Going Deeper with Images and Natural Language

Ph.D. Preliminary Examination

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Overview

Motivation

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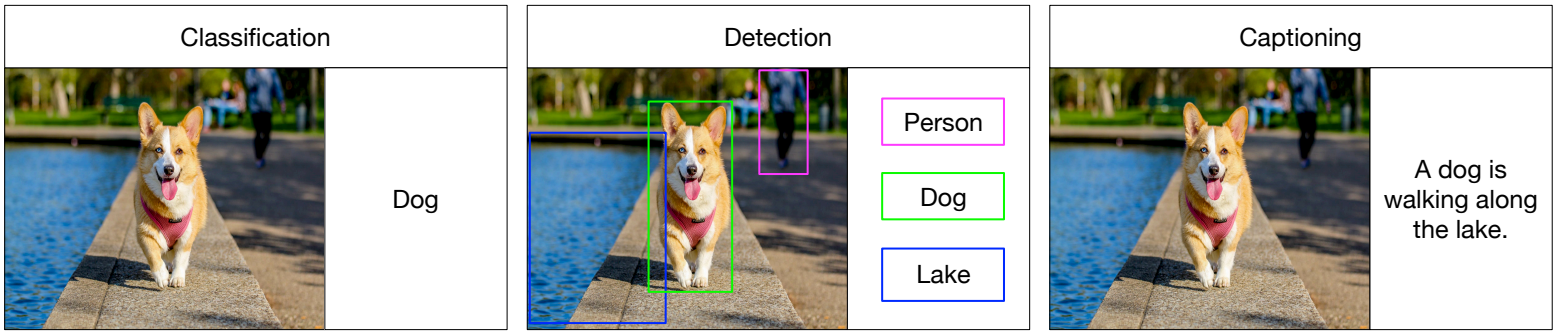

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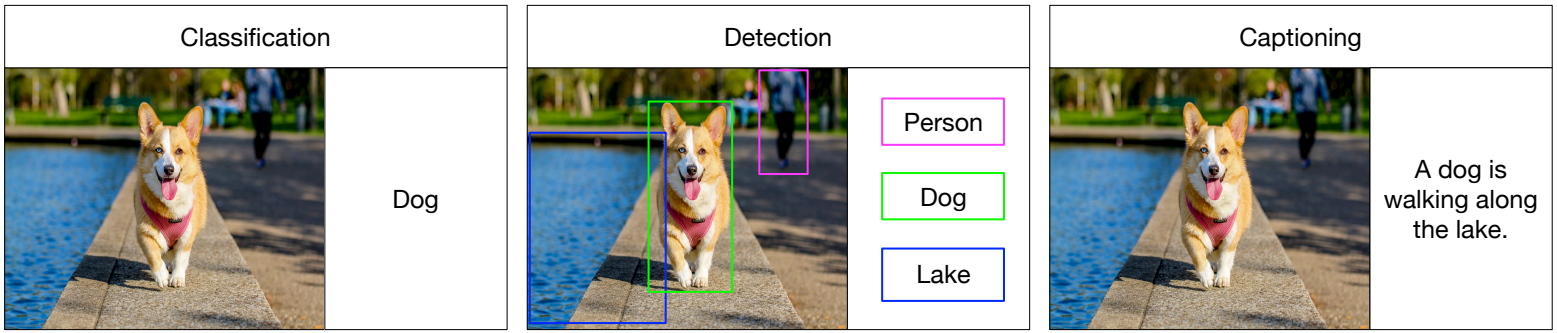

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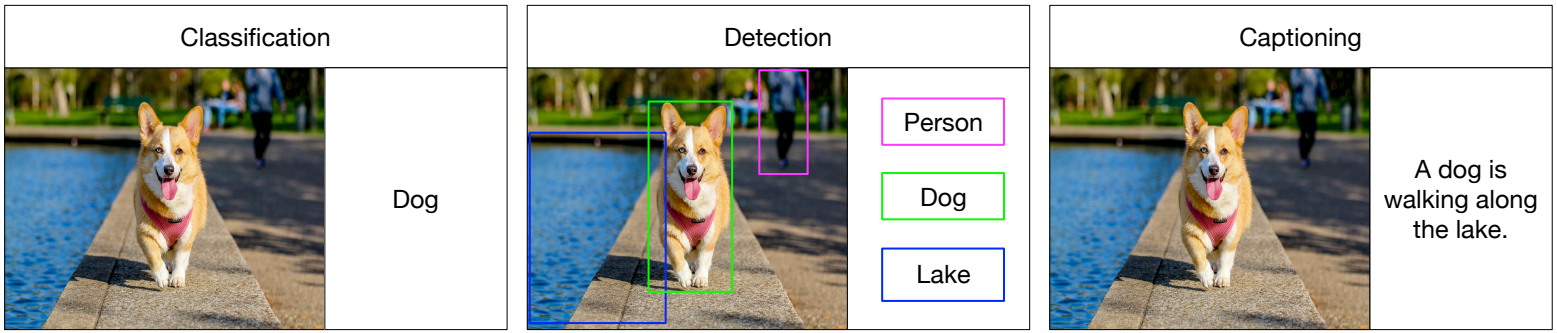

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Encouraging Progress

- CNN: *image classification, object detection, segmentation, ...*
- RNN: *speech recognition, machine translation, question answering, ...*

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What's next? Image $\Leftrightarrow$ NLP

- Connecting semantics in text with entities in images.
- Fine-grained inference w.r.t. aspects in text and images.

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- Fine-grained inference w.r.t. aspects in text and images.

Why?

- Huge amount of tweets/posts/reviews with both images and text.
- Humans are inherently able to connect their semantics effortlessly.
- It's unable for readers to literally look through all of them.

Problem Statement

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1. Generating high quality image descriptions
   that are indistinguishable to ones written by humans.
2. Relating a set of review sentences to images.
3. Recognizing aspects in review text,
   matching with regions in images, and inferring fine-grained ratings.

Deep Learning Backgrounds

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- Deep Supervised Learning
  - Objective Function
  - Regularization

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- Attention Mechanism

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Principal Assumptions

- Neural networks can estimate connections between images and texts.
- CNN is able to extract abstractive concepts in images.
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1. Image caption quality can be improved by training with GANs.
2. Relevances between images and review sentences can be estimated with unsupervised learning.
3. Correlation between aspects in text and images can be computed; and fine-grained ratings can be accurately figured.

Research Questions

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How and by how much can we improve the quality of image captions generated by machines?

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3. Image Aspect Mining

How can we connect aspects mined from text and ones detected in images and do fine-grained inference?

Overview

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Alternative Captions:

1. A picture of a dog laying on the ground
2. Dog snoozing by a bike on the edge of a cobblestone street
3. The white dog lays next to the bicycle on the sidewalk.
4. A white dog is sleeping on a street and a bicycle.
5. A puppy rests on the street next to a bicycle.

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- Captions alleviate the difficulty of image retrieval.
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Related Works

- Visual elements recognition $\rightarrow$ Language modeling (Farhadi et al. 2010, Kulkarni et al. 2013)
- Encoder (CNN) + Decoder (RNN) + Attention (Karpathy et al. 2015, Xu et al. 2015, Lu et al. 2017, Anderson et al. 2017)
- REINFORCE for performance boosting (Rennie et al. 2016)
- GANs for discrete data generation (Jang et al. 2016)

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Issues and Challenges

Differences between machine generated and human written captions

Model Architecture

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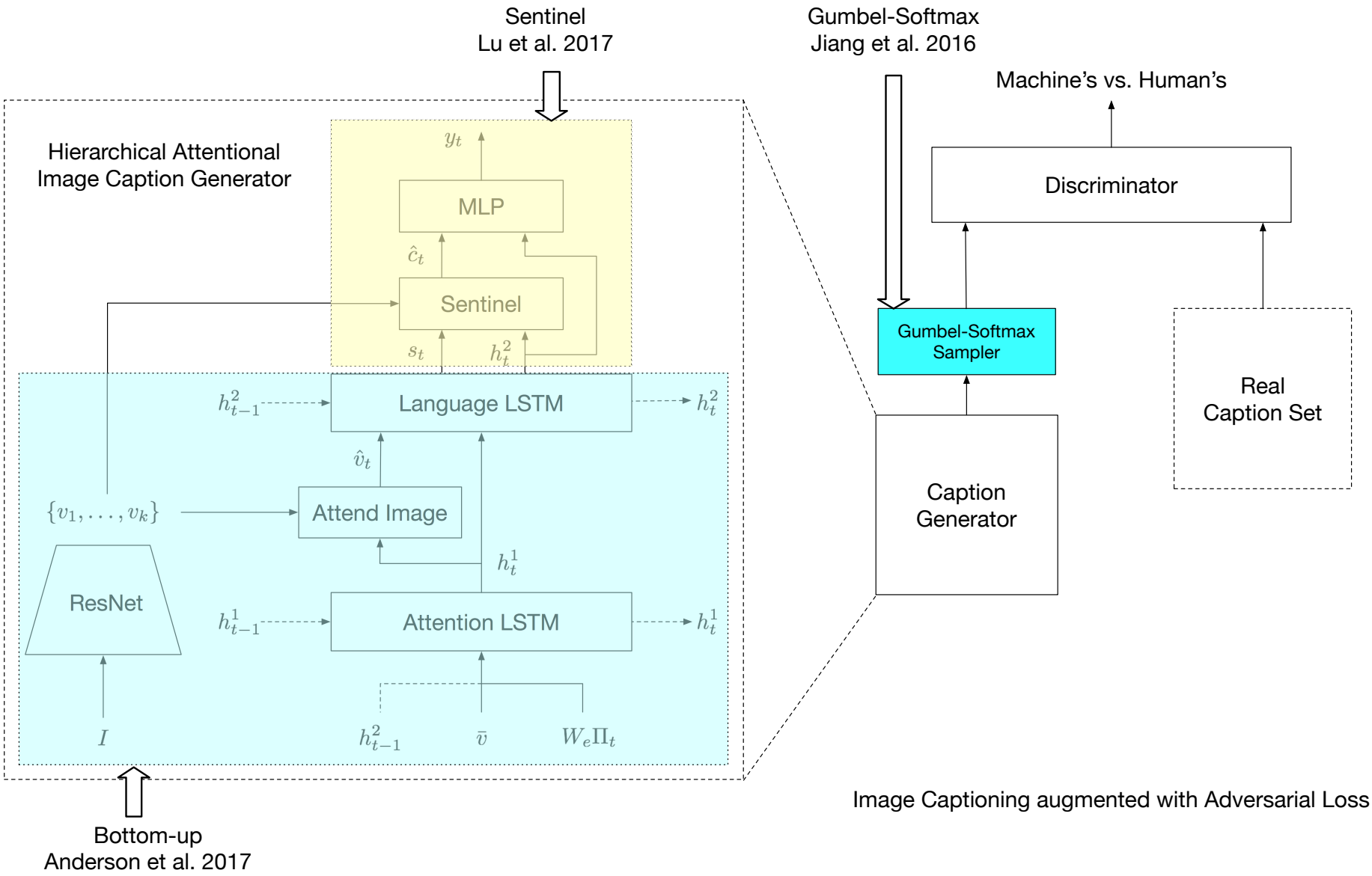

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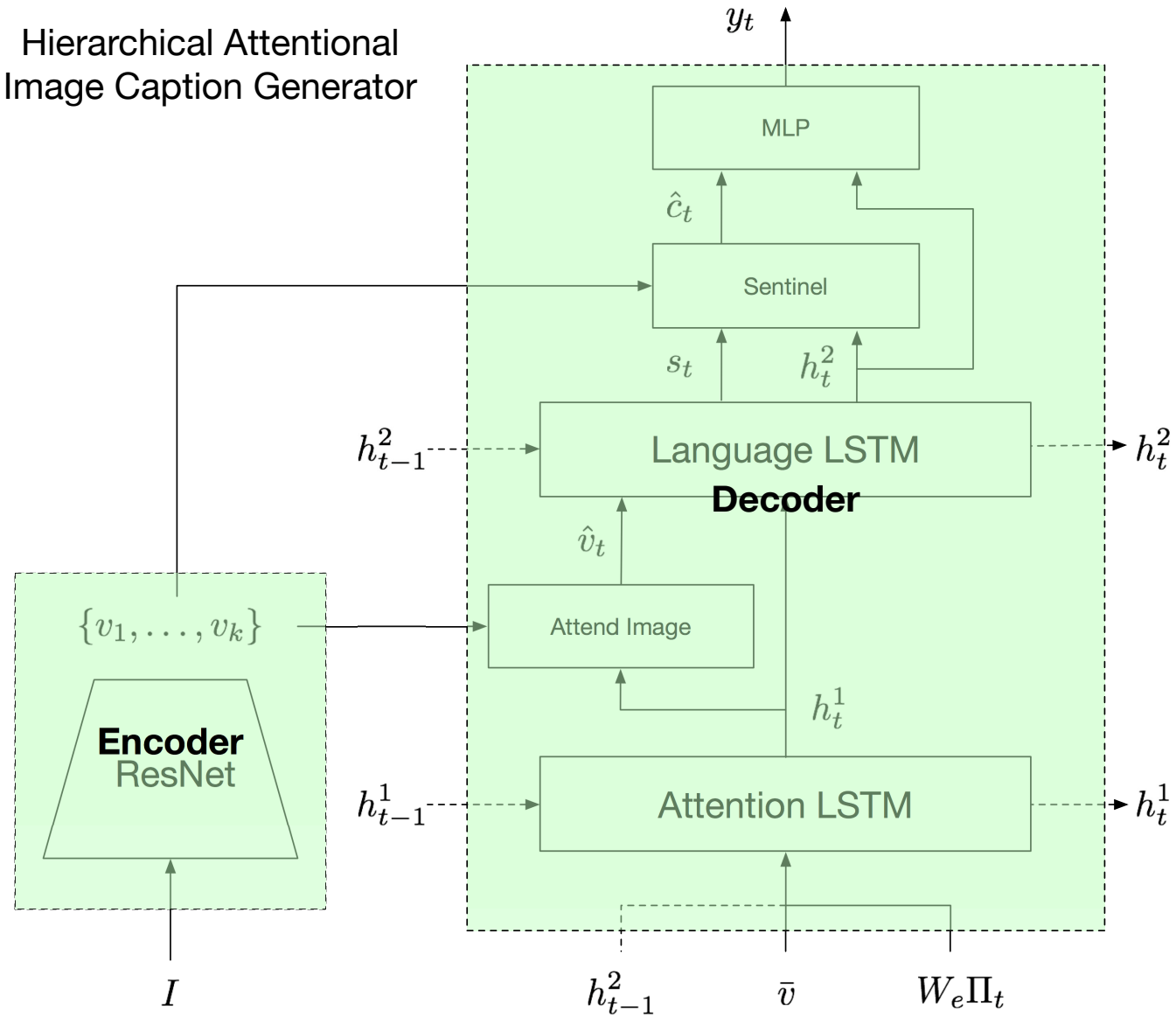

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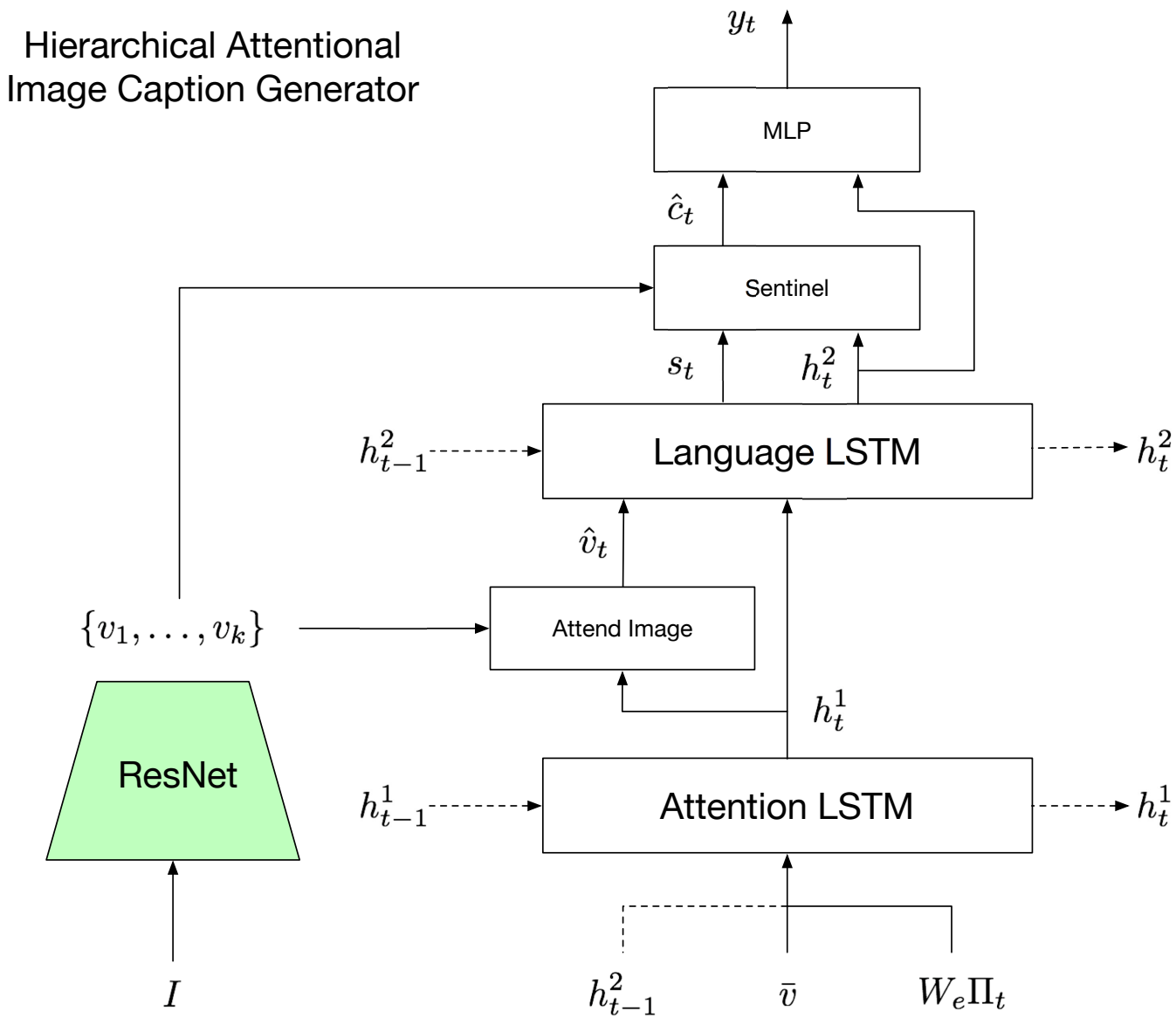

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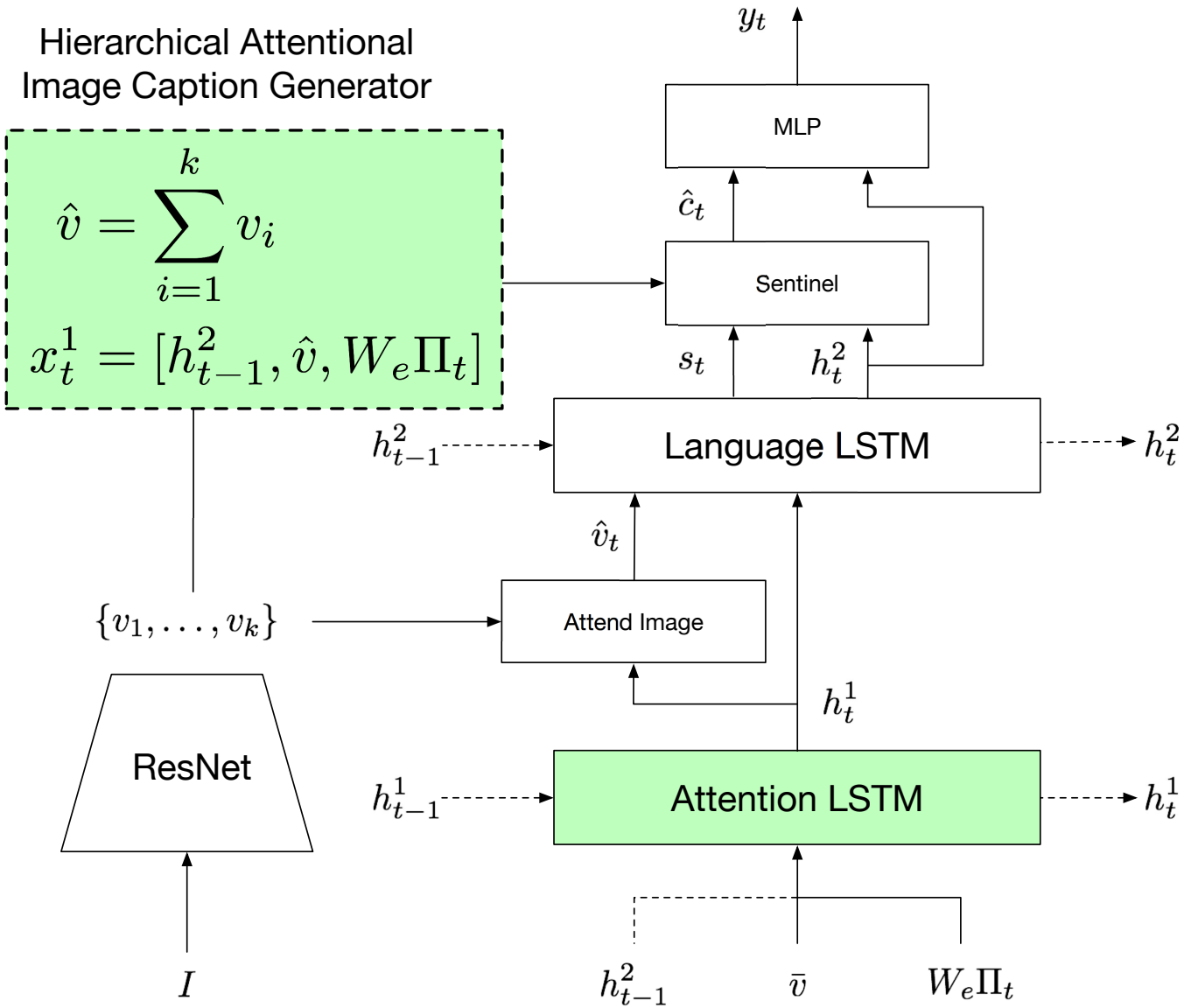

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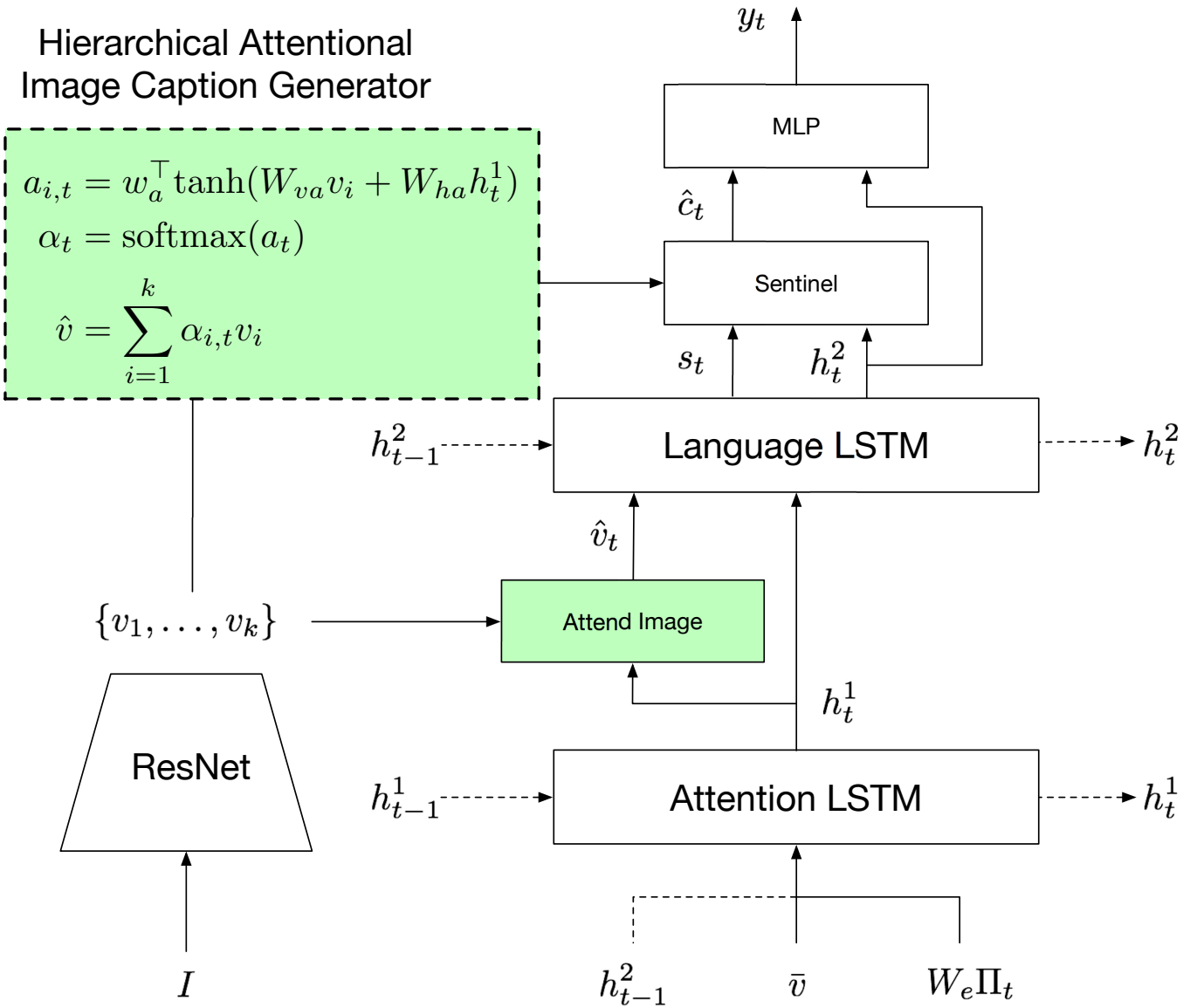

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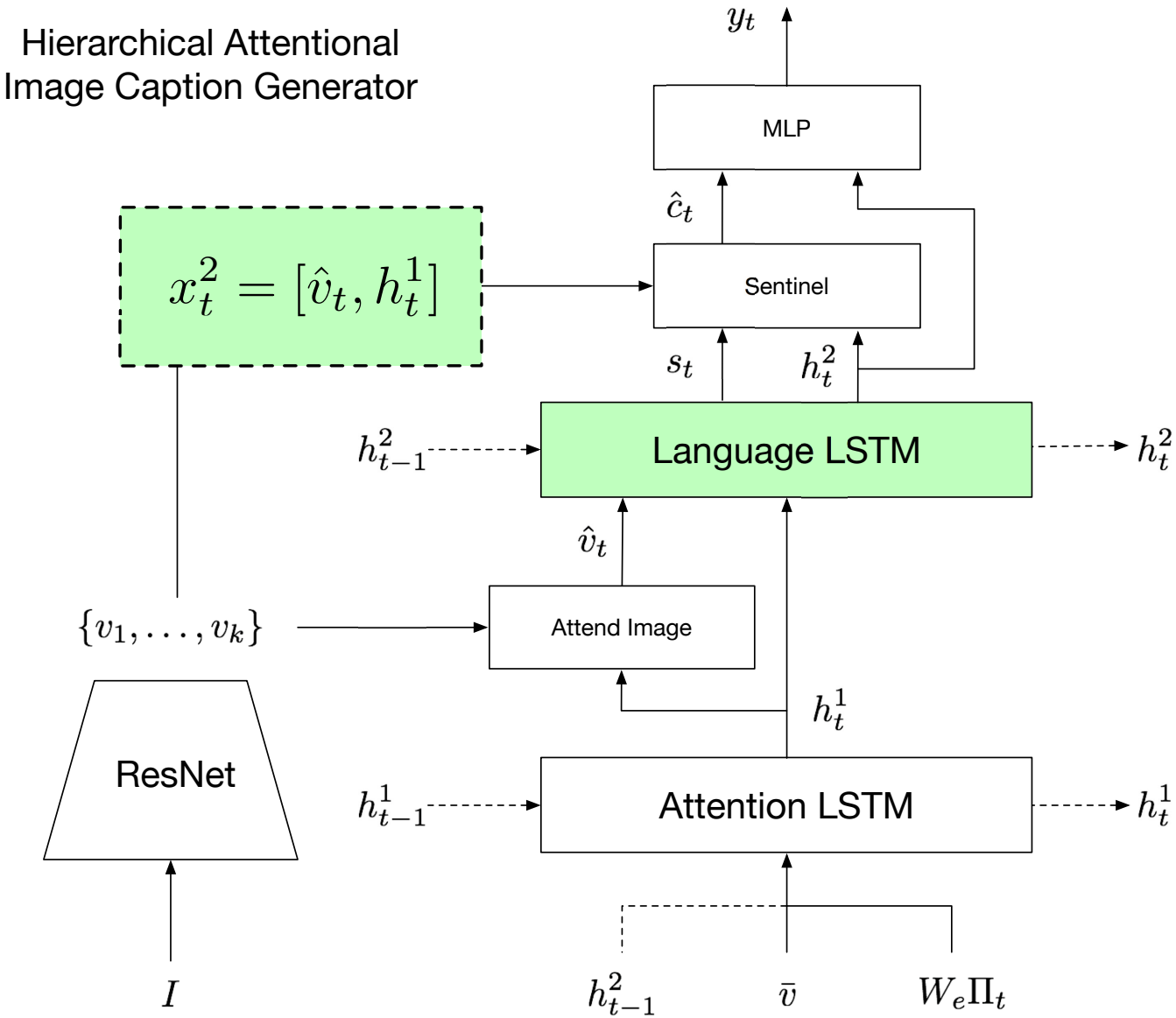

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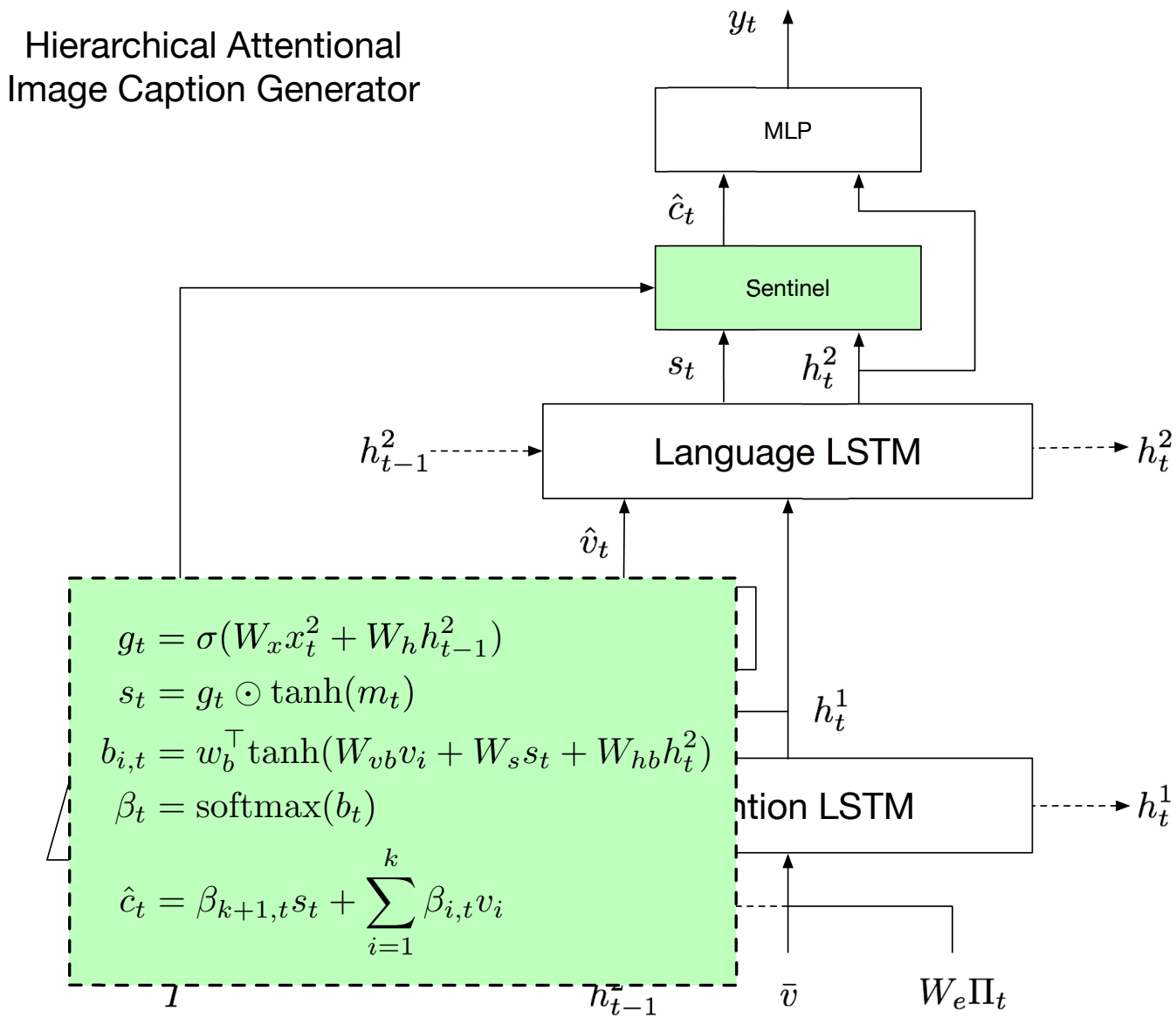

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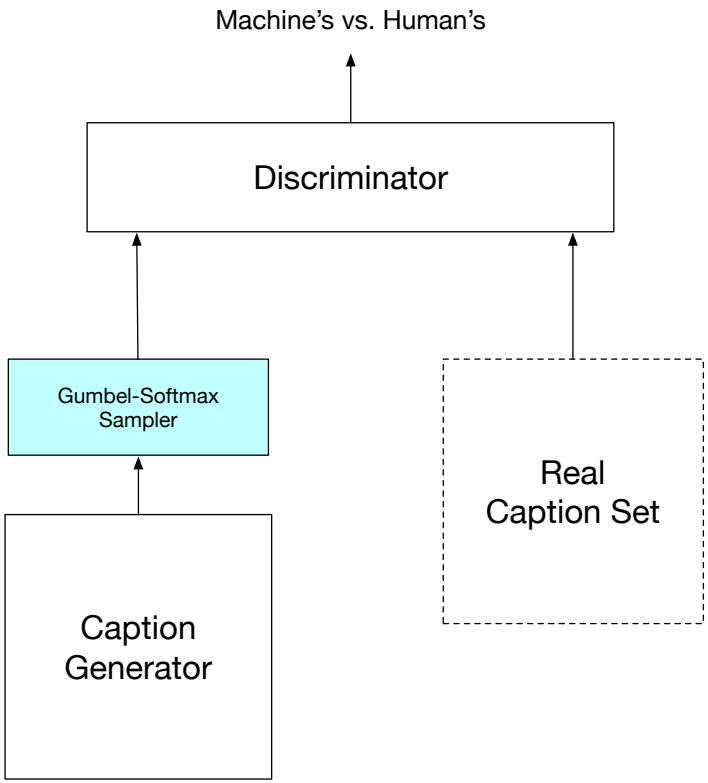

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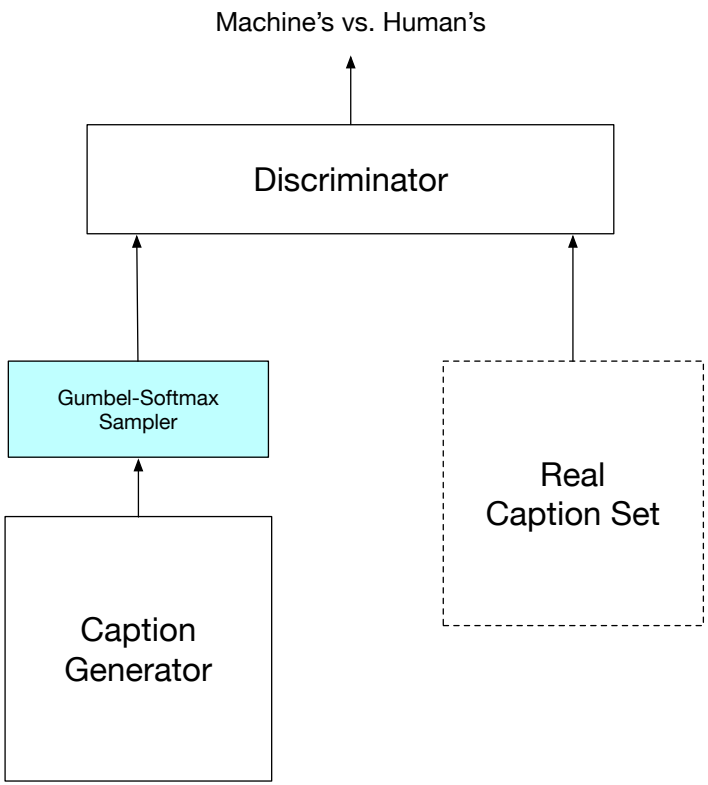

Computational Data Flow

$$\text{hard} = \text{one\_hot}\left[\arg\max_i (g_i + \log\theta_i)\right]$$

$$\text{soft} = \text{softmax}\left(g + \log\theta\right)$$

$$\Pi_t = (\text{hard} - \text{soft}).\text{detach} + \text{soft}$$

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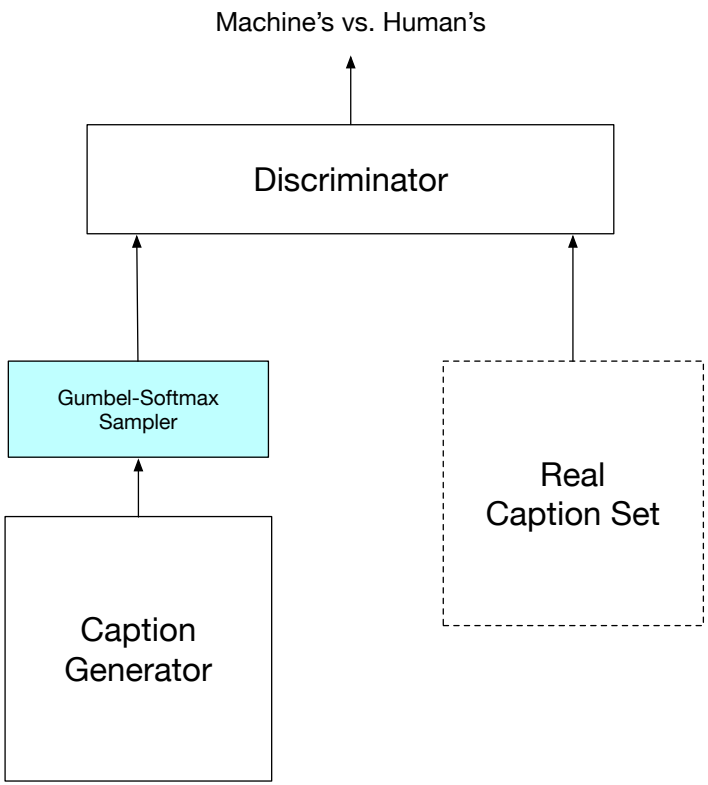

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Equation Notations

$$\theta = \text{Categorical Distribution}$$

$$g_i \sim \text{Gumbel Distribution}$$

Loss Functions

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$$L_R(\theta) = -\mathbb{E}_{y_{1:T}^s \sim p_\theta}[r(y_{1:T}^s)]$$

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Adversarial Loss

$$L_G(\theta) = -\mathbb{E}_{y_{1:T} \sim p_\theta}[D(y_{1:T})]$$

Experiments and Results

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Table 1: A summary of the evaluation metrics used for image captioning

Metric	**Proposed to evaluate**	**Intuition**
BLEU	Machine translation	n-gram precision
ROUGE	Document summarization	n-gram recall
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Table 2: Single-model performance on the MSCOCO Karpathy test

Training Method	**Model**	**BLEU-1**	**BLEU-4**	**METEOR**	**ROUGE-L**	**CIDEr**
REINFORCE CIDEr	SCST	-	0.333	0.263	**0.553**	1.114
	Bottom-up	0.766	0.340	0.265	0.549	1.111
	Ours	**0.767**	**0.342**	**0.266**	0.550	**1.117**
GANs	Ours	**0.770**	**0.345**	**0.269**	**0.554**	**1.121**

Experiments and Results

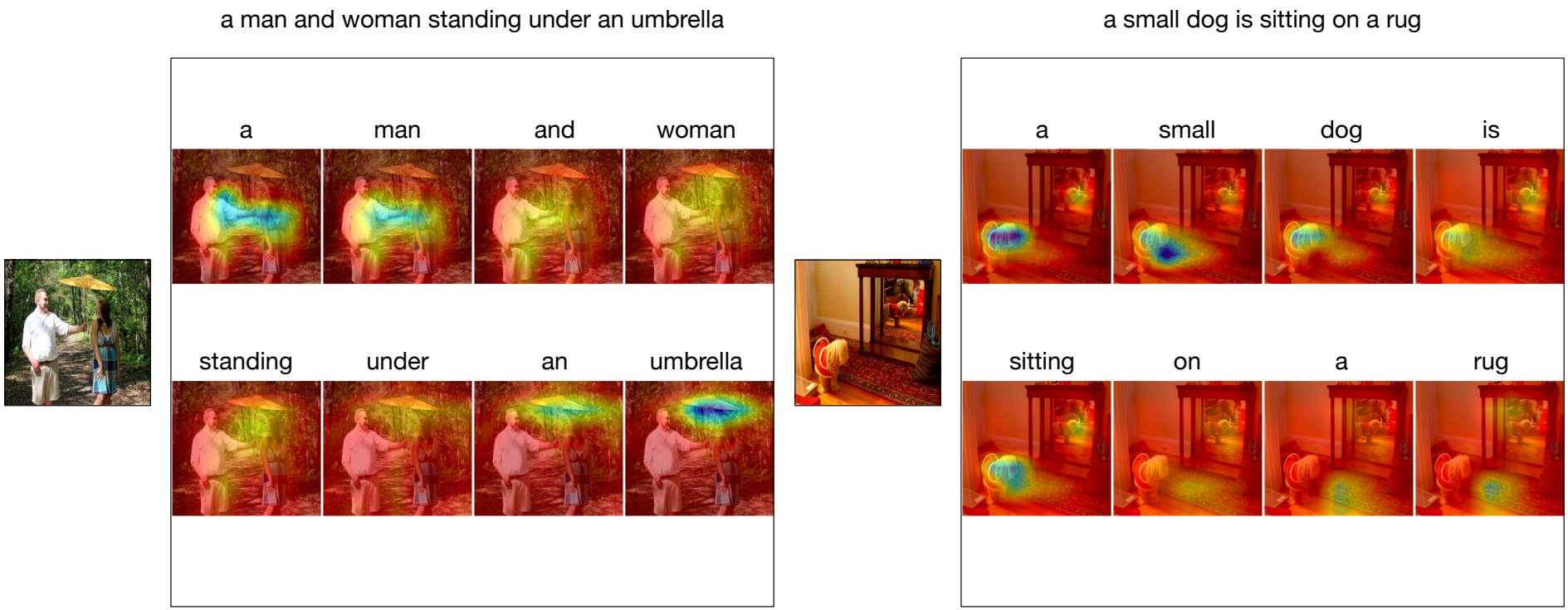

Figure 1: Qualitative captioning examples with first attention layer visualized.

Experiments and Results

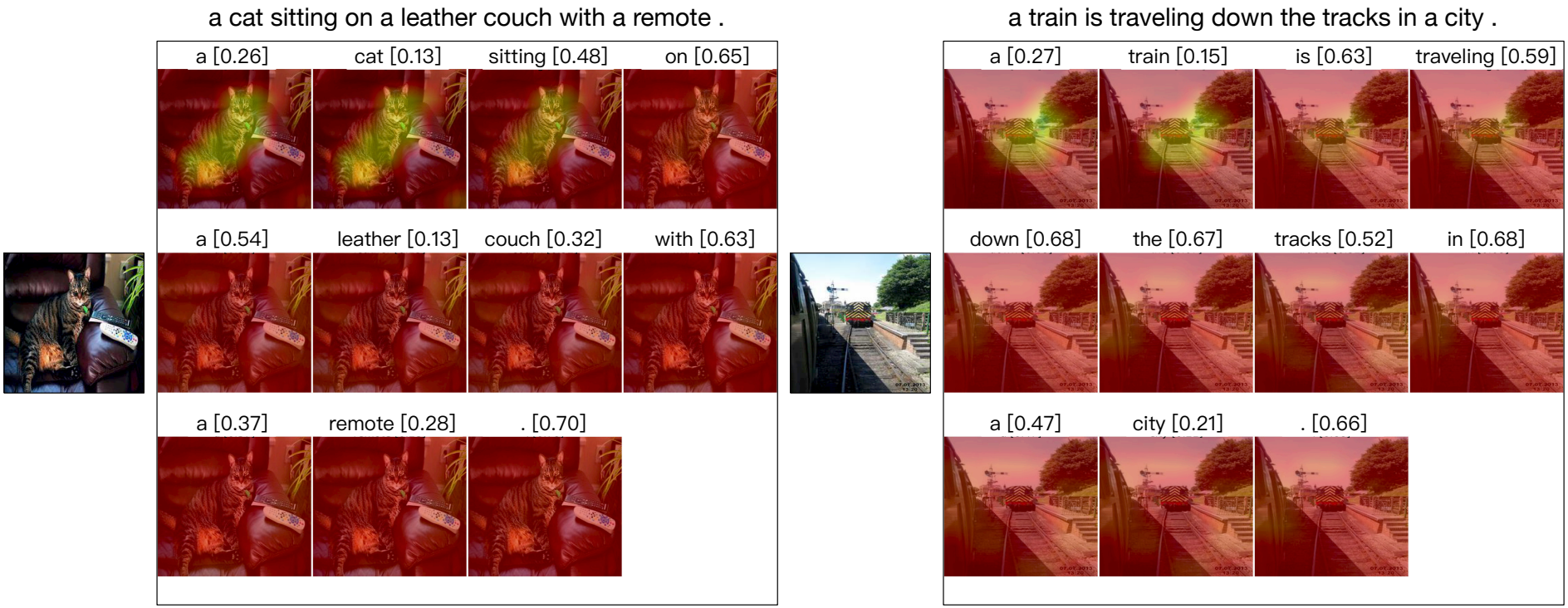

Figure 2: Captioning examples with sentinel (in brackets) and visual attentions.

Experiments and Results

Our Mixed Model: a man on a skateboard riding down the street

Our GANs Model: a man on a skateboard is riding down the ramp .

Our Mixed Model: a baseball player is swinging a bat at a ball .

Our GANs Model: a baseball player in orange shirt is kneeling on the field .

Figure 3: Caption examples of our mixed captioning model vs. our GANs model.

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Matching Sentences to Image

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Review Text:

I tried this place for the first time today. I had the Sadie. It was great. Loved the pulled pork and beans. Just wish I had more BBQ sauce. I will go back again.

Ranked Sentences:

1. Loved the pulled pork and beans.
2. I had the Sadie.
3. It was great.
4. Just wish I had more BBQ sauce.
5. I tried this place for the first time today.
6. I will go back again.

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- Differentiate between text content and image description.
- Direct application for better image retrieval.
- Provide supervised label for image captioning.

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Challenges

- No labeled review dataset for supervised learning.
- How to evaluate trained model quantitatively?

Pseudo Supervised Training

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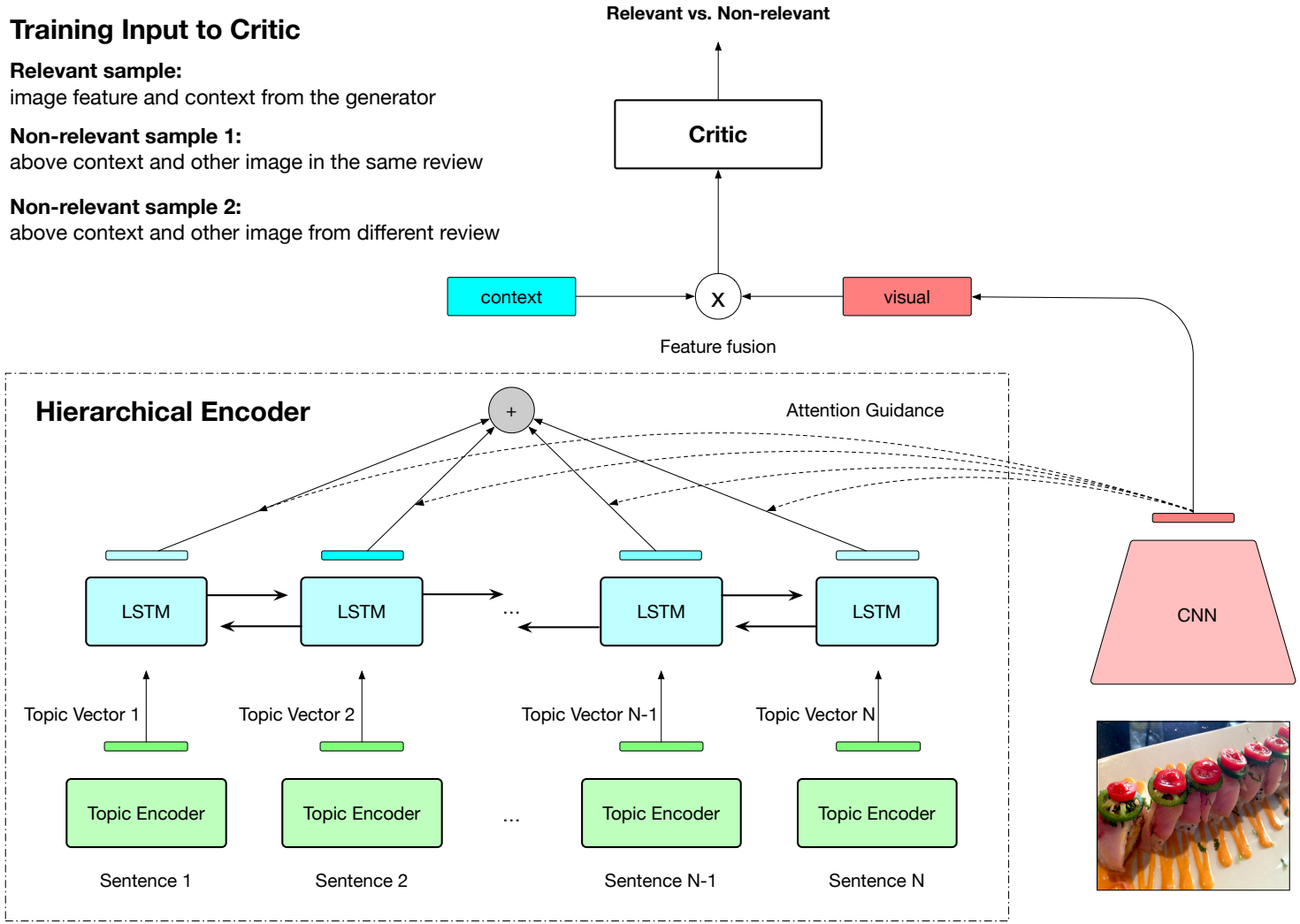
Training Input to Critic

Relevant sample:
image feature and context from the generator

Non-relevant sample 1:
above context and other image in the same review

Non-relevant sample 2:
above context and other image from different review



Multi-task Learning

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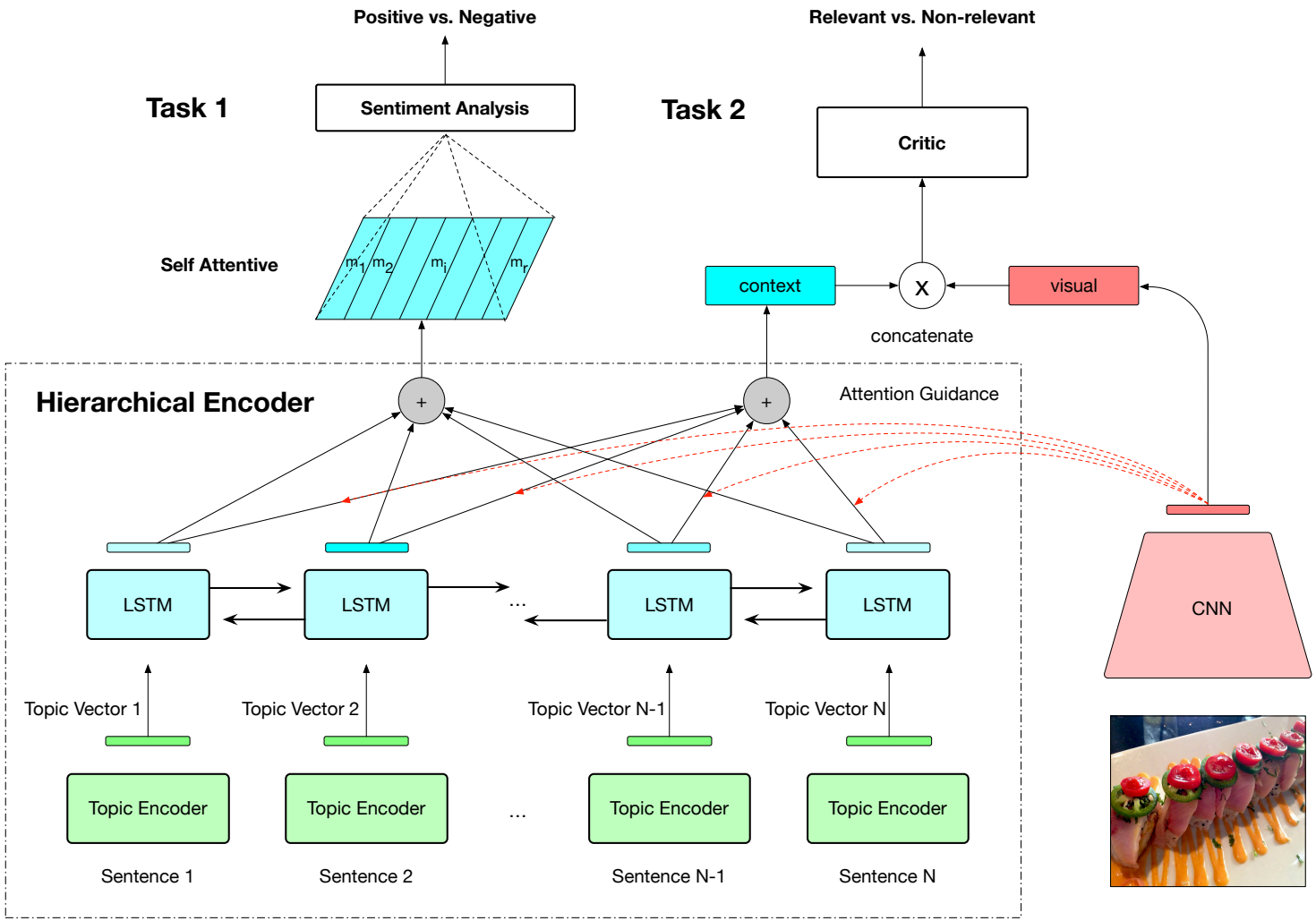

Loss Function

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New Relevance Loss

$$L(\theta; T, I) = \sum_{k=1}^{M} [- f(\mathrm{CNN}(I_{t=k}), g(T, I_{t=k})) + f(\mathrm{CNN}(I_{t\neq k}), g(T, I_{t=k}))]$$

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Self Attention Loss

$$A = \mathrm{softmax}(W_{s2}\tanh(W_{s1}H^{\top} + \cancel{\text{outsidesignal}}))$$

$$L_{\mathsf{sent}} = L_{XE} + \lambda_1 ||A^{\top}A - I||_F$$

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Multi-task Learning Loss

$$L = L(\theta; T, I) + \lambda_2 L_{\text{sent}}$$

Preliminary Results

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Dataset: Yelp restaurant reviews with $13,500$ samples.

	Review Text	Top 3 Sentences with Basic Model	Top 3 Sentences with Multi-task Model
	Want a great, no frills taco? This is your place. The salsa bar is phenomenal too! I had the el Capitan with asada. It was delicious, but a little salty. My boyfriend had the barbacoa, tripe, and lengua tacos, and decided the tripe was his favorite. Great location and great place!	1. My boyfriend had the barbacoa, tripe, and lengua tacos, and decided the tripe was his favorite. (0.132) 2. Great location and great place! (0.121) 3. It was delicious, but a little salty. (0.117)	1. Want a great, no frills taco? (0.144) 2. This is your place.(0.143) 3. The salsa bar is phenomenal too! (0.143)
	I tried this place for the first time today. I had the Sadie. It was great. Loved the pulled pork and beans. Just wish I had more BBQ sauce. I will go back again.	1. Loved the pulled pork and beans. (0.189) 2. I will go back again. (0.168) 3. It was great. (0.166)	1. Loved the pulled pork and beans. (0.191) 2. I had the Sadie. (0.171) 3. It was great. (0.167)

Future Work and Evaluation Plan

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Dataset Labeling

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Baseline

- Relate image captions to review sentences.

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Image Aspect Mining

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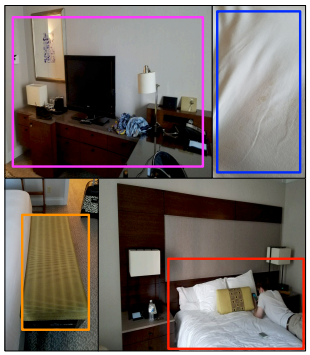
So so. after a week the refrigerator is working fine. the box was dented and had holes in it, and the refrigerator had dents and scratched that matched the damage to the box.

box: dented, holes

refrigerator: dents, scratched

Amazon Review



I was utterly disappointed with my experience here. Literally nothing about this hotel was luxurious in the slightest. Our room was completely lackluster, outdated and even dirty. The sheets were stained and the ancient foot stool at the end of the bed looked filthy. Service was fine, bed was comfortable, and bathroom was clean. Those are the only positives I can list.

Room: lackluster, outdated, dirty

Bed: comfortable

Sheets: ancient, stained

Foot stool: filthy

Yelp Hotel Review

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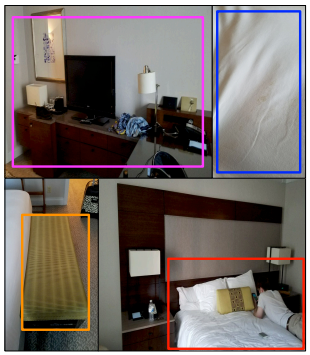

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Image Aspect Mining

- Recognize topical aspects in review text.
- Attend to specific regions in images.
- Infer fine-grained ratings.

Image Aspect Mining

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Impacts

- Aspect ratings for merchants to provide better service, and consumers to target specific requirements.
- Identify aspect rating congruence between text and images.

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Related Works

- Object detection: R-CNN families, YOLO (Girshick et al. 2014, Redmon et al. 2016)
- Image-text feature fusion: MUTAN (Ben et al. 2017)
- Multi-step attention: stacked attention (Yang et al. 2016)

Approaches

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Baseline

- Image Aspect: proposals from R-CNN/YOLO;
- Text: RNN - LSTM;
- Feature fusion: concatenation/element-wise product;

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Generative

- Text2image: Generative Adversarial Networks;
- Gumbel-Softmax, Adversarially Regularized Autoencoder (Kim et al. 2017);

Evaluations

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Metric Definition

$$\Delta^2_{\text{aspect}} = \sum_{d=1}^{|D|} \sum_{i=1}^{k} (s_{di} - s^*_{di})^2 / (k \times |D|).$$

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Datasets

- TripAdvisor hotel reviews: aspect level ratings provided
- Yelp restaurant reviews
- Amazon reviews

Overview

Conclusions

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Image Captioning

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Image Aspect Mining

- Proposed a new AI task
- Datasets, baseline models, and evaluation protocols

Research Timeline

Task	2017		2018		
	Summer	Fall	Spring	Summer	Fall
Topic 1 - Image Captioning with GANs	✓	✓	✓		
Basic image caption model setup	✓				
Training with GANs framework		✓			
Publish the results			✓		
Topic 2 - Matching Sentences to Images			✓	✓	
Model design and experiments			✓		
Dataset labeling and evaluation			✓		
Publish the results				✓	
Topic 3 - Image Aspect Mining				✓	✓
Dataset collection and labeling				✓	
Model implementation and evaluation				✓	
Publish the results					✓
Writing the dissertation					✓
Research defense					✓
Final defense					✓

Publications

[1]. **Yufeng Ma**, Zheng Xiang, Qianzhou Du, and Weiguo Fan, "Effects of user-provided photos on hotel review helpfulness: An analytical approach with deep leaning," *International Journal of Hospitality Management*, vol. 71, pp. 120–131, 2018.

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[3]. Zheng Xiang, Qianzhou Du, **Yufeng Ma**, and Weiguo Fan, "Assessing reliability of social media data: Lessons from mining tripadvisor hotel reviews," in *Information and Communication Technologies in Tourism 2017*, pp. 625–638, Springer, 2017 **Best Research Paper Award**.

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[5]. **Yufeng Ma**, Long Xia, Wenqi Shen, Mi Zhou, and Weiguo Fan, "A surrogate-based generic classifier for Chinese TV series reviews," *Information Discovery and Delivery*, vol. 45, no. 2, pp. 66–74, 2017.

[6]. Long Xia, **Yufeng Ma**, and Weiguo Fan, "VTIR at the NTCIR-12 2016 lifelog semantic access task," *Proceedings of NTCIR-12, Tokyo, Japan*, 2015.

Acknowledgements

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Overview

Thank You!
Questions & Comments?