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**Asymptotic theory for large sample autocovariance matrices with heavy-tailed entries**

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Many fields of modern sciences are faced with high-dimensional data sets. In order to explore the structure in the data the sample covariance matrix can be used. Often dimension reduction techniques facilitate further analyzes of large data matrices in genetic engineering and finance. Principal Component Analysis for example makes a linear transformation of the data to obtain vectors of which the first few contain most of the variation in the data. These principal component vectors correspond to the largest eigenvalues of the sample covariance matrix. This motivates to study the eigenvalue decomposition of the sample covariance matrix. Random Matrix Theory is concerned with the spectral properties of large dimensional random matrices. In this context both the distribution of the entries of a random matrix as well as their dependence structure play a crucial role. The case of heavy-tailed components is of particular interest and the theory is not as well developed as in the light-tailed case. We consider asymptotic properties of sample covariance matrices for heavy-tailed time series, where both the dimension and the sample size tend to infinity simultaneously. We derive the limiting point process of eigenvalues of such matrices via large deviation and extreme value theory techniques. As a consequence, we obtain the asymptotic distribution of the largest eigenvalues.