The task of simultaneously predicting multiple target variables from a common set of input variables is known as multi-target prediction, with multi-label classification (binary targets) and multi-target regression (real-valued targets) being two important special cases. A major concern of most multi-target learning methods is to improve predictive performance by exploiting statistical dependencies between the target variables. For example, a simple yet effective idea is the one of chaining, namely, conditioning the prediction of a target not only on the input variables but also on those target variables preceding that target in a predefined order (chain) on all targets [1].

In spite of showing strong performance in many applications, chaining methods could be criticized from a theoretical perspective. In particular, the learning process exhibits a potential pitfall, namely the discrepancy between the feature spaces used in training and testing: While true target values are used as supplementary attributes for training the binary models along the chain, the same models need to rely on estimations of these targets at prediction time. As shown in [2], this induces attribute noise and may affect the overall prediction performance. In principle, one should expect this problem to be even more relevant for regression than it is for classification, which is somewhat in contrast to the recent findings of [3].

This thesis is meant to provide a critical analysis of the chaining method in multi-target prediction, including both multi-label classification and multi-target regression as special cases. More specifically, the goal is to conduct theoretical analyses as well as carefully designed experimental studies that help understand the properties of the approach, and the conditions under which it is likely to work and fail, respectively.

**Prerequisites:** Background in machine learning, programming skills.

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**References**

