

Verjetnostne metode v računalništvu - zapiski s predavanj prof. Marca

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Poglavlje 1

Introduction

1.1 Probability

(Ω, 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.

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

Example.

```
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

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

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

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,
- $P_r(X \geq a) \leq \frac{E[X]}{a}; \forall a > 0 \ \forall X \geq 0$ Markov inequality.

Example. (Continuing from before).

X = number of trials before return.

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

$$X : 1 \mapsto 1, 01 \mapsto 2, 003 \mapsto 3 \dots$$

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

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

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

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

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

■

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

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

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

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

Proof 1.2.5.

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

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Poglavlje 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 |S| = 1:
        return S
    else:
        a = uniformly at random from S
        S- = {b ∈ S | b < a}
        S+ = {b ∈ S | a < b}
        return Quicksort(S-), a, Quicksort(S+)
```

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

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

Proof 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: (Inductive hypothesis is $C(n) \leq 5n \log n$)

$n = 1 : \checkmark$

$n - 1 \rightarrow n$:

$$\begin{aligned}
E[C(n)] &\leq n + \frac{2}{n} \sum_{i=1}^n E[C(i)] \leq \\
&\leq n + \frac{2}{n} \sum_{i=1}^n 5i \log i \leq \\
&\leq n + \frac{2}{n} \sum_{i=1}^{\lfloor \frac{n}{2} \rfloor} 5i \log i + \frac{2}{n} \sum_{i=1+\lfloor \frac{n}{2} \rfloor}^{n-1} 5i \log i \leq \\
&\leq n + \frac{2}{n} \sum_{i=1}^{\lfloor \frac{n}{2} \rfloor} 5i \log \frac{n}{2} + \frac{2}{n} \sum_{i=1+\lfloor \frac{n}{2} \rfloor}^{n-1} 5i \log n \leq \\
&\stackrel{2.1}{\leq} n + \frac{2}{n} \left(\sum_{i=1}^n 5i \log n - \sum_{i=1}^{\frac{n}{2}} 5i \right) = \\
&= n + \frac{10}{n} \left(\frac{n(n-1)}{2} \log n - \frac{\frac{n}{2}(\frac{n}{2}-1)}{2} \right) \leq \\
&\leq n + 5(n-1) \log n - n < \\
&< 5n \log n.
\end{aligned}$$

$$\log \frac{n}{2} = \log n - 1 \quad (2.1)$$

■

This theorem gives us the following inequality: $P(C(n) \geq b \cdot 5n \log n) \stackrel{\text{Markov}}{\leq} \frac{1}{b}$. We give an alternative proof of the previous theorem:

Proof 2.1.3.

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

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

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

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

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

$E[X_{ij}] = \frac{2}{|S_{ij}|} \leq \frac{2}{j-i+1}$ because $|S_{ij}| \geq j-i+1$ because S_{ij} contains all elements between S_i and S_j .

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

■

2.2 Min-cut

G multigraph.

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

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

Problem min-cut:

Input: G .

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

Algorithm 1:

```

 $x \in V(G)$ 
Call maxFlow(G, x, y)  $\forall y \in V(G)$ 
Take min
    
```

$maxFlow$ is Edmonds-Karp algorithm $O(|V||E|^2)$. This algorithm returns the minimum cut because maximum flow is equal to minimum cut.

A quicker deterministic algorithm is the Stoer-Wagner algorithm with time complexity $O(|E||V| + |V|^2 \log |V|)$.

We give the probabilistic Karger algorithm:

```

Algorithm randMinCut:
   $G_0 = G$ 
   $i = 0$ 
  while  $|V(G_i)| > 2$ :
     $e_i = \text{uniformly at random from } G_i \text{ (} e_i \text{ is an edge)}$ 
     $G_{i+1} = G_i / e_i \text{ (we contract } e_i)$ 
     $i = i + 1$ 
   $u, v = V(G_{n-2}) \# n = |V(G)|$ 
  ( $u, v$  are vertices left after we finish the loop)
   $U = \{w \in V(G) \mid w \text{ is merged into } u\}$ 
  return  $(U, V(G) \setminus U)$ 
```

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

Proof 2.2.2.

Fact 1: $\minCut(G_i) \leq \minCut(G_{i+1})$; Fact 2: $\minCut(G) \leq \delta(G)$.

$k := \minCut(G)$.

Let (A, B) be an optimal cut.

Let ε_i be the event when e_i not in (A, B) .

$$\begin{aligned}
 P_r(\text{Algorithm returning } (A, B)) \\
 &= P_r(\varepsilon_0 \cap \dots \cap \varepsilon_{n-3}) \quad i = 0 \dots n-3 \\
 &= P_r(\varepsilon_0 \cap \dots \cap \varepsilon_{n-4}) \cdot P_r(\varepsilon_{n-3} \mid \varepsilon_0 \cap \dots \cap \varepsilon_{n-4}) \\
 &= P_r(\varepsilon_{n-3} \mid \cap_{i=0}^{n-4} \varepsilon_i) \cdot P_r(\varepsilon_{n-3} \mid \cap_{i=0}^{n-4} \varepsilon_i) \\
 &\quad \dots P_r(\varepsilon_1 \mid \varepsilon_0) \cdot P_r(\varepsilon_0) \\
 &\stackrel{2.3}{\geq} \frac{n-2}{n} \cdot \frac{n-3}{n-1} \cdots \frac{1}{3} = \frac{2}{n(n-1)}.
 \end{aligned}$$

$$\begin{aligned} P_r(\overline{\varepsilon_i} \mid \varepsilon_{i-1} \cap \dots \cap \varepsilon_0) &= \frac{k}{|E(G_i)|} \stackrel{2.2}{\leq} \frac{k}{\frac{(n-i)k}{2}} = \frac{2}{n-i} \\ |E(G_i)| &\geq \frac{(n-i)\delta(G)}{2} \geq \frac{(n-i)k}{2}. \end{aligned} \quad (2.2)$$

$$P_r(\varepsilon_i \mid \varepsilon_{i-1} \cap \dots \cap \varepsilon_0) \geq 1 - \frac{2}{n-i} = \frac{n-2-i}{n-i}. \quad (2.3)$$

■

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

Proof 2.2.4. A_i - event that i -th run gives sub-optimal solution.

$$\begin{aligned} P_r(\text{solution not correct}) &= P_r(A_1 \cap \dots \cap A_{n(n-1)}) \\ &= \prod_{i=1}^{n(n-1)} P_r(A_i) \leq \left(1 - \frac{2}{n(n-1)}\right)^{n(n-1)} \\ &\stackrel{2.4}{\leq} e^{-\frac{2}{n(n-1)} \cdot n(n-1)} = e^{-2} \leq 0.14. \end{aligned}$$

$$1 + x \leq e^x \quad \forall x \in \mathbb{R}. \quad (2.4)$$

■

If we run *randMinCut* $n(n-1) \log(n)$ times, we get an incorrect answer with probability at most $\frac{1}{n^2}$ (repeat the previous proof). Because contracting an edge takes $m = |E|$ operations, we get the time complexity $O(mn^2 \log n)$. We could improve the algorithm to get time complexity $O(mn \log^3 n)$.

Poglavlje 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 but isn't always quick, example: *Quicksort*.
- Monte Carlo algorithms: it can give wrong answers. Monte Carlo algorithms subtypes:

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

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

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

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).

Example. Decision problem: does a graph G have $\min Cut \leq k$?

Run $\text{randMinCut}(G)$ $n(n - 1)$ times.

```
Algorithm randMinCut:
    if one of runs gives |(A,B)| ≤ 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).

$ZPP = RP \cap \text{co-RP}$ (proof: <https://cs.stackexchange.com/questions/54782/why-is-zpp-rp-%E2%88%A9-co-rp>)

Poglavlje 4

Chernoff bounds

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

$$p_i = P_r(X_i = 1),$$

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

$$\mu = E(X) = p_1 + \dots + p_n.$$

For every $\delta \in [0,1]$:

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

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

Proof 4.0.2.

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

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

$$E(e^{tX_i}) = p_i \cdot e^t + (1 - p_i) \cdot e^0 = 1 + p_i(e^t - 1) \stackrel{2.4}{\leq} e^{p_i(e^t - 1)}. \tag{4.2}$$

We want:

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

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

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

$$f(0) = 0$$

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

$$\frac{2}{3}\delta \leq \ln(1 + \delta) \text{ (we prove this by showing that LHS - RHS)}$$

has one stationary point on $[0,1]$ and is negative in $\delta = 1$)

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

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

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

We select $t = \ln(1 - \delta)$

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

$$f(0) = 0$$

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

Similarly to before we prove that $\delta \leq \ln(1 - \delta)$

■

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

$$\mu = \frac{n}{2}$$

$$\begin{aligned} P_r \left(|X - \mu| \geq \sqrt{\frac{3}{2} n \ln(n)} \right) &= P_r \left(|X - \mu| \geq \frac{n}{2} \sqrt{\frac{6}{n} \ln(n)} \right) \\ &\stackrel{\text{Chernoff}}{\leq} 2e^{-\frac{\frac{n}{2} \sqrt{\frac{6}{n} \ln(n)}}{3}} = \frac{2}{n}; \end{aligned}$$

For „big“ n is $\delta \in (0,1)$,

$$\mu = \frac{n}{2}, \delta = \sqrt{\frac{6}{n} \ln(n)}.$$

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

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

Claim 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 $c \geq 4, m \in \mathbb{N}$.

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

Proof 4.0.4.

$$\begin{aligned} P_r(X \leq m) &= P_r \left(\frac{cm}{2} - X \geq \frac{cm}{2} - m \right) \\ &= P_r \left(\frac{cm}{2} - X \geq \frac{cm}{2} \left(1 - \frac{2}{c} \right) \right) \\ &\stackrel{\text{Chernoff}}{\leq} e^{-\frac{\frac{cm}{2} \left(1 - \frac{2}{c} \right)^2}{2}} \\ &\stackrel{4.4}{\leq} e^{-\frac{\frac{cm}{2} \frac{1}{4}}{2}} = e^{-\frac{cm}{16}}. \end{aligned} \tag{4.4}$$

■

Back to Quicksort.

Theorem 4.0.5.

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

Proof 4.0.6.

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

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

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

Notice: after at most $\log_{\frac{4}{3}}(n) = \frac{\ln(n)}{\ln(4)-\ln(3)}$ succesful iterations, the element s is sorted.

Probability that we haven't sorted s after $c \log_{\frac{4}{3}}(n)$ steps is at most:

$$\begin{aligned} P_r \left(\sum_{i=1}^{c \log_{\frac{4}{3}}(n)} X_i < \log_{\frac{4}{3}}(n) \right) &\leq P_r \left(\sum_{i=1}^{c \log_{\frac{4}{3}}(n)} Y_i < \log_{\frac{4}{3}}(n) \right) \quad (4.5) \\ &\stackrel{\text{Chernoff}}{<} e^{-\frac{c \log_{\frac{4}{3}}(n)}{24}} \\ &= e^{-\frac{c 2 \ln(n) \log_{\frac{4}{3}}(e)}{48}} \\ &= \frac{1}{n^2} \frac{c \log_{\frac{4}{3}}(e)}{48} \\ &\stackrel{4.6}{\leq} \left(\frac{1}{n}\right)^2. \end{aligned}$$

4.5 because X_i is not independent, we select such independent $Y_i \sim \begin{pmatrix} 0 & 1 \\ \frac{1}{2} & \frac{1}{2} \end{pmatrix}$, so that $X_i \geq Y_i$ (how do we construct such Y_i ???)

$$\log_{\frac{4}{3}}(e) \approx 3.4, \text{ we select } c = 14. \quad (4.6)$$

Because of 4.6, we know that to sort s we will need at least $48 \ln(n)$ iterations with probability less than $\left(\frac{1}{n}\right)^2$. Denote this event with A_s . The probability that we will need at least $48 \ln(n)$ iterations to sort any $s \in S$ is $P(\bigcup_{s \in S} A_s) \leq \sum_{s \in S} P(A_s) \leq n \frac{1}{n^2} = \frac{1}{n}$. Thus we will need at $48n \ln(n)$ iterations in total with probability less than $\frac{1}{n}$ or in other words, total number of comparisons will be at most $48n \ln(n)$ with probability $1 - \frac{1}{n}$. \blacksquare

Poglavlje 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.

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

$v \cdot E\left(\frac{\sum_{i=1}^n X_i}{n}\right) = I$ where v is the volume of the subset from which we take random (x_i, y_i, z_i) .

5.3 (ε, δ) -approximation

Definition 5.3.1 ((ε, δ) -approximation). A random algorithm gives a (ε, δ) -approximation for value v if the output X satisfies:

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

Theorem 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 $m \geq \frac{3 \ln(\frac{2}{\delta})}{\varepsilon^2 \mu}$, then $P_r(|Y - \mu| \geq \varepsilon \mu) \leq \delta \implies Y$ is (ε, δ) -approximation for μ .

Proof 5.3.3.

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

$$\begin{aligned} E(X) &= mE(x_i) = m\mu \\ m &\geq \frac{3 \ln(\frac{2}{\delta})}{\varepsilon^2 \mu} \end{aligned}$$

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

■

Back to example 1:

$$\begin{aligned} E(Y) &= \frac{\pi}{4}, \delta = \frac{1}{1000} \quad (99.9\% \text{ sure}), \varepsilon = \frac{1}{10000} \\ \implies M &= \frac{3 \ln\left(\frac{2}{\frac{1}{1000}}\right)^4}{\pi\left(\frac{1}{10000}\right)^2} \approx 29106. \end{aligned}$$

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: $(\overline{X_{i_1}} \wedge X_{i_2} \wedge \overline{X_{i_4}}) \vee \dots$ - easy to determine if solution exists - this is the negation of the above CNF.

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

```

$$X_i = \begin{cases} 1 & : F(x_{i1}, \dots, x_{in}) = 1 \\ 0 & : \text{otherwise} \end{cases}$$

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

We attempt to achieve an (ε, δ) -approximation for the number of solutions of the DNF using Y .

$$E(X_i) = P_r(X_i = 1) = \frac{\text{number of solutions of } F}{2^n}$$

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

For Y to be an (ε, δ) -approximation we need $m \geq \frac{3 \ln(\frac{2}{\delta})}{\varepsilon^2 E(X)} = \frac{3 \ln(\frac{2}{\delta})}{\varepsilon^2} \cdot \frac{2^n}{c(F)}$ according to the previous theorem.

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

Definition 5.4.1.

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

Suppose F_i is a conjunction of l_i different variables $a_{i_1}, \dots, a_{i_{l_i}}$ (or their ne-

gations). If $F_i(a_1, \dots, a_n) = 1$, this uniquely determines $a_{i_1}, \dots, a_{i_{l_i}}$ and so $|SC_i| = 2^{n-l_i}$

$$\begin{aligned} U &= \{(i, a) \mid i \in \{1, 2, \dots, t\}, a \in SC_i\} \\ |U| &= \sum_{i=1}^t |SC_i| \text{ (space smaller than } \{0, 1\}^n\text{)} \\ S &= \{(i, a) \in U \mid a \in SC_i, a \notin SC_j \text{ } 1 \leq j < i\} \\ |S| &= c(F) \text{ (each solution appears exactly once in } S\text{).} \end{aligned}$$

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 x / m

```

In order to check whether $a \in S$, we need to check whether there is such i so that $a \in SC_i$ and $a \notin SC_j$ $j = 1 \dots i - 1$. To check whether or not $a \in SC_i$ takes $O(n)$ time, so the it takes $O(tn)$ time to check whether $a \in S$.

We can implement uniform random selection from U with $O(1)$ time complexity so the total time complexity is $O(t \cdot n \cdot m)$.

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

The time complexity follows immediately from the previous analysis. Define

$$\begin{aligned} X_i &= \begin{cases} 1 : i\text{-th selection is in } S \\ 0 : \text{otherwise} \end{cases} \\ Y &= \frac{\sum_{i=1}^m X_i}{m} \end{aligned}$$

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

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

if

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

We have

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

This is because SC_i contains at most $c(F)$ elements for every i and $|S| = c(F)$.

So it suffices to take

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

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

Poglavlje 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 $x_1 \dots x_n$.

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

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

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

Proof 6.0.2. Induction on n .

$n = 1$:

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

Fact: number of zeros \leq degree

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

$n - 1 \rightarrow n$:

rewrite p :

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

for some $j \leq d$

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

because

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

■

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_ABC(A, B, C):

```

for i in range(1, k+1):
    x uniformly at random from {0,1,2}^n
    if A · (B · x) ≠ C · x:
        return false
    
```

```
return true
```

The time complexity of the above algorithm is $O(kn^2)$.

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

If $A \cdot B \neq C$:

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

$\|(AB - C)x\|^2$ - 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 (perfect matching) in bipartite graphs.

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

Represent G with $n \times n$ matrix $Z = (Z_{ij})_{i,j=1}^n$. Let X be a random $n \times n$ matrix with entries from $\{1, 2, \dots, 2n\}$

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

$$\begin{aligned} \det Z &= \sum_{\pi \in S_n} \text{sign}(\pi) Z_{1,\pi(1)} \dots Z_{n,\pi(n)} \\ &= \sum_{\substack{\pi \in S_n \\ \pi \text{ 1-factor}}} \text{sign}(\pi) X_{1,\pi(1)} \dots X_{n,\pi(n)}. \end{aligned}$$

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

```
Rand_1factor(G):
    construct polynomial det Z with variables x11, ..., xn
    for i in range(1, k + 1):
        r <- uniformly at random from {1, 2, ..., 2n}^{n^2}
        compute d = det Z(r11...rn)
        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
$$1 - \left(\frac{n}{2n}\right)^k = 1 - \left(\frac{1}{2}\right)^k$$

Poglavlje 7

Random graphs

7.1 $G(n,p)$ model

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

Example. $G(5, \frac{1}{2})$.

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

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

p can be function of n .

Y_v : degree of v .

By observing the handshaking lemma and using linearity of the expected value and the fact that all vertices have the same expected degree, we get $E(Y_v) = (n - 1)p$.

Definition 7.1.1.

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

Claim 7.1.2.

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

Proof 7.1.3.

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

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

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

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

$$\begin{aligned} P_r(G \text{ has diameter } > 2) &= P_r(X_w = 0 \text{ for all } w \notin u,v \text{ for some non-adjacent } u,v) \\ &\leq P_r(X_w = 0 \text{ for all } w \notin u,v \text{ for some } u,v) \\ &\leq \binom{n}{2} (1 - p^2)^{n-2} \xrightarrow{n \rightarrow \infty} 0 \end{aligned}$$

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

$$p = f(n)$$

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

Theorem 7.1.4. (without proof)

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

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

Theorem 7.1.5.

Let $np = \omega(n) \ln(n)$ for $\omega(n) \rightarrow \infty$. Then $\text{diam}(G) = \Theta\left(\frac{\ln n}{\ln(np)}\right)$ for G in $G(n,p)$ A. S.

Lemma 7.1.6.

Let $S \subset V(G)$, $|S| = cn$ for $c \in (0,1]$ and $v \notin S$. Denote by $N_S(v)$ the number of neighbors of v in S . Then $cnp(1 - \omega^{-\frac{1}{3}}) \leq N_S(v) \leq cnp(1 + \omega^{-\frac{1}{3}})$ A.S.

Proof 7.1.7. (Lemma):

Because each vertex in S is adjacent to v with probability p , we have $E(N_s(v)) = c \cdot n \cdot p$. Define $\delta = \omega^{-\frac{1}{3}}$

$$\begin{aligned} P_r(|N_s(v) - cnp| \geq \delta cnp) &\stackrel{\text{Chernoff}}{\leq} 2e^{-\frac{\omega^{-\frac{2}{3}} cnp}{3}} \\ &= 2e^{-\frac{cnp}{3\omega(n)^{\frac{2}{3}}}} \\ &= 2e^{-\frac{c\omega(n)^{\frac{1}{3}} \ln(n)}{3}} \xrightarrow{n \rightarrow \infty} 0. \end{aligned}$$

We can also see that $n \cdot 2e^{-\frac{cnp}{3\omega(n)^{\frac{2}{3}}}} \xrightarrow{n \rightarrow \infty} 0$. ■

Proof 7.1.8. (Theorem):

Let G be a random graph and let v be any vertex in G . Let N_i be the random variable which maps to the set of all vertices in G whose distance from v is equal to i .

$$|N_0| = 1$$

Every vertex that is at distance i from v , is a neighbor of a vertex in N_{i-1} which isn't contained in N_j for $j < i$. So N_i is a subset of the set of neighbors of N_{i-1} which aren't contained in N_j for $j < i$. By the previous lemma, every vertex in N_{i-1} has at most $n \cdot p \cdot (1 + \omega^{-\frac{1}{3}})$ neighbors which aren't contained in such N_j A. S. Because the sets of neighbors of different vertices in N_i are independent variables, we have that previously described set of neighbors of vertices in N_{i-1} has at most $|N_{i-1}| \cdot n \cdot p \cdot (1 + \omega^{-\frac{1}{3}})$ vertices A. S. and so $|N_i| \leq |N_{i-1}| \cdot n \cdot p \cdot (1 + \omega^{-\frac{1}{3}})$ A. S.

$$\text{Let's select } k = \frac{\log(\frac{n}{3})}{\log(n \cdot p \cdot (1 + \omega^{-\frac{1}{3}}))} = \log_{np(1 + \omega^{-\frac{1}{3}})} \frac{n}{3} = \Theta\left(\frac{\ln(n)}{\ln(np)}\right).$$

$N_{\leq k} = N_1 \cup \dots \cup N_k$. We then have almost surely:

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

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

By the selection of k and by selecting $S = V(G) \setminus N_{\leq i}$, we have $|S| \geq \frac{n}{2}$ and so by previous lemma we have $\frac{1}{2}np(1 - \omega^{-\frac{1}{3}}) \cdot |N_{i-1}| \leq |N_i|$ A. S. Thus we have almost surely:

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

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

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

Number of neighbors in N_k A.S. ≥ 1 ,

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

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

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 modes.

Grow:

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

Theorem 7.2.1.

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

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

Definition 7.2.2.

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

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

Proof 7.2.3.

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

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

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

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

$p_n(k) \cdot n$: 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):

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

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

For degree m :

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

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

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

■

Poglavlje 8

Markov chains

Ω : finite set (of states).

Definition 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 Ω and properties:

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

Example.

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

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

Definition 8.0.2 (Transition matrix).

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

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

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

Definition 8.0.3 (Transition graph).

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

P is stochastic matrix:

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

$$\sum_j p_{ij} = 1 \text{ (row sum).}$$

We choose beginning state randomly.

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

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

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

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

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

Definition 8.0.4.

- Distribution π 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 .

Theorem 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 π regardless of $q(0)$,
- d) if X is aperiodic: $\lim_{t \rightarrow \infty} q(0) \cdot P^t = \pi$.

Example.

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

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

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

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

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

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

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 = (b00 ... bn0)
    for i in range(t):
        if F(bi) = 1:
            return True
        Cl <- clause that is False
        xj <- uniformly at random from xl1 and xl2
        bi+1 = (b0i ... bji ... bni)
    if F(bt) = 1:
        return True
    return False
```

Theorem 8.1.1.

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

Proof 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 $h_{n,0}$.

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

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

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

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

By theorem

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

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

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

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

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

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

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

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

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

■

8.2 Generating a uniformly random element of a set

Ω : set.

Let G be a symmetric graph on Ω .

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.

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

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

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

\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.

Example.

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 $|u \Delta v| = 1$ ($(u \cup \{el\}) = v$)

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

Ω : set,

π : chosen distribution on Ω .

Make G graph on Ω

$$\begin{aligned}
P_{x,y} &= \begin{cases} \frac{1}{M} \cdot \min \left(1, \frac{\pi_y}{\pi_x} \right) : & \text{if } x \neq y \wedge x \sim y \\ 0 : & \text{if } x \neq y \wedge x \not\sim y \\ 1 - \sum_{y \in N(x)} : & \text{if } x = y \end{cases} \\
M &\geq \max_{v \in \Omega} |N(v)| \\
\pi &\stackrel{?}{=} \pi P
\end{aligned}$$

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

Example.

$$\begin{aligned}
\Omega &= \mathbb{Z} \cap [-1000, 1000] \\
\pi &\sim e^{-\frac{(x-\mu)^2}{2\delta}}
\end{aligned}$$

```

X0 arbitrary
for i = in range(1,m):
    y <- uniformly from {X_i - 11, X_i + 1}
    M <- uniformly from [0,1]
    if M <= π(y) / π(x):
        X_{i+1} = y
    else:
        X_{i+1} = X_i
return X_m

```

Example.

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.

$$G = (V, E)$$

Ω = 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 $\frac{1}{\lambda} = \min\{1, \frac{\pi_u}{\pi_x}\}$,
 - $X_{i+1} = X_i$ 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 $X_{i+1} = X_i$.

Example.

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

$B \leftarrow$ 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 μ 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 $h_{s,t}$

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

Lemma 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 .

Proof 8.4.2.

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

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

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

$$|A| = n$$

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

Network centrality

Degree as measure - natural idea.

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

Pagerank.

Let A be the adjacency matrix of G .

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

α : normal random walk,

$1 - \alpha$: jump to any.

$\alpha = 0.85$.

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

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

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

$Y = Y_1 + \dots + Y_n$

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

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

Alg():

```
X1...Xn = random permutation of S
min = X1
for i in range(1, n+1):
    if Xi < min:
        print(\sn{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.

QuicksortRIC(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) # Ii splits interval (Xj, Xk)

```

```

 $I_{i1} = (X_j, X_i)$ 
 $I_{i2} = (X_i, X_k)$ 
for  $X_l \neq X_i, X_l \in P(I)$ :
    add  $X_l$  to  $P(I_{i1})$  or  $P(I_{i2})$  depending on  $X_l < X_i$  or  $X_l > X_i$ 
     $Next(X_j) = X_i$ 
     $Next(X_i) = X_k$ 
return  $[Next(-\infty), Next(Next(-\infty)) \dots]$ 

```

Similarity to quicksort: splitting intervals.

Analysis:

for set i , we need $O(|P(I_i)|)$,

$E(|P(I_i)|) = ?$

e.g.

if $x_4 = a_4$:

if $x_4 = a_2$:

$P(X_i = a_j) = \frac{1}{i}, j \in \{1, 2 \dots i\}$.

Expected value of steps in iteration i

$$\sum_{j=1}^i \frac{1}{i} (P((a_{j-1}, a_j)) + P((a_j, a_{j+1}))) \leq \frac{1}{i} 2(n - i) \leq \frac{2n}{i}$$

$$\begin{aligned}
E(\text{number of steps in QuicksortRIC}) &\leq \sum_{i=1}^n \frac{2n}{i} \\
&\leq 2n(1 + \log n) \rightarrow \text{in } O(n \log n).
\end{aligned}$$

9.2 Linear programming

Task: maximize $f(x_1 \dots x_n) = c_1x_1 + \dots + c_dx_d$.

Constraints:

$$\begin{aligned} a_{11}x_1 + \dots + a_{1d}x_d &\leq b_1 \\ &\vdots \\ a_{n1}x_1 + \dots + a_{nd}x_d &\leq b_n. \end{aligned}$$

Geometric interpretation.

Cases:

- infeasible region
- unbounded
- multiple solutions.

Alg:

- simplex algorithm worst case $O(2^n)$,
- interior point method (polynomial algorithm).

Seidel's algorithm:

running in expected $O(n)$ time when d is constant.

One dimension.

$$\begin{aligned} \max cx \\ a_1x \leq b_1 \\ &\vdots \\ a_nx \leq b_n, \end{aligned}$$

where n is number of constraints.

- a_i positive: $(-\infty, \frac{b_i}{a_i}] \quad \left(x_i \leq \frac{b_i}{a_i} \right)$,
- a_i negative: $[\frac{b_i}{a_i}, \infty) \quad \left(x_i \geq \frac{b_i}{a_i} \right)$.

$a_i \neq 0$.

Alg:

$$R = \min_i \left\{ \frac{b_i}{a_i}; a_i > 0 \right\},$$

$$L = \max_i \left\{ \frac{b_i}{a_i}; a_i < 0 \right\},$$

if $L > R$: program infeasible,

else:

 if $c > 0$: return R ,

 if $c < 0$: return L .

2-dim: assume general position.

$$\max c_1x + c_2y$$

$$a_{11}x + a_{12}y \leq b_1$$

\vdots

$$a_{n1}x + a_{n2}y \leq b_n$$

$$x \leq M \text{ or } x \geq -M$$

$$y \leq M \text{ or } y \geq -M.$$

\leq, \geq depending on c_1, c_2 .

Notation:

h_i : halfspace defined by $a_{i1}x + a_{i2}y \leq b_i$,

m_i : added halfspaces, defined by $X, Y \leq M$ or $\geq -M$,

l_i : line that bounds.

Alg:

- first randomly permute h_i ,

- $H_i = \{m_1, m_2, h_1 \dots h_i\}$,
- $v_i \in \cap H_i$ optimal solution after i constraints,
- $v_0 = (\pm M, \pm M)$,
- inductively add h_i .

Cases:

$$\text{if } v_{i-1} \in h_i \implies v_i = v_{i-1},$$

$$\text{if } v_{i-1} \notin h_i \implies v_i \in h_i:$$

$$a_{i1}x + a_{i2}y = b_i$$

$$a_{i1} \text{ or } a_{i2} \neq 0, \text{ e.g. } a_{i1};$$

$$x = \frac{b_i - a_{i2}y}{a_{i1}}.$$

Insert x in all constraints \implies linear program in 1-dim, i ($i-1?$) constraints \implies get v_i in $O(i)$.

Analysis:

- worst case: $\sum_{i=1}^n O(i) = O(n^2)$,
- expected: $E(X) = \sum_{i=1}^n E(X_i)$,
- X_i = running time of i -th iteration,
- $X_i = \begin{cases} O(1) & \text{case 1} \\ O(i) & \text{case 2} \end{cases}$
- $P(\text{case 2}) \leq \frac{2}{i}$ - optimal point on at most 2 lines,
- $E(X) \leq \sum_{i=1}^n O(1) \cdot 1 + O(i) \cdot \frac{2}{i} = O(n)$.

d -dim

- constraints define half-spaces,
- boundary is hyperplane ($d-1$ dimensional),

- general position: intersection of $d - i$ hyperplanes is i dimensional, intersection of $d + 1$ hyperplanes is \emptyset .

Alg:

first add $X_i \leq M$ or $X_i \geq -M$ depending on c_i ,

random permutation $(h_1 \dots h_n)$,

$$H_i = \{m_1 \dots m_d, h_1 \dots h_i\},$$

$$v_0 \in \cap \partial m_i,$$

inductively add h_i :

$$v_{i-1} \in h_i \implies v_i = v_{i-1},$$

$v_{i-1} \notin h_i \implies$ we need to solve LP in $d - 1$ dimensions with i constraints ($O(i)$ expected),

$$P(v_{i-1} \notin h_i) \leq \frac{d}{i},$$

$$E(X) \leq \sum_{i=1}^n O(1) + \frac{d}{i} O(i) = O(n).$$

X : running time.

Careful implementation runs in $O(d! n) \implies$ very useful for low dimensions.

Problem: let P be convex polygon given by ordered set of vertices

$$y = a_i x + b_i.$$

Find largest disc embeddable in P .

Input: $P_1 \dots P_n$,

output: $(s_1, s_2), r$.

$$\max r$$

$$r = \left| \frac{s_2 - a_i s_1 - b_i}{\sqrt{a_i^2 + 1}} \right|$$

$$\frac{s_2 - a_i s_1 - b_i}{\sqrt{a_i^2 + 1}} \geq r \text{ - line above } P$$

$$-\frac{s_2 - a_i s_1 - b_i}{\sqrt{a_i^2 + 1}} \leq -r \text{ - line below } P$$

\implies LP in 3 dim.

Note: $\frac{s_2 - a_i s_1 - b_i}{\sqrt{a_i^2 + 1}}$ positive if (s_1, s_2) above the line, negative otherwise.

Poglavlje 10

Hashing

A hash function is a random function,

$$h : U \rightarrow \{0, 1 \dots n - 1\} = M,$$

U - universe,

$$u = |U|,$$

$$m = |M|.$$

Ideally we would like for h to be as completely random: $P(h(x) = t) = \frac{1}{m}$.

Standard application.

Let $V \subset U$, $|V| \ll |U|$.

We would like to quickly answer if $x \in V$ for every $x \in U$.

Solution:

- take $h : U \rightarrow M$,
- make a table $T = [0, 1 \dots n - 1]$,
- for $v \in V$:

$$T[h(v)] = 1,$$

$$T[y] = 0 \quad \forall y \in h(V).$$

- Let $x \in V$. Check

- if $T[h(x)] = 1 : x \in V,$
- else: $x \notin V.$

Note: this is not OK: h not injective.

For $x \in U$, tell if $x \in V$ in $O(1)$.

$$h = \text{SHA256} : U \rightarrow \{0, 1\}^{256}.$$

Approach:

- design a family of hash functions,
- study collisions $P_h(h(x) = h(y)),$
- H needs to be „simple“.

Bad example: H = all functions from U to M storing $h \in H$ would take $|U| \log_2 |M|$ bits.

Definition 10.0.1. A family of hash functions to be universal if for

$$\forall x, y \in U, x \neq y, h \in H : P(h(x) = h(y)) \leq \frac{1}{m} \text{ (probability of collision).}$$

k -independent if $\forall x_1 \dots x_k \in U$ pairwise different, $\forall t_1 \dots t_k \in M$

$$P_r(h(x_i) = t_i \ \forall i) \leq \frac{1}{m^k}.$$

Example.

$$U = \{0, 1, 2, 3\},$$

$$M = \{0, 1\},$$

$$H = \{h_0, h_1, h_2\},$$

$$h_0 : \{0 \rightarrow 0, 1 \rightarrow 0, 2 \rightarrow 1, 3 \rightarrow 1\},$$

$$h_1 : \{0 \rightarrow 0, 1 \rightarrow 1, 2 \rightarrow 0, 3 \rightarrow 1\},$$

$$h_2 : \{0 \rightarrow 0, 1 \rightarrow 1, 2 \rightarrow 1, 3 \rightarrow 0\}.$$

$$P(h(0) = h(2)) = \frac{2}{3} > \frac{1}{2} - \text{not universal.}$$

Why universal?

$$U, V, M$$

$$H \text{ universal: } \forall x, y : P(h(x) = h(y)) \leq \frac{1}{m}.$$

X : number of collisions of V .

$$E(X) = E\left(\sum_{x,y \in V, x \neq y} X_{x,y}\right)$$

$$X_{x,y} = \begin{cases} 1 & \text{if } h(x) = h(y) \\ 0 & \text{else} \end{cases}$$

$$E(X) = \sum_{x,y \in V, x \neq y} E(X_{x,y}) \leq \binom{n}{2} \cdot \frac{1}{m}.$$

U, V, M, H

$T[0 \dots m - 1]$

$\forall v \in V$

$T[h(v)] = v.$

For $x \in V$ we check $T[h(x)]$ if equals x ,

for $y \in U \setminus V$, $T[h(y)] \neq y$.

For $z \in V$, $T[h(z)]$ can happen $\neq z$ if h has collisions in V .

Lemma 10.0.2.

Let $m \geq n^2$ and H universal. Then the probability that h has no collisions in V $\geq \frac{1}{2}$.

Proof 10.0.3.

X : number of collisions

$$E(X) \leq \binom{n}{2} \cdot \frac{1}{m} < \frac{n^2}{2} \cdot \frac{1}{n^2} = \frac{1}{2}$$

$$P(X \geq 1) \stackrel{\text{Markov}}{\leq} \frac{E(X)}{1} = \frac{1}{2}$$

$$P(X = 0) \geq \frac{1}{2}. \quad \blacksquare$$

Example (Universal hash family).

$U = \{0, 1 \dots u - 1\}$ (bits \equiv numbers)

$M = \{0, 1 \dots m - 1\}$.

Define: let $p \geq u$, p prime number.

Define for $a, b \in \mathbb{Z}_p$, $a \neq 0$.

$$h_{a,b} = (ax + b) \pmod{m}$$

$$ax + b \in \mathbb{Z}_p$$

$$H = \{h_{a,b} \mid a, b \in \mathbb{Z}_p, a \neq 0\}.$$

Proof 10.0.4.

$$P(h_{a,b}(x) = h_{a,b}(y)) = ?$$

x, y fixed.

For any a, b denote

$$ax + b = t_x$$

$$ay + b = t_y :$$

$$a \sqcup +b \in \mathbb{Z}_p.$$

$$\begin{bmatrix} x & 1 \\ y & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} t_x \\ t_y \end{bmatrix}$$

$$\det \begin{bmatrix} x & 1 \\ y & 1 \end{bmatrix} \neq 0, \text{ because } x \neq y$$

$$\begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} x & 1 \\ y & 1 \end{bmatrix}^{-1} \begin{bmatrix} t_x \\ t_y \end{bmatrix}.$$

For each t_x, t_y there exists 1 a, b mapping to t_x, t_y .

$$h_{a,b}(x) = h_{a,b}(y) \iff t_x = t_y \pmod{m}.$$

This holds for $p(\lceil \frac{p}{m} \rceil + 1)$

p : choice of t_y

$$t_x = t_y + km$$

$$P(h_{a,b}(x) = h_{a,b}(y)) \leq \frac{p(\lceil \frac{p}{m} \rceil - 1)}{p(p-1)} \leq \frac{\frac{p-1}{m}}{p-1} = \frac{1}{m}.$$

■

Function random for 2 elements, fixed for ≥ 3 .

Higher k-independent: better.

10.1 Chaining

$$V, U, h : U \rightarrow V.$$

Answer $x \in V$ in $O(1)$.

$$T[0 \dots m-1]$$

$$n = |V|$$

$\forall v \in V$:

$$h(v_1) = h(v_2) \rightarrow [v_1 \ v_2 \ \dots] - \text{linked list.}$$

Now:

$$x \in U.$$

Check if x is in list at $T[h(x)]$.

Check takes $O(\text{length of a list at } h(x)) = 1 + \text{number of collisions with } x$.

X_x : number of collisions with x .

$$E(X_x) = \sum_{y \in V} E(X_{x,y}) \leq n \cdot \frac{1}{m} \text{ if hash function is universal.}$$

$\alpha = \frac{n}{m}$: load factory (how many elements in 1 place).

$$E(X_x) = 1$$

$$E(\max_x X_x) \neq \max_x E(X_x) = 1.$$

Theorem 10.1.1. Assume we throw n balls into n bins uniformly at random.

Then with high probability the fullest contains $\theta\left(\frac{\log n}{\log(\log n)}\right)$ balls.

Proof 10.1.2.

$$\stackrel{?}{\leq} \frac{3 \ln n}{\ln \ln n}.$$

Let X_j be the number of balls in bin j .

$$P\left(X_j \geq \frac{3 \ln n}{\ln \ln n}\right) = P(\text{there exists subset } S \text{ of balls thrown to bin } j).$$

$$|S| = k$$

$$\begin{aligned} & P\left(\bigcup_{S \text{ balls}, |S|=k} \text{balls from } S \text{ are thrown to bin } j\right) \\ & \leq \sum_{S \text{ balls}, |S|=k} P(\text{balls from } S \text{ are thrown to } j) \\ & = \binom{n}{k} \left(\frac{1}{n}\right)^k \\ & \leq \frac{n^k}{k!} \cdot \frac{1}{n^k} \\ & = \frac{1}{k!} \\ & = \left(\frac{e \ln n}{3 \ln \ln n}\right)^{\frac{3 \ln n}{\ln \ln n}} \\ & \leq e^{\frac{3 \ln n}{\ln \ln n} \cdot (\ln \ln \ln n - \ln \ln n)} \\ & = e^{-3 \ln n + \frac{\ln \ln \ln n \cdot (\ln n \cdot 3)}{\ln \ln n}} \\ & = \frac{1}{n^2}; \end{aligned}$$

$$e^x = \sum_{i=1}^{\infty} \frac{k^i}{i!} \geq \frac{k^k}{k!}, \quad (10.1)$$

$$\frac{\ln \ln \ln n}{\ln \ln n} \rightarrow 0. \quad (10.2)$$

$$P(\text{at least for 1 bin } j \geq k) = n \cdot \frac{1}{n^2} = \frac{1}{n}. \quad \blacksquare$$

U, V, H hash family, $h : U \rightarrow M$

$v \in V$

$n = |V|$

max load $O\left(\frac{\log n}{\log(\log n)}\right)$.

Perfect hashing: we would like

- $O(1)$ lookup (worst case)
- $O(n)$ size of table.

10.2 2 level hashing

Input: V

$n = |V|$.

Take hash function from universal family with $m = |M| = n$.

Count total collisions X .

$$E(X) \leq \binom{n}{2} \cdot \frac{1}{m} \leq \frac{n}{2}$$

$$P(x \geq n) \stackrel{\text{Markov}}{\leq} \frac{1}{2}$$

\implies by repeating sample h we can guarantee

- for each $i \in M$ we store at $T[i]$ another hash table of size C_i^2 , where C_i = number of elements of V , hashed in i ,
- we sample h_i from universal hash family with $M_i = C_i^2$.

$$P(h_i \text{ has no collisions}) \geq \frac{1}{2} \text{ (by lemma).}$$

We resample if h_i has collisions.

$$E(\text{sampling } h_i) = 2.$$

Construction time:

- step 1: $O(n)$
- step 2: $O(C_1 + \dots + C_n) = O(n)$;

together $O(n)$.

Lookup time: $O(1)$ (evaluating $h(x)$ and $h_{h(x)}(x)$).

Space: $O(C_1^2 + \dots + C_n^2)$ in $O(n)$.

By first step:

$$\begin{aligned} n &> \text{number of collisions of } h = \sum_{i=1}^n \binom{C_i}{2} = \sum_{i=1}^n \frac{C_i^2 - C_i}{2} \\ \implies \sum_{i=1}^n C_i^2 &< 2n + \sum_{i=1}^n C_i = 3n. \end{aligned}$$

10.3 The power of 2 choices

Variant: placing n balls in n bins but for each ball we choose d bins uniformly at random and put the ball in bin with minimal load.

Theorem 10.3.1. The above process with $d \geq 2$ results in at most maximum load of $O\left(\frac{\ln(\ln n)}{\ln d}\right)$.

Proof 10.3.2. (sketch).

b_i = upper bound of the number of bins with load at most i .

Height of a ball = the number of balls in the bin, where the ball is placed.

$P(\text{a ball has height at least } i+1) \leq \left(\frac{b_i}{n}\right)^d$ (choose d times independently).

X^{i+1} : number of balls with height $\geq i+1$.

$$X^{i+1} = \sum_{j=1}^n X_j^{i+1}$$

X_j^{i+1} : indicator variable of j -th ball having height $i+1$.

$$E(X^{i+1}) \leq \sum_{j=1}^n \left(\frac{b_i}{n}\right)^d = n \cdot \left(\frac{b_i}{n}\right)^d.$$

Chernoff bound: with high probability $X^{i+1} \leq 2n \left(\frac{b_i}{n}\right)^d$.

$X^{i+1} \geq$ number of bins with load at least $i+1$.

Define (set)

$$b_{i+1} = \frac{\sum b_i^d}{n^{d-1}}$$

$$b_4 = \frac{n}{4}$$

$$b_{i+4} = \frac{n}{2^{2 \cdot d^i - \sum_{j=0}^{i-1} d^j}}$$

$$i = 0: b_4 = \frac{n}{2^{2^1}} = \frac{n}{4}$$

$i \rightarrow i + 1$:

$$\begin{aligned}
 b_{i+4} &= \frac{2 \cdot b_{i+3}}{n^{d-1}} \\
 &\stackrel{IH}{=} \frac{2 \cdot \left(\frac{n}{2^{2 \cdot d^i - \sum_{j=0}^{i-1} d^j}} \right)^d}{n^{d-1}} \\
 &= \frac{2^1 \cdot n^d}{n^{d-1} \cdot 2^{2 \cdot d^{i+1} - \sum_{j=1}^i d^j}} \\
 &= \frac{n}{2^{2 \cdot d^{i+1} - \sum_{j=0}^i d^j}}.
 \end{aligned}$$

In particular: $b_{i+4} \leq \frac{n}{2^{d^i}} < 1$ when?

$$n < 2^{d^i}$$

$$\log_2 n < d^i$$

$$\log_d \log_2 n < i$$

\implies for $i = \frac{\log(\log_2 n)}{\log d}$ is $b_i < 1 \implies$ no bins with load $> \frac{\log(\log_2 n)}{\log d}$. ■

Application:

We sample 2 hash functions $h_1, h_2 : U \rightarrow M$.

For element $v \in V$ we insert in $T[h_1(v)]$ or $T[h_2(v)]$ depending on which list is shorter.

Max load in $O(\log(\log n))$.

10.4 Cockoo hashing

Idea: use 2 hash functions but allow moving elements later.

We want to have at most 1 element at each entry in the table.

Inserting:

- if empty: insert,
- if not empty: push other element to its other choice, repeat recursively.

Questions:

- how many do I need to move,
- how many elements can I insert before problems?

We can think of positions in the table as vertices and elements of V as edges. $|V|$ edges are inserted uniformly at random (if ideal hash function) \implies random graph.

Erdős-reny model: $G_{n,m} \approx G_{n,p}$ if $m = \binom{n}{2} \cdot p$ (A.S. properties).

If $np < 1 - \varepsilon$: all connected components have size at most $O(\log n)$, components are trees or at most 1 cycle per component, expected size of a component is $O(1)$.

Fact: if graph has at most 1 cycle per component, then inserting can be done and takes at most $2 \cdot (\text{size of component})$ time (each edge changes direction at most 2 times).

Theorem 10.4.1.

Let $n = |U|$, $h_1, h_2 : U \rightarrow M$, $m = |M| = 2 \cdot (1 + \varepsilon) \cdot n$, then with high probability cockoo hashing works correctly with

- inserting time:
 - $O(\log n)$ time worst case,
 - $O(1)$ expected case,
- space: $O(n)$,
- lookup time: $O(1)$.

Dynamically add element:

$$\begin{aligned} m &= 2 \cdot (1 + \varepsilon) \cdot n \\ p &= \frac{m'}{\binom{n'}{2}} = \frac{2m'}{n'(n'-1)} \\ pn' &= \frac{2m'}{(n'-1)} = \frac{2n'}{2(1+\varepsilon)n'} = \frac{1}{1+\varepsilon} < 1 + \varepsilon' \end{aligned}$$

10.5 Bloom filter

Take k hash functions $h_1 \dots h_k$ at random, $h_i : U \rightarrow M, T[0 \dots m - 1]$.

$V \subset U$, for every element $v \in V$ set $T[h_i(v)] = 1 \forall i \in \{1 \dots k\}$.

False positives: $x \notin V$ such that $T[h_i(x)] = 1 \forall i \in \{1 \dots k\}$.

For each $T[j]$ $P(T[j] = 0) = \left(1 - \frac{1}{m}\right)^n \approx e^{-\frac{nk}{m}}$;

k : each hash function, n : for each v .

Now

$P(T[h_i(x)] = 1 \forall i, \forall x \notin V) \approx \left(1 - e^{-\frac{nk}{m}}\right)^k = f(k)$ - probability of a false positive.

$\left(1 - e^{-\frac{nk}{m}}\right)$: 1 position.

Searching for a minimum:

$$f'(k) = 0$$

$$\implies k = \ln 2 \cdot \frac{m}{n}$$

$$f\left(\ln 2 \cdot \frac{m}{n}\right) = \left(\frac{1}{2}\right)^{\ln 2 \frac{m}{n}} \approx 0.6185 \frac{m}{n}$$

\implies we choose m such that $0.6185 \frac{m}{n}$ small (in $O(n)$)

$$\implies \text{calculating } k = \ln 2 \cdot \frac{m}{n}$$

\implies hashing with space $O(n)$

\implies checking in $O(1)$

\implies probability of error small.

10.6 Linear probing

$V \subset U, h : U \rightarrow M, T[0 \dots m - 1]$.

- Insert $v \in V$: check $T[h(v)], T[h(v) + 1], T[h(v) + 1] \dots$ until finding empty space, then insert it.
- Check if $x \in V$ by checking $T[h(x)] \stackrel{?}{=} x, T[h(x) + 1] \stackrel{?}{=} x \dots$ until finding x or finding empty.

$x \in U$

X : number of steps to check if $x \in V$.

$E(X) = ?$

Block of size 2^l is bad if it has more than $2^l \cdot \frac{2}{3}$ values.

Set $\frac{n}{m} = \frac{1}{3}$.

Expected number of elements hashed in block of size 2^l is $\frac{1}{3} \cdot 2^l$.

$$\begin{aligned} E(X) &= \sum_{i=0}^n P(X = i) \cdot i \\ &\leq \sum_{j=0}^{\log_2 n} P(2^{j-1} < X \leq 2^j) \cdot 2^j \\ &\leq \sum_{j=0}^{\log_2 n} P(\text{block above } h(x) \text{ of size } 2^j \text{ is bad}) \cdot c \cdot 2^j. \end{aligned}$$

c : not aligned?

$P(\text{block of size } 2^j \text{ is bad}) = P(Y > \frac{2}{3} \cdot 2^j) = P(Y - \frac{1}{3} \cdot 2^j > \frac{1}{3} \cdot 2^j)$;

Y : number of elements hashed to the block.

$$E(Y) = \frac{1}{3} \cdot 2^j$$

$E(X) \stackrel{\text{Chernoff}}{\leq} e^{-k \cdot 2^j}$; Chernoff: sum of independent indicators.

$$E(X) < O(1) \cdot \sum_{j=0}^{\log_2 n} 2^j \cdot e^{-k \cdot 2^j} \text{ in } O(1)$$

\implies checking in $O(1)$.

Chernoff: if ideal hash function; 5 independent is enough.

Poglavlje 11

Data streams

Stream of values

$\sigma = a_1, a_2 \dots a_n$

a_i : tokens

$a_i \in [n]$

m : length of stream (very large).

Definition 11.0.1. $f_i = |\{j \mid a_j = i\}|$

We could be interested in

- number of different token,
- frequency of some token,
- frequent tokens: $\{i \in [n] \mid f_i \geq \frac{m}{10}\}$
- moments: $\|f\|^2 = \sum_{i \in [n]} f_i^2$
- :

We want to use memory in $O(\text{poly}(\log n, \log m)) \ll O(n, m)$.

Most problems cannot be solved precisely, hence we search for (ε, δ) -approximation.

Algorithm $A(G)$:

- initializazion,

- incremental steps,
- finalization

using randomness (oblivious stream - it doesn't know which randomly, e.g. we can choose stream that „attacks algorithm“).

11.1 Count min sketch

For a given $i \in [n]$ (token) at the end of stream give f_i .

$A(\sigma, \varepsilon, \delta)$:

Init: $k = \lceil \frac{2}{\varepsilon} \rceil$, $t = \lceil \log_2 \left(\frac{1}{\delta} \right) \rceil$.

We choose t hash functions $h_1 \dots h_t : [n] \rightarrow M = [k] = \{1 \dots k\}$ from a universal family H .

Let $C[0 \dots t-1][0 \dots k-1]$ be 2-dim (hash) table
 $C[i][j] = 0 \forall i, j$.

Updates:

for every token $a_i \in \sigma$ we update C

for $j = 0, 1 \dots t-1$:

$C[i][h_i(a_j)] += 1$

Output: we asked $a \in [n]$ return $\overline{f_a} = \min_{0 \leq j \leq t-1} C[j][h_j(a)]$;
min collisions.

Theorem 11.1.1.

For every $a \in [n]$ it holds

$$f_a \leq \overline{f_a} \leq f_a + \varepsilon m$$

with probability at least $1 - \delta$.

Notice: space needed $O(t \cdot k \cdot \log m) = O\left(\frac{2}{\varepsilon} \cdot \log_2\left(\frac{1}{\delta}\right) \log m\right)$.

Proof 11.1.2.

$$\forall i \in [t] : C[i][h_i(a)] \geq f_a \implies \overline{f_a} \geq f_a.$$

Fix a .

Let $X_i = C[i][h_i(a)] - f_a$ excess of i -th count.

$$I_{x,y}^i = \begin{cases} 1 & \text{if } h_i(x) = h_i(y) \\ 0 & \text{else} \end{cases}$$

$$X_i = \sum_{y \in [n], y \neq a} I_{x,y}^i \cdot f_y.$$

$$\begin{aligned} E(X_i) &= \sum_{y \in [n], y \neq a} E(I_{x,y}^i) \cdot f_y \\ &\stackrel{11.1}{\leq} \sum_{y \in [n], y \neq a} \frac{1}{k} \cdot f_y \\ &\leq \frac{1}{n} \cdot m \\ &\stackrel{11.2}{\leq} \frac{m}{2}; \end{aligned}$$

hash function from universal family, (11.1)

$$P(X_i \geq \varepsilon m) \stackrel{\text{Markov}}{\leq} \frac{\varepsilon m}{2\varepsilon m} = \frac{1}{2} \text{ for fixed } i. \quad (11.2)$$

$$\begin{aligned} P(\overline{f_a} - f_a \geq \varepsilon m) &\leq P(X_i \geq \varepsilon m \ \forall i) \\ &\stackrel{\text{indep.}}{=} \left(\frac{1}{2}\right)^t \leq \delta. \end{aligned}$$

■

11.2 Estimating the number of distinct elements

We want $d = |\{i \in [n], f(i) > 0\}|$.

Define for $x \in \mathbb{N}$:

$\text{zeros}(x) = \max\{i \mid 2^i \text{ divides } x\}$: number of zeros at the end in binary representation of x .

```

Alg( $\sigma$ ):
  Init:
    h: random hash function from 2-independent family.
    # recall: [n]: all possible elements of  $\sigma$ .

```

```

 $h : [n] \rightarrow [n]$ 
 $\text{unlog? } n = 2^{n'}$ 
 $z = 0$ 
Update:
 $a_i \in \sigma$ 
if  $\text{zeros}(h(a_i)) \geq z$ :
 $z = \text{zeros}(h(a_i))$ 
Output:
 $\bar{d} = 2^{z+\frac{1}{2}}$ 

```

Define $\forall a \in [n], r \in \mathbb{N}$

$$X_{r,a} = \begin{cases} 1 & \text{if } \text{zeros}(h(a)) \geq r \\ 0 & \text{else} \end{cases}$$

$$Y_r = \sum_{a \in \sigma} X_{r,a}.$$

Let \bar{z} be z at the end of the algorithm: $\bar{d} = 2^{\bar{z}+\frac{1}{2}}$.

Notice:

$$Y_r > 0 \iff \bar{z} \geq r$$

$$Y_r = 0 \iff \bar{z} < r.$$

Lemma 11.2.1.

$$P(X_{r,a} = 1) = \frac{1}{2^r},$$

$$P(X_{r,a_1} = 1 \wedge X_{r,a_2} = 1) = \frac{1}{(2^r)^2}.$$

Proof 11.2.2.

$$P(X_{r,a} = 1) = P(\text{zeros}(h(a)) \geq r) = \frac{2^{n'-r}}{2^{n'}} = \frac{1}{2^r};$$

$2^{n'}$: all,

$2^{n'-r}$: fixed.

$$P(X_{r,a_1} = 1 \wedge X_{r,a_2} = 1) \stackrel{h \text{ 2 indep.}}{=} P(X_{r,a_1} = 1) \cdot P(X_{r,a_2} = 1) = \frac{1}{(2^r)^2}. \quad \blacksquare$$

$P(\bar{d} \geq 3d)$ small?

$$E(Y_r) = \sum_{a \in \sigma} E(X_{a,r}) = \sum_{a \in \sigma} \frac{1}{2^r} = \frac{d}{2^r}$$

Let $k \in \mathbb{N}$ be such that $2^{k+\frac{1}{2}} \geq 3d > 2^{k-\frac{1}{2}}$.

$$\begin{aligned}
 P(\bar{d} > 3d) &\leq P(2^{\bar{z}-\frac{1}{2}} > 2^{k-\frac{1}{2}}) \\
 &= P\left(\bar{z} + \frac{1}{2} > k - \frac{1}{2}\right) \\
 &= P(\bar{z} \geq k) \\
 &\stackrel{\text{lemma}}{=} P(Y_k > 0) \\
 &\stackrel{\epsilon \in \mathbb{N}}{=} P(Y_k \geq 1) \\
 &\stackrel{\text{Markov}}{\leq} \frac{E(Y_k)}{1} = \frac{d}{2^k} \\
 &\stackrel{k}{\leq} \frac{d \cdot 2^{\frac{1}{3}}}{3d} = \frac{\sqrt{2}}{3}.
 \end{aligned}$$

$P(\bar{d} \leq \frac{d}{3})$ small?

Let $l \in \mathbb{N}$ be such that $2^{l-\frac{1}{2}} \leq \frac{d}{3} < 2^{l+\frac{1}{2}}$.

$$\begin{aligned}
 P\left(\bar{d} < \frac{d}{3}\right) &\leq P(2^{\bar{z}+\frac{1}{2}} < 2^{l+\frac{1}{2}}) \\
 &= P\left(\bar{z} + \frac{1}{2} < l + \frac{1}{2}\right) \\
 &= P(\bar{z} \leq k) \\
 &\stackrel{\text{lemma}}{=} P(Y_l = 0) \\
 &= P\left(Y_l - \frac{d}{2^l} < -\frac{d}{2^l}\right) \\
 &\leq P\left(|Y_l - \frac{d}{2^l}| \geq \frac{d}{2^l}\right) \\
 &\stackrel{\text{Chebisev}}{\leq} \frac{Var(Y_l)}{\left(\frac{d}{2^l}\right)^2} \\
 &\stackrel{l}{\leq} \frac{d \cdot 2^{\frac{1}{3}}}{3d} = \frac{\sqrt{2}}{3};
 \end{aligned}$$

$$\begin{aligned}
Var(Y_l) &= Var\left(\sum_{a \in \sigma} X_{a,l}\right) \\
&\stackrel{h \text{ 2-indep.}}{=} \sum_{a \in \sigma} Var(X_{a,l}) \\
&= \sum_{a \in \sigma} E(X_{a,l}^2) - E(X_{a,l})^2 \\
&\stackrel{E(X_{a,l}) \in \{0,1\}}{\leq} \sum_{a \in \sigma} E(X_{a,l}) \\
&= \frac{d}{2^l}.
\end{aligned}$$

$$P\left(\frac{d}{3} < \bar{d} < 3d\right) \geq 1 - \frac{2\sqrt{3}}{3}.$$

We use algorithm k -times, getting $\overline{d_1} \dots \overline{d_k}$ (we need independent hash functions).

Define: $\bar{d} = median(\overline{d_1} \dots \overline{d_k})$.

$$\begin{aligned}
P(\bar{d} \geq 3d) &= P\left(\text{at least } \left\lceil \frac{k}{2} \right\rceil \bar{d} - s \text{ are } \geq 3d\right) \\
&= P\left(X \geq \frac{k}{2}\right) \leq e^{-ck};
\end{aligned}$$

c : some constant,

$$\begin{aligned}
X &= \sum_{i=1}^k X_i, \\
X_i &= \begin{cases} 1 : & \text{if } \overline{d_i} \geq 3d \\ 0 : & \text{else} \end{cases} \\
P\left(\bar{d} \leq \frac{d}{3}\right) &= \dots
\end{aligned}$$

Poglavlje 12

Interactive proofs

A protocol between P prover and V verifier for function f .

Both share x ,

r : randomness used,

P, V : algorithms,

$$out(V, x, r, P) = \begin{cases} 1 : V \text{ agrees that } f(x) = y \\ 0 : \text{else} \end{cases}.$$

Goal: minimal communication, minimal work for V .

Completeness:

- for every $x \in D$ (domain)
- $P(out(V, x, r, P) = 1) \geq 1 - \delta_c$ for some $\delta_c \in [0, 1]$.

Soundness:

- for every x such that $f(x) \neq y$
- $P(out(V, x, r, P') = 1) \leq \delta_s$ for every $P', \delta_s \in [0, 1]$.

Computational soundness:

- soundness,
- P' computationally bounded.

Zero-knowledge:

- informally: verifier learns nothing behind the claim.

Example.

Input: G graph,

$$f(G) = \begin{cases} 1 : & \text{if } G \text{ hamiltonian} \\ 0 : & \text{else} \end{cases}$$

$$G \rightarrow P \xrightarrow{m_1:(v_1 \dots v_n)} V \leftarrow G,$$

V : verifies that m_1 is hamiltonian cycle.

Proof: $O(n)$.

Verifier com. $O(n)$.

Example.

Input: A, B matrices,

$$f(A, B) = A \cdot B,$$

$$(A, B) \rightarrow P \xrightarrow{C} P \leftarrow (A, B).$$

P : compute $C = A \cdot B$, send C ,

V : check $A(Bv_i) = Cv_i$ for random v_i .

Prover: matrix multiplication $O(n^3)$ ($O(n^{\log_2(7)})$).

Verifier: $O(n^2)$.

Proof size: $O(n^3)$ (possible to reduce is $O(\log n)$).

Example.

Input: $(n, y) \in \mathbb{N}^2$,

$$f(n, y) = \begin{cases} 1 : & \text{if there exists } x \text{ such that } y = x^2 \pmod{n} \\ 0 : & \text{else} \end{cases};$$

quadratic?? reducibility problem.

$$(n, y) \rightarrow P \rightarrow V \leftarrow (n, y).$$

P : sample $r \in \mathbb{Z}_n$, $s = r^2$, send s ,

V : sample $b \in \{0, 1\}$, send b ,

P : if $b = 0$: $m_2 = r$, if $b = 1$: $m_2 = r \cdot x$, send m_2 ,

V : accepts if $m_2^2 = s \cdot y^b$.

Completeness:

$$m_2^2 \stackrel{?}{=} s \cdot y^b$$

if $b = 0$:

$$m_2 = r$$

$$r^2 = m_2^2 = s \checkmark$$

if $b = 1$:

$$m_2^2 = sy$$

$$r^2 x^2 = sy \checkmark (r^2 = s, x^2 = y)$$

Soundness:

- 2 options for what prover does.

– Send s such that there is no r that $r^2 = s$.

Then with probability $\frac{1}{2}$ is $b = 0$.

Then prover needs to send m_2 such that $m_2^2 = s$ (impossible)

\implies fail with probability at least $\frac{1}{2}$.

– Send s such that $r^2 = s$.

Then with probability $\frac{1}{2}$ is $b = 1$.

$m_2^2 = sy = r^2 y \implies y = (m_2 r^{-1})^2 \implies \exists x : x^2 = y$: contradiction

\implies fail with probability at least $\frac{1}{2}$.

With zero-knowledge.

12.1 Sum-check protocol

Let $g(x_1 \dots x_n)$ be multivariate polynomial of degree d over \mathbb{F} .

Let $H_g = \sum_{b_1 \dots b_n \in \{0,1\}} g(b_1 \dots b_n)$.

P wants to convince V that $c = H_g$.

$g \rightarrow P \rightarrow V \leftarrow g$.

P : sends c ,

P : compute $g_1(x) = \sum_{b_2 \dots b_n \in \{0,1\}} g(x, b_2 \dots b_n)$, send $g_1(x)$,

V : check $g_1(0) + g_1(1) = c$, $\deg(g) \leq d$, sample $r_1 \in \mathbb{F}$, send r_1 ,

for $j = 2 \dots n - 1$:

P : compute $g_j(x) = \sum_{b_{j+1} \dots b_n \in \{0,1\}} g(r_1 \dots r_{j-1}, x, b_{j+1} \dots b_n)$, send $g_j(x)$,

V : checks $g_j(0) + g_j(1) = g_{j-1}(r_{j-1})$, $\deg(g_j) \leq d$, sample $r_j \in \mathbb{F}$, send r_j ,

P : compute $g_n(x) = g(r_1 \dots r_{n-1}, x)$, send $g_n(x)$,

V : checks $g_n(0) + g_n(1) = g_{n-1}(r_{n-1})$, $\deg(g_n) \leq d$, for random $r_n \in \mathbb{F}$ check $g_n(r_n) = g(r_1 \dots r_n)$.

Completeness:

✓ (sum, all possibilities).

Cost:

Prover: $O(2^n)$,

Verifier: evaluate $g_i \forall i$, g at one point, $<< O(2^n)$.

Communication:

$\deg(g_1) + \dots + \deg(g_{n-1}) + O(n)$ elements of \mathbb{F} .

Prove that $H_g = \sum_{b_1 \dots b_n \in \{0,1\}} g(b_1 \dots b_n)$.

Soundness:

P : sends $g_i(x)$.

If P cheats, at least one of polynomials is not correct.

Sends $g'_i(x) \neq g_i(x)$.

Verifier checks $g'_i(r_i) = g_{i+1}(0) + g_{i+1}(1) = g_i(r_i)$

→ probability of this: $\leq \frac{d}{|\mathbb{F}|}$.

Soundness error: $\leq n \cdot \frac{d}{|\mathbb{F}|}$; union bound of rounds.

Application 1:

Counting solutions of SAT.

F SAT formula with s operations and n variables.

Replace with polynomial $g(x_1 \dots x_n)$ such that $F(b_1 \dots b_n) = g(b_1 \dots b_n)$.

For every $b_1 \dots b_n$:

replace $AND(x,y)$ with $x \cdot y$, $OR(x,y)$ with $x + y - x \cdot y$, $NOT(x)$ with $1 - x$.

$$\begin{aligned} \text{Number of SAT solutions} &= \sum_{b_1 \dots b_n \in \{0,1\}} F(b_1 \dots b_n) \\ &= \sum_{b_1 \dots b_n \in \{0,1\}} g(b_1 \dots b_n). \end{aligned}$$

Prover can prove that H_g = number of solutions by using sum-check.

Complexity:

prover: $O(2^n)$,

proof size (communication complexity): $O(n)$ - n polynomials,

verifier: $O(n + s)$.

Error: $\leq \frac{n \cdot s}{|\mathbb{F}|}$; s : number of operations.

Application 2:

Counting triangles in G .

A : adjacency matrix.

Number of triangles in $G = \frac{\text{tr}(A^3)}{6}$.

We think of A as a mapping.

$[n] \times [n] \rightarrow \{0, 1\}$.

Define $A' : \{0, 1\}^{\log_2 n} \times \{0, 1\}^{\log_2 n} \rightarrow \{0, 1\}$,

such that $A(i, j) = A'(binary(i), binary(j))$.

For example: $n = 16$, $A(0, 3) = A'(0000, 0011)$.

Now we define polynomial $f_A : \mathbb{F}^{\log_2 n} \times \mathbb{F}^{\log_2 n} \rightarrow \mathbb{F}$

$f_A(x_1 \dots x_{\log_2 n}, y_1 \dots y_{\log_2 n})$ such that

$f_A(b_1 \dots b_{\log_2 n}) = A'(b_1 \dots b_{\log_2 n})$ for every $b_1 \dots b_{\log_2 n} \in \{0, 1\}$.

Example: $A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$, $f_A(x, y) = x(1 - y) + y(1 - x)$.

In general:

$$\begin{aligned} & f_A(x_1 \dots x_{\log_2 n}, y_1 \dots y_{\log_2 n}) \\ = & \sum_{a,b \in \{0,1\}^{\log_2 n}, A'(a,b)=1} (-1)^{\text{num_zeros}(a,b)} (x_1 - (1 - a_1)) \dots (y_{\log_2 n} - (1 - b_{\log_2 n})). \end{aligned}$$

Now we define $g_A(x, y, z) = f_A(x, y) \cdot f_A(y, z) \cdot f_A(z, x)$, $x, y, z \in \mathbb{F}^{\log_2 n}$.

Number of triangles = $\frac{\sum_{a,b,c \in \{0,1\}^{\log_2 n}} g_A(a,b,c)}{6}$

\implies we can use sum-check.

Proof size: $O(3 \cdot \log_2 n)$ (number of rounds \rightarrow poly),

verifier: $O(\log_2 n) + O(n^2)$.

12.2 SNARK

Succint Non-interactive ARgument of Knowledge.

Succint: proof short and verification fast.

Non-interactive: just sending a proof.

$x \rightarrow P \rightarrow V \leftarrow x$.

P : convince V that $f(x) = y$.

- $f(x) = x^3 + x + 5$ as a algebraic circuit.

Break down into $+, -, *, /$ in some field \mathbb{Z}_p

Proof with states $\vec{s} = (\text{five}, x, \text{out}, s_1, s_2, s_3)$.

Example: proof that $f(3) = 35$.

$$\vec{s} = (1, 3, 35, 9, 27, 30).$$

- To R1CS.

Give vectors $\vec{a}_i, \vec{b}_i, \vec{c}_i$ for each state such that

$$(\vec{a}_i \cdot \vec{s}) \cdot (\vec{b}_i \cdot \vec{s}) = (\vec{c}_i \cdot \vec{s}) \iff \text{gate } i \text{ was correctly calculated.}$$

Example.

For gate 1 (\cdot):

$$\begin{aligned}\vec{a}_1 &= [0, 1, 0, 0, 0, 0] \\ \vec{b}_1 &= [0, 1, 0, 0, 0, 0] \\ \vec{c}_1 &= [0, 0, 0, 1, 0, 0]\end{aligned}$$

$$\vec{a}_1 \cdot \vec{s} = x, \vec{c}_1 \cdot \vec{s} = s_1.$$

For gate 3 (+):

$$\begin{aligned}\vec{a}_3 &= [0, 1, 0, 0, 1, 0] \\ \vec{b}_3 &= [1, 0, 0, 0, 1, 0] \\ \vec{c}_3 &= [0, 0, 0, 0, 0, 1]\end{aligned}$$

$$(x + s_2) \cdot 1 = s_3.$$

We have instead of circuit

$$\begin{bmatrix} \vec{a}_1 \\ \vec{a}_2 \\ \vdots \\ \vec{a}_n \end{bmatrix} \cdot \vec{s} \odot \begin{bmatrix} \vec{b}_1 \\ \vec{b}_2 \\ \vdots \\ \vec{b}_n \end{bmatrix} \cdot \vec{s} - \begin{bmatrix} \vec{c}_1 \\ \vec{c}_2 \\ \vdots \\ \vec{c}_n \end{bmatrix} \cdot \vec{s} = \vec{0}.$$

\odot : coordinate-wise multiplication.

\vec{s} needs to be solution for

$$A \cdot \vec{s} \odot B \cdot \vec{s} = C \cdot \vec{s};$$

A, B, C $m \times n$ matrices.

- To Quadratic Arithmetic Programs (QAP).

Let $a_i(x)$ be a polynomial such that

$$a_i(j) = \vec{a}_j[i] \text{ for } i \in [n], j \in [m].$$

$$A = \begin{bmatrix} a_1(1) & a_2(1) & \dots & a_n(1) \\ a_1(2) & \dots & & \\ \vdots & & & \\ a_1(m) & \dots & & a_n(m) \end{bmatrix}.$$

Example:

$$a_1(x) = -5 + 9.16x + 5x^2 + 0 - 833x^3$$

$$a_2(x) = 8 - 11.33x + 5x^2 - 0.666x^3$$

$$a_3(x) = 0$$

\vdots

$$a_6(x) = \dots$$

$$[a_1(1) \dots a_6(1)] = [0, 1, 0, 0, 0, 0] = \vec{a}_1.$$

We get a_i with interpolation $\deg a_i \leq n - 1$.

$$([a_1(x), a_2(x) \dots a_n(x)] \cdot \vec{s'}) \odot ([b_1(x), b_2(x) \dots b_n(x)] \cdot \vec{s'}) - ([c_1(x), c_2(x) \dots c_n(x)] \cdot \vec{s'})$$

should have zeros in $1, 2 \dots m$

$$\iff A(x) \cdot B(x) \cdot C(x) = (x - 1)(x - 2) \dots (x - m) \cdot h(x).$$

Summary up to now:

- instead of states we have polynomials,
- instead of states, we have coefficients $\cdot \vec{s'}$.

$$a_i(x), b_i(x), c_i(x) \rightarrow P \rightarrow V \leftarrow a_i(x), b_i(x), c_i(x).$$

$P \rightarrow V$: $A(x), B(x), C(x), h(x)$: too much.

$P \rightarrow V$: $A(r), B(r), C(r), h(r)$, r random.

V : checks $A(r) \cdot B(r) = C(r) + h(r) \cdot t(r)$;

works if V doesn't cheat.

Cryptographic background:

– Lets have pairs

$(g_1, h_1), (g_2, h_2) \dots (g_n, h_n)$, where $g_i^k = h_i$, you don't know k .

Cryptographic assumption: if we provide (g', h') such that

$(g')^k = h'$, then $g' = g_1^{k_1} \cdot g_n^{k_n}$, $h' = h_1^{k_1} \cdot h_n^{k_n}$.

– Pairing groups.

In some group one can define a pairing

$e : G \times G \rightarrow G_r$ such that

$$e(g_1 \cdot g_2, h) = e(g_1, h) \cdot e(g_2, h),$$

$$e(g, h_1 \cdot h_2) = e(g, h_1) \cdot e(g, h_2),$$

$$e(g^x, g^y) = e(g, g)^{xy}.$$

Assume P, V have

$$- g^{a_1(r)}, g^{a_2(r)} \dots,$$

$$- g^{b_1(r)}, g^{b_2(r)} \dots,$$

$$- g^{c_1(r)}, g^{c_2(r)} \dots,$$

$$- g^{t(r)},$$

$$- g, g^r, g^{r^2} \dots g^{r^{n-1}}$$

without knowing r .

Improved protocol:

P sends to V

$$- g^{A(r)} = (g^{a_1(r)})^{k_1} \dots (g^{a_n(r)})^{k_n}$$

$$- g^{B(r)} \dots$$

$$- g^{C(r)} \dots$$

$$- g^{h(r)} = g^{h_0} \cdot (g^r)^{k_1} \dots (g^{r^{n-1}})^{k_{n-1}}.$$

V : checks $e(g^{A(r)}, g^{B(r)}) = e(g^{C(r)}, g) \cdot e(g^{h(r)}, g^{t(r)})$.

Problem: $g^{A(r)}$ needs to be linear combination of $g^{a_1(r)} \dots g^{a_n(r)}$, also $g^{B(r)}, g^{C(r)}$.

We need additional values:

- $g^{a_1(r) \cdot k_1} \dots g^{a_n(r) \cdot k_1}$, k_1 unknown,
- $g^{b_i(r) \cdot k_2} \dots$,
- $g^{c_i(r) \cdot k_3} \dots$,
- $g^{k_1}, g^{k_2}, g^{k_3}$.

Prover also submits:

- $g^{k_1 A(r)} = (g^{a_1(r) k_1})^{s_1} \dots (g^{a_n(r) k_1})^{s_1}$
- $g^{k_2 B(r)} = \dots$
- $g^{k_3 C(r)} = \dots$

Verifier calculates

- $e(g^{A(r)}, g^{k_1}) = e(g^{k_1 \cdot A(r)}, g)$,
- $e(g^{B(r)}, g^{k_2}) = \dots$

\implies by crypto assumption $A(r)$ is linear combination of $a_1(r) \dots a_n(r)$.

Downside: we need $g^{a_1(r)} \dots$