

Neural Network and Deep Learning

Homework 3

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1 Introduction

In this exercise a recurrent neural network implemented with `Pytorch` is used to perform a Natural Language Processing task. In particular, the book *La scienza in cucina e l'arte di mangiar bene* by Pellegrino Artusi from the *Gutenberg* project ¹ is chosen to perform the task.

The model implemented works using word embedding unlike the one proposed during the laboratory, which instead is based on `seq2seq`.

2 Data preprocessing and dataset creation

In order to implement the neural network, the text needs to be preprocessed. First of all, introduction, index, appendix and notes by Gutenberg Project's editors are removed and the whole text is set to lower-case. Then, special and rare characters ² are removed, along with figures captions ³. Punctuation symbols are kept, but in order to perform the word embedding, they are changed as shown in Tab.1. The book is split in paragraphs, that corresponds to the different recipes; then, for each paragraphs, all the consecutive groups with a number of words equal to the variable `crop_len` (set to 15 in the final version) are stored as our dataset: this results in 10545 sentences.

Table 1: *Punctuation symbols are replaced in order to be understood by the word embedding.*

Punctuation	Replaced by
!	-ESCLAMATION-
:	-COLUMN-
;	-SEMICOLUMN-
,	-COMMA-
.	-DOT-

The word embedding is performed by `word2vec` algorithm implemented in `gensim` package; this allows to skip the creation of the one hot encoding, since the encoding is handled by `word2vec`.

3 Recurrent Neural Network

The Network is similar to the one provided in class, with the addition of an Embedding layer before the LSTM one. The Embedding layer loads the weights from the `word2vec` model, and it is set to be fixed, so the training procedure does not change it.

4 Model training

In order to train the model, the dataset is split into train (80%) and test (20%) set; monitoring the loss over test set is useful to avoid overfitting. Both the training and test sets

¹<https://www.gutenberg.org/ebooks/59047>

²Removed characters are: _ < > ø - ' ()

³They can be identified because embraced by square brackets: [... caption ...]

are splitted into batches of 500 sentences in order to speed up the learning, and at each iteration the average loss among the batches is saved.

In addition to the division in train/test, other methods are included to avoid overfitting. Adam optimizer is used with L2 penalty and a scheduler (`ReduceLROnPlateau` on Pytorch) tunes the value of the learning rate. Learning rate starts at 10^{-3} and it is reduced by a factor of 0.75 (minimum value allowed is 10^{-7}) if there is no improvement in the test loss for 10 consecutive iterations (with a cooldown of 5 iterations). In addition, the learning is stopped if there is an increment to the test loss for 15 consecutive iterations. At last, the Network has a dropout layer with a probability of 0.3.

In order to improve the learning process, the loss is not calculated only over the last word of the sentence. Using Python list notation, the input to the network are words `[:-1]` (all the phrase execept the last one), and the output is compared to the labels `[1:]` (all but the first). This choice is found to lead to better performance.

Network hyperparameters are tuned using 350 epoches during the training; since the learning is demanding in terms of time, the search is just done over:

- number of hidden units: [64, 128, 256];
- number of layer in the RRN: [2, 3, 4].

Results are summarized in Tab.2. It can be noticed that a Network with a low number of hidden units performs worse, and this may depends on the fact that the architecture is too simple to learn the task. On the other hand, 3 or 4 LSTM layers needs a lot more data to learn, thus they leads to a worse result than a Network with 2 RNN layers and the same number of hidden units.

Table 2: *Results of the hyperparameters tuning.*

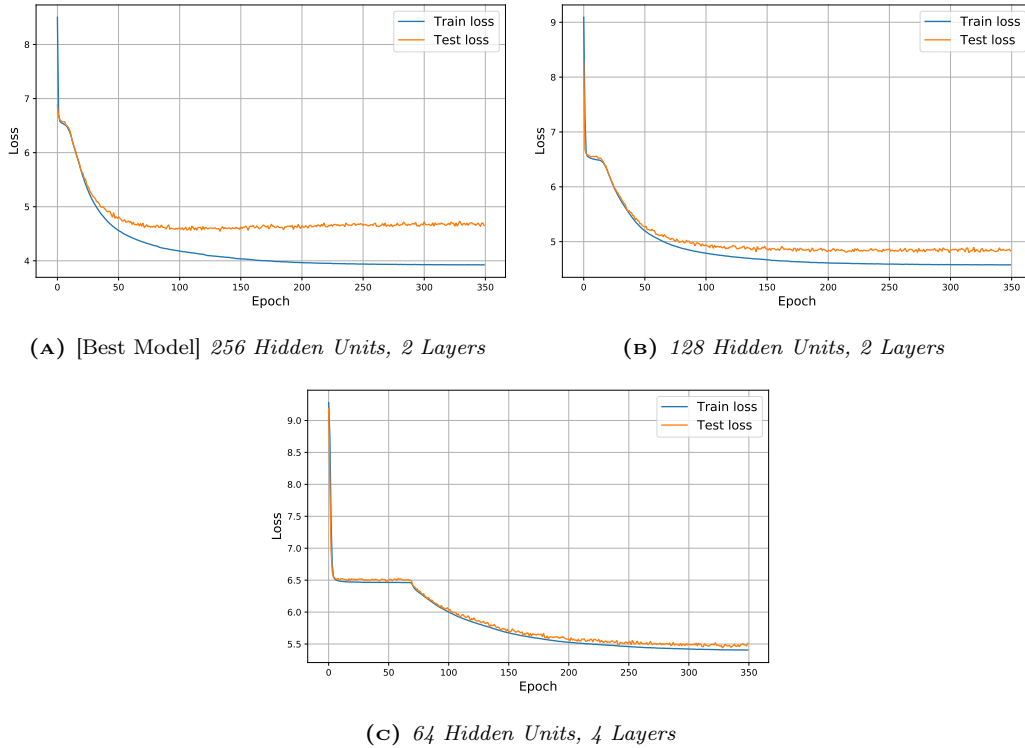
Hidden Units	Layers Number	Train Loss	Test Loss
256	2	3.924397	4.651592
128	2	4.577566	4.834389
256	3	4.007351	4.869990
256	4	4.107300	4.890457
128	3	4.681510	4.965314
128	4	4.775019	5.042004
64	2	5.099188	5.196409
64	3	5.220237	5.300431
64	4	5.405514	5.511552

Fig.1 shows train and test loss for some combinations of the hyperparamters. With an higher number of hidden units, the difference between the two is higher than with a lower number. The step after the plateau indicates a change in the learning rate of the optimizer due to the scheduler.

5 Trained Model and predictions

The final model has 256 hidden units and 2 LSTM layers. The prediction of the next word does not rely only on the maximum of the Softmax distribution of the Network output; in fact, it sampled among the whole dictionary, with each word associated with the corresponding Softmax probability. This policy leads to better results, whereas the first method produces an output composed by the same words repeated multiple times. The explanation of this behaviour could be the fact that there are lots of words that appears only a few times

Figure 1: Train and test loss for some combinations of the hyperparameters.



in the whole dataset, hence the model cannot learn them well enough: if we just take the maximum of the Softmax, these ones will never be chosen in favor of the most recurrent.

Since the output does depend both on the initial seed and the sampling procedure from the Softmax distribution, the command line parameter `--random` is added to fix the RNG seed and obtain reproducible results.

Some examples of text produced by the model are shown below.

Listing 1: SEED: *Carne al pomodoro*, RNG seed: 75832

```
python trained_model.py --seed "Carne al pomodoro" --length 75 --random 75832
=====
SEED: Carne al pomodoro
=====

Carne al pomodoro o conserva di pomodoro; se il sugo ha apertolo ottimo l
digrassatelo, e dal resto pel sugo; versateci il sapore del riso, e quando sar  ancora
rosolata lo zucchero e poi aggiungete la marsala e con un po di burro. rimestate
consuetudine la forma al entremet; ma poi che prima l gettato ne monte mettete in
quando lo zucchero e il composto da vostra tanto per ridurlo da consistenza
```

Listing 2: SEED: *Vino e riso*, RNG seed: 2154

```
python trained_model.py --seed "Vino e riso" --length 75 --random 2154
=====
SEED: Vino e riso
=====

Vino e riso e quando bolle versate il pane ramaiuolo dopo che un brodo sodo e versate
l altro verde col mestolo, liscio, che digrassatelo e poi rosolato un battutino di
aglio, aglio carne, prezzemolo e tritateli pezzettina, spesso ancora, alquanto brodo.
se questi, invece 4 intere, oppure dodici o per levatene tre o temperino con qualche
pezzetto di burro, e quando avesse tiratela a cottura, con
```

Listing 3: SEED: *Farina, olio e pane*, RNG seed: 8594

```
python trained_model.py --seed "Farina, olio e pane" --length 75 --random 8594
=====
SEED: Farina, olio e pane
=====

Farina, olio e pane in padella a cazzaruola un essiccazione. distendete sopra il
coltello, rimestatela cuociono conchiglie dal vetro, delle uova uniteci un
riconosciute delle breviario di questo il suo mediante brodo signorile, ma qualunque
prima all fiorentina, ben augelli, per il uso di funghi dadini, avanti in questo
scudo, poetica gonfie il pollo lasciatelo asciutto tenero e e così descritte si può
rotonda su colle sotto e la lingua che
```

Listing 4: SEED: *Salsiccia con polenta*, RNG seed: 5684

```
python trained_model.py --seed "Salsiccia con polenta" --length 75 --random 5684
=====
SEED: Salsiccia con polenta
=====

Salsiccia con polenta di prosciutto gustate, carota e un chilogrammo di accartocciate.
si possono tedeschi; prosciutto troppo grasso e grasso, conditelo con sale e pepe.
mettete al fuoco con burro, i pomodori e in croce, burro, cioè il dito tagliato al o
anaci e l uovo al torlo, poi ala piacere di farina tale vendo, a fatele fategli entro,
trovandomi di una 11 di giusta cucina.
```