

# Limit Theorems of estimators in the Tensor Curie Weiss Potts Model

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(joint work with S. Mukherjee<sup>2</sup>)

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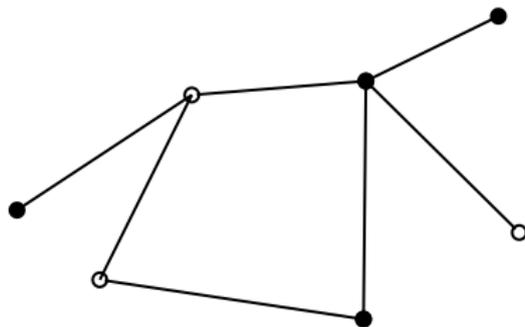
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Thank you Nishant, Siva, and Mathew for the opportunity to present at the Bangalore Probability Seminar.

- 1 Introduction
- 2 Goal
- 3 Asymptotics of Magnetization vector
- 4 Asymptotics of the Maximum Likelihood Estimates

# Spin Glass Model



**Figure:** Magnetic Spins in a graph with black vertices denoting  $-1$  and white vertices denoting  $+1$

$\sigma \in \{-1, 1\}^n$  denotes the magnetic spin vector in the graph.

$$\mathbb{P}(\sigma) \propto \exp\left(\beta \sum_{j=1}^n J_{ij} \sigma_i \sigma_j\right)$$

where  $J$ : interaction matrix,  $\beta > 0$ : inverse temperature.

# Potts Model

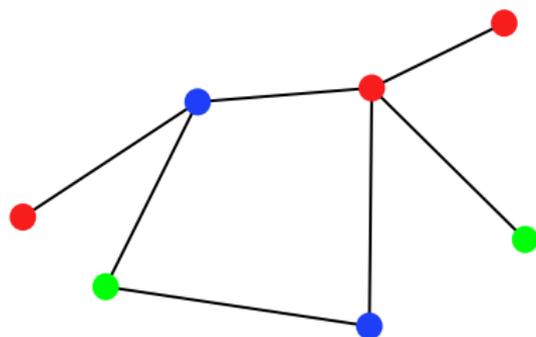


Figure: Coloring with 3 colors in a graph(may not be proper)

$X \in [q]^N$  denotes the coloring in the graph.

$$\mathbb{P}(X) \propto \exp \left( \beta \sum_{j=1}^n J_{ij} \mathbb{1}_{X_i=X_j} \right)$$

# Tensor Potts Model

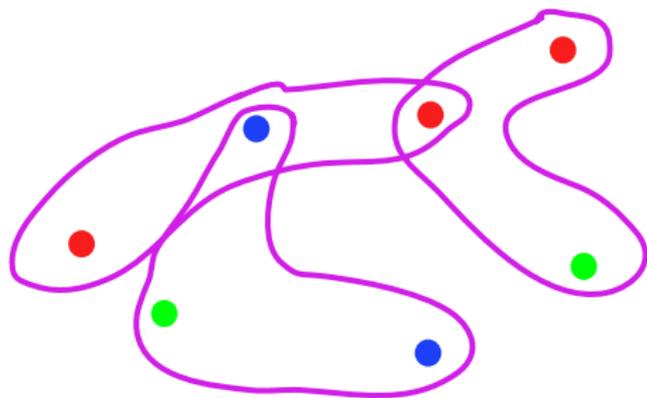


Figure: Introducing peer group interactions

$X \in [q]^n$  denotes the coloring in the hypergraph.

$$\mathbb{P}(X) \propto \exp \left( \beta \sum_{i_1, \dots, i_p} J_{i_1, \dots, i_p} \mathbb{1}_{X_{i_1} = \dots = X_{i_p}} + h \sum_{i=1}^N \mathbb{1}_{X_i=1} \right)$$

where,  $h \geq 0$ : magnetic field.

- Consider the Curie-Weiss setting where  $J_{i_1, \dots, i_p} = \frac{1}{N^{p-1}}$ .

# Set Up

- Consider the Curie-Weiss setting where  $J_{i_1, \dots, i_p} = \frac{1}{N^{p-1}}$ .
- This is an exponential family with parameters  $(\beta, h) \in (0, \infty) \times [0, \infty)$ .

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- Define  $\bar{X}_r = \frac{1}{N} \sum_{i=1}^N \mathbb{1}_{X_i=r}$  then,

$$\mathbb{P}_{\beta, h, N}(\mathbf{X}) := \frac{1}{q^N Z_N(\beta, h)} \exp \left( \beta N \sum_{r=1}^q \bar{X}_r^p + Nh \bar{X}_{\cdot 1} \right) \quad (1.1)$$

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- Magnetization Vector,  $\bar{\mathbf{X}}_N := (\bar{X}_r)_{r=1}^q$

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- Asymptotics of the maximum likelihood (ML) estimates of the parameters  $\beta$  and  $h$ .
- Asymptotics of the magnetization vector ( $\bar{\mathbf{X}}_N$ ).

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# Large Deviation of $\bar{\mathbf{X}}_N$

$\bar{\mathbf{X}}_N$  concentrates around global maximizers of  $H_{\beta,h}$ :

$$H_{\beta,h}(\mathbf{t}) := \beta \sum_{r=1}^q t_r^p + ht_1 - \sum_{r=1}^q t_r \log t_r$$

Theorem (B., Mukherjee (2023))

Let  $\beta_N \rightarrow \beta$  and  $h_N \rightarrow h$ . Then, under  $\mathbb{P}_{\beta_N, h_N, N}$ , the empirical magnetization  $\bar{\mathbf{X}}_N$  satisfies a large deviation principle with speed  $N$  and rate function  $-H_{\beta,h} + \sup H_{\beta,h}$ .

# Partitioning the Parameter Space

- 1 **Regular**: if the function  $H_{\beta,h}$  has a unique global maximizer  $\mathbf{m}_*$  and the  $\mathbf{Q}_{\mathbf{m}_*,\beta} = \text{Hess}(H_{\beta,h})$  is negative definite at  $\mathbf{m}_*$  on  $\mathcal{H}_q := \{\mathbf{t} \in \mathbb{R}^q : \sum_{r=1}^q t_r = 0\}$ .

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- 2 **Critical**: if  $H_{\beta,h}$  has more than one global maximizer.
- 3 **Special**: if  $H_{\beta,h}$  has a unique global maximizer  $\mathbf{m}_*$  and  $\mathbf{Q}_{\mathbf{m}_*,\beta}$  is singular on  $\mathcal{H}_q$ .

# Form of the maximizers

## Lemma

The maximizers  $\mathbf{m}$  are of the form  $\left(\frac{1+(q-1)s}{q}, \frac{1-s}{q}, \dots, \frac{1-s}{q}\right)$

$$f_{\beta,h}(s) := (q-1)k\left(\frac{1-s}{q}\right) + k\left(\frac{1+(q-1)s}{q}\right) + \left(\frac{1+(q-1)s}{q}\right) \cdot h,$$

where  $k(x) = k_{\beta,p}(x) := \beta x^p - x \log x$ .

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Special:

- i. **type-I**, if  $f_{\beta,h}^{(4)}(s) < 0$ .
- ii. **type-II**, if  $f_{\beta,h}^{(4)}(s) = 0$  (**Not observed in Ising Model**)

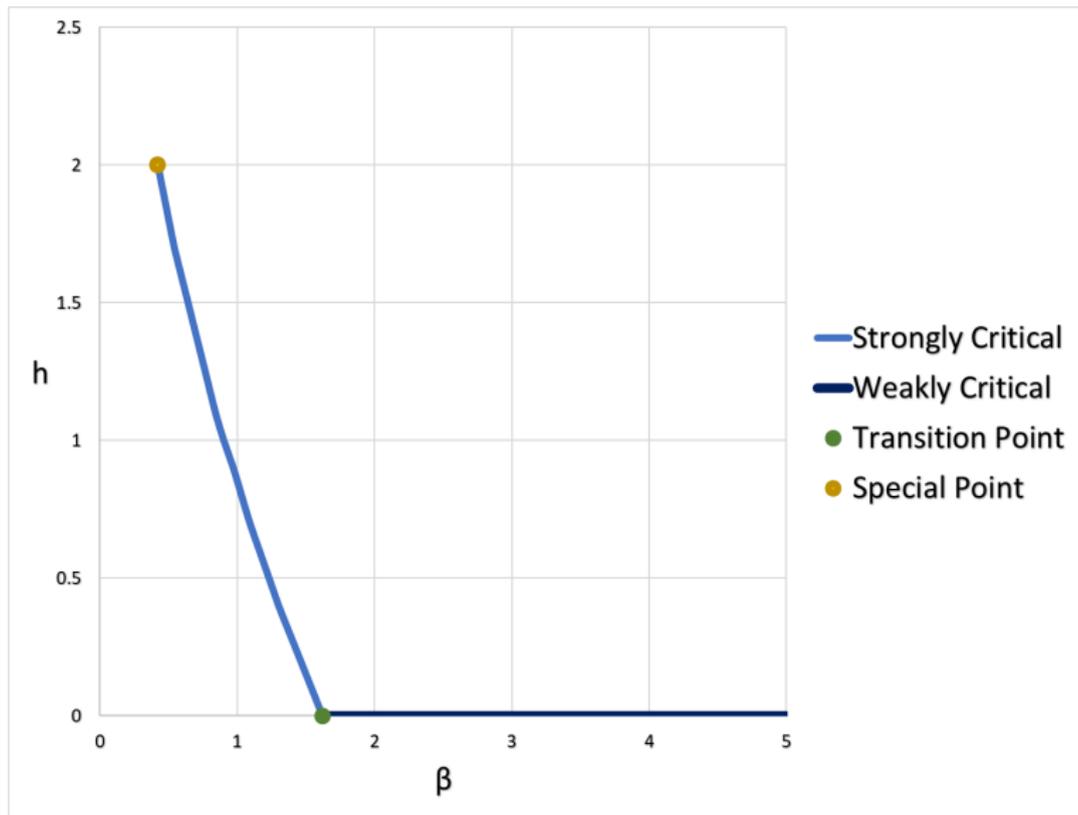


Figure: Partition of the parameter space, for  $p=7, q=5$

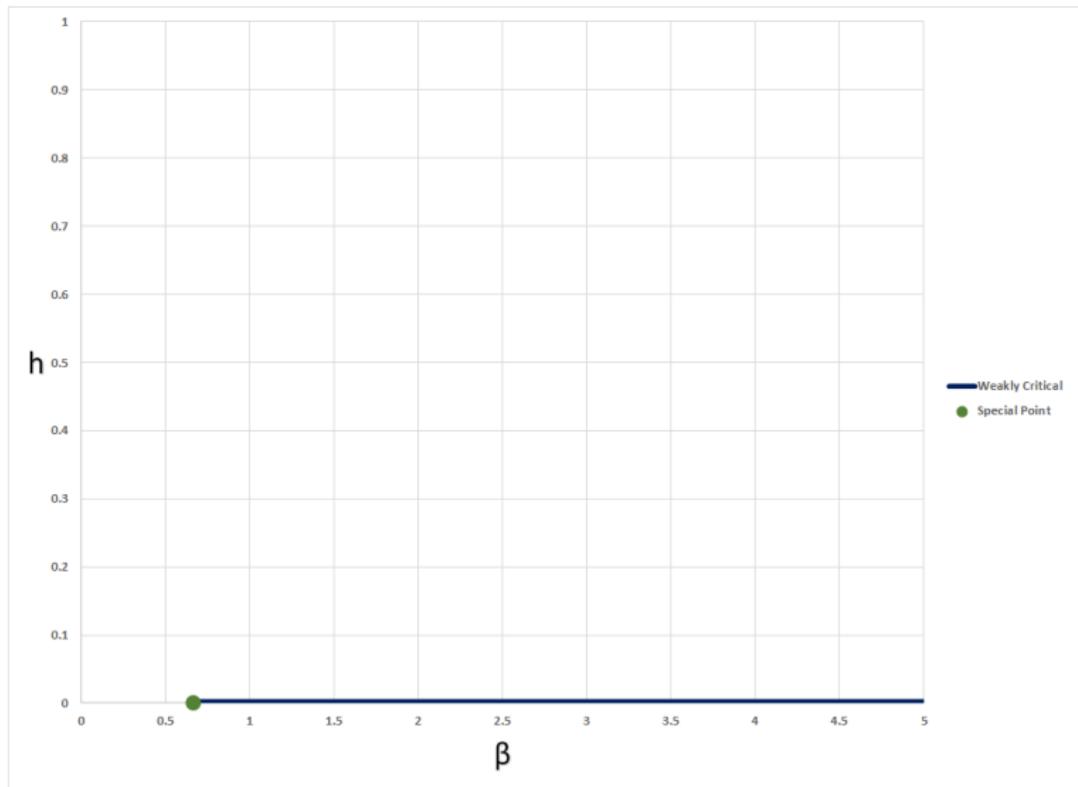


Figure: Partition of the parameter space, for  $p=4, q=2$

# CLT of $\bar{\mathbf{X}}_N$ under perturbation

## Theorem (B., Mukherjee(2023))

① *Regular:* for  $\mathbf{X} \sim \mathbb{P}_{\beta+N^{-\frac{1}{2}}\bar{\beta}, h+N^{-\frac{1}{2}}\bar{h}, p}$  for some  $\bar{\beta}, \bar{h} \in \mathbb{R}$ ,

$$N^{\frac{1}{2}} (\bar{\mathbf{X}}_N - \mathbf{m}_*) \xrightarrow{D} \mathcal{N}_q (\Sigma(\bar{\beta} p \mathbf{m}_*^{p-1} + \bar{h} \mathbf{e}_1), \Sigma),$$

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- ② *Critical:*

- for  $\mathbf{X} \sim \mathbb{P}_{\beta, h, p}$ , as  $N \rightarrow \infty$ , we have:

$$\bar{\mathbf{X}}_N \xrightarrow{P} \sum_{k=1}^K p_k \delta_{m_k},$$

- under  $\mathbb{P}_{\beta_N, h_N} \left( \cdot \mid \bar{\mathbf{X}}_N \in B(\mathbf{m}_i, \varepsilon) \right)$ :

$$\sqrt{N} (\bar{\mathbf{X}}_N - \mathbf{m}_i) \xrightarrow{D} \mathcal{N}_q (\Sigma'(\bar{\beta} p \mathbf{m}_i^{p-1} + \bar{h} \mathbf{e}_1), \Sigma'),$$

# CLT of $\bar{\mathbf{X}}_N$ under perturbation

## Theorem ((contd.))

- ③ *Special: Let  $\mathbf{u} ::= (1 - q, 1, \dots, 1)$ ,*
- *Type-I: Under  $\mathbb{P}_{\beta + N^{-\frac{3}{4}}\bar{\beta}, h + N^{-\frac{3}{4}}\bar{h}, p}$ , as  $N \rightarrow \infty$ ,*

$$N^{\frac{1}{4}}(\bar{\mathbf{X}}_N - \mathbf{m}_*) \xrightarrow{D} T_{\bar{\beta}, \bar{h}} \mathbf{u},$$

where  $T_{\bar{\beta}, \bar{h}}$  has density proportional to,

$$\exp\left(\frac{x^4}{24} q^4 f_{\beta, h}^{(4)}(s) + (\bar{\beta} p \langle \mathbf{m}_*^{p-1}, \mathbf{u} \rangle + \bar{h}(1 - q))x\right).$$

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- *Type-II: Under  $\mathbb{P}_{\beta+N^{-\frac{5}{6}}\bar{\beta}, h+N^{-\frac{5}{6}}\bar{h}, p}$ ,*

$$N^{\frac{1}{6}}(\bar{\mathbf{X}}_N - \mathbf{m}_*) \xrightarrow{D} F_{\bar{h}} \mathbf{u}.$$

where  $F_{\bar{h}}$  has density proportional to  $\exp\left(-\frac{32}{15}x^6 - \bar{h}x\right)$ .

# Proof Sketch

- Denote  $\mathbf{W}_N := \sqrt{N} (\bar{\mathbf{X}}_N - \mathbf{m}_*)$ .
- $g : \mathbb{R}^q \rightarrow \mathbb{R}$  a bounded, continuous function .

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- Denote  $\mathbf{W}_N := \sqrt{N} (\bar{\mathbf{X}}_N - \mathbf{m}_*)$ .
- $g : \mathbb{R}^q \rightarrow \mathbb{R}$  a bounded, continuous function .
- Weak Convergence:

$$\begin{aligned} & q^N Z_N(\beta_N, h_N) \mathbb{E}_{\beta_N, h_N, N} [g(\mathbf{W}_N) \mathbb{1}_{\|\mathbf{w}_N\| \leq M}] \\ &= \sum g(\mathbf{w}(\mathbf{v})) \mathbb{1}_{\|\mathbf{w}(\mathbf{v})\| \leq M} q^N Z_N(\beta_N, h_N) \mathbb{P}_{\beta_N, h_N, N}(\bar{\mathbf{X}}_N = \mathbf{v}) \end{aligned}$$

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- A small lemma,

$$q^N Z_N(\beta, h) \mathbb{P}_{\beta, h, N}(\bar{\mathbf{X}}_N = \mathbf{v}) \sim N^{-\frac{q-1}{2}} A(\mathbf{v}) e^{NH_{\beta, h}(\mathbf{v})}$$

where  $A(\mathbf{v}) := (2\pi)^{-(q-1)/2} \prod_{r=1}^q v_r^{-1/2}$ .

Taylor expand  $H_{\beta_N, h_N}$  to get,

$$q^N Z_N(\beta_N, h_N) \mathbb{E}_{\beta_N, h_N, N} [g(\mathbf{W}_N) \mathbb{1}_{\|\mathbf{w}_N\| \leq M}]$$

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Hence, under  $\mathbb{P}_{\beta_N, h_N, N}$ ,  $\mathbf{W}_N$  conditioned on  $\|\mathbf{W}_N\| \leq M$  converges weakly to the density proportional to

$$\mathbf{w} \mapsto e^{\langle \bar{\beta} p m_*^{p-1} + \bar{h} \mathbf{e}_1, \mathbf{w} \rangle + \frac{1}{2} Q_{m_*, \beta}(\mathbf{w})} .$$

Conclude the proof by uniform integrability of  $\{X_N\}$ .

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# MLE of the parameters

We interested to estimate:

- 1  $\beta$  with  $h$  known,
- 2  $h$  with  $\beta$  known.

# MLE of the parameters

Define  $u_{N,p}$  and  $u_{N,1}$  as,

$$u_{N,p}(\beta, h, \rho) := \mathbb{E}_{\beta, h, \rho}(\|\bar{\mathbf{X}}_N\|_p^\rho) \quad \text{and} \quad u_{N,1}(\beta, h, \rho) := \mathbb{E}_{\beta, h, \rho}(\bar{X}_1).$$

From classical results of exponential family the ML estimate  $\hat{\beta}$  satisfies the equation for fixed  $h$ :

$$u_{N,p}(\beta, h, \rho) = \|\bar{\mathbf{X}}_N\|_p^\rho$$

and for fixed  $\beta$ , the ML estimate  $\hat{h}$  satisfies the equation:

$$u_{N,1}(\beta, h, \rho) = \bar{X}_1.$$

## Lemma

$u_{N,p}(\beta, h)$  and  $u_{N,1}(\beta, h)$  are increasing in  $\beta$  and  $h$  respectively.

Proof Sketch:

Define  $F_N := \log q^N Z_N(\beta, h)$ . Then note that  $\frac{\partial}{\partial \beta} F_N = u_{N,p}(\beta, h)$  and  $\frac{\partial}{\partial h} F_N = u_{N,1}(\beta, h)$ . From holder's inequality  $F_N$  is convex in  $\beta, h$ .

## Theorem (B., Mukherjee(2023))

For regular points we have:

$$N^{\frac{1}{2}} \left( \hat{h}_N - h \right) \xrightarrow{D} \mathcal{N} \left( 0, -\frac{q^2}{(q-1)^2} f''_{\beta,h}(s) \right)$$

Proof.

$$\begin{aligned} & \mathbb{P}_{\beta,h,p} \left( N^{\frac{1}{2}} \left( \hat{h}_N - h \right) \leq t \right) \\ &= \mathbb{P}_{\beta,h,p} \left( \hat{h}_N \leq h + \frac{t}{N^{\frac{1}{2}}} \right) \\ &= \mathbb{P}_{\beta,h,p} \left( u_{N,1} \left( \beta, \hat{h}_N, p \right) \leq u_{N,1} \left( \beta, h + \frac{t}{N^{\frac{1}{2}}}, p \right) \right) \end{aligned}$$

## Proof(contd.)

$$\begin{aligned} &= \mathbb{P}_{\beta,h,p} \left( \bar{X}_1 \leq \mathbb{E}_{\beta,h+N^{-\frac{1}{2}}t,p} (\bar{X}_1) \right) \\ &= \mathbb{P}_{\beta,h,p} \left( N^{\frac{1}{2}} (\bar{X}_1 - m_1) \leq \mathbb{E}_{\beta,h+N^{-\frac{1}{2}}t,p} \left( N^{\frac{1}{2}} (\bar{X}_1 - m_1) \right) \right) \\ &\rightarrow \mathbb{P}_{\beta,h,p} \left( \mathcal{N} \left( 0, -\frac{(q-1)^2}{q^2 f''_{\beta,h}(s)} \right) \leq -\frac{t(q-1)^2}{q^2 f''_{\beta,h}(s)} \right) \\ &= \mathbb{P}_{\beta,h,p} \left( \mathcal{N} \left( 0, -\frac{q^2 f''_{\beta,h}(s)}{(q-1)^2} \right) \leq t \right). \end{aligned}$$



# Asymptotics of $\hat{\beta}_N$ and $\hat{h}_N$

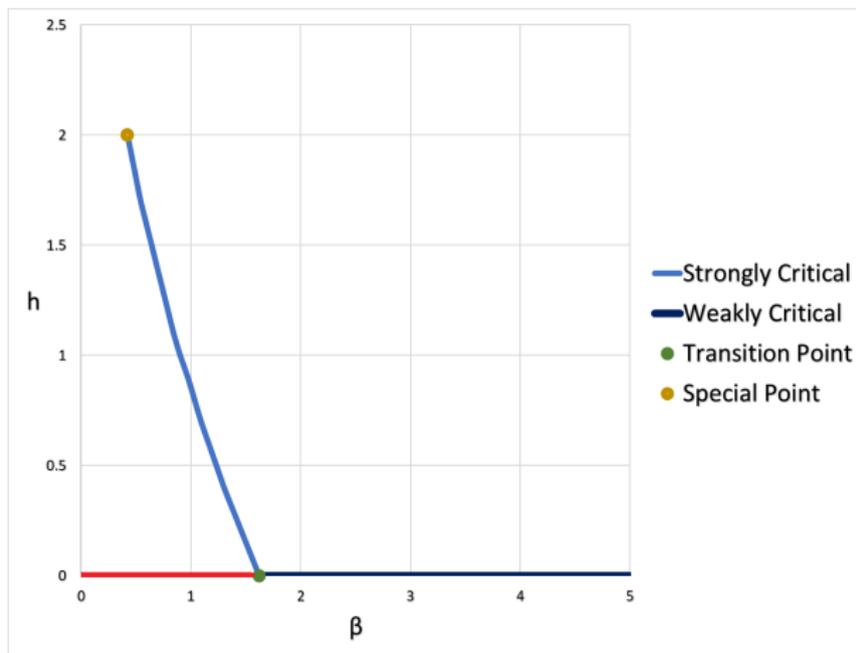


Figure: Regular:  $\hat{\beta}_N$  is  $\sqrt{N}$  consistent except at the red line.  $\hat{h}_N$  is  $\sqrt{N}$  consistent

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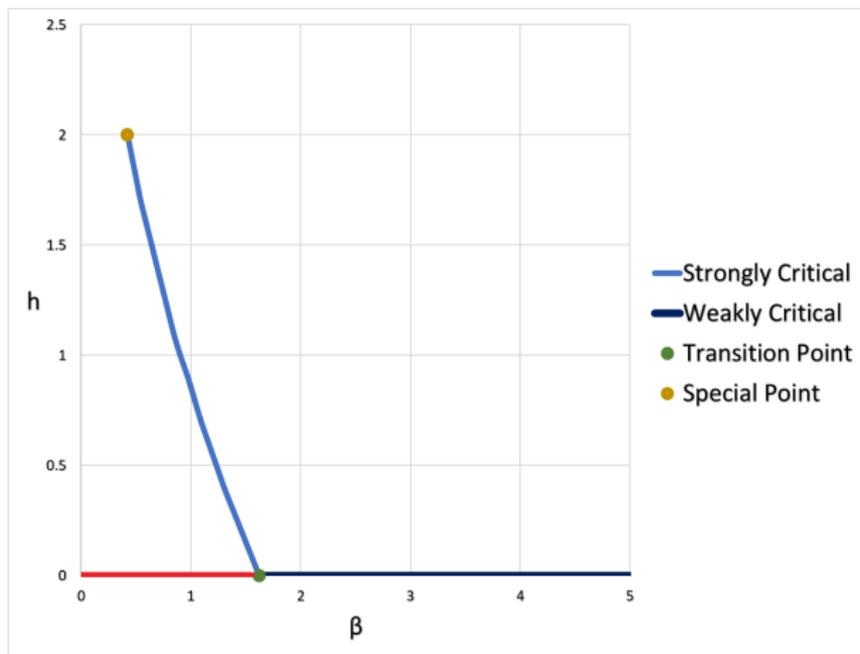


Figure: Strongly Critical:  $\hat{\beta}_N$  is  $\sqrt{N}$  consistent.  $\hat{h}_N$  is  $\sqrt{N}$  consistent

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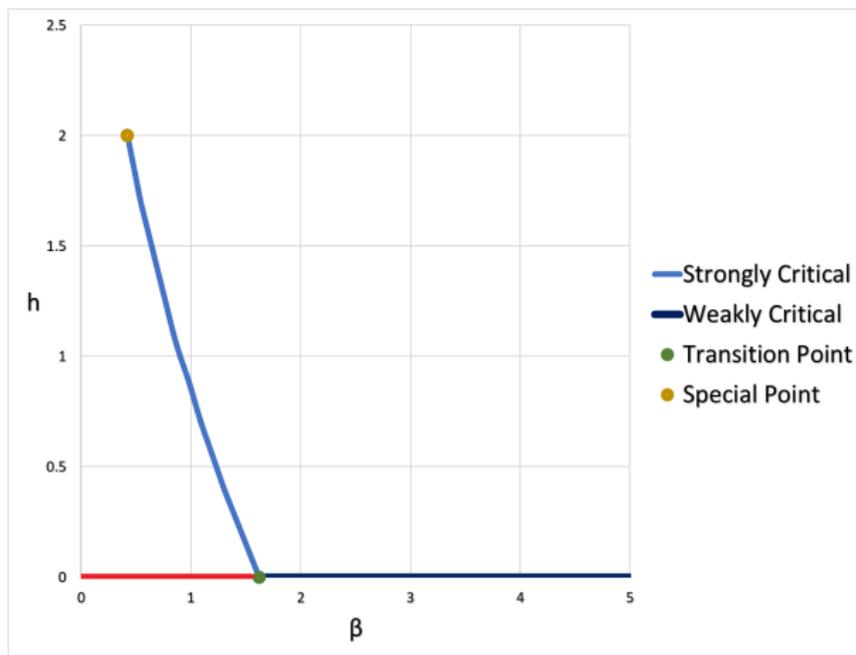


Figure: Weakly Critical:  $\hat{\beta}_N$  is  $\sqrt{N}$  inconsistent.  $\hat{h}_N$  is  $\sqrt{N}$  consistent

# Asymptotics of $\hat{\beta}_N$ and $\hat{h}_N$

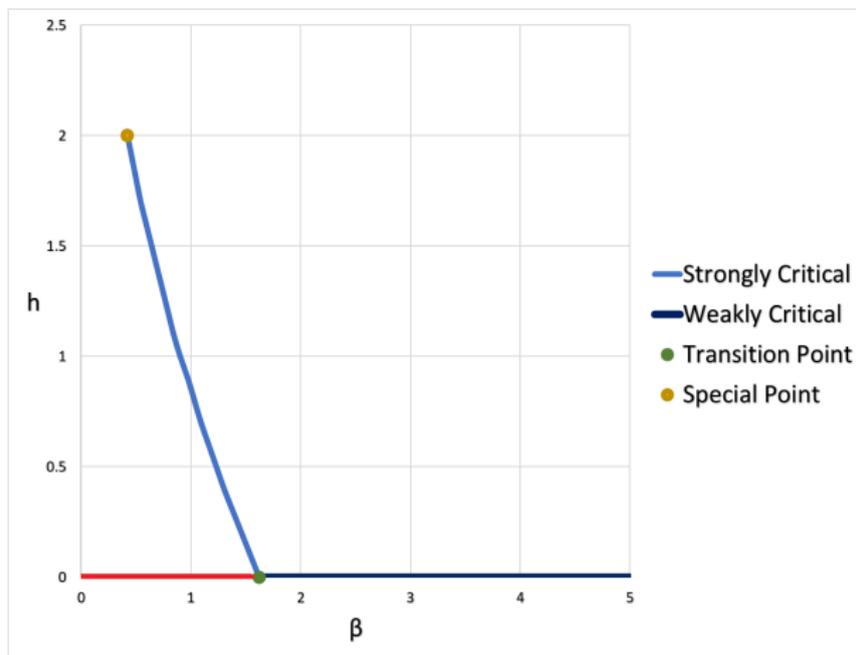
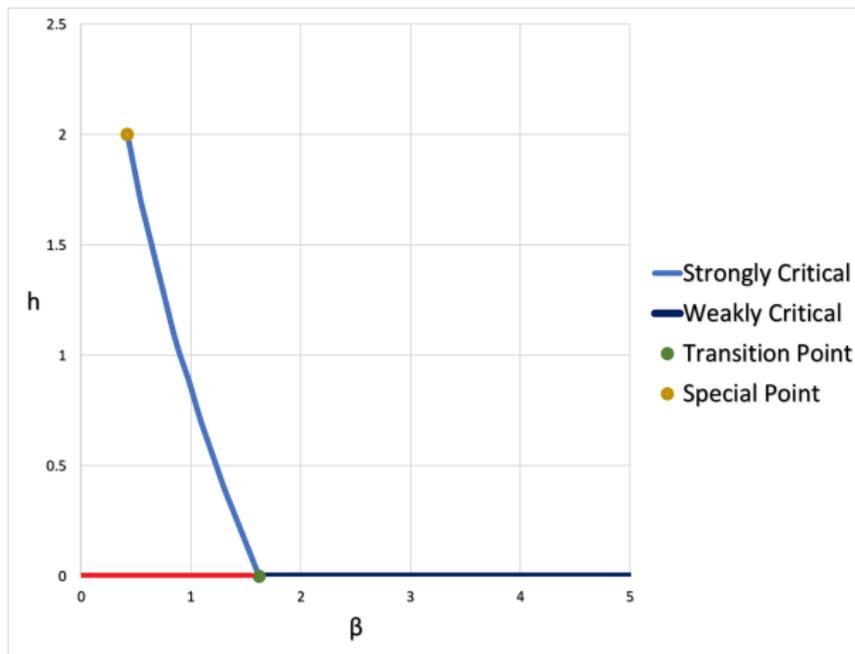


Figure: Transition Point:  $\hat{\beta}_N$  is  $\sqrt{N}$  inconsistent.  $\hat{h}_N$  is  $\sqrt{N}$  consistent

# Asymptotics of $\hat{\beta}_N$ and $\hat{h}_N$



**Figure:** Special Point:  $\hat{\beta}_N$  is  $N^{3/4}$  consistent except for  $(p, q) = (2, 2), (3, 2)$ .  $\hat{h}_N$  is  $N^{3/4}$  consistent.

# Special Case of $p = 4, q = 2$

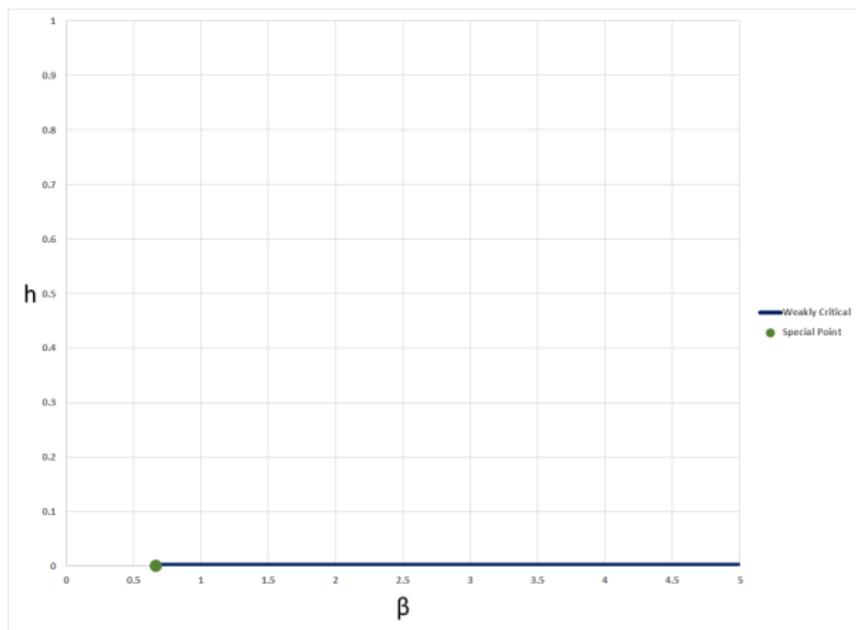


Figure: Special Point:  $\hat{\beta}_N$  is  $N^{5/6}$  in-consistent.  $\hat{h}_N$  is  $N^{5/6}$  consistent.

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- There exists a **continuous** curve in the interior of the parameter plane, on which the MLEs have mixture distributions. The components are normal/half-normal and point masses.
- The curious case of  $(p, q) = (4, 2)$ , where  $\hat{h}_N$  can converge at rate of  $N^{5/6}$  to a non-Gaussian distribution.

*Thank You!*