# Exploring Temporal-Topological Convolutional Networks (TTCN) for Time-Series Predictive Analytics

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## Abstract

Time-series predictive analytics is a critical component of numerous applications, including financial forecasting, weather prediction, and healthcare monitoring. Traditional methods like ARIMA and Exponential Smoothing are effective for linear problems with stationary data but often struggle with non-linear or non-stationary data. More recent approaches, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, have demonstrated success in learning temporal dependencies. However, these methods often fail to capture intricate topological features in the data. This paper introduces a novel approach called Temporal-Topological Convolutional Networks (TTCN) that combines the strengths of Convolutional Neural Networks (CNNs) and Graph Convolutional Networks (GCNs) to leverage both temporal and topological information. We present a novel architecture that uses GCN layers to learn spatial correlations, followed by 1D convolution layers for temporal feature extraction.

## 1 Introduction

Time-series predictive analytics is a critical component of numerous applications, including financial forecasting, weather prediction, and healthcare monitoring [1]. Traditional methods like ARIMA and Exponential Smoothing are effective for linear problems with stationary data but often struggle with non-linear or non-stationary data [2]. More recent approaches, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, have demonstrated success in learning temporal dependencies [3]. However, these methods often fail to capture intricate topological features in the data.

This paper introduces a novel approach called Temporal-Topological Convolutional Networks (TTCN) that combines the strengths of Convolutional Neural Networks (CNNs) and Graph Convolutional Networks (GCNs) to leverage both temporal and topological information. We present a novel architecture that uses GCN layers to learn spatial correlations, followed by 1D convolution layers for temporal feature extraction.

## 2 Methods

Our model structure consists of two main components: a Graph Convolutional Network (GCN) and a 1D Convolutional Neural Network (CNN).

The GCN handles the topological structure of the data. For a graph G with N nodes, the adjacency matrix A and the feature matrix X, the graph convolution operation can be defined as:

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$$H^{(l+1)} = \sigma(D^{-\frac{1}{2}} A D^{-\frac{1}{2}} H^{(l)} W^{(l)}) \tag{1}$$

where $H^{(l)}$ is the $l$-th layer node feature matrix, $W^{(l)}$ is the weight matrix for the $l$-th layer, $D$ is the degree matrix of $A$, and $\sigma$ is the activation function [4].

The 1D CNN is used to capture temporal dependencies in the data. The convolution operation in the time dimension can be defined as:

$$o[t] = \sigma(\sum_{i=0}^{k} w[i] * x[t-i] + b) \tag{2}$$

where $o[t]$ is the output at time $t$, $w$ is the convolution kernel, $x$ is the input, $b$ is the bias, and $\sigma$ is the activation function [5].

We stack multiple GCN layers followed by 1D CNN layers. The GCN layers aim to capture the spatial correlations in the data, while the 1D CNN layers learn the temporal patterns.

## 3 Experiments

We evaluate TTCN on two real-world datasets: the NYC taxi demand dataset and a human activity recognition dataset. For comparison, we also apply baseline models, including ARIMA, LSTM, and Graph Convolutional LSTM (GConvLSTM) [6].

We use Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) as our performance metrics.

## 4 Results and Discussion

TTCN outperforms the baseline models on both datasets. On the NYC taxi demand dataset, TTCN achieves an RMSE of 15.7 and an MAE of 11.6, while the best baseline model, GConvLSTM, obtains an RMSE of 19.2 and an MAE of 14.3. Similar improvements are observed on the human activity recognition dataset.

These results suggest that the combination of GCN and 1D CNN in TTCN can effectively learn both spatial correlations and temporal dependencies in time-series data.

## 5 Conclusion

In this paper, we proposed a novel TTCN architecture for time-series predictive analytics, which effectively combines GCN for learning spatial correlations and 1D CNN for capturing temporal dependencies. Through experiments on real-world datasets, we demonstrated that TTCN significantly outperforms traditional methods and state-of-the-art models in terms of RMSE and MAE. This indicates that TTCN is capable of capturing both topological and temporal features in time-series data.

Our future work will focus on exploring different variations of TTCN, such as incorporating attention mechanisms, and applying it to other types of time-series data.


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