GSTCN: Graph-based Spatial-Temporal Convolutional Networks for Advanced ENSO Forecasting

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***Abstract*—The El Niño-Southern Oscillation (ENSO) phenomenon is one of the factors that has a major impact on global climate change. It may cause natural disasters such as floods, droughts, and heavy rainfall, and have a serious impact on public health. Therefore, how to accurately predict the ENSO phenomenon has become a top priority in current research and mitigation efforts. Although physical models and traditional statistical models can improve ENSO prediction capabilities, accurately predicting ENSO remains challenging due to the nonlinearity of ENSO. In recent years, the introduction of deep learning methods has brought new possibilities to ENSO prediction. In this paper, we utilize existing deep learning models to construct a novel spatiotemporal model called adaptive graph spatiotemporal convolutional network (GSTCN). We first develop a graph convolution space module to adapt it to the characteristics of evolving states. Furthermore, we introduce a time series module to capture the relationship between time series output and input. We conduct experiments on simulated and historical climate data sets, and the experimental results show that GSTCN outperforms contemporary deep learning models in ENSO prediction, with a 20-month prediction horizon.**

Keywords—ENSO; GCN; informer; Long lead prediction; sea surface temperature；

I. INTRODUCTION

ENSO refers to a climate phenomenon involving the interaction between the equatorial Pacific Ocean and the atmosphere, resulting in global climate variations. It is closely tied to changes in sea surface temperatures and encompasses three distinct phases: the onset, maturity, and decay. Driven by oscillations in winds and sea temperatures, ENSO can trigger extreme weather events like floods, droughts and hurricanes[1]. Consequently, ENSO events have far-reaching impacts on global climates, societies, ecosystems, and economies. ENSO prediction holds significant importance in meteorology, climatology, and society at large. Therefore, accurately forecasting the occurrence and development trends of ENSO events holds crucial value for society's preparedness against extreme weather events, formulation of meteorological disaster alerts, agricultural production, and water resource management.

The Nino3.4 index was developed to reveal the complexity of ENSO-related climate changes and is considered a good indicator for monitoring the evolution of ENSO phases [2]. The basic method for Nino3.4 index prediction is numerical simulation of atmospheric and oceanic processes, which utilizes general physical laws as well as partial differential equations and numerical models [3]. For example, atmosphere-ocean coupling model, intermediate coupling model [4], hybrid coupling model, etc. Prediction accuracy is limited as they often have difficulty capturing complex details and interactions between all relevant factors, as well as requiring large amounts of computational resources and physical quantities.

Instead of using physical equations, some researchers adopt statistical methods for historical time series modeling [5]. A first attempt was made by Petrova et al., who decomposed the time series into a series of stochastically time-varying components, but despite progress, the forecast horizon of such methods is still limited to one year.

In order to overcome these limitations, deep learning [6] technology is gradually introduced into the field of ENSO prediction. Neural network methods do not rely on a priori assumptions about ENSO formation mechanisms [7]. Instead, they learn features and patterns from data to better capture the complexity of ENSO events[8]. For example, Cachay et al. jointly learned large-scale spatial interactions by applying graph neural networks to actual ENSO prediction tasks to improve the prediction accuracy of Nino 3.4[9]; Zhao et al. introduced spatiotemporal semantic network to capture the spatiotemporal information of atmospheric and oceanic factors, and get longer delivery times[10]. However, even with the neural network approach, ENSO prediction still encounters some challenges that need to be solved .

Therefore, we adopt a dual perspective encompassing space and time to tackle the key challenges in ENSO prediction. Through the incorporation of both the graph module and the informer module, we present the GSTCN model. This empowers us to effectively capture the spatiotemporal relationships of ENSO events, facilitating accurate predictions of ENSO occurrences and evolutions with a prediction horizon extending up to two years.

II. THE GSTCN MODEL

ENSO event prediction is a prediction problem involving both space and time levels. The entire process can be explained as using known historical data (SST, T300) to predict the Nino 3.4 index in the coming months.

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A. The Graph Convolution Network

1) Dynamic Graph

A dynamic graph is a graph composed of a set of nodes V and a set of edges ε, and its representation is $G^t = (V^t, \varepsilon^t)$, where t represents the number of time stamps, and where $V^t = \{V^1, V^2, V^3, \ldots V^t\}$ represents the grid cells of the climate dataset. Each grid cell V^i is a node defined by its latitude and longitude.

2) Graph Convolution Network

For this task, we employed the GCN[9] architecture to extract spatial features. Within GCN, the nodes and edges we defined are used to construct an adjacency matrix for subsequent computations. GCN operates on the principle of neighbour-based information propagation, leveraging the neighbour information of nodes to update their representations. The representation of each node is derived by aggregating the features of its adjacent nodes. This propagation of neighbour information enables nodes to infer their own feature representations by considering connected nodes, a process often referred to as message passing. GCN utilizes graph convolutional layers to conduct information aggregation. These layers aggregate the information from neighbouring nodes to generate new representations for each node. By combining node features with information from neighbouring nodes, graph convolutional layers employ convolutional operations to update node representations.

Furthermore, in our specific experiments, we introduced skip connections and residual connections to enhance the performance of spatial aggregation. Skip connections refer to linking the node embeddings from intermediate GCN layers to the final layer. Additionally, graph convolutions normalize the input node embeddings and convert them into high-dimensional feature vectors before feeding them into subsequent time-series modules. Figure 1 shows the results of SST and T300 by GCN.

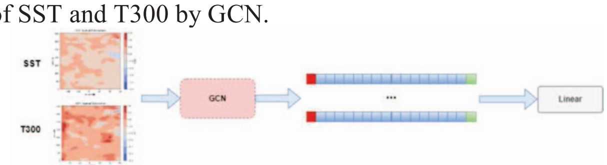


Figure 1. The results of SST and T300 by GCN

B. The informer model

Informer[7] is a time series forecasting model built upon the Transformer architecture, specifically designed for predictive tasks with time series data. It inherits the self-attention mechanism of the Transformer[12] and extends it to ProSparse attention mechanism, derived to address long-term dependencies while integrating the advantages of Convolutional Neural Networks (CNN) for achieving long-range forecasting. This amalgamation allows Informer to capture long-range dependencies between input and output, generating predictions step by step ahead[11]. This combination enables Informer to effectively handle ultra-long sequences of data, showcasing enhanced robustness. Figure 2 illustrates the internal architecture of Informer.

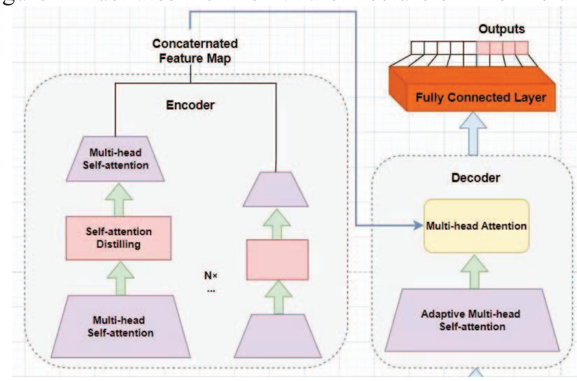


Figure 2. The internal architecture of Informer

In informer, each element matches all other input elements, determining attention distribution and optimal matches. The self-attention mechanism employs scaled dot-product attention across nodes, using softmax to compute adjacency-based attention. The computation of the self-attention mechanism is as follows:

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

Figure 3 illustrates the computation process of the self-attention mechanism in the Transformer. The self-attention mechanism comprises three steps: linear transformations of queries (Q), keys (K), and values (V), computation of attention scores, and weighted summation. For a given input sequence, linear transformations are performed to obtain W_q, W_k, and W_v. Subsequently, similarities between Q and K are computed. For each query (Q) vector, its dot product with all key (K) vectors is calculated, followed by a scaling operation. Finally, attention score matrices are computed, multiplied by the W_v matrix to achieve the weighted sum.

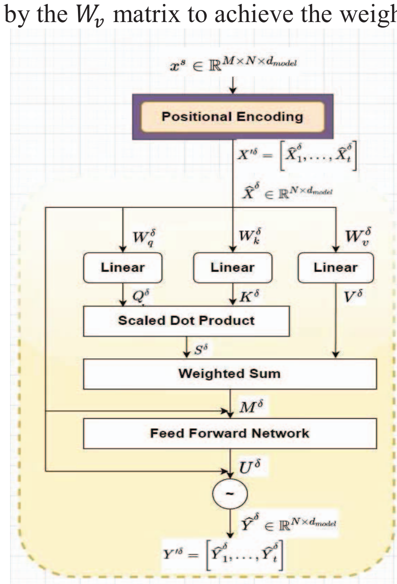


Figure 3. The computation process of the self-attention mechanism

III. EXPERIMENTAL PROCESS AND RESULT ANALYSIS

The experiments were implemented in the PyTorch framework on an RTX 3090 server with 20GB memory. The entire model was optimized using the Adam optimizer.

A. Data Sets

In our experimentation, we utilized three distinct datasets: CMIP5, a simulated dataset, and two real-world datasets—SODA and GODAS. CMIP5 served as the foundation for training, while SODA played the role of the validation set, and GODAS was designated as the test set.

CMIP5 offers a diverse array of variables, including sea surface temperature (SST) and heat content (HC), derived from a spectrum of climate modeling experiments. Encompassing the geographical range between 180°W-180°E and 55°S-60°N, these simulations were consistently conducted using uniform driving data and experimental protocols across 21 distinct regions and countries.

SODA contains an array of ocean variables, comprising sea surface temperature and ocean surface height, spanning various global regions and depth levels. Stored as multidimensional arrays, this dataset was primarily utilized for validation purposes.

GODAS similarly encompasses multiple ocean variables like sea surface temperature and ocean surface height, represented in grid points. Our application focused on utilizing this dataset for the consecutive 24-month prediction of the Nino3.4 index.

B. Evaluation Metrics

We evaluate the superiority of our models and predictions using two common evaluation metrics:

1) Root Mean Square Error

$$\mathrm{RMSE} = \sqrt{\frac{1}{MN}\sum_{j=1}^{M}\sum_{i=1}^{N}\left(y_i^j - \hat{y}_i^j\right)^2}$$

RMSE is the standard deviation of the prediction error.

2) Correlation Coefficient

$$\mathrm{cor_i} = \frac{\sum(\mathrm{X}-\mathrm{X_{mean}})(\mathrm{Y}-\mathrm{Y_{mean}})}{\sqrt{\sum(\mathrm{X}-\mathrm{X_{mean}})^2\sum(\mathrm{Y}-\mathrm{Y_{mean}})^2}}$$

Where X is the actual value, $\mathrm{X_{mean}}$ is the mean of the actual value over 24 months, Y is the predicted value, and $\mathrm{Y_{mean}}$ is the mean of the predicted value over 24 months.

C. Result

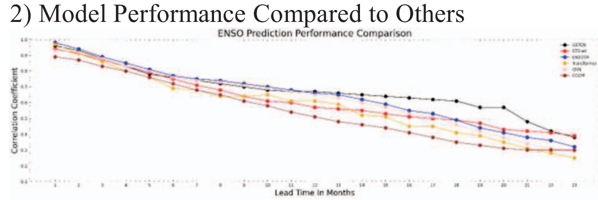
The GSTCN model was compared with several state-of-the-art methods in the ENSO domain, including both physical model numerical predictions and deep learning methods. The physical model methods included ENSO Time Series Regression (ENSOTR), while the deep learning methods included EEMD- TCN, STSnet, Conv-LSTM, CNN. The results are shown in Figure 4, displaying the correlation coefficient (Corr) and root mean square error (RMSE) of the average Nino3.4 index from 1982 to 2017.Several conclusions can be drawn from the comparison:

1) Comparison between Physical Models and Deep Learning

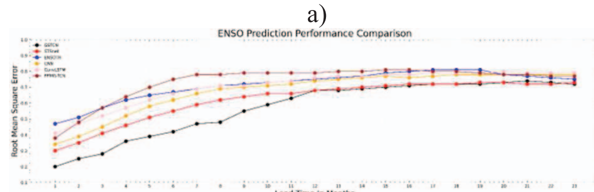
In the context of ENSO prediction, a comparison was drawn between the methods of physical modeling and deep learning. Numerical forecasting methods rely on complex mathematical models and extensive computational processes for prediction. In contrast, deep learning methods utilize data- driven approaches to automatically learn and capture the intricate patterns and features of ENSO phenomena. The comparative results indicate that, for all prediction months, our model outperforms the STSnet.

Deep learning methods outperform physical modeling in ENSO prediction. This advantage can be attributed to the fact that deep learning models can extract meaningful representations directly from data without explicit reliance on the underlying physical processes involved in ENSO dynamics. By learning directly from data, deep learning models demonstrate a stronger capability to capture complex temporal dependencies and nonlinear relationships, thereby achieving more accurate and reliable ENSO predictions. This comparison highlights the advantages of deep learning in ENSO prediction, emphasizing its potential for improving insights and forecasts in climate research and prediction tasks.

2) Model Performance Compared to Others



a)



b)

Figure 4. The Corr a) and RMSE b) of the average Nino3.4 index

Our model combines the strengths of graph convolution networks and informer self-attention mechanisms to capture the spatiotemporal characteristics of ENSO data. It successfully models the nonlinearity and long-term dependencies in ENSO data. The results show that our model predicts months with a Nino3.4 index correlation above 0.5 more frequently. Our method outperforms all competing methods in the ENSO prediction field in the long term. Although our model is an ensemble of two recently proposed models, it has undergone multiple rounds of adjustments and improvements, enabling it to accurately predict ENSO event cycles up to 20 months in advance.

Additionally, we compared the performance with different input data lengths, with particular focus on the performance of the initial token length input to the decoder. The Table 1 display the correlation coefficients of prediction results.

Table 1. The Corr and RMSE of the prediction results

Forecast lead	E:3	E:6	E:9	E:12
1	**0.99**	0.98	0.98	0.96
3	**0.90**	0.88	0.90	0.88
6	0.69	0.70	0.75	**0.76**
9	0.42	0.52	0.61	**0.70**
12	0.33	0.52	0.62	**0.67**
15	0.46	0.61	**0.67**	0.64
18	0.56	0.62	**0.62**	0.61
21	0.50	**0.56**	0.52	0.48
23	0.42	**0.43**	0.42	0.38

IV. CONCLUSION

In this paper, we combine the previous GCN and informer models to construct a GSTCN model for multi-year ENSO prediction, which has significant advantages in capturing the spatio-temporal characteristics of ENSO phenomena. By introducing a Graph and a spatio-temporal transformation network, GSTCN can adaptively model spatial and temporal dependencies, and effectively capture the continuous characteristics of global and cli- mate change. Experimental results show that GSTCN achieves better prediction performance than traditional numerical prediction methods, such as INTEXF and NMME, as well as CNN and Transformer based models. It shows high accuracy in the prediction of various leading months. In the future, we will further explore and optimize the GSTCN model and start to study the exponential smoothing algorithm, and integrate it into the informer model, so that our model can better capture the seasonal and periodic characteristics of ENSO phenomenon, so as to cope with more complex climate phenomena and improve the stability and robustness of prediction.

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