

# Few shots learning LLM for Relevance Classification

---

- [Dataset](#)
- [Implementation](#)
  - [Model](#)
  - [Low-Rank Adaptation \(LoRA\) - APPROACH 1](#)
  - [Model fine-tuning - APPROACH 2](#)
  - [Results](#)
- [Contributors:](#)

Project done in the scope of the course Web and Text Analytics given at the University of Liège in 2023. The approach taken is to fine-tune a small existing model using the dataset provided by the Teaching Staff.

## Dataset

The [dataset](#) is composed of 25112 sentences, each classified as being relevant to the context or not. The context of relevance is thus the whole dataset context (the 25112 sentences).

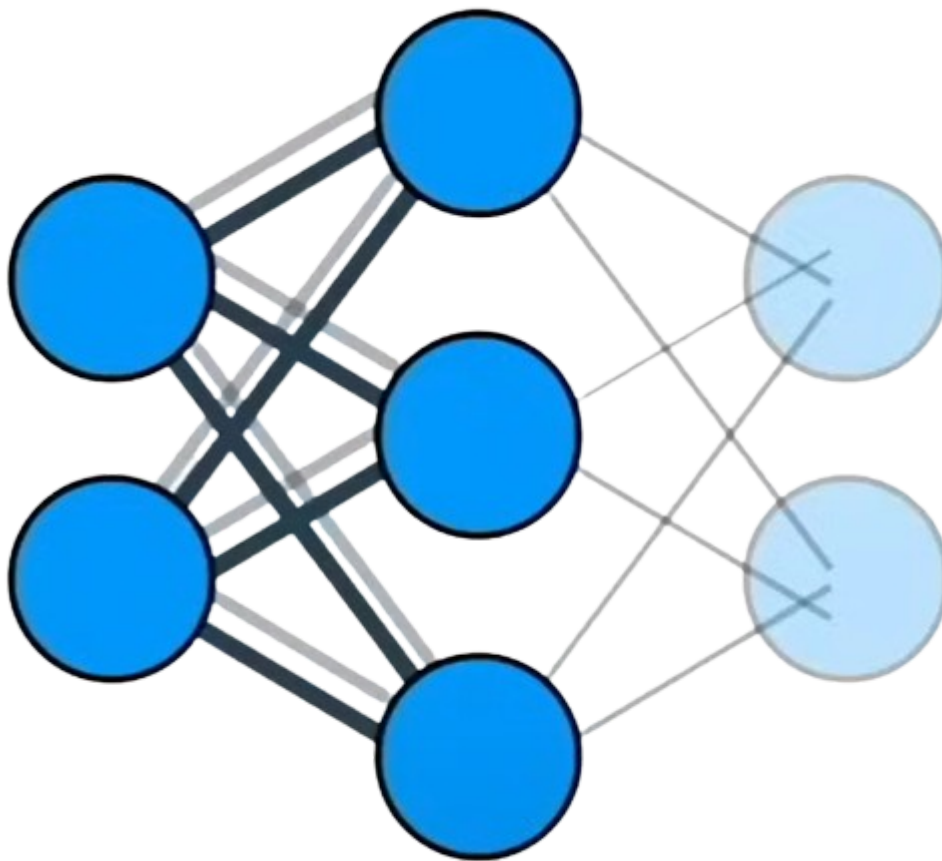
## Implementation

### Model

The model used is [distilbert-base-uncased](#). It offers the advantages of being small and thus possible to train with limited resources and having good performances in regards to other bigger transformer models.

### Low-Rank Adaptation (LoRA) - APPROACH 1

The principle of LoRA is to freeze the initial model parameters and to fine-tune additional parameters to adapt the model to a new task. This yields an adaptation of the initial model with a relatively low number of parameters to train.



This first approach can be found in the [LoRA](#) notebook.

## Model fine-tuning - APPROACH 2

The second approach is to fine-tune the whole model using pytorch. This approach can be found in the [pytorch](#) notebook.

## Results

At the end of the fine tuning :

Method	Training Loss	Validation Loss	Accuracy	Precision	Recall	F1
LoRA	0.122800	0.493573	0.8918	0.9216	0.937	0.8566
Total Fine-tune			0.8918	0.88017	0.93848	0.90839

## Contributors:

The team which contributes to this work is composed of :

- [Cédric HONS](#)
- [Dylan PROVOOST](#)
- [Adrien VINDERS](#)