TVQA: Localized Compositional Video Question Answering

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What Are We Going to Learn

The contents of this lecture is as follows:

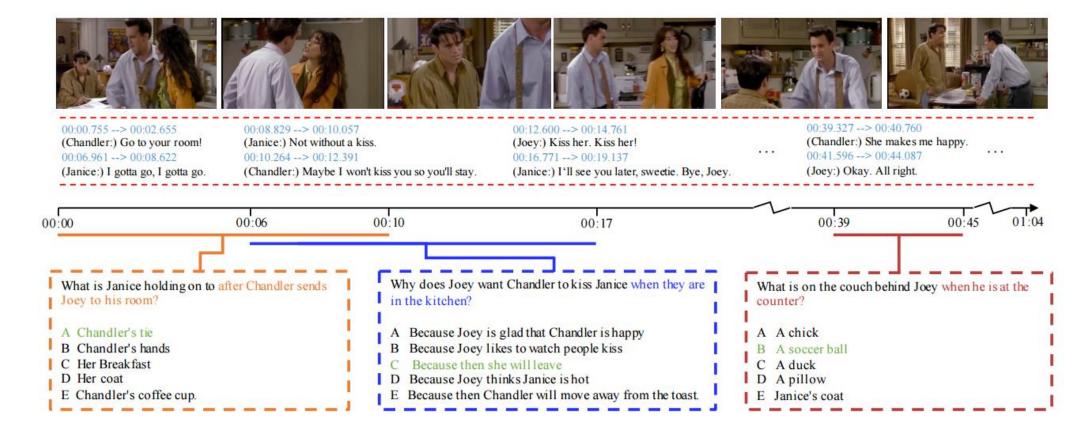
1. TVQA dataset and its characteristic

2. Introduce for Multi-modal Video QA model with its composition and operation

3. Code review for Multi-modal Video QA model

What is the TVQA Dataset?

TVQA [Lei18] is a localized, compositional video question answering dataset containing 153K question-answer pairs from 22K clips in 6 TV series.



Dataset Collection

Amazon Mechanical Turk was used for VQA collection on video clips, where workers were presented with both videos and aligned named subtitles.











 $00:03 \rightarrow UNKNAME:$ Hey. I got some bad news. (Ellipsis)

 $01:31 \rightarrow UNKNAME: Your food is abysmal!$



Difference from Existing Datasets

After extracting question answer pairs based on its subtitle, existing datasets added the frames corresponding to each subtitle.

00:03 → UNKNAME: Hey. I got some bad news. (Ellipsis)

01:31 → UNKNAME: Your food is abysmal!



Question & Answers





Dataset	V. Src.	QType	#Clips / #QAs	Avg.	Total	Q. Src.		Timestamp
				Len.(s)	Len.(h)	text	video	annotation
MovieFIB (Maharaj et al., 2017a)	Movie	OE	118.5k / 349k	4.1	135	✓	-	-
Movie-QA (Tapaswi et al., 2016)	Movie	MC	6.8k / 6.5k	202.7	381	✓	-	✓
TGIF-QA (Jang et al., 2017)	Tumblr	OE&MC	71.7k / 165.2k	3.1	61.8	\checkmark	✓	-
Pororo-QA (Kim et al., 2017)	Cartoon	MC	16.1k / 8.9k	1.4	6.3	✓	\checkmark	-
TVQA (our)	TV show	MC	21.8k / 152.5k	76.2	461.2	✓	✓	✓

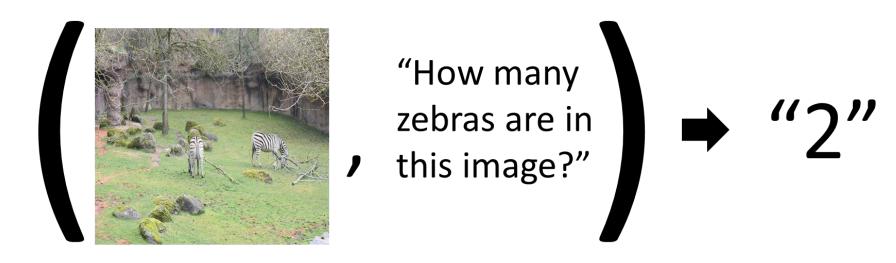
Comparison between VQA datasets

(OE = open-ended, MC = Multiple-choices, Q. Src. = Question Source)

TVQA tried to solve this limitation by collecting question answer pairs from both visual and text information.

Difference from Visual Question Answering

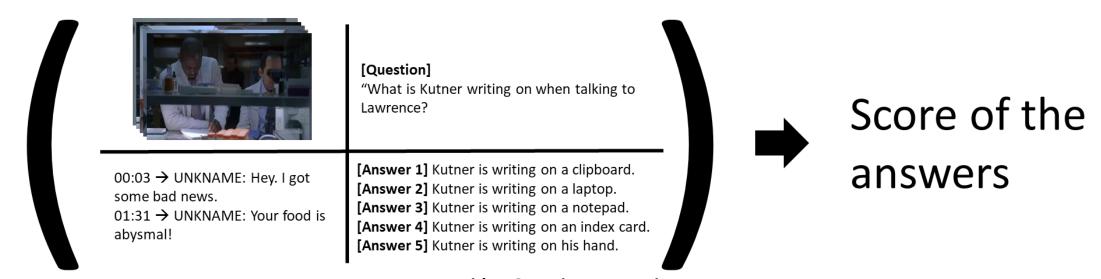
Visual question answering model *takes an image and question* as input and *outputs exact word for an answer*.



Visual Question Answering

Difference from Visual Question Answering

In video question answering task, the model takes a question, subtitle, frame and answer as input and outputs score of the answers.

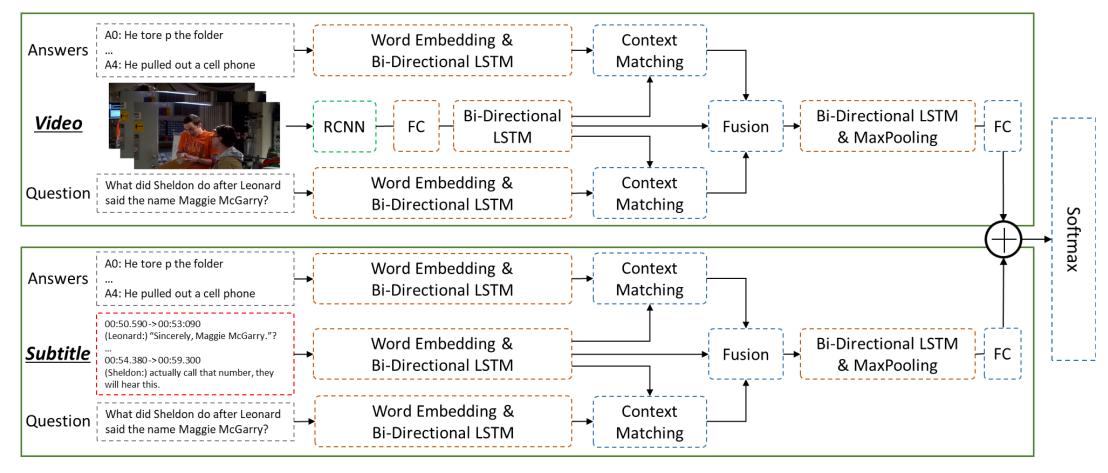


Video Question Answering

VQA task requires a model that is able to understand multi-modal information from spatio-temporal format.

Multi-Modal Video QA

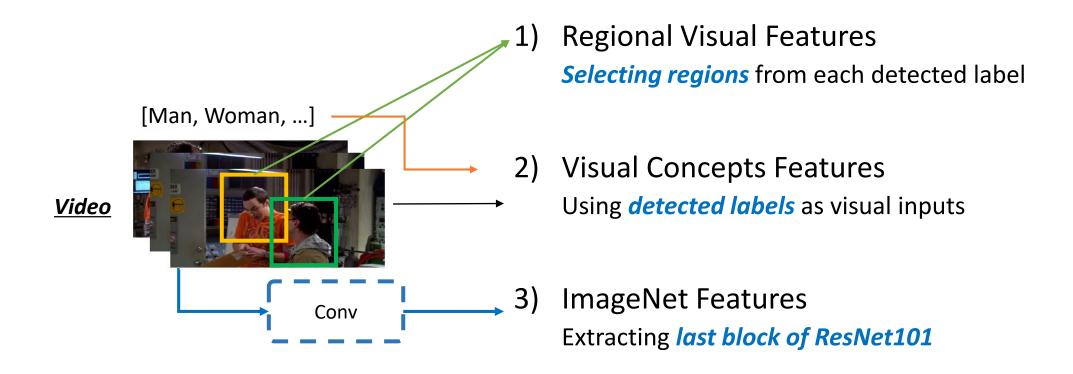
In this lecture, we explore *Multi-Modal Video QA* which is first attempt in order to solve TVQA dataset.



[Lei18] J. Lei, L. Yu, M. Bansal, T. L. Berg, TVQA: Localized, Compositional Video Question Answering. EMNLP 2018

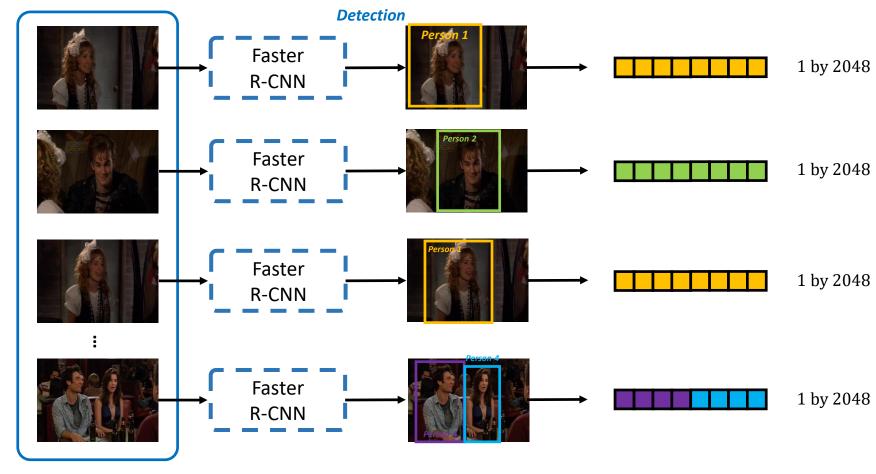
Spatial Information Extraction from a Video

It used three different type of extracting methods in order to capture spatial information.



Regional Visual Features

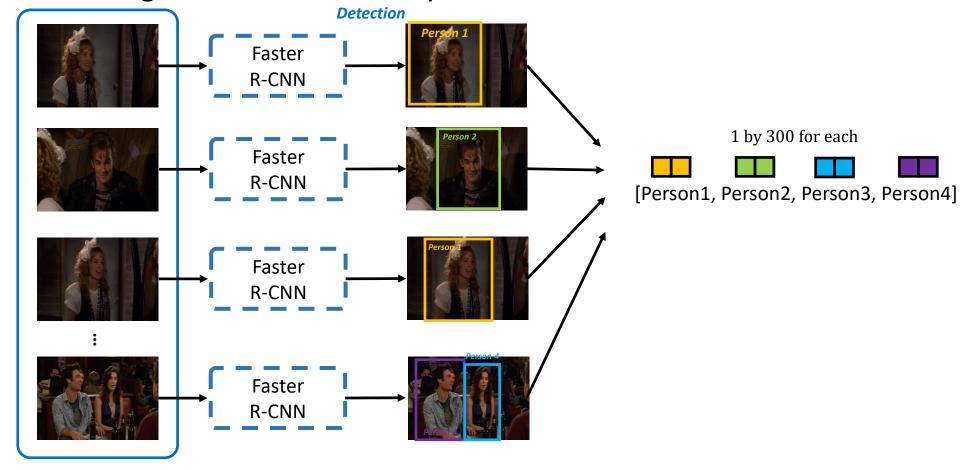
The model *extracts spatial information* from a video using *object detection network* [Ren15].



[Ren15] S. Ren, K. He, R. B. Girshick, J. Sun, Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. NIPS 2015

Visual Concepts Features

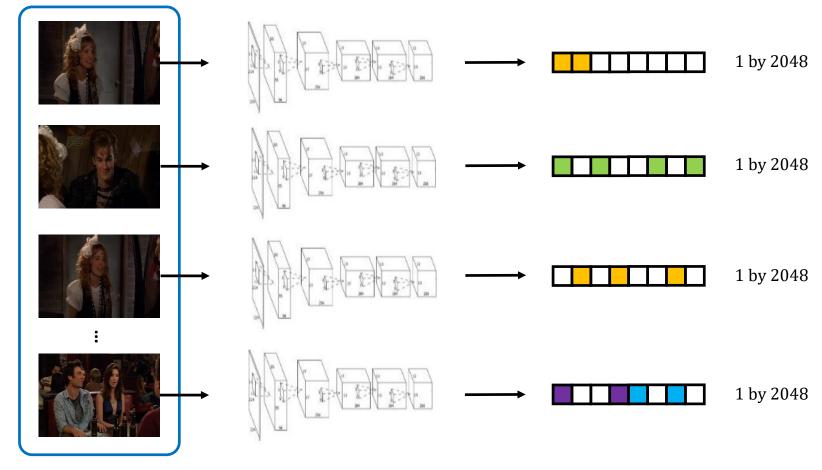
[Yu18] found that *using detected object labels* as input to an image *gave comparable performance* to using CNN features directly.



[Yu18] L. Yu, Z. Lin, X. Shen, J. Yang, X. Lu, M. Bansal, T. L. Berg, MAttNet: Modular Attention Network for Referring Expression Comprehension. CVPR 2018

ImageNet Features

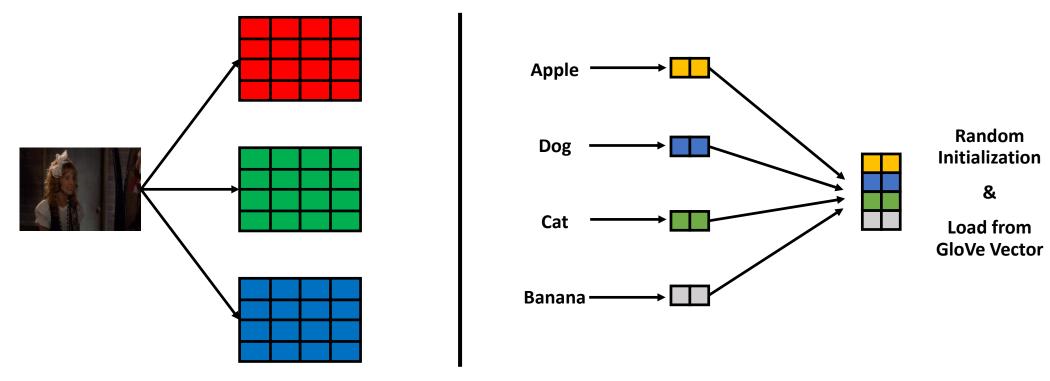
It is the simplest way to *extract spatial information* by using *famous CNN architecture* such as ResNet101 [He16].



[He16] K. He, X. Zhang, S. Ren, J. Sun, Deep Residual Learning for Image Recognition. CVPR 2016

Word Representation

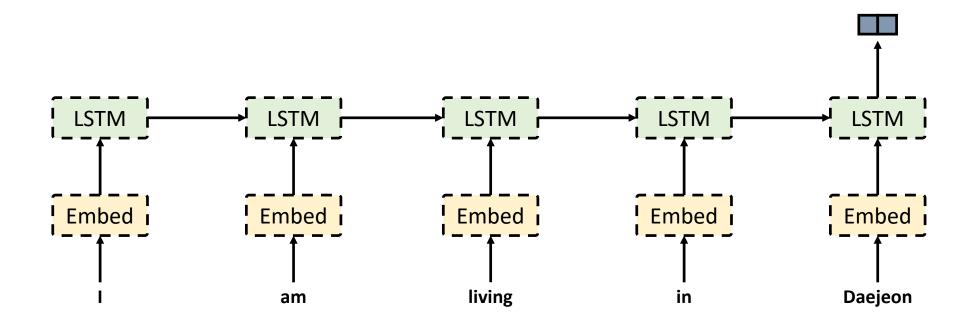
Unlike an image represented as RGB channels, how can we represent a word to other format?



We can represent a word as a vector and synthesize all words to create a single vocabulary.

Sentence Representation

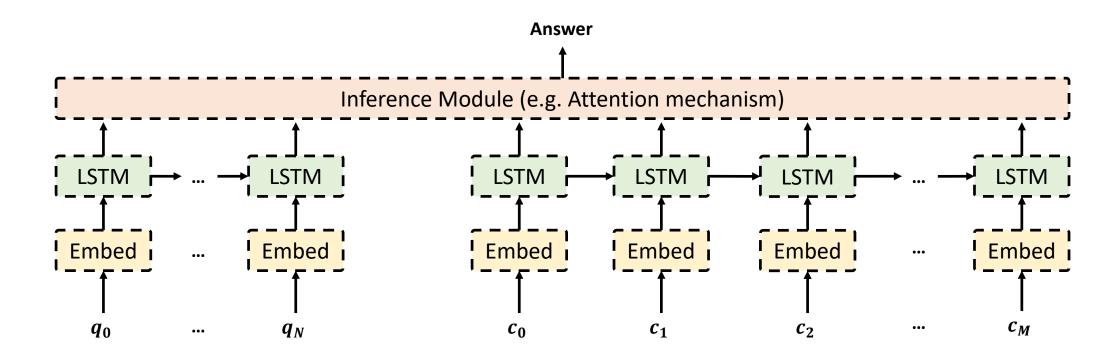
After generating the representation for words, there need a module to encode words to one.



RNN can extract important representation among them.

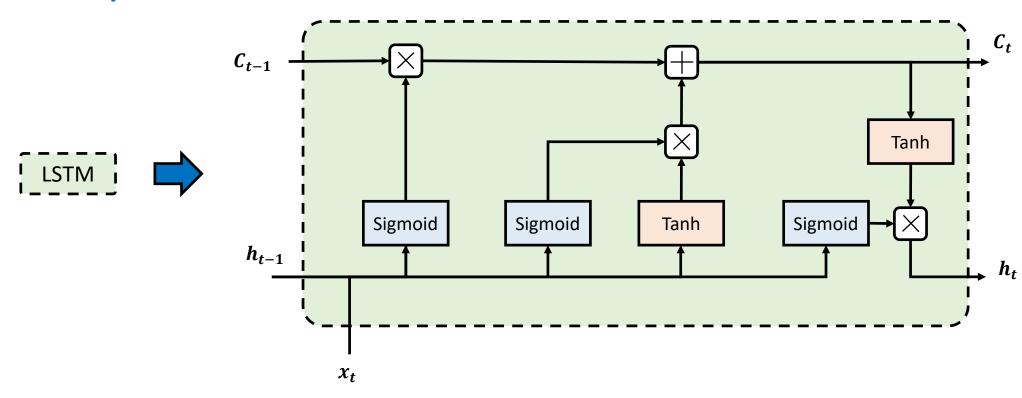
Representation on Question Answering Task

In question answering task, the hidden states for each LSTM is used for a word representation for each word.



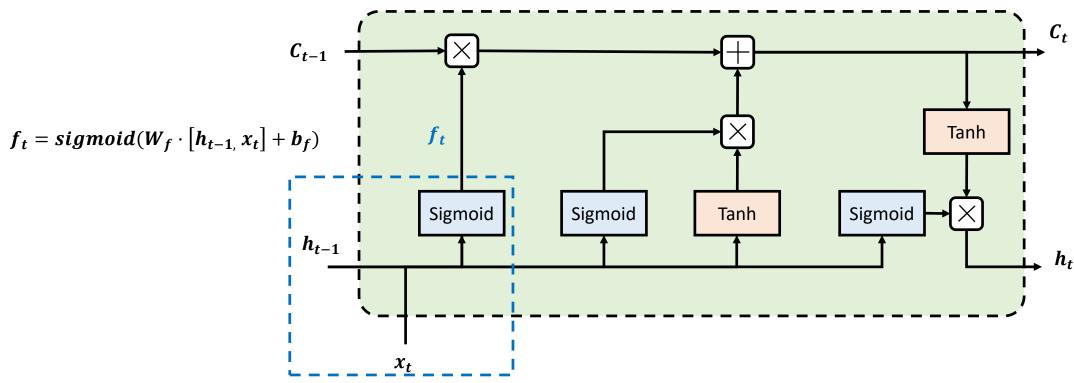
Long Short-Term Network

In general manner, many researchers utilize *Long Short-Term Network to capture important representation*.



Forget Gate Layer (LSTM)

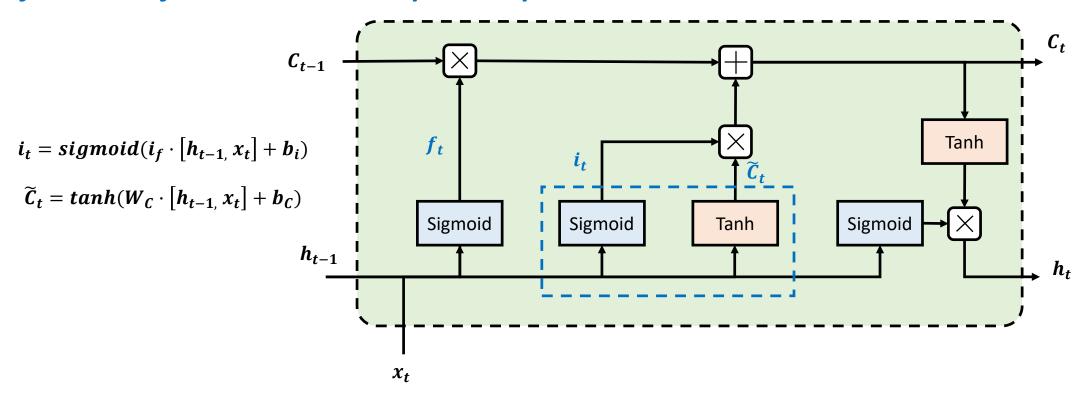
Forget gate layer decides what information should be thrown away or kept.



The closer to 0 means to forget, and the closer 1 means to keep.

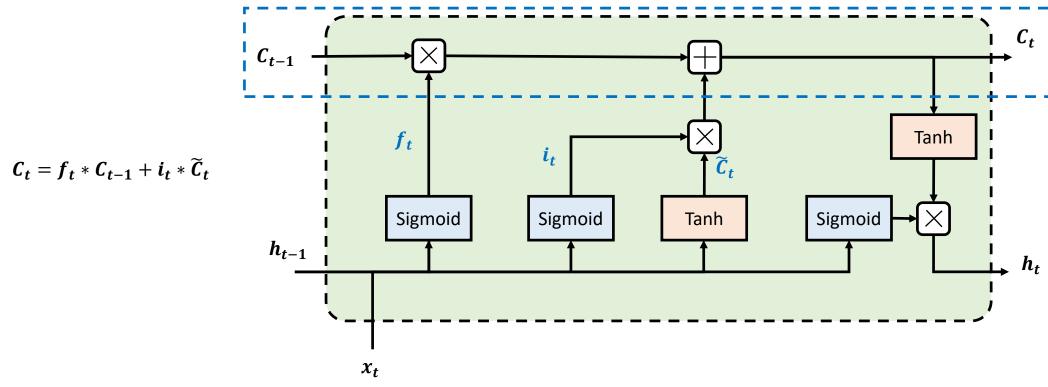
Input Gate Layer (LSTM)

Input gate layer is to update the cell state, which means how it takes the information from the current input and previous hidden state.



Cell State Update (LSTM)

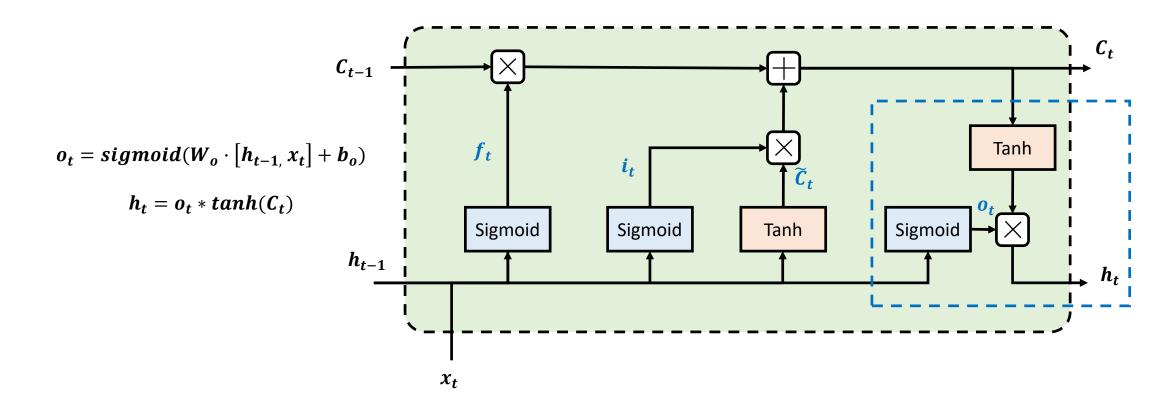
From last two layers, it combines the previous cell state with the information.



Namely, it is the process of making representative information.

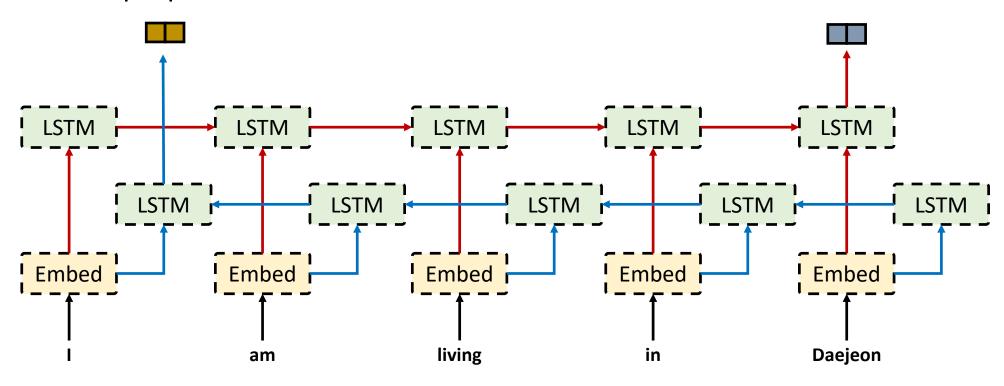
Output Gate Layer (LSTM)

Output gate layer decides what the next hidden state should be.



Bi-directional LSTM

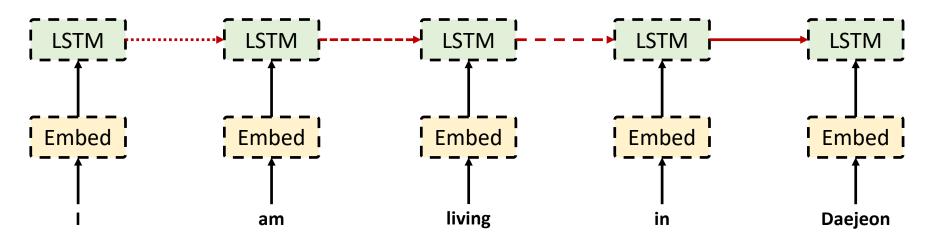
Uni-directional LSTM only consider a single forward pass, therefore, Bi-directional LSTM has been proposed.



Limitation of Long Short-Term Network

Despite of considering Bi-directional way, it *cannot compare the representation equally*.

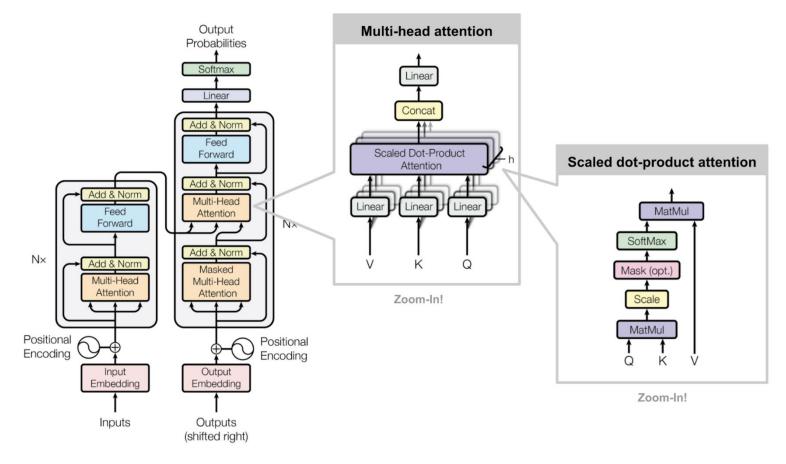
The relationship between 'I' and 'Daejeon' might be weak than other relationships.



Also, it cannot work well when the sequence is long.

Transformer

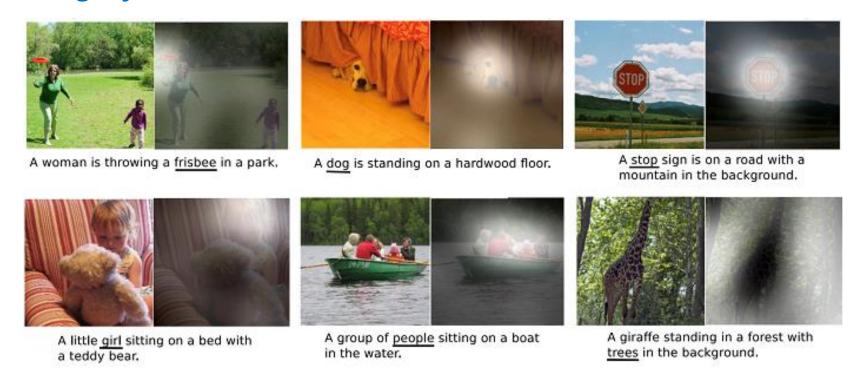
[Vaswani17] proposed *a self-attention mechanism* to *compare the representations equally*.



[Vaswani17] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, I. Polosukhin, Attention is All you Need. NIPS 2017

Attention Mechanism

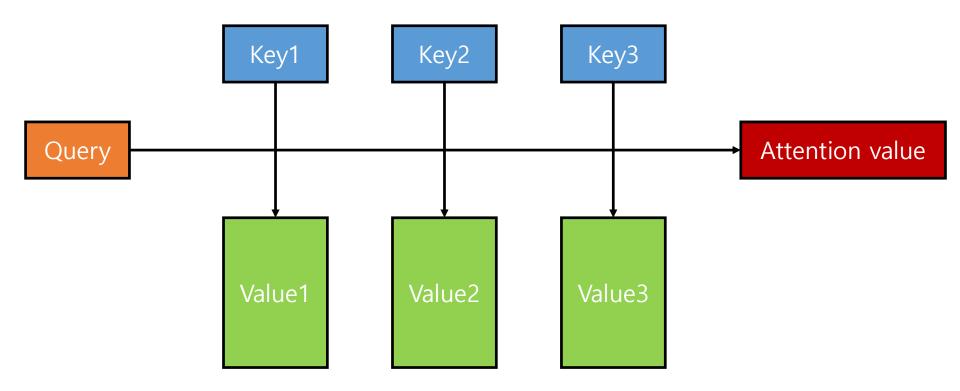
After generating the representations, attention mechanism can generate a high-level reasoning information.



This method is *interpretable*, which means a person can analyze why a word is outputted from the input.

Attention Mechanism

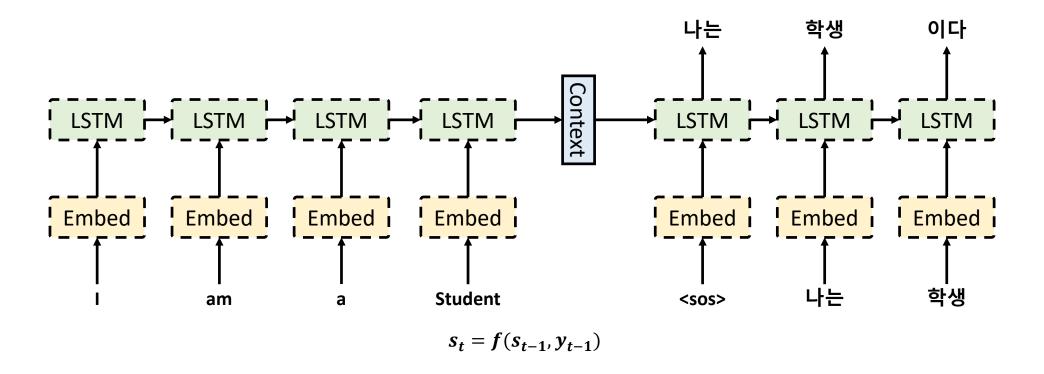
Attention value is computed by *Keys, Query* and *Values*.



Attention(Q, K, V) = Attention value

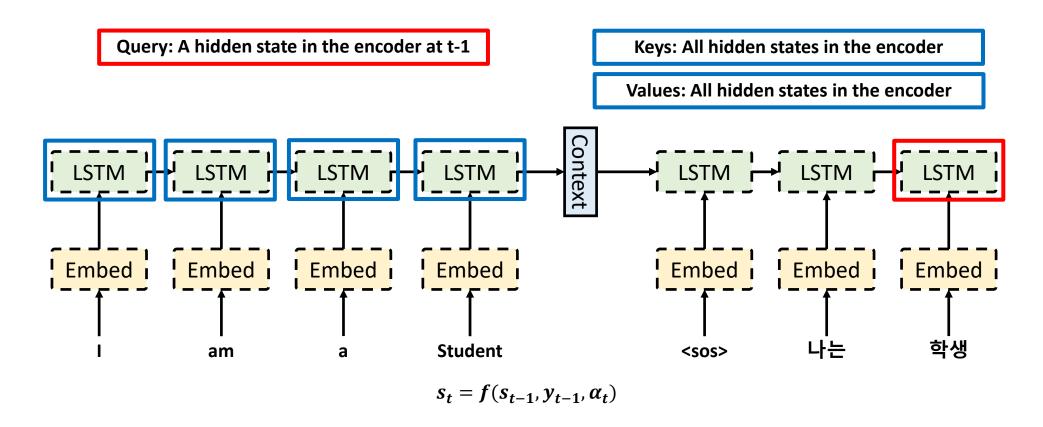
Sequence to Sequence Model (Seq2seq)

Sequence to sequence model is used in machine translation, speech recognition and video captioning.



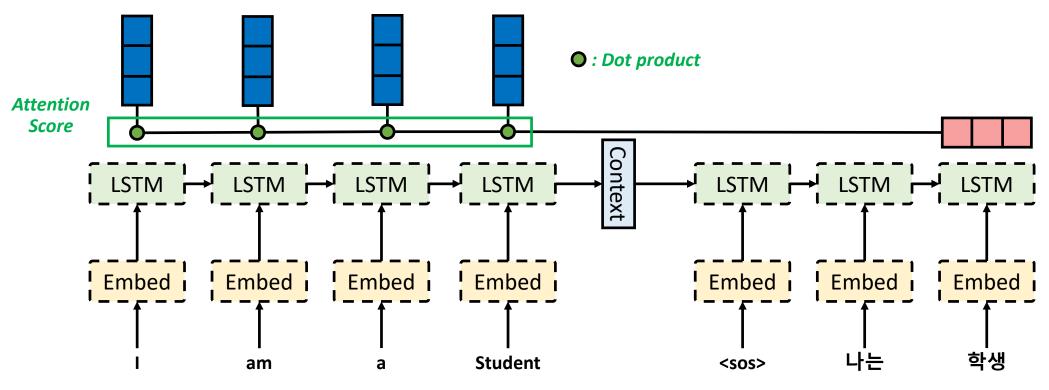
Attention Mechanism on Seq2seq Model

In Seq2seq model, *three components* for using attention mechanism *come from the encoder and decoder*.



Calculation for Attention Score

Attention score is a score measuring similarity between previous hidden state and all hidden states from the encoder.



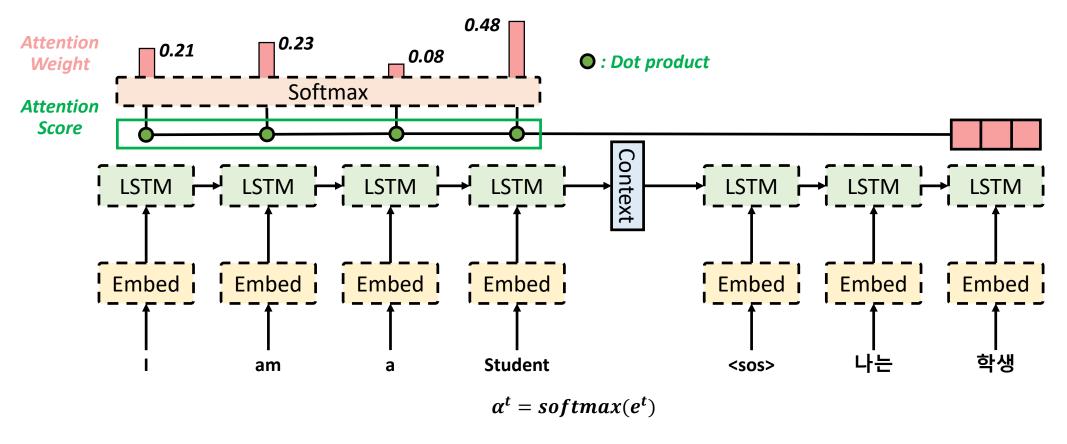
$$score(s_{t-1},h_i) = s_{t-1}^T h_i$$

$$e^t = [s_{t-1}^T h_0, ..., s_{t-1}^T h_N]$$

https://wikidocs.net/22893

Calculation for Attention Weight

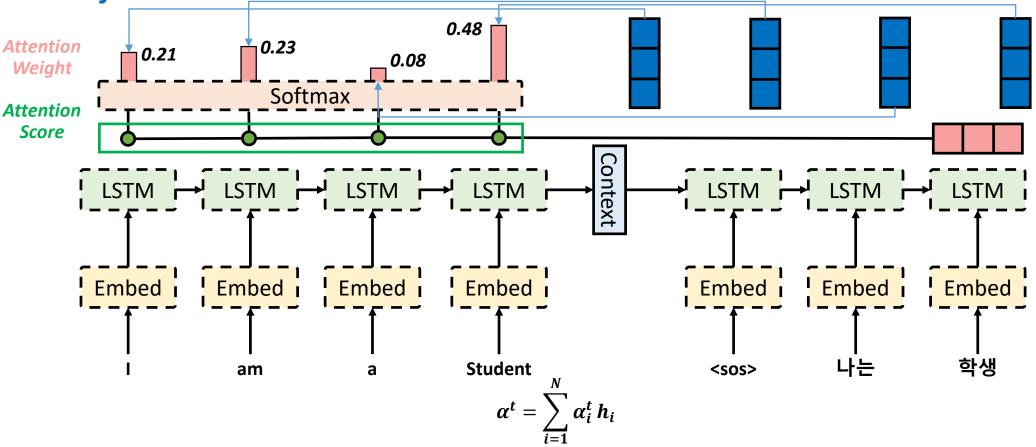
After calculating attention score, attention weight for **each hidden state** of the encoder is calculated by **softmax function**.



Calculation for Attention Value

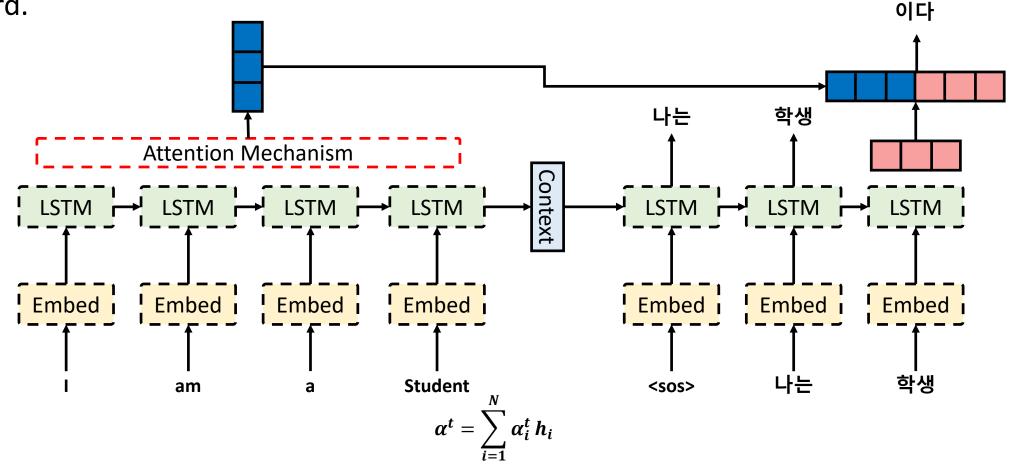
Attention value is *multiplication process* between *the attention weight* and *hidden*

states from the encoder.



Concatenation and Prediction

Attention value is *concatenated with previous hidden state* in order to predict next word.



Different Type of Attention Mechanism

There are several variant versions of attention mechanism such as using cosine similarity, tanh function and location-based.

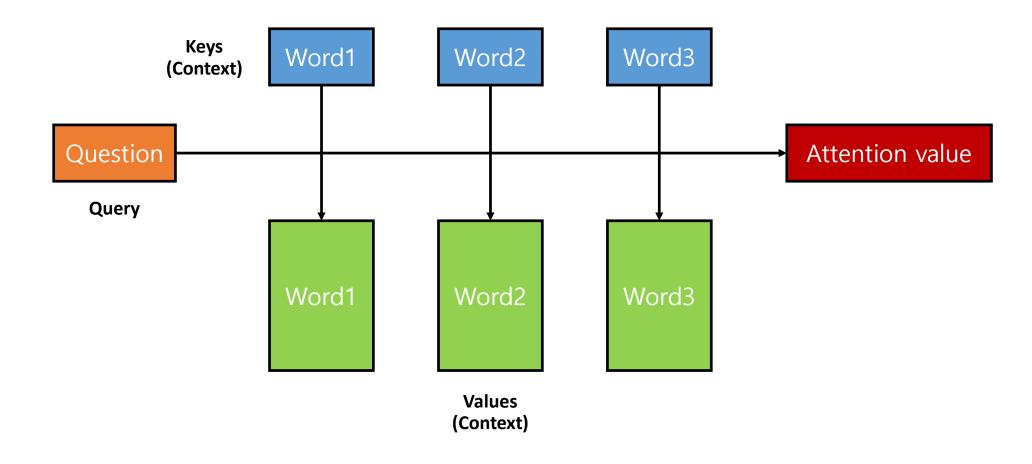
1. Content-base attention: $score(s_i, h_i) = cosine[s_i, h_i]$

2. Additive: $score(s_i, h_i) = v_{\alpha}^T \tanh(W_{\alpha}[s_i; h_i])$

3. Location-base: $\alpha_{t,i} = softmax(W_{\alpha}s_t)$

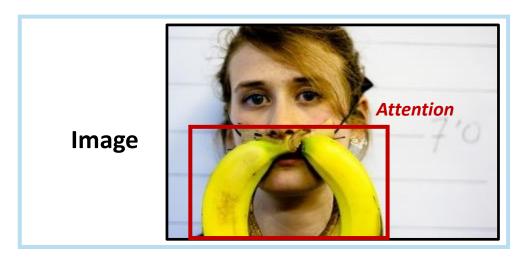
Attention Mechanism on Question Answering

In question answering task, it is easily applied on QA task since we can *substitute the inputs into Query, Keys and Values*.



Attention Mechanism on Question Answering

This is an example of (Q, K, V) in visual question answering task.



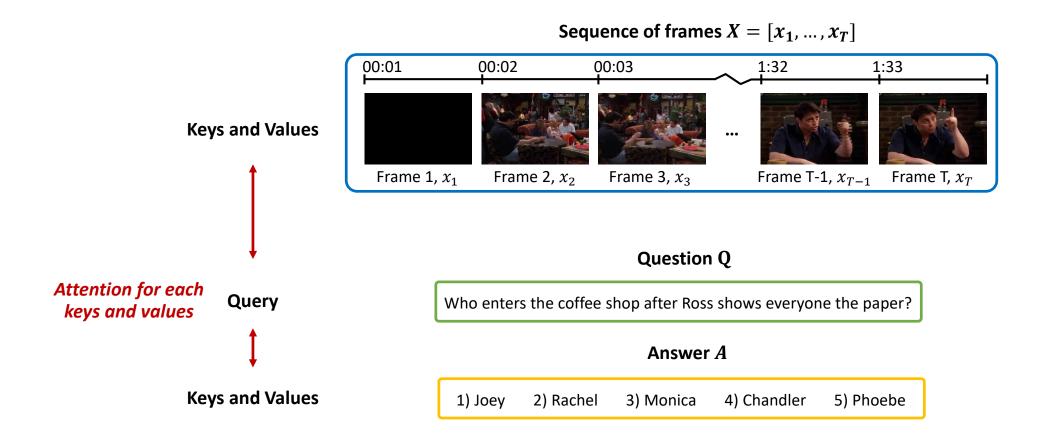
Keys and Values

Question What is the *mustache* made of?

Query

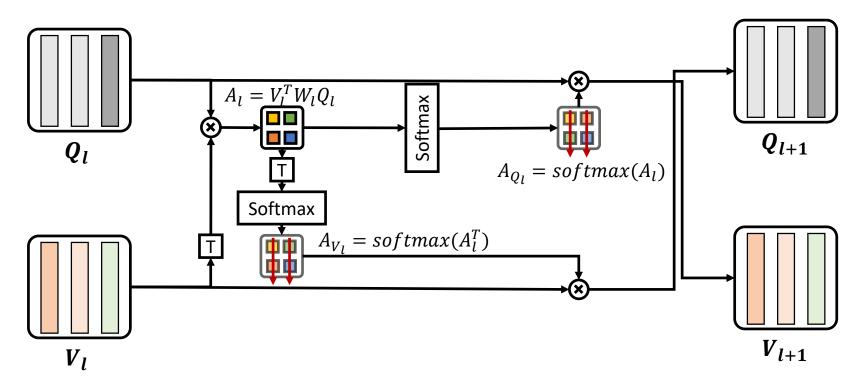
Attention Mechanism on Question Answering

This is an example of (Q, K, V) in video question answering task.



Bi-directional Attention Mechanism

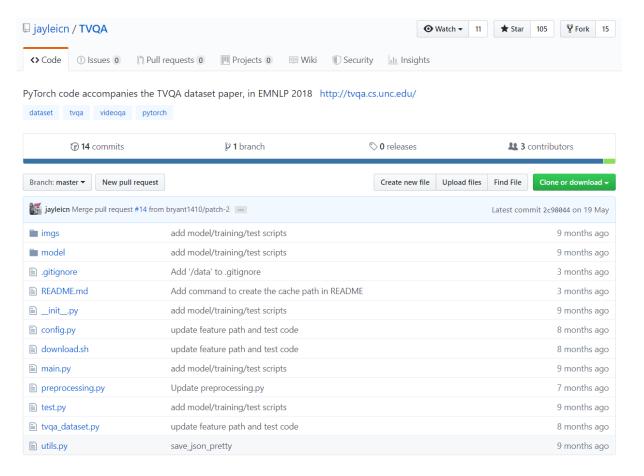
It applies the attention mechanism both directional way for a question and context.



In [Lei18], they used uni-directional attention mechanism due to limitations on memory capacity.

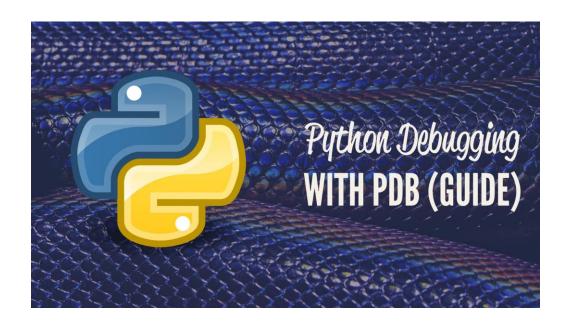
Code Review

We are going to explore how Multi-Modal Video QA is written by Python code.



Python Debugger (PDB)

Before exploring, we should know about a useful tool called 'PDB' to debug Python code.



Using Pdb

Import pdb, then insert where you'd like to start debugging:

```
numbers = [1, 2, 3, 4, 10, -4, -7, 0]
import pdb; pdb.set_trace()
def all_even(1):
    even_numbers = []...
```

1. Open a terminal, >> Ctrl + Shift + t



2. Create a vim file, >> vim test.py



3. Type below lines on your vim file.

```
>> i
>> import pdb
>> a = 20
>> b = 40
>> pdb.set_trace()
>> print(a + b)
```

```
pdb.set_trace()
When you push the button 'i', it located in the red box will be printed.
                                                                                         [+] /st2/mshan/test.py\
                                                                           "mshan@ai8: /st2/mshan" 00:23 03-Aug
```

4. Save the vim file and run

>> ESC

>>:

>> wq

>> python3 test.py

```
pdb.set_trace()
It means that save and quit.
6·12 [All]
                                                                                               [+] /st2/mshan/test.py\
                                                                                "mshan@ai8: /st2/mshan" 00:25 03-Aug-
```

5. The code will be stopped at the code 'pdb.set_trace()'.

```
>> n
```

```
mshan@ai8:/st2/mshan$ python test.py

> /st2/mshan/test.py(6)<module>()

-> print(a + b)
(Pdb) 

(Pdb)
```

What result can you see on the screen? It should output 60 by 'print(a + b)'.

Python Debugger (PDB)

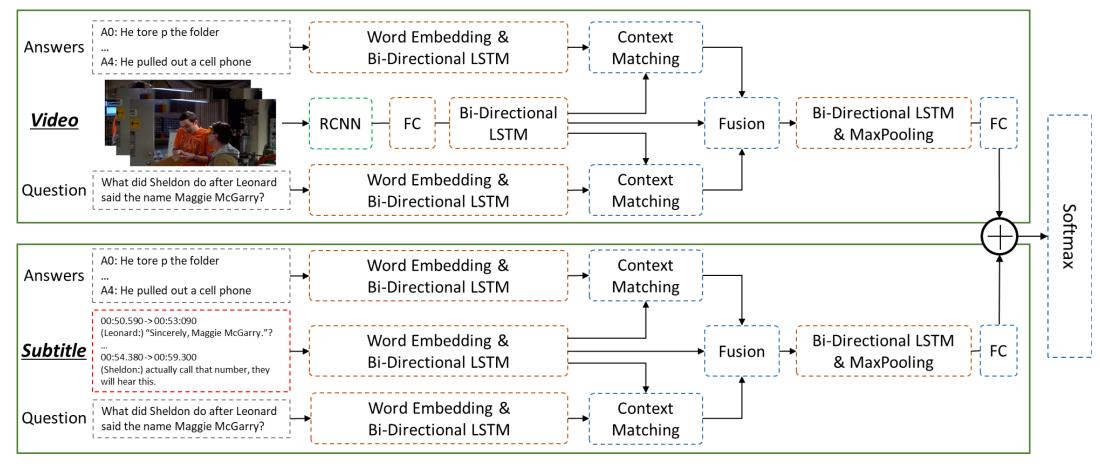
Using this example, we can explore all codes written in Python.

PDB 명령어	실행내용
help	도움말
next	다음 문장으로 이동
print	변수값 화면에 표시
list	소스코드 리스트 출력. 현재 위치 화살표로 표시됨
where	콜스택 출력
continue	계속 실행. 다음 중단점에 멈추거나 중단점 없으면 끝까지 실행
step	Step Into 하여 함수 내부로 들어감
return	현재 함수의 리턴 직전까지 실행
!변수명 = 값	변수에 값 재설정

You can see more information about PDB on https://docs.python.org/3/library/pdb.html

Multi-Modal Video QA

The main components of this model are **Word Embedding**, **Bi-directional LSTM**, **Context Matching** and **Fusion layer**.



[Lei18] J. Lei, L. Yu, M. Bansal, T. L. Berg, TVQA: Localized, Compositional Video Question Answering. EMNLP 2018

Download TVQA GitHub

>> git clone https://github.com/jayleicn/TVQA.git

```
mshan@ai8:/st2/mshan/models/ex$ git clone https://github.com/jayleicn/TVQA.git
Cloning into 'TVQA'...
remote: Enumerating objects: 8, done.
remote: Counting objects: 100% (8/8), done.
remote: Compressing objects: 100% (8/8), done.
remote: Total 64 (delta 1), reused 1 (delta 0), pack-reused 56
Unpacking objects: 100% (64/64), done.
Checking connectivity... done.
mshan@ai8:/st2/mshan/models/ex$
```

Dependency Installation

- >> pip install torch torchvision
- >> pip install h5py
- >> pip install tqdm
- >> pip install pysrt
- >> pip install tensorboardX
- >> pip install numpy

Download TVQA Dataset

- >> cd TVQA
- >> bash download.sh (or sh download.sh)

Download GloVe

Move to https://github.com/stanfordnlp/GloVe and download a file in the red box.

Download pre-trained word vectors

The links below contain word vectors obtained from the respective corpora. If you want word vectors trained on massive web datasets, you need only download one of these text files! Pre-trained word vectors are made available under the Public Domain Dedication and License.

- Common Crawl (42B tokens, 1.9M vocab, uncased, 300d vectors, 1.75 GB download): glove.42B.300d.zip
- Common Crawl (840B tokens, 2.2M vocab, cased, 300d vectors, 2.03 GB download): glove.840B.300d.zip
- Wikipedia 2014 + Gigaword 5 (6B tokens, 400K vocab, uncased, 300d vectors, 822 MB download): glove.6B.zip
- Twitter (2B tweets, 27B tokens, 1.2M vocab, uncased, 200d vectors, 1.42 GB download): glove.twitter.27B.zip

Download GloVe

Move 'glove.6B.zip' to TVQA/data

```
mshan@ai8:/st2/mshan/models/ex/TVQA/data$ ls
det_visual_concepts_hq.pickle.tar.gz frm_cnt_cache.tar.gz glove.6B.zip tvqa_qa_release.tar.gz tvqa_subtitles.tar.gz
mshan@ai8:/st2/mshan/models/ex/TVQA/data$
```

Decompression for GloVe

- >> cd TVQA/data
- >> unzip glove.6B.zip

```
2. ai0.kaist.ac.kr (mshan)
mshan@ai8:/st2/mshan/models/ex/TVQA/data$ tar -zxvf det visual concepts hq.pickle.tar.qz
det visual concepts hq.pickle
mshan@ai8:/st2/mshan/models/ex/TVQA/data$ unzip glove.6B.zip
Archive: glove.6B.zip
 inflating: glove.6B.100d.txt
 inflating: glove.6B.200d.txt
 inflating: glove.6B.300d.txt
 inflating: glove.6B.50d.txt
mshan@ai8:/st2/mshan/models/ex/TVQA/data$ ls
det visual concepts hq.pickle
                                     frm cnt cache.tar.gz
                                                            glove.6B.200d.txt glove.6B.50d.txt tvqa qa release.tar.gz
det_visual_concepts_hq.pickle.tar.gz glove.6B.100d.txt
                                                            glove.6B.300d.txt glove.6B.zip
                                                                                                 tvqa subtitles.tar.qz
mshan@ai8:/st2/mshan/models/ex/TVQA/data$
```

Decompression for TVQA Dataset

```
>> cd TVQA/data
>> tar -zxvf tvqa_qa_release.tar.gz
>> tar -zxvf tvqa subtitles.tar.gz
>> tar -zxvf frm_cnt_cache.tar.gz
mshan@ai8:/st2/mshan/models/ex/TVQA/data$ tar -zxvf tvqa qa release.tar.gz
tvga ga release/
tvqa qa release/tvqa train.jsonl
tvqa qa release/tvqa val.jsonl
tvqa qa release/tvqa test public.jsonl
mshan@ai8:/st2/mshan/models/ex/TVQA/data$ tar -zxvf tvga subtitles.tar.gz
mshan@ai8:/st2/mshan/models/ex/TVQA/data$ tar -zxvf frm cnt cache.tar.gz
frm cnt cache.json
mshan@ai8:/st2/mshan/models/ex/TVQA/data$
mshan@ai8:/st2/mshan/models/ex/TVQA/data$ ls
det_visual_concepts_hq.pickle
                                 frm cnt cache.tar.gz
                                                    glove.6B.300d.txt srt data cache.json
                                                                                         tvga subtitles
det visual concepts hq.pickle.tar.gz glove.6B.100d.txt
                                                                    tvga ga release
                                                    glove.6B.50d.txt
                                                                                         tvga subtitles.tar.gz
                                                                    tvqa qa release.tar.gz
frm cnt cache.json
                                 glove.6B.200d.txt
                                                    glove.6B.zip
mshan@ai8:/st2/mshan/models/ex/TVQA/data$
```

Pre-processing for TVQA Dataset

>> preprocessing.py

```
mshan@ai8:/st2/mshan/models/ex/TVQA$ python preprocessing.py
Loading srt files from ./data/tvqa subtitles ...
             21793/21793 [01:10<00:00, 309.26it/s]
Tokenize subtitle ...
               [ 21793/21793 [00:24<00:00, 889.08it/s]
Processing ./data/tvqa qa release/tvqa val.jsonl
Tokenize OA ...
               | 15253/15253 [00:04<00:00, 3756.89it/s]
Adding subtitle ...
                15253/15253 [00:00<00:00, 99078.25it/s]
Found frame cnt cache, loading ...
                15253/15253 [00:00<00:00, 20818.64it/s]
There are 6 NaN values in ts, which are replaced by [10, 30], will be fixed later
Processing ./data/tvga ga release/tvga test public.jsonl
                7623/7623 [00:02<00:00, 3671.02it/s]
                7623/7623 [00:00<00:00, 65175.57it/s]
Found frame cnt cache, loading ...
                7623/7623 [00:00<00:00, 19019.46it/s]
There are 3 NaN values in ts, which are replaced by [10, 30], will be fixed later
Processing ./data/tvqa_qa_release/tvqa_train.jsonl
Tokenize QA ...
               | 122039/122039 [00:33<00:00, 3684.69it/s]
Adding subtitle ...
                122039/122039 [00:01<00:00, 106054.20it/s]
Found frame cnt cache, loading ...
               | 122039/122039 [00:07<00:00, 15454.28it/s]
There are 36 NaN values in ts, which are replaced by [10, 30], will be fixed later
mshan@ai8:/st2/mshan/models/ex/TVQA$
```

! Notice

Original code provided by TVQA is based on Python2.

Therefore, you must convert Python2 into Python3.

→ See the code installed on your desktop, which is already converted.

Pre-processing for TVQA Dataset

- >> cd TVQA
- >> mkdir cache
- >> python tvqa_dataset.py

```
mshan@ai8:/st2/mshan/models/ex/TVQA$ mkdir cache
mshan@ai8:/st2/mshan/models/ex/TVQA$ python tvga dataset.py
----- Options -----
bsz: 32
debug: False
device: 0
embedding size: 300
glove path: ./data/glove.6B.300d.txt
hsz1: 150
hsz2: 300
idx2word path: ./cache/idx2word.pickle
input streams: ['sub']
log freg: 400
 r: 0.0003
max es cnt: 3
nax sub l: 300
max vcpt l: 300
max vid l: 480
```

! Notice

Original code provided by TVQA is based on Python2.

Therefore, you must convert Python2 into Python3.

→ See the code installed on your desktop, which is already converted.

Run

- >> cd TVQA
- >> python main.py --input_streams sub vcpt

```
mshan@ai8:/st2/mshan/models/ex/TVQA$ python main.py --input stream sub vcpt
 ..... Options
bsz: 32
debug: False
device: 0
embedding_size: 300
glove_path: ./data/glove.6B.300d.txt
hsz1: 150
hsz2: 300
idx2word path: ./cache/idx2word.pickle
input_streams: ['sub', 'vcpt']
log freg: 400
lr: 0.0003
max es cnt: 3
max_sub_l: 300
max vcpt l: 300
max vid l: 480
n epoch: 100
n layers cls: 1
no core driver: False
no_glove: False
no normalize v: False
no_ts: False
results dir base: results/results
test bsz: 100
test path: ./data/tvqa test public processed.json
train_path: ./data/tvqa_train_processed.json
valid_path: ./data/tvqa_val_processed.json
vcpt_path: ./data/det_visual_concepts_hq.pickle
vid feat path: ./data/tvqa imagenet pool5.h5
vid feat size: 2048
vocab embedding path: ./cache/vocab embedding.pickle
vocab size: 0
wd: 1e-05
word2idx_path: ./cache/word2idx.pickle
word count threshold: 2
 ----- End -----
```

```
word_count_threshold: 2
..... End ....
Loading cache ...
activate sub stream
activate vcpt stream
/home/mshan/.local/lib/python2.7/site-packages/torch/nn/_reduction.py:46: UserWarning: size_average and
' instead.
    warnings.warn(warning.format(ret))
0it [00:00, ?it/s] Train Epoch 0 loss 1.6104 acc 0.0938 Val loss 1.6093 acc 0.2092
52it [03:11, 1.10it/s]
```

```
name == " main "<mark>:</mark>
torch.manual seed(\frac{2018}{})
opt = BaseOptions().parse()
writer = SummaryWriter(opt.results_dir)
opt.writer = writer
dset = TVQADataset(opt)
opt.vocab size = len(dset.word2idx)
model = ABC(opt)
if not opt.no_glove:
    model.load embedding(dset.vocab embedding)
model.to(opt.device)
cudnn.benchmark = True
criterion = nn.CrossEntropyLoss(size average=False).to(opt.device)
optimizer = torch.optim.Adam(filter(lambda p: p.requires grad, model.parameters()),
                             lr=opt.lr, weight decay=opt.wd)
best acc = 0.
early stopping cnt = 0
early stopping flag = False
for epoch in range(opt.n_epoch):
    if not early_stopping_flag:
        # train for one epoch, valid per n batches, save the log and the best model
        cur acc = train(opt, dset, model, criterion, optimizer, epoch, best acc)
        is best = cur acc > best acc
        best acc = max(cur acc, best acc)
        if not is best:
            early stopping cnt += 1
            if early_stopping_cnt >= opt.max_es_cnt:
                early stopping flag = True
        print("early stop with valid acc %.4f" % best_acc)
        opt.writer.export scalars to json(os.path.join(opt.results dir, "all scalars.json"))
        opt.writer.close()
        break # early stop break
```

```
if __name__ == "__main__":
    torch.manual_seed(2018)
    opt = BaseOptions().parse()
    writer = SummaryWriter(opt.results_dir)
    opt.writer = writer

    dset = TVQADataset(opt)
    opt.vocab_size = len(dset.word2idx)
    model = ABC(opt)
    if not opt.no_glove:
        model.load_embedding(dset.vocab_embedding)
```

```
if __name__ == "__main__"
    torch.manual_seed(2018)
    opt = BaseOptions().parse()
    writer = SummaryWriter(opt.results_dir)
    opt.writer = writer

    dset = TVQADataset(opt)
    opt.vocab_size = len(dset.word2idx)
    model = ABC(opt)

if not opt.no_glove:
    model.load_embedding(dset.vocab_embedding)
GloVe initialization
```

```
best acc = 0.
                                                     Training process
early stopping cnt = 0
early stopping flag = False
for epoch in range(opt.n epoch):
    if not early_stopping flag:
        # train for one epoch, valid per n batches, save the log and the best model
        cur_acc = train(opt, dset, model, criterion, optimizer, epoch, best_acc)
        # remember best acc
        is best = cur acc > best acc
        best acc = max(cur acc, best acc)
        if not is best:
            early stopping cnt += 1
            if early stopping cnt >= opt.max es cnt:
                early stopping flag = True
    else:
        print("early stop with valid acc %.4f" % best acc)
        opt.writer.export_scalars_to_json(os.path.join(opt.results_dir, "all_scalars.json"))
        opt.writer.close()
        break # early stop break
```

Train

```
ef train(opt, dset, model, criterion, optimizer, epoch, previous_best_acc):
  dset.set mode("train")
 model.train()
 train loader = DataLoader(dset, batch size=opt.bsz, shuffle=True, collate fn=pad collate)
  train loss = []
  valid_acc_log = ["batch_idx\tacc"]
 train corrects = []
  torch.set grad enabled(True)
 for batch idx, batch in tqdm(enumerate(train_loader)):
      model inputs, targets, = preprocess inputs(batch, opt.max sub l, opt.max vcpt l, opt.max vid l,
                                                  device=opt.device)
      outputs = model(*model inputs)
      loss = criterion(outputs, targets)
      optimizer.zero grad()
      loss.backward()
      optimizer.step()
      # measure accuracy and record loss
      train loss.append(loss.item())
      pred ids = outputs.data.max(1)[1]
      train corrects += pred ids.eq(targets.data).cpu().numpy().tolist()
      if batch idx % opt.log freq == 0:
         niter = epoch * len(train loader) + batch idx
          train acc = sum(train corrects) / float(len(train corrects))
          train loss = sum(train loss) / float(len(train corrects))
         opt.writer.add scalar("Train/Acc", train acc, niter)
          opt.writer.add scalar("Train/Loss", train loss, niter)
          valid_acc, valid_loss = validate(opt, dset, model, mode="valid")
          opt.writer.add scalar("Valid/Loss", valid loss, niter)
          valid log str = "%02d\t%.4f" % (batch idx, valid acc)
          valid acc log.append(valid log str)
          if valid acc > previous best acc:
              previous best acc = valid acc
              torch.save(model.state_dict(), os.path.join(opt.results_dir, "best_valid.pth"))
          print(" Train Epoch %d loss %.4f acc %.4f Val loss %.4f acc %.4f"
```

Train

```
def train(opt, dset, model, criterion, optimizer, epoch, previous best acc);
    dset.set mode("train")
   model.train()
    train loader = DataLoader(dset, batch size=opt.bsz, shuffle=True, collate fn=pad collate)
    train loss = []
    valid acc log = ["batch idx\tacc"]
    train corrects = []
    torch.set grad enabled(True)
                                                             Forward and Backward
    for batch idx, batch in tqdm(enumerate(train loader)):
       model inputs, targets, = preprocess inputs(batch, opt.max sub l, opt.max vcpt l, opt.max vid l,
                                                     device=opt.device)
        outputs = model(*model inputs)
        loss = criterion(outputs, targets)
        optimizer.zero grad()
        loss.backward()
        optimizer.step()
```

```
# model confid
self.parser.add argument("--no glove", action="store true", help="not use glove vectors")
self.parser.add_argument("--no_ts", action="store_true", help="not use glove initialization for embedding layer
self.parser.add_argument("--input_streams", type=str, nargs="+", help="not use both 'vcpt' and 'sub' streams")
self.parser.add_argument("--n_layers_cls", type=int, default=1, help="number of layers in classifier")
self.parser.add_argument("--hsz1", type=int, default=300, help="hidden size for the first lstm")
self.parser.add_argument("--embedding_size", type=int, default=300, help="word embedding_dim")
self.parser.add_argument("--max_sub_l", type=int, default=300, help="max_length for subtitle")
self.parser.add_argument("--max_vcpt_l", type=int, default=300, help="max_length for visual concepts")
self.parser.add_argument("--max_vid_l", type=int, default=480, help="max_length for video feature")
self.parser.add_argument("--vocab_size", type=int, default=0, help="vocabulary_size")
self.parser.add_argument("--no_normalize_v", action="store_true", help="do not normalize_video featrue")
```

```
# path config
self.parser.add argument("--train path", type=str, default="./data/tvqa train processed.json",
                         help="train set path")
self.parser.add argument("--valid path", type=str, default="./data/tvga val processed.json",
                         help="valid set path")
self.parser.add_argument("--test_path", type=str, default="./data/tvqa_test_public_processed.json",
                         help="test set path")
self.parser.add_argument("--glove_path", type=str, default="./data/glove_6B_300d_txt"
                                                                     The paths of TVQA dataset
                         help="GloVe pretrained vector path")
self.parser.add argument("--vcpt path", type=str, default="./data/det visual concepts hg.pickle",
                         help="visual concepts feature path")
self.parser.add argument("--vid feat path", type=str, default="./data/tvga imagenet pool5.h5",
                         help="imagenet feature path")
self.parser.add argument("--vid feat size", type=int, default=2048,
                         help="visual feature dimension")
self.parser.add argument("--word2idx path", type=str, default="./cache/word2idx.pickle",
                         help="word2idx cache path")
self.parser.add argument("--idx2word path", type=str, default="./cache/idx2word.pickle",
                         help="idx2word cache path")
self.parser.add argument("--vocab embedding path", type=str, default="./cache/vocab embedding.pickle",
                         help="vocab embedding cache path")
self.initialized = True
```

```
# path config
self.parser.add argument("--train path", type=str, default="./data/tvqa train processed.json",
                         help="train set path")
self.parser.add argument("--valid path", type=str, default="./data/tvga val processed.json",
                         help="valid set path")
self.parser.add_argument("--test_path", type=str, default="./data/tvo The path of GloVe
                                                                                      ocessed.json",
                         help="test set path")
self.parser.add argument("--glove_path", type=str, default="./data/glove.6B.300d.txt",
                         help="GloVe pretrained vector path")
self.parser.add_argument("--vcpt_path", type=str, default="./data/det visual concepts hq.pickle",
                         help="visual concepts feature path")
self.parser.add argument("--vid feat path", type=str, default="./data/tvga imagenet pool5.h5",
                         help="imagenet feature path")
self.parser.add argument("--vid feat size", type=int, default=2048,
                         help="visual feature dimension")
self.parser.add argument("--word2idx path", type=str, default="./cache/word2idx.pickle",
                         help="word2idx cache path")
self.parser.add argument("--idx2word path", type=str, default="./cache/idx2word.pickle",
                         help="idx2word cache path")
self.parser.add argument("--vocab embedding path", type=str, default="./cache/vocab embedding.pickle",
                         help="vocab embedding cache path")
self.initialized = True
```

```
# path config
self.parser.add argument("--train path", type=str, default="./data/tvqa train processed.json",
                         help="train set path")
self.parser.add argument("--valid path", type=str, default="./data/tvga val processed.json",
                         help="valid set path")
self.parser.add_argument("--test_path", type=str, default="./data/tvqa_test_public_processed.json",
                         help="test set path")
self.parser.add argument("--glove path", type=str, default="./data/glove.6B.300d.txt",
                         help="GloVe pretrained vector path")
self.parser.add argument("--vcpt path", type=str, default="./data/det visual concepts hq.pickle",
                         help="visual concepts feature path")
self.parser.add argument("--vid feat path", type=str, default="./data/tvqa imagenet pool5.h5",
                         help="imagenet feature path")
self.parser.add argument("--vid feat size", type=int, default=2048,
                         help="visual feature dimension")
self.parser.add_argument("--word The paths and parameters of Visual concepts features and ImageNet features
self.parser.add argument("--idx2word path", type=str, default="./cache/idx2word.pickle",
                         help="idx2word cache path")
self.parser.add argument("--vocab embedding path", type=str, default="./cache/vocab embedding.pickle",
                         help="vocab embedding cache path")
self.initialized = True
```

```
# path config
self.parser.add argument("--train path", type=str, default="./data/tvqa train processed.json",
                         help="train set path")
self.parser.add argument("--valid path", type=str, default="./data/tvga val processed.json",
                         help="valid set path")
self.parser.add_argument("--test_path", type=str, default="./data/tvqa_test_public_processed.json",
                         help="test set path")
self.parser.add_argument("--glove_path", type=str, default="./data/glove.6B.300d.txt",
                         help="GloVe pretrained vector path")
self.parser.add argument("--vcpt path", type=str, default="./data/det visual concepts hq.pickle",
                         help="visual concepts feature path")
self.parser.add argument("--vid feat path", type=str, default="./data/tvga imagenet pool5.h5",
                         help="imagenet feature path")
self.parser.add argument("--vid feat size", type=int, default=2048,
                                                                      The paths of pre-processed files
                         help="visual feature dimension")
self.parser.add argument("--word2idx path", type=str, default="./cache/word2idx.pickle",
                         help="word2idx cache path")
self.parser.add argument("--idx2word path", type=str, default="./cache/idx2word.pickle",
                         help="idx2word cache path")
self.parser.add argument("--vocab embedding path", type=str, default="./cache/vocab embedding.pickle",
                         help="vocab embedding cache path")
self.initialized = True
```

>> vim model/tvqa_abc.py

```
class ABC(nn.Module):
    def init (self, opt):
        \overline{\text{super}}(\overline{ABC}, \text{self}), \text{ init } ()
        self.vid flag = "imagenet" in opt.input streams
        self.sub flag = "sub" in opt.input streams
                                                                  The flags for whether using each feature or not
        self.vcpt flag = "vcpt" in opt.input streams
        hidden size 1 = opt.hsz1
        hidden size 2 = opt.hsz2
        n layers cls = opt.n layers cls
        vid feat size = opt.vid feat size
        embedding size = opt.embedding size
        vocab size = opt.vocab size
        self.embedding = nn.Embedding(vocab size, embedding size)
        self.bidaf = BidafAttn(hidden size \overline{1} * 3, method="\overline{dot}") # no parameter for dot
        self.lstm raw = RNNEncoder(30\overline{0}, hidden size 1, bidirectional=True, dropout p=0, n layers=1, rnn type="lstm")
```

>> vim model/tvqa abc.py

```
class ABC(nn.Module):
    def init (self, opt):
        \overline{\text{super}}(\overline{ABC}, \text{ self}). \text{ init } ()
        self.vid flag = "imagenet" in opt.input streams
        self.sub flag = "sub" in opt.input streams
        self.vcpt flag = "vcpt" in opt.input streams
        hidden size 1 = opt.hsz1
        hidden size 2 = opt.hsz2
        n = \frac{1}{100} n layers cls
                                                                  The parameters for the model
        vid feat size = opt.vid feat size
        embedding size = opt.embedding size
        vocab size = opt.vocab size
        self.embedding = nn.Embedding(vocab size, embedding size)
        self.bidaf = BidafAttn(hidden size \overline{1} * 3, method="\overline{dot}") # no parameter for dot
        self.lstm raw = RNNEncoder(30\overline{0}, hidden size 1, bidirectional=True, dropout p=0, n layers=1, rnn type="lstm")
```

>> vim model/tvqa_abc.py

```
class ABC(nn.Module):
    def init (self, opt):
        \overline{\text{super}}(\overline{ABC}, \text{ self}). \text{ init } ()
        self.vid flag = "imagenet" in opt.input streams
        self.sub flag = "sub" in opt.input streams
        self.vcpt flag = "vcpt" in opt.input streams
        hidden size 1 = opt.hsz1
        hidden size 2 = opt.hsz2
        n layers cls = opt.n layers cls
        vid feat size = opt.vid feat size
        embedding size = opt.embedding size
                                                                Word embedding layer
        vocab size = opt.vocab size
        self.embedding = nn.Embedding(vocab size, embedding size)
        self.bidaf = BidafAttn(hidden size 1 * 3, method="dot") # no parameter for dot
        self.lstm raw = RNNEncoder(30\overline{0}, hidden size 1, bidirectional=True, dropout p=0, n layers=1, rnn type="lstm")
```

Word Embedding

torch.nn.Embedding – 2 arguments

- 6 optional arguments
- 2 required arguments: *num_embeddings, embedding_dim*

CLASS torch.nn.Embedding(num_embeddings, embedding_dim, padding_idx=None, max_norm=None, norm_type=2.0, scale_grad_by_freq=False, sparse=False, _weight=None)

[SOURCE]

Parameters

- num_embeddings (int) size of the dictionary of embeddings
- embedding_dim (int) the size of each embedding vector

>> vim model/tvqa abc.py

```
class ABC(nn.Module):
    def init (self, opt):
        super(ABC, self). init ()
        self.vid flag = "imagenet" in opt.input streams
        self.sub flag = "sub" in opt.input streams
        self.vcpt flag = "vcpt" in opt.input streams
        hidden size 1 = opt.hsz1
        hidden size 2 = opt.hsz2
        n_layers_cls = opt.n_layers_cls
        vid feat size = opt.vid feat size
        embedding size = opt.embedding size
                                                                 Attention layer
        vocab size = opt.vocab size
                                                               (Context Matchina)
       self.embedding = nn.Fmbedding(vocab size, embedding size)
       self.bidaf = BidafAttn(hidden size \overline{1} * 3, method="\overline{dot}") # no parameter for dot
        self.lstm raw = RNNEncoder(300, hidden size 1, bidirectional=True, dropout p=0, n layers=1, rnn type="lstm")
```

>> vim model/tvqa_abc.py

Long Short-Term Memory

torch.nn.LSTM – 7 arguments

- 5 optional arguments
- 2 required arguments: *input_size*, *hidden_size*

CLASS torch.nn.LSTM(*args, **kwargs)

[SOURCE]

Parameters

- input_size The number of expected features in the input x
- **hidden_size** The number of features in the hidden state h

:

>> vim model/tvqa abc.py

```
if self.vid flag:
    print("activate video stream")
                                                                      Layers for ImageNet Features
    self.video fc = nn.Sequential(
        nn.Dropout(0.5),
        nn.Linear(vid feat size, embedding size),
        nn.Tanh(),
    self.lstm mature vid = RNNEncoder(hidden size 1 * 2 * 5, hidden size 2, bidirectional=True,
                                      dropout p=0, n layers=1, rnn type="lstm")
    self.classifier vid = MLP(hidden size 2*2, 1, 500, n layers cls)
if self.sub flag:
    print("activate sub stream")
    self.lstm mature sub = RNNEncoder(hidden size 1 * 2 * 5, hidden size 2, bidirectional=True,
                                      dropout p=0, n layers=1, rnn type="lstm")
    self.classifier sub = MLP(hidden size 2*2, 1, 500, n layers cls)
if self.vcpt flag:
    print("activate vcpt stream")
    self.lstm mature vcpt = RNNEncoder(hidden_size_1 * 2 * 5, hidden_size_2, bidirectional=True,
                                       dropout_p=0, n_layers=1, rnn_type="lstm")
    self.classifier vcpt = MLP(hidden size 2*2, 1, 500, n layers cls)
```

>> vim model/tvqa abc.py

```
if self.vid flag:
    print("activate video stream")
    self.video fc = nn.Sequential(
        nn.Dropout(0.5),
        nn.Linear(vid feat size, embedding size),
        nn.Tanh(),
    self.lstm mature vid = RNNEncoder(hidden size 1 * 2 * 5, hidden size 2, bidirectional=True,
                                      dropout p=0, n layers=1, rnn type="lstm")
    self.classifier vid = MLP(hidden size 2*2, 1, 500, n layers cls)
if self.sub flag:
                                                                                Layers for subtitle
    print("activate sub stream")
    self.lstm mature sub = RNNEncoder(hidden size 1 * 2 * 5, hidden size 2, bidirectional=True,
                                      dropout p=0, n layers=1, rnn type="lstm")
    self.classifier sub = MLP(hidden size 2*2, 1, 500, n layers cls)
if self.vcpt flag:
    print("activate vcpt stream")
    self.lstm mature vcpt = RNNEncoder(hidden size 1 * 2 * 5, hidden size 2, bidirectional=True,
                                       dropout_p=0, n_layers=1, rnn_type="lstm")
    self.classifier vcpt = MLP(hidden size 2*2, 1, 500, n layers cls)
```

https://github.com/jayleicn/TVQA

>> vim model/tvqa abc.py

```
if self.vid flag:
    print("activate video stream")
    self.video fc = nn.Sequential(
        nn.Dropout(0.5),
        nn.Linear(vid feat size, embedding size),
        nn.Tanh(),
    self.lstm mature vid = RNNEncoder(hidden size 1 * 2 * 5, hidden size 2, bidirectional=True,
                                       dropout p=0, n layers=1, rnn type="lstm")
    self.classifier vid = MLP(hidden size 2*2, 1, 500, n layers cls)
if self.sub flag:
    print("activate sub stream")
    self.lstm mature sub = RNNEncoder(hidden size 1 * 2 * 5, hidden size 2, bidirectional=True,
                                       dropout p=0, n layers=1, rnn type="lstm")
    self.classifier sub = MLP(hidden size 2*2, 1, 500, n layers cls)
if self.vcpt flag:
                                                                   Layers for visual concepts features
    print("activate vcpt stream")
    self.lstm mature vcpt = RNNEncoder(hidden size 1 * 2 * 5, hidden size 2, bidirectional=True,
                                        dropout_p=0, n_layers=1, rnn_type="lstm")
    self.classifier vcpt = MLP(hidden size 2*2, 1, 500, n layers cls)
```

GloVe Initialization

>> vim model/tvqa_abc.py

```
def load_embedding(self, pretrained_embedding):
    self.embedding.weight.data.copy_(torch.from_numpy(pretrained_embedding))
```

Inputs

- >> vim model/tvqa_abc.py
- >> (Line 55) import pdb; pdb.set_trace()

Inputs

>> python main.py --input_streams sub vcpt

```
def forward(self, q, q_l, a0, a0_l, a1, a1_l, a2, a2_l, a3, a3_l, a4, a4_l,
             sub, sub_l, vcpt, vcpt_l, vid, vid_l):
(Pdb) print(a2)
                             (Pdb) print(a3)
                                                            (Pdb) print(a4)
tensor([[735,
           2]], device='cuda:0')
                             tensor([[9197,
                                         2]], device='cuda:0')
                                                                        2]], device='cuda:0')
                                                            tensor([[1387,
(Pdb) print(vcpt)
                 597, 64, 1398,
                                      132,
                                             597, 1832,
tensor([[ 139,
                                                           510,
                                                                 1359,
                                                                          122,
           139,
                 597, 315,
                               735, 1590, 1526, 1253,
                                                            611,
                                                                  1398,
                                                                         1590,
           132,
                2505, 1396, 597, 1590,
                                            1595,
                                                      58, 3274,
                                                                   316,
                                                                         1387,
          132,
                2650, 597, 638, 980, 2972, 1590, 1117,
                                                                  213,
                                                                          597,
          1771, 1590, 418, 2972,
                                      884, 2972, 132, 1398, 12328,
                                                                         4302.
                   2]], device='cuda:0')
          510,
(Pdb)
```

Embedding and Encoding Layer

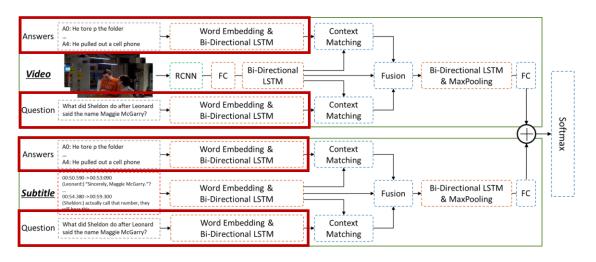
>> vim model/tvqa_abc.py or go to next ('n') using PDB

```
e_q = self.embedding(q)
e_a0 = self.embedding(a0)
e_a1 = self.embedding(a1)
e_a2 = self.embedding(a2)
e_a3 = self.embedding(a3)
e_a4 = self.embedding(a4)
```

Word embedding for question and answers

```
raw_out_q, _ = self.lstm_raw(e_q, q_l)
raw_out_a0, _ = self.lstm_raw(e_a0, a0_l)
raw_out_a1, _ = self.lstm_raw(e_a1, a1_l)
raw_out_a2, _ = self.lstm_raw(e_a2, a2_l)
raw_out_a3, _ = self.lstm_raw(e_a3, a3_l)
raw_out_a4, _ = self.lstm_raw(e_a4, a4_l)
```

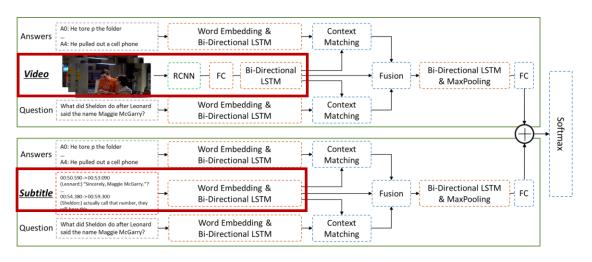
Bi-directional LSTM for question and answers



The overview of Multi-Modal Video QA

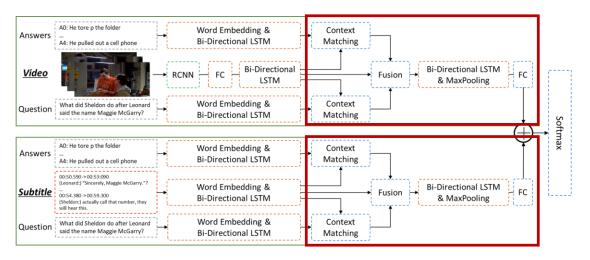
Embedding and Encoding Layer

>> vim model/tvqa_abc.py or go to next ('n') using PDB



The overview of Multi-Modal Video QA

>> vim model/tvqa_abc.py or go to next ('n') using PDB



The overview of Multi-Modal Video QA

```
def stream processor(self, lstm mature, classifier, ctx embed, ctx l,
                    g embed, g l, a0 embed, a0 l, a1 embed, a1 l, a2 embed, a2 l, a3 embed, a3 l, a4 embed, a4 l):
   u q, = self.bidaf(ctx embed, ctx l, q embed, q l)
   u a0, = self.bidaf(ctx embed, ctx l, a0 embed, a0 l)
   u a1, = self.bidaf(ctx embed, ctx l, a1 embed, a1 l)
                                                             Context matching
   u a2, = self.bidaf(ctx embed, ctx l, a2 embed, a2 l)
   u a3, = self.bidaf(ctx embed, ctx l, a3 embed, a3 l)
   u a4, = self.bidaf(ctx embed, ctx l, a4 embed, a4 l)
   concat a0 = torch.cat([ctx embed, u a0, u q, u a0 * ctx embed, u q * ctx embed], dim=-1)
   concat al = torch.cat([ctx embed, u al, u q, u al * ctx embed, u q * ctx embed], dim=-1)
   concat a2 = torch.cat([ctx embed, u a2, u q, u a2 * ctx embed, u q * ctx embed], dim=-1)
   concat a3 = torch.cat([ctx embed, u a3, u q, u a3 * ctx embed, u q * ctx embed], dim=-1)
   concat a4 = torch.cat([ctx embed, u a4, u q, u a4 * ctx embed, u q * ctx embed], dim=-1)
   mature maxout a0, = lstm mature(concat a0, ctx l)
   mature maxout_a1, = lstm mature(concat_a1, ctx l)
   mature maxout a2, = lstm mature(concat a2, ctx l)
   mature maxout a3, = lstm mature(concat a3, ctx l)
   mature maxout a4, = lstm mature(concat a4, ctx l)
   mature maxout a0 = max along time(mature maxout a0, ctx l).unsqueeze(1)
   mature maxout a1 = max along time(mature maxout a1, ctx l).unsqueeze(1)
   mature maxout a2 = max along time(mature maxout a2, ctx l).unsqueeze(1)
   mature maxout a3 = max along time(mature maxout a3, ctx l).unsqueeze(1)
   mature maxout a4 = max along time(mature maxout a4, ctx l).unsqueeze(1)
   mature answers = torch.cat([
       mature maxout a0, mature maxout a1, mature maxout a2, mature maxout a3, mature maxout a4
   ], dim=1)
   out = classifier(mature answers) # (B, 5)
   return out
```

```
def stream processor(self, lstm mature, classifier, ctx embed, ctx l,
                    q embed, q l, a0 embed, a0 l, a1 embed, a1 l, a2 embed, a2 l, a3 embed, a3 l, a4 embed, a4 l):
   u q, = self.bidaf(ctx embed, ctx l, q embed, q l)
   u a0, = self.bidaf(ctx embed, ctx l, a0 embed, a0 l)
   u a1, = self.bidaf(ctx embed, ctx l, a1 embed, a1 l)
   u a2, = self.bidaf(ctx embed, ctx l, a2 embed, a2 l)
   u a3, = self.bidaf(ctx embed, ctx l, a3 embed, a3 l)
   u a4, = self.bidaf(ctx embed, ctx l, a4 embed, a4 l)
   concat a0 = torch.cat([ctx embed, u a0, u q, u a0 * ctx embed, u q * ctx embed], dim=-1)
   concat a1 = torch.cat([ctx embed, u a1, u q, u a1 * ctx embed, u q * ctx embed], dim=-1)
   concat a2 = torch.cat([ctx embed, u a2, u q, u a2 * ctx embed, u q * ctx embed], dim=-1)
                                                                                                   Fusion
   concat a3 = torch.cat([ctx embed, u a3, u q, u a3 * ctx embed, u q * ctx embed], dim=-1)
   concat a4 = torch.cat([ctx embed, u a4, u q, u a4 * ctx embed, u q * ctx embed], dim=-1)
   mature maxout a0, = lstm mature(concat a0, ctx l)
   mature maxout_a1, = lstm mature(concat_a1, ctx l)
   mature maxout a2, = lstm mature(concat a2, ctx l)
   mature maxout a3, = lstm mature(concat a3, ctx l)
   mature maxout a4, = lstm mature(concat a4, ctx l)
   mature maxout a0 = max along time(mature maxout a0, ctx l).unsqueeze(1)
   mature maxout a1 = max along time(mature maxout a1, ctx l).unsqueeze(1)
   mature maxout a2 = max along time(mature maxout a2, ctx l).unsqueeze(1)
   mature maxout a3 = max along time(mature maxout a3, ctx l).unsqueeze(1)
   mature maxout a4 = max along time(mature maxout a4, ctx l).unsqueeze(1)
   mature answers = torch.cat([
       mature maxout a0, mature maxout a1, mature maxout a2, mature maxout a3, mature maxout a4
   1, dim=1)
   out = classifier(mature answers) # (B, 5)
   return out
```

```
def stream processor(self, lstm mature, classifier, ctx embed, ctx l,
                    q embed, q l, a0 embed, a0 l, a1 embed, a1 l, a2 embed, a2 l, a3 embed, a3 l, a4 embed, a4 l):
   u q, = self.bidaf(ctx embed, ctx l, q embed, q l)
   u a0, = self.bidaf(ctx embed, ctx l, a0 embed, a0 l)
   u a1, = self.bidaf(ctx embed, ctx l, a1 embed, a1 l)
   u a2, = self.bidaf(ctx embed, ctx l, a2 embed, a2 l)
   u a3, = self.bidaf(ctx embed, ctx l, a3 embed, a3 l)
   u a4, = self.bidaf(ctx embed, ctx l, a4 embed, a4 l)
   concat a0 = torch.cat([ctx embed, u a0, u q, u a0 * ctx embed, u q * ctx embed], dim=-1)
   concat a1 = torch.cat([ctx embed, u a1, u q, u a1 * ctx embed, u q * ctx embed], dim=-1)
   concat a2 = torch.cat([ctx embed, u a2, u q, u a2 * ctx embed, u q * ctx embed], dim=-1)
   concat a3 = torch.cat([ctx embed, u a3, u q, u a3 * ctx embed, u q * ctx embed], dim=-1)
   concat a4 = torch.cat([ctx embed, u a4, u q, u a4 * ctx embed, u q * ctx embed], dim=-1)
   mature maxout a0, = lstm mature(concat a0, ctx l)
   mature maxout_a1, = lstm mature(concat_a1, ctx l)
                                                                                        Bi-directional LSTM
   mature maxout a2, = lstm mature(concat a2, ctx l)
                                                                                          (Second LSTM)
   mature maxout a3, = lstm mature(concat a3, ctx l)
   mature maxout a4, = lstm mature(concat a4, ctx l)
   mature maxout a0 = max along time(mature maxout a0, ctx l).unsqueeze(1)
   mature maxout a1 = max along time(mature maxout a1, ctx l).unsqueeze(1)
   mature maxout a2 = max along time(mature maxout a2, ctx l).unsqueeze(1)
   mature maxout a3 = max along time(mature maxout a3, ctx l).unsqueeze(1)
   mature maxout a4 = max along time(mature maxout a4, ctx l).unsqueeze(1)
   mature answers = torch.cat([
       mature maxout a0, mature maxout a1, mature maxout a2, mature maxout a3, mature maxout a4
   1, dim=1)
   out = classifier(mature answers) # (B, 5)
   return out
```

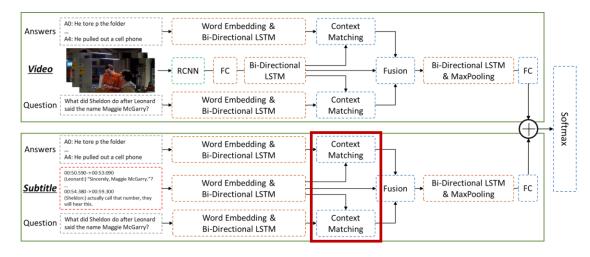
```
def stream processor(self, lstm mature, classifier, ctx embed, ctx l,
                    q embed, q l, a0 embed, a0 l, a1 embed, a1 l, a2 embed, a2 l, a3 embed, a3 l, a4 embed, a4 l):
   u q, = self.bidaf(ctx embed, ctx l, q embed, q l)
   u a0, = self.bidaf(ctx embed, ctx l, a0 embed, a0 l)
   u a1, = self.bidaf(ctx embed, ctx l, a1 embed, a1 l)
   u a2, = self.bidaf(ctx embed, ctx l, a2 embed, a2 l)
   u a3, = self.bidaf(ctx embed, ctx l, a3 embed, a3 l)
   u a4, = self.bidaf(ctx embed, ctx l, a4 embed, a4 l)
   concat a0 = torch.cat([ctx embed, u a0, u q, u a0 * ctx embed, u q * ctx embed], dim=-1)
   concat al = torch.cat([ctx embed, u al, u q, u al * ctx embed, u q * ctx embed], dim=-1)
   concat a2 = torch.cat([ctx embed, u a2, u q, u a2 * ctx embed, u q * ctx embed], dim=-1)
   concat a3 = torch.cat([ctx embed, u a3, u q, u a3 * ctx embed, u q * ctx embed], dim=-1)
   concat a4 = torch.cat([ctx embed, u a4, u q, u a4 * ctx embed, u q * ctx embed], dim=-1)
   mature maxout a0, = lstm mature(concat a0, ctx l)
   mature maxout_a1, = lstm mature(concat_a1, ctx l)
   mature maxout a2, = lstm mature(concat a2, ctx l)
   mature maxout a3, = lstm mature(concat a3, ctx l)
   mature maxout a4, = lstm mature(concat a4, ctx l)
   mature maxout a0 = max along time(mature maxout a0, ctx l).unsqueeze(1)
   mature maxout a1 = max along time(mature maxout a1, ctx l).unsqueeze(1)
   mature maxout a2 = max along time(mature maxout a2, ctx l).unsqueeze(1)
                                                                                            Max pooling
   mature maxout a3 = max along time(mature maxout a3, ctx l).unsqueeze(1)
   mature maxout a4 = max along time(mature maxout a4, ctx l).unsqueeze(1)
   mature answers = torch.cat([
       mature maxout a0, mature maxout a1, mature maxout a2, mature maxout a3, mature maxout a4
   1, dim=1)
   out = classifier(mature answers) # (B, 5)
   return out
```

```
def stream processor(self, lstm mature, classifier, ctx embed, ctx l,
                    q embed, q l, a0 embed, a0 l, a1 embed, a1 l, a2 embed, a2 l, a3 embed, a3 l, a4 embed, a4 l):
   u q, = self.bidaf(ctx embed, ctx l, q embed, q l)
   u a0, = self.bidaf(ctx embed, ctx l, a0 embed, a0 l)
   u a1, = self.bidaf(ctx embed, ctx l, a1 embed, a1 l)
   u a2, = self.bidaf(ctx embed, ctx l, a2 embed, a2 l)
   u a3, = self.bidaf(ctx embed, ctx l, a3 embed, a3 l)
   u a4, = self.bidaf(ctx embed, ctx l, a4 embed, a4 l)
   concat a0 = torch.cat([ctx embed, u a0, u q, u a0 * ctx embed, u q * ctx embed], dim=-1)
   concat a1 = torch.cat([ctx embed, u a1, u q, u a1 * ctx embed, u q * ctx embed], dim=-1)
   concat a2 = torch.cat([ctx embed, u a2, u q, u a2 * ctx embed, u q * ctx embed], dim=-1)
   concat a3 = torch.cat([ctx embed, u a3, u q, u a3 * ctx embed, u q * ctx embed], dim=-1)
   concat a4 = torch.cat([ctx embed, u a4, u q, u a4 * ctx embed, u q * ctx embed], dim=-1)
   mature maxout a0, = lstm mature(concat a0, ctx l)
   mature maxout_a1, = lstm mature(concat_a1, ctx l)
   mature maxout a2, = lstm mature(concat a2, ctx l)
   mature maxout a3, = lstm mature(concat a3, ctx l)
   mature maxout a4, = lstm mature(concat a4, ctx l)
   mature maxout a0 = max along time(mature maxout a0, ctx l).unsqueeze(1)
   mature maxout a1 = max along time(mature maxout a1, ctx l).unsqueeze(1)
   mature maxout a2 = max along time(mature maxout a2, ctx l).unsqueeze(1)
   mature maxout a3 = max along time(mature maxout a3, ctx l).unsqueeze(1)
   mature maxout a4 = max along time(mature maxout a4, ctx l).unsqueeze(1)
   mature answers = torch.cat([
       mature maxout a0, mature maxout a1, mature maxout a2, mature maxout a3, mature maxout a4
   ], dim=1)
                                                                                           Fusion and FC
   out = classifier(mature answers) # (B, 5)
    return out
```

>> vim model/tvqa_abc.py or go to step into ('s') using PDB

```
u_q, _ = self.bidaf(ctx_embed, ctx_l, q_embed, q_l)
u_a0, _ = self.bidaf(ctx_embed, ctx_l, a0_embed, a0_l)
u_a1, _ = self.bidaf(ctx_embed, ctx_l, a1_embed, a1_l)
u_a2, _ = self.bidaf(ctx_embed, ctx_l, a2_embed, a2_l)
u_a3, _ = self.bidaf(ctx_embed, ctx_l, a3_embed, a3_l)
u_a4, _ = self.bidaf(ctx_embed, ctx_l, a4_embed, a4_l)
```

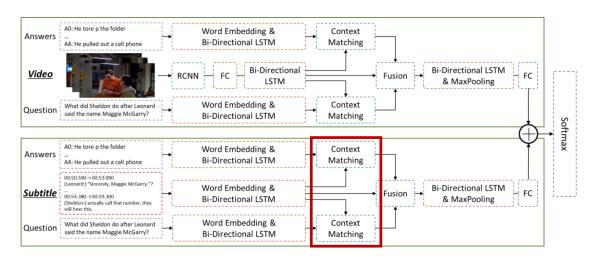
Calculation for attention value from subtitle by question and answers



The overview of Multi-Modal Video QA

>> vim model/bidaf.py or go to step into ('s') using PDB

```
def forward(self, s1, l1, s2, l2):
    s = self.similarity(s1, l1, s2, l2)
    u_tile = self.get_u_tile(s, s2)
    # h_tile = self.get_h_tile(s, s1)
    h_tile = self.get_h_tile(s, s1) if self.get_h else None
    return u_tile, h_tile
# return u_tile
```



The overview of Multi-Modal Video QA

>> vim model/bidaf.py or go to step into ('s') using PDB

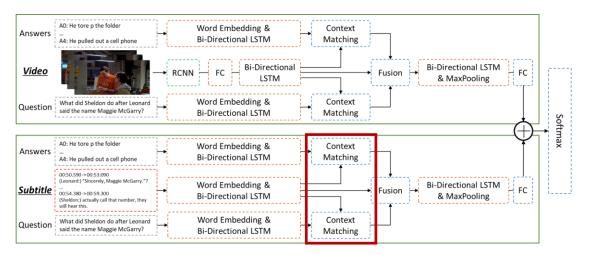
```
def similarity(self, s1, l1, s2, l2):
    :param s1: [B, t1, D]
    :param l1: [B]
    :param s2: [B, t2, D]
    :param 12: [B]
    :return:
    if self.method == "original":
        t1 = s1.size(1)
        t2 = s2.size(1)
        repeat s1 = s1.unsqueeze(2).repeat(1, 1, t2, 1) # [B, T1, T2, D]
        repeat s2 = s2.unsqueeze(1).repeat(1, t1, 1, 1) # [B, T1, T2, D]
        packed s1 s2 = torch.cat([repeat s1, repeat s2, repeat s1 * repeat s2], dim=3) # [B, T1, T2, D*3]
        s = self mln(packed s1 s2) squeeze() # s is the similarity matrix from biDAF paper. [B, T1, T2]
    elif self.method == "dot":
                                                   Attention score
        s = torch.bmm(s1, s2.transpose(1, 2))
    s mask = s.data.new(*s.size()).fill (1).byte() # [B, T1, T2]
    # Init similarity mask using lengths
    for i, (l 1, l 2) in enumerate(zip(l1, l2)):
        s mask[i][:l 1, :l 2] = 0
    s mask = Variable(s mask)
    s.data.masked fill (s mask.data.byte(), -float("inf"))
    return s
```

>> vim model/bidaf.py or go to step into ('s') using PDB

```
def similarity(self, s1, l1, s2, l2):
    :param s1: [B, t1, D]
    :param l1: [B]
    :param s2: [B, t2, D]
    :param 12: [B]
    :return:
    if self.method == "original":
                                                                                     Bi-directional
        t1 = s1.size(1)
        t2 = s2.size(1)
                                                                                    attention score
        repeat s1 = s1.unsqueeze(2).repeat(1, 1, t2, 1) # [B, T1, T2, D]
        repeat s2 = s2.unsqueeze(1).repeat(1, t1, 1, 1) # [B, T1, T2, D]
        packed s1 s2 = torch.cat([repeat s1, repeat s2, repeat s1 * repeat s2], dim=3) # [B, T1, T2, D*3]
        s = self.mlp(packed s1 s2).squeeze() # s is the similarity matrix from biDAF paper. [B, T1, T2]
    elif self.method == "dot":
        s = torch.bmm(s1, s2.transpose(1, 2))
    s mask = s.data.new(*s.size()).fill (1).byte() # [B, T1, T2]
    # Init similarity mask using lengths
    for i, (l 1, l 2) in enumerate(zip(l1, l2)):
        s mask[i][:l 1, :l 2] = 0
    s mask = Variable(s mask)
    s.data.masked fill (s mask.data.byte(), -float("inf"))
    return s
```

Context Matching

>> vim model/bidaf.py or go to step into ('s') using PDB



The overview of Multi-Modal Video QA

Context Matching

>> vim model/bidaf.py or go to step into ('s') using PDB

Context Matching

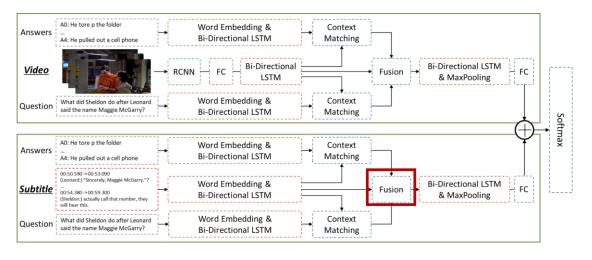
>> vim model/bidaf.py or go to step into ('s') using PDB

```
@classmethod
def get_u_tile(cls, s, s2):
    """
    attended vectors of s2 for each word in s1,
    signify which words in s2 are most relevant to words in s1
    """
    a_weight = F.softmax(s, dim=2) # [B, t1, t2]
    a_weight.data.masked_fill_(a_weight.data != a_weight.data, 0) # remove nan_from_softmax_on_-inf
    u_tile = torch.bmm(a_weight, s2) # [B, t1, t2] * [B, t2, D] -> [B, t1, D]
    Attention value
    return u_tile
```

Fusion

```
concat_a0 = torch.cat([ctx_embed, u_a0, u_q, u_a0 * ctx_embed, u_q * ctx_embed], dim=-1)
concat_a1 = torch.cat([ctx_embed, u_a1, u_q, u_a1 * ctx_embed, u_q * ctx_embed], dim=-1)
concat_a2 = torch.cat([ctx_embed, u_a2, u_q, u_a2 * ctx_embed, u_q * ctx_embed], dim=-1)
concat_a3 = torch.cat([ctx_embed, u_a3, u_q, u_a3 * ctx_embed, u_q * ctx_embed], dim=-1)
concat_a4 = torch.cat([ctx_embed, u_a4, u_q, u_a4 * ctx_embed, u_q * ctx_embed], dim=-1)
```

Concatenate all representations to one



The overview of Multi-Modal Video QA

Fusion

torch.cat – 3 arguments

- 2 optional arguments
- 1 required arguments: **tensors**

```
\texttt{torch.cat}(\textit{tensors}, \textit{dim=0}, \textit{out=None}) \rightarrow \mathsf{Tensor}
```

Parameters

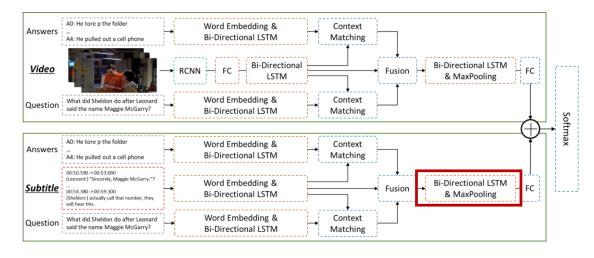
- **tensors** (sequence of Tensors) any python sequence of tensors of the same type. Non-empty tensors provided must have the same shape, except in the cat dimension.
- dim (int, optional) the dimension over which the tensors are concatenated
- out (Tensor, optional) the output tensor

```
concat_a0 = torch.cat ([ctx_embed, u_a0, u_q, u_a0 * ctx_embed, u_q * ctx_embed], dim=-1)
concat_a1 = torch.cat ([ctx_embed, u_a1, u_q, u_a1 * ctx_embed, u_q * ctx_embed], dim=-1)
concat_a2 = torch.cat ([ctx_embed, u_a2, u_q, u_a2 * ctx_embed, u_q * ctx_embed], dim=-1)
concat_a3 = torch.cat ([ctx_embed, u_a3, u_q, u_a3 * ctx_embed, u_q * ctx_embed], dim=-1)
concat_a4 = torch.cat ([ctx_embed, u_a4, u_q, u_a4 * ctx_embed, u_q * ctx_embed], dim=-1)
```

Bi-directional LSTM

```
mature_maxout_a0, _ = lstm_mature(concat_a0, ctx_l)
mature_maxout_a1, _ = lstm_mature(concat_a1, ctx_l)
mature_maxout_a2, _ = lstm_mature(concat_a2, ctx_l)
mature_maxout_a3, _ = lstm_mature(concat_a3, ctx_l)
mature_maxout_a4, _ = lstm_mature(concat_a4, ctx_l)
```

Second LSTM for question and answers



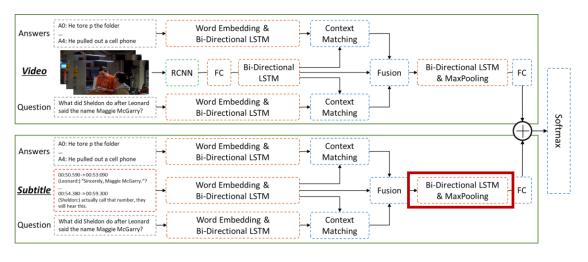
The overview of Multi-Modal Video QA

Max Pooling

>> vim model/tvqa_abc.py or go to next ('n') using PDB

```
mature_maxout_a0 = max_along_time(mature_maxout_a0, ctx_l).unsqueeze(1)
mature_maxout_a1 = max_along_time(mature_maxout_a1, ctx_l).unsqueeze(1)
mature_maxout_a2 = max_along_time(mature_maxout_a2, ctx_l).unsqueeze(1)
mature_maxout_a3 = max_along_time(mature_maxout_a3, ctx_l).unsqueeze(1)
mature_maxout_a4 = max_along_time(mature_maxout_a4, ctx_l).unsqueeze(1)
```

Max pool along with time axis



The overview of Multi-Modal Video QA

Max Pooling

max_along_time - 2 arguments

- 2 required arguments: *outputs, lengths*

```
70 def max_along_time(outputs, lengths):
71    """ Get maximum responses from RNN outputs along time axis
72    :param outputs: (B, T, D)
73    :param lengths: (B, )
74    :return: (B, D)
75    """
76    outputs = [outputs[i, :int(lengths[i]), :].max[dim=0)[0] for i in range(len(lengths))]
77    return torch.stack(outputs, dim=0)
```

```
mature_maxout_a0 = max_along_time(mature_maxout_a0, ctx_l).unsqueeze(1)
mature_maxout_a1 = max_along_time(mature_maxout_a1, ctx_l).unsqueeze(1)
mature_maxout_a2 = max_along_time(mature_maxout_a2, ctx_l).unsqueeze(1)
mature_maxout_a3 = max_along_time(mature_maxout_a3, ctx_l).unsqueeze(1)
mature_maxout_a4 = max_along_time(mature_maxout_a4, ctx_l).unsqueeze(1)
```

Max Pooling

torch.max – 1 arguments

- 1 required arguments: *tensors*

```
\texttt{torch.max}(\textit{input}) \rightarrow \texttt{Tensor}
```

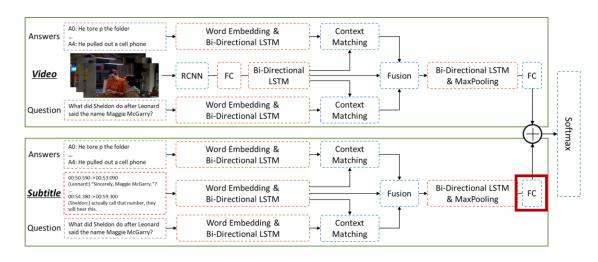
Returns the maximum value of all elements in the input tensor.

Parameters

input (*Tensor*) – the input tensor

FC

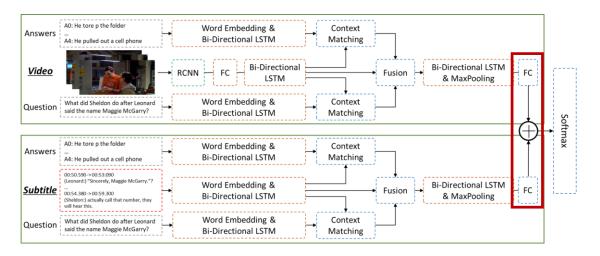
```
mature_answers = torch.cat([
    mature_maxout_a0, mature_maxout_a1, mature_maxout_a2, mature_maxout_a3, mature_maxout_a4
], dim=1)
out = classifier(mature_answers) # (B, 5)
return out
```



The overview of Multi-Modal Video QA

Prediction

```
out = sub_out + vcpt_out + vid_out # adding zeros has no effect on backward
return out.squeeze()
```

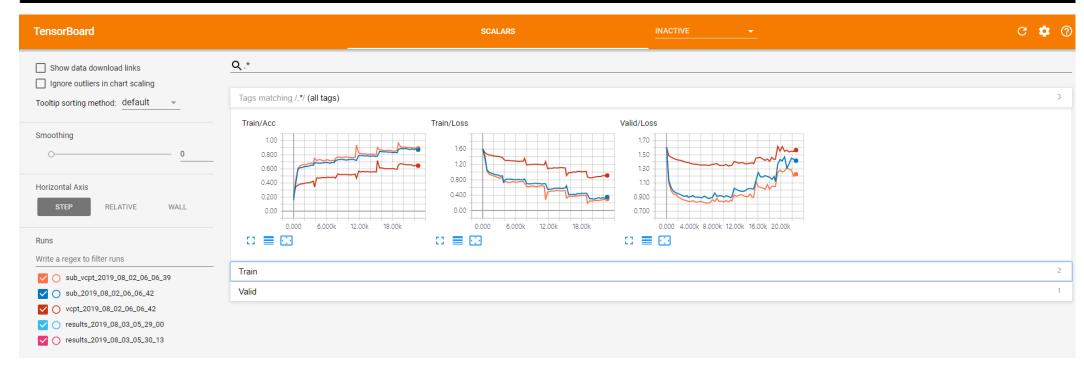


The overview of Multi-Modal Video QA

Visualization of Training Process

>> tensorboard --logdir [results_dir] --port [Number]

mshan@ai8:/st2/mshan/models/ex2/TVQA\$ tensorboard --logdir=results --port=5005 TensorBoard 0.1.8 at http://ai8:5005 (Press CTRL+C to quit)



Inference

>> python test.py --model_dir [results_dir] --mode valid

```
mshan@ai8:/st2/mshan/models/ex2/TVQA$ python test.py --model_dir sub_vcpt_2019_08_02_06_06_39 --mode valid

Loading cache ...
activate sub stream
activate vcpt stream
153it [01:59, 1.44it/s]
In valid mode, accuracy is 0.6909
mshan@ai8:/st2/mshan/models/ex2/TVQA$
```

Assignments

We have 2 assignments for Multi-Modal Video QA on TVQA dataset.

1. Why did TDIDF model in TVQA paper show good performance? (2.5 points) (See https://arxiv.org/abs/1809.01696)

2. What is the main difference between TVQA and TVQA+? (In terms of model) (2.5 points) (See https://arxiv.org/abs/1809.01696 and https://arxiv.org/abs/1904.11574)

Any questions?