

# EDAN20 - Assignment 4

## A simple language classifier

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## 1 Objectives and dataset

### 1.1 Objectives

The objectives of the assignment were to use both sklearn and PyTorch to create neural networks that classify languages.

### 1.2 Dataset

The dataset used was Tatoeba, downloaded on 2014-10-05.

## 2 Method and program structure

### 2.1 Compact Language Detector v3 - CLD3

CDL3 extracts character n-grams from a text and hashes down to an id within a small range. It also computes the relative frequency for each of them within the text. These n-gram ids and frequencies are then in some way averaged down to an embedding and concatenated together to produce the embedding layer.

### 2.2 My program

My program finds all uni-, bi- and trigrams and their relative frequencies from a sentence. The n-grams themselves are then hashed and, using modulo, reduced to fit into a smaller interval. This modulo reduction creates overlap between different n-gram sizes, so the id ranges for bi- and trigrams are shifted upwards. All the n-gram ids and frequencies are then concatenated to create the final representation of a given sentence.

The difference between my architecture and CDL3 is that I don't perform any sort of averaging on the n-gram frequencies, they stay as a raw relative sentence frequency.

## 2.3 scikit-learn vs PyTorch

Both scikit-learn and PyTorch are great libraries/frameworks when doing some sort of machine-learning. The main difference between them is that sklearn seems to be a more high-level library making it easier to use. PyTorch instead is more low-level and therefore expects more of the user, but instead granting finer control and better understanding.

## 3 Results

We can see that both the sklearn and PyTorch models performed similarly.

### 3.1 The feature matrix - X

8	0	8	1	0	0
0	0	1	0	0	0
1	0	0	0	0	0
1	0	1	0	0	0
3	1	2	1	0	0
4	1	6	1	0	0
4	0	1	1	0	0
5	2	2	0	1	0
2	0	2	1	0	0

Table 1: The feature matrix - X

### 3.2 sklearn

	Precision	Recall	F1-Score	Support
<b>cmn</b>	1.00	1.00	1.00	9866
<b>dan</b>	0.99	0.97	0.98	9963
<b>eng</b>	1.00	1.00	1.00	10059
<b>fra</b>	1.00	1.00	1.00	10041
<b>jpn</b>	1.00	1.00	1.00	10005
<b>swe</b>	0.97	0.99	0.98	10066
<b>accuracy</b>			0.99	60000
<b>macro avg</b>	0.99	0.99	0.99	60000
<b>weighted avg</b>	0.99	0.99	0.99	60000
<b>Micro F1:</b>	0.9921			
<b>Macro F1:</b>	0.9921			

Table 2: sklearn accuracy

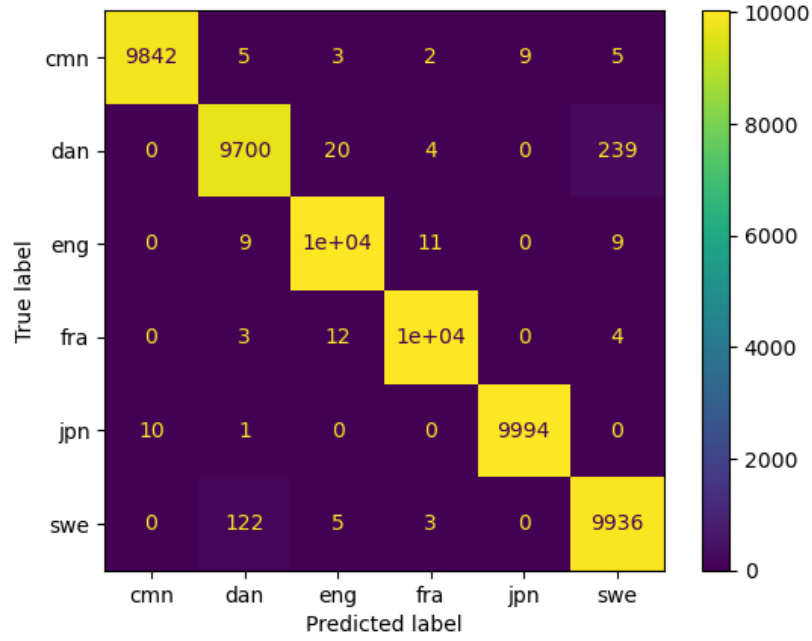


Figure 1: sklearn confusion matrix

### 3.3 PyTorch

	Precision	Recall	F1-Score	Support
<b>cmn</b>	1.00	1.00	1.00	9866
<b>dan</b>	0.98	0.99	0.98	9963
<b>eng</b>	1.00	1.00	1.00	10059
<b>fra</b>	1.00	1.00	1.00	10041
<b>jpn</b>	1.00	1.00	1.00	10005
<b>swe</b>	0.99	0.98	0.98	10066
<b>accuracy</b>			0.99	60000
<b>macro avg</b>	0.99	0.99	0.99	60000
<b>weighted avg</b>	0.99	0.99	0.99	60000
<b>Micro F1:</b>	0.9929			
<b>Macro F1:</b>	0.9929			

Table 3: PyTorch accuracy

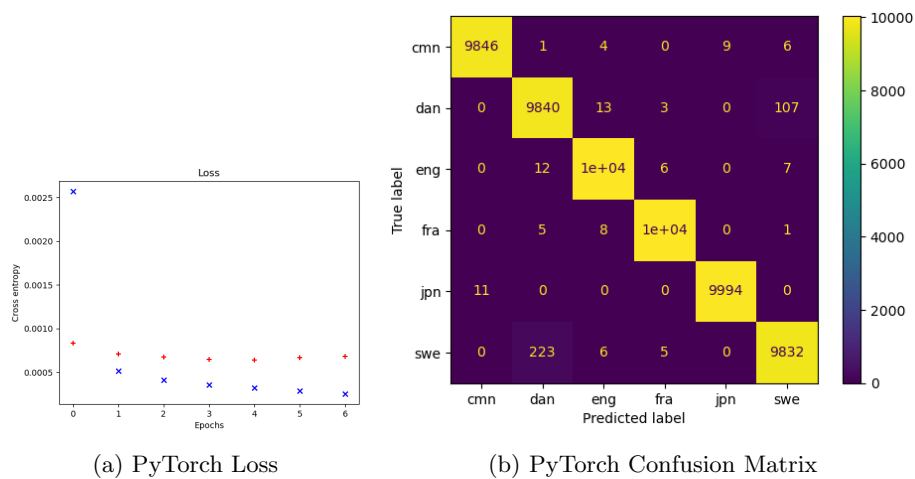


Figure 2: PyTorch Loss and Confusion Matrix

## 4 Conclusion

The objective of this assignment, to create a language classification model was accomplished. Both sklearn and PyTorch were used and they both performed very similarly to each other.