Graphical models, from graphs to trees (and back)

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1 What is this talk about, and why should one care

2 Uniform decorrelation

3 Non-Uniform decorrelation

Trees vs graphs: from reconstruction to pure states

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Trees vs graphs: from reconstruction to pure states

What is this talk about, and why should one care

2

Graphical models



$$G = (V, E), V = [n], \quad \underline{x} = (x_1, \dots, x_n), x_i \in \mathcal{X}$$

$$\mu(\underline{x}) = \frac{1}{Z} \prod_{(ij)\in G} \psi_{ij}(x_i, x_j).$$

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1. *G* has bounded degree (on average).

2. G has girth $\ell(n) \to \infty$ (apart from o(n) vertices).

3. G is random.

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Example 1: q-coloring



G = (V, E) graph.

 $\mathbf{\underline{x}}=(x_1,x_2,\ldots,x_n)$, $x_i\in\{1,\ldots,q\}$ variables

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Example 1: q-coloring



G = (V, E) graph. $\underline{x} = (x_1, x_2, \dots, x_n), x_i \in \{1, \dots, q\}$ variables

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Uniform measure over proper colorings



$$\mu(\underline{x}) = \frac{1}{Z} \prod_{(i,j)\in E} \psi(x_i, x_j), \qquad \psi(x, y) = \mathbb{I}(x \neq y).$$

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n variables:
$$\underline{x} = (x_1, x_2, ..., x_n), x_i \in \{0, 1\}$$

m k-clauses

$$(x_1 \lor \overline{x_5} \lor x_7) \land (x_5 \lor x_8 \lor \overline{x_9}) \land \dots \land (\overline{x_{66}} \lor \overline{x_{21}} \lor \overline{x_{32}})$$

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Image: Image:

Uniform measure over solutions



• Communications/signal processing (technologically relevant)

• . . .

Probability, physics, computer science, information theory,...

Image: Image:

• Communications/signal processing (technologically relevant)

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Probability, physics, computer science, information theory,...

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• Approximation of sparse graph models by trees.

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[cf. Aldous' local weak convergence]

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• . . .

[cf. Aldous' local weak convergence]

Uniform decorrelation

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Each clause is uniformly random among the $2^k \binom{n}{k}$ possible ones.

 $n \rightarrow \infty, m = \alpha n$

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$n \rightarrow \infty, m = \alpha n$

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$$Z_n(\beta) = \sum_{\underline{x}} \exp\left\{-2\beta \ \#[\text{clauses violated by } \underline{x}]\right\}$$

Theorem (Montanari, Shah, 2007)

If $lpha<lpha_{\mathrm{u}}(k)=(2\log k)k^{-1}\;[1+o_k(1)]$ then

$$\frac{1}{n}\log Z_n(\beta) \xrightarrow{a.s.} \phi(\alpha,\beta),$$

where ...

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...where...

$$\begin{split} \phi(\alpha,\beta) &= -k\alpha \mathbb{E}\log[1 + \tanh h \tanh u] + \alpha \mathbb{E}\log\left\{1 - \frac{1}{2^k}(1 - e^{-\beta})\prod_{i=1}^k (1 - \tanh h_i)\right\} + \\ &+ \mathbb{E}\log\left\{\prod_{i=1}^{\ell_+} (1 + \tanh u_i^+)\prod_{i=1}^{\ell_-} (1 - \tanh u_i^-) + \prod_{i=1}^{\ell_+} (1 - \tanh u_i^+)\prod_{i=1}^{\ell_-} (1 + \tanh u_i^-)\right\}, \end{split}$$

and h, u are the *unique* solution of

$$h \stackrel{d}{=} \sum_{a=1}^{l_+} u_a - \sum_{b=1}^{l_-} u'_b, \qquad u \stackrel{d}{=} f_\beta(h_1, \ldots, h_{k-1}).$$

[Conjectured by Monasson, Zecchina 1999]

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Sufficient to prove

$$\frac{1}{n}\mathbb{E}\log Z_n(\beta)\longrightarrow \phi(\alpha,\beta)\,,$$

The tree ensemble $T(\ell)$, $T(\infty)$

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Poisson $(k\alpha/2)$ Poisson $(k\alpha/2)$

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The tree ensemble $T(\ell)$, $T(\infty)$



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The tree ensemble $T(\ell)$, $T(\infty)$



The tree ensemble $T(\ell)$, $T(\infty)$



The tree ensemble $T(\ell)$, $T(\infty)$



1. Check it for $\beta = 0$: $\phi(\alpha, 0) = \log 2 = n^{-1} \mathbb{E} \log Z_n(0)$.

2. Write $\frac{d}{d\beta} \log Z_n(\beta)$ in terms of local expectations. ????

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Local expectations ????



$$\begin{array}{lll} \mu(\underline{x}) & = & \displaystyle \frac{1}{Z_n(\beta)} \prod_{a=1}^m \psi_{\beta,a}(x_{i_1(a)}, \dots, x_{i_k(a)}) \\ \psi_{\beta,a}(\cdots) & = & \left\{ \begin{array}{ll} 1 & \text{if clause } a \text{ is satisfied} \\ e^{-2\beta} & \text{otherwise} \end{array} \right. \end{array}$$
$$\frac{d}{d\beta} \log Z_n(\beta) = -2 \sum_{a=1}^{M} \mu(\text{clause } a \text{ is not satisfied})$$

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1. Check it for $\beta = 0$: $\phi(\alpha, 0) = \log 2 = n^{-1} \mathbb{E} \log Z_n(0)$.

2. Express $\frac{d}{d\beta} \log Z_n(\beta)$ in terms of local expectations.

- 3. Prove that local expectations on G converge to expectations on $T(\infty)$.
- 4. Show $\frac{d\phi(\alpha,\beta)}{d\beta}$ is equal to the same expectations on $T(\infty)$.

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Convergence to tree values





infinite k-SAT tree first ℓ generations Boltzmann measure on T(ℓ) boundary condition z root variable marginal

Convergence to tree values





Convergence to tree values



 $\begin{array}{ll} \mathsf{T}(\infty) & \text{infinite } k\text{-}\mathsf{SAT tree} \\ \mathsf{T}(\ell) & \text{first } \ell \text{ generations} \\ \mu^{\ell,z}(\cdot) & \text{Boltzmann measure on } \mathsf{T}(\ell) \text{ boundary condition } z \\ \mu^{\ell,z}_r(\cdot) & \text{root variable marginal} \end{array}$

(Gibbs measure uniqueness)

$$\mathbb{E}\left\{\max_{z(1),z(2)}||\mu_r^{t,z(1)}(\,\cdot\,)-\mu_r^{t,z(2)}(\,\cdot\,)||_{\scriptscriptstyle \mathrm{TV}}\right\}\to 0\,.$$

'Easy' sufficient condition

True only at very small α $(\alpha_{\rm u}(k) \simeq (2 \log k)/k$, conjecture up to $\simeq 2^k \log 2)$

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Non-Uniform decorrelation

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Ferromagnetic Ising model



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Ferromagnetic Ising model

$$G_n = (V_n \equiv [n], E_n)$$
$$x_i \in \{+1, -1\}$$

$$\mu(\underline{x}) = \frac{1}{Z_n(\beta, B)} \exp\left\{\beta \sum_{(ij)\in E_n} x_i x_j + B \sum_i x_i\right\}$$

[Johnston, Plechác 1998, Leone et al 2004]

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Ferromagnetic Ising model

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[Johnston, Plechác 1998, Leone et al 2004]

Theorem (Dembo, Montanari 2008)

If G_n converges locally to T(P), then

$$\frac{1}{n}\log Z_n(\beta,B) \xrightarrow{a.s.} \phi(P,\beta,B).$$

where...

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For $B \ge 0$, let $\theta \equiv \tanh \beta$, $h^{(0)} > 0$, and

$$h^{(\ell+1)} \stackrel{\mathrm{d}}{=} \tanh\left\{B + \sum_{i=1}^{K-1} \operatorname{atanh}(\theta h_i^{(\ell)})\right\},$$

Then
$$h^{(\ell)} \xrightarrow{a} h^*$$
 and

$$\phi(P,\beta,B) \equiv \log \cosh B + \frac{\overline{P}}{2} \log \cosh \beta - \frac{\overline{P}}{2} \mathbb{E} \log(1 + \theta h_1^* h_2^*) + \\ + \mathbb{E} \log \left\{ (1 + \tanh B) \prod_{i=1}^{L} (1 + \theta h_i^*) + (1 - \tanh B) \prod_{i=1}^{L} (1 - \theta h_i^*) \right\}.$$

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For $B \ge 0$, let $\theta \equiv \tanh \beta$, $h^{(0)} > 0$, and

$$h^{(\ell+1)} \stackrel{\mathrm{d}}{=} \tanh\left\{B + \sum_{i=1}^{K-1} \operatorname{atanh}(\theta \ h_i^{(\ell)})\right\},\,$$

Then $h^{(\ell)} \stackrel{d}{\rightarrow} h^*$ and

$$\phi(P, \beta, B) \equiv \log \cosh B + rac{\overline{P}}{2} \log \cosh \beta - rac{\overline{P}}{2} \mathbb{E} \log(1 + \theta h_1^* h_2^*) + + \mathbb{E} \log \left\{ (1 + \tanh B) \prod_{i=1}^{L} (1 + \theta h_i^*) + (1 - \tanh B) \prod_{i=1}^{L} (1 - \theta h_i^*) \right\} \,.$$

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 $\bigcirc P_k$

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 $\mathsf{T}(P,\ell)$



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'Converges locally'

$$\begin{split} P &\equiv \{P_k\}_{k\geq 0} & \text{Degree distribution} \\ \mathsf{T}(P,\ell) & \ell\text{-generations Galton-Watson tree} \\ \mathsf{B}_i(\ell) & \text{Ball of radius } \ell \text{ around uniformly random node} \end{split}$$

Definition

 G_n converges locally to T(P) if uniform bound on the edge number distribution and, for any ℓ ,

 $B_i(\ell)$ converges in distribution to $T(P, \ell)$.

For $\beta > \beta_c \equiv \operatorname{atanh}(1/\overline{\rho})$

$$\lim_{B\to 0+} \lim_{n\to\infty} \mathbb{E}_i \langle x_i \rangle = -\lim_{B\to 0-} \lim_{n\to\infty} \mathbb{E}_i \langle x_i \rangle > 0$$

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... and its tree counterpart



$$egin{array}{lll} z=(+1,+1,\ldots,+1)&\Rightarrow&\lim_{\ell o\infty}\langle x_r
angle_\ell>0\ z=(-1,-1,\ldots,-1)&\Rightarrow&\lim_{\ell o\infty}\langle x_r
angle_\ell<0 \end{array}$$

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$$\mu(\underline{x}) = \frac{1}{Z} \exp\left\{\beta \sum_{(ij)\in E_n} J_{ij} x_i x_j + B \sum_i x_i\right\}$$

 $J_{ij} \in \{+1, -1\}$ uniformly random

[Viana, Bray 1985] [Other approaches: Talagrand 2001, Guerra, Toninelli 2003] [Approximation by trees: Montanari, Gerschenfeld, in preparation]

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Trees vs graphs: from reconstruction to pure states

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Alice and Bob



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Alice, Bob and G



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Exit Bob



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Alice samples a proper coloring (uniformly)...



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\dots and hides a ball B(root, t)



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...guesses right!



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Does Bob have a chance?

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Formally

 $X = \{X_i : i \in V\}$ uniformly random proper coloring.

 $\mu_U(\cdot | G)$ distribution of $X_U \equiv \{X_i : i \in U \subseteq V\}$

$$\overline{\mathsf{B}}(r,t) = \{i \in V : d(i,r) \ge t\}$$

Definition

The reconstruction problem is solvable for the sequence of random rooted graphs $G_n = (V_n = [n], E_n)$ if for some $\varepsilon > 0$,

$$||\mu_{r,\overline{\mathsf{B}}(r,t)}(\cdot,\cdot|G_n) - \mu_r(\cdot|G_n)\mu_{\overline{\mathsf{B}}(r,t)}(\cdot|G_n)||_{\mathrm{TV}} \geq \varepsilon,$$

with positive probability (bounded away from 0 as $n \to \infty$).

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- \rightarrow Bleher, Ruiz, Zagrebenov (1995): Ising model on *b*-ary trees
- \rightarrow Evans, Kenyon, Peres, Schulman (2000): Ising on general trees
- \rightarrow Mossel, Peres (2003): Non binary variables
- \rightarrow Brightwell, Winkler (2004), Martin (2004): Independent sets.
- \rightarrow Chayes et al. (2006): Asymmetric Ising.

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Pure states decomposition in q-COL



$$\gamma_{
m d}(q) \qquad \gamma_{
m c}(q) \qquad \gamma_{
m s}(q)$$

[Biroli, Monasson, Weigt 2001] [Mézard, Parisi, Zecchina 2003] [Achlioptas, Ricci 2007] [Krzakala, Montanari, Ricci, Semerjian, Zdeborova 2007]

Conjecture (Mézard, Montanari, 05)

$$\gamma_{
m d}({m q})$$
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- = Multiple pure states
- Graph reconstruction threshold
- Tree reconstruction threshold

Theorem (Gerschenfeld, Montanari, 2007)

If $\mu(\cdot|G)$ is roughly spherical then

Graph solvable \Leftrightarrow Tree solvable.

If $\mu(\cdot|G)$ is not roughly spherical then

Graph reconstruction is solvable

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Theorem (Gerschenfeld, Montanari, 2007)

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If $\mu(\cdot|G)$ is roughly spherical then

 $Graph \ solvable \Leftrightarrow \ Tree \ solvable.$

If $\mu(\cdot|G)$ is not roughly spherical then

Graph reconstruction is solvable

Roughly spherical???

$$X_i \in \{0, 1\}.$$

 $X^{(1)} = \{X_i^{(1)}\}, X^{(2)} = \{X_i^{(2)}\}$ independent with distribution $\mu(\cdot | G_n)$



 $\mu(\cdot|G_n)$ is roughly spherical if $d(X^{(1)},X^{(2)}) \approx n/2$ with high probability.

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Roughly spherical???

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 $\mu(\cdot | G_n)$ is roughly spherical if $d(X^{(1)}, X^{(2)}) \approx n/2$ with high probability.

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Theorem

- 1. q-coloring, $\gamma < (q-1)\log(q-1)$: roughly spherical.
- 2. Ising spin glass $2\gamma(\tanh\beta)^2 < 1$: roughly spherical.
- 3. Ising ferromagnet:

not roughly spherical

[Tree reconstruction threshold

- 1. Bhatayangar, Vera, Vigoda 2008, Sly 2008
- 2. Evans, Kenyon, Peres, Schulman 2000
- 3. Tree≠Graph]

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Theorem

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- 1. Bhatayangar, Vera, Vigoda 2008, Sly 2008
- 2. Evans, Kenyon, Peres, Schulman 2000
- 3. Tree \neq Graph]

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Combinatorics/Probability problems on random sparse graphs.

Unifying approach: approximation by trees.

Naturally leads to analytc questons.

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