

Going Deeper with Images and Natural Language

Ph.D. Preliminary Examination

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Overview

1 Introduction

- Motivation
- Problem Statement
- Deep Learning Backgrounds
- Hypotheses
- Research Questions

2 Improved Image Captioning with Adversarial Loss

- Model Architecture
- Optimizations and Experiment Results

3 Congruence Measure between Image and Sentences

- Pseudo Supervised Training
- Loss Functions and Preliminary Results

4 Image Aspect Mining

- Task Descriptions and Approaches

5 Conclusions and Research Timeline

6 Acknowledgements

Motivation

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Alan Turing

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Current Progress in Artificial Intelligence

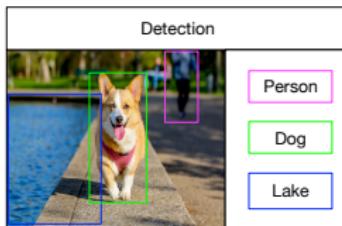
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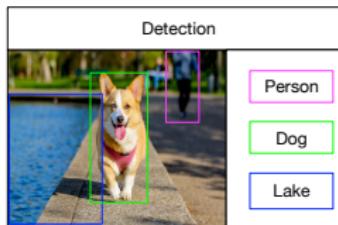
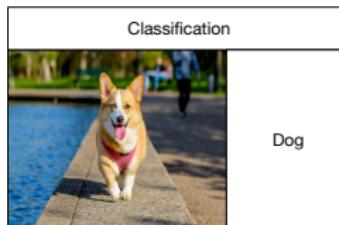
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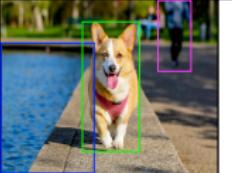
NLP: machine translation, text summarization, sentiment analysis, etc.

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Current Progress in Artificial Intelligence

	Classification	Detection	Captioning
Vision:	 Dog	 Person Dog Lake	 A dog is walking along the lake.

NLP: machine translation, text summarization, sentiment analysis, etc.

Encouraging Progress

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

Motivation

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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- Connecting semantics in text with entities in images.
- 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

Hypotheses

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Principal Assumptions

- Neural networks can estimate connections between images and texts.
- CNN is able to extract abstractive concepts in images.
- RNN can accurately deliver textual semantics.

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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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*How can we **measure** the congruence of sentence-image pair if there is **no** human annotated label for model training?*

3. Image Aspect Mining

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

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What's image captioning?

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What's image captioning?



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.

Image Captioning

Image Captioning

Impacts

- Help visually impaired perceive the surroundings.
- Captions alleviate the difficulty of image retrieval.
- Tweets/posts/reviews with images and text: better understanding.

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Related Works

- Visual elements recognition → 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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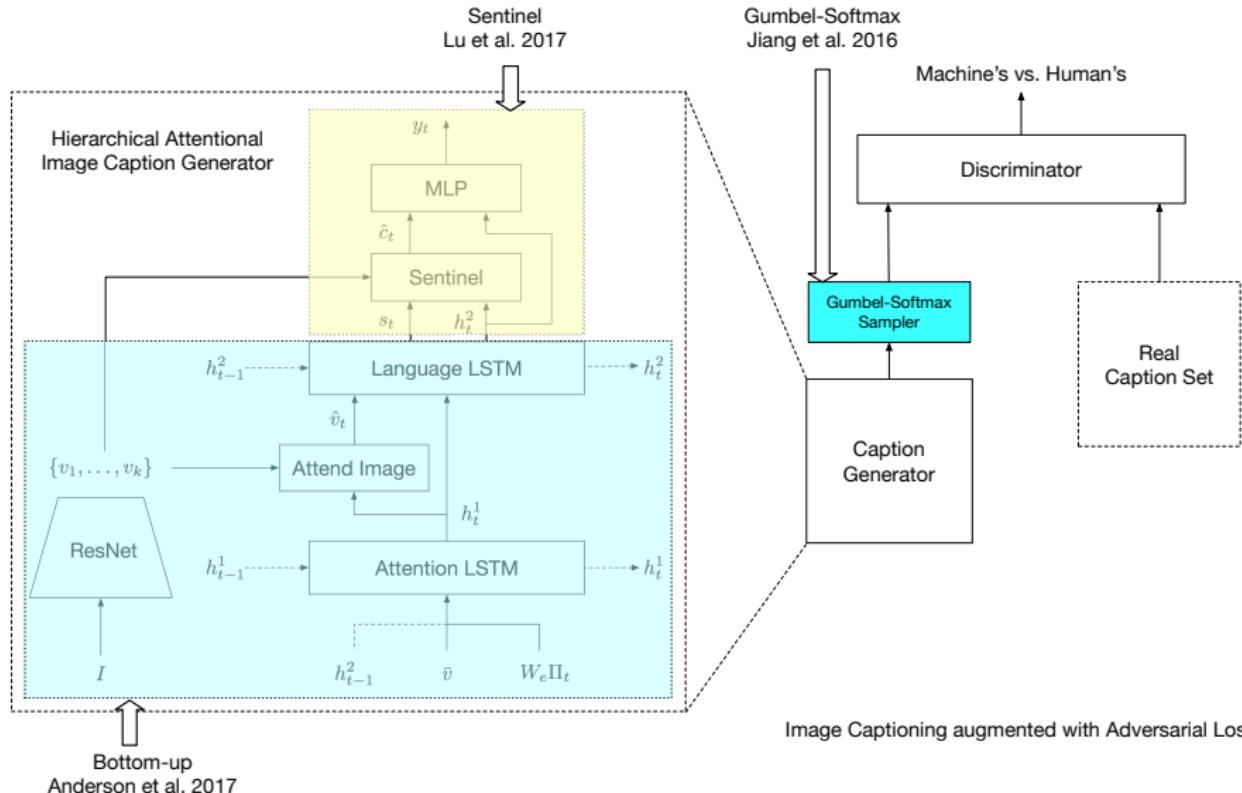
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Issues and Challenges

Differences between machine generated and human written captions

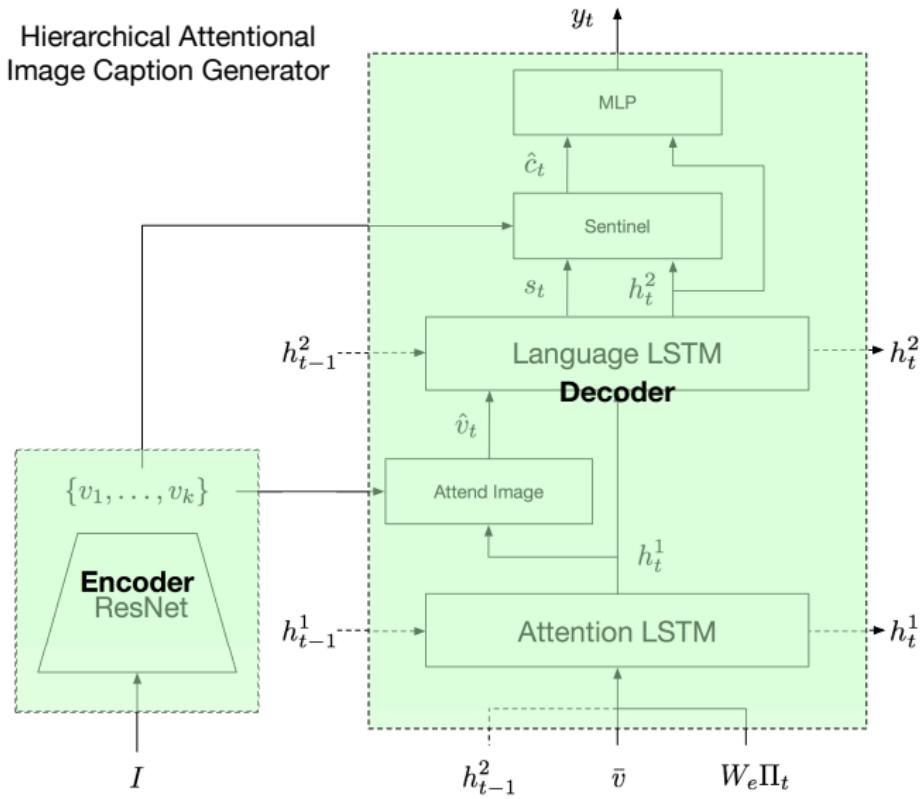
Model Architecture

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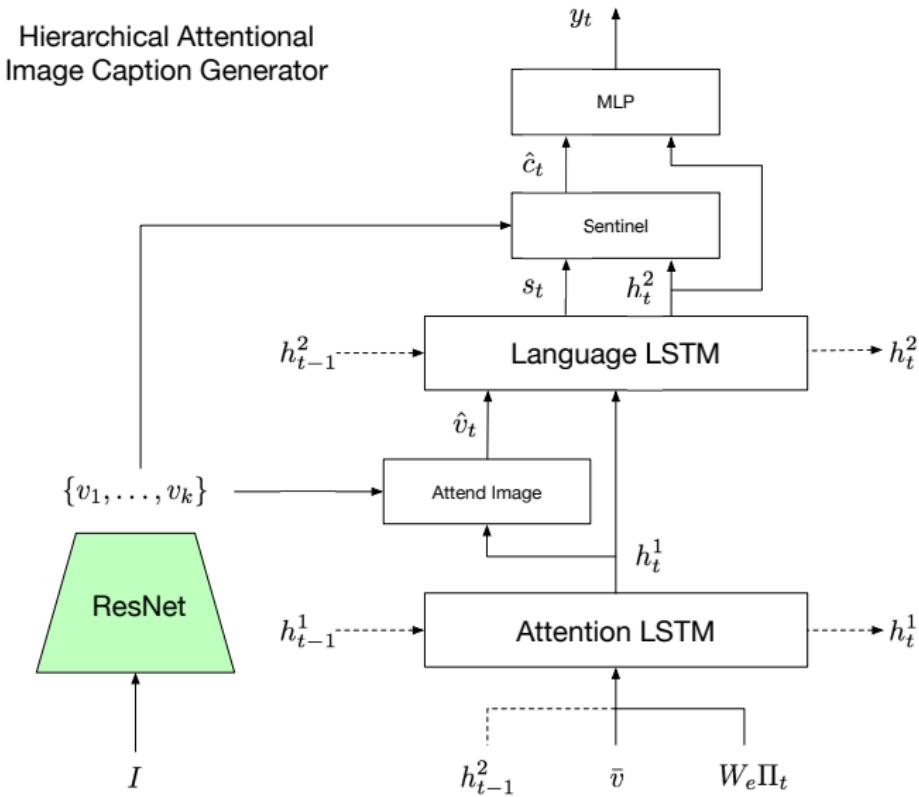


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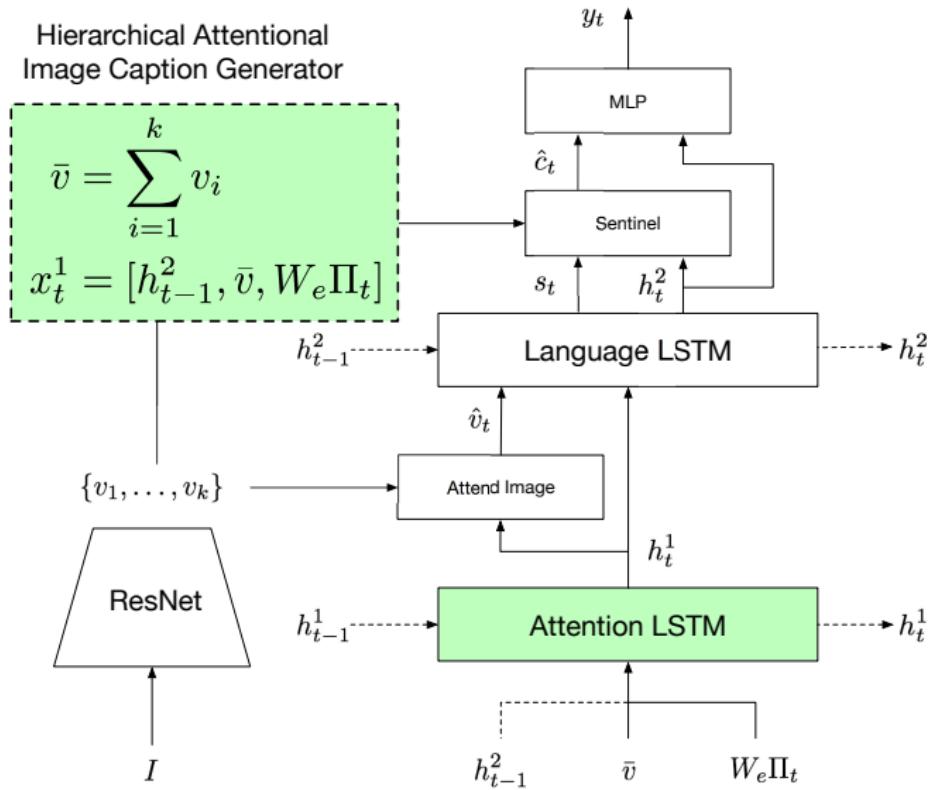
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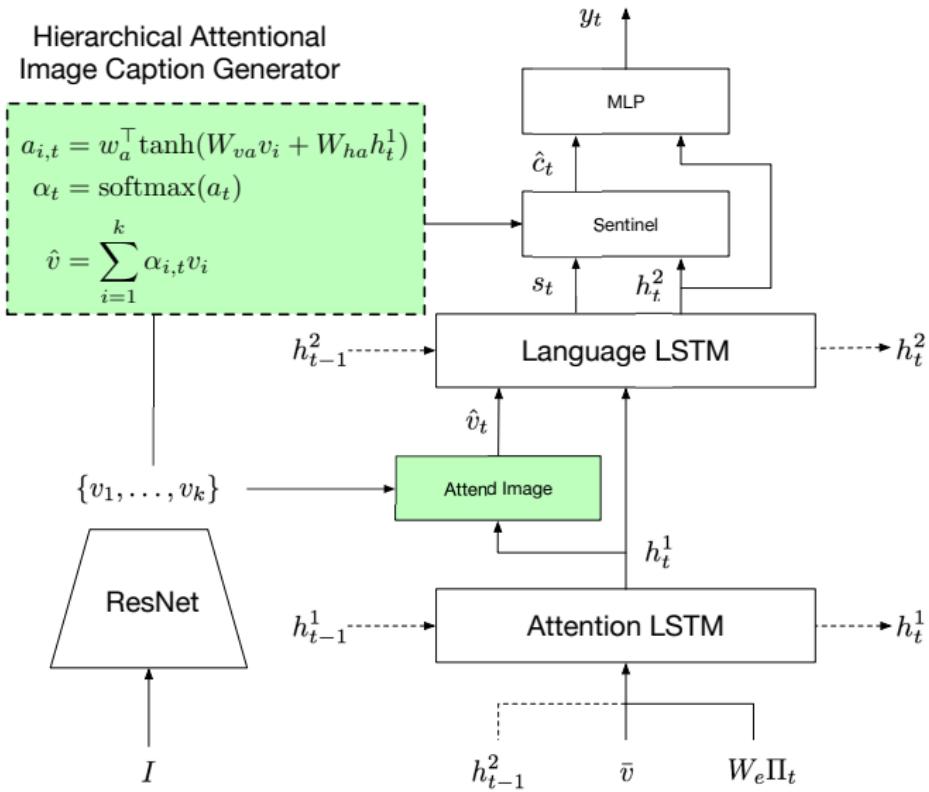
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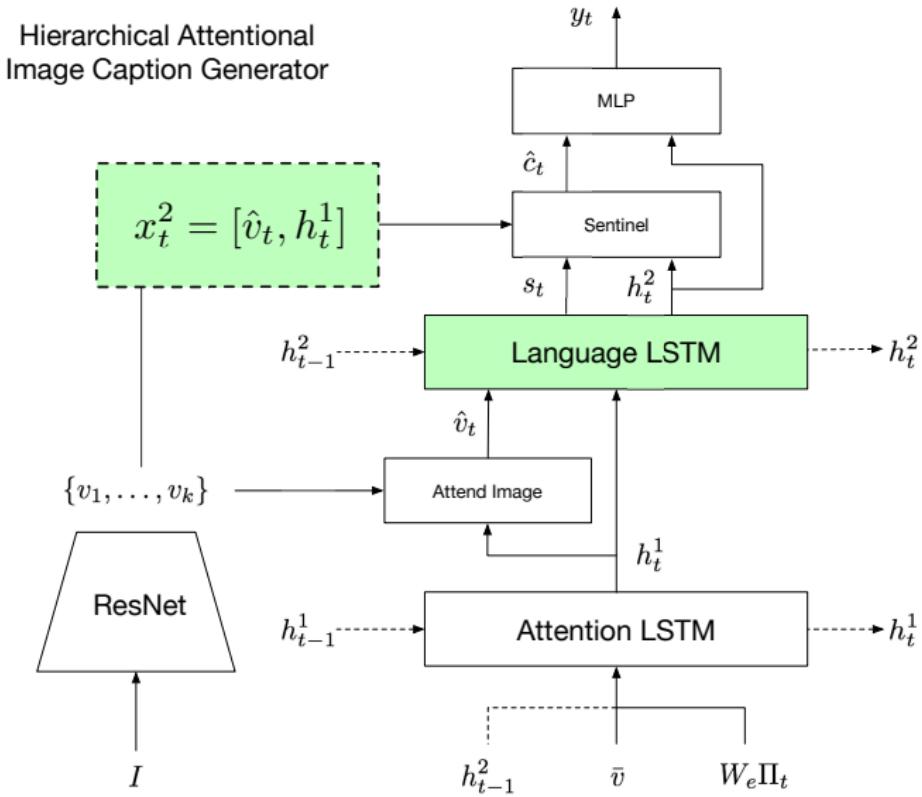
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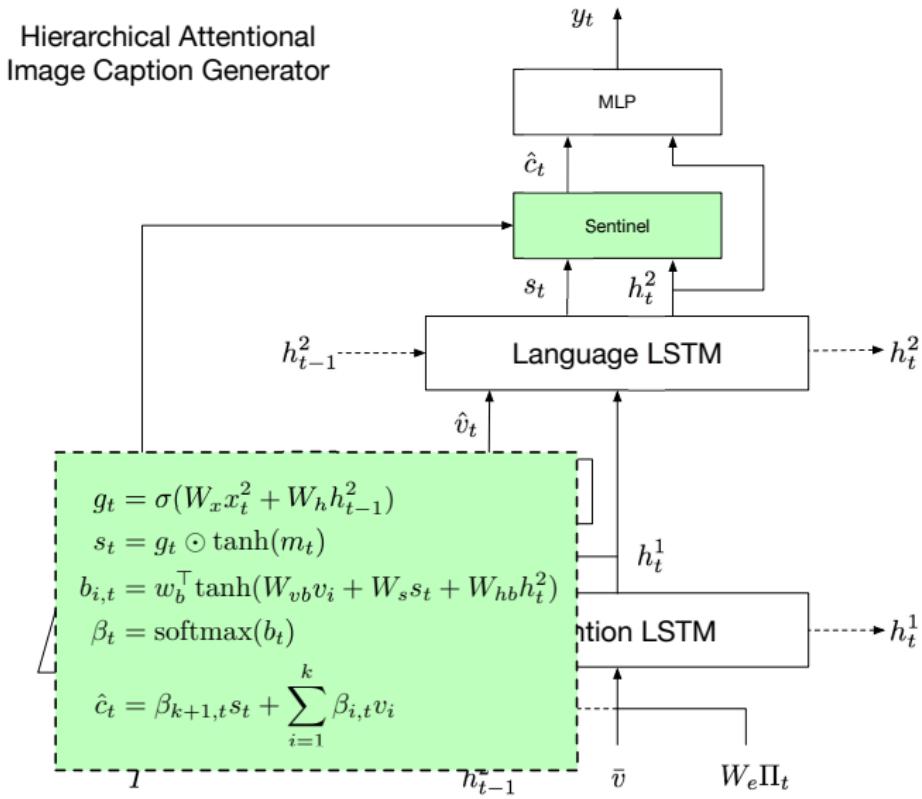
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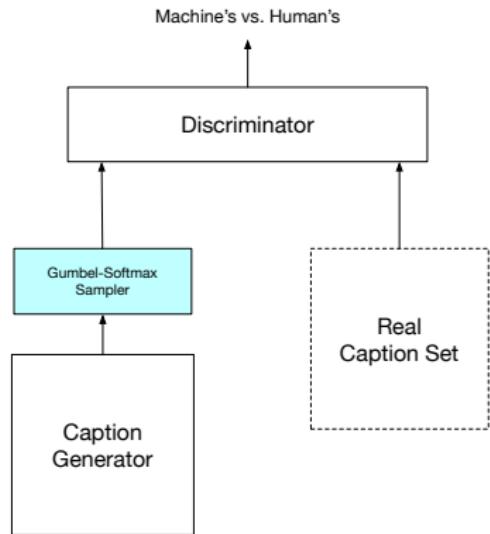


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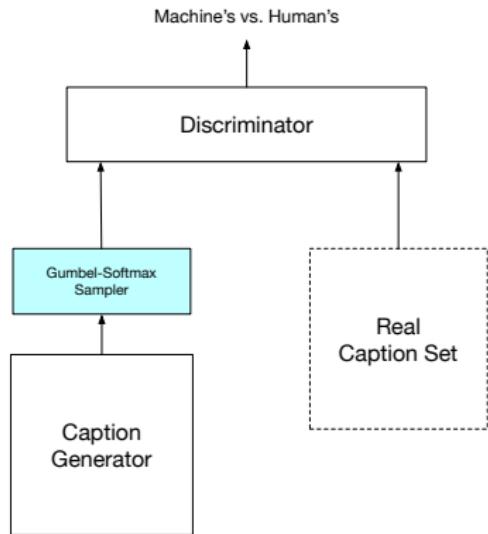


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Computational Data Flow

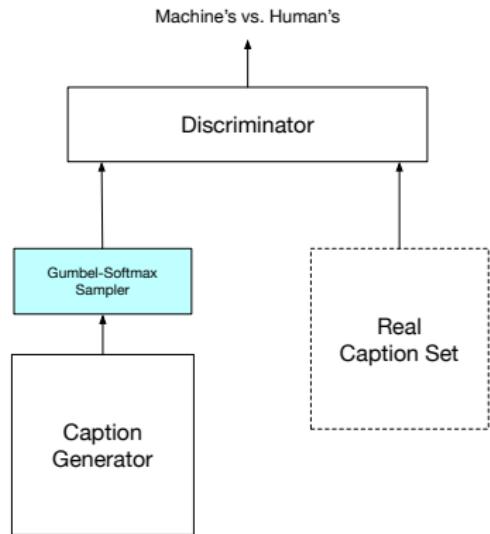
$$\text{hard} = \text{one_hot} \left[\arg \max_i (g_i + \log \theta_i) \right]$$

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

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

$$w_t = W_e \Pi_t$$

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Equation Notations

θ = Categorical Distribution

$g_i \sim$ Gumbel Distribution

Loss Functions

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Teacher Forcing

$$L_{XE}(\theta) = - \sum_{t=1}^T \log(p_\theta(y_t^* | y_{1:t-1}^*))$$

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

$$\nabla_\theta(\theta) \approx -(r(y_{1:T}^s) - r(\hat{y}_{1:T})) \nabla_\theta \log p_\theta(y_{1:T}^s)$$

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Adversarial Loss

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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
METEOR	Machine translation	n -gram with synonym matching
CIDEr	Image description generation	$tf\text{-}idf$ weighted n -gram similarity

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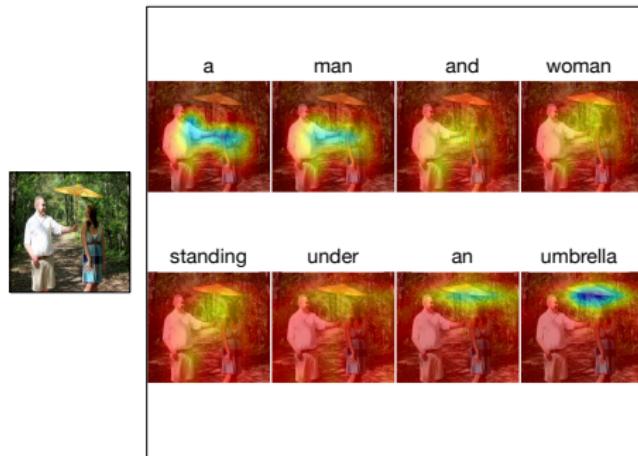
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Table 2: Single-model performance on the MSCOCO Karpathy test

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

a man and woman standing under an umbrella



a small dog is sitting on a rug

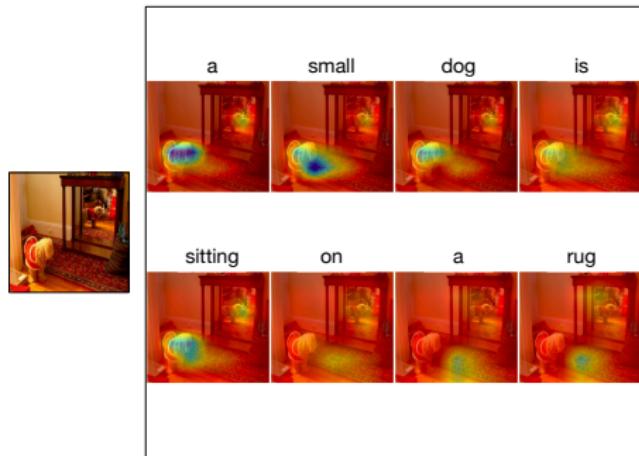


Figure 1: Qualitative captioning examples with first attention layer visualized.

Experiments and Results

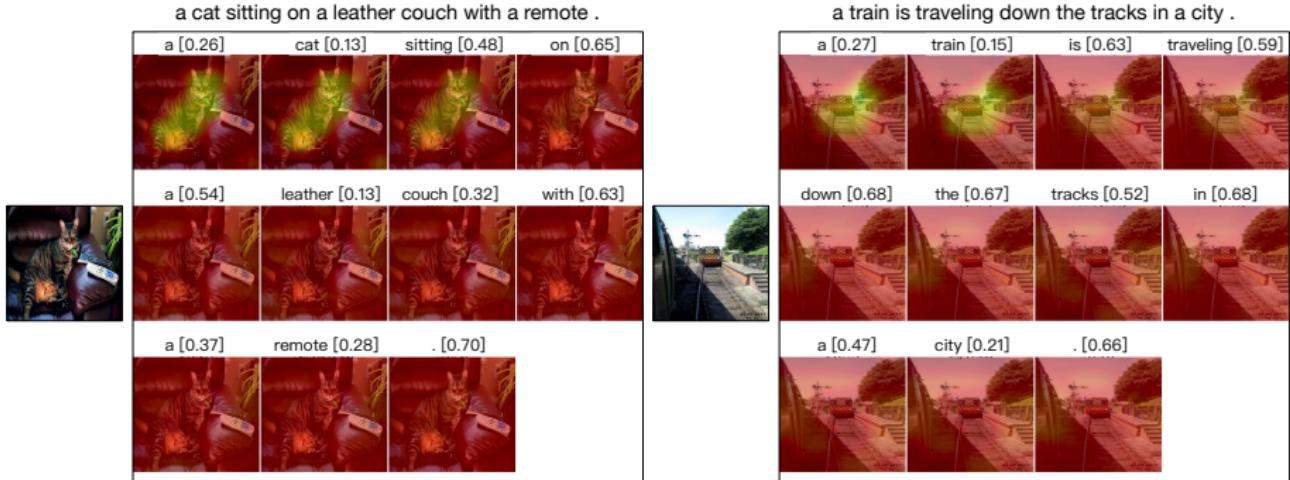
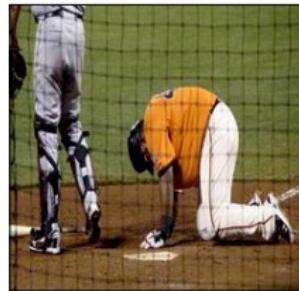


Figure 2: Captioning examples with sentinel (in brackets) and visual attentions.

Experiments and Results



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

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

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

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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Relevance of a sentence to an 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.

Matching Sentences to Image

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Impacts

- 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

Pseudo Supervised Training

Training Input to Critic

Relevant sample:

image feature and context from the generator

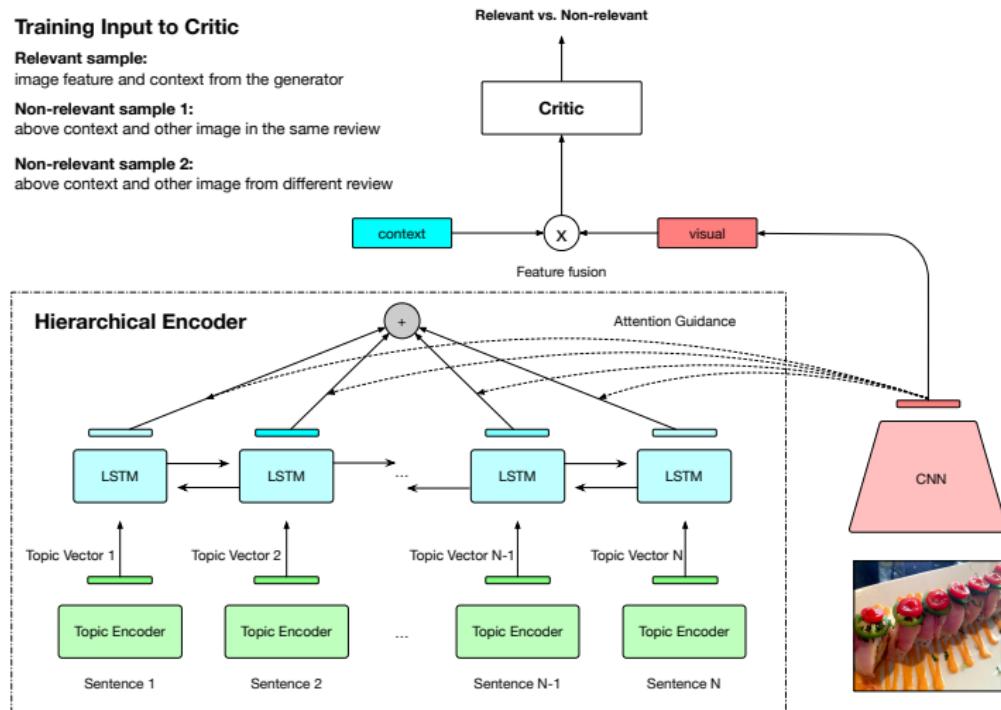
Non-relevant sample 1:

above context and other image in the same review

Non-relevant sample 2:

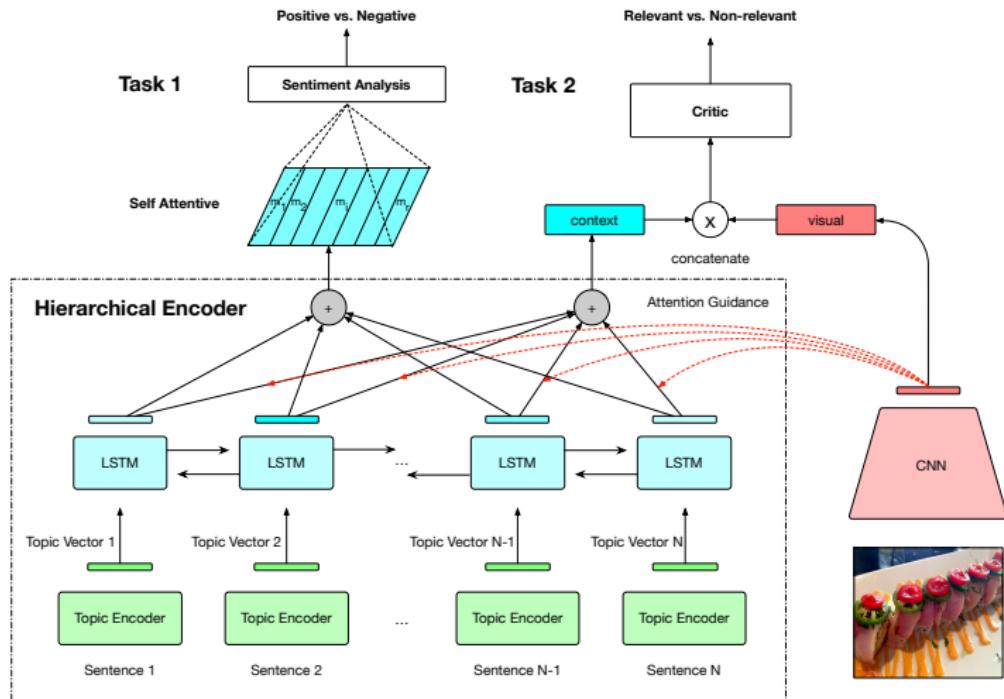
above context and other image from different review

Relevant vs. Non-relevant



Multi-task Learning

Multi-task Learning



Loss Function

Loss Function

New Relevance Loss

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

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Self Attention Loss

$$A = \text{softmax}(W_{s2} \tanh(W_{s1} H^\top + \underbrace{\text{outsidesignal}}_{\text{out}}))$$
$$L_{\text{sent}} = L_{XE} + \lambda_1 \|A^\top A - I\|_F$$

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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.



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!

Review Text

Top 3 Sentences with Basic Model

Top 3 Sentences with Multi-task Model

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

- Yelp restaurant dataset from 17 U.S. major cities.
- 1,000 reviews manually tagged, more being done.

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Baseline

- Relate image captions to review sentences.

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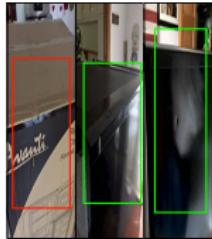
Image Aspect Mining

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What is 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.

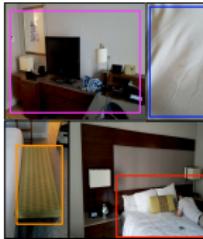
box: dented, holes



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



Sheets: ancient, stained



Bed: comfortable



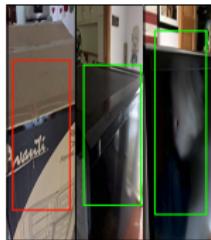
Foot stool: filthy



Yelp Hotel Review

Image Aspect Mining

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Room: lackluster, outdated, dirty



Sheets: ancient, stained



Bed: comfortable



Foot stool: filthy



Yelp Hotel Review

Image Aspect Mining

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

Image Aspect Mining

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

Approaches

Baseline

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

Approaches

Baseline

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

Bilinear + Attention

- Bilinear feature fusion: $y = x_1 * A * x_2$;
- Stacked attentions: multi-step glimpses;

Approaches

Baseline

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

Bilinear + Attention

- Bilinear feature fusion: $y = x_1 * A * x_2$;
- Stacked attentions: multi-step glimpses;

Generative

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

Evaluations

Evaluations

Metric Definition

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

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- Review corpus D and k pre-defined aspects;
- s_{di} : predicted rating on aspect i in review d ;
- s_{di}^* : ground truth rating on aspect i in review d ;

Evaluations

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Datasets

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

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- Research Questions

2 Improved Image Captioning with Adversarial Loss

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3 Congruence Measure between Image and Sentences

- Pseudo Supervised Training
- Loss Functions and Preliminary Results

4 Image Aspect Mining

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5 Conclusions and Research Timeline

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Image Captioning

- Neural image captioning models fine-tuned with GANs
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Matching Sentences to Image

- Pseudo supervised training for matching sentences to image
- Preliminary qualitative effectiveness

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.
- [2]. **Yufeng Ma**, Tingting Jiang, Chandani Shrestha, Edward Alan Fox, Jian Wu, and C. Lee Giles, "Scenarios for advanced services in an ETD digital library," in *Proceedings of ETD2017, the 20th international symposium on electronic theses and dissertations, Washington, DC, August 7-9, 2017*.
- [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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- [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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Thank You!
Questions & Comments?