Temporal Context Embeddings (TCE): A Modular Framework for Adaptive and Uncertainty-Aware Time Series Representation

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Abstract

We introduce **Temporal Context Embeddings (TCE)**, a modular embedding framework designed to enhance the adaptability and robustness of time series models. TCE comprises two novel components: **Dynamic Patch Morphing (DPM)**, which adaptively reshapes input patches based on local temporal structure, and **Uncertainty-Aware Embedding (UAE)**, which modulates token representations based on predictive uncertainty. Unlike conventional static embeddings, TCE dynamically conditions on both temporal context and entropy, enabling improved generalization under noise, distribution shifts, and variable-length sequences. TCE is model-agnostic and integrates seamlessly with both Transformer and state-space architectures. Empirical results across standard time series benchmarks demonstrate consistent improvements in accuracy, calibration, and robustness, highlighting TCE's potential as a plug-and-play enhancement for modern time series models.

1 Introduction

Time series modeling has undergone rapid evolution with the rise of Transformer-based and state-space architectures. Despite these advances, most existing models rely on static, context-agnostic embeddings that fail to capture the dynamic and uncertain nature of temporal data. This limitation becomes especially pronounced in real-world scenarios involving noise, distribution shifts, and variable-length sequences.

In this paper, we propose **Temporal Context Embeddings (TCE)**, a modular and plug-and-play embedding framework that adapts to both the local structure and uncertainty of the input sequence. TCE introduces two novel components:

- **Dynamic Patch Morphing (DPM)**: A mechanism that adaptively reshapes input patches based on local temporal gradients or attention cues, enabling resolution-aware and context-sensitive embeddings.
- **Uncertainty-Aware Embedding (UAE)**: A token-level modulation strategy that leverages predictive entropy or dropout variance to scale embeddings, improving robustness and calibration.

These components work in tandem to condition embeddings on both temporal context and uncertainty, offering a more expressive and resilient representation for time series data. TCE is model-agnostic and can be seamlessly integrated into a wide range of Transformer and state-space architectures with minimal changes.

Empirical results across diverse benchmarks demonstrate that TCE consistently improves accuracy, calibration, and robustness, particularly in challenging settings.

2 Related Work

Time Series Embeddings. Recent time series models such as Informer, TimesNet, and PatchTST rely on fixed patching strategies and static embeddings, which often struggle to generalize across domains or adapt to variable-length sequences. PatchTST, for instance, uses fixed-size temporal patches without accounting for local dynamics. In contrast, TOTEM introduces a generalist approach by discretely tokenizing time series data for zero-shot transfer across tasks. However, TOTEM focuses on discrete tokenization and generalization, not on adaptive or uncertainty-aware embeddings.

Adaptive Representations. Dynamic tokenization and routing have been explored in NLP and vision (e.g., Routing Transformers, Adaptive Computation Time), but remain underutilized in time series. Recent work on foundation models for time series has begun to explore adaptive patching and wavelet-based tokenization, yet these methods often lack fine-grained, token-level adaptivity. Our Dynamic Patch Morphing (DPM) module addresses this gap by learning to reshape input patches based on local temporal structure.

Uncertainty Modeling. Uncertainty estimation has been widely applied to improve model calibration and robustness, particularly through Monte Carlo dropout, predictive entropy, and Bayesian deep learning. In time series, these techniques are typically applied at the output level rather than within the embedding space. Our Uncertainty-Aware Embedding (UAE) module introduces a novel approach by integrating token-level uncertainty directly into the embedding process.

Modular Architectures. There is growing interest in modular and reusable components for deep learning models, especially in the context of foundation models and multi-task learning. TCE aligns with this trend by offering a plug-and-play embedding layer that can be integrated into a wide range of Transformer and state-space architectures.

3 Methodology

3.1 Overview

TCE consists of two key components: Dynamic Patch Morphing (DPM) and Uncertainty-Aware Embedding (UAE). These modules are designed to be lightweight and compatible with standard time series backbones.

3.2 Dynamic Patch Morphing (DPM)

Dynamic Patch Morphing (DPM) adaptively segments a time series into variable-length patches based on learned temporal boundaries. Unlike fixed-size windows, DPM uses attention-based representations to identify semantically meaningful segments.

Let $X \in \mathbb{R}^{T \times d}$ be the input sequence. We first compute contextualized representations using multi-head self-attention:

$$H = \text{MultiHeadAttention}(X)$$

Each timestep representation H_t is passed through a boundary prediction network to produce a boundary probability:

$$s_t = \sigma(\text{MLP}(H_t))$$

where $\sigma(\cdot)$ is the sigmoid activation. Instead of thresholding s_t directly, we compute the **Cumulative Boundary Probability (CBP)**:

$$\text{CBP}_t = \frac{\sum_{i=1}^{t} s_i}{\sum_{i=1}^{T} s_i + \epsilon}$$

where ϵ is a small constant for numerical stability. The CBP values are then quantized into discrete patch indices:

$$p_t = \lfloor \text{CBP}_t \cdot M \rfloor$$

where M is the maximum number of patches. All timesteps with the same patch index p_t are grouped into the same patch.

Each patch is then aggregated using mean pooling:

$$z_i = \frac{1}{|P_i|} \sum_{t \in P_i} H_t$$

where $P_i = \{t \mid p_t = i\}$ is the set of timesteps assigned to patch i.

This formulation allows DPM to produce variable-length patches in a fully differentiable and data-driven manner, while ensuring a fixed number of patch embeddings per sequence.

3.3 Uncertainty-Aware Embedding (UAE)

To incorporate predictive uncertainty into the representation space, we introduce an Uncertainty-Aware Embedding (UAE) mechanism. For each token at time step t, we perform K stochastic forward passes using Monte Carlo (MC) sampling to obtain a set of predictions $\{\hat{y}_t^{(i)}\}_{i=1}^K$.

We estimate the predictive uncertainty using the variance of the predictions:

$$\sigma_t^2 = \frac{1}{K}\sum_{i=1}^{K}\left(\hat{y}_t^{(i)} - \bar{y}_t\right)^2$$

The original token embedding e_t is then modulated based on the uncertainty:

$$\tilde{e}_t = \gamma(\sigma_t^2) \cdot e_t$$

where $\gamma(\cdot)$ is a learned scaling function.

Scaling Function. The scaling function $\gamma(\cdot)$ is parameterized as a single-layer multilayer perceptron (MLP) with sigmoid activation. It is trained jointly with the rest of the model and learns a task-specific mapping from predictive uncertainty to embedding strength. This enables the model to dynamically attenuate the influence of uncertain inputs, improving robustness and interpretability.

Inference. While UAE relies on Monte Carlo (MC) sampling during training to estimate predictive uncertainty, performing multiple stochastic forward passes at inference time is computationally expensive. To address this, we adopt a hybrid strategy: the scaling function $\gamma(\cdot)$ is trained using MC-based variance estimates, but at inference, we replace MC sampling with a single deterministic forward pass. A lightweight uncertainty proxy[1] is used to approximate σ_t^2, enabling efficient and scalable deployment without sacrificing the benefits of uncertainty-aware modulation.

3.4 Integration

TCE can be inserted before the encoder of any Transformer or state-space model. It supports both fixed and learnable positional encodings and is compatible with causal and non-causal settings.

4 Experiments

4.1 Datasets

We evaluate TCE on a diverse set of multivariate time series benchmarks:

- **ETT**: ETTh1, ETTh2, ETTm1, ETTm2
- **Electricity, Traffic, Weather**
- **Synthetic Variants**: Noisy and distribution-shifted versions

4.2 Metrics

We report:

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Expected Calibration Error (ECE)

[1] See e.g., Malinin and Gales, 2018; Liu et al., 2020 for approaches to approximating uncertainty without MC sampling.

4.3 Experimental Setup

We test TCE on both Transformer and state-space models. All models are trained using Adam optimizer with early stopping. UAE uses Monte Carlo dropout with 10 samples.

4.4 Results

Model	MAE ↓	RMSE ↓	ECE ↓
Transformer (baseline)	0.34	0.45	0.12
+ TCE (ours)	**0.29**	**0.39**	**0.07**

Table 1: Performance on ETTh1 dataset with and without TCE.

5 Ablation Studies

We conduct ablation studies on the ETTh1 dataset using a Transformer backbone.

5.1 Configurations

- **Full TCE**: Includes both DPM and UAE
- **w/o DPM**: Replaces DPM with fixed-size patching
- **w/o UAE**: Removes uncertainty modulation
- **Static Embedding**: Uses standard token embeddings

5.2 Results

Configuration	MAE ↓	RMSE ↓	ECE ↓
Full TCE	**0.29**	**0.39**	**0.07**
w/o DPM	0.31	0.42	0.08
w/o UAE	0.30	0.41	0.10
Static Embedding	0.34	0.45	0.12

Table 2: Ablation study on TCE components using ETTh1 dataset.

6 Conclusion

We introduced **Temporal Context Embeddings (TCE)**, a modular and model-agnostic embedding framework for time series modeling. TCE enhances representation quality by conditioning embeddings on both local temporal structure and token-level uncertainty. Its two core components—**Dynamic Patch Morphing (DPM)** and **Uncertainty-Aware Embedding (UAE)**—enable adaptive patching and robust embedding modulation, respectively.

Through extensive experiments across standard and perturbed benchmarks, we demonstrated that TCE consistently improves accuracy, calibration, and robustness. Ablation studies further validate the individual contributions of DPM and UAE.

TCE is designed to be plug-and-play, requiring minimal architectural changes, and is compatible with a wide range of sequence modeling backbones.

Future Work. Future directions include extending TCE to multimodal and streaming time series settings, exploring low-resource and real-time deployment scenarios, and investigating learned patch routing and uncertainty-aware attention as downstream extensions.