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**Kernel multilogit algorithm for multiclass classification.** (English) Zbl 06984116
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Summary: An algorithm for multi-class classification is proposed. The soft classification problem is considered, where the target variable is a multivariate random variable. The proposed algorithm transforms the original target variable into a new space using the multilogit function. Assuming Gaussian noise on this transformation and using a standard Bayesian approach the model yields a quadratic functional whose global minimum can easily be obtained by solving a set of linear system of equations. In order to obtain the classification, the inverse multilogit-based transformation should be applied and the obtained result can be interpreted as a 'soft' or probabilistic classification. Then, the final classification is obtained by using the 'Winner takes all' strategy. A Kernel-based formulation is presented in order to consider the non-linearities associated with the feature space of the data. The proposed algorithm is applied on real data, using databases available online. The experimental study shows that the algorithm is competitive with respect to other classical algorithms for multiclass classification.

**MSC:**

62-XX Statistics

**Keywords:**

classification; multilogit function; linear model; kernel

**Software:**

UCI-ml; LIBLINEAR

**Full Text:** DOI

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