Ph.D. in Information Technology
Thesis Defense

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Aula BIO1– building 21

Paolo BONETTI - XXXVII Cycle

Interpretable Machine Learning for Meaningful Variable Extraction: Methods and Applications to Climate Extreme Events

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Abstract:

Machine Learning is a core field of Artificial Intelligence, designed to extract meaningful patterns from data, with the purpose of generalizing across different environments. One of the main aspects of this field is the choice and processing of input variables. Ideally, considering a large set of available candidate variables, the designer should ponder the number of input features, considering a restricted subset of relevant variables and non-redundant ones, preserving most of the information shared with the target variable. This way, the collinearity among variables should be reduced, together with their dimensionality, mitigating issues like overfitting or the curse of dimensionality, typical of high-dimensional problems. In this context, the sub-field of feature extraction has been designed to identify a reduced set of relevant variables. This can be done through feature selection methods, aiming to identify a subset of reduced features. On the other hand, dimensionality reduction approaches can be exploited to project the entire set of features into a lower dimensional space. In the first case, some features are simply discarded, which improves the interpretability of the final results, although they may be exploited to extract more information on the target variable. On the other hand, in the second case, all features are potentially exploited at a cost of interpretability. Indeed, the obtained projected features can be linear or non-linear transformation of eventually all the original ones. In this dissertation we discuss three dimensionality reduction approaches designed to reduce the number of features, while preserving their interpretability. The main idea in this case is to aggregate subsets of variables with their mean, and we provide theoretical results and algorithms in linear, non-linear and multi-task settings. Additionally, we explore the possibility to select relevant and non-redundant variables in a causal feature selection approach based on transfer entropy. This is an asymmetric measure of the flow of information, allowing to identify causally relevant features for a target variable. Then, in the second part of this thesis we present two machine learning workflows for climate data, focusing on drought detection problems. These applications can be both considered as an empirical assessment, on challenging real world tasks, of some of the novel approaches introduced in the methodological sections, and applied results in the field of drought detection, showing enhanced performances and driving some conclusions on the effect of some meteorological variables on the state of vegetation.

PhD Committee

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