Inference for extremal regression with dependent heavy-tailed data

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Abstract

Nonparametric inference on tail conditional quantiles and their least squares analogs, expectiles, remains limited to iid data. We develop a fully operational inferential theory for extreme conditional quantiles and expectiles in the challenging framework of strongly mixing, conditional heavy-tailed data whose tail index may vary with covariate values. This requires a dedicated treatment to deal with data sparsity in the far tail of the response, in addition to handling difficulties inherent to mixing, smoothing, and sparsity associated to covariate localization. We prove the pointwise asymptotic normality of our estimators and obtain optimal rates of convergence reminiscent of those found in the iid regression setting, but which had not been established in the conditional extreme value literature. Our assumptions hold in a wide range of models. We propose full bias and variance reduction procedures, and simple but effective data-based rules for selecting tuning hyperparameters. Our inference strategy is shown to perform well in finite samples and is showcased in applications to stock returns and tornado loss data.