TAYSIR

User Manual

Table of Content

About the competition

This competition is an on-line challenge on **extracting simpler models from already trained neural networks**. These neural nets are trained on sequential categorial (=symbolic) data. Some of these data are artificial, some come from real world problems (NLP, Bioinformatics, Software Engineering, etc.).

The competition offers 2 tracks:

Track 1: Binary classification. The neural nets were trained on data belonging to 2 classes. This corresponds to a language in the formal language theory sense.

Track 2: Language modelling. The neural nets were trained to provide a distribution over the potential next symbols given the beginning of a sequence (a prefix). They then are seen as models assigning a probability to any sequence (density estimator):

$$p(\rtimes a_1 a_2 \ldots a_n \ltimes) = p(a_1|\rtimes)p(a_2|\rtimes a_1) \ldots p(\ltimes|\rtimes a_1 a_2 \ldots a_n)$$

where a_i are the integers forming the sequence and $\rtimes$ and $\ltimes$ are the start and final symbols, respectively.

The website presenting the competition can be found at https://remieyraud.github.io/TAYSIR/

The platform hosting the competition, where you can access the data and submit your simple models is codalab: https://codalab.lisn.upsaclay.fr/ You will need to create an account there to be able to participate.

There will be (are) **two competitions on that platform**: one for the first Track, one for the second. We have (had) a third one to beta test both our framework and yours.
Each competition is divided into **several phases: each phase corresponds to one Neural Net** from which to extract a simpler model. Phases might not all start at the same time, but they will all end on April 30th.
Beta link:
Track 1 link:
Track 2 link:

We provide a **starter kit with notebooks** to show you how to play with our models and how to generate the archive that will be needed to submit your surrogate models.

We created a **discord server** dedicated to the competition: https://discord.gg/ZubJfV2gKd

The Datasets

All the data used for training the neural nets are **sequential and symbolic**. Practically, they are sequences of integers.
We do not provide the training datasets since this is not a learning competition. However, we provide the datasets that were used for **validation** (around 10% of all the data).
The provided files are in the following format :

```
[Number of sequences] [Alphabet size]
[Length of sequence] [List of symbols]
[Length of sequence] [List of symbols]
[Length of sequence] [List of symbols]
…
[Length of sequence] [List of symbols]
```

For example the following dataset:

```
5 10
6 8 6 5 1 6 7 4 9
12 8 6 9 4 6 8 2 1 0 6 5 9
7 8 9 4 3 0 4 9
4 8 0 4 9
8 8 1 5 2 6 0 5 3 9
```

is composed of 5 sequences and has an alphabet size of 10 (so symbols are integers between 0 and 9) and the first sequence is composed of 6 symbols: [8, 6, 5, 1, 6, 7, 4, 9]. Notice that here 8 is the start symbol and 9 is the end symbol.

The Neural Nets

RNNs

We provide the RNNs as MLFlow pytorch models. This allows the models to be used cross-platform with easy access to their inner processes.

The architectures cover a large spectrum of hyperparameters:

- ❖ Type of recurrent layers: SRN, GRU, LSTM[1]
- ❖ Number of neurons per recurrent layers
- ❖ Number of recurrent and dense layer(s)
- ❖ Batch size
- ❖ Patience
- ❖ Optimizer

None of these architectures contains an embedding layer as we want to focus on the recurrent part.

The implementation of the RNN is given in the file *tnetwork.py* that you can find inside all MLFlow models.
Here are the main variable of the class:

- *n_layers*: number of recurrent layers
- *neurons_per_layer*: number of cells per recurrent layer
- *dropout*: whether dropout is used
- *cell_type*: the type of recurrent cell
- *final_type*: the type of feedforward used for the final dense layer(s)
- *bidirectional*: whether the network is bidirectional
- *split_dense*: whether there is one or two dense final layer(s)
- *task*: “binary” or “lm” depending on the competition track
- *hides_pairs*: boolean, True if the cell type is LSTM

The module comes with a handful of functions that we hope will be useful:

one_hot_encode(self, word): This function takes a sequence as a list of integers and returns a tensor containing the sequence one-hot encoded (without padding)

predict(self, x): This function takes a one-hot encoded sequence (or several) and returns the prediction of the model. This prediction is a float (or a tensor of floats) that contains:

- 0 or 1 for Track 1 (Binary Classification).
- The probability assigned to the sequence for Track 2 (Language Modelling). This probability is defined as $p(⋊a_1a_2…a_n⋉) = p(a_1|⋊)p(a_2|⋊a_1) … p(⋉|⋊a_1a_2…a_n)$ where a_i are the integers forming the sequence and $⋊$ and $⋉$ are the start and final symbols, respectively.

forward(self, x, hidden=None, full_ret=False): usual forward. *hidden=None* corresponds to the initialisation of the hidden state of the model. You do not need to know what *full_ret* is doing ;-)

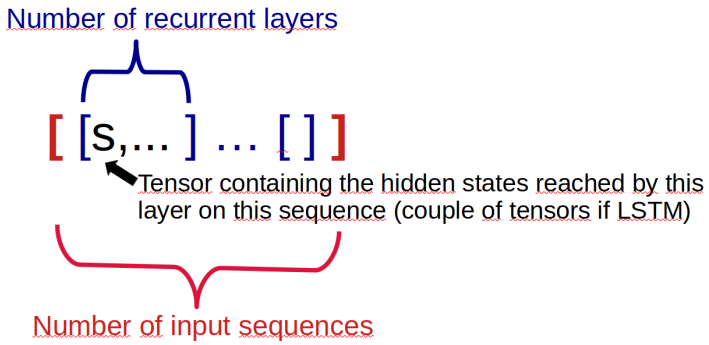
forward_bin(self,x, hidden=None, full_ret=False): This function is the usual forward for binary classification. However, it can be used on a RNN trained for language modelling: in this case it provides a vector containing the probability of each symbol to be the next one once *x* is fully parsed.

forward_lm(self, x, hidden=None, full_ret=False): This function provides a tensor containing vectors of next symbols probability after each symbol in *x*.

---

[1] The pytorch LSTM does not give access to the values of the carry during the parsing, so we use our own designed module *lstmx.py*, based on torch.nn.LSTMCell

reached_hidden(self, x, hidden=None): This function parses a 1-hot encoded sequence (or a list of sequences) from the hidden state passed in argument (uses initial state if None, otherwise requires a list of tensors, one per recurrent layer) and returns a list of lists of hidden states encountered. The number of lists is the number of words. Each list is made of a list of tensors whose number corresponds to the number of hidden recurrent layers. Each tensor contains the hidden states encountered at this layer while parsing the word (if LSTM, these elements are tuples of two tensors, one for the hidden state and one for the carry). The dimension of one tensor is (1, sequence length, size of the layer). An example of its use is given in the Track 1 notebook for baseline.



feed_dense(self, h): This function takes the output of the last recurrent layer and computes the output of the dense layer(s)

Transformers

The models that are going to be offered are DistilBERT trained on the hidden datasets from scratch. The reason why DistilBERT is used is that it has a simple and standard Transformer-type structure. The models were adjusted to have smaller hyperparameters than the original version as far as their test accuracies did not largely drop, so that participants easily dealt with them with lower computational cost.

Submission

We provide a **tool** that allows you to save any python function in the MLFlow needed format. You then will need to wait for us to run your model on the (not known to participants) test set (our server works in a FIFO mode and assigns a max of 5 minutes to each submission). When this computation is done, you will see the feedback on the website (its scores if everything goes well, an error log otherwise).

For each Track, the **number of submissions per day is fixed** and will not vary during the competition. There is also **a limit on the total amount of submissions** you can do during one competition. This aims at having a smoothly working server. But then you have to use them with sparsity!

Evaluation

The submissions will be evaluated on 3 criterias:

- **Score:** This is the error rate for the binary classification and the mean square error for language modelling.
- **Memory usage :** The memory footprint of your model during a prediction, in mebibytes.
- **CPU time :** The CPU time spent by your model during a prediction, in milliseconds.

Your goal is to reach the best score possible on all these criterias.

Videos

This video shows **how to use the notebook** and how to submit your model to the TAYSIR competition:

A video presenting the competition can be found here:
https://www.youtube.com/watch?v=LY36ek4EcwA
Warning: this talk was given months before the competition, some elements are not relevant anymore - starting with the name of the competition that changed! Another difference is that we are **only providing MLFlow models** (but they are able to do way more than what we thought at the time of this talk). **Track 2 will be only on language modelling neural nets** (and not general regression as stated in the talk). The timeline and the URL also changes, but if you are reading this, you already know that.

Timeline

February 2023:	Beginning of the competition, starting with Track 1
April 30th 2023:	End of the competition
May 15th 2023:	Submission deadline for the extended abstracts presenting your work
July 10-13th 2023:	ICGI 2023 in Morocco, half a day dedicated to the competition