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Overview

Everyone uses Gibbs sampling!

- ▷ De facto Markov Chain Monte Carlo method for inference.
- ▷ Works very well in practice.
- ▷ Used by many systems such as Factorie, OpenBugs, PGibbs, and DeepDive — including competition-winners.



But it's hard to tell when Gibbs sampling will work!

- ▷ Standard metric is *mixing time*, the amount of time needed to produce samples that are "close" to the true distribution.
- ▷ *Finding the mixing time is hard* there's little theory.

Our contribution: fast mixing with hierarchy width

- ▷ Introduce a new factor graph width: the *hierarchy width*.
- ▷ Hierarchy width is a structural property of the factor graph.
- ▷ Bounding the hierarchy width is a sufficient condition to ensure that Gibbs sampling will mix in polynomial time.
- ▷ This gives us new understanding of a class of factor graphs for which Gibbs sampling is guaranteed to be feasible.

Problem Setup

Gibbs sampling: Sample from distribution π over variables V

Require: Initial state X_i for $i \in V$, number of samples T.

for t = 0 to T - 1 do

Select i_t uniformly from V. Resample X_{i_t} conditionally from π given $X_{V \setminus \{i_t\}}$. Output sample $z_t \leftarrow X$.

end for

We study Gibbs sampling on discrete-valued *factor graphs*. A factor graph is a graphical model over a set of variables V and factors Φ that has distribution

$$\pi(I) = \frac{1}{Z} \exp\left(\sum_{\phi \in \Phi} \phi(I)\right)$$

where *I* is a world — an assignment of a value to each variable in V — and Z is the constant required to make π a distribution.

We focus on bounding the *mixing time*, the first time t at which the estimated distribution μ_t is close to the true distribution π .

 $t_{\min} = \min\left\{t : \max_{A \subset \Omega} |\mu_t(A) - \pi(A)| \le \frac{1}{4}\right\}.$

Hierarchy Width and Rapid Mixing

The *hierarchy width* hw(G) of a factor graph G is defined such that, for any *connected* factor graph $G = \langle V, \Phi \rangle$,

$$\mathsf{hw}(G) = 1 + \min_{\phi^* \in \Phi} \mathsf{h}$$

and for any *disconnected* factor graph Gwith connected components G_1, G_2, \ldots ,

 $\mathsf{hw}(G) = \max_{i} \mathsf{hw}(G_i).$

All factor graphs G with no factors have

 $\mathsf{hw}(\langle V, \emptyset \rangle) = 0.$

Hierarchy Width Examples

Intuitively, we can think of labeling each factor with a positive integer, its *level in the hierarchy*. For two factors F and G to have the same level, they must only interact through their superiors: every path from F to G must pass through a factor with a smaller label. The hierarchy width is the minimum value, across all labellings, of the largest label. Here are some examples (labels in red).



This model has only two (large) factors, which can't have the same label because they are adjacent. Therefore, its hierarchy width is hw(G) = 2.

 \triangleright Actually mixes in $O(n \log n)$ time.

Experiments



The first plot shows that, of the two voting models, the *bounded-hierarchy-width model has lower error*. The second plot shows the same thing for templates on a real dataset — in particular, the model in Hierarchical 2 was used as part of a *competition-winning* system (TAC KBP '14). The third plot shows, for an ensemble of synthetic Ising models, how error varies with hierarchy width.

Rapidly Mixing Gibbs Sampling for a Class of Factor Graphs Using Hierarchy Width

Christopher De Sa, Ce Zhang, Kunle Olukotun, and Chris Ré

 $\mathsf{hw}(\langle V, \Phi - \{\phi^*\}\rangle),$

Main Theorem: Bounding the mixing time.

Let $G = \langle V, \Phi \rangle$ be a factor graph with n variables, at most s states per variable, e factors, and hierarchy width h. If we let

$$M = \max_{\phi \in \Phi} \left(\max_{I} \phi(I) - \min_{I} \phi(I) \right),$$

then we can bound the mixing time of Gibbs sampling on Gwith

$$t_{\min} \le \left(\log(4) + n\log(s) + eM\right) n \exp(3hM).$$

In particular, if $hM = O(\log n)$, then Gibbs sampling mixes in polynomial time.

Example: Voting model (logical). *Example:* Voting model (linear).

1 2 n n+1 $\left(\begin{array}{c}F_1\end{array}\right)$

 $\left(\begin{array}{c}F_2\end{array}\right)\cdots\left(\begin{array}{c}F_n\end{array}\right)$ This model has 2n factors, all of which are

adjacent. Therefore, its hierarchy width is $\mathsf{hw}(G) = 2n.$

 \triangleright Actually mixes in $\exp(\Omega(n))$ time. ▷ This means Gibbs is *infeasible*.

Example: Path graph.



Removing factor ϕ_2 disconnects the graph, so we can label both ϕ_1 and ϕ_3 as 2. So, this graph has hw(G) = 2.

$$v_1$$
 ϕ_1 v_2 ϕ_2 v_3 ϕ_3 v_4 \cdots v_r

In general, the path graph has hierarchy width $hw(G) = \lceil \log_2 n \rceil$.

▷ Guaranteed to mix in polynomial time.

Hierarchy width is an *upper bound* on the commonly-used graph metric, *hypertree width*. Hierarchy width is also an upper bound on the maximum degree of a variable in the graph.

Hierarchical Templates

Our contribution: we introduce *hierarchical templates*, which when instantiated on any dataset produce models that are guaranteed to *mix in polynomial time*.

We call \hat{x} a *head symbol*, and y a *body symbol*. (Details of template instantiation appear in the paper.)

A template factor is *hierarchical* if all its head symbols appear in the same order in each of its terms. (In particular, our example above is hierarchical.) A template is hierarchical if all its factors are hierarchical.





Facts about Hierarchy Width

One of the useful properties of the hierarchy width is that, for any fixed k, computing whether a graph G has *hierarchy width* $hw(G) \leq k$ can be done in time polynomial in the size of G. ▷ This is similar to many other useful graph widths.

A factor graph template is an abstract model that can be instantiated on a dataset to produce a factor graph. They are commonly used to construct models, including in state-of-the-art systems.

A template consists of template factors like

 ϕ (TweetedAbout(\hat{x}, y), IsPopular(\hat{x})).

Hierarchical templates always mix fast.

The hierarchy width of a template instance is no greater than the number of template factors in the template. Combining this with our other result, **hierarchical templates** produce models that always mix in polynomial time!

Here is an outline of our results:

