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Applications of Bayesian Networks in Geo-Sciences

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For complex systems as encountered in geo-sciences the knowledge about the underlying mechanism is often lacking and much effort is being put into obtaining an improved understanding of the dependencies of involved variables and parameters. However, gaining insight into the "working" of a system is just one aspect: often one is also (or perhaps more) interested in being able to predict one or several target variables given a set of measurements on some other variables of the system(s), e.g., forward or inverse problems. Moreover, both epistemic uncertainty (lack of knowledge) and/or aleatoric uncertainty (uncontrollable/nature's randomness) associated with complex systems and measurements play an important role and should not be neglected when dealing with complex systems.

Using the all-round probabilistic framework of Bayesian networks (BNs) we faced the above mentioned challenges, considering modelling problems coming from different geo-scientific domains: 1) We simplified a complex so-called stochastic model for a better understanding of the driving forces behind Ground Motion caused by Earthquakes. 2) For the prediction of damage caused by floods and for an improved understanding about the influencing factors we learned a BN based on data collected after the 2002 and 2005/2006 floods in the Elbe and Danube catchments. 3) First steps have been undertaken to learn a BN from landslide data from Japan.

In contrast to classical approaches like regression, where the functional form is derived from already existing expert knowledge, BNs allow an entirely data-driven approach and can provide additional understanding of the underlying complex system. Capturing the (in-)dependencies of the involved variables, BNs describe a joint probability distribution, decomposing it into a product of (local) conditional probability distributions according to a directed acyclic graph. In particular, this allows to infer about any conditional or marginal distribution in an efficient way for predictive purposes. Additionally the graph structure gives insight into the relations between the variables.

The handling of missing values and continuous variables poses a challenge in BN learning. Trade-offs between computational expenses and information loss have to be made depending on the observed data set. Solutions we developed for our needs are adaptable to other applications not only in geo-sciences.