Bitdefender

# Describing images and videos in natural language

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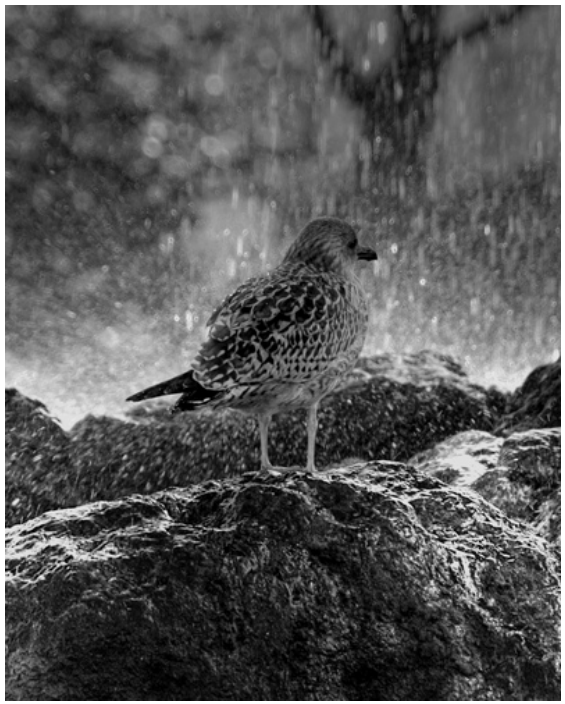
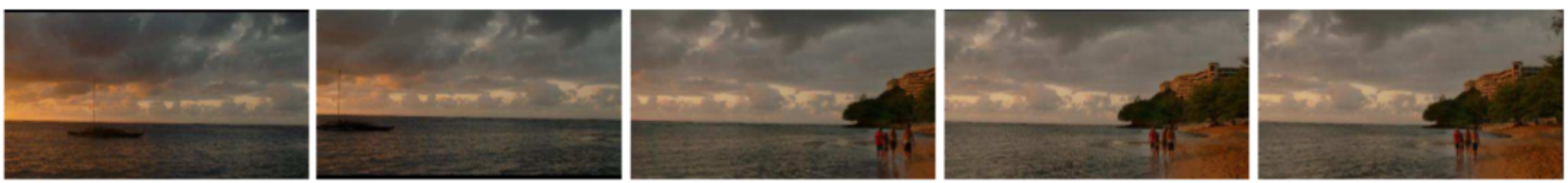
# Intro - Captioning

Bitdefender



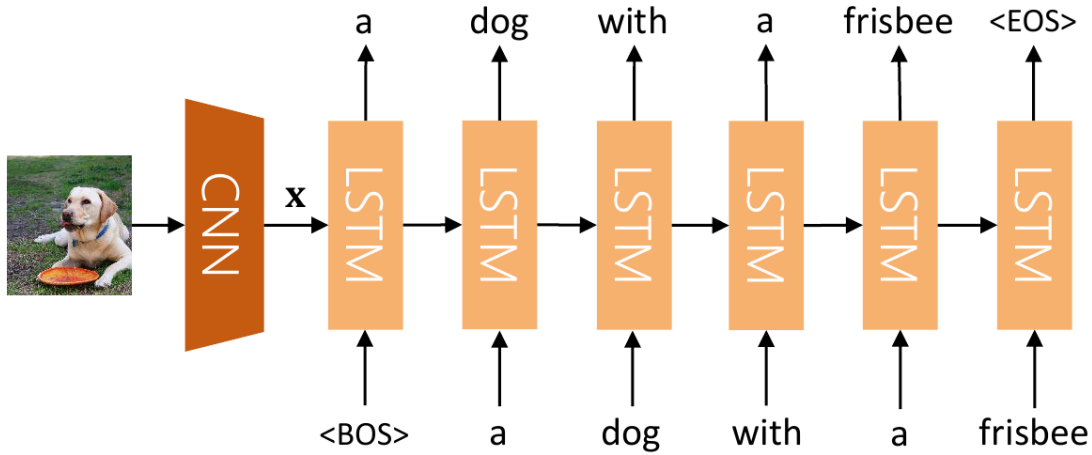
**Ours :** A bird is standing on a rock in the water.

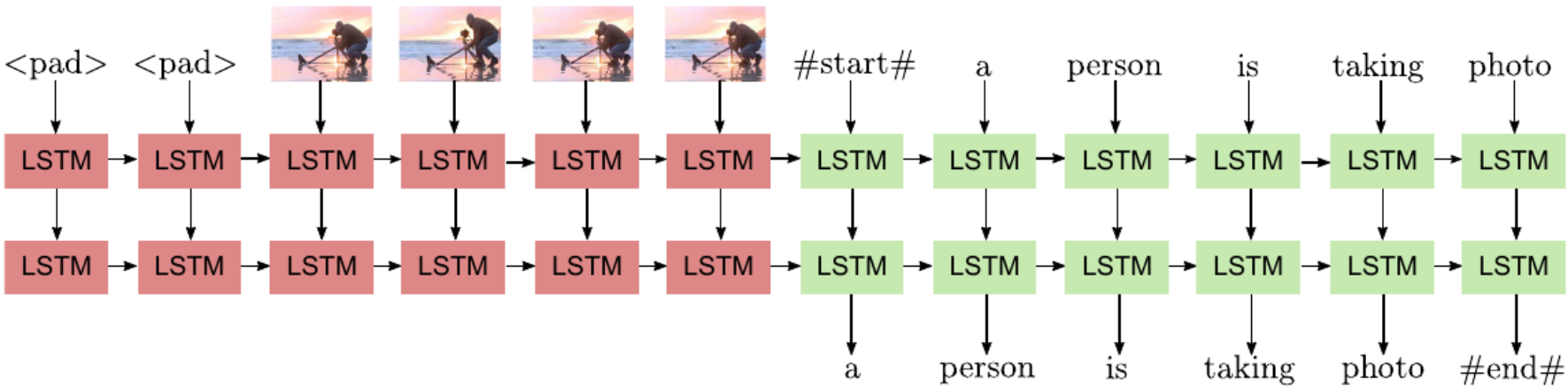


**GT** : The sun sets behind the watery horizon as the foursome continues along the shore toward a distant resort.

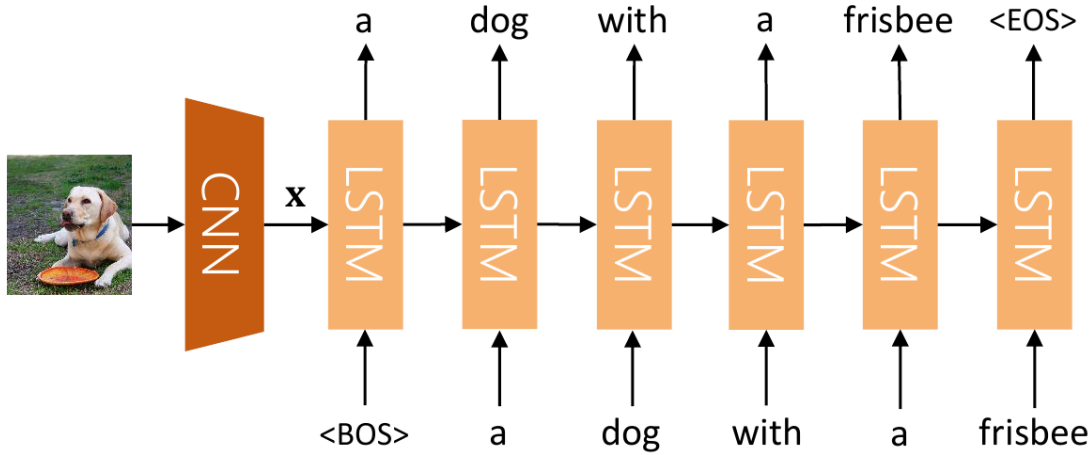
**Ours** : The sun shines as the sun sets to the horizon.

# Baseline Architectures



# Baseline Architectures



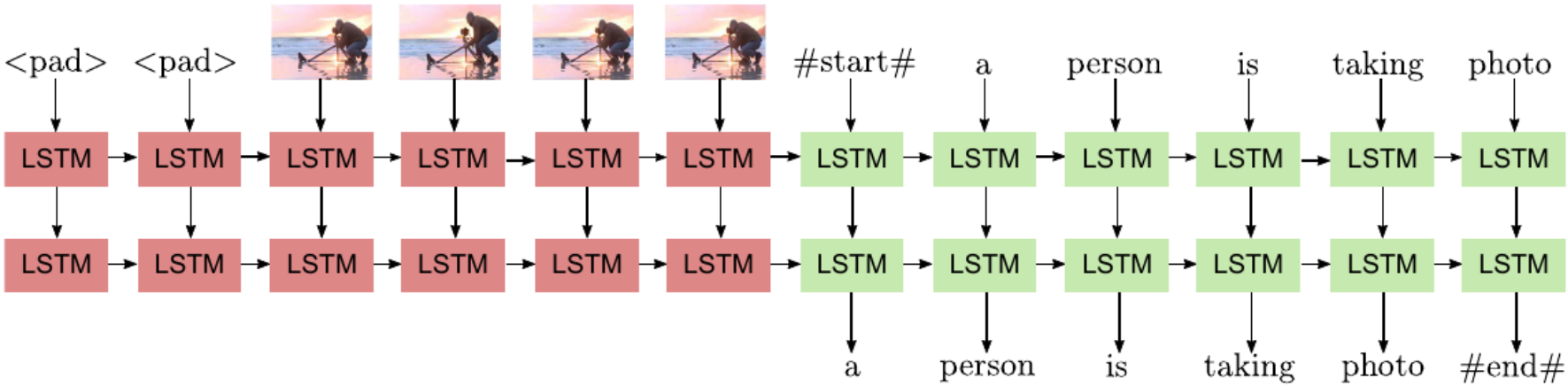

$$h_0 = CNN(Img)$$

$$w_0 =< BeginSentenceToken >$$

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

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

# Baseline Architectures




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

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

$$w_0 = < BeginSentenceToken >$$

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

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

# Baseline Architectures - Problems

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

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# Baseline Architectures - Problems

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

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

# Multi-Task Video Captioning with Video and Entailn Generation

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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 Entailn Generation

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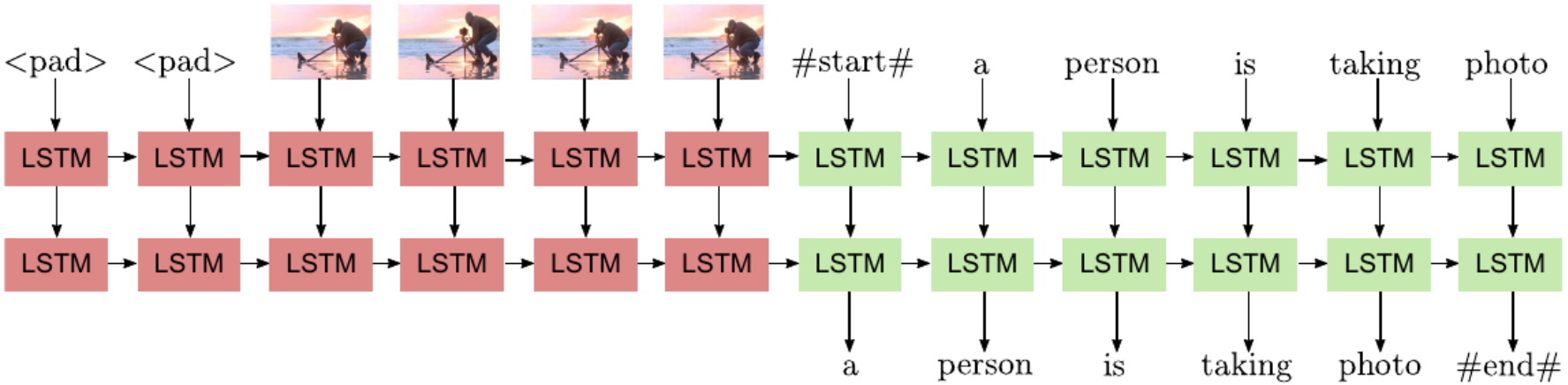
Pasunuru and Bansal [2017]

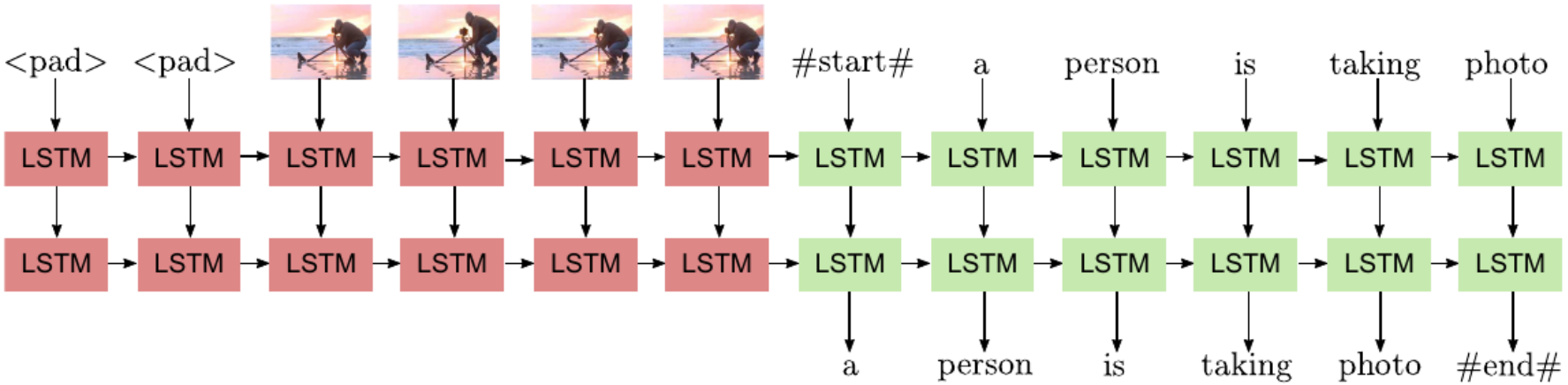
- improve captioning by sharing knowledge with other tasks
- use 2 other generative tasks
- a temporally-directed unsupervised video prediction
  - predict the next frames of a video
- logically-directed language entailment generation task
  - given a sentence, generate a sentence that can be seen as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

# Baseline: Seq2seq




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

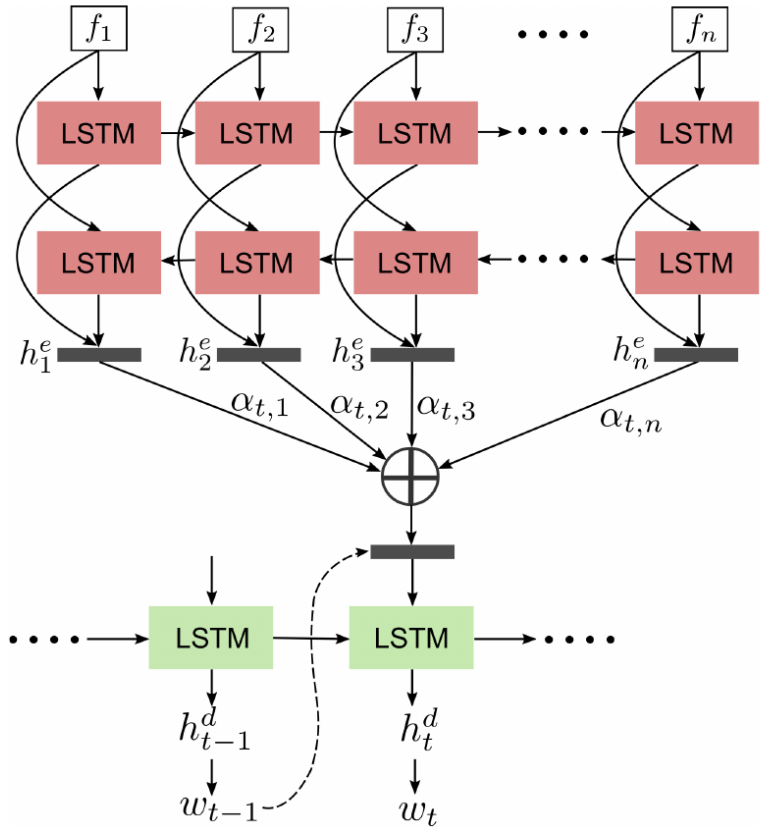
# Baseline: Seq2seq




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

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

# Baseline: Seq2seq + Attention




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

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

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

# Use external language knowledge

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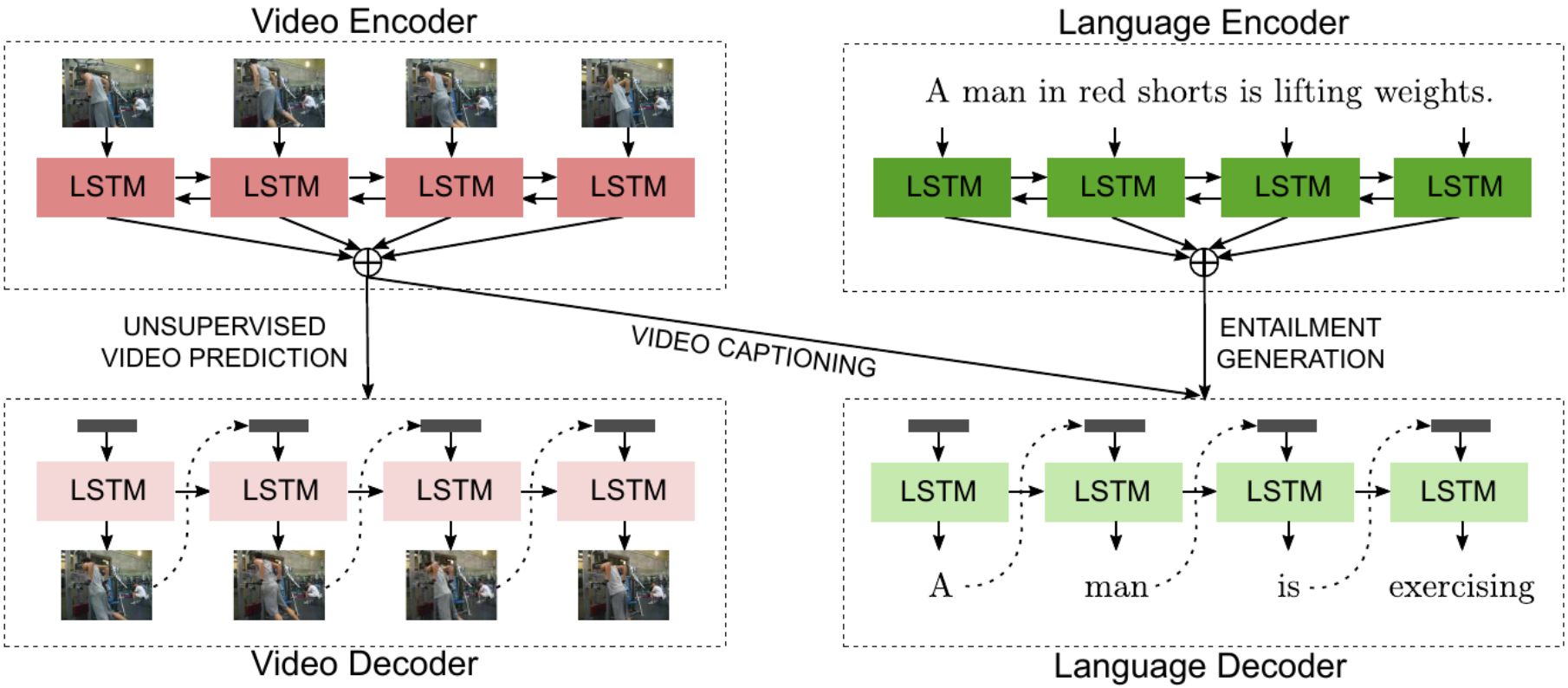
- Venugopalan et al. [2016] uses external language model **W** to improve video captioning model **C**
- learns language model with a recurrent model trained on Wikipedia
- improve captioning network
  - finetuning **C** from **W**
  - multiply the predictions of both models
  - use **W** hidden representation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

# Overall architecture



# Entailment Generation

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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 $\{w_1, w_2, .., w_m\}$ predict an entailment [1] $\{w_1^p, .., w_n^p\}$
- generate a sentence with a similar encoding-decoding architecture
  - encode the premise
  - decode the entailment

[1] `https://nlp.stanford.edu/projects/snli/`

# Unsupervised Video Prediction

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- given frame-level features $\{f_1, f_2, .., f_k\}$ predict the rest $\{f_{k+1}, .., f_n\}$
- 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

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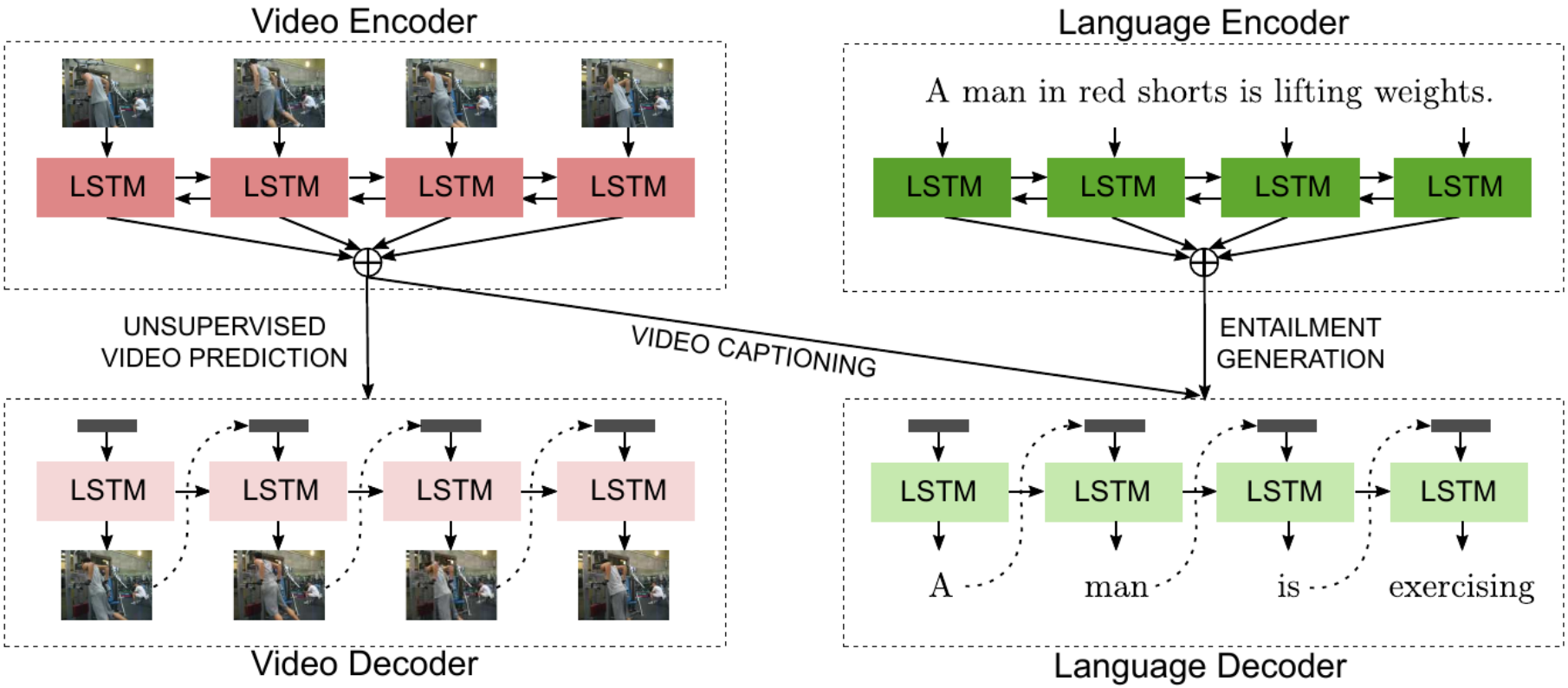
- improve captioning by sharing information with other tasks
  - share network parameters between tasks
- captioning shares video **encoder** video prediction task
- captioning shares video **decoder** entailment generation task
- attention parameters keept separated for the best results
- learn by alternating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

# Overall architecture



# Results - Quantitative

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| 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) | **36.0** | **92.4** | **72.8** | **54.5** |

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

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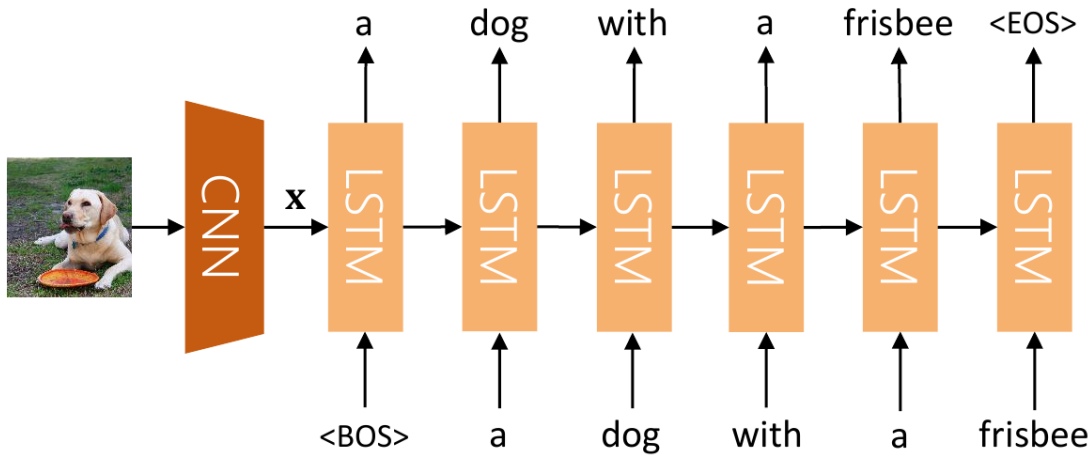
S. Liu, Z. Zhu, N. Ye, S. Guadarrama, and K. Murphy. Improvedimage captioning via policy gradient optimization of spider. InThe IEEE International Conference on Computer Vision (ICCV),Oct 2017. Liu et al. [2017]

# 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

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- **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

# Solutions?

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- 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

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- 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

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

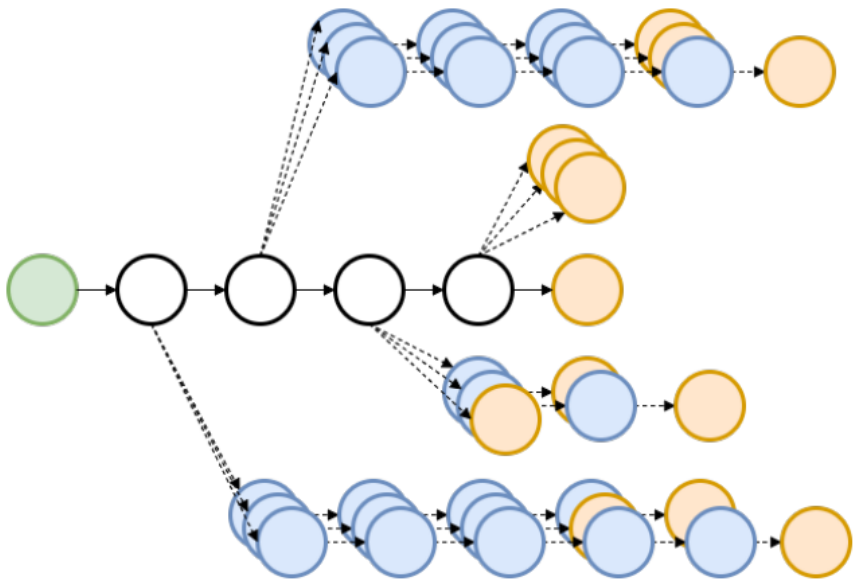
$$J(\theta) = \sum_t \mathbb{E}_{\mathbf{y_t}} \pi_\theta(y_t^m | \mathbf{x}, \mathbf{y}_{t-1}^m) Q(s_t^m, y_{t-1}^m) \tag{2}$$

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

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

# 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

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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

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| 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-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

[2] From Kilickaya et al. [2016]

# Choosing Language Scores

Bitdefender

- SPICE Anderson et al. [2016] strong 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

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| 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 | **0.455** | **0.346** |
| 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 | **0.258** | 0.545 | 0.747 | 0.579 | 0.431 | 0.317 |
| PG-BCMR | **1.013** | **0.257** | **0.55** | **0.754** | **0.591** | 0.445 | 0.332 |
| PG-SPIDEr | 1.000 | 0.251 | 0.544 | 0.743 | 0.578 | 0.433 | 0.322 |

# Results - Human perception

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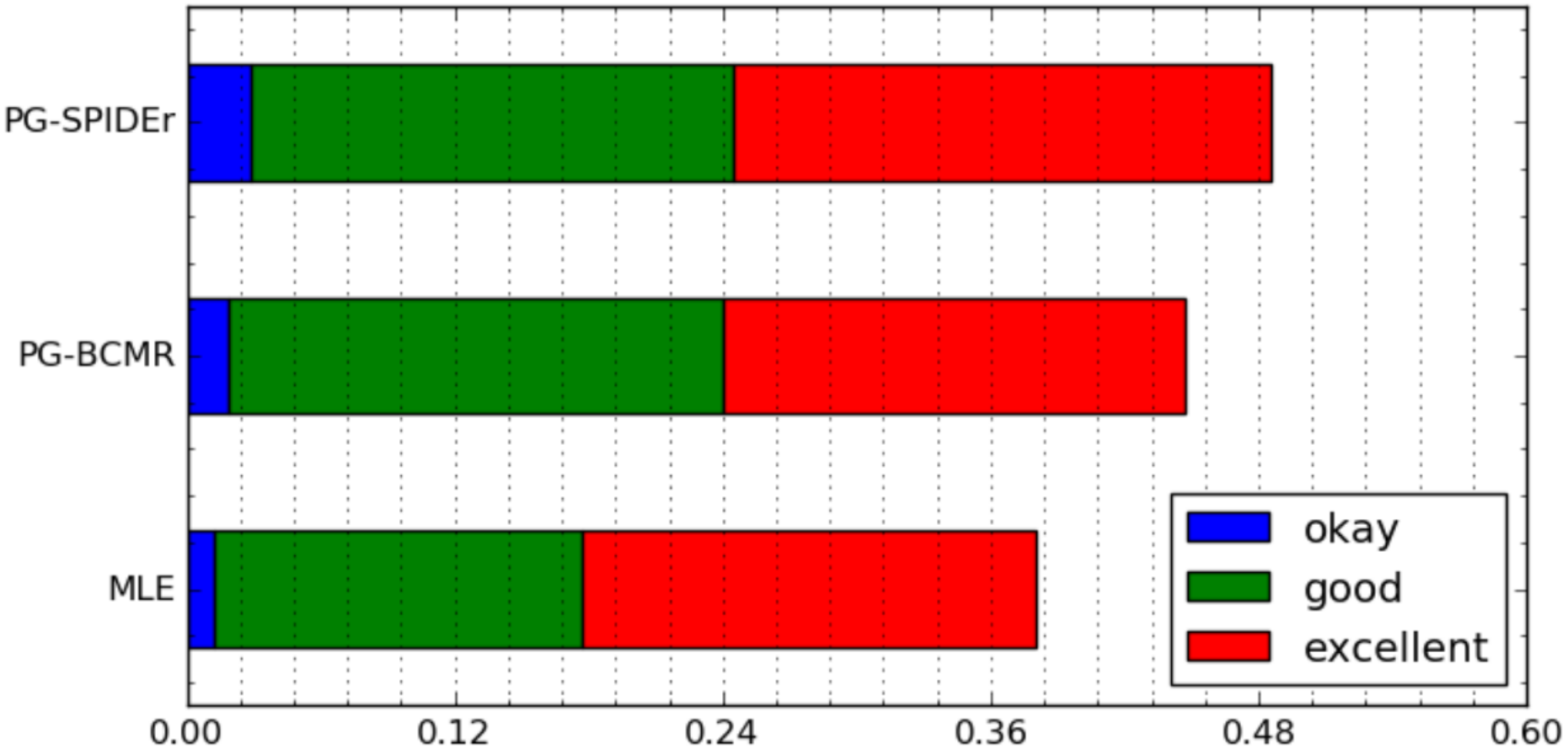
Human annotated captions with labels: "bad", "okay", "good" or "excellent"



# 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

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

Chen et al. [2017]

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

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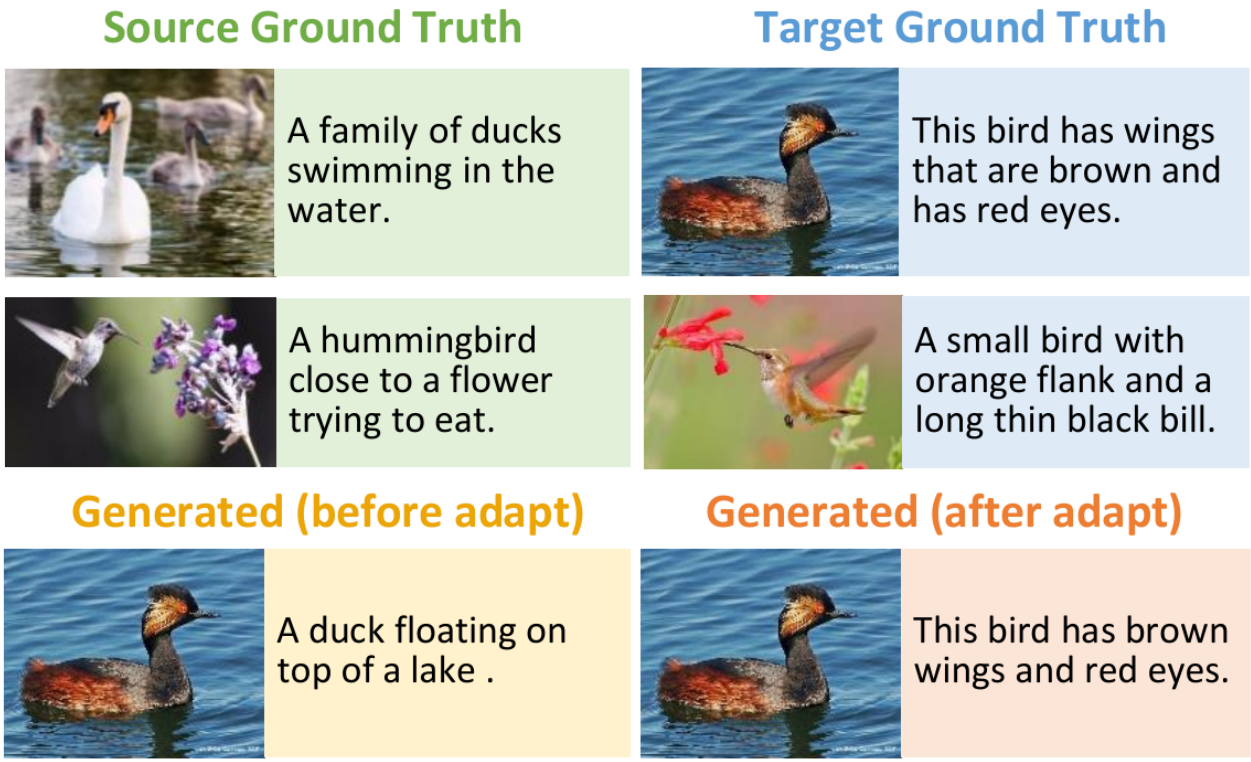
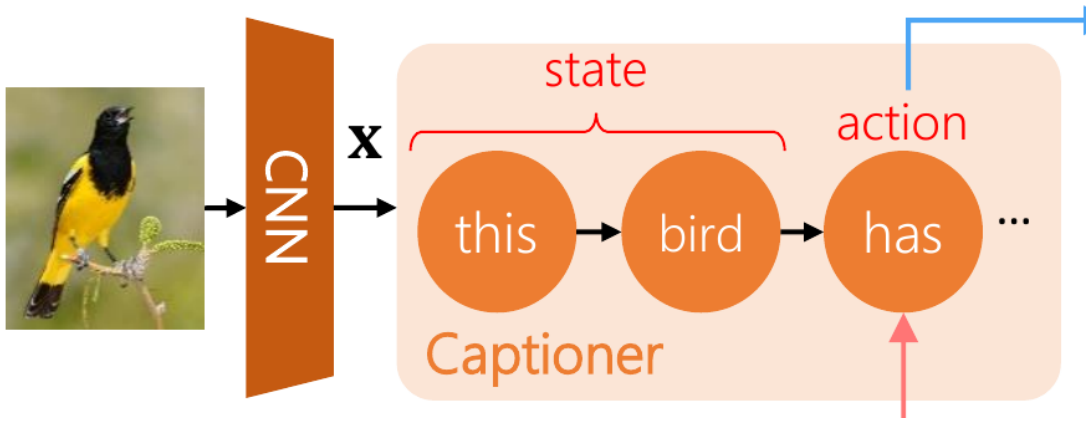
- method for image captioning
- adapting to a new dataset that does **not** have image-descriptions pairs



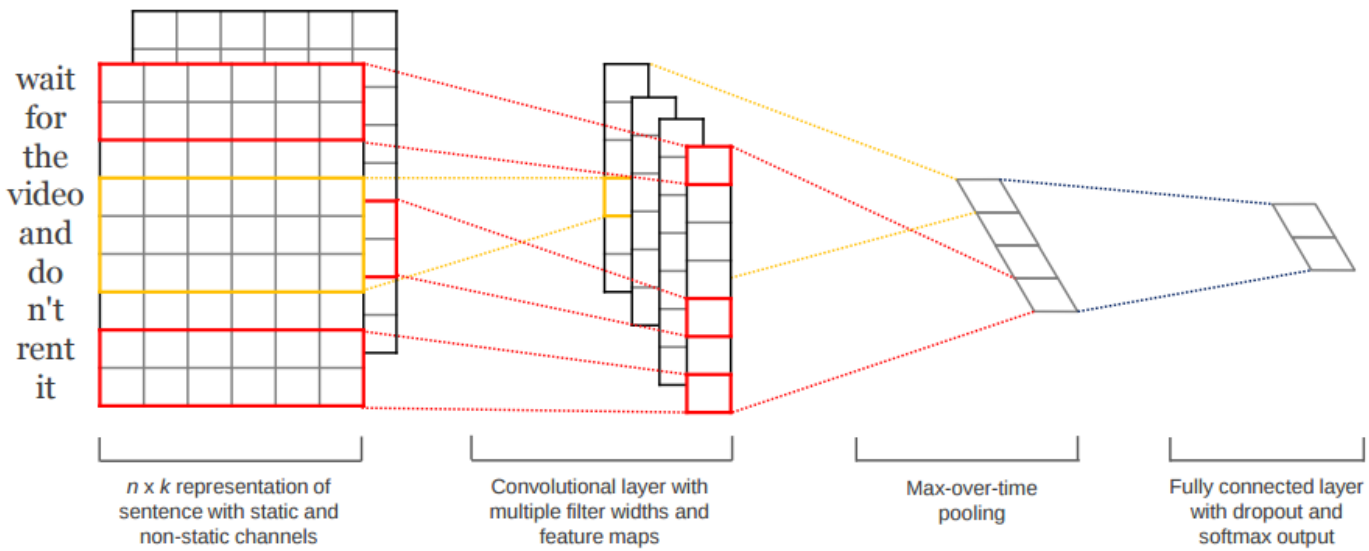
# Cross Domain Learning

- 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

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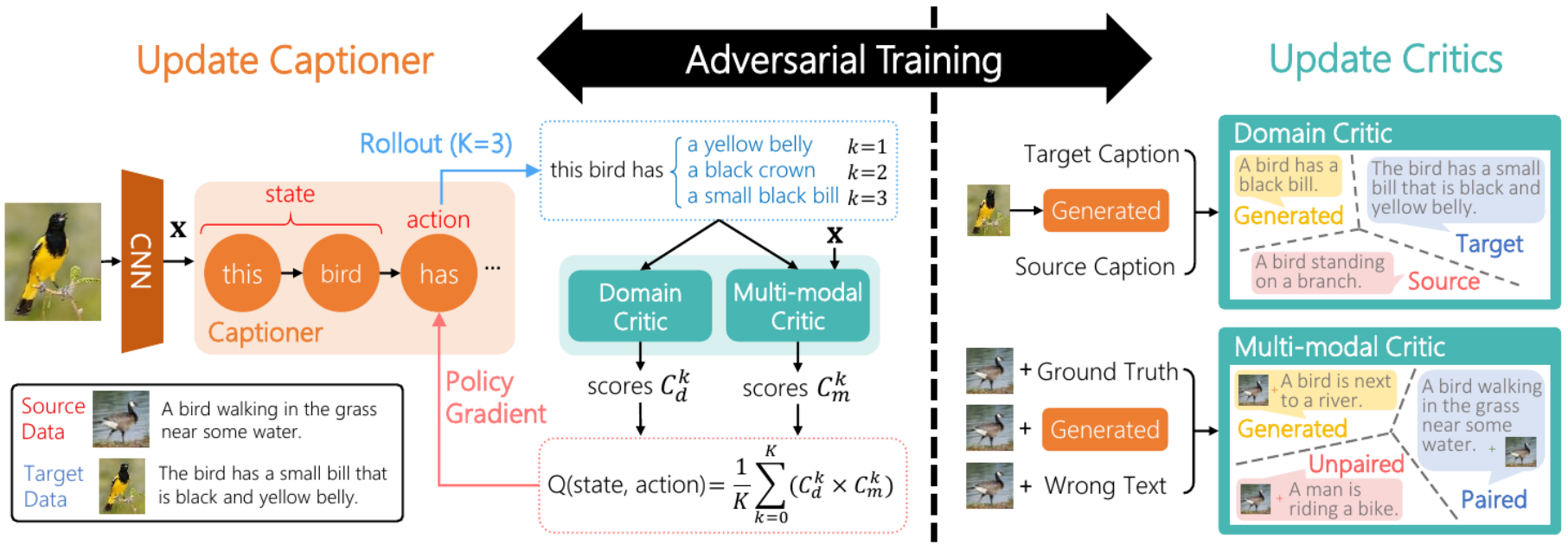
- reward sentence relevant to the input image
- classify image-sentence pair as "paired:, "unpaired", or "generated" data
- use LSTM to encode the sentence
- final class assigned based on image and text encoding

# Overall Architecture



# Adversarial Training

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

# Training

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- 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

Bitdefender

| 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 | **91.4** | **73.1** | **51.9** | **32.8** | **27.6** | **58.6** | **24.8** | **13.2** |
| 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 | **85.6** | **76.9** | **67.4** | **60.5** | **36.4** | **72.1** | **29.3** | **17.9** |
| 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 | **47.5** | **29.2** | **17.9** | **10.3** | **14.5** | **37** | **22.2** | **10.6** |
| 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 | **62.1** | **41.7** | **27.6** | **17.9** | **16.7** | **42.1** | **32.6** | **9.9** |
| Fine-tuning | Flickr30k | 59.8 | 41 | 27.5 | 18.3 | 18 | 42.9 | 35.9 | 11.5 |

# Results

Bitdefender

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

Bitdefender

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?

Bitdefender

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.