__/__/2022

Visual Question Answering

Final project for the Deep Learning course

Cocci Federica (1802435)
Proietti Michela (1739846)
Santilli Sofia (1813509)

Task

Input:
image + free-form, open-ended, natural language question

Output:
natural language answer

AI capability required	Questions examples
fine-grained recognition	“What kind of cheese is on the pizza?”
object detection	“How many bikes are there?”
activity recognition	“Is this man crying?”
knowledge-base reasoning	“Is this a vegetarian pizza?”
commonsense reasoning	“Is this person expecting company?”
other	“.....”

Proposed approaches

Visual Question Answering

- Random baseline
- Prior yes baseline
- Approach 1: CNN + LSTM
- Approach 2: Generative LXMERT

Dataset

Visual Q&A v2.0 https://visualqa.org/download.html

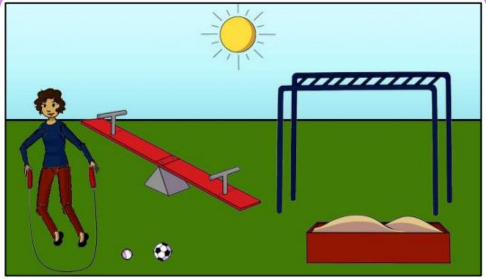
- ➢ Images from MS COCO and Abstract scene datasets

  MS COCO: 123.287 images, 443.753 questions

  Abstract scene: 29.998 images, 60.000 questions

- ➢ At least 3 questions per image (5.4 on average)
- ➢ 10 ground truth answers per question
- ➢ Confidence (*yes*, *maybe*, *no*) associated to each answer
- ➢ 3 plausible (but likely incorrect) answers per question

How many bikes are there?	2 2 2	3 4 12
What number is the bus?	48 48 48	4 46 number 6



How many balls are there?	2 2 2	1 2 3
What side of the teeter totter is on the ground?	right right right side	left left right side

Preprocessing

In order to lighten the computational burden:

- ➢ Build a dictionary with image_id-image_filename pairs
- ➢ Randomly consider just a portion of the total number of samples (10%)
- ➢ Perform some data preprocessing and save it in a file before the actual creation of the dataset

Format of each sample in the file :

approach 1: `img_filename, qst_id, quest, confidences, ann_vector`

approach 2: `img_filename, qst_id, quest, ann_vector`

yes : 1.0
maybe : 0.5
no : 0.0

vector in which each element is an answer represented as the corresponding index in the dictionary of the K=1000 most frequent answers

without punctuation

the most frequent answer to the question. Each word is represented through the correspondent index in the vocabulary of all words in questions and answers from the training set

Dataset creation

After loading back the preprocessed samples, we further process them as follows:

Approach 1	Approach 2
➢ Encode questions using GloVe embeddings.	➢ Encode questions using LXMERT tokenizer, which outputs input_ids, token_type_ids, attention_mask. ➢ Pad all answers to the same length.
⇩	⇩
`image_filename, question_id, question, preferences, labels`	`image_filename, question_id, question, labels, input_ids, attention_mask, token_type_ids`

Evaluation 

Before performing the evaluation, both answers and predictions are preprocessed as follows:

- ➢ Make them lowercase
- ➢ Substitute numbers with digits
- ➢ Remove punctuation and articles

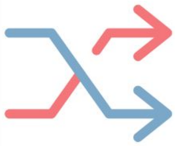
Metric robust to inter-human variability in phrasing the answers:

$$Acc(ans) = min(\frac{\text{number of humans that said } ans}{3}, 1)$$

The metric implementation is the same of the contest on VQA task: https://github.com/GT-Vision-Lab/VQA

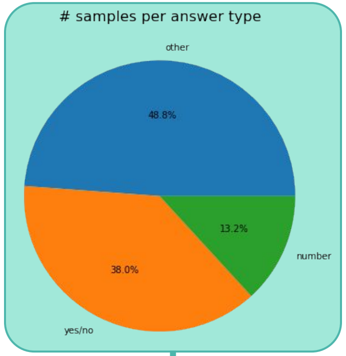
Trivial baselines: Random and Prior yes

As trivial baselines, we have chosen to implement:



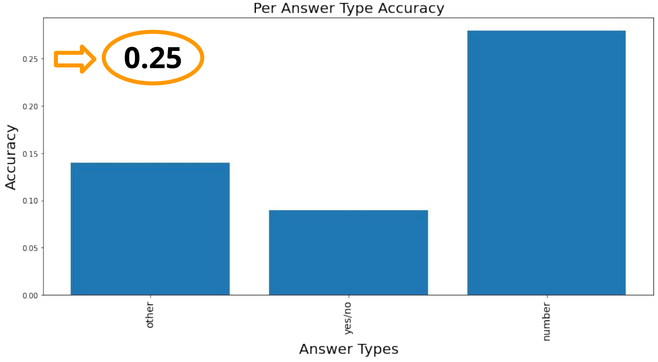
1) **Random**: the output answer is taken randomly from the K (1000) most frequent answers

2) **Prior yes**: for every sample, the prediction is yes



Reference paper “VQA: Visual Question Answering”, Agrawal et al.: https://arxiv.org/pdf/1505.00468v7.pdf

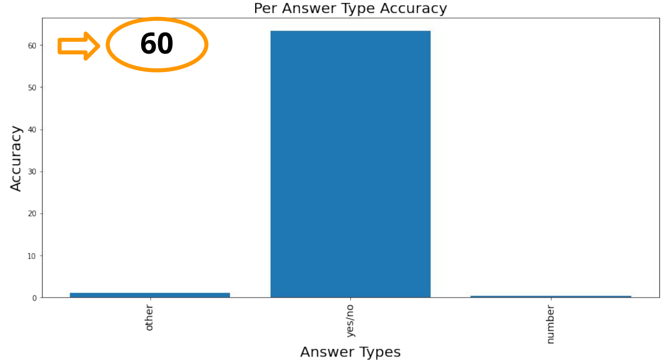
Trivial baselines: evaluation



Random

Overall Accuracy	0.14
Per Answer Type Accuracy is the following:	
other	0.14
yes/no	0.09
number	0.28

Prior yes

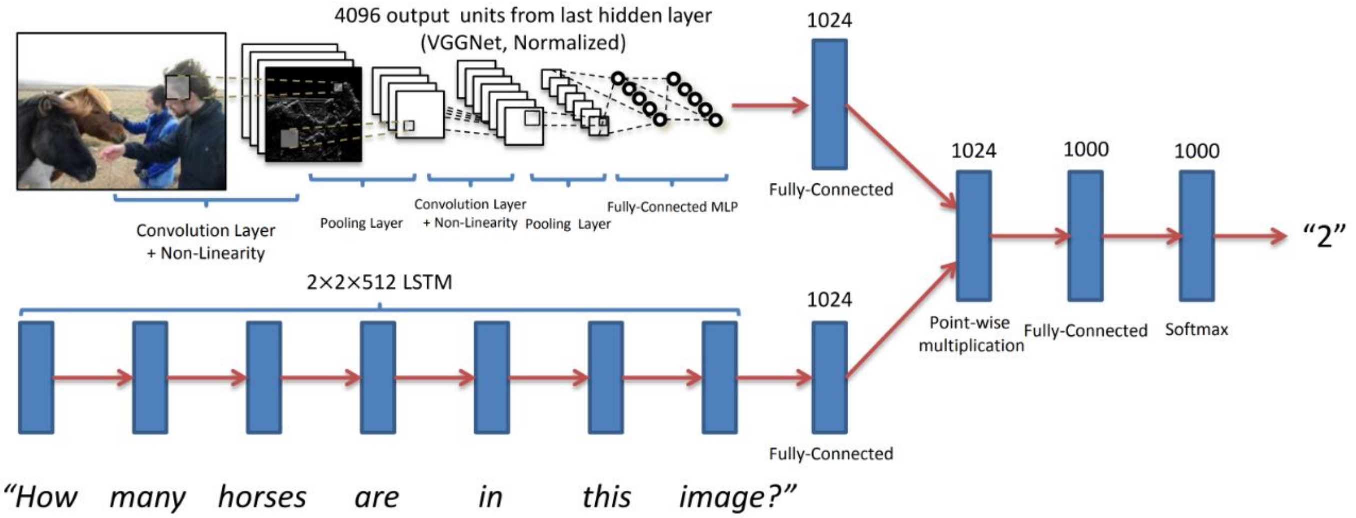


Overall Accuracy	24.99
Per Answer Type Accuracy is the following:	
other	0.99
yes/no	63.43
number	0.32

Approach 1
CNN + LSTM

Vision channel

Language channel



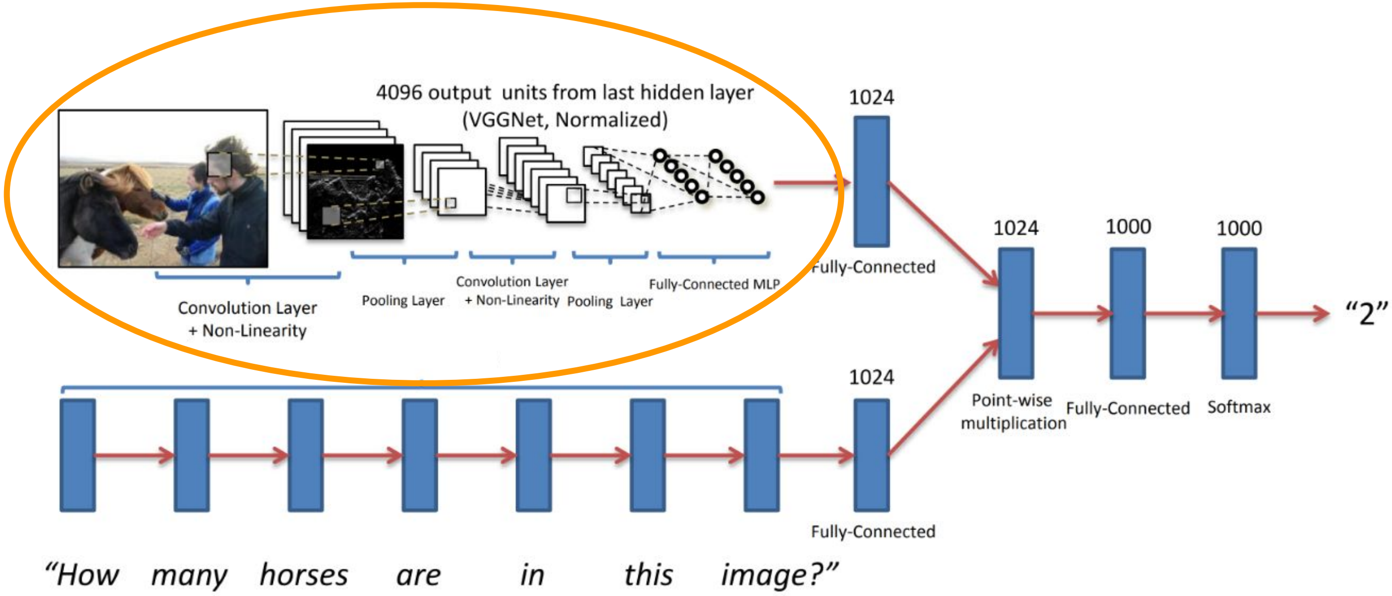
Reference paper "VQA: Visual Question Answering", Agrawal et al.: https://arxiv.org/pdf/1505.00468v7.pdf

Approach 1
CNN + LSTM

4096-dim activation values from the last hidden layer of pre-trained VGG are l2 normalized.

Vision channel

Language channel

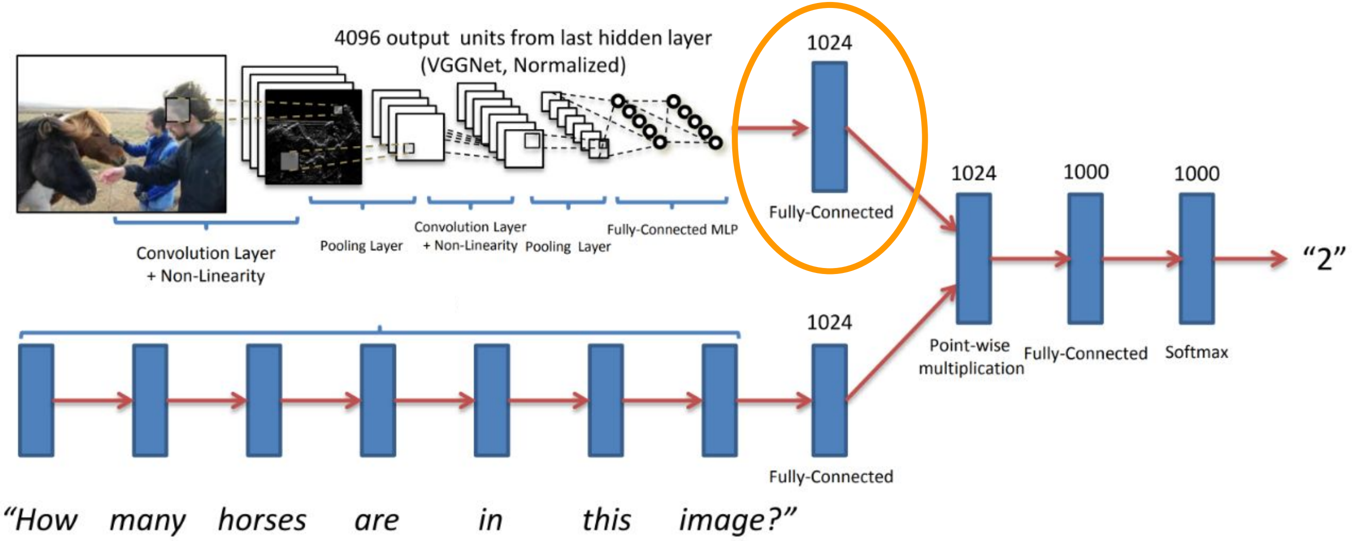


Approach 1
CNN + LSTM

Fully-connected layer with tanh nonlinearity to make image embedding 1024-dimensional.

Vision channel

Language channel



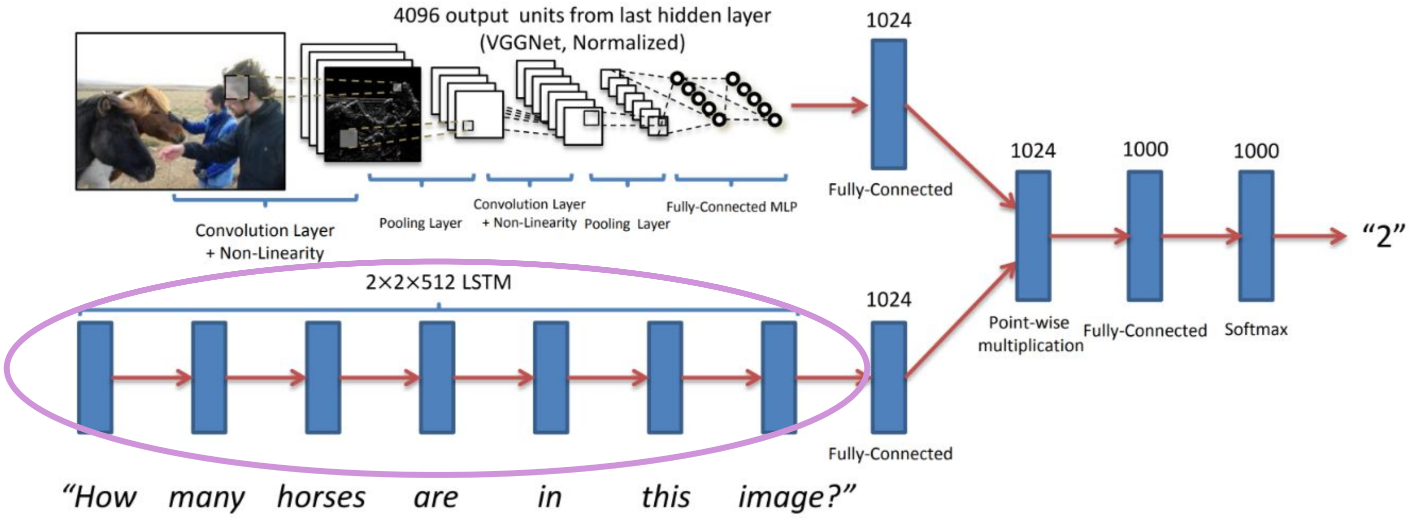
Approach 1
CNN + LSTM

LSTM with 2 hidden layers. Last hidden state and cell state are concatenated to obtain a 2048-dimensional embedding.

GloVe pre-trained embeddings are used in the embedding layer.

Vision channel

Language channel

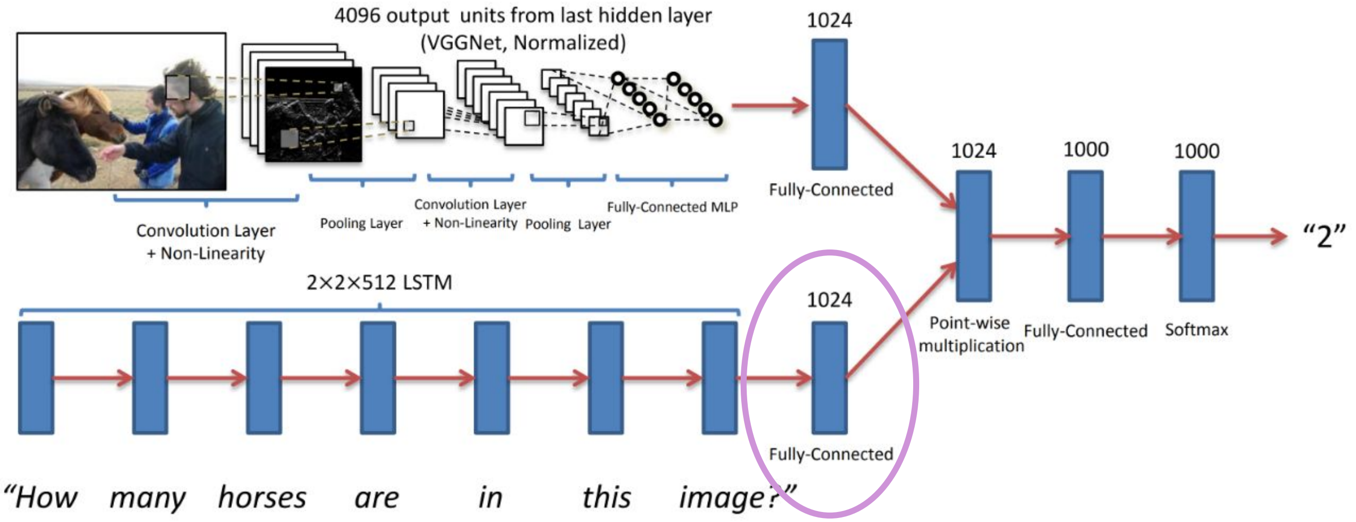


Approach 1
CNN + LSTM

Fully-connected layer with tanh nonlinearity to make language embedding 1024-dimensional.

Vision channel

Language channel

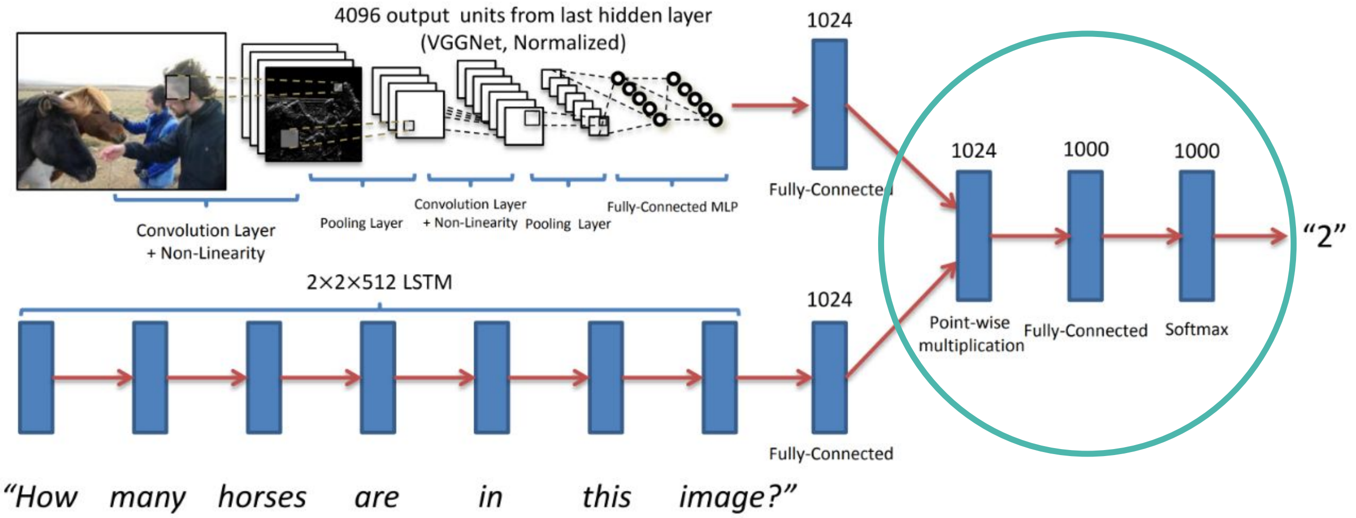


Approach 1
CNN + LSTM

Image and question embeddings are combine via element-wise multiplication. The combined embedding is passed to an MLP with a linear layer of 1000 hidden units followed by tanh non-linearity and 0.5 dropout, and a final layer with K units followed by the softmax activation function, to obtain a probability distribution over the K most frequent answers.

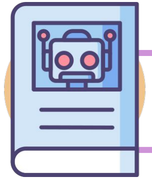
Vision channel

Language channel



Approach 1: Losses

- ❖ Just answers among the K (1000) most frequent ones in the training set are considered.
- ❖ According to the reference paper, **cross-entropy loss** has been used.



Standard loss

Label: index of the most frequent answer among the possible one for the given question.

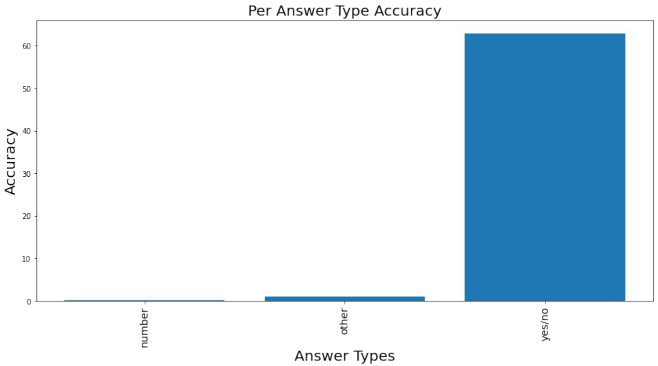
All other answers will be considered as wrong if predicted by our model.

Novel loss

Label: K-dimensional vector values:

- ➢ 1 for answers with preference ‘yes’;
- ➢ 0.5 for answers with preference ‘no’;
- ➢ 0 for answers with preference ‘no’ or for not given answers.

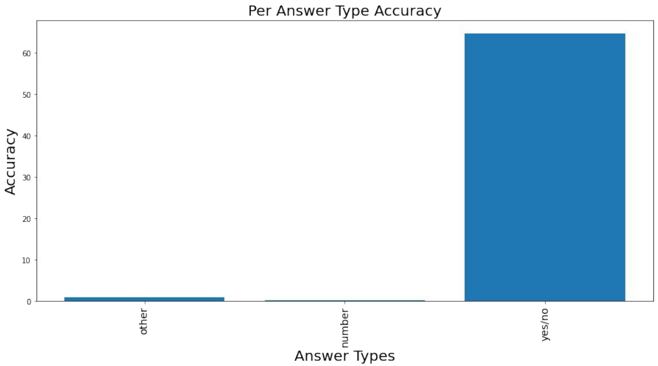
Approach 1: Evaluation



Standard loss

Overall Accuracy	25.79
Per Answer Type Accuracy is the following:	
other	1.13
yes/no	62.90
number	0.17

Novel loss



Overall Accuracy	26.45
Per Answer Type Accuracy is the following:	
other	0.99
yes/no	64.71
number	0.20

Approach 1: Results

Question: Is there a person in the picture?

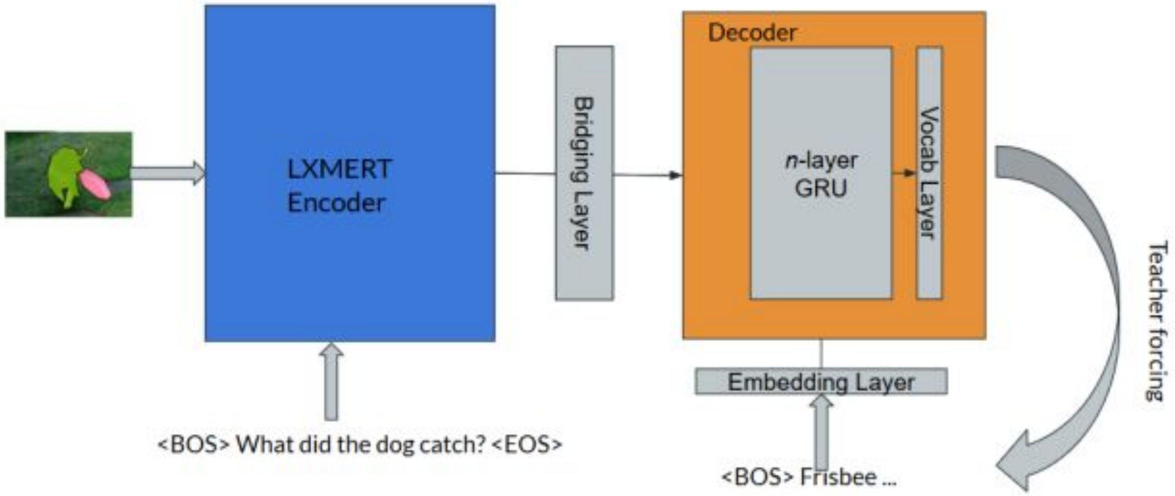
Answer 1: yes
Answer 2: yes
Answer 3: yes
Answer 4: yes
Answer 5: yes
Answer 6: yes
Answer 7: yes
Answer 8: yes
Answer 9: yes
Answer 10: yes

Generated answer (accuracy 100.0)

Answer: yes

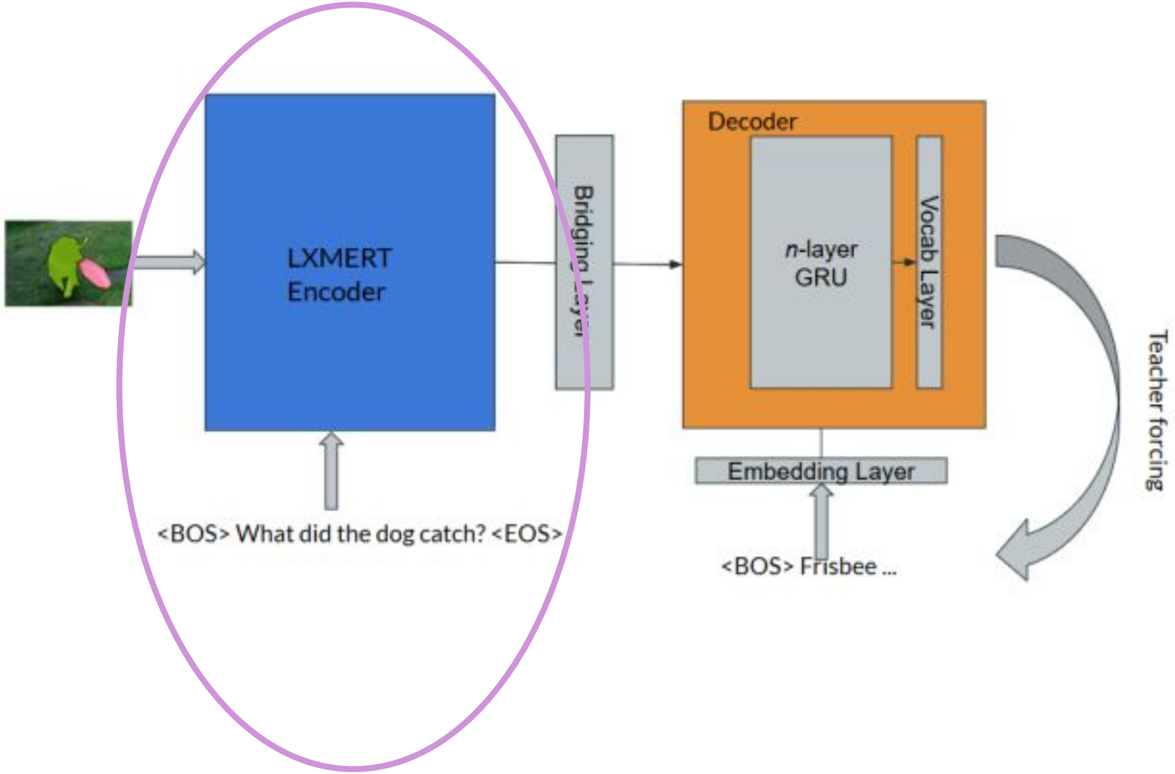
Approach 2: Generative LXMERT

Encoder-decoder architecture which generates one answer's word at a time.



Reference paper "Generative Visual Question Answering using Cross-Modal Visual-Linguistic Embeddings", Guan, Chen: [Generative_Visual_Question_Answering_using_Cross-Modal_Visual-Linguistic_Embeddings.pdf]

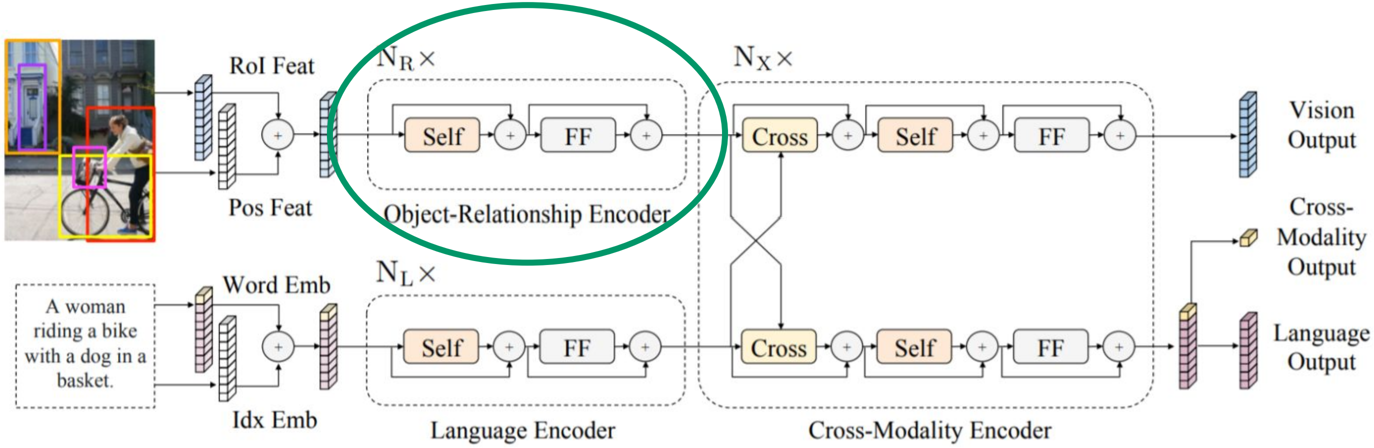
Approach 2: Generative LXMERT



Encoder: pre-trained LXMERT model

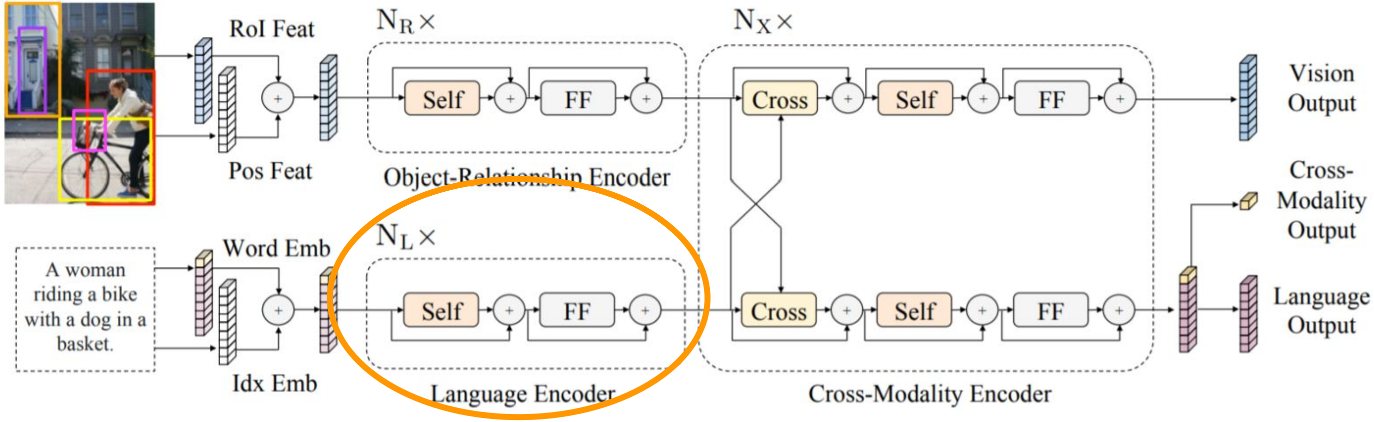
Encoder: LXMERT model

➔ The **object-relationship encoder** uses the Region of Interest (RoI) features extracted by faster RCNN backbones and processes them using a BERT-style encoder.



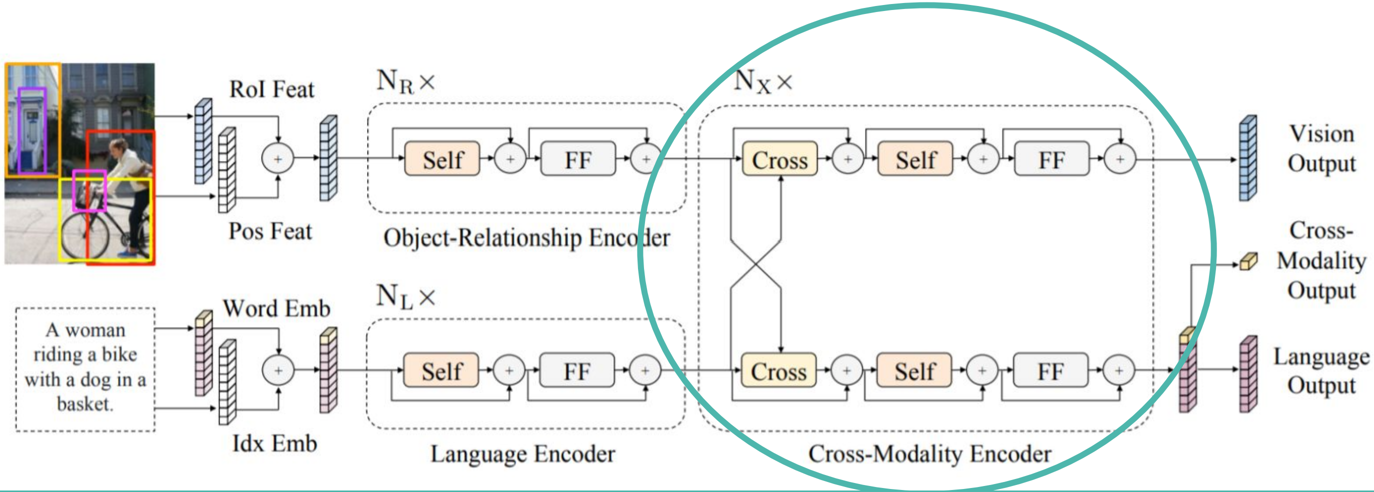
Encoder: LXMERT model

- ➔ The **object-relationship encoder** uses the Region of Interest (RoI) features extracted by faster RCNN backbones and processes them using a BERT-style encoder.
- ➔ The **language encoder** is essentially the same as a BERT style self-attention based language encoder.



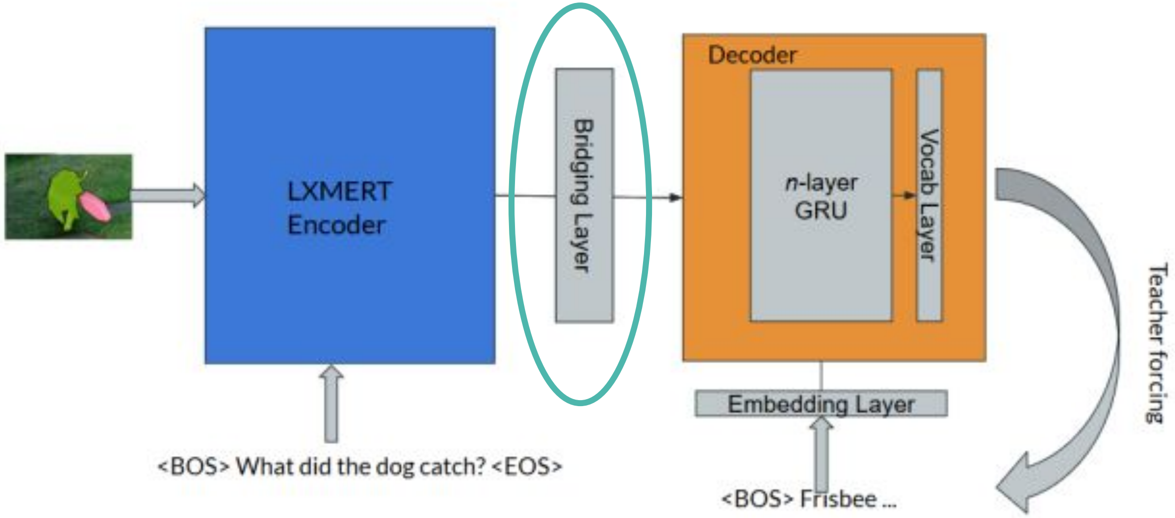
Encoder: LXMERT model

- ➔ The **object-relationship encoder** uses the Region of Interest (RoI) features extracted by faster RCNN backbones and processes them using a BERT-style encoder.
- ➔ The **language encoder** is essentially the same as a BERT style self-attention based language encoder.
- ➔ A **cross-modality encoder** allows language and visual embeddings to attend to each other, fusing information together for downstream visual-language related tasks.



Approach 2: Generative LXMERT

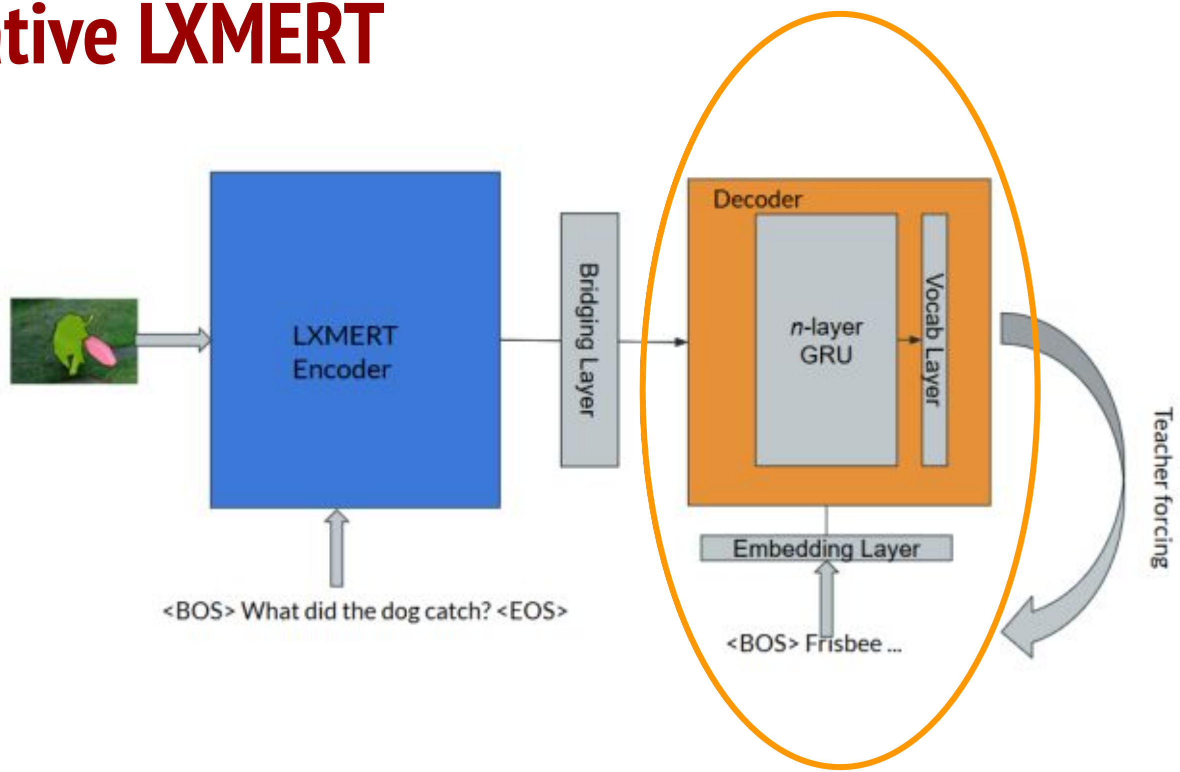
Bridging layer:
MLP with a single linear layer and ReLU activation function. Another linear layer is used to reduce the sequence length to 3, so that the output dimension matches the hidden dimension of the GRU in the decoder.



Approach 2: Generative LXMERT

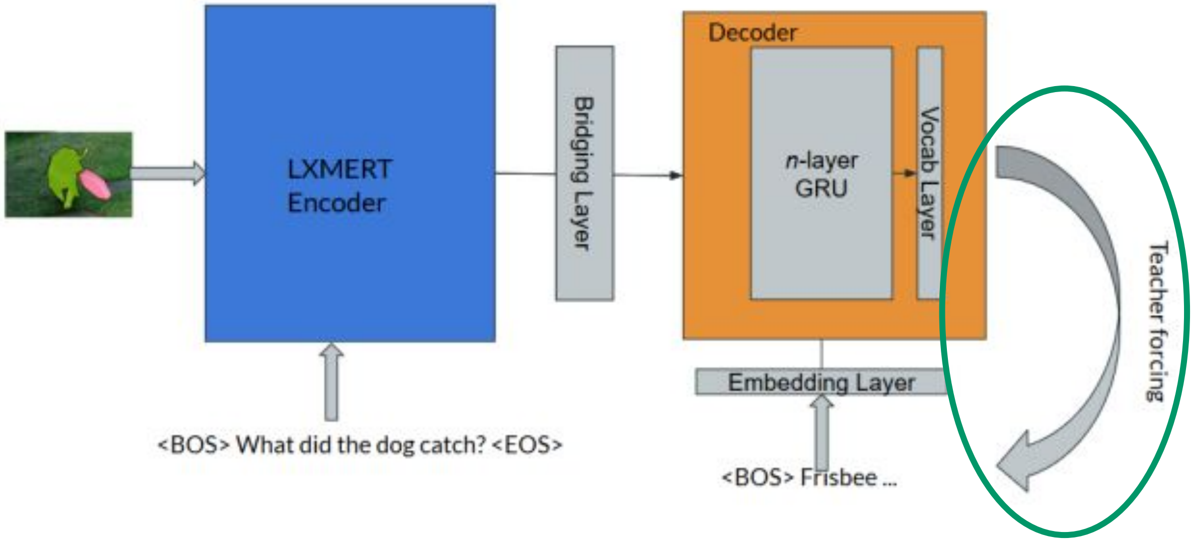
Decoder:

- ➢ 300-dimensional word embedding layer
- ➢ 3-layer GRU RNN
- ➢ Vocabulary layer of size ||V||, which is the size of the vocabulary containing all the words in questions and answers in the training set



Approach 2: Generative LXMERT

Teacher forcing:
Once a token has been generated by the decoder, with probability *r* we set the input token for the next decoding step equal to the ground truth one.



Approach 2: modifications and evaluation

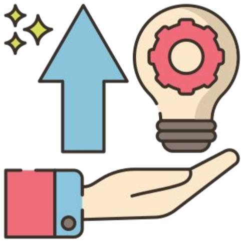
Issue: model always predicts [PAD] token after some time

We have tried several changes:

- ➢Add *gradient clipping*
- ➢*Weight* the [PAD] token in the loss computation
- ➢Test different optimizers:
  - *Adam* → [PAD] token occurs too early during the training
  - *SGD* → MAX_ANSW_LEN random tokens prediction
  - *AdamW* → [PAD] token occurs later during the training

Overall Accuracy	0.00
Per Answer Type Accuracy is the following:	
other	0.00
yes/no	0.00
number	0.00

Possible improvements (with more resources)



- ★ Train for more epochs
- ★ Use the entire dataset during training
- ★ Increase the batch size (accumulate_grad_batches has been already used)
- ★ (2) Fine-tune LXMERT and the embedding layers
- ★ (2) Try to combine word2vec and GloVe embeddings
- ★ (2) Use teacher forcing with a higher probability in the first epochs and stabilize the 0.5 probability after a certain number of epochs.

Thank you