





## QUADRATIC ENERGY

$$x = \{x_i\}_{i=1}^N, x_i \in \mathbb{R}$$

$$E(x) = \frac{1}{2} \sum_{(i,j)} K_{ij}(x_i - a_i)(x_j - a_j)$$

$K$  SYMMETRIC  $\Rightarrow$  DIAGONALISABLE  
 $K > 0$  (POS. SEMIDEF.)  $\Rightarrow$  ENERGY HAS A MINIMUM

$$\vec{z} = \int dx_1 \dots dx_N e^{-E(\vec{x})}$$

1. DIAGONALISE  $K$  WITH ORTHONORMAL BASIS

$$2. (\vec{x} - \vec{a}) = \sum_n \vec{y}_n \vec{U}_n \quad \text{NEW BASIS}$$

$$3. z = \int dy_1 \dots dy_N e^{-\frac{\beta}{2} \sum_{i=1}^N k_{ii} y_i^2} \cdot |\det J^{-1}| \quad (\text{BY ORTHONORM})$$

$$4. \text{ BY EXP, } P(\vec{y}_1 \dots \vec{y}_N) = \prod_{i=1}^N P(y_i) \quad \text{SUM BECOMES PRODUCT OF GAUSSIANS}$$

$$P(y_i) = \frac{e^{-\frac{1}{2} k_{ii} y_i^2}}{\sqrt{2\pi/\beta k_{ii}}} \quad \text{USING N EIGEN...}$$

$$5. Z = \prod_{n=1}^N \int_{-\infty}^{\infty} dy_n = \sqrt{\frac{2\pi}{\beta}}^N \frac{1}{\sqrt{\det(K)}} \quad U = -\frac{1}{\beta} \log(Z)$$

## DISCRETE TEACHER-STUDENT SETUP (ANNEALED APPROXIMATION)

$$\vec{w} \in \{\pm 1\}^N, \vec{t} \in \{\pm 1\}^N \quad \text{ONLY THE ANGLES MATTER, SO BETWEEN CUBE AND SPHERE IT'S THE SAME IF } N \gg 1.$$

$$E_{\text{TEST}} = \frac{1}{2} \int d\vec{w} \mathbb{1}(R) \prod_{i=1}^N \delta\left(\frac{\vec{w} \cdot \vec{t}}{\sqrt{N}}\right) \quad \alpha N = p$$

$$= \frac{1}{2} \left( \sum_{\{\pm 1\}^N} \prod_{i=1}^N \left( \frac{\vec{w} \cdot \vec{t}}{\sqrt{N}} = R \right) \right) \left[ 1 - \frac{1}{\pi} \arccos(R) \right]^{\alpha N}$$

$$\sum_{\{\pm 1\}^N} \mathbb{1}\left(\frac{1}{N} \sum_{i=1}^N w_i t_i = R\right) \rightarrow \text{THIS LOOKS LIKE } N(R), \quad w_i \mapsto w_i t_i = s_i \text{ AND } E(s_i) = \sum_i w_i$$

FOR A FIXED  $R$ , THE

$$\sum \mathbb{1} = 0 + \dots + 0 + 1 + 1 + 1 + 0 + \dots$$

$$= \# \text{ CONFIGURATIONS ST. } R = \text{ENERGY}$$

$$\rightarrow e^{Nf(R)} = e^N \left( \frac{1+R}{2} \log\left(\frac{1+R}{2}\right) - \frac{1-R}{2} \log\left(\frac{1-R}{2}\right) \right)$$

$$\bar{P}(R) = \frac{1}{Z} \exp \left[ N \left( f(R) + \log \left( 1 - \frac{1}{\pi} \arccos(R) \right) \right) \right]$$

AT SOME POINT THE MAX GOES  $S(R) > 0$  TO  $S(R') = 0$

$\exists \alpha^*$  THRESHOLD TO HAVE ENOUGH INFORMATION TO FULLY DETERMINE  $\vec{t}$



THE PHASE CHANGE CORRESPONDS TO A CHANGE IN HOW ENERGY IS DISTRIBUTED:

IN THE SOLID  $\leftrightarrow$  LIQUID TRANSITION, THE VALUES ARE THE SAME

$$F = U - TS = U_{\text{Liq}} - TS_{\text{Liq}}$$

(FREE ENERGY)

FIND THE ORDER OF  $X$  RV:  
 $\sigma(x)$

FIND THE SCALE OF  $f(x)$ :  $x = \frac{1}{k}$

(RELATION BETWEEN SPINS)

$$E(S) = -\mu B \sum_i S_i - \frac{J}{k} \sum_{(i,j) \in S} S_i S_j$$

AS  $J$  INCREASES CONNECTIONS BECOME MORE IMPORTANT IN DETERMINING ALIGNMENT (TRADEOFF)

$$\begin{cases} (B=0) P(S) = \frac{1}{2} e^{\mu BS} \\ \beta J \gg 1 \rightarrow \text{LOWEST } E \text{ TAKES OVER, ALL UP OR ALL DOWN (2X GROUND STATE)} \end{cases}$$

$$\beta J \ll 1 \rightarrow S_i \sim \text{Unif}(\{\pm 1\})$$

$$\langle M_i \rangle = \sum S_i q_i(S) = 0$$

$$V(\bar{M}) = \frac{1}{4N}$$

## I-SING MODEL

SOLID, DISCRETE LATTICE

$$S_i \in \{\pm 1\}$$

$$E(S) = -\mu B \sum_i S_i$$

$$P(S) = \frac{1}{Z} e^{\beta S} = \frac{1}{\prod_{i=1}^N \sum_{S_i} e^{BS_i}} = \prod_{i=1}^N P_i(S_i)$$

## ASSUMING INDEPENDENT SPINS

$$\begin{aligned} P(S) &= \frac{1}{Z} e^{\mu B \sum_i S_i} \\ &= \frac{1}{Z} \frac{e^{\mu B S}}{\prod_{i=1}^N 2 \cosh(\mu B)} \\ &= \frac{e^{\mu B E(S)}}{(2 \cosh(\mu B))^N} \end{aligned}$$

$$\begin{aligned} \langle M \rangle &= \sum S_i q_i(S) \\ &= \mu \tanh(\mu B) \end{aligned}$$

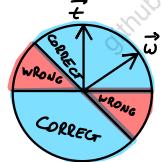
## TEACHER-STUDENT SETUP (PERCEPTRON LEARNING)

TEACHER:  $\vec{t}$  ST.  $y_{\text{TRUE}} := \text{SIGN}(\vec{t} \cdot \vec{s})$

DATABASE: SET OF DATA-LABEL TUPLES  $\{(\vec{s}^i, y_i)\}$

STUDENT:  $\vec{w}$  CHECKS FOR DIFFERENCE IN SIGN

$$E_{\text{TEST}}(\vec{w}) = \int d\vec{s} c(\vec{s}) \mathbb{1}\left(\frac{\vec{t} \cdot \vec{s} \cdot \vec{w}}{\|\vec{w}\|} < 0\right) \rightarrow E_{\text{TEST}} = \frac{1}{\pi} \arccos\left(\frac{\vec{t} \cdot \vec{w}}{\|\vec{t}\| \|\vec{w}\|}\right)$$



$$\text{ASSUME SOME BOLTZMANN DISTRIBUTION } P_D(\vec{w}) = \frac{1}{Z} e^{-\beta E(\vec{w}, \mathcal{D})}$$

$\beta \gg 1 \rightarrow w$  WITH LEAST ERROR

$\beta \approx 0 \rightarrow$  UNIFORM ON SPHERE WITH  $\|\vec{w}\|^2 = N$

$P = \alpha/N$  PATTERNS (#dim) AS YOU ADD MORE DATAPoints, YOU RESTRICT THE SPACE OF VALID  $w$  STUDENTS

SUPPOSE  $\beta = \infty$ ,  $P_D(\vec{w}) = \mathbb{1}(E(\vec{w}, \mathcal{D}) = 0)$

TAKE  $P_D(R) = \frac{\vec{w} \cdot \vec{t}}{N}$  NORMALISED COLLINEARITY

ANNEALED APPROXIMATION:  $\bar{P}(R) = \mathbb{E}_{\mathcal{D}}[P_D(R)]$   $\vartheta(x) = \begin{cases} 1 & x \geq 0 \\ 0 & \text{else} \end{cases}$

$$\bar{P}(R) = \mathbb{E}_{\mathcal{D}} \left[ \frac{1}{Z} \int d\vec{w} \mathbb{1}\left(\frac{\vec{w} \cdot \vec{t}}{N} = R\right) \prod_{i=1}^N \vartheta\left(\frac{\vec{w}_i \cdot \vec{t}_i}{\sqrt{N}}\right) \right]$$

$$\begin{aligned} (\text{BRING}) &= \frac{1}{Z} \int d\vec{w} \mathbb{1}\left(\frac{\vec{w} \cdot \vec{t}}{N} = R\right) \mathbb{E}_{\mathcal{D}} \left[ \prod_{i=1}^N \vartheta\left(\frac{\vec{w}_i \cdot \vec{t}_i}{\sqrt{N}}\right) \right] \quad \vec{w}_i \text{ ARE IID AND GAUSSIAN} \\ &= \left( \frac{1}{Z} \int d\vec{w} \mathbb{1}\left(\frac{\vec{w} \cdot \vec{t}}{N} = R\right) \right) \cdot \mathbb{E}_{\mathcal{D}} \left[ \prod_{i=1}^N \vartheta\left(\frac{\vec{w}_i \cdot \vec{t}_i}{\sqrt{N}}\right) \right] \\ \rightarrow \vec{u} &= \frac{\vec{w} \cdot \vec{t}}{\sqrt{N}} \quad \text{ARE GAUSSIAN} \rightarrow \langle u^2 \rangle = \frac{1}{N} \sum_{(i,j)} w_i w_j \vec{t}_i \cdot \vec{t}_j = \delta_{ij} \\ \rightarrow \vec{v} &= \frac{\vec{t}}{\sqrt{N}} \quad \langle u v \rangle = \frac{1}{N} \sum_{(i,j)} w_i t_j \vec{t}_i \cdot \vec{t}_j = \frac{1}{N} \sum_i w_i t_i = \frac{1}{N} \vec{w} \cdot \vec{t} = R \quad \text{SINCE MAGNITUDE IS NORMALISED TO BE ONE AND IN HIGH-DIM } a \cdot b \approx 0 \end{aligned}$$

$$\mathbb{E}(u, v) \sim \mathcal{N}(\mu=0, C=C) \quad (u, v) = \frac{1}{2\pi} \int dudv e^{-\frac{1}{2} \frac{1}{1-R^2} (u^2 + v^2 - 2uv)} = 1 - \frac{1}{\pi} \arccos(R)$$

$$\bar{P}(R) = \frac{1}{Z} \int_{S^{N-1}} d\vec{w} \mathbb{1}\left(\frac{\vec{w} \cdot \vec{t}}{N} = R\right) \left[ 1 - \frac{1}{\pi} \arccos(R) \right]^{\alpha N}$$

AKA CONE [VOLUME OF  $S^{N-1}$  WITH RADIUS  $\sqrt{N(1-R^2)}$ ]:  $\vec{w} = R \vec{t} + \vec{w}_{\perp}$ , USING  $\vec{w} \cdot \vec{t} = 0$

$$V_{\text{vol}} = \frac{(2\pi)^{N/2}}{\Gamma(N/2)} R^{N-1} \int_{\vec{w}_{\perp}}^{\sqrt{N(1-R^2)}} d\vec{w}_{\perp}$$

$$\|\vec{w}\|^2 = R^2 N + \|\vec{w}_{\perp}\|^2 = R^2 N$$

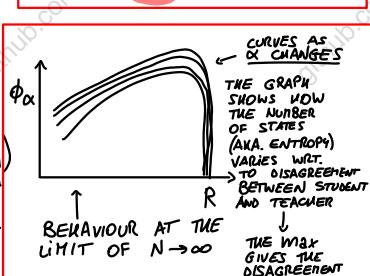
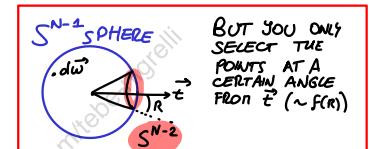
$$\|\vec{w}_{\perp}\|^2 = R^2 N + \|\vec{w}_{\perp}\|^2 = N$$

$$\|\vec{w}\| = \sqrt{N(1-R^2)}$$

$$\bar{P}(R) = \frac{1}{Z} \exp \left( N \left[ \frac{1}{2} \log(1-R^2) + \alpha \log \left( 1 - \frac{1}{\pi} \arccos(R) \right) \right] \right)$$

GIVING AS ENTROPY  $\Phi_{\alpha}(R)$  CONCENTRATES NEAR  $R^*$  WITH  $N$  POINTS, BOUNDING HOW GOOD YOU CAN GET

LARGE OUTLIERS DOMINATE AND  $E$ , SO THE CALCULATION IS WRONG



BUT YOU ONLY SELECT THE POINTS AT A CERTAIN ANGLE FROM  $\vec{t}$  ( $\sim f(R)$ )

DEPENDS ON  $\beta$ :

$$\beta < \beta_c : M_+ = M_- = 0$$

$$\beta = \beta_c : M_+ > 0$$

$$M_- = -M_+$$

$$\beta = \infty : M_+ = 1$$

$$M_- = -1$$

$$(B \approx \epsilon) \text{ SYMMETRY BREAK } \quad (\text{LIMITS ARE NOT COMMUTATIVE})$$

$$\lim_{N \rightarrow \infty} \lim_{B \rightarrow 0^{\pm}} \frac{1}{N} \sum_i \langle S_i \rangle = M_{\pm}$$

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(J=0) NO INTERACTION BETWEEN SPINS

$$(B=0, d=1) \text{ NO PHASE TRANSITION}$$

$$S_{n-1} S_n S_{n+1} \dots, z = \sum_s e^{\beta \sum_i S_i S_{i+1}} \quad * \text{ TOTAL ENERGY OF STATE}$$

$\{s\}$   $\rightarrow$  ALL POSSIBLE STATES

CHANGE VARIABLES:  $t_n = S_{n-1} \cdot S_n$   
 (ONLY COUNT CHANGES)

# DISCRETE ISING MODEL, $B=0$ , $d=1$

$$Z = \sum_{\{S_i\}} \prod_{i=1}^N e^{\beta \sum_{j=1}^N t_j S_i}$$

EXPLOIT THE SYMMETRY:  
FOR EACH  $S$  STATE  
THERE IS A  $-S$  STATE

$$= 2 \sum_{(t_1, \dots, t_N) \in \mathbb{Z}^N} \prod_{i=1}^N e^{\beta t_i}$$

$$= 2 \prod_{i=1}^N (e^\beta + e^{-\beta}) \quad | \quad \cosh(x) = \frac{e^x + e^{-x}}{2}$$

$$= 2 (2 \cosh(\beta))^N$$

$$U = -\frac{d \log(z)}{d\beta}$$

$$= -N \frac{d \log(2 \cosh(\beta))}{d\beta}$$

$$\frac{U}{N} = -\tanh\left(\frac{1}{\beta}\right)$$

$$\langle S_h S_{h+r} \rangle = ?$$

IN THE PRODUCT,  
 $\{S_i\} = S_1 \cdot t_2 \cdot t_3 \cdots t_n$   
 $\{S_{h+r}\} = S_1 \cdot t_2 \cdots t_n \cdots t_{n+r}$  WHETHER  $t_i$  OR  $t_{i+r}$  ARE  $\pm 1$

$$\langle S_h S_{h+r} \rangle = \langle t_{n+1} \cdots t_{n+r} \rangle \quad | \text{BY iid}$$

$$= \prod_{i=1}^r \langle t_{n+i} \rangle \quad | \quad \langle S_h S_{h+r} \rangle$$

$$= \langle t_n \rangle^r = \tanh(\beta)^r$$

$$\approx e^{-r \log(\tanh(\beta))} \approx e^{-r/\beta}$$

$$\langle S_h S_{h+r} \rangle = -\frac{U}{N} = \tanh(\beta)^r$$

$$U = \langle E(S) \rangle = -\sum_h \langle S_h S_{h+r} \rangle$$

$$= -N \langle S_h S_{h+r} \rangle \quad | \quad t_n = S_h S_{h+r}$$

$$\langle t_n \rangle = \frac{1}{2} P(1) - \frac{1}{2} P(-1) \quad | \quad P(t) = \frac{e^{\beta t}}{2 \cosh(\beta)}$$

$$= \tanh(\beta)$$

### 1 SYMMETRY BREAKING IN DEPTH

$(d=1) \rightarrow \text{NO: AT } \beta=0, \infty$ :  
 $P(S) = \frac{1}{2} \left( \prod_{i=1}^N S_{i,1} + \prod_{i=1}^N S_{i,-1} \right)$   
 $\sim (\text{up}(\{\text{all up}\}), \text{down}(\{\text{all down}\}))$

$(d \geq 2) \rightarrow \text{NO EXACT SOLUTION}$

USING MEAN FIELD THEORY (GENERAL STATEMENT)

$$E(S) = -\sum_{i,j} J_{ij} S_i S_j - \sum_i B_i S_i$$

$$P(S) = \frac{1}{Z} e^{-\beta E(S)} \quad | \text{APPROXIMATE WITH iid}$$

$$\downarrow$$

$$\min \Delta_{KL}(Q || P) = \sum_s Q(s) \log \frac{Q(s)}{P(s)}$$

$$= \sum_s Q(s) \log Q(s) - \sum_s Q(s) \log P(s)$$

REQUIRES PARALLELISING:  
 $\{Q(s)\} \rightarrow Q_j(s)$  A  
 $Q_j(s) = \frac{1+m_j}{2}$   
 $Q_j(-s) = \frac{1-m_j}{2}$

USE  $\theta = m$ :  
 $Q_j(s) = \frac{1+m_j}{2} S_j \quad \left\{ \langle S_j \rangle = m_j \right.$   
 $Q_j(-s) = \frac{1-m_j}{2} \quad \left. \langle S_j \rangle = m_j \right\}$

A)  $E_Q(\log Q(s)) = \sum_s Q(s) \log(Q(s))$

$$= \sum_{i,j} \frac{N}{(S_1 \cdots S_N)^i} \left( \frac{1+m_j S_j}{2} \right)^N \sum_j \log \left( \frac{1+m_j S_j}{2} \right) \quad | \quad E(\Sigma) = \sum(E)$$

$$= \sum_j \left[ \sum_i \frac{N}{(S_1 \cdots S_N)^i} \left( \frac{1+m_j S_j}{2} \right) \log \left( \frac{1+m_j S_j}{2} \right) \right] \quad | \quad \text{SWAP}$$

$$= \sum_j \left[ \sum_i \left( \frac{N}{i} \sum_{j=1}^2 \left( \frac{1+m_j S_j}{2} \right) \right) \log \left( \frac{1+m_j S_j}{2} \right) \right] \quad | \quad \text{FACTOR OUT THE TERM } i=j \text{ FROM THE PRODUCT}$$

$$= \sum_j \left[ \frac{(1+m_j S_j)}{2} \log \left( \frac{1+m_j S_j}{2} \right) + \frac{(1-m_j S_j)}{2} \log \left( \frac{1-m_j S_j}{2} \right) \right] \quad | \quad \left[ \sum_{i=1}^N \left( \frac{1+m_i S_i}{2} \right) \right] = 1 \quad | \quad \text{GIVES THE ENTROPY}$$

B)  $\sum_s Q(s) \log P(s) = E_Q(\log P(s))$

$$= E_Q[-\log(z) + \beta \sum_{i,j} J_{ij} S_i S_j + \beta \sum_i B_i S_i]$$

$$= -\log(z) + \beta \sum_{i,j} J_{ij} \langle S_i S_j \rangle_Q + \beta \sum_i B_i \langle S_i \rangle_Q \quad | \quad S_i, S_j \text{ ARE iid BY ASSUMPTION OF MEAN FIELD THEORY}$$

$$= -\log(z) + \beta \sum_{i,j} J_{ij} m_i m_j + \beta \sum_i B_i m_i$$

$$\Delta_{KL}(Q || P) = \sum_j \left[ \frac{1+m_j}{2} \log \left( \frac{1+m_j}{2} \right) + \frac{1-m_j}{2} \log \left( \frac{1-m_j}{2} \right) \right] - \beta \sum_{i,j} J_{ij} m_i m_j - \beta \sum_i B_i m_i + \log(z)$$

NOTE:  $Z$  IS CONST. WRT  $m_i$  SO IT IS IGNORED

$m_i$  APPEARS ONLY FOR ITS NEIGHBOURS

$$\frac{\partial \Delta_{KL}}{\partial m_i} = \frac{1}{2} \log \left( \frac{1+m_i}{1-m_i} \right) - \frac{1}{2} \log \left( \frac{1-m_i}{1+m_i} \right) - \beta \sum_{j \neq i} J_{ij} m_j - \beta B_i = 0 \quad | \quad \text{FOR MINIMISATION}$$

CHAIN RULE

$$\frac{\partial \Delta_{KL}}{\partial m_i} = \frac{1}{2} \log \left( \frac{1+m_i}{1-m_i} \right) = \beta \sum_{j \neq i} J_{ij} m_j + \beta B_i$$

$m_i = \tanh(\beta \sum_{j \neq i} J_{ij} m_j + \beta B_i)$

THIS IS A POLYNOMIAL NUMBER OF CONSTRAINTS, FROM EXPONENTIAL ORIGINALLY

USING WEISS APPROXIMATION ( $m := \langle S \rangle$ )

$$m = \tanh(\beta \sum_{j \neq i} J_{ij} m + \beta B)$$

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## CURIE-WEISS MODEL (ISING MODEL BUT $J, B$ ARE CONSTANT)

$$S_i \in \{\pm 1\}, |\{S_i\}| = 2^N$$

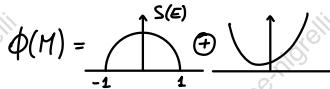
$\boxed{N \text{ SO } E \propto N}$

$$E(S) = -\frac{J}{N} \sum_{i,j} S_i S_j - B \sum_i S_i$$

ALL  $S_i$  INTERACT IN THE SAME WAY AND SYMMETRIC. DYNAMICS FROM THE BRAIN. MAGNETISATION IS ALSO GLOBAL.

$$\begin{aligned} z &= \sum_i e^{\frac{\beta J}{N} \sum_{i,j} S_i S_j + \beta B S_i} \\ \{S_i\} &\text{ USE } M(S) = \frac{1}{N} \sum_i S_i \\ \sum_i S_i S_j &= \frac{1}{2} \left( \sum_{i,j} S_i S_j - N \right) \\ &= \frac{1}{2} (\sum_i S_i)^2 - \frac{1}{2} N \\ &= \sum_i e^{\frac{\beta J N}{2} [M(S)]^2 + \beta B N M(S)} \quad \text{BBN} \\ &= \sum_{M(S)} \mathbb{1}(M(S)=M) e^{-\frac{\beta J N}{2} M^2 + \beta B N} \quad \text{CONSTANT SO IT SIMPLIFIES IN THE EXPRESSION} \\ &\rightarrow \text{COUNTS #S ST. } M(S)=M \quad \text{ENTROPY: } NS(M) \\ &= \sum_M e^{NS(M) - \frac{\beta J N}{2} M^2 + \beta B N} \quad \text{EXCHANGE SUM WITH INTEGRAL} \\ &= \int e^{N[S(M) - \frac{\beta J N}{2} M^2 + \beta B N]} dM \quad \text{LAPLACE METHOD} \\ &\approx e^{N\phi_{\max}} \sqrt{\frac{2\pi}{\beta J N}} \cdot \frac{1}{\sqrt{N}} \end{aligned}$$

$$(B=0) \quad \phi(M) = \phi(-M)$$



$$\phi''(M) = -1 + \beta J$$

$$\begin{cases} \beta < \beta_c = \frac{1}{J} \quad M=0 / \phi_{\max} \rightarrow \text{PARAN.} \\ \beta > \beta_c = \frac{1}{J} \quad \phi_{\max} = \pm M^*(\beta) \rightarrow \text{FERROM.} \end{cases}$$

$\hookrightarrow$  IP GETS CONCENTRATED ON  $S$  ST.  $\frac{1}{N} \sum_i S_i = M^*$  STABLE VARIABLE

## ALTERNATIVE FORMULATION

$$E(S) = -B \sum_i S_i - \frac{3}{N} \sum_{i,j} S_i S_j \quad \text{SINCE } E \text{ IS ADDITIVE, IP FACTORISES}$$

$$P(S) = \frac{e^{-BE(S)}}{Z} = \frac{e^{-B\sum_i S_i - \frac{3}{N} \sum_{i,j} S_i S_j}}{Z} = \frac{e^{-B\sum_i S_i - \frac{3}{N} (\frac{\sum_i S_i}{N})^2}}{Z} \quad \text{THE TERM SIMPLIFIES WITH } Z, \text{ COMPLETE THE SQUARE}$$

$$\left[ \frac{dx}{\sqrt{\frac{2\pi}{\beta J N}}} e^{-\frac{-2\beta S_i (\sum_i S_i)}{2} x^2} \right] = e^{\frac{\beta J (\sum_i S_i)^2}{2N}}$$

$$\left[ \frac{dx}{\sqrt{2\pi/\alpha}} e^{-\frac{\alpha}{2} x^2} \right] = e^{\frac{\alpha^2}{2\alpha}}$$

$$= \frac{1}{N} \sum_i \langle S_i \rangle$$

HENCE  $X$  IS A GLOBAL VARIABLE, GIVING MAGNETISATION

## HOW TO INTERPRET $X$ ?

USING THE MEAN:

$$\langle X \rangle = \int x P(x) dx$$

$$= \frac{1}{C} \int x \cdot e^{-\frac{\beta J N}{2} x^2 + \sum_i}$$

$$= \frac{1}{N} \sum_i \langle S_i \rangle$$

CONSIDER ADDING SOME  $x$  VAR:

$$P(S) = \frac{1}{Z} \int \frac{dx}{\sqrt{\frac{2\pi}{\beta J N}}} e^{-\frac{\beta J N}{2} x^2 + \beta (J+B) \sum_i S_i} \quad \begin{cases} \alpha = \beta J N \\ b = \beta J \sum_i S_i \\ \frac{\alpha^2}{2\alpha} = \frac{\beta J}{N} (\sum_i S_i)^2 \end{cases}$$

$$= \frac{1}{C} \left( \int \frac{dx}{\sqrt{\frac{2\pi}{\beta J N}}} e^{-\frac{\beta J N}{2} x^2} \right) e^{\beta J \sum_i S_i}$$

$x, s$  ARE INDEPENDENT, CONDITIONING ON  $x$   
 $P(x, s) = P(x)P(s)$

CURIE-WEISS IS THE TRUE MODEL YOU GET WHEN THE ISING APPROXIMATION WITH MFT BECOMES EXACT

$$\begin{aligned} z &= \int \frac{dx}{\sqrt{\frac{2\pi}{\beta J N}}} e^{-\frac{\beta J N}{2} x^2} \cdot \sum_{(S_1 \dots S_N)} e^{\beta (Jx+B) \sum_i S_i} \\ &= \sum_{(S_1 \dots S_N)} \prod_{i=1}^N e^{\beta (Jx+B) S_i} \\ &= \int \frac{dx}{\sqrt{\frac{2\pi}{\beta J N}}} e^{N(-\frac{\beta J N}{2} x^2 + \log(2 \cosh(Jx+B)))} \quad \phi(x) \text{ ENTROPY} \\ &= \int \frac{dx}{\sqrt{\frac{2\pi}{\beta J N}}} e^{N\phi(x)} \\ x^* &= \tanh(\beta(Jx^* + B)) \end{aligned}$$

## MARKOV SYSTEM

- $x \in \mathcal{E}$
- A STATE ALL STATES

THE SYSTEM EVOLVES:

$$P(X_{t+1} = b | X_t = a) = M_{ba}$$

$$P_{t+1}(a) = \sum_{b \in \mathcal{E}} M_{ab} P_t(b)$$

THE EVOLUTION IS WITHOUT MEMORY:  $P(a)$  DEPENDS ONLY ON  $(t-1)$  POSITION, NOT  $t$

### M TRANSITION MATRIX

$$\begin{aligned} \rightarrow M_{ab} &\geq 0 \quad (\forall a, b \in \mathcal{E}) \\ \rightarrow \sum_a M_{ab} &= 1 \quad (\forall b) \end{aligned}$$

$$M_{ab} = P(X_{t+k} = a | X_t = b)$$

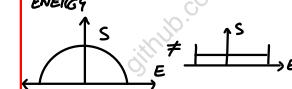
## PROBLEM OF SAMPLING

$$P(x) = \frac{1}{Z} e^{-\beta E(x)}$$

PRODUCE  $x \sim P(x)$  SO YOU CAN GET  $\langle O(x) \rangle \approx \frac{1}{P} \sum_p O(x^p)$  CURSE OF DIM  $\downarrow$  YOU NEED  $N$  ( $P$  SAMPLES) #EXPONENTIAL

YOU WANT AN INDICATIVE SAMPLE OF THE POPULATION WITHOUT EXPLORING A SIZEABLE PART OF ALL CONFIGURATIONS

DIRECT SAMPLING DOES NOT REFLECT THE DISTRIBUTION OF ENTROPY GIVEN BY ENERGY



## METROPOLIS-HASTINGS ALGORITHM

$$C_t = b$$

$$E = E(b)$$

PROPOSAL =  $a$  (SAMPLED WITH SOME DISTRIBUTION ST.  $P(a \rightarrow b) = P(b \rightarrow a)$ )

COMPUTE  $E(a)$

$$\text{IF } E(a) \leq E(b) \text{ OR WITH } P(\text{ACCEPT}) = e^{-\frac{(E(b)-E(a))}{T}}$$

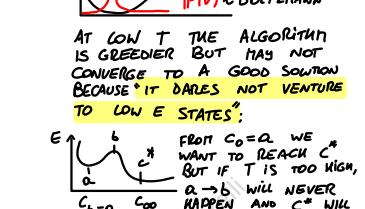
$C_{t+1} = a$  AS ITERATING, DECREASE T SLOWLY, TO ZERO. HIGHER T, ANY  $\Delta E$  IS ACCEPTED

LESS GREEDY

AT HIGH T THE ALGORITHM IS NOT GREEDY ENOUGH

AT LOW T THE ALGORITHM IS GREEDY BUT MAY NOT CONVERGE TO A GOOD SOLUTION BECAUSE IT DARES NOT VENTURE

TO LOW E STATES:



## ERGODICITY

$$\exists t > 0 \text{ st. } \forall t' > t, \forall a, c \in \mathcal{E} : (M^{t'})_{ac} > 0$$

FOR ALL TIME AFTER  $t$  SUFF. LARGE, YOU COULD BE TRANSITIONING BETWEEN ANY OF THE STATES

EG  $\mathcal{E} = \{\pm 1\}^N$   
RULE: DRAW  $j \in \{1 \dots N\}$  UNIFORMLY AND FLIP IT

NOT ERGODIC: SOME CONFIGURATIONS CAN ONLY BE REACHED AT  $t$  EVEN/ODD

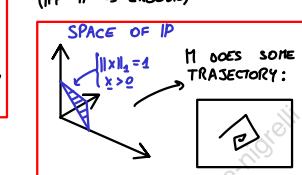
## STATIONARY DISTRIBUTION

$$M \text{ ERGODIC} \Rightarrow \exists! \pi \text{ st. } \pi M = \pi, \quad (\forall b \in \mathcal{E})$$

(FIXED STATE)  $\lim_{t \rightarrow \infty} (M^t)_b = \pi_b$  NO  $b$  DEPENDENCY

$\pi$  IS THE ONLY EIGENVECTOR OF  $M$  WITH  $\lambda = 1$ . ALL OTHER EIGENVALUES HAVE  $|\lambda| < 1$

A MATRIX CAN FIT AT MOST ONE ATTRACTOR (IFF IT IS ERGODIC)



$$\begin{aligned} M_{ab} &\neq 0 \quad \text{FROM } b \text{ TO } a \\ M_{ba} &\neq 0 \quad \text{FROM } a \text{ TO } b \\ \sum_b M_{ab} &= 1 \quad (\forall a) \\ \sum_a M_{ab} &= 1 \quad (\forall b) \end{aligned}$$

$$\boxed{\sum_a M_{ab} = 1}$$

## TOPICS

- HIGH-DIM. GEOMETRY → SPACE EXPANDS RAPIDLY  $N \dots$
- DETERMINISTIC CHAOS → ERROR  $\propto e$
- RANDOM WALKS
  - DISCRETE
  - CONTINUOUS
- MAXWELL DISTRIBUTION
- THERMODYNAMICS
  - THERMAL ENGINE
- MICROCANONICAL ENSEMBLE
- PARAMAGNETIC CRYSTAL
- TEMPERATURE / EQUILIBRIUM
- CANONICAL ENSEMBLE
- BOLTZMANN DISTRIBUTION
  - DISCRETE
  - \* → CONTINUOUS
- HEAT SPECIFICITY
- \* • MICRO/CAN EQUIVALENCE
- ADDITIVE ENERGY ( $N^3$  LATTICE)
- \* • EQUIPARITION THEOREM
  - IDEAL GAS
  - \* → EINSTEIN SPRING
- QUADRATIC ENERGY
- TEACHER/STUDENT PERCEPTION
- PHASE TRANSITIONS
- ISING MODEL (1D)
  - MEAN FIELD THEORY
  - ISING MODEL
  - CORRELATIONS
- \* • CURIE WEISS
- MARKOV PROCESS
- \* • METROPOLIS HASTINGS

## MATERIALS

- LECTURE NOTES
- VIDEOS
- STANFORD
- BOOK

### LIST OF DOUBTS

- PHASE TRANSITION (FREE ENERGY)
  - $\sum e^{\phi(n)} \approx N e^{\phi(n)}$
  - $\sum e^{\phi(n)} = \int dm e^{\phi(n)}$
  - $\sum e^{-\beta E(s)} \approx N e^{-\beta E(s)} ?$   
 $\{s\}$
- WHAT IS THE POINT OF THE X VAR CONDITIONING?

THERMAL EQUILIBRIUM →  $P(S)$  IS TIME INDEP.



$E_i + E_{\text{ENV}} = \text{CONST}$   
# PARTICLES = CONST  
IN  $E_i$