

## Shortest Paths

Let the arcs of the complete digraph  $D_n$  on  $[n]$  be given independent lengths  $X_e$ ,  $e \in [n]^2$ .

Here  $X_e$  is exponential with mean 1

i.e.

$$P(X_e \geq t) = e^{-t}$$

for all  $t \geq 0$ .

## Theorem

Let  $X_{ij}$  = distance from  $i$  to  $j$ . Then

(i) For any **fixed**  $i, j$ ,

$$P\left(\left|\frac{X_{ij}}{\log n/n} - 1\right| \geq \epsilon\right) \rightarrow 0, \quad \forall \epsilon > 0$$

(ii) For any **fixed**  $i$ ,

$$P\left(\left|\frac{Z_i}{2 \log n/n} - 1\right| \geq \epsilon\right) \rightarrow 0, \quad \forall \epsilon > 0$$

Here  $Z_i = \max_j X_{ij}$

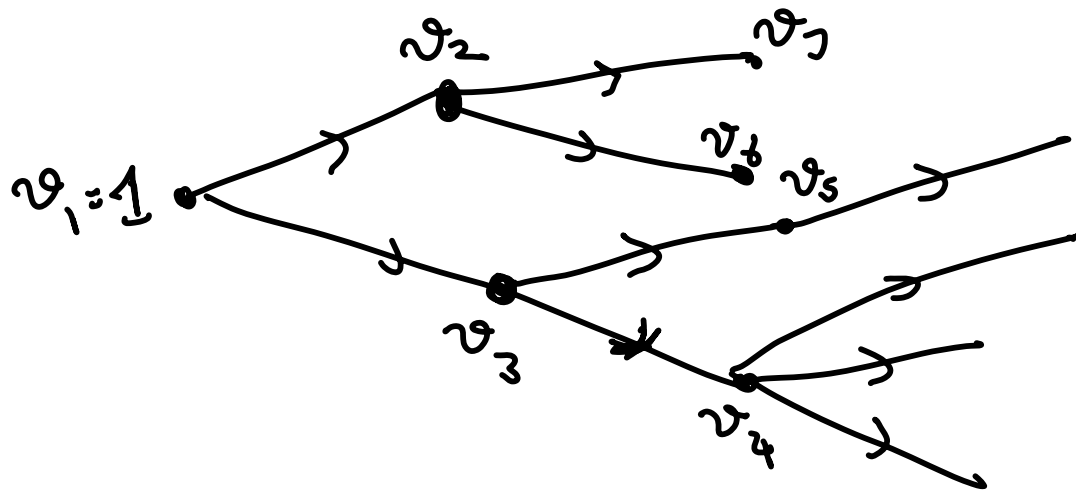
## Proof

Two main properties of exponential  $X$ :

$$(P1) \Pr(X > \alpha + \beta \mid X > \alpha) = \Pr(X > \beta).$$

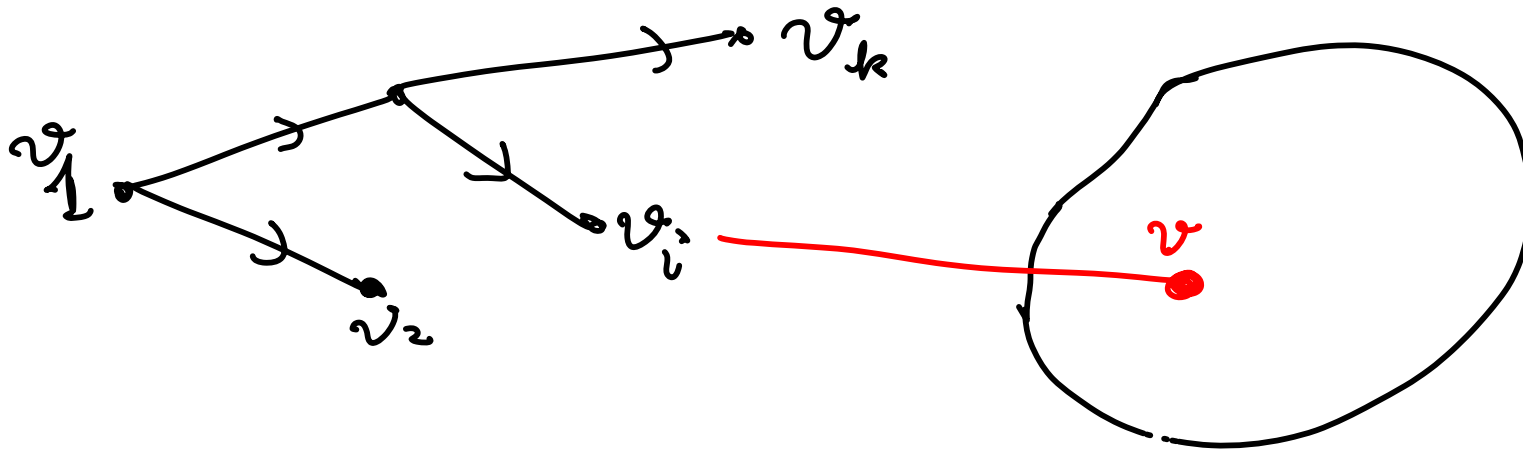
(P2) If  $X_1, X_2, \dots, X_m$  are independent exponentials then  $\min\{X_1, X_2, \dots, X_m\}$  is an exponential with mean  $1/m$ .

Fix  $i=1$  and consider Dijkstra's shortest path algorithm. This produces a tree



Suppose that vertices are added to the tree in the order  $v_1, v_2, \dots, v_n$  and that  $\text{dist}(v_1, v_i) = \gamma_i$ .

It follows from P1 (p3) that



$$Y_{k+1} = \min_{i=1, \dots, k} \left[ \underbrace{Y_i + X(v_i, v)}_{\geq Y_k} \right]$$

$\stackrel{d}{=} Y_k + \text{Exponential}$

So  $Y_{k+1} = Y_k + E_k$

where  $E_k$  is exponential with mean  $\frac{1}{k(n-k)}$  and is independent of  $Y_k$ .

So

$$E(Y_n) = \sum_{k=1}^{n-1} \frac{1}{k(n-k)}$$

$$= \frac{1}{n} \sum_{k=1}^{n-1} \left( \frac{1}{k} + \frac{1}{n-k} \right)$$

$$= \frac{2}{n} \sum_{k=1}^{n-1} \frac{1}{k}$$

$$\sim \frac{2 \log n}{n}.$$

$$\begin{aligned} \text{Also } \text{Var}(Y_n) &= \sum_{k=1}^{n-1} \text{Var}(E_{1/n}) = \sum_{k=1}^{n-1} \left( \frac{1}{k(n-k)} \right)^2 \\ &\leq 2 \sum_{k=1}^{n/2} \left( \frac{1}{k(n-k)} \right)^2 \leq \frac{8}{n^2} \sum_{k=1}^{n/2} \frac{1}{k^2} = O(n^{-2}) \end{aligned}$$

and we can use Chebyshev to prove (ii).

Now fix  $j=2$ . Then if  $i$  is defined by  $n_{i,j}=2$ , we see that  $i$  is uniform over  $\{2, 3, \dots, n\}$ .

$$\begin{aligned} \text{So } E(X_{1,2}) &= \frac{1}{n-1} \sum_{i=2}^n \sum_{k=1}^i \frac{1}{k(n-k)} \\ &= \frac{1}{n-1} \sum_{k=1}^{n-1} \frac{n-k}{k(n-k)} \\ &\stackrel{**}{=} \frac{\log_e n}{n}. \end{aligned}$$

For variance we have

$$X_{1,2} = \delta_2 Y_2 + \delta_3 Y_3 + \dots + \delta_n Y_n$$

where

$$\delta_i \in \{0,1\}; \delta_2 + \dots + \delta_n = 1; P(\delta_i = 1) = \frac{1}{n-1}$$

$$\text{Var}(X_{1,2}) = \sum_{i=2}^n \text{Var}(\delta_i Y_i)$$

$$+ \sum_{i \neq j} \text{Cov}(\delta_i Y_i, \delta_j Y_j)$$

$$\leq \sum_{i=2}^n \text{Var}(\delta_i Y_i)$$

$$\text{Cov}(\delta_i Y_i, \delta_j Y_j) = E(\delta_i Y_i \delta_j Y_j) - E(\delta_i Y_i) E(\delta_j Y_j) \leq 0$$

$\uparrow 0$



$$\begin{aligned}
\text{Var}(X_{1,2}) &\approx \sum_{i=2}^n \text{Var}(\beta_i Y_i) \\
&\ll \sum_{i=2}^n \frac{1}{n-1} \sum_{k=1}^{i-1} \left( \frac{1}{k(n-k)} \right)^2 \\
&= O\left(\frac{1}{n^2}\right).
\end{aligned}$$

Split sum  
at  $n/2$

We can now use Chebyshev.