

Lecture 12: The LASSO risk.

① The LASSO problem.

Signal: $x_0 \in \mathbb{R}^d$, Noise: $w \in \mathbb{R}^n$, Sensing matrix: $A \in \mathbb{R}^{n \times d}$.

Response: $y = Ax_0 + w \in \mathbb{R}^n$.

Assumption 1: $A_{ij} \sim \text{iid } N(0, \frac{1}{n})$, $w_i \sim \text{iid } N(0, \sigma^2)$, $\frac{1}{d} \sum_{j=1}^d \delta_{x_0, j} \rightarrow P_0$ (potentially sparse).

Goal: Observe y and A , estimate x_0 .

LASSO estimator:

$$\hat{x} = \underset{x}{\operatorname{argmin}} \frac{1}{2n} \|y - Ax\|_2^2 + \frac{\lambda}{n} \|x\|_1.$$

② Main result (to be shown using the replica method today).

Theorem: Consider the asymptotic regime $n/d \rightarrow s \in (0, \infty)$ as $d \rightarrow \infty$. Let (A, x_0, w, y) be a sequence of problem instances satisfy Assumption 1. Let \hat{x} be the LASSO estimator.

(A) We have \mathbb{E} is w.r.t. A, w .

$$\lim_{\substack{d, n \rightarrow \infty \\ n/d \rightarrow s}} \mathbb{E} \|\hat{x} - x_0\|_2^2 / d = \mathbb{E}_{(x_0, G) \sim P_0 \times N(0, 1)} [(\eta(x_0 + \tau_* G; \tau_* \alpha_*) - x_0)^2]$$

where $\eta(x; s) = \operatorname{sign}(x) \cdot (|x| - s)_+$ is the soft thresholding function. \leftarrow shrink to 0.

Here, we define a function $\tau(\alpha)$ to be the largest solution of

$$\tau^2 = \sigma^2 + \delta^{-1} \mathbb{E}_{(x_0, G) \sim P_0 \times N(0, 1)} \{ [\eta(x_0 + \tau G; \alpha \tau) - x_0]^2 \}.$$

and denote α_* by the unique non-negative solution of

$$\lambda = \alpha \cdot \tau(\alpha) \cdot \{ 1 - \delta^{-1} \mathbb{E} [\eta'(x_0 + \tau(\alpha) G; \alpha \cdot \tau(\alpha))] \}.$$

Self consistent equation.

Hereby we define $\tau_* = \tau(\alpha_*)$.

$$\begin{aligned} x_0 &\sim P_0, \\ Y &= x_0 + \tau_* G \\ \hat{x} &= \eta(Y; \alpha_* \tau_*) \end{aligned}$$

(B) Moreover, for any pseudo-Lipschitz function $\psi: \mathbb{R}^2 \rightarrow \mathbb{R}$, we have

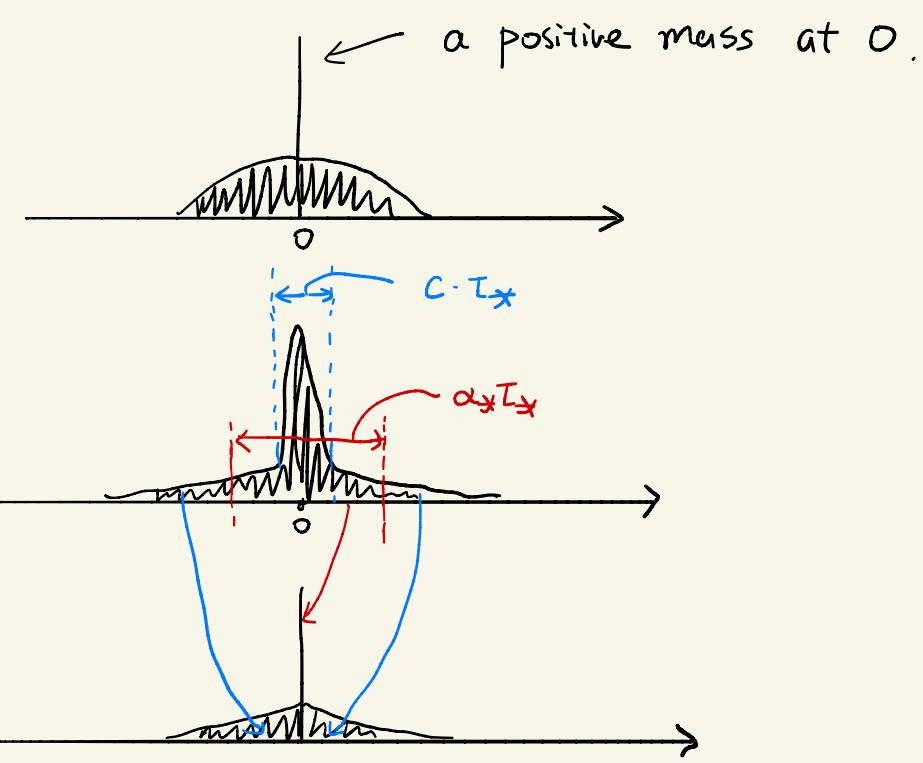
$$\lim_{\substack{d \rightarrow \infty \\ n/d \rightarrow s}} \mathbb{E} \left[\frac{1}{d} \sum_{j=1}^d \psi(\hat{x}_j, x_{0,j}) \right] = \mathbb{E}_{(x_0, G) \sim P_0 \times N(0, 1)} \left[\psi \left(\underbrace{\eta(x_0 + \tau_* G; \alpha_* \tau_*)}_{\text{The solution of a one dim problem}}, x_0 \right) \right].$$

Heuristic result: [Guo, Baron, Shamai, 2009], [Kabashima, Wadayama, Tanaka, 2009]

Rigorous proof: [Bayati, Montanari, 2010] \leftarrow AMP

Alternative proof: CGMT, leave-one-out.

X_0 distribution



Application: Want to estimate the support of X_0

$$S = \{j : X_{0,j} \neq 0\},$$

using the support of Lasso solution

$$\hat{S}(\lambda) = \{j : \hat{x}_{\lambda,j} \neq 0\}.$$

False discovery proportion:

$$FDP(\lambda) = \frac{|\{j : \hat{x}_{\lambda,j} \neq 0, X_{0,j} = 0\}|}{|\{j : \hat{x}_{\lambda,j} \neq 0\}|}$$

True positive proportion:

$$TPP(\lambda) = \frac{|\{j : \hat{x}_{\lambda,j} \neq 0, X_{0,j} \neq 0\}|}{|\{j : X_{0,j} \neq 0\}|}$$

Goal: choose a λ , s.t. $\underline{\mathbb{E}[FDP(\lambda)]} \leq \alpha$, $\underline{\mathbb{E}[TPP(\lambda)]}$ as large as possible.

Under the model assumption ($A_{ij} \stackrel{iid}{\sim} N(0, \frac{1}{n})$, $w_i \stackrel{iid}{\sim} N(0, \sigma^2)$)

$$\begin{aligned} \frac{1}{d} |\{j : \hat{x}_{\lambda,j} \neq 0, X_{0,j} = 0\}| &= \frac{1}{d} \sum_{j=1}^d \mathbb{1}\{\hat{x}_{\lambda,j} \neq 0, X_{0,j} = 0\} \\ &\rightarrow \mathbb{P}(X_0 = 0, \eta(X_0 + \tau_* G; \alpha\tau_*) \neq 0). \end{aligned}$$

$X_0 \sim P_0 \perp G \sim N(0, 1)$

$$\begin{aligned} \frac{1}{d} |\{j : \hat{x}_{\lambda,j} \neq 0\}| &= \frac{1}{d} \sum_{j=1}^d \mathbb{1}\{\hat{x}_{\lambda,j} \neq 0\} \\ &\rightarrow \mathbb{P}(\eta(X_0 + \tau_* G; \alpha\tau_*) \neq 0). \end{aligned}$$

$$\Rightarrow \lim_{d \rightarrow \infty} \mathbb{E}[FDP(\lambda)] = \frac{\mathbb{P}(X_0 = 0, \eta(X_0 + \tau_* G; \alpha\tau_*) \neq 0)}{\mathbb{P}(\eta(X_0 + \tau_* G; \alpha\tau_*) \neq 0)}.$$

Similarly for $TPP(\lambda)$.

This gives a "simple" expression for the power.

③ The free energy trick and the replica trick

The configuration space: $\Omega = \mathbb{R}^d$, ν_0 = Lebesgue measure

Hamiltonian : $H_{\lambda, h}(x) = \frac{1}{2} \|y - Ax\|_2^2 + \lambda \|x\|_1 + h \sum_{j=1}^d \psi(x_j, x_{0,j})$

Randomness : $y = \underline{A} x_0 + \underline{\omega}$ 2 source of randomness.

free entropy density: $\varphi(\beta, \lambda, h) \equiv \lim_{d \rightarrow \infty} \left[\frac{1}{d} \log \int_{\mathbb{R}^d} \exp \{-\beta H_{\lambda, h}(x)\} dx \right]$

Limiting ensemble average : The free energy trick.

$$\lim_{d \rightarrow \infty} \mathbb{E} \left[\frac{1}{d} \sum_{j=1}^d \psi(x_j, x_{0,j}) \right] = \partial_h \lim_{\beta \rightarrow \infty} \left[-\frac{1}{\beta} \varphi(\beta, \lambda, h) \right] \Big|_{h=0}$$

(A) The $d \rightarrow \infty$ limit.

$$S(k, \beta, \lambda, h) \equiv \lim_{d \rightarrow \infty} \frac{1}{d} \log \mathbb{E} \left[\left(\int_{\mathbb{R}^d} \exp \{-\beta H_{\lambda, h}(x)\} dx \right)^k \right].$$

(B) The $k \rightarrow 0$ limit.

$$\varphi(\beta, \lambda, h) = \lim_{k \rightarrow 0} \left[\frac{1}{k} S(k, \beta, \lambda, h) \right].$$

(C) The h differentiation and $\beta \rightarrow \infty$ limit

$$m_x(\lambda) = \left\{ \partial_h \lim_{\beta \rightarrow \infty} \left[-\frac{1}{\beta} \varphi(\beta, \lambda, h) \right] \right\} \Big|_{h=0}.$$

④ The calculation

(A) The $d \rightarrow \infty$ limit. ($n/d \rightarrow \delta$).

$$x^\circ = x_0 \in \mathbb{R}^d$$

$$\begin{aligned} \mathbb{E}[Z_n^k] &= \mathbb{E} \int_{\mathbb{R}^{dk}} \exp \left\{ -\beta \sum_{a=1}^k \|y - Ax^a\|_2^2 / 2 - \beta \lambda \sum_{a=1}^k \|x^a\|_1 - \beta h \sum_{j=1}^d \psi(x_j^a, x_j^\circ) \right\} \prod_{a=1}^k dx^a \\ &= \int_{\mathbb{R}^{dk}} \mathbb{E} \left[\exp \left\{ -\beta \sum_{a=1}^k \|y - Ax^a\|_2^2 / 2 \right\} \right] \\ &\quad \times \exp \left\{ -\beta \lambda \sum_{a=1}^k \|x^a\|_1 - \beta h \sum_{j=1}^d \psi(x_j^a, x_j^\circ) \right\} \prod_{a=1}^k dx^a \end{aligned}$$

w.r.t. A, ω

w.r.t. A, ω

$E(x)$

$$E(x) = \mathbb{E} \left[\exp \left\{ - \beta \sum_{a=1}^k \|y - Ax^a\|_2^2 / 2 \right\} \right]$$

$$= \mathbb{E} \left[\exp \left\{ - \beta \sum_{a=1}^k \|w - A(x^o - x^a)\|_2^2 / 2 \right\} \right]$$

$$= \mathbb{E} \left[\exp \left\{ - \beta k \|w\|_2^2 / 2 + \beta \langle w, \sum_{a=1}^k A(x^o - x^a) \rangle - \frac{\beta}{2} \sum_{a=1}^k \|A(x^o - x^a)\|_2^2 / 2 \right\} \right]$$

$$= \mathbb{E} \int_{\mathbb{R}^n} \frac{1}{(2\pi\sigma^2)^n} \exp \left\{ - \beta k \|w\|_2^2 / 2 - \frac{\|\varepsilon\|_2^2}{2\sigma^2} + \beta \langle \varepsilon, \sum_{a=1}^k A(x^o - x^a) \rangle \right\} d\varepsilon$$

w.r.t.
A
 ε is dummy for w

$$\times \exp \left\{ - \frac{\beta}{2} \sum_{a=1}^k \|A(x^o - x^a)\|_2^2 / 2 \right\}.$$

Gaussian integration

$$\bar{\sigma}^2 = \frac{\sigma^2}{1 + \beta k \sigma^2}.$$

$$= C_n \underbrace{\left(k \beta \sigma^2 + 1 \right)^{-\frac{n}{2}}}_{C_n} \times \mathbb{E} \left[\exp \left\{ \beta^2 \left\| \sum_{a=1}^k A(x^o - x^a) \right\|_2^2 \bar{\sigma}^2 / 2 - \frac{\beta}{2} \sum_{a=1}^k \|A(x^o - x^a)\|_2^2 / 2 \right\} \right].$$

Note $A = \begin{bmatrix} u_1^\top \\ \vdots \\ u_n^\top \end{bmatrix}$, $u_i \sim_{iid} N(0, \frac{1}{n} I_d) \Rightarrow \left\| A(x^o - x^a) \right\|_2^2 = \sum_{i=1}^n (u_i^\top (x^o - x^a))^2$

w.r.t. $u \sim N(0, \frac{1}{n} I_d)$ $= C_n \cdot \mathbb{E} \left[\exp \left\{ \beta^2 \left(\sum_{a=1}^k u^\top (x^o - x^a) \right)^2 \bar{\sigma}^2 / 2 - \frac{\beta}{2} \sum_{a=1}^k [u^\top (x^o - x^a)]^2 \right\} \right]^n$

Define $G_a = u^\top (x^o - x^a)$, Then $\mathbb{E}[G_a G_b] = (x^o - x^a)^\top (x^o - x^b) / n \equiv \Sigma_{ab}(x)$

$$\begin{aligned} &= C_n \cdot \left[\int \frac{1}{(2\pi)^{\frac{k}{2}} \det(\Sigma)^{\frac{1}{2}}} \exp \left\{ \beta^2 \left(\sum_{a=1}^k G_a \right)^2 \bar{\sigma}^2 / 2 - \frac{\beta}{2} \sum_{a=1}^k G_a^2 - \underbrace{G^\top \Sigma^{-1} G / 2}_{\text{density of } G} \right\} dG \right]^n \\ &= C_n \cdot \left[\det \left(\Sigma^{-1} + \beta I_k - \beta^2 \bar{\sigma}^2 I_k I_k^\top \right) \det(\Sigma) \right]^{-\frac{n}{2}} \\ &= (1 + k \beta \bar{\sigma}^2)^{-\frac{n}{2}} \left\{ \det \left[I_k + \sum (\beta I_k - \beta^2 \bar{\sigma}^2 I_k I_k^\top) \right] \right\}^{-\frac{n}{2}} \end{aligned}$$

Define $\bar{Q}(x) = (\langle x^a, x^b \rangle / d)_{a, b \in [k]}$.

$$\bar{\mu}(x) = (\langle x^a, x^o \rangle / d)_{a \in [k]}.$$

$$P = \|x^o\|_2^2 / d$$

$$\Rightarrow \Sigma(x) = \bar{Q}(x) - \bar{\mu}(x) I_k^\top + I_k \bar{\mu}(x)^\top + P I_k I_k^\top.$$

$$\Rightarrow E(x) = E(\bar{Q}(x), \bar{\mu}(x)). \quad \leftarrow \text{abuse notation}$$

$$\Rightarrow \mathbb{E}[Z_n^n] = \int_{\mathbb{R}^{d \times k}} \mathbb{E}(\bar{Q}(x), \bar{\mu}(x))$$

$$\times \exp \left\{ - \beta \lambda \sum_{a=1}^k \|x^a\|_1 - \beta h \sum_{j=1}^d 4(x_j^a, x_j^o) \right\} \prod_{a=1}^k dx^a$$

$$= \int dQ d\mu E(Q, \mu) \times \text{Ent}(Q, \mu)$$

$$S(k, \beta, \lambda, h) \doteq \sup_{Q, \mu} \left[\frac{1}{d} \log E(Q, \mu) \right] \times \left[\frac{1}{d} \log \text{Ent}(Q, \mu) \right].$$

$$\text{where } \text{Ent}(Q, \mu) = \int \delta(\bar{Q}(x) - Q) \delta(\bar{\mu}(x) - \mu) \times \exp\left\{-\beta \lambda \sum_{a=1}^k \|x^a\|_1 - \beta h \sum_{j=1}^d 4(x_j^a, x_j^o)\right\} \prod_{a=1}^k dx^a$$

$$\delta = n/d$$

$$\underbrace{\frac{1}{d} \log E(Q, \mu)}_{e(Q, \mu)} = -\frac{\delta}{2} \log(1 + k\beta\sigma^2) - \frac{\delta}{2} \log \det\left[I_k + (Q - \mu 1^T + 1 \mu^T + P 1 1^T)(\beta I_k - \beta^2 \bar{\epsilon}^2 1 1^T)\right].$$

$$\bar{\epsilon}^2 = \frac{\sigma^2}{1 + k\beta\bar{\epsilon}^2}$$

By delta identity formula + saddle point approx :

$$\text{Ent}(Q, \mu) = \underset{r_{ab}, \xi_a \in \mathbb{R}^{dk}}{\text{ext}} \int \exp\left\{-\sum_{ab} r_{ab} (d \cdot Q_{ab} - \langle x^a, x^b \rangle)/2 - \sum_a \xi_a (d \cdot \mu_a - \langle x^a, x^o \rangle) - \beta \lambda \sum_{a=1}^k \|x^a\|_1 - \beta h \sum_{j=1}^d 4(x_j^a, x_j^o)\right\} \prod_{a=1}^k dx^a$$

$$= \underset{r_{ab}, \xi_a}{\text{ext}} \left[\frac{d}{\prod_{j=1}^d} \left(\int_{\mathbb{R}^k} \exp\left\{-\sum_{ab} r_{ab} (Q_{ab} - x^a x^b)/2 - \sum_a \xi_a (\mu_a - x^a x^o) - \beta \lambda \sum_{a=1}^k |x^a| - \beta h 4(x^a, x^o)\right\} \prod_{a=1}^k dx^a \right) \right]$$

$$\text{Law of large numbers, uniform in } r_{ab}, \xi_a \quad \frac{1}{d} \log \text{Ent} = \underset{r}{\text{ext}} \frac{1}{d} \sum_{j=1}^d \log M(x_j^o, r) \rightarrow \underset{r}{\text{ext}} \mathbb{E}_{x^o \sim P_o} [\log M(x^o, r)].$$

$$\Rightarrow \frac{1}{d} \log \text{Ent} \rightarrow \underset{r_{ab}, \xi_a}{\text{ext}} \mathbb{E}_{x^o} \left[\log \int_{\mathbb{R}^k} \exp\left\{-\sum_{ab} r_{ab} (Q_{ab} - x^a x^b)/2 - \sum_a \xi_a (\mu_a - x^a x^o) - \beta \lambda \sum_{a=1}^k |x^a| - \beta h 4(x^a, x^o)\right\} \prod_{a=1}^k dx^a \right]$$

$$\Rightarrow S(k, \beta, \lambda, h) = \underset{\substack{Q, \mu \\ r, \xi}}{\text{ext}} [e(Q, \mu) + \text{ent}(Q, \mu, r, \xi)]. \quad \boxed{Q, r \in \mathbb{R}^{k \times k}, \mu, \xi \in \mathbb{R}^k}$$

where

$$e(\cdot) = -\frac{\delta}{2} \log(1 + k\beta\sigma^2) - \frac{\delta}{2} \log \det\left[I_k + (Q - \mu 1^T + 1 \mu^T + P 1 1^T)(\beta I_k - \beta^2 \bar{\epsilon}^2 1 1^T)\right].$$

$$\bar{\epsilon}^2 = \frac{\sigma^2}{1 + k\beta\bar{\epsilon}^2}$$

$$\text{ent}(\cdot) = \mathbb{E}_{x^o} \left[\log \int_{\mathbb{R}^k} \exp\left\{-\sum_{ab} r_{ab} (Q_{ab} - x^a x^b)/2 - \sum_a \xi_a (\mu_a - x^a x^o) - \beta \lambda \sum_{a=1}^k |x^a| - \beta h 4(x^a, x^o)\right\} \prod_{a=1}^k dx^a \right]$$

(B) The $k \rightarrow 0$ limit.

Replica symmetric ansatz.

$$Q = \begin{bmatrix} q_1 & & & \\ & \ddots & & q_0 \\ & & \ddots & \\ q_0 & & & \ddots & q_1 \end{bmatrix}, \quad r = \begin{bmatrix} r_1 & & & & r_o \\ & \ddots & & & \\ & & \ddots & & \\ r_o & & & \ddots & \\ & & & & r_1 \end{bmatrix}, \quad \mu = \begin{bmatrix} \mu \\ \vdots \\ \mu \end{bmatrix}, \quad \xi = \begin{bmatrix} \xi \\ \vdots \\ \xi \end{bmatrix}.$$

Consider that later we'll take $\beta \rightarrow \infty$.

do reparametrization here:

will be clear later.

$$q_0 = q, \quad q_1 = q + \frac{w}{\beta}, \quad r_0 = \beta^2 \rho, \quad r_1 = \beta^2 \rho - \beta v$$

$$\mu = \mu, \quad \xi = \beta \zeta$$

$$\Rightarrow \lim_{k \rightarrow \infty} \frac{1}{k} e = -\frac{\delta}{2} \log(1 + \frac{w}{\delta}) - \frac{\beta \delta}{2(\delta + w)} (\rho - 2\mu + q + \delta \sigma^2) \equiv \bar{e}$$

Need to use $\log \det(aI_k + b11^\top) = (k-1)\log b + \log(a+kb)$

$$\text{and ent} = -[\beta^2 k^2 \rho q - \beta k v q + \beta k \rho w - k v w]/2 - k \beta \mu \zeta$$

$$+ \mathbb{E}_{x^0} \left[\log \int_{\mathbb{R}^k} \exp \left\{ \underbrace{\frac{\beta^2 \rho}{2} \cdot \left(\sum_{a=1}^k x^a \right)^2}_{- \beta \lambda \sum_{a=1}^k |x_a| - \beta h_4(x^a, x^0)} - \frac{\beta v}{2} \sum_{a=1}^k (x^a)^2 + \beta \zeta \sum_{a=1}^k x^a x^0 \right\} \frac{1}{k!} dx^a \right]$$

use $\mathbb{E}[e^{\lambda(\sum_{a=1}^k x^a) G}] = \exp \left\{ \frac{\lambda^2}{2} \left(\sum_{a=1}^k x^a \right)^2 \right\}$.

$$= -[\beta^2 k^2 \rho q - \beta k v q + \beta k \rho w - k v w]/2 - k \beta \mu \zeta$$

$$+ \mathbb{E}_{x^0} \left\{ \log \mathbb{E}_G \left[\int_{\mathbb{R}^k} \exp \left\{ \underbrace{\beta \sqrt{\rho} \cdot \sum_{a=1}^k x^a G}_{- \beta \lambda \sum_{a=1}^k |x_a| - \beta h_4(x^a, x^0)} - \frac{\beta v}{2} \sum_{a=1}^k (x^a)^2/2 + \beta \zeta \sum_{a=1}^k x^a x^0 \right\} \frac{1}{k!} dx^a \right] \right\}$$

$$= -[\beta^2 k^2 \rho q - \beta k v q + \beta k \rho w - k v w]/2 - k \beta \mu \zeta$$

$$+ \mathbb{E}_{x^0} \log \mathbb{E}_G \left[\left(\int_{\mathbb{R}} \exp \left\{ \beta \sqrt{\rho} \cdot x \cdot G - \frac{\beta v}{2} \cdot x^2 + \beta \zeta \cdot x \cdot x^0 - \beta \lambda |x| - \beta h_4(x, x^0) \right\} dx \right)^k \right]$$

$$\Rightarrow \lim_{k \rightarrow \infty} \frac{1}{k} \text{ent} = -[-\beta X q + \beta \rho w - v w]/2 - \beta \mu \zeta$$

$$+ \mathbb{E}_{G, x^0} \left[\log \int_{\mathbb{R}} \exp \left\{ \beta \sqrt{\rho} \cdot x \cdot G - \frac{\beta v}{2} \cdot x^2 + \beta \zeta \cdot x \cdot x^0 - \beta \lambda |x| - \beta h_4(x, x^0) \right\} dx \right]$$

$$\varphi(\beta, \lambda, h) = \underset{\substack{q, w, \mu \\ \rho, v, \zeta}}{\text{ext}} \quad [\bar{e} + \bar{ext}]$$

ent

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$$(C) \quad f(\lambda, h) = \lim_{\beta \rightarrow \infty} -\frac{1}{\beta} \varphi(\beta, \lambda, h)$$

$$= \underset{\substack{q, w, \mu \\ p, v, \zeta}}{\text{ext}} \left\{ \lim_{\beta \rightarrow \infty} \left[-\frac{1}{\beta} \bar{e} \right] + \lim_{\beta \rightarrow \infty} \left[-\frac{1}{\beta} \bar{\text{ext}} \right] \right\}.$$

$$\lim_{\beta \rightarrow \infty} \left[-\frac{1}{\beta} \bar{e} \right] = \frac{\delta}{2(\delta+w)} (p - 2\mu + q + \delta \sigma^2)$$

$$\lim_{\beta \rightarrow \infty} \left[-\frac{1}{\beta} \bar{\text{ext}} \right] = (-v q + p w) / 2 + \mu \zeta$$

$$\lim_{\beta \rightarrow \infty} \frac{1}{\beta} \log \int \exp \{ \beta U(x) \} dx = \max_x U(x)$$

$$- \mathbb{E}_{G, X^0} \left\{ \max_x \left[\sqrt{p} \cdot x \cdot G - \frac{v}{2} \cdot x^2 + \zeta \cdot x \cdot x^0 - \lambda |x| - h_4(x, x^0) \right] \right\}$$

$$\Rightarrow f(\lambda, h) = \underset{q, w, \mu, p, v, \zeta}{\text{ext}} f_{mf}(\lambda, h; q, w, \mu, p, v, \zeta).$$

$$f_{mf}(\lambda, h; q, w, \mu, p, v, \zeta) = \frac{\delta}{2(\delta+w)} (p - 2\mu + q + \delta \sigma^2) + (-v q + p w) / 2 + \mu \zeta$$

$$- \mathbb{E}_{G, X^0} \left\{ \max_x \left[\sqrt{p} \cdot x \cdot G - \frac{v}{2} \cdot x^2 + \zeta \cdot x \cdot x^0 - \lambda |x| - h_4(x, x^0) \right] \right\}$$

$$\frac{\partial f_{mf}}{\partial q} = \frac{\delta}{2(\delta+w)} - \frac{v}{2} = 0, \quad \frac{\partial f_{mf}}{\partial \mu} = -\frac{\delta}{\delta+w} + \zeta = 0$$

$$\Rightarrow v = \zeta = \frac{\delta}{\delta+w}$$

$$\Rightarrow f(\lambda, h) = \underset{p, v}{\text{ext}} f_{mf}(\lambda, h; p, v)$$

$$f_{mf}(\lambda, h; p, v) = \frac{v}{2} (p + \delta \sigma^2) + \frac{p\delta}{2} \left(\frac{1}{v} - 1 \right)$$

$$- \mathbb{E}_{G, X^0} \left\{ \max_x \left[\sqrt{p} \cdot x \cdot G - \frac{v}{2} \cdot x^2 + v \cdot x \cdot x^0 - \lambda |x| - h_4(x, x^0) \right] \right\}$$

$$\partial f(\lambda, h)|_{h=0} = \partial_h f_{mf}(\lambda, h; p, v)|_{h=0} = \mathbb{E}_{G, X^0} [4(\hat{x}, x^0)]$$

$$\hat{x} = \arg \max_x \left[-\frac{v}{2} x^2 + x(v x_0 + \sqrt{p} G) - \lambda |x| \right]$$

$$= \arg \min_x \left[\frac{1}{2} (x - (x_0 + \frac{\sqrt{p}}{v} G))^2 + \frac{\lambda}{v} |x| \right]$$

$$= \eta(x_0 + \frac{\sqrt{p}}{v} G; \frac{\lambda}{v}). \quad \begin{matrix} \text{soft-thresholding function} \\ \text{c.f. Theorem.} \end{matrix}$$

where v, p is s.t. $f_{mf}(\lambda, 0; p, v)$ is stationary.

$$\begin{aligned}\partial_\rho f_{mf} &= \frac{\delta}{2} \left(\frac{1}{\nu} - 1 \right) - \frac{1}{2\sqrt{\rho}} \mathbb{E} \left[\hat{x} G \right] \xrightarrow{\text{integration by part.}} \eta(x_0 + \frac{\sqrt{\rho}}{\nu} G; \frac{\lambda}{\nu}) \\ &= \frac{\delta}{2} \left(\frac{1}{\nu} - 1 \right) - \frac{1}{2\nu} \mathbb{E} \left[\partial \eta(x_0 + \frac{\sqrt{\rho}}{\nu} G; \frac{\lambda}{\nu}) \right] = 0\end{aligned}$$

$$\begin{aligned}\partial_\nu f_{mf} &= \frac{1}{2} (\rho + \delta \sigma^2) - \frac{\rho \delta}{2\nu^2} + \mathbb{E} \left[\frac{\hat{x}^2}{2} - x_0 \hat{x} \right] \\ &= \frac{1}{2} \mathbb{E} [(\hat{x} - x_0)^2] + \frac{1}{2} \sigma^2 - \frac{\rho}{2\nu^2} = 0.\end{aligned}$$

$$\Rightarrow \begin{cases} \frac{\rho}{\nu^2} = \sigma^2 + \delta^{-1} \mathbb{E} [(\eta(x_0 + \frac{\sqrt{\rho}}{\nu} G; \frac{\lambda}{\nu}) - x_0)^2] \\ \nu = 1 - \delta^{-1} \mathbb{E} [\partial \eta(x_0 + \frac{\sqrt{\rho}}{\nu} G; \frac{\lambda}{\nu}) - x_0] \end{cases} \quad \begin{cases} \frac{\rho}{\nu^2} = \tau^2 \\ \nu = \frac{\lambda}{\alpha \tau} \end{cases}$$

This recovers the self consistent equation of the theorem.