Literature Review Update:

# A novel framework for spatio‑temporal prediction of environmental data using deep learning.

Amato et al. [1] designed a deep learning-based architecture called “Empirical Orthogonal Functions principal component analysis” EOF-PCA in which the EOF framework decomposes the spatiotemporal input data, in terms of a sum of products of temporally referenced basis functions and of stochastic spatial coefficients which can be spatially modelled and mapped on a regular grid. Then, the input layer spatial covariates are processed by a “Fully Connected Neural Network” (FCNN) to obtain predictive coefficient to be recomposed altogether with the decomposed data stream, obtaining a spatiotemporal signal reconstruction.

According to [1], the authors stated that their problem is the spatiotemporal data prediction (i.e., climate & environmental change) is not enough to be done with physically based models, so that is why Machine learning algorithms will do the prediction, which are efficient in analysing and modelling spatially and temporally variable environmental data. Deep learning methods, capable of feature auto-extraction (CNN in spatial domain, and RNN in temporal domain), is a promising approach to tackle this challenge. DL also could capture spatio-temporal dependencies through their automatic FRL. Despite the astounding efficiency of the DL architectures, the problem of the interpolation of continuous spatio-temporal fields measured on a set of irregular points in space is still under-investigated - and it still requires an adaptation effort for an environmental S.T. problem.

And the second problem is that it is arduous effort to handle a climato-environmental S.T. data – The data input in DL models are in both time and space domains, a set of irregular points in space—rather than with raster data. To tackle this gap, we introduce here a framework for spatio-temporal prediction of climate and environmental data using deep learning, which is briefly described above. The proposed framework will allow to reconstruct coherent spatio-temporal fields.

## Related works [Consider reading the full paper for its in-reference]

Classical methods for spatiotemporal modelling include state-space models and Gaussian Processes based on spatiotemporal kernels (a.k.a kriging models)

The kriging models face several issues, such as reproduction accuracy of non-linear spatio-temporal behaviours, the data structure dependence of covariance representation, and involvement in high number of covariates.

The traditional ML in S.T. problems also has drawbacks - it requires human-engineered spatio-temporal features. The DL, however, can automatically learn feature representations from the raw spatio-temporal data.

There are some examples of DL in S.T. data mining - Geospatial problems have been studied with non-Euclideian spatial graphs via graph-CNNs. GAN+Autocorrelations improve the spatial pattern representation – E.G., we use GAN to imprint some missing climate data into a satellite image. Still, these approaches did not consider the temporal dimension of the studied phenomena.

When the temporal dimension is considered and the data are collected as raster, the ST-field can be modelled and extracted using a CNN, or an RNN Bayesian methods have also been proposed together with RNNs to quantify prediction uncertainties.

Few approaches have been proposed to model data collected at spatially irregular locations. Some ML techniques are implemented to interpolate the missing data in environmental time series. The main limitations of such methodology are 1. We need to take the location difference correlations (treat them as nodes on a graph), and 2. the prediction is only possible on the measured location, not the location we are interested.

Up to now, no study has been conducted on the possibility of performing interpolation of STD at any spatial location using DL, highlighting the novelty of the framework proposed in this paper.

# A Deep Learning Approach Combined Spatio-Temporal Features for Short-Term Forecast in Rail Transit

Tang et al. [2] designed an LSTM based framework to learn and forecast the rail traffic. The short-term forecast of rail transit is an issue in intelligent transportation system (ITS). Accurate forecast can forewarn travel outburst, helping the passengers with their travel plans. Even though the LSTM is notably effective in temporal data, it cannot correlate the time domain with the space domain. That is why we propose ST-LSTM. Compared with other conventional models, ST-LSTM network can achieve a better performance in experiments.

LSTM network is widely recognized as the most suitable model to deal with traffic forecast. LSTM unit has three gates, namely, input gate, forget gate, and output gate, which can adjust the state of unit dynamically, so LSTM network is able to capture the features on longer time span.

In this paper, the object of study is the short-term forecast of rail transit. With the trains having fixed station, uniform speed, and regular schedule, the spatial correlation between stations can be transformed into the time cost.

In this work, the data in the temporal (directly) and the spatial domains (With the TCM & SCM) before entering the FC-input-layers to combine them as the input. Then, we set the weight matrices & bias vectors for our ST-LSTM, and fine tune them to minimize the cost function output. Then, the ST-LSTM learns and captures the features of both domains. The training-testing data is of the space domain (100 stations) and the time domain (March 2017, daily) Compared with most existing methods, the proposed model has a better performance on accuracy and meets the real-time requirement.

## Related works [Consider reading the full paper for its in-reference]

traffic forecast is a problem with spatio-temporal complexity, i.e., the problem of spatial transportation in temporal dimension. In, Zheng Zhao et al’s work[2.1]. establish a network by connecting several LSTM units, but failed to imitate the structure of large urban scale. Xiaobo Chen et al. [2.2] proposed a new method to process spatial features by using sparse hybrid genetic algorithm. Liu Qingchao et al. [2.3] proposed a model based on manifold similarity to capture the spatial regularity from freeway data. These two approaches are sensitive to the spatial features, but compared with LSTM network, they cannot process temporal features well.

There are many methods that have been proposed to improve traffic forecast - historical average and smoothing, dynamic linear methods, traffic theory-based methods, and machine learning methods – all of them are divided into parametric approaches and nonparametric approaches. Autoregressive integrated moving average (ARIMA) is a parametric approach. Parametric approaches have favorable properties and capture regular variations very well. However, traffic data usually shows irregular variations. Nonparametric approaches are usually implemented against temporal features, such as nonparametric regression models, support vector machine (SVM), and recurrent neural network (RNN), which is widely recognized as a suitable method to capture the temporal features of passenger flow – but failed to capture the long-term features because of vanishing/exploding gradient – That is why we need an LSTM.

# Spatial-Temporal Deep Learning Network for Traffic Forecasting

Lu et al. [3], designed a spatial-temporal deep learning network, termed ST-TrafficNet, for traffic flow forecasting, whose architecture works as follows. 1. The Spatial Aware Multi-Diffusion Convolution Bloc (ADC-Block – who introduces Graph Attention Mechanism (GAM) into the MDC) uncovers unseen spatial dependencies from traffic graph signals automatically 2. From the data stream, the multi-diffusion convolution (MDC) block harvests ST-features of the spatial domain. 3. The ST-TrafficNet, an LSTM based framework, harvests the features of the temporal domain. 4. The output from both ANN are summed up to achieve convolutional results. And 5. The ST-TrafficNet is evaluated on two benchmark datasets and compare it with various baseline methods for traffic forecasting.

Intelligent transportation systems (ITSs) is gaining prominence in signal control, navigation, and guidance in road transport. Traffic forecasting, gathered in a form of a spatiotemporal dataset, is challenging due to the natural complexity and uncertainty of traffic patterns. E.g., we need several sensors to collect traffic data, which is collected as traffic graph signals, and there is a seasonality in the data itself. The idea of traffic forecasting is to extract S.T. dependencies of historic TGS to learn traffic patterns and make accurate predictions. There are some neural networks in ITS – the CNN (including GCN) captures the space domain of the input data, and the RNN (including LSTM) captures the time domain one. On the other hand, the GCN also has drawbacks – 1. the GCN-based approaches require a predetermined graph structure - the predetermined graph structure could have some mistakes under several conditions. 2. The socioeconomic-demographic factors also influence the raw input graph (a.k.a. input data) 3. Current traffic forecasting methods are ineffective to learn high-dimension temporal features (HDTF) of intricate traffic graph signals – so that it must work along with an LSTM, which still struggles to learn HDTF from traffic data.

To overcome these, The MDC block, performing diffusion convolution (i.e., forward, backward, and attentive), capture spatial dependencies in parallel with ST-TrafficNet (an LSTM) of the time domain. The ADC block introduces Graph Attention Mechanism (GAM) into the MDC to learn graph structure from traffic graph signals without prior graph structure knowledge.

## Related works [Consider reading the full paper for its in-reference]

Early traffic forecasting studies mainly employ model-driven approaches such as Autoregressive Integrated Moving Average (ARIMA) [3.12] and Kalman Filter (KF) family [3.13–16]. These methods fail to deal with complex non-linear traffic node signals due to the stationary assumption of time-series.

The data-driven methods, however, employ ML approaches to discover the traffic patterns in the historic traffic data automatically. ML methods, such as Support Vector Regression (SVR) [19,20], Extreme Learning Machine (ELM) [3.21], k-Nearest Neighbors algorithm (kNN) etc., can handle the intricate traffic data in high-dimensional Euclidean space considering the non-linearity of data; improving the forecasting accuracy.

Sequence driven DL methods, such as Deep Belief Network (DBN) [3.24] and Stacked Autoencoder (SAE) [3.25-26], and the Recurrent Neural Network (RNN), proved to be practical to harvest temporal dependencies of traffic node signals, but they neglect the spatial correlations.

To cover the spatial domain, a Convolutional Neural Network (CNN) or Graph Convolutional Network (GCN) is integrated into an RNN. Zhang et al. modeled the spatial dependencies as a heatmap image and used a branch of CNN units to extract different spatial properties of crowd traffic [3.5].

Yao et al. proposed a gated CNN mechanism to capture the potential spatial features and combined them with temporal features that captured by Long Short-Term Memory (LSTM) to tackle the spatial-temporal traffic forecasting problem [3.8]. CNN are limited on grid structures, while the traffic network has a topology nature as a graph. Thus, A GCN is more capable to deal with the traffic network graph structure. Seo et al. proposed Graph Convolutional Recurrent Network (GCRN) to generalize RNN to traffic graph signals structured by an arbitrary graph with GCN [3.7].

Li et al. proposed Diffusion Convolutional Recurrent Neural Network (DCRNN), which introduced a diffusion convolution operator into Gated Recurrent Units (GRU) [3.31]; hence, it can capture spatial-temporal dependencies with a recurrent random walks process on traffic network data [3.6]. Most recently, the hybrid GCN–RNN models achieve state-of-the-art performance of traffic forecasting [3.32]. These methods require predefined graph structures to function well, which are highly related on the domain knowledge of the traffic engineers. Although the technical conditions of the road pavements are the same, subjected to the social circumstance, such the economics and the demography, the traffic flow pattern may be totally different. Furthermore, the methods suffer from the ineffectiveness to learn high-dimensional temporal features of intricate traffic signals. In this paper, we propose a spatial-temporal deep learning network to address these two shortcomings.

References

[1] Amato, F., Guignard, F., Robert, S., & Kanevski, M. (2020). A novel framework for spatio‑temporal prediction of environmental data using deep learning. Scientific Reports, 2020(10), 22243. doi:<https://doi.org/10.1038/s41598-020-79148-7>

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[3] Lu, H., Huang, D., Song, Y., Jiang, D., Zhou, T., & Qin, J. (2020). ST-TrafficNet: A Spatial-Temporal Deep Learning Network for Traffic Forecasting. Electronics, 2020(9), 1474.