



A limit theorem for scaled eigenvectors of random dot product graphs

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We prove a central limit theorem for the components of the largest eigenvector of the adjacency matrix of a one-dimensional random dot product graph whose true latent positions are unknown. In particular, we follow the methodology outlined in Sussman et al. [2013] to construct consistent estimates for the latent positions, and we show that the appropriately scaled differences between the estimated and true latent positions converge to a mixture of Gaussian random variables. As a corollary, we obtain a central limit theorem for the first eigenvector of the adjacency matrix of an Erdos-Renyi random graph. We conjecture an analogous central limit theorem in the case of a higher-dimension random dot product graph, and we illustrate the multi-dimensional case through numerical simulations. A proof of this conjecture will have implications for the development of statistical procedures for random graphs analogous to the results on estimation, hypothesis testing, and clustering in the setting of a mixture of normal distributions in Euclidean space.

Subjects: **Statistics Theory (math.ST)**; Machine Learning (stat.ML)

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