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** ([?], late 1950s).
- Ups and downs, then **Yann LeCun** ([?], handwriting recognition, 1989).
- *Attention is all you need* [?], 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

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

- 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

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

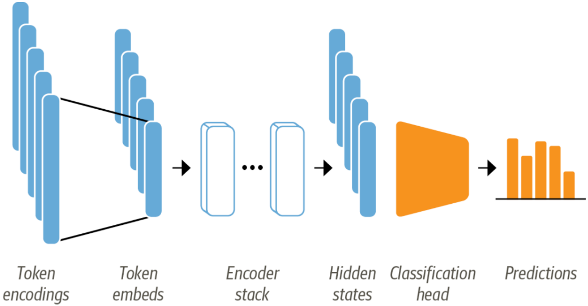
- The deeper we go into the layers, the more abstract the representation r_i of the initial sentence becomes. The vector r_k ("latent state") contains the information extracted by the network from the initial sentence r_0.

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 [?, ?]):



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: `https://github.com/phelluy/DLAA_2025/blob/main/mini_llm.py`
- Don't expect this to give interesting inference ! It just shows the main structure of a training procedure.

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 com
### Time Series Description:
The provided time series consists of daily values for several variables over a period of one year (
### 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. [1]
- Now go to `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 [?].

[1] 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