

# Chapter-28

Sunday, March 21, 2021 11:50 AM

## Deep Generative Models.

### Deep Directed Networks-

If all nodes are binary and all CPDs are logistic functions, this is called a sigmoid belief net.

$$p(h_1, h_2, h_3, v | \Theta) = \prod_i \text{Ber}(v_i | \text{sigm}(h_1^T w_{0i})) \prod_j \text{Ber}(h_j | \text{sigm}(h_2^T r_{1j})) \prod_k \text{Ber}(h_{2k} | \text{sigm}(h_3^T r_{2k})) \prod_l \text{Ber}(h_{3l} | w_{3l}).$$

Inference is intractable since the posterior on hidden nodes is correlated due to the explaining away.

### Deep Boltzmann Machines-

Construct a deep undirected model by stacking a series of RBMs on top of each other.

$$p(h_1, h_2, h_3, v | \Theta) = \frac{1}{Z(\Theta)} \exp \left( \underbrace{\sum_{ij} v_i h_{1j} w_{ij}}_{\text{visible-hidden interactions}} + \underbrace{\sum_{jk} h_{1j} h_{2j} w_{jk} + \sum_{kl} h_{2k} h_{3l} w_{kl}}_{\text{hidden-hidden interactions}} \right).$$

One can efficiently perform black Gibbs sampling since all nodes in each layer are conditionally independent of each other given the layers above and below.

### Deep Belief Networks-

"Partially directed and partially undirected"

$$p(h_1, h_2, h_3, v | \Theta) = \prod_i \text{Ber}(v_i | \text{sigm}(h_1^T r_{1i})) \prod_j \text{Ber}(h_{1j} | \text{sigm}(h_2^T r_{2j})) \frac{1}{Z(\Theta)} \exp \left( \sum_{kl} h_{2k} h_{3l} w_{kl} \right).$$

For a model of the form  $p(h_1, h_2, v | w)$ ,

$$p(h_1, v | w) = \sum_{h_2} p(h_2, h_1, v | w).$$

$$\Rightarrow p(h_1, v | w) = \frac{1}{Z(w)} \exp(v^T w / h_1).$$

This is equivalent to an RBM.

Thus, we can infer the posterior  $p(h_1 | v, w)$  in the DBN exactly as in the RBM.

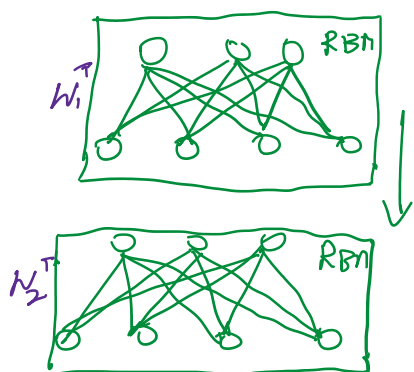
Now,  $p(h_1 | w)$  is the complementary prior.

$$\Rightarrow p(h_1, v | w) = p(v | h_1) p(h_1 | w)$$

The top-down inference in a DBN is not tractable, so DBNs are usually used in a feedforward manner.

### Greedy layer-wise learning of DBNs -

- 1) Fit an RBM to learn  $w_1$ .
- 2) Unroll the RBM into a DBN with 2 hidden layers.
- 3) Freeze  $w_1$  and let  $w_2$  be unrolled. Learn  $p(h_1 | w_2)$  by fitting a second RBM with inputs as activation of hidden units  $E[h_1 | v, w_1]$ .
- 4) Continue to add more layers.



Following greedy layer-wise training strategy, it is standard to "fine tune" the weights using a technique called backfitting.