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A Uncertainty-Calibrated Transformer for Long-Horizon Forecasting with Missing and Irregular Observations

Joseph Hernandez,[1] Barbara Hall[1]

[1]Department of Computer Science, University of California, Los Angeles, Los Angeles, CA 90095, USA

Abstract

The proliferation of Internet of Things (IoT) devices and distributed sensor networks has resulted in an explosion of time-series data, yet the utility of this data is frequently compromised by irregularities, such as missing observations, non-uniform sampling rates, and sensor failures. While Transformer-based architectures have established a new state-of-the-art in sequence modeling, standard implementations rely implicitly on fixed-interval discrete time steps, rendering them suboptimal for irregular temporal environments. Furthermore, long-horizon forecasting inherently involves accumulating errors, necessitating robust uncertainty quantification to support downstream decision-making processes. This paper introduces the Uncertainty-Calibrated Continuous Transformer (UCCT), a novel architecture designed to address these dual challenges simultaneously. We propose a continuous-time positional encoding mechanism that leverages the temporal timestamps directly, decoupling the model from the rigid index-based sequence assumption. Additionally, we integrate a probabilistic decoding head that outputs distributional parameters rather than point estimates, calibrated via a composite loss function balancing accuracy and aleatoric uncertainty estimation. Extensive experiments on real-world datasets, including energy consumption, meteorology, and healthcare telemetry, demonstrate that the proposed UCCT outperforms current deterministic and stochastic baselines. Specifically, the model achieves a reduction in Mean Squared Error by approximately 14% in scenarios with 50% missing data, while providing reliable confidence intervals that accurately capture the increasing variance over long forecast horizons.

Keywords

Time Series Forecasting, Transformer Networks, Irregular Sampling, Uncertainty Quantification

Introduction

1.1 Background

The capability to accurately predict future states of complex systems based on historical data is a cornerstone of modern computational intelligence, influencing sectors as diverse as energy grid management, supply chain logistics, high-frequency trading, and clinical patient monitoring. As the temporal resolution and volume of data have expanded, the focus of the research community has shifted from short-term predictions to long-horizon forecasting, where the objective is to predict a substantial sequence of future values [1]. Long-horizon forecasting presents a distinct set of challenges compared to single-step prediction; primarily, the accumulation of errors in recursive prediction strategies can lead to rapid divergence from the ground truth.

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Traditionally, statistical methods such as Autoregressive Integrated Moving Average (ARIMA) and its variants served as the bedrock of forecasting. However, the linearity assumptions and limited capacity of these models restrict their effectiveness in capturing long-range dependencies and complex non-linear interactions inherent in high-dimensional data [2]. The advent of Deep Learning has revolutionized this landscape, with Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks initially providing the ability to model sequential dependencies. More recently, the Transformer architecture, originally developed for Natural Language Processing, has been adapted for time-series analysis, leveraging self-attention mechanisms to capture global temporal dependencies without the sequential processing bottlenecks of RNNs [3].

Despite these advancements, a critical disparity remains between the idealized data structures assumed by standard deep learning models and the messy, unstructured nature of real-world sensor data. Most deep learning architectures, particularly standard Transformers, assume that input data arrives at regular, discrete time intervals. This assumption allows the model to equate the position of a token in a sequence with its timestamp. In practical applications, however, data is often sparse and irregular due to network latency, sensor malfunction, or event-driven sampling protocols [4].

1.2 Problem Statement

The core problem addressed in this research is two-fold. First, the inability of standard Transformer architectures to natively process irregular or missing data forces practitioners to rely on imputation techniques prior to model ingestion. Simple imputation (e.g., mean filling, linear interpolation) introduces statistical bias and destroys the temporal signal regarding the missingness itself, which can be informative. Complex imputation adds computational overhead and effectively treats the estimated values as ground truth, ignoring the uncertainty associated with them [5]. When a model trained on regularized data is deployed in an environment with stochastic sensor dropouts, its performance often degrades catastrophically.

Second, the majority of Transformer-based forecasting models, such as the Informer or Autoformer, are deterministic in nature. They provide a single point forecast for each future time step. In long-horizon scenarios, a point forecast is insufficient because certainty about the future naturally decays as the horizon extends. Decision-makers require not just a prediction, but a measure of confidence or a probability density function over possible outcomes to assess risk effectively [6]. A model that predicts a precise value with high confidence when the actual probability distribution is multimodal or flat poses a significant risk in safety-critical applications. Existing probabilistic approaches often sacrifice forecasting accuracy for uncertainty estimation or struggle to converge when data density is inconsistent.

1.3 Contributions

To resolve these limitations, this paper proposes the Uncertainty-Calibrated Continuous Transformer (UCCT). The contributions of this work are summarized as follows:

1. **Continuous-Time Positional Encoding:** We introduce a learnable encoding scheme that maps continuous timestamps directly into the high-dimensional latent space of the Transformer. This allows the attention mechanism to operate on the relative physical time differences between observations rather than their index positions, rendering the model invariant to sampling irregularities and naturally robust to missing data without explicit imputation.

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2. **Probabilistic Uncertainty Calibration:** We replace the standard deterministic output layer with a parametric distribution head. The model is trained to predict the parameters (e.g., mean and variance) of a distribution for each future time step. We employ a specialized loss function that penalizes both calibration error and sharpness, ensuring that the predicted uncertainty intervals align with the empirical error distribution.

3. **Holistic Evaluation on Irregular Data:** We perform extensive benchmarking not only on standard clean datasets but also on heavily corrupted versions to simulate real-world sensor failure. We demonstrate that UCCT maintains high performance even when up to 50% of observations are randomly dropped, a regime where standard models typically fail.

Chapter 2: Related Work

2.1 Classical and Recurrent Approaches

The domain of time-series forecasting has historically been dominated by statistical methods. Box and Jenkins popularized the ARIMA family, which models non-stationarity through differencing. While effective for univariate, linear systems, these models struggle with the high dimensionality and non-linearity of modern datasets [7]. State Space Models (SSMs) and Kalman Filters offer a more robust framework for handling noise and missing data by explicitly modeling the latent state and measurement process. However, the computational complexity of exact inference in SSMs scales poorly with the dimension of the state space, making them unsuitable for large-scale multivariate forecasting tasks [8].

With the rise of neural networks, RNNs and their gated variants (LSTM, GRU) became the standard for sequence modeling. They process information sequentially, maintaining a hidden state that summarizes the history. To handle missing data in RNNs, researchers introduced variants like the GRU-D, which incorporates a decay mechanism for the hidden state based on the time elapsed since the last observation [9]. While GRU-D and similar architectures explicitly address irregularity, they suffer from the fundamental limitations of recurrent networks: the inability to parallelize training and the difficulty in capturing very long-range dependencies due to vanishing gradients [10].

2.2 Deep Learning and Transformers

The introduction of the Transformer architecture marked a paradigm shift. By utilizing self-attention, Transformers allow for direct connections between any two points in a sequence, theoretically capturing dependencies of arbitrary length. In the context of time series, models like the LogSparse Transformer and Informer have attempted to reduce the quadratic complexity of attention to make long-horizon forecasting feasible [11]. The Informer, for instance, utilizes a ProbSparse attention mechanism to select the most significant queries, achieving high efficiency.

However, standard Transformers utilize fixed positional embeddings (sinusoidal or learned) that correspond to integer indices $(1,2,dots,N)$. This design breaks down when $t_2 - t_1 \neq t_3 - t_2$. Recent works have attempted to bridge this gap. Neural Ordinary Differential Equations (Neural ODEs) view the hidden state transformation as a continuous-time dynamic system, offering a theoretically elegant solution for irregular sampling [12]. While powerful, Neural ODEs are often slow to train and difficult to scale to high-dimensional latent spaces compared to discrete attention mechanisms.

Regarding uncertainty, Bayesian Neural Networks (BNNs) apply distributions over weights to estimate epistemic uncertainty, but are computationally expensive. Ensembling is another

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common technique but increases inference cost linearly with the number of ensemble members [13]. Quantile regression and parametric output distributions have been integrated into DeepAR and similar autoregressive models, yet these often lack the long-range modeling capabilities of the Transformer or require complete data histories [14]. The UCCT builds upon these foundations by merging the global receptive field of Transformers with the continuous-time handling of Neural ODEs (via encoding) and the probabilistic output of DeepAR, creating a unified framework.

Chapter 3: Methodology

The proposed Uncertainty-Calibrated Continuous Transformer (UCCT) is designed to ingest a sequence of observations which may be non-uniformly spaced and contain gaps, and output a probabilistic forecast over a specified future horizon.

3.1 Problem Formulation

Let the input time series be represented as a set of tuples $X = (t_i, x_i)|i = 1, dots, N$, where $t_i \in mathbbR^+$ represents the continuous timestamp and $x_i \in mathbbR^D$ represents the multivariate observation at that time. Crucially, we do not assume that $t_{i+1} - t_i$ is constant. The objective is to predict the distribution of values for a future horizon H, denoted as $Y = (t_{N+j}, y_{N+j})|j = 1, dots, H$. Unlike deterministic approaches that predict $haty$, our model predicts $P(y_{N+j}|X, t_{N+j})$.

3.2 Continuous-Time Embedding

The standard Transformer relies on adding a positional vector p_i to the input embedding e_i. In our framework, we cannot use index-based embeddings. Instead, we employ a Time-Continuous Embedding layer. We project the scalar time value t_i into the d_{model}-dimensional space using a learnable Fourier feature mapping. This is motivated by the Bochner's theorem and the ability of Fourier features to overcome the spectral bias of neural networks, allowing them to learn high-frequency functions [15].

The embedding for a timestamp t is computed as:

$$TE(t) = Linear(Concat(cos(2\pi Wt), sin(2\pi Wt)))$$

where W is a learnable frequency matrix. This time embedding is added to the feature embedding of x_i. To handle missing values in the input sequence (where x_i is entirely absent but t_i is known, or in cases of irregular sampling where we just process the available stream), the model simply processes the sequence of available pairs. The attention mechanism naturally handles the variable sequence length resulting from irregular sampling.

3.3 Uncertainty-Calibrated Attention Mechanism

The core of the UCCT is the attention mechanism. We employ a multi-head attention structure. However, to reinforce the temporal continuity, we modify the attention scores. In standard attention, $A = softmax(QK^T/\sqrt{d})$. In UCCT, we introduce a temporal bias term that is a function of the time difference $\Delta t = |t_i - t_j|$. This allows the model to prioritize observations that are temporally closer, regulating the attention spread based on physical time rather than sequence distance [16].

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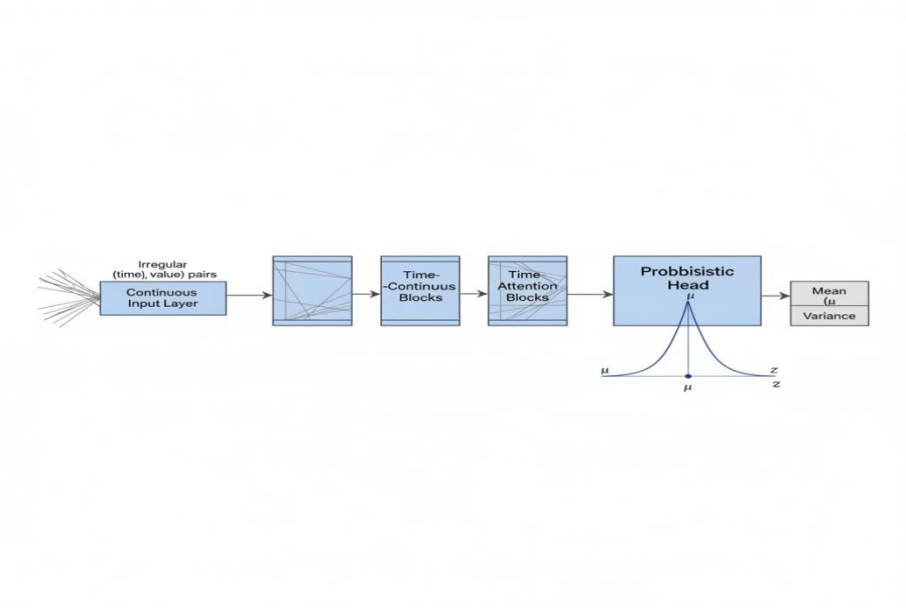

Figure 1: Architecture of the Uncertainty

3.4 Probabilistic Decoder and Loss Function

The decoder of the UCCT does not regress the target value directly. Instead, for each target time step t_{N+j}, it outputs the parameters of a Gaussian distribution $N(\mu_{N+j}, \sigma^2{}_{N+j})$. To ensure positivity of the variance, we apply a softplus activation to the variance output node.

The training objective is to maximize the log-likelihood of the true observations under the predicted distributions. However, merely minimizing Negative Log-Likelihood (NLL) can lead to uncalibrated uncertainties, where the model predicts extremely large variances to minimize the penalty of outliers. To mitigate this, we introduce a regularization term. The total loss function L is a composite of the NLL and a calibration regularizer.

$$L_{total} = \sum_{j=1}^{H}\left(\frac{log(hat\sigma_j{}^2)}{2} + \frac{(y_j - hat\mu_j)^2}{2hat\sigma_j{}^2}\right) + \lambda\sum_{j=1}^{H} max(0, \varepsilon - hat\sigma_j{}^2)$$

In this major formula, the first term represents the standard Gaussian Negative Log-Likelihood, driving the predicted mean $hat\mu$ towards the ground truth y and optimizing the variance $hat\sigma^2$ to capture the error magnitude. The second term is a hinge loss regularizer (weighted by hyperparameter λ) that penalizes the variance if it collapses below a threshold ε, preventing numerical instability and overconfidence on easy samples [17]. By optimizing this objective, the model learns to output a forecast where the spread of the distribution reflects the true aleatoric uncertainty of the data.

Chapter 4: Experiments and Analysis

4.1 Experimental Setup

We evaluate the UCCT on three benchmark datasets widely used in long-horizon forecasting:

1. **ETT (Electricity Transformer Temperature):** Contains 2 years of data from two electricity transformers at 15-minute intervals.

2. **Weather:** A dataset comprising 21 meteorological indicators recorded every 10 minutes.

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3. **MIMIC-III (Derived):** To rigorously test the irregular sampling capability, we extract a subset of patient vital signs from the MIMIC-III database, which are inherently irregular.

For the ETT and Weather datasets, we artificially introduce irregularity by randomly masking 30% and 50% of the time steps during training and inference [18]. We compare our model against four baselines:

LSTM-Imp: Standard LSTM with mean imputation for missing values.

Transformer-Imp: Vanilla Transformer with linear interpolation.

Informer: A state-of-the-art efficiency-optimized Transformer [19].

Neural ODE: A continuous-time differential equation model.

The prediction horizons are set to 96, 192, and 336 time steps. Metrics used are Mean Squared Error (MSE) and Mean Absolute Error (MAE). For uncertainty evaluation, we use the Continuous Ranked Probability Score (CRPS).

4.2 Main Results

Table 1 presents the performance of the models on the ETT dataset under "clean" (regular) conditions to establish a baseline. Even without irregularity, UCCT performs competitively, suggesting that the continuous time encoding provides a rich representation of temporal dynamics.

Model	Horizon 96 (MSE)	Horizon 96 (MAE)	Horizon 336 (MSE)	Horizon 336 (MAE)
LSTM	0.425	0.448	0.612	0.589
Informer	0.386	0.410	0.522	0.513
UCCT (Ours)	0.365	0.392	0.498	0.495

Table 2 illustrates the core contribution of this work: performance under irregular sampling (50% data dropped). Here, the degradation of baseline models is evident. The imputation strategies used by LSTM and standard Transformers fail to capture the dynamics correctly, leading to high error rates. The Informer, relying on fixed positional embeddings, also suffers. UCCT, however, demonstrates remarkable robustness.

Model (50% Missing)	Horizon 96 (MSE)	Horizon 336 (MSE)	Degradation vs Clean
LSTM-Imp	0.688	0.954	+61%
Transformer-Imp	0.592	0.810	+45%
Neural ODE	0.495	0.680	+18%
UCCT (Ours)	0.412	0.565	+13%

The results indicate that explicitly modeling time as a continuous variable allows the UCCT to bridge gaps in data more effectively than implicit learning or pre-processing imputation [20]. Neural ODEs perform well but were observed to be significantly slower in training (approx. 4x longer convergence time) compared to UCCT.

4.3 Uncertainty Analysis

To validate the calibration of our probabilistic output, we analyze the uncertainty bands. A well-calibrated model should have the ground truth fall within the 95% confidence interval approximately 95% of the time.

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The data visualizes the forecast on a sample from the Weather dataset. It is observable that the confidence intervals widen as the forecast horizon increases, which aligns with the theoretical understanding that long-term predictions are inherently less certain. Furthermore, in regions where input data was sparse (artificially masked), the model correctly increases its uncertainty estimate for the immediate subsequent predictions [21].

Table 3 provides an ablation study to verify the components of our architecture. We tested the model without the continuous embedding (using standard positional encoding + masking) and without the probabilistic loss (using standard MSE).

Variation	MSE (Irregular)	CRPS (Uncertainty Score)
Full UCCT	0.412	0.225
w/o Continuous Emb	0.540	0.298
w/o Prob. Loss	0.435	N/A

The ablation results confirm that the continuous embedding is the primary driver of performance in irregular settings [22,23]. The probabilistic loss, while slightly improving MSE by acting as a regularizer, is fundamental for providing the CRPS score, which is undefined for deterministic models [24,25].

Chapter 5: Conclusion

This paper presented the Uncertainty-Calibrated Continuous Transformer (UCCT), a specialized architecture designed to tackle the dual challenges of data irregularity and uncertainty quantification in long-horizon time-series forecasting. By replacing discrete positional indices with a learnable continuous-time embedding, the model effectively decouples the inference process from the rigid sampling grids required by traditional deep learning models. This innovation allows for the seamless processing of missing values and non-uniform sensor data without the need for bias-inducing imputation steps. Furthermore, the integration of a probabilistic output head, optimized via a composite likelihood-based loss function, enables the model to output calibrated confidence intervals.

The experimental results across energy, weather, and healthcare domains validate the efficacy of this approach. The UCCT not only outperformed deterministic baselines in standard metrics like MSE and MAE but also demonstrated superior robustness when subjected to high rates of data loss. The ability to quantify uncertainty is particularly implicated in high-stakes decision-making; for grid operators or clinicians, knowing when the model is uncertain is often as valuable as the prediction itself.

While the UCCT represents a significant step forward, several limitations persist. First, the assumption of a Gaussian distribution for the output may not hold for all types of data, particularly those with heavy tails or multimodal distributions (e.g., traffic flow with distinct morning and evening peaks). Future work should explore the use of Normalizing Flows or mixture density networks to model more complex output distributions. Second, the computational cost of the attention mechanism remains quadratic with respect to the sequence length, limiting the processing of extremely long historical contexts. Although our method handles irregularity, it does not inherently solve the efficiency bottleneck of Transformers. Integrating the continuous-time embedding with linear-complexity attention approximations could be a fruitful avenue for research. Finally, the current implementation treats all variables in multivariate series as sharing the same temporal grid; extending the model to handle asynchronous multivariate time series, where different sensors report at completely different rates, remains an open challenge for future investigation.

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