

# Simplicity and Complexity of Belief-Propagation

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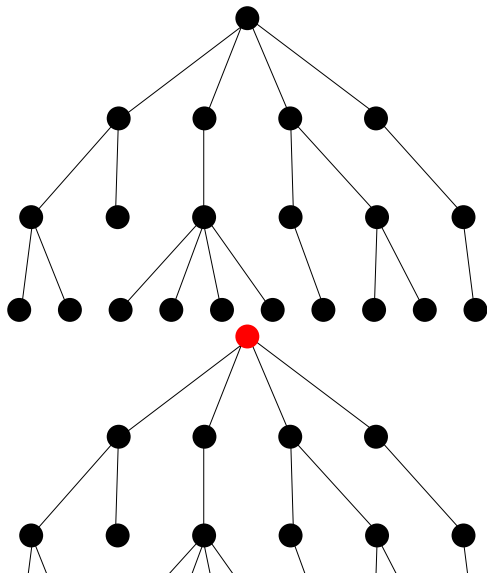
# Markov Random Fields and Information Flow on Trees

Consider the following process on a tree.

Color the root randomly.

Repeat: Copy color of parent with probability  $\theta$ . Otherwise, chose color  $\sim U[q]$ .

Will mostly consider full  $d$ -ary tree / Branching process trees.



# Inference - Machine Learning Perspective

- Inference problem (V1): Infer root color from leaf colors?
- A: **No!** Even in one level,  $\exists$  randomness in root given children.
- Inference Problem (V2): How much can infer on the root color from leaf colors?
- Machine Learning: We can compute the posterior exactly!
- Moreover: Belief-Propagation does it in linear time.
- Remark: Belief Propagation is often applied to non-tree graphs [Pearl 82]. Applications to trees were known in biology and statistical physics before [Hidden 1970, Preston 1974].

# Part 1: LINEAR THEORY

## $q = 2$

## Inference - Asymptotic Perspective

- Let  $q = 2$ , fix the  $d$ -ary tree of  $h$  levels and call the two colors  $+1, -1$ . Let  $X_v$  be the color of node  $v$ . Let  $X_0$  denote the root color and  $X_h$  are labels at level  $h$  of the tree.
- Inference Problem (V2): How much can infer on the root color from leaf colors?
- Q1: Can we analyze the optimal estimator (BP)?
- Q2: Is **Majority**  $= \text{sgn}(\sum_i X_h(i))$  a good estimator as  $h \rightarrow \infty$ ?
- Question asked in Statistical Physics in terms of the extremality of the free measure of the **Ising/Potts model** on the **Bethe lattice**.

# The Majority Estimator

- Let  $S_h = \sum_i X_h(i)$ .
- Exercise 1.  $\mathbb{E}[S_h|X_0] = (d\theta)^h X_0$  and

$$\frac{\mathbb{E}[S_h|X_0]^2}{\text{Var}[S_h|X_0]} = \frac{(d\theta)^{2h}}{\text{Var}[S_h|X_0]} \rightarrow \begin{cases} C(\theta), & d\theta^2 > 1, \\ 0, & d\theta^2 \leq 1 \end{cases}$$

- $\implies \lim_{h \rightarrow \infty} d_{\text{TV}}(S_h|X_0 = +, S_h|X_0 = -) > 0$  if  $d\theta^2 > 1$ .
- $\implies \lim_{h \rightarrow \infty} \mathbb{E}[\text{sgn}(S_h)X_0] > 0$  if  $d\theta^2 > 1$ .
- Analyzing Fourier Transform of  $S_h$  Kesten-Stigum-66 proved:
- $d\theta^2 \leq 1 \implies S_h \xrightarrow{h \rightarrow \infty}$  a **normal law** independent of  $X_0$  (\*).
- $d\theta^2 > 1 \implies S_h \xrightarrow{h \rightarrow \infty}$  a **non-normal law dependent** on  $X_0$ .
- $d\theta^2 = 1$  is referred to as the **Kesten-Stigum** threshold.
- Exercise: Apply the martingale CLT, to prove the normal case.

## Perspectives United:

- Thm for  $q = 2$ : If  $d\theta^2 \leq 1$  then  $\mathbb{P}[BP \rightarrow_{h \rightarrow \infty} (0.5, 0.5)] = 1$ .
- $\implies$  BP infers non-trivially **iff** Majority infers non-trivially.
- Multiple proofs: Bleher, Ruiz, and Zagrebnov (95), Ioffe (96), Evans-Kenyon-Peres-Schulmann (00), Borg, Tour-Chayes, M, Roch (06), etc. (also: Chayes, Chayes, , Sethna, Thouless, (1986)).
- EKPS: Also for random trees, where  $d$  is the **average degree**.
- All use some *concavity* of the functionals of the distribution.
- Next: A proof sketch and applications areas of the linear theory.

## Recursion of Random Variables for Binary Tree

- Let  $P_T^+$  denote the measure of  $X_h$  when root is +, let  $P_T^- = 0.5(P_T^- + P_T^+)$ .
- $M := M_T := P_T[X_0 = + | X_h] - P_T[X_0 = - | X_h]$ .
- Ex: (Bayes):  $\frac{dP_T^\pm}{dP_T} = 1 \pm M$ ,  $E_T^+[M] = E_T[M^2] = E_T^+[M^2]$ .
- Claim 1: If  $T = 0- > S$ ,  $M = M_T$ ,  $N = M_S$ :
- $M = \theta N$ ,  $E_T^+[N] = \theta E_S^+[N]$ ,  $E_T^+[N^2] = \theta E_S^+[N^2] + (1 - \theta)E_S[N^2]$ .
- Claim 2: If  $T_1, T_2$  are two trees joined at the root to form  $T$  and  $N_i = X_{T_i}$  then:

$$M = \frac{N_1 + N_2}{1 + N_1 N_2}.$$

$$\implies \text{Belief Propagation Recursion : } M_{n+1} = \theta \frac{M_n + M'_n}{1 + \theta^2 M_n M'_n}.$$



$2\theta^2 < 1 \implies E[M_n^2] \rightarrow 0$ , i.e., asymptotic independence

$$M = \theta \frac{N_1 + N_2}{1 + \theta^2 N_1 N_2}, \quad \frac{1}{1+r} = 1 - r + \frac{r^2}{1+r} \implies$$

$$M = \theta(N_1 + N_2) - \theta^3 N_1 N_2 (N_1 + N_2) + \theta^4 N_1^2 N_2^2 M$$

$$M \leq \theta(N_1 + N_2) - \theta^3 N_1 N_2 (N_1 + N_2) + \theta^4 N_1^2 N_2^2$$

$\implies$  (taking  $E_T^+$  recalling  $E_T^+[M] = E_T[M^2]$ )

$$E_T[M^2] \leq 2\theta^2 E_S[N^2] - \theta^4 E_{S^+}[N^2]$$

$\implies$

$$E[M_n^2] \leq (2\theta^2)^n$$

# Application 1: The Phylogenetic Inference Problem

