FilinGPT: A Byte-Level Financial Language Model

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Abstract

This document presents *FilinGPT*, a byte-level autoregressive language model trained on financial 10-K filings. The system was implemented from scratch using NumPy, including training, inference, dataset pipeline, and evaluation tools.

Two training configurations are compared: a short baseline (200 steps) and a full financial checkpoint (100,000 steps). Quantitative and qualitative evaluations demonstrate substantial convergence and language structure acquisition.

1 Introduction

FilinGPT is a minimal autoregressive language model designed to:

- Operate at byte-level (vocabulary size = 258),
- Learn financial language patterns from 10-K filings,
- Provide reproducible training and evaluation pipelines,
- Demonstrate measurable convergence using perplexity.

The project emphasizes transparency and explicit implementation rather than reliance on high-level deep learning frameworks.

2 Model Architecture

The model is a simple multi-layer perceptron (MLP) trained for next-token prediction.

Given a context window of length $L = 16$, the model predicts the probability distribution over the next byte.

2.1 Input Representation

Each input token is represented as a one-hot vector:

$$x_t \in \mathbb{R}^V$$

where $V = 258$ is the vocabulary size.

The context window is flattened:

$$X \in \mathbb{R}^{L \cdot V}$$

2.2 Forward Pass

The model computes:

$$h = \sigma(W_1 X + b_1)$$

$$z = W_2 h + b_2$$

$$\hat{y} = \mathrm{softmax}(z)$$

where σ is a non-linear activation function.

3 Training Objective

The model is trained using cross-entropy loss:

$$\mathcal{L} = -\sum_{i=1}^{V} y_i \log(\hat{y}_i) \tag{1}$$

Perplexity is defined as:

$$\mathrm{PPL} = \exp(\mathcal{L}) \tag{2}$$

Perplexity measures how well the model predicts the next token.

4 Dataset Pipeline

The training data is built from SEC 10-K filings:

- Bronze: raw filings
- Silver: cleaned full documents
- Gold: extracted Management Discussion and Analysis (MDA)

Pipeline steps:

1. Extract MDA sections
2. Chunk documents
3. Byte-level tokenization
4. Batch construction

Dataset statistics:

- Vocabulary size: 258
- Context length: 16
- Sequence length: 256
- Total sequences: 609

5 Training Configurations

5.1 Baseline (200 Steps)

- Steps: 200
- Learning rate: 0.01
- Final loss: 5.3182
- Final perplexity: 204.02

5.2 Financial Checkpoint (100k Steps)

- Steps: 100,000
- Learning rate: 0.02
- Final loss: 0.8071
- Final perplexity: 2.24

Perplexity reduction:

$$99.13\% \text{ reduction}$$

6 Quantitative Results

6.1 Perplexity (Full Training)

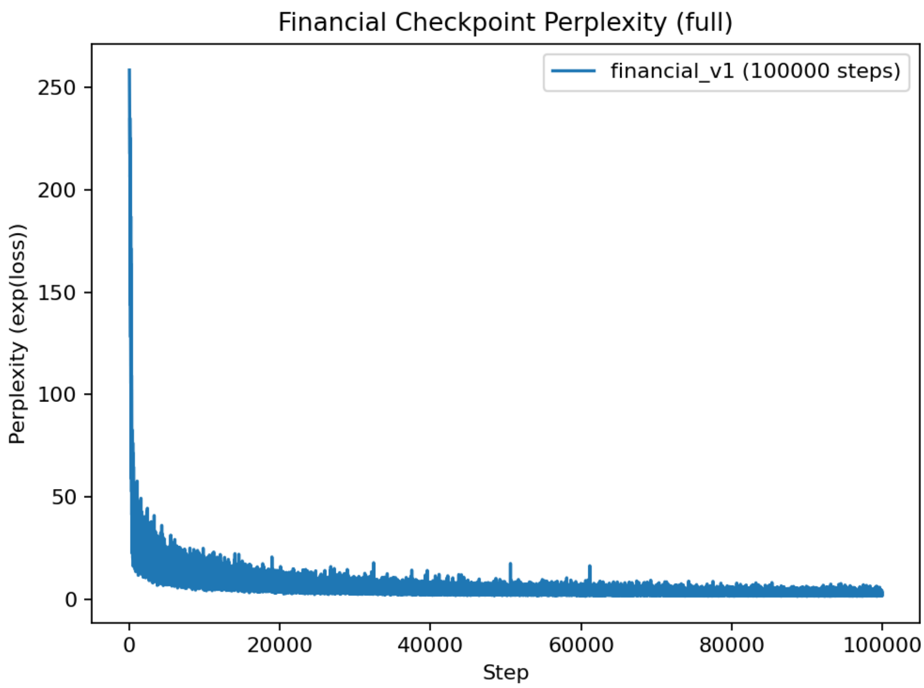


Figure 1: Perplexity evolution during full 100k-step training.

6.2 Loss Comparison (Log Scale)

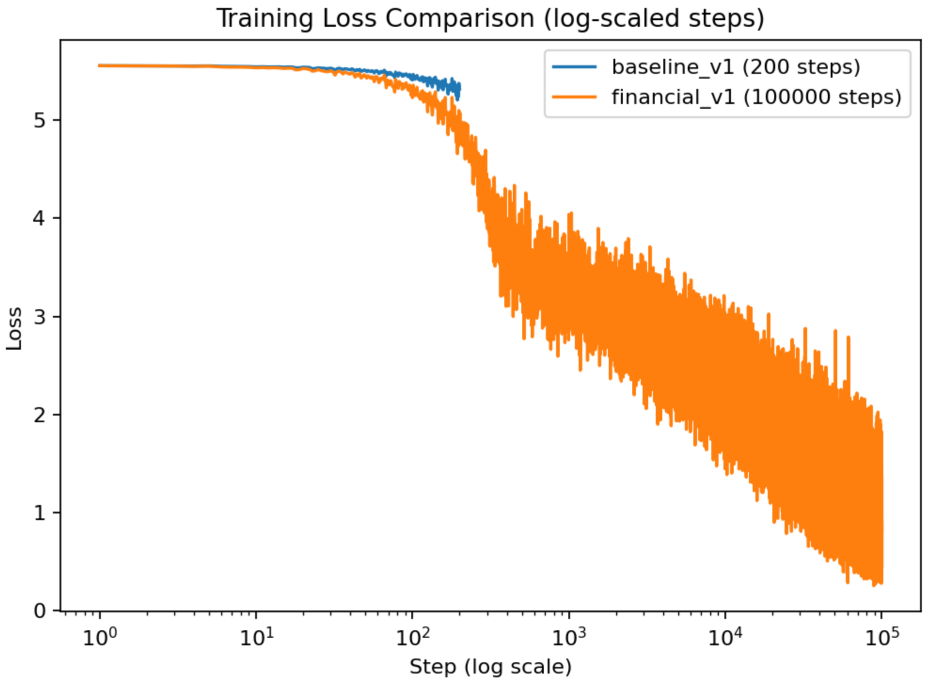


Figure 2: Loss comparison with log-scaled steps.

6.3 Perplexity Comparison (First 200 Steps)

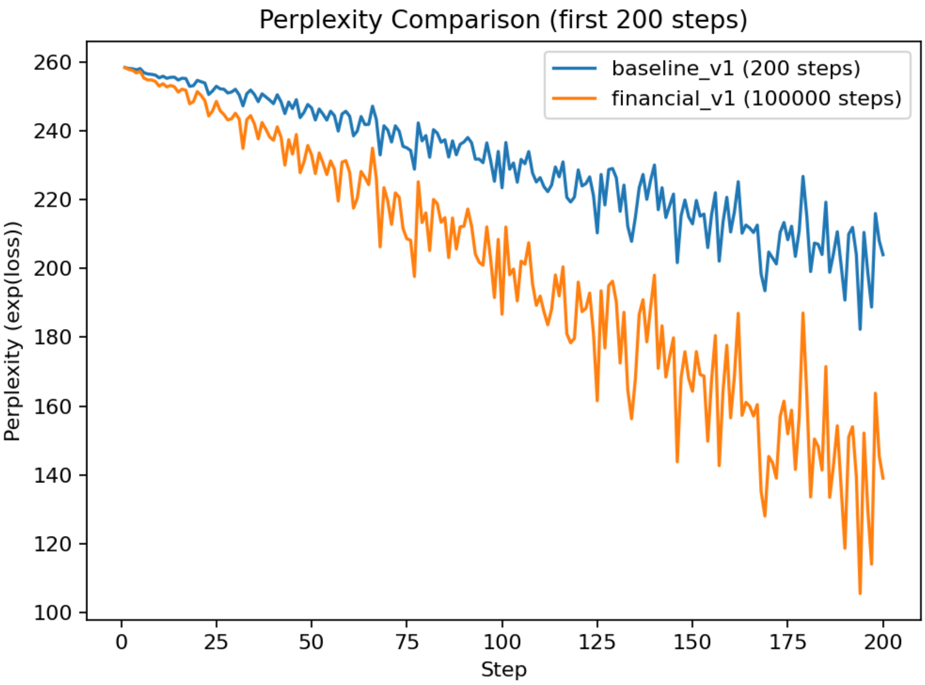


Figure 3: Perplexity comparison during first 200 steps.

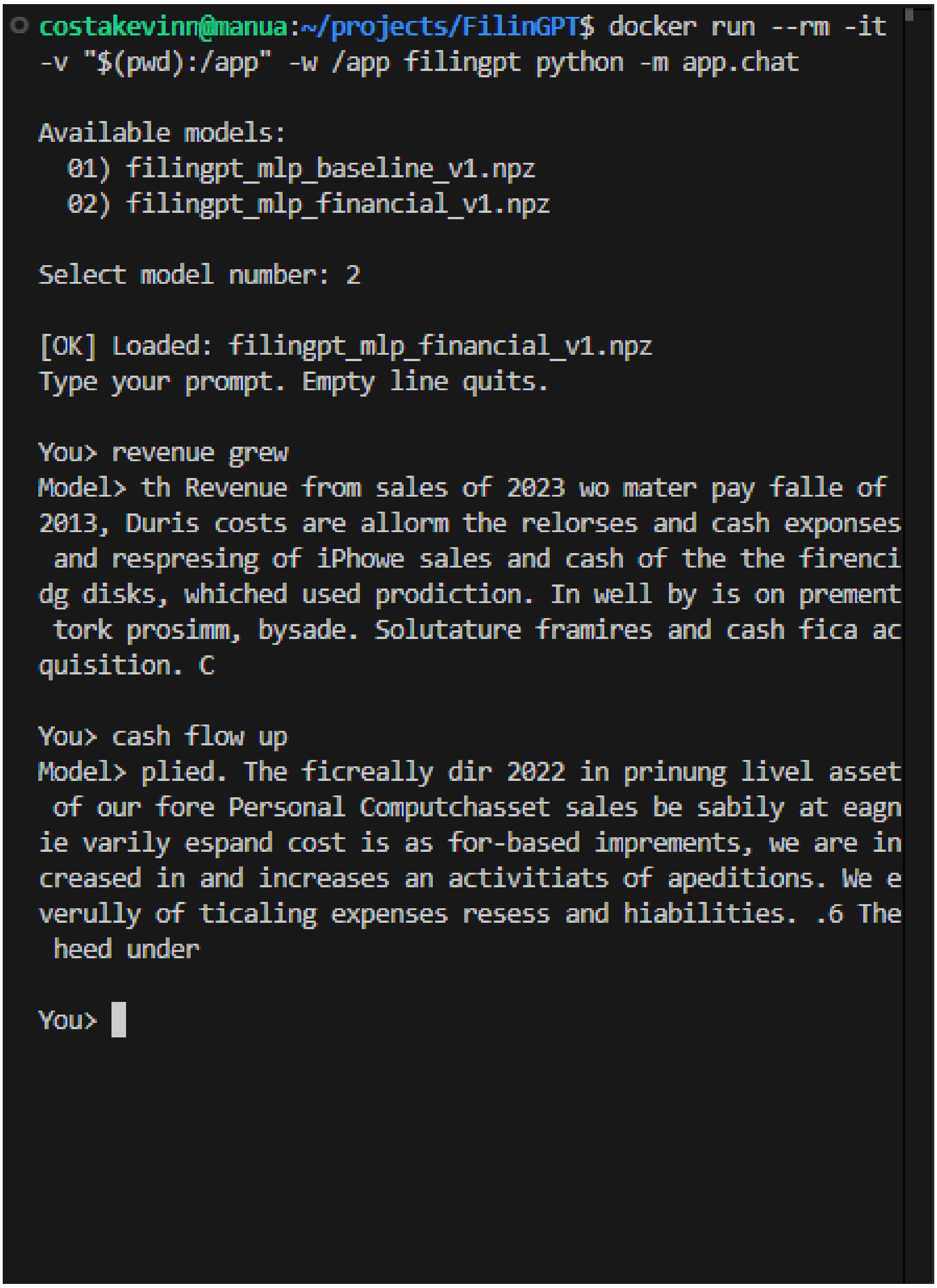
7 Qualitative Evaluation

7.1 Baseline Output

Figure 4: Baseline model output after 200 steps.

The baseline model produces mostly incoherent byte-level noise.

7.2 Financial Model Output



```
costakevinn@manua:~/projects/FilinGPT$ docker run --rm -it
-v "$(pwd):/app" -w /app filingpt python -m app.chat

Available models:
  01) filingpt_mlp_baseline_v1.npz
  02) filingpt_mlp_financial_v1.npz

Select model number: 2

[OK] Loaded: filingpt_mlp_financial_v1.npz
Type your prompt. Empty line quits.

You> revenue grew
Model> th Revenue from sales of 2023 wo mater pay falle of
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Figure 5: Financial checkpoint output after 100k steps.

The financial model produces structured English text with recognizable financial terminology, showing learned statistical patterns.

8 Discussion

The comparison between baseline and full training highlights:

- Stable convergence of cross-entropy loss,
- Massive perplexity reduction (258 $\rightarrow$ 2.24),
- Emergence of structured financial language,
- Clear qualitative improvement in generation.

Despite its simplicity, the model demonstrates that even small MLP architectures can capture structured domain-specific language when trained sufficiently.

9 Conclusion

FilinGPT demonstrates:

- End-to-end language model training from scratch,
- Byte-level autoregressive modeling,
- Reproducible data and training pipelines,
- Quantitative evaluation using perplexity,
- Observable emergence of domain language structure.

This project serves as a foundational implementation of language modeling principles applied to financial documents.