

σ : ACT FUNC
 w_{ij} : weights
 $a_{e,i}$: hidden layer combination
 $o_{e,i} = \sigma(a_{e,i})$

Problem: $\{s, 1, 2, \dots, m\}$
 Claim: For any m there is a network of depth 2
 s.t. the hypothesis class contains all m -boolean functions



For every neuron h_i for which $f(w_i)$ is TRUE
 We add a neuron in the hidden layer that chain is $x \cdot w_i$
 i.e. the neuron implements the function $g(x) = \text{sign}(\sum w_i x_i)$

$$b(x) = \text{sign}\left(\sum_{i=1}^m w_i x_i\right) + 1$$

then $M = O(2^m)$

Theorem: For any m , let $\mathcal{H}(m)$ be the maximal
 hypothesis set \exists graph $G(E)$ with $|V| = m$ and
 whose hypothesis class contains all m -boolean
 functions $\Pi(m)$ is separable in m

Assumption: $VC(\mathcal{H}_{\text{sep}, m}) = O(|V|)$
 $VC \dim(\mathcal{H}_{\text{sep}, m}) = 2^m$
 $|V| \geq \Omega(2^{m/3})$
 $E, E' = \{1, \dots, m\}$

Theorem: For $T: N \rightarrow N, \forall m \in N$,
 F_m is the set of functions that can be
 implemented with a Turing Machine on
 above $O(m)$ steps, \exists graph G s.t.
 $\forall m$ there exists a graph $G(E)$
 with $|V| \leq O(m)$ and whose hypothesis
 class contains F_m

$$\Pi_{\mathcal{H}}^*(m) = \max_{C \subseteq \mathcal{H}, |C|=m} |H_C| \leq 2^m$$

Growth function
 the maximal number $|H_C|$ over all
 subsets C of size m $\Pi_{\mathcal{H}}(C) = |C|$
 Assumption: growth is $O(m)$
 Computation of hypothesis class is
 bounded by the product of the growth and
 nodes for each hypothesis class

Theorem: VC dimension of $\mathcal{H}_{\text{sep}, m}$ is $O(|E| \log |E|)$

$$H = \bigcap_{i=1}^m H_i = H_1 \cap H_2 \cap \dots \cap H_m$$

ACE TO ASSUMPTION

$$T_H(m) \leq \prod_{i=1}^m T_{H_i}(m) \leq \prod_{i=1}^m T_{H_i}(m)$$

VC dim of H_i space is d .

by Sauer's theorem

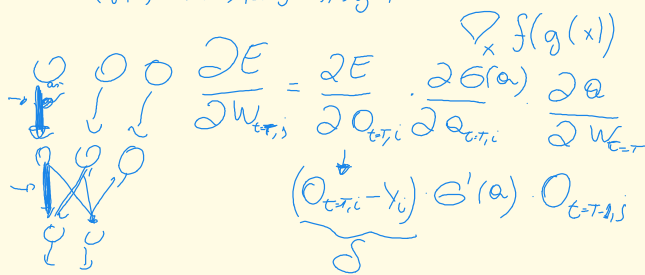
$$T_{H_i}(m) \leq \binom{em}{d_{e,i}} \leq (em)^{d_{e,i}}$$

$$T_H(m) \leq (em)^{\sum_{e,i} d_{e,i}} \leq em^{|\mathcal{E}|}$$

If there are m Shattered points then,

$$T_H(m) = 2^m \text{ and}$$

$$2^m \leq (em)^{|\mathcal{E}|} \Rightarrow m \geq |\mathcal{E}| \log(em) / \log(2)$$



$$\frac{\partial E}{\partial w_{t+1,j}} = \frac{\partial E}{\partial a_{t+1,i}} \cdot \frac{\partial a_{t+1,i}}{\partial w_{t+1,j}} = \frac{\partial E}{\partial a_{t+1,i}} \cdot \sigma'(a) \cdot o_{t-T+1,j}$$

$$\frac{\partial E}{\partial o_{t+1,i}} = \sum_{j=1}^{K_{t+1}} \frac{\partial E}{\partial a_j} \cdot \frac{\partial a_j}{\partial o_{t+1,i}} = \sum_{j=1}^{K_{t+1}} \delta_j \cdot \sigma'(a) \cdot w_{j,i}$$

