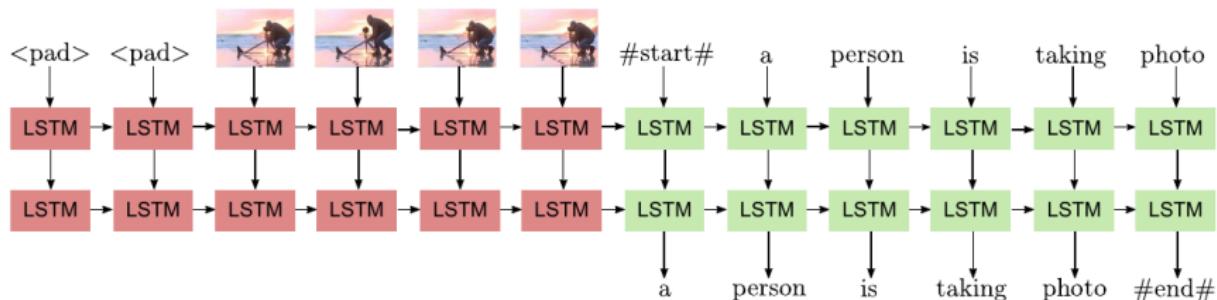
$$h_0 = \text{CNN}(\text{Img})$$

$$w_0 = <\text{Begin Sentence Token}>$$

$$h_t = \text{RNN}(w_{t-1}, h_{t-1})$$

$$p(w_t) = f(h_t)$$

# Baseline Architectures



$$h_t^{enc} = RNN(CNN(Img_{t-1}), h_{t-1}^{enc})$$

$$h_0 = h_{last}^{enc}$$

$$w_0 = <\text{BeginSentenceToken}>$$

$$h_t = RNN(w_{t-1}, h_{t-1})$$

$$p(w_t) = f(h_t)$$

# Baseline Architectures - Problems



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$$p(w_1, w_2, \dots, w_m | visual) = \prod_{t=1}^m p(w_t | h_t)$$

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- ▶ Big assumption:  $p(w_t)$  are independent given  $h_t$

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  - ▶ **Q:** does  $h_t$  contain enough information?
- ▶ Learning by maximization at every step of cross-entropy between
  - ▶ distribution of words in the predicted sentence,  $p(w_t)$
  - ▶ distribution of words in the ground truth sentence,  $p(\hat{w}_t)$

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  - ▶ distribution of words in the predicted sentence,  $p(w_t)$
  - ▶ distribution of words in the ground truth sentence,  $p(\hat{w}_t)$
  - ▶ **Q:** is this the best way of computing a loss?

# Multi-Task Video Captioning with Video and Entailment Generation



Pasunuru, Ramakanth, and Mohit Bansal. "Multi-Task Video Captioning with Video and Entailment Generation." In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, July 2017

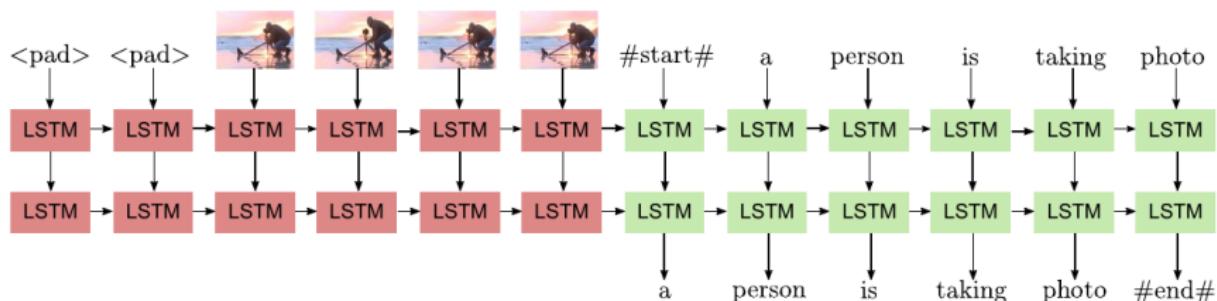
# Multi-Task Video Captioning with Video and Entailment Generation



Pasunuru and Bansal [2017]

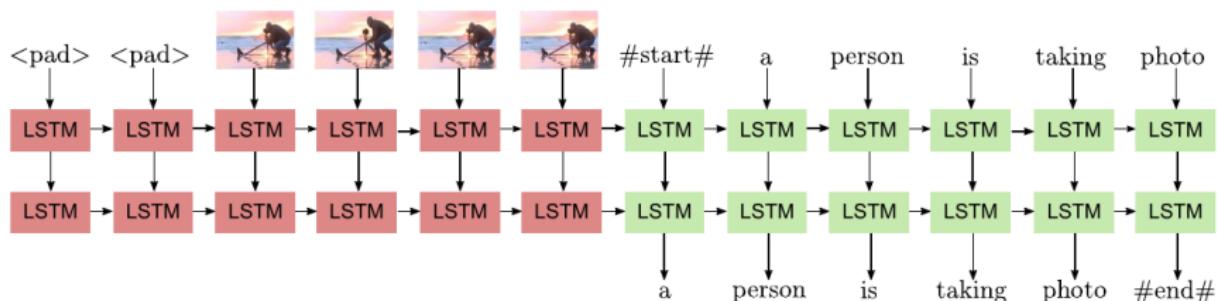
- ▶ improve captioning by sharing knowledge with other tasks
- ▶ use 2 other generative tasks
- ▶ a temporally-directed unsupervised video prediction
  - ▶ predict the next frames of a video
- ▶ logically-directed language entailment generation task
  - ▶ given a sentence, generate a sentence that can be seen as a consequence of the first

# Baseline: Seq2seq



$$p(w_1, w_2, \dots, w_m | f_1, f_2, \dots, f_n) = \prod_{t=1}^m p(w_t | h_t) \quad (1)$$

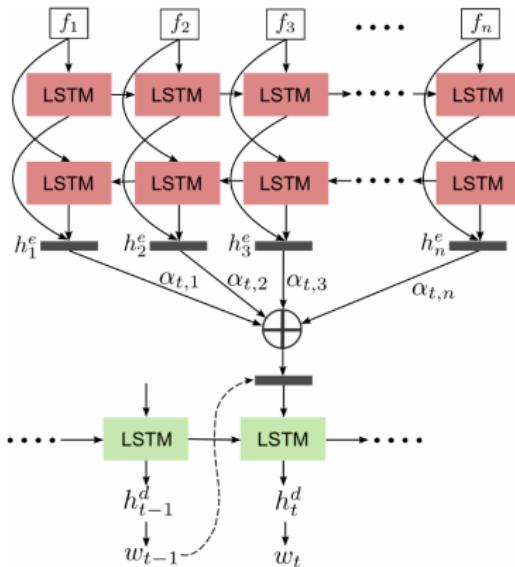
# Baseline: Seq2seq



$$p(w_1, w_2, \dots, w_m | f_1, f_2, \dots, f_n) = \prod_{t=1}^m p(w_t | h_t) \quad (1)$$

- Q: Is  $h_t$  enough to represent all frames?

# Baseline: Seq2seq + Attention



$$h_t = f(h_{t-1}, w_{t-1}, c_t)$$

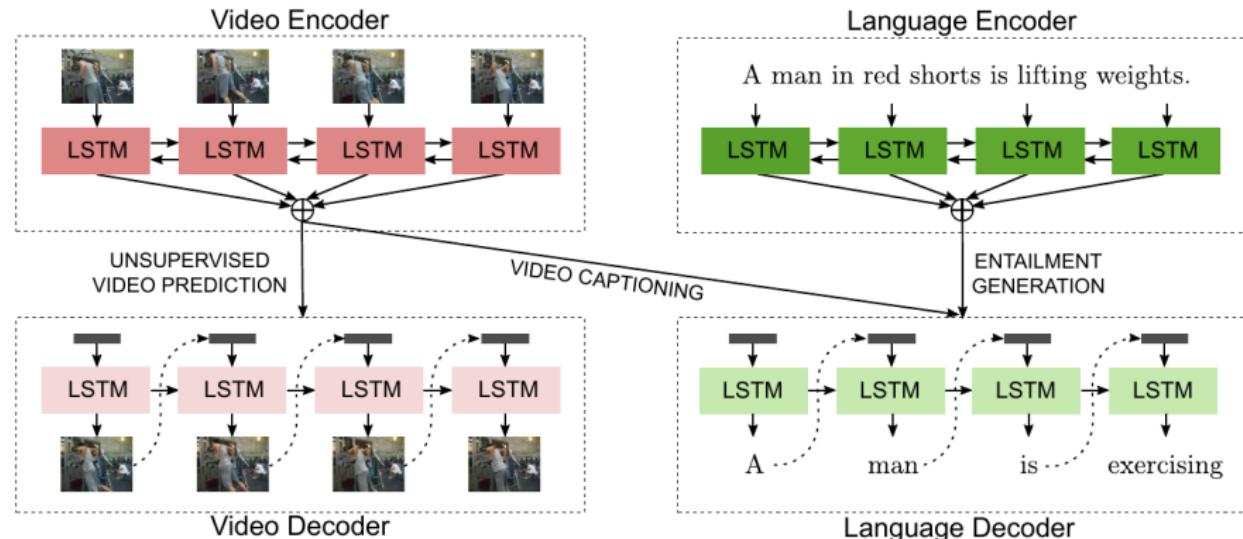
$$c_t = \sum_{i=1}^N att_{t,i} h_i^{enc}$$

$$att_{t,i} = f(h_{t-1}, h_i^{enc})$$

# Use external language knowledge

- ▶ Venugopalan et al. [2016] uses external language model **W** to improve video captioning model **C**
- ▶ learns language model with a recurrent model trained on Wikipedia
- ▶ improve captioning network
  - ▶ finetuning **C** from **W**
  - ▶ multiply the predictions of both models
  - ▶ use **W** hidden representation in the final prediction

# Overall architecture



# Entailment Generation

Premise:

- ▶ A soccer game with multiple males playing.
- ▶ A dog jumping for a Frisbee in the snow

Entailment:

- ▶ Some men are playing a sport.
- ▶ An animal is outside in the cold weather, playing with a plastic toy

- ▶ given a sentence  $\{w_1, w_2, \dots, w_m\}$  predict an entailment <sup>1</sup>  $\{w_1^P, \dots, w_n^P\}$
- ▶ generate a sentence with a similar encoding-decoding architecture
  - ▶ encode the premise
  - ▶ decode the entailment

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<sup>1</sup><https://nlp.stanford.edu/projects/snli/>

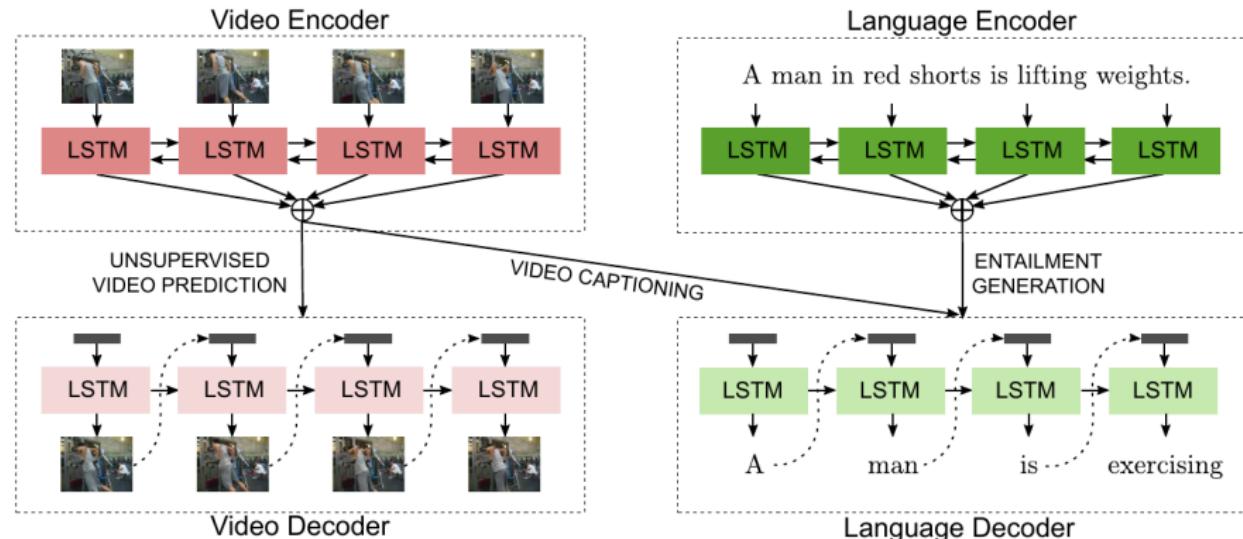
# Unsupervised Video Prediction

- ▶ given frame-level features  $\{f_1, f_2, \dots, f_k\}$  predict the rest  $\{f_{k+1}, \dots, f_n\}$
- ▶ predict future video frames with a similar encoding-decoding architecture
  - ▶ encode the features of the first  $k$  frames
  - ▶ decode the features of the remaining frames
- ▶ minimize the L2 norm between the predicted features and the ground truth

# Multi-Task Learning

- ▶ improve captioning by sharing information with other tasks
  - ▶ share network parameters between tasks
- ▶ captioning shares video **encoder** video prediction task
- ▶ captioning shares video **decoder** entailment generation task
- ▶ attention parameters kept separated for the best results
- ▶ learn by alternating optimizing each task

# Overall architecture



# Results - Quantitative

Models	METEOR	CIDEr-D	ROUGE-L	BLEU-4
PREVIOUS WORK				
LSTM-YT (V) (Venugopalan et al., 2015b)	26.9	-	-	31.2
S2VT (V + A) (Venugopalan et al., 2015a)	29.8	-	-	-
Temporal Attention (G + C) (Yao et al., 2015)	29.6	51.7	-	41.9
LSTM-E (V + C) (Pan et al., 2016b)	31.0	-	-	45.3
Glove + DeepFusion (V) (E) (Venugopalan et al., 2016)	31.4	-	-	42.1
p-RNN (V + C) (Yu et al., 2016)	32.6	65.8	-	49.9
HNRE + Attention (G + C) (Pan et al., 2016a)	33.9	-	-	46.7
OUR BASELINES				
Baseline (V)	31.4	63.9	68.0	43.6
Baseline (G)	31.7	64.8	68.6	44.1
Baseline (I)	33.3	75.6	69.7	46.3
Baseline + Attention (V)	32.6	72.2	69.0	47.5
Baseline + Attention (G)	33.0	69.4	68.3	44.9
Baseline + Attention (I)	33.8	77.2	70.3	49.9
Baseline + Attention (I) (E) $\otimes$	35.0	84.4	71.5	52.6
OUR MULTI-TASK LEARNING MODELS				
$\otimes$ + Video Prediction (1-to-M)	35.6	88.1	72.9	54.1
$\otimes$ + Entailment Generation (M-to-1)	35.9	88.0	72.7	54.4
$\otimes$ + Video Prediction + Entailment Generation (M-to-M)	<b>36.0</b>	<b>92.4</b>	<b>72.8</b>	<b>54.5</b>

Results on YouTube2Text dataset

## Results - Qualitative



**Ground truth:** Two women are shopping in a store.  
Two girls are shopping.

**Baseline model:** A man is doing a monkey in a store.

**Multi-task model:** A woman is shopping in a store.



**Ground truth:** Two men are fighting.  
A group of boys are fighting.

**Baseline model:** A group of men are dancing.

**Multi-task model:** Two men are fighting.

(a)

## Results - Qualitative



**Ground truth:** A woman slices a shrimp tail.  
A girl is cutting a fish tale.

**Baseline model:** A person is cutting the something.

**Multi-task model:** A woman is cutting a piece of meat.



**Ground truth:** Two men are talking aggressively.  
The boy is talking.

**Baseline model:** A man is crying.

**Multi-task model:** A man is talking.

(b)

# Improved Image Captioning via Policy Gradient optimization of SPIDER

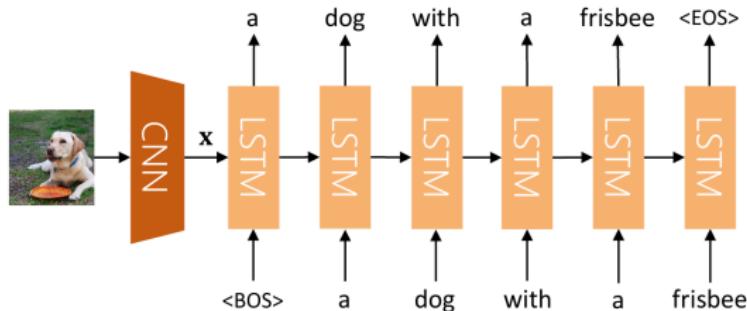
S. Liu, Z. Zhu, N. Ye, S. Guadarrama, and K. Murphy.  
Improved image captioning via policy gradient optimization of spider. In The IEEE International Conference on Computer Vision (ICCV), Oct 2017. Liu et al. [2017]

# Captioning

- at every step maximize cross-entropy between distribution of words in the predicted and in the ground truth sentences

$$J(\theta) = \sum_{n=1}^N \sum_{t=1}^{T_n} \text{Loss}(\pi_\theta(\hat{y}_t^n | \mathbf{x}^n, \hat{\mathbf{y}}_{t-1}^n)) ,$$

$$\text{Loss}(\pi_\theta(\hat{y}_t^n | \mathbf{x}^n, \hat{\mathbf{y}}_{t-1}^n)) = -\log \pi_\theta(\hat{y}_t^n | \mathbf{x}^n, \hat{\mathbf{y}}_{t-1}^n)$$



# Problem of Maximum Likelihood

- ▶ **exposure bias** Ranzato et al. [2015]:
  - ▶ at training time the previous **ground truth word** is used
  - ▶ at test time the previous **generated word** is used
  - ▶ **problem:** training/ testing use different distributions
  - ▶ **problem:** errors are accumulated with time
- ▶ **word level supervision:**
  - ▶ the loss is computed just based the current word

- ▶ generate the whole sentence just using the model own predictions
- ▶ compute a score for the sentence, **not** just for every word
  - ▶ optimize for sentence level metrics like: BLEU / METEOR / CIDEr
  - ▶ problem: these scores are **not differentiable**
- ▶ use reinforcement learning method with **policy gradient**

# Policy gradient

- ▶ cast the captioning task as a reinforcement learning task
- ▶ the words are predicted according to a policy:  $\pi_\theta(y_t|\mathbf{x}, \mathbf{y}_{t-1})$
- ▶ actions at time  $t < - >$  word prediction at time  $t$
- ▶ state at time  $t < - >$  image features and first  $t-1$  words
- ▶ estimate  $Q(s_t, a_t)$ 
  - ▶ expected future reward starting from state  $s_t$  and choosing action  $a_t$
  - ▶ expectation is over the future words

# Policy gradient - Training

- ▶ we want to change the policy in order to predict better actions(words)
- ▶ better actions - better rewards
- ▶ maximize expected future reward

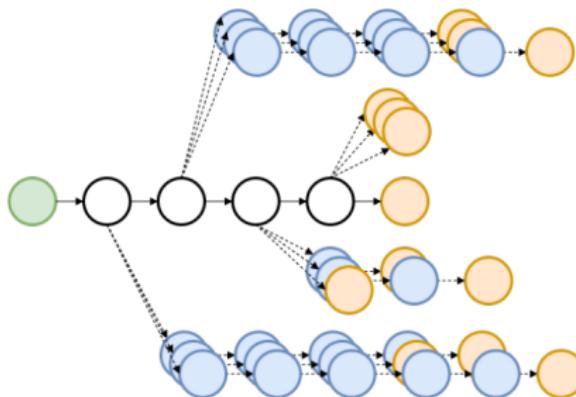
$$J(\theta) = \sum_t \mathbb{E}_{\mathbf{y}_t} \pi_\theta(y_t^m | \mathbf{x}, \mathbf{y}_{t-1}^m) Q(s_t^m, y_{t-1}^m) \quad (2)$$

- ▶ using policy gradient is computed by Sutton et al. [2000]:

$$\nabla_\theta J(\theta) = \frac{1}{M} \sum_m \sum_t \nabla_\theta \pi_\theta(y_t^m | \mathbf{x}, \mathbf{y}_{t-1}^m) Q(s_t^m, y_{t-1}^m) \quad (3)$$

# Estimating Q

- ▶ at every step we must estimate the expected reward  $Q(s_t^m, y_t^m)$
- ▶ use Monte Carlo rollout to generate full sentences
- ▶ compute any kind of score:
  - ▶ BLEU, METEOR, CIDEr, SPICE



# Training Algorithm

1. pretrain  $\pi_\theta$  using Maxim Likelihood Estimation
2. repeat until  $\pi_\theta$  converge
3.     for each (image-sentence) pair
4.         generate sentence according to  $\pi$
5.         for each word in sentence
6.             estimate  $Q$  using Monte Carlo rollouts
7.             compute the gradient of the loss w.r.t  $\theta$
8.             update the policy  $\pi_\theta$  using SGD

# Choosing Language Scores

Metric	Proposed to evaluate	Underlying idea
BLEU (Papineni et al., 2002)	Machine translation	$n$ -gram precision
ROUGE (Lin, 2004)	Document summarization	$n$ -gram recall
METEOR (Banerjee and Lavie, 2005)	Machine translation	$n$ -gram with synonym matching
CIDEr (Vedantam et al., 2015)	Image description generation	$tf\text{-}idf$ weighted $n$ -gram similarity
SPICE (Anderson et al., 2016)	Image description generation	Scene-graph synonym matching

2

- ▶ BLEU, METEOR, ROUGE, CIDEr (BMRC)
  - ▶ don't correlate with human evaluation of quality
  - ▶ human captions actually score lower on these metrics

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<sup>2</sup>From Kilickaya et al. [2016]

# Choosing Language Scores

- ▶ SPICE Anderson et al. [2016] strongly correlate with human ratings
  - ▶ parses each of the reference sentences
  - ▶ derive an abstract scene graph representation
  - ▶ generated sentence is parsed, and compared to the graph
- ▶ SPICE ignores syntactic quality
  - ▶ generate ungrammatical sentences, with repeated phrases



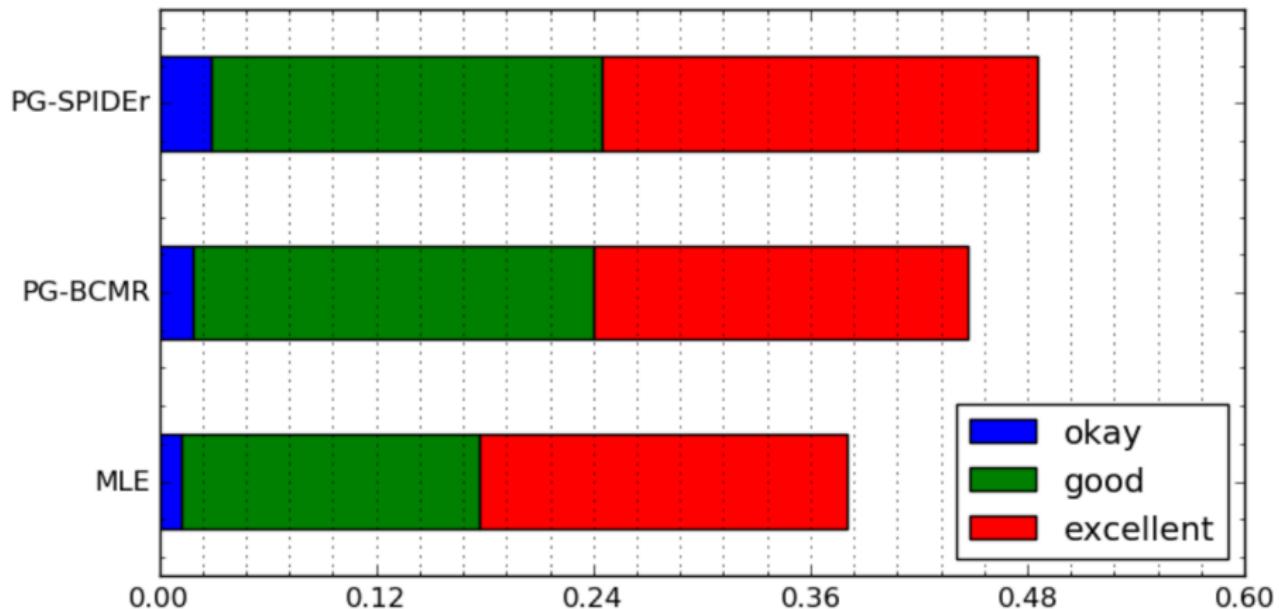
- ▶ Solution: SPICE + CIDEr = SPIDEr
  - ▶ SPICE - captions are semantically faithful to the image
  - ▶ CIDEr - captions are syntactically fluent

# Results

Submissions	CIDEr-D	Meteor	ROUGE-L	BLEU-1	BLEU-2	BLEU-3	BLEU-4
MSM@MSRA [28]	0.984	0.256	0.542	0.739	0.575	0.436	0.330
Review Net [27]	0.965	0.256	0.533	0.720	0.550	0.414	0.313
ATT [29]	0.943	0.250	0.535	0.731	0.565	0.424	0.316
Google [22]	0.943	0.254	0.530	0.713	0.542	0.407	0.309
Berkeley LRCN [7]	0.921	0.247	0.528	0.718	0.548	0.409	0.306
MLE	0.947	0.251	0.531	0.724	0.552	0.405	0.294
PG-BLEU-4	0.966	0.249	0.550	0.737	0.587	<b>0.455</b>	<b>0.346</b>
PG-CIDEr	0.995	0.249	0.548	0.737	0.581	0.442	0.333
MIXER-BCMR	0.924	0.245	0.532	0.729	0.559	0.415	0.306
MIXER-BCMR-A	0.991	<b>0.258</b>	0.545	0.747	0.579	0.431	0.317
PG-BCMR	<b>1.013</b>	<b>0.257</b>	<b>0.55</b>	<b>0.754</b>	<b>0.591</b>	0.445	0.332
PG-SPIDER	1.000	0.251	0.544	0.743	0.578	0.433	0.322

## Results - Human perception

Human annotated captions with labels: "bad", "okay", "good" or "excellent"



# Results

## Captions:



1. MLE: a woman walking down a street while holding an umbrella .
2. PG-SPICE: group of people walking down a street with a man on a street holding a traffic light and a traffic light on a city street with a city street
3. PG-BCMR: a group of people walking down a city street.
4. PPG-SPIDER: a group of people walking down a street with a traffic light .

# Results

Captions:



1. MLE: a man sitting in front of a laptop computer .
2. PG-SPICE: a man sitting in front of a book and a laptop on a table with a laptop computer on top of a table with a laptop computer on top of
3. PG-BCMR: a man sitting in front of a book .
4. PG-SPIDER: a man sitting at a table with a book .

# Show, Adapt and Tell: Adversarial Training of Cross-domain Image Captioner

MLA Chen, Tseng-Hung, et al. "Show, adapt and tell": Adversarial training of cross-domain image captioner. In The IEEE International Conference on Computer Vision (ICCV), Oct 2017  
Chen et al. [2017]

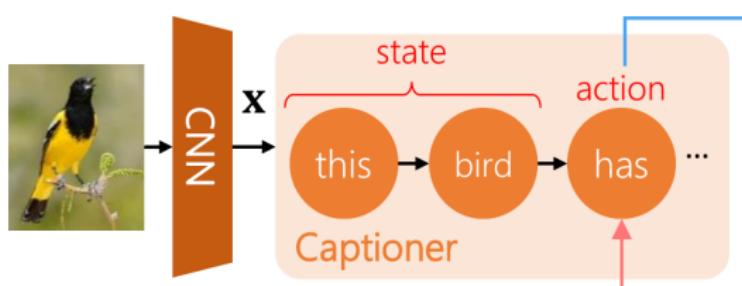
# Show, Adapt and Tell: Adversarial Training of Cross-domain Image Captioner

- ▶ method for image captioning
- ▶ adapting to a new dataset that does **not** have image-descriptions pairs

Source Ground Truth	Target Ground Truth
 A family of ducks swimming in the water.	 This bird has wings that are brown and has red eyes.
 A hummingbird close to a flower trying to eat.	 A small bird with orange flank and a long thin black bill.
Generated (before adapt)	Generated (after adapt)
 A duck floating on top of a lake .	 This bird has brown wings and red eyes.

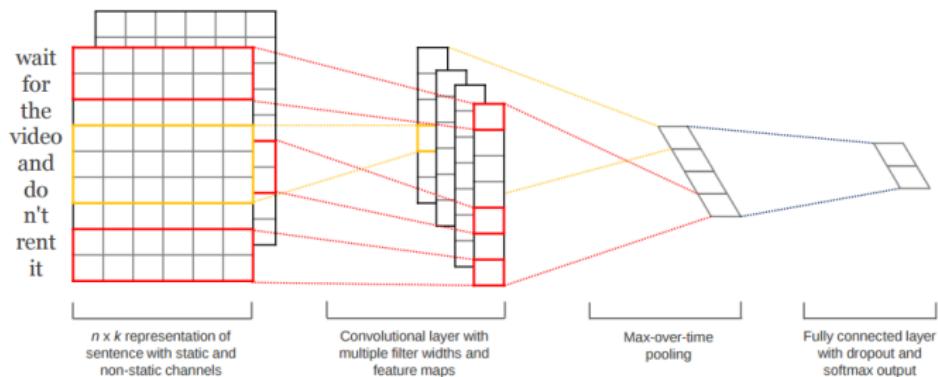
# Cross Domain Learning

- ▶ problem lack of ground truth (image, sentence) pairs
- ▶ cannot use maximum likelihood – > use **policy gradient**
  - ▶ generate complete sentences then evaluate them
- ▶ cannot calculate a final loss based on ground truth
  - ▶ Solution: use **critics**
  - ▶ Critic 1: similarity between 2 sentences
  - ▶ Critic 2: relevancy between an image and a sentence



# Domain critic

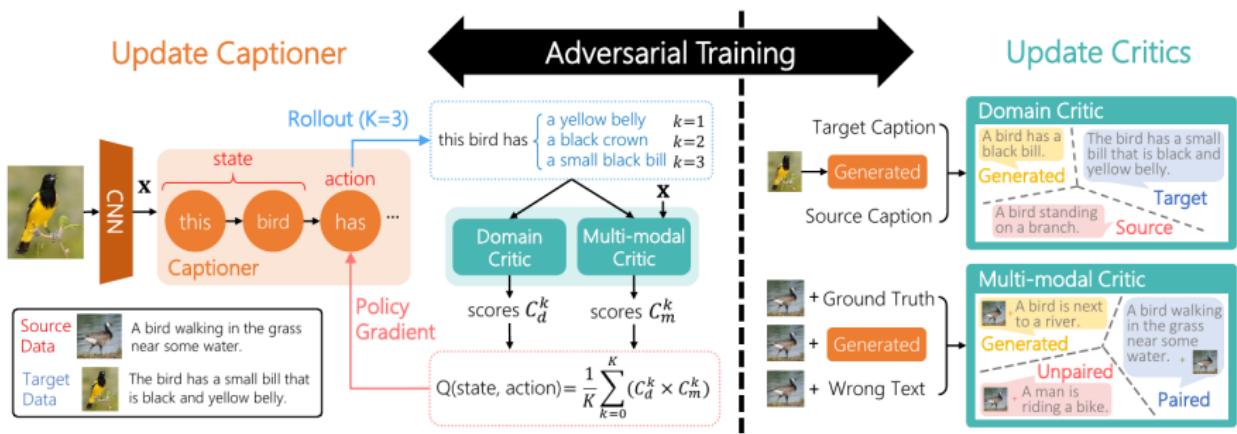
- ▶ reward sentence that resembles the sentence drawn from the target domain
- ▶ classify sentences as "source" domain, "target" domain, or "generated"
  - ▶ use convolutional network for classification Kim [2014]



# Multi-modal critic

- ▶ reward sentence relevant to the input image
- ▶ classify image-sentence pair as "paired:", "unpaired", or "generated" data
- ▶ use LSTM to encode the sentence
- ▶ final class assigned based on image and text encoding

# Overall Architecture



# Adversarial Training

- ▶ given image  $x$  and generated caption  $y$
- ▶ the policy  $\pi_\theta$  is optimized to have high reward
  - ▶ critics should predict **high values** for  $\text{CriticDomain}(\text{target}|y)$  and  $\text{CriticModal}(\text{paired}|x, y)$
- ▶ critics are optimized for
  - ▶ high values for  $\text{CriticDomain}(\text{generated}|y)$  and  $\text{CriticModal}(\text{generated}|x, y)$
  - ▶ **low values** for  $\text{CriticDomain}(\text{target}|y)$  and  $\text{CriticModal}(\text{paired}|X, Y)$

# Training

- ▶ Pretrain  $\pi_\theta$  on the source domain
- ▶ repeat until  $\pi_\theta$  converge
  - ▶ repeat for  $N_c$  steps
    - ▶ generate sentence from **target** domain image according to  $\pi$
    - ▶ compute the gradients and update the domain critic
    - ▶ generate sentence from **source** domain image according to  $\pi$
    - ▶ compute the gradients and update the multi-model critic
  - ▶ repeat for  $N_g$  steps
    - ▶ generate sentence from **target** domain image according to  $\pi$
    - ▶ for each step compute the reward according to critics with monte carlo rollouts
    - ▶ compute the gradient and update the policy  $\pi_\theta$

# Results

Method	Target (test)	Bleu-1	Bleu-2	Bleu-3	Bleu-4	Meteor	ROUGE	CIDEr	SPICE
Source Pre-trained	CUB-200	50.8	28.3	13.9	6.1	12.9	33	3	4.6
DCC	CUB-200	68.6	47.3	31.4	21.4	23.8	46.4	11.9	11.1
Ours	CUB-200	<b>91.4</b>	<b>73.1</b>	<b>51.9</b>	<b>32.8</b>	<b>27.6</b>	<b>58.6</b>	<b>24.8</b>	<b>13.2</b>
Fine-tuning	CUB-200	91.3	80.2	69.2	59	36.1	69.7	61.1	17.9
Source Pre-trained	Oxford-102	48.3	21.6	6.2	1.3	10.5	25.8	3.1	4.4
DCC	Oxford-102	51	33.8	24.1	16.7	21.5	38.3	6	9.8
Ours	Oxford-102	<b>85.6</b>	<b>76.9</b>	<b>67.4</b>	<b>60.5</b>	<b>36.4</b>	<b>72.1</b>	<b>29.3</b>	<b>17.9</b>
Fine-tuning	Oxford-102	87.5	80.1	72.8	66.3	40	75.6	36.3	18.5
Source Pre-trained	TGIF	41.6	23.3	12.6	7	12.7	32.7	14.7	8.5
DCC	TGIF	34.6	17.5	9.3	4.1	11.8	29.5	7.1	7.3
Ours	TGIF	<b>47.5</b>	<b>29.2</b>	<b>17.9</b>	<b>10.3</b>	<b>14.5</b>	<b>37</b>	<b>22.2</b>	<b>10.6</b>
Fine-tuning	TGIF	51.1	32.2	20.2	11.8	16.2	39.2	29.8	12.1
Source Pre-trained	Flickr30k	57.3	36.2	21.9	13.3	15.1	38.8	25.3	8.6
DCC	Flickr30k	54.3	34.6	21.8	13.8	16.1	38.8	27.7	9.7
Ours	Flickr30k	<b>62.1</b>	<b>41.7</b>	<b>27.6</b>	<b>17.9</b>	<b>16.7</b>	<b>42.1</b>	<b>32.6</b>	<b>9.9</b>
Fine-tuning	Flickr30k	59.8	41	27.5	18.3	18	42.9	35.9	11.5

# Results

CUB-200



Before: A bird is standing on a table with flowers.

After: A small bird with a white belly and a black head.



Before: A red bird sitting on a tree branch.

After: This is a red bird with a black wing and a small beak.

Oxford-102



Before: A white flower in a vase on a table.

After: This flower has petals that are pink and has a yellow center.



Before: A yellow flower is in a clear vase.

After: This flower has petals that are yellow and has red lines.

# Results

TGIF



Before: A cat is standing in a room with a cat.

After: A cat is playing with a toy in a room.



Before: A baseball player is a ball on a field.

After: A group of men are playing soccer on a field.

Flickr30k



Before: A young baseball player is a ball in the field.

After: A young baseball player is sliding into a base.



Before: A boy in a field playing with a frisbee.

After: A young boy playing with a soccer ball in a field.

# Questions?

Thank you!

## References I

- P. Anderson, B. Fernando, M. Johnson, and S. Gould. Spice: Semantic propositional image caption evaluation. In *European Conference on Computer Vision*, pages 382–398. Springer, 2016.
- T.-H. Chen, Y.-H. Liao, C.-Y. Chuang, W.-T. Hsu, J. Fu, and M. Sun. Show, adapt and tell: Adversarial training of cross-domain image captioner. In *The IEEE International Conference on Computer Vision (ICCV)*, Oct 2017.
- M. Kilickaya, A. Erdem, N. Ikizler-Cinbis, and E. Erdem. Re-evaluating automatic metrics for image captioning. *arXiv preprint arXiv:1612.07600*, 2016.
- Y. Kim. Convolutional neural networks for sentence classification. *arXiv preprint arXiv:1408.5882*, 2014.

## References II

- S. Liu, Z. Zhu, N. Ye, S. Guadarrama, and K. Murphy. Improved image captioning via policy gradient optimization of spider. In *The IEEE International Conference on Computer Vision (ICCV)*, Oct 2017.
- R. Pasunuru and M. Bansal. Multi-task video captioning with video and entailment generation. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics*, July 2017.
- M. Ranzato, S. Chopra, M. Auli, and W. Zaremba. Sequence level training with recurrent neural networks. *arXiv preprint arXiv:1511.06732*, 2015.
- R. S. Sutton, D. A. McAllester, S. P. Singh, and Y. Mansour. Policy gradient methods for reinforcement learning with function approximation. In *Advances in neural information processing systems*, pages 1057–1063, 2000.

## References III

- S. Venugopalan, L. A. Hendricks, R. Mooney, and K. Saenko.  
Improving lstm-based video description with linguistic knowledge  
mined from text. In *Proceedings of the 2016 Conference on  
Empirical Methods in Natural Language Processing*, pages  
1961–1966. Association for Computational Linguistics, 2016.  
doi: 10.18653/v1/D16-1204. URL  
<http://www.aclweb.org/anthology/D16-1204>.