

# Multimodal Learning Using Recurrent Neural Networks

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This talk follows from joint work with Alan Yuille, Wei Xu, Yi Yang, Jiang Wang, Zhiheng Huang, Haoyuan Gao, Jonathan Huang, Kevin Murphy, Jiajing Xu, and Kevin Jing, among others.

# Content

- The m-RNN image captioning model
  - Image caption generation
  - Image retrieval (given query sentence)
  - Sentence retrieval (given query image)
- Extensions
  - Incremental novel concept captioning
  - Multimodal word embedding learning
  - Referring expressions
  - Visual Question Answering

# The m-RNN Image Captioning Model

<http://www.stat.ucla.edu/~junhua.mao/m-RNN.html>



a close up of a bowl of food  
on a table



a train is traveling down the  
tracks in a city



a pizza sitting on top of a  
table next to a box of pizza

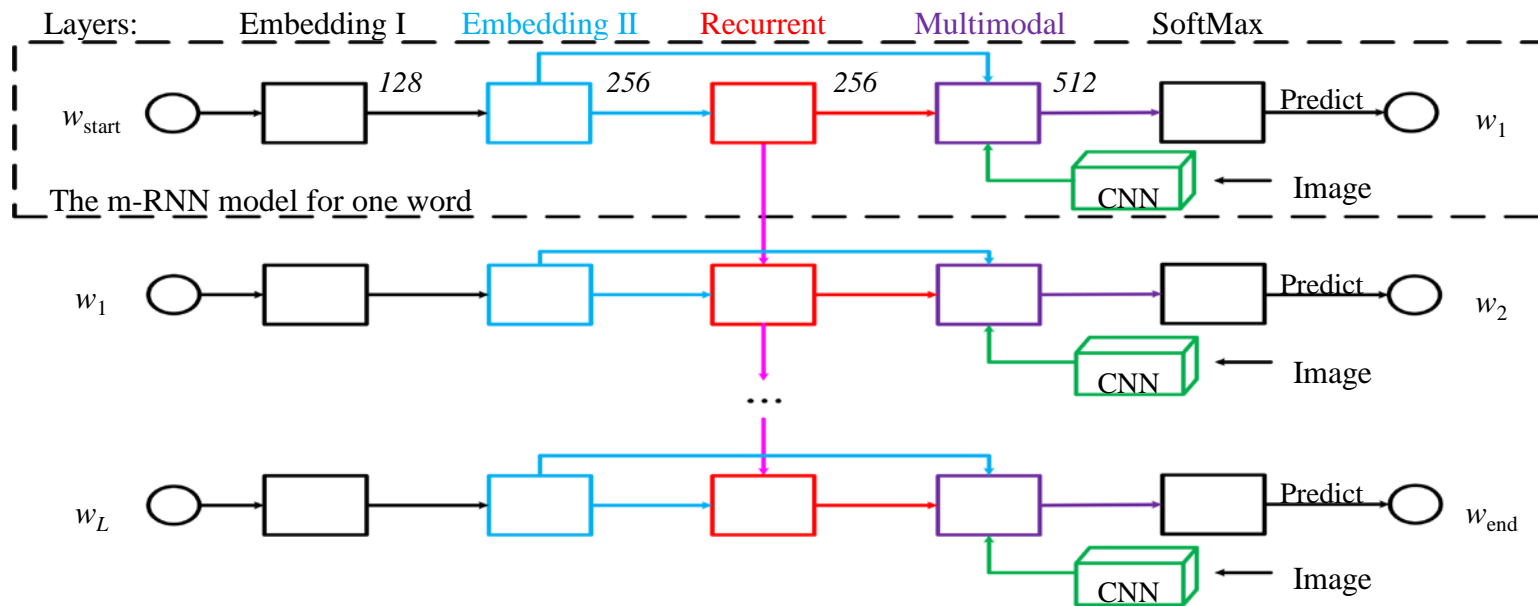


a cat laying on a bed with a  
stuffed animal

# Abstract

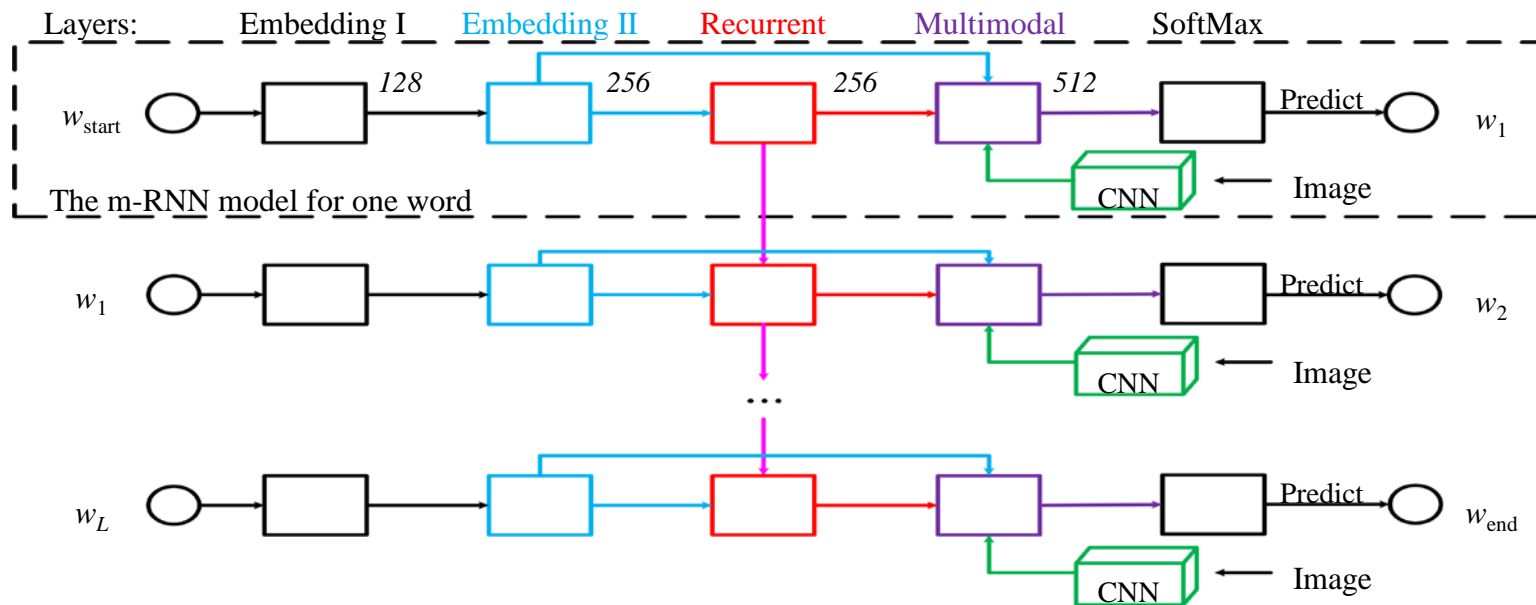
- Three Tasks:
  - Image caption generation
  - Image retrieval (given query sentence)
  - Sentence retrieval (given query image)
- One model (m-RNN):
  - A deep Recurrent NN (RNN) for the sentences
  - A deep Convolutional NN (CNN) for the images
  - A multimodal layer connects the first two components
- State-of-the-art Performance:
  - For three tasks
  - On four datasets: IAPR TC-12 [Grubinger et al. 06'], Flickr 8K [Rashtchian et al. 10'], Flickr 30K [Young et al. 14'] and MS COCO [Lin et al. 14']

# The m-RNN Model



$w_1, w_2, \dots, w_L$  is the sentence description of the image  
 $w_{start}, w_{end}$  is the start and end sign of the sentence

# The m-RNN Model



The output of the trained model:

$$P(w_n | w_{1:n-1}, \mathbf{I})$$

# Application

- Image caption generation:
  - Begin with the start sign  $w_{start}$
  - Sample next word from  $P(w_n | w_{1:n-1}, \mathbf{I})$
  - Repeat until generating  $w_{end}$

# Application

- Image caption generation:
  - Begin with the start sign  $w_{start}$
  - Sample next word from  $P(w_n | w_{1:n-1}, \mathbf{I})$
  - Repeat until generating  $w_{end}$
- Image retrieval given query sentence:
  - Ranking score:  $P(w_{1:L}^Q | \mathbf{I}^D) = \prod_{n=2}^L P(w_n^Q | w_{1:n-1}^Q, \mathbf{I}^D)$
  - Output the top ranked images



# Application

- Image caption generation:
  - Begin with the start sign  $w_{start}$
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  - Output the top ranked images
- Sentence retrieval given query image:
  - *Challenge*: Some sentences have high probability for any image query
  - *Solution*: **Normalize** the probability.  $\mathbf{I}'$  are sampled images:

$$\frac{P(w_{1:L}^D | \mathbf{I}^Q)}{P(w_{1:L}^D)} = \sum_{\mathbf{I}'} P(w_{1:L}^D | \mathbf{I}') \cdot P(\mathbf{I}')$$

# Application

- Image caption generation:
  - Begin with the start sign  $w_{start}$
  - Sample next word from  $P(w_n | w_{1:n-1}, \mathbf{I})$
  - Repeat until generating  $w_{end}$
- Image retrieval given query sentence:
  - Ranking score:  $P(w_{1:L}^Q | \mathbf{I}^D) = \prod_{n=2}^L P(w_n^Q | w_{1:n-1}^Q, \mathbf{I}^D)$
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$$\frac{P(w_{1:L}^D | \mathbf{I}^Q)}{P(w_{1:L}^D)} \quad P(w_{1:L}^D) = \sum_{\mathbf{I}'} P(w_{1:L}^D | \mathbf{I}') \cdot P(\mathbf{I}') \quad \Longrightarrow \quad P(\mathbf{I}^Q | w_{1:L}^D) = \frac{P(w_{1:L}^D | \mathbf{I}^Q) \cdot P(\mathbf{I}^Q)}{P(w_{1:L}^D)}$$

Equivalent

# Experiment: Retrieval

R@K: The recall rate of the groundtruth among the top K retrieved candidates

Med r: Median rank of the top-ranked retrieved groundtruth

	Sentence Retrieval (Image to Text)				Image Retrieval (Text to Image)			
	R@1	R@5	R@10	Med r	R@1	R@5	R@10	Med r
<i>Flickr30K</i>								
Random	0.1	0.6	1.1	631	0.1	0.5	1.0	500
DeepFE-RCNN (Karpathy et al. 14')	16.4	40.2	54.7	8	10.3	31.4	44.5	13
RVR (Chen & Zitnick 14')	12.1	27.8	47.8	11	12.7	33.1	44.9	12.5
MNLM-AlexNet (Kiros et al. 14')	14.8	39.2	50.9	10	11.8	34.0	46.3	13
MNLM-VggNet (Kiros et al. 14')	23.0	50.7	62.9	5	16.8	42.0	56.5	8
NIC (Vinyals et al. 14')	17.0	56.0	/	7	17.0	<b>57.0</b>	/	7
LRCN (Donahue et al. 14')	14.0	34.9	47.0	11	/	/	/	/
DeepVS-RCNN (Karpathy et al. 14')	22.2	48.2	61.4	4.8	15.2	37.7	50.5	9.2
Ours-m-RNN-AlexNet	18.4	40.2	50.9	10	12.6	31.2	41.5	16
Ours-m-RNN-VggNet	<b>35.4</b>	<b>63.8</b>	<b>73.7</b>	<b>3</b>	<b>22.8</b>	50.7	<b>63.1</b>	<b>5</b>
<i>MS COCO</i>								
Random	0.1	0.6	1.1	631	0.1	0.5	1.0	500
DeepVS-RCNN (Karpathy et al. 14')	29.4	62.0	75.9	2.5	20.9	<b>52.8</b>	69.2	4
Ours-m-RNN-VggNet	<b>41.0</b>	<b>73.0</b>	<b>83.5</b>	<b>2</b>	<b>29.0</b>	42.2	<b>77.0</b>	<b>3</b>

(\*) Results reported on 04/10/2015.

# Experiment: Captioning

Results on the MS COCO test set

	B1	B2	B3	B4	CIDEr	ROUGE <sub>L</sub>	METEOR
Human-c5 (**)	0.663	0.469	0.321	0.217	0.854	0.484	0.252
m-RNN-c5	0.668	0.488	0.342	0.239	0.729	0.489	0.221
m-RNN-beam-c5	0.680	0.506	0.369	0.272	0.791	0.499	0.225
Human-c40 (**)	0.880	0.744	0.603	0.471	0.910	0.626	0.335
m-RNN-c40	0.845	0.730	0.598	0.473	0.740	0.616	0.291
m-RNN-beam-c40	0.865	0.760	0.641	0.529	0.789	0.640	0.304

c5 and c40: evaluated using 5 and 40 reference sentences respectively.

“-beam” means that we generate a set of candidate sentences, and then selects the best one. (beam search)

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(\*\*) Provided in <https://www.codalab.org/competitions/3221#results>

(\*\*\*) We evaluate it on the MS COCO evaluation server: <https://www.codalab.org/competitions/3221>

# Discussion: Chinese captions



一个年轻的男孩坐在长椅上。

A young boy sitting on a bench.



一列火车在轨道上行驶。

A train running on the track.



一辆双层巴士停在一个城市街道上。

A double decker bus stop on a city street.

We acknowledge Haoyuan Gao and Zhiheng Huang from Baidu Research for designing the Chinese image captioning system

# Novel Visual Concept Learning

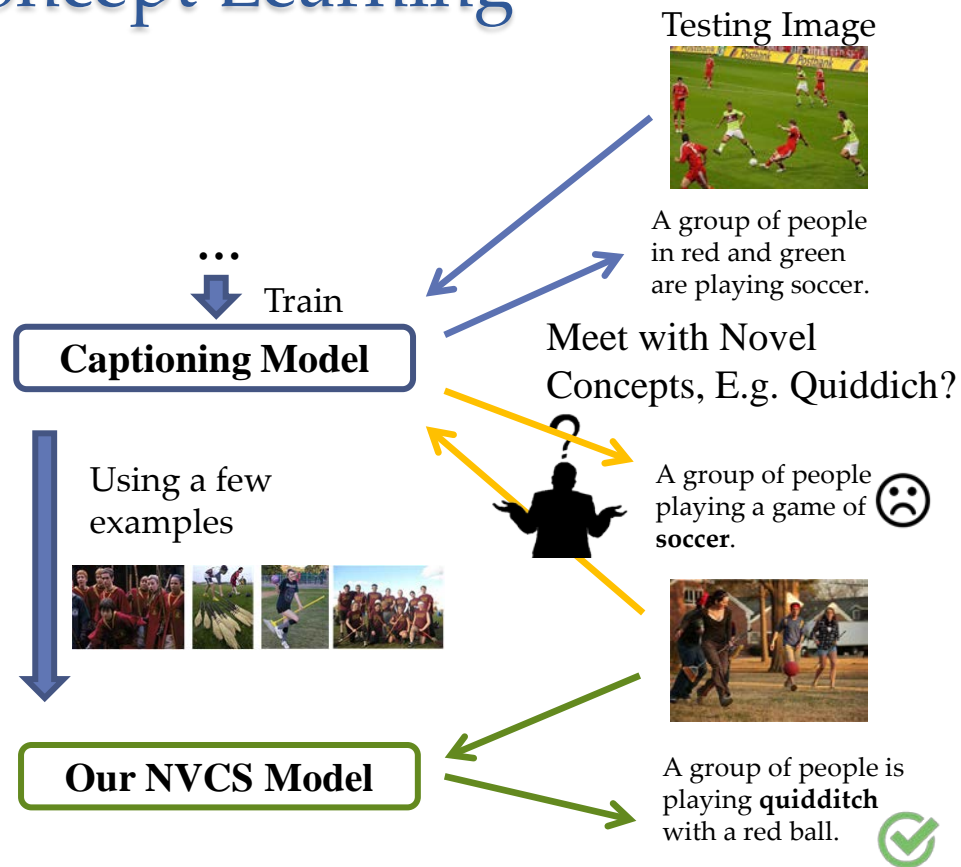
# Novel Visual Concept Learning

The learning Novel Visual Concept from Sentences (*NVCS*) Task:

- Hard but important
  - Slow if retrain the whole model
  - Lack of training samples
  - Overfit easily

Our contributions to this new task:

- Datasets **[Released]**
- A novel framework
  - Fast, simple and effective
  - No extensive retraining



# The Novel Visual Concept Dataset

- Released on project page: [http://www.stat.ucla.edu/~junhua.mao/projects/child\\_learning.html](http://www.stat.ucla.edu/~junhua.mao/projects/child_learning.html)
- Contains 11 novel visual concepts
  - 100 images per concept, 5 sentences per image

Windmill



A windmill with a white body and a dark roof stands in a field of tulips. The tulips are in various colors, including white, yellow, and purple, and are in full bloom. The background shows green trees under a clear blue sky.

Rocket Gun



A plate of golden-brown, fried food, likely tempura, is garnished with fresh vegetables, including orange and green bell peppers. In the background, there are some bottles and a black pot.

Huan Opera



Two performers on a stage. One performer is wearing a green and white costume, and the other is wearing a pink and white costume. They are both in traditional Chinese opera attire. The background is dark, and there are some trees visible.

Wedding Dress



Two women in white wedding dresses. One woman is standing and looking towards the camera, while the other is standing next to her, looking towards the first woman. They are both wearing long, flowing veils. The background is a simple indoor setting.



# Our NVCS model & Results

## Key components:

- Transposed Weight Sharing
  - Reduce ~50% parameters
- Baseline Probability Fixation
  - Avoid overfitting to novel concepts
  - Do not disturb previously learned concepts
  - Only need a few samples

Compared to the re-training strategy from scratch

- Performs comparable or even better
- Much Faster ( $\geq 50$  X speed up)

## Example results:

Novel Concepts:

Cat



T-tex



Before NVCS  
Training

a window with a  
window

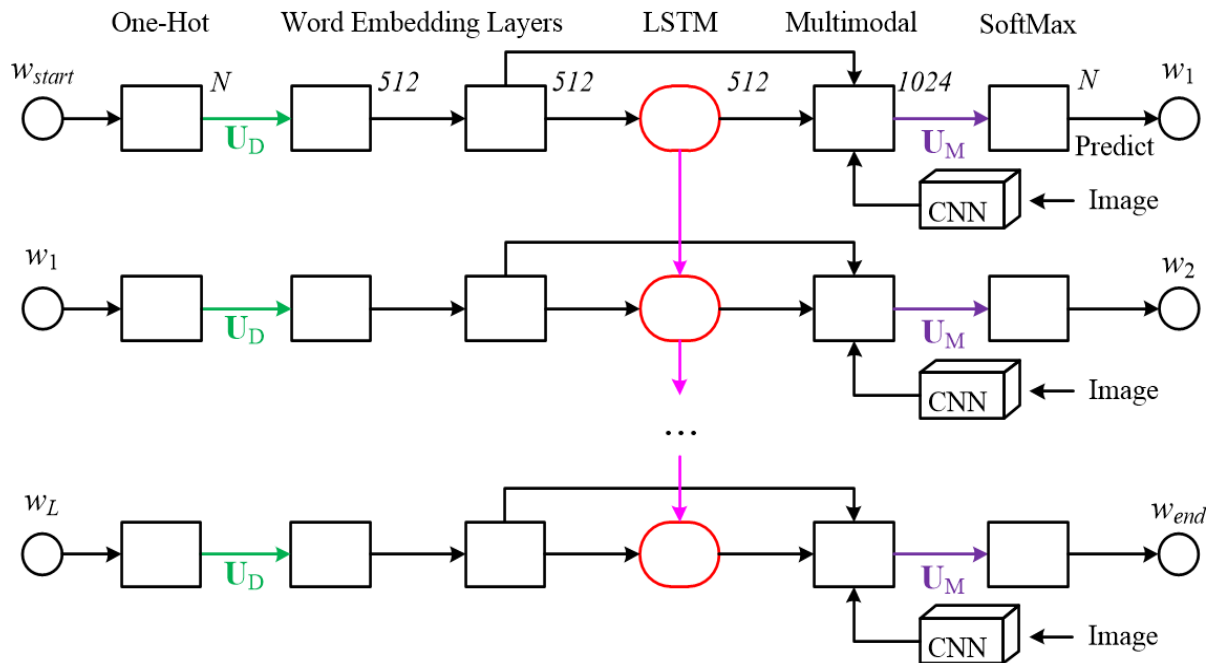
a man in blue shirt  
is riding a horse

After NVCS  
Training

a cat standing in  
front of a  
window

a t-rex is standing  
in a room with a  
man

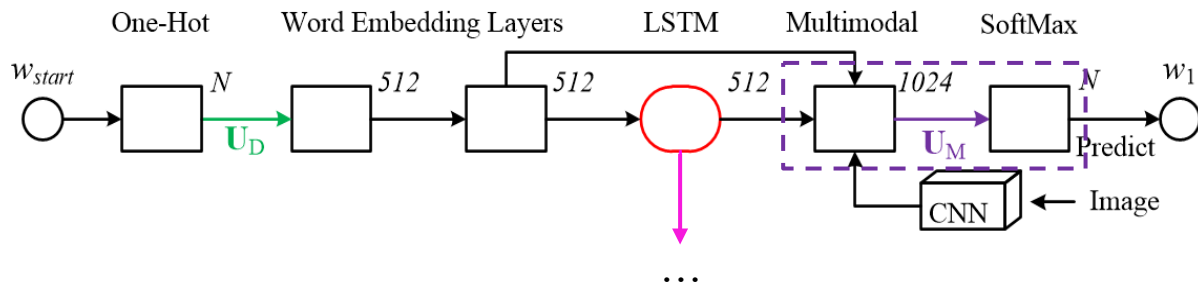
# Transposed Weight Sharing



$$\mathbf{w}(t) = f(\mathbf{U}_D \mathbf{h}(t))$$

$$\mathbf{y}(t) = g(\mathbf{U}_M \mathbf{m}(t) + \mathbf{b})$$

# Transposed Weight Sharing

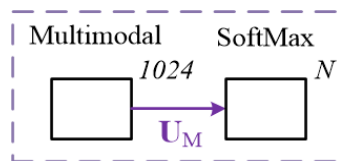


$$\mathbf{w}(t) = f(\mathbf{U}_D \mathbf{h}(t))$$

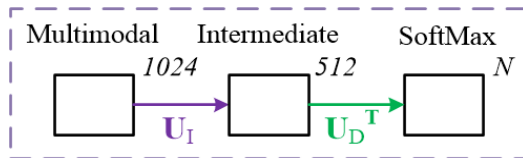
$$\mathbf{y}(t) = g(\mathbf{U}_M \mathbf{m}(t) + \mathbf{b})$$

Decompose  $\mathbf{U}_M$   $\Downarrow$

$$\mathbf{y}(t) = g[\mathbf{U}_D^T f(\mathbf{U}_I \mathbf{m}(t)) + \mathbf{b}]$$



$\Downarrow$  Transposed Weight Sharing with  $\mathbf{U}_D$



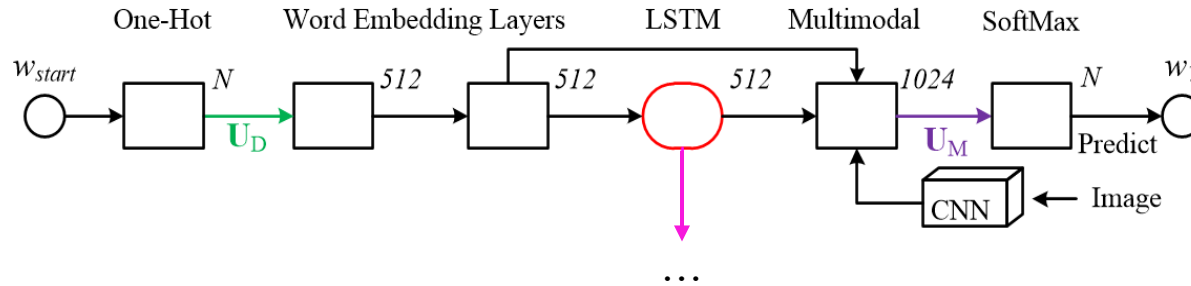
# Transposed Weight Sharing

	B-1	B-2	B-3	B-4	METEOR	CIDEr	ROUGE.L
m-RNN [38]	0.680	0.506	0.369	0.272	0.225	0.791	0.499
ours-TWS	<b>0.685</b>	<b>0.512</b>	<b>0.376</b>	<b>0.279</b>	<b>0.229</b>	<b>0.819</b>	<b>0.504</b>

	BiasFix	Centralize	TWS	$f$
Deep-NVCS-UnfixedBias	×	×	✓	0.851
Deep-NVCS-FixedBias	✓	×	✓	0.860
Deep-NVCS-NoBPF-NoTWS	×	×	×	0.839
Deep-NVCS-BPF-NoTWS	✓	✓	×	0.850
Deep-NVCS-BPF-TWS	✓	✓	✓	<b>0.875</b>

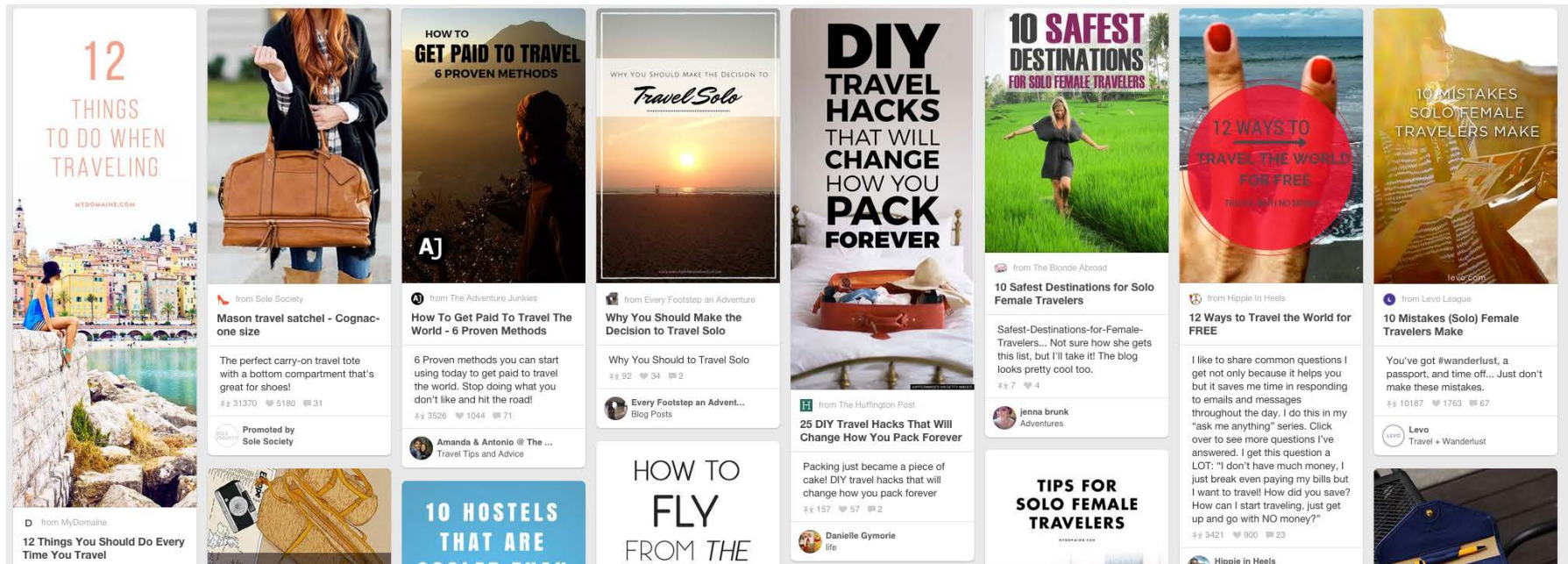
# Discussion: Word Embeddings

New Word	Five nearest neighbours
cat	kitten; tabby; puppy; calico; doll;
motorcycle	motorbike; moped; vehicle; motor; motorbikes;
quidditch	soccer; football; softball; basketball; frisbees;
t-rex	giraffe's; bull; pony; goat; burger;
samisen	guitar; wii; toothbrushes; purse; contents;



Will learned word embedding benefit from the transposed weight sharing strategy?

# Learning Multimodal Word Embeddings



# The Pinterest40M training dataset



This strawberry limeade cake is fruity, refreshing, and gorgeous! Those lovely layers are impossible to resist.



This is the place I will be going (hopefully) on my first date with Prince Stephen. It's the palace gardens, and they are gorgeous. I cannot wait to get to know him and exchange photography ideas!



White and gold ornate library with decorated ceiling, iron-work balcony, crystal chandelier, and glass-covered shelves. (I don't know if you're allowed to read a beat-up paperback in this room.)



This flopsy-wopsy who just wants a break from his walk. | 18 German Shepherd Puppies Who Need To Be Snuggled Immediately



Make two small fishtail braids on each side, then put them together with a ponytail.

# The Pinterest40M training dataset

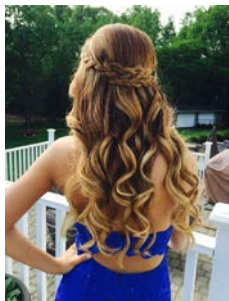
	Image	Sentences
Flickr8K [15]	8K	40K
Flickr30K [35]	30K	150K
IAPR-TC12 [12]	20K	34K
MS COCO [22]	200K	1M
Im2Text [28]	1M	1M
Pinterset40M	40M	300M



# The Pinterest related phrase testing dataset

User Query

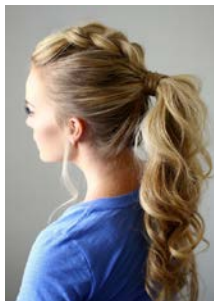
hair styles



Annotations:

hair tutorial  
prom night ideas  
long hair  
beautiful  
...

Most Clicked Items

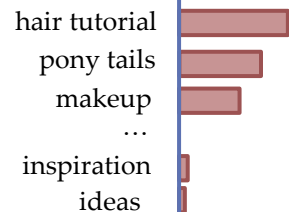


Annotations:

pony tails  
unique hairstyles  
hair tutorial  
picture inspiration  
...

Positive Phrases for the Query

Sorted by Click



Final List

pony tails  
makeup  
...

Remove overlapping words

Related Phrase 10M dataset (RP10M)

Crowdsourcing cleaned up



Gold Related Phrase 10K dataset (Gold RP10K)

For the word or phrase: **alchemy tattoo**

Which phrase is more related to the text above?(required)

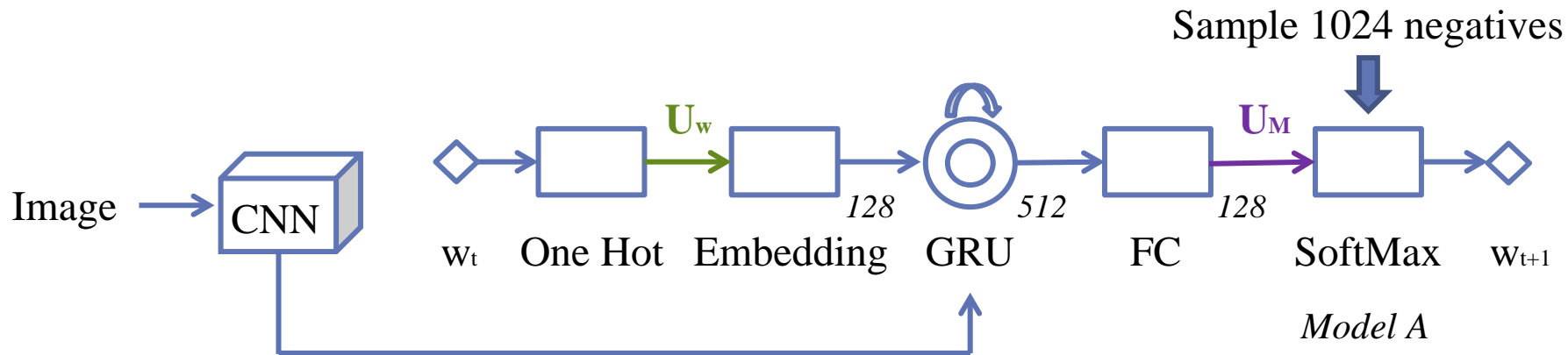
TYPE: CML:RADIOS VALIDATORS: REQUIRED

- A is more related
- B is more related
- They are both equally good
- They are both equally bad
- I can't tell/don't know what the terms mean

A **valentines arts and crafts**

B **witch**

# The Multimodal Word Embedding Models



Baselines (No transposed weight sharing):

*Model B: Supervision on the final GRU state*  $\mathcal{L}_{state} = \frac{1}{n} \sum_s \| h_{l_s} - \text{ReLU}(W_I f_{I_s}) \|$

*Model C: Supervision on the embeddings*  $\mathcal{L}_{emb} = \frac{1}{n} \sum_s \frac{1}{l_s} \sum_t \| e_t - \text{ReLU}(W_I f_{I_s}) \|$

# Experiments

	Gold RP10K	RP10M	dim
Model A without visual (Pure text RNN)	0.748	0.633	128
Model A without weight sharing	0.773	0.681	128
Model A (weigh shared multimodal RNN)	<b>0.843</b>	<b>0.725</b>	128
Model B (direct visual supervisions on the final RNN state)	0.705	0.646	128
Model C (direct visual supervisions on the embeddings)	0.771	0.687	128
Word2Vec-GoogleNews [25]	0.716	0.596	300



# Content

- The m-RNN image captioning model
  - Image caption generation
  - Image retrieval (given query sentence)
  - Sentence retrieval (given query image)
- Extensions
  - Incremental novel concept captioning
  - Multimodal word embedding learning
  - **Referring expressions**
  - Visual Question Answering

# Unambiguous Object Descriptions

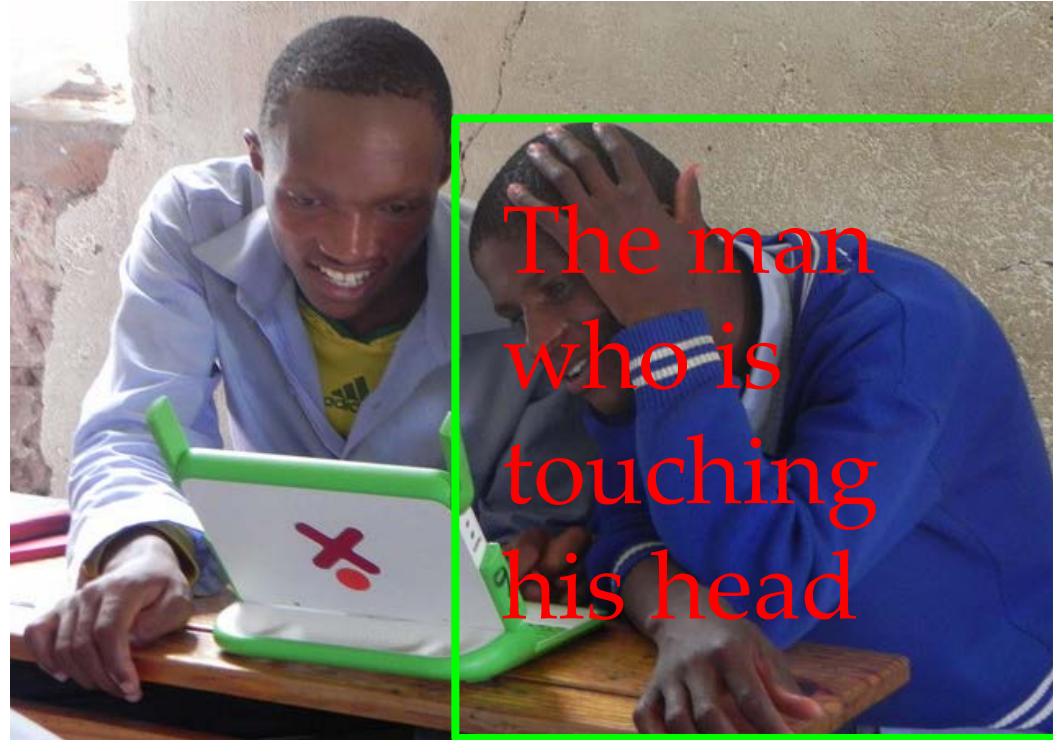
- ✗ A man.
- ✗ A man in blue.
- ✓ A man in blue sweater.
- ✓ A man who is touching his head.



# *Unambiguous* Object Descriptions

(Referring Expressions [Kazemzadeh *et.al* 2014]):

**Uniquely** describes the relevant object or region within its context.



# It is hard to evaluate image captions.

Two men are sitting next to each other.



Two men are sitting next to each other in front of a desk watching something from a laptop.



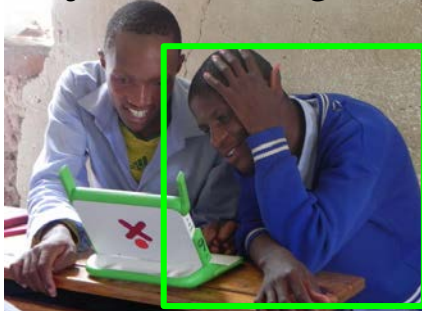


# Speaker

Whole frame image



Object bounding box



Input

Input

Output

Our Model

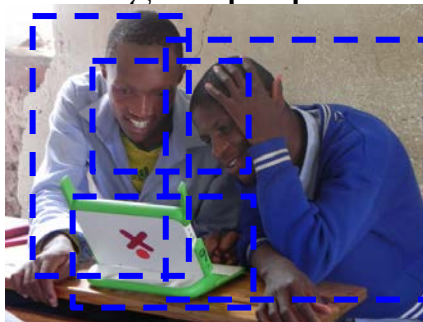
Input

Input

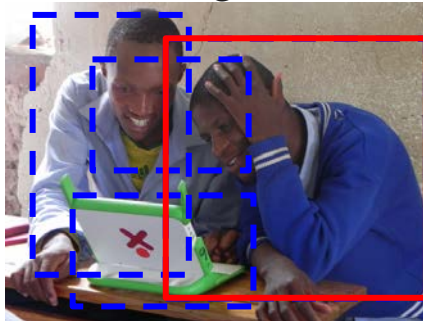
Output

# Listener

Whole frame image & Region proposals



Chosen region in red



Referring Expression

*"The man who is touching his head."*

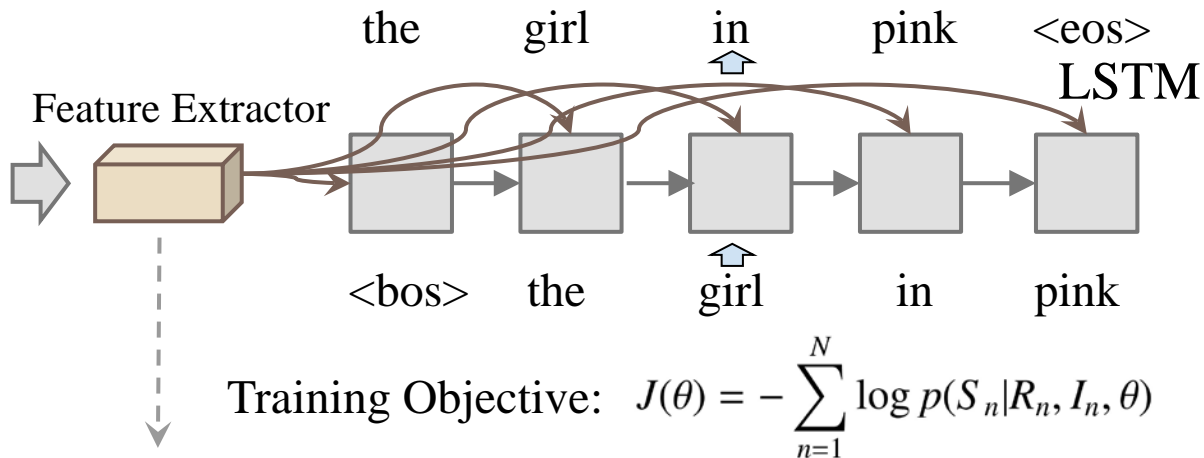
# The Baseline Model

[Mao *et.al* 2015]

[Vinyals *et. al* 2015] ... )

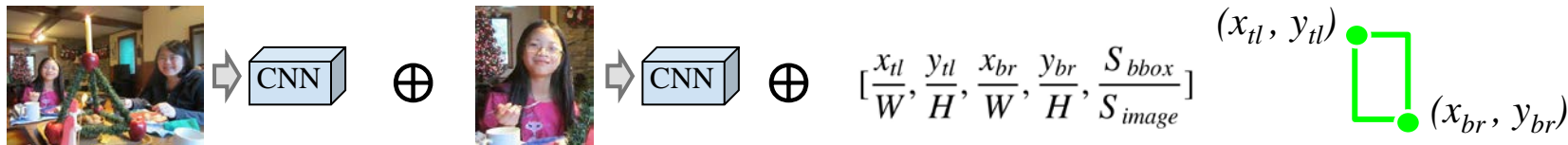
[Donahue *et.al* 2015]

Adapting a LSTM image captioning model



 VGGNet  
[Simonyan *et. al* 2015]

Feature Extractor (2005 dimension feature)



# The Speaker-Listener Pipeline

Speaker module:

1. Decode with beam search
2. Hard to evaluate by itself?

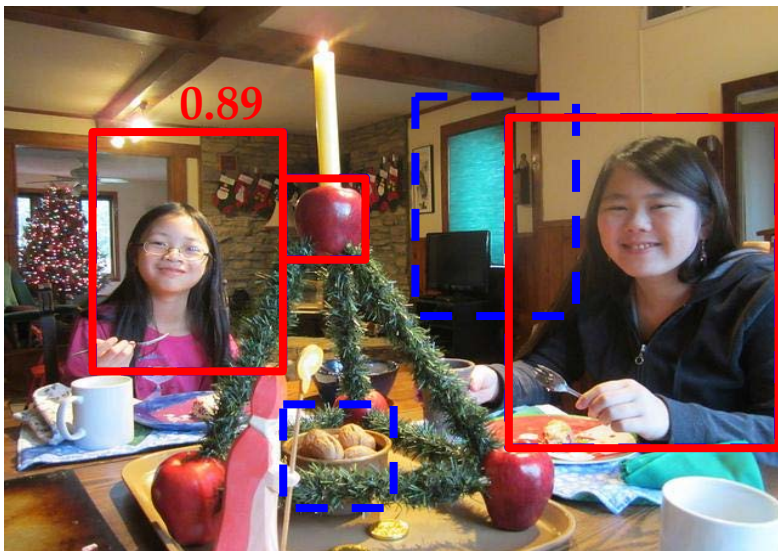
# The Speaker-Listener Pipeline

Speaker module:

1. Decode with beam search
2. Hard to evaluate by itself?

Listener module:

“A girl in pink”



$$p(S/R_n, I)$$

0.89

0.32

0.05

...

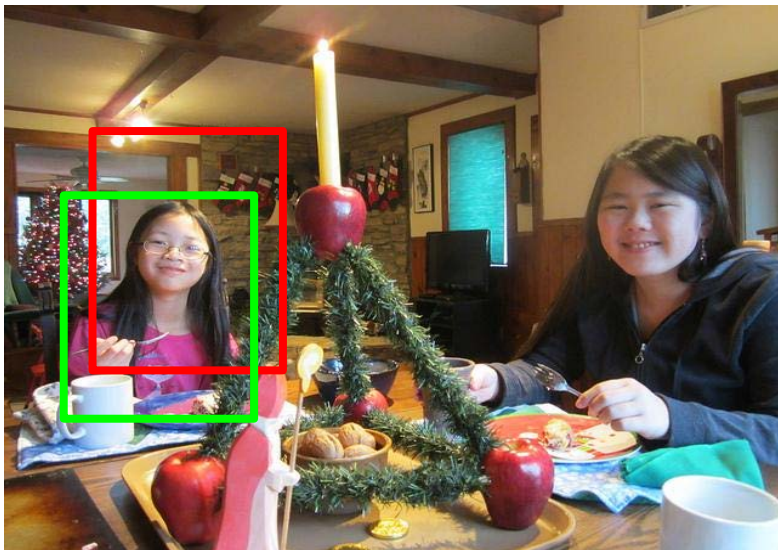
Multibox Proposals [Erhan *et.al* 2014]

# The Speaker-Listener Pipeline

Speaker module:

1. Decode with beam search
2. Hard to evaluate by itself?

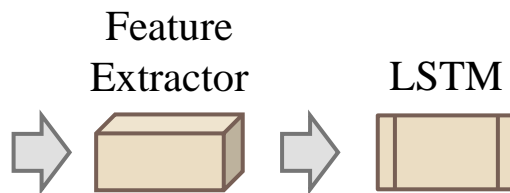
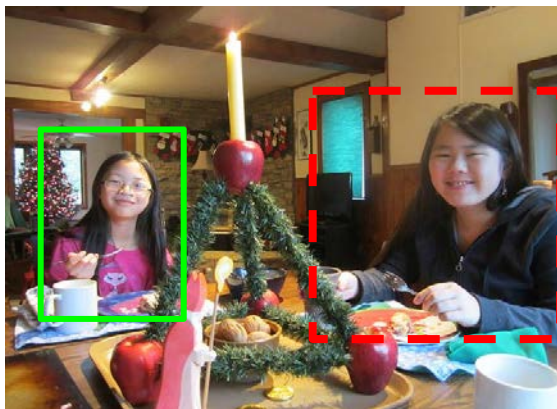
Listener module:



“A girl in pink”

- Easy to objectively evaluate.
  - *Precision@1*
- Evaluate the whole system in an end-to-end way

# Speaker needs to *consider the listener*



"A smiling girl"?

The baseline model want to maximize the  $p(S/R, I)$

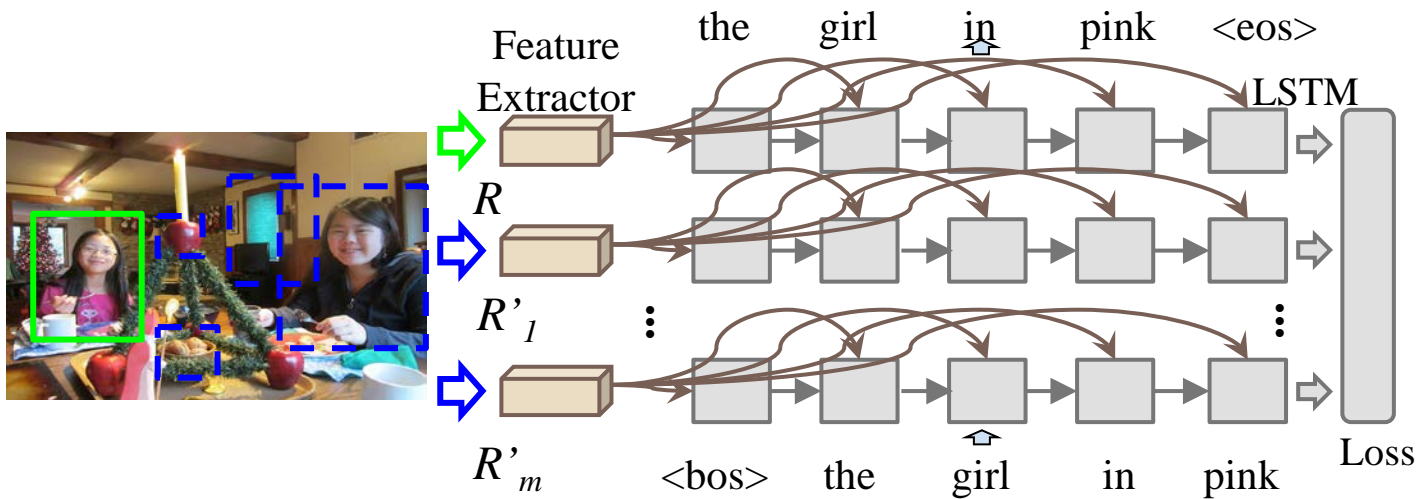
- Good to generate generic descriptions
- Not discriminative

A better, more discriminative model:

- Consider all possible regions
- maximize the gap between  $p(S/R, I)$  and  $p(S/R', I)$

$R'$ : regions serve  
as negatives for  $R$

# Our Full Model



Training Objective:

$$J'(\theta) = - \sum_{n=1}^N \log \frac{p(S_n | R_n, I_n, \theta)}{\sum_{R' \in C(I_n)} p(S_n | R', I_n, \theta)} = - \sum_{n=1}^N \log p(R_n | S_n, I_n, \theta)$$

$$J''(\theta) = - \sum_{n=1}^N \left\{ \log p(S_n | R_n, I_n, \theta) + \lambda \max(0, M - \log p(S_n | R_n, I_n, \theta) + \log p(S_n | R'_n, I_n, \theta)) \right\}$$

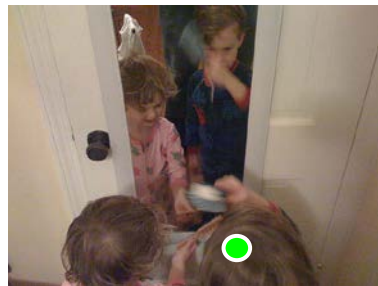
# Dataset

Available at [https://github.com/mjhucla/Google\\_Refexp\\_toolbox](https://github.com/mjhucla/Google_Refexp_toolbox)



The black and yellow backpack sitting on top of a suitcase.

A yellow and black back pack sitting on top of a blue suitcase.



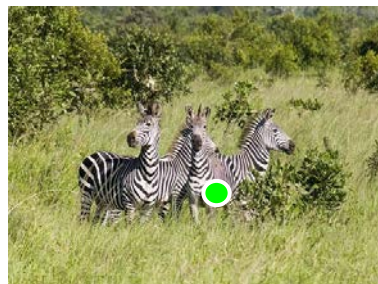
A boy brushing his hair while looking at his reflection.

A young male child in pajamas shaking around a hairbrush in the mirror.



An apple desktop computer.

The white iMac computer that is also turned on.



Zebra looking towards the camera.

A zebra third from the left.

26,711 images (from MS COCO [Lin et.al 2015]), 54,822 objects and 104,560 referring expressions.



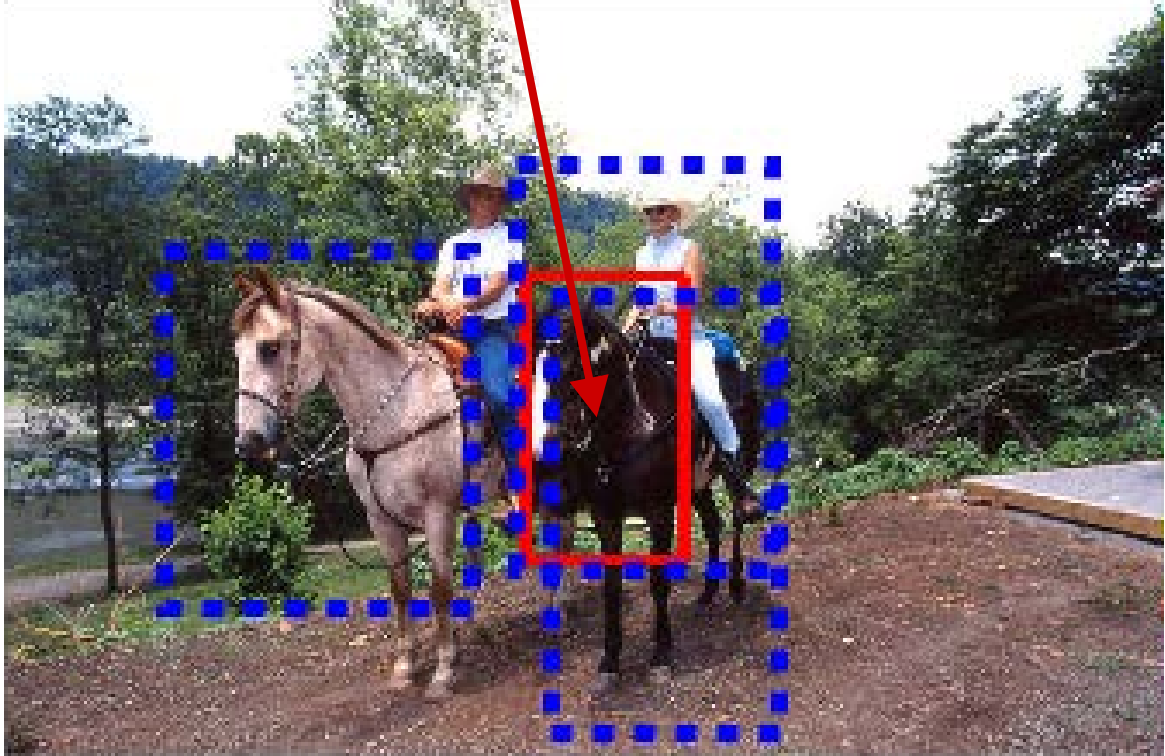
# Listener Results



A dark brown horse with a white stripe wearing a black studded harness.



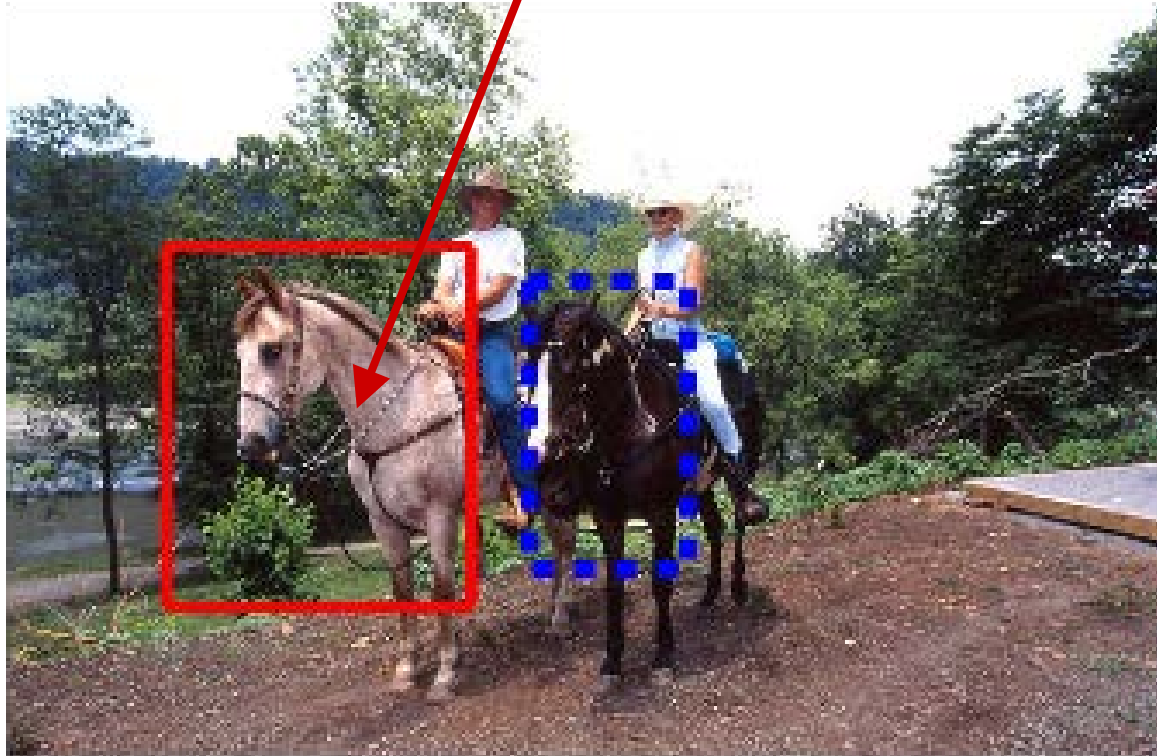
A dark brown horse with a white stripe wearing a black studded harness.



A white horse carrying a man.



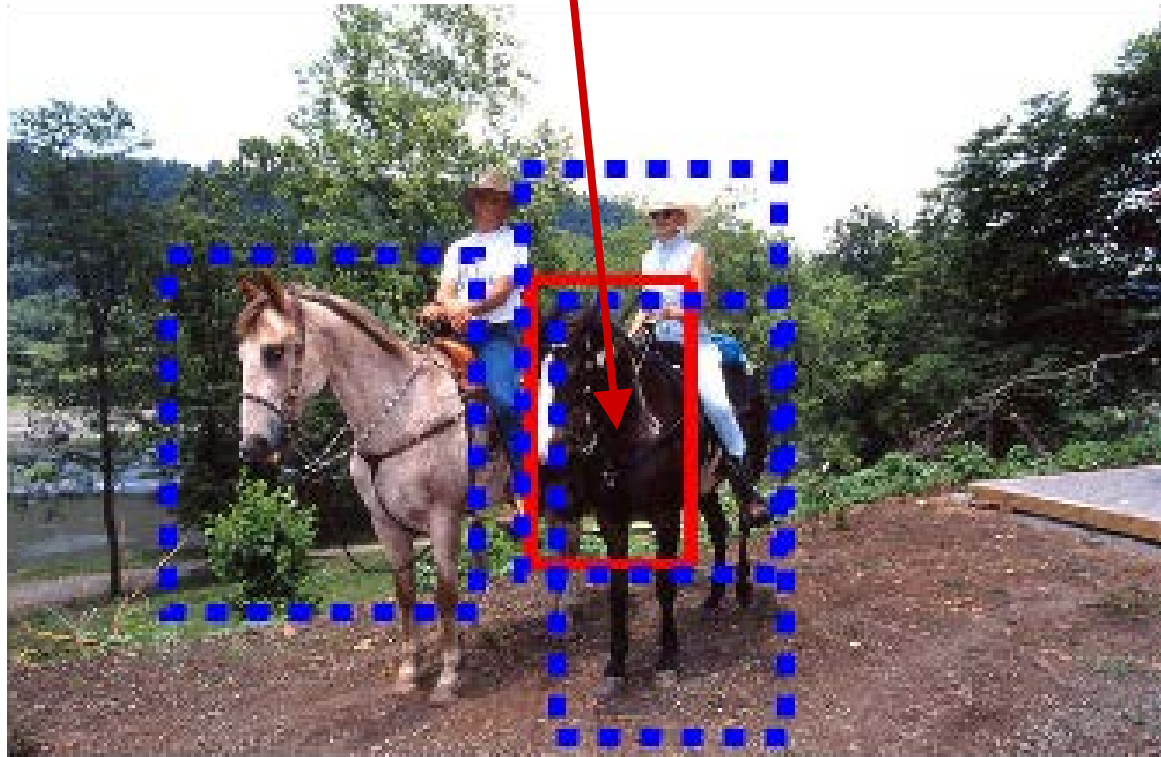
A white horse carrying a man.



A dark horse carrying a woman



A dark horse carrying a woman

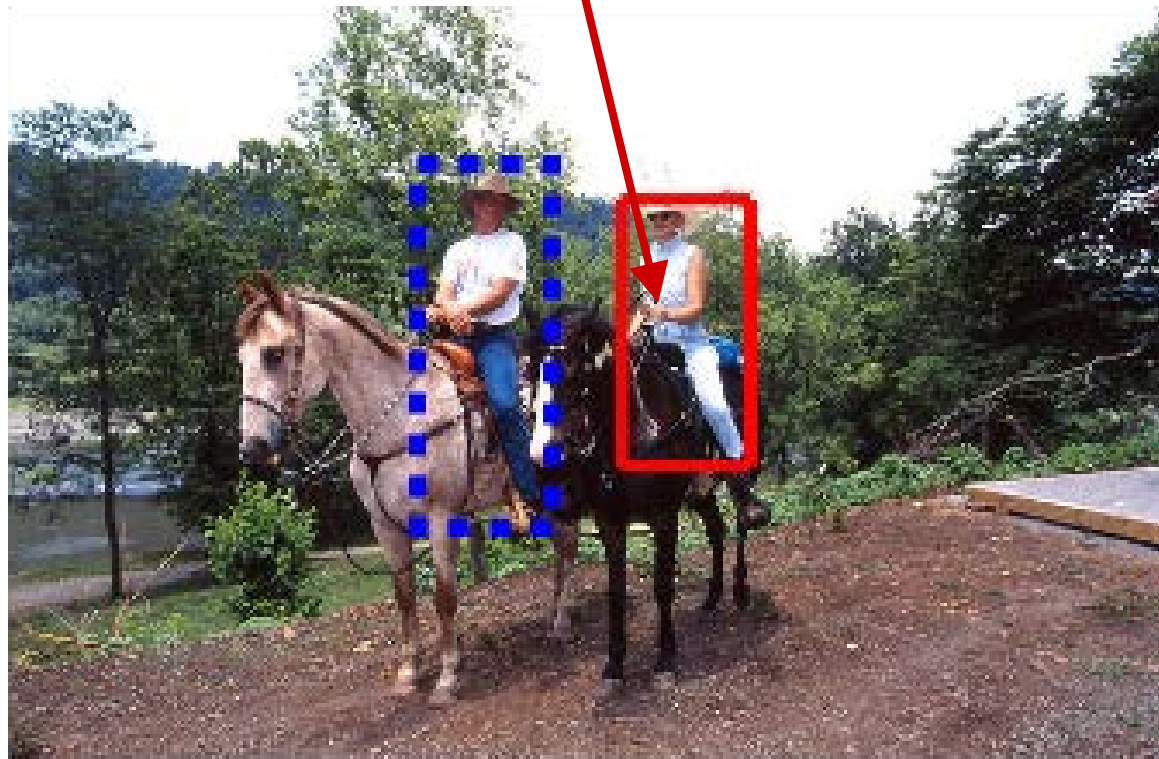


A woman on the dark horse.

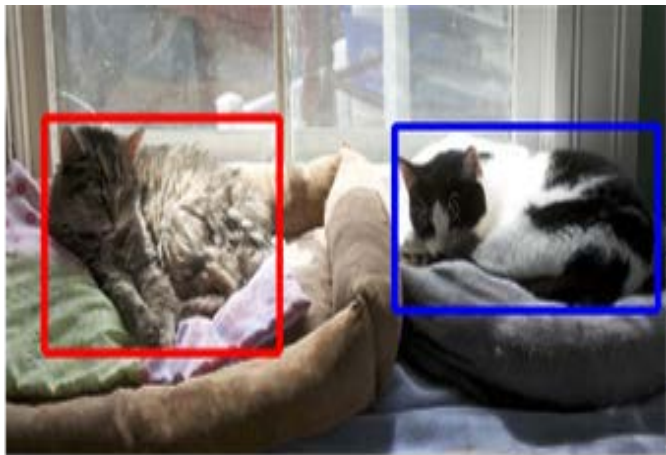




A woman on the dark horse.



# Speaker Results



A cat laying on a bed.

A black and white cat.

-----

A cat laying on the left.

A black cat laying on  
the right.

Baseline

Our Full Model

# Experiments: 4% improvement for precision@1

	Baseline	Our full model	Improvement
Listener Task	40.6	44.6	4.0
End-to-End (Speaker & Listener)	48.5	51.3	2.8
<hr/>			
Human Evaluation (Speaker Task)	15.9	20.4	4.5

# Take Home Message

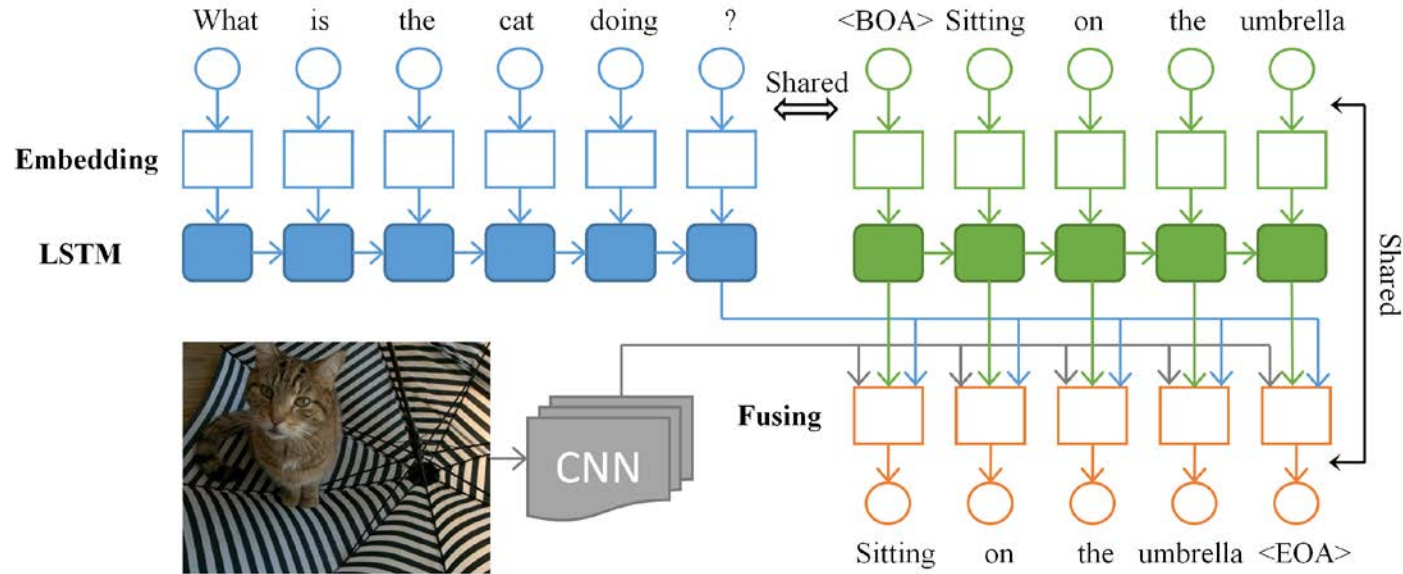
*To be a better  
communicator, need  
to be a better  
listener!!*





# Content

- The m-RNN image captioning model
  - Image caption generation
  - Image retrieval (given query sentence)
  - Sentence retrieval (given query image)
- Extensions
  - Incremental novel concept captioning
  - Multimodal word embedding learning
  - Referring expressions
  - **Visual Question Answering**

# Visual Question Answering



# Visual Question Answering

Image					
Question	公共汽车是什么颜色的? What is the color of the bus?	黄色的是什么? What is there in yellow?	草地上除了人以外还有什么动物? What is there on the grass, except the person?	猫咪在哪里? Where is the kitty?	观察一下说出食物里任意一种蔬菜的名字? Please look carefully and tell me what is the name of the vegetables in the plate?
Answer	公共汽车是红色的。 The bus is red.	香蕉。 Bananas.	羊。 Sheep.	在椅子上。 On the chair.	西兰花。 Broccoli.

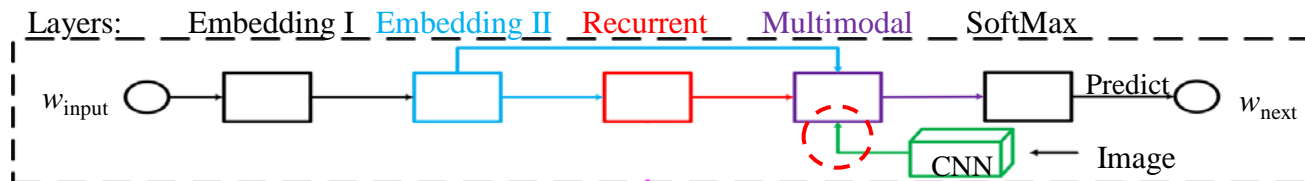
The results of the mQA model on FM-IQA dataset.

	Visual Turing Test			Human Rated Scores			
	Pass	Fail	Pass Rate (%)	2	1	0	Ave. Score
Human	948	52	94.8	927	64	9	1.918
blind-QA	340	660	34.0	-	-	-	-
mQA	647	353	64.7	628	198	174	1.454





# Discussion: Nearest Image Search



$$\mathbf{m}(t) = g(\mathbf{V}_w \cdot \mathbf{w}(t) + \mathbf{V}_r \cdot \mathbf{r}(t) + (\mathbf{V}_I \cdot \mathbf{I})) \quad \text{Refined Image Features}$$

