Unsupervised learning (UL) is a type of algorithm that learns patterns from untagged data. The hope is that through mimicry, the machine is forced to build a compact internal representation of its world. In contrast to supervised learning (SL) where data is tagged by a human, e.g. as "car" or "fish" etc, UL exhibits self-organization that captures patterns as neuronal predilections or probability densities. The other levels in the supervision spectrum are reinforcement learning where the machine is given only a numerical performance score as its guidance, and semi-supervised learning where a smaller portion of the data is tagged. Two broad methods in UL are Neural Networks and Probabilistic Methods.

Two of the main methods used in unsupervised learning are principal component and cluster analysis. Cluster analysis is used in unsupervised learning to group, or segment, datasets with shared attributes in order to extrapolate algorithmic relationships. Cluster analysis is a branch of machine learning that groups the data that has not been labelled, classified or categorized. Instead of responding to feedback, cluster analysis identifies commonalities in the data and reacts based on the presence or absence of such commonalities in each new piece of data. This approach helps detect anomalous data points that do not fit into either group.

One of the statistical approaches for unsupervised learning is the method of moments. In the method of moments, the unknown parameters (of interest) in the model are related to the moments of one or more random variables, and thus, these unknown parameters can be estimated given the moments. The moments are usually estimated from samples empirically. The basic moments are first and second order moments. For a random vector, the first order moment is the mean vector, and the second order moment is the covariance matrix (when the mean is zero). Higher order moments are usually represented using tensors which are the generalization of matrices to higher orders as multi-dimensional arrays.

In particular, the method of moments is shown to be effective in learning the parameters of latent variable models. Latent variable models are statistical models where in addition to the observed variables, a set of latent variables also exists which is not observed. A highly practical example of latent variable models in machine learning is the topic modeling which is a statistical model for generating the words (observed variables) in the document based on the topic (latent variable) of the document. In the topic modeling, the words in the document are generated according to different statistical parameters when the topic of the document is changed. It is shown that method of moments (tensor decomposition techniques) consistently recover the parameters of a large class of latent variable models under some assumptions.

The Expectation–maximization algorithm (EM) is also one of the most practical methods for learning latent variable models. However, it can get stuck in local optima, and it is not guaranteed that the algorithm will converge to the true unknown parameters of the model. In contrast, for the method of moments, the global convergence is guaranteed under some conditions