

Lecture 16

Lecture date: Oct. 19

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Recall that a distribution tree factorizes according to some factor graph $([N], [M], \{\partial a : 1 \leq a \leq M\})$,

$$P(x) = \frac{1}{Z} \prod_{a=1}^M \psi_a(x_{\partial a}).$$

Definition 1 A family of factorized distributions is $\{P_n\}$, where each P_n factorizes.

Example 2 The free 2-dimensional β Ising model: G_n are graphs ($n \times n$ grids) and

$$P_n(\sigma) = \frac{1}{Z} \exp \left(\beta \sum_{\substack{i,j \in G_n \\ i \sim j}} \sigma_i \sigma_j \right).$$

Example 3 The 2-dimensional β Ising model: Let $\partial_V G_n$ denote the vertex boundary and let $\tau \in \{-1, 1\}^{\partial_V G_n}$. Then $(P_n^\tau)_{1 \leq n < \infty}$ are given by

$$P_n^\tau(\sigma) = \frac{1}{Z} \exp \left(\beta \sum_{\substack{i,j \in G_n \\ i \sim j}} \sigma_i \sigma_j \right) \exp \left(\sum_{i \in \partial_V G_n} \tau_i \sigma_i \right).$$

Note that the same procedure can be applied when you have an infinite factor graph G_V , factor node potentials (ψ) and a sequence $G_n \uparrow G$.

Example 4 3-Regular Graphs: Consider the collection of all 3-regular graphs, $\{G_n^J\}$, where J is the edge function on G . Let

$$P_n^J(x) = \frac{1}{Z} \prod_{i \sim j} \exp(\beta J_{i,j} x_i x_j).$$

Definition 5 Let G be a factor graph and v a variable node in G . Let $B(v, l) = \{w : d(v, w) \leq l\}$ and $S(v, l) = \{w : d(v, w) = l\}$.

Definition 6 Suppose P_n factorizes according to G_n and let A and B be disjoint subsets of vertices of G_n . We define the following quantities:

$$P_{n,A}^{\sigma_B}(\sigma_A) = P_n(\sigma|_A = \sigma_A \mid \sigma_B)$$

$$[A : B]_{P_n} = (P_{n,A}^{\sigma_B})_{\text{all } \sigma_B}$$

$$\text{diam}[A : B]_{P_n} := \sup_{\sigma_B, \sigma'_B} d_{\text{TV}} \left(P_{n,A}^{\sigma_B}, P_{n,A}^{\sigma'_B} \right),$$

where d_{TV} is the total variation distance.

Definition 7 Let P_n be a family of factorized distributions. We say that uniqueness holds if $\forall l \forall \epsilon > 0 \exists r > l$ such that $\forall n \forall v$

$$\text{diam} [B(v, l) : S(v, r)]_{P_n} < \epsilon.$$

That is, uniqueness means that the probability distribution on the l -ball isn't affected by what we see on the boundary of the r ball (where $r > l$).

A variant of uniqueness is exponential uniqueness. The definition of exponential uniqueness is essentially the same as for uniqueness except that we only consider ϵ of the form $\epsilon = (1 - \eta)^{r-l}$.

As a final note to this discussion of uniqueness, we mention the connection between Definition 7 and the notion of uniqueness for infinite graphs: Given ψ (the factor node potentials), there exists a unique measure satisfying the Markov Property. This notion of uniqueness on infinite graphs is equivalent to uniqueness given by Definition 7 for all finite subgraphs.

Definition 8

$$\langle A : B \rangle = \sup_{f,g} \{ \mathbf{E}_n[fg] : f \text{ depends on } \sigma_A, g \text{ depends only on } \sigma_B, \mathbf{E}[f] = \mathbf{E}[g] = 0, |f|_\infty < 1, |g|_\infty < 1 \}$$

Definition 9 We say that non-reconstruction holds if $\forall l \forall \epsilon > 0 \exists r > l$ such that $\forall n \forall v$
 $\langle B(v, l), S(v, r) \rangle \leq \epsilon$.

Informally, in determining non-reconstruction, we want to know if in the factorized measure and with no conditioning we can get any information about the l -ball from the boundary of the r ball. If not, we call it non-reconstruction.

Proposition 1: Uniqueness implies non-reconstruction.

Proof: We want to compute $\mathbf{E}[fg]$. Then,

$$\mathbf{E}[fg|\sigma_{S(v,r)} = \bar{\sigma}] - \mathbf{E}[f]\mathbf{E}[g] = g(\bar{\sigma})\mathbf{E}[f|\sigma_{S(v,r)} = \bar{\sigma}]$$

because $\mathbf{E}[f] = \mathbf{E}[g] = 0$. From uniqueness,

$$d_{\text{TV}}\left(P_{n,B(v,l)}^{\sigma_{S(v,r)}}, P_{n,B(v,l)}\right) \leq \epsilon$$

Thus,

$$|\mathbf{E}[f] - \mathbf{E}[f|\sigma_{S(v,r)} = \bar{\sigma}]| \leq 2\epsilon$$

and therefore:

$$\mathbf{E}[fg] \leq 2\epsilon E[|g|] \leq 2\epsilon.$$

□

Proposition 2: Non-reconstruction implies $\forall \epsilon > 0 \exists r$ such that $\forall n, \forall f, g$ with $|f|_{\infty} \leq 1, |g|_{\infty} \leq 1, \forall u, v$ such that $d(u, v) \geq r$

$$\mathbf{Cov}[f(\sigma_u), g(\sigma_v)] \leq \epsilon.$$

One dimensional systems. Here we show that for one dimensional systems we always have exponential uniqueness.

Claim 3: Consider a family $\{P_n\}$ where P_n factorizes over G_n . Assume

1. $\exists \eta > 0$ such that $\forall \psi, \eta \leq \psi \leq \frac{1}{\eta}$
2. $\exists D < \infty$ such that for every connected set of variable nodes, S , it holds that $|\partial_0 S| \leq D$, where $\partial_0 S = \{w \notin S : \exists v \in S, \partial_a : v, w \in \partial_a\}$

Then P_n has exponential uniqueness.

Proof: Let $P^{\sigma_1}, P^{\sigma_2} \in [B(v, l), S(v, l + r)]$. We'll show $d_{\text{TV}}(P^{\sigma_1}, P^{\sigma_2}) \leq (1 - \epsilon)^r$ by induction on r .

The case $r = 0$ is trivial. For $r = 1$, consider two probability measures, $Q^{\sigma_1}, Q^{\sigma_2} \in [B(v, l + (r - 1), S(v, l + r))]$.

The boundedness of the potential coupled with the fact that the set $B(v, l + (r - 1))$ has at most D neighbors implies that $\frac{dQ^{\sigma_1}}{dQ^{\sigma_2}} \in [\eta^{2D}, \eta^{-2D}]$. Therefore:

$$d_{\text{TV}}(Q^{\sigma_1}, Q^{\sigma_2}) \leq 1 - \epsilon$$

where $\epsilon = \epsilon(D, \eta) > 0$.

This implies in particular that for $R^{\sigma_1}, R^{\sigma_2} \in [S(v, l + (r - 1), S(v, l + r))]$ we have $d_{\text{TV}}(R^{\sigma_1}, R^{\sigma_2}) \leq 1 - \epsilon$.

Now we consider each of the measures $P^{\sigma_1}, P^{\sigma_2}$ by first conditioning on the values in $S(v, l + (r - 1))$ – we then obtain that:

$$P^{\sigma_1} - P^{\sigma_2} = (1 - \epsilon) \sum l_i (P^{i, \tau_i} - P^{i, \bar{\tau}_i})$$

where $l_i \geq 0$, $\sum l_i = 1$ and $P^{i, \tau_i}, P^{i, \bar{\tau}_i} \in [B(v, l) : S(v, l + r - 1)]$. By the inductive hypothesis we have

$$d_{\text{TV}}(P^{i, \tau_i}, P^{i, \bar{\tau}_i}) \leq (1 - \epsilon)^{r-1},$$

for all i . Summing over all i , we obtain

$$d_{\text{TV}}(P^{\sigma_1}, P^{\sigma_2}) \leq (1 - \epsilon)^r$$

as needed. \square