Concordant models for latent space projections in the complex structured prediction tasks*

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Abstract: The paper examines the problem of predicting a complex structured target variable. Complexity refers to the presence of dependencies, whether linear or non-linear. The source data is assumed to be heterogeneous. This means that the spaces of the independent and target variables are of different nature. It is proposed to build a predictive model that takes into account the dependence in the input space of the independent variable, as well as in the space of the target variable. It is proposed to make model agreement procedure in a low-dimensional latent space. The projection to latent space method is used as the basic algorithm. The paper compares the linear and proposed nonlinear models. The comparison is performed on heterogeneous data in high-dimensional spaces.

Keywords: partial least squares, model concordance, nonlinear projection to latent space

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