High-dimensional data sets present one of the most profound analytic challenges in the “big data” era. High-dimensional data are collected daily in many fields of work, such as DNA analysis and social media data analysis. The presence of clusters in a data set can be crucial to discovering new trends and patterns, e.g., disease subtypes. Therefore, it is necessary to have reliable and quick techniques which can detect and define clusters. Model-based clustering is a very popular method and uses a mixture of distributions where each component density corresponds to a cluster. The most common model-based clustering techniques are based on using a mixture of multivariate normal distributions. A method called high-dimensional data clustering (HDDC) has given rise to a very computationally efficient family of Gaussian mixture models for high-dimensional data. HDDC is based on the idea that high-dimensional data can be represented in much lower-dimensional subspaces. The HDDC family of models has gained vast attention due to its superior performance compared to other families of mixture models. We propose to extend this family of models to utilize the multivariate-t distribution as well as the generalized hyperbolic distribution. These distributions are more flexible and can incorporate skewness. Hence, the resulting models allow for robust clustering, providing an important advance in practice. The novel families are illustrated using simulated and real data.