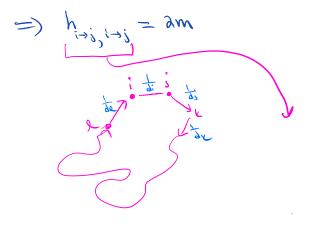
$$h_{ii} = \frac{1}{\pi_i} = \frac{2m}{d_i}$$

$$Pf: \quad (ansider \ corresponding random walkon directed edges (states are  $\frac{i-j}{j}$   $f(i) \neq e$ )  $\underline{\partial}m \ states$   
transition probabilities:  $9(i-j, e-r) = \begin{cases} d_j & e=j \\ 0 & o.w. \\ i & j & i \end{cases}$   
$$Q = (9z_i^2) \quad is \ donbly \ stochastic \\ (-j_2) & \frac{1}{2} &$$$$



\*

$$(\operatorname{crellang}) \begin{cases} (\operatorname{crellang}) \\ Y & G = (V, E) \\ \operatorname{connected} \\ \operatorname{han bipartite} \\ (\operatorname{or lazy}) \end{cases} \begin{pmatrix} (G) = expected cover time \leq 2 \operatorname{dm}(n-1) \\ \operatorname{d} \operatorname{random undle} \\ \operatorname{on } G \\ \operatorname{on } G \\ \operatorname{on } G \\ \operatorname{constand} \\ \operatorname{det} \\ (\operatorname{or} ) \\ \operatorname{end} \\ \operatorname{det} \\ (\operatorname{und}) \\ \operatorname{constand} \\ \operatorname{det} \\ \operatorname{tree} \\ \operatorname{constand} \\ \operatorname{constand} \\ \operatorname{tree} \\ \operatorname{constand} \\ \operatorname{tree} \\ \operatorname{constand} \\ \operatorname{tree} \\ \operatorname{constand} \\ \operatorname{tree} \\ \operatorname{constand} \\ \operatorname{constand} \\ \operatorname{tree} \\ \operatorname{consta$$

Examples  

$$(G) = \Theta(n^2)$$
  
 $d_{size} n d_{size} n d_{si$ 

Fact: Starting from v., Pr(nuch v. before reduring to vo)=ty



Observation: very simple randomized alg using logspace (input on separate read-only tape

Both algorithms 
$$\widetilde{O}(mn)$$
 space-time  
(an we interpolate?,

## Monte Canlo Methods

collection of tools for entimating values three sampling & estimation

## (E, S) Approximation

A randomized all gives an (E,E) approx for value V if the antput X of the alg satisfies Pr(1X-V1 > E1V1) = 5

## Example

Sample indep random vans whose mean is quantity we want  
to estimate  
Let 
$$X_{1}, X_{3}, ..., X_{m}$$
 iid. Barmanlli with  $E(X_{i}) = M$   
If  $m \ge \frac{3 \ln(\frac{2}{5})}{\epsilon^{2}m}$  then  
 $P(\left| \frac{1}{m}, \frac{m}{\epsilon} X_{i} - M\right| \ge \epsilon M) \le \delta$  P(; Chandi bounds

Monte Carlo Thm

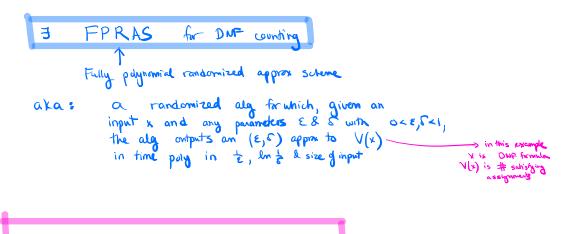
DNF Counting

Suppose want to know # sodisfying assignments  
$$(\overline{x}_1, n\overline{x}_2) \vee (\overline{x}_2, n\overline{x}_3) \vee (\overline{x}_1, n\overline{x}_2, n\overline{x}_4) \vee (\overline{x}_3, n\overline{x}_4)$$

Obviously satisfying such a formula is easy counting # satisfying assequents is hand If could do this, could solve 35AT

.

Approximate DNF Counting? Obvious approach: sample vandom assignments, indep in times  $X_i = \begin{cases} 1 & \text{im random assignments} \\ \infty & \text{output} \end{cases}$  ruturn  $\sum_{i=1}^{\infty} \frac{X_i}{m} - 2^n$  as astract



$$\overline{V}$$
 is  $(\varepsilon, \varepsilon)$  approx to  $V \equiv \Pr((\overline{V} - V) > \varepsilon V) \leq \varepsilon$ 

DNF counting illustrates fundamental connection  
sampling 
$$\iff$$
 counting  
From approx sampling  $\implies$  approx counting  
(counting Independent Sets  
Imput:  
 $x_1 \in \bigoplus$  FPAUS  
Fully polynomial  
almost uniform  
sampler  
 $Y_S |Pr(weS) - \frac{1SI}{DI}| \leq \epsilon$   
runs in time  
polynomial in sized x  
 $\mathcal{L}(t)$ 

y.

Want to show:

$$G=(V_{1}E) = e_{1}e_{1}\dots e_{m} \text{ arbitrary ordering d edges}$$

$$E_{i} = \{e_{1}e_{2}\dots e_{i}\} \quad G_{i} = (V_{1}E_{i}) \quad G_{m}=G \quad G_{0}=(V_{1}\varphi)$$

$$\mathcal{N}(G_{i}): \text{set } g \quad I \leq s \quad \text{in } G_{i};$$

$$|\mathcal{N}(G_{i})| = \frac{|\mathcal{N}(G_{m})|}{|\mathcal{N}(G_{m})|} \times \frac{|\mathcal{N}(G_{m})|}{|\mathcal{N}(G_{m})|} \times$$

So need to bound 
$$R = \prod_{i=1}^{n} \prod_{r=1}^{n} \prod_{r=1}$$

For this to work, need  $r_{i=} \frac{I2(G_i)}{IN(G_{i-1})}$  not too small (no node in harshulk)

(laum: r: >1

=) with polynomially many alls to FPAOS, we can get good approx F: to r: using Manke Carle Thm Two errors we need to bound;

() FPAUS 
$$\neq$$
 exact sampler so unique  $\neq r$ :  
But using, say,  $\frac{\varepsilon}{6m}$  sampler  $|E(\vec{r}_i) - r_i| \leq \frac{\varepsilon}{6m}$   
(2) With samples we get approx to  $E(\vec{r}_i)$   
since  $r_i$  big  $(2, \frac{1}{2})$ ,  $E(\vec{r}_i)$  big =)  
Monte (and Three =)  $O(\frac{m^2}{\varepsilon^2} lm(\frac{1}{\varepsilon}))$  samples suffix

Approach works for many "self-reducible" problems

Another example: counting # matchings in agraph  
Again: 
$$E = \{e_1, \dots, em\}$$
  
 $G_i = (V, E_i)$  where  $E_i = \{e_1, \dots, ei\}$   
 $IM(G) = IM(Gm) | IM(Gmn) | \dots | M(G_2) | [M(G_1)]$   
 $IM(G) | = IM(Gm) | IM(Gmn) | \dots | M(G_2) | [M(G_1)]$ 

Like before: 
$$\frac{M(G_{i})}{M(G_{i+1})} > \frac{1}{2}$$

Big question remains: how to construct approx sampler?

How to sample elts from a universe R according to some distin TT?

- Cool idea! design MC whose state space is IL that has stationary distin TT • simulate MC until it "mixes" • use state at that fine as sample
  - 2 key questions: (D) how to design their with right TT? (2) how to bound mixing time?
  - Example: Sampling indep sets uniformly from G-(V,E) States: indep sets X<sub>t</sub>: some indep set MC: in each step choose ventex v u.a.r. from V y v ∈ X<sub>t</sub>, then X<sub>t+i</sub>:= X<sub>t</sub>/v y v ∉ X<sub>t</sub> & can be added us/ violating independence, then X<sub>t+i</sub>:= X<sub>t</sub> UV Otherwise X<sub>t+i</sub>:= X<sub>t</sub>