Prioritizing Financially Informative Comments via Group Relative Policy Optimization

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Abstract

We propose a reinforcement learning (RL) framework for ranking and prioritizing social media comments to inform algorithmic trading decisions. Focusing on Twitter, a high-frequency platform for market discourse, we introduce a market-aligned reward signal that directly links comment relevance to real-world financial outcomes—bypassing shallow engagement metrics such as likes or retweets. To address the challenges of sparse and delayed feedback, we adopt Group Relative Policy Optimization (GRPO), a sample-efficient RL method that eliminates the need for a critic network. Our approach enables efficient, real-time extraction of actionable financial insights from social data streams. We validate the method through theoretical analysis and outline future directions in multi-modal and cross-platform signal integration.

1 Introduction

In the era of data-driven finance, extracting actionable insights from vast streams of unstructured information has become increasingly critical for the success of quantitative and algorithmic trading strategies. Social media has emerged as a high-frequency, information-rich platform for market discourse among the diverse sources of alternative data. Notably, Key Opinion Leaders (KOLs)—including prominent traders, project founders, and financial influencers—frequently share time-sensitive insights that may precede significant asset price movements (Bollen et al., 2011; Zhang et al., 2021; Xiao and Chen, 2018).

However, leveraging this data presents unique challenges. While large language models (LLMs) have succeeded in modeling structured financial texts (e.g., earnings calls or analyst reports) (Chen et al., 2023), their application to social media remains limited due to inherent noise and sparse reliable signals. A fundamental challenge lies in distinguishing predictive insights—such as KOLs' informed commentary—from superficial content like hype, misinformation, or irrelevant chatter. Traditional engagement metrics (e.g., likes, retweets) further compound this problem by prioritizing popularity over financial substance (Sharma et al., 2021).

Among social platforms, Twitter is uniquely suited for financial analysis due to its high user engagement, structured metadata (timestamps, mentions), and dominance in cryptocurrency and retail trading discussions. Twitter offers time-aligned data compatible with real-time modeling. Yet, its content is notoriously noisy, plagued by bots, sarcasm, and misinformation (Galletta et al., 2021; Zhang et al., 2021). Additionally, the indirect and delayed relationship between language signals and market outcomes adds another layer of complexity to predictive tasks.

To bridge these gaps, we integrates delayed financial feedback into training signals and employs the GRPO algorithm to model inter-social-media correlations, aligning social media analysis with real-world financial trading signals. The framework directly optimizes for long-term financial relevance objectives, enabling real-time extraction of market insights from noisy text streams and efficient derivation of actionable insights. The main contributions are summarized below.

Market-grounded reward signal. To achieve learning aligned with real economic behavior, we introduce a novel reward function design paradigm that directly links comment value to subsequent financial market performance.

Efficient optimization with GRPO. We highlight that GRPO relies on relative superiority among groups as the optimization signal during training. This characteristic aligns with the adversarial nature of social media's influence on financial markets.

2 Methodology

Our framework combines supervised fine-tuning (SFT) and reinforcement learning (RL) to prioritize social media comments based on their alignment with real-world financial signals. We first fine-tune a base language model using structured examples in the financial domain to enhance reasoning capabilities. Subsequently, we refine the policy using Group Relative Policy Optimization (GRPO), with a dual reward function designed to optimize both response formatting and predictive accuracy with respect to market trends.

Figure 1 illustrates the overall architecture of our proposed framework, which integrates supervised fine-tuning (SFT) and reinforcement learning (RL) for market-aligned comment ranking. The model takes as input both social media tweet data and on-chain price data. During the SFT stage, the model is trained to generate structured outputs of the form `<think>...</think>` and `<answer>...</answer>` to capture domain-specific reasoning.

The RL stage refines this base using a dual reward mechanism. A **format reward** R_{fmt} encourages syntactic adherence to the required output template, while a **financial reward** $R_{\text{fin}}(\hat{s}, s^*)$ measures directional prediction accuracy relative to future token price changes.

To address the sparse and delayed nature of reward signals, we adopt **Group Relative Policy Optimization (GRPO)**. As shown in the right portion of the figure, GRPO estimates group-relative advantage values a_i by standardizing reward deviations within each candidate set. The policy update is guided by the clipped importance ratio $r_i(\theta)$ and penalized by a KL-divergence term to maintain stability.

This architecture enables the system to prioritize social media content that is both well-structured and financially predictive, improving signal extraction for downstream trading tasks.

2.1 Supervised Fine-Tuning (SFT)

During the SFT stage, the model is trained on a curated dataset constructed from blockchain-related prompts and social media content. Each training sample $v \in \mathcal{V}$ is represented as a triplet:

$$v = (x,\, c,\, y^*),$$

where x is the input (e.g., a KOL tweet), c is the chain-of-thought rationale formatted as `<think>...</think>`, and y^* is the final prediction enclosed in `<answer>...</answer>`. The model is optimized to jointly generate c and y^*, minimizing a supervised loss $\mathcal{L}_{\text{SFT}}$ that penalizes both content inaccuracy and formatting errors:

$$\mathcal{L}_{\text{SFT}} = \mathbb{E}_{v\sim\mathcal{V}}\left[\text{CE}(c,\, \hat{c}) + \text{CE}(y^*,\, \hat{y})\right],$$

where CE denotes cross-entropy loss between reference and generated sequences. This procedure instills the model with domain-specific reasoning patterns.

To construct high-quality SFT data, we extract prompt templates from blockchain expert rules and generate corresponding outputs using multiple autonomous LLM agents. The outputs are filtered for consistency and informativeness, then uniformly formatted and used to fine-tune the Qwen3-7B-Instruct(Yang et al., 2025) model, enhancing token-level financial understanding.

2.2 Reinforcement Learning via GRPO

To further optimize the model under a delayed-feedback setting, we employ Group Relative Policy Optimization (GRPO), a policy gradient method that improves upon PPO by eliminating the need for a critic network and introducing group-wise advantage estimation.

We design a composite reward signal that encourages well-structured responses and market-aware predictions.

Format Reward The format reward ensures that model outputs strictly follow the template:

```
<think> ... </think>
<answer> ... </answer>
```

Let y be a generated response. The format reward is:

$$R_{\text{fmt}}(y) = \begin{cases} 1, & \text{if } y \text{ contains template pair,} \\ 0, & \text{otherwise.} \end{cases}$$

Financial Reward To assess the correctness of the model's market prediction, we define a directional financial reward. Let P_t denote the asset price at prediction time and P_{t+1} the price after a fixed horizon. Let:

$$s^* = \text{sign}(P_{t+1} - P_t) \in \{-1, +1\}$$

where, $\hat{s} \in \{-1, +1\}$ be the model's predicted direction. The financial reward is:

$$R_{\text{fin}}(\hat{s}, s^*) = \begin{cases} 1, & \hat{s} = s^*, \\ 0, & \text{otherwise.} \end{cases}$$

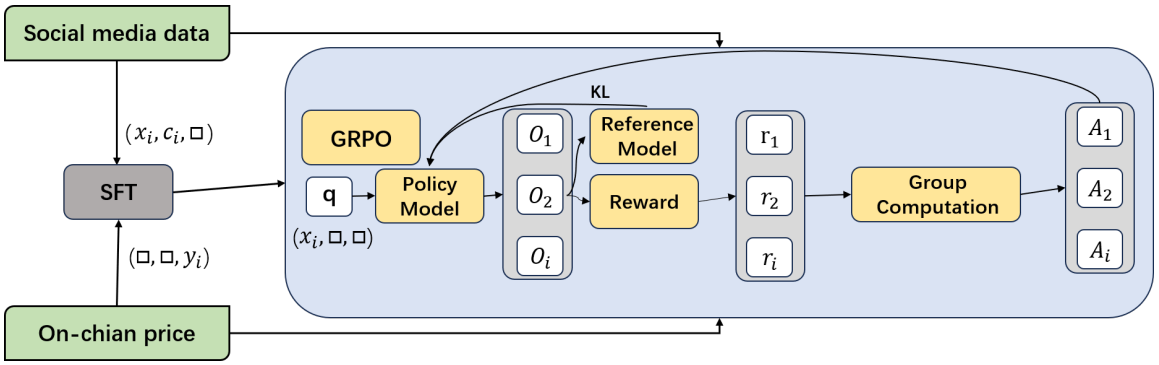

Figure 1: Overview of our proposed reinforcement learning framework for comment ranking with market-aligned reward design. The framework integrates supervised fine-tuning (SFT) using structured social media inputs (x_i, c_i, y), and reinforcement learning via Group Relative Policy Optimization (GRPO). The RL model receives rewards from two channels: a format reward R_{fmt} enforcing template adherence, and a financial reward $R_{\text{fin}}(\hat{s}, s^*)$ based on directional accuracy in token price movement. GRPO refines the policy using group-wise advantage a_i, importance ratio $r_i(\theta)$, and a clipped surrogate objective. This end-to-end design enables efficient optimization of market-relevant language responses.

Total Reward The final reward combines both components:

$$R(o) = \alpha \cdot R_{\text{fmt}}(o) + \gamma \cdot R_{\text{fin}}(o),$$

where α and γ are weighting hyperparameters.

This reward structure encourages the model to produce syntactically correct and financially meaningful responses under conditions of delayed and noisy feedback.

3 Experiment and Results

We evaluate our reinforcement learning framework for comment ranking through a comprehensive set of experiments designed to answer the following questions: (1) How effective is the proposed GRPO-based method in identifying market-relevant insights? (2) How does the design of delayed market-grounded rewards affect learning? (3) Can the system operate efficiently under large-scale social media input?

3.1 Experimental Setup

We construct a dataset of tweets and associated comments from high-impact Twitter KOLs in the crypto/finance domains. Each data instance includes the tweet content, KOL metadata (follower count, engagement), and a comment set with sentiment labels. To compute reward labels, we collect token price data from on-chain sources for the 48 hours following tweet publication. Each comment is then labeled by its alignment with observed market movement, creating a delayed, market-grounded reward signal.

We compared our method against three baseline approaches: engagement-based ranking (which sorts comments by likes/retweets), sentiment-based ranking (prioritizing highly emotional content), and random ranking (as a non-informative reference). Evaluation metrics included market alignment accuracy (measuring how well top-ranked comments matched actual market trends), comment relevance (rated by human annotators on a 0–1 scale), and computational efficiency (total time in seconds required to rank all comments for a batch of tweets).

3.2 Handling Delayed Feedback

To address the delayed nature of price-based rewards, we use offline RL techniques such as experience replay and batch updates. Our experiments show that GRPO's ability to optimize over groups of candidates significantly improves credit assignment in this delayed feedback regime.

3.3 Hyperparameter Tuning

We perform a grid search over key hyperparameters: learning rate, discount factor γ, and reward weights α, β. The best configuration was found to be $\gamma = 0.95$, $\alpha = 0.3$, and $\beta = 0.7$.

Table 3: Hyperparameter Tuning Results (Fixed $\alpha = 0.3$)

γ	β	Acc (%)	Relative Change
0.90	0.5	71.3	-3.5
0.95	**0.7**	**74.8**	—
0.95	0.9	72.1	-2.7

Table 1: Performance Comparison

Model	Market Acc. (%)	Relevance (Human)	Time (s)
Random Ranking	49.3	0.52	**1.2**
Engagement Heuristic	55.6	0.57	1.9
Sentiment Ranking	61.2	0.62	2.0
Ours (GRPO-RL)	**74.8**	**0.75**	2.4

Table 2: Impact of Experience Replay on Market Alignment Accuracy

Replay Strategy	Market Acc. (%)
With Experience Replay	**74.8**
Without Replay	65.1

Observation: GRPO is robust to moderate hyperparameter variations (±0.05), with less than 3% drop in accuracy across tested configurations.

3.4 Experimental Validation and Ablation

We validated the effectiveness of each core component in our framework: removing the format reward led to a 4.8% accuracy drop, while eliminating the financial reward caused a more significant 10.3% decline. Under the same data and reward settings, the PPO algorithm achieved 67.4% accuracy, A2C reached 65.1%, and GRPO performed best at 74.8%. Additionally, when the KL regularization coefficient (β) exceeded 1.0, it suppressed policy exploration, with experiments showing β=0.7 achieved the optimal balance.

Table 4: RL Algorithm Comparison

Algorithm	Market Acc. (%)	Runtime (s)
A2C	65.1	2.6
PPO	67.4	2.7
Ours (GRPO)	**74.8**	**2.4**

3.5 Open-Ended Analysis

In addition to directional prediction, we evaluate the model's ability to generate coherent and insightful free-form responses through open-ended reasoning prompts. Specifically, we randomly sampled 100 test-time generations where the model was asked to explain its token recommendation (e.g., buy/sell/hold) in natural language.

4 Conclusion

We presented a reinforcement learning framework for comment ranking that leverages delayed market feedback to prioritize valuable insights from social media, particularly Twitter. By incorporating a market-aligned reward function and employing Group Relative Policy Optimization (GRPO), our model effectively filters noise and identifies content that correlates with real-world financial outcomes. Additionally, the two-phase filtering strategy improves scalability without compromising performance, and our open-ended analysis shows that the model produces coherent, interpretable reasoning beyond directional predictions. Through comprehensive experiments, we demonstrated that our approach outperforms heuristic baselines and traditional RL algorithms in both market alignment and comment relevance. Ablation studies further confirm the importance of each component, including experience replay and reward shaping. Our method highlights the potential of reinforcement learning in aligning language generation with downstream real-world impact. In future work, we plan to explore explainability techniques and human-in-the-loop training to further bridge the gap between AI-driven analysis and trader trust.

Limitations

Despite its promising performance, our study has several limitations. First, the reliance on on-chain token price movements as the sole financial reward signal may overlook important off-chain market dynamics and macroeconomic factors, potentially biasing the model's notion of "informativeness." Second, our dataset focuses exclusively on comments responding to tweets from a selected group of crypto-finance KOLs, which may limit generalization to other financial domains, social platforms, or less prominent users. Third, the binary directional reward and simple format reward do not capture gradations in comment quality or the magnitude of market impact, restricting the gran-

ularity of learning. Finally, GRPO's offline training regime may struggle with concept drift in live social streams, and real-time deployment would require additional mechanisms for continuous adaptation and anomaly detection.

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