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Study of Robust Parameter Estimation

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ABSTRACT:-
We provided a first comprehensive evaluation of the different properties of heavier-tailed distributions when calibrating dynamic mathematical models to experimental data. Therefore, we derived the necessary gradients and Hessian matrices of the objective function to ensure an efficient optimization. The proposed approach has substantial practical value, since it allows to use of statistical tools, such as model selection, and it yields robust parameter estimates in the presence of outliers. This facilitates more accurate and reliable predictions, which are important to gain a better understanding of the biological processes of interest.

Keywords: Parameter, Estimation, Optimization
Introduction :

I. INTRODUCTION

We introduce the considered dynamical and statistical models along with optimization and model selection methods. Quantitative dynamic models are widely used to gain a mechanistic understanding of biological processes. These dynamic models facilitate the integration of multiple experimental datasets and the analysis of system properties that are not within reach of biological experiments. For this, the models need to be calibrated based on experimental data in order to determine the unknown parameters, e.g. initial values or kinetic rates. Experimental data used for parameter estimation are collected using a broad spectrum of techniques.While measurement devices provide increasingly precise quantitative data , there are numerous potential sources of measurement errors during data collection and data processing . These include technical limitations and human errors, such as pipetting errors or incorrect labeling, which result in potentially large errors. Individual data points which are corrupted by large errorsare usually denoted as outliers and assumed to be generated from a different mechanism as the remainder of the data points and might be misleading in the further analysis . Therefore, parameter estimation using outlier-corrupted data can result in large estimation errors and limits the validity of models. Since outlier-corrupted data distorts results in various fields, many methods for the detection and subsequent removal of outliers have been developed . Most of the algorithms either assign a score for the degree of abnormality or a binary label to a data point. This labeling is usually based on a fit to a distribution or distance measure e.g. nearest neighbor distance . Eventually, it however remains a subjective decision on whether or not a data point is sufficiently abnormal to be removed. Noisy measurements complicate the distinction even more and the increasing size and complexity of biological data make the removal of outliers a challenging task. Furthermore, the elimination of data points which are indeed no outliers, as well as the retention of outliers in the data, will yield less reliable results inthe further analysis .

II. METHODOLOGY :

The robust estimation of hydrologic model parameters is one of the major challenges in hydrology. A good definition of the term robust parameter vectors in the context of hydrologic modelling is given by Balrdossy and Singh . According to this definition, model parameter vectors are called robust if they lead to good model performance over the selected time period.. Considering the fact that one model parameter vector is not yet able to equally well describe the full range of processes that drive the runoff generation, the goal of a technique for robust parameterization should be the estimation of a set of model parameter vectors that satisfy the properties . Furthermore the operation of such a method is supposed to be as simple as possible. The definition of complicated likelihood functions is supposed to be avoided. The achievement of robustness requires a sound implementation of the principle of parsimony, the selection of appropriate calibration data, suitable objective functions and the application of advanced calibration strategies. A typical example for an application of such a method is the estimation of hydrologic model parameters that can be transferred to other catchments. Another example is an application for operational flash flood forecasting in small to

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medium sized catchments with fast response time.

Schmitz presented an operational framework, entitled PAI-OFF, that substitutes a process-oriented hydrologic model by an artificial neural network in order to predict flash flood events. One of the major assumptions of this approach is that the calibrated hydrologic model can be used for the extrapolation to extreme flood events. This however requires the robust calibration of the used hydrologic model. The following section of this work comprises a general review of recent developments in the field of hydrologic model parameterization
that focus on improved robustness. This includes both various classical approaches and tentative alternatives.

A general robust parameterization technique using a geometric approach, based on the concept of data depth, was presented by Bárdossy and Singh . The proposed approach,entitled robust parameter estimation (ROPE) , applies the concept of data depth to identify parameters that are deep, i.e. in a central position, with respect to a previously identified set of parameters with sufficiently high model performance. The underlying assumption is that parameters next to the boundary are more sensitive to small changes and less likely to show a good transferability on other time periods than those used in calibration.

The ROPE approach was studied using the commonly used conceptual hydrologic model HBV for a medium sized catchment in Southwest Germany on a daily time step. The application of the concept of data depth is advisable for calibration problems where
the good model parameters are geometrically well-structured, i.e. they form one or several clouds with a considerable volume in the parameter space. In a previous study it was shown that the parameter space of common hydrologic models usually satisfies this requirement .

III. RESULT :

The results estimated by the application of ROPE are very promising. The approach circumvents the requirement of prior probability distributions and likelihood definitions while estimating a robust set of model parameters that is more likely to be behavioural in validation. Notwithstanding the progress made, the sampling of deep and robust parameters using ROPE involves a range of challenges. A simple uniform sampling of deep parameter vectors increases tremendously with the rising dimension of the parameter space. In consequence this leads to an unacceptable computational effort. Furthermore most existing depth measures cannot cope with non-elliptic or multimodal distributions. Such problems might however occur when focussing on processes with high nonlinearity.Conclusion :

The main contribution of this work consists of developing a stratified sampling algorithm for the sampling of deep parameters. The new method improves the efficiency of the sampling in higher dimensions. Existing uniform depth-based sampling strategies are computationally intensive for dimensions greater than three. In addition, this opens the possibility to sample from non-elliptic and multimodal distributions. This is for instance an advantage for the sampling with respect to banana shaped distributions that are more frequent for parameterization problems that are characterized by nonlinearities. In such cases the new strategy estimates sets whose boundaries are much more indicative of the underlying data set or distribution.

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