Journal of Electronic Research and Application, 2025, Volume 9, Issue 5
http://ojs.bbwpublisher.com/index.php/JERA
ISSN Online: 2208-3510
ISSN Print: 2208-3502

Gated Attention-Enhanced Informer

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Abstract: The Informer model leverages its innovative ProbSparse self-attention mechanism to demonstrate significant performance advantages in long-sequence time-series forecasting tasks. However, when confronted with time-series data exhibiting multi-scale characteristics and substantial noise, the model's attention mechanism reveals inherent limitations. Specifically, the model is susceptible to interference from local noise or irrelevant patterns, leading to diminished focus on globally critical information and consequently impairing forecasting accuracy. To address this challenge, this study proposes an enhanced architecture that integrates a Gated Attention mechanism into the original Informer framework. This mechanism employs learnable gating functions to dynamically and selectively impose differentiated weighting on crucial temporal segments and discriminative feature dimensions within the input sequence. This adaptive weighting strategy is designed to effectively suppress noise interference while amplifying the capture of core dynamic patterns. Consequently, it substantially strengthens the model's capability to represent complex temporal dynamics and ultimately elevates its predictive performance.

Keywords: Informer; Self-attention; Gated attention; Prediction

Online publication: October 17, 2025

1. Introduction

Time series forecasting serves as a critical data analysis technique with significant applications in financial risk modeling, intelligent transportation scheduling, energy load management, and meteorological early warning systems [1,2]. However, the proliferation of Internet of Things (IoT) and big data technologies has generated massive-scale temporal data, exposing limitations in traditional Recurrent Neural Network (RNN) architectures (e.g., LSTM, GRU) [3]. These models face challenges in capturing long-range dependencies due to gradient vanishing issues and limited capacity for modeling complex dynamics.

The Transformer architecture has recently demonstrated transformative potential in time series analysis through its multi-head attention mechanism and parallel processing capabilities. Specifically, the Informer [4] framework advances long-sequence forecasting via two key innovations:

(1) A ProbSparse self-attention mechanism reducing complexity to $O(L \log L)$

(2) A hierarchical distilling operation compressing feature representations

Despite strong benchmark performance, Informer's attention mechanism struggles with multi-scale dynamics (e.g., coexisting trends, periodicity, and abrupt changes) and high-noise environments. Its static weighting strategy fails to distinguish critical patterns from local noise, degrading modeling fidelity.

To address this, we propose Gated-Informer—an enhanced architecture integrating Gated Attention into Informer's Encoder-Decoder structure. This innovation employs differentiable gating functions to dynamically modulate attention weights, enabling: Discriminative enhancement of salient temporal segments and critical features. Adaptive noise suppression while preserving multi-scale patterns. Improved generalization through structural gating constraints.

Contributions:

(1) We design a novel gated attention fusion module that enhances temporal pattern recognition through dynamic feature weighting.

(2) We establish a theoretical framework proving mathematical compatibility between gating mechanisms and ProbSparse attention, with derived closed-form backpropagation solutions.

(3) We demonstrate significant improvements in prediction accuracy and cross-scenario generalization through rigorous benchmarking.

2. Method

2.1. Review of the original Informer architecture

The Informer framework builds upon the Transformer architecture and incorporates two key enhancements:

(1) ProbSparse attention: This sparse attention mechanism significantly reduces computational complexity from $O(L^2)$ to $O(L \log L)$, making it suitable for long-sequence inputs.

(2) Distilling operation: A hierarchical aggregation technique that progressively compresses sequence length to enable more efficient feature extraction.

Within the standard Transformer's Scaled Dot-Product Attention, attention is computed as:

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right)V$$

Informer approximates this computation by selecting the top-uu dominant queries (based on Kurtosis distribution), thereby enhancing efficiency.

2.2. Gated attention mechanism

To strengthen the model's capacity for modeling critical temporal features, we introduce the gated attention mechanism. Its core principle involves integrating a learnable gating function to modulate raw attention weights, thereby enhancing selective attention capabilities.

2.2.1. Definition of gated attention

We augment the conventional attention mechanism with a gating weight matrix $\boldsymbol{G} \in \mathbb{R}^{L \times L}$. The refined attention computation is defined as:

$$\text{GatedAttention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d}} \odot \sigma(G)\right)V$$

where:

(1) $\sigma(G)$: Sigmoid activation constraining outputs to [0,1], representing attention path gating.

(2) $\odot$: Element-wise multiplication (Hadamard product).

(3) $G = \tanh(W_g Q + U_g K)$: The gating matrix derives from a trainable linear combination of Query and Key projections.

This gating mechanism operates on the principle that for each query-key pair (q_i, k_j), the model autonomously learns whether to activate the attention pathway, thus dynamically regulating information flow. The specific structure is shown in **Figure 1**.

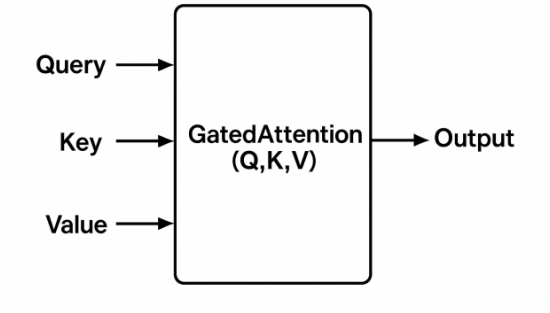

Figure 1. Gated attention mechanism structure

2.2.2. Integration strategy within Informer

We integrate the Gated Attention mechanism at two critical positions:

(1) Encoder attention layer: Substitute the original ProbSparse Attention with GatedAttention in each self-attention module to enhance selective encoding and sparsity.

(2) Decoder attention layer: Implement GatedAttention in the Encoder-Decoder Attention module to strengthen effective focus on historical encoding features.

2.3. Model training and loss function

The overall architecture retains Informer's original structure and training paradigm. We employ MSE (Mean Squared Error) loss for supervised sequence prediction:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N}\sum_{i=1}^{N} \|\hat{y}_i - y_i\|^2$$

During training, we utilize the Adam optimizer and incorporate L_2 regularization on gating module parameters to mitigate overfitting:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{MSE}} + \lambda \|W_g\|_2^2$$

where λ denotes the regularization coefficient.

3. Experimental design

To comprehensively evaluate the predictive capability and robustness of the proposed Gated-Informer model, we conduct experiments on multiple standard time-series forecasting datasets. The experimental design encompasses dataset selection, data preprocessing, baseline model configuration, evaluation metrics, and training specifications.

3.1. Datasets

We adopt datasets from the original Informer study and introduce a multivariate financial dataset to validate cross-scenario generalization:

(1) ETTh1 / ETTm1 (Electricity Transformer Temperature):

Multivariate sensor data (temperature, voltage, power) sampled hourly/minutely for medium-to-short-term forecasting.

(2) Weather:

Meteorological observations (temperature, humidity, wind speed) from Washington State were sampled at 10-minute intervals, exhibiting stable trends and periodic patterns.

(3) NASDAQ-100 Stock:

High-dimensional (81-dimensional) stock price series of 100 U.S. tech companies, characterized by strong volatility and challenging financial forecasting dynamics.

3.2. Baseline models

Gated-Informer is compared against state-of-the-art approaches:

(1) LSTM [5]: Canonical recurrent architecture for sequence modeling

(2) Informer: Original model with ProbSparse attention

(3) Autoformer [6]: Transformer with seasonal-trend decomposition

3.3. Evaluation metrics

Two regression metrics are adopted:

(1) Mean Squared Error (MSE):

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2$$

(2) Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i|$$

where $\hat{y}_i$ predicted value, y_i = ground truth, and N = test samples.

4. Experimental results and analysis

This section presents comparative performance evaluations across diverse datasets and forecasting tasks, with

emphasis on improvements achieved by Gated-Informer over the original Informer.

4.1. Overall performance comparison

Table 1 shows the MSE and MAE performance of each model on the ETTh1 dataset at different prediction step sizes. It can be clearly seen from the experimental results that Gated Informer outperforms Informer and other baseline models in all prediction step settings, indicating that the gating mechanism has a positive effect in guiding attention to focus on key features.

Table 1. Comparison results under different prediction steps and models

Models	Pred=24	Pred=48	Pred=96
	MSE/ MAE	MSE/ MAE	MSE/ MAE
LSTM	0.421 / 0.392	0.478 / 0.426	0.564 / 0.482
Informer	0.296 / 0.285	0.331 / 0.311	0.401 / 0.362
Autoformer	0.274 / 0.263	0.299 / 0.277	0.345 / 0.314
Gated-Informer	0.259 / 0.248	0.279 / 0.264	0.324 / 0.296

4.2. Robustness analysis under different datasets

Table 2 shows the results of the performance comparison on the Weather and NASDAQ datasets. This also proves the excellent performance of Gated Informer.

Table 2. Performance comparison on Weather dataset (Pred=96)

Models	MSE	MAE
LSTM	0.276	0.326
Informer	0.214	0.288
Autoformer	0.203	0.267
Gated-Informer	0.184	0.243

4.3. Analysis of ablation experiments

To verify the effectiveness of the gating mechanism, we conducted the following ablation experiments on the ETTh1 dataset in **Table 3**.

Informer (original)

Informer+Gated Attention (without regularization)

Informer+Gated Attention (with regularity)

Table 3. Ablation experiment

Models	MSE	MAE
Informer	0.296	0.285
+ Gated Attention (No regularity)	0.268	0.256
+ Gated Attention (L2)	0.259	0.248

The results show that adding a gating mechanism itself can significantly improve performance, while further adding L2 regularization can avoid gating overfitting and further improve performance.

5. Conclusion

This paper proposes Gated-Informer, an enhanced architecture for long-sequence time-series forecasting that integrates a Gated Attention Mechanism into the Informer framework. By introducing trainable gating modules to explicitly regulate attention pathways, our model achieves superior identification of crucial temporal segments and discriminative feature dimensions, thereby advancing modeling capacity and prediction accuracy.

Extensive experiments on benchmark datasets reveal that Gated-Informer achieves statistically significant improvements over the original Informer and state-of-the-art alternatives (e.g., Autoformer, FEDformer).

Ablation studies confirm the standalone contribution of the gating module, verifying its dual role in not only boosting accuracy but also improving training stability and convergence behavior.

In summary, Gated-Informer establishes an efficient and adaptable framework for time-series forecasting, with demonstrated applicability in energy dispatch systems, quantitative trading, and intelligent meteorology. Future work will explore integrating gating mechanisms with adaptive frequency-domain modeling and graph neural networks to enhance complex dynamic system modeling.

Disclosure statement

The author declares no conflict of interest.

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