

Generative Adversarial Networks (GANs) & Restricted Boltzmann Machines (RBMs)

Lecture 23

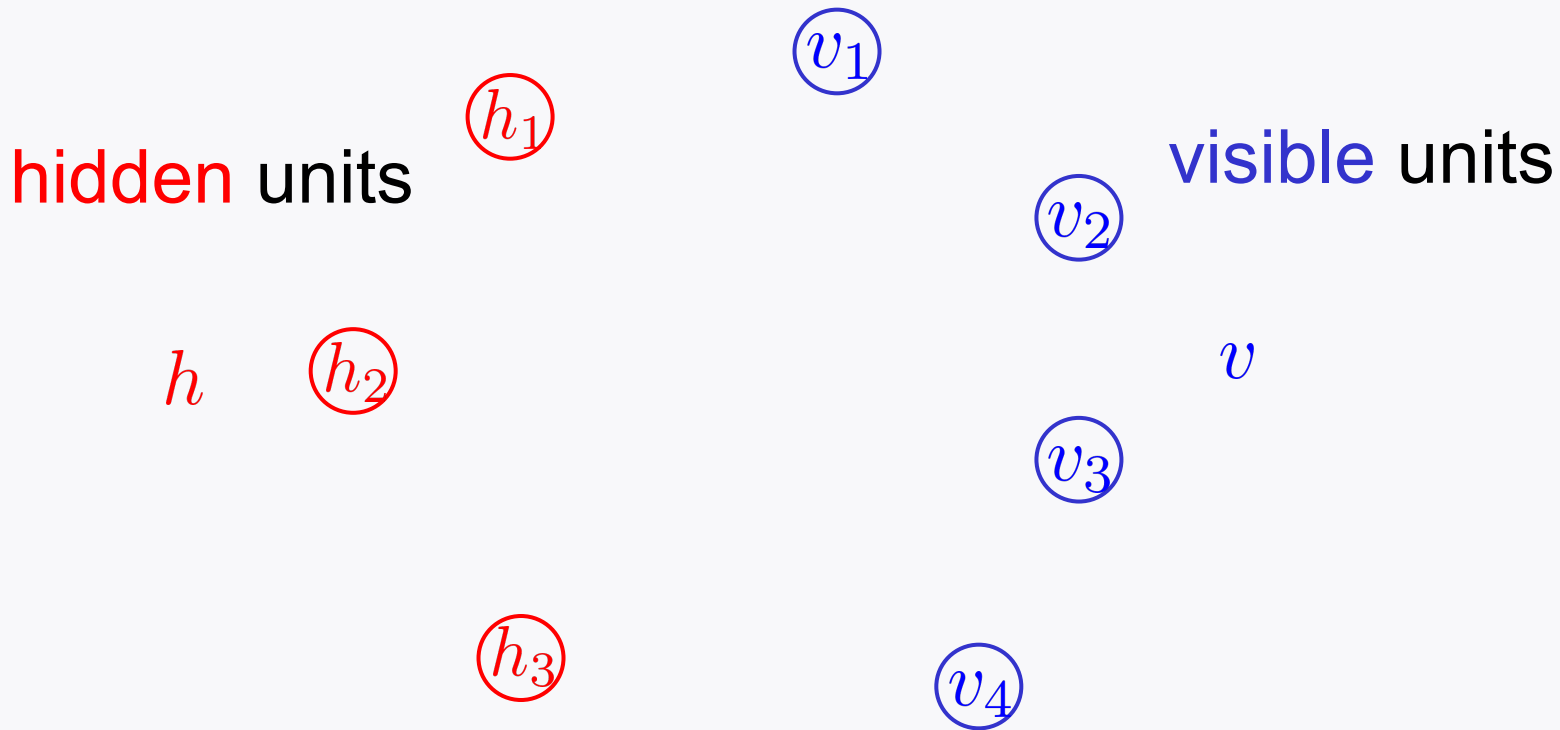
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Outline

1. Figure out Boltzmann Machine (BM) and then RBM.
2. Study how RBM can serve as a generative model.
3. Study a couple of concepts regarding RBM.

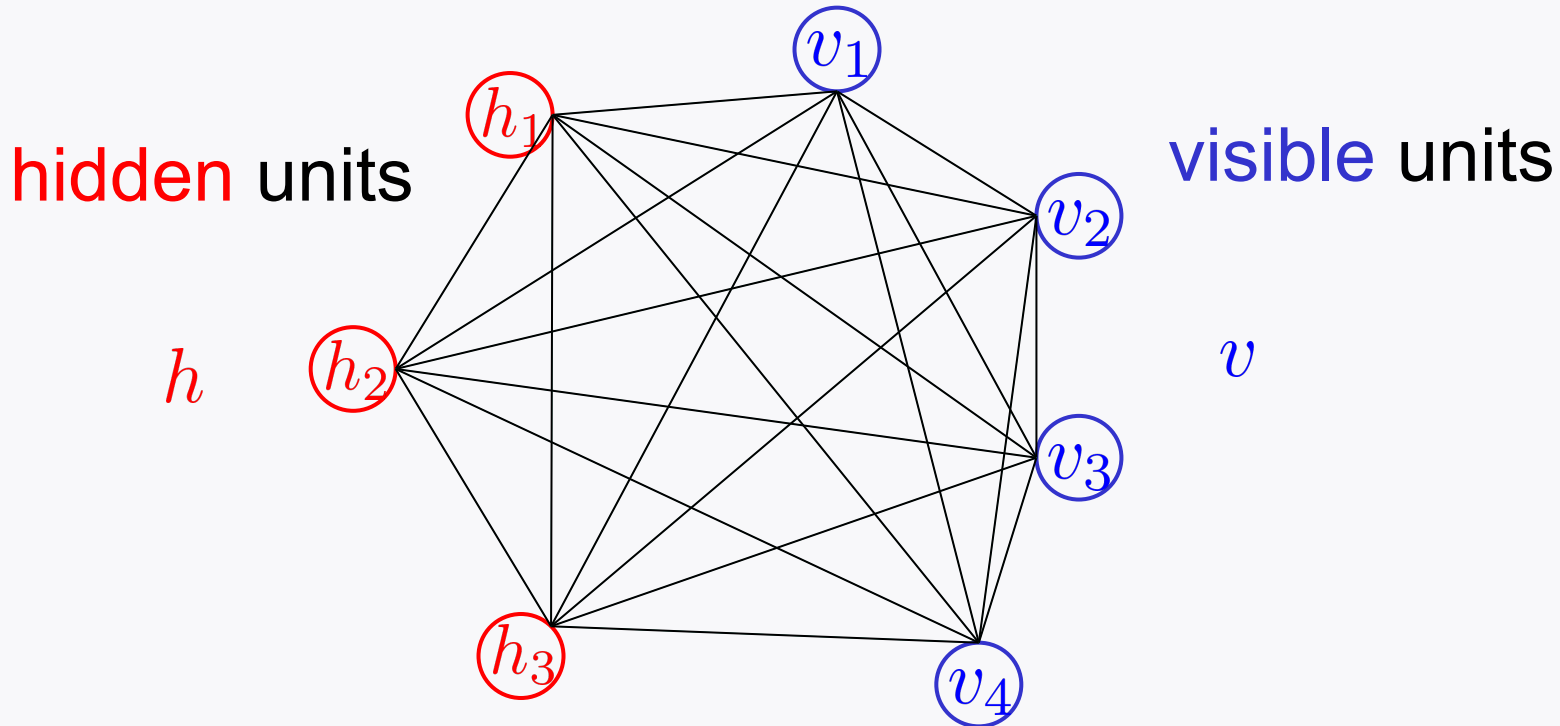
Boltzmann Machine (BM)



Represent relationship between nodes often via edges.

Suppose: All of the **hidden** and **visible** units are arbitrarily correlated.

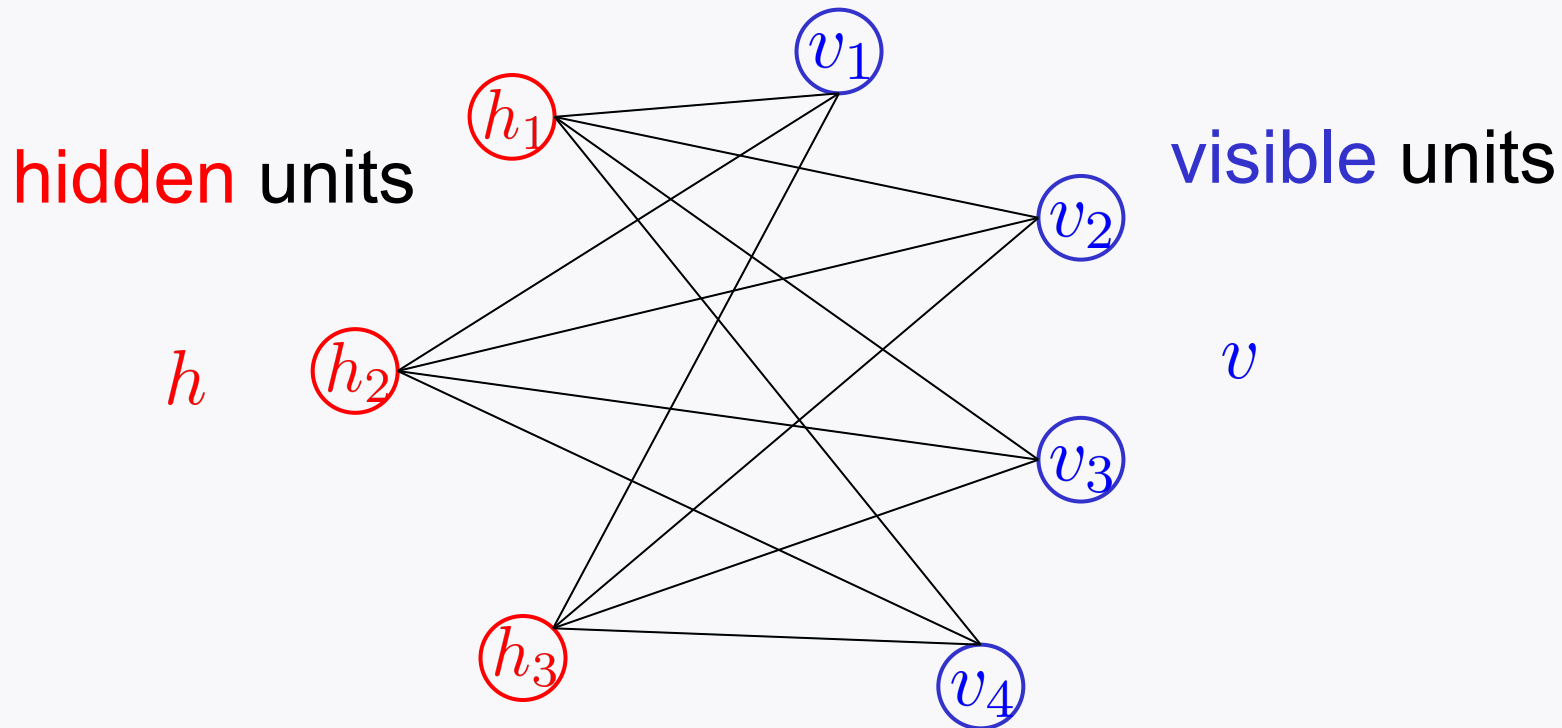
Boltzmann Machine (BM)



The above picture captures such arbitrary distribution:

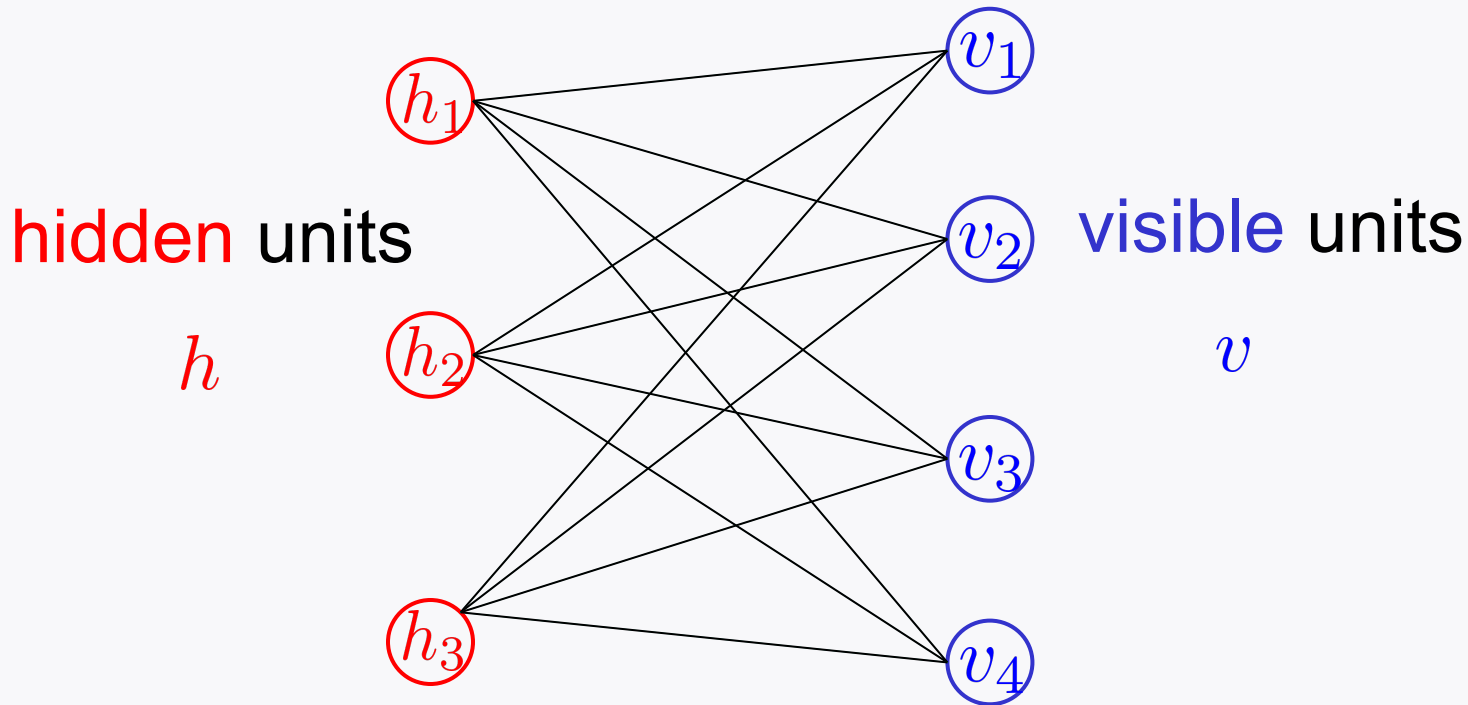
$$\mathbb{P}(h, v)$$

Restricted Boltzmann Machine (RBM)



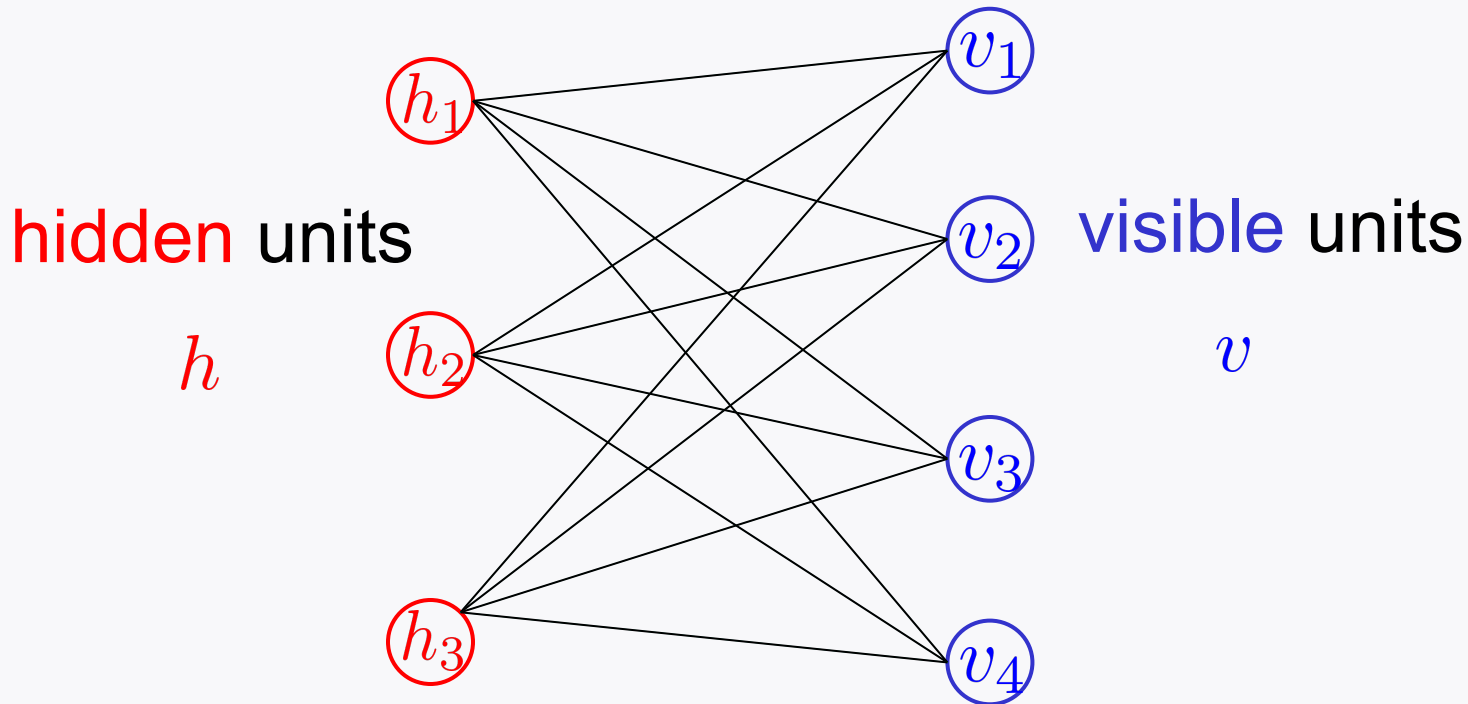
RBM is a simplified BM in which there is no edge within hidden units as well as within visible units.

Representation of RBM



Usually it is represented a **bipartite** graph.

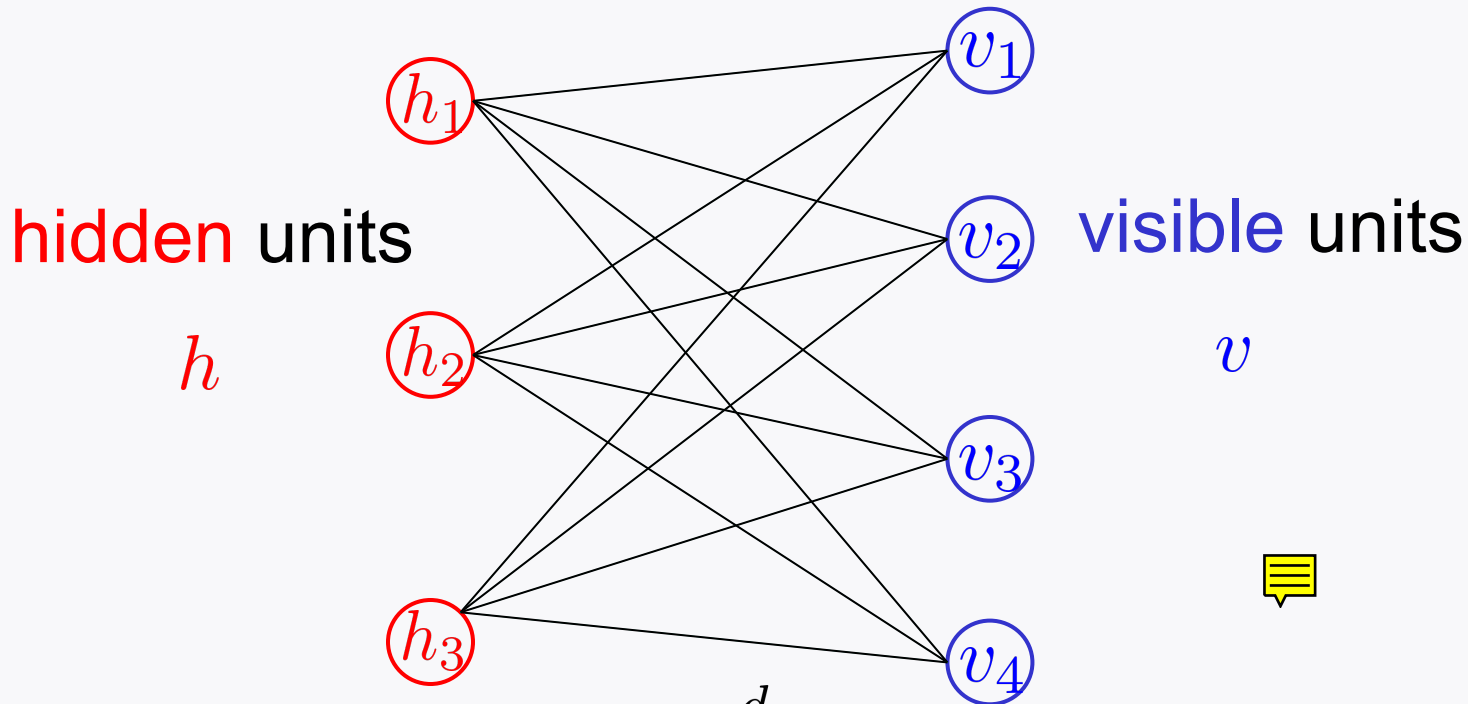
Property of RBM



Given the visible units, hidden units are independent:

$$\mathbb{P}(h|v) = \prod_{i=1}^d \mathbb{P}(h_i|v)$$

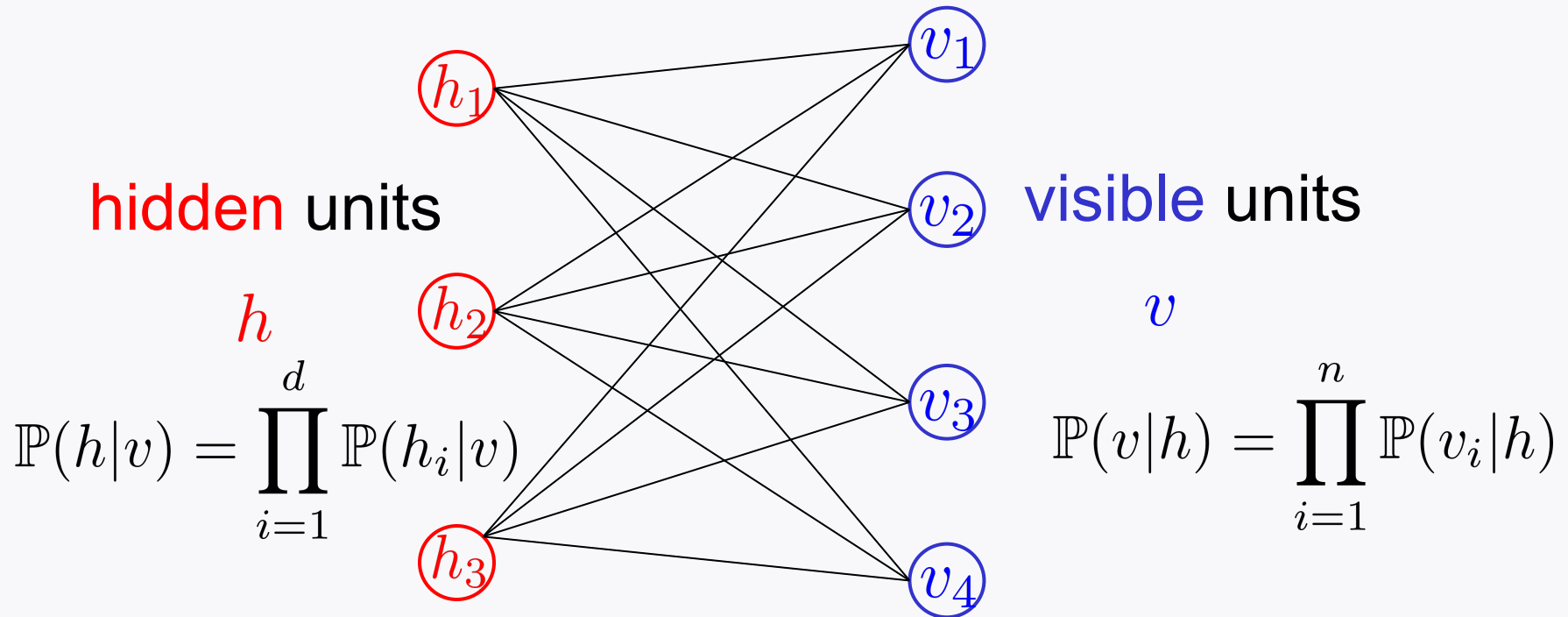
Property of RBM



$$\mathbb{P}(h|v) = \prod_{i=1}^d \mathbb{P}(h_i|v)$$

Similarly:
$$\mathbb{P}(v|h) = \prod_{i=1}^n \mathbb{P}(v_i|h)$$

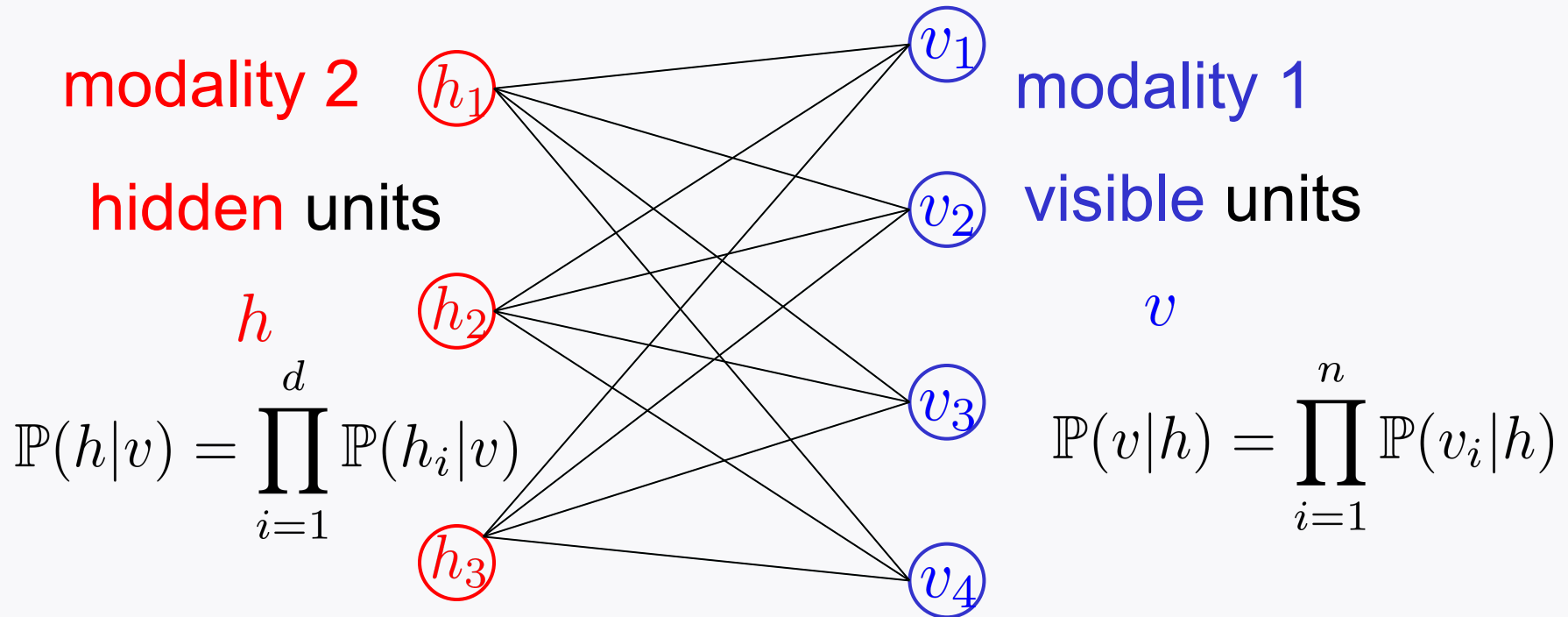
Main role of RBM



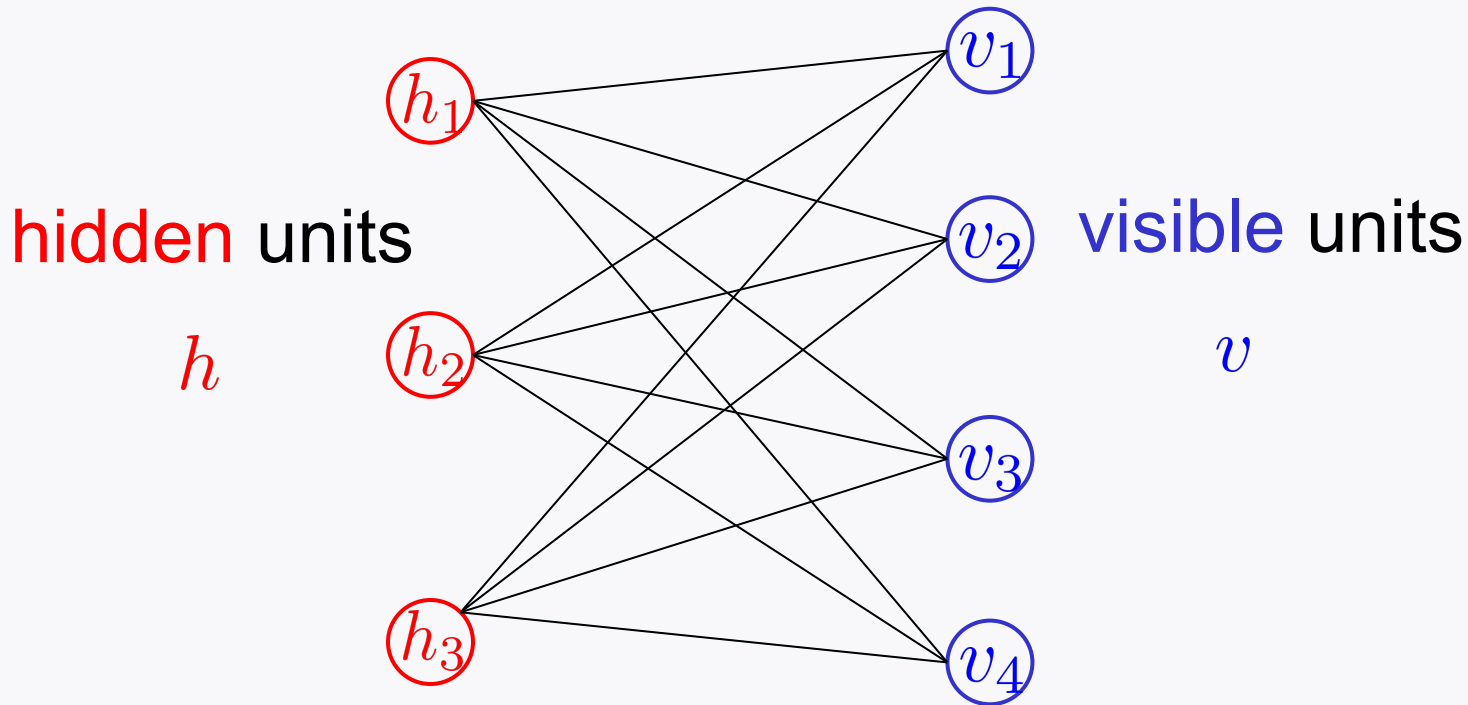
Can serve as a **generative model**.

When only the visible units are available, can generate hidden units via $\prod_{i=1}^d \mathbb{P}(h_i|v)$.

Use of RBMs in practice



Probability distribution in RBMs?



In RBM, the description of probability distribution requires one important concept:

Energy

Energy

Energy is a key function that determines the probability distribution.

It is denoted by $E(v, h)$ and defined such that:

$$\mathbb{P}(v, h) = \frac{e^{-E(v, h)}}{Z} \quad \text{where } Z = \sum_v \sum_h e^{-E(v, h)}$$

Interpretation:

Lower energy \rightarrow more stable \rightarrow more probable

Energy of visible units

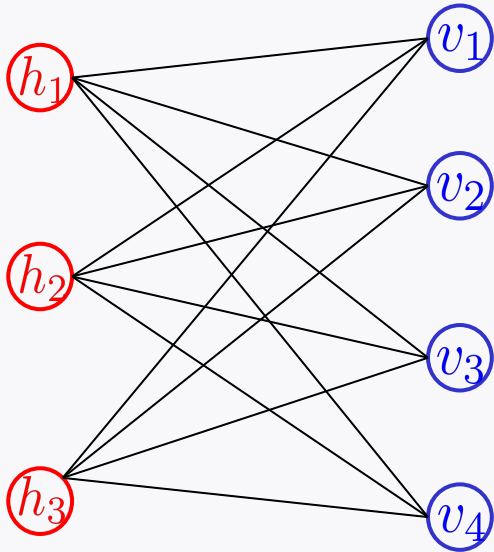
$$\begin{aligned}\mathbb{P}(v) &= \sum_h \mathbb{P}(v, h) && \text{total probability law} \\ &= \sum_h \frac{e^{-E(v, h)}}{Z}\end{aligned}$$

Wish to find energy of v , say $F(v)$, such that

$$\mathbb{P}(v) = \sum_h \frac{e^{-E(v, h)}}{Z} = \frac{e^{-F(v)}}{Z}$$

$$F(v) = -\log \left(\sum_h e^{-E(v, h)} \right) \quad \text{Called "Free Energy".}$$

How can RBM serve as a generative model?



How to compute: $\mathbb{P}(h|v) = \prod_{i=1}^d \mathbb{P}(h_i|v)$?

In RBM, we define $E(v, h)$ as:

$$E(v, h) := -b^T v - c^T h - h^T W v$$

↖ bias w.r.t. hidden units $\in \mathbb{R}^d$
↖ weight matrix $\in \mathbb{R}^{d \times n}$
↖ bias w.r.t. visible units $\in \mathbb{R}^n$

Computation of $\mathbb{P}(h|v) = \prod_{i=1}^d \mathbb{P}(h_i|v)$?

$$E(v, h) := -b^T v - c^T h - h^T W v$$

$$\mathbb{P}(v, h) = \frac{e^{-E(v, h)}}{Z}$$

$$\mathbb{P}(h|v) = \frac{\mathbb{P}(v, h)}{\mathbb{P}(v)} = \frac{\mathbb{P}(v, h)}{\sum_h \mathbb{P}(v, h)} = \frac{e^{-E(v, h)}}{\sum_h e^{-E(v, h)}}$$

$$= \frac{e^{b^T v + c^T h + h^T W v}}{\sum_h e^{b^T v + c^T h + h^T W v}}$$

$$= \frac{e^{c^T h + h^T W v}}{\sum_h e^{c^T h + h^T W v}} = \frac{\prod_{i=1}^d e^{c_i h_i + h_i W_i v}}{\sum_h e^{c^T h + h^T W v}}$$

$$W = \begin{bmatrix} | \\ W_i \\ | \end{bmatrix}$$

Binary case: $\mathbb{P}(h|v) = \prod_{i=1}^d \mathbb{P}(h_i|v)?$

$$\mathbb{P}(h_i|v) \sim e^{c_i h_i + h_i W_i v}$$

$$\mathbb{P}(h_i = 1|v) \sim e^{c_i + W_i v}$$

$$\mathbb{P}(h_i = 0|v) \sim e^0$$

$$\begin{aligned} \mathbb{P}(h_i = 1|v) &= \frac{e^{c_i + W_i v}}{1 + e^{c_i + W_i v}} \\ &= \frac{1}{1 + e^{-c_i - W_i v}} = \sigma(c_i + W_i v) \end{aligned}$$

Conditional probabilities

$$\mathbb{P}(h|v) = \frac{e^{c^T h + h^T W v}}{\sum_h e^{c^T h + h^T W v}}$$

$$\mathbb{P}(v|h) = \frac{e^{b^T v + v^T W^T h}}{\sum_v e^{b^T v + v^T W^T h}}$$

Binary case:

$$\mathbb{P}(h_i = 1|v) = \sigma(c_i + W_i v)$$

$$\mathbb{P}(v_i = 1|h) = \sigma(b_i + [W^T]_i h)$$

To compute this, need to figure out:

$$\theta := (W, b, c) \quad \text{parameters}$$

How to train parameters θ ?

Look ahead

Will study how to train RBM.