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Janus-Q: End-to-End Event-Driven Trading via Hierarchical-Gated Reward Modeling

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Financial market movements are often driven by discrete financial events conveyed through news, whose impacts are heterogeneous, abrupt, and difficult to capture under purely numerical prediction objectives. These limitations have motivated growing interest in using textual information as the primary source of trading signals in learning-based systems. Two key challenges hinder existing approaches: (1) the absence of large-scale, event-centric datasets that jointly model news semantics and statistically grounded market reactions, and (2) the misalignment between language model reasoning and financially valid trading behavior under dynamic market conditions. To address these challenges, we propose Janus-Q, an end-to-end event-driven trading framework that elevates financial news events from

auxiliary signals to primary decision units. Janus-Q unifies event-centric data construction and model optimization under a two-stage paradigm. Stage I focuses on event-centric data construction, building a large-scale financial news event dataset comprising 62,400 articles annotated with 10 fine-grained event types, associated stocks, sentiment labels, and event-driven cumulative abnormal return (CAR). Stage II performs decision-oriented fine-tuning, combining supervised learning with reinforcement learning guided by a Hierarchical Gated Reward Model (HGRM), which explicitly captures trade-offs among multiple trading objectives. Extensive experiments demonstrate that Janus-Q achieves more consistent, interpretable, and profitable trading decisions than market indices and LLM baselines, improving the Sharpe Ratio by up to 102.0% while increasing direction accuracy by over 17.5% compared to the strongest competing strategies.

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