

#### POLITECNICO DI MILANO ARTIFICIAL NEURAL NETWORK AND DEEP LEARNING

# Visual Question Answering

Third Challenge

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## Chapter 1

## Setting Up the Environment

#### 1.1 Prepare the Training

Firstly, we opened the training JSON file and extracted the total number of questions and we tokenized all the used words.

Then, we created our custom DataGenerator class to handle the datasets. Its main methods are:

- \_\_getitem\_\_(self, index): retrieves the i-th batch ([RGBimage0, ...], [input\_question0, ...]), [answer0, ...]).
- \_generate\_X(self, indexes): indexes is the list of indexes to take the values from. This function generates as output the couple [RGBimages, questions].
- \_generate\_Y(self, indexes): indexes is the list of indexes to take the values from. This function generates the output in categorical form.
- def \_load\_image(self, img\_name, img\_w, img\_h): loads the img, resizes and normalizes it.

We divided the dataset in 70% for training and 30% for validation. We extracted from the JSON the list of questions, images and answers both for training and for validation with the function readTrainJson. Instead, for the test set we extracted the list of questionids, images and questions with the function readTestJson.

Finally, we extracted from the tokenizer the tokens for the training, validation and test set and we padded them. In this way, we have all the element we need to create the train, val and test generator with the custom DataGenerator class.

#### 1.2 Create the Final CSV

We create an external script to generate the final csv to submit our model. We made this decision to try different checkpoints of the same training. The function is very simple and it is shown below:

```
def create_csv(results, results_dir='./drive/MyDrive'):
    csv_fname = 'results_'
    csv_fname += datetime.now().strftime('%b%d_%H-%M-%S') + '.csv'
```

```
with open(os.path.join(results_dir, csv_fname), 'w') as f:
    f.write('Id,Category\n')
    for key, value in results.items():
        f.write(key + ',' + str(value) + '\n')

pred = VQA_net.predict(test_generator)
results = {}

for i in range(len(pred)):
    results[test_generator.answers[i]] = np.argmax(pred[i])

create_csv(results)
```

### Chapter 2

## Model Experiments

The final model multiplies a CNN with a RNN or a Transformer-based net or a BERT and connects it to a FFNN to classify the right answer to corresponding the couple (image, question).

#### 2.1 Networks for the Images (CNN)

We used as a base some famous CNN models (with fine tuning). After this, we added on top some dense layers with batch-normalization, ReLu and drop out. The CNN used are relatively simple because the total model has to fit in the GPU and to reduce the training time.

The net that reached the best performance are:

- VGG19: with this CNN we reached a test accuracy of 55%
- MobileNetV2: this net has only 3,538,984 parameters (compared to the 143,667,240 of the VGG19) and the training with that is much faster. This has permitted to use data argumentation. With this CNN we reached a test accuracy of: 57%

# 2.2 Networks for the Questions (LSTM, Transformer, BERT)

For this part, we experimented with different models:

The first network that we have implemented is a LSTM-based net, it is formed by:

- Embedding layer
- LSTM layer with return sequence=True
- Dropout layer
- LSTM layer with return sequence=False
- Dropout layer
- Dense layer

With this net we reached a test accuracy of 57%. The second model is a Transformer-based net, it was formed by:

- Token and position Embedding layer
- Transformer Block
- GlobalAveragePooling1D layer
- A series of dense layers and dropout

With this net we reached our best result of 62%. Finally, we try to use the BERT net with a final test accuracy of 55%.

#### 2.3 Final VQA net

To create this network:

- Multiply the CNN and the LSTM or Transformer-based net or BERT
- Add a dense layer
- Add a batch-normalization, relu and dropout layer
- Add the last classification layer with the number of neurons equals to the number of answer-classes and with the softmax as activation function.

# Chapter 3

## Final Result

Our best test accuracy is: 62%. We reached this result with:

- MobileNetV2-based CNN
- Transformer-based net
- Data Argumentation
- Input size = (200x350)
- $\bullet \ \operatorname{Loss} = \operatorname{Categorical} \, \operatorname{Cross} \, \operatorname{Entropy}$
- $\bullet$  Optimizer = Adam

Model: "model_1"						
Layer (type)	Output		Param #	Connected to		
mobilenetv2_1.00_224_input (Inp						
mobilenetv2_1.00_224 (Functiona	(None,	7, 11, 1280)	2257984	mobilenetv2_1.00_224_input[0][0]		
global_average_pooling2d_1 (Glo	(None,	1280)	0	mobilenetv2_1.00_224[0][0]		
dense_6 (Dense)	(None,	1024)	1311744	global_average_pooling2d_1[0][0]		
batch_normalization_4 (BatchNor	(None,	1024)	4096	dense_6[0][0]		
activation_4 (Activation)	(None,	1024)	0	batch_normalization_4[0][0]		
dropout_6 (Dropout)	(None,	1024)	0	activation_4[0][0]		
dense_7 (Dense)	(None,	512)	524800	dropout_6[0][0]		
batch_normalization_5 (BatchNor	(None,	512)	2048	dense_7[0][0]		
embedding_1_input (InputLayer)	[(None	, 20)]	0			
activation_5 (Activation)	(None,	512)	0	batch_normalization_5[0][0]		
embedding_1 (Embedding)	(None,	20, 512)	256000	embedding_1_input[0][0]		
dropout_7 (Dropout)	(None,	512)	0	activation_5[0][0]		
1stm_2 (LSTM)	(None,	20, 512)	2099200	embedding_1[0][0]		
dense_8 (Dense)	(None,	1024)	525312	dropout_7[0][0]		
dropout_9 (Dropout)	(None,	20, 512)	0	1stm_2[0][0]		
batch_normalization_6 (BatchNor	(None,	1024)	4096	dense_8[0][0]		
1stm_3 (LSTM)	(None,	512)	2099200	dropout_9[0][0]		
activation_6 (Activation)	(None,	1024)	0	batch_normalization_6[0][0]		
dropout_10 (Dropout)	(None,	512)	0	1stm_3[0][0]		
dropout_8 (Dropout)	(None,	1024)	0	activation_6[0][0]		
dense_9 (Dense)	(None,	1024)	525312	dropout_10[0][0]		
multiply_1 (Multiply)	(None,	1024)	0	dropout_8[0][0] dense_9[0][0]		
dense_10 (Dense)	(None,	1024)	1049600	multiply_1[0][0]		
batch_normalization_7 (BatchNor	(None,	1024)	4096	dense_10[0][0]		
activation_7 (Activation)	(None,	1024)	0	batch_normalization_7[0][0]		
dropout_11 (Dropout)	(None,	1024)	0	activation_7[0][0]		
dense_11 (Dense)	(None,		59450	dropout_11[0][0]		

Figure 3.1: CNN-LSTM Model

mobilenetv2_1.00_224 (Functiona	(None,	7, 11, 1280)	2257984	mobilenetv2_1.00_224_input[0][0]
global_average_pooling2d_2 (Glo	(None,	1280)	0	mobilenetv2_1.00_224[0][0]
dense_20 (Dense)	(None,	1024)	1311744	global_average_pooling2d_2[0][0]
batch_normalization_8 (BatchNor	(None,	1024)	4096	dense_20[0][0]
activation_8 (Activation)	(None,	1024)	0	batch_normalization_8[0][0]
dropout_20 (Dropout)	(None,	1024)	0	activation_8[0][0]
dense_21 (Dense)	(None,	512)	524800	dropout_20[0][0]
input_6 (InputLayer)	[(None	, 500)]	0	
batch_normalization_9 (BatchNor	(None,	512)	2048	dense_21[0][0]
token_and_position_embedding_2	(None,	500, 512)	512000	input_6[0][0]
activation_9 (Activation)	(None,	512)	0	batch_normalization_9[0][0]
transformer_block_2 (Transforme	(None,	500, 512)	5253120	token_and_position_embedding_2[0]
dropout_21 (Dropout)	(None,	512)	0	activation_9[0][0]
global_average_pooling1d_2 (Glo	(None,	512)	0	transformer_block_2[0][0]
dense_22 (Dense)	(None,	1024)	525312	dropout_21[0][0]
dropout_27 (Dropout)	(None,	512)	0	global_average_pooling1d_2[0][0]
batch_normalization_10 (BatchNo	(None,	1024)	4096	dense_22[0][0]
dense_26 (Dense)	(None,	20)	10260	dropout_27[0][0]
activation_10 (Activation)	(None,	1024)	0	batch_normalization_10[0][0]
dropout_28 (Dropout)	(None,	20)	0	dense_26[0][0]
dropout_22 (Dropout)	(None,	1024)	0	activation_10[0][0]
dense_27 (Dense)	(None,	1024)	21504	dropout_28[0][0]
multiply_2 (Multiply)	(None,	1024)	0	dropout_22[0][0] dense_27[0][0]
dense_28 (Dense)	(None,	1024)	1049600	multiply_2[0][0]
batch_normalization_11 (BatchNo	(None,	1024)	4096	dense_28[0][0]
activation_11 (Activation)	(None,	1024)	0	batch_normalization_11[0][0]
dropout_29 (Dropout)	(None,	1024)	0	activation_11[0][0]
dense_29 (Dense)	(None,		59450	dropout_29[0][0]

Total params: 11,540,110 Trainable params: 11,495,470 Non-trainable params: 44,640

Figure 3.2: CNN-Transformer Model

mobilenetv2_1.00_224 (Functiona	(None,	7, 11, 1280)	2257984	mobilenetv2_1.00_224_input[0][0]
global_average_pooling2d_1 (Glo	(None,	1280)	0	mobilenetv2_1.00_224[0][0]
dense_10 (Dense)	(None,	1024)	1311744	global_average_pooling2d_1[0][0]
batch_normalization_4 (BatchNor	(None,	1024)	4096	dense_10[0][0]
activation_4 (Activation)	(None,	1024)	0	batch_normalization_4[0][0]
dropout_10 (Dropout)	(None,	1024)	0	activation_4[0][0]
dense_11 (Dense)	(None,	512)	524800	dropout_10[0][0]
input_4 (InputLayer)	[(None	, 500)]	0	
batch_normalization_5 (BatchNor	(None,	512)	2048	dense_11[0][0]
token_and_position_embedding_1	(None,	500, 512)	512000	input_4[0][0]
activation_5 (Activation)	(None,	512)	0	batch_normalization_5[0][0]
transformer_block_1 (Transforme	(None,	500, 512)	5253120	token_and_position_embedding_1[0]
dropout_11 (Dropout)	(None,	512)	0	activation_5[0][0]
global_average_pooling1d_1 (Glo	(None,	512)	0	transformer_block_1[0][0]
dense_12 (Dense)	(None,	1024)	525312	dropout_11[0][0]
dropout_17 (Dropout)	(None,	512)	0	global_average_pooling1d_1[0][0]
batch_normalization_6 (BatchNor	(None,	1024)	4096	dense_12[0][0]
dense_16 (Dense)	(None,	20)	10260	dropout_17[0][0]
activation_6 (Activation)	(None,	1024)	0	batch_normalization_6[0][0]
dropout_18 (Dropout)	(None,	20)	0	dense_16[0][0]
dropout_12 (Dropout)	(None,	1024)	0	activation_6[0][0]
dense_17 (Dense)	(None,	1024)	21504	dropout_18[0][0]
multiply_1 (Multiply)	(None,	1024)	0	dropout_12[0][0] dense_17[0][0]
dense_18 (Dense)	(None,	1024)	1049600	multiply_1[0][0]
batch_normalization_7 (BatchNor	(None,	1024)	4096	dense_18[0][0]
activation_7 (Activation)	(None,	1024)	0	batch_normalization_7[0][0]
dropout_19 (Dropout)	(None,	1024)	0	activation_7[0][0]
dense_19 (Dense)	(None,	-	59450	dropout_19[0][0]

Total params: 11,540,110 Trainable params: 11,495,470 Non-trainable params: 44,640

Figure 3.3: CNN-BERT Model