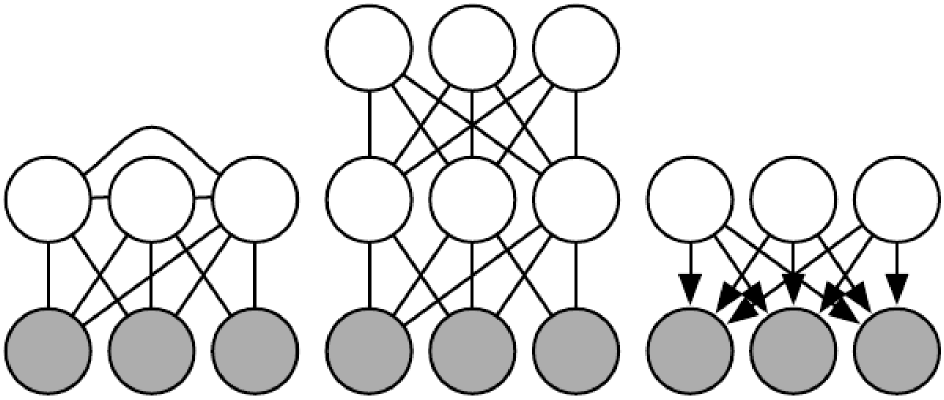

Figure 19.1: Intractable inference problems in deep learning are usually the result of interactions between latent variables in a structured graphical model. These can be due to edges directly connecting one latent variable to another, or due to longer paths that are activated when the child of a V-structure is observed. *(Left)*A **semi-restricted Boltzmann machine** (Osindero and Hinton, 2008) with connections between hidden units. These direct connections between latent variables make the posterior distribution intractable due to large cliques of latent variables. *(Center)*A deep Boltzmann machine, organized into layers of variables without intra-layer connections, still has an intractable posterior distribution due to the connections between layers. *(Right)*This directed model has interactions between latent variables when the visible variables are observed, because every two latent variables are co-parents. Some probabilistic models are able to provide tractable inference over the latent variables despite having one of the graph structures depicted above. This is possible if the conditional probability distributions are chosen to introduce additional independences beyond those described by the graph. For example, probabilistic PCA has the graph structure shown in the right, yet still has simple inference due to special properties of the specific conditional distributions it uses (linear-Gaussian conditionals with mutually orthogonal basis vectors).