Visual Question Answering

Danna Gurari
University of Colorado Boulder
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Review

- Last week:
  - Image captioning applications
  - Image captioning datasets
  - Image captioning evaluation
  - Challenge winner: encoder decoder pipeline with attention
- Assignments (Canvas)
  - Lab assignment 3 grades are out
  - Problem set 4 due earlier today
  - Lab assignment 4 due the week following spring break
- Questions?

Today’s Topics

- Visual question answering applications
- Visual question answering datasets
- Visual question answering evaluation
- Mainstream challenge 2015 winner: baseline approach
- Mainstream challenge 2019 winner: transformer-based approach
- Programming tutorial

Today’s Topics

- Visual question answering applications
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Task: Answer Visual Questions (VQs)

Is my monitor on?

Hi there can you please tell me what flavor this is?

Does this picture look scary?

Which side of the room is the toilet on?

Visual Assistance for People with Vision Loss; e.g.,

VizWiz

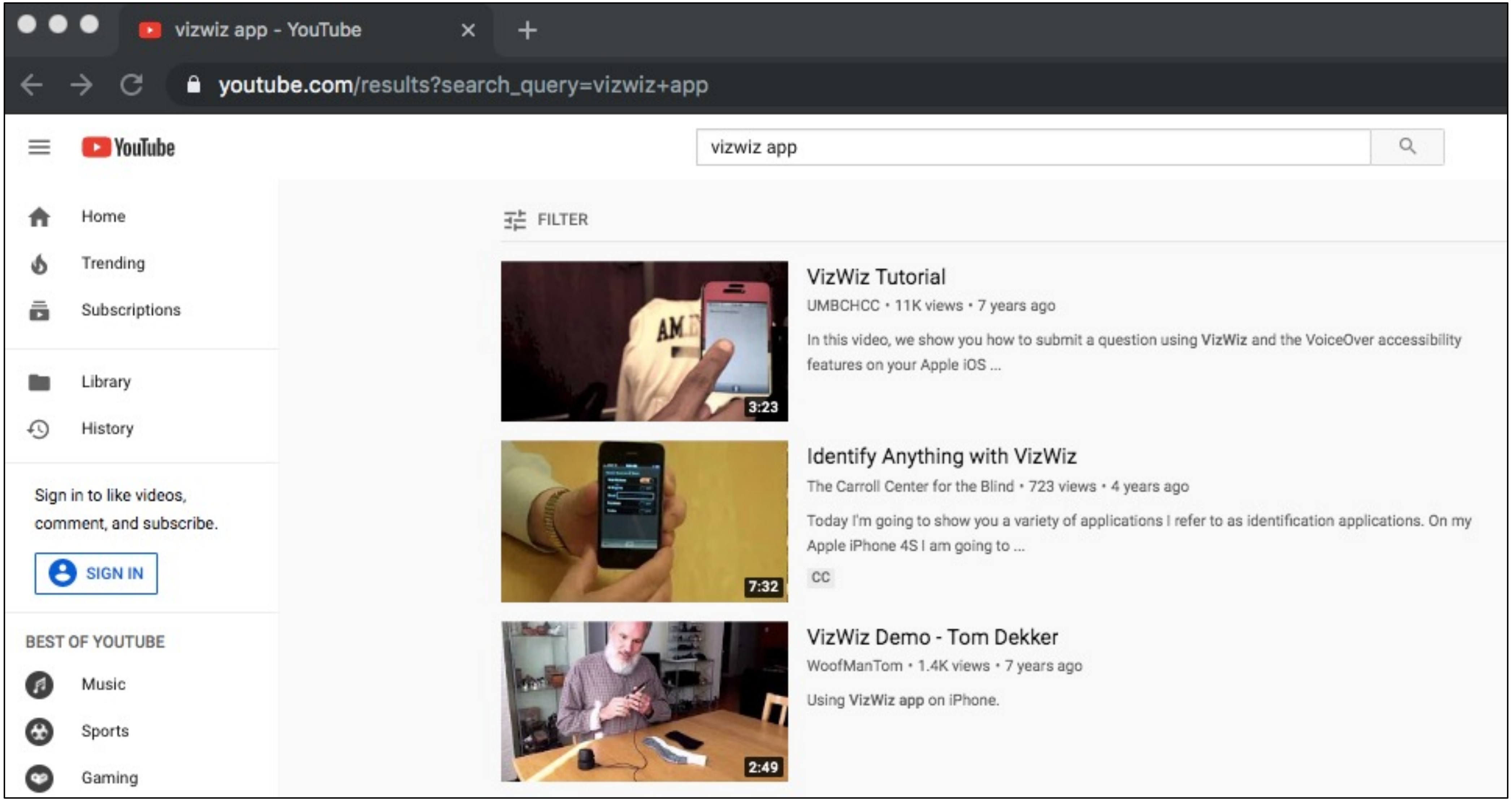
aira

BeSpecular

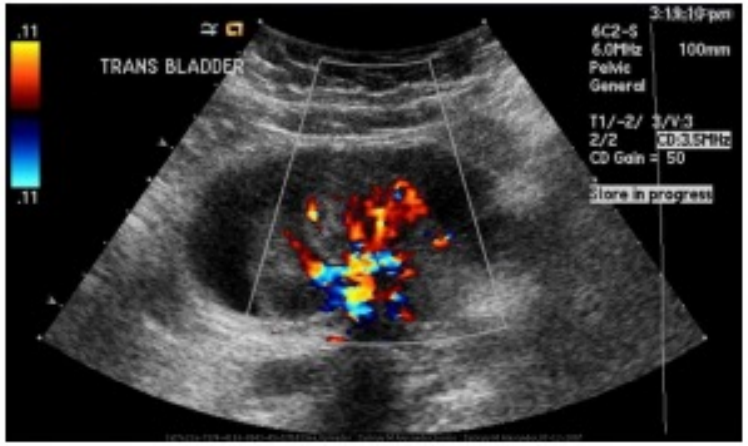
Through the world's eyes

Be My Eyes

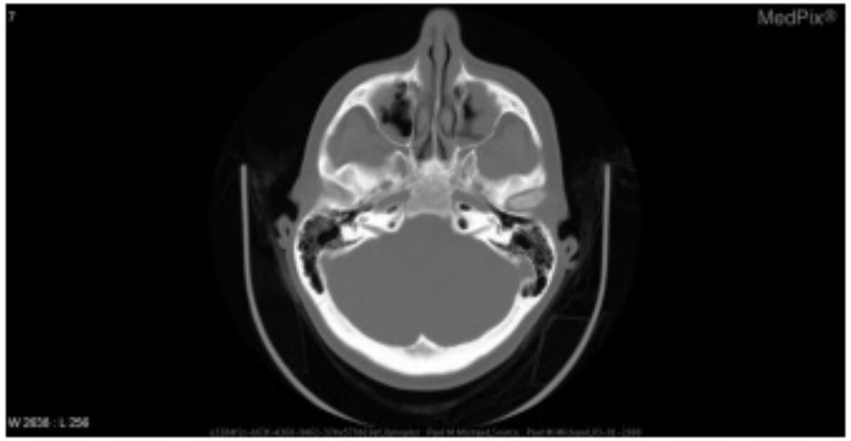
Visual Assistance for People with Vision Loss; e.g.,



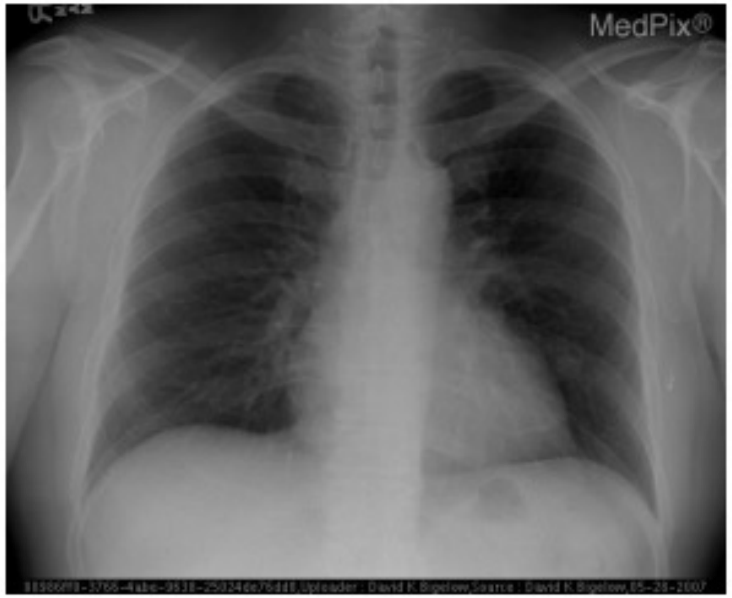
Medical VQA



(a) **Q**: what imaging method was used? **A**: us-d - doppler ultrasound



(b) **Q**: which plane is the image shown in? **A**: axial



(e) **Q**: what abnormality is seen in the image? **A**:nodular opacity on the left#metastastic melanoma

Abacha et al. VQA-Med: Overview of the Medical Visual Question Answering Task at ImageCLEF 2019

Video Surveillance

Attribute-based Query:

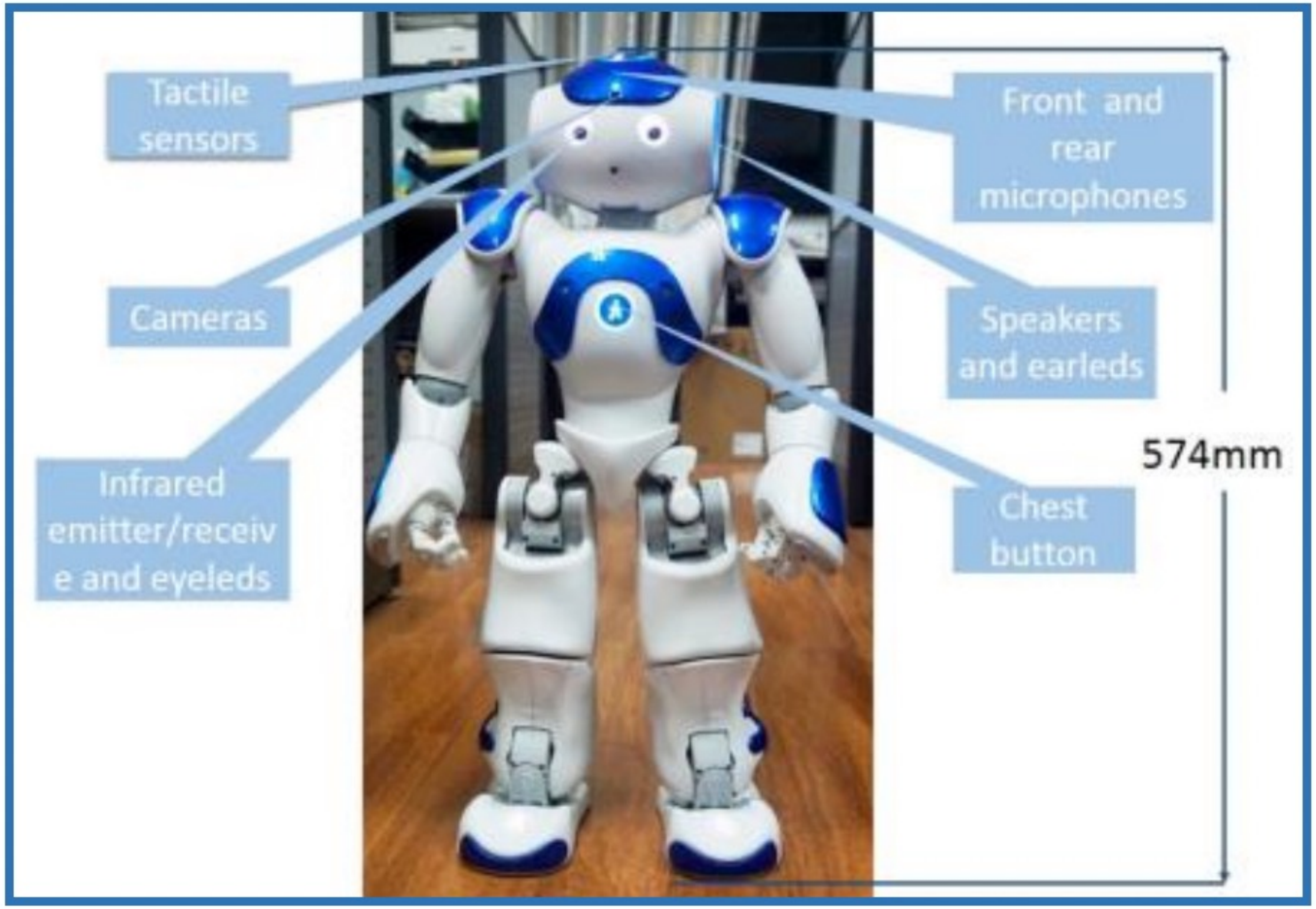
Q: Is it a person in the green bounding box? ***A: Yes***
(Define the person as P1)
Q: Is P1 female? A: Yes
Q: Does P1 hold a bag? A: Yes
Q: Does P1 has long hair and wear leather shoes? A: Yes
Q: Is P1 in padded jacket and skirt? A: No
Q: … A: …

Relationship-based Query:

Q: Are they persons in both of the two red bounding boxes? ***A: Yes***
(Define the upper one as P2, and define the lower one as P3)
Q: Are P2 and P3 the same person? A: Yes

Li et al. ISEE: An Intelligent Scene Exploration and Evaluation Platform for Large-Scale Visual Surveillance. 2019.

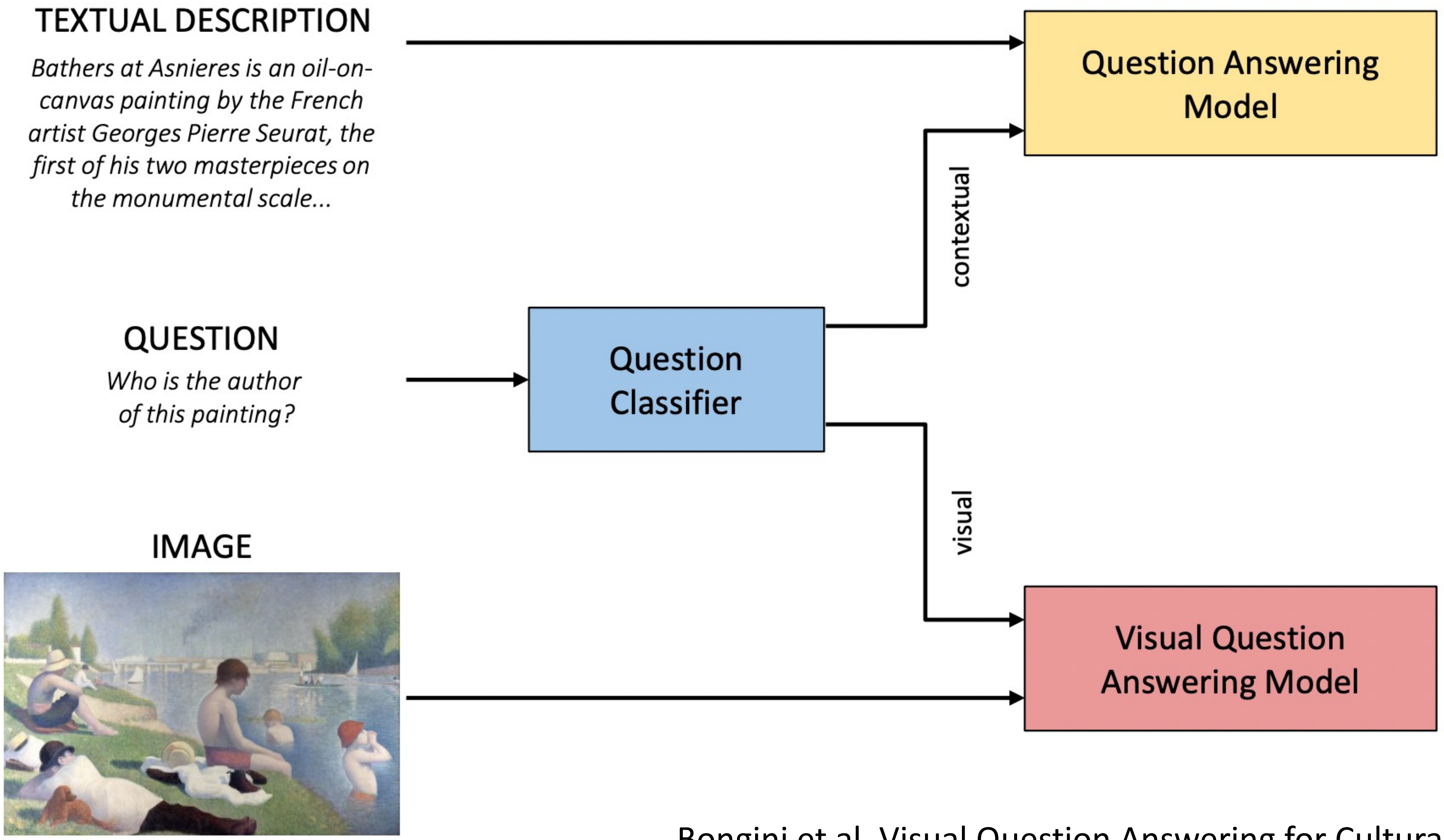
Education (e.g., for Preschoolers)



Answers questions about **quantity** and **colors** of detected objects

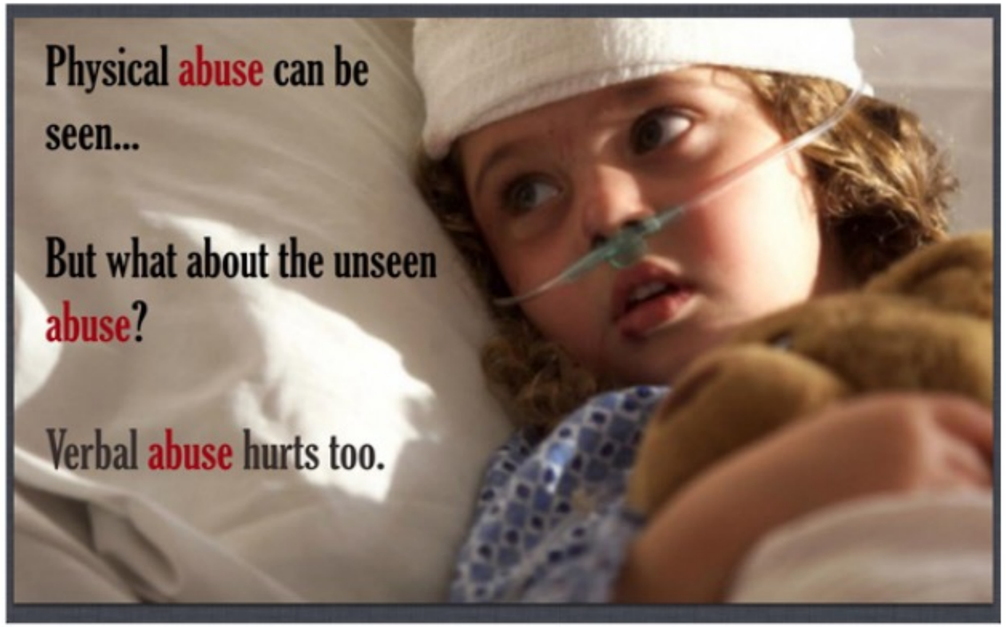
He et al. An Educational Robot System of Visual Question Answering for Preschoolers. 2017.

Audio Guide for Museums and Art Galleries



Bongini et al. Visual Question Answering for Cultural Heritage. 2020.

Advertising: Understanding the Messaging and Identifying Effective Persuasion Strategies



What should I do, according to this ad?	Why, according to this ad, should I take this action?
I should try this lipstick	Because it is better than the brand Mac

What should I do, according to this ad?	Why, according to this ad, should I take this action?
I should sign up for the Asus promo	Because there are free gifts

What should I do, according to this ad?	Why, according to this ad, should I take this action?
I should prevent verbal abuse	Because its as bad as physical abuse

Hussain et al. Automatic Understanding of Image and Video Advertisements. CVPR 2017.

For what other applications might visual question answering systems be useful?

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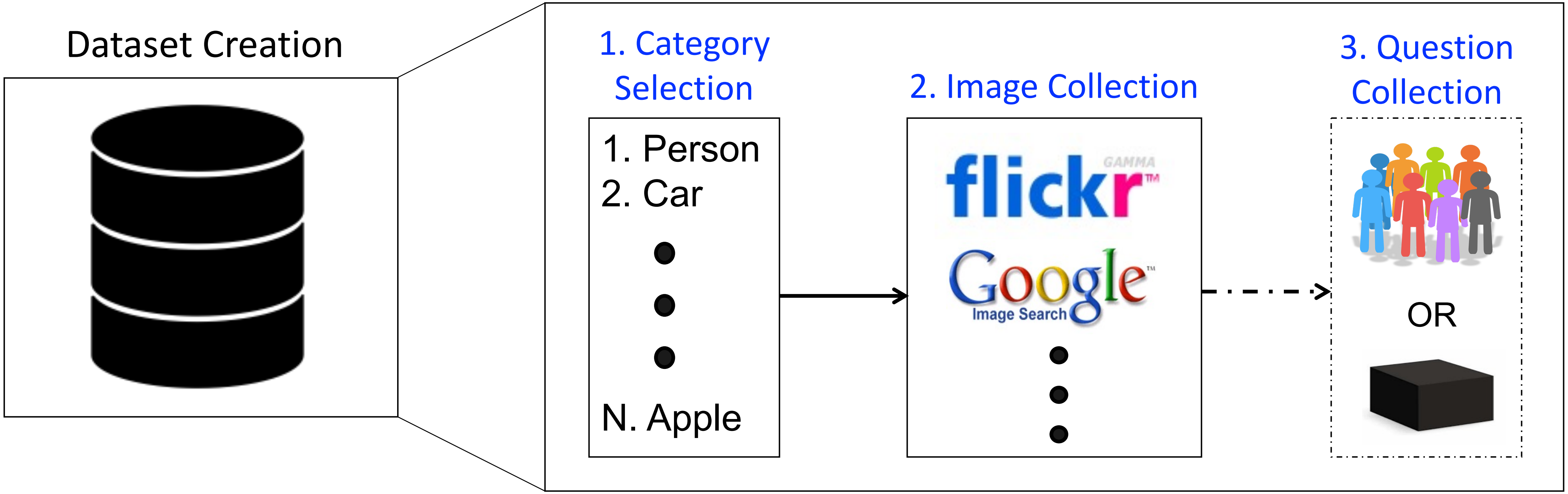
Status Quo (Approach to Create 14+ Datasets)



Constrained set of concepts

Pre-qualified images (quality, privacy)

Contrived Questions

e.g., Question Generation

Stump a smart robot! Ask a question about this scene that a human can answer, but a smart robot probably can't!

Updated instructions: Please read carefully

Hide Show

We have built a smart robot. It understands a lot about scenes. It can recognize and name all the objects, it knows where the objects are, it can recognize the scene type (e.g., kitchen, beach), people's expressions and poses, and properties of objects (e.g., the color of objects, their texture). Your task is to stump this smart robot! In particular, it already knows answers to some questions about this scene. We will tell you what these questions are.

Ask a question about this scene that this SMART robot probably can not answer, but any human can easily answer while looking at the scene in the image.
IMPORTANT: The question should be about this scene. That is, the human should need the image to be able to answer the question -- the human should not be able to answer the question without looking at the image.

Your work will get rejected if you do not follow the instructions below:

- Do not ask questions that are similar to the ones listed below each image. As mentioned, the robot already knows the answers to those questions for the scene in this image. Please ask about something different.
- Do not repeat questions. Do not ask the same questions or the same questions with minor variations over and over again across images. Think of a new question each time specific to the scene in each image.
- Each question should be a single question. Do not ask questions that have multiple parts or multiple sub-questions in them.
- Do not ask generic questions that can be asked of many other scenes. Ask questions specific to the scene in each image.

Below is a list of questions the smart robot can already answer. Please ask a different question about this scene that a human can answer *if* looking at the scene in the image (and not otherwise), but would stump this smart robot:

Q1: What is unusual about this mustache? (The robot already knows the answer to this question.)

Q2: What is her facial expression? (The robot already knows the answer to this question.)

Q3: Write your question, different from the questions above, here to stump this smart robot.

Agrawal et al. VQA: Visual Question Answering. CVPR 2015.

e.g., Answer Generation

Help Us Answer Questions About Images!

Updated instructions: Please read carefully

Hide Show

Please answer some questions about images **with brief answers**. Your answers should be how most other people would answer the questions. If the question doesn't make sense, please try your best to answer it and indicate via the buttons that you are unsure of your response.

If you don't follow the following instructions, your work will be rejected.

Your work will get rejected if you do not follow the instructions below:

- Answer the question based on what is going on in the scene depicted in the image.
- Your answer should be a brief phrase (not a complete sentence).
  - "It is a kitchen." -> "kitchen"
- For yes/no questions, please just say yes/no.
  - "You bet it is!" -> "yes"
- For numerical answers, please use digits.
  - "Ten." -> "10"
- If you need to speculate (e.g., "What just happened?"), provide an answer that most people would agree on.
- If you don't know the answer (e.g., specific dog breed), provide your best guess.
- Respond matter-of-factly and avoid using conversational language or inserting your opinion.

10 answers collected from 10 crowdworkers

Please answer the question using as few words as possible:

Q1: What is unusual about this mustache?

A1: Write your answer here.

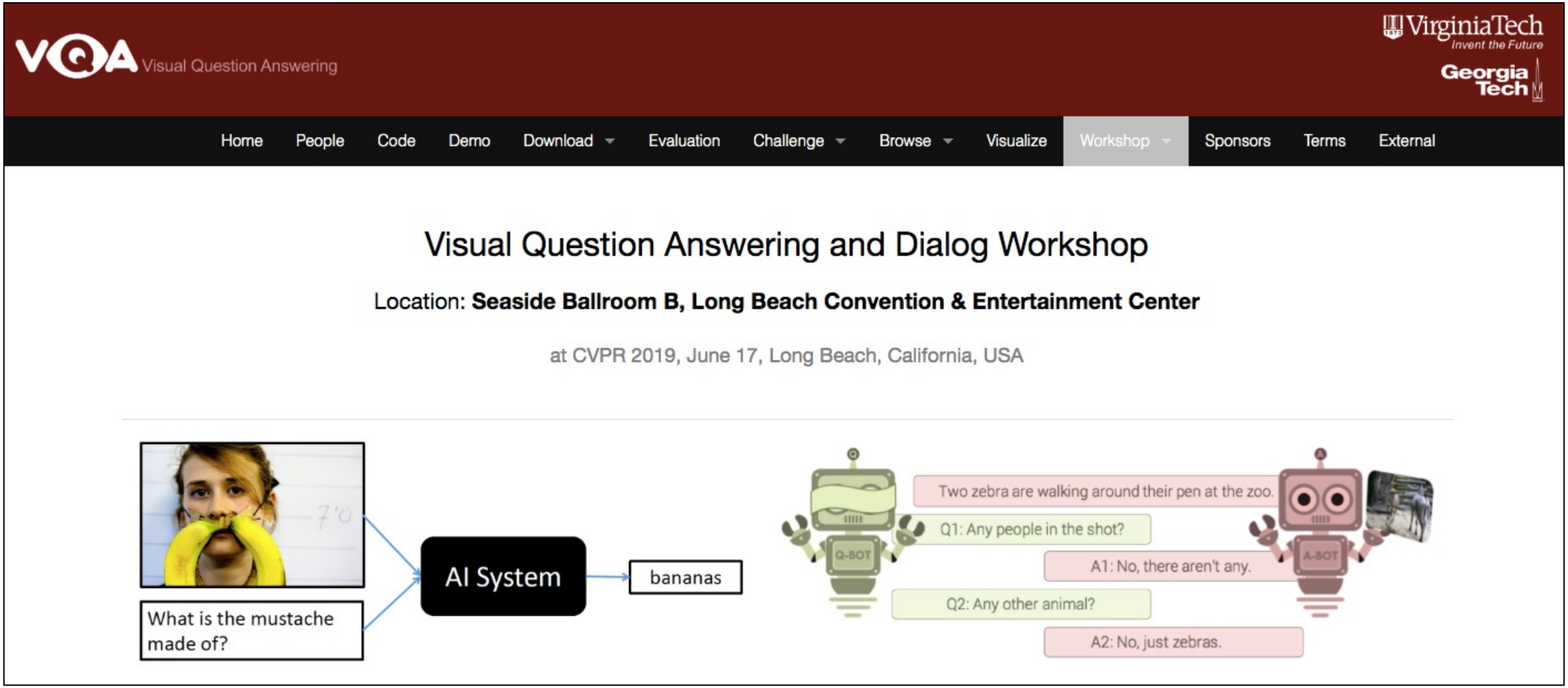
Do you think you were able to answer the question correctly?

(Clicking an option will take you to the next question.)

no maybe yes **Page 1/2**

Agrawal et al. VQA: Visual Question Answering. CVPR 2015.

Mainstream VQA Challenge (held for 6 years)



https://visualqa.org/workshop.html

VizWiz: Authentic Use Case

Jeffrey Bigham et al. VizWiz: Nearly Real-time Answers to Visual Questions. UIST 2010

VizWiz: Authentic Use Case

Image

Jeffrey Bigham et al. VizWiz: Nearly Real-time Answers to Visual Questions. UIST 2010

VizWiz: Authentic Use Case

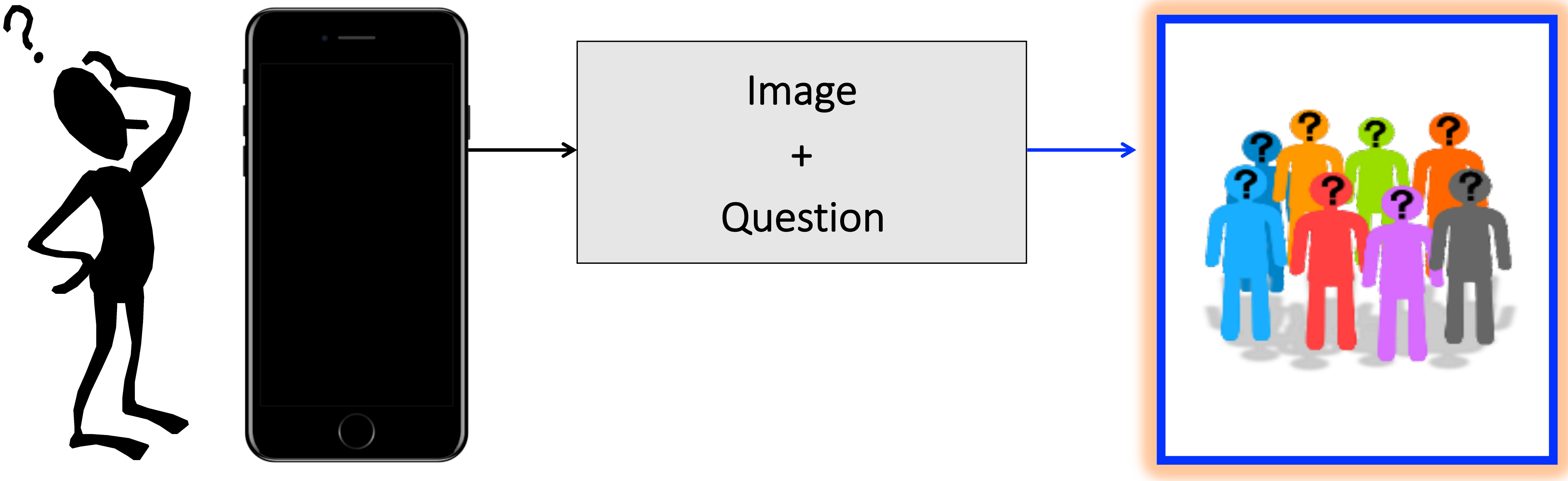
Image

+

Question

Jeffrey Bigham et al. VizWiz: Nearly Real-time Answers to Visual Questions. UIST 2010

VizWiz: Authentic Use Case



Jeffrey Bigham et al. VizWiz: Nearly Real-time Answers to Visual Questions. UIST 2010

VizWiz: Authentic Use Case

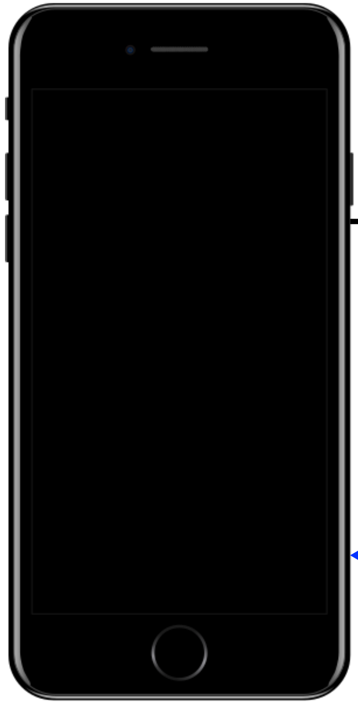


Image
+
(Optionally) Question

Answer

Jeffrey Bigham et al. VizWiz: Nearly Real-time Answers to Visual Questions. UIST 2010

VizWiz: Authentic Use Case

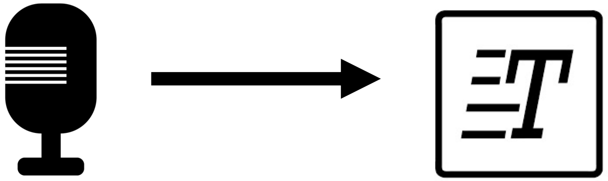
Users agreed to share 44,799 (62%) of requests for dataset creation

Jeffrey Bigham et al. VizWiz: Nearly Real-time Answers to Visual Questions. UIST 2010

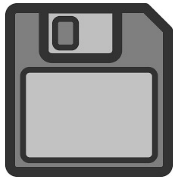
VizWiz: Authentic Use Case

Anonymization

1. Transcribe questions (removes voice)



2. Re-save images (removes metadata)



VizWiz: Authentic Use Case

Anonymization

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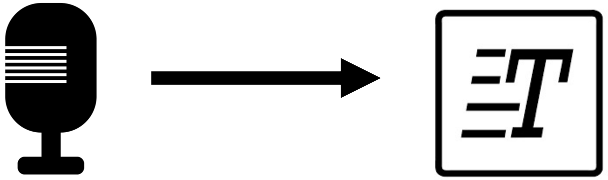
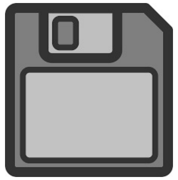
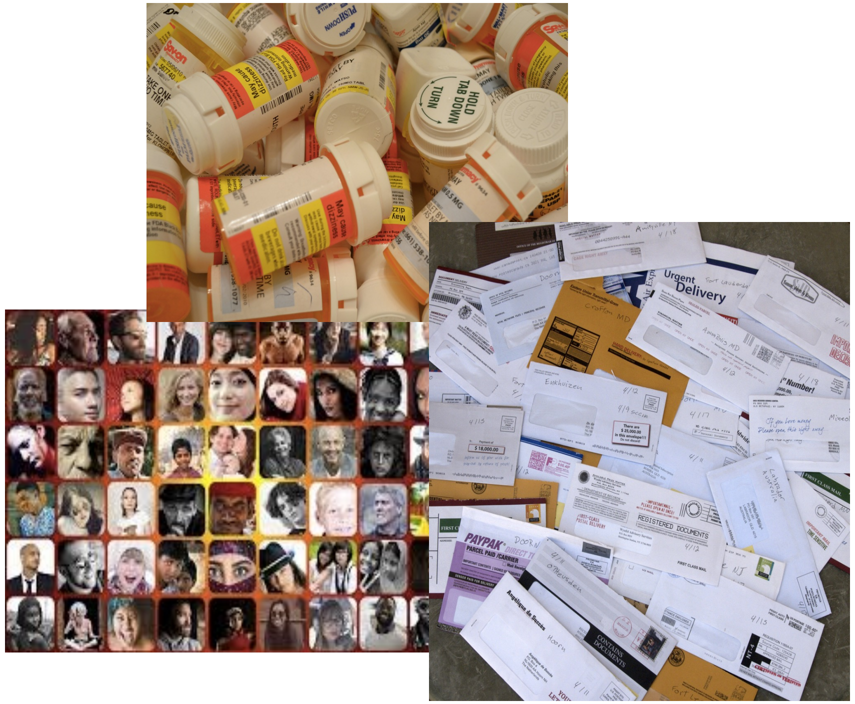


2. Re-save images



In-House Filtering

(personally identifying information)

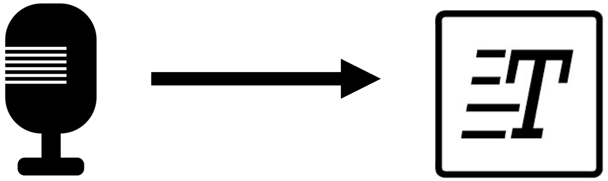


Gurari et al. CVPR 2018

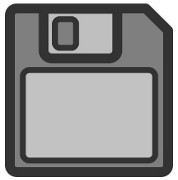
VizWiz: Authentic Use Case

Anonymization

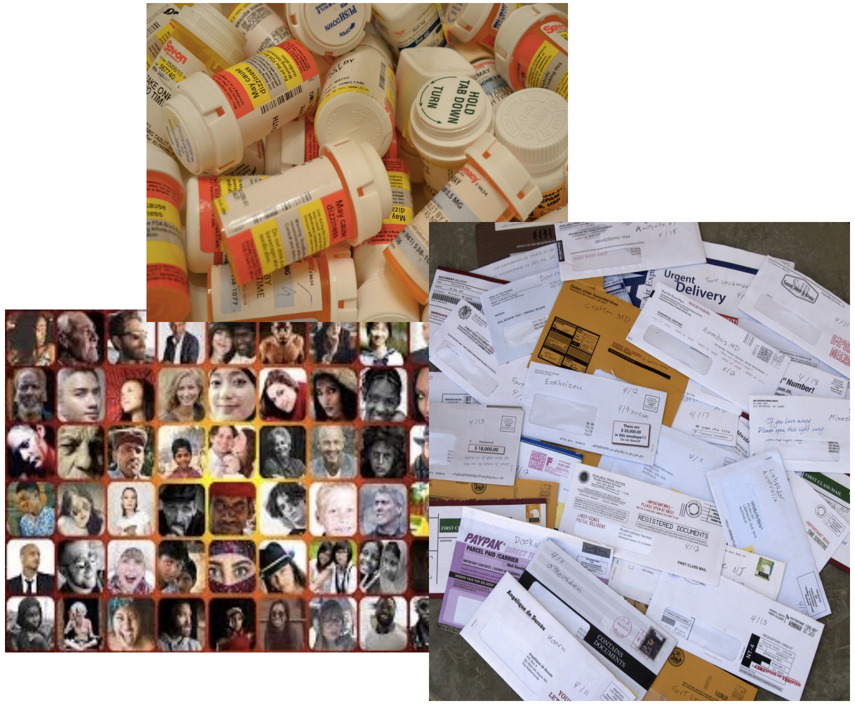
1. Transcribe questions



2. Re-save images



In-House Filtering



Data Labeling

(high quality captions & answers)

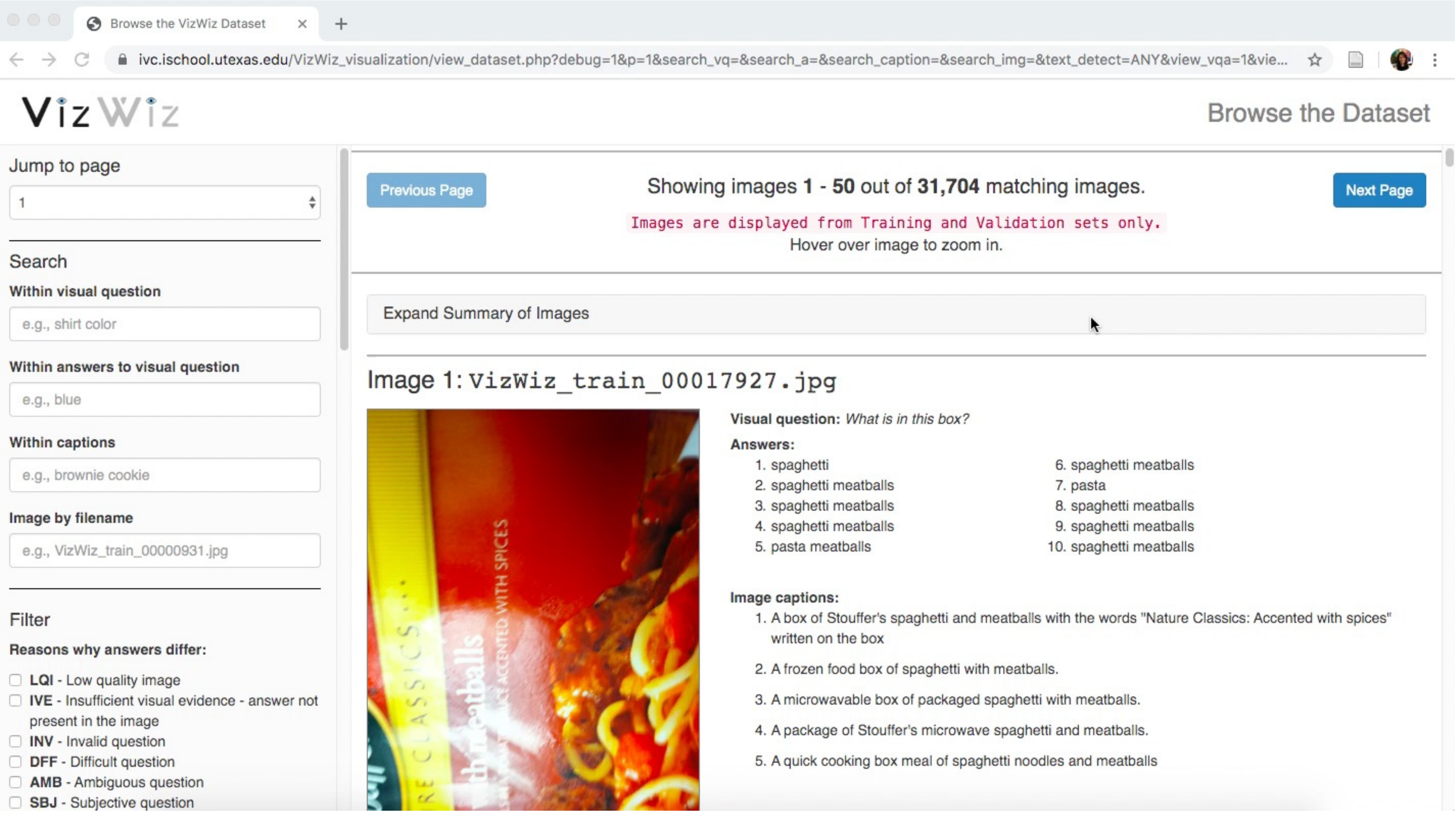
Gurari et al. CVPR 2018

VizWiz: Authentic Use Case

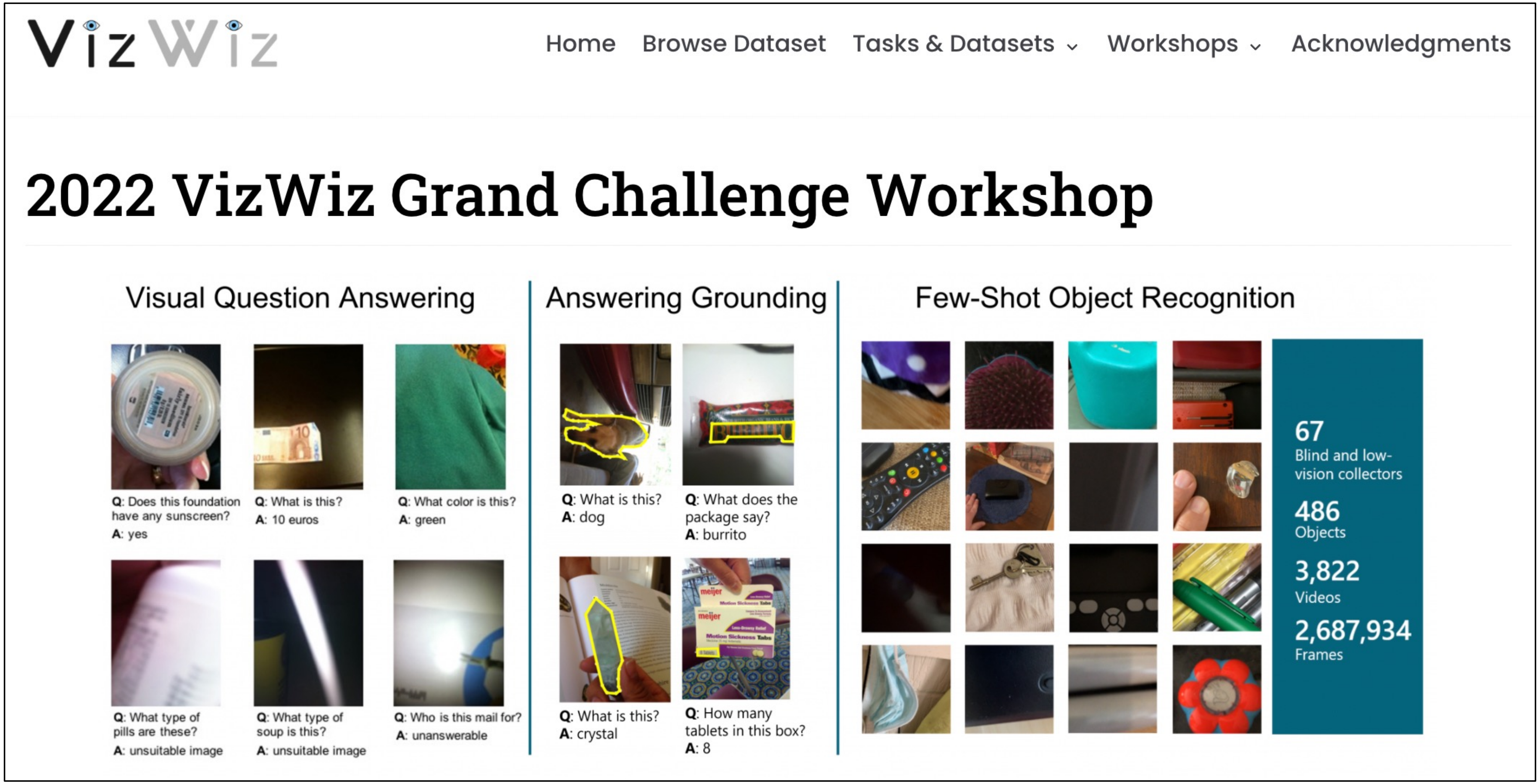
VQA: 32,842 image/question pairs → 328,420 answers

Gurari et al. CVPR 2018

VizWiz: Authentic Use Case (https://vizwiz.org)



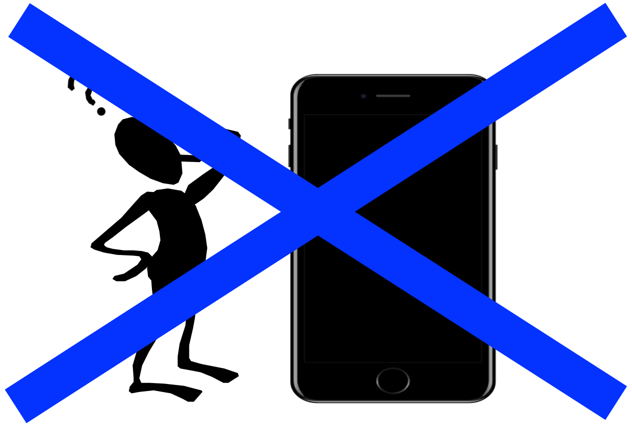
VizWiz-VQA Grand Challenge (4th year in 2022)



https://vizwiz.org

Difference Between Status Quo and the Real-World Use Case

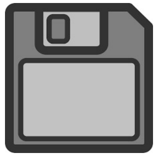
Widely-Used Application



Anonymization

1. Transcribe questions

2. Re-save image



In-House Filtering

Data Labeling

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Class Task: Answer Visual Question

Is my monitor on?

(1)

Hi there can you please tell me what flavor this is?

(2)

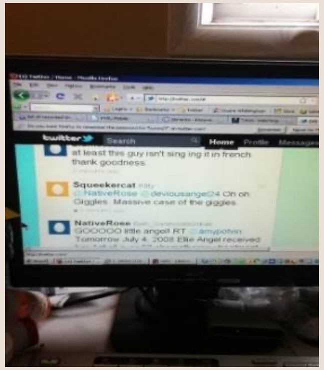
Does this picture look scary?

(3)

Which side of the room is the toilet on?

(4)

Crowdsourced Answers



Is my monitor on?

(1) yes
(2) yes
(3) yes
(4) yes
(5) yes
(6) yes
(7) yes
(8) yes
(9) yes
(10) yes

Hi there can you please tell me what flavor this is?

(1) sweet pepper
(2) sweet pepper
(3) sweet pepper
(4) sweet pepper
(5) sweet pepper
(6) sweet pepper
(7) sweet pepper
(8) sweet pepper
(9) sweet pepper
(10) sweet pepper

Does this picture look scary?

(1) yes
(2) no
(3) no
(4) yes
(5) no
(6) yes
(7) yes
(8) no
(9) no
(10) no

Which side of the room is the toilet on?

(1) right
(2) left
(3) right
(4) right
(5) right
(6) right
(7) right side
(8) right
(9) center
(10) right

Class Discussion

1. Why do different answers arise for a visual question?

2. How would you decide what answer you use when different answers arise? Of note, a method must scale to efficiently support large datasets.

3. All crowdworkers were restricted to US locations for many datasets. How might different cultural backgrounds affect VQA datasets?

Evaluating Automated Predictions

VQA: Ask any question about this image

Is this man thirsty?

Answer

Answer	Confidence
yes	0.8778
no	0.1211
6	0.0001
5	0.0001
pink	0.0001

https://vqa.cloudcv.org/

Evaluating Automated Predictions

Is my monitor on?

Hi there can you please tell me what flavor this is?

Does this picture look scary?

Which side of the room is the toilet on?

(1) yes

(2) chocolate

(3) yes

(4) right

https://vqa.cloudcv.org/

Evaluating Automated Predictions

$$\text{accuracy} = \min\left(\frac{\text{\# humans that provided that answer}}{3}, 1\right)$$

Aishwarya Agrawal, Jiasen Lu, Stanislaw Antol, Margaret Mitchell, C. Lawrence Zitnick, Dhruv Batra, and Devi Parikh. VQA: Visual Question Answering. CVPR 2015.

Evaluation: Example

Does this picture look scary?

(1) yes
(2) no
(3) no
(4) yes
(5) no
(6) yes
(7) yes
(8) no
(9) no
(10) no

What is the accuracy of an algorithm prediction of

- "yes"?
- "no"?
- "maybe"?

$$\text{accuracy} = \min\left(\frac{\#\text{ humans that provided that answer}}{3}, 1\right)$$

Evaluation: Example

Which side of the room is the toilet on?

(1) right
(2) left
(3) right
(4) right
(5) right
(6) right
(7) right side
(8) right
(9) center
(10) right

What is the accuracy of an algorithm prediction of

- "right"?
- "left"?
- "right side"?
- "center"?
- "bottom"?

$$\text{accuracy} = \min\left(\frac{\#\text{ humans that provided that answer}}{3}, 1\right)$$

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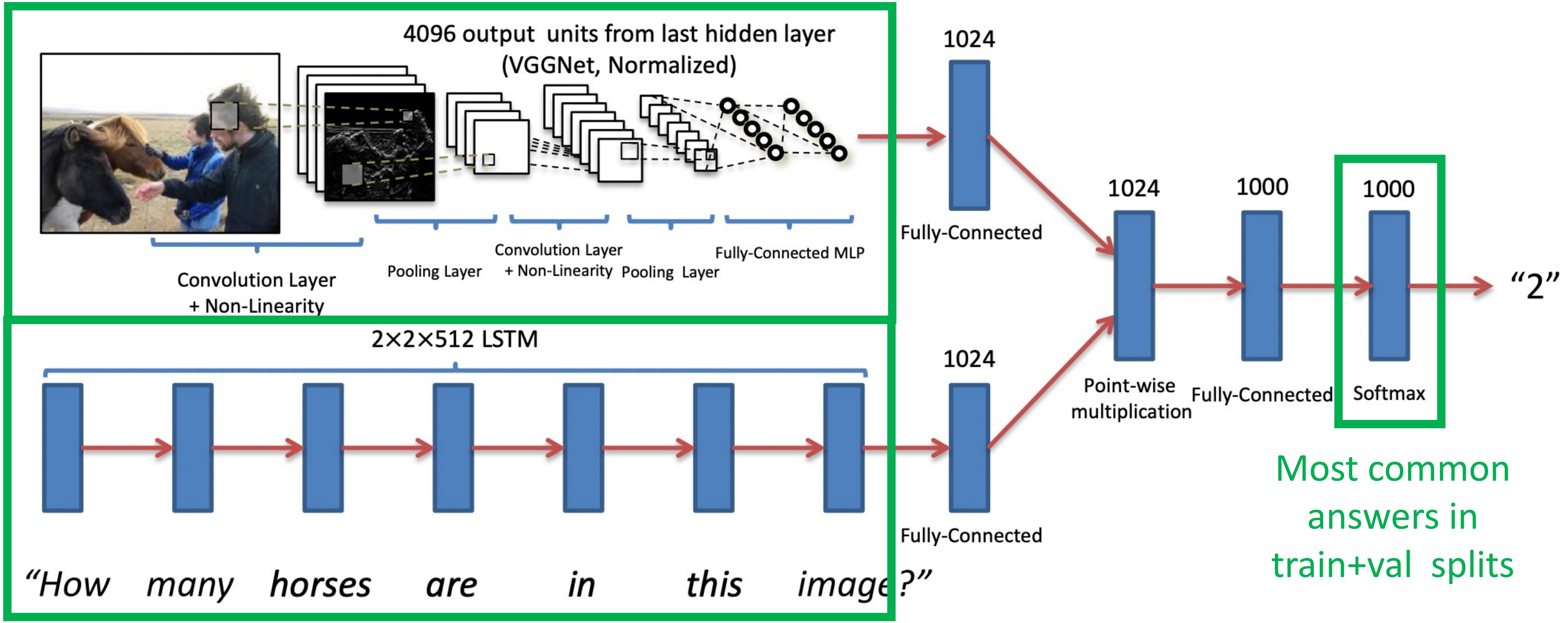
Architecture

Image representation



Most common answers in train+val splits

Question representation: concatenates cell and hidden states of last hidden layer

Agrawal et al. VQA: Visual Question Answering. arXiv 2016.

Experimental Results (Fine-Grained Analysis with Respect to Answer Type)

All	Yes/No	Number	Other
57.75	**80.50**	**36.77**	**43.08**

On which answer type, does the model achieve the best performance?

Agrawal et al. VQA: Visual Question Answering. arXiv 2016.

Experimental Results (Fine-Grained Analysis with Respect to Answer Type)

All	Yes/No	Number	Other
57.75	**80.50**	**36.77**	**43.08**

On which answer type, does the model achieve the worst performance?

Agrawal et al. VQA: Visual Question Answering. arXiv 2016.

Experimental Results (Fine-Grained Analysis with Respect to Answer Type)

All	Yes/No	Number	Other
57.75	**80.50**	**36.77**	**43.08**

Why might we observe the above performance trends for answer types?

Agrawal et al. VQA: Visual Question Answering. arXiv 2016.

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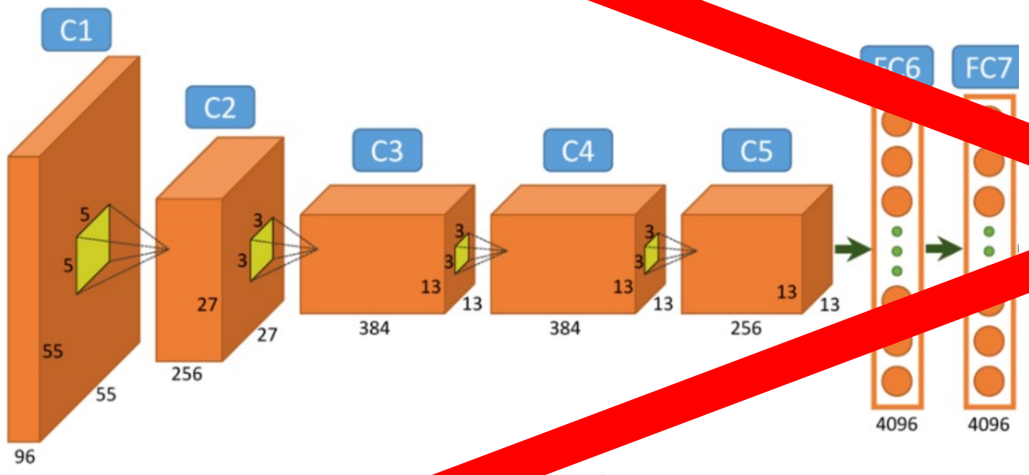
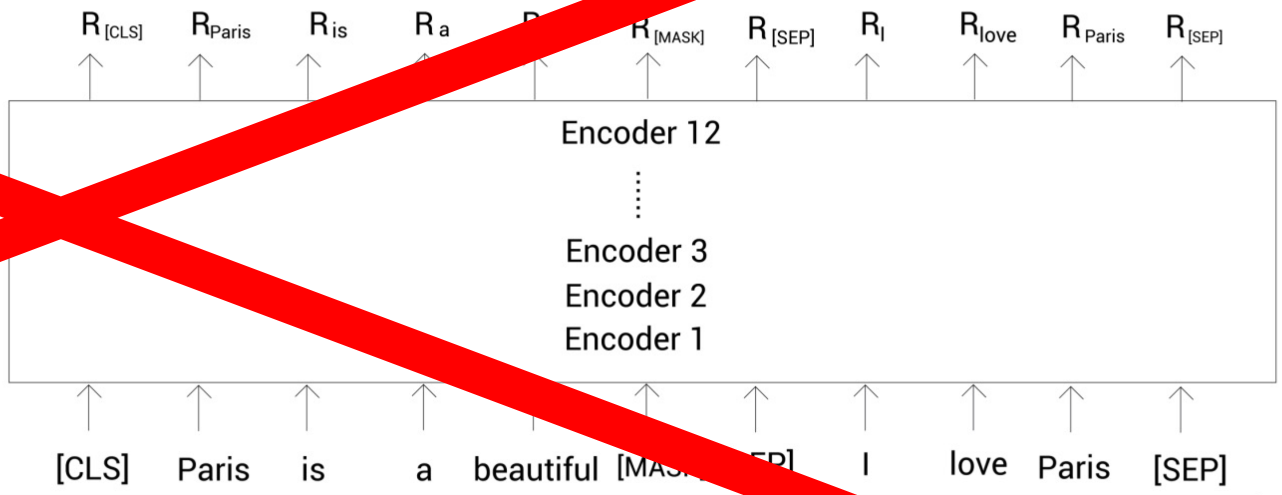
Key Idea: Multimodal Representation Rather Than Single Modality Representations

e.g., vision representation with AlexNet



https://www.researchgate.net/figure/Architecture-of-Alexnet-From-left-to-right-input-to-output-five-convolutional-layers_fig2_312303454

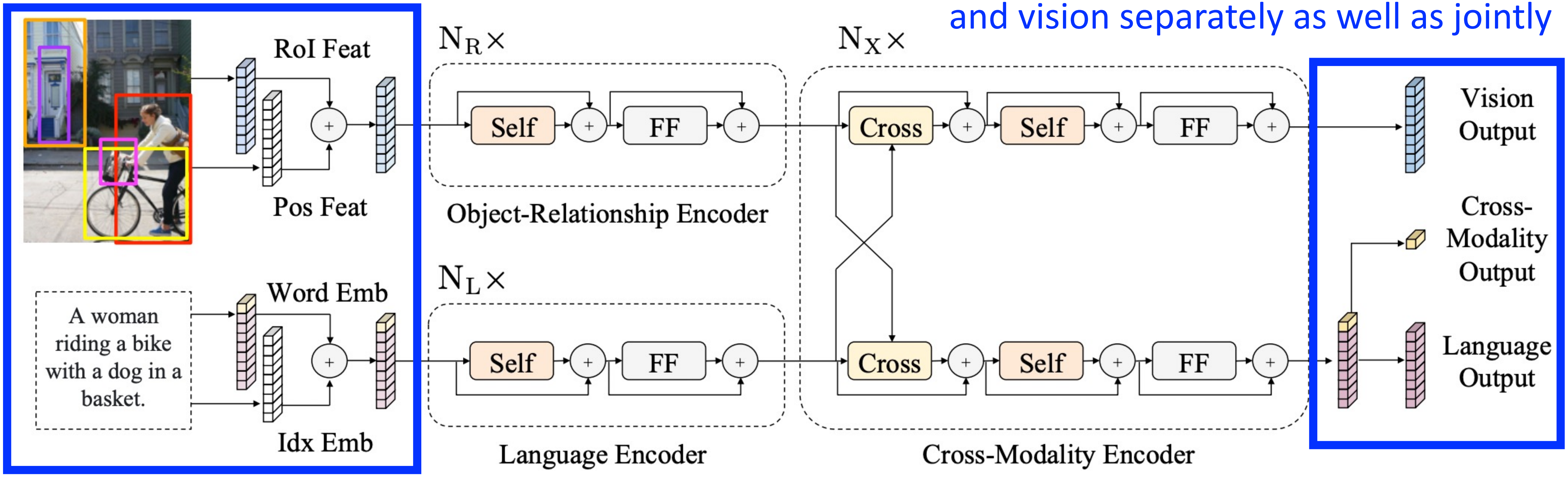
e.g., language representation with BERT



https://static.packt-cdn.com/downloads/97818388215[illegible]olorImages.pdf

LXMERT: Learning Cross-Modality Encoder Representations from Transformers

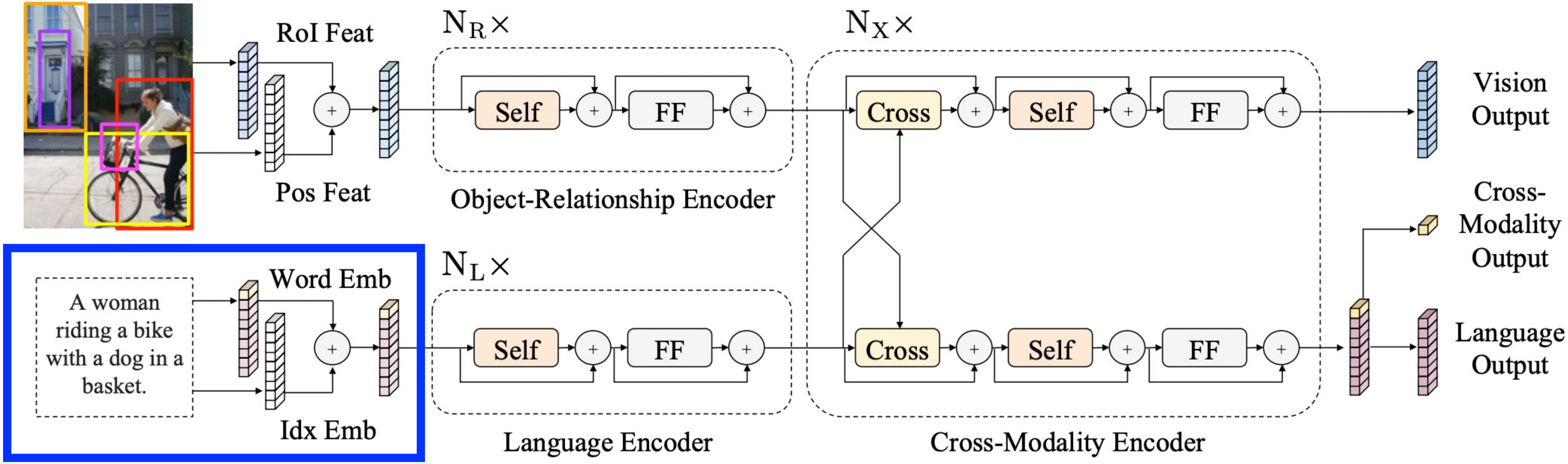
Generates representations for image and vision separately as well as jointly



Pretrains using language and vision input

Tan and Bansal, EMNLP 2019.

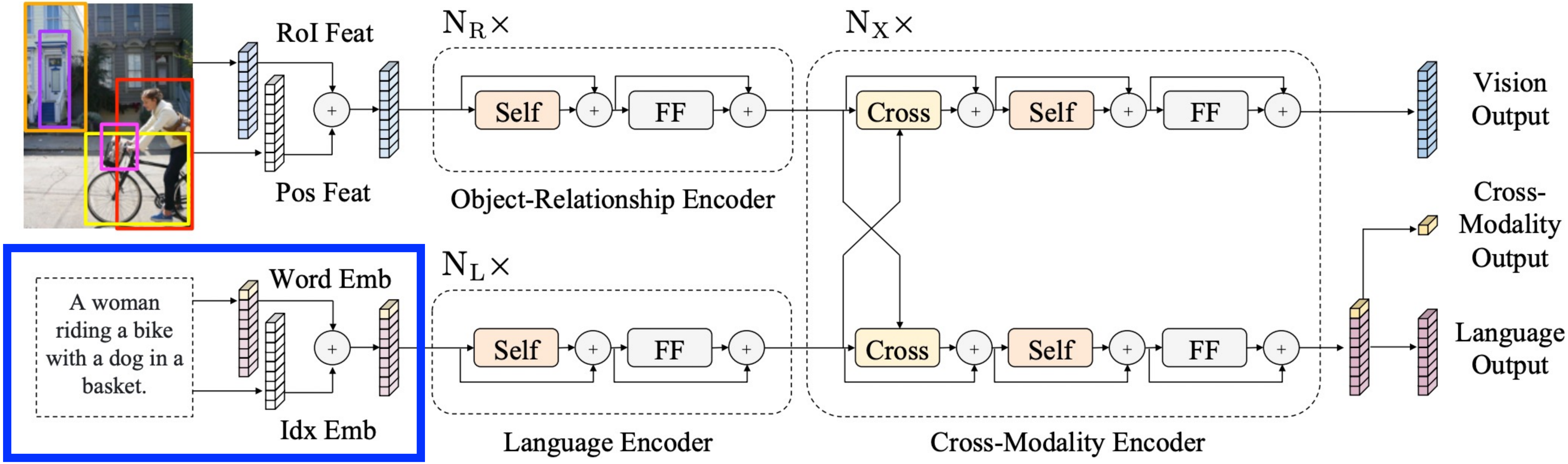
LXMERT: Language Input



[CLS] is added to the start of the sequence

Tan and Bansal, EMNLP 2019.

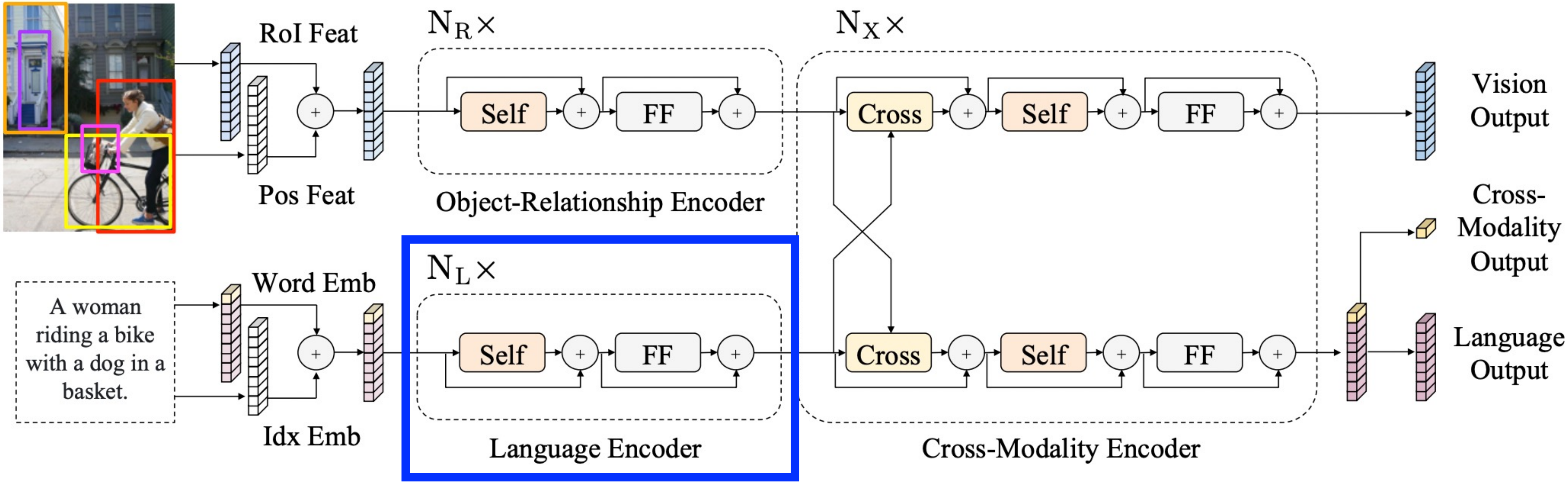
LXMERT: Language Input



Each word is represented as sum of its word embedding and position encoding

Tan and Bansal, EMNLP 2019.

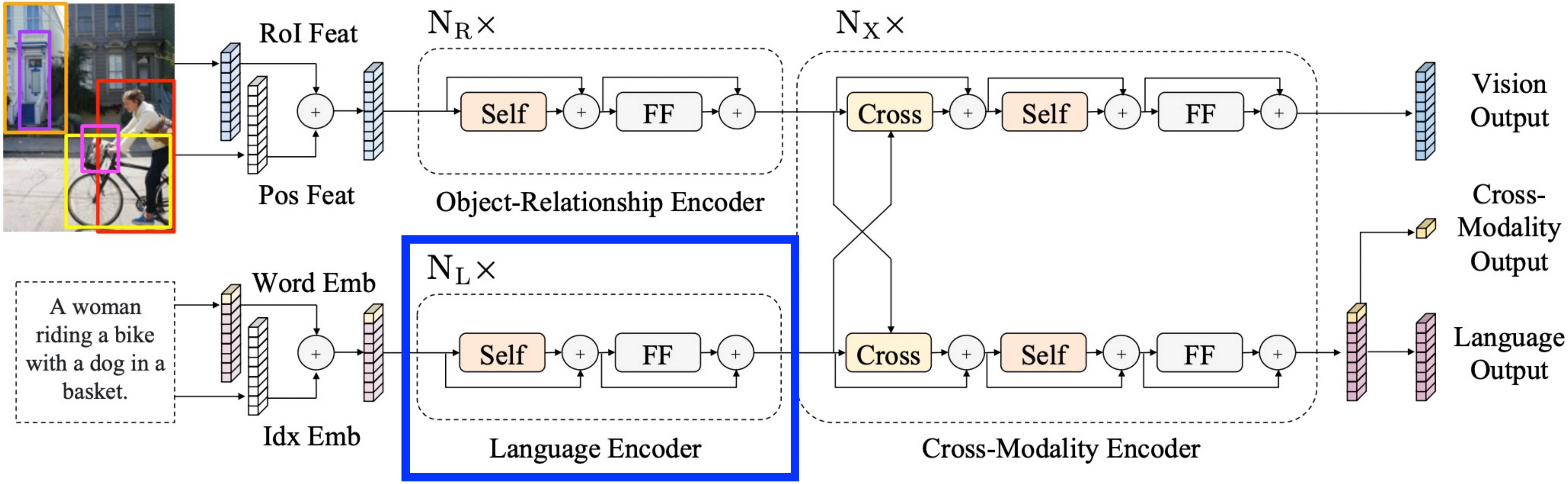
LXMERT: Language Input



Transformer encoder (i.e., BERT);
what does its output represent?

Tan and Bansal, EMNLP 2019.

LXMERT: Language Input

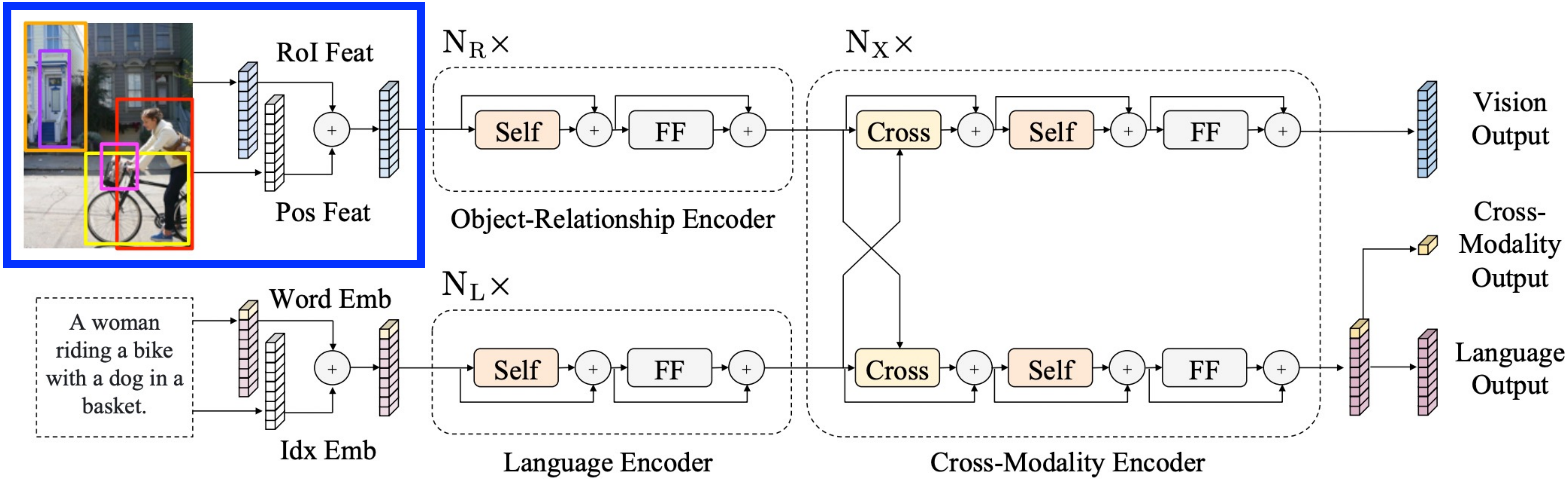


Transformer encoder (i.e., BERT); represents words with their relationships to all words

Tan and Bansal, EMNLP 2019.

LXMERT: Vision Input

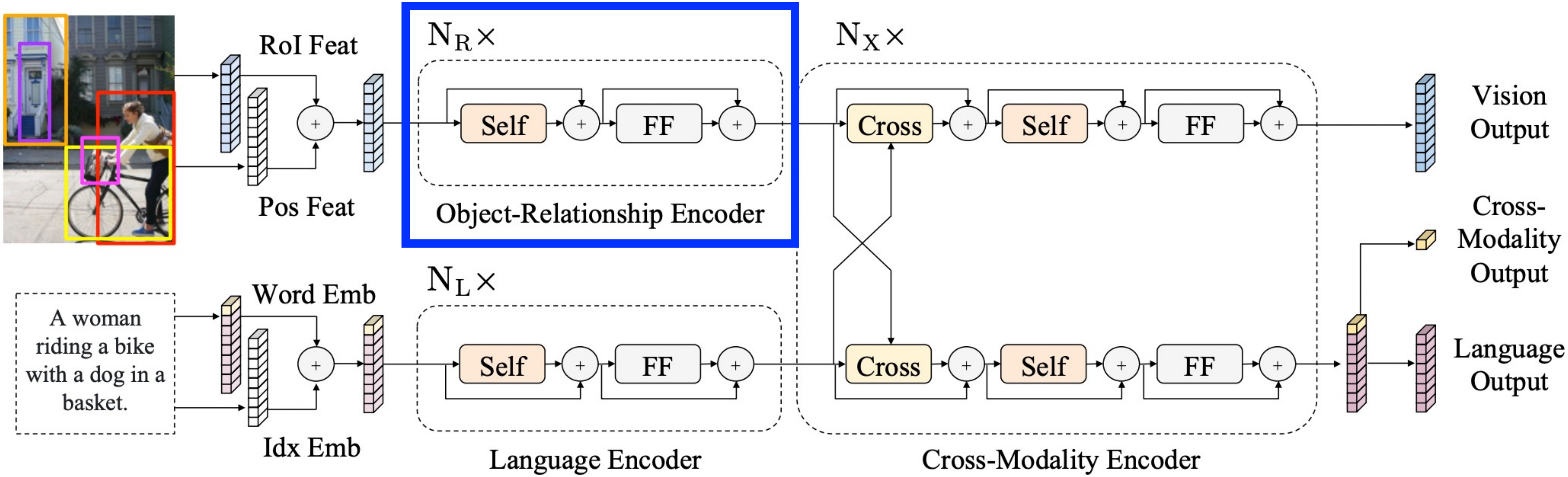
Each image is represented as a description of *m* objects detected with Faster R-CNN using features from Faster R-CNN and position encodings



Tan and Bansal, EMNLP 2019.

LXMERT: Architecture

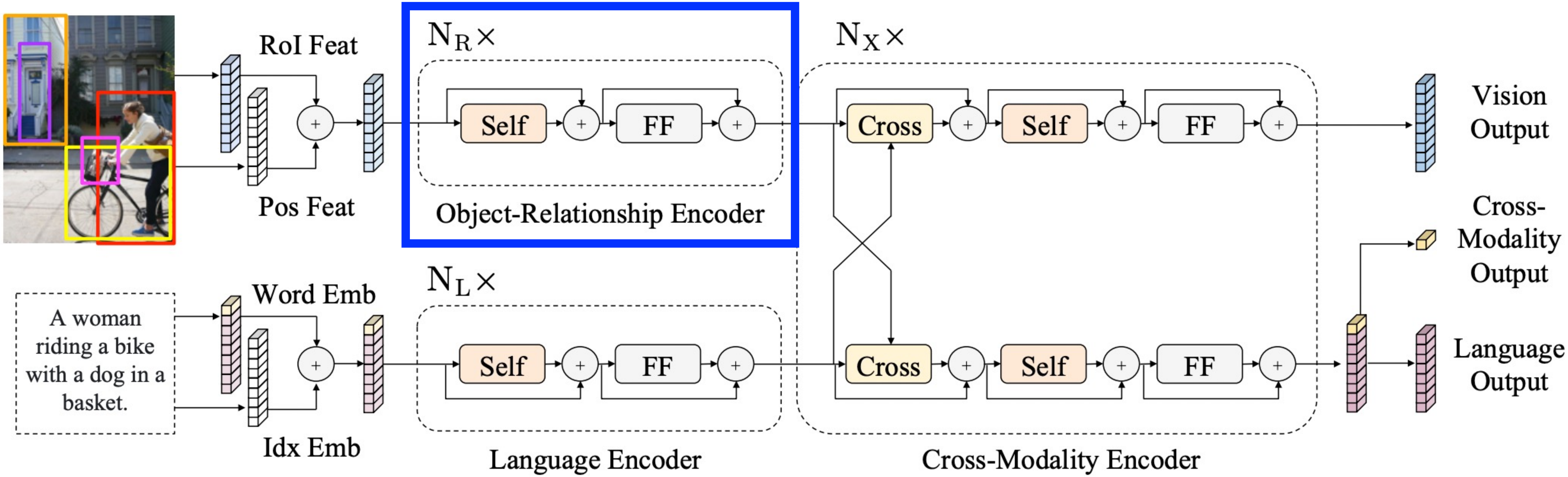
Transformer encoder (i.e., BERT);
what does its output represent?



Tan and Bansal, EMNLP 2019.

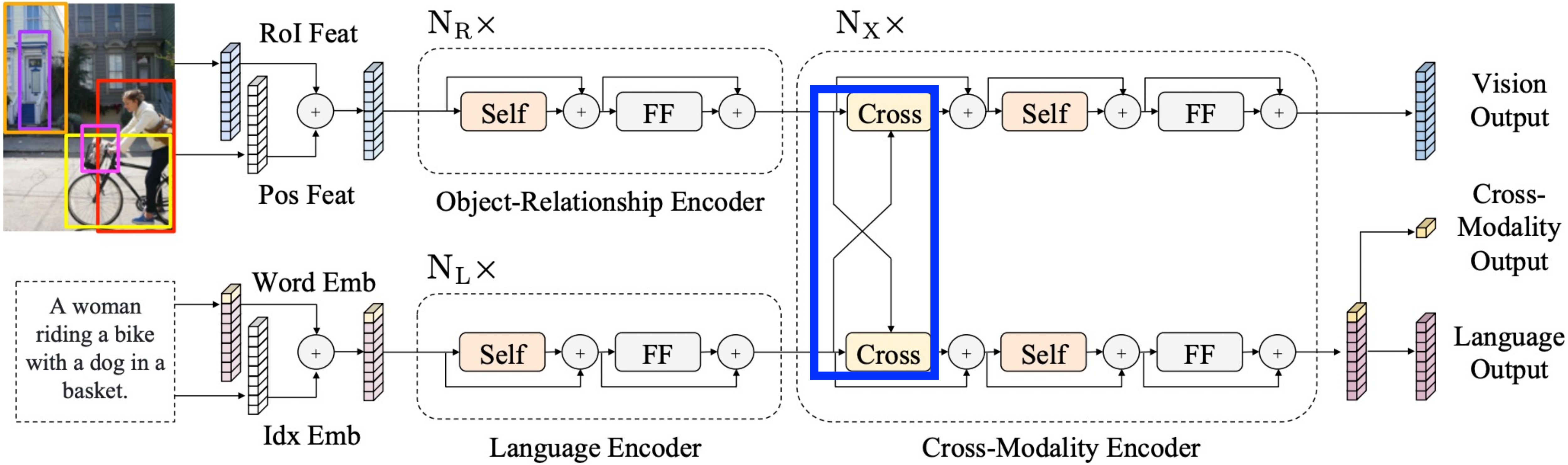
LXMERT: Architecture

Transformer encoder (i.e., BERT); represents objects with their relationships to all objects



Tan and Bansal, EMNLP 2019.

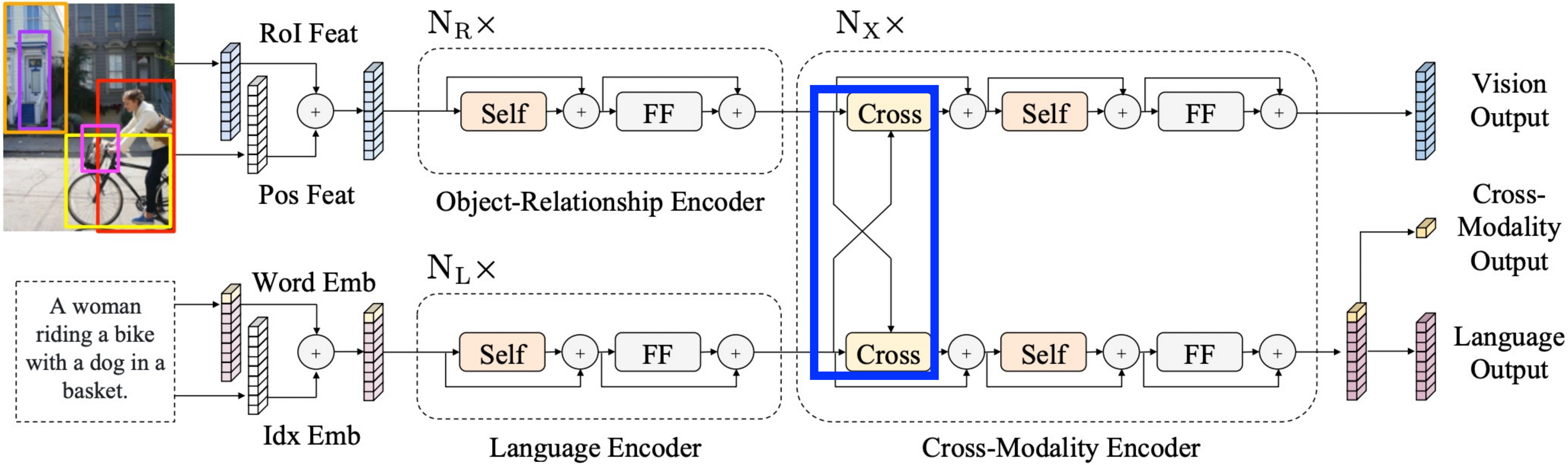
LXMERT: Architecture



Learns cross-modality representations
by aligning entities in the two modalities

Tan and Bansal, EMNLP 2019.

LXMERT: Architecture



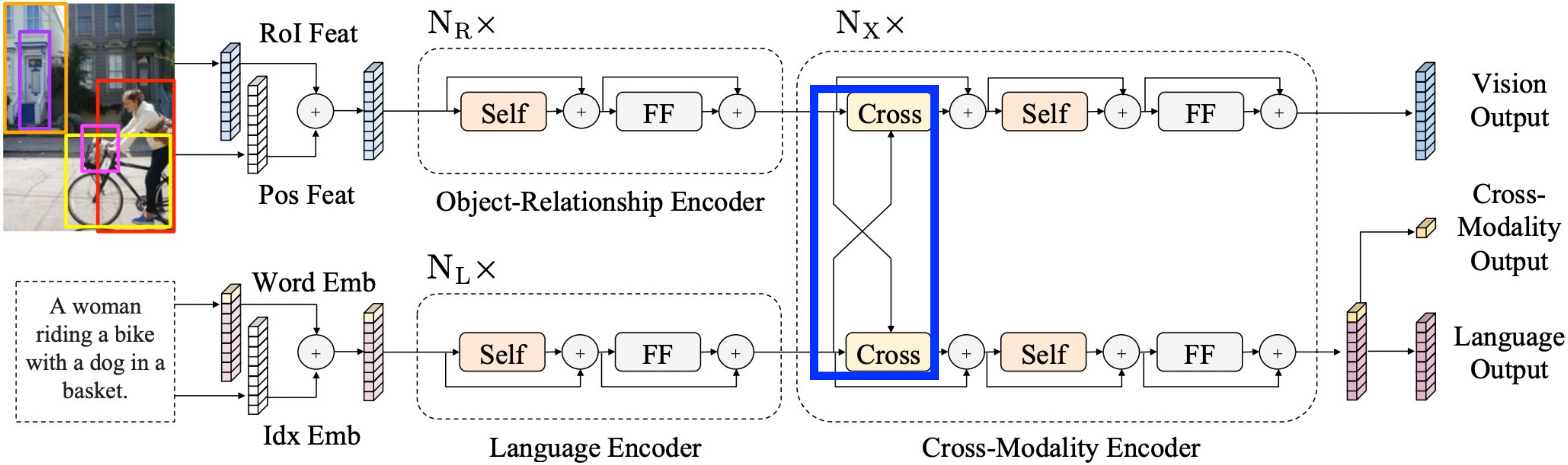
$$a_j = \mathrm{score}(x, y_j)$$

$$\alpha_j = \exp(a_j) / \sum_k \exp(a_k)$$

Two cross-attention layers are functions of the “query” and “context” vectors which are language and vision features

Tan and Bansal, EMNLP 2019.

LXMERT: Architecture



$$a_j = \text{score}(x, y_j)$$

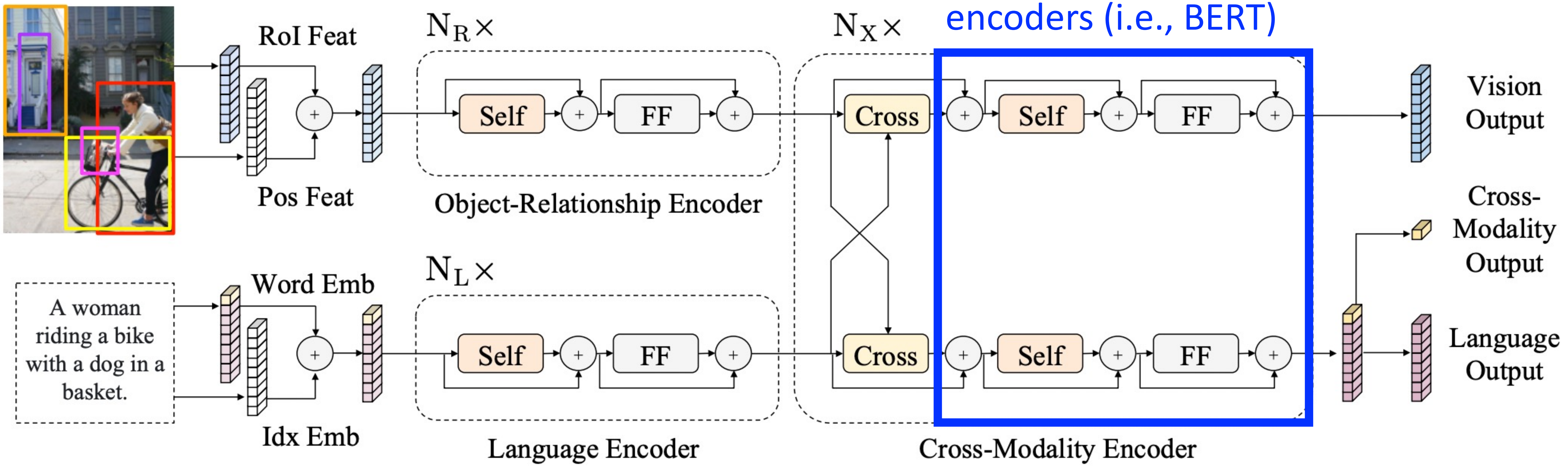
$$\alpha_j = \exp(a_j) / \sum_k \exp(a_k)$$

Output is weighted sum of context vectors, weighted by the attention scores

Tan and Bansal, EMNLP 2019.

LXMERT: Architecture

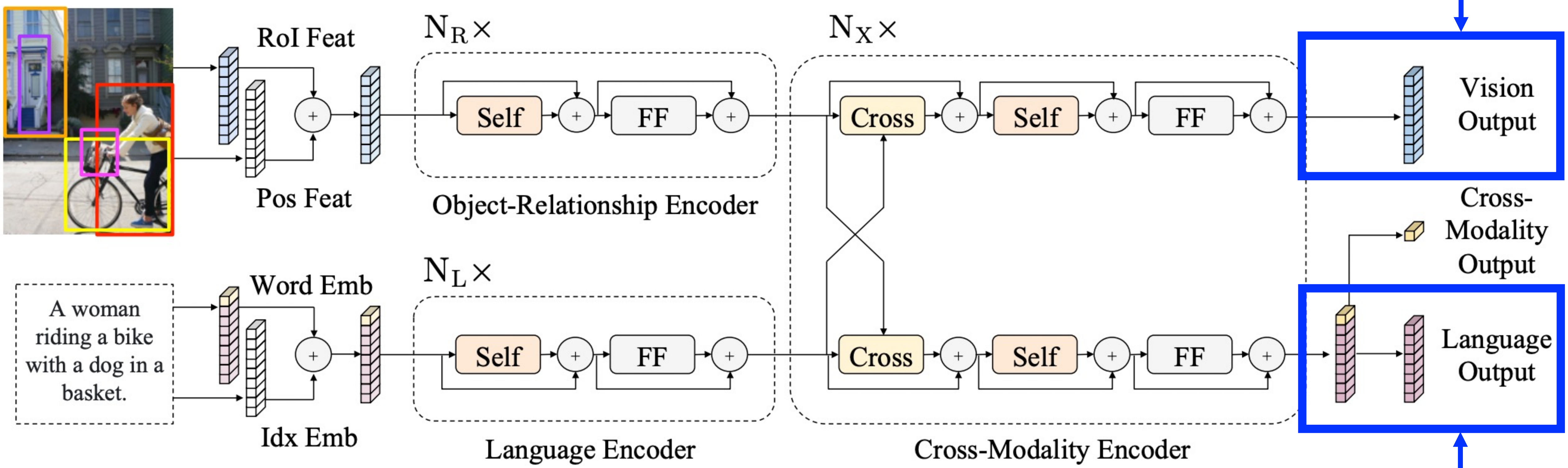
Two more layers of transformer encoders (i.e., BERT)



Tan and Bansal, EMNLP 2019.

LXMERT: Output

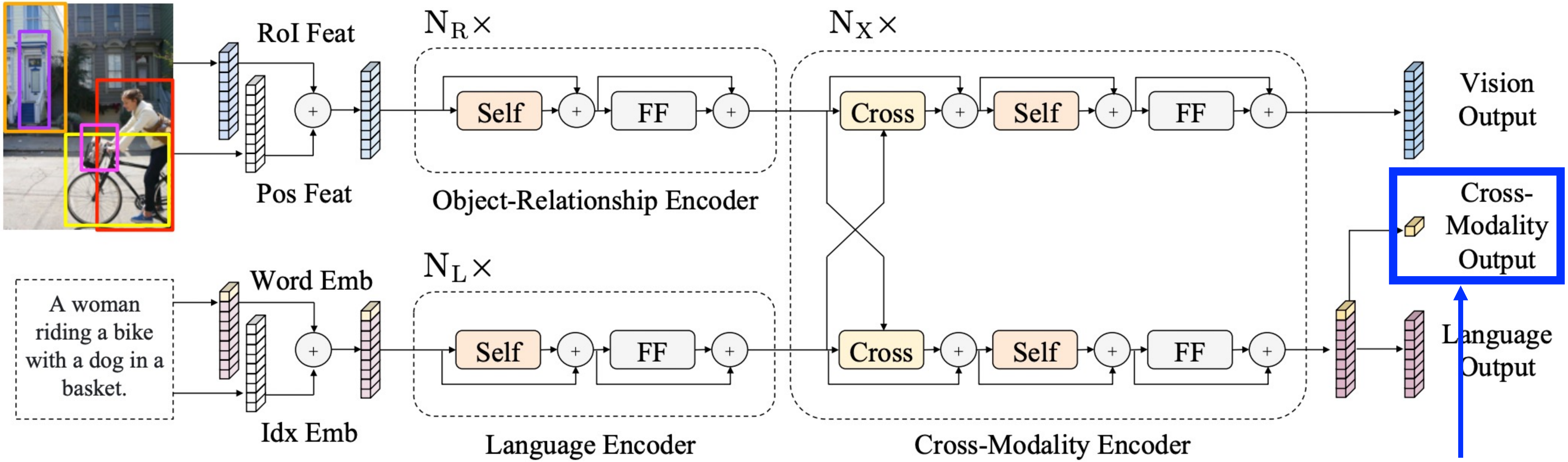
New representation of input detected objects



New representation of input language sequence

Tan and Bansal, EMNLP 2019.

LXMERT: Output

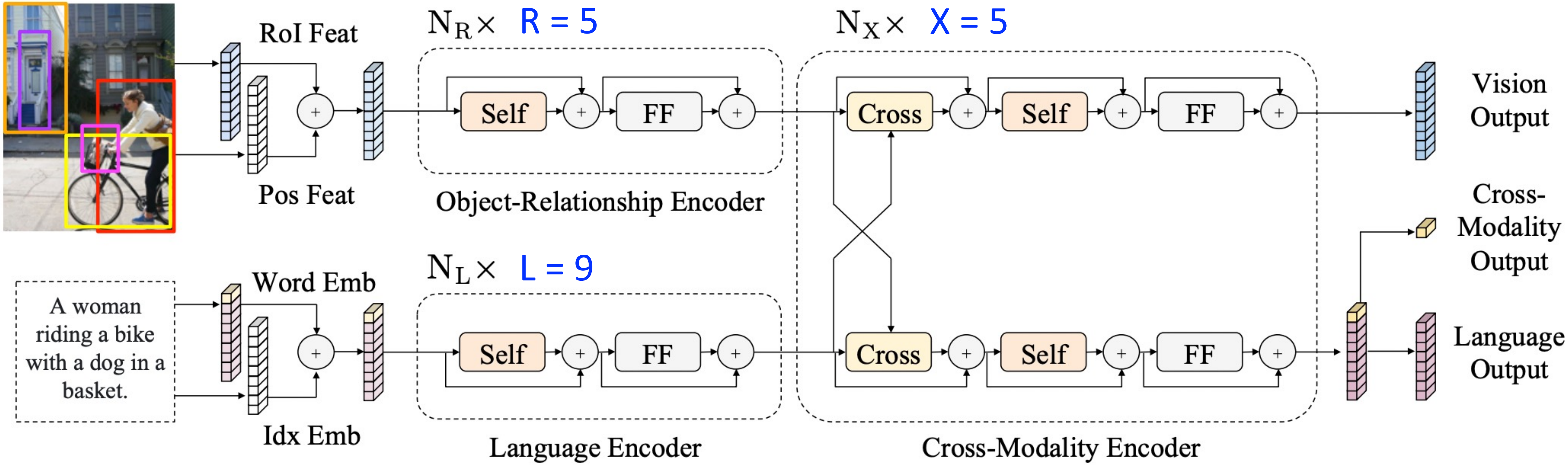


Cross-modality representation is the [CLS] token appended at the start of the sentence

Tan and Bansal, EMNLP 2019.

LXMERT: Implementation Details

Pretrained Faster R-CNN can locate 1,600 categories
and only 36 object detections are kept per image

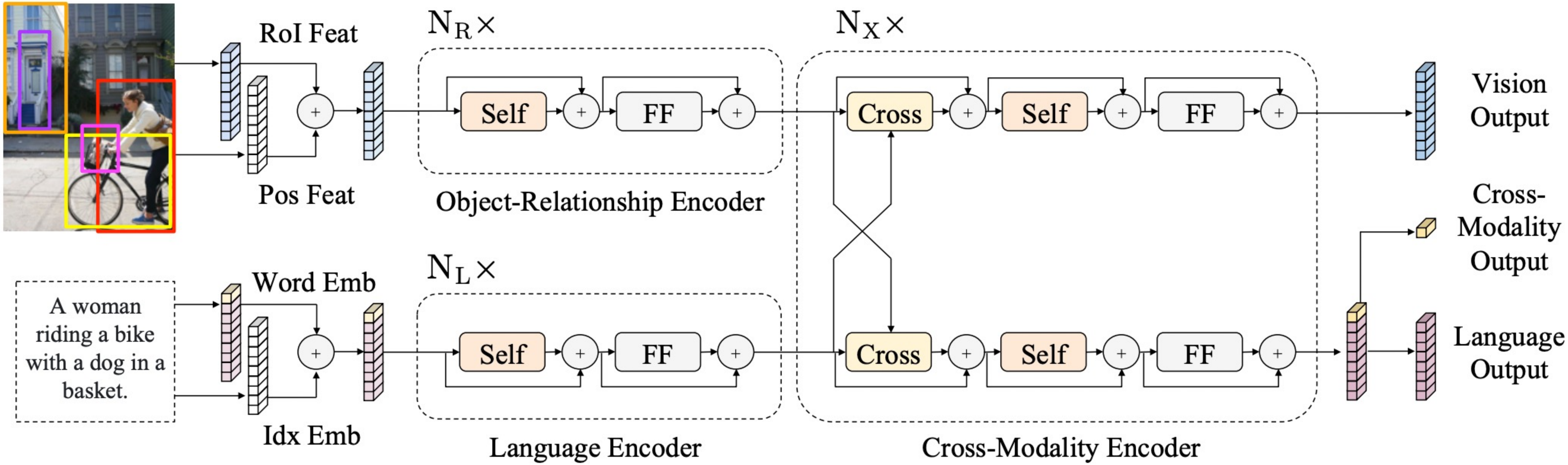


Number of layers mimics the size of BERT base of 12 layers;
i.e., (5+9)/2 + 5

Tan and Bansal, EMNLP 2019.

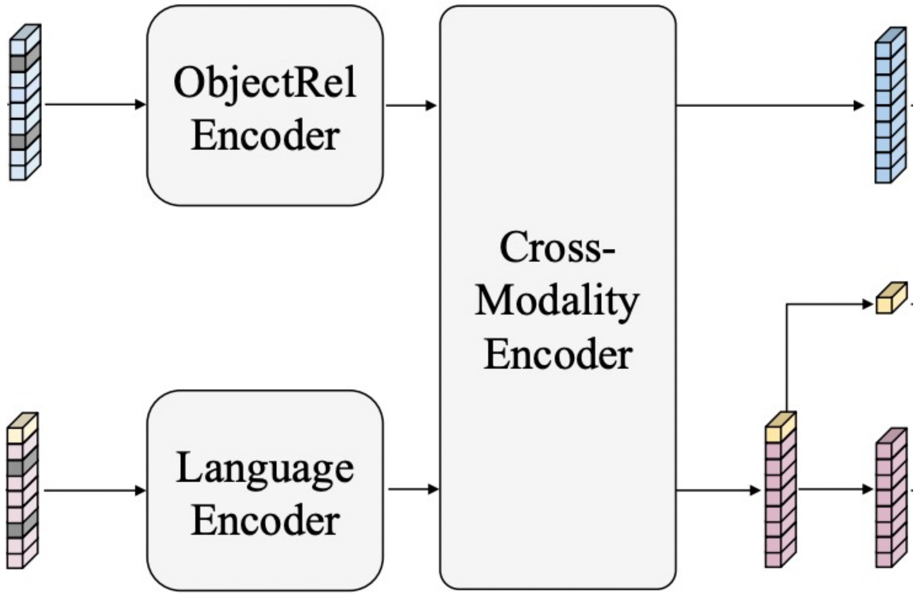
LXMERT: Architecture

What might be strengths and limitations of the resulting feature representations based on the architecture used?



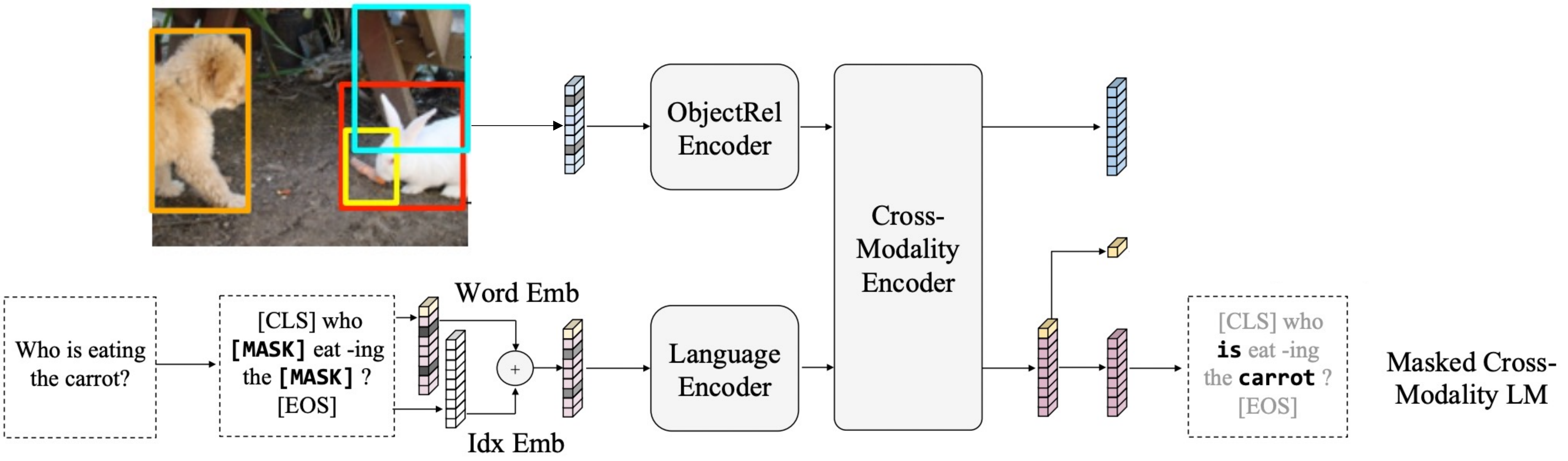
Tan and Bansal, EMNLP 2019.

LXMERT: Summary of Architecture



Tan and Bansal, EMNLP 2019.

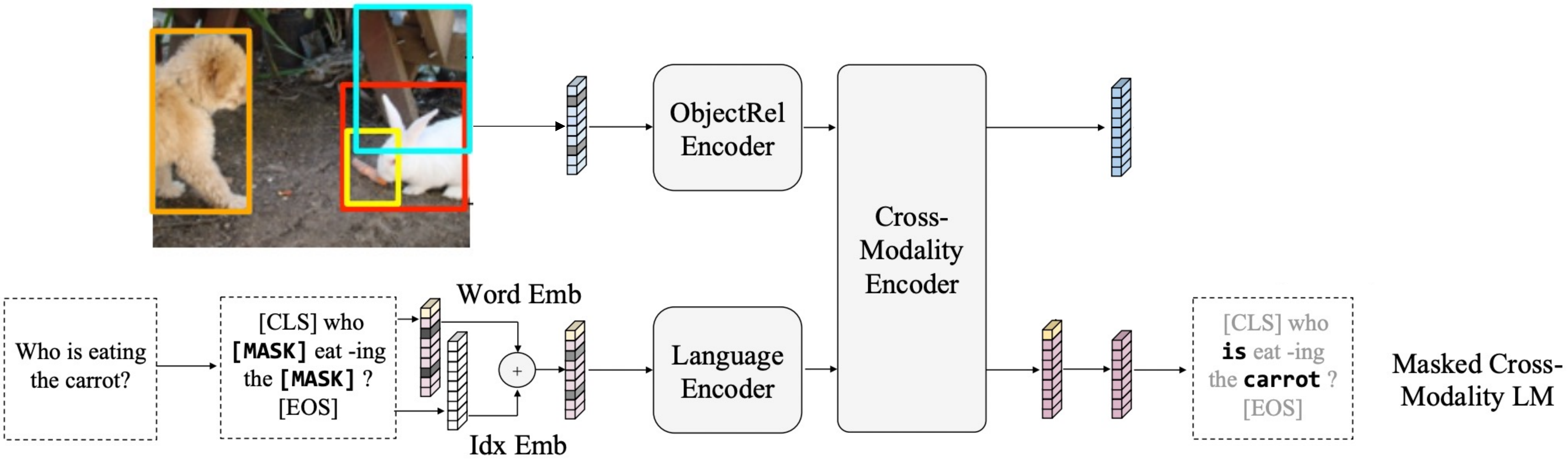
LXMERT: Pretraining Task 1 (Language)



Task used for BERT: mask 15% of input words and then predict them

Tan and Bansal, EMNLP 2019.

LXMERT: Pretraining Task 1 (Language)

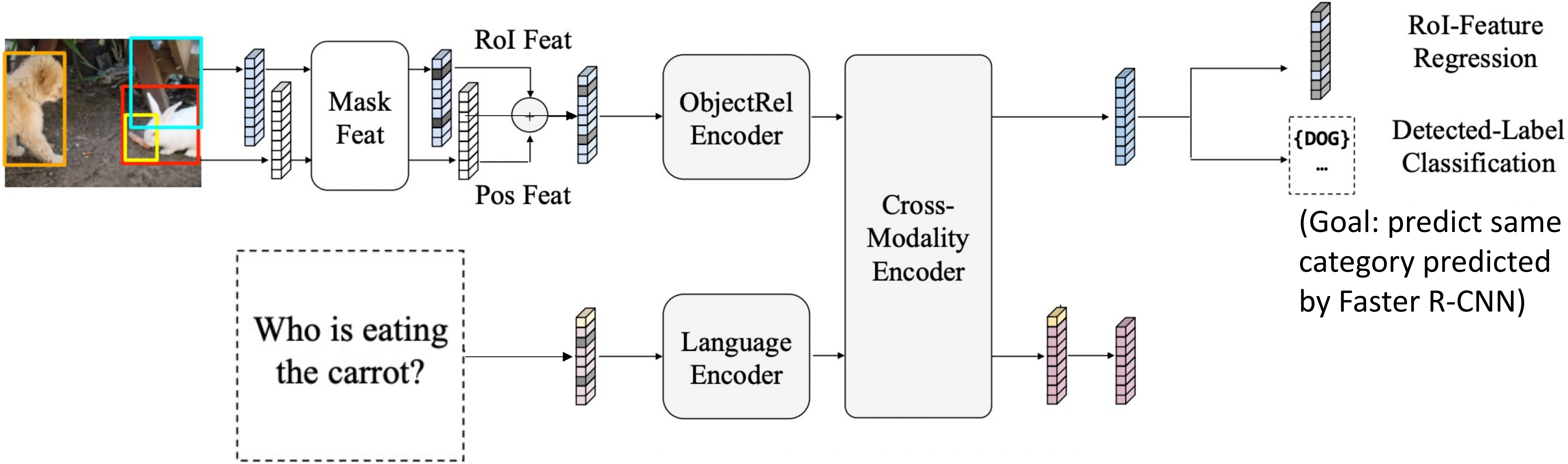


Unlike BERT, vision modality can resolve language ambiguity; e.g., shows what is being eaten

Tan and Bansal, EMNLP 2019.

LXMERT: Pretraining Tasks 2 & 3 (Vision)

Mask 15% of input objects and then predict their original feature values and categories

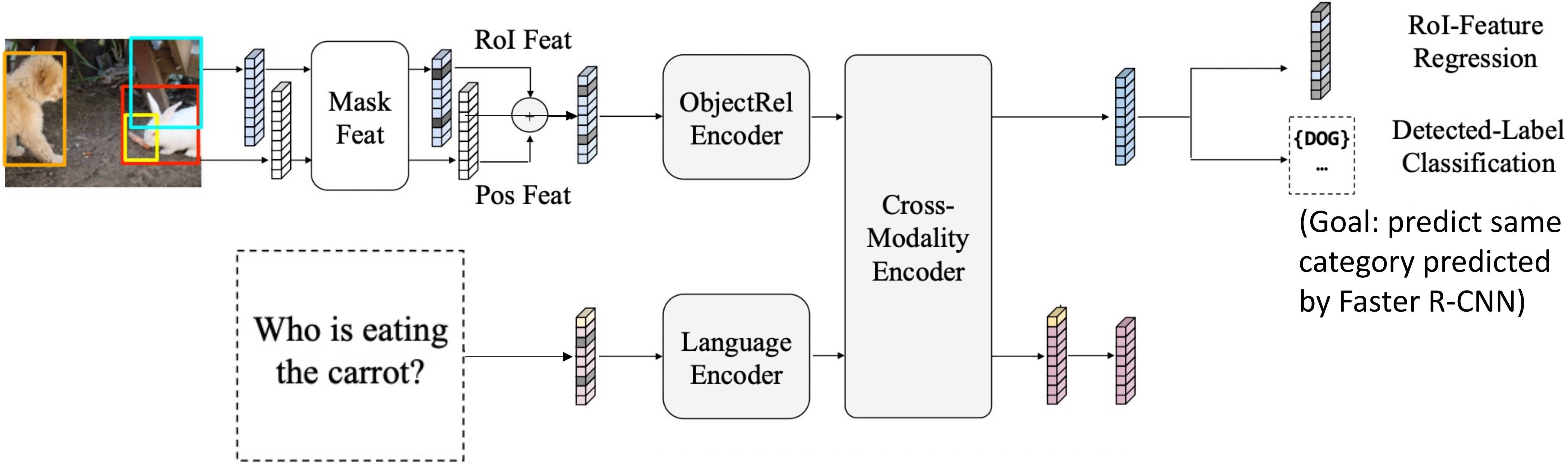


(Goal: predict same category predicted by Faster R-CNN)

Tan and Bansal, EMNLP 2019.

LXMERT: Pretraining Tasks 2 & 3 (Vision)

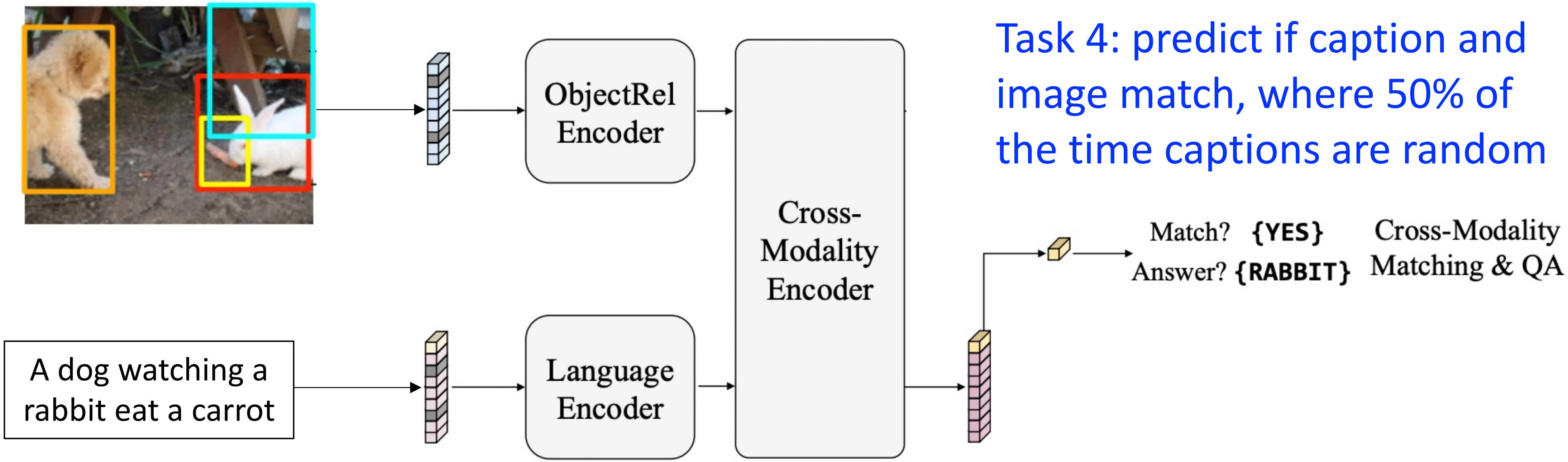
Knowledge about other objects and the language should help predict masked objects



(Goal: predict same category predicted by Faster R-CNN)

Tan and Bansal, EMNLP 2019.

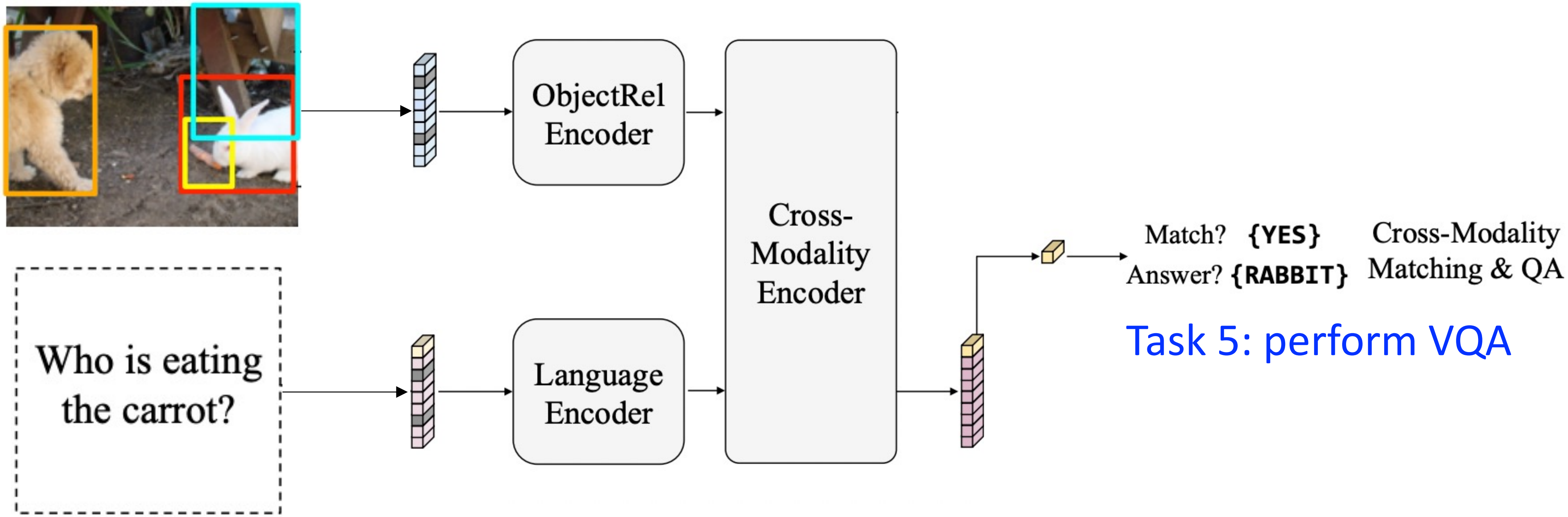
LXMERT: Pretraining Tasks 4 & 5 (Both Modalities)



Task 4: predict if caption and image match, where 50% of the time captions are random

Tan and Bansal, EMNLP 2019.

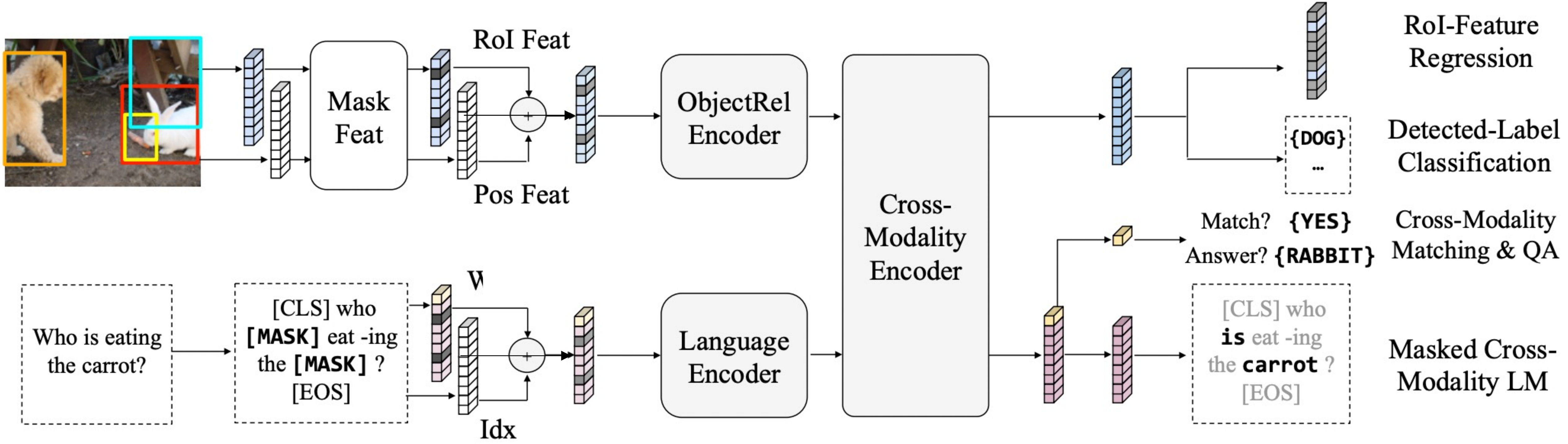
LXMERT: Pretraining Tasks 4 & 5 (Both Modalities)



Task 5: perform VQA

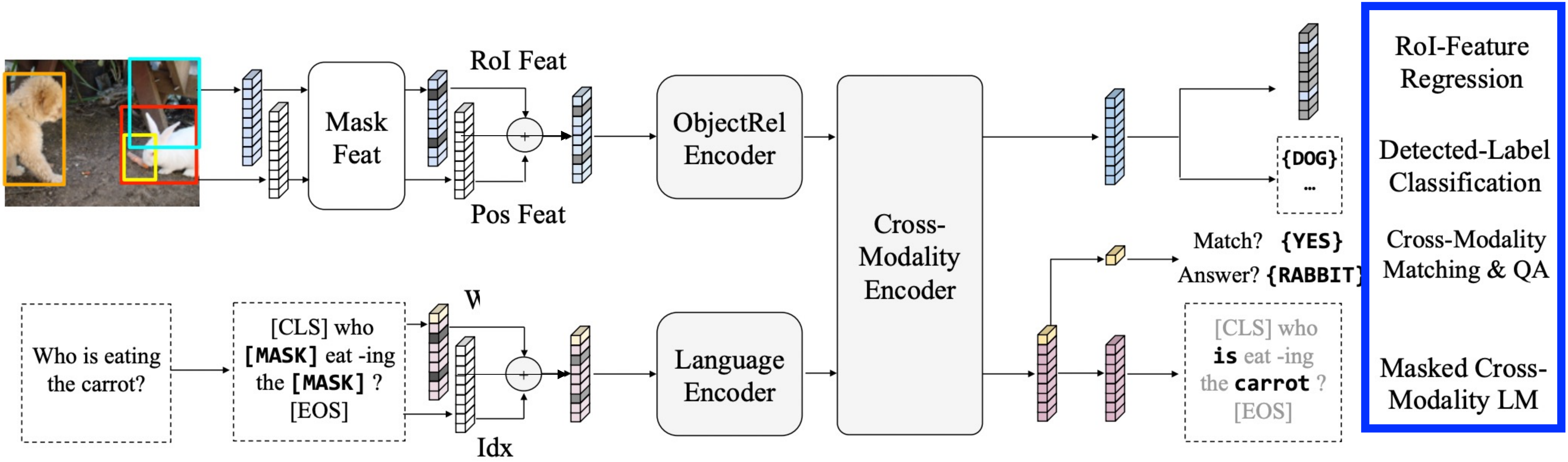
Tan and Bansal, EMNLP 2019.

LXMERT: 5 Pretraining Tasks



Tan and Bansal, EMNLP 2019.

LXMERT: All Pretraining Task Losses Are Summed During Training



What might be strengths and limitations of the resulting feature representations based on the type of pretraining tasks used?

Tan and Bansal, EMNLP 2019.

LXMERT: Training Data for Pretraining

Image Split	Images	Sentences (or Questions)					
		COCO-Cap	VG-Cap	VQA	GQA	VG-QA	All
MS COCO - VG	72K	361K	-	387K	-	-	0.75M
MS COCO $\cap$ VG	51K	256K	2.54M	271K	515K	724K	4.30M
VG - MS COCO	57K	-	2.85M	-	556K	718K	4.13M

All images are from two image sets, MS COCO and Visual Genome, which were collected by scraping images from the photo-sharing website Flickr

(Visual Genome includes the MS COCO images)

Tan and Bansal, EMNLP 2019.

LXMERT: Training Data for Pretraining

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Language annotations came from 2 image captioning and 3 VQA datasets, authored by crowdworkers paid to create captions, questions, and answers

Tan and Bansal, EMNLP 2019.

LXMERT: Training Data for Pretraining

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All	180K	617K	5.39M	658K	1.07M	1.44M	9.18M

A total of 9.18M image-sentence pairs are included for 180,000 images (questions in VQA datasets are used for the image-sentence pairs)

Tan and Bansal, EMNLP 2019.

LXMERT: Training Data for Pretraining

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What might be strengths and limitations of the resulting feature representations based on the type of training data that is used?

Tan and Bansal, EMNLP 2019.

LXMERT: Fine-Tuning Experimental Results

Method	VQA			
	Binary	Number	Other	**Accu**
Human	-	-	-	-
Image Only	-	-	-	-
Language Only	66.8	31.8	27.6	44.3
State-of-the-Art	85.8	53.7	60.7	70.4
LXMERT	**88.2**	**54.2**	**63.1**	**72.5**

Achieved the best performance, with stronger gains over prior work for questions that lead to "binary" and "other" answers

Tan and Bansal, EMNLP 2019.

LXMERT: Fine-Tuning Experimental Results

Method	VQA				GQA			NLVR^2	
	Binary	Number	Other	**Accu**	Binary	Open	**Accu**	Cons	**Accu**
Human	-	-	-	-	91.2	87.4	89.3	-	96.3
Image Only	-	-	-	-	36.1	1.74	17.8	7.40	51.9
Language Only	66.8	31.8	27.6	44.3	61.9	22.7	41.1	4.20	51.1
State-of-the-Art	85.8	53.7	60.7	70.4	76.0	40.4	57.1	12.0	53.5
LXMERT	**88.2**	**54.2**	**63.1**	**72.5**	**77.8**	**45.0**	**60.3**	**42.1**	**76.2**

The representations also led to the best performance for an additional VQA dataset and a visual reasoning task (i.e., does statement describe two images or not)

Tan and Bansal, EMNLP 2019.

Today’s Topics

- Visual question answering applications
- Visual question answering datasets
- Visual question answering evaluation
- Mainstream challenge 2015 winner: baseline approach
- Mainstream challenge 2019 winner: transformer-based approach
- Programming tutorial

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The End