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Spatial prediction of soil type maps with Neural Networks including quantification of model uncertainty

Kerstin Rau[1,3], Thomas Gläßle[2,3], Philipp Hennig[2,3], and Thomas Scholten[1,3]
[1]Department of Geosciences, University of Tübingen
[2]Department of Computer Sciences, University of Tübingen
[3]Cluster of Excellence Machine Learning: New Perspectives for Sciene, University of Tübingen

Artificial neural networks (ANN), which are mainly used in pattern and image recognition, have now found a wide range of applications. In recent years, different variants of ANN have also been increasingly used in the geosciences. They have proven to be a useful tool for complex questions that also involve a large amount of data. In their basic form, however, deep-learning algorithms do not provide interpretable predictive uncertainty. In the geosciences in particular, they have been used more as black-box models that require interpretation by an expert or do not allow for specific interpretation. Therefore, we implement in our explorative study on soil classification a Bayesian deep learning approach (i.e. a method to add uncertainty to deep networks) known as last layer Laplace approximation. This is a technique that can be applied as a post-hoc "add-on" without destroying the otherwise good performance of deep classifiers.
Our target soil type variable provides us with a large amount of information about soil processes and properties, which is a great advantage since it would take a lot of time and money to collect all this information individually. At the same time, soil maps are in high demand by authorities, construction companies or farmers. In our study area around Tübingen in southern Germany, there are 39 different soil types, determined according to the German soil systematics, which we consider individually for the prediction, but also combine into superordinate categories with similar properties, which is possible at low computational cost under the Laplace approximation. In addition to the underlying soil map, remotely sensed variables such as satellite imagery, a digital elevation model and its derivatives, and climate data are used as input to the model, which is designed to learn the relationship between these and the soil type. As a test case, we then explicitly include the Swabian Jura as a prediction region for the environment. This region is characterised by very different soil types due to its extremely different development and the resulting geology, climate and terrain.
Our goal is then to enrich soil type maps with a structured uncertainty, which is estimated to be high in the area of the Swabian Jura. This will help to better understand the causality of machine learning models in soil science and their transferability to regions other than the training and validation area.