Potential mapping, prospectivity modeling, prediction of occurrence of discrete events has been a major topic of mathematical geosciences and is the most voluminous chapter in the recently published book [1]. Due to its numerical simplicity Geologists’ most favorite method is weights-of-evidence [2] where weights of categorical variables are estimated by way of counting occurrences of events and combinations of events in terms of pixels or voxels. Generally, the result depends on the spatial resolution, which usually goes tacitly. Using the non-geostatistical concept of identical independent distributed random variables, this simplicity is basically implied by the mathematical modeling assumption of joint conditional independence of all predictors given the target, which itself is not simple at all. Conditionally independent random variables may be (significantly) correlated or not. Independence does not imply conditional independence and vice versa. Pairwise conditional independence does not imply joint conditional independence [3,4].

When the assumption of conditional independence is violated, the application of conventional weights-of-evidence does not only corrupt the predicted conditional probabilities, but also their rank transform. Lacking conditional independence can effectively be counterbalanced by general weights-of-evidence and corresponding multivariate Bayes factors or by corresponding interaction terms to be included in logistic regression models. Multivariate Bayes factors can be estimated by counting and applied for prediction as usually. A logistic regression model with interaction terms is generally parsimonious, and is especially parsimonious if only the interactions are included which are required to compensate the actual lack of conditional independence. Therefore, it seems worthwhile to spend some effort to recognize the stochastic dependence/independence structure, and in particular those predictors which are not conditional independent given the target. The hypothesis of joint conditional independence can be tested in terms of log-linear models, i.e., if the joint probability distribution of all predictors and the target is log-linear. Their joint distribution is log-linear if all variables are indicator or categorical variables. A kernel-based test of pairwise conditional independence of real variables exits [5], which does not seem to possess an obvious generalization for joint conditional independence of all predictors given the target. A look at the matrix of conditional covariances and correlations, respectively, may provide a makeshift: If the conditional correlation is significantly different from 0, then the variables are not conditionally independent. The general key to conditional covariances and correlations, respectively, is Schur’s complement of a block matrix. If the conditioning variable is dichotomous, conditional covariances and correlations, respectively, can be determined straightforwardly.

Procedures to test or check conditional independence are presented, and mathematical findings will be confirmed with examples using fabricated and observed data. In particular, applications of weights-of-evidence, generalized weights-of-evidence, boost weights-of-evidence [6], logistic regression and other methods will be compared using fabricated and observed data.
References:
