Abstract

The construction of r-nets offers a powerful tool in computational and metric geometry. We focus on high-dimensional spaces and present a new randomized algorithm which efficiently computes approximate r-nets with respect to Euclidean distance. For any fixed $\epsilon > 0$, the approximation factor is $1 + \epsilon$ and the complexity is polynomial in the dimension and subquadratic in the number of points. The algorithm succeeds with high probability. Specifically, we improve upon the best previously known (LSH-based) construction of Eppstein et al. (D. Eppstein, S. Har-Peled, and A. Sidiropoulos. Approximate greedy clustering and distance selection for graph metrics. CoRR, abs/1507.01555, 2015) in terms of complexity, by reducing the dependence on ϵ, provided that ϵ is sufficiently small. Our method does not require LSH but, instead, follows Valiant's (G. Valiant. Finding correlations in subquadratic time, with applications to learning parities and the closest pair problem. J. ACM, 62(2):13, 2015) approach in designing a sequence of reductions of our problem to other problems in different spaces, under Euclidean distance or inner product, for which r-nets are computed efficiently and the error can be controlled. Our result immediately implies efficient solutions to a number of geometric problems in high dimension, such as finding the $(1+\epsilon)$-approximate kth nearest neighbor distance in time subquadratic in the size of the input.