Abstract

In the last decades, the availability of spatial and spatio-temporal data has increased substantially, mainly due to the advances in computational tools which allow us to collect real-time data coming from GPS, satellites, etc. This means that nowadays in a wide range of fields, from epidemiology to ecology, to climatology and social science, researchers have to deal with geo-referenced data, i.e., including information about space (and possibly also time). There are countless scientific papers in peer review journals which use more or less complex and innovative statistical models (especially Bayesian models), to deal with the spatial and/or the temporal structure of the data, covering a wide range of applications. Machine Learning and Deep learning has attracted tremendous attention from researchers in various fields of information engineering such as AI, computer vision, and language processing, but also from more traditional sciences such as physics, biology, and manufacturing. Main advantages of these types of algorithms concern the few or no assumptions that need to be taken care of. They are far more flexible than statistical models as they have relaxed requirements about collinearity, normal distribution of residuals, etc. Thus, they have high uncertainty tolerance. Neural networks, image processing tools such as convolutional neural networks, sequence processing models such as recurrent neural networks, and regularisation tools such as dropout, are used extensively. However, fields such as physics, biology, business and manufacturing are ones in which representing model uncertainty is of crucial importance. With the recent shift in many of these fields towards the use of Bayesian uncertainty, new needs arise from deep learning. The goal of this thesis project thesis is to create a model that is able to infer both the spatial and temporal components and that combines the advantages of both approaches: the flexibility of a neural networks and the quantification of uncertainty like a traditional bayesian regression model. To implement this model different tools were used:

- Embeddings, a relatively low-dimensional space into which we translate high-dimensional vectors, to model the space-time static components in order to feed them into the network.

- A Neural Networks Architecture able to handle sequences of data and quantify the uncertainty with respect to each prediction.

To do that we apply the Bayesian learning paradigm to neural networks which

results in a flexible and powerful nonlinear modelling framework that can be used for Forecasting task. Within this framework, all sources of uncertainty are expressed and measured by probabilities. This formulation allows for a probabilistic treatment of our a priori knowledge, domain specific knowledge, model selection schemes, parameter estimation methods and noise estimation techniques. The main contributions of this thesis project are the following:

- Use of Bayesian Neural Networks for forecasting purposes and uncertainty quantification;
- Use of Probabilistic Layers to model the response variable;
- Use of different types of Embeddings to synthesize Temporal and Spatial component;
- Use of Recurrent, Convolutional Layer and Attention Mechanism to model dynamical temporal sequences of data;

in a Neural Network Architecture that reaches satisfactory goodness-of-fit performances, provides precise prediction of events over varying size time intervals and outperform traditional parametric and nonparametrics temporal and spatio-temporal techniques.