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What is the coeff. of x_k^2 in ①?

$$H(x_1, \dots, x_{2^n}) = n + \sum_{j=1}^{2^n} \sum_{i=1}^{\infty} a_{ij} x_j^i$$

Need: a_{2k}

$$\frac{\partial^2 H}{\partial x_k^2} = [2a_{2k} + \text{terms involving } x_k]$$

$$\frac{1}{2} \cdot \frac{\partial^2 H}{\partial x_k^2} \Big|_{x_k=0} = a_{2k}$$

$$H(x_1, \dots, x_m) \quad ; \quad \sum x_i \leq 1$$

$$u = \left(\frac{1}{m+1}, \dots, \frac{1}{m+1} \right)$$

← entropy of x , expanded around

$$d \|x\|_2^2 \leq \underbrace{\log(1)}_{H(u)} - \underbrace{H(x-u)}_{\leq c \cdot \|x\|_2^2} \leq c \cdot \|x\|_2^2$$

$\left(\frac{1}{2} \right)^c$

$$\begin{aligned} & 1 - \frac{(x-\frac{1}{2})^2}{\ln 2} \leq 1 - \frac{(x-\frac{1}{2})^2}{\ln 2} \\ & \geq 1 - H(x-\frac{1}{2}) \geq \frac{(x-\frac{1}{2})^2}{\ln 2} \end{aligned}$$

9/8/10

TAYLOR EXPANSIONS FOR $h(x)$:

$$h(x) = -x \log x - (1-x) \log(1-x)$$

$$\begin{aligned} & = 1 - \frac{2}{\ln 2} \left(x - \frac{1}{2}\right)^2 - \frac{4}{3 \ln 2} \left(x - \frac{1}{2}\right)^4 - \frac{32}{15 \ln 2} \left(x - \frac{1}{2}\right)^6 \\ & \quad + o\left(\left(x - \frac{1}{2}\right)^8\right) \end{aligned}$$

$$1-h(x) = \frac{2}{\ln 2} \left(x - \frac{1}{2}\right)^2 + \frac{4}{3 \ln 2} \left(x - \frac{1}{2}\right)^4 + \frac{32}{15 \ln 2} \left(x - \frac{1}{2}\right)^6 + o\left(\left(x - \frac{1}{2}\right)^8\right)$$

$$\geq \frac{2}{\ln 2} \left(x - \frac{1}{2}\right)^2$$

Claim $1-h(x) \leq c \left(x - \frac{1}{2}\right)^2$

$$\frac{\partial h(x)}{\partial x} = \cancel{-x} \left(\frac{1}{x}\right) - \log x \left(\frac{-1}{x^2}\right) - \cancel{\frac{(1-x)}{(1-x)}} \frac{1}{(1-x)} (-1)$$

$$- \log(1-x) \cdot (-1)$$

$$= \frac{\log x}{x^2} + \log(1-x)$$

$$\frac{\partial^2 h(x)}{\partial x^2} = \log x \frac{(-2)}{x^3} + \frac{1}{x^3} + \frac{1}{1-x} (-1)$$

$$= -\frac{2}{x^3} \log x + \frac{1}{x^3} - \frac{1}{1-x}$$

$$\frac{\partial^3 h(x)}{\partial x^3} = -\frac{2}{x^3} \frac{1}{x} - 2 \log x \frac{(-3)}{x^4} - \frac{3}{x^4} + \frac{1}{(1-x)^2}$$

22/09/10

THOUGHTS ON SPIN-GLASS WORKS :

- These works give us upper bounds on entropy / MI

$$I(x; Z) \leq \text{---}$$

which in-turn give us lower bounds on

$$P_n \{ I(x; Z) < n \text{Cap}(\epsilon) \} \geq \text{---} \begin{cases} \epsilon^0 \\ \epsilon^2 \end{cases}$$

Can we use these upper bounds to show the other side of our conjecture?



How sharp is the threshold obtained from these

24/09/10

GAUSSIAN WEIGHTS FOR HOPFIELD N/Ws :

$$w_{ij} = \frac{1}{N} \sum_{m=1}^P \xi_i^m \xi_j^m$$

P patterns
N neurons

If P is large, then $w_{ij} \rightarrow N(\mu, \sigma^2)$
Suppose that ξ_i^m and ξ_j^m are picked iid Bernoulli(1/2)
Then for $i \neq j$,

$$\mathbb{E}[w_{ij}] = \frac{1}{N} \sum_{m=1}^P \mathbb{E}[\xi_i^m] \mathbb{E}[\xi_j^m]$$

$$= \frac{P}{4N}$$

$$\mathbb{E}[w_{ij}^2] = \frac{1}{N^2} \sum_{m=1}^P \sum_{n=1}^P \mathbb{E}[\xi_i^m \xi_j^m \xi_i^n \xi_j^n]$$

$$= \frac{1}{N^2} \sum_{m=1}^P \mathbb{E}[(\xi_i^m)^2 (\xi_j^m)^2]$$

$$+ \frac{1}{N^2} \sum_{\substack{m, n=1 \\ m \neq n}}^P \mathbb{E}[\xi_i^m] \mathbb{E}[\xi_j^m] \mathbb{E}[\xi_i^n] \mathbb{E}[\xi_j^n]$$

$$\mathbb{E}[(\xi_i^m)^2] = \frac{1}{2}(0) + \frac{1}{2}(1)^2 = \frac{1}{2}$$

$$\mathbb{E}[w_{ij}^2] = \frac{P}{4N^2} + \frac{P}{16N^2} = \frac{5P}{16N^2}$$

Qn. Storing codewords instead of random patterns will increase correlation among weights (?). Will an inc in correlation increase the capacity of the hopfield

THOUGHT: Assume that the patterns stored are codewords:

corresponding to a (random?) linear code. WOLOG assume that all-zero pattern is fed as $1/P$. What is the condition for it to be stable?
 \rightarrow In order for us to be able to store 2^k patterns "reliably" through this linear coding scheme, what is the 'n' that is required?

Linear coding framework:

$$P = 2^k, \quad N = n$$

Let v_i^t denote the output of a neuron at the t iteration. Assume that

$$P_n \} v_i^t$$

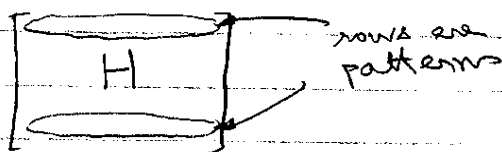
THINGS TO WORK ON:

- ① Can we compute $\mathbb{E}[w_{ij}]$ & $\mathbb{E}[w_{ij}^2]$ for families of linear codes, whose codewords are used as patterns. In order to do this, we need to compute the correlation between codeword bits of a linear code (asymptotically?)
One method: use a systematic code, so that first k codeword bits are uncorrelated among each other. Then t to bound correlation with other bits combinatorially.
- ② Assume $N(\mu, \sigma^2)$ for the weights. Since we memorize codewords of a linear code, the all (-1) vector is a pattern. Assume that the Hopfield N/W is fed with the all (-1) pattern, with d errors. Can we write down the density evolution equations, given this initial condition? Try to determine the rate of the code for convergence to the correct pattern. Can this Hopfield decoder correct d

all the way till dim of the code?

IMPACT OF CORRELATION ON CAPACITY

Assume we use a Hadamard matrix to obtain our patterns.

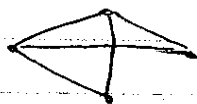


$$H \in \{+1, -1\}^n$$

Columns of H are orthogonal

$$\Rightarrow w_{ij} = 0 \quad \forall i \neq j$$

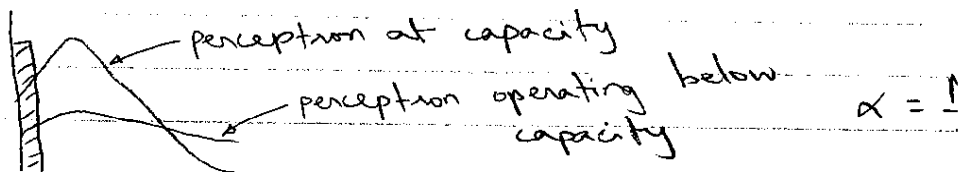
This tells us that if there are no correlations between pattern bits, recalling patterns is possible



would like some strong & weak connections for recalling patterns, not all strong

Evidence that correlation increases capacity:

By increasing correlation between \sum_i^m & \sum_j^m $E[w_{ij}]$ decreases, so does $\sigma^2[w_{ij}]$ (check th



This observation is consistent with results obtained in the perception literature (Optimal storage & synaptic weights - Brunel, ')

CONTOUR PLOTS IN MAPLE

To generate the contour plots, maple uses equal spacing on the z-axis (assume a 2-D fn. $f(x,y)$, wh values are plotted on the z-axis).

29/09/2010

TAYLOR SERIES FOR 3-D ENTROPY FUNCTION:

$$h(x,y) = -x \log_2 x - y \log_2 y - (1-x-y) \log_2 (1-x-y)$$

Need a bound

$$2 - h(x,y) \leq \underline{\hspace{2cm}}$$

From the Taylor series expansion of $2 - h(x,y)$, drop -ve terms to get a bound.

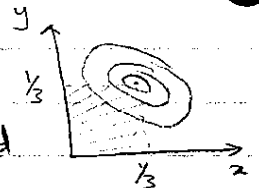
Assume first that both $x, y \leq \frac{1}{3}$

In this case, can drop all terms with odd degree from the Taylor series in

entropy - taylor - 2D. mw

Define $x' = x - \frac{1}{3}$, $y' = y - \frac{1}{3}$

$$3x'y' + 9x'^3y' + \frac{27}{2}x'^2y'^2 + 9x'y'^3 + \frac{243}{5}x'^5y' + \frac{243}{2}x'^4y'^2 + 162x'^3y'^3 + \frac{243}{2}x'^2y'^4 + \frac{243}{5}x'y'^5 + \dots$$



30/09/2010

HOPFIELD N/Ws - MATRIX UPDATES?

$$w_{ij} = \frac{1}{N} \sum_{m=1}^P \sum_i^m \sum_j^m, \quad \begin{matrix} i, j = 1, \dots, N \\ i \neq j \end{matrix}$$

Let $v_i^{(t)}$ denote the state of the neuron at time t .
Update rule:

$$v_i^{(t+1)} = f\left(\sum_{j=1}^N w_{ij} v_j^{(t)}\right) \quad (\text{Assume } w_i = w_j)$$

$$\begin{bmatrix} v_1^{(t+1)} \\ v_2^{(t+1)} \\ \vdots \\ v_N^{(t+1)} \end{bmatrix} = f\left(\begin{bmatrix} 0 & w_{12} & \dots & w_{1N} \\ w_{21} & 0 & & \\ \vdots & & \ddots & \\ w_{N1} & & & 0 \end{bmatrix} \begin{bmatrix} v_1^{(t)} \\ v_2^{(t)} \\ \vdots \\ v_N^{(t)} \end{bmatrix}\right)$$

Assume that $w_{ij} \sim N(\mu, \sigma^2)$. Further, WOLOG that $v_1^{(t)}, \dots, v_d^{(t)} = 1, v_{d+1}^{(t)}, v_{d+2}^{(t)}, \dots, v_N^{(t)} = -1$.

$$\begin{aligned} P_n \{v_i^{(t+1)} = 1\} &= P_n \left\{ \underbrace{w_{12} + w_{13} + \dots + w_{1d} - w_{1,d+1} - \dots - w_{1N}}_{\sim N(\mu(d-d), (N-1)\sigma^2)} > 0 \right\} \\ &= P_n \left\{ N(0, (N-1)\sigma^2) > \mu(N-d - (d-1)) \right\} \\ &= P_n \left\{ N(0, 1) > \frac{\mu(N-2d+1)}{\sqrt{N-1}\sigma} \right\} \\ &= Q\left(\frac{\mu(N-2d+1)}{\sqrt{N-1}\sigma}\right) \end{aligned}$$

{ Assume that $\mu(N+1-2d) > 0$

w_{ij} 's are correlated Gaussian RVs. Can we est the correlation between these RVs?

Patterns are codewords of a linear code (say LDGM with each col. d ones)

$$\begin{matrix} \cong A \\ \begin{bmatrix} 00\dots 0 \\ 00\dots 1 \\ \vdots \\ 11\dots 1 \end{bmatrix} \\ 2^k \times k \end{matrix} \quad G_{k \times n} = \begin{bmatrix} \xi_1 \\ \xi_2 \\ \vdots \\ \xi_{2^k} \end{bmatrix} \cong \Xi \\ 2^k \times n \end{matrix}$$

$$W = \frac{1}{N} (2\Xi - \mathbb{1})^T (2\Xi - \mathbb{1}), \quad \text{where } \mathbb{1} \rightarrow \text{all ones matrix } (2^k \times n \text{ in this case})$$

$$A^T A = \begin{bmatrix} 2^{k-1} & 2^{k-2} & \dots & 2^{k-2} \\ 2^{k-2} & 2^{k-1} & \dots & 2^{k-2} \\ \vdots & \vdots & \ddots & \vdots \\ 2^{k-2} & 2^{k-2} & \dots & 2^{k-1} \end{bmatrix} = 2^{k-2} \left\{ \frac{I}{k} + \begin{bmatrix} 1 & \dots & 1 \\ 1 & \dots & 1 \\ \vdots & & \vdots \\ 1 & \dots & 1 \end{bmatrix} \right\}_{k \times k}$$

↑
real ops.