**Extreme quantile regression for high-dimensional spatio-temporal applications using partially interpretable neural networks**

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**Abstract**

Quantile regression is a powerful tool for modelling environmental data which exhibits spatio-temporal non-stationarity in its marginal behaviour. If our interest lies in quantifying risk associated with particularly extreme or rare weather events, we may want to estimate conditional quantiles that are outside the range of observable data; in these cases, it is practical to describe the data using some parametric extreme value model with its parameters represented as functions of predictor variables. Classical approaches of this type assume linear or additive relationships between predictors and parameters, and such approaches suffer in either their predictive capabilities or computational efficiency.

Neural networks can capture highly complex non-linear relationships between variables and scale well to high-dimensional data. Whilst they have been successfully applied in the context of fitting extreme value models, statisticians may choose to forego the use of neural networks as a result of their “black box" nature; although they facilitate highly accurate prediction, it is difficult to perform statistical inference with neural networks as their outputs cannot be readily interpreted. To that end, we propose a framework for performing extreme quantile regression using partially interpretable neural networks. Extreme value distribution parameters are represented as functions of predictors with three main components; a linear function, an additive function and a neural network that are applied separately to complementary subsets of predictors. The output from the linear and additive components can be interpreted whilst the neural network component contributes to the high prediction accuracy of our method; in this way we pursue a comfortable middle ground between fully interpretable regression models and black-box deep learning techniques.

Our approach can be used to fit both threshold exceedance and point process-type extreme value models. For the latter, we experience numerical problems when attempting to train our networks, which can be attributed to the finite lower bound of the corresponding block maxima distribution. Hence to complement our framework and overcome this issue, we also develop a novel point process model for extremes. We illustrate the efficacy of our partially interpretable deep learning approach for extreme quantile regression by applying our method to data describing wildfires across the contiguous U.S.