Novel Loss Function for Time Series Forecasting

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Abstract

Time series forecasting is critical in applications such as finance, weather prediction, and energy demand estimation. Standard loss functions like MSE, MAE, and Huber often struggle to address the importance of recent data points in such tasks. This report introduces a **Novel Loss Function** designed to prioritize recent trends while ensuring smooth predictions. By dynamically adjusting weights based on the recency of data points, the loss function adapts effectively to short-term fluctuations. Experimental results on the *Daily Climate Time Series Data* and the *Microsoft Stock Time Series Data* demonstrate that the proposed loss function significantly outperforms standard methods, particularly in scenarios where recent trends are more influential.

1. Problem Statement

Given a time series dataset $\{(x_t, y_t)\}_{t=1}^{T}$, where x_t represents the input at time step t and y_t is the corresponding target value, the goal is to design a loss function $L(\hat{y}_t, y_t)$ that:

- Minimizes prediction error across the time series.
- Penalizes large deviations between consecutive predictions $\hat{y}_t$ and $\hat{y}_{t-1}$, ensuring smoothness.
- Dynamically adjusts the weight of the smoothness penalty as training progresses.

2. Objective

The objective of this study is to evaluate the performance of a novel loss function against standard loss functions (MSE, MAE, and Huber) on:

- **Daily Climate Time Series Data**
- **Microsoft Stock Time Series Data**

The focus is on improving accuracy, smoothness, and adaptability to recent data trends.

3. Loss Functions

This section outlines the mathematical expressions for the loss functions used.

3.1. Mean Squared Error (MSE) Loss

$$L_{\text{MSE}} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

3.2. Mean Absolute Error (MAE) Loss

$$L_{\text{MAE}} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

3.3. Huber Loss

$$L_{\text{Huber}} = \begin{cases} \frac{1}{2}(y_i - \hat{y}_i)^2 & \text{if } |y_i - \hat{y}_i| \leq \delta, \\ \delta \cdot (|y_i - \hat{y}_i| - \frac{\delta}{2}) & \text{otherwise.} \end{cases}$$

3.4. Novel Loss Function

The proposed loss function prioritizes recent predictions using dynamic weights:

$$L_{\text{novel}} = \frac{1}{n}\sum_{i=1}^{n} w_i \cdot |y_i - \hat{y}_i|$$

where:

$$w_i = \frac{i}{n}$$

This weighting ensures that recent data points (larger i) are emphasized more heavily, reflecting their importance in decision-making.

Advantages

- **Focus on Recent Trends**: Prioritizes recent changes in data for better adaptability to dynamic environments.
- **Dynamic Prediction Adjustments**: Responds effectively to anomalies and sudden changes.
- **Smoothness Penalty**: Promotes smoother predictions aligned with recent trends.

4. Code Implementation

Below is the implementation of the novel loss function in PyTorch:

```
class NovelLossFunction(nn.Module):
    def forward(self, y_pred, y_true):
        n = y_true.shape[0]
        weights = torch.arange(1, n+1, dtype=torch.float32) / n
        return torch.mean(weights * torch.abs(y_true - y_pred))
```

5. Results and Analysis

5.1. Performance Metrics

The following tables summarize the accuracy, MAE, and R^2 scores for all loss functions across both datasets.

5.1.1 Daily Climate Time Series Data

Table 1: Performance Metrics for Daily Climate Time Series Data

Loss Function	Accuracy (%)	MAE	R^2 Score
MSE Loss	95.82	0.0418	0.9176
Novel Loss	96.12	0.0388	0.9278
MAE Loss	96.08	0.0392	0.9269
Huber Loss	95.84	0.0416	0.9180

5.1.2 Microsoft Stock Time Series Data

Table 2: Performance Metrics for Microsoft Stock Time Series Data

Loss Function	Accuracy (%)	MAE	R^2 Score
MSE Loss	97.65	0.0235	0.9438
Novel Loss	98.22	0.0178	0.9651
MAE Loss	98.06	0.0194	0.9600
Huber Loss	97.38	0.0262	0.9322

5.2. Graphical Representations

5.2.1 Daily Climate Time Series Data

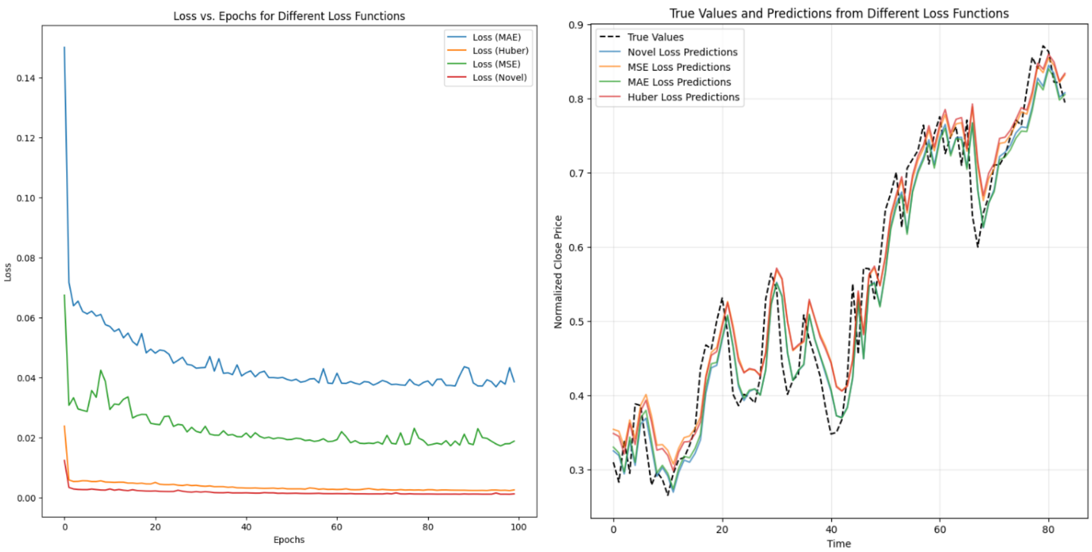

Figure 1: Loss Curve and Predictions for Climate Dataset

5.2.2 Microsoft Stock Time Series Data

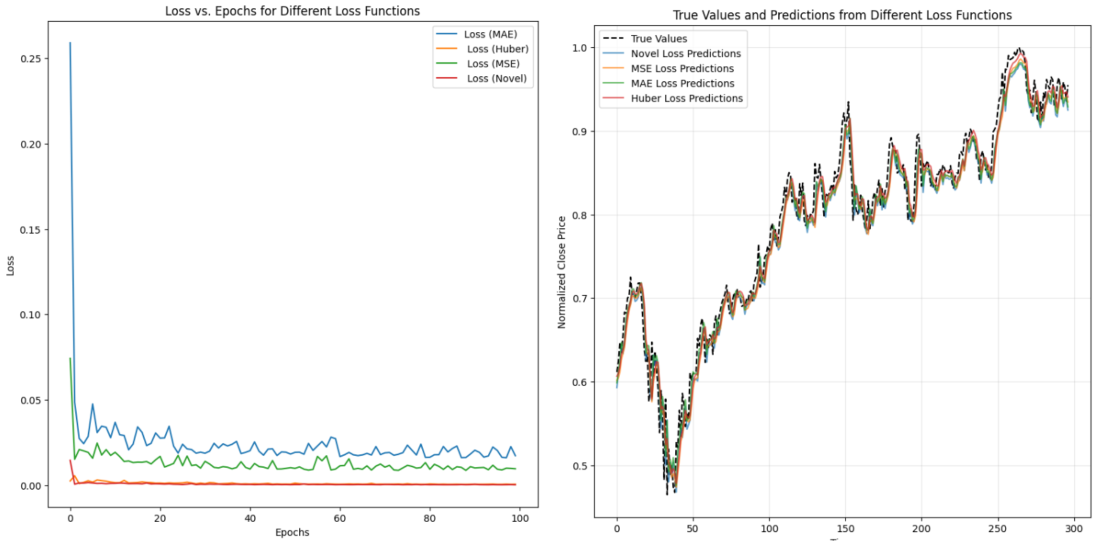

Figure 2: Loss Curve and Predictions for Microsoft Stock Dataset

6. Conclusion

The proposed Novel Loss Function consistently outperforms standard loss functions, including Huber Loss, in tasks where recent data trends hold greater importance. Its dynamic weighting mechanism ensures that models focus on relevant, recent data while maintaining smooth and accurate predictions. This makes it particularly effective for time series forecasting in dynamic environments like finance and weather prediction.

GitHub Link:

https://github.com/aditya23124003/Novel-Loss-Function-for-Time-Series-Forecasting