

Content Based Visual Question Answer

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CS676A:Computer Vision and Image Processing
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Type of Question

- Fine-grained recognition (e.g., What kind of cheese is on the pizza?).
- Object detection (e.g., How many bikes are there?).
- Activity recognition (e.g., Is this man crying?).
- Knowledge base reasoning (e.g., Why did Katappa killed Bahubali?).
- Commonsense reasoning (e.g., Does this person have 20/20 vision?, Is this person expecting company?)..

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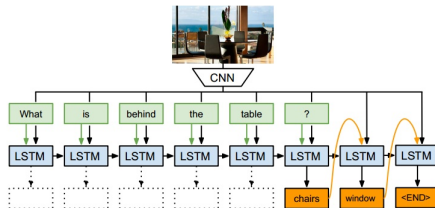
Problem Statement: Given an image, and content based question, find the correct answer and confidence of the answer.

- Training on a set of triplets (image, question, answer).
- Free-form and open-ended(*) questions.
- Answers can be single word or multiple word, depending on dataset.

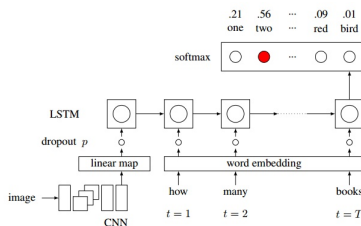
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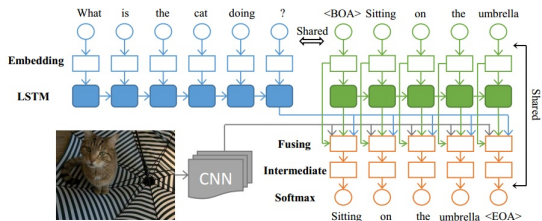
1 Neural Image-QA(Malinowski et al.,2015)[4]



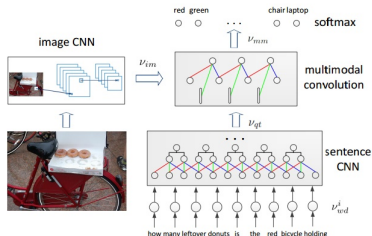
2 VSE model- VIS LSTM(Ren et al.,May,2015)[3]



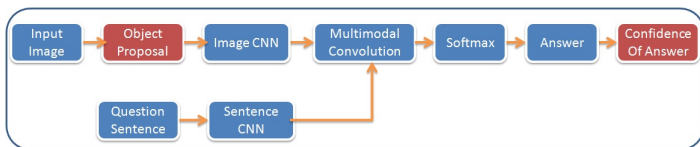
3 mQA(Gao et al.,Nov, 2015)[2]



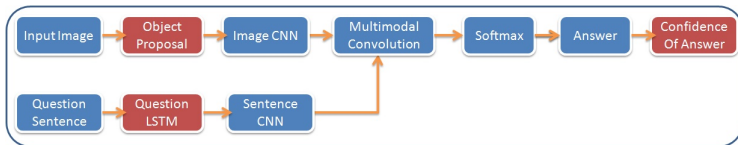
4 3CNN(Ma et al.,Nov,2015)[1]



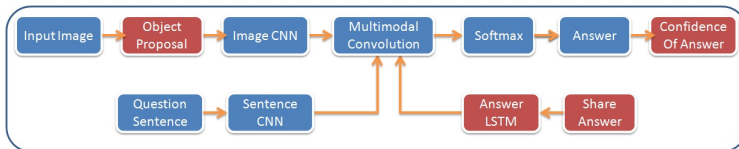
1 Modified CNN,[Ma et al.]



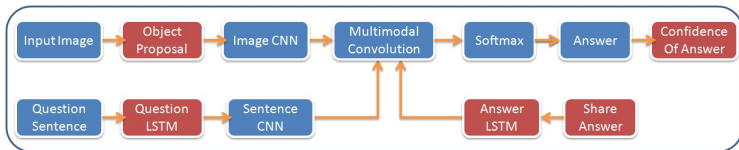
2 Modified CNN with QuestionLSTM,[Ma et al.]



3 Modified CNN with AnswerLSTM,[Geo et al.]



4 Final Approach,[Ma et al.] & [Geo et al.]



Component of Proposed Algorithm

- Object Proposal: Find Interest Object
- Image CNN: to extract the visual representation
- Question LSTM : extract the question representation
- Sentence CNN: question representation
- Multimodal Convolution: a fusing component to combine the information from the first three components and generate the answer.
- Answer LSTM: for storing the linguistic context in an answer

1 Object Proposal[Cheng et al. [?]and Endres et al. [6]]

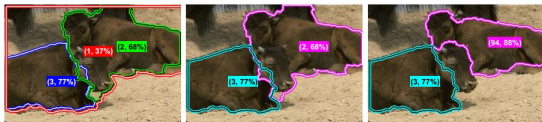


Figure: The left column shows the 3 highest ranked proposals, The center column shows the highest ranked proposal with 50% overlap for each object. The right column shows the same for a 75% threshold

2 Image CNN

$$v_{im} = \sigma(w_{im}(CNN_{im}(I)) + b_{im})$$

σ : Nonlinear activation function.

$w_{im} | d \times 4096$: Mapping matrix

CNN_{im} takes image as input and outputs a fixed length vector.

b_{im} constant

3 LSTM

- LSTM layer stores the context information in its memory cells and serves as the bridge among the words in a sequence (e.g. a question).
- It has three gate :
 - Input gate and Output gate : Regulate the read and write access to the LSTM memory cells.
 - Forget gate: Resets the memory cells when their contents are out of date.

2 Sentence CNN

- For sequential input σ , convolution unit for feature map of type f on the l^{th} layer is

$$v_{(l,f)}^i = \text{def } \sigma(w_{(l,f)} \vec{v}_{(l)}^i + b_{(l,f)})$$

-

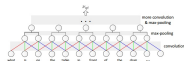
$$\vec{v}_{(l-1)}^i = \text{def } v_{(l-1)}^i \parallel v_{(l-1)}^{i+1} \parallel v_{(l-1)}^{i+1}$$

-

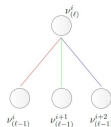
$$\vec{v}_{(0)}^i = \text{def } v_{wd}^i \parallel v_{wd}^{i+1} \parallel v_{wd}^{i+1}$$

- Max-pooling after each convolution

$$v_{(l+1,f)}^i = \max(v_{(l,f)}^{2i}, v_{(l,f)}^{2i+1})$$



(a) High Level.



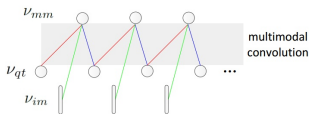
(b)
Detailed
Level.

2 Multimodal Convolution

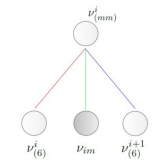
- input: $v_{qt} = [v_{(6)}^0 \dots v_{(6)}^n]$
- Capturing the interaction between two multimodal inputs

$$\vec{v}_6^i = v_6^i \parallel v_{im} \parallel v_6^{i+1} \quad (1)$$

$$v_{(mm,f)}^i = \sigma(w_{(mm,f)} \vec{v}_6^i + b_{(mm,f)}) \quad (2)$$



(a) High Level.



(b) Detailed Level.

Figure: Multimodal Convolution[1].

2 VQA performances on DAQUAR-Reduced[1]

Table 2: Image QA performances on DAQUAR-Reduced.

	Accuracy	WUPS @0.9	WUPS @0.0
Multi-World Approach (Malinowski and Fritz 2014a)	12.73	18.10	51.47
Neural-Image-QA (Malinowski, Rohrbach, and Fritz 2015)			
-multiple words	29.27	36.50	79.47
-single word	34.68	40.76	79.54
Language Approach			
-multiple words	32.32	38.39	80.05
-single word	31.65	38.35	80.08
VSE (Ren, Kiros, and Zemel 2015)			
-single word			
GUESS	18.24	29.65	77.59
BOW	32.67	43.19	81.30
LSTM	32.73	43.50	81.62
IMG+BOW	34.17	44.99	81.48
VIS+LSTM	34.41	46.05	82.23
2-VIS+BLSTM	35.78	46.83	82.14
Proposed CNN			
-multiple words	38.38	43.43	80.63
-single word	42.76	47.58	82.60

(a) DAQUAR-Reduced.

Table 3: Image QA performances on COCO-QA.

	Accuracy	WUPS @0.9	WUPS @0.0
VSE (Ren, Kiros, and Zemel 2015)			
GUESS	6.65	17.42	73.44
BOW	37.52	48.54	82.78
LSTM	36.76	47.58	82.34
IMG	43.02	58.64	85.85
IMG+BOW	55.92	66.78	88.99
VIS+LSTM	53.31	63.91	88.25
2-VIS+BLSTM	55.09	65.34	88.64
FULL	57.84	67.90	89.52
Proposed CNN without multimodal convolution layer	56.77	66.76	88.94
Proposed CNN without image representation	37.84	48.70	82.92
Proposed CNN	58.40	68.50	89.67

(b) COCO-QA.

Figure: VQA performances on DAQUAR-Reduced[1].

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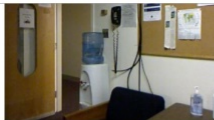
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VQA Demo[1]



Question: what is the largest blue object in this picture?

Ground truth: water carboy

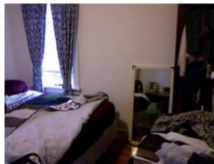
Proposed CNN: water carboy



Question: what color is the shade of the table lamp close to the bookshelf?

Ground truth: white

Proposed CNN: white



Question: how many pieces does the curtain have?

Ground truth: 2

Proposed CNN: 2



Question: what is the object close to the wall right and left of the cabinet?

Ground truth: television

Proposed CNN: television

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