# FPTAS for #BIS with degree bounds on one side

**Pinyan Lu, ITCS@SUFE** Institute for Theoretical Computer Science Shanghai University of Finance and Economics

## Outline

Counting and probability distribution

Correlation decay approach

 FPTAS for #BIS with degree bounds on one side

- SAT: Is there a satisfying assignment for a given a CNF formula?
- Counting SAT: How many?
- Counting Colorings of a graph
- Counting Independent sets of a graph
- Counting perfect matchings of a bipartite graph (Permanent)

• Probability

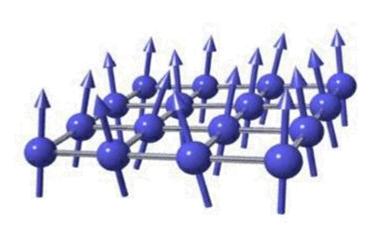
Blackjack Card Counting Learn How to Count Cards- An Interactive Games Quiz Book

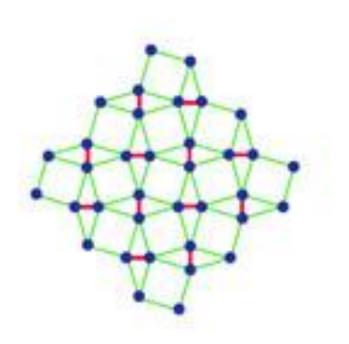




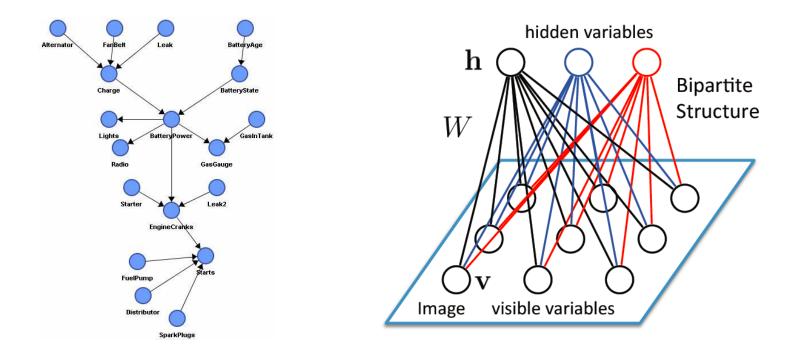


- Probability
- Partition function on statistical physics

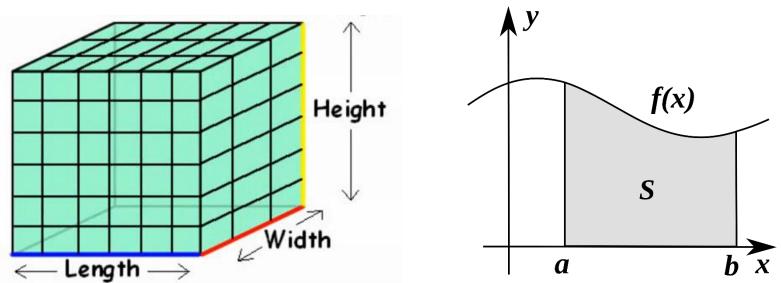




- Probability
- Partition function on statistical physics
- Inference on Graphical Models



- Probability
- Partition function on statistical physics
- Inference on Graphical Models
- Volume estimation and numerical integration



- Probability
- Partition function on statistical physics
- Inference on Graphical Models
- Volume estimation and numerical integration
- Query on probabilistic database
- Optimization on stochastic model
- •

## Approximate Counting

- Let  $\epsilon > 0$  be an approximation parameter and Zbe the correct counting number of the instance, the algorithm returns a number Z' such that  $(1 - \epsilon)Z \leq Z' \leq (1 + \epsilon)Z$ , in time ploy $(n, 1/\epsilon)$ .
- Fully polynomial-time approximation scheme (FPTAS).
- Fully polynomial-time randomized approximation scheme (FPRAS) is its randomized version.

## **Counting vs Distribution**

- IS(G): the set of independent sets of graph G
- X is chosen from IS(G) uniformly at random
- $P_G(v)$ : the probability that v is not in X

• 
$$\Pr(X = \emptyset) = \frac{1}{|IS(G)|}$$

•  $Pr(X = \emptyset) = P_{G_1}(v_1)P_{G_2}(v_2) \dots P_{G_n}(v_n),$ where  $G_1 = G, G_{i+1} = G_i - v_i$ 

## **Counting vs Distribution**

- $\frac{1}{|IS(G)|} = P_{G_1}(v_1)P_{G_2}(v_2)\dots P_{G_n}(v_n)$
- If we can compute (estimate)  $P_G(v)$ , we can (approximately) compute |IS(G)|.

- FPRAS: Estimate  $P_G(v)$  by sampling
- FPTAS: Approximately compute  $P_G(v)$  directly and deterministically

#### **Counting vs Distribution**



# **Counting vs Distribution** Correlation Decay Sampling Probability Counting FPRAS Other methods

## Outline

Counting and probability distribution

Correlation decay approach

 FPTAS for #BIS withdegree bounds on one side

#### **Computation Tree**

• Relate the probability  $P_G(v)$  to these of its neighbors in smaller instances.

•  $P_G(v) = f(P_{G_1}(v_1), P_{G_2}(v_2), \dots, P_{G_d}(v_d))$  $P_{G_1}(v_1)$   $P_{G_2}(v_2)$   $P_{G_d}(v_d)$ 

#### An example of independent sets

•  $P_G(v) = \frac{Z(G-v)}{Z(G)} = \frac{Z(G-v)}{Z(G-v) + Z(G-v-N(v))}$ 1+Z(G-v-N(v))/Z(G-v)•  $\frac{Z(G-\nu-N(\nu))}{Z(G-\nu)} = P_{G-\nu}(\nu_1\nu_2\cdots\nu_d)$  $= P_{G_1}(v_1)P_{G_2}(v_2) \dots P_{G_d}(v_d)$ where  $G_1 = G - v_i G_{i+1} = G_i - v_i$ •  $P_G(v) = \frac{1}{1 + P_{G_1}(v_1) P_{G_2}(v_2) \dots P_{G_d}(v_d)}$ 

#### **Computation Tree**

• Relate the probability  $P_G(v)$  to these of its neighbors in smaller instances.

•  $P_G(v) = f(P_{G_1}(v_1), P_{G_2}(v_2), \dots, P_{G_d}(v_d))$  $P_{G_1}(v_1)$   $P_{G_2}(v_2)$   $P_{G_d}(v_d)$ 

## **Correlation Decay**

Truncate the computation tree at depth L, we can compute an estimation  $P_G^L(v)$ .

The system is called of exponential correlation decay if

$$\left|P_G^L(v) - P_G(v)\right| \le \exp(-L).$$

We can estimate  $P_G(v)$  by set  $L = O(\log n + \log \frac{1}{\epsilon})$ 

#### **Computational Efficient Correlation Decay**

• M-based depth:

 $-L_M(root)=0;$ 

- $-L_M(u) = L_M(v) + \lceil \log_M(d+1) \rceil$ , if u is one of the d children of v.
- Exponential correlation decay with respect to M-based depth.
- Computational efficient correlation decay supports FPTAS for general graph.

#### **Proof Sketch for Correlation Decay**

• 
$$p = f(p_1, p_2, ..., p_d)$$

• Estimate the error for one recursive step:

$$\begin{aligned} \epsilon &= \frac{\partial f}{\partial p_1} \epsilon_1 + \frac{\partial f}{\partial p_2} \epsilon_2 + \dots + \frac{\partial f}{\partial p_d} \epsilon_d \\ |\epsilon| &\leq \left( \left| \frac{\partial f}{\partial p_1} \right| + \left| \frac{\partial f}{\partial p_2} \right| + \dots + \left| \frac{\partial f}{\partial p_d} \right| \right) \max(|\epsilon_i|) \\ \left( \left| \frac{\partial f}{\partial p_1} \right| + \left| \frac{\partial f}{\partial p_2} \right| + \dots + \left| \frac{\partial f}{\partial p_d} \right| \right) < 1 \end{aligned}$$

## **Potential Function**

- This may not be correct stepwise. We use a potential function to amortize it.
- Let  $\phi: R^+ \to R^+$  be a bijective function.  $q = \phi(p), q_i = \phi(p_i).$
- $q = \phi(f(\phi^{-1}(q_1), \phi^{-1}(q_2), \dots, \phi^{-1}(q_d)))).$
- Then we show that the error for *q* is stepwise decreased by a constant factor.
- The main difficulty is to find the potential function  $\phi$ .

#### Some examples

- Independent set [Weitz 06]
- Graph coloring [Gamarnik, Katz 07][L., Yin 13]
- Anti-Ferromagnetic 2-spin system [Li, L., Yin 12,13] [Sinclair, Srivastava, Thurley 12]
- Ferromagnetic 2-spin system [Guo, L. 15]
- Edge covers [Lin, Liu, L. 14] [Liu, L., Zhang 14]
- Monotone CNF [Liu, L. 15][L. Yang, Zhang 16] [Bezakova, Galanis, Goldberg, Guo, Stefankovic 16]
- Hyper graph matching [Liu, L. 15] [Yin, Zhao 15]

## Outline

Counting and probability distribution

Correlation decay approach

 FPTAS for #BIS with degree bounds on one side

# Counting Independent Sets (#IS)

- NP-hard (reduced from maximum IS)
- FPRAS for maximum degree 3 and then 4 [Dyer, Greenhill 00][Luby, Vigoda 97]
- NP-hard if Δ achieves 25 (reduced from Max Cut) [Dyer, Frieze, Jerrum 02]
- FPTAS for  $\Delta \leq 5$  [Weitz 06]
- NP-hard if  $\Delta = 6$  (reduced from Max Cut) [Sly 10]

#### Correlation decay for #IS

• 
$$P_G(v) = \frac{1}{1 + P_{G_1}(v_1)P_{G_2}(v_2)...P_{G_d}(v_d)}$$
  
• Define:  $R_G(v) = \frac{1 - P_G(v)}{P_G(v)}$ 

• 
$$R_{G}(v) = \prod_{i=1}^{d} \frac{1}{1 + R_{G_{i}}(v_{i})}$$

• Define: 
$$f(x) = \prod_{i=1}^{d} \frac{1}{1+x_i}$$

## Correlation decay for #IS (cont.)

• 
$$f(\mathbf{x}) = \prod_{i=1}^{d} \frac{1}{1+x_i}$$

• Find  $\Phi(\cdot)$  such that  $\sum_{i=1}^{d} \left| \frac{\partial f}{\partial x_i} \right| \left| \frac{\Phi(f)}{\Phi(x_i)} \right| < 1$ 

• Choose 
$$\Phi(x) = \frac{1}{\sqrt{x(1+x)}}$$

• 
$$\sum_{i}^{d} \left| \frac{\partial f}{\partial x_{i}} \right| \frac{\Phi(f)}{\Phi(x_{i})} = \sqrt{\frac{f}{1+f}} \sum_{i} \sqrt{\frac{x_{i}}{1+x_{i}}}$$

- Symmetrize x<sub>i</sub> by Jensen's inquality and get a function with a single variable
- It works!

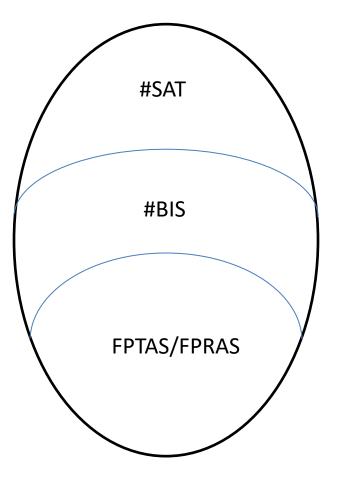
## #BIS

- Counting independent sets for bipartite graphs.
- Local MCMCs mixes slowly even on bipartite graphs.
- Max IS and Max-CUT are easy for bipartite graphs.
- #BIS with a maximum degree of 6 is already as hard as general #BIS (#BIS-hard). [CGGGJSV14]
- No algorithmic evidence to distinguish #BIS from #IS.

### #BIS

- Conjectured to be of intermediate complexity.
- Plays a similar role as the Unique Game for optimization problems.
- A large number of other problems are proved to have the same complexity as #BIS (#BISequivalent) or at least as hard as #BIS (#BIS-hard)

## Some approximation trichotomies



- Boolean CSP [Dyer, Goldberg, Jerrum 10]
- Degree bounded Boolean CSP [Dyer, Goldberg, Jalsenius, Richerby 12]
- Conservative weighted Boolean CSPs[Bulatov, Dyer, Goldberg, Jerrum, McQuillan 13]

## Our new algorithm

- FPTAS for #BIS when the maximum degree for one side is no larger than 5. [Liu, L. 2015]
- No restriction for the degrees on the other side.
- Identical to Weitz's algorithm for general #IS.
- Combine two recursion steps into one, and work with this two-layer recursion instead.

#### **Two-layer recursion**

• 
$$R_{G}(v) = \prod_{i=1}^{d} \frac{1}{1 + R_{G_{i}}(v_{i})}$$

• 
$$R_{G_i}(v_i) = \prod_{j=1}^{d_i} \frac{1}{1 + R_{G_{ij}}(v_{ij})}$$

• 
$$R_{G}(v) = \prod_{i=1}^{d} \left( 1 + \prod_{j=1}^{d_{i}} \frac{1}{1 + R_{G_{ij}}(v_{ij})} \right)^{-1}$$

• Define 
$$f(\mathbf{x}) = \prod_{i=1}^{d} \left( 1 + \prod_{j=1}^{d_i} \frac{1}{1 + x_{ij}} \right)^{-1}$$

#### **Choice of the Potential Function**

Recall: 
$$f(\mathbf{x}) = \prod_{i=1}^{d} \left( 1 + \prod_{j=1}^{d_i} \frac{1}{1 + x_{ij}} \right)^{-1}$$
  

$$\sum_{i,j} \left| \frac{\partial f}{\partial x_{ij}} \right| \frac{\Phi(f)}{\Phi(x_{ij})}$$

$$= \Phi(f) f \sum_{i} \frac{\prod_{j=1}^{d_i} \frac{1}{1 + x_{ij}}}{1 + \prod_{j=1}^{d_i} \frac{1}{1 + x_{ij}}} \sum_{j} \frac{1}{\Phi(x_{ij})(1 + x_{ij})}$$
Choose:  $\Phi(\mathbf{x}) = \frac{1}{(1 + x)Log(1 + x)}$ 
 $Log \prod_{j=1}^{d_i} (1 + x_{ij})$ 

• 
$$\Phi(x) = \frac{1}{(1+x)Log(1+x)}$$
  
• 
$$S_i \triangleq \prod_{j=1}^{d_i} \frac{1}{(1+x_{ij})}$$

• 
$$f(\mathbf{x}) = \prod_{i=1}^{d} \frac{1}{1+s_i}$$

• 
$$\sum_{i,j} \left| \frac{\partial f}{\partial x_{ij}} \right| \left| \frac{\Phi(f)}{\Phi(x_{ij})} \right| = -\Phi(f) f \sum_i \frac{s_i}{1+s_i} Log(s_i)$$

- Symmetrize s<sub>i</sub> and get a function with a single variable
- It works!

#### **Adaptive** Truncation

• 
$$R_{G}(v) = \prod_{i=1}^{d} \left( 1 + \prod_{i=1}^{d_{i}} \frac{1}{1 + R_{G_{ij}}(v_{ij})} \right)^{-1}$$

• d is bounded by 4 but there is no bound for  $d_i$ 

• Some  $d_i$  may even be super constant

• Computational efficient correlation decay

# Analogy with MCMC

- Algorithm design part is kind of standard.
- The over framework for the analysis is the same.
- A number of techniques and tools have been developed to the analysis.
- However, it is still very challenging to prove and many problems remains open.

#### Thank You!

Q & A