Deep Learning for Computer Vision

Going beyond Captioning: Visual QA, Visual Dialog

Vineeth N Balasubramanian

Department of Computer Science and Engineering
Indian Institute of Technology, Hyderabad

Review: Question

Can we do the opposite (caption-to-image) of what we learned in the previous lecture? How?

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Yes, we will see deep generative models soon that can do this

Visual Question Answering (VQA): Task Overview[1]

Credit: Aishwarya Agrawal, Devi Parikh, Georgia Tech

[1] Agrawal et al, VQA: Visual Question Answering, IJCV 2015

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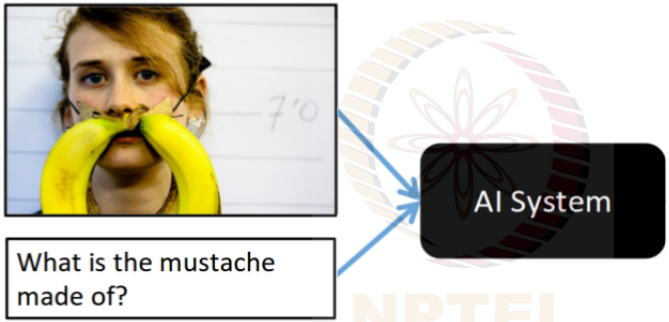

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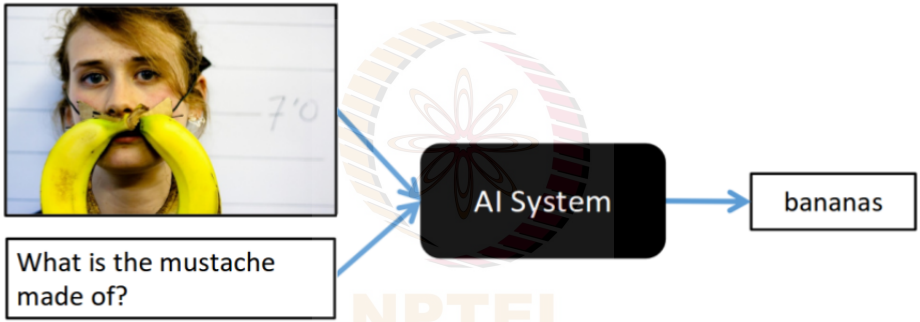

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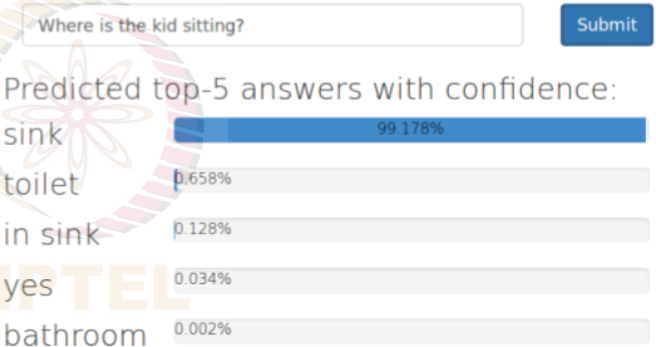
VQA CloudCV Demo

Where is the kid sitting?

Submit

VQA CloudCV Demo



Feel free to try VQA on your images on this link!

VQA Dataset[2]

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How many slices of pizza are there?
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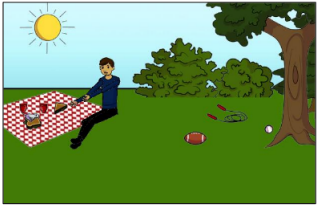

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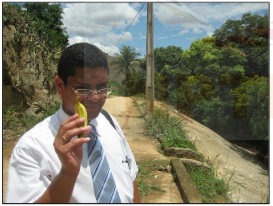

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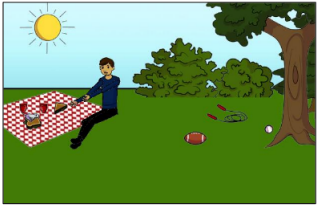

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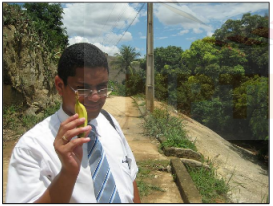

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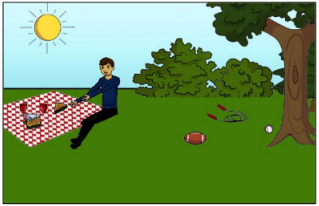

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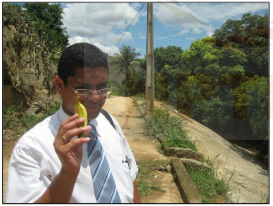

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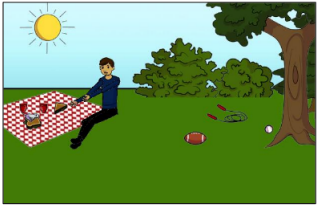

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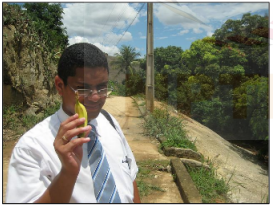

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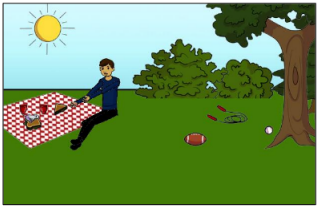

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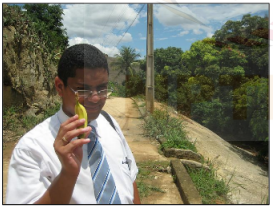

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- **Open-ended answers** and **Multiple-choice answers**
- $250K$ images (MS COCO + $50K$ abstract images)
- $750K$ questions, $10M$ answers
- Each question is answered by 10 human annotators

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COCO-QA[3]

COCOQA 5078
How many leftover donuts is the red bicycle holding?
Ground truth: three

COCOQA 1238
What is the color of the tee-shirt?
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Where is the gray cat sitting?
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- Automatically generate QA pairs with MS COCO captions
- $118K$ QA pairs on $123K$ images
- 4 types of questions: **What object, How many, What color, Where**

[3]Ren et al, Exploring Models and Data for Image Question Answering, NeurIPS 2015

Visual7W[4]

Q: What endangered animal is featured on the truck?

A: **A bald eagle.**
A: A sparrow.
A: A humming bird.
A: A raven.

Q: Where will the driver go if turning right?

A: **Onto 24 ¾ Rd.**
A: Onto 25 ¾ Rd.
A: Onto 23 ¾ Rd.
A: Onto Main Street.

Q: When was the picture taken?

A: **During a wedding.**
A: During a bar mitzvah.
A: During a funeral.
A: During a Sunday church service.

- 7W stands for what, where, when, who, why, how and

[4] Zhu et al, Visual7W: Grounded Question Answering in Image, CVPR 2016

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- 7W stands for what, where, when, who, why, how and which
- $328K$ QA pairs on $\sim 47K$ images

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Visual7W[4]

- 7W stands for what, where, when, who, why, how and which
- $328K$ QA pairs on $\sim 47K$ images
- Two types of tasks: **telling** and **pointing**

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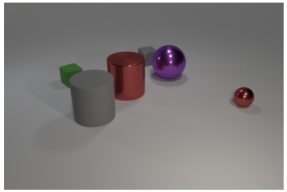
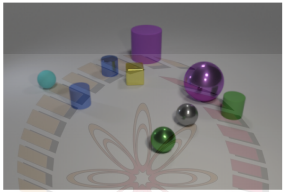
CLEVR[5]



Q: How big is the gray rubber object that is behind the big shiny thing behind the big metallic thing that is on the left side of the purple ball?
A: small
Q-type: query_size
Size: 17

Q: There is a purple ball that is the same size as the red cylinder; what material is it?
A: metal
Q-type: query_material
Size: 9



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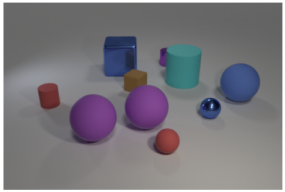

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A: blue
Q-type: query_color
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Q: Is the size of the red rubber sphere the same as the purple metal thing?
A: yes
Q-type: equal_size
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[5] Johnson et al, CLEVR: A Diagnostic Dataset for Compositional Language and Elementary Visual Reasoning, CVPR 2017

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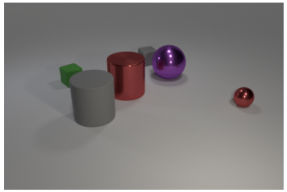

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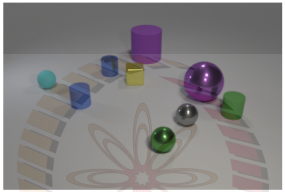

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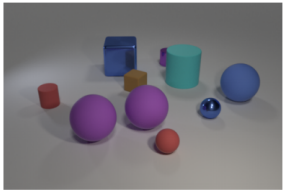

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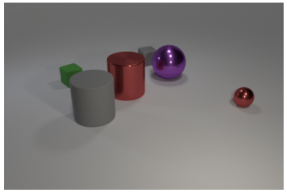

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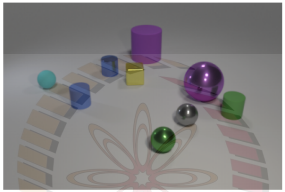

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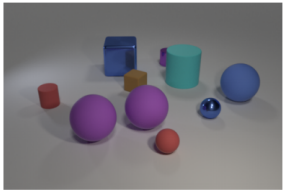

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- $100K$ **rendered images** and $1M$ **automatically generated questions**
- Questions are complex and require reasoning skills

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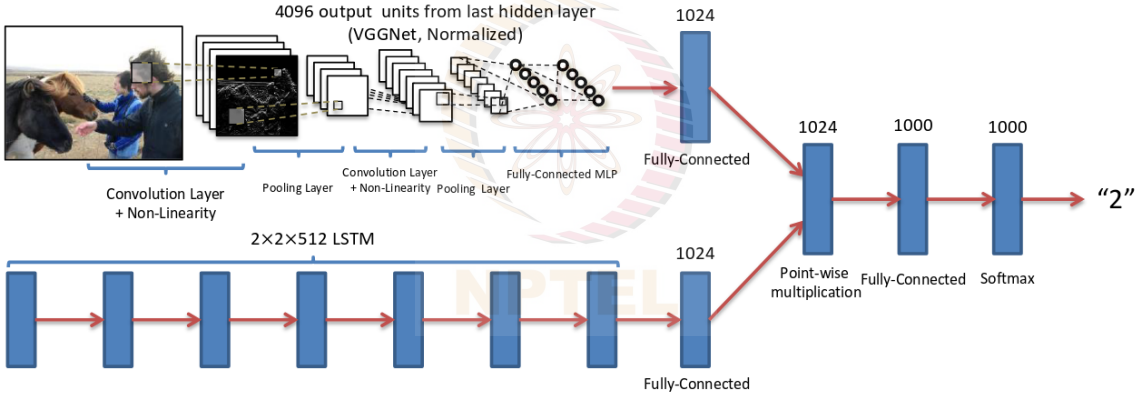
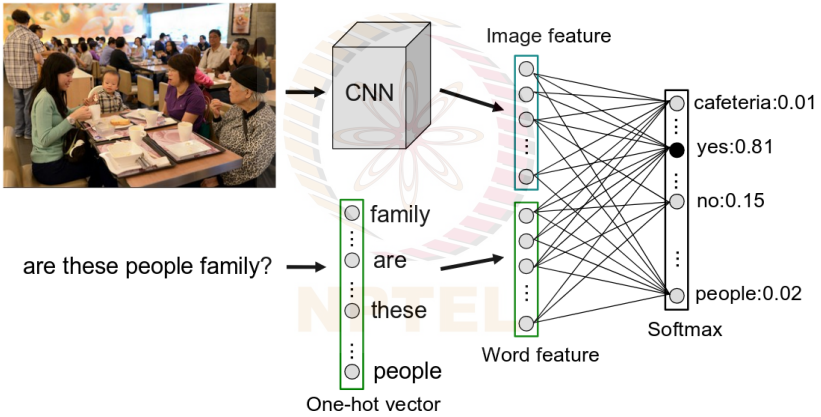
VQA Models

Simple Baseline Model: **LSTM + Image feature**[6]



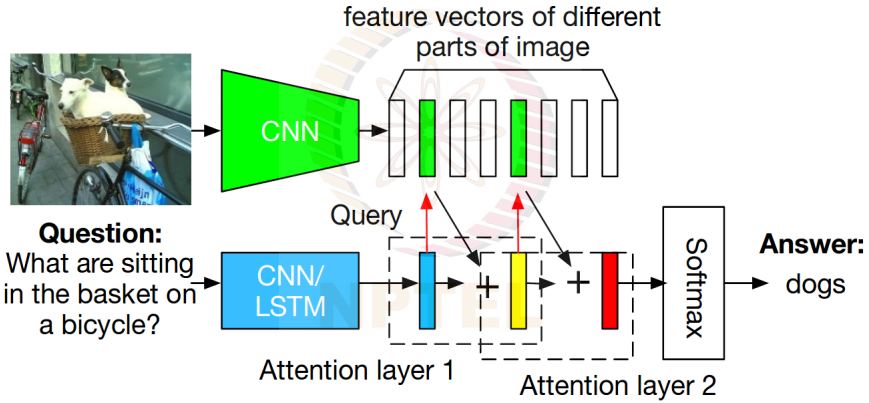
[6] Agrawal et al, VQA: Visual Question Answering, IJCV 2015

VQA Models: Bag-of-words + Image Features (iBOWIMG)[7]



[7] Zhou et al, Simple Baseline for Visual Question Answering, arXiv 2015

VQA Models: Stacked Attention Networks for Image Question Answering[8]



[8]Yang et al, Stacked Attention Networks for Image Question Answering, CVPR 2016

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Original Image First Attention Layer Second Attention Layer

The stacked attention network **first focuses on all referred concepts**, e.g., *bicycle, basket* and objects in the basket (*dogs*) in the first attention layer

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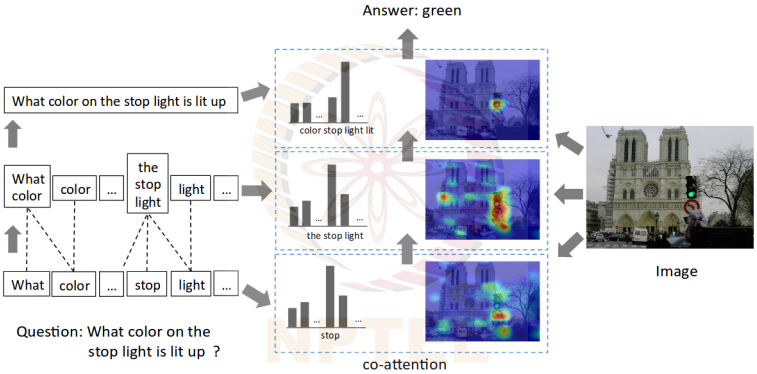
VQA Models

Can we do attention on question as well?

VQA Models: Hierarchical Co-Attention Model[9]



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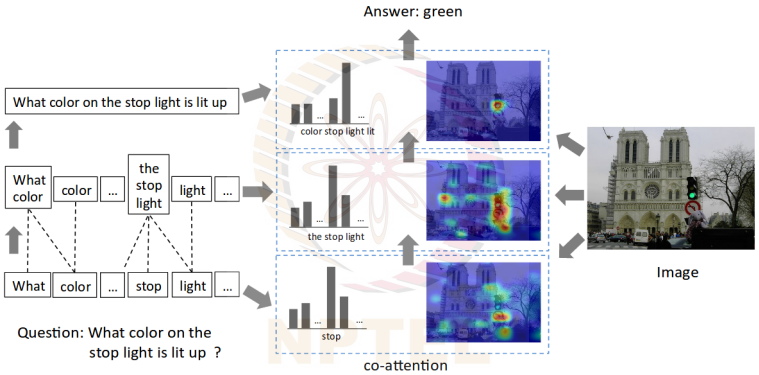

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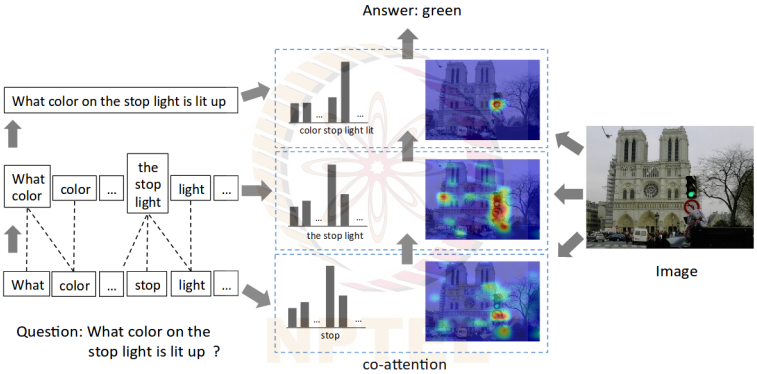

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At each level, apply co-attention on both image and question

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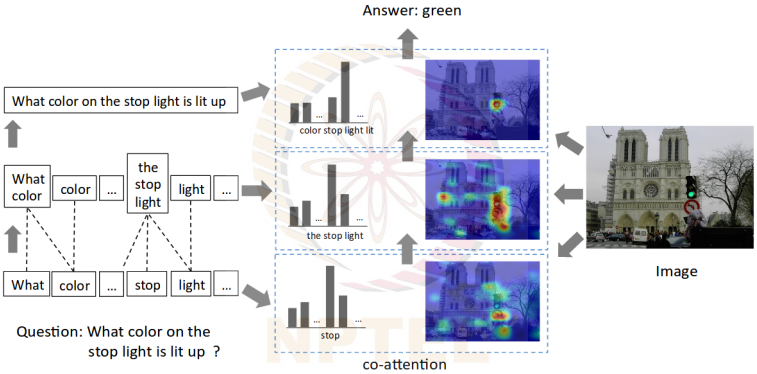

Given a question, extract its word level, phrase level and question level embeddings

At each level, apply co-attention on both image and question

Final answer prediction is based on all co-attended image and question features

[9] Lu et al, Hierarchical Question-Image Co-Attention for Visual Question Answering, NeurIPS 2016

VQA Models: Hierarchical Co-Attention Model

Question hierarchy

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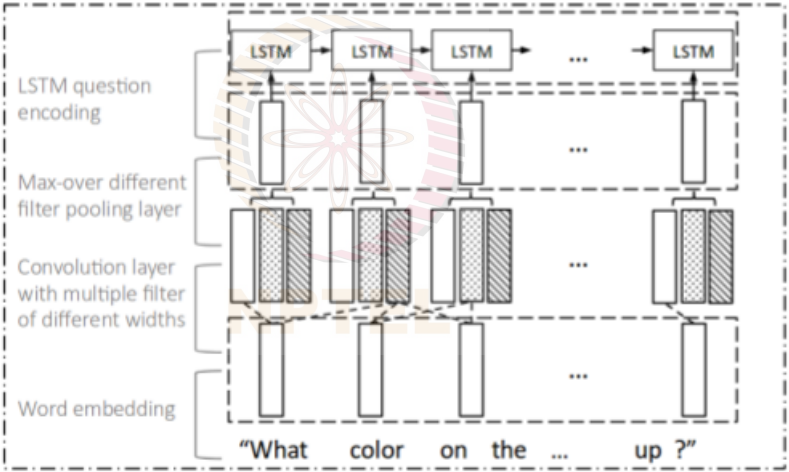

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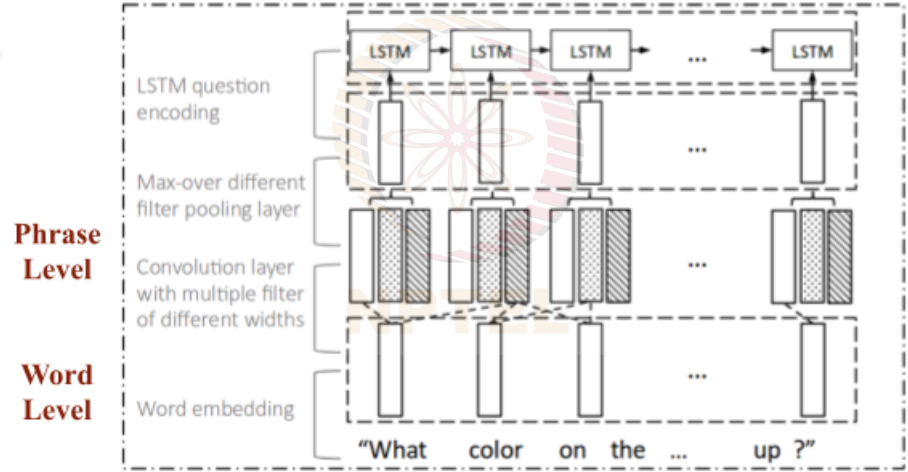
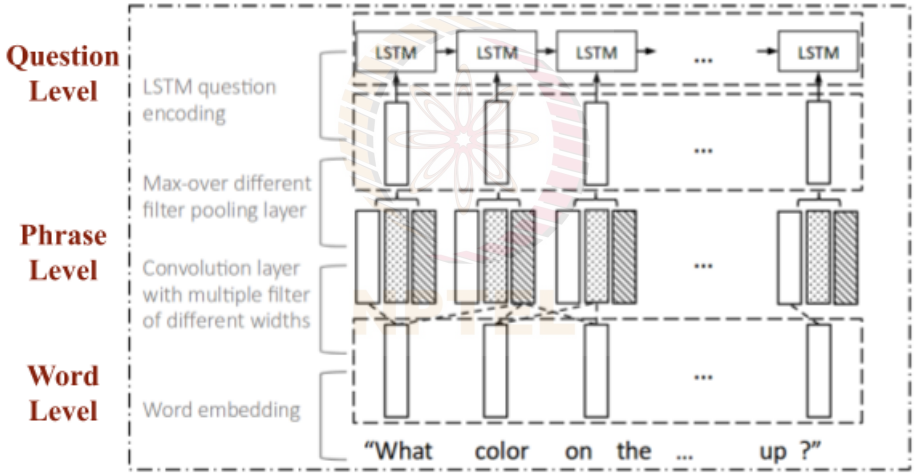


VQA Models: Hierarchical Co-Attention Model

Question hierarchy



VQA Models: Hierarchical Co-Attention Model

Visualization of image and question co-attention map

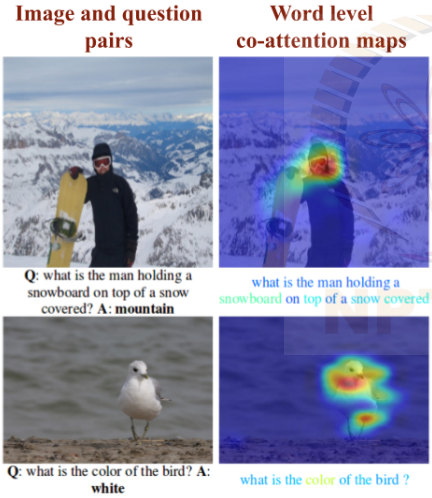
Image and question pairs

Q: what is the man holding a snowboard on top of a snow covered? **A**: **mountain**

Q: what is the color of the bird? **A**: **white**

VQA Models: Hierarchical Co-Attention Model

Visualization of image and question co-attention map



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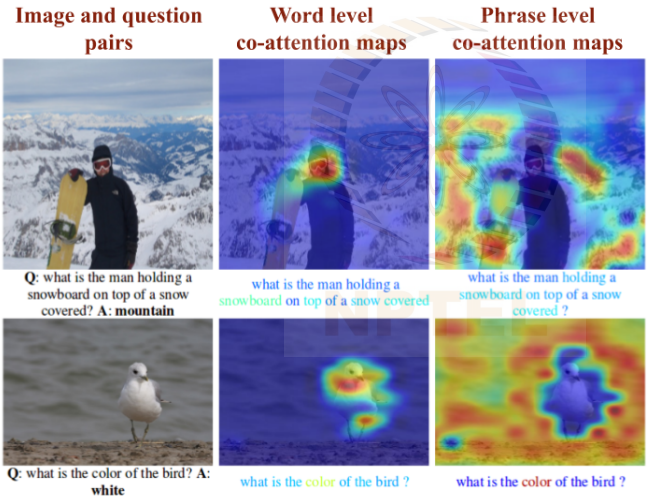
Visualization of image and question co-attention map



VQA Models: Hierarchical Co-Attention Model

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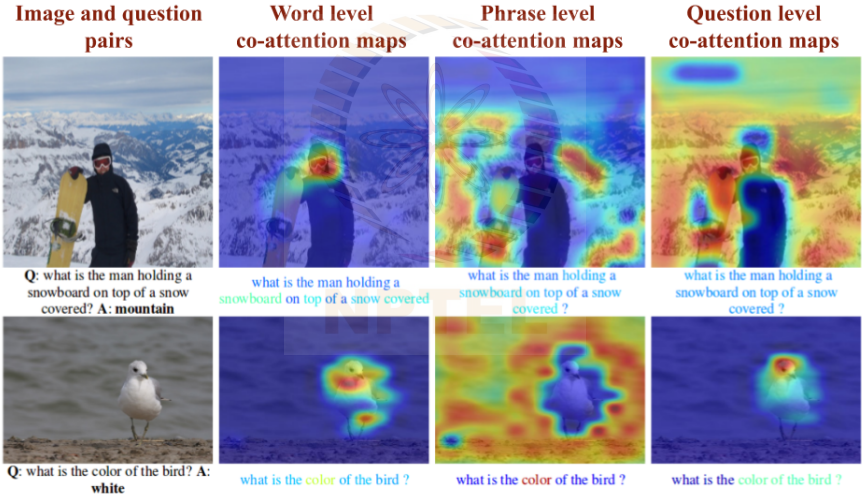

Visual Dialog: Task Overview[10]

[10] Das et al, Visual Dialog, CVPR 2017

Visual Dialog: CloudCV Demo

Visual Dialog: CloudCV Demo

A man and a woman are holding umbrellas

Visual Dialog: CloudCV Demo

A man and a woman are holding umbrellas

What color is his umbrella?

Visual Dialog: CloudCV Demo

A man and a woman are holding umbrellas

What color is his umbrella?

His umbrella is black

Visual Dialog: CloudCV Demo

A man and a woman are holding umbrellas

What color is his umbrella?

His umbrella is black

What about hers?

Visual Dialog: CloudCV Demo

A man and a woman are holding umbrellas

What color is his umbrella?

His umbrella is black

What about hers?

Hers is multi-colored

Visual Dialog: CloudCV Demo

A man and a woman are holding umbrellas

What color is his umbrella?

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What about hers?

Hers is multi-colored

How many other people are in the image?

Visual Dialog: CloudCV Demo

A man and a woman are holding umbrellas

What color is his umbrella?

His umbrella is black

What about hers?

Hers is multi-colored

How many other people are in the image?

I think 3. They are occluded

You can try Visual Dialog on this link!

Visual Dialog: Task Description

- **Given**
  - Image I

Credit: Abhishek Das, Georgia Tech

Visual Dialog: Task Description

- **Given**
  - Image I
  - Human dialog history $(Q_1, A_1), (Q_2, A_2), ..., (Q_{t-1}, At-1)$

Q: How many people on wheelchairs?
A: Two
Q: What gender are the people in the wheelchairs?
A: One is female, one is male
Q: Which one is holding the racket?
A: The female

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Visual Dialog: Task Description

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Q: What gender are the people in the wheelchairs?
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Q: Is the other one holding anything?

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- **Task**
  - Produce free-form natural language answer A_t

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A: One is female, one is male
Q: Which one is holding the racket?
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A: He is not

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Visual Dialog: Evaluation

- A fundamental challenge in dialog systems is **evaluation**[11]

[11] Liu et al, How NOT To Evaluate Your Dialogue System, EMNLP 2016

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- Existing **word-overlap based metrics** such as BLEU, METEOR, ROUGE are known to correlate poorly with human judgement

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Visual Dialog: Evaluation

- A fundamental challenge in dialog systems is **evaluation**[11]
- Existing **word-overlap based metrics** such as BLEU, METEOR, ROUGE are known to correlate poorly with human judgement
- Human Turing test
  - expensive
  - subjective

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Visual Dialog: Evaluation Protocol

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  - Human dialog history $(Q_1, A_1), (Q_2, A_2), ..., (Q_{t-1}, At-1)$
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  - 100 answer options

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  - 100 answer options
    - Answers to 50 most similar questions

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    - Answers to 50 most similar questions
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    - 20 random answers
- **Evaluation Task**

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    - 20 random answers
- **Evaluation Task**
  - Rank the list of 100 options

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  - Image I
  - Human dialog history
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  - Follow-up question Q_t
  - 100 answer options
    - Answers to 50 most similar questions
    - 30 popular answers
    - 20 random answers
- **Evaluation Task**
  - Rank the list of 100 options
- **Accuracy/Error**

Q: How many people on wheelchairs?
A: Two
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    - 30 popular answers
    - 20 random answers
- **Evaluation Task**
  - Rank the list of 100 options
- **Accuracy/Error**
  - Mean rank w.r.t. ground truth, Mean reciprocal rank

Q: How many people on wheelchairs?
A: Two
Q: What gender are the people in the wheelchairs?
A: One is female, one is male
Q: Which one is holding the racket?
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Visual Dialog: Models

Encoder-Decoder frameworks

Credit: Abhishek Das, Georgia Tech

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- Encoders

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Visual Dialog: Models

Encoder-Decoder frameworks

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  - Memory Network Encoder
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Visual Dialog: Models

Encoder-Decoder frameworks

- Encoders
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  - Hierarchical Recurrent Encoder
  - Memory Network Encoder
- Decoders
  - Generative

Credit: Abhishek Das, Georgia Tech

Visual Dialog: Models

Encoder-Decoder frameworks

- Encoders
  - Late Fusion Encoder
  - Hierarchical Recurrent Encoder
  - Memory Network Encoder
- Decoders
  - Generative
  - Discriminative

Credit: Abhishek Das, Georgia Tech

Visual Dialog: Late Fusion Encoder

Image I

Do you think the woman is with him?

Question Q_t

The man is riding his bicycle on the sidewalk. Is the man wearing a helmet? No he does not have a helmet on. ... Are there any people nearby? Yes there's a woman walking behind him.

t rounds of history (concatenated)

CNN

LSTM

LSTM

4096

512

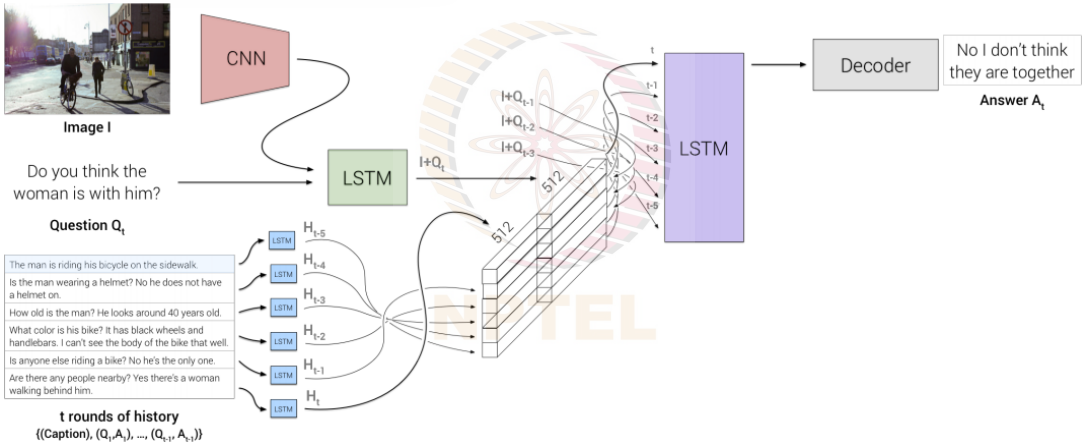
512

Decoder

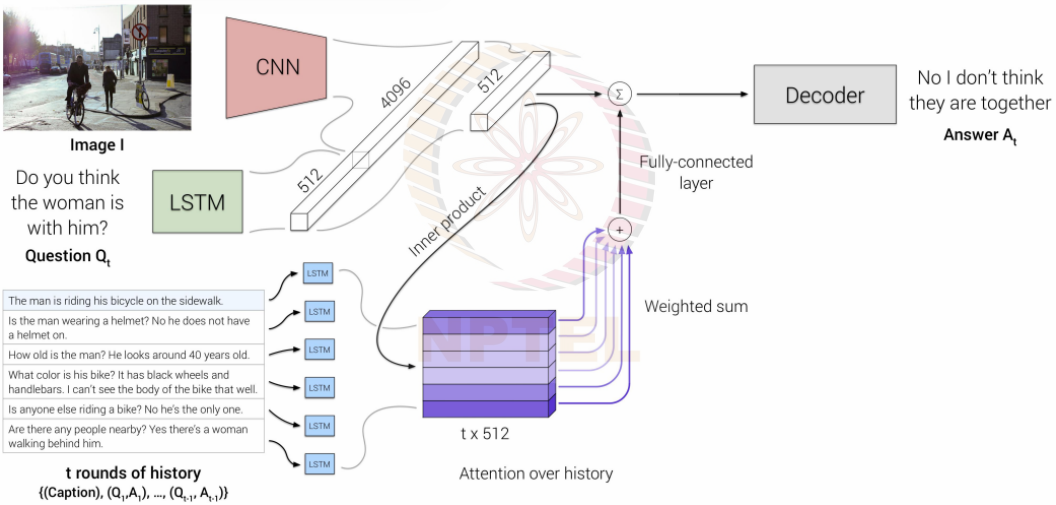
No I don't think they are together

Answer A_t

Visual Dialog: Hierarchical Recurrent Encoder



Visual Dialog: Memory Network Encoder



Visual Dialog: Decoders

- Generative (LSTM) Decoder

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- Generative (LSTM) Decoder
  - During training, maximize log-likelihood of ground truth answer sequence

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  - During evaluation, use model's log likelihood scores and rank candidate answers

Visual Dialog: Decoders

- Generative (LSTM) Decoder
  - During training, maximize log-likelihood of ground truth answer sequence
  - During evaluation, use model's log likelihood scores and rank candidate answers
- Discriminative (softmax) Decoder

Visual Dialog: Decoders

- Generative (LSTM) Decoder
  - During training, maximize log-likelihood of ground truth answer sequence
  - During evaluation, use model's log likelihood scores and rank candidate answers
- Discriminative (softmax) Decoder
  - Computes dot product similarity between input encoding and LSTM encoding of each answer option

Visual Dialog: Decoders

- Generative (LSTM) Decoder
  - During training, maximize log-likelihood of ground truth answer sequence
  - During evaluation, use model's log likelihood scores and rank candidate answers
- Discriminative (softmax) Decoder
  - Computes dot product similarity between input encoding and LSTM encoding of each answer option
  - Dot products are fed into a softmax to compute posterior probability over the options

Visual Dialog: Decoders

- Generative (LSTM) Decoder
  - During training, maximize log-likelihood of ground truth answer sequence
  - During evaluation, use model's log likelihood scores and rank candidate answers
- Discriminative (softmax) Decoder
  - Computes dot product similarity between input encoding and LSTM encoding of each answer option
  - Dot products are fed into a softmax to compute posterior probability over the options
  - During training, maximize log-likelihood of correct option

Visual Dialog: Decoders

- Generative (LSTM) Decoder
  - During training, maximize log-likelihood of ground truth answer sequence
  - During evaluation, use model's log likelihood scores and rank candidate answers
- Discriminative (softmax) Decoder
  - Computes dot product similarity between input encoding and LSTM encoding of each answer option
  - Dot products are fed into a softmax to compute posterior probability over the options
  - During training, maximize log-likelihood of correct option
  - During evaluation, options are simply ranked based on their posterior probabilities

Visual Dialog: Results

Caption: The skiers stood on top of the mountain.
Person A (1): how many skiers are there
Person B (1): hundreds
Person A (2): are they getting ready to go downhill
Person B (2): i think so my view is at end of line
Person A (3): is it snowing
Person B (3): no, there is lot of snow though
Person A (4): can you see anybody going downhill
Person B (4): no my view shows people going up small hill on skis i can't see what's going on from there
Person A (5): do you see lift
Person B (5): no
Person A (6): can you tell if they are male or female
Person B (6): skiers closest to me are male
Person A (7): are there any children
Person B (7): i don't see any but there could be it's huge crowd
Person A (8): does anybody have hat on
Person B (8): they all have winter hat of some sort on
Person A (9): is sun shining
Person B (9): yes, all blue sky
Person A (10): do you see any clouds
Person B (10): no clouds

Visual Dialog: Results

Caption: A dog with goggles is in a motorcycle side car.
Person A (1): can you tell what kind of dog this is
Person B (1): he looks like beautiful pit bull mix
Person A (2): can you tell if motorcycle is moving or still
Person B (2): it's parked
Person A (3): is dog's tongue lolling out
Person B (3): not really
Person A (4): is picture in color
Person B (4): yes it is
Person A (5): what color is dog
Person B (5): light tan with white patch that runs up to bottom of his chin and he has white paws on 2 front feet
Person A (6): can you see motorcycle
Person B (6): from side, yes
Person A (7): what color is motorcycle
Person B (7): black with white or silver accents, sun is glaring so it's hard to tell
Person A (8): is there anybody sitting on motorcycle
Person B (8): no
Person A (9): is there anybody in picture
Person B (9): in cars on street behind motorcycle
Person A (10): does dog look like he's having fun
Person B (10): yes

Homework

Questions

- Are there better methods to evaluate Visual Dialog systems? How?

Readings (Optional)

- VQA
  - Deep Compositional Question Answering with Neural Module Networks, CVPR 2016
  - Learning to Reason: End-to-End Module Networks for Visual Question Answering, ICCV 2017
  - MUTAN: Multimodal Tucker Fusion for Visual Question Answering, ICCV 2017
  - Learning Conditioned Graph Structures for Interpretable Visual Question Answering, NeurIPS 2018
  - Bottom-Up and Top-Down Attention for Image Captioning and Visual Question Answering, CVPR 2018
  - Towards VQA Models That Can Read, CVPR 2019
  - Deep Modular Co-Attention Networks for Visual Question Answering, CVPR 2019

Homework

Readings (Optional)

- Visual Dialog
  - Evaluating Visual Conversational Agents via Cooperative Human-AI Games, HCOMP 2017
  - Learning Cooperative Visual Dialog Agents with Deep Reinforcement Learning, ICCV 2017
  - Visual Coreference Resolution in Visual Dialog using Neural Module Networks, ECCV 2018
  - Improving Generative Visual Dialog by Answering Diverse Questions, EMNLP 2019
  - Large-scale Pretraining for Visual Dialog: A Simple State-of-the-Art Baseline, ECCV 2020
  - Efficient Attention Mechanism for Visual Dialog that can Handle All the Interactions between Multiple Inputs, ECCV 2020
  - History for Visual Dialog: Do we really need it?, ACL 2020
  - Iterative Context-Aware Graph Inference for Visual Dialog, CVPR 2020

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