Medical Visual Question Answering

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# Abstract

This paper describes the work done in the scope of ImageCLEF 2019 VQA-Med Challenge.

The outline of the work can be described in the following main steps.

1. Preprocessing
   1. Structuring the data
   2. Clean and Enrich data
   3. Feature extraction
   4. Data augmentation
2. Creating meta data
3. Model(s) creation
   1. Creating a model for each question category
4. Model(s) training
5. Evaluation
6. Results submission
   1. Fine tuning models
   2. Composing a Model collection
   3. Evaluating Composition
7. Additional attempts
   1. A single model to rule them all
   2. Reducing dimensions of answers
   3. Data Generators

# Preprocessing

<https://github.com/turner11/VQA-MED/blob/master/VQA-MED/VQA.Python/0_bringing_data_to_expected_format.ipynb>

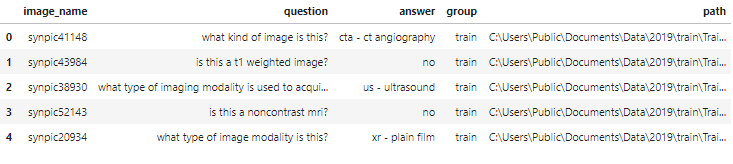
## Structuring the data

The raw input data was composed from a pipe-delimited text with a folder of images corresponding to text lines.



Figure 1: Raw data

The first step was to bring it to a convenient to work with format. We chose to use pandas Data frame.



## Clean and Enrich data

As part of the preprocessing we removed stop words and tokenized the text.

For Date enrichment, we added a "question category" labeling to data (i.e. question & image pair). This information was given for the train / validation sets and predicted for the test set using thumb rules / NN for the test set.

Another enrichment we have added was a 'diagnosis' label, based on presence of most frequent words in the "Abnormality" Category's answers (Note: Eventually, we did not use this information).

## Feature extraction

Using the NLP library *Spacy*, we have extracted embedding for the questions.

The embedding will eventually be used as the input for the text branch of our model.

For this was have used Spacy's pre trained "en\_core\_web\_lg" vector as described in their home page:

"English multi-task CNN trained on OntoNotes, with GloVe vectors trained on Common Crawl. Assigns word vectors, context-specific token vectors, POS tags, dependency parse and named entities."

In order to reduce data size, the image features are extracted in run time using Keras background Data Generator.

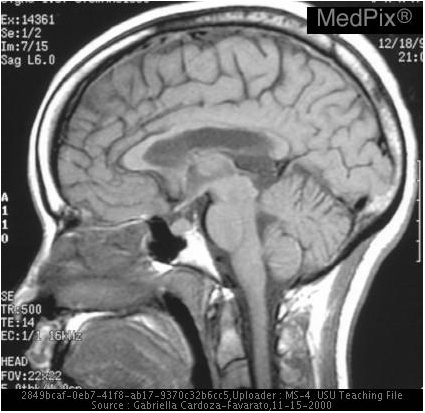
## Data augmentation

Since the amount of given data seems to be insufficient for meaningful results, we have also used data augmentation in order to get a larger train / validation set.

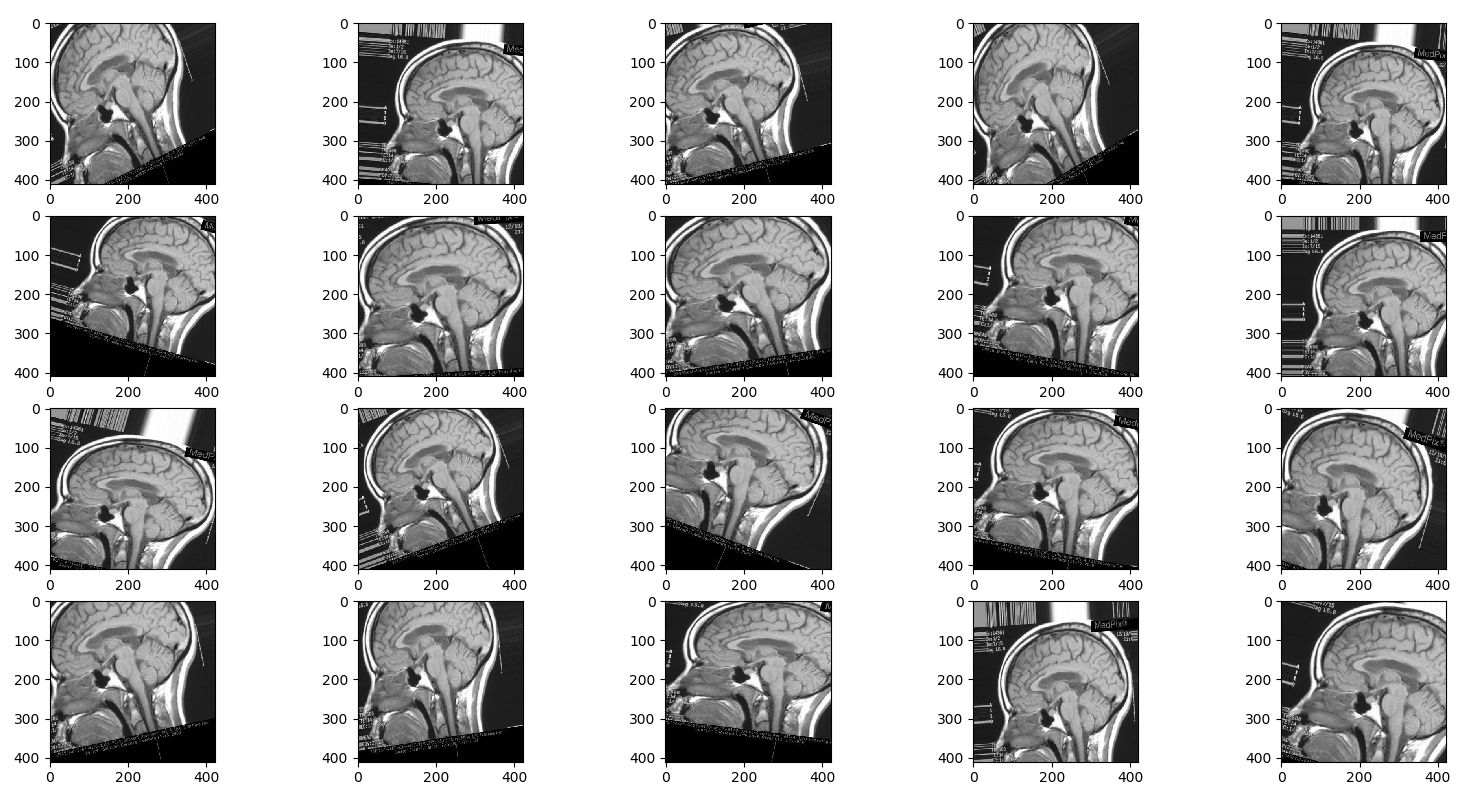
For each question-image pair, we have produced 20 new pairs with the same questioned and a slightly transformed image. The transformation varied in following range:

* rotation\_range: 25 degrees
* width\_shift\_range: 0.15,
* height\_shift\_range: 0.15,
* zoom\_range: 0.15,
* fill\_mode: nearest,

For example:

From: 

We extracted:



# Creating meta data

The Meta data holds information about which unique words and answers exists in training & validation datasets, and in which categories they appeared (e.g. Modality. Plain etc.).  
Later in the process, this information will allow us to build dedicated models for each category.

# Model creation

When creating the model, we use a basic structure (image branch, text branch, merging the branches, and FC layer(s), and a multi class evaluation output layer).

The parameter that we can play with out of the box are:

1. loss function
2. output activation function
3. LSTM units (will use 'Flatten' instead for 0)
4. Post merge dense units (could be a list to specify multiple layers)
5. Optimizer
6. prediction vector name ('answers' / 'words')
7. question category (for limiting the model to Abnormality / Plane / Organ system / Modality. The default is one model for all).
8. Use text inputs attention (Specifies if attention should be applied for the input of the text branch)

## Creating a model for each question category

For each of the categories (Abnormality / Plane / Organ system / Modality / Abnormality yes no) we have tried multiple configuration, in order to maximize the overall performance.

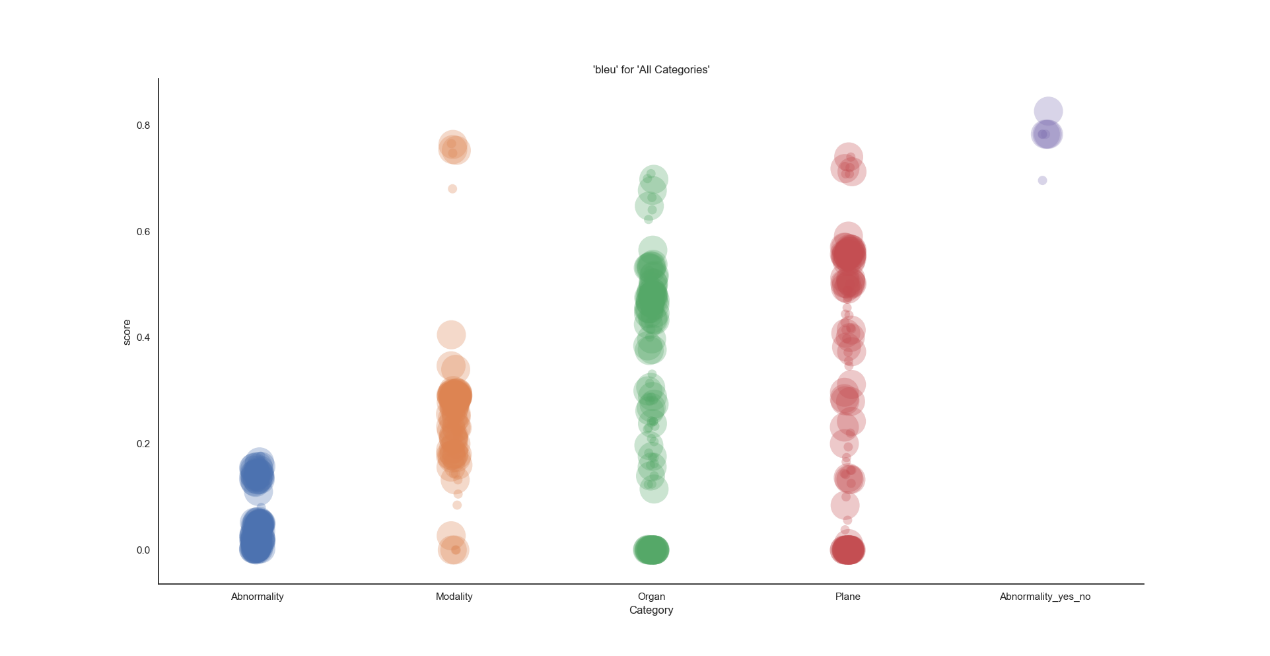


Figure 2: Models Bleu Score by categories. Size is number of dense units

# Model(s) training

When training the model, we have several parameters we can use for getting better results:

1. augmentations - How many augmentations should be used for each question-image pair.
2. batch size
3. epochs
4. class weight - should class weights be used for compensating for skewed data.

A picture containing text

Description automatically generated

Figure 3: Models Bleu Score by categories. Size is number of dense units

# Evaluation

# Results submission

## Fine tuning models

## Composing a Model collection

## Evaluating Composition

# Additional attempts

## A single model to rule them all

## Reducing dimensions of answers

## Data Generators