

# Coursework 1: Question classification

This coursework is a group (3-4 students) project. Your task is to build two question classifiers using (i) bag-of-words and (ii) BiLSTM.

- Input: a question (e.g. *"How many points make up a perfect fivepin bowling score ?"*)
- Output: one of N predefined classes (e.g. *NUM:count*)

## Instructions

Your implementation has to be in **python3**, using **PyTorch** (<https://pytorch.org/>). If you are not familiar with PyTorch, check out some tutorials first (e.g. <https://medium.com/biaslyai/learn-pytorch-basics-6d433f186b7a>, chapters 1, 2, and 3, [https://pytorch.org/tutorials/beginner/nlp/sequence\\_models\\_tutorial.html](https://pytorch.org/tutorials/beginner/nlp/sequence_models_tutorial.html)).

## Data

You use the data from <https://cogcomp.seas.upenn.edu/Data/QA/QC/> (Training set 5). Because there is no dev set, you will randomly split the training set into 10 portions. 9 portions are for training, and the other is for development (e.g. early stopping, hyperparameter tuning).

## Word embeddings

Your implementation accepts two kinds of word embeddings.

1. You randomly initialize word embeddings. (To build a vocabulary, you can select those words appearing at least  $k$  times in the training set.)
2. You use pre-trained word embeddings such as word2vec (<https://code.google.com/archive/p/word2vec/>) or GloVe (<https://nlp.stanford.edu/projects/glove/>). Note: your implementation has an option to **freeze** or to **fine-tune** the pre-trained word embeddings during training.

For preprocessing, you can ignore stop-words (e.g. "up", "a"), or lowercase all words (e.g. "How" becomes "how"). *Don't forget to handle words that are **not** in the vocabulary!*

## Sentence representations

### Bag-of-words

1. A bag-of-words is a set of words (we can ignore word frequency here). For instance, the bag-of-words of the question above is

```
bow("How many points...") =
```

```
{"How", "many", "points", "make", "up", "a", "perfect", "fivepint",  
"bowling", "score"}
```

2. Turning a bag-of-words to a vector:

$$\text{vec}_{\text{bow}}(s) = \frac{1}{|\text{bow}(s)|} \sum_{w \in \text{bow}(s)} \text{vec}(w)$$

where  $s$  is a sentence/question,  $\text{vec}_{\text{bow}}(s)$  is  $s$ ' vector representation.  $\text{vec}(w)$  is word  $w$ 's vector representation.

For example:

```
vec("How many points...") =  
1/10 * (vec("How") + vec("many") + ... + vec("score"))
```

## BiLSTM

[https://pytorch.org/tutorials/beginner/nlp/sequence\\_models\\_tutorial.html](https://pytorch.org/tutorials/beginner/nlp/sequence_models_tutorial.html) is a good tutorial for using LSTM. You just need to do an extra step to replace LSTM by BiLSTM. Let's denote

$$\text{vec}_{\text{bilstm}}(s) = \text{BiLSTM}(s)$$

## Classifier

Given  $\text{vec}_{\text{bow}}(s)$  or  $\text{vec}_{\text{bilstm}}(s)$  above, you will use a feed-forward neural network with a softmax output layer for classification.

## Classifier (plus)

You can build more sophisticated classifiers, by

1. combining  $\text{vec}_{\text{bow}}(s)$  and  $\text{vec}_{\text{bilstm}}(s)$  into one vector  $\text{vec}(s)$ , and/or
2. combining several classifiers (i.e. ensemble).

## Interface

Your main should be in a file named `question_classifier.py`

For training, run

```
% python3 question_classifier.py train -config  
[configuration_file_path]
```

For testing, run

```
% python3 question_classifier.py test -config  
[configuration_file_path]
```

The program will load a configuration file storing all needed information, such as:

```
# Paths To Datasets And Evaluation
path_train : ../data/train.txt
path_dev : ../data/dev.txt
path_test : ../data/test.txt

# model
model : bow # bow, bilstm, bow_ensemble, bilstm_ensemble...
path_model : ../data/model.bow

# Early Stopping
early_stopping : 50

# Model Settings
epoch : 10
lowercase : false

# Using pre-trained Embeddings
path_pre_emb : ../data/glove.txt

# Network Structure
word_embedding_dim : 200
batch_size : 20

# Hyperparameters
lr_param : 0.0001

# Evaluation
path_eval_result : ../data/output.txt
```

**Note:**

- If your code supports more than two required models (bow, bilstm), such as an ensemble of 5 bilstm models, your configuration file may include:

```
model : bilstm_ensemble
ensemble_size : 5
path_model : ../data/model.bilstm_ensemble
```

**5 bilstm models will be stored in**

```
../data/model.bilstm_ensemble.0
../data/model.bilstm_ensemble.1
...
../data/model.bilstm_ensemble.4
```

- Output (e.g. `../data/output.txt`) is a file in which each line is a class for each testing question, and the performance (i.e. accuracy).
- You may need to store some more information of the model (e.g. vocabulary). Don't hesitate to make use of the configuration file.

## Deliverables

There are two deliverables for this coursework:

1. (50 marks) Your implementation (in a zip file). The implementation should come with three folders:

- `document`: a document containing a description for each function, a README file instructing how to use the code, (5 marks)
- `data`: training, dev, test, configuration files (excluding word embeddings), and some extra files needed for your models (e.g. vocabulary). Note: for each model, you need one configuration file (e.g. `bow.config`, `bilstm.config`)
- `src`: your source code. (45 marks)

2. (50 marks) Short paper reporting results. This should be in the form of a research paper (2-3 pages excluding references) <http://acl2020.org/downloads/acl2020-templates.zip> (latex is highly recommended). The report should contain at least below points:

- Introduction (2 marks)
  - What is the problem?
- Describe your approaches, e.g. (10 marks)
  - How to turn sentences into vectors?
  - What are your models?
- Describe your experiments, e.g. (38 marks)
  - Experiment set-up, (2 marks)
    - What is the used data?
    - Describe your preprocessing steps (e.g. removing stopwords, lowering words.)
    - What is the performance metric?
  - Results, (6 marks)
  - Ablation study, e.g. (15 marks)
    - What if you freeze/fine-tune the pre-trained word embeddings?
    - What if you use randomly initialized word embeddings instead of pre-trained word embeddings?
  - Some in-depth analyses, e.g. (15 marks)
    - What if you use only part of the training set?
    - Which classes are more difficult than the other?
    - Confusion matrix?

- What if you use other preprocessing steps?

## Note

### 1. Source code

- The code has to be runnable on **Linux/MacOS**. (You can develop the code on Windows, but make sure that it can run on Linux or MacOS.)
- **Only** pytorch, numpy, and python3 standard libs are allowed. (You don't need any fancy libs like NLTK, Spacy or/and sklearn for preprocessing the data. If you want to remove stopwords, you can find a stopwords list here <https://gist.github.com/sebleier/554280>)
- Don't include your trained models in the submission.
- Don't include pre-trained word embeddings in the submission.
- If none of your models work (i.e. the code is not runnable or the performance is less than 50%) , you will get **0** marks for this coursework.
- If only one model works, you will get 35 marks maximum for the implementation/report (so 70 marks maximum in total).

### 2. Report

- The report has to include the information (name, student number...) of every member.
- Don't need to state clearly the duty of each member. Every member will get the same marks.

### 3. Bonus

- If you build an extra classifier (check out "classifier plus"), you will get a bonus of 10 marks. (But your total marks can't exceed 100.)

## Suggestions

### 1. Embeddings

For randomly initialized word embeddings, use the class

<https://pytorch.org/docs/stable/nn.html?highlight=embedding#torch.nn.Embedding>

For using pre-trained word embeddings, use the function

[https://pytorch.org/docs/stable/nn.html?highlight=embedding#torch.nn.Embedding.from\\_pretrained](https://pytorch.org/docs/stable/nn.html?highlight=embedding#torch.nn.Embedding.from_pretrained)

### 2. Handling unknown words

To handle unknown words, you can use #UNK# tokens. The embedding of #UNK# can be initialized randomly by drawing from  $N(0, 1)$ .

### 3. Pruning pre-trained embeddings

Instead of loading whole pre-trained word embeddings, you can remove the embeddings of those words that do not appear in the dataset. You can find here ([glove.small.zip](#)) such word embeddings from glove.

The word embeddings file also includes an embedding for #UNK#.

**Deadline: 17:00, Tuesday, 3rd March, via Blackboard.**