

We connect high-dimensional subset selection and submodular maximization. Our results extend the work of Das and Kempe (2011) from the setting of linear regression to arbitrary objective functions. This connection allows us to obtain strong multiplicative performance bounds on several greedy feature selection methods without statistical modeling assumptions. This is in contrast to prior work that requires data generating models to obtain theoretical guarantees. Our work shows that greedy algorithms perform within a constant factor from the best possible subset-selection solution for a broad class of general objective functions. Our methods allow a direct control over the number of obtained features as opposed to regularization parameters that only implicitly control sparsity.