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Bayesian Evidential Learning for 1D geological imaging from geophysical data

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Abstract: Geophysics is widely used to model the subsurface due to its combination of low-cost and large spatial coverage. However, proper uncertainty quantification based on geophysical data is rarely performed due to the high computational cost of such operation (Bayesian approach) or the poor quality of the uncertainty estimation (error propagation). Bayesian Evidential Learning (BEL) approximates the Bayesian problem in a reduced space, leading to a reduced computational cost. When applied to 1D geological imaging, we demonstrate that BEL produces coherent posterior uncertainty under a reasonable CPU time. Moreover, our implementation of BEL for 1D geological imaging (BEL1D) is fully separated into two phases, similar to machine learning: a learning phase and a prediction phase. This means that prediction of posterior model space can be reduced to only the prediction phase since learning can be reused as much as wanted, leading to extremely rapid estimations of uncertainty. During the learning phase, we derive a statistical relationship from a training set of geophysical models and their associated geophysical response in reduced space. During the prediction phase, we simply extract the conditional probability of the geological models given the geophysical data. This latter process is extremely rapid numerically and results in the approximated posterior in reduced space. Then, sampling as many models from this posterior space as needed and transforming them back into the original space leads to a set of models from the posterior. The algorithm (implemented into a set of open-source Matlab toolboxes) is already applied with success on surface nuclear magnetic resonance and dispersion curves from seismic surface waves. In further version of the algorithm, we plan on extending the capabilities of BEL1D to other geophysical methods and to relax the constrains on the prior definition (currently 1D blocky models).

***Keywords**:* Geophysics; Bayesian Evidential Learning; Machine Learning;