abstract

COMPUTER SCIENCE/DISCRETE MATH I
Topic:

Speaker:

Affiliation:

Date:

Time/Room:

We study combinatorial group testing schemes for learning d-sparse boolean vectors using highly unreliable disjunctive measurements. We consider an adversarial noise model that only limits the number of false observations, and show that any noise-resilient scheme in this model can only approximately reconstruct the sparse vector. On the positive side, we take this barrier to our advantage and show that approximate reconstruction (within a satisfactory degree of approximation) allows us to break the information theoretic lower bound of Omega(d^2 log n/ log d) that is known for exact reconstruction of d-sparse vectors of length n via non-adaptive measurements, by a multiplicative factor of almost linear in d.

Specifically, we give simple randomized constructions of non-adaptive measurement schemes, with m=O(d log (n)) measurements, that allow efficient reconstruction of d-sparse vectors up to O(d) false positives even in the presence of delta*m false positives and O(m/d) false negatives within the measurement outcomes, for any constant delta < 1. We show that, information theoretically, none of these parameters can be substantially improved without dramatically affecting the others. Furthermore, we obtain several explicit constructions, in particular one matching the randomized trade-off but using m = O(d^(1+o(1)) log n) measurements. We also obtain explicit constructions that allow fast reconstruction in time polynomial in m, which would be sublinear in n for sufficiently sparse vectors.

An immediate consequence of our result is an adaptive scheme that runs in only two non-adaptive "rounds" and exactly reconstructs any d-sparse vector using a total O(d log (n)) measurements, a task that would be impossible in one round and fairly easy in O(log (n/d)) rounds.