

$$\hat{\text{Var}}(\hat{S}(t)) = \hat{S}(t)^2 \sum_{i \leq t} \frac{d_i}{n_i(n_i - d_i)}$$

First off, my  $\tau$ 's are in  $\mathbb{N}$ , so I think I can simplify this expression

$$\hat{\text{Var}}(\hat{S}(\tau)) = \hat{S}(\tau)^2 \sum_{i=1}^{\tau} \frac{d_i}{n_i(n_i - d_i)}$$

$$\leq \sum_{i=1}^{\tau} \frac{d_i}{n_i(n_i - d_i)}$$

$$V_{\tau} \leq \sum_{i=1}^{\tau} \frac{d_i}{n_i(n_i - d_i)}$$

$$\tau=1: V_1 \leq \frac{d_1}{n_1(n_1 - d_1)}$$

12/6/22  
Usually,  $i$  is ~~not~~ an index of nodes, but I'm just used to working with it.

$n_{i+1} = n_i - d_i - c_i$  — this is a random variable  
 $n_0 = \#$  messages injected, this is what I can control.

Note: Usually, the extinction

times are limited to 1, but since some messages die immediately, it may be handy to define this.

There's a question of the correct interval type. For now, we'll focus on this problem; it's hard enough.

Probability

Probability extinction time exceeds  $t$ :  $S(t)$

Probability censorship time exceeds  $t$ :  $U(t)$

A projected variance estimate is

$$S^2(t) \left[ \frac{1}{rT} \int_0^t \frac{\lambda(u) du}{S(u)U(u)} + \frac{1}{r} \mathbb{1}[t > T] \int_T^t \frac{\lambda(u) du}{S(u)U(u)(T+t-u)} \right]$$

Uniform accrual of patients to the trial at rate  $r$

$T$ : The time horizon

$\theta(t)$ : Loss to follow up at a rate  $t$   
 $\lambda(t)$ : hazard function.

We also don't need to involve integrals since the set of possible extinction times is discrete.

This is not satisfied by my problem, the loss to follow up happens once we've observed some number of extinctions  $M$  from each node. So there is  $\theta$  depends on  $M$ .

The time horizon  $T$

is a stopping time, if  $M$  is the smallest number of ~~let  $t > 0$ , we~~

~~want~~ Fix ~~the~~ errors  $\epsilon$  and  $\alpha$ . We want

$\hat{S}(t) \pm z_{\alpha/2} \sqrt{V_{\tau}}$  to be of length  $\epsilon$ , so we need

$$z_{\alpha/2} \sqrt{V_{\tau}} < \epsilon \Rightarrow \sqrt{V_{\tau}} < \frac{\epsilon}{z_{\alpha/2}}$$

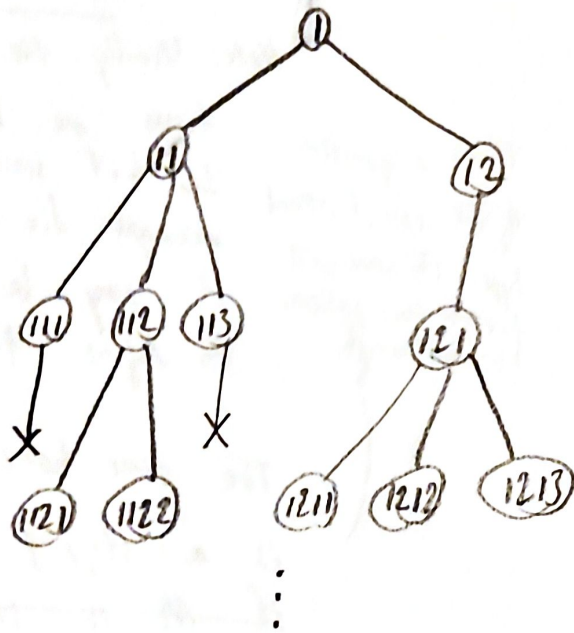
$$\Rightarrow V_{\tau} < \left( \frac{\epsilon}{z_{\alpha/2}} \right)^2$$

Use Hermite normal forms to give an algorithm for the stationary distribution

Use good notation for the kind of sets such as

$$\{x \in [1]_0^n : x_1=1, x_2 \text{ free}, x_3=1, x_4 \text{ free, etc.}\}$$

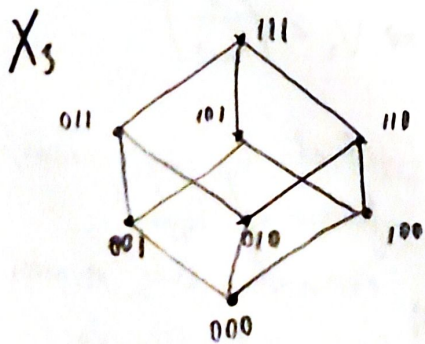
and a good labeling of a message tree, i.e.,



May be convenient to label by nodes

$$\{i\} \times \{j\} : \vec{v}_i$$

to give an algorithm expressing the probabilities of message survival  
(I started this way back in NB2, maybe I can find it)



for  $x \in X_n$ , let  $[x]$  be the set of all  $y \in X_n$  s.t.  $y \geq x$

now we can talk about sets like the example above with the characters

$$\bigcup_{h \in \bar{N}_i} [e_h], \text{ where } e_h \text{ is a standard basis vector in the } h\text{-th direction.}$$



all you have to do is express these events.

$\tau=1$  means that a node in  $\tilde{N}_i$  was active, which happens w/p

$\sum \{\pi_x \text{ for } x \in \bigcup_{h \in \tilde{N}_i} [e_h]\}$  — Let's extend the notation. If we pass  $[e]$ , a ~~subset~~ of neighborhood to, ~~for~~, then let

$$[\tilde{N}_i] = \bigcup_{h \in \tilde{N}_i} [e_h]$$

$$P(\tau=1) = \sum_{x \in [\tilde{N}_i]} \pi_x$$

$$P(\tau=2) = [1 - P(\tau=1)] \times P(\text{all the children die}).$$

for every non-empty subset  $M_i$  of  $\tilde{N}_i$ :  
for each  $i$  in  $M_i$ :

$$\sum_{M_i \in \tilde{N}_i} P(\text{each } j \in M_i \text{ has a collision \& no injection}) + P(\text{each } j \in M_i \text{ has no coll. but injection}) + P(\dots)$$

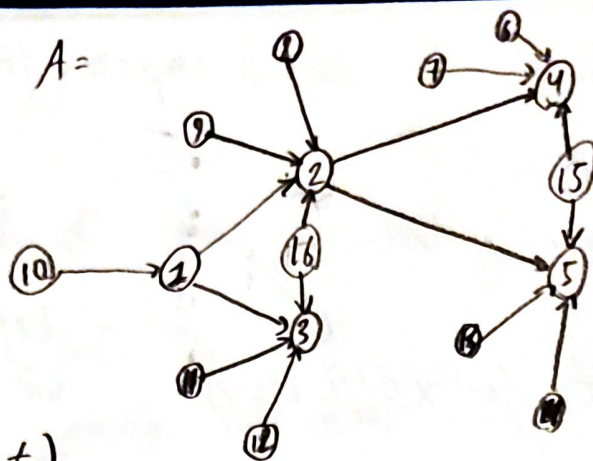
OMG.

Once I know  $P(\tau=2)$ , I can attempt induction.

I want good error analysis in this work!

example

We inject a message at ①



$$P(\tau=1)$$

$$= P(\text{node 10 was active in the previous state})$$

$$= \sum_{x \in \hat{N}_1} \pi_x$$

$$P(\tau=2)$$

$$= P(\tau \neq 1) \times P$$

a node in  $\hat{N}_2 - \{1\}$  is active or

I have to be careful here: it  $P(\text{no col at 2} | 1 \text{ was occupied})$

$$P(\tau \geq 1) = 1$$

$$P(\tau \geq 2) = P(\text{one outgoing copy survives})$$

$$= P[(\text{no collision at 2} \& \text{no injection at 2}) \text{ or } (\text{no collision at 3} \& \text{no injection at 3})]$$

$$= P[\text{no coll 2}]P[\text{no inj 2}] + P[\text{no coll 3}]P[\text{no inj 3}] - P[\text{no coll 2} \& \text{no coll 3}]P[\text{no inj 2} \& \text{no inj 3}]$$

$$P(\hat{N}_2 - \{1\} \text{ not active})P[\text{no inj 2}] + P(\hat{N}_3 - \{1\} \text{ not active})P[\text{no inj 3}]$$

$$- P(\hat{N}_2 \cup \hat{N}_3 - \{1\} \text{ not active})P[\text{no inj 2} \& 3]$$

So a key ingredient is a formula for the probability of no collision occurring at one set of nodes given that another set of nodes is known to be active.



formula for  $P[\text{no inj at } 2, 3, \dots, n]$  is much more complicated due to the  $\epsilon$  modification to the chain.

→ If I go back to the old ~~formula~~ modification, the formula is simple again. Or yet a third modification.

$$B = B_L \cup \{1\}, \quad b_t \sim \begin{cases} (1-\epsilon)\text{unif}(B_L) & \text{on } B_L \\ \epsilon \{1\} & \text{on } \{1\} \end{cases} \quad \begin{array}{l} \text{This alphabet everywhere} \\ \text{except the } 0 \text{ state} \end{array}$$

$$B = [1]_0^n, \quad b_t \sim \begin{cases} (1-\epsilon)\text{unif}(B_L) & \text{on } B_L \\ \epsilon \text{unif}([1]_0^n - B_L) & \text{on } [1]_0^n - B_L \end{cases} \quad \text{at the } 0 \text{ state}$$

I believe we can use "convex combination" to simplify this notation.

→ This is good because the alphabet is the same for every state that could possibly lead to a collision; the last state could not have been  $\bar{0}$  because a message was injected (except for the ~~very first state that could be~~ state right before the message was injected, that could be  $\bar{0}$ ).