# A random matrix perspective on random tensors

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Recent years saw substantial progress on the statistical limits of the so-called tensor PCA problem, where one wants to recover a planted signal vector $x$ which gives rise to a symmetric rank-one tensor $x^{\otimes d}$ from observations corrupted by Gaussian noise. However, some of the most significant results are largely based on rather technical tools coming from spin glass theory, thus limiting their accessibility. Moreover, relevant extensions to more general and/or structured tensor models is likely difficult with this approach. Our work proposes a sharply distinct and somewhat more elementary approach, relying on tools from random matrix theory. The key idea is to study random matrices arising from contractions of a large random tensor, which give access to its spectral properties. In particular, for a symmetric $d$th-order rank-one model with Gaussian noise, this yields a novel characterization of the asymptotic performance of maximum likelihood (ML) estimation in terms of a fixed-point equation valid in the regime where weak recovery is possible. For $d = 3$, the solution to this equation matches the existing results. We conjecture that the same holds for any order $d$, based on numerical evidence for $d \in \{4, 5\}$. Our approach can be (and has been) extended to other models, including asymmetric and non-Gaussian ones.

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