

LLM fine-tuning for time series annotation

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Outlines

How it works (roughly...)

Fine tuning of Qwen LLM for time series annotation

How it works (roughly...)

Very brief history

- ▶ Artificial neural networks have existed for a **long time** ([Rosenblatt, 1958], late 1950s).
- ▶ Ups and downs, then **Yann LeCun** ([LeCun *et al.*, 1989], handwriting recognition, 1989).
- ▶ *Attention is all you need* [Vaswani *et al.*, 2017], invention of **transformers** at Google.
- ▶ Without huge **computing power**, it would not work.

Completion is all you need

- ▶ Principle: we are given the beginning of a text. The task is to predict the next word. Example: "the cat eats the ..." (we must guess "mouse").

- ▶ Words (or *tokens*):

| | | | | | |
|-------|-------|-------|-------|--------|-------------|
| t_1 | t_2 | t_3 | t_4 | t_5 | $t_6 = t_m$ |
| . | cat | the | eats | tomcat | mouse |

- ▶ Corpus: "the cat eats the mouse.", "the tomcat eats the mouse.", "..the cat eats.", "..the mouse eats.", "..the tomcat eats.", etc.
- ▶ Remark: all sentences have $\ell = 6$ words (we pad with the filler word ".").

Digitization

- ▶ Encoding: to each word (or *token*) we associate a vector of $m = 6$ dimensions

$$\text{"."} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad \text{"cat"} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad \text{"the"} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad \text{etc.}$$

- ▶ Embedding into a lower-dimensional space of size p (to account for synonyms, among other things). For example $p = 5$. The embedding E_{w_0} is a function from \mathbb{R}^m to \mathbb{R}^p .
- ▶ Each token t_i is represented by a vector v_i . The embedding parameters w_0 are unknown.

$$v_i = E_{w_0}(t_i).$$

Encoder

- ▶ A sentence is thus represented by a "tensor" of ℓ numerical vectors stacked together:

$$r_0 = v_{i_1} v_{i_2} \dots v_{i_\ell}$$

It is therefore an object in a space of dimension $N = \ell \times p = 30$.

- ▶ The sentence goes through k layers of transformers T_{w_i} , which are mappings from \mathbb{R}^N to \mathbb{R}^N with unknown parameter vectors w_i

$$r_i = T_{w_i}(r_{i-1}), \quad i = 1 \dots k.$$

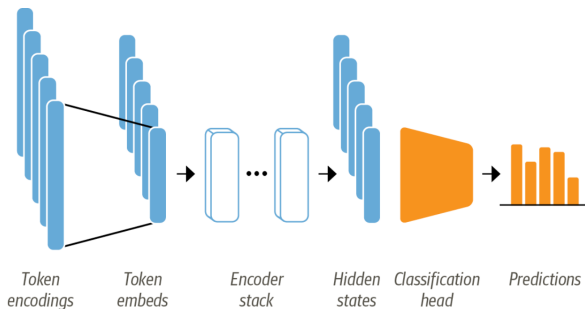
- ▶ The deeper we go into the layers, the more abstract the representation r_i of the initial sentence becomes. The vector r_k ("latent state") contains the information extracted by the network from the initial sentence r_0 .

Decoder

Finally, the decoder allows us to predict a probability vector p in \mathbb{R}^m : p_i is the probability that the next word is m_i .

$$p = D_{w_{k+1}}(r_k).$$

In summary (more details in [Tunstall *et al.*, 2022, Vigon, 2023]):



Training

- ▶ Choosing the form of the functions E_{w_0} , T_{w_i} , $D_{w_{k+1}}$: a trade-off between cost, efficiency, and simplicity. For now, it is as much an art as it is a science.
- ▶ Historically, several possible architectures: CNN, RNN, LSTM, transformers. Evolution is strongly linked to available computing power.
- ▶ The parameter vector w , of size s , is **unknown**.
- ▶ Training consists in optimizing these parameters so that the model best reproduces the sentences from the corpus.
- ▶ This is the most difficult part of the computation: it requires a supercomputer, specialized processors, and costs millions of euros.
- ▶ Orders of magnitude for GPT-3: $\ell = 2000$, $m = 50000$, $p = 20000$, $s = 170$ billion...

Inference

- ▶ Once the parameters w are computed, inference is fast.
- ▶ A network can be retrained for a specific task at a reduced cost (*fine tuning*). For example, Copilot and ChatGPT are specialized versions of GPT- x ($x = 3, 4, 5$)
- ▶ The *pre-prompt* is essential to obtain high-quality results.
- ▶ For computational cost reasons, **ChatGPT does not learn in real time**. Its short-term memory is therefore limited to a few thousand words.

Example with PyTorch

- ▶ PyTorch is a free software library developed by Huggingface to manipulate neural networks.
- ▶ Minimal example for creating a toy LLM from scratch with PyTorch (ask me).

Fine tuning of Qwen LLM for time series annotation

Objectives

- ▶ Teach a small LLM (Qwen2.5 0.5 billions parameters) to describe a time series

- ▶ Example of prompt:

Describe the time series in three sentences.

First sentence: describe trend (increasing/decreasing/flat).

Second sentence: noise intensity (low/medium/high).

Third sentence: approximate localisation of global maximum (beginning/middle/end) and global minimum (beginning/middle/end).

Put the description in a JSON format with the following pattern

```
<json>{ "trend": <sentence1>,  
  "noise": <sentence2>,  
  "extrema": <sentence3> }  
</json>
```

Series: [02, 01, 00, 03, ...]

- ▶ Tokenization is essential: the values in the series are scaled to the range 00..99.

Necessity of training

- ▶ Small LLM fails to answer properly. It generates total garbage.
- ▶ Example of output:

```
series name: \"series\"
time interval: 1 day
``` To provide a detailed analysis of the given time series data, I will break it down into its components.

Time Series Description:
The provided time series consists of daily values for several variables over a period of one year (2023-01-01 to 2023-12-31).

Trend Analysis:
- **Increase**: The values increase steadily from 01 to 04, then decrease again.
- **Decrease**: The values decrease from 04 onwards
...
```

- ▶ Let's try to improve this with supervised fine tuning

## Practical methodology

- ▶ Generate a dataset of correct examples with a large LLM (Mistral, ChatGPT, etc.)
- ▶ Use 90% of the dataset for training and the 10% left for evaluation.
- ▶ Apply a supervised fine tuning (SFT) procedure on a small LLM from this dataset.
- ▶ In order to reduce the cost we adopt a LoRA approach. <sup>1</sup>
- ▶ Now go to [https://github.com/phelluy/DLAA\\_2025](https://github.com/phelluy/DLAA_2025) and follow the README file.
- ▶ The Colab GPU memory is limited, I had to reduce the size of the computations. For full results see [Boileau *et al.*, 2025].

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<sup>1</sup>The LoRA (Low-Rank Adaptation) approach in supervised fine-tuning (SFT) freezes the original model weights and injects small trainable low-rank matrices into certain layers (typically linear projections in attention/FFN). This drastically reduces the number of parameters that need updating, making fine-tuning large models much more memory- and compute-efficient while still achieving strong adaptation.

# Bibliographie I



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