On the Inclusion of Spatial Information for Spatio-Temporal Neural Networks

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Abstract—When confronting a spatio-temporal regression, it is sensible to feed the model with any available prior information about the spatial dimension. For example, it is common to define the architecture of neural networks based on spatial closeness, adjacency, or correlation. A common alternative, if spatial information is not available or is too costly to introduce it in the model, is to learn it as an extra step of the model. While the use of prior spatial knowledge, given or learnt, might be beneficial, in this work we question this principle by comparing spatial agnostic neural networks with state of the art models. Our results show that the typical inclusion of prior spatial information is not really needed in most cases. In order to validate this counterintuitive result, we perform thorough experiments over ten different datasets related to sustainable mobility and air quality, substantiating our conclusions on real world problems with direct implications for public health and economy.

Index Terms—Neural Networks, Spatio-temporal Series, Spatial Dimension, Convolutional Neural Networks

I. INTRODUCTION

Convolutional neural networks (CNN) are well known for their ability to handle spatial data in several contexts, like images, videos, or spatial series. However, in the last few years they have demonstrated to hold a good position when dealing with temporal data too. Thus, they are widely used in spatio-temporal regression problems, with outstanding behavior when coping with both spatial and temporal dimensions.

Due to its parameters structure, CNNs are usually employed when it is possible to order input data in a grid. Furthermore, they treat each location equally, learning and sharing the same weights for all spatial points. Given that its common that the phenomenon under study presents the same nature all over the grid (or at least, it is an appropriate assumption), in a wide range of applications this property is a clear advantage in order to minimize the number of parameters and calculations for learning an specific task. This leads to good performance with fewer resources compared to feedforward networks (FNN) and recurrent neural networks (RNN). For example, pollution and traffic share an approximately equivalent temporal behavior and distribution at each location (at least in a close environment), meaning that it is possible to share parameters and get a smooth approximation for these phenomena via traditional CNNs.

However, this property of CNNs (which is usually known as equivariance), might not always be the best deal when solving some typical problems: sometimes, although similar, treating all locations agnostically does not hold as a valid or acceptable hypothesis and so, learning a spatial shared-based representation might not be the best option if the system representation is not chosen carefully. In the previous example, it is obvious that different traffic sensors or pollution stations will have different properties, even though their temporal dynamic will be pretty similar. For spatio-temporal regression specifically, several proposals have been made in order to tackle this problem, but two of them stand out for their wide acceptance:

- Ordering your grid by Euclidean closeness (from now on, just closeness) and use CNNs.
- Defining your system in a graph structure and model it via Graph Convolutional Networks (GCN).

In both cases, a classical assumption is made: closer locations have similar properties and, by that, shared-weights learned by the networks are more reliable. This way, the spatial dimension in CNNs keeps a low number of parameters.

However, these solutions do have some disadvantages. First, they do not completely solve the fact that each location, although related to the rest, has its own properties. Even more, although the assumption that closer locations behave similarly is usually blindly accepted, might not hold always for real problems contrary to what is commonly accepted: not only depends on the phenomenon, but also on the temporal and spatial granularity with which the data is taken. Thus, the benefits of learning a latent representation based on sharing parameters are conditioned by the particularities of each specific problem and, contrary to popular belief, the spatial proximity between locations is not necessarily the main factor. Second, in both cases it is necessary to introduce prior spatial knowledge to the system, making them less ‘intelligent’ and more laborious to work with. Through this paper, we propose an architecture of spatial agnostic neural networks (SANNs from now on) that will allow us to easily contrast our hypotheses. Based on naive CNNs for spatio-temporal regression, SANNs do not make use of prior spatial assumptions or information. We show that no improvement is reported when using prior spatial knowledge, rejecting the idea that models with an appropriate bias will result systematically in better forecasters. Also, their spatial agnostic nature makes them a suitable choice when spatial information is not easily achievable or within reach.
What happens if we look closer to the temporal dimension? In multiple real applications in which this spatial agnosticism does not exactly hold, temporal equivalence between locations is more plausible: temporal distributions along spatial points might fulfill better the assumption of sharing parameters compared to the spatial dimension. This means that, while it is common to use some sort of recurrent module to model temporal relations, convolutions can be perfectly valid candidates for this work using a lower number of parameters. Thus, our proposal is based on sharing parameters for all locations between subsequent past timesteps, which are ordered by nature and do not need prior information. This way we can achieve several advantages: while treating the spatial dimension might require more parameters than state of the art models, the temporal dimension will depend on fewer of them; no prior information is needed at all; and as a consequence, simpler and more compact models are obtained while preserving regression performance.

To validate our proposal, we make a comparison with several baselines and deepen in the proposed model operation through extensive experimentation. For this purpose, the field of air quality and sustainable mobility has been chosen. With a wide number of long spatio-temporal series with spatial particularities but approximately equivalent temporal dynamics (due to its relation with human behavior) and high non-linearity, it is a perfect field to corroborate our hypotheses. As it is considered of great importance for public health and also to economy, it is potentially beneficial to have simpler and easily deployable models in this field.

The main contributions of this study are summarized as follows:

- We delve into the counterintuitive idea that including spatial relations based on closeness are not necessarily the most optimal option when working with neural networks in spatio-temporal problems.
- A new spatial agnostic deep neural network framework specially designed to validate our hypotheses is proposed.
- The contribution is illustrated by tackling a variety of prediction problems related to air quality and sustainable mobility. All of them are considered of great importance and show to be hard for both spatial and temporal dimensions.
- Results show that our proposal equals other state-of-the-art models in accuracy without the need of prior spatial information or specific temporal considerations.

The rest of the paper is organized as follows: related work is discussed in Section I, while Section II presents the proposed spatial agnostic framework for spatio-temporal regression and all needed theory. Then, in Section III we introduce our datasets, experimental design, and its properties. Section IV illustrates the evaluation of the proposed architecture as derived after appropriate experimentation. Finally, in Section V we point out future research directions and conclusions.

II. RELATED WORK

A. The rise of convolutions

Since CNNs were proposed as neural architectures [1], they have shown to handle especially well spatially-ordered data. During the last decades, this kind of neural networks have grown in importance, becoming one of the most used neural paradigms for a wide number of applications.

In the case of intrinsic 2D problems, like images, CNNs have turned out to be the option per excellence. Concretely, with [2] started a reign of CNN for computer vision problems. Not much later, the idea that weight sharing could lead to potentially suboptimal performance for some images, like portraits, was studied [3]. In the present, CNNs are widely used for this kind of problem and have been well characterized.

However, CNNs are not constrained to natural 2D systems. For example, time series seen as a 1D sequence have been handled by convolutional models with good results [4], [5]. Spatio-temporal series have growth in importance and CNNs have been well studied and are already a standard when dealing with this kind of series [6], [7]. A similar field to spatio-temporal series is video-sequence analysis, where both spatial and temporal relations need to be modeled [8]. Within this last topic, some examples in which parameter sharing is indeed highly positive can be found, as for example enhancing video spatial resolution for creating smooth results [9].

B. Spatial dimension in spatio-temporal neural networks

In spatio-temporal regression specifically, convolution based networks are one of the leading options too. As explained in Section I, convolution shines in a wide range of applications involving physical spatial locations. However, how this dimension is treated by the convolution has not received particular attention. Thus, we have several options that are widely used but not necessarily optimal.

For example, in traffic forecasting, defining your space as a natural grid [10] is a good example of 2D image-to-image prediction problem in which, by using channels as timesteps and 3D kernels, spatio-temporal relations are exploited. As average traffic speeds for each road segment is used, no need to prior spatial information is needed and the grid arrangement is natural. However, closer areas are not necessarily more related. In [11] it is shown that the 3D convolution might work better, but the same spatial arrangements and assumptions are made.

When measurement points are directly used as an arrangement for the spatial dimension, not only it is necessary to impose same closeness supposition than before, but a special treatment is usually needed to arrange locations correctly. Some examples are [12], where the authors order traffic sensors in a 1D grid; or [13], where measurement points are ordered as 2D images.

In recent years, graphs-based networks have received increasing attention. GCNs not only have shown a very competitive performance, but a graph structure is more suitable than grids for some specific problems where relations might be non-Euclidean and directional [14]. Among the different convolutions in graphs, all of them depend heavily on an adjacency matrix which usually needs to be manually defined. This adjacency matrix is of great importance as it defines the graph relations and structure. Depending on the proposal, this matrix might be defined differently: it usually is defined by spatial closeness [15], [16], but there are no restrictions. While
this freedom to define the adjacency matrix might help to avoid the closeness assumption, it would force you to find which prior information may be more optimal for your particular problem. If compared to traditional CNN, GCN presents another advantage: they can naturally process information from a $K$-hop neighborhood [17], not restricting themselves to uniquely adjacent nodes.

Temporal relations with neural networks are usually constrained to using some kind of RNNs. Although many proposals have been done, through this work we will not focus on this broad topic and we will limit its use to standards.

C. Non-locally dependent proposals

The idea that a fixed arrangement for learning spatial relations might not be the best deal is not new in spatio-temporal series forecasting. Lu et al [13] state that "the existence of spatial heterogeneity imposes great influence on modeling the extent and degree of road traffic correlation, which is usually neglected by the traditional distance based method", and proposed a data-driven approach to measure these correlations. From this starting point, we can select several works that have contributed to refine and depend less on prior information in the spatial dimension using neural models.

By using a hierarchical clustering over the spatio-temporal data, [19] refines spatial relations. However, it uses a distance matrix in the process, introducing the aforementioned bias by closeness. In [20], a lasso methodology is used to obtain a sparse model of the system dynamics, which simultaneously identifies spatial correlation along with model parameters.

Attention mechanisms, which appeared on the deep learning scene a few years ago, are a natural way to learn relations beyond the network original assumptions. In this context, several works have used attention weights to improve performance and demonstrate the correctness of their work with both, grid structure [21] and graph structure [22]. However, [13] shows how closer locations are not necessarily more related, and depending on the problem and the characteristics of the regression, other considerations might be more important when learning spatial relations.

Closer to our work, in [23] a similar issue but with general multivariate time series forecasting is put on the table: existing methods usually fail to fully exploit latent spatial dependencies between pairs of variables and GCNs require well-defined graph structures which means they cannot be applied directly for multivariate time series where the dependencies are not known in advance. In their proposal, they construct a new model that tackles both problems. [24] focus its efforts on dealing with the fact that different spatial locations might have at some degree different dynamics by using traditional CNNs but with the introduction of learnable local inputs/latent variables and learnable local transformations of the inputs.

In the end, all these works focus its attention on solving a specific regression problem, but not delve into how the spatial dimension should be really treated. Furthermore, all these methodologies have in common the need to make their models considerably more complex in order to overcome spatial agnosticism, generally starting from usual convolution operators and refining themselves via extra mechanisms or modules.

III. Spatial Agnostic Neural Networks

Through this section, we present all the theoretical methods and foundations in which our study bases its ideas and experiments about spatial agnostism in spatio-temporal series. The code for this paper is available in [https://github.com/ramonedrano/SANN](https://github.com/ramonedrano/SANN)

A. Spatial agnosticism via Convolutional Networks: SANNs

Given a spatio-temporal sequence $X$, let us call $N$ to the total number of timesteps and $S$ the total number of spatial points. With this notation, a spatio-temporal sample from the series writes as $x_{i,s} : i = 1, ..., T; s = 1, ..., S$, being $T$ the total number of timesteps conforming the sample. $X_{i}$ is the slice of series $X$ for timestep $i$ at all locations, and $X_{T,s}$ is the slice of series $X$ in location $s$ for all timesteps. The predicted series is represented by $\hat{x}_{i,s} : i = 1, ..., T'; s = 1, ..., S$, where $T'$ is the total number of predicted timesteps. We assume that the number of spatial locations is always the same for both the input and output series.

As described in Section I we propose a spatial agnostic framework based solely in convolutional blocks for spatio-temporal regression called Spatial Agnostic Convolutional Networks that will help us probe the main hypothesis of this work. This last statement means that each block needs to fulfill two requirements:

- No spatial information is introduced to the network.
- Past temporal information can be handled and introduced in the calculation of each new state.

Thus, we will have a spatio-temporal methodology that let us contrast our main premise. In order to do so, the input sequence scheme relies upon a $C \times T \times S$ images as shown in Figure [1] where the number of channels $C$ represents the number of input spatio-temporal variables. During this paper, we will work with $C = 1$ (the studied series by itself), but is easily extensible to any value. Similar to the usual input scheme presented in GNNs, this methodology let us treat both spatial and temporal dimension simultaneously.

The convolution itself (*) operator has the usual form for 2D images:

$$\langle x * K \rangle(i,j) = \sum_{m} \sum_{n} x(m,n)K(i-m,j-n) \quad (1)$$

However, the kernel size is regularly used with equivalent values for its two dimensions $k_1 = k_2 = k$. In this case, not only this kernel uses different values for each component, but kernel size for spatial dimension must be equal to the number of spatial zones: $k_2 = S$. As a result, the convolution operation is made over all locations at once. The kernel size in the temporal dimension is defined as $t_{past}$ and needs to be stipulated as part of the network architecture. An example of this kind of filter can be found in Figure [2].

The temporal dimension is dominated by a causal convolution. Generally, causal convolution ensures that the state created at time $t$ derives only from inputs from time $t$ to $t - t_{past}$. In other words, it shifts the filter in the right temporal...
Fig. 1. Input sequence schematic. As long as all variables are spatio-temporal and have an equivalent structure for both dimensions, these sequences can be easily introduced as $C \times T \times S$ images, with variable, temporal and spatial dimension respectively.

Fig. 2. Example of causal convolution spatially agnostic with $t_{past} = 3$ through a spatio-temporal sequence of just one variable as defined previously. Direction. Thus $t_{past}$ can be interpreted as how many lags are been considered when processing an specific timestep. Given that previous temporal states are taken into account for each step and that parameters are shared all over the convolution, this methodology might be seen as some kind of memory mechanism by itself. Unlike memory-based RNNs (like LSTMs and GRUs) where the memory mechanism is integrated solely by learned via the hidden state, in this case $t_{past}$ act as a variable that lets us take some control over this property.

In order to ensure that each input timestep has a corresponding new state when convolving, a padding of $P = t_{past} - 1$ at the top of the image is required. To guarantee temporal integrity, this padding must be done only at the top. By using convolution in this form, once the kernel has moved over the entire input image $T \times S$, the output image will be $T \times 1$. This process is summarised in Fig 3.

Now, if we repeat this operation $H$ times, we will create a new hidden state with $H$ channels an output an image with $H \times T$ dimensions as the example in Fig 4.

To give the network the opportunity to cover a spectrum of possibilities in terms of expressiveness as wide as a usual CNN for each channel, we simply use transposed convolution with a kernel size $k = (1, S)$ so the system can learn a $T \times S$ representation from a $T \times 1$ image. Fig 5 illustrate this idea.

Evidently, our new representation is usually composed by $H$ hidden states, so this transposed convolution will use $H$ filters. Finally, the complete procedure for an entire agnostic convolutional block is described graphically in Fig 6.

Obviously, there are no restrictions with respect to the width dimension. For simplicity, we have considered convolutions in which only the number of channels are changed, meaning that images keep an $T \times S$ structure during all the computations. As we will discuss later, this will help to normalize our experiments. However, as with CNNs, the dimensionality of hidden and output states might be different.
which is ways, it is desirable for this regressor block to fulfill several

of magnitude, we can be sure this layer has a similar impact

meaning that this regressor scheme can be applied to all of
the spatial dimension. This way, we make sure that

part of the network.

C. Temporal vs spatial distribution

Our work is based on the hypothesis that real spatio-
temporal series might not share a similar behavior in their
two dimensions. Even the well known fact that closer, spatially
speaking, locations behaves similarly does not always suit well,
meaning that the parameter sharing scheme of traditional CNNs
might not be the best option. Concretely, when dealing with real
problems, the system might have a high dependency on non-
spatial phenomena and data collection can have a great impact.
As a result, closeness information can be lost or modified.

On the contrary, temporal information (or distribution)
usually keeps the same structure for a wide range of problems.
As air quality and mobility are high correlated to human being,
the temporal pattern of this kind of series for each location
tends to remain alike.

In order to prove our hypotheses, we will make use of sta-
tistical tools that characterize the aforementioned information.

1) Spatial dimension: Moran’s I: According to [25], “Spatial
autocorrelation or spatial dependence can be defined as a
particular relationship between the spatial proximity among
observational units and the numeric similarity among their
values; positive spatial autocorrelation refers to situations in
which the nearer the observational units, the more similar their
values (and vice versa for its negative counterpart). This fea-
ture violates the assumption of independent observations upon
which many standard statistical treatments are predicated.”.
This property, which is precisely what we are interested in,
can be measured by the well know Moran’s I. This test will
let us quantify the degree of spatial autocorrelation existing in
the different datasets that we will use between close locations
taking into account this interdependency. As it is a test, Moran’s
I comes with a p-value which typify statistical significance of
the result. It is defined as:

\[
I = \frac{S}{W} \sum_{i} \sum_{j} w_{ij}(x_i - \bar{x})(x_j - \bar{x}) \sum_{i}(x_i - \bar{x})^2
\]  

(2)

where S is the number of spatial units indexed by i and
j, x is the variable of interest, \( \bar{x} \) is the mean of \( x \), \( w_{ij} \) is a
matrix of spatial weights based on neighbours, and \( W \) is the
sum of all \( w_{ij} \). As its value varies usually between −1 and
+1, it is easily interpretable. Concretely, +1 implies similar
values for close locations, 0 a random arrangement, and −1
opposite values.

As we also have a temporal dimension, we will average
I for all timesteps. Through this test we want to compute
solely spatial autocorrelation, without intervention of temporal
relations between locations.

2) Temporal dimension: Adaptive Temporal Dissimilarity
Measure: To compare the similarity between different time
series (in our case, different spatial points) the same problem
arises than with spatial autocorrelation: due to the interdependence relationship between measurements classical correlation index can not be applied. For example, Euclidean, Fréchet distances and Dynamic time warping are well known and widely used techniques when measuring time series similarity but do not handle the aforementioned issue well. To solve this problem, [26] proposed the Adapative Temporal Dissimilarity Measure (ATDM) as an index that lets us measure the similarity between time series more robustly as it balances the proximity with respect to values and the proximity with respect to behavior. It writes as:

\[
\text{ATDM}(X_{T,i}, X_{T,j}) = f(cort(X_{T,i}, X_{T,j})) \cdot \delta(X_{T,i}, X_{T,j}),
\]

where \(\delta\) references a classical distance (we will use Euclidean) and \(cort\) is

\[
cort(X_{T,i}, X_{T,j}) = \frac{\sum_{t=1}^{T-1} (X_{t+1,i} - X_{t,i})(X_{t+1,j} - X_{t,j})}{\sqrt{\sum_{t=1}^{T-1}(X_{t+1,i} - X_{t,i})^2} \sqrt{\sum_{t=1}^{T-1}(X_{t+1,j} - X_{t,j})^2}}.
\]

Lastly, \(f\) writes as follow:

\[
f(x) = \frac{2}{1 + \exp(kx)}, k \geq 0.
\]

With this metric, the distance is squeezed into a coefficient in the interval \((0, 2)\). When the correlation coefficient is 0, the ATDM is 1, and the correlation is not significant. When the correlation is positive, the value of the ATDM is less than 1; the more similar the two series are, the smaller the value is. On the contrary, the ATDM is more than 1 if the correlation is negative. The less similar the two series are, the larger the value is.

Thus, we can average the ATDM between all locations pairs for each spatio-temporal series. As this measure takes into account both values and behavior of the series, we can approximately get a global measure of temporal distribution similarity among points for each dataset.

When working with real data, in which depending on time granularity local properties of time series might be noisy, ATDM might not extract information correctly. In order to solve this, we compute an adjusted ATDM coefficient (ATDM_{adj}) which uses a smoother version of the input series as we are interested in global behavior of the temporal distribution. Concretely, we use moving average as it is simple and has shown to be a good approximator for time series. As moving average just smooth the series, we do not expect to corrupt the coefficient between series which are not really temporally correlated.

IV. EXPERIMENTAL DESIGN

A. Data description

The different forecasting problems and the corresponding datasets are described below. Main dataset characteristics and statistics are provided in Table I.
• AcPol dataset: Provided by the Municipality of Madrid through its open data portal[4] Acoustic pollution in Madrid in decibels, it measures equivalent continuous level with a frequency weighting, which is the assumed noise level constant and continuous over a period of time, corresponding to the same amount of energy than that actual variable level measured in the same period.

• Beijing dataset: Presented by [27], it consist of traffic speed measurements for 15000 road segments recorded per minute. To make the traffic speed predictable for each road segment, it is aggregated via moving average in 15 minutes intervals. For this work, we select a subgroup of road segments spatially close.

• BiciMad dataset: Supplied by EMT (Municipal Transport Company for its initials in Spanish) through its open data portal[6]. In this case we tackle the bike sharing demand prediction by aggregating the overall number of bikes per station and timestep.

• LOOP dataset: It contains data collected from inductive traffic loop detectors deployed on four connected freeways (I-5, I-405, I-90, and SR-520) in the Greater Seattle Area. It can be found in [28].

• MATRA dataset: This dataset contains historical data of traffic measurements in the city of Madrid. The measurements are taken every 15 minutes at each point, including traffic intensity in number of cars per hour. Data is aggregated for each hour. While a dense and populated network of over 4000 sensors is available, we decided to simplify and use only a selection of them. Available in the Municipality of Madrid open data portal[1].

• METR-LA dataset: This dataset contains traffic information recopilated from loop detectors in the highway of Los Angeles County. We use the partition provided by [14].

• NO2 dataset: NO2 in the city of Madrid. Hourly data for all measurement stations which include this pollutant. Available in the Municipality of Madrid open data portal[4].

• NYTaxi dataset: Provided by Taxi & Limousine Commission[1] it consist of taxi trip location and duration in the city of New York. We focus our work in forecasting number of taxi travels for each New York neighborhood with an average minimum number of one trip per day.

• O3 dataset: O3 in the city of Madrid. Hourly data for all measurement stations which include this pollutant. Available in the Municipality of Madrid open data portal[4].

• PEMS-BAY dataset: This traffic dataset is collected by California Transportation Agencies (CalTrans) Performance Measurement System (PeMS). We use the partition provided by [14].

All datasets are Z-Score normalized by spatial point. We take as reference previous work as a criterion to choose $T$ and $T'$. Thus, we can be sure of the plausibility of the results for all models. When no previous work is known, we use autocorrelation as a measurement of number of minimum lags ($T$) and focus only on a single timestep prediction ($T' = 1$).

From Table I we can see how our chosen datasets cover a wide range of spatio-temporal circumstances and the high variety and variability of data. Also, our main hypotheses are confirmed: Moran’s $I$ show a clear no-spatial autocorrelation pattern for our series, and although not completely uncorrelated, most series are close to 0. All p-values are lower than 0.05. It is worth noting as proof of plausibility for these values that [18] computed the coefficient $I$ for the complete Beijing traffic dataset at some hours, reporting a similar value to ours. ATDM values tend to be low, which is representative of similar temporal distributions in the datasets. As we expected, ATDM$_{adj}$ represents better this idea. Datasets with a clear temporal pattern but locally noisy, as Beijing, LOOP, and PEMS-BAY, are better described by this coefficient.

Given that spatial locations are by default in arbitrary order, it is necessary to sort and structure them in order to fully exploit spatial information with CNN and GCN based models. By computing a hierarchical tree (dendrogram) using an agglomerative hierarchical clustering algorithm and traversing recursively the tree it is possible to approximately sort the points by distance. Once points are sorted, the adjacency matrix $A$ for all datasets is built as:

$$A_{i,j} = \begin{cases} 1 & (i, j \text{ are neighbors}) \\ 0 & (\text{otherwise}) \end{cases}$$ (6)

For convenience and normalization, two locations $i$ and $j$ are considered neighbors if they are among the 4 closest areas without counting themselves.

B. Benchmark models

We compare SANN with widely used spatio-temporal series regression models based on the convolution operator, including:

• CNN: A standard CNN followed by a batch normalization layer and ReLU activation function. It uses a $3 \times 3$ kernel. As it does not present any specific temporal mechanism, it is the main competitor for SANN.

• ConvLSTM: Similar to the previous one, the ConvLSTM bases its functioning in the convolution operator but introduces a LSTM structure as described in [29]. Again, it uses a $3 \times 3$ kernel.

• SGC-LSTM: A spectral graph convolution layer as presented in [30] and an LSTM layer.

• SpGC-LSTM: A classical approach for GCN which let us exploit explicitly information from the $k$-hop ($k$-th order) neighborhood of each node in the graph as proposed in [17]. In our experiments, we set $k = 3$.

As we are interested in deepening in how the convolution operator and the spatial dimension are related, we do not include any RNN or FNN based approach.

C. Experimental design

In order to make a comparison as fair as possible, we decided to proceed with all models as follows:
particularly, a 10-cross-validation scheme without repetition is to specify a separation border among previously defined sets. It is not possible to create random folds and it is necessary prior different sets (training, validation and test), given that some input sequences might share elements among for our problem, the second one needs to be specifically treated. And that we have serially uncorrelated errors.

Stationary nonlinear process, that we can ensure that the leave-

several conditions are met. Specifically, that we are modeling a

As stated in \[31\], standard k-cross-validation is the way to go when validating neural networks for time series if several conditions are met. Specifically, that we are modeling a stationary nonlinear process, that we can ensure that the leave-one-out estimation is a consistent estimator for our predictions and that we have serially uncorrelated errors.

While the first and the third conditions are trivially fulfilled for our problem, the second one needs to be specifically treated. Given that some input sequences might share elements among different sets (training, validation and test), prior information could be entangled leading to data leakage. Due to this problem, it is not possible to create random folds and it is necessary to specify a separation border among previously defined sets. Particularly, a 10-cross-validation scheme without repetition is used during all experiments, with a 80%/10%/10% scheme for train/validation/test sets for each fold.

To evaluate the precision of each model, we computed root mean squared error (RMSE), bias and weighted mean absolute percentage error (WMAPE). In a spatio-temporal context \[32\], they are defined as:

\[
RMSE = \sqrt{\frac{1}{T S} \sum_{t=1}^{T} \sum_{s=1}^{S} (\hat{x}_{t,s} - x_{t,s})^2},
\]

\[
\text{bias} = \frac{1}{T S} \sum_{t=1}^{T} \sum_{s=1}^{S} (\hat{x}_{t,s} - x_{t,s}),
\]

\[
\text{WMAPE} = 100 \times \frac{\sum_{t=1}^{T} \sum_{s=1}^{S} | \hat{x}_{t,s} - x_{t,s} |}{\sum_{t=1}^{T} \sum_{s=1}^{S} | x_{t,s} |}.
\]

For all these metrics, the closer to zero they are the better the performance is. While RMSE already provides a dispersion measure respect to real series, bias is better to find particular predispositions when making predictions. WMAPE is scale independent and can handle 0s in the series, which makes it interesting for comparing different zones.

V. RESULTS

A. Performance comparison

A general comparison of the different error metrics can be seen in Table II. WMAPE is not presented in BiciMad and NYTaxi datasets as they are categorical regressions.

First of all, we can verify the goodness of our experiments by direct comparison with analogous studies \[13\], \[14\], \[27\], \[28\], \[33\], showing that our results are in line with them. Since most of the datasets have already been used, we can extrapolate this idea to those who have not. To better visualize error over all datasets, Fig 8 show RMSE distribution. From this figure we can suspect that, as we expected, SANN shows a better behavior than its main competitor, CNN.

In Table III we can see average performance for each model in all datasets and the resulting ranking. In order to inquire into this and provide statistical evidence, a Friedman rank test was performed over the errors distribution for all datasets. A Friedman statistic of $F = 18$, distributed according a $\chi^2$ with 4 degrees of freedom obtains a p-value of $1.23e−3$. Table I

| Dataset        | Dates                                      | Timestep | $T$ | $T'$ | $S$ | Mean | Median | Std | ATDM | ATDMadj | Moran’s $I$ |
|----------------|--------------------------------------------|----------|-----|-----|-----|------|--------|-----|------|----------|-------------|
| Acl          | 2014/01/01 – 2019/03/31                    | 1 day    | 7   | 1   | 30  | 56.8 | 60.2   | 15.1 | 0.36 | 0.36     | 0.03        |
| Beijing      | 2017/01/04 – 2017/05/31                    | 15 min   | 10  | 1   | 200 | 29.0 | 28.7   | 9.3  | 0.09 | 0.09     | 0.37        |
| BiciMad      | 2019/01/01 – 2019/06/30                    | 1 hour   | 6   | 1   | 168 | 0    | 0      | 3.2  | 1.04 | 1.03     | 0.12        |
| LOOP         | 2015/01/01 – 2015/03/31                    | 5 min    | 10  | 1   | 323 | 57.2 | 60.6   | 11.8 | 0.84 | 0.47     | 0.31        |
| MATR         | 2018/01/01 – 2019/12/31                    | 1 hour   | 24  | 6   | 120 | 445.5| 539.6  | 5.6E-4| 4.8E-4| 0.19      |             |
| METR-LA      | 2012/03/01 – 2012/06/30                    | 5 min    | 12  | 3   | 207 | 53.4 | 62.3   | 20.6 | 0.02 | 0.02     | 0.24        |
| NO2          | 2017/01/01 – 2017/03/31                    | 1 hour   | 48  | 48  | 24  | 37.5 | 29     | 8.9  | 0.04 | 0.0      | 0.13        |
| NYTaxi       | 2016/01/01 – 2016/06/30                    | 1 hour   | 6   | 1   | 70  | 4.8  | 0      | 11.3 | 0.55 | 0.34     | 0.24        |
| O3           | 2017/01/01 – 2017/09/31                    | 1 hour   | 48  | 48  | 14  | 50.6 | 50     | 34.3 | 0.03 | 0.0      | 0.11        |
| PEBS-BAY     | 2017/01/01 – 2017/05/31                    | 5 min    | 12  | 3   | 325 | 62.6 | 65.3   | 9.6  | 0.64 | 0.15     | 0.23        |

Some other minor details are that all the models are trained using the mean squared error (MSE) as objective function with the RMSprop optimizer, as it has shown good performance in non-stationary scenarios. Batch size is 256, momentum is set to 0.9, the initial learning rate is 0.001 and both early stopping and learning rate decay are implemented in order to avoid overfitting and improve performance. The experiments are run in a NVIDIA RTX 2070.

As we have standardized the experiments, no hyperparameter tuning is needed in general. Solely $t_{past}$ for SANN needs to be adjusted, which will be tuned via standard grid search.

D. Validation and error metrics

As stated in \[31\], standard k-cross-validation is the way to go when validating neural networks for time series if several conditions are met. Specifically, that we are modeling a stationary nonlinear process, that we can ensure that the leave-one-out estimation is a consistent estimator for our predictions and that we have serially uncorrelated errors.

While the first and the third conditions are trivially fulfilled for our problem, the second one needs to be specifically treated. Given that some input sequences might share elements among different sets (training, validation and test), prior information could be entangled leading to data leakage. Due to this problem, it is not possible to create random folds and it is necessary to specify a separation border among previously defined sets. Particularly, a 10-cross-validation scheme without repetition is used during all experiments, with a 80%/10%/10% scheme for train/validation/test sets for each fold.

To evaluate the precision of each model, we computed root mean squared error (RMSE), bias and weighted mean absolute percentage error (WMAPE). In a spatio-temporal context \[32\], they are defined as:

\[
RMSE = \sqrt{\frac{1}{T S} \sum_{t=1}^{T} \sum_{s=1}^{S} (\hat{x}_{t,s} - x_{t,s})^2},
\]

\[
\text{bias} = \frac{1}{T S} \sum_{t=1}^{T} \sum_{s=1}^{S} (\hat{x}_{t,s} - x_{t,s}),
\]

\[
\text{WMAPE} = 100 \times \frac{\sum_{t=1}^{T} \sum_{s=1}^{S} | \hat{x}_{t,s} - x_{t,s} |}{\sum_{t=1}^{T} \sum_{s=1}^{S} | x_{t,s} |}.
\]
with \( \alpha \) parameters per dataset for all models (recall that, to facilitate average run time per fold, model, and dataset, and the number of differently.

Lastly, there is no evidence that SGC-LSTM and CNN work than state of the art models for spatio-temporal regression. While hypothesis (II) refers to ConvLSTM vs ConvLSTM-perm. Thus, we carry out a post-hoc pairwise non-parametric based comparison to check the differences between the models with Holm and Benjamini-Hochberg adjustments. However, in this case we are not interested in rankings. Table IV shows the aforementioned \( p \)-values, marking with asterisks (*) those that are statistically significant. Hypothesis (I) refers to SANN vs SANN-perm, while hypothesis (II) refers to ConvLSTM vs ConvLSTM-perm.

This table lets us conclude that SANN shows spatial agnosticism and its performance is unaffected by how the spatial dimension is treated. However, the ConvLSTM presents agnosticism and its performance is unaffected by how the spatial dimension of data before training. As we just want to compare the behavior of the different methods when input data is not sorted, we are only interested in studying how the error distributions are modified when this perturbation is introduced in the system, and not in pure performance. Given that ConvLSTM has shown to be a statistically significant better option than CNNs, and that its performance is closer to SANN, we will use it as baseline. GCN models define their graph topology based on an adjacency matrix so it would not make sense to test their spatial agnosticism through this test.

In Fig. we can visualize the RMSE results for both models before and after (model name-perm) the random permutation.

From this last figure we can suspect that error distributions for SANN and SANN-perm are equivalent, while that does not happen for ConvLSTM and ConvLSTM-perm. Thus, we carry out a post-hoc pairwise non-parametric based comparison to check the differences between the models with Holm and Benjamini-Hochberg adjustments. However, in this case we are not interested in rankings. Table IV shows the aforementioned \( p \)-values, marking with asterisks (*) those that are statistically significant. Hypothesis (I) refers to SANN vs SANN-perm, while hypothesis (II) refers to ConvLSTM vs ConvLSTM-perm.

This table lets us conclude that SANN shows spatial agnosticism and its performance is unaffected by how the spatial dimension is treated. However, the ConvLSTM presents an important discrepancy in terms of performance when unsorting the grid. Although this premise holds in general terms over all datasets, the results are directly related to correlation metrics in Table those datasets with a higher value of Moran’s \( I \) tend to suffer more with the permutation test. As in these cases the spatial autocorrelation is higher, sharing parameters
RMSE distribution for each model and dataset. Dashed vertical line represents the mean, dotted vertical line represents median.

TABLE V
AVERAGE RUN TIME PER FOLD IN SECONDS AND APPROXIMATE NUMBER OF PARAMETERS USED PER DATASET.

| Dataset | AcPol | Beijing | BiciMad | LOOP | MATR | METR-LA | NO2 | NYTaxi | O3 | PEMS-BAY | Average |
|---------|-------|---------|---------|------|------|---------|-----|--------|----|----------|---------|
| SANN    | 1.0   | 16.7    | 4.1     | 97.7 | 26.7 | 36.5    | 36.5| 42.8   | 67.9| 36.3     |         |
| CNN     | 1.4   | 8.1     | 13.4    | 117.5| 44.5 | 66.6    | 33.2| 22.5   | 48.0| 37.8     |         |
| ConvLSTM| 2.6   | 103.2   | 38.2    | 350.0| 422.5| 238.7   | 74.8| 13.0   | 56.8| 400.7    | 171.6   |
| SGC-LSTM| 4.3   | 34.7    | 8.4     | 122.3| 78.8 | 120.9   | 12.4| 113.5  | 92.4| 68.4     |         |
| SpGC-LSTM| 13.3  | 71.9    | 12.5    | 190.5| 111.7| 467.4   | 30.5| 221.6  | 199.9| 141.6    |         |
| Number of parameters | ∼50K | ∼200K | ∼150K | ∼250K | ∼200K | ∼150K | ∼250K | ∼150K | ∼250K | ∼150K | ∼250K |

TABLE VI
ADJUSTED HOLM AND BENJAMINI-HOCBERG P-VALUES WITH PAIRWISE REJECTED HYPOTHESIS AT $\alpha = 0.05$ FOR ALL DATASETS AFTER TESTING SPATIAL AGNOSTICISM VIA RANDOM PERMUTATION.

| Dataset | AcPol | Beijing | BiciMad | LOOP | MATR | METR-LA | NO2 | NYTaxi | O3 | PEMS-BAY |
|---------|-------|---------|---------|------|------|---------|-----|--------|----|----------|
| P$_{unajusted}$ | $0.922$ | $0.922$ | $0.922$ | $0.004^*$ | $0.027^*$ | $0.005^*$ | $0.862$ | $0.002^*$ | $0.002^*$ | $0.432$ |
| P$_{holm}$   | $1$    | $0.846$ | $0.014^*$ | $0.027^*$ | $0.027^*$ | $0.027^*$ | $0.862$ | $0.012^*$ | $0.432$ |
| P$_{BH}$     | $0.011^*$ | $0.02^*$ | $0.012^*$ | $0.846$ | $0.004^*$ | $0.012^*$ | $0.492$ | $0.492$ | $0.492$ |

Through this work, we have explored how classical spatial assumptions based on closeness are not always the best deal when working with convolutional neural networks in spatio-temporal series. Due to their usual lack of spatial autocorrelation, other alternatives need to be suggested. To do so, we have proposed a new spatio-temporal neural framework, called spatial agnostic neural networks, that makes no use of prior spatial information (neither directly nor indirectly) and compared it with state-of-the-art convolution-based models. Our framework is a perfect tool to test our hypotheses as it does not use extra modules or steps as others, but tackles the problem directly via purely convolutions.

After extensive and standardized experimentation, we can confirm our main hypothesis: the inclusion of representations of the spatial distribution of real data does not necessarily fit well for the classical convolutional shared-weights scheme. Concretely, without using any specific spatio-temporal mechanism, SANNs have shown to be better than traditional CNNs and equal in performance some of the most notable spatio-temporal models. Also, we have shown how SANNs, unlike traditional

VI. Conclusions and Future Work

Through this work, we have explored how classical spatial assumptions based on closeness are not always the best deal when working with convolutional neural networks in spatio-temporal series. Due to their usual lack of spatial autocorrelation, other alternatives need to be suggested. To do so, we have proposed a new spatio-temporal neural framework, called spatial agnostic neural networks, that makes no use of prior spatial information (neither directly nor indirectly) and compared it with state-of-the-art convolution-based models. Our framework is a perfect tool to test our hypotheses as it does not use extra modules or steps as others, but tackles the problem directly via purely convolutions.

After extensive and standardized experimentation, we can confirm our main hypothesis: the inclusion of representations of the spatial distribution of real data does not necessarily fit well for the classical convolutional shared-weights scheme. Concretely, without using any specific spatio-temporal mechanism, SANNs have shown to be better than traditional CNNs and equal in performance some of the most notable spatio-temporal models. Also, we have shown how SANNs, unlike traditional
convolutional methods, are really spatially agnostic, and how all this information is related to the spatial autocorrelation of the series. That way, not only our premises are demonstrated, but also it is proved that our methodology is simpler and less laborious to work with, offering the possibility of obtaining good performance without having to carry out extra research about the application domain. Concretely, by analyzing ten different datasets with different spatio-temporal conditions each, we can confirm the statistical significance of these statements with a confidence of 95%.

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