

Chapter 2

Multicommodity Routing

Advanced Algorithms

SS 2019

Fabian Kuhn

The Multicommodity Flow Problem

Given:

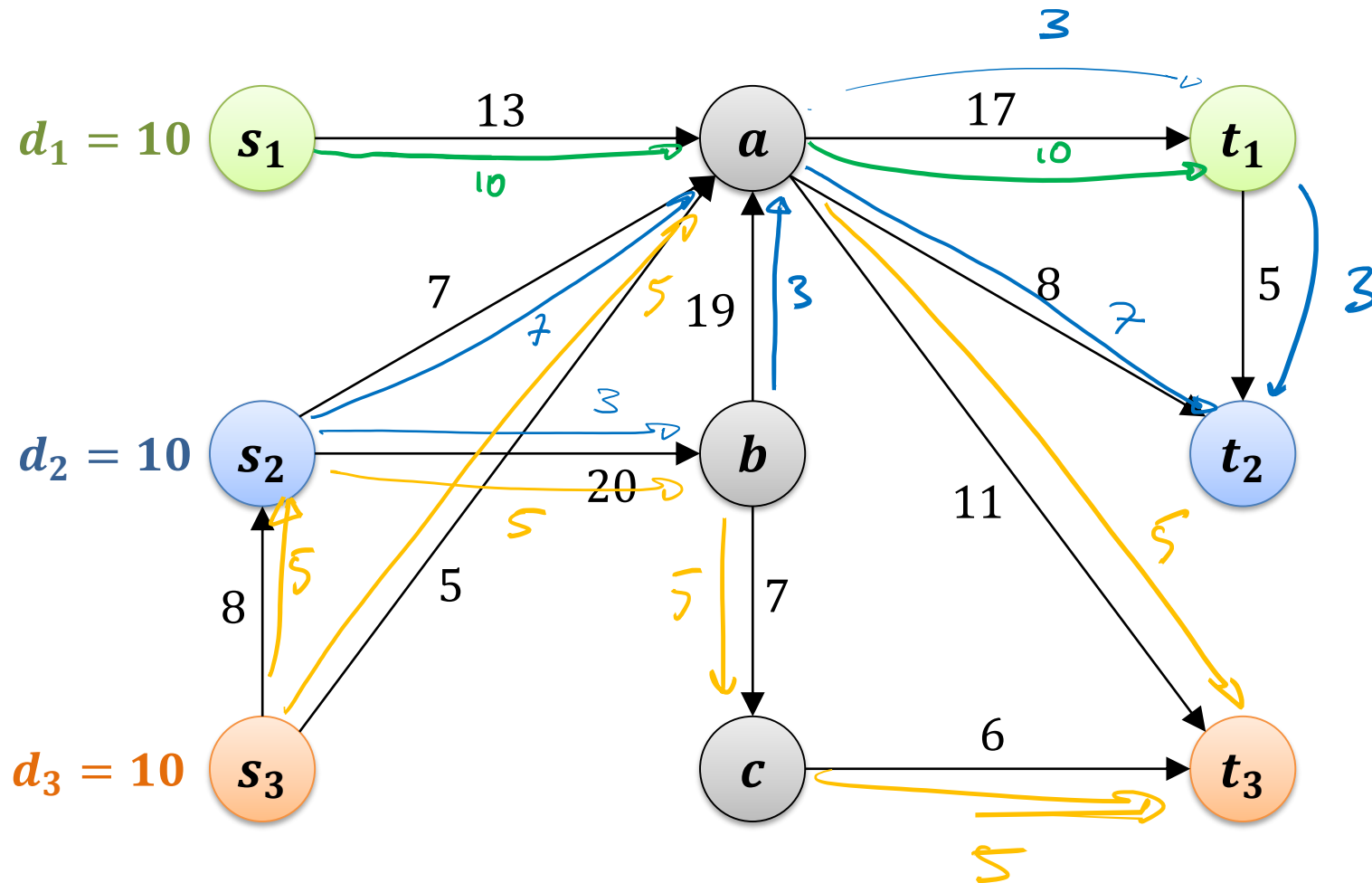
- Directed graph $G = (V, E)$, each edge $e \in E$ has a capacity $c_e > 0$
- $k \geq 1$ source-destination pairs (s_i, t_i) with demand $d_i > 0$
 - these are the commodities

Goal:

- For each $i \in \{1, \dots, k\}$, compute an **s_i - t_i flow** $f_i: E \rightarrow \mathbb{R}_{\geq 0}$ of value 1
 - Flow f_i needs to satisfy the usual flow constraints:
 - flow conservation for $v \notin \{s_i, t_i\}$
 - net flow leaving s_i has value 1, net flow entering t_i has value 1
- Minimize maximum edge congestion λ :

$$\lambda := \max_{e \in E} \frac{1}{c_e} \cdot \sum_{i=1}^k d_i \cdot f_i(e)$$

Example: Multicommodity Flow



Multicommodity Flow as an LP $G = (V, E)$

For $v \in V$: $\text{in}(v)$: ~~edges~~ into v , $\text{out}(v)$: edges out of v

min λ

$$\forall i \in \{1, \dots, k\}: \quad \forall v \notin \{s_i, t_i\} \quad \sum_{e \in \text{in}(v)} f_i(e) = \sum_{e \in \text{out}(v)} f_i(e)$$

$$\sum_{e \in \text{out}(s_i)} f_i(e) - \sum_{e \in \text{in}(s_i)} f_i(e) = 1$$

$$\sum_{e \in \text{in}(t_i)} f_i(e) - \sum_{e \in \text{out}(t_i)} f_i(e) = 1$$

$$\forall e \in E: \quad \sum_{i=1}^k d_i f_i(e) \leq \lambda \cdot c_e, \quad \lambda \geq 0, \quad f_i(e) \geq 0 \quad (\forall i, e)$$

The Multicommodity Routing Problem

Goal:

- For each $i \in \{1, \dots, k\}$, compute an s_i - t_i path P_i
- Minimize maximum edge congestion λ :

$$\lambda := \max_{e \in E} \frac{1}{c_e} \cdot \sum_{i: e \in \underline{P_i}} d_i$$

- The same as the multicommodity flow problem, however, each of the flows has to be routed on a single path

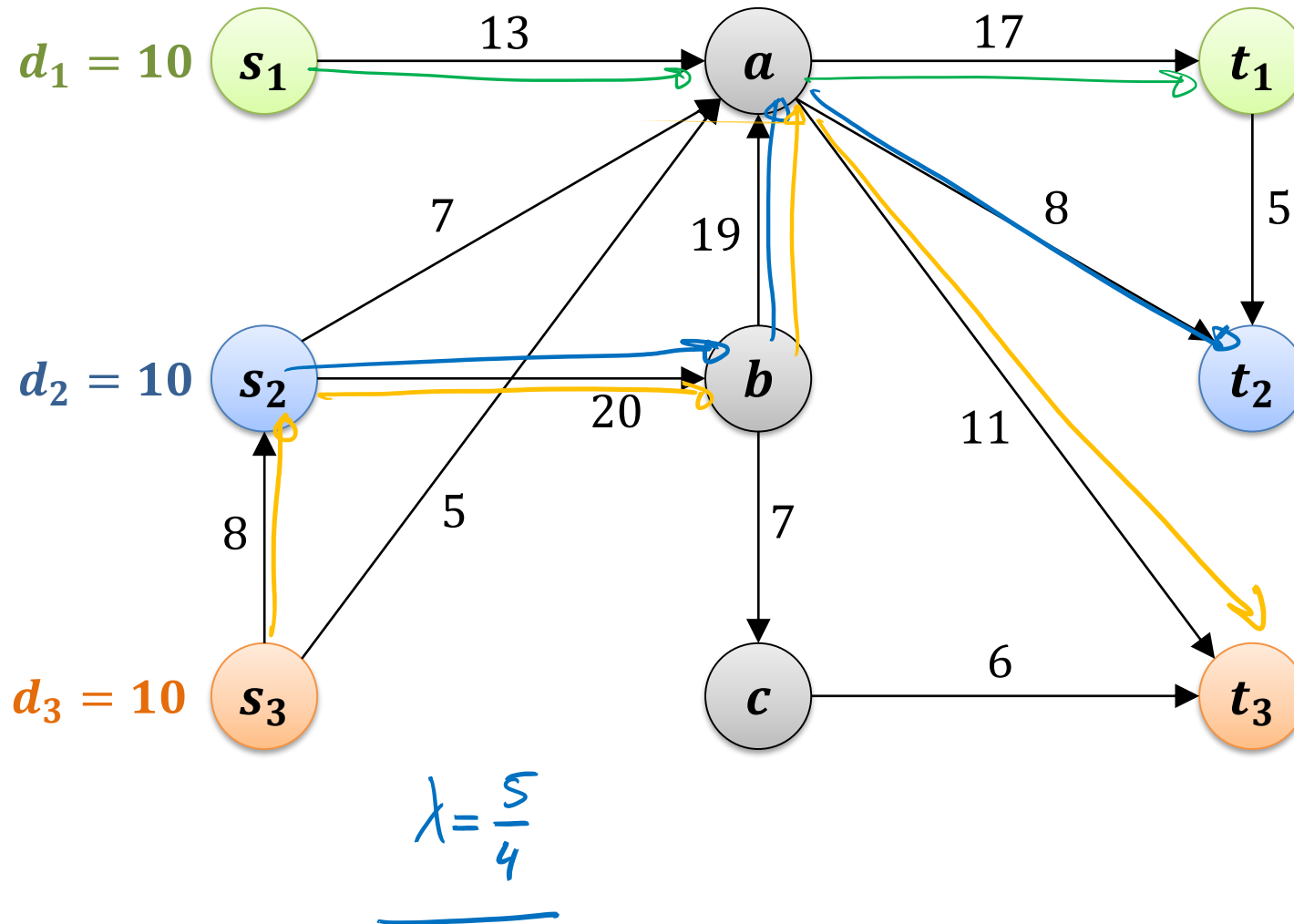
Remark: For the routing problem, we assume that for a constant $\alpha > 0$,

$$\forall i \in \{1, \dots, k\}, \forall e \in E : \underline{d_i} \leq \underline{\alpha \cdot c_e}$$

can be phrased as an ILP:

require $f_i(e) \in \{0, 1\}$

Example: Multicommodity Routing



Rounding the Multicommodity Flow LP

Let's start with a simpler problem:

- For each of the k source-destination pairs (s_i, t_i) , we are given a collection $\mathcal{P}_i = \{P_{i,1}, \dots, P_{i,\ell_i}\}$ of s_i - t_i paths
- s_i and t_i have to be connected by one of the paths in \mathcal{P}_i

Integer Linear Program:

Variables $x_{i,j} \in \{0,1\}$ $x_{i,j}=1 \iff \text{choose path } P_{i,j} \in \mathcal{P}_i \text{ for conn. } i$

$$\min \lambda$$

$$\forall i \in \{1, \dots, k\} : \sum_{j=1}^{\ell_i} x_{i,j} = 1$$

$$\forall e \in E : \sum_{i=1}^k \sum_{j: e \in P_{i,j}} x_{i,j} \cdot d_i \leq \lambda \cdot c_e$$

$$\lambda \geq 0$$

Rounding the Multicommodity Flow LP

Let's start with a simpler problem:

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- s_i and t_i have to be connected by one of the paths in \mathcal{P}_i

LP Relaxation:

relax condition $x_{i,j} \in \{0,1\} \rightarrow x_{i,j} \in [0,1]$

assume that λ^* opt. LP solution

Rounding the Multicommodity Flow LP

- For each of the k source-destination pairs (s_i, t_i) , we are given a collection $\mathcal{P}_i = \{P_{i,1}, \dots, P_{i,\ell_i}\}$ of s_i - t_i paths

Randomized Rounding:

For each $i \in \{1, \dots, k\}$: value $x_{i,j} \in [0, 1]$ for path $P_{i,j} \in \mathcal{P}_i$

$$\sum x_{i,j} = 1$$

→ pick path from \mathcal{P}_i according to distr. given by $x_{i,j}$

rand. rar. $X_{i,j} = 1 \iff$ rand. rounding picks path $P_{i,j}$ $\mathbb{E}[X_{i,j}] = x_{i,j}$

$Y_{e,i}$: contribution of comm. i to edge e for comm. i
 $Y_{e,i} = d_{i,e} \iff$ edge e is in the path chosen by rounding

congestion of edge $e \rightarrow Y_e = \sum_{i=1}^k Y_{e,i}$ $\mathbb{E}[Y_e] \leq \lambda^*$

Rounding the Multicommodity Flow LP

- For each of the k source-destination pairs (s_i, t_i) , we are given a collection $\mathcal{P}_i = \{P_{i,1}, \dots, P_{i,\ell_i}\}$ of s_i - t_i paths

Randomized Rounding:

- Random variables Y_e for all $e \in E$:

$$Y_e := \sum_{i=1}^k Y_{e,i}, \quad \text{where } Y_{e,i} := \frac{d_i}{c_e} \cdot \sum_{j: e \in P_{i,j}} X_{i,j}$$

$$E[Y_e] = \sum_{i=1}^k \frac{d_i}{c_e} \sum_{j: e \in P_{i,j}} x_{i,j} \leq \lambda^*$$

$$E[Y_{e,i}] = \frac{d_i}{c_e} \cdot \sum_{j: e \in P_{i,j}} x_{i,j}$$

to show that max. edge cong. $\leq \beta \cdot \lambda^*$

$$\hookrightarrow \forall e \in E: Y_e \leq \beta \cdot \lambda^* \rightarrow \mathbb{P}(Y_e > \beta \cdot \lambda^*) = ? \leq \alpha$$

$Y_{e,i}$ are indep. for diff. i , $Y_{e,i} \in \{0, \frac{d_i}{c_e}\}$

Chernoff Bounds

Theorem: Let X_1, \dots, X_n be independent random variables and let a_1, \dots, a_n be positive numbers such that $0 < a_i \leq A$ for all i . Assume that each variable X_i can take values 0 or a_i such that $\mathbb{P}(X_i = a_i) = p_i$. Define $X := X_1 + \dots + X_n$ and let μ be chosen such that $\mu \geq \mathbb{E}[X] = \sum_{i=1}^n p_i \cdot a_i$. Then, for all $\varepsilon > 0$, it holds that

$$\mathbb{P}(X \geq (1 + \varepsilon) \cdot \mu) \leq \left(\frac{e^\varepsilon}{(1 + \varepsilon)^{1+\varepsilon}} \right)^{\mu/A} \leq e^{-\frac{\varepsilon^2}{2+\varepsilon} \cdot \frac{\mu}{A}}$$

$$\mathbb{P}(X \leq (1 - \varepsilon) \cdot \mu) \leq \left(\frac{e^{-\varepsilon}}{(1 - \varepsilon)^{1-\varepsilon}} \right)^{\mu/A} \leq e^{-\frac{\varepsilon^2}{2A} \cdot \mu}$$

need to assume
that $\mu \leq \mathbb{E}[X]$

Rounding the Multicommodity Flow LP

- For each of the k source-destination pairs (s_i, t_i) , we are given a collection $\mathcal{P}_i = \{P_{i,1}, \dots, P_{i,\ell_i}\}$ of s_i - t_i paths

Randomized Rounding:

- Random variables Y_e for all $e \in E$:

$$Y_e := \sum_{i=1}^k Y_{e,i}, \quad \text{where } Y_{e,i} := \frac{d_i}{c_e} \cdot \sum_{j: e \in P_{i,j}} X_{i,j}$$

- $Y_{e,i}$ can take values $\frac{d_i}{c_e} \leq \alpha$ or 0, $\mathbb{E}[Y_e] \leq \lambda^*$
- $Y_{e,i}$ are independent for different i

- Chernoff Bound:**

$$\forall e \in E : \mathbb{P}(Y_e \geq (1 + \varepsilon) \cdot \lambda^*) \leq \left(\frac{e^\varepsilon}{(1 + \varepsilon)^{1+\varepsilon}} \right)^{\lambda^*/\alpha}$$

$$\lambda \leq O\left(\frac{\log n}{\log \log n}\right) \cdot \max\{1, \lambda^{\frac{1}{2}}\}$$
$$\forall e \in E : \mathbb{P}(Y_e \geq (1 + \varepsilon) \cdot \lambda^*) \leq \left(\frac{e^\varepsilon}{(1 + \varepsilon)^{1+\varepsilon}} \right)^{\lambda^*/\alpha}$$

$$\begin{aligned} \mathbb{P}(\text{some } Y_e \geq (1+\epsilon)\lambda') &\leq |E| \cdot \frac{1}{n^3} \\ &\leq \frac{1}{n} \end{aligned}$$

choose $1+\varepsilon = C \cdot \frac{\ln n}{\ln \ln n}$

$$\frac{\lambda'}{\alpha} (\varepsilon - (1+\varepsilon) \ln(1+\varepsilon)) \leq \frac{\lambda'}{\alpha} \cdot \left(c \frac{\ln n}{\ln \ln n} - c \frac{\ln n}{\ln \ln n} \cdot \underbrace{\ln \left(c \frac{\ln n}{\ln \ln n} \right)}_{\Theta(\log \log n)} \right)$$

then: $\lambda \leq (1+\varepsilon) \lambda'$
with prob. $1 - \frac{1}{n}$

Proofing the Chernoff Bound

- $X_i \in \{0, a_i\}$, $0 < a_i \leq A$, $\mathbb{P}(X_i = a_i) = p_i$,
- $X = X_1 + \dots + X_n$, $\mu \geq \mathbb{E}[X] = \sum_{i=1}^n a_i \cdot p_i$

Chernoff Bound:

$$\mathbb{P}(X \geq (1 + \varepsilon) \cdot \mu) \leq \left(\frac{e^\varepsilon}{(1 + \varepsilon)^{1+\varepsilon}} \right)^{\mu/A}$$

Let's start with some useful tools:

- Markov inequality:

$$\text{For } \underline{Z} \geq 0 : \underline{\mathbb{P}(Z \geq z)} \leq \mathbb{E}[Z]/z$$

- Linearity of expectation:

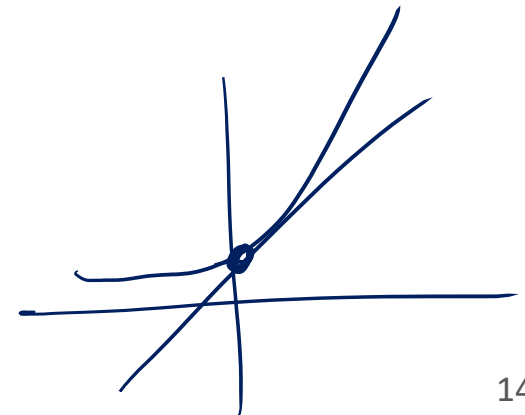
$$\mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y]$$

- For independent rand. var.:

$$\mathbb{E}[X \cdot Y] = \mathbb{E}[X] \cdot \mathbb{E}[Y]$$

- For all $x \in \mathbb{R}$:

$$\underline{(1 + x) \leq e^x}$$



Proofing the Chernoff Bound

- $X_i \in \{0, a_i\}$, $0 < a_i \leq A$, $\mathbb{P}(X_i = a_i) = p_i$,
- $X = X_1 + \dots + X_n$, $\mu \geq \mathbb{E}[X] = \sum_{i=1}^n a_i \cdot p_i$

$$e^{tx}$$

$$1+x \leq e^x$$

← assume $a_i \geq 1$

Chernoff Bound:

$$\mathbb{P}(X \geq (1 + \varepsilon) \cdot \mu) \leq \left(\frac{e^\varepsilon}{(1 + \varepsilon)^{1+\varepsilon}} \right)^{\mu/A}$$

Proof:

$$\mathbb{P}(X \geq (1 + \varepsilon)\mu) \stackrel{\forall t > 0}{=} \mathbb{P}(e^{tX} \geq e^{t(1+\varepsilon)\mu}) \stackrel{\text{Markov}}{\leq} \frac{\mathbb{E}[e^{tX}]}{e^{t(1+\varepsilon)\mu}}$$

$$\mathbb{E}[e^{tX}] = \mathbb{E}[e^{t \sum_{i=1}^n X_i}] = \mathbb{E}\left[\prod_{i=1}^n e^{tX_i}\right] \stackrel{\text{indep. of } X_i}{=} \prod_{i=1}^n \mathbb{E}[e^{tX_i}] = \prod_{i=1}^n (p_i e^{ta_i} + (1-p_i))$$

$$= \prod_{i=1}^n (1 + p_i(e^{ta_i} - 1)) \leq \prod_{i=1}^n e^{p_i(e^{ta_i} - 1)} \stackrel{(a_i \leq A)}{\leq} e^{\sum p_i(e^{tA} - 1)} \stackrel{(a_i \leq A)}{\leq} e^{(e^{tA} - 1)\mu/A}$$

$$\sum p_i \leq \mu/A$$

Proofing the Chernoff Bound

- $X_i \in \{0, a_i\}$, $0 < a_i \leq A$, $\mathbb{P}(X_i = a_i) = p_i$,
- $X = X_1 + \dots + X_n$, $\mu \geq \mathbb{E}[X] = \sum_{i=1}^n a_i \cdot p_i$

Chernoff Bound:

$$\mathbb{P}(X \geq (1 + \varepsilon) \cdot \mu) \leq \left(\frac{e^\varepsilon}{(1 + \varepsilon)^{1+\varepsilon}} \right)^{\mu/A}$$

Proof:

$$\mathbb{P}(X \geq (1 + \varepsilon)\mu) \leq \frac{\mathbb{E}[e^{tX}]}{e^{t(1+\varepsilon)\mu}} \leq e^{(e^{tA} - 1)\mu - t(1+\varepsilon)\mu}$$

choose t s.t. $(e^{tA} - 1 - t(1+\varepsilon))$ is min.

$$A \cdot e^{tA} = 1 + \varepsilon \Rightarrow tA = \ln\left(\frac{1+\varepsilon}{A}\right) \Rightarrow t = \frac{\ln\left(\frac{1+\varepsilon}{A}\right)}{A}$$

$$\mathbb{P}(X \geq (1 + \varepsilon)\mu) \leq e^{\left(\frac{1+\varepsilon}{A} - \frac{1}{A} - \frac{(1+\varepsilon) \ln\left(\frac{1+\varepsilon}{A}\right)}{A}\right)\mu} = \left(\frac{e^{1+\varepsilon-A}}{\left(\frac{1+\varepsilon}{A}\right)^{1+\varepsilon}} \right)^{\mu/A}$$

not quite what we wanted.

Proofing the Chernoff Bound

$$e^x = \sum_{i=0}^{\infty} \frac{x^i}{i!}$$

- $X_i \in \{0, a_i\}$, $0 < a_i \leq A$, $\mathbb{P}(X_i = a_i) = p_i$,
- $X = X_1 + \dots + X_n$, $\underline{\mu} \geq \mathbb{E}[X] = \sum_{i=1}^n a_i \cdot p_i$

Chernoff Bound:

$$\mathbb{P}(X \geq (1 + \varepsilon) \cdot \mu) \leq \left(\frac{e^\varepsilon}{(1 + \varepsilon)^{1+\varepsilon}} \right)^{\mu/A}$$

Proof:

$$\mathbb{E}[e^{tX}] \leq \prod_{i=1}^n e^{p_i(e^{ta_i} - 1)} = e^{\sum_{i=1}^n p_i(e^{ta_i} - 1)} \leq e^{\sum_{i=1}^n \frac{a_i p_i}{A} (e^{tA} - 1)} = e^{(e^{tA} - 1) \cdot \frac{\mu}{A}} \leq e^{\varepsilon \mu / A}$$

$$e^{ta_i} - 1 \leq \frac{a_i}{A} (e^{tA} - 1) \xrightarrow{a=a_i} A(e^{ta} - 1) \leq a(e^{tA} - 1)$$

$$A\left(ta + \sum_{i=2}^{\infty} \frac{(ta)^i}{i!}\right) \leq a\left(tA + \sum_{i=2}^{\infty} \frac{(tA)^i}{i!}\right)$$

$$\sum_{i=2}^{\infty} \frac{(ta)^i \cdot A}{i!} \leq \sum_{i=2}^{\infty} \frac{(tA)^i \cdot a}{i!} \quad \begin{matrix} i \geq 2 \\ a^{i-1} \leq A^{i-1} \\ a^i A \leq A^i a \end{matrix}$$

$$\underline{0 \leq a \leq A}$$

- What if the possible paths \mathcal{P}_i for commodity i are not given?
 - Using all exponentially many possible paths is not feasible

We can reduce to the rounding problem with fixed paths:

1. Solve the multicommodity flow LP
 - Returns a valid flow of value 1 for each commodity
2. Compute a set of paths \mathcal{P}_i for each $i \in \{1, \dots, k\}$ such that the flow f_i corresponds to a probability distribution on the paths in \mathcal{P}_i
 - Using flow decomposition, one can always find a collection \mathcal{P}_i of at most m paths
3. Round as before by using the path sets \mathcal{P}_i

Flow Decomposition

Flow Decomposition Lemma:

$$\forall e : f(e) \geq \sum_{i=1}^h f_i(e)$$

Let $G = (V, E)$ be a directed network with edge capacities $c_e > 0$, let $s, t \in V$, and let f be a flow in the network. Then there is a collection of feasible flows f_1, \dots, f_h and a collection of s - t paths P_1, \dots, P_h such that

- The number of paths is $h \leq |E|$
- The value of f is equal to the sum of the values of f_1, \dots, f_h
- Flow f_i sends positive flow only on the edges of P_i

Proof: Inductively construct P_1, \dots, P_h (and corresponding flows f_1, \dots, f_h)

- For details, see, e.g., mins 17:00 – 29:50 of <https://www.youtube.com/watch?v=zgutyzA9JM4&t=1020s>

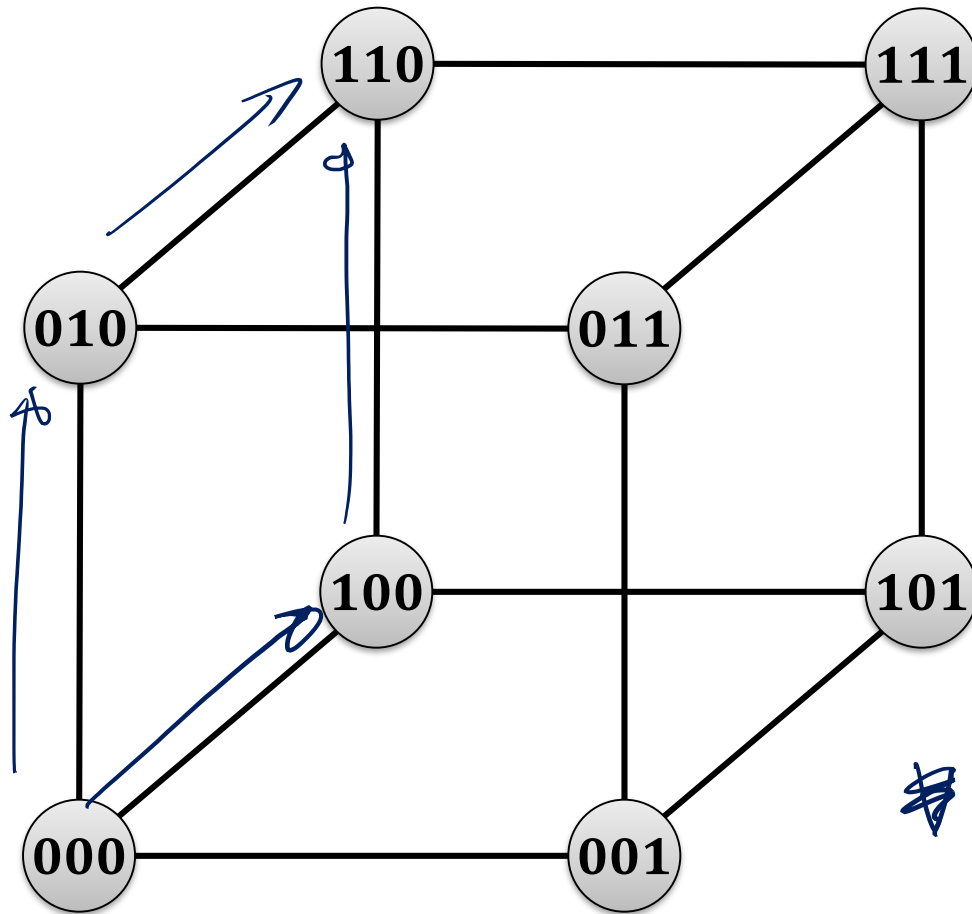
Application to Multicommodity Routing

- Decompose flow of each commodity $i \in \{1, \dots, k\}$
- Value of flow on each path is used as sampling probability

Oblivious Routing

- An “online” version of the multicommodity routing problem
- Decide for each source-destination request independently on which path to route it
 - For each $s, t \in V$, there is a probability distribution on s - t paths
 - If a message is sent from s to t , a path is chosen according to this distribution
- **Goal:** Be competitive with best multicommodity flow solution
- In this lecture, we will look at a very specific example:
permutation routing on the d -dimensional hypercube
- **Permutation routing:**
each node is source and destination of exactly one routing request
- **Hypercube $Q = (V, E)$:**
 $V = \{0,1\}^d$, edge between u and v if Hamming distance = 1

Hypercube



$V = \{0, 1\}^d$

Routing on the Hypercube

Bit Fixing Algorithm:

- Fix “wrong” bits from left to right
- Example: 00101100 \rightarrow 10010110
 \rightarrow **1**0101100 \rightarrow 10**0**01100 \rightarrow 100**1**1100 \rightarrow 1001**0**100 \rightarrow 100101**1**0

Permutation Routing:

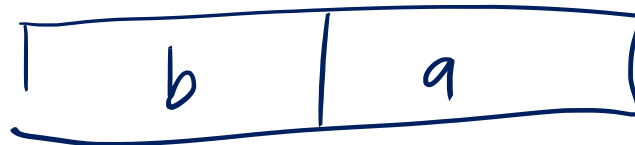
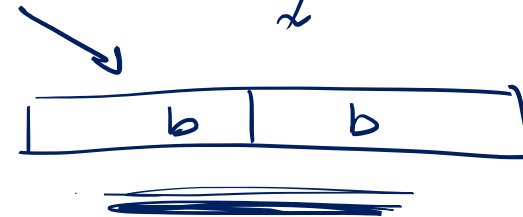
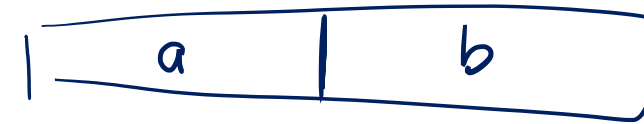
- Assumption: d -dimensional hypercube $Q = (V, E)$, $n = |V|$
- $n = 2^d$ routing requests (s_i, t_i) (each of demand 1)
- Each node $v \in V$ is source s_i and destination t_i for exactly one request
 - Within these assumptions, requests are given in a worst-case manner
- Round-based model, ≤ 1 message per edge and round
 - In each round, every node can forward one message on each of its edges

Bad Example for Bit Fixing Algorithm

$$n = 2^d \quad d = \log n$$

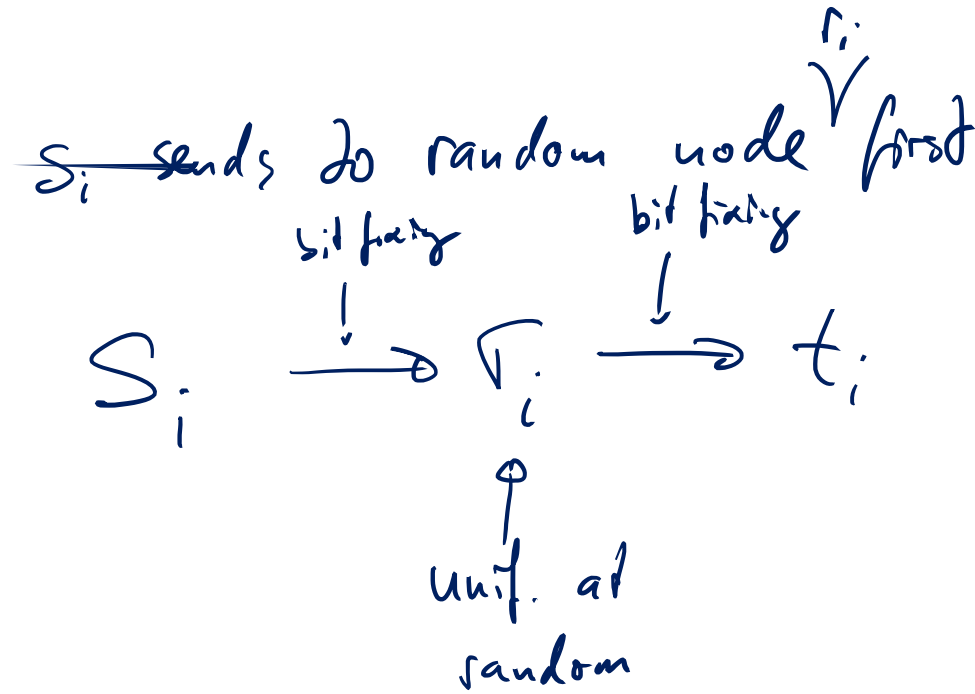
instances where we need time $\frac{\sqrt{n}}{\log n}$

$$\frac{\sqrt{n}}{d}$$

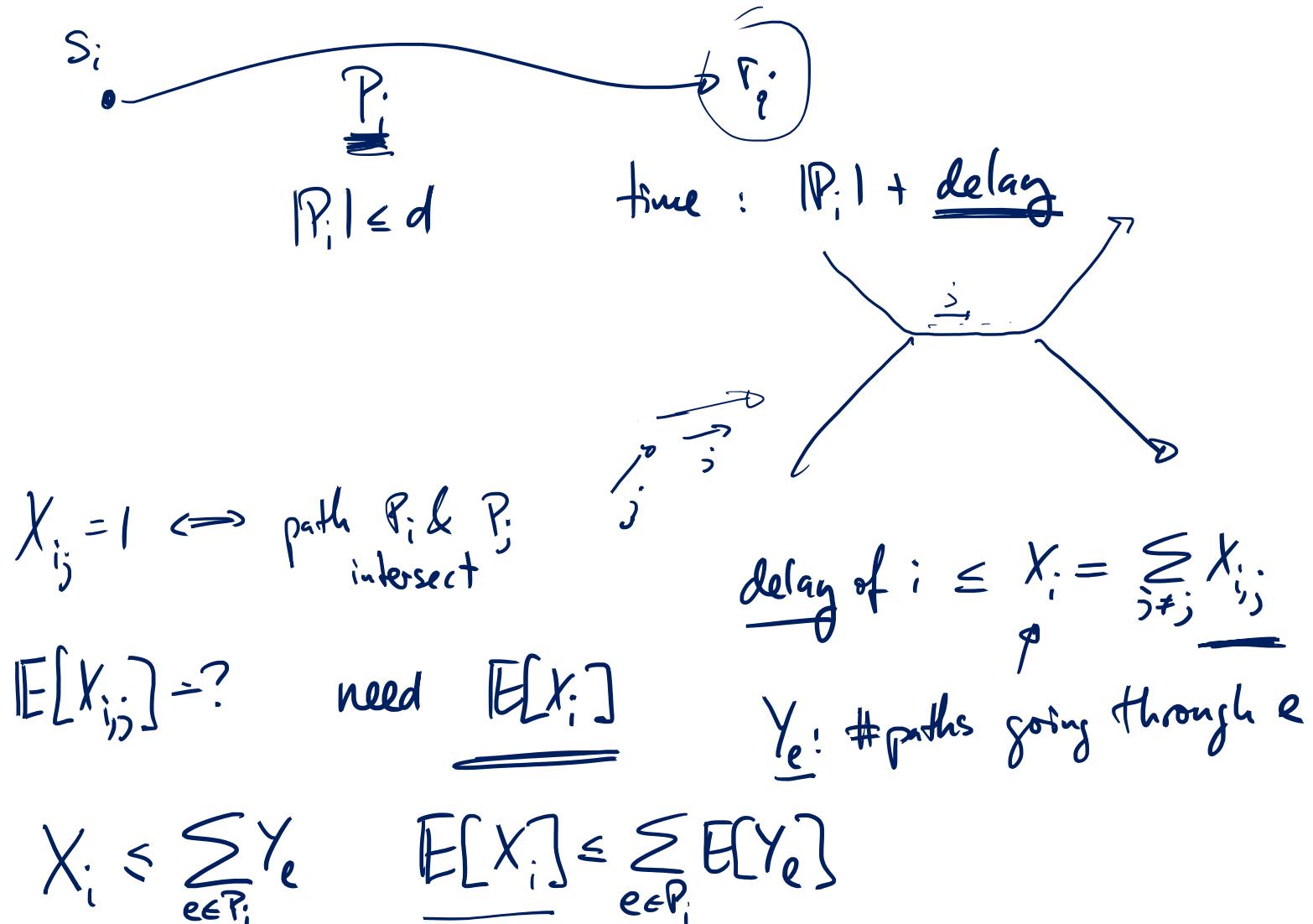


$$2^{d/2} = \sqrt{n}$$

Valiant's Trick



Analyzing Bit Fixing with Valiant's Trick



Analyzing Bit Fixing with Valiant's Trick

what is $E[Y_e]$?

$$Y = \sum_{e \in E} Y_e$$

$$E[Y_e] = E[Y_{e'}]$$

↑ total path length (over all n paths)

$$\begin{aligned} E[Y] &= \text{exp. total path length} \\ &= n \cdot E[\text{length of single path}] = n \cdot \frac{d}{2} \end{aligned}$$

$$E[Y_e] = \frac{1}{|E|} \cdot E[Y] = \frac{1}{n \cdot d} \cdot \frac{n \cdot d}{2} = \frac{1}{2}$$

~~Chernoff~~
↓ $-3d$

$$\underline{\underline{E[X_i]}} \leq \sum_{e \in P_i} E[Y_e] \leq d/2$$

$$P(X_i \geq \underline{\underline{3d}}) \leq 2$$

routing completes in $O(d)$ steps w.h.p.