IMAGE CLEF 2019 VISUAL QUESTION ANSWERING IN THE MEDICAL DOMAIN

Under the Guidance of *Lijiya A.*

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ABSTRACT

- Visual Question Answering is a model in which questions are answered based on the given image.
- In our project we will be focusing on medical domain.
- We use UNET architecture to extract image features, and use LSTM to encode the questions.
- Finally, we concatenate the encoded questions with the image features to generate the answers.

INTRODUCTION

This project is about building a model where the input is an image and a question related to it written in a natural language and the output is the correct answer to the question.

- For image processing, we use UNET Architecture where Image features are extracted from the last pooling layer of the UNET architecture.
- For question processing, we use LSTMs. Question vectors are extracted from the final hidden layer of the LSTMs.
- These two are then concatenated to get the result.

LITERATURE REVIEW

NLM at ImageCLEF 2018 VQA in the Medical Domain

- Studied deep learning networks with state of-the-art performance in open-domain VQA.
- Selected Stacked Attention Network (SAN) and Multimodal Compact Bilinear pooling (MCB) for their official runs.

Stacked Attention Network(SAN)

- Proposed to allow multi-step reasoning for answer prediction.
- Includes three components
  - Image model based on a CNN to extract high level image representations.
  - Question model using an LSTM to extract a semantic vector of the question.
  - Stacked attention model which locates the image regions that are relevant to answer the question.

Multimodal Compact Bilinear pooling(MCB)

- Is an attention mechanism that implicitly computes the outer product of visual and textual vectors.
- MCB architecture contains
  - CNN image model.
  - LSTM question model.
  - MCB pooling that first predicts the spatial attention and then combines the attention representation with the textual representation to predict the answers.

PROBLEM STATEMENT

- Given a medical image accompanied with a clinically relevant question, our desired model is supposed to answer the question based on the visual image content.
- This may vary from simple problem such as classification of the image to a complex one such as answer generation.

DATASET COLLECTION

In the scope of the VQA-Med challenge, three datasets were provided:

- The training set contains 12792 question-answer pairs associated with 3200 training images.
- The validation set contains 2000 question-answer pairs associated with 500 validation images.
- The test set contains 500 questions associated with 500 test images.

DESIGN

- Our model consists of four modules:
  - Image feature extraction.
  - Question semantic encoder
  - Feature fuse with co-attention mechanism
  - Answer prediction.

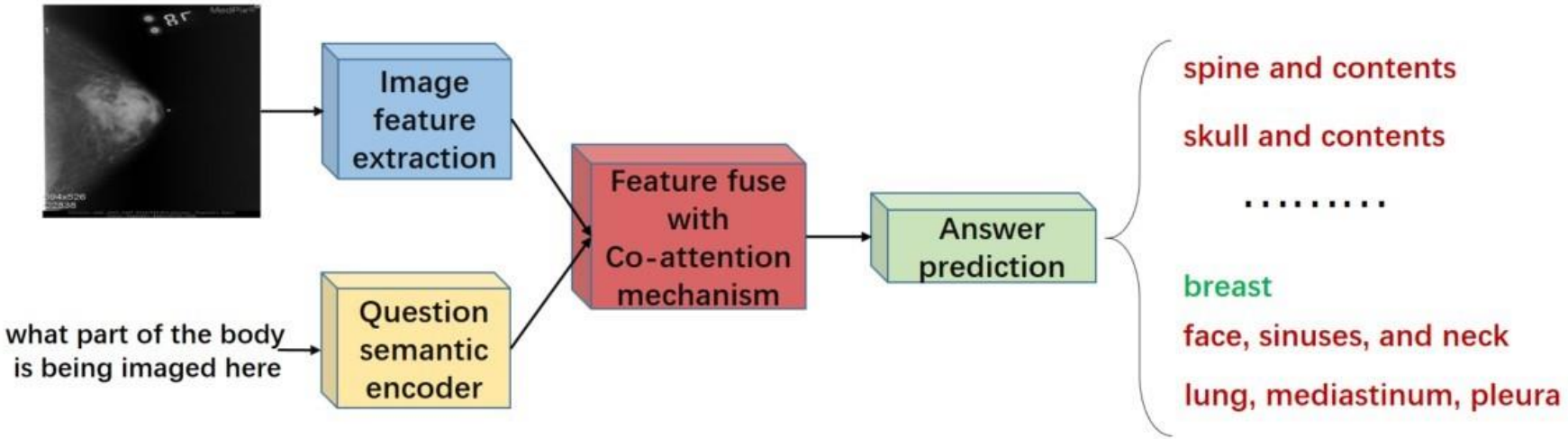


IMAGE FEATURE EXTRACTION

- We have used UNET architecture in order to extract image features.

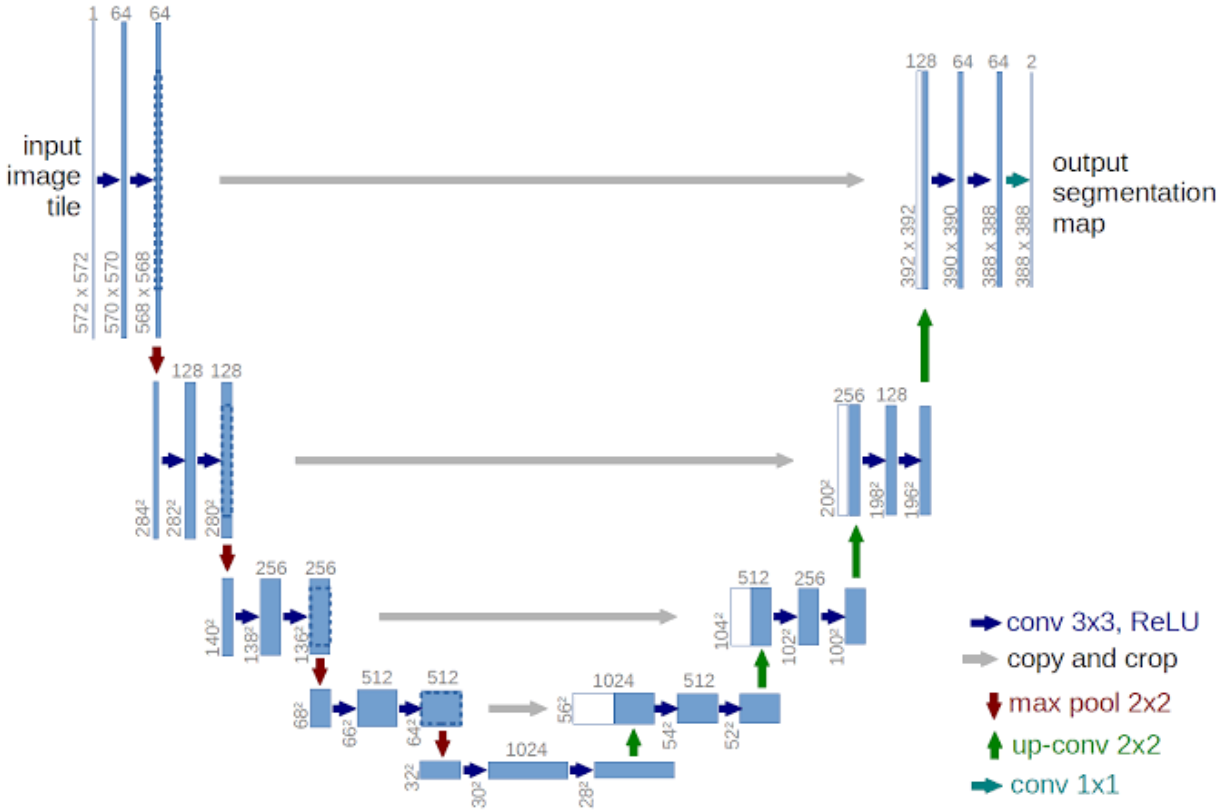


IMAGE FEATURE EXTRACTION

- The steps involved in UNET architecture are
  - Convolution operation
  - Max pooling operation
  - Transposed Convolution

IMAGE FEATURE EXTRACTION

Convolution operation

- There are two inputs to a convolution operation
  - Input image of size (nin x nin)
  - A set of 'k' filters (also called as kernels) each one of size (f x f), where f is typically 3 or 5.
- The kernel strides over the input matrix of numbers(pixels) moving horizontally column by column, sliding over the first rows in the matrix containing the images pixel values.
- Then the kernel strides down vertically to subsequent rows.
- Note, the filter may stride over one or several pixels at a time.
- The output of a convolution operation is also an output image or feature map of size (nout x nout x k).
- $nout = (nin + 2p - k)/s + 1$

IMAGE FEATURE EXTRACTION

Max Pooling Operation

- Function of pooling is to reduce the size of the feature map so that we have fewer parameters in the network.
- The idea is to retain only the important features from each region and throw away the information which is not important.

Transposed Convolution

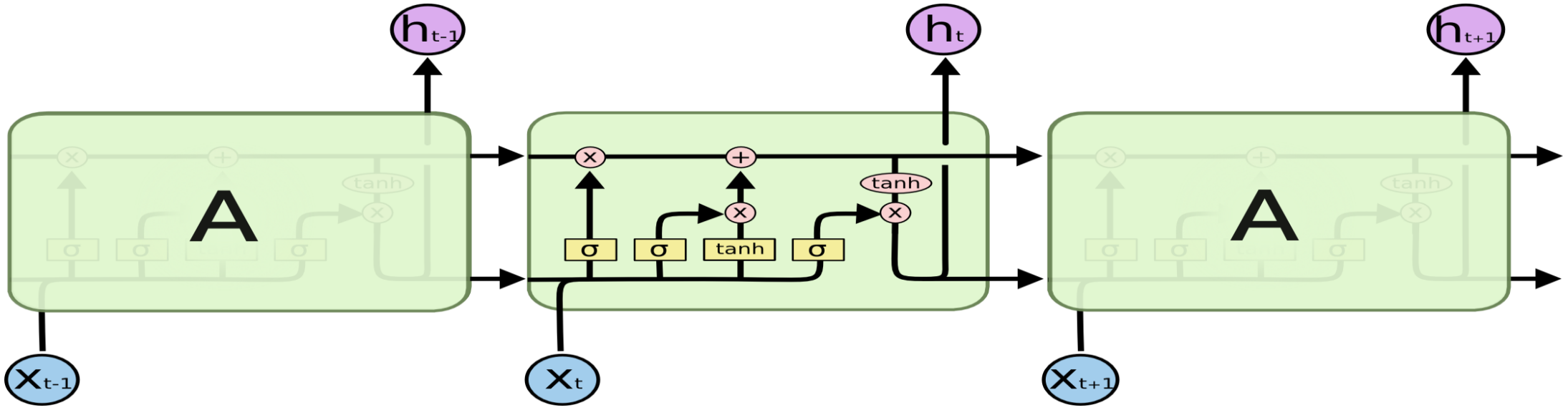
- It is a technique to perform up sampling of an image with learnable parameters.
- It is exactly the opposite process of a normal convolution i.e., the input volume is a low resolution image and the output volume is a high resolution image.

QUESTION PREPROCESSING

- For a given question, we start with text normalization.
- Text normalization includes:
  - Converting all letters to lower or upper case.
  - Removing punctuations.
  - Removing white spaces.
  - Removing stop words, sparse terms, and particular words.

QUESTION SEMANTIC ENCODER

- LSTM(Long Short Term Memory Networks) are a special kind of RNN, capable of learning long-term dependencies.
- LSTMs have this chain like structure, with four neural network layers, interacting in a very special way.

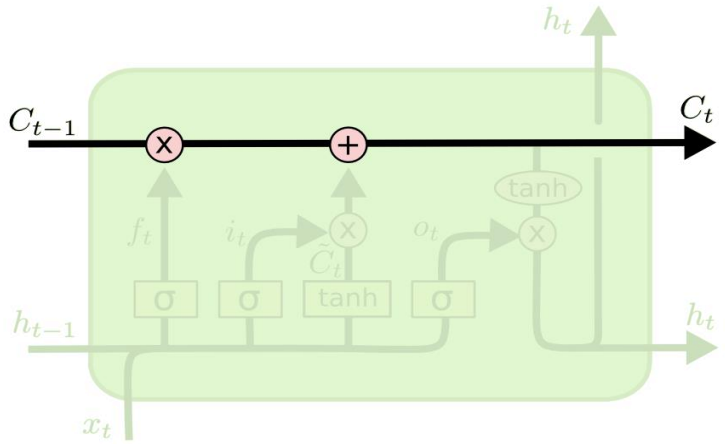


QUESTION SEMANTIC ENCODER

Different layers in LSTM

LSTM does have the ability to remove or add information to the cell state, carefully regulated by structures called gates.

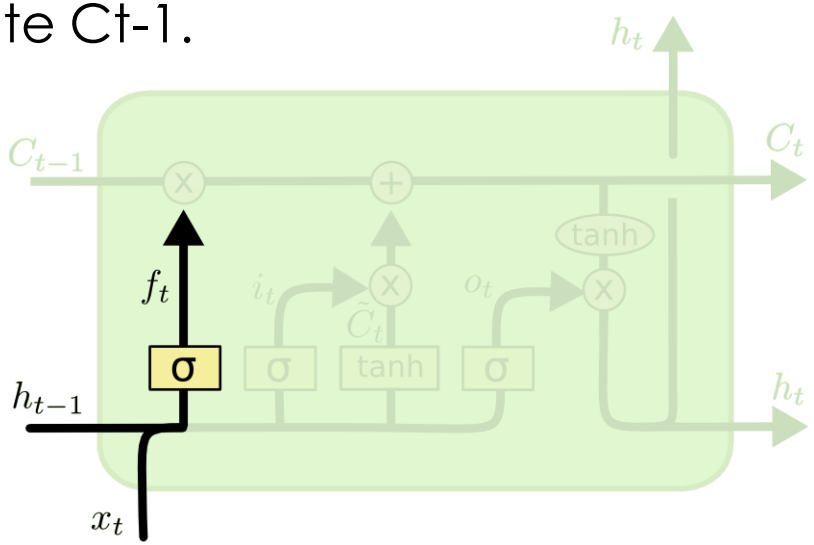
- The key to LSTMs is the cell state, the horizontal line running through the top of the diagram.



QUESTION SEMANTIC ENCODER

Step1

- The first step in our LSTM is to decide what information we're going to throw away from the cell state.
- This decision is made by a sigmoid layer called the "forget gate layer."
- It looks at ht-1 and xt, and outputs a number between 0 and 1 for each number in the cell state Ct-1.

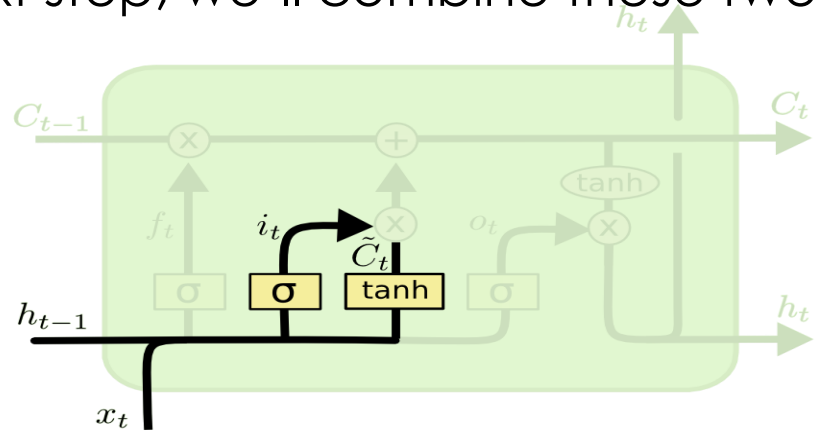


$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

QUESTION SEMANTIC ENCODER

Step2

- The next step is to decide what new information we're going to store in the cell state.
- This has two parts.
  - A sigmoid layer called the "input gate layer" decides which values we'll update.
  - A tanh layer creates a vector of new candidate values, C't, that could be added to the state.
- In the next step, we'll combine these two to create an update to the state.



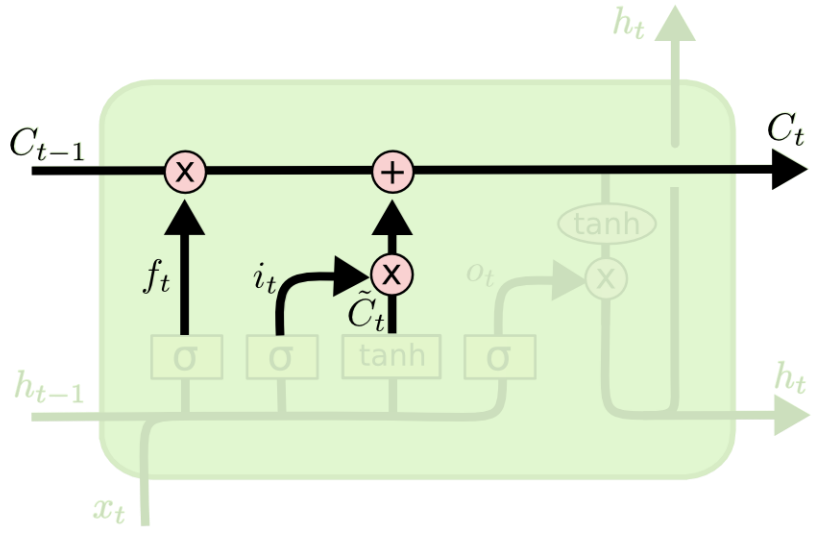
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

QUESTION SEMANTIC ENCODER

Step3

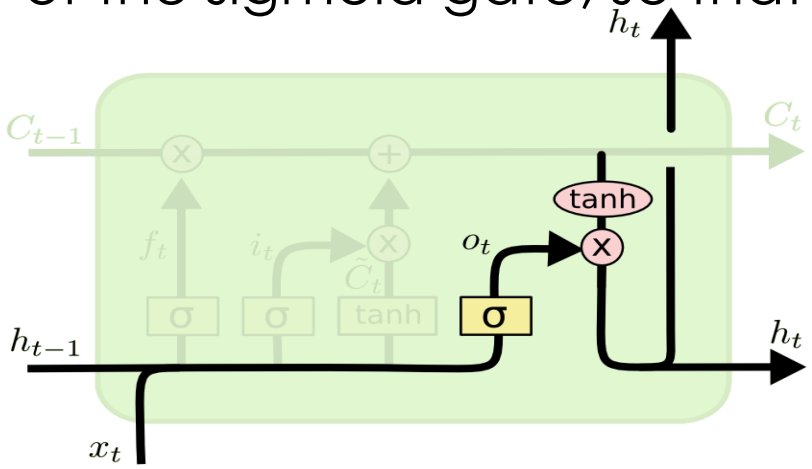
- It's now time to update the old cell state, Ct-1, into the new cell state Ct.
- We multiply the old state by ft, forgetting the things we decided to forget earlier.
- Then we add it to C't. This is the new candidate values, scaled by how much we decided to update each state value.



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Step4

- Finally, the output will be based on our cell state, but will be a filtered version.
- First, we run a sigmoid layer which decides what parts of the cell state we're going to output.
- Then, we put the cell state through tanh (range is [-1,1]) and multiply it by the output of the sigmoid gate, so that we only output the parts we decided to.



$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

ANSWER GENERATION

- There are two co-attention mechanisms that differ in the order in which image and question attention maps are generated.
  - Parallel co-attention
  - Alternating co-attention

Parallel co-attention

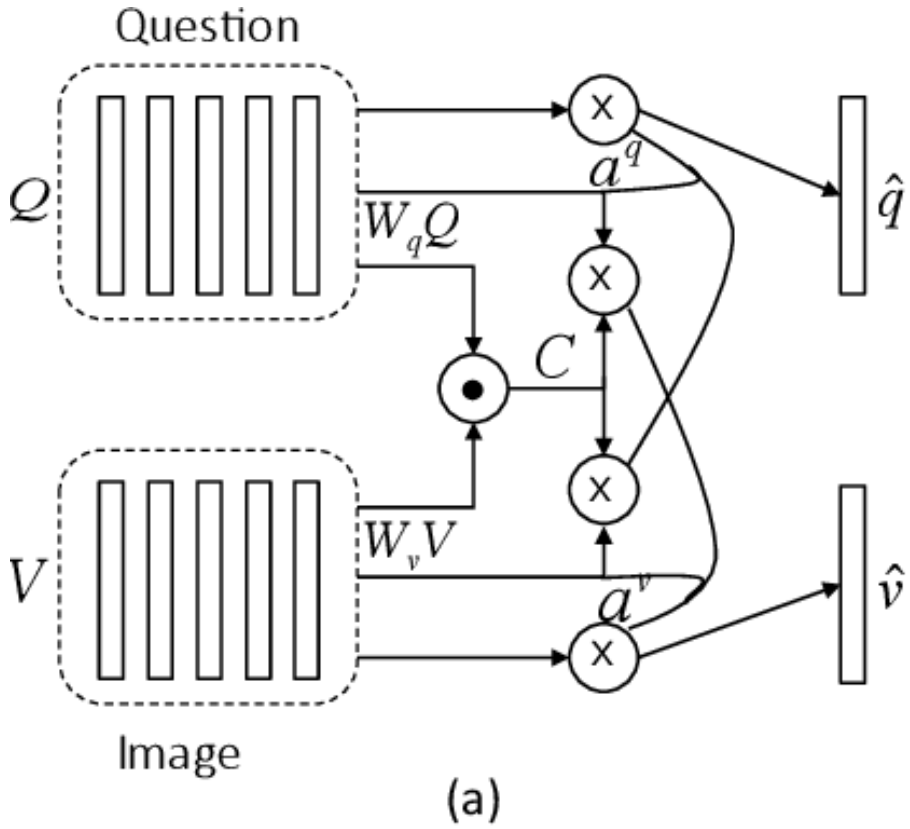
  - Parallel co-attention attends to the image and question simultaneously.
  - Here we connect the image and question by calculating the similarity between image and question features at all pairs of image-locations and question locations.

ANSWER GENERATION

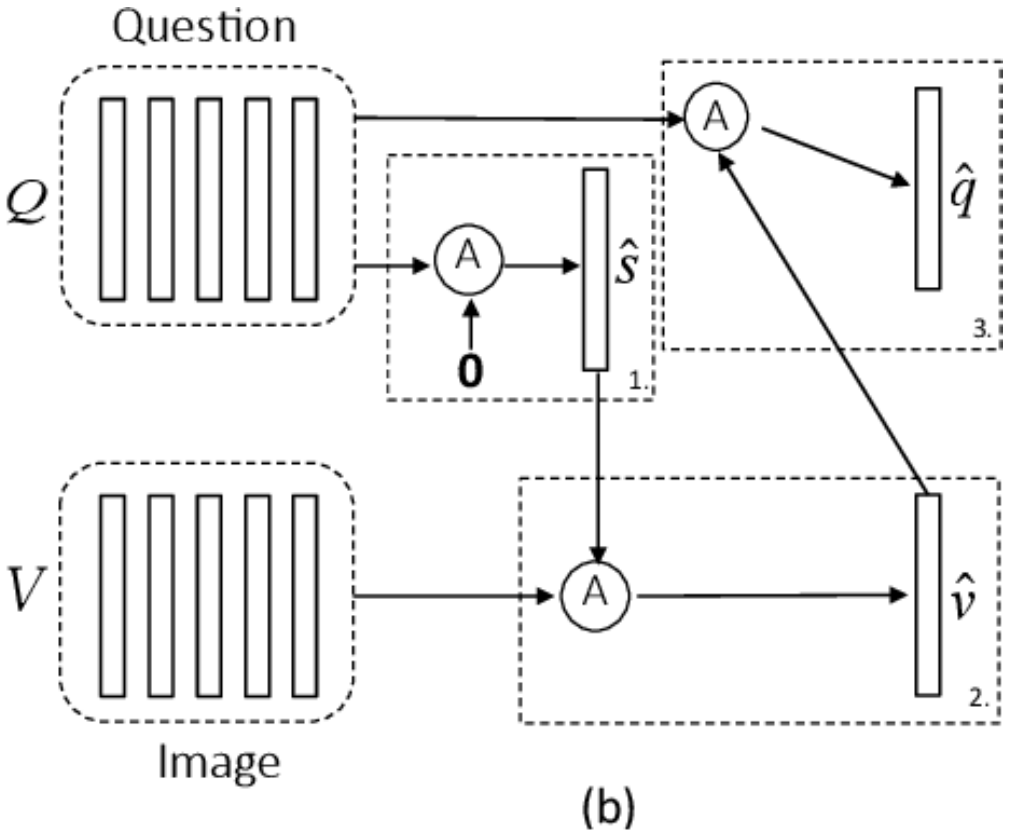
Alternating co-attention

- In this attention mechanism, we sequentially alternate between generating image and question attention. Briefly, this consists of three steps
  - Summarize the question into a single vector q.
  - Attend to the image based on the question summary.
  - Attend to the question based on the attended image feature.

ANSWER GENERATION



Parallel Co-attention mechanism



Alternating Co-attention mechanism

WORK TO BE DONE

- We are left with the implementation part which we will be doing in the coming semester.
- In the implementation we will be processing our data set.
- As mentioned above we will be using
  - UNET architecture for image feature extraction.
  - LSTM for question understanding
  - An attention mechanism with Simple multi layer perceptron for answer generation
- We will seek new models based on the accuracy of the present model and try to increase accuracy as much as possible.

CONCLUSION

- We reviewed popular methods in deep learning, and are trying to build a VQA model for ImageCLEF 2019.
- We will compare our model with the presently accurate model and try to make changes accordingly to increase accuracy.
- Despite shortcomings of current practices in VQA, we identified a number of promising research avenues that could potentially bring future breakthroughs for both VQA and visual scene understanding.
- Since deep learning techniques are significantly improving, we can expect that VQA is going to be more accurate in the next years.

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THANK YOU