UNIVERSITY OF CAMBRIDGE

M2 Deep Learning - Coursework Assignment

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Introduction

Recent advances have demonstrated that Large Language Models (LLMs) can be effective not only in natural language tasks but also in domains such as time-series forecasting [1]. In this coursework, we explore the application of Low-Rank Adaptation (LoRA) [2] to the Qwen2.5-Instruct model [3], a transformer-based LLM, for forecasting predator-prey population dynamics as described by the Lotka–Volterra equations [4].

Utilising the preprocessing methodology in the LLMTIME framework [1], we examine how Qwen2.5-Instruct can be repurposed for numerical prediction tasks. The objective is to fine-tune the model on a dataset of simulated predator-prey trajectories using LoRA, which allows for the adaptation of pretrained models without updating all weights.

This report describes the implementation of LLMTIME preprocessing, baseline evaluation of the untrained model, LoRA fine-tuning with hyperparameter sweeps, and analysis of forecasting performance under compute constraints.

1 Compute Constraint

This coursework requires efficient experimentation under a strict compute budget of 10^{17} floating point operations (FLOPs) across all reported experiments.

FLOP Accounting Principles

FLOP costs are calculated using simplified, hardware-agnostic assumptions. Table 1 provides the per-operation FLOP estimates. For example, multiplying an $m \times n$ matrix by an $n \times p$ matrix requires:

$$\text{FLOPs}_{\text{matmul}} = m \times p \times (2n - 1) \tag{1}$$

Operation	FLOPs
Addition / Subtraction / Negation (float or int)	1
Multiplication / Division / Inverse (float or int)	1
ReLU / Absolute Value	1
Exponentiation / Logarithm	10
Sine / Cosine / Square Root	10

Table 1: FLOPs Accounting for Primitive Operations

FLOP Estimator Implementation

To estimate the computational cost of each experiment, we implemented a FLOP estimator in Python (flops_model.py and compute_flops.py). This estimator models a forward pass through the Qwen2.5-0.5B architecture. These scripts were validated through a corresponding test set.

The estimator accounts for every trainable and non-trainable component of the model. For a given sequence length n, the estimator computes the total number of FLOPs for each of the following:

- **Token Embeddings**: Retrieved via indexing and incur no arithmetic FLOPs.
- **Positional Embeddings**: Sinusoidal encodings are added to token embeddings, requiring $n \times d_{\text{model}}$ additions.
- **Multi-head Attention (per layer)**:
  - Query, Key, and Value projections: Linear transformations to d_{head} per head; includes multiplications and bias additions.
  - Dot-product attention: Computation of $QK^\top$, scaling, softmax, and weighted sum with V.
  - Softmax operation: Includes exponentiations, summations, and divisions.
  - Output projection: Concatenation of heads followed by a linear transformation.
- **Feedforward MLP with SwiGLU**: As described by Shazeer [5], this block consists of:
  - Two parallel linear up-projections from the model dimension to the hidden dimension: one to produce the activation input, and one to produce the gating values.
  - A SwiGLU activation function, which applies the SiLU nonlinearity to one stream and multiplies it elementwise with the other (gating).
  - A final down-projection from the hidden dimension back to the model dimension.
- **RMSNorm Layers**: Following Zhang and Sennrich [6], these involve:
  - Elementwise squaring, summation, square root, division, and scaling by a learned parameter γ.

- **LoRA Projections**: As proposed by Hu et al. [2], LoRA introduces:
  - Low-rank down- and up-projection matrices added to the frozen base weights.
  - FLOPs from these include multiplications, additions, and a residual connection.
- **Final Projection to Vocabulary Logits**:
  - A linear layer projecting to the vocabulary space: $n \times d_{\text{model}} \times V$ multiplications and additions.

The exact computation of FLOPs for backpropagation is non-trivial and implementation-specific. For the purposes of this coursework, we assume that the backward pass is approximately double the cost of the forward pass. This is a conservative estimate, as it does not account for optimisations such as gradient checkpointing or memory reuse.

Thus, the total training FLOPs are given by:

$$\text{FLOPs}_{\text{train}} \approx 3 \times \text{FLOPs}_{\text{forward}} \tag{2}$$

2 LLMTIME Preprocessing Implementation

We implemented the LLMTIME preprocessing scheme [1] to convert multivariate time-series data into a format suitable for Qwen2.5-Instruct. This was done by creating a dedicated Python module (preprocessor.py) containing a class LLMTIMEPreprocessor, which formats and tokenizes time-series data.

Scaling and Formatting

Each sample consists of a pair of sequences - prey and predator population values over time. These values can vary in magnitude both within and across samples, which can lead to inconsistent token lengths after formatting and impair the model's ability to generalise.

To account for this, we compute a per-sample scaling factor α that normalises the numerical range before tokenisation:

$$\alpha = \frac{1}{10} \cdot \max\left(\text{percentile}_{95}(\text{prey}),\ \text{percentile}_{95}(\text{predator})\right) \tag{3}$$

We then divide each value in the prey and predator sequences by α, ensuring that the majority of values fall within the range $[0, 10]$. This sample-specific scaling avoids the limitations of global normalisation and makes the model more robust to differences in scale across the dataset.

Finally, all scaled values are rounded to two decimal places. This rounding step reduces the number of unique numeric tokens, improving tokenisation consistency and helping prevent overfitting to insignificant digit-level variation.

LLMTIME Encoding

Following the LLMTIME convention, each timestep is represented as a pair of variables (prey, predator), separated by a comma. Consecutive timesteps are separated by a semicolon. While the original LLMTIME implementation by Gruver et al. [1] removes decimal

points to reduce sequence length, especially for GPT-style models that tokenize numbers into subword units, we keep the decimal point in our implementation for several important reasons:

- Removing the decimal point would introduce additional digits and increase sequence length without benefit.
- Preserving the decimal enhances human interpretability and simplifies decoding during inference.
- The coursework specification explicitly recommends retaining the decimal point.

Tokenization

Once formatted, the numeric string is passed through Qwen2.5's tokenizer using Hugging Face's AutoTokenizer interface [7]. Each digit and punctuation mark is tokenized into its own token.

Example 1.

- **Original Input:**

```
Prey:     [2.9, 3.2, 3.8, 4.5, 5.1]
Predator: [1.1, 0.9, 0.7, 0.6, 0.5]
```

- **Scale Factor α:** 0.498
- **Formatted Sequence:**

```
5.82,2.21;6.43,1.81;7.63,1.41;9.04,1.20;10.24,1.00
```

- **Tokenized Output (Qwen2.5 input IDs):**

```
[20, 13, 23, 17, 11, 17, 13, 17, 16, 26, 21, 13, 19, 18, 11,
16, 13, 23, 16, 26, 22, 13, 21, 18, 11, 16, 13, 19, 16, 26,
24, 13, 15, 19, 11, 16, 13, 17, 15, 26, 16, 15, 13, 17, 19,
11, 16, 13, 15, 15]
```

Example 2.

- **Original Input:**

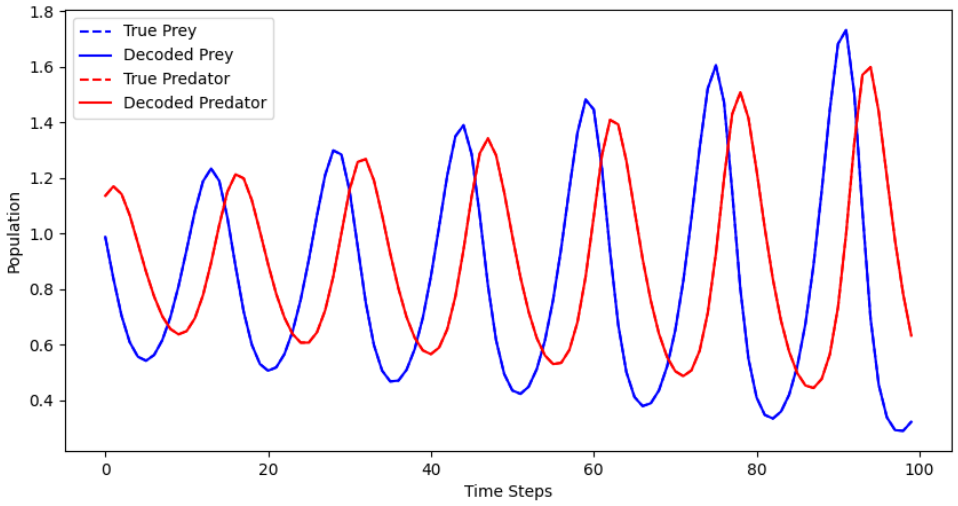
```
Prey:     [1.5, 1.8, 2.1, 2.4, 2.7]
Predator: [2.8, 2.5, 2.2, 1.9, 1.6]
```

- **Scale Factor α:** 0.274
- **Formatted Sequence:**

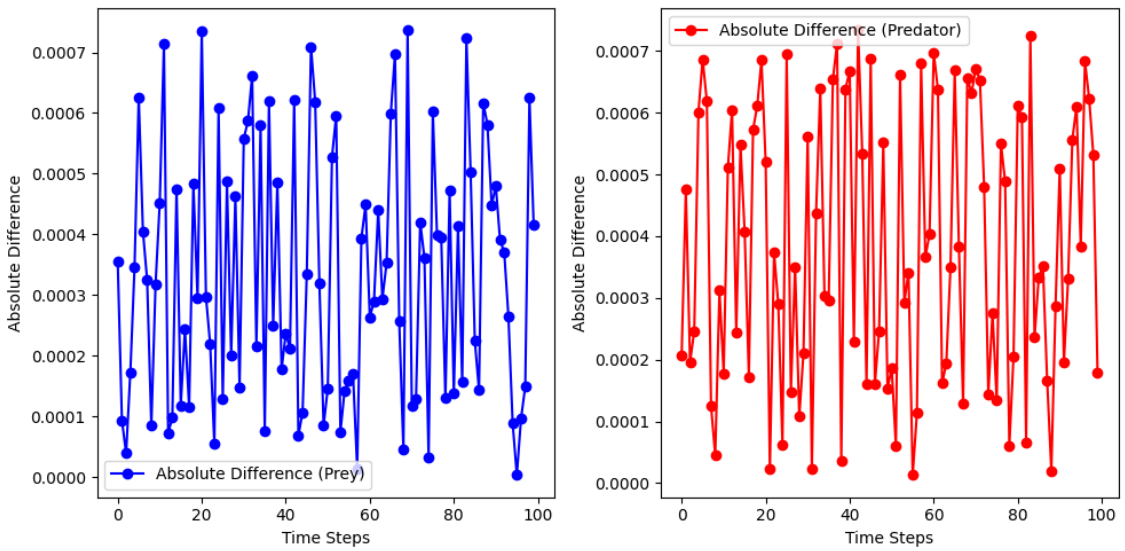
```
5.47,10.22;6.57,9.12;7.66,8.03;8.76,6.93;9.85,5.84
```

- **Tokenized Output (Qwen2.5 input IDs):**

```
[20, 13, 19, 22, 11, 16, 15, 13, 17, 17, 26, 21, 13, 20, 22,
11, 24, 13, 16, 17, 26, 22, 13, 21, 21, 11, 23, 13, 15, 18,
26, 23, 13, 22, 21, 11, 21, 13, 24, 18, 26, 24, 13, 23, 20,
11, 20, 13, 23, 19]
```



(a) Decoded output vs. ground truth for the 972nd Lotka-Volterra trajectory in the test set. This sequence was passed through the LLMTIME preprocessing pipeline, the resulting output was decoded and rescaled using the same scale factor α applied during encoding.



(b) Absolute differences between true and decoded prey (left) and predator (right) values for the 972nd test sequence. The close alignment between original and decoded values confirms that the preprocessing, tokenization, and decoding pipeline is working as intended.

Figure 1: Encoding - Decoding check for Sample 972.

3 Baseline Evaluation

We assessed the forecasting ability of the untrained Qwen2.5-0.5B-Instruct model [3] using Sample ID 972. The first 50 timesteps were provided as input in LLMTIME format, and the model was tasked with generating the remaining 50 steps.

Using the Hugging Face 'generate()' API [7], the model predicted one token at a time, with each new token requiring a full forward pass.

Forecasting Performance

We evaluate the model's forecasting accuracy on Sample ID 972 by comparing the decoded and rescaled predictions to the true population values using standard regression metrics. The results are summarised below:

- **Prey Population**
  - Mean Squared Error (MSE): 0.3812
  - Mean Absolute Error (MAE): 0.3597
  - Coefficient of Determination (R^2 Score): -1.7590
- **Predator Population**
  - Mean Squared Error (MSE): 0.1324
  - Mean Absolute Error (MAE): 0.1904
  - Coefficient of Determination (R^2 Score): -0.4884

The negative R^2 scores for both prey and predator indicate that the model performs worse than a simple mean-based baseline.

Due to the autoregressive nature of language models and the sampling-based decoding used during generation, repeated runs on the same input often give different output sequences. This non-determinism, unless explicitly controlled with fixed seeds or deterministic decoding settings, contributes to the variability in forecasting performance across trials.

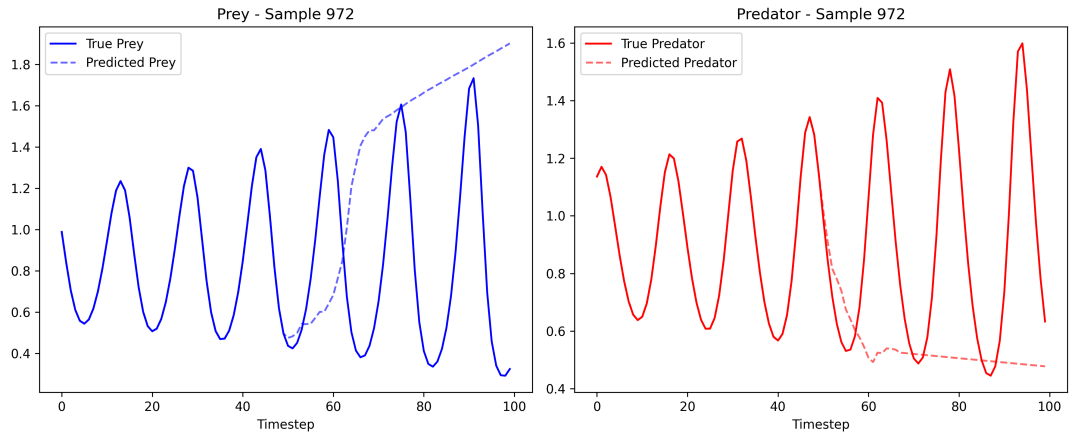


Figure 2: Forecasting output of the untrained Qwen2.5-Instruct model on Sample ID 972. The model is prompted with the first 50 timesteps and generates the next 50.

4 FLOP Model

To estimate the total FLOPs used by the Qwen2.5-0.5B-Instruct model, we mapped every major component in the forward pass to arithmetic operations and computed their FLOP costs using Table 1. For inference, we assume reuse of Key/Value caches, meaning dot-product attention scores are only computed for new tokens, not the full input sequence.

Token and Positional Embeddings

- **Token Embeddings:** Retrieved via table lookup — **0 FLOPs**.
- **Positional Embedding Addition:** $n \times d_{\text{model}}$ additions.

RMSNorm (applied before attention, after attention, and before MLP)

The Root Mean Square Layer Normalisation (RMSNorm) [6] normalises each input token $x \in \mathbb{R}^d$ using the root mean square of its elements, without subtracting the mean. The operation is defined as:

$$\text{RMSNorm}(x) = \frac{x}{\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2 + \epsilon}} \cdot \gamma \tag{4}$$

where $\gamma \in \mathbb{R}^d$ is a learned scaling parameter and ϵ is a small constant for numerical stability.

For a batch of n tokens (each of dimension d), the FLOPs are as follows:

- Square each element: $n \times d$ multiplications.
- Sum across dimensions: $n \times (d-1)$ additions.
- Compute the square root of the mean: n square root operations.
- Divide each element by the norm: $n \times d$ divisions.
- Scale with learned weight γ: $n \times d$ multiplications.

Total: $2nd$ multiplications, $n(d-1)$ additions, nd divisions, n square roots.

Multi-Head Attention (per layer)

Let h be the number of heads and $d_h = d/h$ which refers to the dimensionality fo each attention head.

- **Q/K/V Projections:** $3 \times n \times d \times d_h$ multiplications and $3 \times n \times (d-1) \times d_h$ additions.
- **Attention Scores:** $n \times n \times d_h$ multiplications and $n \times n \times (d_h - 1)$ additions.
- **Softmax:** For n^2 elements:
  - Exponentiation: n^2

  - Summation: $n \times (n-1)$ additions
  - Normalisation: n^2 divisions
- **Softmax-Value Multiplication:** $n \times n \times d_h$ multiplications and $n \times d_h \times (n-1)$ additions.
- **Concatenation:** Memory operation — **0 FLOPs**.
- **Final Output Projection:** $n \times d \times d$ multiplications and $n \times (d-1) \times d$ additions.

MLP Block with SwiGLU (per layer)

Let d be the model embedding dimension, d_{ff} the hidden (feedforward) dimension, and n the number of tokens in the sequence. The MLP block consists of two parallel up-projections (one gated) and a down-projection, followed by a SwiGLU activation [5].

- **Up-Projections and Gating:** Two parallel linear layers (one for gate, one for activation) each compute:

  $$\text{Multiplications: } n \times d \times d_{\text{ff}}, \quad \text{Additions: } n \times (d-1) \times d_{\text{ff}}$$

  Multiplied by 2 for both paths:

  $$\Rightarrow 2 \times n \times d \times d_{\text{ff}} \text{ multiplications, and } 2 \times n \times (d-1) \times d_{\text{ff}} \text{ additions.}$$

- **SwiGLU Activation:** The gated activation combines SiLU and elementwise multiplication:
  - Each unit requires: 1 exponentiation, 1 division, 2 multiplications, and 1 addition.
  - Total per token: $n \times d_{\text{ff}}$ of each (add, div, exp) and $2 \times n \times d_{\text{ff}}$ multiplications.
- **Down-Projection:** A single linear layer reduces dimensionality:

  $$\text{Multiplications: } n \times d_{\text{ff}} \times d, \quad \text{Additions: } n \times (d_{\text{ff}} - 1) \times d$$

Final Projection to Vocabulary Logits

- **Linear Projection:** $n \times d \times V$ multiplications and $n \times (d-1) \times V$ additions.

LoRA Projections

LoRA replaces a standard linear layer $W \in \mathbb{R}^{d \times d}$ with a low-rank approximation consisting of two smaller matrices:

- A **down-projection** matrix $A \in \mathbb{R}^{r \times d}$ (reducing dimensionality),
- An **up-projection** matrix $B \in \mathbb{R}^{d \times r}$ (projecting back to the original space).

Let:

- n be the number of tokens in the input sequence,

- d be the model's hidden dimension,
- r be the LoRA rank.
- **Down-Projection (Ax):** Projects from $\mathbb{R}^d$ to $\mathbb{R}^r$:
  - Multiplications: $n \times d \times r$
  - Additions: $n \times (d-1) \times r$
- **Up-Projection ($B(Ax)$):** Projects from $\mathbb{R}^r$ back to $\mathbb{R}^d$:
  - Multiplications: $n \times r \times d$
  - Additions: $n \times (r-1) \times d$
- **Scaling and Residual Addition:** The result is scaled (typically by α/r) and added to the original output:
  - Multiplications: $n \times d$
  - Additions: $n \times d$

Total FLOPs for one LoRA adapter:

- **Multiplications:** $2 \times n \times d \times r + n \times d$
- **Additions:** $2 \times n \times d \times r + n \times d$ (approximately)

This total assumes that both the down and up projections are active and used once per token per transformer block.

The total FLOPs are computed as:

$$\text{Total FLOPs} = \sum_{i=1}^{n} (a_i + m_i + d_i + 10e_i + 10s_i) \tag{5}$$

where a_i, m_i, d_i, e_i, and s_i represent the counts of additions, multiplications, divisions, exponentiations, and square roots respectively.

5 LoRA Adaptation and Fine-Tuning Procedure

Low-Rank Adaptation enablea parameter-efficient fine-tuning of the Qwen2.5-0.5B-Instruct model. It is applied to the query (Q) and value (V) projection layers in each transformer block. Specifically, we wrapped each of these layers with a custom LoRALinear module that augments the frozen base projection with a trainable low-rank update.

For each modified projection layer, we introduced two trainable matrices:

- A down-projection matrix $A \in \mathbb{R}^{r \times d}$
- An up-projection matrix $B \in \mathbb{R}^{d \times r}$

The output of a LoRA-adapted linear layer becomes:

$$\text{output} = Wx + \frac{\alpha}{r} BAx \tag{6}$$

where W is the original frozen weight matrix and α is a scaling factor (typically set equal to r) [2].

We fine-tuned only the LoRA parameters (A, B) while keeping the base model parameters frozen. The adapted layers were implemented by replacing `q_proj` and `v_proj` in each transformer block.

Training was performed for 600 steps using default hyperparameters:

- `lora_rank` = 4
- `learning_rate` = 1e-5
- `batch_size` = 4
- `context_length` = 512

We compared the trained model against an untrained baseline (LoRA-enabled but with zero optimisation steps). Both models were evaluated on a held-out validation set of 200 trajectories, using cross-entropy loss as the evaluation metric.

Results

- **Untrained model (LoRA only, 0 steps):** Validation loss = **1.1926**
- **LoRA-trained model (600 steps):** Validation loss = **0.9651**

The performance improvement demonstrates that even a modest number of training steps is sufficient to adapt the model to the domain of Lotka–Volterra trajectories.

6 LoRA Hyperparameter Search

To understand how key hyperparameters affect forecasting performance, we carried out a targeted grid search over:

- **LoRA Rank** $\in \{2, 4, 8\}$
- **Learning Rate** $\in \{10^{-5}, 5 \times 10^{-5}, 10^{-4}\}$

Increasing the LoRA rank introduces more trainable parameters per adapted layer, improving flexibility but increasing FLOP usage. The learning rate controls the speed of adaptation: values that are too high may destabilise training, while those too low may cause underfitting or slow convergence.

Each configuration was trained for 600 optimiser steps and evaluated on a held-out validation set — cross-entropy loss was used as the primary metric to quantify forecasting accuracy in token space. Due to FLOP constraints and clear trends in performance, not all combinations were run: validation loss consistently decreased as we moved to a higher LoRA rank and to a higher learning rate. These trends allowed us to avoid redundant runs while still identifying the most promising setup.

LoRA Rank	LR $= 10^{-4}$	LR $= 5 \times 10^{-5}$	LR $= 10^{-5}$
2	0 steps 0.0000% n/a	600 steps 4.2212% 0.8099	0 steps 0.0000% n/a
4	600 steps 4.22252% 0.6515	600 steps 4.22252% 0.7351	600 steps 4.22252% 0.9651
8	600 steps 4.22516% 0.6162	600 steps 4.22516% 0.6744	0 steps 0.0000% n/a

Table 2: LoRA Hyperparameter Search Results. Each cell contains: training steps (top), percentage of FLOPs used (middle), and validation loss (bottom). Results for LoRA rank=4 and LR=1e-5 were reused from the previous section

As shown in Table 2, the best-performing configuration used LoRA rank 8 and a learning rate of 10^{-4}, achieving a validation loss of 0.6147.

Effect of Context Length on Forecasting Performance

We next explored how the model's performance is influenced by context length—the number of input tokens the model sees at once. Using the same LoRA rank (8) and learning rate (10^{-4}), we trained models using context lengths of {128, 512 (already done), 768}:

Context Length	Validation Loss	Optimiser Steps	FLOPs Used (%)
128	0.7229	600	1.02421
512	0.6147	600	*(from previous section)* 4.22516
768	0.4207	600	6.46607

Table 3: Effect of context length on validation loss using LoRA rank 8 and learning rate 10^{-4}.

As expected, validation loss improves with increasing context length: longer contexts provide the model with more of the input sequence, enabling it to learn temporal patterns — especially important in cyclical systems like the Lotka–Volterra dynamics.

However, this benefit comes at a computational cost. Moving from 128 to 768 tokens increases the proportion of total FLOPs used from approximately 1% to over 6%, with the same number of training steps.

7 Final Model Training and Evaluation

We selected the following hyperparameters for our final model configuration:

- **LoRA Rank:** 8
- **Learning Rate:** 10^{-4}
- **Context Length:** 768

We trained the model for 5,000 steps using this setup, which was approximately 51.90% of the total FLOP budget. Evaluation on a held-out validation set yielded a final loss of 0.2981 and a perplexity of 1.35.

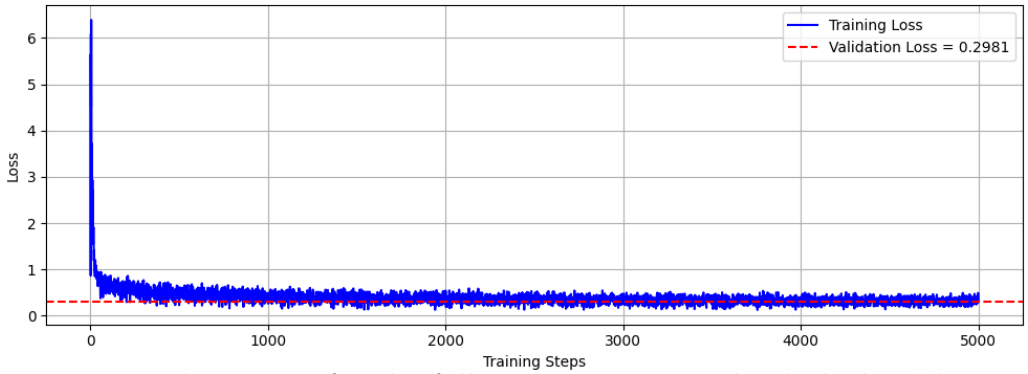


Figure 3: Training loss curve for the full 5,000-step run. The dashed red line indicates final validation loss.

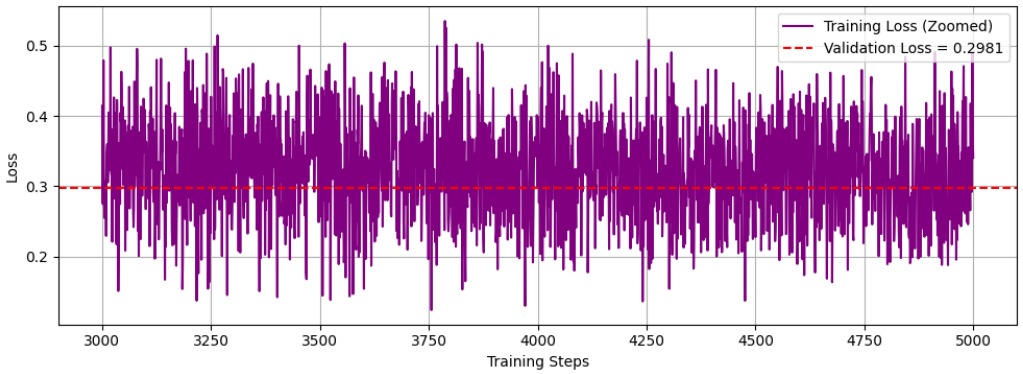


Figure 4: Training loss over the last 2,500 steps.

The validation loss is comparable to the training loss throughout, suggesting that the model generalises well to unseen data and is not overfitting.

Evaluation

To assess forecasting performance, we used the trained model to generate and visualise predictions on Sample ID 972. As shown in Figure 5, the model closely tracks the ground-truth oscillatory behaviour of both prey and predator populations. We also generate predictions for samples 990 - 999 in the test set to compute key evaluation metrics as shown in table 5.

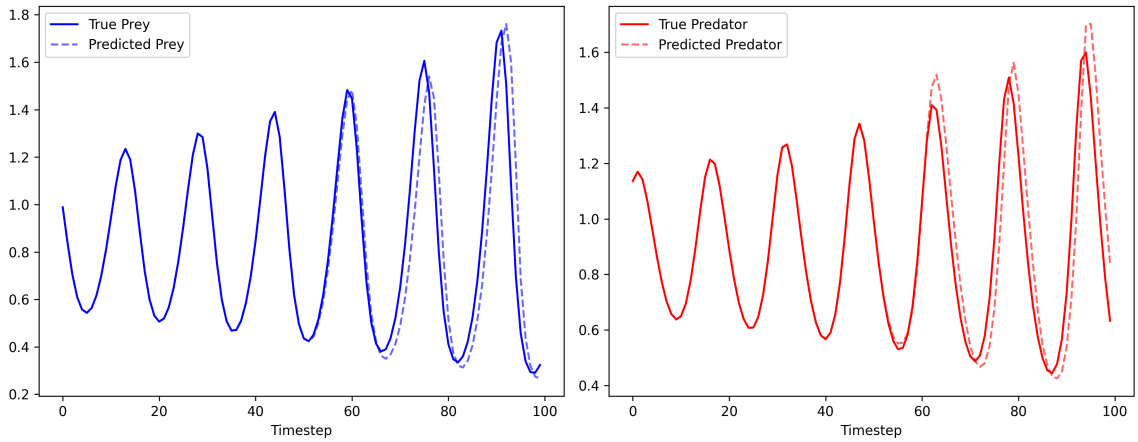


Figure 5: Forecasting results on Sample 972.

Species	MSE	MAE	R^2
Prey	0.0170	0.0671	0.8772
Predator	0.0125	0.0608	0.8600

Table 4: Evaluation metrics for Sample 972

Target	MSE	MAE	R^2
Prey	0.1178	0.1483	0.8155
Predator	0.0250	0.0687	0.7004

Table 5: Average evaluation metrics for samples 990–999.

Our experiments demonstrate that LLMs can be fine-tuned for time-series forecasting with tight FLOP constraints.

The final model (LoRA rank 8, LR=10^{-4}, context length 768) achieved imporved prediction accuracy for sample 972 representing a great improvement over the untrained model, which exhibited negative R^2 values and unstable forecasts.

8 Conclusion

This project demonstrates that large language models can be effectively repurposed for time-series forecasting under stringent compute constraints when enhanced with parameter-efficient techniques like Low-Rank Adaptation (LoRA). By integrating the LLMTIME preprocessing framework, adopting a FLOP-aware design, and performing systematic hyperparameter tuning, we successfully adapted Qwen2.5-Instruct to model predator-prey dynamics as described by the Lotka–Volterra equations. Our results indicate that increasing the LoRA rank incurs only a marginal increase in FLOP usage compared to full fine-tuning—an overhead that is more than compensated for by the significant improvements in forecasting accuracy. In particular, our final configuration—with a LoRA rank of 8, a learning rate of 10^{-4}, and a context length of 768—achieved robust predictive performance while operating well within the 10^{17} FLOP budget.

Our work also revealed several important considerations. Due to the sampling-based nature of autoregressive decoding, the model produces varying outputs across runs, showing the need to account for non-determinism in evaluations. Our hyperparameter search

suggests that we were operating near the edge of optimal performance; validation loss consistently improved with higher LoRA ranks, larger learning rates, and longer context lengths. Future experiments should therefore extend the search space beyond a rank of 8 and learning rates above 10^{-4}, as well as explore the model's architectural limits in terms of context length.

Additionally, our current implementation does not incorporate dynamic inference strategies such as early exit or adaptive computation (e.g., SkipDecode [8]), which could further reduce computational costs by terminating the forward pass when sufficient confidence is reached. We recommend that future work explores these techniques, and perhaps more tailored loss functions—such as sequence-level objectives that better capture forecasting accuracy. Hybrid architectures that integrate transformers with classical dynamical systems or recurrent elements could also further enhance performance and interpretability.

Overall, this project presents a promising approach to leveraging large language models for structured prediction tasks under strict compute limitations by employing Low-Rank Adaptation.

Experiment	**Training Steps**	**Total FLOPs**	**% Budget Used**
2b - Untrained Qwen model	0	2.85×10^{14}	0.285%
3a - Trained LoRA (r=4, LR=1e-5, Context=512)	600	4.22×10^{15}	4.22%
3a - Untrained LoRA (r=4, LR=1e-5, Context=512)	0	1.69×10^{14}	0.169%
3b - LoRA=2, LR=1e-5, Context=512	n/a	–	–
3b - LoRA=2, LR=5e-5, Context=512	600	4.22×10^{15}	4.22%
3b - LoRA=2, LR=1e-4, Context=512	n/a	–	–
3b - LoRA=4, LR=1e-5, Context=512	same as 3a	same as 3a	same as 3a
3b - LoRA=4, LR=5e-5, Context=512	600	4.22×10^{15}	4.22%
3b - LoRA=4, LR=1e-4, Context=512	600	4.22×10^{15}	4.22%
3b - LoRA=8, LR=1e-5, Context=512	n/a	–	–
3b - LoRA=8, LR=5e-5, Context=512	600	4.23×10^{15}	4.23%
3b - LoRA=8, LR=1e-4, Context=512	600	4.23×10^{15}	4.23%
3b - LoRA=8, LR=1e-4, Context=128	600	1.02×10^{15}	1.02%
3b - LoRA=8, LR=1e-4, Context=768	600	6.47×10^{15}	6.47%
Sum of pre-main model experiments	–	3.33×10^{16}	**33.28%**
Total FLOPs available	–	6.67×10^{16}	**66.72%**
3c - Final model	5000	5.17×10^{16}	51.90%
3c - Model evaluation	–	3.14×10^{15}	3.14%
Total FLOPs Used	–	8.83×10^{16}	**88.32%**
Remaining FLOPs	–	1.17×10^{16}	**11.68%**

Table 6: Summary of total FLOP usage across all experiments.

References

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Declaration of Use of AI Tools

I declare that all ideas, methods, and approaches used in this project were conceived and developed independently through my own research, understanding and engagement with lecture and supervision material. The work presented here is entirely my own.

The following AI tools were used for support purposes:

- **ChatGPT:** Used to refine code snippets, assist with LaTeX formatting, and improve the clarity and structure. All content generated by this tool was critically evaluated and adapted.
- **GitHub Copilot:** Used to suggest coding snippets and assist the implementation of functions. All suggested code was reviewed, modified, and tested.