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FOIL it! Find One mismatch between Image and Language caption

ACL, Vancouver, 31st July, 2017

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Overview

Research Question

- Do Language and Vision models genuinely integrate both modalities, plus their interaction?

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- Do Language and Vision models genuinely integrate both modalities, plus their interaction?
  - Image Captioning

- People riding bicycles down the road approaching a pigeon.
- A group of people on bicycles coming down a street

Image Captioning

Overview

Research Question

- Do Language and Vision models genuinely integrate both modalities, plus their interaction?
  - Visual Question Answering

- Question: How many people are riding a bicycle?
- Answer: three

Visual Question Answering

Overview

Research Question

- Do Language and Vision models genuinely integrate both modalities, plus their interaction?

Our contribution

- FOIL dataset and tasks as a (challenging) benchmark for SoA models

Take-home

- Current models fail in deeply integrating the two modalities

Related Work

- Binary Forced-Choice Tasks (Hodosh and Hockenmaier, 2016)
  - given two captions, original & distractor, an image captioning model has to pick one
  - model fails to pick the original caption

  - limitations
    - hard to pinpoint the reason for the model failure: due to multiple word change simultaneously
    - easier problem: due to selection between two captions

Related Work

- CLEVR Dataset (Johnson et al., 2016)
  - artificial dataset to evaluate visual reasoning
  - analysed shortcoming of VQA models

  - limitations
    - task specific model achieves super human performance (Santoro et al., 2017)
    - some questions are hard to answer by human's (Santoro et al., 2017)

Johnson et al. "*CLEVR: A Diagnostic Dataset for Compositional Language and Elementary Visual Reasoning.*" CVPR, 2017
Santoro et al. "*A simple neural network module for relational reasoning.*" Arxiv, 2017

Motivation

- Need of automatically generate resource with less effort
- Need tasks such that automatic and human evaluation have the same metric
- Need of diagnostics way to evaluate limitations of SoA models

FOIL Dataset

- For a given image and original captions, generate foil captions by replacing one NOUN in the original caption

A person on bike going through green light with red **bus** nearby in a sunny day.

Original Caption

Target Word : bus
Foil Word : truck
Target - Foil pair = bus - truck

A person on bike going through green light with red **truck** nearby in a sunny day.

Generated Foil Caption

FOIL Dataset

- For a given image and original captions, generate foil captions by replacing one NOUN in the original caption
- Original caption based on the MS-COCO (Lin et al., 2014) dataset for image and caption
- Target-Foil pair creation based on MS-COCO object super-category
  - replace objects within same super-category with each other
    - e.g. cat-dog, car-truck etc

Tsung-Yi Lin et al. "*Microsoft coco: Common objects in context.*" ECCV, 2014

FOIL Dataset : Criteria

- Foil not present
  - perform replacement only if the ‘foil’ word is not present
- Salient Target
  - replace a ‘target’ word only if it is visually salient
- Mining hardest foil caption
  - by using ‘neuraltalk’ (Karpathy and Fei-Fei, 2015) loss

FOIL Dataset : Sample

- Sample Generated Example

1. An orange cat hiding on the wheel of a red **car**.
2. A **cat** sitting on a wheel of a vehicle.

Original Caption

1. An orange cat hiding on the wheel of a red **boat**.
2. A **dog** sitting on a wheel of a vehicle.

Generated Foil Captions

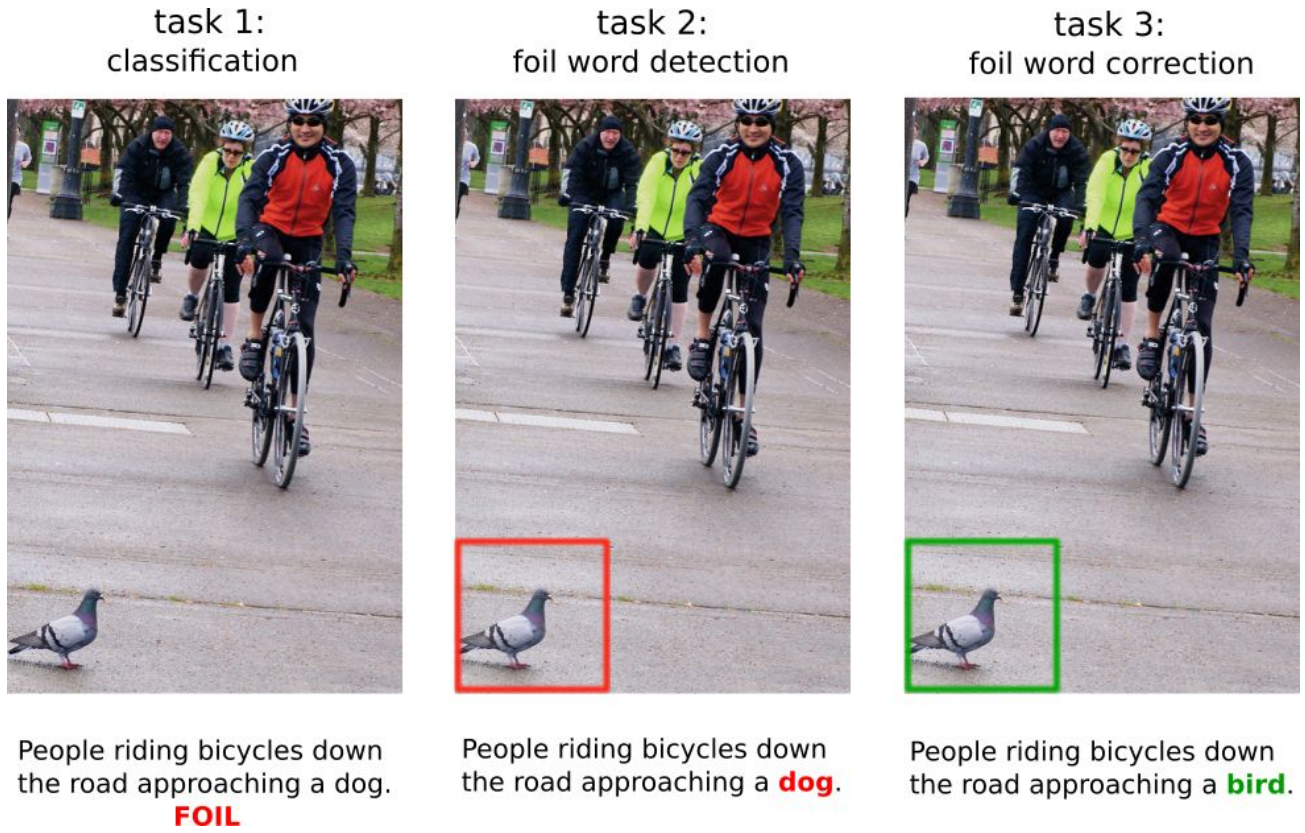
FOIL Dataset : Composition

- Composition of FOIL-COCO dataset

	# datapoints	# images	# captions	# target-foil pairs
Train	197,788	65,697	395,576	256
Test	99,480	32,150	198,960	216

FOIL Dataset : Proposed Tasks

- Task 1 : Binary classification : Original or Foil
- Task 2 : Foil word detection
- Task 3 : Foil word correction



Proposed Tasks : Task 1

- Binary classification: Original or Foil
  - Given an image and a caption decide original or foil caption

People riding bicycles down the road approaching a bird.

Original Caption

People riding bicycles down the road approaching a dog.

Foil Caption

Proposed Tasks : Task 1

- Binary classification: Original or Foil
  - Given a image and a caption decide original or foil caption

People riding bicycles down the road approaching a bird.

Original Caption

People riding bicycles down the road approaching a dog.

Foil Caption

Human performance (AMT)

- **Majority (2/3) : 92.89**
- **Unanimity (3/3) : 76.32**

Proposed Tasks : Task 2

- Foil word detection
  - Given an image and a ‘foil’ caption identify the ‘foil’ word

People riding bicycles down the road approaching a dog..

Where is the mistake in caption?

People riding bicycles down the road approaching a dog..

Proposed Tasks : Task 2

- Foil word detection
  - Given an image and a ‘foil’ caption identify the ‘foil’ word

Human performance (AMT)

- **Majority (2/3) : 97.00**
- **Unanimity (3/3) : 73.60**

People riding bicycles down the road approaching a dog..

Where is the mistake in caption?

People riding bicycles down the road approaching a dog..

Proposed Tasks : Task 3

- Foil word correction
  - Given an image, a ‘foil’ caption and ‘foil’ word location, correct the ‘foil’ caption

People riding bicycles down the road approaching a dog..

Can you correct the mistake?

People riding bicycles down the road approaching a bird..

FOIL Dataset : is NOT Equal to

- Visual Question Answering

- In VQA, answers are highly dependent on the (linguistic) context of the question.

What man is riding?

≠

A person on motorcycle going through green light with red bus nearby in a sunny day.

- In FOIL, we are asked a context independent fine-grained information about the image.

FOIL Dataset : is NOT Equal to

- Object Classification/Detection

- In computer vision tasks, generally question is, what objects are present in the image

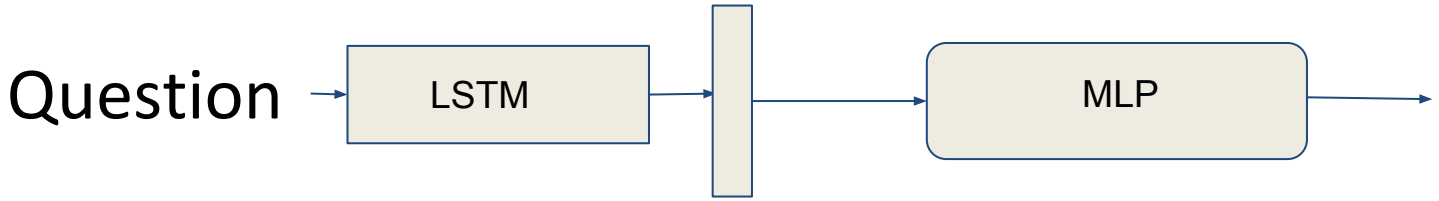
- In FOIL, question is "what object is NOT in the image (foil classification/detection) and understand what object is there based on the context(correction)?"

Models Tested

- VQA Models
- Image Captioning Model

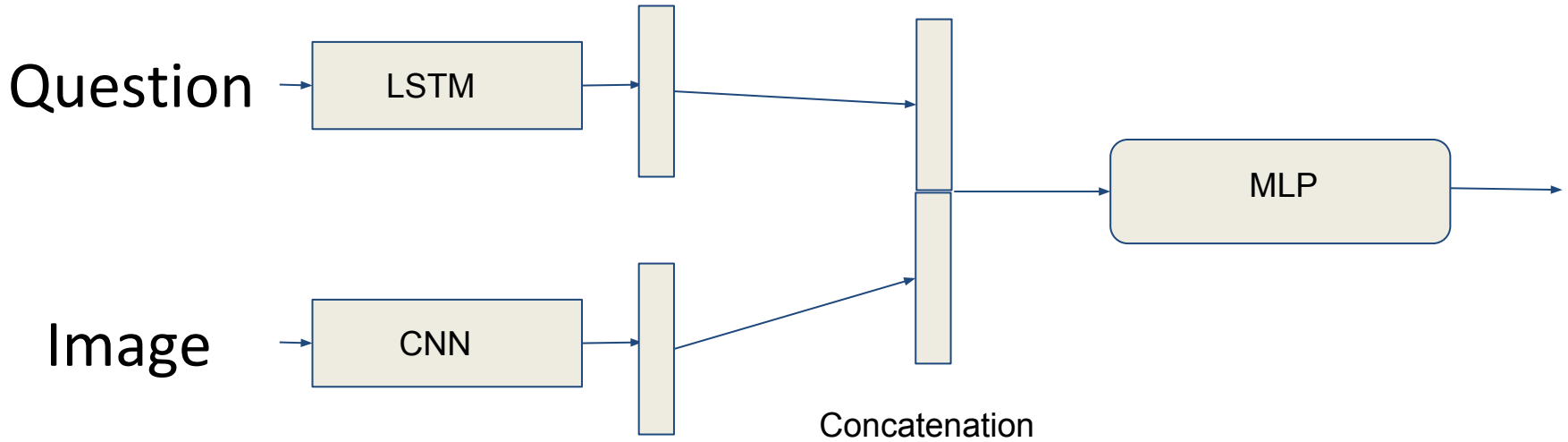
Models Tested

- Baseline Models
  - Language Only (Blind)
    - LSTM (Question) followed by MLP



Models Tested

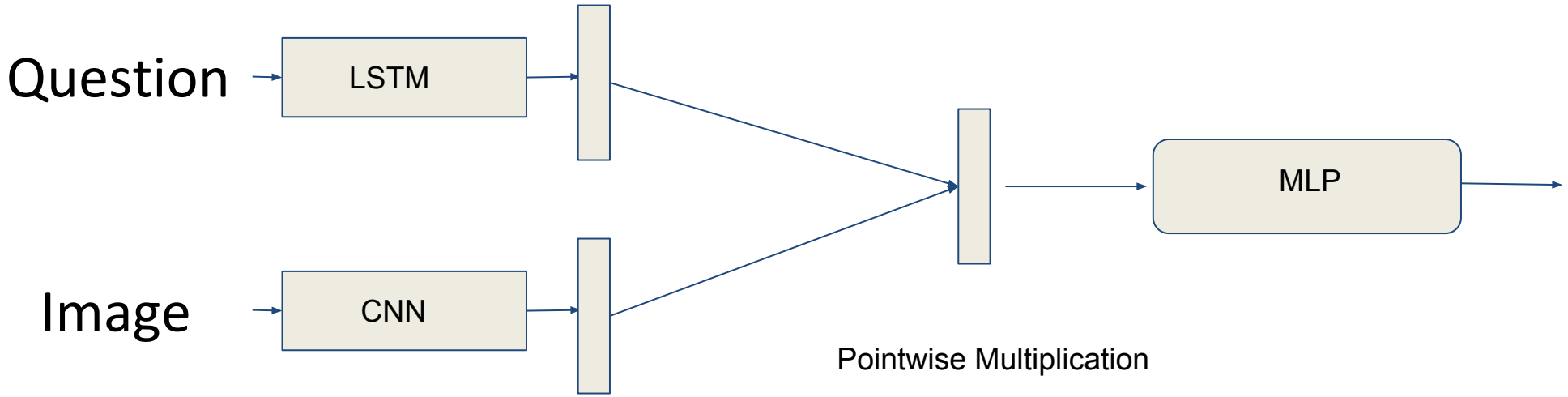
- Baseline Models
  - Language Only (Blind)
  - CNN + LSTM (Zhou et al., 2015)
    - CNN (Image), LSTM (Question) joined by concatenation followed by MLP



Zhou et al. "*Simple Baseline for Visual Question Answering.*" Arxiv, 2015

Models Tested

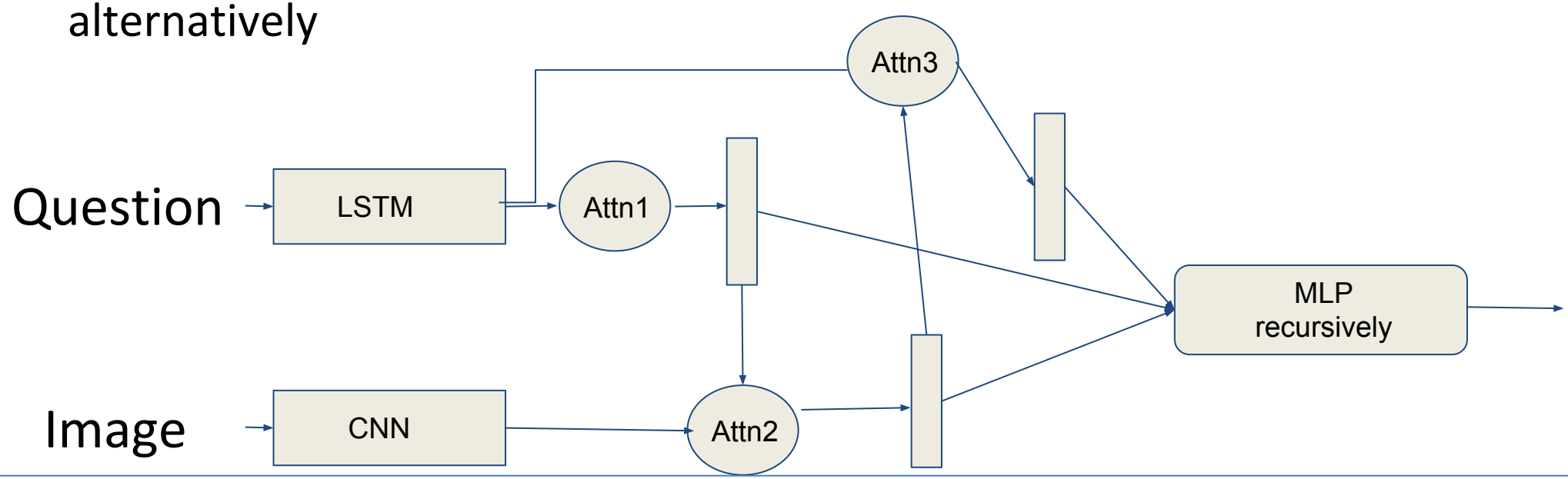
- VQA Models
  - LSTM + norm I (Antol et al., 2015)
    - CNN (Image), LSTM (Question) joined by pointwise multiplication followed by MLP



Antol et al. "*VQA: Visual Question Answering.*" ICCV, 2015

Models Tested

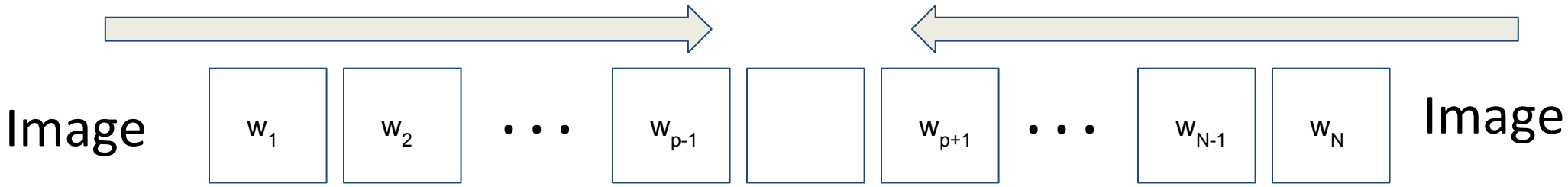
- VQA Models
  - LSTM + norm I (Antol et al., 2015)
  - Hierarchical Co-attention (HieCoAttn) (Lu et al., 2016)
    - CNN (Image), LSTM (Question), both Image & Question is co-attended in alternatively



Lu et al. "*Hierarchical Question-Image Co-Attention for Visual Question Answering.*" NIPS, 2016

Models Tested

- Image Captioning Model
  - Bi-directional IC Model (IC-Wang) (Wang et al., 2016)
    - Given Image, and past and future context model predicts current word



Wang et al. "*Image captioning with deep bidirectional LSTMs.*" MM, 2016

Results

- Task 1 : Binary Classification

	Overall	Correct	Foil
Blind	55.62	86.20	25.04
CNN + LSTM	61.07	89.16	32.98
LSTM + norm I	63.26	**92.02**	34.51
HieCoAttn	**64.14**	91.89	**36.38**
IC-Wang	42.21	38.98	45.44
Human (Majority)	92.89	91.24	94.52
Human (Unanimity)	76.32	73.73	78.90

Results

- Task 2 : Foil word detection

	Only Nouns	All Words
Chance	23.25	15.87
LSTM + norm I	26.32	24.25
HieCoAttn	**38.79**	**33.69**
IC-Wang	27.59	23.32
Human (Majority)	_	97.00
Human (Unanimity)	_	73.60

Results

- Task 3 : Foil word correction

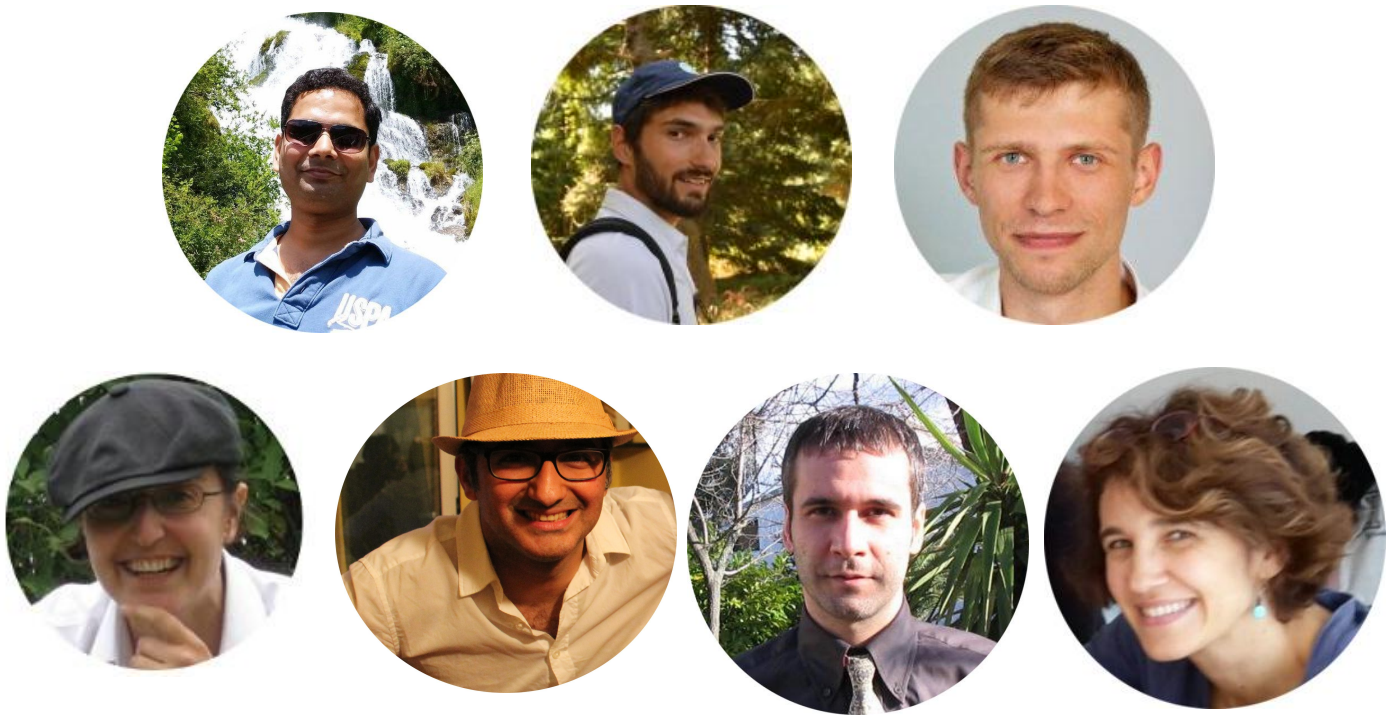
	All Target Words
Chance	1.38
LSTM + norm I	4.7
HieCoAttn	4.21
IC-Wang	**22.16**

Conclusion

- Created a challenging dataset and corresponding challenging tasks
  - used to evaluate limitations of language and vision models
  - can be extended to other part of speech (see Shekhar et al., 2017), scene etc
  - by knowing source of error, will help in designing better models

- Need fine-grained joint understanding of language and vision

Thank You !!!
Q & A



Dataset https://foilunitn.github.io

Crowdflower

- **Read** and **understand** the caption and carefully **watch** the image
- **Determine** if the caption provides a correct description of what is depicted in the image
- If you judge the caption as "wrong", you will be asked to type **the word** that makes the caption incorrect

Crowdflower

Caption:
a man riding a bull through part of a parking lot

Does the caption provide a correct or wrong description of the image? (required)

- correct
- wrong

Crowdflower

Caption:
a man riding a bull through part of a parking lot

Does the caption provide a correct or wrong description of the image? (required)

- [x] correct
- [ ] wrong

Crowdflower

Caption:
a man riding a bull through part of a parking lot

Does the caption provide a correct or wrong description of the image? (required)

- correct
- wrong

Type the wrong word (one word) (required)

FOIL Dataset : Criteria

- Foil not present
- Salient Target

FOIL Dataset : Criteria

- Foil not present
  - Perform replacement only if ‘Foil’ word is not present in the image
    - Check that ‘Foil’ word is not used by any other ms-coco annotator

For e.g.,

I. “A **boy** is running on the beach”
II. “A boy and a little girl are playing on the beach”

- Target - Foil = Boy - Girl

FOIL Dataset : Criteria

- Salient Target
  - Replace ‘Target’ words only if it is visually salient in the image
    - Based on annotator agreement i.e. more than one annotator used ‘Target’ word

For e.g.,

I. Two **zebras** standing in the grass near rocks.
II. Two **zebras** grazing together near rocks in their enclosure.
III. Two **Zebras** are standing near some rocks.
IV. two **zebras** in a field near one another
V. A grassy area shows artificially arranged rocks and two **zebras**, as well as part of the lower half of a **deer**.

- Target - Foil = Zebra - Dog (Used)
- Target - Foil = Deer - Dog (Not Used)

FOIL Dataset : Mining Hardest Foil Caption

- To eliminate visual-language bias
  For every original caption could produce one or more foil caption

- Neuraltalk loss is used to mine hardest foil caption
  Eliminates both visual and language bias