

1. Design Markov Chain

- (a) *Proof.* We prove that graph G is strongly connected. Consider $\sigma, \sigma' \in V$, if $\sigma = \sigma'$, then path p is the self-loop. If $\sigma \neq \sigma'$, then we can construct a path p from σ to σ' . In each step of the path, let i be the first index such that $\sigma_i \neq \sigma'_i$, we add the edge that swaps σ_i with σ_j for some index j where $\sigma_j = \sigma'_i$. We claim that such index $j \geq i$, and after the swap, the first i integers of the destination vertex equals $\sigma'_1 \cdots \sigma'_i$. For $i = 1$, every other $j > 1$, and we get σ'_1 at index 1 after one swap, so claim is true. Now we prove claim is true for $i > 1$. By induction hypothesis, the first $i - 1$ integers of the vertex is $\sigma'_1 \cdots \sigma'_{i-1}$ and that $\sigma'_i \neq \sigma'_k = \sigma_k$ for $k = 1, \dots, i - 1$ since σ' is a permutation. So there is some $j \neq k$ for $k = 1, \dots, i - 1$ such that $\sigma_j = \sigma'_i$ and we swap σ_j with σ_i such that the first i integers in the permutation is equal to $\sigma'_1 \cdots \sigma'_i$, hence the claim is true in the inductive case. By $i = n$, we have $\sigma'_1 \cdots \sigma'_n$ as the resulting vertex. Since choice of σ, σ' arbitrary, we can always find such path, so graph is strongly connected. \square
- (b) To find the transition probabilities P on Markov chain on G such that stationary distribution p has $p_\sigma \propto 2^{-\text{inv}(\sigma)}$, we first note that the maximum number of degrees is same for all vertices, specifically $r = \binom{n}{2}$, since we have edge connecting two vertices by arbitrarily swapping 2 numbers. Therefore,

$$P_{ij} = \frac{1}{\binom{n}{2}} \min\{1, 2^{\text{inv}(\sigma_1) - \text{inv}(\sigma_2)}\} \quad P_{ii} = 1 - \sum_{j \neq i} P_{ij}$$

2. Streaming

- (a) We express $\mathbb{E}\{c\}$ in terms of $f_1 = |\{t : \sigma_t = i\}|$. Let c_j be arbitrary where $j \in [k]$, then we can express c_j as follows

$$c_j = f_1 h_j(1) + \cdots + f_n h_j(n) = \sum_{i=1}^n f_i h_j(i)$$

Also note that $(h_j(i))^2 : [n] \rightarrow \{1\}$ outputs 1 with probability 1, so then $\mathbb{E}\{(h_j(i))^2\} = 1$. Also we have that $\mathbb{E}\{h_j(i)\} = 0$ for arbitrary hash function h_j and arbitrary input $i = 1, \dots, n$.

$$\begin{aligned} \mathbb{E}\{c_j^2\} &= \mathbb{E}\{(f_1 h_j(1) + \cdots + f_n h_j(n))^2\} \\ &= \mathbb{E}\left\{\sum_{i=1}^n f_i^2 (h_j(i))^2 + \sum_{i' \neq i}^n f_{i'} f_i h_j(i') h_j(i)\right\} \\ &= \sum_{i=1}^n f_i^2 \mathbb{E}\{(h_j(i))^2\} + \mathbb{E}\left\{\sum_{i' \neq i}^n f_{i'} f_i h_j(i') h_j(i)\right\} \\ &= \sum_{i=1}^n f_i^2 + \sum_{i' \neq i}^n f_{i'} f_i \mathbb{E}\{h_j(i') h_j(i)\} \\ &= \sum_{i=1}^n f_i^2 + \sum_{i' \neq i}^n f_{i'} f_i \mathbb{E}\{h_j(i')\} \mathbb{E}\{h_j(i)\} \quad (h_j(i), h_j(i') \text{ independent}) \\ &= \sum_{i=1}^n f_i^2 \end{aligned}$$

$$\text{So then, } \mathbb{E}\{c\} = \mathbb{E}\left\{\frac{1}{k}(c_1^2 + \cdots + c_k^2)\right\} = \frac{1}{k} \sum_{j=1}^k \mathbb{E}\{c_j^2\} = \frac{1}{k} \sum_{j=1}^k \sum_{i=1}^n f_i^2 = \sum_{i=1}^n f_i^2$$

- (b) Note

$$(1 - \epsilon)\mathbb{E}\{c\} \leq c \leq (1 + \epsilon)\mathbb{E}\{c\} \iff |\mathbb{E}\{c\} - c| \leq \epsilon \mathbb{E}\{c\}$$

So proving $\mathbb{P}((1 - \epsilon)\mathbb{E}\{c\} \leq c \leq (1 + \epsilon)\mathbb{E}\{c\}) \geq \frac{1}{2}$ is equivalent to

$$\mathbb{P}(|\mathbb{E}\{c\} - c| \leq \epsilon \mathbb{E}\{c\}) \geq \frac{1}{2} \quad \text{or} \quad \mathbb{P}(|\mathbb{E}\{c\} - c| > \epsilon \mathbb{E}\{c\}) < \frac{1}{2}$$

We note the previous expression can be reformulated with chebyshev's inequality

$$\mathbb{P}(|\mathbb{E}\{c\} - c| > \epsilon \mathbb{E}\{c\}) < \frac{\mathbb{V}\{c\}}{\epsilon^2 \mathbb{E}\{c\}^2}$$

Note from previous $\mathbb{E}\{c_j^2\} = \mathbb{E}\{c\} = \sum_{i=1}^n f_i^2$. We then compute $\mathbb{V}\{c\}$

$$\begin{aligned}
\mathbb{V}\{c\} &= \frac{1}{k^2} \sum_{j=1}^k \mathbb{V}\{c_j^2\} \\
&= \frac{1}{k^2} \sum_{j=1}^k \mathbb{E}\{c_j^4\} - \mathbb{E}\{c_j^2\}^2 \\
&\leq \frac{1}{k^2} \sum_{j=1}^k 3\mathbb{E}\{c_j^2\}^2 - \mathbb{E}\{c_j^2\}^2 \\
&= \frac{2}{k^2} \sum_{j=1}^k \mathbb{E}\{c_j^2\}^2 \\
&= \frac{2}{k} \mathbb{E}\{c\}^2
\end{aligned}$$

So then

$$\mathbb{P}(|\mathbb{E}\{c\} - c| > \epsilon \mathbb{E}\{c\}) < \frac{\mathbb{V}\{c\}}{\epsilon^2 \mathbb{E}\{c\}^2} \leq \frac{\frac{2}{k} \mathbb{E}\{c\}^2}{\epsilon^2 \mathbb{E}\{c\}^2} = \frac{2}{k\epsilon^2}$$

Let $k = \frac{4}{\epsilon^2}$ such that $\mathbb{P}(|\mathbb{E}\{c\} - c| > \epsilon \mathbb{E}\{c\}) < \frac{1}{2}$, which satisfies the probability constraint given in the problem specification.

3. Linear Programming