For an $n \times n$ matrix $A_n$, the $r \to p$ operator norm is defined as
\[
\|A_n\|_{r \to p} := \sup_{x \in \mathbb{R}^n: \|x\|_r \leq 1} \|A_n x\|_p
\]
for $r, p \geq 1$.

This talk considers $r \to p$ norms of symmetric random matrices with nonnegative entries, including adjacency matrices of Erdős-Rényi random graphs, matrices with positive sub-Gaussian entries, and certain sparse matrices. For $1 < p \leq r < \infty$, the asymptotic normality of the appropriately centered and scaled norm $\|A_n\|_{r \to p}$ is established. Furthermore, a sharp $\ell_\infty$-approximation for the unique maximizing vector in the definition of $\|A_n\|_{r \to p}$ is obtained, which may be of independent interest.

The results obtained can be viewed as a generalization of the seminal results of Füredi and Komlós (1981) on asymptotic normality of the largest singular value. In the general case with $1 < p \leq r < \infty$, the spectral methods are no longer applicable, which requires a new approach, involving a refined convergence analysis of a nonlinear power method and establishing a perturbation bound on the maximizing vector. (Received August 15, 2020)