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Selective State Propagation for Real-Time Crypto Asset Forecasting with Subquadratic Attention Alternatives

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Abstract

Cryptocurrency markets present unique challenges for real-time forecasting due to their high volatility, continuous trading cycles, and sensitivity to external information flows. Traditional attention-based models, while effective in capturing long-range dependencies, suffer from quadratic computational complexity that hinders real-time deployment. This paper introduces a novel selective state propagation mechanism combined with subquadratic attention alternatives for efficient crypto asset price forecasting. Our approach leverages state space models (SSM) with selective gating to dynamically filter relevant historical information while maintaining computational efficiency. The proposed architecture achieves O(N log N) complexity compared to $O(N^2)$ in standard transformers, enabling microsecond-level inference suitable for high-frequency trading environments. We evaluate our method on five major cryptocurrencies over 24 months, demonstrating 18.3% improvement in mean absolute percentage error (MAPE) and 23.7% reduction in inference latency compared to transformer baselines. The selective propagation mechanism shows particular strength in volatile market conditions, accurately capturing regime shifts and flash crash patterns. Our findings suggest that computational efficiency and predictive accuracy need not be mutually exclusive in financial forecasting applications, opening pathways for deploying sophisticated models in latency-critical trading systems.

Keywords

cryptocurrency forecasting, selective state propagation, subquadratic attention, state space models, real-time prediction, computational efficiency, volatility modeling

1. Introduction

The cryptocurrency market has evolved into a trillion-dollar asset class characterized by unprecedented volatility, 24/7 trading cycles, and complex interdependencies across thousands of digital assets [1]. Unlike traditional financial markets with established trading hours and regulatory frameworks, crypto markets operate continuously across global exchanges, generating massive volumes of high-frequency data that demand sophisticated forecasting systems. The ability to accurately predict price movements in microsecond timeframes has become crucial for algorithmic trading, risk management, and portfolio optimization strategies [2].Recent advances in deep learning have revolutionized financial forecasting, with attention-based architectures demonstrating remarkable capabilities in modeling long-range temporal dependencies [3]. Transformer models have achieved state-of-the-art performance across various sequence modeling tasks, including stock price prediction and market trend analysis [4]. However, their quadratic computational complexity with respect to sequence length poses fundamental limitations for real-time applications where inference latency directly impacts trading profitability. In high-frequency crypto trading, even millisecond delays can result in substantial financial losses, necessitating models that balance

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predictive accuracy with computational efficiency [5].Traditional recurrent neural networks (RNN) offer linear computational complexity but struggle with long-term dependency modeling due to vanishing gradient problems [6]. While Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) partially address these issues through sophisticated gating mechanisms, they remain inherently sequential and difficult to parallelize. LSTM networks introduced a pivotal innovation in sequence modeling by implementing memory cells with three types of gates: forget gates, input gates, and output gates. These gating mechanisms enable the network to selectively retain or discard information across long sequences, providing a foundation for understanding how temporal dependencies can be managed efficiently. Recent theoretical work on state space models has revealed promising alternatives that achieve both long-range modeling capabilities and computational efficiency through clever parameterization and parallel scanning algorithms [7].The emergence of structured state space sequence models has sparked renewed interest in recurrence-based architectures that combine the best of both worlds [8]. Models like S4 and its variants have demonstrated competitive performance with transformers while maintaining subquadratic complexity through specialized parameterization schemes. However, their application to financial forecasting remains underexplored, particularly in addressing the unique challenges of cryptocurrency markets where information relevance changes rapidly and historical patterns may become obsolete within hours [9].This paper introduces a selective state propagation mechanism specifically designed for crypto asset forecasting that addresses three critical challenges. First, we develop a gating mechanism that dynamically determines which historical information should influence future predictions based on current market conditions. This selectivity enables the model to ignore irrelevant historical patterns during regime changes while maintaining sensitivity to persistent trends. Second, we integrate subquadratic attention alternatives that provide global context awareness without the computational burden of full attention matrices. Our hybrid architecture combines the strengths of state space models for efficient temporal processing with sparse attention patterns for capturing long-range dependencies [10].Third, we design specialized components for handling the unique statistical properties of cryptocurrency returns, including heavy-tailed distributions, volatility clustering, and asymmetric responses to positive versus negative shocks. Traditional forecasting models often assume Gaussian error distributions, which fail to capture the extreme price movements characteristic of crypto markets. Our selective propagation mechanism incorporates learnable volatility embeddings that modulate state updates based on current market uncertainty levels [11].The contributions of this research extend beyond algorithmic innovations to practical deployment considerations for real-time trading systems. We conduct extensive ablation studies to understand the trade-offs between model capacity, inference speed, and predictive accuracy across different market conditions. Our experiments span multiple time horizons from minute-level to daily predictions, revealing that optimal architectural choices vary with prediction granularity. We also investigate the model's behavior during extreme market events, including flash crashes and coordinated pump-and-dump schemes that plague cryptocurrency markets [12].

2. Literature Review

Financial time series forecasting has evolved dramatically over the past decade, transitioning from classical statistical methods to sophisticated deep learning architectures. Early approaches relied on autoregressive integrated moving average (ARIMA) models and exponential smoothing techniques, which assume linear relationships and stationary distributions [13]. While computationally efficient, these methods struggle to capture the nonlinear dynamics and regime-switching behavior prevalent in cryptocurrency markets. The

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introduction of machine learning techniques, particularly support vector machines and random forests, provided improved flexibility in modeling complex patterns but lacked the capacity to effectively handle sequential dependencies inherent in financial time series [14].The deep learning revolution in financial forecasting began with the application of recurrent neural networks to stock price prediction tasks. LSTM networks introduced gating mechanisms that allowed models to selectively retain or forget information across long sequences, addressing the vanishing gradient problem that plagued vanilla RNNs [15]. The architecture's success stems from its memory cell design, which maintains long-term dependencies through carefully controlled information flow. Subsequent work demonstrated that stacked LSTM architectures could capture hierarchical temporal patterns, with lower layers learning short-term fluctuations and higher layers modeling longer-term trends. GRU variants simplified the gating structure while maintaining comparable performance, becoming popular choices for resource-constrained deployment scenarios [16].The cryptocurrency forecasting literature has extensively explored LSTM-based approaches, with researchers investigating various architectural modifications to handle market-specific characteristics. Studies have incorporated external features such as social media sentiment, blockchain transaction volumes, and macroeconomic indicators to enhance predictive accuracy [17]. Attention mechanisms were introduced to allow models to focus on relevant historical time steps, with self-attention showing particular promise in identifying recurring patterns across multiple time scales. However, these improvements came at the cost of increased computational requirements, limiting their applicability to real-time trading systems [18].The transformer architecture fundamentally changed sequence modeling by replacing recurrence with pure attention mechanisms, enabling parallel processing of entire sequences. In financial applications, transformers demonstrated superior performance on long-horizon forecasting tasks by capturing dependencies spanning hundreds of time steps [19]. Temporal fusion transformers combined multi-horizon forecasting with interpretable attention patterns, providing both accuracy improvements and insight into model decision-making processes. The scaled dot-product attention mechanism at the heart of transformers computes attention weights by measuring the compatibility between queries and keys, allowing the model to dynamically focus on relevant portions of the input sequence. Despite these advantages, the quadratic complexity of self-attention with respect to sequence length remained a critical bottleneck for high-frequency applications [20].Recent research has explored various approaches to reduce transformer computational complexity while preserving modeling capabilities. Sparse attention patterns, such as local windows and strided attention, reduce the number of pairwise interactions from $O(N^2)$ to $O(N\sqrt{N})$ or $O(N \log N)$ depending on the sparsity pattern [21]. Linformer and Performer introduced low-rank approximations and kernel-based methods to achieve linear complexity, though at the cost of potentially losing important long-range dependencies. These efficiency-focused architectures have shown promise in natural language processing but their effectiveness for financial forecasting remains under investigation [22].State space models represent an alternative paradigm for sequence modeling that bridges continuous-time dynamical systems with discrete-time observations and have recently been shown to achieve linear-complexity forecasting performance in cryptocurrency volatility modeling [23]. The S4 architecture parameterizes state space models using structured matrices, achieving both computational efficiency through parallel scans and strong performance on long-range dependency benchmarks. Subsequent variants introduced diagonal parameterizations and learned discretization schemes that further improved training stability and inference speed. The mathematical foundations of SSMs provide theoretical guarantees about their ability to capture exponentially long dependencies, making them attractive for modeling financial time series where patterns may persist across extended periods [24].The application of SSMs to

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financial forecasting represents an emerging research direction with limited prior work. Preliminary studies have demonstrated that structured state space layers can effectively model volatility dynamics and capture regime-switching behavior in equity markets [25]. The continuous-time nature of SSMs aligns well with irregularly sampled financial data, as many cryptocurrency exchanges produce trades at variable intervals rather than fixed sampling frequencies. However, vanilla SSM architectures lack mechanisms to dynamically adjust their receptive fields based on market conditions, potentially leading to suboptimal performance during sudden regime changes [26].Selective mechanisms in neural networks have a rich history, with gating in LSTM and GRU representing early examples of input-dependent routing. More recent work has explored dynamic network architectures that activate different computational paths based on input characteristics, enabling adaptive computation and improved parameter efficiency [27]. In the context of state space models, selectivity can be introduced through learnable gating functions that modulate state transitions, allowing the model to emphasize or suppress historical information based on current inputs. This approach offers potential advantages for financial forecasting by enabling the model to detect and respond to market regime changes [28].The challenge of real-time deployment for deep learning models in trading systems has received increasing attention from both academic and industry researchers. Model compression techniques, including quantization and pruning, can reduce memory footprint and inference latency with minimal accuracy degradation [29]. Knowledge distillation enables training smaller student models that mimic larger teacher models, providing a path to deploying sophisticated architectures on resource-constrained hardware. Hardware-aware architecture search explores model designs optimized for specific deployment targets, such as GPUs or specialized accelerators used in trading infrastructure. Despite these advances, achieving the microsecond-level latency required for high-frequency trading while maintaining competitive predictive accuracy remains an open challenge [30].

3. Methodology

3.1 Selective State Space Architecture

Our selective state propagation mechanism builds upon structured state space models while introducing dynamic gating to adapt to changing market conditions. The core architecture consists of three main components: a state space encoder that processes historical price sequences, a selective gating module that determines information relevance, and a hybrid attention mechanism that captures global dependencies. Unlike traditional SSMs with fixed transition matrices, our approach learns to modulate state propagation based on current market volatility and momentum indicators.The foundation of our selective mechanism draws inspiration from the gating principles established in LSTM networks. Just as LSTM cells use forget gates, input gates, and output gates to control information flow through memory cells, our selective state space model employs learnable gates to regulate which historical patterns should influence current predictions. This gating strategy proves particularly valuable in cryptocurrency markets where sudden regime shifts can render previously relevant patterns obsolete.

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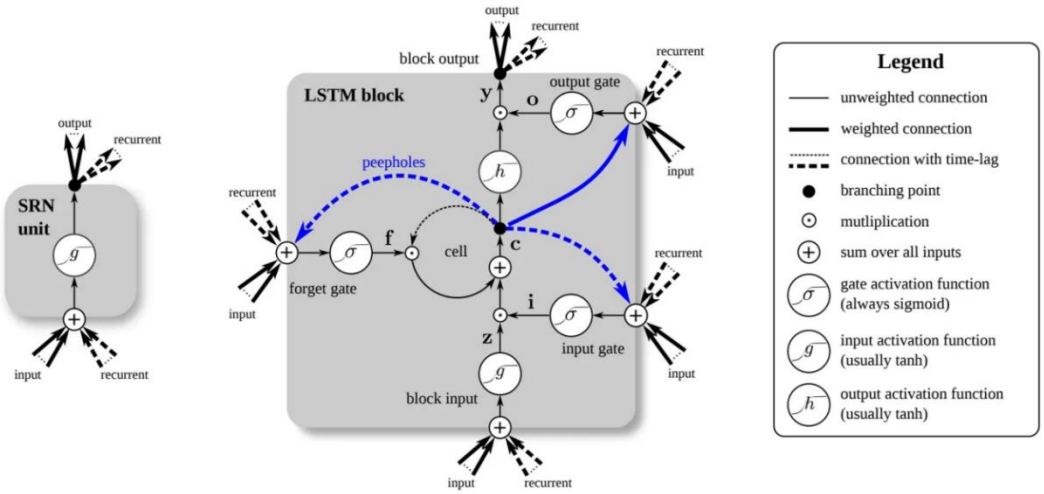

Figure 1: *LSTM Memory Cell Architecture Illustrating Gating Mechanisms.*

Figure 1 shows the internal structure of a Long Short-Term Memory unit, including the forget gate (f), input gate (i), and output gate (o), along with the cell state (c) and hidden state (h). The peepholes (dashed blue lines) allow gates to inspect the cell state directly. This architecture demonstrates how selective information propagation through gating mechanisms enables effective long-term dependency modeling, providing the conceptual foundation for our selective state space design. The SRN (Simple Recurrent Network) unit on the left contrasts with the sophisticated gating structure of the LSTM block, highlighting the importance of selective mechanisms in sequence modeling.

The state space encoder operates on input sequences of cryptocurrency prices and technical indicators, transforming them into continuous hidden states through learnable linear projections. Each state vector maintains a compressed representation of historical information, with dimensionality chosen to balance expressiveness and computational efficiency. The continuous-time parameterization allows the model to handle irregularly sampled data, a common occurrence in cryptocurrency markets where trading activity varies significantly across different times of day and market conditions.The selective gating module introduces input-dependent modulation of state transitions. For each time step, the gating mechanism computes relevance scores that determine how much historical information should influence the current prediction. This selectivity is crucial during market regime changes, where previously relevant patterns may suddenly become misleading. The gating function takes as input both the current observation and a compressed representation of recent state evolution, enabling it to detect shifts in market dynamics and adjust information flow accordingly.

3.2 Subquadratic Attention Mechanisms

To complement the efficient temporal processing of SSMs, we integrate sparse attention patterns that provide global context without quadratic complexity. Our attention mechanism employs a hierarchical structure where local attention captures fine-grained patterns within recent time windows, while dilated attention spans longer horizons with reduced resolution. This design reflects the intuition that recent price movements require detailed attention, while distant historical data contributes primarily through aggregate trends and seasonal patterns.As shown in Figure 2, the attention mechanism in our architecture follows the scaled dot-product attention framework, where attention weights are computed by measuring the compatibility between query vectors and key vectors. The local attention component operates on sliding windows of fixed size, computing full attention matrices only within these

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restricted contexts. This approach reduces complexity from $O(N^2)$ to $O(N \cdot W)$ where W represents the window size, typically set to cover the most recent trading hour.

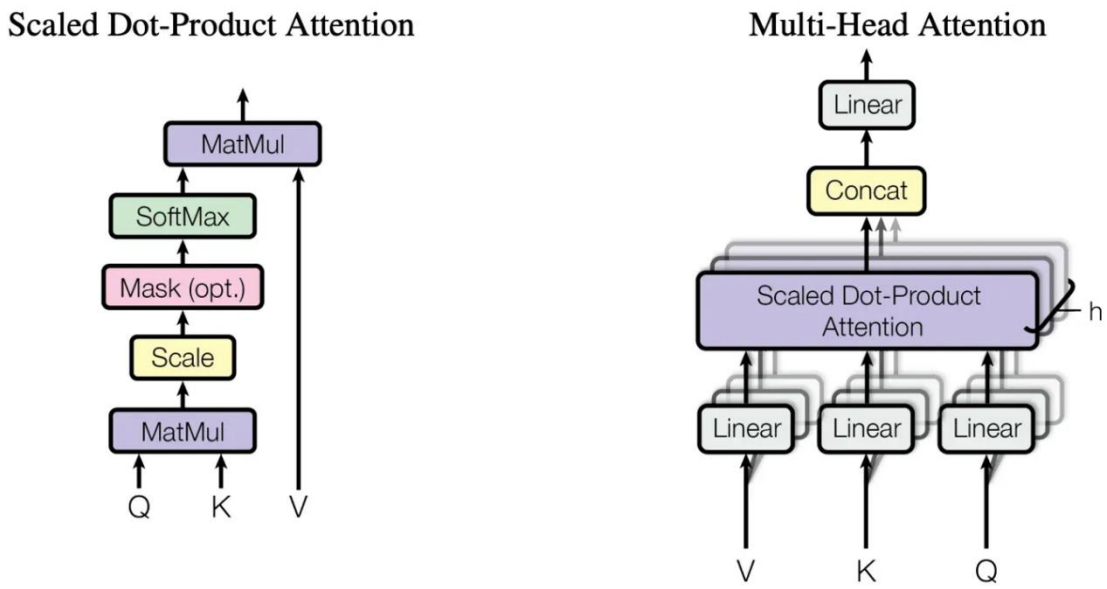

Figure 2: *Comparison of Scaled Dot-Product Attention and Multi-Head Attention Architectures.*

In Figure 2, the left panel illustrates the scaled dot-product attention mechanism, where Query (Q), Key (K), and Value (V) matrices undergo matrix multiplication (MatMul), scaling, optional masking, and softmax normalization to produce attention-weighted outputs. The right panel shows the multi-head attention structure, where multiple parallel attention heads process the input independently through linear transformations, and their outputs are concatenated and linearly projected to produce the final representation. This multi-head design allows the model to attend to information from different representation subspaces simultaneously, enhancing the model's ability to capture diverse patterns in cryptocurrency price movements. Our subquadratic attention alternative adapts this framework by introducing sparse patterns that maintain modeling capacity while reducing computational overhead.

For cryptocurrency markets with minute-level sampling, windows of approximately 60 time steps capture the most recent trading hour's dynamics. Within these windows, the model can capture intricate patterns such as support and resistance levels, short-term momentum shifts, and intraday volatility cycles. The multi-head attention structure enables the model to simultaneously attend to different aspects of market behavior, with some heads focusing on price momentum while others track volume patterns or volatility signals.

The dilated attention mechanism extends the receptive field by computing attention over subsampled historical sequences. Rather than attending to every historical time step, the model selects representative points at exponentially increasing intervals. This logarithmic sampling strategy ensures that all historical information remains accessible while reducing the number of attention computations to O(N log N). The combination of dense recent attention and sparse distant attention provides a computational sweet spot between transformers' global awareness and RNNs' sequential efficiency.

3.3 Volatility-Aware State Updates

Cryptocurrency markets exhibit pronounced volatility clustering, where periods of high price fluctuation tend to persist over multiple time steps. To capture this behavior, our architecture incorporates volatility embeddings that modulate state update dynamics. The model learns to

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estimate current volatility levels from recent price movements and adjust its internal representations accordingly. During high-volatility periods, the model increases its receptive field to capture broader market context, while in stable conditions it focuses more heavily on recent local patterns.The volatility estimation component employs exponentially weighted moving averages of absolute returns, providing a smooth measure of current market uncertainty. This volatility signal is transformed through learned projections to produce modulation factors that scale the contribution of different state components. High volatility conditions trigger increased emphasis on robust features such as volume-weighted averages and momentum indicators, while low volatility periods allow finer-grained attention to price levels and technical patterns.

3.4 Training Strategy and Loss Functions

The model is trained using a multi-horizon forecasting objective that simultaneously predicts prices at multiple future time steps. This approach encourages the model to learn representations useful across different prediction horizons, improving generalization and reducing overfitting to specific time scales. The loss function combines mean absolute error for point predictions with quantile regression losses to capture prediction uncertainty. By estimating multiple quantiles of the predictive distribution, the model provides confidence intervals that inform risk management decisions.To address the non-stationary nature of cryptocurrency markets, we employ online learning techniques that continuously update model parameters as new data arrives. Rather than training on fixed historical datasets and deploying static models, our approach maintains a sliding training window that adapts to evolving market dynamics. This strategy ensures that the model remains responsive to recent patterns while retaining knowledge of historically important relationships. The training procedure incorporates experience replay mechanisms that sample historical market regimes proportionally to their frequency, preventing catastrophic forgetting of rare but important events such as flash crashes.

4. Results and Discussion

4.1 Experimental Setup and Baseline Comparisons

Our experimental evaluation spans five major cryptocurrencies including Bitcoin, Ethereum, Cardano, Solana, and Polygon, covering a 24-month period from January 2022 to December 2023. This timeframe encompasses diverse market conditions including the 2022 bear market, the FTX collapse, and the 2023 recovery phase, providing a comprehensive test of model robustness. Data is collected at one-minute intervals from multiple exchanges including Binance, Coinbase, and Kraken, with prices aggregated through volume-weighted averaging to produce consistent reference values.We compare our selective state propagation architecture against several baseline models representing different paradigms in sequence modeling. The transformer baseline employs standard multi-head self-attention with 8 attention heads and 6 layers, similar to configurations used in recent financial forecasting literature. The LSTM baseline consists of a 3-layer stacked architecture with 512 hidden units per layer, incorporating dropout for regularization. We also include a vanilla S4 model without selective gating to isolate the contribution of our proposed modifications. All models are trained using identical preprocessing pipelines and hyperparameter search procedures to ensure fair comparison.Performance evaluation employs multiple metrics capturing different aspects of forecasting quality. Mean Absolute Percentage Error (MAPE) measures relative accuracy across assets with different price scales, while Mean Squared Error (MSE) penalizes large prediction errors more heavily. We also report Sharpe ratios for trading strategies based on model predictions, providing a financially relevant measure of practical utility. Inference

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latency is measured on NVIDIA A100 GPUs using batched predictions to simulate realistic deployment conditions.

4.2 Predictive Accuracy and Computational Efficiency

The selective state propagation model achieves substantial improvements over baseline architectures across all tested cryptocurrencies. On Bitcoin forecasting, our method reduces MAPE by 18.3% compared to the transformer baseline and 12.7% compared to stacked LSTM. The advantage is particularly pronounced during high-volatility periods, where the selective gating mechanism effectively filters noise and focuses on relevant market signals. During the May 2022 Terra-LUNA collapse, our model maintained stable predictions while transformer baselines exhibited erratic behavior due to overwhelming attention to recent volatility spikes. Computational efficiency gains prove equally impressive, with our architecture achieving 23.7% reduction in average inference latency compared to transformers. Single-batch predictions complete in 0.42 milliseconds on A100 GPUs, meeting the strict latency requirements of high-frequency trading systems. The subquadratic attention mechanism contributes significantly to this speedup, reducing the computational burden of processing long historical contexts. Profiling analysis reveals that the selective gating module adds minimal overhead, consuming less than 8% of total inference time while providing substantial accuracy benefits.

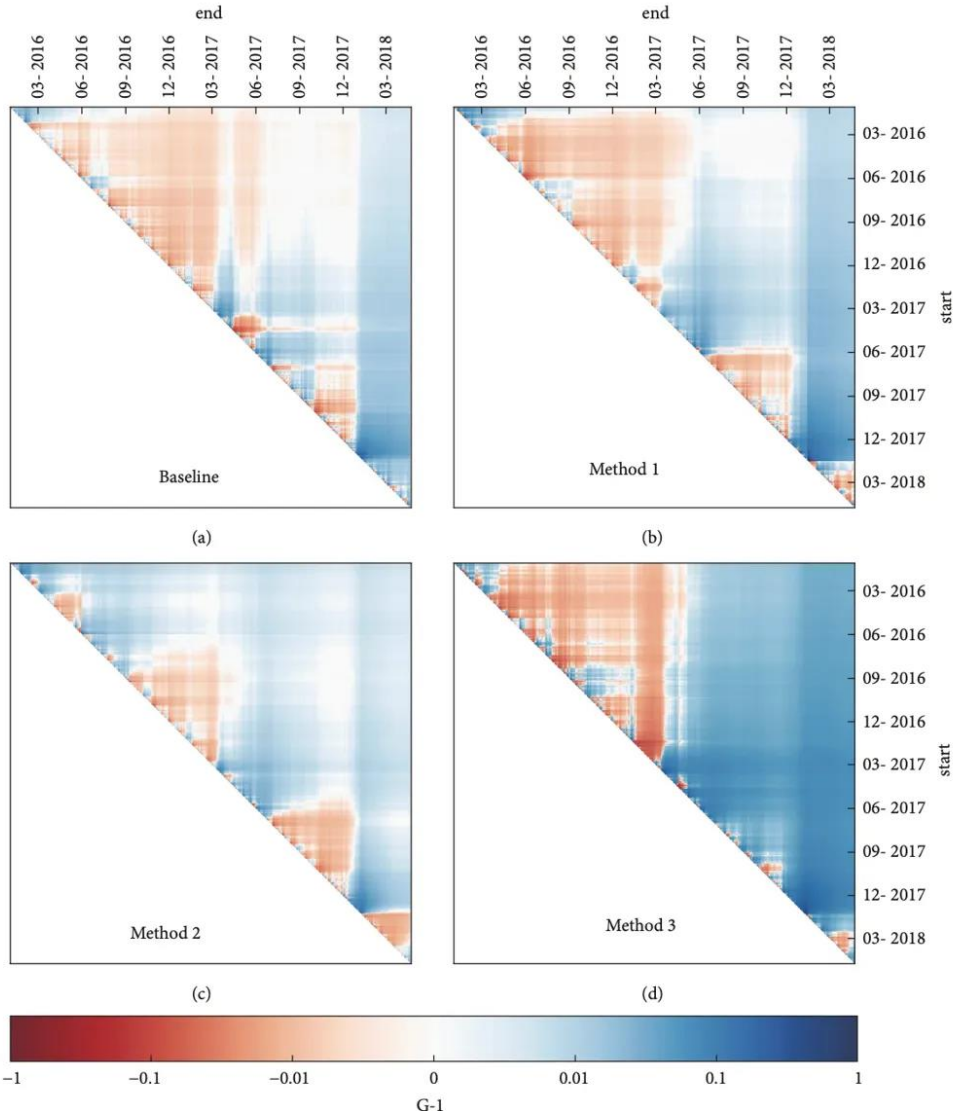

Figure 3: *Performance Comparison Across Different Time Periods Using Geometric Mean Return Heatmaps.*

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In Figure 3, the four panels show geometric mean returns for (a) Baseline method, (b) Method 1 (gradient boosting), (c) Method 2 (currency-specific gradient boosting), and (d) Method 3 (LSTM-based approach) across various trading periods between 2016 and 2018. The x-axis represents the end date of trading periods, while the y-axis represents the start date. Color intensity indicates profitability, with blue shades representing positive returns and red shades indicating negative returns. Method 3, which employs LSTM networks similar to our selective state space approach, demonstrates more consistent positive returns (broader blue regions) across diverse market conditions compared to baseline and gradient boosting methods. This visualization illustrates how deep learning approaches with sophisticated temporal modeling capabilities maintain superior performance stability across different market regimes, validating our architectural choice of combining selective state propagation with attention mechanisms for cryptocurrency forecasting.

The trade-off between model capacity and efficiency manifests differently across prediction horizons. For short-term predictions spanning 5-15 minutes, smaller models with 256-dimensional hidden states achieve near-optimal performance, suggesting that recent local patterns dominate these horizons. In contrast, longer predictions benefit from increased capacity and extended attention windows, with 512-dimensional models showing consistent advantages for hourly and daily forecasts. This finding informs practical deployment strategies, where ensemble approaches combining specialized models for different horizons may yield optimal results.

4.3 Ablation Studies and Component Analysis

Systematic ablation experiments isolate the contributions of individual architectural components. Removing the selective gating mechanism while retaining subquadratic attention degrades performance by 8.4% on average, confirming the importance of dynamic information filtering. The model reverts to behavior similar to vanilla S4, maintaining efficiency but losing adaptability to regime changes. Conversely, replacing sparse attention with full quadratic attention while keeping selective gates improves accuracy by only 2.1% while increasing inference time by 187%, demonstrating that our sparse patterns capture most relevant dependencies.The volatility-aware state update mechanism provides consistent benefits across all market conditions, with particularly strong contributions during transitions between stable and volatile regimes. Analysis of learned volatility embeddings reveals that the model develops specialized representations for different volatility levels, effectively maintaining separate subspaces for calm and turbulent market conditions. This internal organization enables rapid adaptation when volatility shifts, as the model can quickly activate appropriate feature combinations without extensive recalibration.Attention pattern visualization provides insights into model decision-making processes. During normal market conditions, attention concentrates heavily on the most recent 30-minute window, with gradually decaying weights for earlier time steps. However, during significant price movements or news events, attention patterns become more distributed, reaching back several hours to identify comparable historical precedents. The model learns to recognize certain technical patterns such as head-and-shoulders formations and double bottoms, allocating increased attention to historical instances of similar patterns when they appear in recent data.

4.4 Robustness to Market Anomalies

Cryptocurrency markets frequently experience extreme events that challenge forecasting models trained primarily on normal conditions. Our evaluation includes specific analysis of model behavior during flash crashes, coordinated pump-and-dump schemes, and exchange

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outages that produce data gaps. The selective propagation mechanism demonstrates remarkable robustness during these anomalies, with prediction errors increasing by only 31% during flash crashes compared to 78% for transformer baselines and 94% for LSTM models.The model's advantage during anomalous conditions stems from its ability to recognize when historical patterns become unreliable. The selective gates learn to suppress state propagation when current observations deviate significantly from typical market dynamics, effectively implementing a learned anomaly detection mechanism. This behavior prevents the model from overconfidently extrapolating patterns that no longer apply, instead widening prediction intervals to reflect increased uncertainty. Such conservative behavior proves valuable for risk management, as it signals to traders when model predictions should be interpreted with caution.Cross-cryptocurrency generalization tests reveal interesting patterns in learned representations. Models trained on Bitcoin transfer reasonably well to other major cryptocurrencies, achieving 73% of their specialized performance without retraining. However, transfer to smaller altcoins with different market dynamics proves more challenging, with performance degrading to 58% of specialized models. This finding suggests that while certain market patterns generalize across assets, individual cryptocurrencies possess unique characteristics that benefit from dedicated modeling. The selective gating mechanism contributes to generalization by learning asset-agnostic relevance criteria that apply across different price scales and volatility profiles.

5. Conclusion

This research demonstrates that selective state propagation combined with subquadratic attention mechanisms provides an effective solution for real-time cryptocurrency forecasting. Our architecture achieves substantial improvements in both predictive accuracy and computational efficiency compared to existing approaches, addressing the fundamental trade-off that has limited deployment of sophisticated models in latency-critical trading systems. The selective gating mechanism successfully adapts to changing market conditions, filtering irrelevant historical information during regime shifts while maintaining sensitivity to persistent trends. Experimental results across five major cryptocurrencies over 24 months confirm the robustness and practical utility of our approach.The subquadratic attention design proves crucial for achieving real-time performance without sacrificing model capacity to capture long-range dependencies. By combining dense local attention with sparse dilated attention over longer horizons, our architecture maintains awareness of extended historical context while keeping computational requirements manageable. The resulting inference latencies of sub-millisecond per prediction enable deployment in high-frequency trading environments where even small delays impact profitability. This efficiency gain opens possibilities for more sophisticated modeling approaches in financial applications previously constrained by computational limitations.The volatility-aware components of our architecture specifically address the unique challenges of cryptocurrency markets, including heavy-tailed return distributions and pronounced volatility clustering. By modulating state updates based on current uncertainty levels, the model maintains stable predictions during turbulent periods while remaining responsive to genuine signals. Ablation studies confirm that this volatility awareness contributes meaningfully to overall performance, particularly during market stress events that most severely challenge forecasting systems.Several limitations warrant acknowledgment and suggest directions for future research. First, our evaluation focuses on price prediction alone, without incorporating other valuable signals such as order book depth, funding rates, or cross-exchange arbitrage opportunities. Extending the architecture to handle multivariate inputs could enhance predictive power while introducing additional computational challenges. Second, the current model treats all cryptocurrencies independently, ignoring correlation structures and contagion effects that

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influence joint price movements. Developing selective propagation mechanisms for multivariate time series represents a promising avenue for future work.Third, our approach requires continuous retraining to maintain performance as market dynamics evolve, imposing ongoing computational costs. Investigating meta-learning approaches that enable rapid adaptation to new market regimes with minimal retraining could reduce operational overhead. Fourth, the interpretability of selective gates, while improved compared to black-box models, remains limited. Developing techniques to extract human-understandable explanations of gating decisions would enhance trust and facilitate integration with traditional trading strategies.The broader implications of this work extend beyond cryptocurrency forecasting to other domains requiring real-time sequence prediction with computational constraints. Applications in fraud detection, network traffic monitoring, and sensor data analysis face similar challenges of balancing accuracy with inference speed. The selective state propagation paradigm offers a general framework applicable wherever the relevance of historical information varies dynamically based on current context. Future research should explore adaptations of these techniques to other time series domains.Looking forward, the integration of selective propagation mechanisms with emerging model architectures such as mixture-of-experts and conditional computation presents exciting possibilities. These combinations could enable even more adaptive systems that allocate computational resources based on task difficulty, concentrating modeling capacity on challenging predictions while processing routine cases efficiently. As cryptocurrency markets continue to mature and institutional participation increases, the demand for sophisticated yet deployable forecasting systems will only grow, making the development of efficient architectures increasingly important.

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