

Mean Field Asymptotics in Statistical Learning.

Jan 27 th.

Chapter 2
[MM08]

Lecture 3: A. Ising models.

B. Basic concepts in statistical decision theory.

A. Ising model.

① Curie-Weiss model.

Ferromagnets.

$$\Omega = \{+1, -1\}^n, \quad H_\lambda(\sigma) = -\frac{1}{2n} \sum_{\substack{1 \leq i, j \leq n \\ i \neq j}} \sigma_i \sigma_j + \lambda \sum_{i=1}^n \sigma_i$$

$$M(\sigma) = \frac{1}{n} \sum_{i=1}^n \sigma_i \quad P_{\beta, \lambda}(\sigma) \propto \exp\{-\beta H_\lambda(\sigma)\}$$

$$= -\frac{1}{2n} \left(\left(\sum_{i=1}^n \sigma_i \right)^2 - n \right) + \lambda \sum_{i=1}^n \sigma_i$$

Interested in $m_*(\beta, \lambda) = \lim_{n \rightarrow \infty} \langle M \rangle_{\beta, \lambda} / n$

Intuition:

High temp limit: $\beta \rightarrow 0, T \rightarrow \infty$.

$$P_{0, \lambda} = \text{Unif}(\{\pm 1\})$$

$$m_*(0, \lambda) = 0.$$

Low temp limit: $\beta \rightarrow \infty, T \rightarrow 0$

$$\lambda = 0$$

$$\arg \min H_0(\sigma) = \{\pm 1_n\}$$

$$P_{\infty, 0} = \frac{1}{2} \delta_{1_n} + \frac{1}{2} \delta_{-1_n}, \quad m_*(\infty, 0) = 0$$

$$\lambda = 0+$$

$$\arg \min H_\lambda(\sigma) = -1_n$$

$$P_{\infty, 0} = \delta_{-1_n}$$

$$\lim_{\lambda \rightarrow 0+} m_*(\infty, \lambda) = -1$$

$$\lambda = 0-$$

$$\arg \min H_\lambda(\sigma) = 1_n$$

$$P_{\infty, 0} = \delta_{1_n}$$

$$\lim_{\lambda \rightarrow 0-} m_*(\infty, \lambda) = 1.$$

Goal: $m_*(\beta, \lambda)$ phase transition at β_c

a) Calculate the $f(\beta, \lambda)$

b) Calculate $\partial_\lambda f(\beta, \lambda) = m_*(\beta, \lambda)$,

c) Plot some figure.

a). $Z_n(\beta, \lambda) = \sum_{\sigma \in \{\pm 1\}^n} \exp\{-\beta H_\lambda(\sigma)\}, \quad \phi(\beta, \lambda) = \lim_{n \rightarrow \infty} \frac{1}{n} \log Z_n(\beta, \lambda) \quad f(\beta, \lambda) = -\frac{1}{\beta} \phi(\beta, \lambda).$

$$\bar{m}(\sigma) = \frac{1}{n} \sum_{i=1}^n \sigma_i \quad \text{instantaneous magnetization}$$

$$H_\lambda(\sigma) = \frac{1}{2} n (1 - \bar{m}(\sigma)^2) + n \lambda \bar{m}(\sigma).$$

$$Z_n(\beta, \lambda) = \sum_{m \in \mathcal{M}_n} \sum_{\bar{m}(\sigma)=m} \exp\{-\beta H_\lambda(\sigma)\}$$

$$\mathcal{M}_n = \{-1, -\frac{n+2}{n}, \dots, \frac{n-2}{n}, 1\}.$$

$$= \sum_{m \in \mathcal{M}_n} \mathcal{N}_n(m) \cdot \exp\left\{-\beta \left(\frac{1}{2} n (1 - m^2) + n \lambda m\right)\right\}.$$

$$\mathcal{N}_n(m) = |\{\sigma : \bar{m}(\sigma) = m\}|$$

$$= \sum_{m \in \mathcal{M}_n} \exp\{n \phi_{mf}(m; \beta, \lambda)\}.$$

$$= \binom{n}{n \frac{1+m}{2}}$$

$$\phi_{mf}(m; \beta, \lambda) = -\frac{\beta}{2} (1 - m^2) - \beta \lambda m + \mathcal{H}\left(\frac{1+m}{2}\right)$$

$$\doteq \exp\{n \mathcal{H}\left(\frac{1+m}{2}\right)\}.$$

$$\phi(\beta, \lambda) = \lim_{n \rightarrow \infty} \frac{1}{n} \log \sum_{m \in \mathcal{M}_n} \exp(n \phi_{mf}(m; \beta, \lambda))$$

$$= \max_{m \in [-1, 1]} \phi_{mf}(m; \beta, \lambda)$$

$$\mathcal{H}(p) = -p \log p - (1-p) \log (1-p).$$

$$" \doteq " \quad a_n \doteq b_n$$

$$f(\beta, \lambda) = -\frac{1}{\beta} \phi(\beta, \lambda) = \min_{m \in [-1, 1]} \left[\frac{1}{2} (1 - m^2) + \lambda m - \frac{1}{\beta} \mathcal{H}\left(\frac{1+m}{2}\right) \right]$$

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log a_n = \lim_{n \rightarrow \infty} \frac{1}{n} \log b_n$$

b) $m_*(\beta, \lambda) = \partial_\lambda f(\beta, \lambda) = m_*(\beta, \lambda)$

$m_* = \arg \min$
 $m_* = \tanh(\beta m_* - \beta \lambda).$

Convex envelope thm
Implicit differentiation

$$f(\lambda) = \min_m f(m; \lambda)$$

$$m_* = \arg \min_m f(m; \lambda)$$

$$f'(\lambda) = \partial f(m; \lambda) |_{m=m_*}.$$

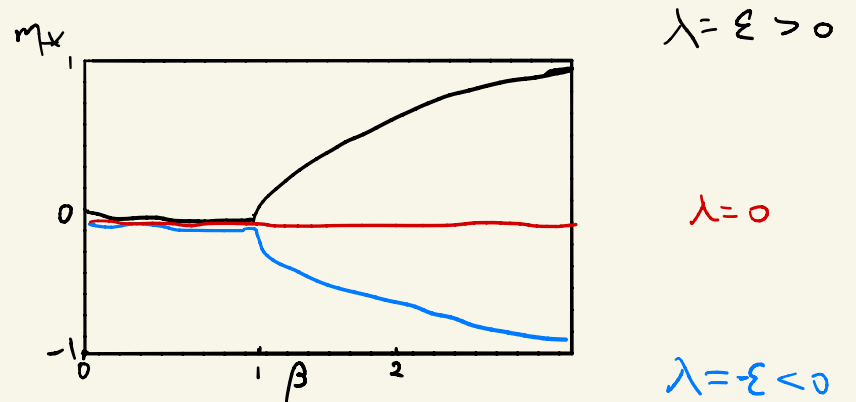
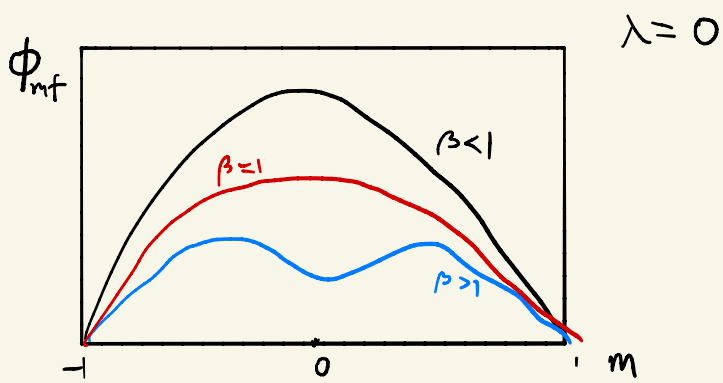
c).

$$\bar{m}(\sigma), \sigma \sim P_{3,0} \quad \mu_{\bar{m}} \approx \frac{1}{2} \delta_{m_+} + \frac{1}{2} \delta_{-m_+}$$

Property:

$$P_{\beta,0}(\sigma) = P_{\beta,0}(-\sigma) \quad \langle m \rangle_{\beta,0} = 0$$

$$m_{\pm}(\beta, \lambda) = \arg \max_m \phi_{mf}(m; \beta, \lambda) = \arg \max_m \left\{ -\frac{\beta}{2} (1-m^2) - \beta \lambda m + h\left(\frac{1+m}{2}\right) \right\}.$$



Phase transition at $\beta = 1$.

For $\beta < 1$. (High temperature)

$$\lim_{\lambda \rightarrow 0+} m_{\pm}(\beta, \lambda) = \lim_{\lambda \rightarrow 0-} m_{\pm}(\beta, \lambda) = 0. \quad \text{No residual magnetization.}$$

For $\beta > 1$ (Low temperature)

$$\lim_{\lambda \rightarrow 0+} m_{+}(\beta, \lambda) > 0 \quad \lim_{\lambda \rightarrow 0-} m_{-}(\beta, \lambda) < 0, \quad \text{Residual magnetization.}$$

Property of ferromagnet.

② Spin-glass model.

Sherrington-Kirkpatrick

$$\Omega = \{\pm 1\}^n$$

$$H_{\lambda}(\sigma) = - \sum_{i,j=1}^n J_{ij} \sigma_i \sigma_j - \frac{\lambda}{n} \sum_{i=1}^n \sigma_i \sigma_j$$

$$J_{ij} \stackrel{i.i.d.}{\sim} N(0, \frac{1}{n}), \quad i < j \quad J_{ii} \stackrel{i.i.d.}{\sim} N(0, \frac{2}{n}).$$

$$\text{Free entropy: } \Phi_n(\beta, \lambda) = \log \sum_{\sigma \in \{\pm 1\}^n} \exp \{-\beta H_{\lambda}(\sigma)\}.$$

$$\phi(\beta, \lambda) = \lim_{n \rightarrow \infty} \Phi_n(\beta, \lambda)/n$$

$$\phi(\beta, \lambda) = \inf_{q, b} \left[\phi_{mf}(q, b; \lambda, \beta) = \frac{1}{4} \beta^2 (1-q)^2 - \frac{1}{2} \beta \lambda b^2 + \mathbb{E}_{g \sim N(0,1)} [\log 2 \cosh(\beta \lambda b + \sqrt{q} g)] \right]$$

for some region of β and λ .

$\mathbb{Z}_2$ synchronization.

Statistical physics

Configuration space Ω

Reference measure ν_0

random
Hamiltonian

$H: \Omega \rightarrow \mathbb{R} \longleftrightarrow$

log-Likelihood function $\log l_{\theta}(Y)$

Gibbs - measure $\propto \exp \{-\beta H(\sigma)\} \nu_0(d\sigma)$

Bayes posterior
 $\propto l_{\theta}(Y) Q(d\sigma)$

Average configuration
under Gibbs measure $\begin{cases} \text{finite } \beta & \longleftrightarrow \text{Bayes estimator} \\ \beta = \infty & \longleftrightarrow \text{M-estimator (MLE)} \end{cases}$

Ensemble average
of an observable $\begin{pmatrix} \text{choose proper} \\ \text{observable} \end{pmatrix} \begin{cases} \text{finite } \beta & \longleftrightarrow \text{Risk of Bayes estimator} \\ \beta = \infty & \longleftrightarrow \text{Risk of M-estimator.} \end{cases}$

Free energy $-\frac{1}{\beta} \log \int \exp\{-\beta H(\sigma)\} \nu_0(d\sigma) \longleftrightarrow$ Mutual information
 $I(\text{observation}; \text{signal}).$

