

**Verjetnostne metode v  
računalništvu - zapiski s  
predavanj prof. Marca**

Tomaž Poljanšek

študijsko leto 2023/24

# Kazalo

<b>1</b>	<b>Introduction</b>	<b>1</b>
1.1	Probability . . . . .	1
1.2	Random variables . . . . .	2
<b>2</b>	<b>Quicksort, min-cut</b>	<b>4</b>
2.1	Quicksort . . . . .	4
2.2	Min-cut . . . . .	6
<b>3</b>	<b>Complexity classes</b>	<b>9</b>
<b>4</b>	<b>Chernoff bounds</b>	<b>11</b>
<b>5</b>	<b>Monte Carlo methods</b>	<b>16</b>
5.1	Example 1 . . . . .	16
5.2	Example 2 . . . . .	16
5.3	$(\epsilon, \delta)$ -approximation . . . . .	17
5.4	DNF counting . . . . .	18
<b>6</b>	<b>Polynomials</b>	<b>20</b>
<b>7</b>	<b>Random graphs</b>	<b>24</b>
7.1	$G(n, p)$ model . . . . .	24
7.2	Barbási-Albert Model . . . . .	27
<b>8</b>	<b>Markov chains</b>	<b>29</b>

8.1	2-SAT . . . . .	32
8.2	Generating a uniformly random element of a set . . . . .	33
8.3	Metropolis algorithm . . . . .	34
8.4	M.C. for 1-factor in bipartite graphs . . . . .	37
<b>9</b>	<b>Randomized incremented constructions (RIC)</b>	<b>39</b>
9.1	Quicksort as RIC . . . . .	40

# Poglavje 1

## Introduction

### 1.1 Probability

$(\Omega, F, P_r)$ :

- $\emptyset \in F$ ,
- $A \in F \implies A^c \in F$ ,
- $A_1, A_2 \dots \in F \implies \cup_{i=1}^{\infty} A_i \in F$ .

$P_r(A) \geq 0$ ,

$P_r(\cup_{i=1}^{\infty} A_i) = \sum_{i=1}^{\infty} P_r(A_i)$  if  $A_i$  disjoint,

$P_r(\cup_{i=1}^{\infty} A_i) \leq \sum_{i=1}^{\infty} P_r(A_i)$ ,

$\Omega = \{\omega_1, \omega_2 \dots\}$  - countable case.

$$\begin{pmatrix} \omega_1 & \omega_2 & \dots \\ p_1 & p_2 & \dots \end{pmatrix}$$

*Primer.*

`Alg():`

`while True:`

`B = sample as random from {0,1} # 1 with probability p`

`if B = 1:`

return

$$\Omega = \{1, 01, 001, 0001 \dots\}$$

$$\begin{pmatrix} 1 & 01 & 001 & 0001 & \dots \\ p & (1-p)p & (1-p)^2p & (1-p)^3p & \dots \end{pmatrix}.$$

## 1.2 Random variables

$X : \Omega \rightarrow \mathbb{Z}$ .

$E[X] = \sum_{c \in \mathbb{Z}} c \cdot P_r(X = c)$  expected value of  $X$ .

Properties:

- $E[f(X)] = \sum_{c \in \mathbb{Z}} f(c) \cdot P_r(X = c)$ ,
- $E[aX + bY] = aE[X] + bE[Y]$ ,
- $E[X \cdot Y] = E[X] \cdot E[Y]$  if  $X, Y$  independent,
- $P_r(X \geq a) \leq \frac{E[X]}{a} \forall a > 0, X \geq 0$  Markov inequality.

*Primer.* (Continuing from before).

$X$  = number of trials before return.

$X : \Omega \rightarrow \mathbb{Z}$ .

$X : 1 \rightarrow 1, 01 \rightarrow 2, 001 \rightarrow 3 \dots$

$$\begin{pmatrix} 1 & 2 & 3 & 4 & \dots \\ p & (1-p)p & (1-p)^2p & (1-p)^3p & \dots \end{pmatrix} - \text{geometric distribution.}$$

**Trditev 1.2.1.**  $E[X] = \frac{1}{p}$ .

**Dokaz 1.2.2.**  $X = \sum_{i=1}^{\infty} X_i$ .

$$X_i = \begin{cases} 1 & \text{if trial } i \text{ is executed} \\ 0 & \text{else} \end{cases}$$

$$\begin{aligned} E[X] &= E\left[\sum_{i=1}^{\infty} X_i\right] = \sum_{i=1}^{\infty} E[X_i] = \\ &= \sum_{i=1}^{\infty} (1-p)^{i-1} = \frac{i=0}{\infty} (1-p)^i = \frac{1}{1-(1-p)} = \frac{1}{p}. \end{aligned}$$

$$E[X] = \frac{1}{p}.$$

$$P_r(X \geq 100 \cdot \frac{1}{p}) \leq \frac{E[X]}{\frac{1}{p}} = \frac{1}{100}.$$

**Definicija 1.2.3.**  $H_n = 1 + \frac{1}{2} + \frac{1}{3} + \dots + \frac{1}{n} = \sum_{i=1}^{\infty} \frac{1}{i}$ .

**Izrek 1.2.4.**  $H_n \leq 1 + \ln(n)$ .

**Dokaz 1.2.5.**

$$H_n = 1 + \sum_{i=2}^n \frac{1}{i} \stackrel{\text{integral}}{\leq} 1 + \int_1^n \frac{dx}{x} = 1 + \ln(x)|_1^n = 1 + \ln(n).$$

# Poglavje 2

## Quicksort, min-cut

### 2.1 Quicksort

Input: set (no equal element) (unordered list)  $S \in \mathbb{R}$   
(or whatever you can compare linearly)

Output: ordered list

Code:

```
def Quicksort(S):  
    if |S| = 0 or 1:  
        return S  
    else:  
        a = uniformly at random from S  
         $S^- = \{b \in S \mid b < a\}$   
         $S^+ = \{b \in S \mid a < b\}$   
        return Quicksort( $S^-$ ), a, Quicksort( $S^+$ )
```

$C(n)$  - random variable, the number of comparisons in evaluation of Quicksort with  $|S| = n$ .

**Izrek 2.1.1.**  $E[C(n)] = O(N \log(n))$ .

**Dokaz 2.1.2.**  $C(0) = C(1) = 0$ .

$$\begin{aligned}
E[C(n)] &= n - 1 + \sum_{i=1}^n (E[C(i-1)] + E[C(n-i)]) \cdot P_r(a \text{ is } i\text{-it element}) \leq \\
&\leq n + \frac{2}{n} \sum_{i=1}^{n-1} E[C(i)].
\end{aligned}$$

Induction:

$n = 1 : \checkmark$

$n - 1 \rightarrow n$ :

$$\begin{aligned}
E[C(n)] &\leq n + \frac{2}{n} \sum_{i=1}^n E[C(i)] \leq \\
&\leq n + \frac{2}{n} \sum_{i=1}^n 5i \log i \leq \\
&\leq n + \frac{2}{n} \sum_{i=1}^{\lfloor \frac{n}{2} \rfloor} 5i \log i + \frac{2}{n} \sum_{i=1+\lfloor \frac{n}{2} \rfloor}^{n-1} 5i \log i \leq \\
&\leq n + \frac{2}{n} \sum_{i=1}^{\lfloor \frac{n}{2} \rfloor} 5i \log \frac{n}{2} + \frac{2}{n} \sum_{i=1+\lfloor \frac{n}{2} \rfloor}^{n-1} 5i \log n \leq \\
&(\log \frac{n}{2} = \log n - 1) \\
&\leq n + \frac{2}{n} \left( \sum_{i=1}^n 5i \log n - \sum_{i=1}^{\frac{n}{2}} 5i \right) = \\
&= n + \frac{10}{n} \left( \frac{n(n-1)}{2} \log n - \frac{\frac{n}{2}(\frac{n}{2}+1)}{2} \right) \leq \\
&\leq n + 5(n-1) \log n - n < \\
&< 5n \log n.
\end{aligned}$$

$$P(C(n) \geq b \cdot 5n \log n) \stackrel{\text{Markov}}{\leq} \frac{1}{b}.$$

**Dokaz 2.1.3.**

2:

Let  $S_1, S_2 \dots S_n$  sorted elements of  $S$ .

Define random variable  $X_{ij} = \begin{cases} 1 & \text{if } S_i \text{ and } S_j \text{ are compared} \\ 0 & \text{else} \end{cases}$



$$C(n) = \sum_{1 \leq i < j \leq n} E[X_{ij}].$$

$$E[X_{ij}] = P(S_i \text{ and } X_j \text{ compared}).$$

$S_{ij}$  - the last set including  $S_i$  and  $S_j$ .

$$E[X_{ij}] = \frac{2}{|S_{ij}|} \leq \frac{2}{j-i+1}.$$

$$|S_{ij}| \geq j - i + 1.$$

$S_{ij}$  has everything in between.

$$\begin{aligned} \Rightarrow E[C(n)] &\leq \sum_{1 \leq i < j \leq n} \frac{2}{j-i+1} = \\ &= \sum_{k=j-i+1}^{n-1} \sum_{i=1}^{n-1} \frac{2}{k} \leq \\ &\leq 2 \cdot n \cdot H_n \leq \\ &\leq 2n(1 + \log n). \end{aligned}$$

## 2.2 Min-cut

$G$  multigraph.

Cut:  $U \subset V(G)$ ,  $U \neq \emptyset, V(G)$ .

$$(U, V(G) \setminus U) = \{uv \in E(G) \mid u \in U, v \in V(G) \setminus U\}.$$

Problem min-cut:

Input:  $G$ .

Output:  $\min |(U, V(G) \setminus U)|$  - cut size.

Algorithm 1:

$x \in V(G)$

Call  $\text{maxFlow}(G, x, y) \forall y \in V(G)$

Take  $\min$

$\text{maxFlow}$  is Edmonds-Karp algorithm  $O(|V||E|^2)$ .

Algorithm 2 (Stoer Wagner)

Is  $O(|E||V| + |V|\log|V|)$ .

Algorithm *randMinCut*:

```

G_0 = G
i = 0
while |V(G_i)| > 2:
    e_i = uniformly at random from G_i
    G_{i+1} = G_i / e_i
    i = i + 1
u, v = V(G_{n-2}) // n = |V(G)|
U = {w ∈ V(G) | w is merged into u}
return (U, V(G) \ U)

```

**Izrek 2.2.1.** Algorithm *randMinCut* gives you a minimal cut with probability greater or equal to  $\frac{2}{n(n-1)}$ .

**Dokaz 2.2.2.**

Fact 1:  $\minCut(G_i) \leq \minCut(G)$ ;

$\nexists$ : *minCut* remains.

Fact 2:  $\minCut(G) \leq \delta(G)$ .

$k := \minCut(G)$ .

Let  $(A, B)$  be an optimal cut.

$\epsilon_i$  not in  $(A, B)$ .

$$\begin{aligned}
 & P_r(\text{Algorithm not returning } (A, B)) \\
 &= P_r(\epsilon_0 \cap \dots \cap \epsilon_{n-3}) \\
 &= P_r(\epsilon_0 \cap \dots \cap \epsilon_{n-4}) \cdot P_r(\epsilon_{n-3} \mid \epsilon_0 \cap \dots \cap \epsilon_{n-4}) \\
 &= P_r(\epsilon_{n-3} \mid \cap_{i=0}^{n-4} \epsilon_i) \cdot P_r(\epsilon_{n-3} \mid \cap_{i=0}^{n-4} \epsilon_i) \\
 &\dots P_r(\epsilon_1 \mid \epsilon_0) \cdot P_r(\epsilon_0). (*)
 \end{aligned} \tag{2.1}$$

$$P_r(\bar{\epsilon}_i \mid \epsilon_{i-1} \cap \dots \cap \epsilon_0) = \frac{k}{|E(G_i)|} \stackrel{(**)}{\leq} \frac{k}{\frac{(n-i)k}{2}} = \frac{2}{n-i}$$

$$|E(G_i)| \geq \frac{(n-i)\delta(G)}{2} \geq \frac{(n-i)k}{2}. (**) \tag{2.2}$$

$$P_r(\epsilon_i \mid \epsilon_{i-1} \cap \dots \cap \epsilon_0) \geq 1 - \frac{2}{n-i} = \frac{n-2-i}{n-i}.$$

$$(*) \geq \frac{n-2}{n} \cdot \frac{n-3}{n-1} \cdots \frac{1}{3} = \frac{2}{n(n-1)}.$$

**Izrek 2.2.3.** Running *randMinCut*  $n(n-1)$  times and taking best output gives correct solution with probability  $\geq 0.86$ .

**Dokaz 2.2.4.**  $A_i$  - event that  $i$ -th run gives sub-optimal solution.

$$\begin{aligned} P_r(\text{solution not correct}) &= P_r(A_1 \cap \dots \cap A_{n(n-1)}) \\ &= \prod_{i=1}^{n(n-1)} P_r(A_i) \leq \left(1 - \frac{2}{n(n-1)}\right)^{n(n-1)} \\ &\leq e^{-\frac{2}{n(n-1)} \cdot n(n-1)} = e^{-2} \leq 0.14. \end{aligned}$$

$$1 - x \leq e^x \quad \forall x \in \mathbb{R}.$$

If we run  $n(n-1)\log(n)$  times  $\rightarrow O\left(\frac{1}{n}\right)$ .

$O(n^2 \log n \cdot n)$ .

Improved:  $O(n^2 \log^3 n)$ .

# Poglavje 3

## Complexity classes

Decision problem - yes/no question on a set of inputs = asking  $w \in \Pi$ .

Randomized algorithms:

- Las Vegas algorithms: always gives correct solution, example: *Quicksort*.
- Monte Carlo algorithms: it can give wrong answers. Monte Carlo algorithms subtypes:

$$- \text{type}(1): \begin{cases} \text{if } \omega \in \Pi \implies \text{algorithm returns „}\omega \in \Pi\text{“ with probability } \geq \frac{1}{2} \\ \text{if } \omega \notin \Pi \implies \text{algorithm returns „}\omega \in \Pi\text{“ with probability } = 0 \end{cases}$$

$$- \text{type}(2): \begin{cases} \text{if } \omega \in \Pi \implies \text{algorithm returns „}\omega \in \Pi\text{“ with probability } = 1 \\ \text{if } \omega \notin \Pi \implies \text{algorithm returns „}\omega \in \Pi\text{“ with probability } \leq \frac{1}{2} \end{cases}$$

$$- \text{type}(3): \begin{cases} \text{if } \omega \in \Pi \implies \text{algorithm returns „}\omega \in \Pi\text{“ with probability } \geq \frac{3}{4} \\ \text{if } \omega \notin \Pi \implies \text{algorithm returns „}\omega \in \Pi\text{“ with probability } \leq \frac{1}{2} \end{cases}$$

type(1) and type(2): one-sided error, type(3): 2-sided error.

$\frac{1}{2}$ ,  $\frac{3}{4}$  and  $\frac{1}{4}$  arbitrary numbers, can be something different (for type(3) better than coin flip).

*Primer.* Decisional problem: does a graph  $G$  have  $\text{minCut} \leq k$ ?

Run  $randMinCut(G)$   $n(n-1)$  times.

```
Algorithm randMinCut:
  if one of runs gives  $|A, B| \leq k$ :
    return true
  else:
    return false
```

Complexity classes:

- RP (randomized polynomial time): decisional problems for which there exists Monte Carlo algorithm of type(1) with polynomial time complexity (worst case).
- co-RP: decisional problems for which there exists Monte Carlo algorithm of type(2) with polynomial time complexity (worst case).
- BRP (bounded-error probabilistic polynomial time): decisional problems for which there exists Monte Carlo algorithm of type(3) with polynomial time complexity (worst case).
- ZPP (zero-error probabilistic polynomial time): decisional problems for which there exists Las Vegas algorithm with expected polynomial time complexity (worst case).

$ZPP = RP \cap co-RP$ .

## Poglavje 4

### Chernoff bounds

**Izrek 4.0.1.** Let  $X_1, X_2 \dots X_n$  independent random variables with image  $\{0, 1\}$ .

Let  $p_i = P_r(X_i = x_i)$ ,  $X = \sum_{i=1}^n X_i$  and  $\mu = E(X) = p_1 + \dots + p_n$ .

For every  $\delta \in (0, 1)$ :

$$\begin{aligned} P_r(X - \mu \geq \delta\mu) &\leq e^{-\frac{\delta^2\mu}{3}} \\ P_r(\mu - X \leq \delta\mu) &\leq e^{-\frac{\delta^2\mu}{2}} \\ \implies P_r(|X - \mu| \geq \delta\mu) &\leq e^{-\frac{\delta^2\mu}{3}}. \end{aligned}$$

Probability falls extremely quickly after  $E(X)$ .

**Dokaz 4.0.2.**

$$\begin{aligned}
P_r(X - \mu \geq \delta\mu) &= P_r(X \geq \mu(1 + \delta)) \\
&\stackrel{t \geq 0}{=} P_r(tX \geq t\mu(1 + \delta)) \\
&\stackrel{e^y \geq 0}{=} P_r(e^{tX} \geq e^{t\mu(1 + \delta)}) \\
&\stackrel{\text{Markov}}{\leq} \frac{E(e^{tX})}{e^{t\mu(1 + \delta)}} \\
&\stackrel{4.1}{\leq} \frac{e^{(e^t - 1)\mu}}{e^{t\mu(1 + \delta)}} \\
&\stackrel{4.3}{\leq} e^{-\mu \frac{\delta^2}{3}}.
\end{aligned}$$

$$\begin{aligned}
E(e^{tX}) &= E(e^{tX_1 + \dots + tX_n}) \\
&= E(e^{tX_1} \dots e^{tX_n}) \\
&\stackrel{\text{independent}}{=} \prod_{i=1}^n E(e^{tX_i}) \\
&\stackrel{4.2}{\leq} \prod_{i=1}^n e^{p_i(e^t - 1)} \\
&= e^{(e^t - 1) \sum_{i=1}^n p_i} \\
&= e^{(e^t - 1)\mu}. \tag{4.1}
\end{aligned}$$

$$E(e^{tX_i}) = p_i \cdot e^t + (1 - p_i) \cdot e^0 = 1 + p_i(e^t - 1) \stackrel{1+x \leq e^x}{\leq} e^{p_i(e^t - 1)}. \tag{4.2}$$

Want:

$$e^t - 1 - t(1 + \delta) \leq -\frac{\delta^2}{3} \quad \forall \delta \in (0,1) \tag{4.3}$$

$$t = \ln(1 + \delta)$$

$$f(\delta) = 1 + \delta - 1 - (1 + \delta) \ln(1 + \delta) + \frac{\delta^2}{3} \stackrel{?}{\leq} 0$$

$$f(0) = 0$$

$$f'(\delta) = 1 - \ln(1 + \delta) - 1 + \frac{2}{3}\delta = \frac{2}{3}\delta - \ln(1 + \delta) \stackrel{?}{\leq} 0$$

$$\frac{2}{3}\delta \leq \ln(1 + \delta)$$

$$\delta = 1 : \frac{2}{3} \stackrel{?}{\leq} \ln(2) \approx 0.69 \checkmark$$

$$\begin{aligned}
P_r(\mu - X \leq \delta\mu) &= P_r(X \geq \mu(1 - \delta)) \\
&\stackrel{t \geq 0}{=} P_r(tX \geq t\mu(1 - \delta)) \\
&\stackrel{e^y \geq 0}{=} P_r(e^{tX} \geq e^{t\mu(1 - \delta)}) \\
&\leq \dots \leq \frac{e^{(e^t - 1)\mu}}{e^{t\mu(1 - \delta)}}.
\end{aligned}$$

Want:  $e^t - 1 - t(1 - \delta) \leq -\frac{\delta^2}{2} \forall \delta \in (0,1)$ :

$$\begin{aligned}
t &= \ln(1 - \delta) \\
f(\delta) &= 1 - \delta - 1 - (1 - \delta) \ln(1 - \delta) + \frac{\delta^2}{2} \stackrel{?}{\leq} 0 \\
f(0) &= 0 \\
f'(\delta) &= -1 + 1 - \ln(1 - \delta) + \delta \stackrel{?}{\leq} 0 \\
\frac{2}{3}\delta &\leq \ln(1 + \delta) \\
\ln(1 - \delta) &\stackrel{?}{\leq} -\delta \checkmark
\end{aligned}$$

■

$$\begin{aligned}
X_i &\sim \begin{pmatrix} 0 & 1 \\ \frac{1}{2} & \frac{1}{2} \end{pmatrix} \\
X &= \sum_{i=1}^n X_i \\
\mu &= \frac{n}{2}
\end{aligned}$$

$$\begin{aligned}
P_r(|X - \mu| \geq \sqrt{\frac{3}{2}n \ln(n)}) &= P_r(|X - \mu| \geq \frac{n}{2} \sqrt{\frac{6}{n} \ln(n)}) \\
\mu &= \frac{n}{2}, \delta = \sqrt{\frac{6}{n} \ln(n)}, \\
\text{for „big“ } n\delta &\in (0,1) \\
&\stackrel{\text{Chernoff}}{\leq} 2e^{-\frac{\frac{n}{2} \frac{6}{n} \ln(n)}{3}} = \frac{2}{n}.
\end{aligned}$$

$$d = \sqrt{\frac{3}{2}n \ln(n)}$$

$$\implies P_r(X \in (\mu - \sqrt{\frac{3}{2}n \ln(n)}, \mu + \sqrt{\frac{3}{2}n \ln(n)})) \geq 1 - \frac{2}{n}.$$



**Trditev 4.0.3.**

Let  $X_1, X_2 \dots$  independent random variables with image  $\{0,1\}$ .

$$P_r(X_i = 1) = \frac{1}{2} \forall i.$$

Let  $X = \sum_{i=1}^{cm} X_i$  where  $c \geq 4$ .

Then  $P_r(X \leq m) \leq e^{-\frac{cm}{16}}$ .

**Dokaz 4.0.4.**

$$\begin{aligned} P_r(X \leq m) &= P_r\left(\frac{cm}{2} - X \geq \frac{cm}{2} - m\right) \\ &= P_r\left(\frac{cm}{2} - X \geq \frac{cm}{2}\left(1 - \frac{2}{c}\right)\right) \\ &\stackrel{\text{Chernoff}}{\leq} e^{-\frac{\frac{cm}{2}\left(1 - \frac{2}{c}\right)^2}{2}} \\ &\quad 1 - \frac{2}{c} \geq \frac{1}{2} \text{ if } c \geq 4 \\ &\leq e^{-\frac{\frac{cm}{2} \cdot \frac{1}{4}}{2}} = e^{-\frac{cm}{16}}. \end{aligned}$$

■

Back to Quicksort.

**Izrek 4.0.5.**

With probability  $\geq 1 - \frac{1}{n}$  Quicksort uses at most  $48n \ln(n)$  comparisons.

**Dokaz 4.0.6.**

For  $s \in S$  define  $S_1^S \dots S_{t_s}^S \neq \emptyset$  sets that include  $s$ ,  $t_s$  - number of comparisons with  $s$  where  $s$  is not a pivot +1.

Define: iteration  $i$  is successful if  $|S_{i+1}| \leq \frac{3}{4}|S_i|$  ( $\frac{1}{2}$  is too strict).

$$X_i = \begin{cases} 1 & \text{if iteration } i \text{ is successful} \\ 0 & \text{else} \end{cases}$$

$$P_r(X_i = 1) \geq \frac{1}{2}$$

$$S_i : n \rightarrow \frac{3}{4}n \rightarrow \left(\frac{3}{4}\right)^2 n \rightarrow \dots \rightarrow 1.$$

Notice: max number of iteration is  $\log_{\frac{4}{3}}(n) = \frac{\ln(n)}{\ln(4) - \ln(3)}$ .

Probability that we haven't succeeded in  $\log_{\frac{4}{3}}(n)$  steps:

$$P_r\left(\sum_{i=1}^{c \log_{\frac{4}{3}}(n)} X_i < \log_{\frac{4}{3}}(n)\right) \leq P_r\left(\sum_{i=1}^{c \log_{\frac{4}{3}}(n)} Y_i < \log_{\frac{4}{3}}(n)\right) \quad (4.4)$$

$$\stackrel{\text{Chernoff}}{<} e^{-\frac{c \log_{\frac{4}{3}}(n)}{24}} \quad (4.5)$$

$$= e^{-\frac{c \ln(n) \log_{\frac{4}{3}}(e)}{24}} \quad (4.6)$$

$$= \frac{1}{n} \frac{c \log_{\frac{4}{3}}(e)}{24} \quad (4.7)$$

$$\log_{\frac{4}{3}}(e) \approx 3.4, \quad c = 14 \quad (4.8)$$

$$\leq \left(\frac{1}{n}\right)^2 \quad (4.9)$$

4.4 because  $X_i$  not independent,  $Y_i \sim \begin{pmatrix} 0 & 1 \\ \frac{1}{2} & \frac{1}{2} \end{pmatrix}$  independent.

$P_r(t_s \geq c \log_{\frac{4}{3}}(n)) \geq \left(\frac{1}{n}\right)^2$  for one  $s$ .

$c = 14 \implies$  at least  $48 \ln(n)$  iterations with probability  $\leq \left(\frac{1}{n}\right)^2$ .

With probability as least  $1 - \frac{1}{n}$  for all  $s \in S$  it holds that  $s$  has  $\leq 48 \ln(n)$  comparisons with a pivot.

$\implies$  total number of comparisons  $n \cdot 48 \ln(n)$  with probability as least  $1 - \frac{1}{n}$ . ■

## Poglavje 5

# Monte Carlo methods

### 5.1 Example 1

Area of circle =  $\frac{\pi}{4}$ .

$$X_i = \begin{cases} 1 & \text{if you hit the area of circle} \\ 0 & \text{else} \end{cases}$$

$$P_r(X_i = 1) = \frac{\frac{\pi}{4}}{1} = \frac{\pi}{4}.$$

$$E(X_i) = \frac{\pi}{4}.$$

$$X = \frac{\sum_{i=1}^n X_i}{n}.$$

$$E(X) = \frac{n \cdot E(X_i)}{n} = E(X_i).$$

### 5.2 Example 2

$I = \int_{\Omega} f(x) dx$  - volume.

$$X_i = \begin{cases} 1 & F(x_i, y_i) \leq z_i \\ 0 & \text{otherwise} \end{cases}$$

$$v \cdot E\left(\frac{\sum_{i=1}^n X_i}{n}\right) = I.$$

### 5.3 $(\epsilon, \delta)$ -approximation

**Definicija 5.3.1**  $((\epsilon, \delta)$ -approximation). A random algorithm gives a  $(\epsilon, \delta)$ -approximation for value  $v$  if the output  $X$  satisfies:

$$P_r(|X - v| \leq \epsilon v) \geq 1 - \delta.$$

**Izrek 5.3.2.** Let  $X_1 \dots X_n$  be independent and identically distributed indicator variables. Let  $\mu = E(X_i)$ ,  $Y = \frac{\sum_{i=1}^m X_i}{m}$ . If  $m \geq \frac{3 \ln(\frac{2}{\delta})}{\epsilon^2 \mu}$ , then  $P_r(|Y - \mu| \geq \epsilon \mu) \leq \delta \implies Y$  is  $(\epsilon, \delta)$ -approximation for  $\mu$ .

**Dokaz 5.3.3.**

$$X = \sum_{i=1}^n X_i$$

$$E(X) = mE(x_i) = m\mu$$

$$m \geq \frac{3 \ln(\frac{2}{\delta})}{\epsilon^2 \mu}$$

$$\begin{aligned} P_r(|Y - \mu| \geq \epsilon \mu) &= P_r\left(\left|\frac{X}{m} - \mu\right| \geq \epsilon \mu\right) \\ &= P_r\left(\frac{1}{m} |X - E(X)| \geq \frac{1}{m} \epsilon E(x)\right) \\ &\stackrel{\text{Chernoff}}{\leq} 2e^{-\frac{\epsilon^2 E(x)}{3}} \\ &= 2e^{-\frac{\epsilon^2 \mu m}{3}} \\ &\leq 2e^{-\frac{\epsilon^2 \mu}{3} \cdot \frac{3 \ln(\frac{2}{\delta})}{\epsilon^2 \mu}} = \delta. \end{aligned}$$

Back to example 1:

$$E(Y) = \frac{\pi}{4}, \delta = \frac{1}{1000} \text{ (99.9\% sure)}, \epsilon = \frac{1}{10000}$$

$$\implies M = \frac{3 \ln\left(\frac{2}{\frac{1}{1000}}\right)^4}{\pi \left(\frac{1}{10000}\right)^2} \approx 29106.$$

Problems for MC (Monte-Carlo):

- rare events, e.g.  $X \sim \begin{pmatrix} 0 & 10^{100} \\ 1 - 10^{-20} & 10^{-20} \end{pmatrix}$ ,  $E(X) = 10^{80}$

## 5.4 DNF counting

CNF:  $(X_{i_1} \vee \overline{X_{i_2}} \vee X_{i_4}) \wedge (X_{i_1} \vee \overline{X_{i_3}}) \wedge \dots$

DNF:  $(\overline{X_{i_1}} \wedge X_{i_2} \vee \overline{X_{i_4}}) \vee \dots$  - easy to determine if solution exists.

Question: number of solutions to a given DNF?

Observation: CNF  $F$  has a solution  $\iff$  DNF  $\neg F$  has less than  $2^n$  solutions,  
 $n$  is number of samples.

ALG\_1(F):

$x = 0$

for  $i$  in range(1,m+1):

$x_1 \dots x_n$  uniformly random from  $\{0,1\}^n$

if  $F(x_1 \dots x_n) = 1$ :

$x += 1$

return  $\frac{x}{m} \cdot 2^n$

$$Y = \frac{\sum_{i=1}^m X_i}{m}$$

$(\epsilon, \delta)$ -approximation for  $Y$

$$E(Y) = \frac{\text{number of solutions of } F}{2^n} = \frac{c(F)}{2^n}$$

$$m \geq \frac{3 \ln(\frac{2}{\delta})}{\epsilon^2 E(X)} = \frac{3 \ln(\frac{2}{\delta})}{\epsilon^2} \cdot \frac{2^n}{x(F)}$$

$c(F)$  very small  $\rightarrow m$  exponentially big  $\rightarrow$  not good (we need a lot of samples).

### Definicija 5.4.1.

$SC_i = \{(a_1 \dots a_n) \in \{0,1\}^n \text{ such that } F = F_1 \vee \dots \vee F_t, F_i(a_1 \dots a_n) = 1\}$ .

$|SC_i| = 2^{n-l_i}$ ,  $l_i$ : number of values in  $F_i$

$U = \{(i, a) \mid i \in \{1, 2 \dots t\}, a \in SC_i\}$

$U = \sum_{i=1}^t |SC_i| - O(tn)$  (space smaller than  $\{0,1\}^n$ )

$S = \{(i, a) \in U \mid a \in SC_i, a \notin SC_j \ 1 \leq j < i\}$

$|S| = |SC_1| + \dots + |SC_t| = c(F)$ .

ALG\_2(F):

$x = 0$

for  $i$  in range(1,m+1):

```

    (i, a) uniformly random from U (**)
    if (i, a) ∈ S: (*)
        x += 1
    return  $\frac{x}{m} \cdot |U|$ 

```

(\*)  $a \in SC_i \rightarrow O(n)$ ,  $a \notin SC_j \ j = 1 \dots i - 1 \rightarrow O(tn) \implies O(tn), m$  times.

(\*\*): watch for details on how to, e.g.  $x_2, x_2 \wedge x_3$ :  $x_2$  is more probable than  $x_2 \wedge x_3 \rightarrow O(1)$ .

**Izrek 5.4.2.** For  $m = \lceil \frac{3t \ln(\frac{2}{\delta})}{\epsilon^2} \rceil$  algorithm returns  $(\epsilon, \delta)$ -approximation in  $O\left(\frac{t^n n \ln(\frac{2}{\delta})}{\epsilon^2}\right)$  time.

**Dokaz 5.4.3.**  $O(t \cdot n \cdot m)$ .

Insert  $m = \dots$

Prove

$$P_r(Y|U| - c(F) > \epsilon c(F)) < \delta :$$

$$c(F) = |S|, E(Y) = \frac{|S|}{|U|}$$

$$P_r(Y|U| - c(F) > \epsilon c(F)) = P_r(|U|(Y - E(Y)) > \epsilon |U|E(Y)) \leq \delta$$

if

$$m \geq \frac{3 \ln\left(\frac{2}{\delta}\right)}{\epsilon^2 E(Y)} \geq \frac{3 \ln\left(\frac{2}{\delta}\right) t}{\epsilon^2}$$

where

$$E(Y) = \frac{|S|}{|U|} \geq \frac{1}{t}$$

(= if disjoint).

In new space  $E(Y)$  much larger  $\implies m$  smaller.

# Poglavje 6

## Polynomials

Let  $\mathbb{F}$  be a field.

$\mathbb{F}$  can be  $\mathbb{R}, \mathbb{C}, \mathbb{Z}_p, \mathbb{F}_{p^n}$ .

$\mathbb{F}[x_1 \dots x_n]$  algebra of polynomials with values  $x_1 \dots x_n$ .

$f \in \mathbb{F}[x_1 \dots x_n]$

$\deg(f[x_1 \dots x_n]) := \deg(f[x \dots x])$ .

**Izrek 6.0.1.** Let  $p(x_1 \dots x_n) \in \mathbb{F}[x_1 \dots x_n]$  have the degree  $d \geq 0$  and  $p \neq 0$ .

Let  $s \subset \mathbb{F}$  be finite. If  $(r_1 \dots r_n)$  is uniformly at random element from  $S^n$ .

Then  $P_r(p(r_1 \dots r_n) = 0) \leq \frac{d}{|S|}$ .

**Dokaz 6.0.2.** Induction on  $n$ .

$n = 1$ :

$$p(x) = (x - z_1)(x - z_2) \dots (x - z_j)q(z)$$

number of zeros  $\leq$  degree - fact

$$P_r(p(r_1) = 0) = \frac{\text{number of zeros}}{|S|} \leq \frac{d}{|S|}.$$

$n - 1 \rightarrow n$ :

rewrite  $p$  :

$$p(x_1 \dots x_n) = \sum_{i=0}^j x^i p_i(x_2 \dots x_n)$$

$$j \leq d$$

$$\begin{aligned} P_r(p(r_1 \dots r_n) = 0) &= P_r(p(r_1 \dots r_n = 0) \mid p_j(r_2 \dots r_n) = 0) \cdot P_r(p_j(r_2 \dots r_n) = 0) \\ &\quad + P_r(p(r_1 \dots r_n = 0) \mid p_j(r_2 \dots r_n) \neq 0) \cdot P_r(p_j(r_2 \dots r_n) \neq 0) \\ &\leq 1 \cdot \frac{d-j}{|S|} + \frac{j}{|S|} \cdot 1, \end{aligned}$$

because

$$\begin{aligned} P_r(p(r_1 \dots r_n = 0) \mid p_j(r_2 \dots r_n) \neq 0) &\leq \frac{d-j}{|S|} \\ P_r(p_j(r_2 \dots r_n) \neq 0) &\leq \frac{j}{|S|}. \end{aligned}$$

Problem:

Let  $A, B, C \in \mathbb{F}^{n \times n}$ , is  $A \cdot B = C$ ?

Computing  $A \cdot B$ :

- school-book algorithm:  $O(n^3)$ ,
- Strassen algorithm:  $O(n^{2,807\dots})$ ,
- galactic algorithm:  $O(n^{2,372\dots})$  - has enormous constants.

`RAND_ACB(A,B,C) :`

`for i in range(1,k+1):`

`x uniformly at random from  $\{0,1\}^n$`

`if  $A \cdot (B \cdot x) \neq x$ :`

`return false`

`return true`



$O(kn^2)$ .

If  $A \cdot B = C$ , algorithm returns true.

If  $A \cdot B \neq C$ :

$$\begin{aligned} P_r(ABx = Cx) &= P_r((AB - C)x = 0) \\ &= P_r(\|(AB - C)x\|^2 = 0) \stackrel{\text{Poly}}{\leq} \frac{2}{3}. \end{aligned}$$

$\|(AB_C)x\|^2$  - polynomial in  $x_1 \dots x_n$  of degree 2.

If  $A \cdot B \neq C$ , then algorithm return false with probability at least  $1 - \left(\frac{2}{3}\right)^k$ .

Problem:

1-factor in bipartite graphs.

$$|V(g)| = 2n.$$

Represent  $G$  with  $n \times n$  matrix  $Z = (Z_{ij})_{i,j=1}^n$

$$Z_{ij} = \begin{cases} X_{ij} & \text{if } a_i b_j \in E(x) \\ 0 & \text{else} \end{cases} \quad (X: \text{variable})$$

$$\begin{aligned} \det Z(x_{11} \dots x_{nn}) &= \sum_{\pi \in S_n} \text{sign}(\pi) z_{1,\pi(1)} \dots z_{n,\pi(n)} \\ &= \sum_{\pi \in S_n, \pi \text{ defines 1-factor}} \text{sign}(\pi) x_{1,\pi(1)} \dots x_{n,\pi(n)}. \end{aligned}$$

$\det Z \neq 0 \iff G$  has 1-factor.

```

Rand_1factor(G):
  construct Z with variables x11 ... xnn
  for i in range(1,k+1):
    u <- uniformly at random from 1,2..2n-1n2 (r11 ... rnn)
    compute d = det Z(r11 ... rnn)
    if d != 0:
      return true
  return false

```

Complexity:  $k \cdot$  computing determinant:  $O(n^3)$  (Gaussian elimination).  
or apply approximation algorithm:

- if  $G$  has no 1-factor it always returns false,
- if  $G$  has 1-factor, it returns true with probability at least  $1 - \left(\frac{n}{2n}\right)^k = 1 - \left(\frac{1}{2}\right)^k$  ( $k$  konstant, larger set  $\implies$  smaller  $k$  needed).

# Poglavje 7

## Random graphs

### 7.1 $G(n,p)$ model

$G$  is a random Erdős-Rény graph if it has  $n$  vertices and each pair of vertices is connected with probability  $p$ .

*Primer.*  $G\left(5, \frac{1}{2}\right)$ .

$E(\text{ edges in } G \text{ from } G(n,p)) = \sum_{1 \leq i < j \leq n} E(X_{ij}) = \binom{n}{2}p$ .

$$X_{ij} = \begin{cases} 1 & \text{if } i \text{ and } j \text{ have edge} \\ 0 & \text{otherwise} \end{cases}$$

$p$  can be function of  $n$ .

$Y_v$  : degree of  $v$ .

$$E(Y_v) = (n-1)p.$$

#### **Definicija 7.1.1.**

We say that a random graph has some property almost surely (A.S.) if  $P_r(G \in G(n,p) \text{ has property}) \xrightarrow{n \rightarrow \infty} 1$ .

#### **Trditev 7.1.2.**

Let  $p$  be constant. Then  $G \in G(n,p)$  has diameter 2 A.S.

#### **Dokaz 7.1.3.**

Let  $u, v \in V(G)$

$$X_w = \begin{cases} 1 & \text{if } uw \in E(G) \text{ in } vw \in E(G) \\ 0 & \text{otherwise} \end{cases}$$

$$P_r(X_w = 1) = p^2$$

$$P_r(X_w = 0 \text{ for all } w \neq u, v) = (1 - p^2)^{n-2}.$$

$$P_r(G \text{ has diameter } > 2)$$

$$= P_r(X_w = 0 \text{ for all } w \notin u, v \text{ for some } u, v)$$

$$\leq \binom{n}{2} (1 - p^2)^{n-2} \xrightarrow{n \rightarrow \infty} 0;$$

$$\binom{n}{2} - \text{polynomial, } e^{\dots} - \text{exponent.}$$

$$p = f(n)$$

$$\frac{1}{n}, \frac{1}{n^3}, \frac{\log n}{n}$$

**Izrek 7.1.4.** (without proof)

Let  $p$  be a function of  $n$ : let  $G \in G(n, p)$ :

- $np < 1$  -  $G$  A.S. disconnected with connected components of size  $O(\log n)$
- $np = 1$  -  $G$  A.S. has 1 large component of size  $O\left(n^{\frac{2}{3}}\right)$
- $np = c > 1$  -  $G$  A.S. has giant component of size  $dn$ ,  $d \in (0, 1)$
- $np \leq (1 - \epsilon) \ln n$  -  $G$  A.S. disconnected with isolated vertices
- $np > (1 - \epsilon) \ln n$  -  $G$  A.S. connected.

**Izrek 7.1.5.**

Let  $np = \omega(n) \ln(n)$  for  $\omega(n) \rightarrow \infty$  „very slowly“ think of  $\omega(n) = \log(\log n)$ , then  $\text{diam}(G)$  in  $\Theta\left(\frac{\ln n}{\ln(np)}\right)$  for  $G$  in  $G(n, p)$ .

**Lema 7.1.6.**

Let  $S \subset V(G)$ ,  $|S| = cn$  for  $c \in (0, 1]$  and  $v \notin S$ .

then  $cnp(1 - \omega^{-\frac{1}{3}}) \leq N_S(v) \leq cnp(1 + \omega^{-\frac{1}{3}})$  A.S. ( $\omega^{-\frac{1}{3}} \rightarrow 0$  very slowly).

**Dokaz 7.1.7.** (Lemma):

$$E(N_s(v)) = c \cdot n \cdot p, \delta = \omega^{-\frac{1}{3}}$$

$$\begin{aligned}
P_r(|N_s(v) - cnp| \geq \delta cnp) &\stackrel{\text{Chernoff}}{\leq} 2e^{-\frac{\omega^{-\frac{2}{3}} cnp}{3}} \\
&= 2e^{-\frac{cnp}{3\omega(n)^{\frac{2}{3}}}} \xrightarrow{n \rightarrow \infty} 0.
\end{aligned}$$

For all  $v$ :  $n \cdot 2e^{-\frac{cnp}{3\omega(n)^{\frac{2}{3}}}} \xrightarrow{n \rightarrow \infty} 0$ .

**Dokaz 7.1.8.** (Theorem):

$k$  be such that  $\sum_{i=0}^{k-1} |N_i| \leq \frac{n}{2}, \sum_{i=0}^k |N_i| > \frac{n}{2}$ .

$$|N_0| = 1$$

$$|N_i| \leq |N_{i-1}| \cdot n \cdot p \cdot (1 + \omega^{-\frac{1}{3}}):$$

$$|S| \leq n, np(1 + \omega^{-\frac{1}{3}})\text{-each element.}$$

$$\begin{aligned}
k &= \frac{\log\left(\frac{n}{3}\right)}{\log\left(n \cdot p \cdot \left(1 + \omega^{-\frac{1}{3}}\right)\right)} \\
&= \log_{np(1 + \omega^{-\frac{1}{3}})} \frac{n}{3} = \Theta\left(\frac{\ln(n)}{\ln(np)}\right). \\
|N_{\leq k}| &= |N_1 \cup \dots \cup N_k|.
\end{aligned}$$

$$\begin{aligned}
|N_{\leq k}| &\leq \sum_{i=0}^k (np(1 + \omega^{-\frac{1}{3}}))^i \\
&= \frac{(np(1 + \omega^{-\frac{1}{3}}))^{k+1} - 1}{np(1 + \omega^{-\frac{1}{3}}) - 1} \\
&< \frac{np(1 + \omega^{-\frac{1}{3}})^{k+1}}{\frac{1}{2}np(1 + \omega^{-\frac{1}{3}})} \\
&= 2np(1 + \omega^{-\frac{1}{3}})^k \\
&\stackrel{k}{=} 2 \cdot \frac{n}{3} \text{ haven't covered all} \\
&\implies \text{diam}(G) > k \text{ bound from below.}
\end{aligned}$$

$$N_i \subseteq S$$

$$\frac{1}{2}np(1 - \omega^{-\frac{1}{3}}) \cdot |N_{i-1}| \leq |N_i|$$

$$\begin{aligned}
n &\geq \sum_{i=0}^k |N_i| \\
&\geq \sum_{i=0}^k \left( \frac{1}{2} np \left( 1 - \omega^{-\frac{1}{3}} \right) \right)^i \\
&= \frac{\left( \frac{1}{2} np \left( 1 - \omega^{-\frac{1}{3}} \right) \right)^{k+1} - 1}{\frac{1}{2} np \left( 1 - \omega^{-\frac{1}{3}} \right) - 1} \\
&\geq \left( \frac{1}{2} np \left( 1 - \omega^{-\frac{1}{3}} \right) \right)^k / \ln
\end{aligned}$$

$$\frac{\ln n}{\ln(np)} \approx \frac{\ln n}{\ln\left(\frac{1}{2} np \left( 1 - \omega^{-\frac{1}{3}} \right)\right)} \geq k.$$

$$\implies w \in S'.$$

Number of neighbors in  $N_k$  A.S.  $\geq 1$ ,

$$|N_k| \geq \left( \frac{1}{2} np \left( 1 - \omega^{-\frac{1}{3}} \right) \right)^k \approx c \cdot n$$

$$\implies \text{diam}(G) = k + 1 \text{ A.S.}$$

### 7.1.1 Scale free property

$$G \in G(n, p).$$

In real world:  $p(k)$  = proportion of degree  $k$  vertices.

$$\log(p(k)) = -\gamma \cdot \log k$$

$$p(k) = k^{-\gamma}.$$

Internet:  $\gamma \approx 3.42$ ,

protein reactions:  $\gamma \approx 2.89$ .

## 7.2 Barbási-Albert Model

B.A. model.

Start with  $m$  nodes.

Grow:

- add node  $v$ ,

- add  $m$  edges from  $v$  (to  $u$ ),
- for each new edge:  $P(v \sim u) = \frac{\deg u}{\sum_x \deg x}$ .

**Izrek 7.2.1.**

B.A. model has scale free property, in particular

$$p_k = \frac{2m(m+1)}{k(k+1)(k+2)}.$$

**Definicija 7.2.2.**

$p_n(k)$ : expected proportion of degree  $k$  vertices in graph with  $k$  vertices,

$$p_k := \lim_{n \rightarrow \infty} p_n(k).$$

**Dokaz 7.2.3.**

$p_n(k) \cdot n$ : expected number of degree  $k$  vertices,

$p_n(k)n \cdot \sum_u \frac{k}{\deg u} m = p_n(k) \cdot \frac{k}{2}$ : expected number of degree  $k$  vertices changing into degree  $k+1$  vertices.

$$\sum_u \deg u = 2|E|$$

$$p_{n+1}(k) \cdot (n+1) = p_n(k) \cdot n - p_n(k) \cdot \frac{k}{2} + p_n(k-1) \cdot \frac{k-1}{2}, \text{ where}$$

$$p_n(k) \cdot n: \text{ degree } k \rightarrow k,$$

$$p_n(k) \cdot \frac{k}{2}: k \rightarrow k+1,$$

$$p_n(k-1) \cdot \frac{k-1}{2}: k-1 \rightarrow k.$$

For  $n$  very big (very close to limit):

$$p_n \cdot (n+1) = p_k \cdot n - p_{k-1} \cdot \frac{k}{2} + p_{k-1} \cdot \frac{k-1}{2}$$

$$\implies p_k = \frac{k-1}{k+2} p_{k-1}.$$

For degree  $m$ :

$$(n+1) \cdot p_{n+1}(m) = p_n(m) \cdot n - p_n(m) \cdot \frac{m}{2} + 1$$

$$\begin{aligned} p_m &= \frac{2}{m+2} \\ \implies p_{m+1} &= \frac{2}{m+2} \cdot \frac{m}{m+3} \\ \implies p_{m+2} &= \frac{2m(m+1)}{(m+2)(m+3)} \\ \implies p_k &= \frac{2m(m+1)}{k(k+1)(k+2)}. \end{aligned}$$

# Poglavje 8

## Markov chains

$\Omega$ : finite set (of states).

**Definicija 8.0.1** (Markov chain).

(Discrete time) Markov chain is a sequence of random variables  $X = X_0, X_1, X_2 \dots$  with image  $\Omega$  and properties:

- $P(X_{i+1} = x \mid X_i = x_i, X_{i-1} = x_{i-1} \dots X_0 = x_0) = P(X_{i+1} = x \mid X_i = x_i),$
- $PX_{i+1} = x \mid X_i = y = P(X_1 = x \mid X_0 = y)$  - time is homogenous.

*Primer.*

$$\Omega = \mathbb{Z}_5$$

$$P(X_{i+1} = x + 1 \mid X_i = x) = \frac{1}{2}$$

$$P(X_{i+1} = x - 1 \mid X_i = x) = \frac{1}{2}.$$

**Definicija 8.0.2** (Transition matrix).

$$\Omega = \{x_1 \dots x_n\}$$

$$p_{ij} = P(X_{t+1} = j \mid X_t = i)$$



$$\begin{bmatrix} p_{11} & \dots & \\ p_{1n} & & \\ \vdots & & \vdots \\ p_{n1} & \dots & p_{nn} \end{bmatrix}.$$

**Definicija 8.0.3** (Transition graph).

Edge between states  $i$  and  $j$  exists if  $p_{ij} > 0$ .

$P$  is stochastic matrix:

$$p_{ij} \in [0,1]$$

$$\sum_j p_{ij} = 1.$$

We choose beginning state randomly.

$$q(0) = (q_1(0) \dots q_n(0))$$

$$P(X_0 = i) = q_i(0).$$

$$\text{Let } q(t) = (q_1(t) \dots q_n(t))$$

$$P(X_t = i) = q_i(t).$$

$$\text{It holds: } q(t) = q(t-1) \cdot P = q(0) \cdot P^t.$$

$$\begin{bmatrix} 0 & \frac{1}{2} & 0 & 0 & \frac{1}{2} \\ \frac{1}{2} & 0 & \frac{1}{2} & 0 & 0 \\ 0 & \frac{1}{2} & 0 & \frac{1}{2} & 0 \\ 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ \frac{1}{2} & 0 & 0 & 0 & \frac{1}{2} \end{bmatrix}$$

$$q(0) = (1, 0, 0, 0, 0)$$

$$q(1) = (1, \frac{1}{2}, 0, 0, \frac{1}{2})$$

$$q(2) = (\frac{1}{2}, 0, \frac{1}{4}, \frac{1}{4}, 0)$$

$\vdots$

**Definicija 8.0.4.**

- Distribution  $\pi$  is stationary if  $\pi = \pi \cdot P$ ,
- $f_{ij}$ : probability that  $X_t = x_j$  for some  $t$  assuming  $X_0 = x_i$ ,

- $h_{ij}$ : expected number of steps needed to get to state  $X_j$  starting in  $X_i$  (hitting time),
- $N(i, t, q(0))$ : expected number of times we visit  $x_i$  after  $t$  steps starting with distribution  $q(0)$ ,
- $\forall f_{ij} > 0 \iff$  transition graph is strongly connected  $\iff$  we say the chain is irreducible,
- M.C. is aperiodic if there is no  $c \in \{2, 3, 4, \dots\}$  such that all lengths of cycles are divisible by  $c$ .

**Izrek 8.0.5.**

Let  $X$  be finite irreducible M.C. Then:

- a) there exists unique stationary distribution  $\pi = (\pi_1 \dots \pi_n)$ ,
- b)  $f_{ii} = 1, h_{ii} = \frac{1}{\pi_i}$ ,
- c)  $\lim_{t \rightarrow \infty} \frac{N(i, t, q(0))}{t} = \pi_i$  - approaches  $\pi$  regardless of  $q(0)$ ,
- d) if  $X$  is aperiodic:  $\lim_{t \rightarrow \infty} q(0) \cdot P^t = \pi$ .

*Primer.*

$$P = \begin{bmatrix} 0 & \frac{1}{2} & \dots & \frac{1}{2} \\ \frac{1}{2} & 0 & \dots & 0 \\ \vdots & & & \vdots \\ \dots & & \frac{1}{2} & 0 \end{bmatrix}$$

$$\pi = (\frac{1}{n} \dots \frac{1}{n})$$

$$h_{i,i} = n$$

$$n = h_{i,i} = 1 + \frac{1}{2}h_{i-1,i} + \frac{1}{2}h_{i+1,i}, \quad h_{i-1,i} = h_{i+1,i}$$

$$n - 1 = h_{i-1,i}$$

$$E(\text{steps around}) \leq h_{0,1} + h_{1,2} + \dots + h_{n-1,n} \leq n(n-1).$$

## 8.1 2-SAT

Recall: k-SAT:

$$F = C_1 \wedge \cdots \wedge C_m$$

$$C_i = X_{i1} \vee \cdots \vee X_{ik}.$$

3-SAT: NP complete.

Algorithm:

```
def rand2SAT(F):
    b0 = (b_00 ... b_n0)
    for i in range(t):
        if F(bi) = 1:
            return True
        Cl <- clause that is False
        xj <- uniformly at random from x11 and x12
        bi+1 = (b_0i ... not b_ji ... b_ni)
    if F(Xt) = 1:
        return True
    return False
```

**Izrek 8.1.1.**

If  $k = 8n^2$ , then  $P(\text{rand2SAT} = \text{True} \mid \text{correct answer is True}) \geq \frac{3}{4}$ .

**Dokaz 8.1.2.** Let  $a = (a_1 \dots a_n)$  be a correct solution.

Let  $X_i$  = Hamming distance from  $b^i$  to  $a$ .

Goal: bound  $h_{n,0}$ .

$P(\text{distance of } b^{i+1} \text{ to } a \text{ is } j-1 \mid \text{distance of } b^i \text{ to } a \text{ is } j) \geq \frac{1}{2}$ .

$$P = \begin{bmatrix} 0 & 1 & \dots & 0 \\ \frac{1}{2} & 0 & \dots & 0 \\ \vdots & & & \vdots \\ \dots & & 1 & 0 \end{bmatrix}$$

$$\pi \stackrel{?}{=} \pi P$$

$$\pi = (\frac{1}{2n}, \frac{1}{n} \dots \frac{1}{n}, \frac{1}{2n})$$

By theorem

$$h_{i,i} = \frac{1}{\pi_i} = n \text{ for } i = 1, 2 \dots n-1$$

$$h_{0,0} = h_{n,n} = 2n$$

$$n = h_{i,i} = 1 + \frac{1}{2}h_{i+1,i} + \frac{1}{2}h_{i-1,i}$$

$$h_{i+1,i} \leq 2n$$

$$i = 0 : 2n = h_{0,0} = 1 + h_{1,0} \implies h_{1,0} < 2n$$

$$h_{n,0} \leq h_{n,n-1} + \dots + h_{1,0} \leq 2n^2$$

$$E(\text{steps in algorithm to reach corrc solution}) = E(Z) \leq 2n^2$$

$$P(\text{algorithm hasn't reached correct solution after } 8n^2 \text{ steps})$$

$$= P(Z > 8n^2) \stackrel{\text{Markov}}{\leq} \frac{E(Z)}{8n^2} \leq \frac{1}{4}.$$

## 8.2 Generating a uniformly random element of a set

$\Omega$ : set.

Let  $G$  be a symmetric graph on  $\Omega$ .

We form M.C:

$$P_{x,y} = \begin{cases} \frac{1}{M} & \text{if } x \neq y \wedge x \sim y \\ 0 & \text{if } x \neq y \wedge x \not\sim y \\ 1 - \frac{|N(x)|}{M} & \text{if } x = y \end{cases}$$

$$M \geq \max_{v \in \Omega} |N(v)|.$$

If  $G$  is connected  $\implies$  M.C. is irreducible.

$$\pi = (\frac{1}{|\Omega|} \dots \frac{1}{|\Omega|})$$

$$\pi \stackrel{?}{=} \pi P$$

$$\begin{aligned}
(\pi P)_x &= \sum_y \pi_y P_{y,x} \\
&= \sum_{y \in N(x)} \frac{1}{M} \cdot \frac{1}{|\Omega|} + \frac{1}{|\Omega|} \left( 1 - \frac{|N(x)|}{M} \right) = \frac{1}{|\Omega|} = \pi_x.
\end{aligned}$$

$\implies$  if we walk on the Markov chain long enough, we end up in state  $x$  with probability  $\pi_x = \frac{1}{|\Omega|}$

$\implies$  we can sample uniformly.

*Primer.*

$G$  graph, finding largest independent set ( $\forall u, v : u \not\sim v$ ) is NP-complete.

Lets try sampling a uniformly random independent set

$\Omega = \{\text{independent sets}\}$

$u \sim v$  if  $|u \triangle v| = 1$  ( $(u \cup \{el\}) = v$ )

M.C.:  $X_0 =$  arbitrary independent set

$X_{i+1}$ :

- pick uniformly at random  $v \in V(G)$ ,
- if  $v \in U$  then  $X_{i+1} = U \setminus \{v\}$ ,
- if  $U \cup \{v\}$  is independent then  $X_{i+1} = U \cup \{v\}$ ,
- else  $X_{i+1} = U$ .

$M$  is number of vertices

$\implies \forall u \in \Omega : \lim_{t \rightarrow \infty} P(X_t = u) = \frac{1}{|\Omega|}$ .

Note: irreducible;  $U \rightarrow \emptyset \rightarrow V$ , aperiodic.

## 8.3 Metropolis algorithm

$\Omega$ : set,

$\pi$ : chosen distribution on  $\Omega$ .

Make  $G$  graph on  $\Omega$

$$P_{x,y} = \begin{cases} \frac{1}{M} \cdot \min\left(1, \frac{\pi_y}{\pi_x}\right) & \text{if } x \neq y \wedge x \sim y \\ 0 & \text{if } x \neq y \wedge x \not\sim y \\ 1 - \sum_{y \in N(x)} & \text{if } x = y \end{cases}$$

$$M \geq \max_{v \in \Omega} |N(v)|$$

$$\pi \stackrel{?}{=} \pi P$$

$$\begin{aligned} (\pi P)_x &= \sum_y \pi_y P_{y,x} = \sum_{y \in N(x)} \pi_y \frac{1}{M} \min\left(1, \frac{\pi_y}{\pi_x}\right) + \pi_x \left(1 - \sum_{y \in N(x)} \frac{1}{M} \min\left(1, \frac{\pi_y}{\pi_x}\right)\right) \\ &= \sum_{y \in N(x), \pi_y \geq \pi_x} \pi_y \frac{1}{M} \cdot 1 + \sum_{y \in N(x), \pi_y < \pi_x} \pi_y \frac{1}{M} \frac{\pi_y}{\pi_x} + \pi_x \\ &\quad - \sum_{y \in N(x), \pi_y \geq \pi_x} \pi_x \frac{1}{M} \frac{\pi_y}{\pi_x} - \sum_{y \in N(x), \pi_y < \pi_x} \frac{1}{M} \cdot 1 \\ &= \pi_x. \end{aligned}$$

*Primer.*

$$\Omega = \mathbb{Z} \cap [-1000, 1000]$$

$$\pi \sim e^{-\frac{(x-\mu)^2}{2\delta}}$$

```

X0 arbitrary
for i = in range(1,m):
    y <- uniformly from Xi+1,Xi-1
    M <- uniformly from [0,1]
    if M ≤  $\frac{\pi(y)}{\pi(x)}$ :
        Xi+1 = y
    else:
        Xi+1 = Xi
return Xm

```

*Primer.*

Find maximum of a positive function  $f$ .

Use metropolis algorithm to sample proportional to  $f$ .

Note: all I need to know is ratios  $\frac{f(y)}{f(x)}$ .

Back to independent sets.

$$G = (V, E)$$

$\Omega$  = independent sets.

$$\lambda \in (1, \infty)$$

$$\pi(u) \sim \lambda^{|u|}$$

$$\pi(u) = \frac{\lambda^{|u|}}{\sum_{v \text{ independent set}} \lambda^{|v|}}.$$

How to calculate the sum?

No problem: only need proportions.

$X_0$ : arbitrary independent set.

$X_i \rightarrow X_{i+1}$ :

- we pick  $v \in V$  uniformly at random,
- if  $v \in X_i \implies$ 
  - $X_{i+1} = X_i \setminus \{v\}$  with probability  $\frac{1}{\lambda} = \min\{1, \frac{\pi_v}{\pi_x}\},$
  - $X_{i+1} = X_i$  with probability  $1 - \frac{1}{\lambda},$
- if  $v \in X_j$  and  $X_i \cup \{v\}$  is independent  $\implies X_{i+1} = X_i \cup \{v\},$
- otherwise  $X_{i+1} = X_i.$

*Primer.* Bayes:  $P(A | B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B|A)P(A)}{P(B)}.$

$B \leftarrow$  machine is giving values, e.g.  $y_1 = 0.05, y_2 = -0.1, y_3 = 0.07, y_4 = 3.$

We believe  $B \sim N(\mu, 0.05).$

$\mu = \text{laplacian}(0, 0.01).$

$$P(\mu | B) = \frac{e^{\frac{|\mu|}{0.01}} e^{-\sum \frac{(x_i - \mu)^2}{0.05}}}{\int \dots}$$

Integral is difficult to calculate.

Sample  $\mu$  with Metropolis algorithm.

## 8.4 M.C. for 1-factor in bipartite graphs

$G$  regular graph

$$|A| = |B|.$$

How to find 1-factor?

Augmenting paths.

Let  $M$  be (suboptimal) matching.

If we find  $s - t$  path, we switch edges and get bigger matching.

Starting point.

$G$   $d$ -regular graph.

Graph  $G = (A \cup B, E)$ ,  $M$  suboptimal matching.

- Add  $s$  and add directed edges to vertices in  $A$  that are not matched with weight  $d$ ,
- add  $t$  and add directed edges to vertices in  $B$  that are not matched with weight  $d$ ,
- orient edges in  $M$  from  $B$  to  $A$  that weight  $d - 1$ ,
- orient edges in  $E \setminus M$  from  $B$  to  $A$  that weight  $1$ ,
- we add edge from  $t$  to  $s$  that weight  $(|A| - |M|)d$ .

Observation:

- for each vertex  $x$  :  $\deg^-(x) = \deg^+(x)$  (out weights = in weights),
- if  $|A| > |M|$ , then graph is eulerian  $\implies$  there is an augmenting path.

How to find  $s - t$  path?

Do a random walk.

Expected time to get from  $s$  to  $t$  is  $h_{s,t}$

$$\frac{1}{\pi(s)} = h_{s,s} = h_{s,t} + 1.$$

### Lema 8.4.1.

Let  $X$  be a M.C. defined as a random walk on directed (weighted) graph with  $\deg^-(x) = \deg^+(x)$  for each  $x$ . Then the stationary distribution is



$$\pi = \left[ \frac{\deg^+(x_i)}{|E|} \right]_{i=1}^n.$$

$w_{ij}$ : weight from  $i$  to  $j$ .

#### Dokaz 8.4.2.

$$\pi P = \pi \left[ \frac{w_{ij}}{\deg^+(x_i)} \right]_{i,j=1}^n = \left[ \frac{\sum_j w_{ji}}{|E|} \right]_{i=1}^n = \left[ \frac{\deg^-(x_i)}{|E|} \right]_{i=1}^n = \left[ \frac{\deg^+(x_i)}{|E|} \right]_{i=1}^n.$$

$$h_{s,s} = \frac{1}{\pi_s} \leq \frac{|E|}{\deg^+(s)} \leq \frac{3(|A|-|M|)d+|M|(d-1)+(|A|-|M|)d+|M|(d-1)}{(|A|-|M|)d} \leq \frac{4|A|}{|A|-|M|}.$$

Expected time to find augmenting path  $\leq \frac{4|A|}{|A|-|M|}$ .

$$|A| = n$$

Expected time to find 1-factor  $\leq \frac{4n}{n-1} = 4n \sum_{i=1}^{n-1} \frac{1}{i} \leq 4n(1 + \ln n)$  - in  $O(n \log n)$ .

### 8.4.1 Network centrality

Degree as measure - natural idea.

Use M.C: walk randomly on the network, those that are visited more often are more important.

Pagerank.

Let  $A$  be the adjacency matrix of  $G$ .

$$P_{ij} = \alpha \frac{A_{ij}}{\deg_i} + (1 - \alpha) \frac{1}{n};$$

$\alpha$ : normal random walk,

$1 - \alpha$ : jump to any.

$$\alpha = 0.85.$$

## Poglavje 9

# Randomized incremented constructions (RIC)

Observation:

Let  $S$  be a set of  $n$  distinct elements.

Let  $X_1 \dots X_n$  be a random permutation of the elements.

Let  $S_i = \{X_1 \dots X_i\}$ .

$$P(X_i = \min(S_i)) = \frac{1}{i}.$$

$$Y = |\{j \in \{1 \dots n\} \mid j = \text{minimal of } S_j\}|$$

$$Y = Y_1 + \dots + Y_n$$

$$Y_j = \begin{cases} 1 & \text{if } j = \min S_j \\ 0 & \text{otherwise} \end{cases}$$

$$E(Y) = \sum_{i=1}^n E(Y_i) = \sum_{i=1}^n \frac{1}{i} \text{ in } O(\log n).$$

Alg():

```
X1 .. Xn = random permutation of S
```

```
min = X1
```

```
for i in range(1,n+1):
```

```
    if Xi < min:
```

```
        print("HA")
```

```
    min = Xi
```

We get  $O(\log n)$  „HA“ printed.

Incremental construction (IC).

Input  $S = \{s_1 \dots s_n\}$ .

We will build structures  $DS(S_i)$ :

$DS(S_1 \rightarrow \dots \rightarrow DS(S_n))$ .

$DS(S_n)$  will help us give answer.

Randomized: permute  $S$  at the beginning.

## 9.1 Quicksort as RIC

$S$ : set of elements we want to order.

$X_1 \dots X_n$ : random permutation of  $S$ .

$S_i = \{X_1 \dots X_i\}$ .

$S_i$  splits  $\mathbb{R}$ .

Define  $DS(S_i)$ :

- save intervals: each interval will be saved by endpoints,
- for each interval we will be saving its points,
- for each  $X_j$ ,  $j > i$  we will save in which interval it is,
- for each left point of the interval we will save the right point.

QuicksortEIC(S):

```
# start of DS(Si)
I=[(-∞,∞)]
P[(-∞,∞)] = S
for each Xi:
    Int(Xi) = (-∞,∞)
Next(∞) = ∞
# end of DS(Si)
for i in range(1,n+1):
    Ii = Int(Xi) = (Xj,Xk)
```

---

```
Ii1 = (Xj,Xi)
Ii2 = (Xi,Xk)
for Xl  $\neq$  Xi, Xi  $\in$  P(I):
    add Xl to P(Ii1) or P(Ii2) depending on Xl < Xi or Xl > Xi
Next(Xj) = Xi
Next(Xi) = Xk
return [Next( $-\infty$ ), Next(Next( $-\infty$ )) ..]
```

Similarity to quicksort: splitting intervals.