

# **Stochastic fixed-points and periodicities in combinatorial structures**

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Goethe-University  
Frankfurt am Main

ALEA in Europe Workshop, Vienna, Austria  
October 9–13, 2017

# Bucket Selection

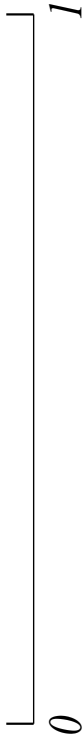
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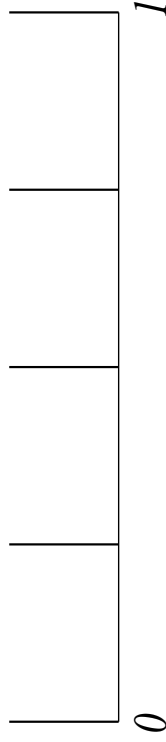
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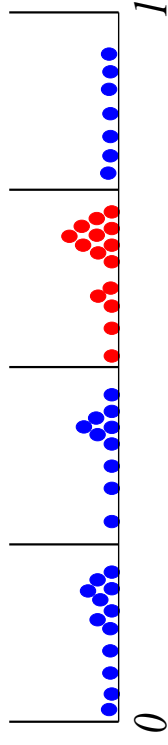
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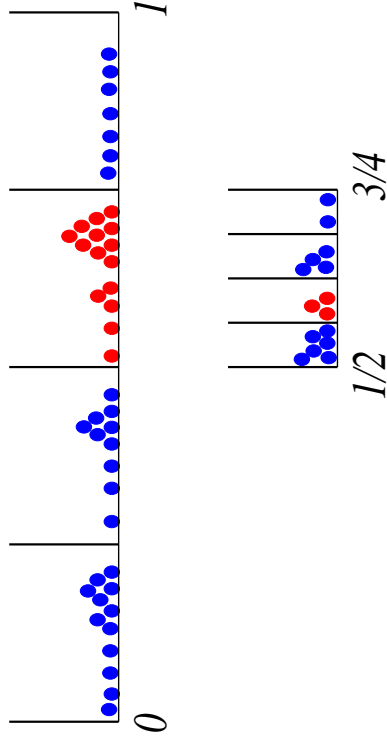
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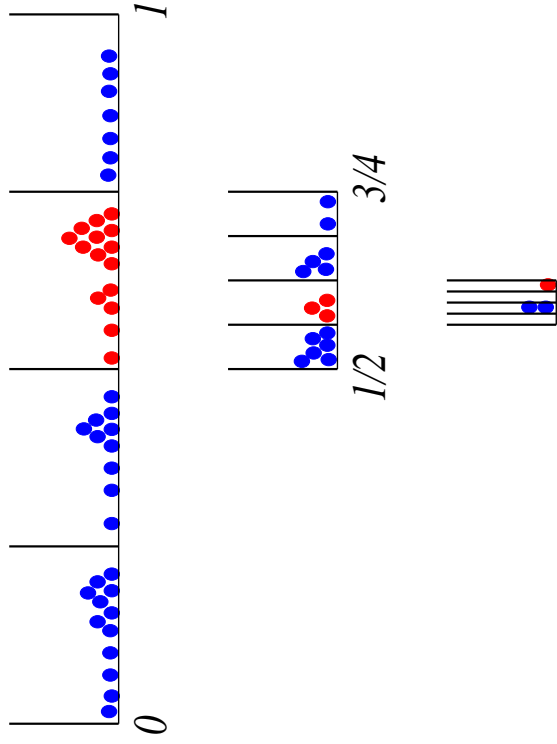
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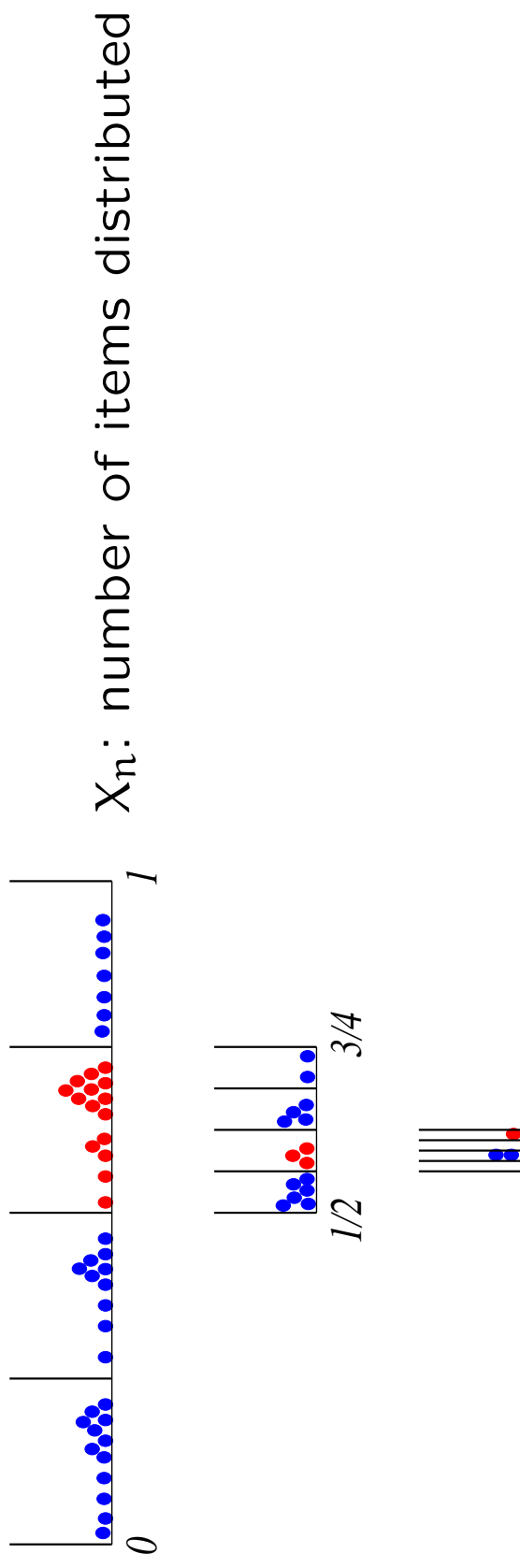
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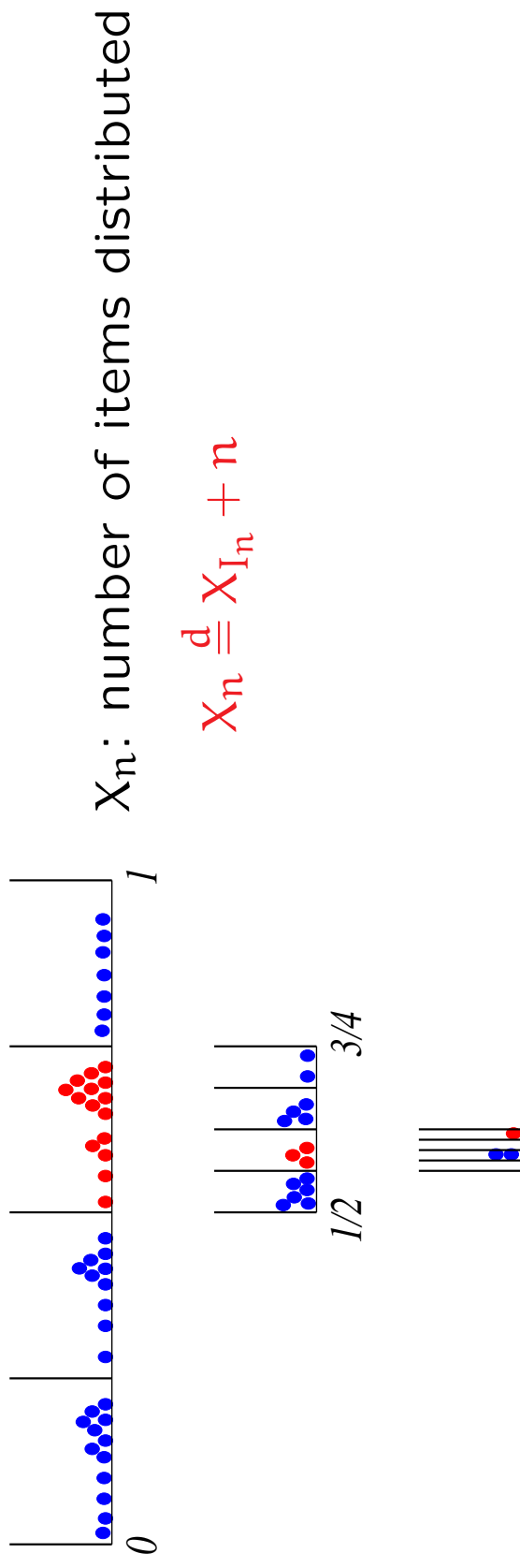




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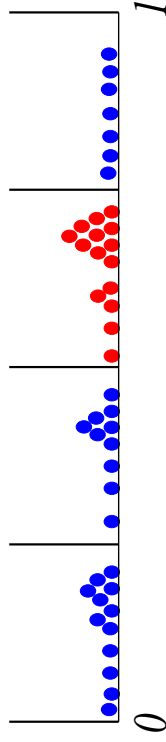
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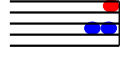
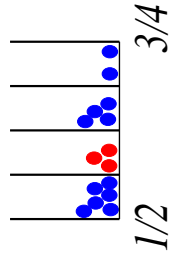
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$X_n$ : number of items distributed

$$X_n \stackrel{d}{=} X_{I_n} + n$$

$I_n = \#$  items in relevant bucket



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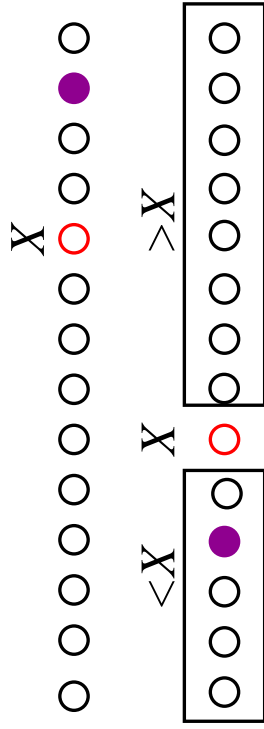
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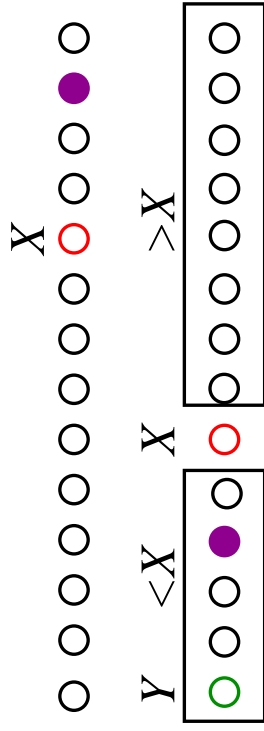
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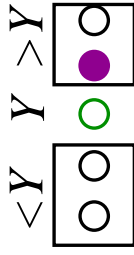
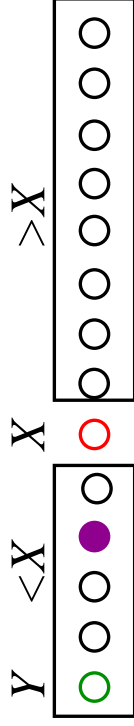
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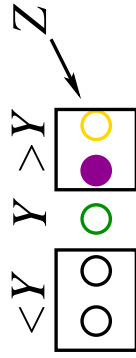
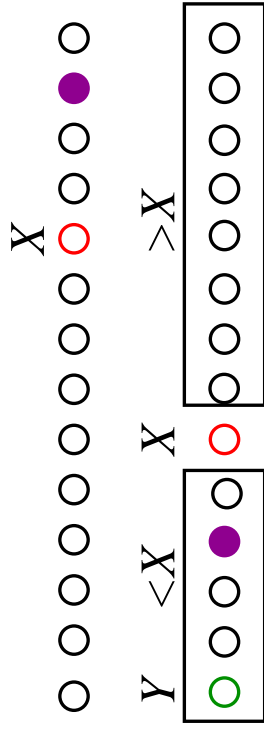




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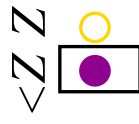
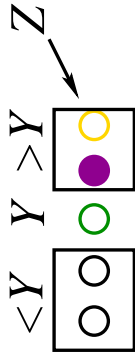
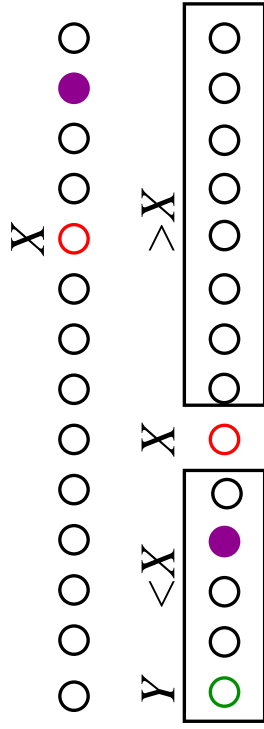
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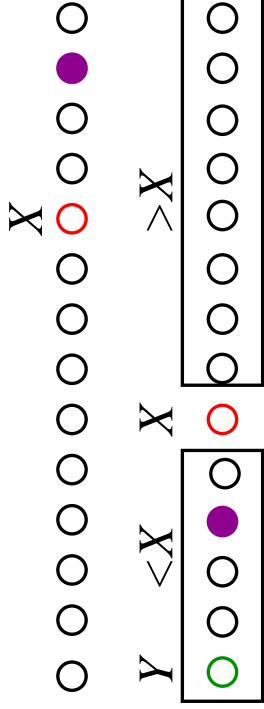
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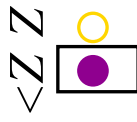
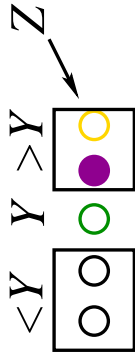
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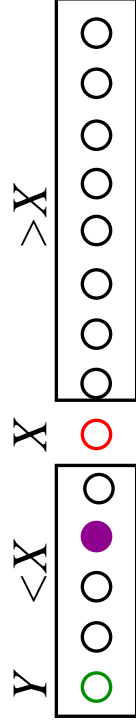
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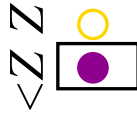
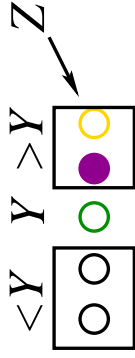
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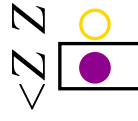
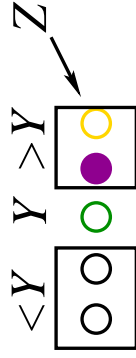
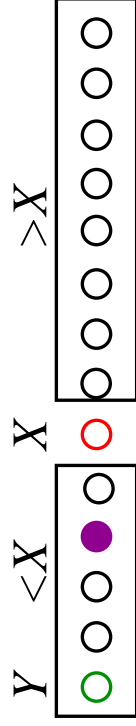
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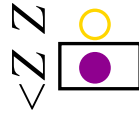
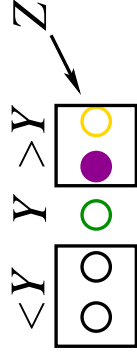
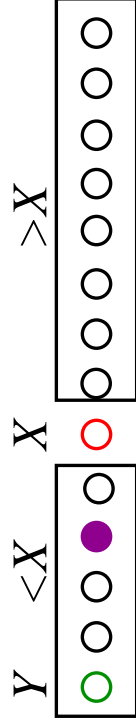
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with  $U, Y$  independent and  $U \stackrel{d}{=} \text{unif}[0, 1]$ .

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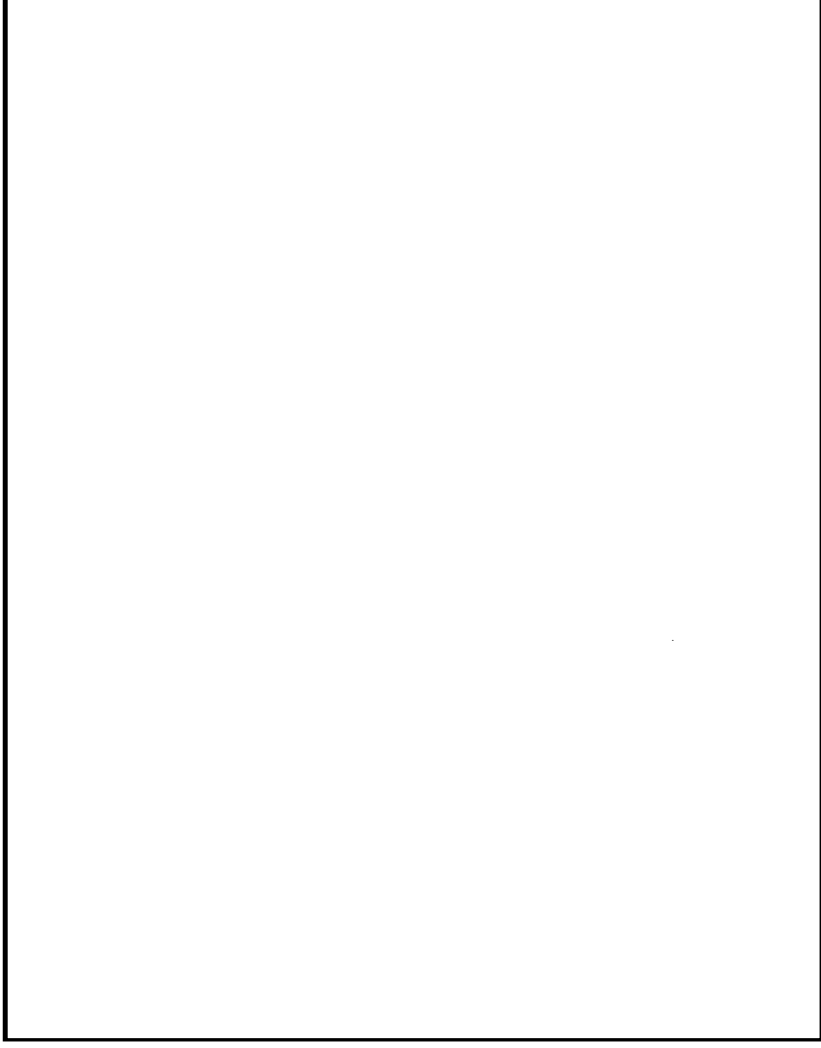
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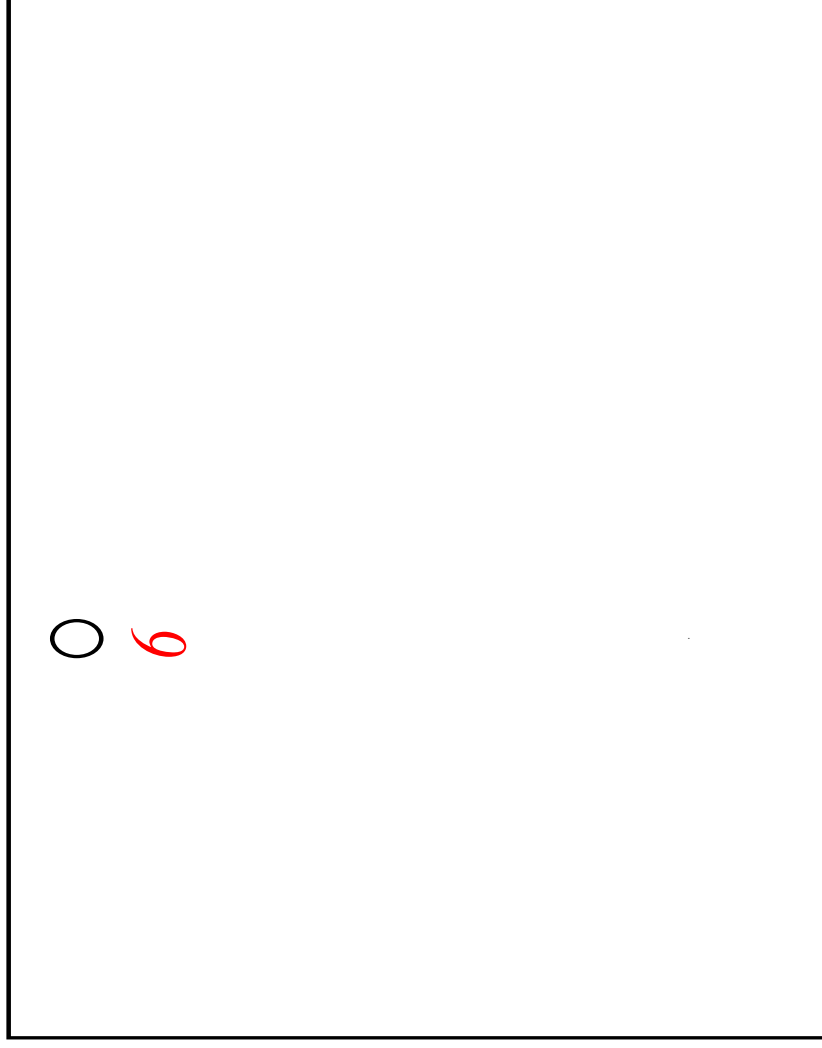
# Binary search tree

Given numbers: 6, 1, 8, 7, 5, 3, 10, 2, 11, 4, 9.



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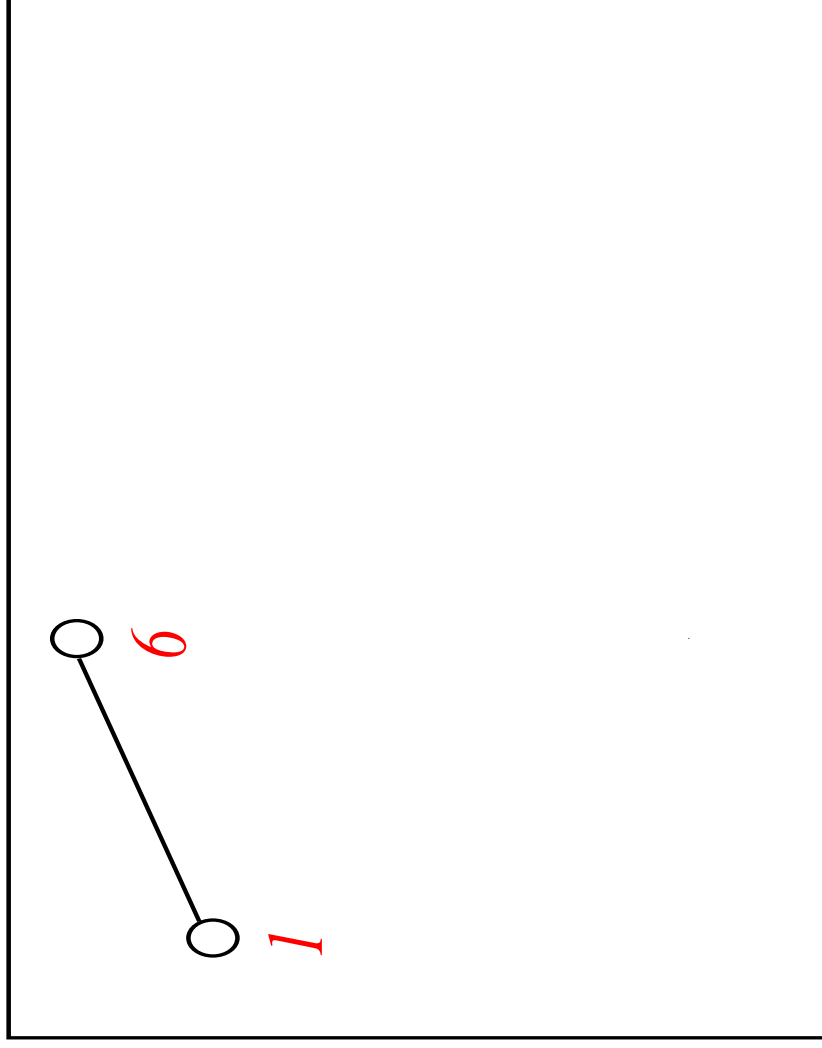


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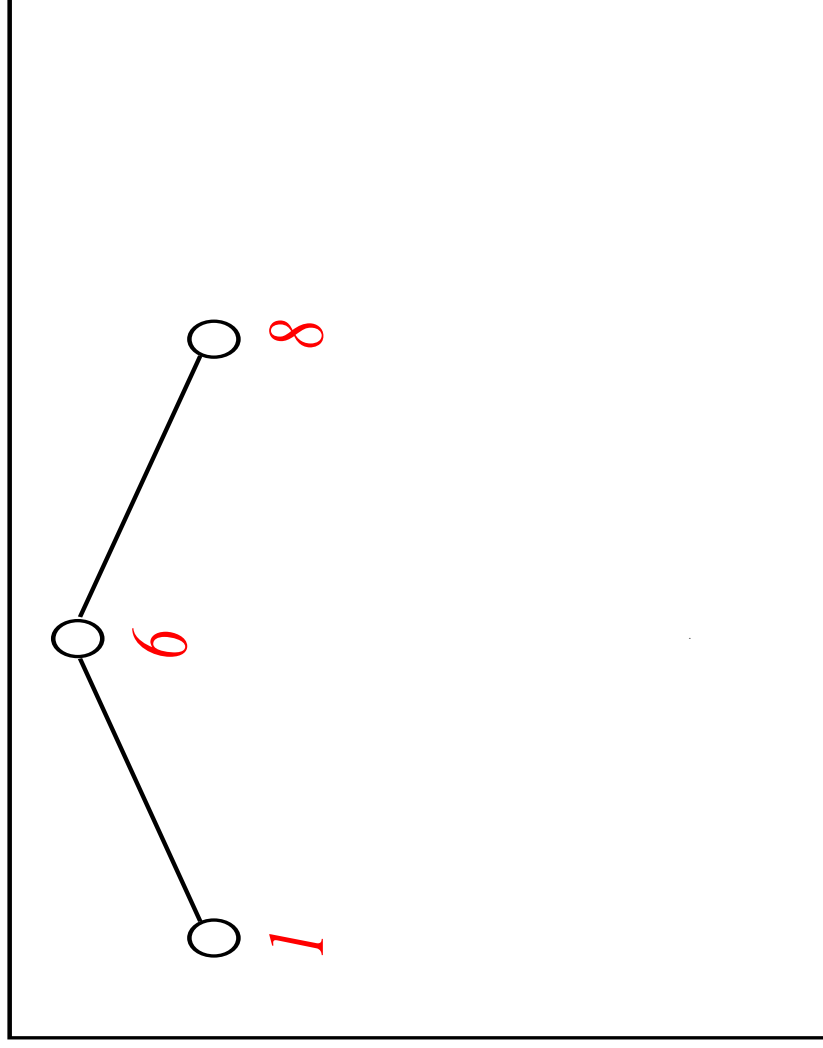
# Binary search tree

Given numbers: 6, 1, 8, 7, 5, 3, 10, 2, 11, 4, 9.



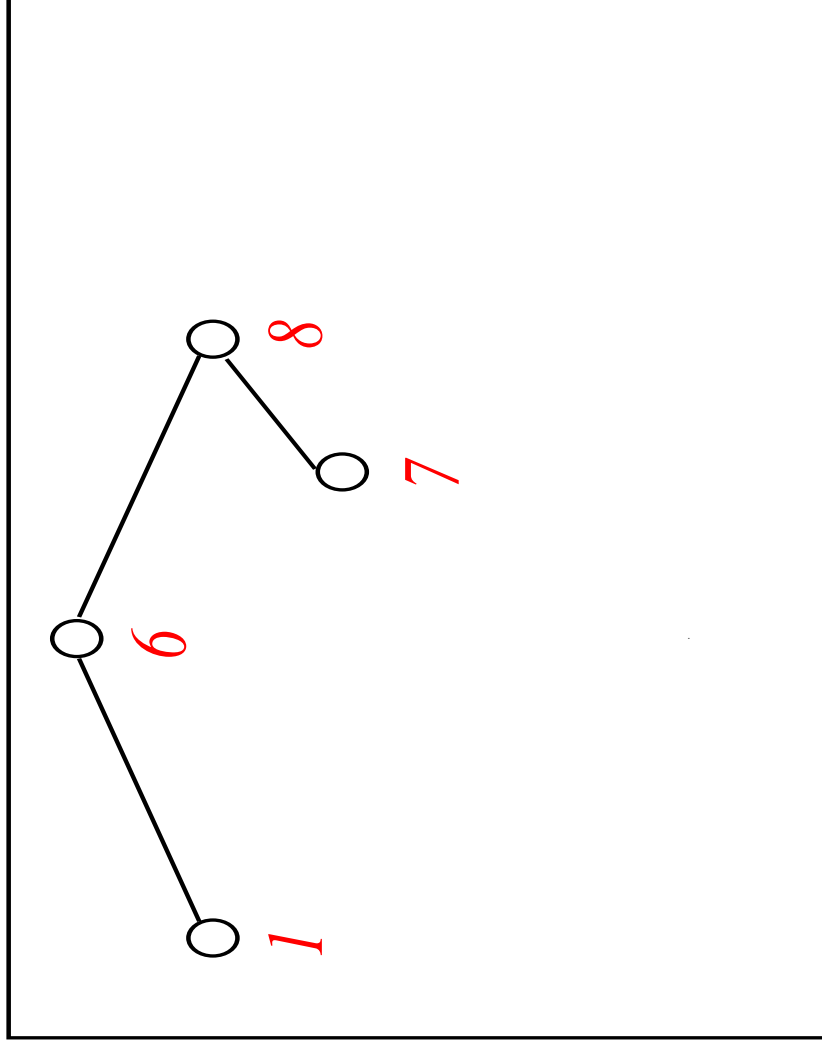
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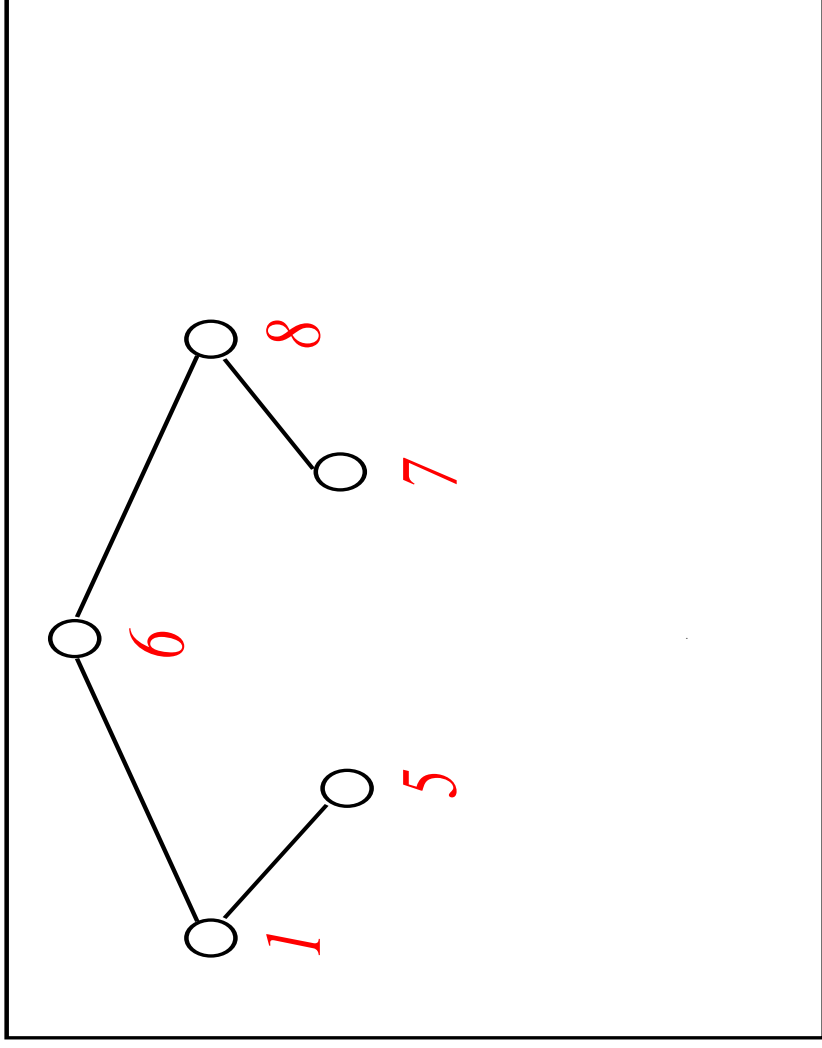
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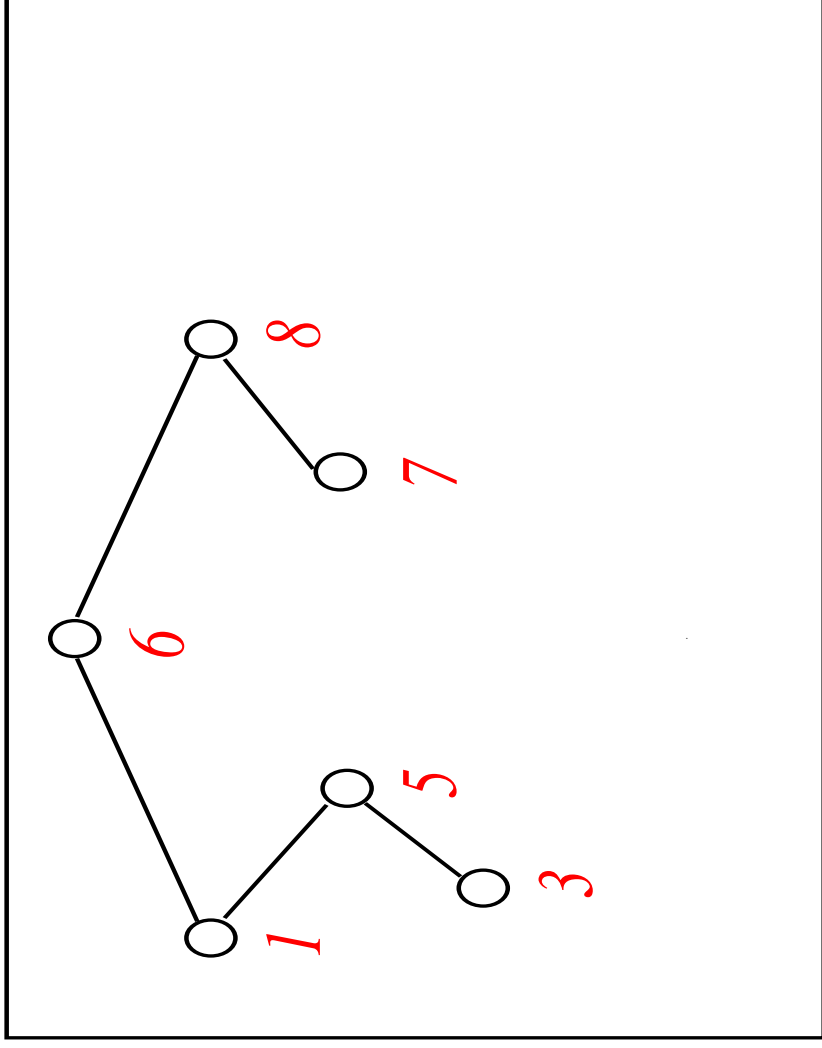
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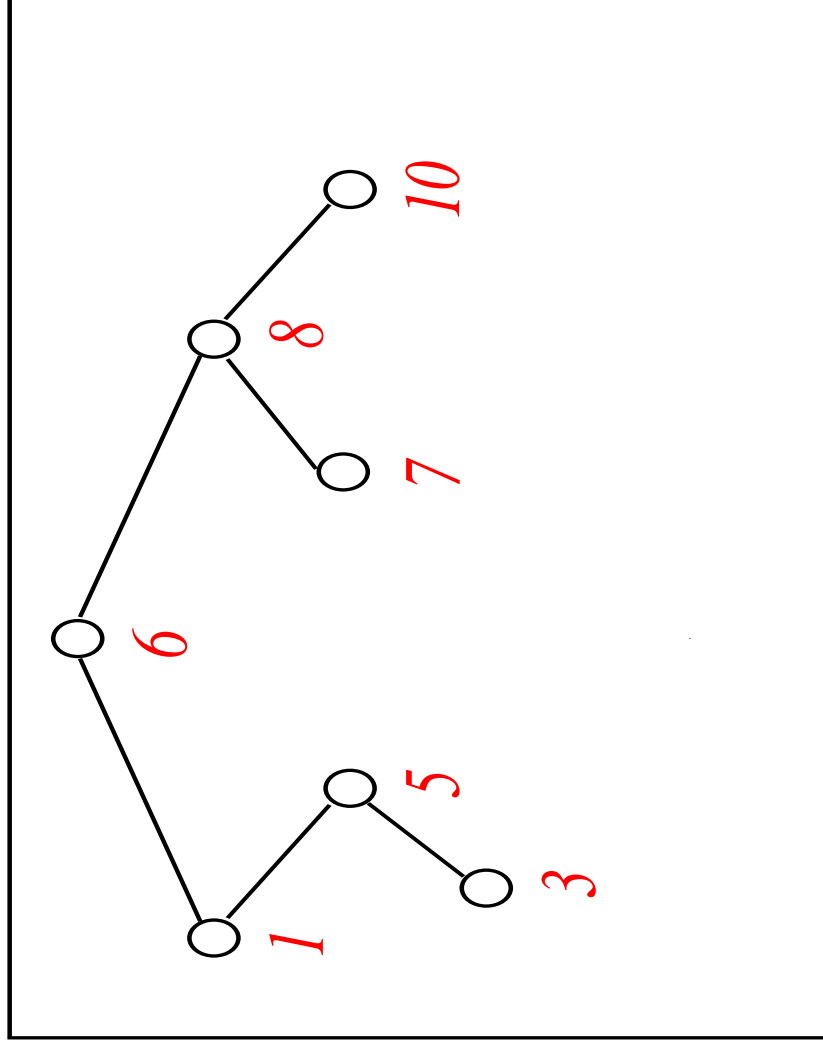
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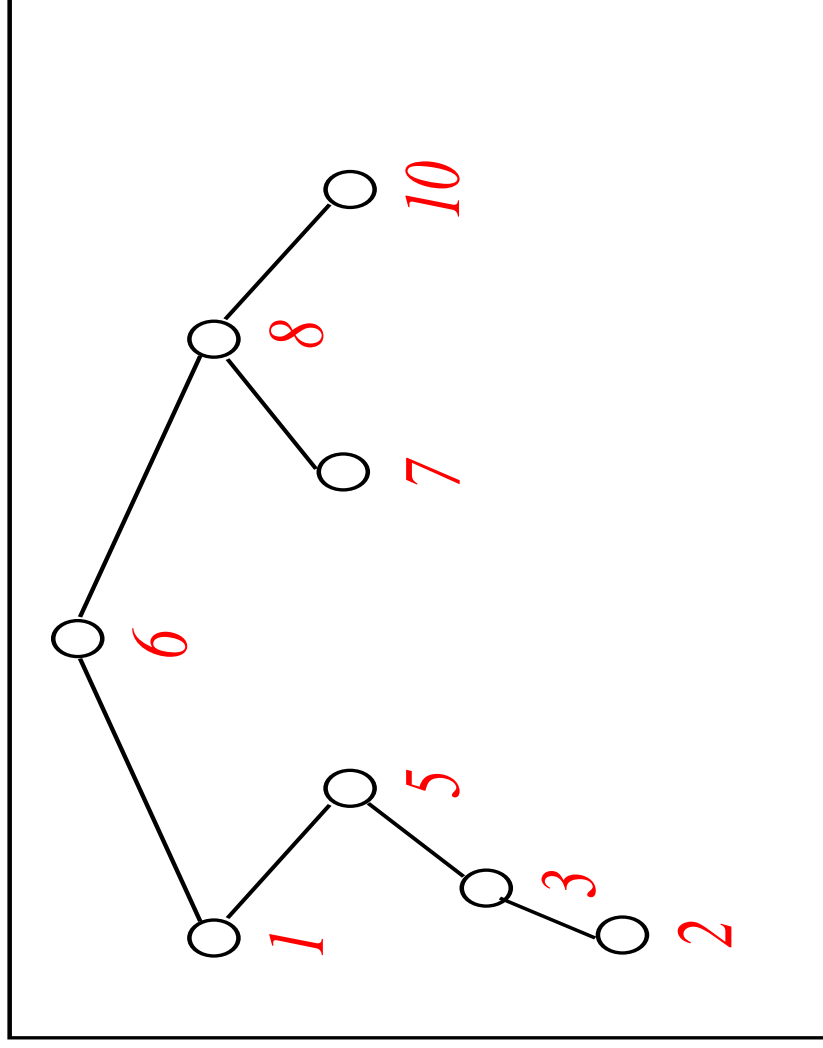
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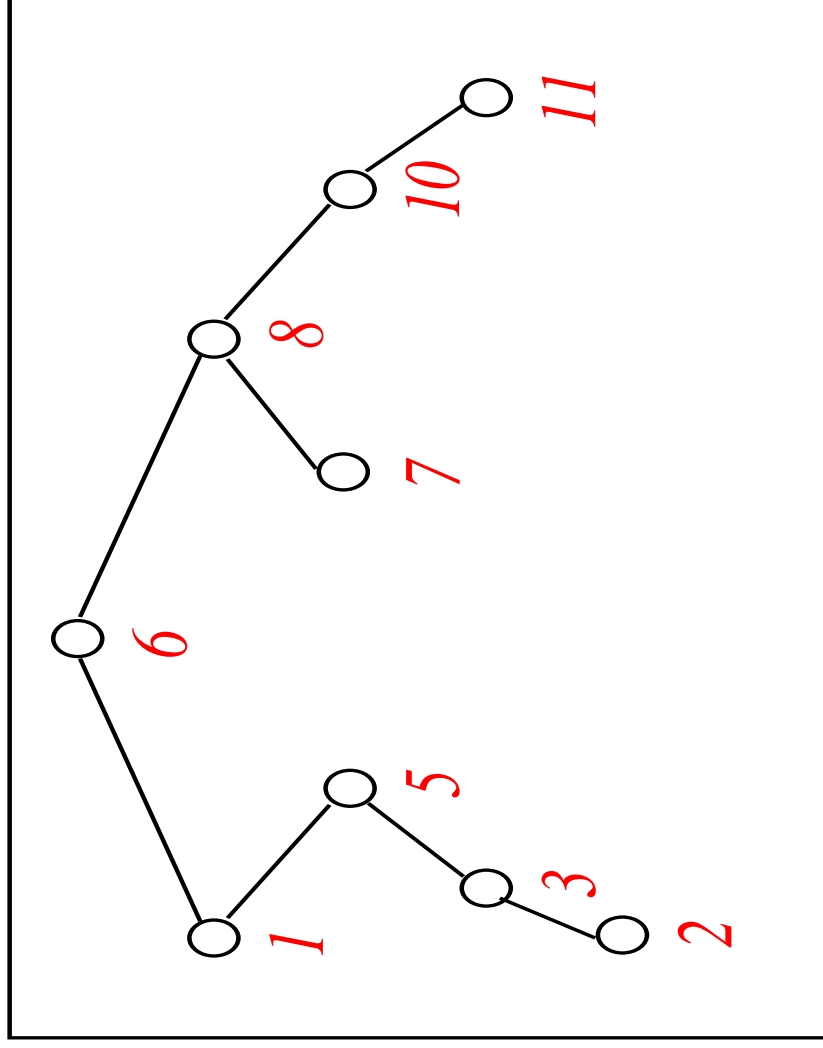
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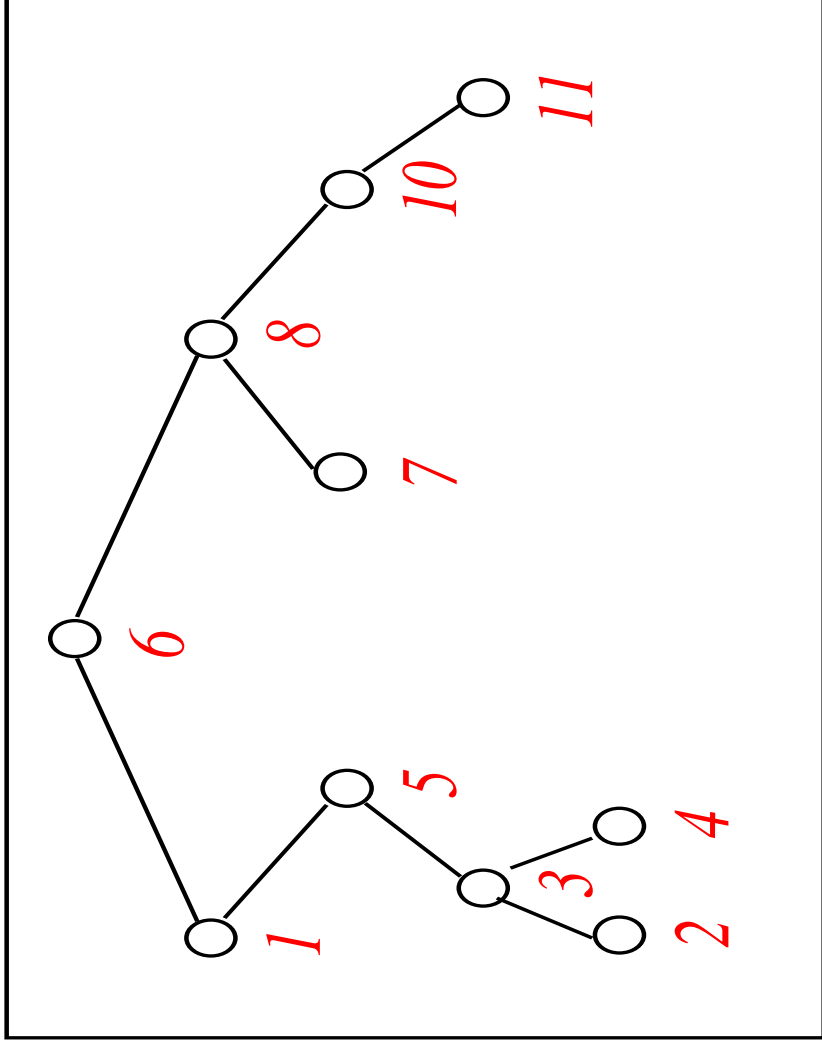
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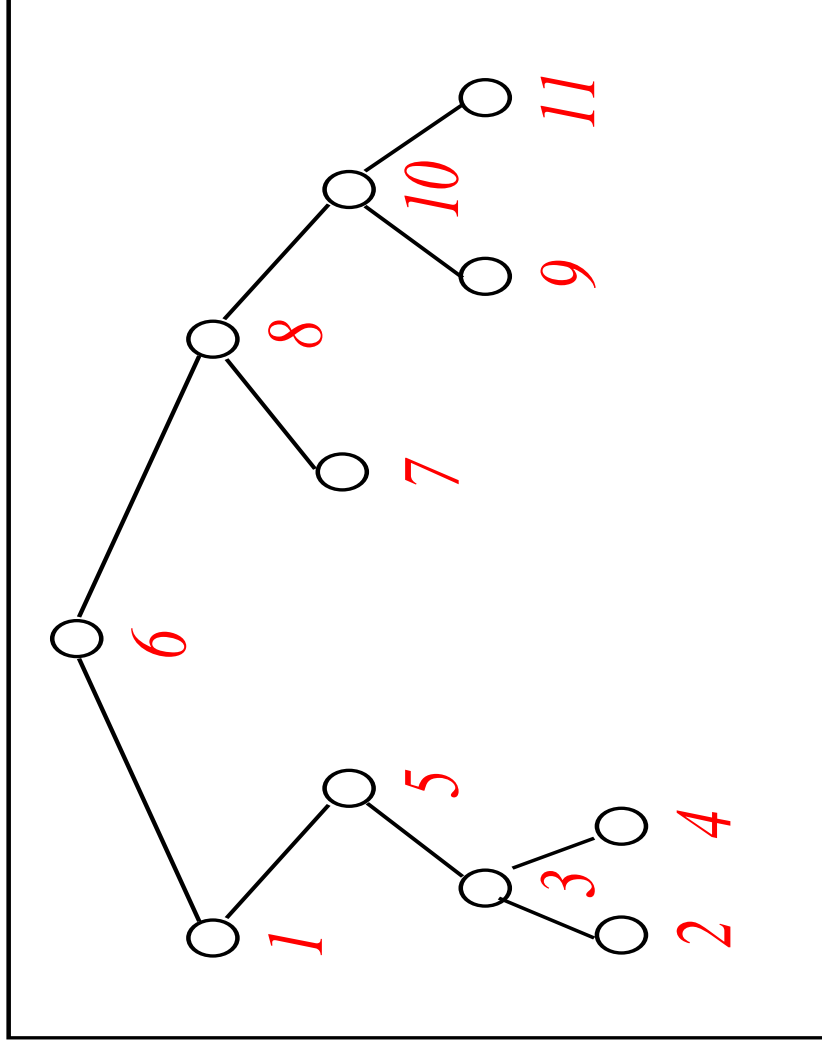
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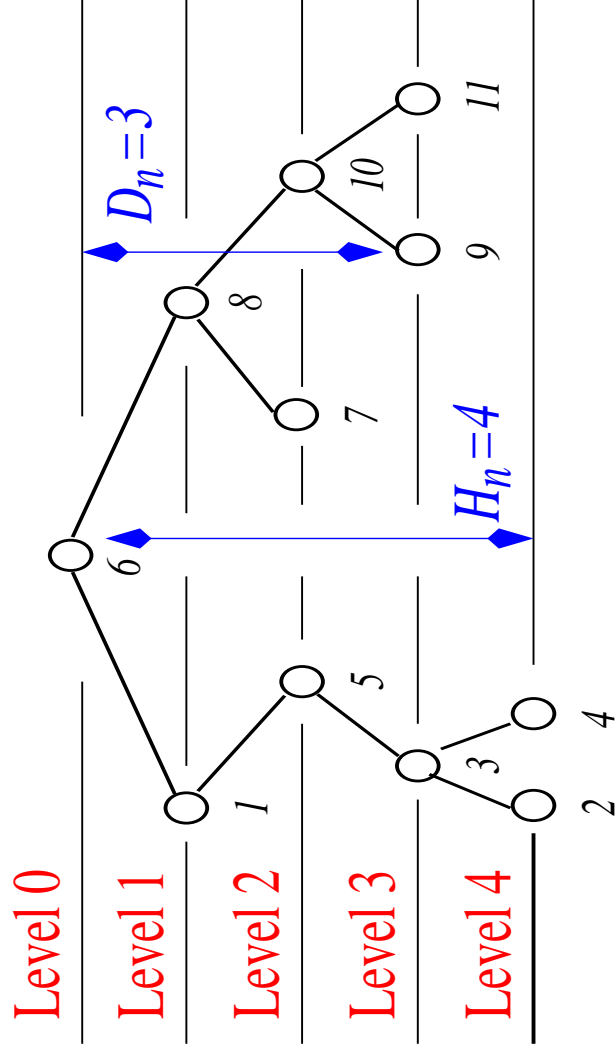


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Given numbers: 6, 1, 8, 7, 5, 3, 10, 2, 11, 4, 9.

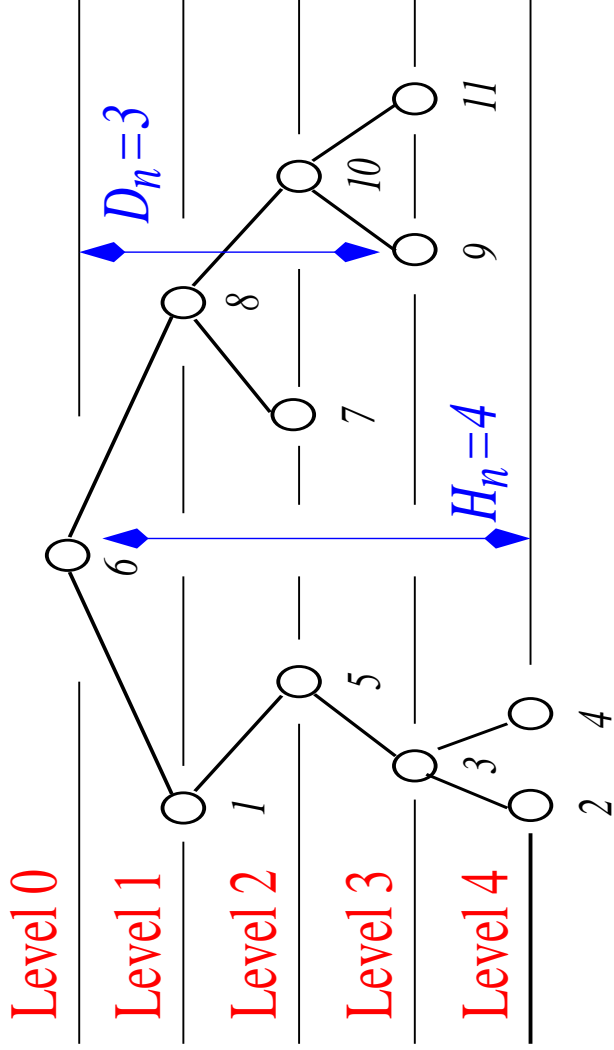


# Quantities in BST



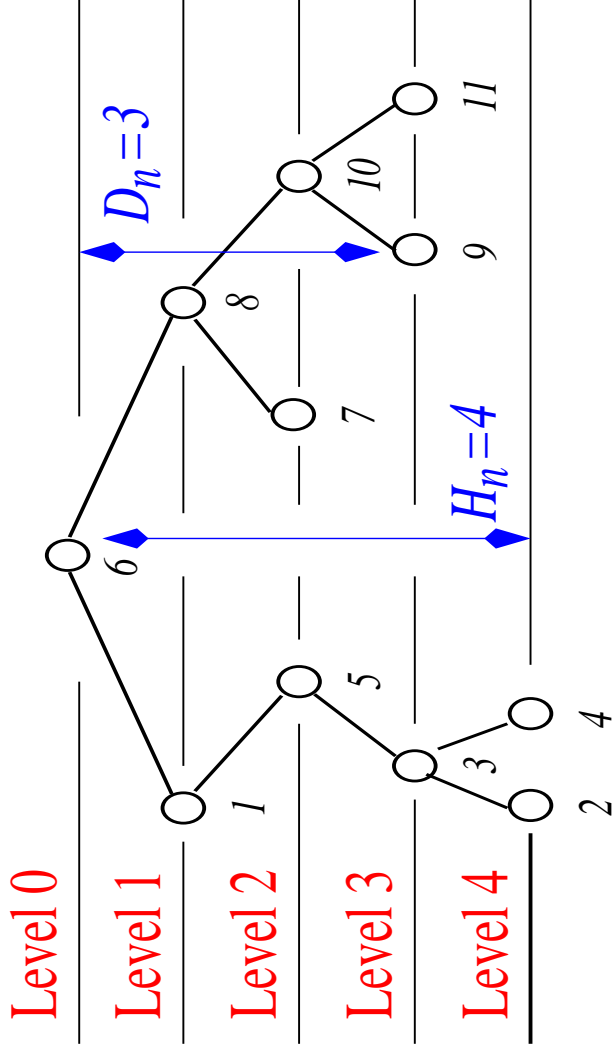


# Quantities in BST



$D_n$  — depth = distance root to  $n$ -th inserted node

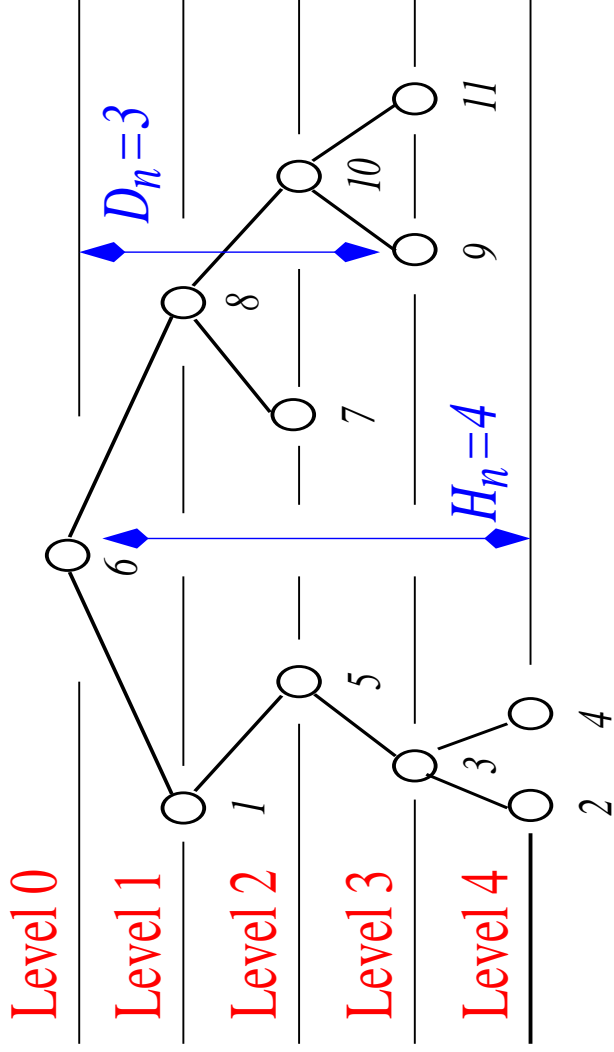
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$H_n = \max_{1 \leq j \leq n} D_j$  — height

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$D_n$  — depth = distance root to  $n$ -th inserted node

$H_n = \max_{1 \leq j \leq n} D_j$  — height

$Q_n = \sum_{1 \leq j \leq n} D_j$  — internal path length

# Random binary search tree

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Model of randomness:

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All permutations of  $1, \dots, n$  equally likely.

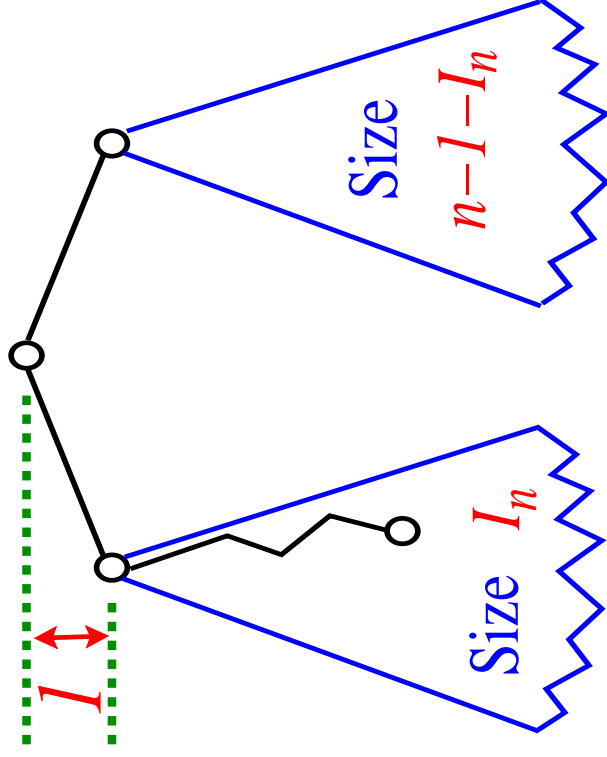
Equivalent: Use  $U_1, \dots, U_n$  i.i.d.  $\text{unif}[0, 1]$ .



# Internal path length

Internal path length  $Q_n$ :

$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1$$

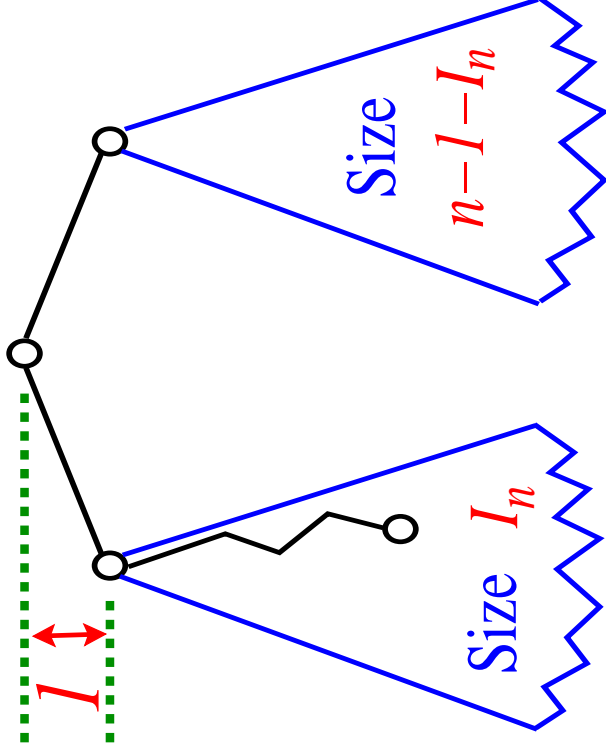


# Internal path length

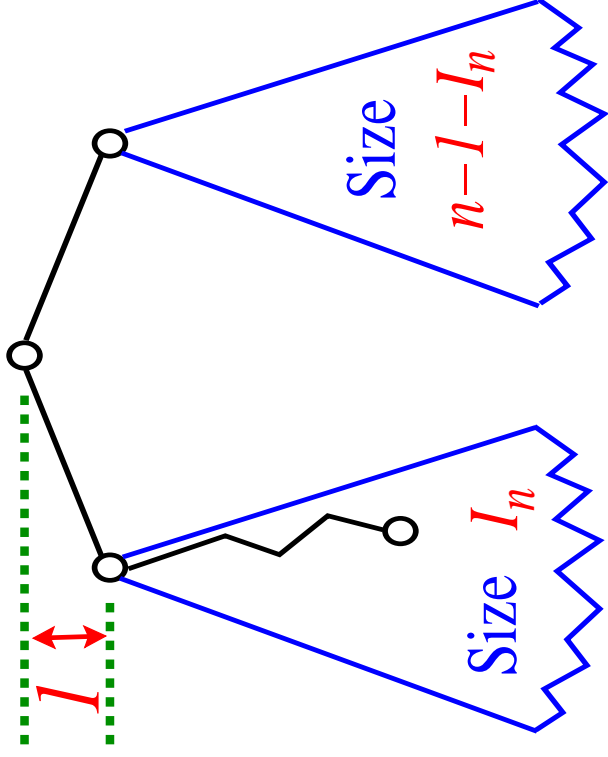
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$Q_0^*, \dots, Q_{n-1}^*, Q_0^{**}, \dots, Q_{n-1}^{**}, I_n$   
indep.,



# Internal path length



Internal path length  $Q_n$ :

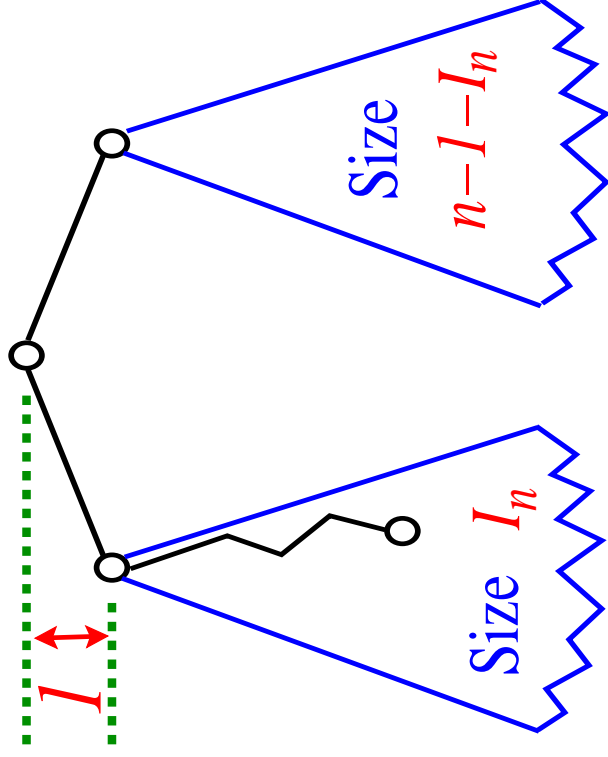
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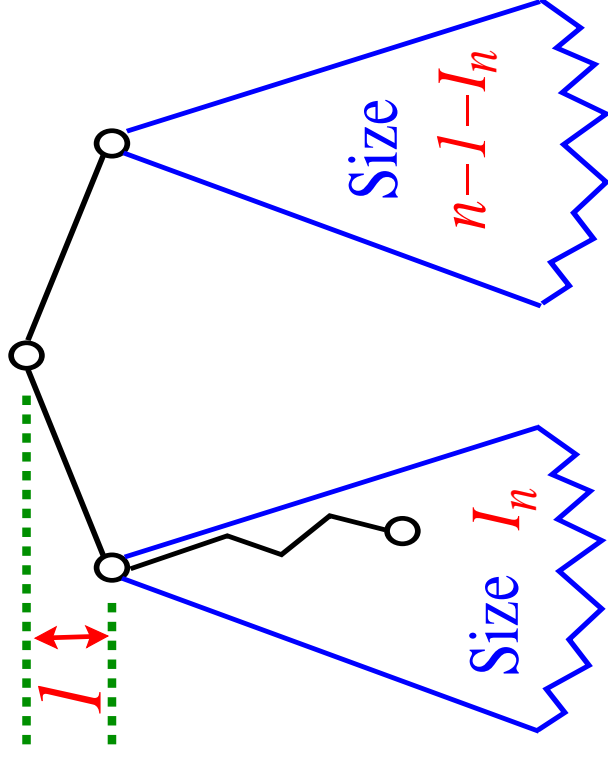
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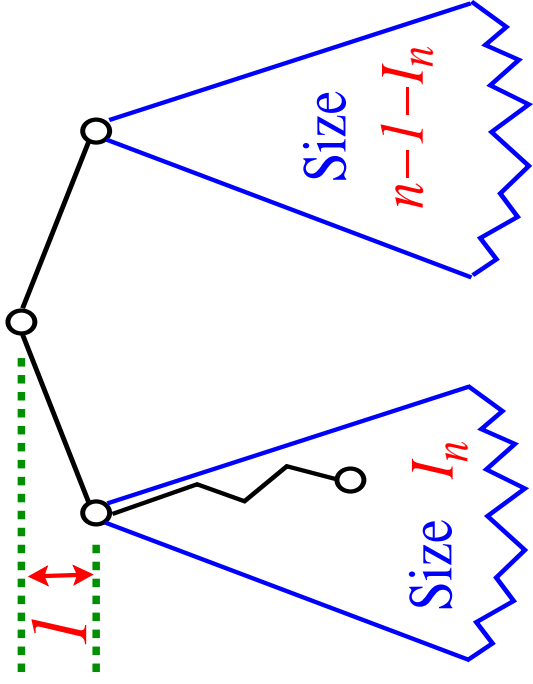
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This needs a proof!

# Internal path length $Q_n$



$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1$$

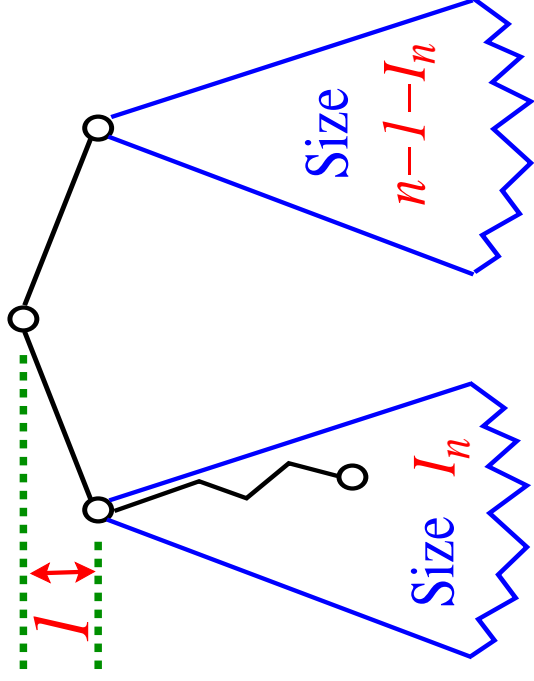
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indep.,

$$Q_j^* \stackrel{d}{=} Q_j^{**} \stackrel{d}{=} Q_j,$$

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# Internal path length $Q_n$



$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1 =: Z_n,$$

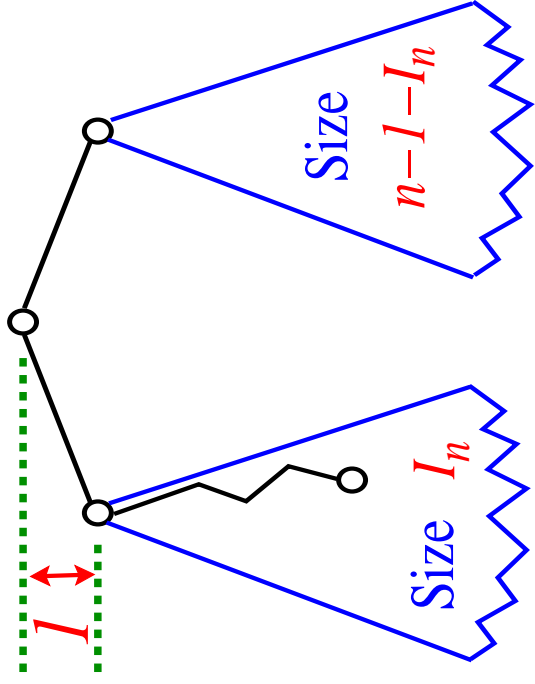
$Q_0^*, \dots, Q_{n-1}^*, Q_0^{**}, \dots, Q_{n-1}^{**}$ ,  $I_n$   
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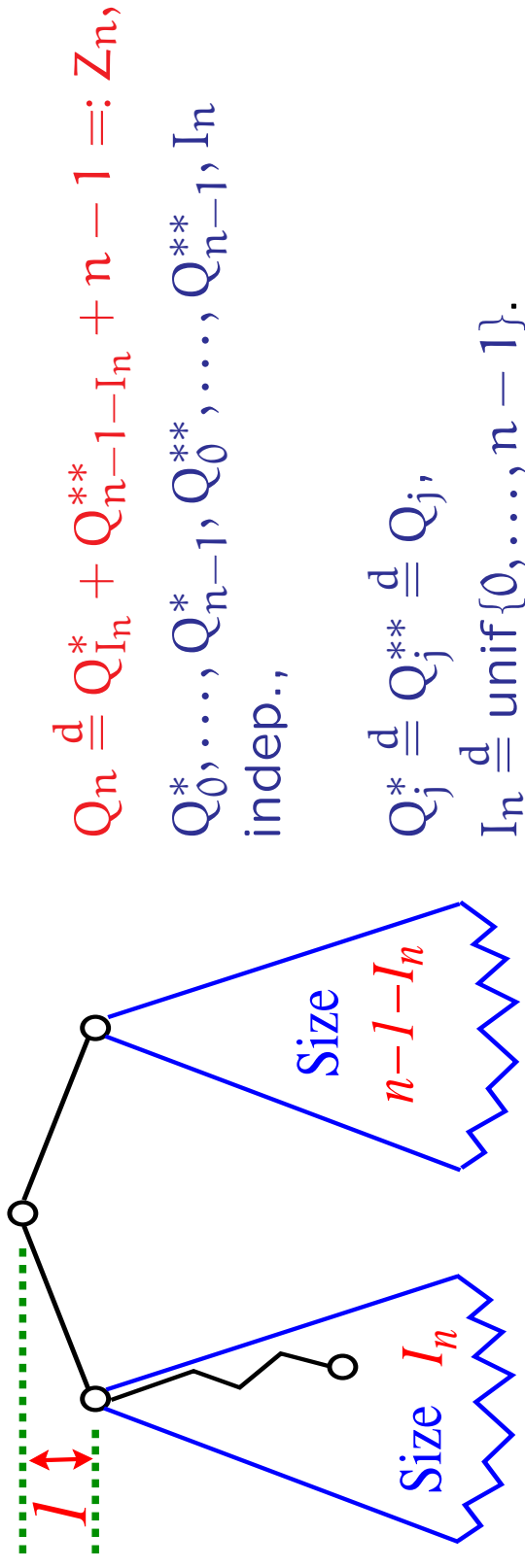
$$I_n \stackrel{d}{=} \text{unif}\{0, \dots, n-1\}.$$

Sufficient:  $\mathbb{P}(Q_n = j) = \mathbb{P}(Z_n = j)$  for all  $j \in \mathbb{N}$ .

Show: For all  $j \in \mathbb{N}$ ,  $k \in \{0, \dots, n-1\}$ :

$$\mathbb{P}(Q_n = j \mid I_n = k) = \mathbb{P}(Z_n = j \mid I_n = k).$$

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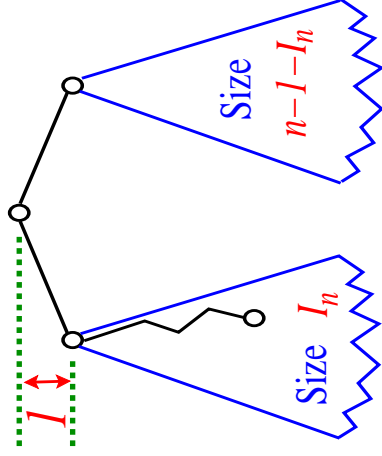
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$$\mathbb{P}(Q_n = j | I_n = k) = \mathbb{P}(Z_n = j | I_n = k).$$

[Total probability theorem yields:

$$\begin{aligned} \mathbb{P}(Q_n = j) &= \sum_k \mathbb{P}(I_n = k) \mathbb{P}(Q_n = j | I_n = k) \\ &= \sum_k \mathbb{P}(I_n = k) \mathbb{P}(Z_n = j | I_n = k) = \mathbb{P}(Z_n = j). \end{aligned}$$

# Proof of the recurrence

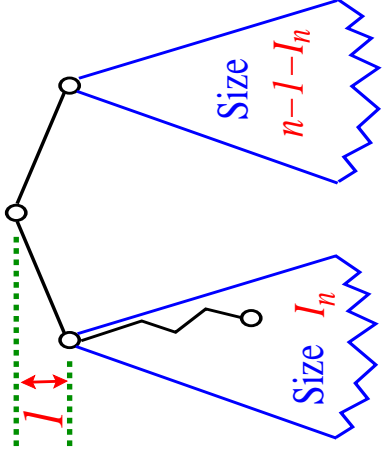


To prove:

$$\begin{aligned} & \mathbb{P}(Q_n = j \mid I_n = k) \\ &= \mathbb{P}(Q_k^* + Q_{n-1-k}^{**} + n - 1 = j). \end{aligned}$$



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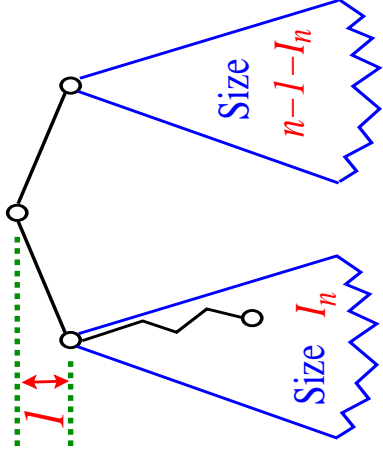
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We show: Given  $\{I_n = k\}$  we have:

- a)  $\mathcal{T}_1$  and  $\mathcal{T}_2$  independent,
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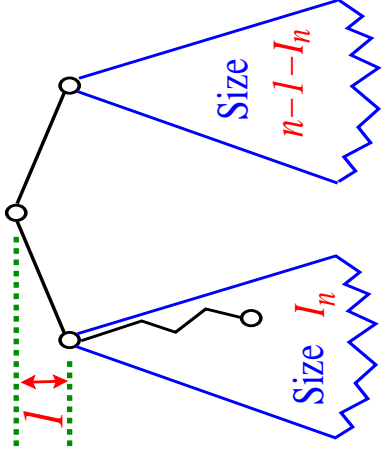
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$\pi = (5, 7, 3, 2, 6, 8, 1, 4)$      $\pi$  equiprobable permutation in  $S_n$ .

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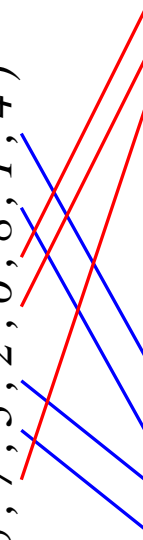
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$$\pi = (5, 7, 3, 2, 6, 8, 1, 4)$$

$$\pi_{<} = (3, 2, 1, 4) \quad \pi_{>} = (7, 6, 8)$$

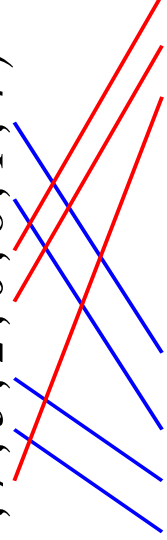


# Proof of the recurrence II

$\pi$  equiprobable in  $S_n$ .

$$\pi = (5, 7, 3, 2, 6, 8, 1, 4)$$

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## Proof of the recurrence II

$\pi$  equiprobable in  $S_n$ .

$$\pi = (5, 7, 3, 2, 6, 8, 1, 4)$$

We show: Given  $\pi_1 = k + 1$ :

$$\pi_{<} = (3, 2, 1, 4) \quad \pi_{>} = (7, 6, 8)$$

$\pi_{<}$  and  $\pi_{>}$  independent and equiprobable on  $S_k$  and  $S_{n-1-k}$  resp.

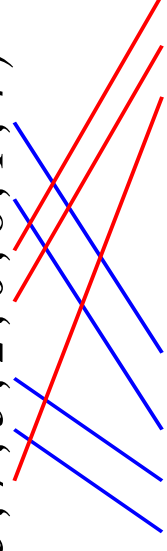
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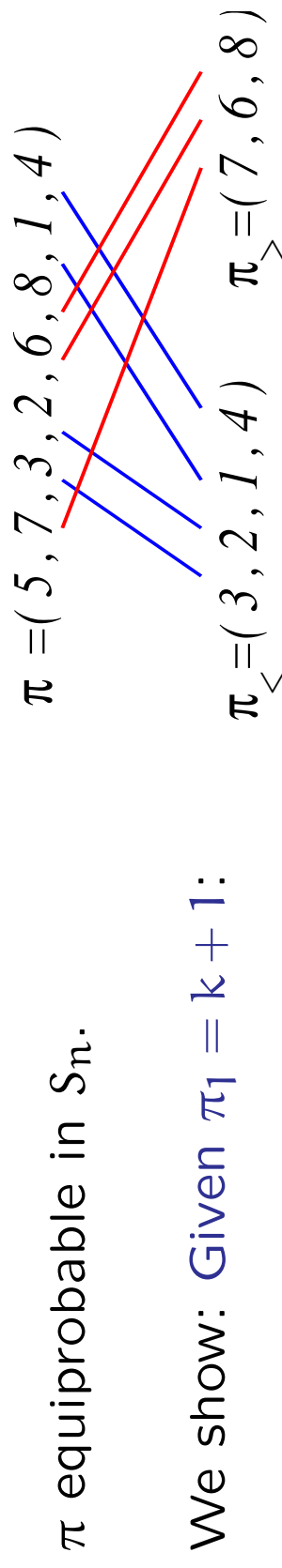


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$$\mathbb{P}(\pi_{<} = \sigma \mid \pi_1 = k + 1) = \frac{1}{1/n} \frac{\binom{n-1}{k} (n-1-k)!}{n!} = \frac{1}{k!}$$

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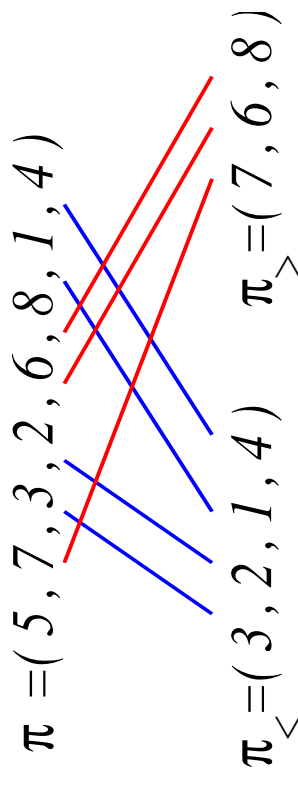
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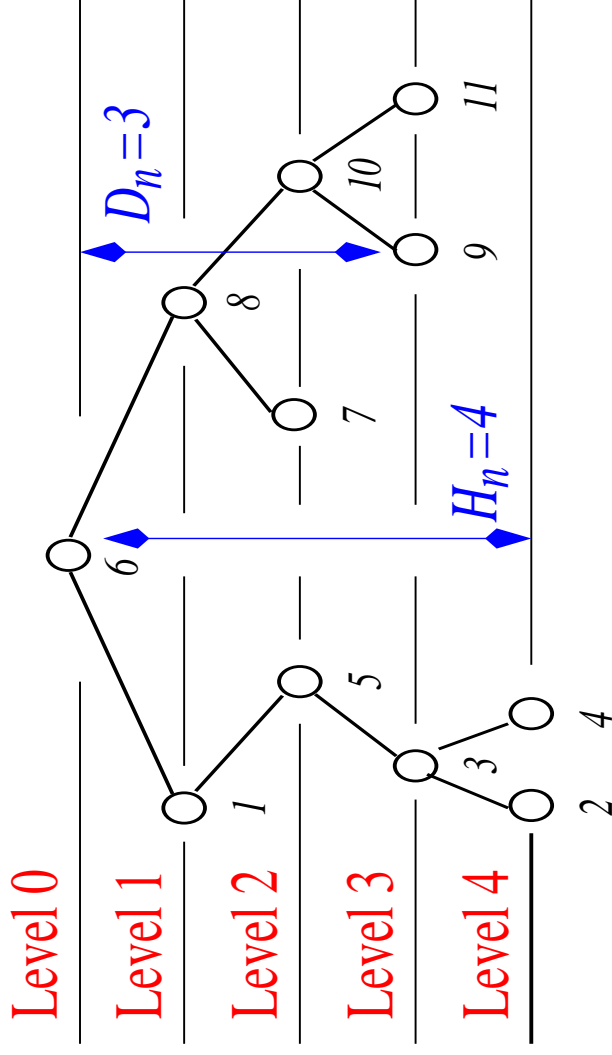
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Given  $\pi_1 = k + 1$  hence  $\pi_{<}$  equiprobable on  $S_k$ .

Second assertion similar.

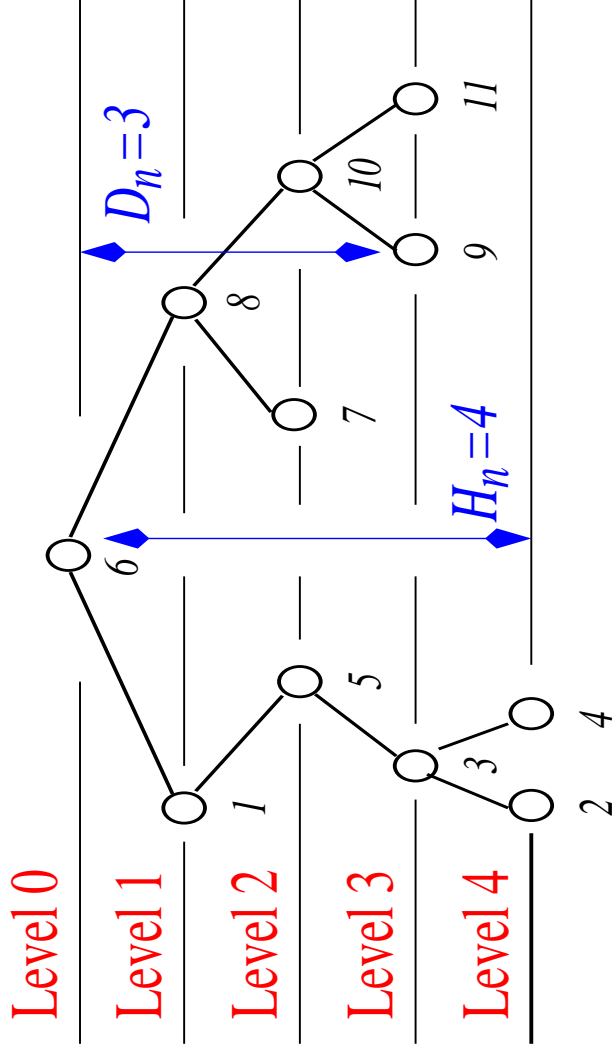


# Other BST recurrences



$$Q_n \stackrel{d}{=} Q_{I_n}^{(1)} + Q_{n-1-I_n}^{(2)} + n - 1$$

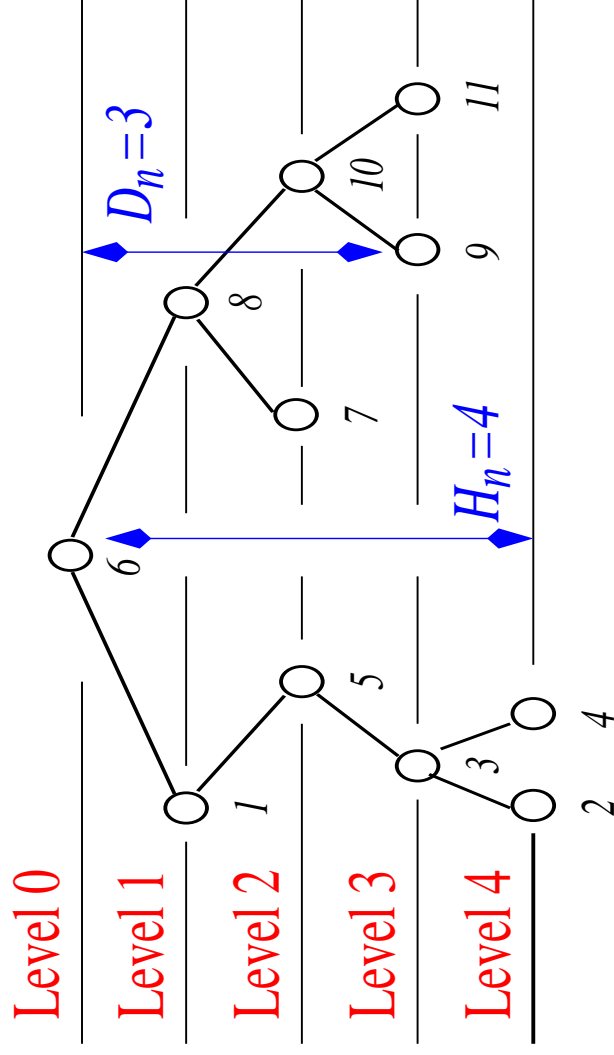
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$$Q_n \stackrel{d}{=} Q_{I_n}^{(1)} + Q_{n-1-I_n}^{(2)} + n - 1$$

$$H_n \stackrel{d}{=} H_{I_n}^{(1)} \vee H_{n-1-I_n}^{(2)} + 1$$

# Other BST recurrences

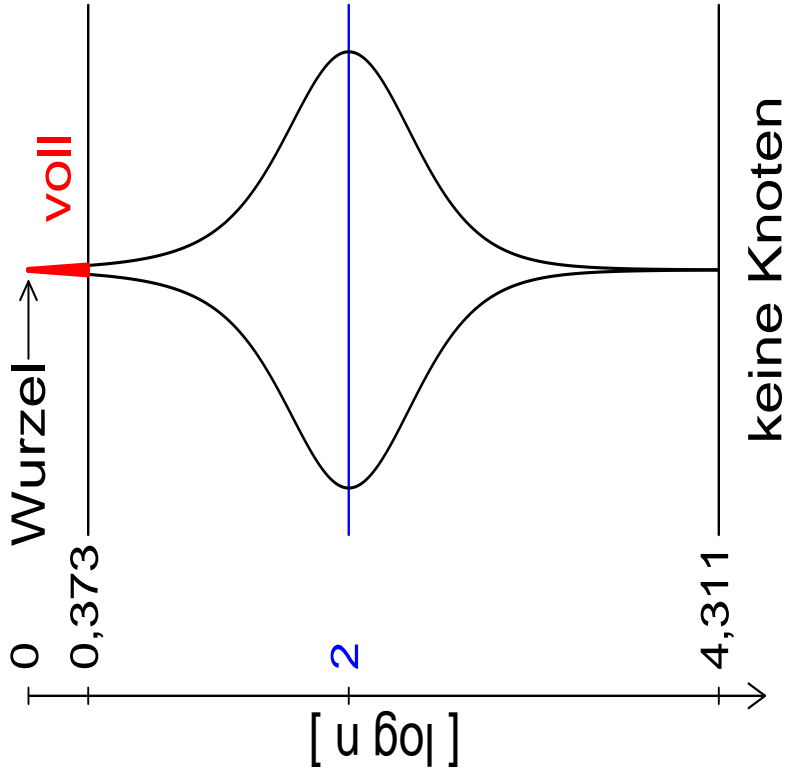


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$$D_n \stackrel{d}{=} \mathbf{1}_{A_n} D_{I_n} + \mathbf{1}_{A_n^c} D_{n-1-I_n} + 1$$

# The height



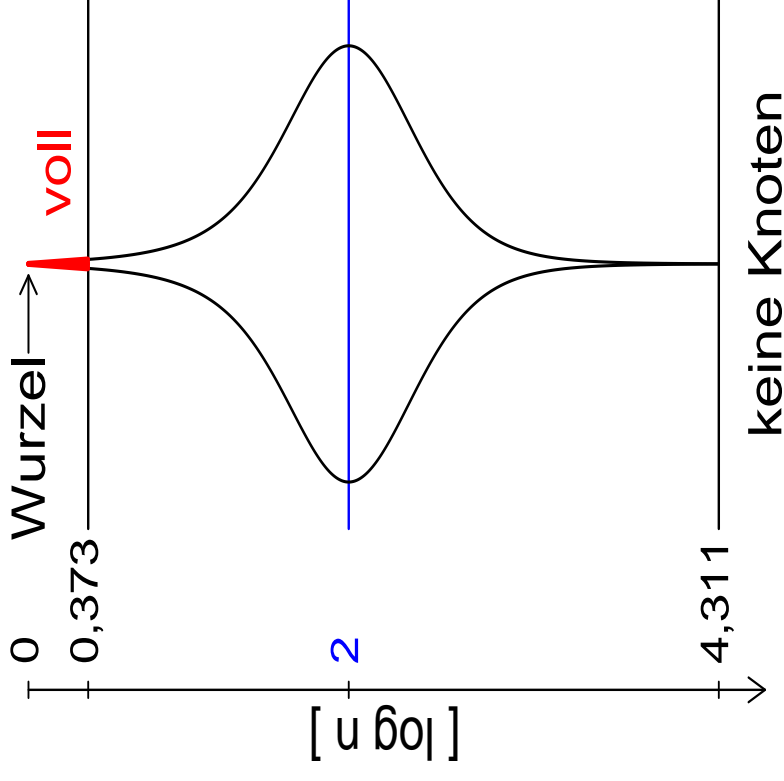
...

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height  $H_n$ :

$$\mathbb{E} H_n \sim \alpha_+ \log n,$$

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...

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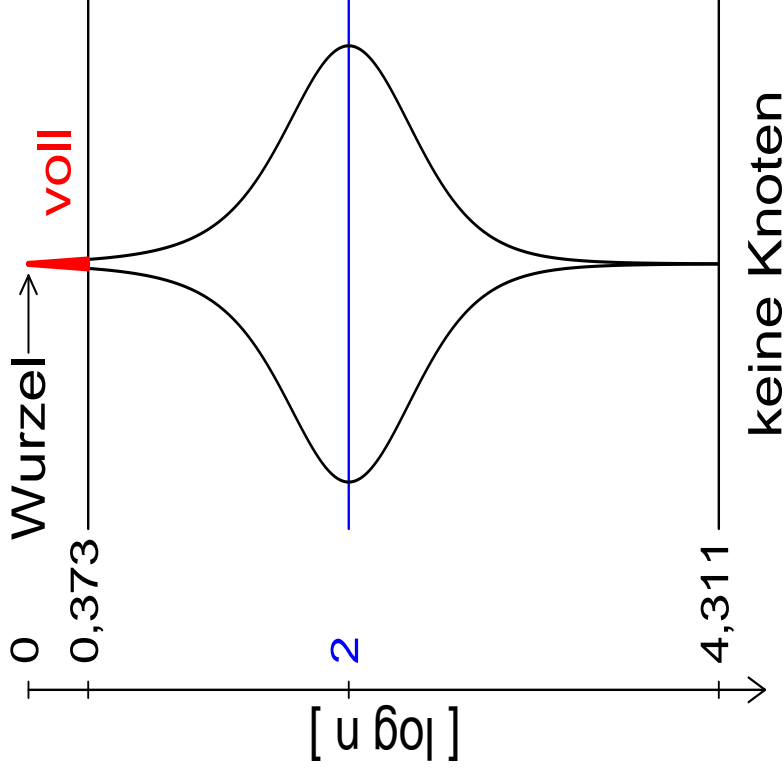
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saturation level  $S_n$ :

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...

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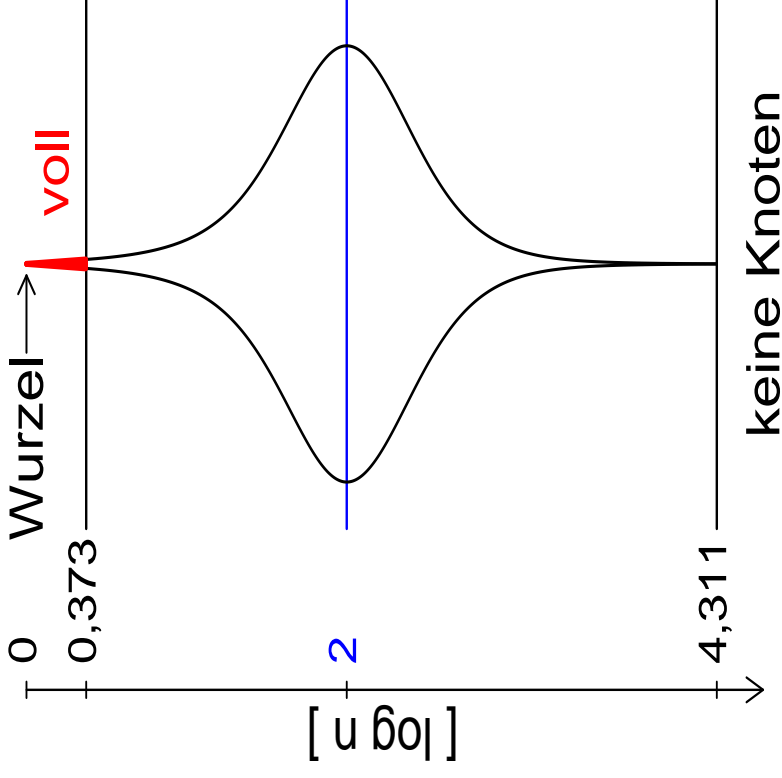
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saturation level  $S_n$ :

$$\mathbb{E} S_n \sim \alpha_- \log n,$$

$$\frac{S_n}{\log n} \xrightarrow{\mathbb{P}} \alpha_-$$



Here,  $0 < \alpha_- < 2 < \alpha_+$  are the solutions of

$$\alpha \log \left( \frac{2e}{\alpha} \right) = 1, \quad \alpha_- \doteq 0,373, \quad \alpha_+ \doteq 4,311$$

Pittel ('84), Devroye ('86), Reed ('03), Drmota ('03),...

Expected internal path length



## Expected internal path length

$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1, \quad I_n \stackrel{d}{=} \text{unif}\{0, \dots, n-1\}.$$

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$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1, \quad I_n \stackrel{d}{=} \text{unif}\{0, \dots, n-1\}.$$

$$q_n := \mathbb{E} Q_n = \mathbb{E} [Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1]$$

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## Expected internal path length

$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**}, \quad I_n \stackrel{d}{=} \text{unif}\{0, \dots, n-1\}.$$

$$\begin{aligned} q_n := \mathbb{E} Q_n &= \mathbb{E} [Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1] \\ &= \frac{1}{n} \sum_{k=0}^{n-1} \mathbb{E} [Q_k^* + Q_{n-1-k}^{**} + n - 1] \\ &= \frac{1}{n} \sum_{k=0}^{n-1} (q_k + q_{n-1-k} + n - 1) \\ &= n - 1 + \frac{2}{n} \sum_{k=0}^{n-1} q_k. \end{aligned}$$

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$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1, \quad I_n \stackrel{d}{=} \text{unif}\{0, \dots, n-1\}.$$

$$\begin{aligned} q_n := \mathbb{E} Q_n &= \mathbb{E} [Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1] \\ &= \frac{1}{n} \sum_{k=0}^{n-1} \mathbb{E} [Q_k^* + Q_{n-1-k}^{**} + n - 1] \\ &= \frac{1}{n} \sum_{k=0}^{n-1} (q_k + q_{n-1-k} + n - 1) \\ &= n - 1 + \frac{2}{n} \sum_{k=0}^{n-1} q_k. \end{aligned}$$

Solves easily:

$$q_n = 2(n+1)\mathcal{H}_n - 4n = 2n \log(n) + (2\gamma - 4)n + o(n).$$

[ $\mathcal{H}_n := \sum_{i=1}^n 1/i$  harmonic numbers.]

# Rescaling

$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1, \quad q_n = 2n \log(n) + cn + o(n).$$

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$$Y_n := \frac{Q_n - q_n}{n}.$$



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$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1, \quad q_n = 2n \log(n) + cn + o(n).$$

Scaling

$$Y_n := \frac{Q_n - q_n}{n}.$$

Then

$$Y_n \stackrel{d}{=} \frac{1}{n} (Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1 - q_n)$$

# Rescaling

$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1, \quad q_n = 2n \log(n) + cn + o(n).$$

Scaling

$$Y_n := \frac{Q_n - q_n}{n}.$$

Then

$$\begin{aligned} Y_n &\stackrel{d}{=} \frac{1}{n} (Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1 - q_n) \\ &= \frac{1}{n} \left( \frac{Q_{I_n}^* \pm q_{I_n}}{I_n} + (n - 1 - I_n) \frac{Q_{n-1-I_n}^{**} \pm q_{n-1-I_n}}{n - 1 - I_n} + n - 1 - q_n \right) \end{aligned}$$

# Rescaling

$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1, \quad q_n = 2n \log(n) + cn + o(n).$$

Scaling

$$Y_n := \frac{Q_n - q_n}{n}.$$

Then

$$\begin{aligned} Y_n &\stackrel{d}{=} \frac{1}{n} (Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1 - q_n) \\ &= \frac{1}{n} \left( \frac{Q_{I_n}^* \pm q_{I_n}}{I_n} + (n - 1 - I_n) \frac{Q_{n-1-I_n}^{**} \pm q_{n-1-I_n}}{n - 1 - I_n} + n - 1 - q_n \right) \\ &= \underbrace{\frac{I_n}{n} Y_{I_n}^*}_{\underbrace{\frac{n-1-I_n}{n}}_n} + Y_{n-1-I_n}^{**} + b^{(n)} \end{aligned}$$

# Rescaling

$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1, \quad q_n = 2n \log(n) + cn + o(n).$$

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$$Y_n := \frac{Q_n - q_n}{n}.$$

Then

$$\begin{aligned} Y_n &\stackrel{d}{=} \frac{1}{n} (Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1 - q_n) \\ &= \frac{1}{n} \left( \frac{Q_{I_n}^* \pm q_{I_n}}{I_n} + (n-1-I_n) \frac{Q_{n-1-I_n}^{**} \pm q_{n-1-I_n}}{n-1-I_n} + n - 1 - q_n \right) \\ &= \underbrace{\frac{I_n}{n} Y_{I_n}^* + \frac{n-1-I_n}{n} Y_{n-1-I_n}^{**}}_n + b^{(n)} \end{aligned}$$

with

$$b^{(n)} = \frac{1}{n} (q_{I_n} + q_{n-1-I_n} - q_n + n - 1).$$

# Rescaling

$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1, \quad q_n = 2n \log(n) + cn + o(n).$$

Scaling

$$Y_n := \frac{Q_n - q_n}{n}.$$

Then

$$\begin{aligned} Y_n &\stackrel{d}{=} \frac{1}{n} (Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1 - q_n) \\ &= \frac{1}{n} \left( \frac{Q_{I_n}^* \pm q_{I_n}}{I_n} + (n-1-I_n) \frac{Q_{n-1-I_n}^{**} \pm q_{n-1-I_n}}{n-1-I_n} + n-1-q_n \right) \\ &= \underbrace{\frac{I_n}{n} Y_{I_n}^*}_{\rightarrow u} + \underbrace{\frac{n-1-I_n}{n} Y_{n-1-I_n}^{**}}_{\rightarrow 1-u} + b^{(n)} \end{aligned}$$

with

$$b^{(n)} = \frac{1}{n} (q_{I_n} + q_{n-1-I_n} - q_n + n - 1).$$

## Rescaling II

$$q_n = 2n \log(n) + cn + o(n).$$

$$b^{(n)} = \frac{1}{n} (q_{I_n} + q_{n-1-I_n} - q_n + n - 1).$$

## Rescaling II

$$q_n = 2n \log(n) + cn + o(n).$$

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$$\begin{aligned} &= \frac{1}{n} (2I_n \log(I_n) + cI_n + 2(n-1-I_n) \log(n-1-I_n) + c(n-1-I_n) \\ &\quad - 2n \log(n) - cn + o(n) + n - 1) \end{aligned}$$

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$$= \frac{1}{n} (2I_n \log(I_n) + cI_n + 2(n-1-I_n) \log(n-1-I_n) + c(n-1-I_n) - 2n \log(n) - cn + o(n) + n - 1)$$

$$= \frac{1}{n} (2I_n \log(I_n) + 2(n-1-I_n) \log(n-1-I_n) - 2(I_n + (n-1-I_n) + 1) \log(n) + o(n) + n - 1)$$



## Rescaling II

$$q_n = 2n \log(n) + cn + o(n).$$

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$$\begin{aligned} &= \frac{1}{n} (2I_n \log(I_n) + cI_n + 2(n-1-I_n) \log(n-1-I_n) + c(n-1-I_n) \\ &\quad - 2n \log(n) - cn + o(n) + n - 1) \end{aligned}$$

$$\begin{aligned} &= \frac{1}{n} (2I_n \log(I_n) + 2(n-1-I_n) \log(n-1-I_n) \\ &\quad - 2(I_n + (n-1-I_n) + 1) \log(n) + o(n) + n - 1) \end{aligned}$$

$$= 2 \frac{I_n}{n} \log\left(\frac{I_n}{n}\right) + 2 \frac{n-1-I_n}{n} \log\left(\frac{n-1-I_n}{n}\right) + 1 + o(1)$$

## Rescaling II

$$q_n = 2n \log(n) + cn + o(n).$$

$$\begin{aligned} b^{(n)} &= \frac{1}{n} (q_{I_n} + q_{n-1-I_n} - q_n + n - 1). \\ &= \frac{1}{n} (2I_n \log(I_n) + cI_n + 2(n-1-I_n) \log(n-1-I_n) + c(n-1-I_n) \\ &\quad - 2n \log(n) - cn + o(n) + n - 1) \\ &= \frac{1}{n} (2I_n \log(I_n) + 2(n-1-I_n) \log(n-1-I_n) \\ &\quad - 2(I_n + (n-1-I_n) + 1) \log(n) + o(n) + n - 1) \\ &= 2 \frac{I_n}{n} \log\left(\frac{I_n}{n}\right) + 2 \frac{n-1-I_n}{n} \log\left(\frac{n-1-I_n}{n}\right) + 1 + o(1) \\ &\rightarrow 2u \log(u) + 2(1-u) \log(1-u) + 1 =: g(u) \end{aligned}$$

## Rescaling: Summary

$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1, \quad q_n = 2n \log(n) + cn + o(n).$$

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$$Y_n := \frac{Q_n - q_n}{n}.$$

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Then

$$Y_n = \underbrace{\frac{I_n}{n}} Y_{I_n}^* + \underbrace{\frac{n-1-I_n}{n}} Y_{n-1-I_n}^{**} + \underbrace{b^{(n)}}.$$

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Scaling

$$Y_n := \frac{Q_n - q_n}{n}.$$

Then

$$Y_n = \underbrace{\frac{I_n}{n}}_{\rightarrow U} Y_{I_n}^* + \underbrace{\frac{n-1-I_n}{n}}_{\rightarrow 1-U} Y_{n-1-I_n}^{**} + \underbrace{b^{(n)}}_{\rightarrow g(U)}$$

## Rescaling: Summary

$$Q_n \stackrel{d}{=} Q_{I_n}^* + Q_{n-1-I_n}^{**} + n - 1, \quad q_n = 2n \log(n) + cn + o(n).$$

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Then

$$Y_n = \underbrace{\frac{I_n}{n}}_{\rightarrow u} Y_{I_n}^* + \underbrace{\frac{n-1-I_n}{n}}_{\rightarrow 1-u} Y_{n-1-I_n}^{**} + \underbrace{b^{(n)}}_{\rightarrow g(u)}$$

with

$$g(u) = 2u \log(u) + 2(1-u) \log(1-u) + 1$$

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with

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Hence, this suggests

$$Y_n \rightarrow Y$$

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$$Y_n = \underbrace{\frac{I_n}{n}}_{\rightarrow u} Y_{I_n}^* + \underbrace{\frac{n-1-I_n}{n}}_{\rightarrow 1-u} Y_{n-1-I_n}^{**} + \underbrace{b^{(n)}}_{\rightarrow g(u)}$$

with

$$g(u) = 2u \log(u) + 2(1-u) \log(1-u) + 1$$

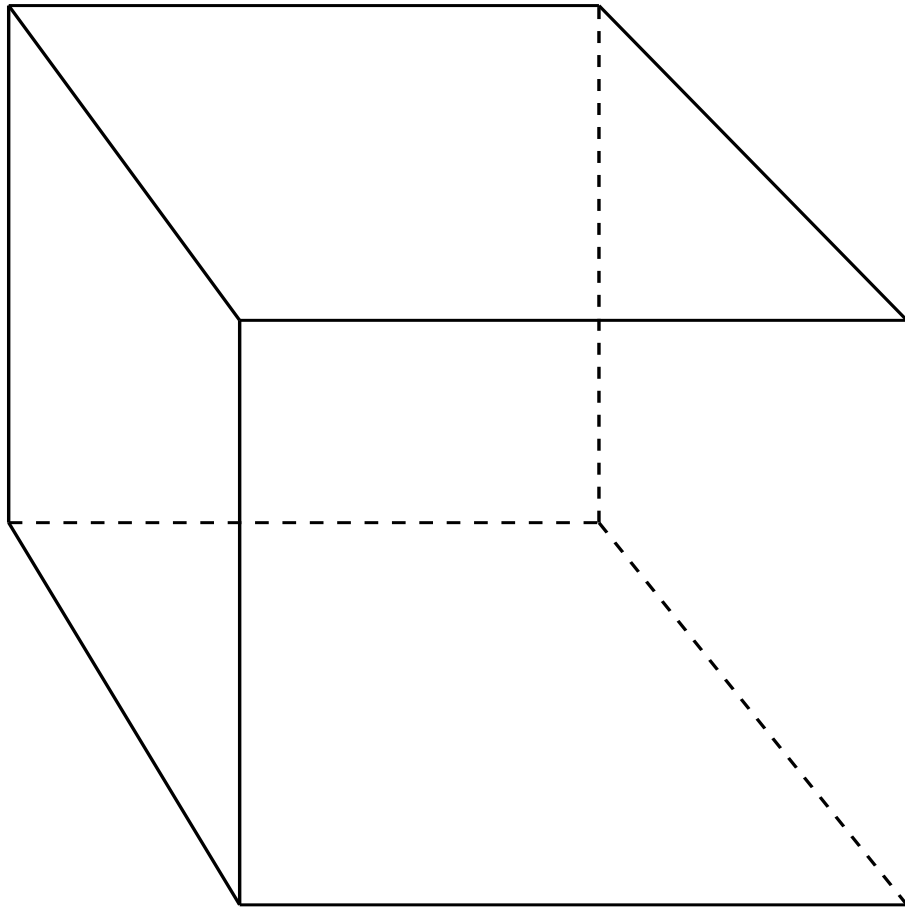
Hence, this suggests

$$Y_n \rightarrow Y \stackrel{d}{=} uY^* + (1-u)Y^{**} + g(u),$$

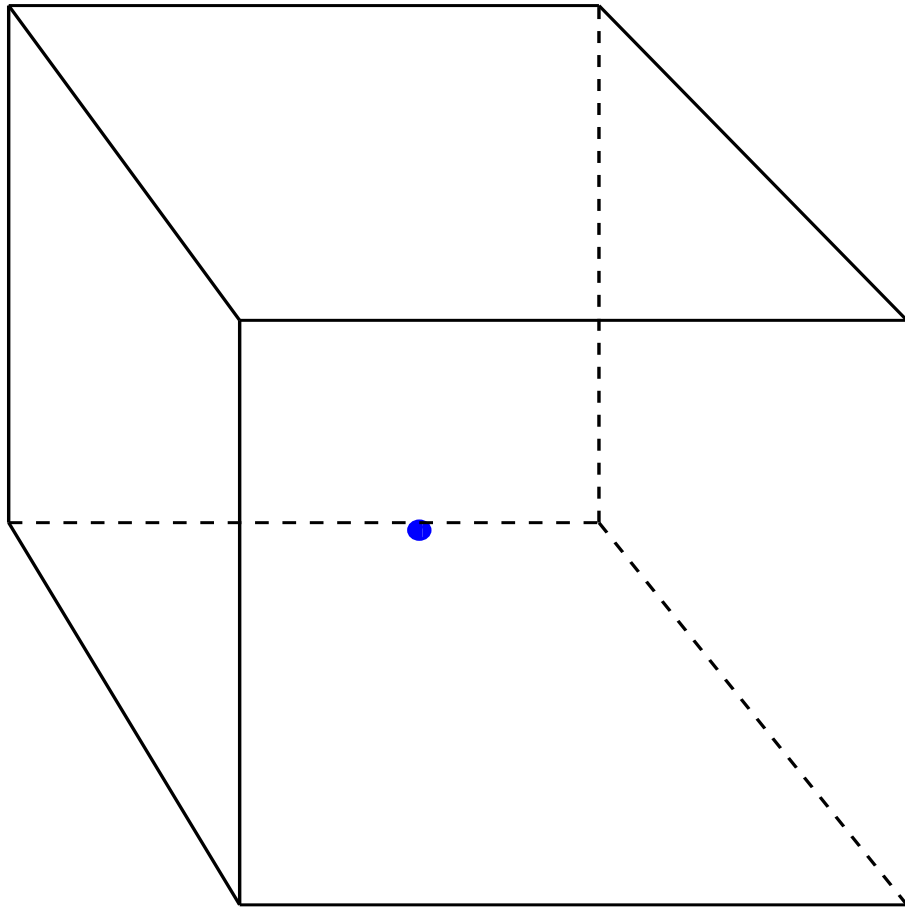
with  $Y^*, Y^{**}, U$  independent,  $Y \stackrel{d}{=} Y^* \stackrel{d}{=} Y^{**}$ .



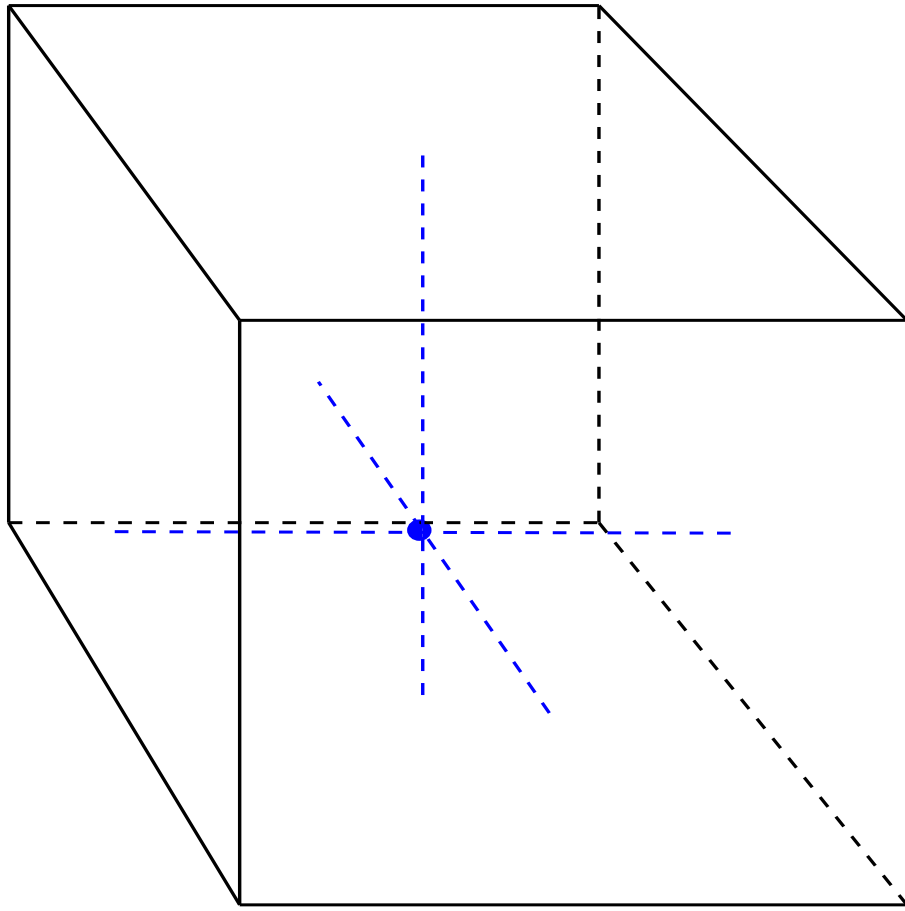
# Quadtrees: higher dimensions



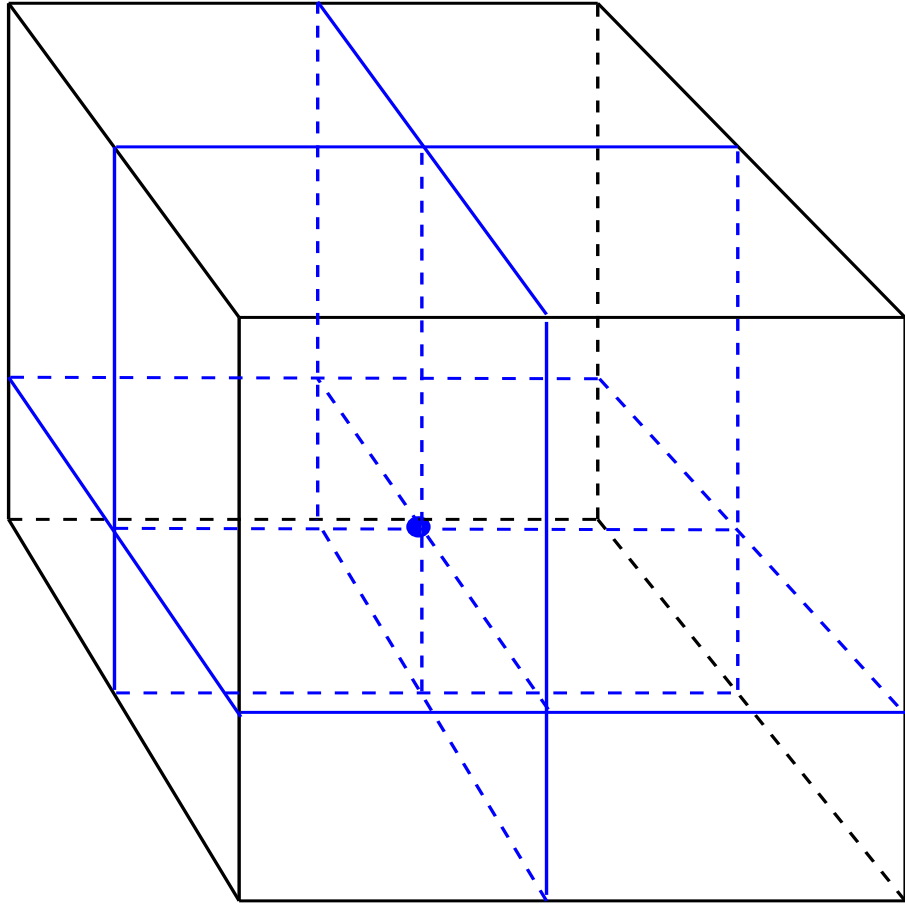
# Quadtrees: higher dimensions



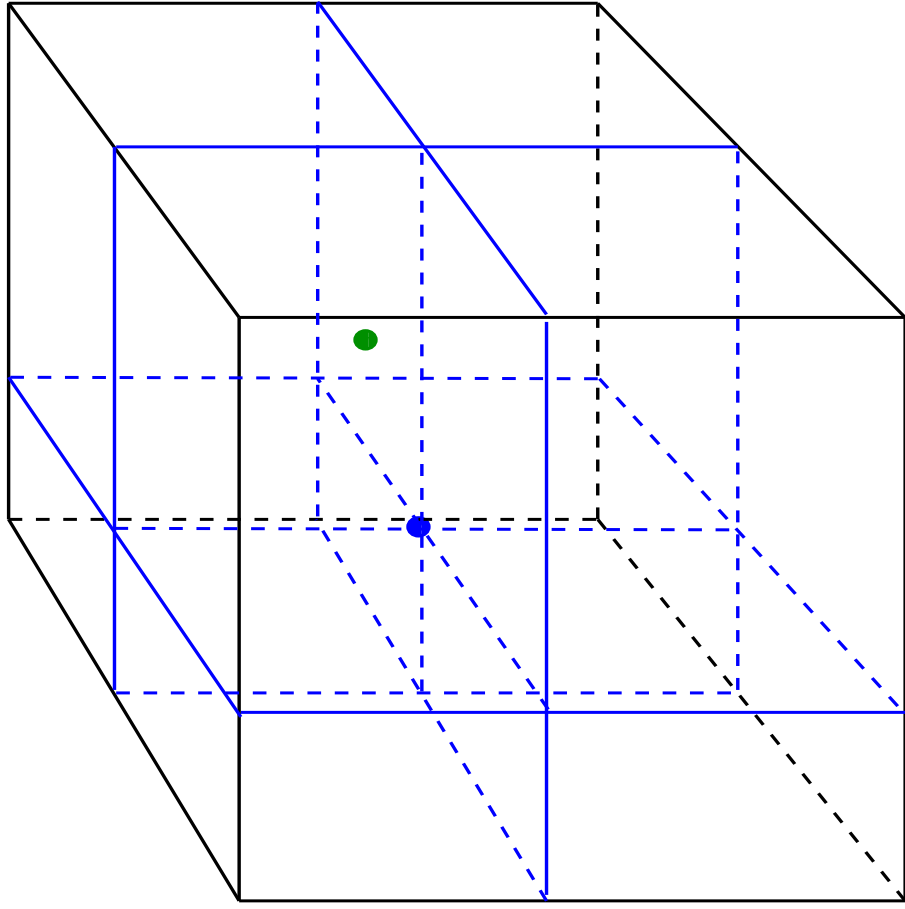
# Quadtrees: higher dimensions



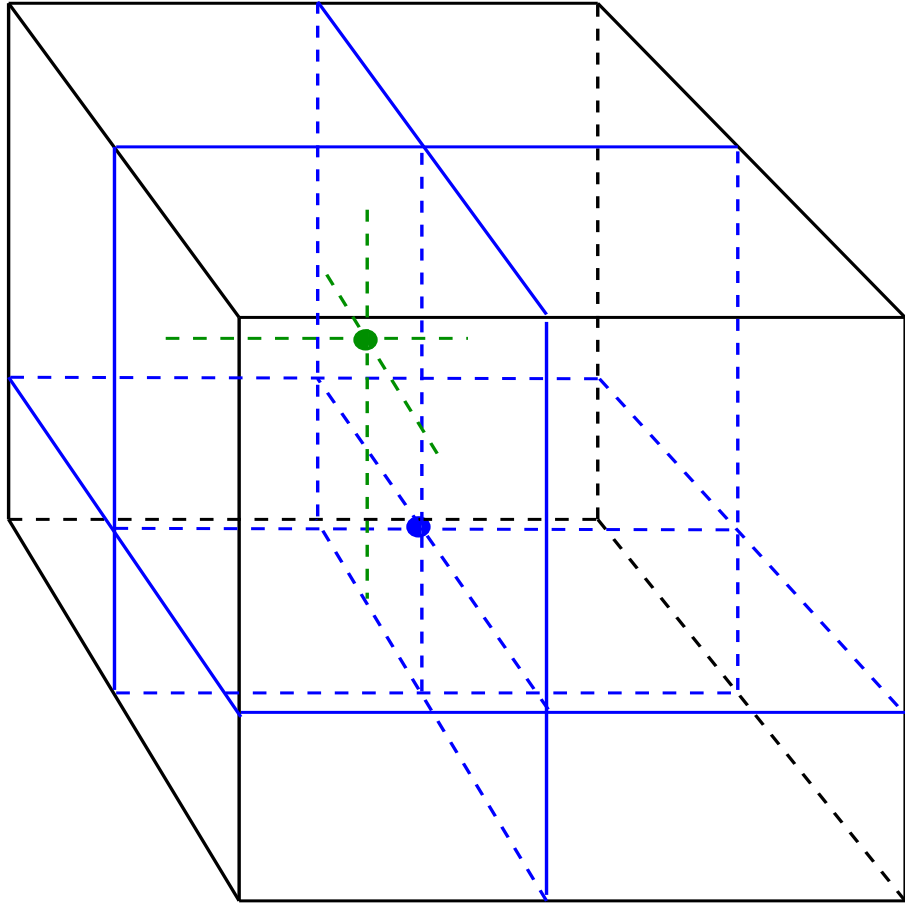
# Quadtrees: higher dimensions



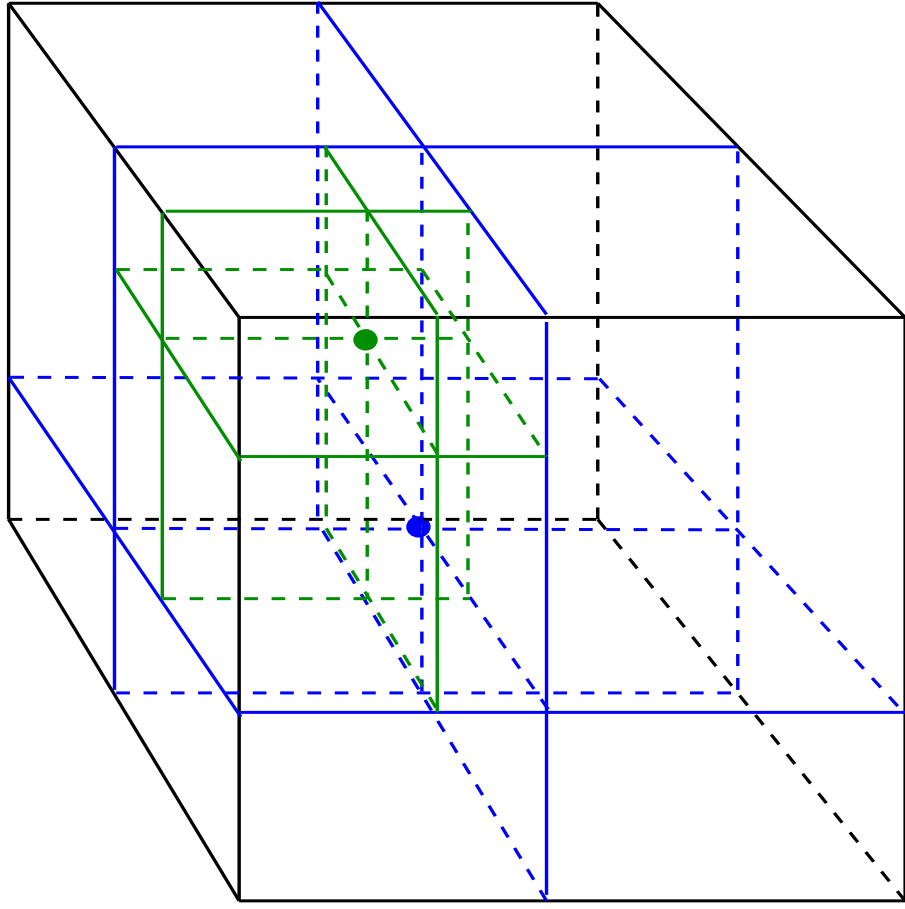
# Quadtrees: higher dimensions



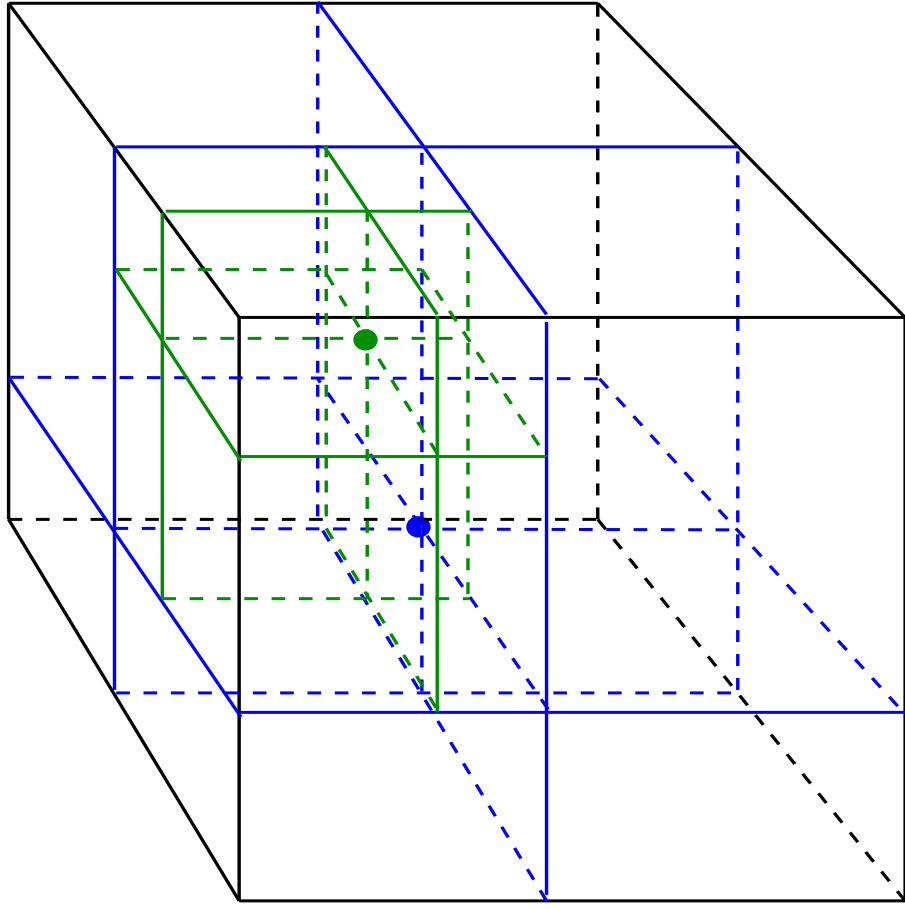
# Quadtrees: higher dimensions



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# Quadtrees: higher dimensions

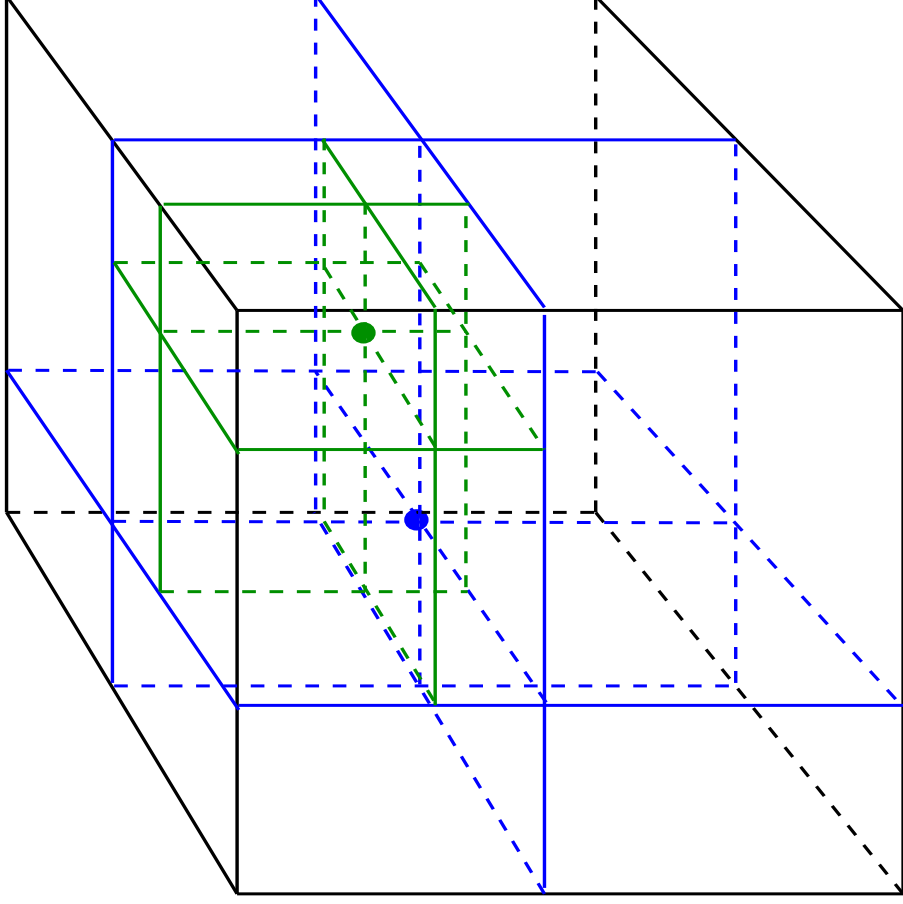




# Quadtrees: higher dimensions

Data:

$U_1, \dots, U_n$  i.i.d.  $\text{unif}[0, 1]$



# Quadtrees: higher dimensions

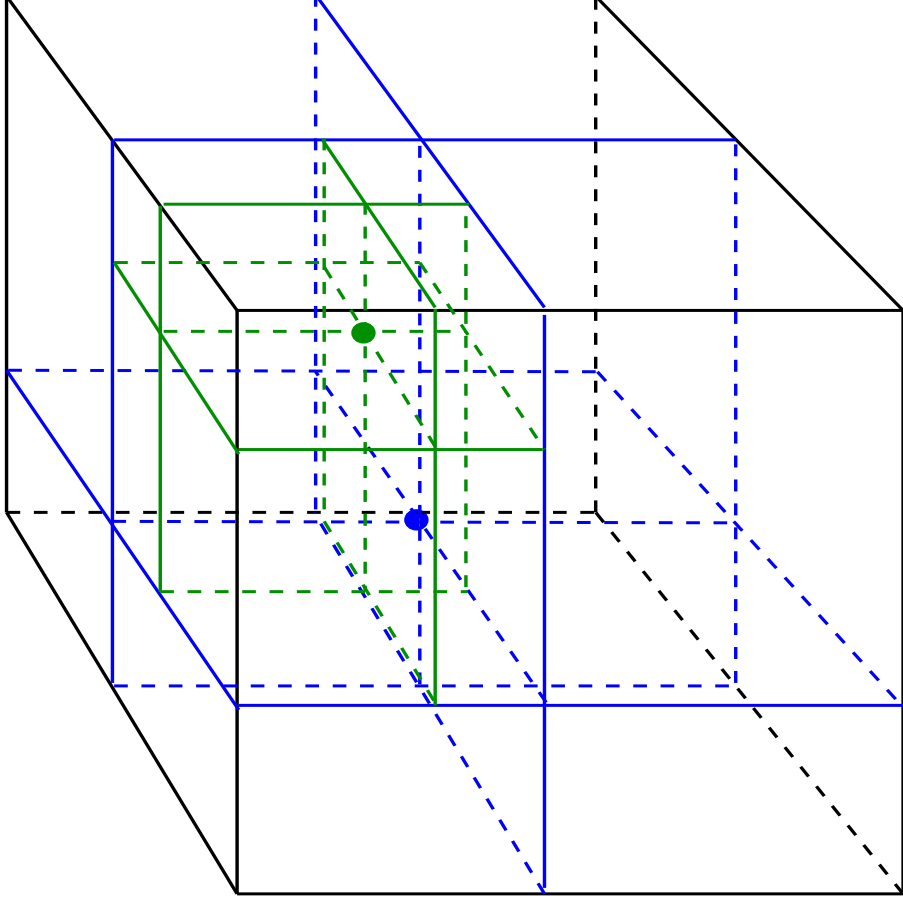
Data:

$U_1, \dots, U_n$  i.i.d. unif[0, 1]

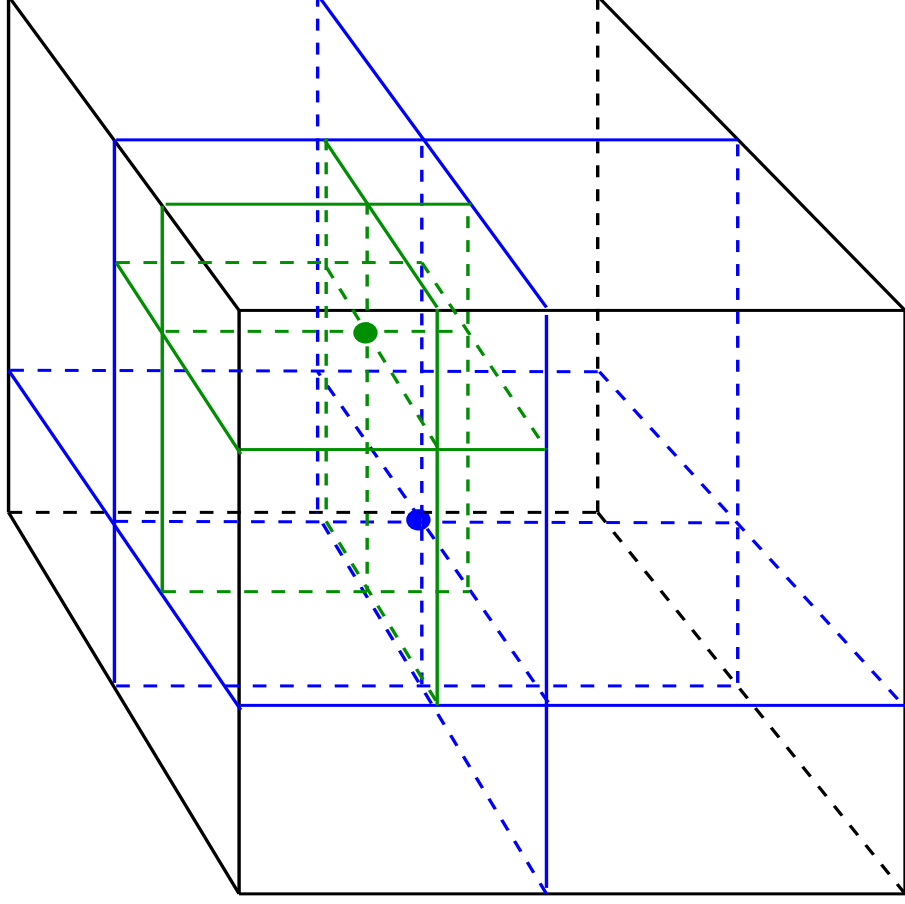
$(\langle U_1 \rangle_1, \dots, \langle U_1 \rangle_{2^d})$  volumes of quadrants

Sizes of subtrees:

$I^{(n)} \stackrel{d}{=} M(n-1; \langle U_1 \rangle_1, \dots, \langle U_1 \rangle_{2^d})$ ,



# Quadrees: higher dimensions



Data:

$U_1, \dots, U_n$  i.i.d.  $\text{unif}[0, 1]$

$(\langle U_1 \rangle_1, \dots, \langle U_1 \rangle_{2^d})$  volumes of quadrants

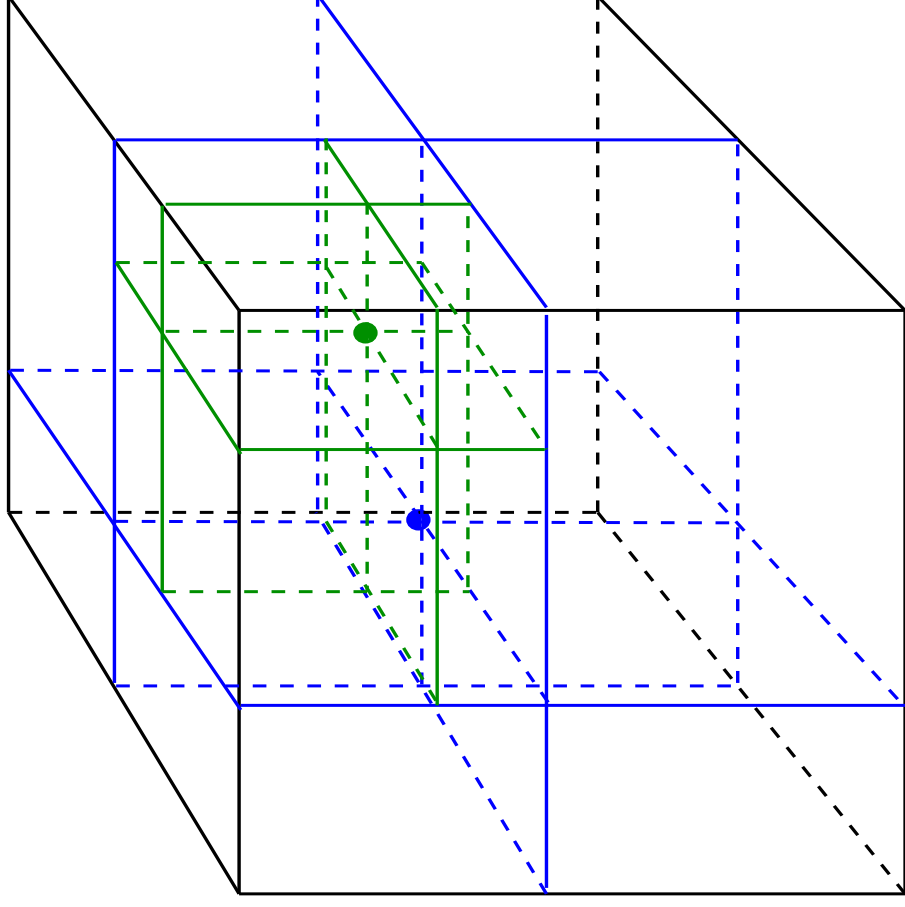
Sizes of subtrees:

$I^{(n)} \stackrel{d}{=} M(n-1; \langle U_1 \rangle_1, \dots, \langle U_1 \rangle_{2^d}),$

Number of leaves:

$$X_n \stackrel{d}{=} \sum_{r=1}^{2^d} X_{I_r^{(n)}}^{(r)} + 1, \quad n \geq m.$$

# Quadrees: higher dimensions



Data:

$U_1, \dots, U_n$  i.i.d.  $\text{unif}[0, 1]$

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Sizes of subtrees:

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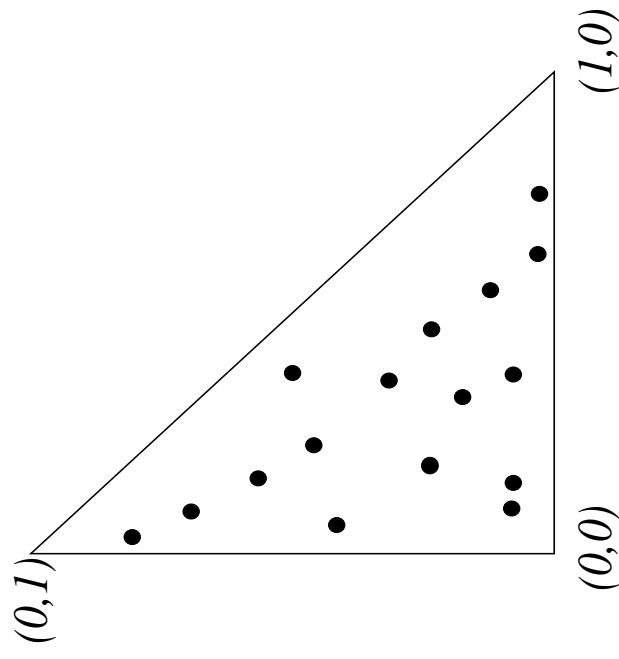
Number of leaves:

$$X_n \stackrel{d}{=} \sum_{r=1}^{2^d} X_{I_r^{(n)}}^{(r)} + 1, \quad n \geq m.$$

$X_0 = 0, X_1 = 1.$

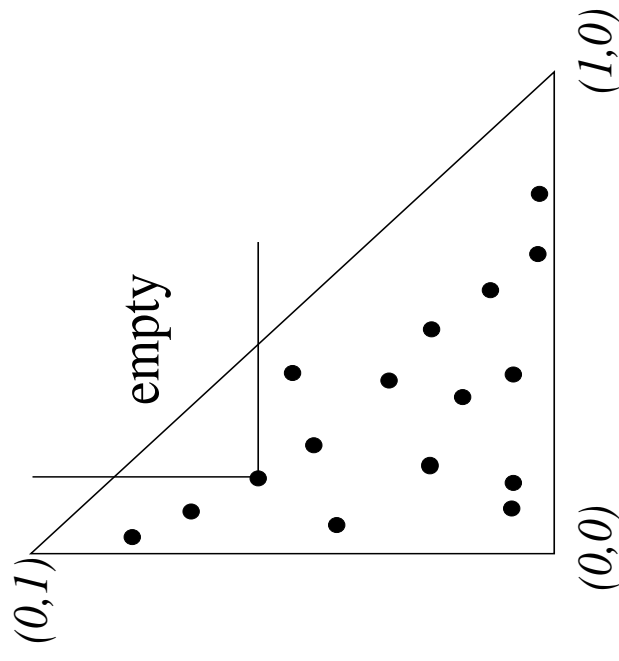
# Maxima in right triangles

Data:  $U_1, \dots, U_n$  indep. unif. in right triangle



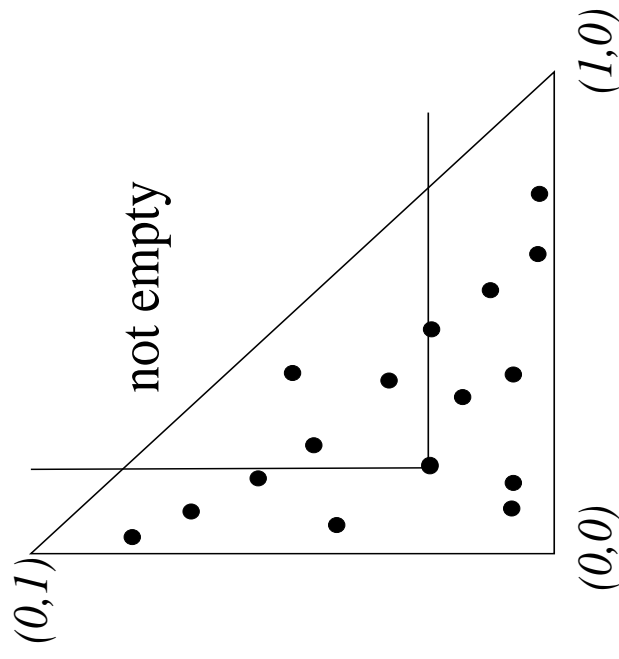
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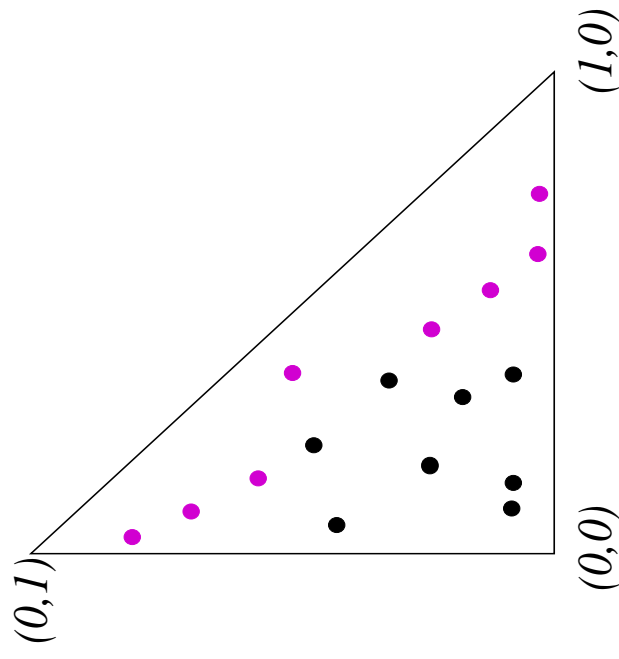
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# Maxima in right triangles

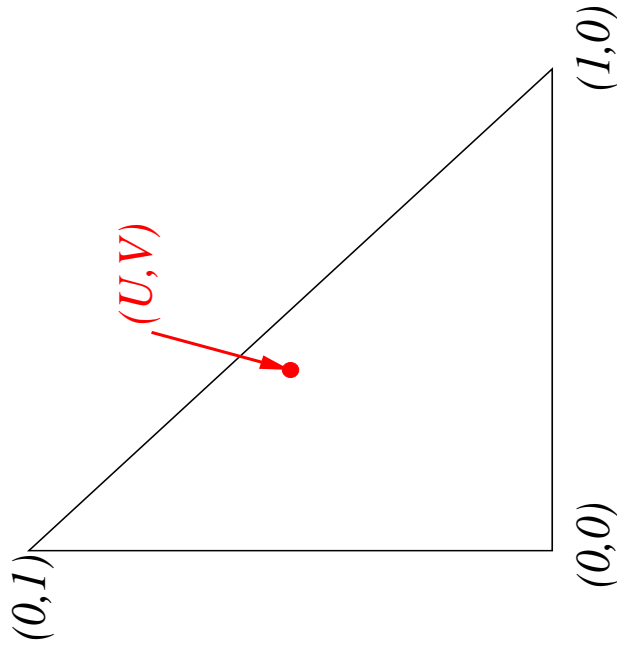
Data:  $U_1, \dots, U_n$  indep. unif. in right triangle





# Maxima in right triangles

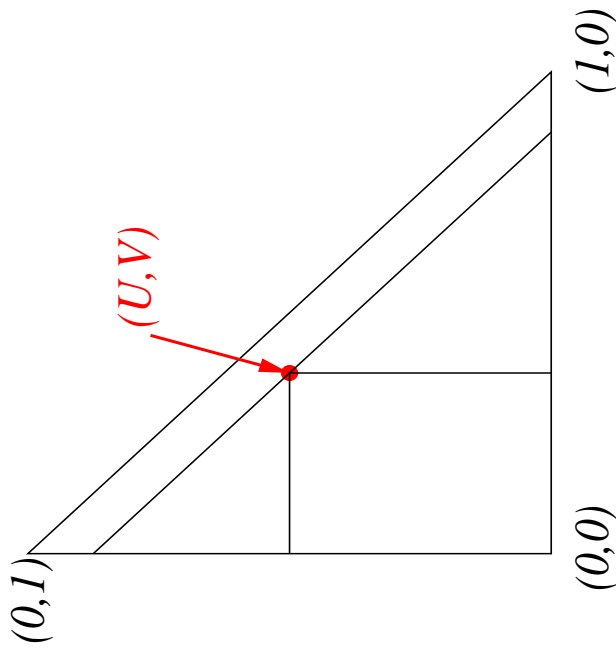
Data:  $U_1, \dots, U_n$  indep. unif. in right triangle



$(U, V)$  has maximal sum of coordinates.

# Maxima in right triangles

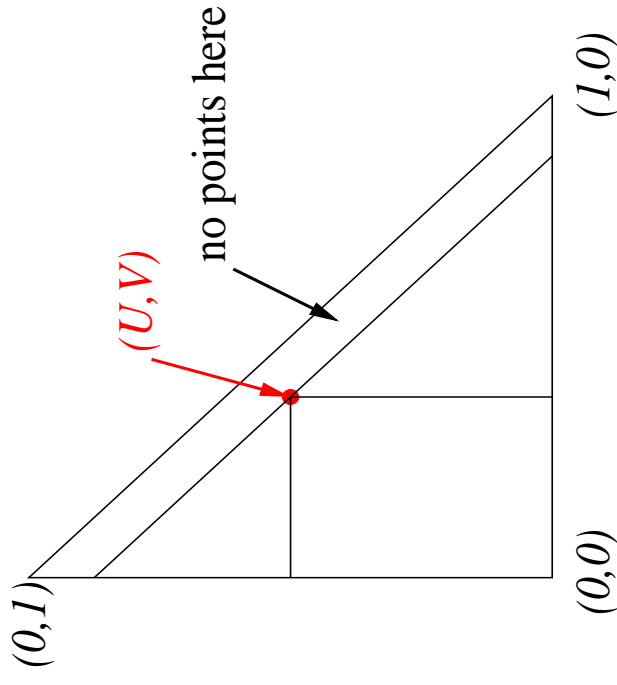
Data:  $U_1, \dots, U_n$  indep. unif. in right triangle



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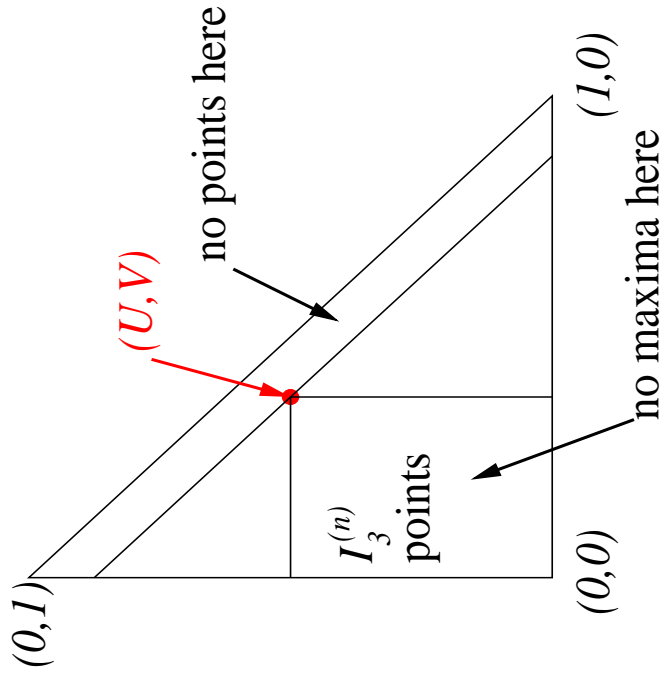
Data:  $U_1, \dots, U_n$  indep. unif. in right triangle



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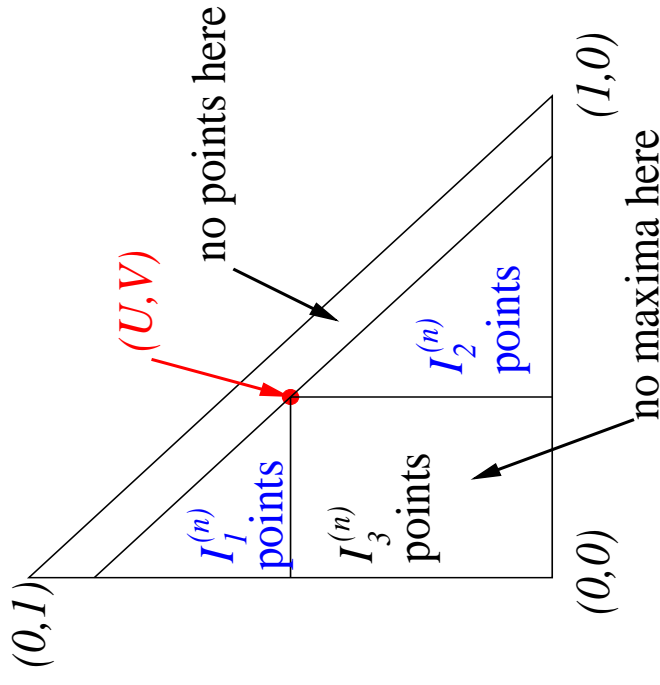
Data:  $U_1, \dots, U_n$  indep. unif. in right triangle



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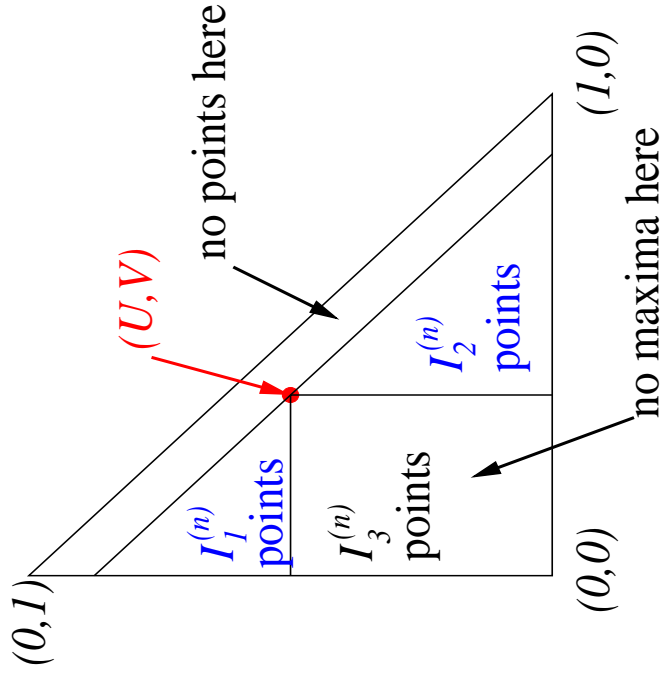
Data:  $U_1, \dots, U_n$  indep. unif. in right triangle



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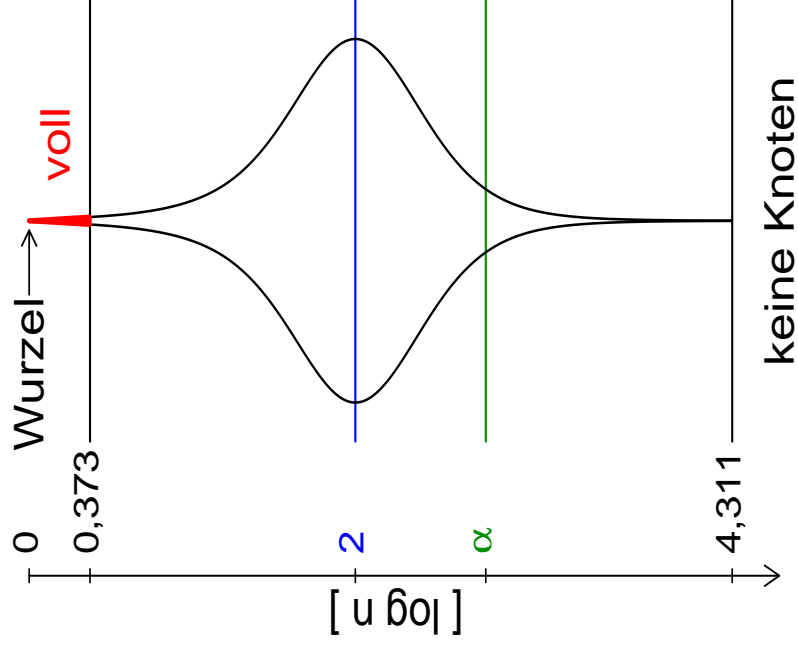
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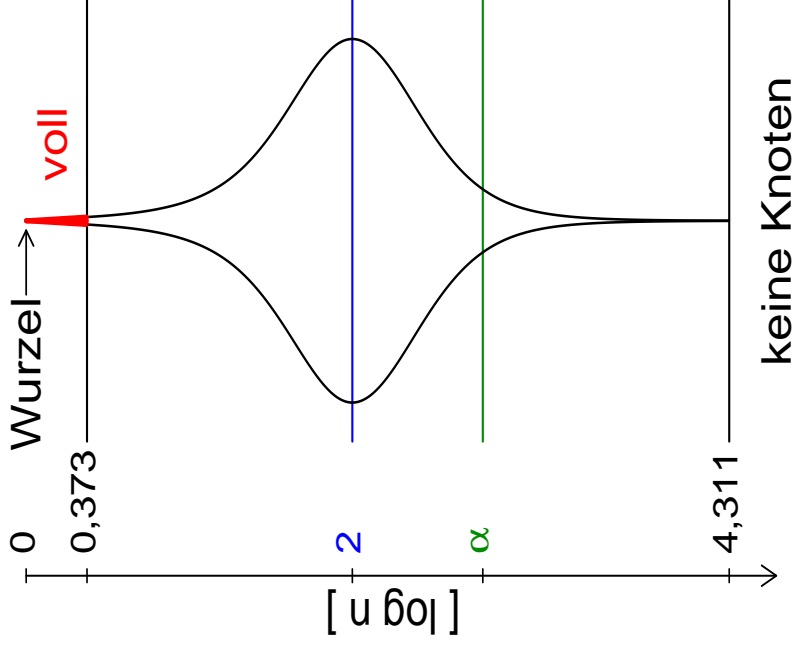
$$X_n \stackrel{d}{=} X_{I_1}^{(1)} + X_{I_2}^{(2)} + 1, \quad n \geq 2.$$

# Profile in BST



Profile:  $Y_{n,k}$  (external nodes)

# Profile in BST

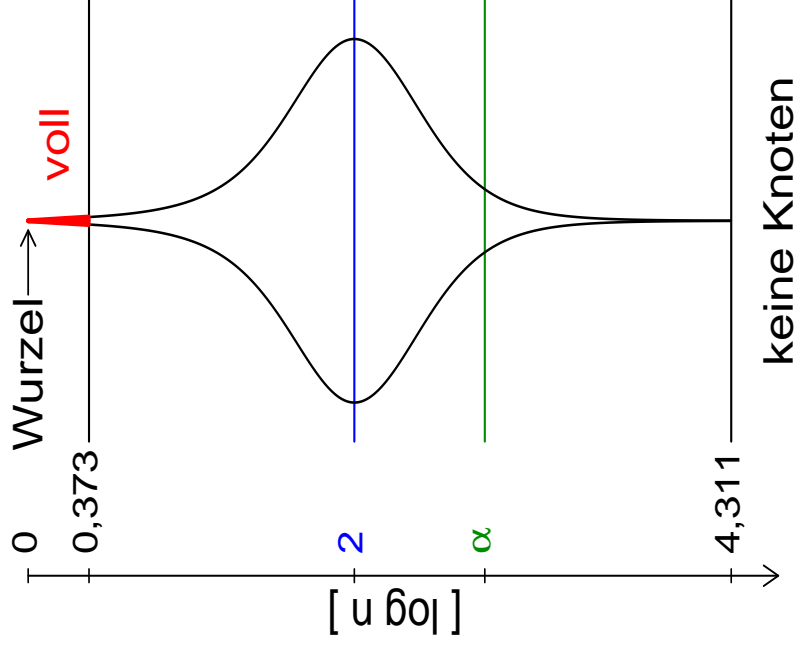


Profile:  $Y_{n,k}$  (external nodes)

Consider:  $k \sim \alpha \log n$



# Profile in BST

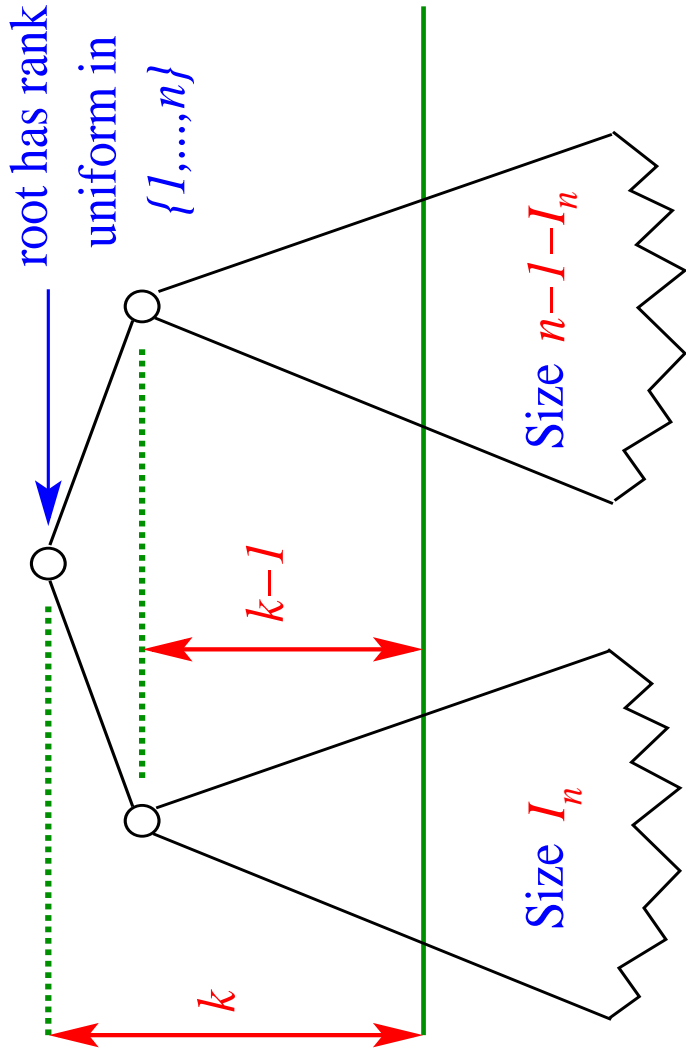


Profile:  $Y_{n,k}$  (external nodes)

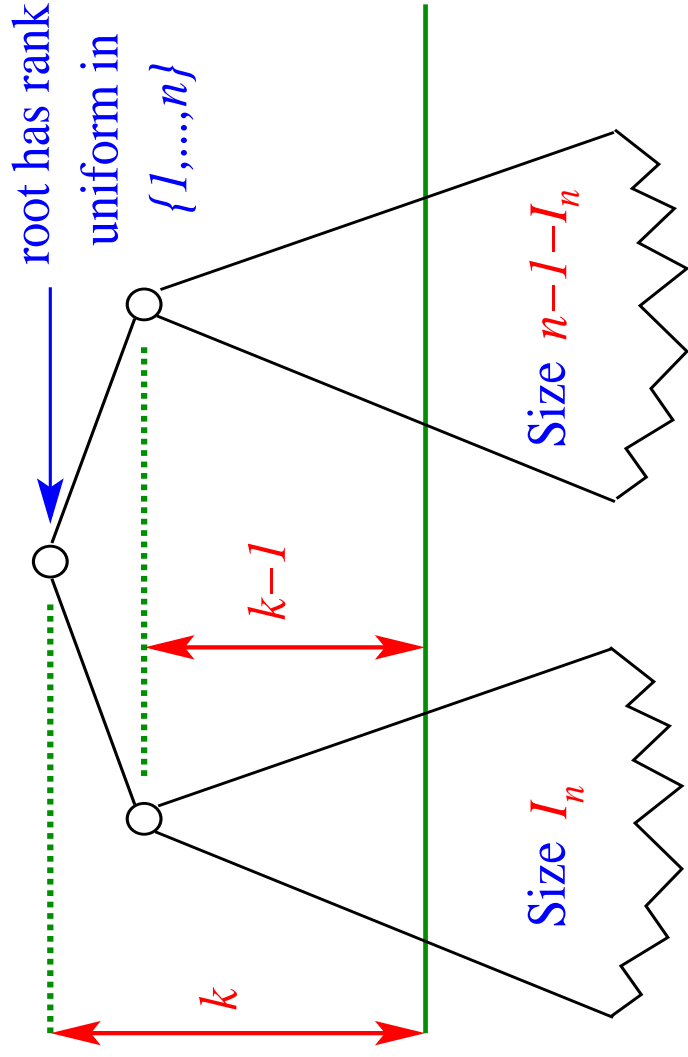
Consider:  $k \sim \alpha \log n$

with  $\alpha \in (\alpha_-, \alpha_+)$ .

# Recursive description of profile

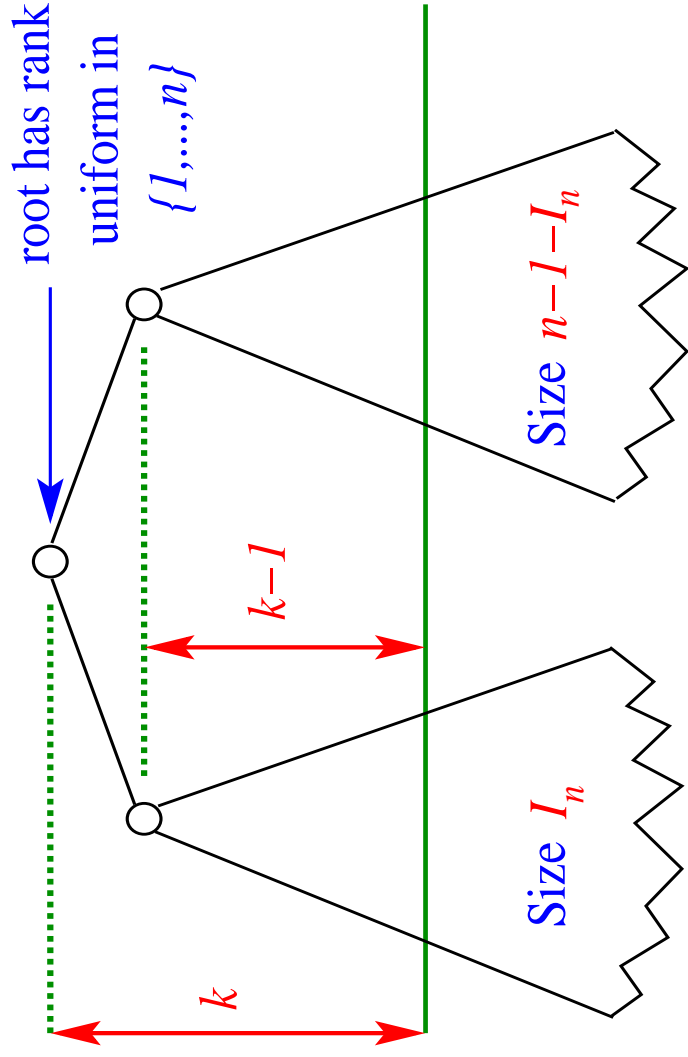


# Recursive description of profile



$$Y_{n,k} \stackrel{d}{=} Y_{I_n, k-1}^{(1)} + Y_{n-1-I_n, k-1}^{(2)}$$

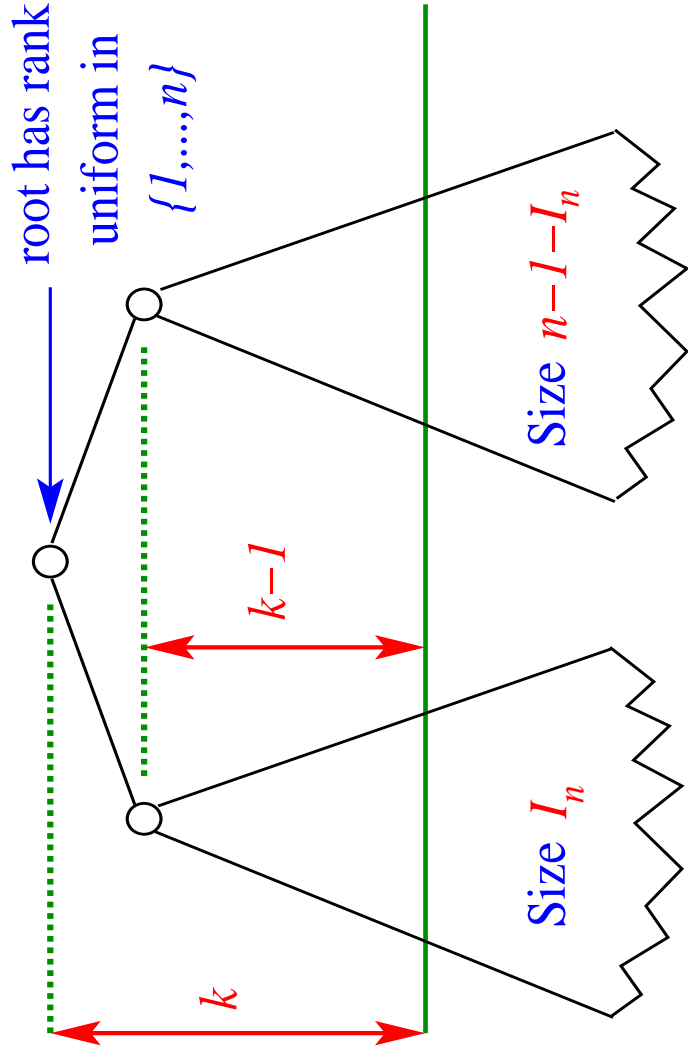
# Recursive description of profile



$$Y_{n,k} \stackrel{d}{=} Y_{I_n, k-1}^{(1)} + Y_{n-1-I_n, k-1}^{(2)}$$

$Y_{0, k-1}^{(1)}, \dots, Y_{n-1, k-1}^{(1)}, Y_{0, k-1}^{(2)}, \dots, Y_{n-1, k-1}^{(2)}, I_n$  independent,

# Recursive description of profile



$$Y_{n,k} \stackrel{d}{=} Y_{I_n, k-1}^{(1)} + Y_{n-1-I_n, k-1}^{(2)}$$

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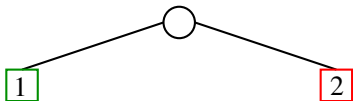
$I_n$  uniform distributed on  $\{0, \dots, n-1\}$ .

# Approach: Embedding into random BST: $m = 3$

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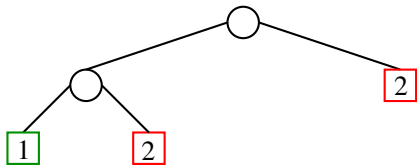
1

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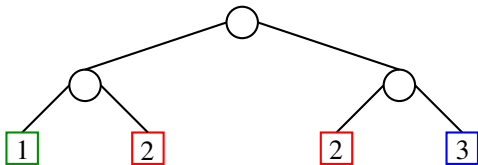




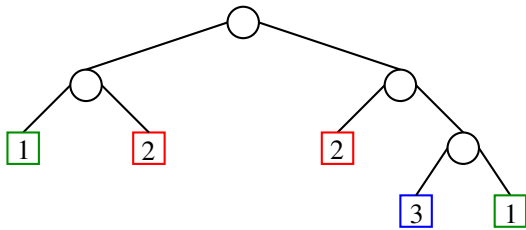
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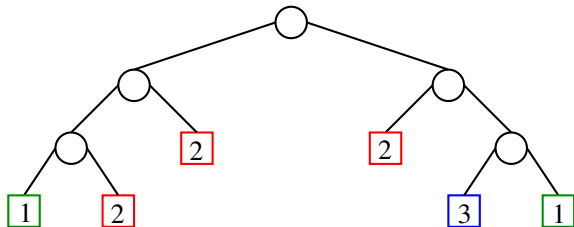
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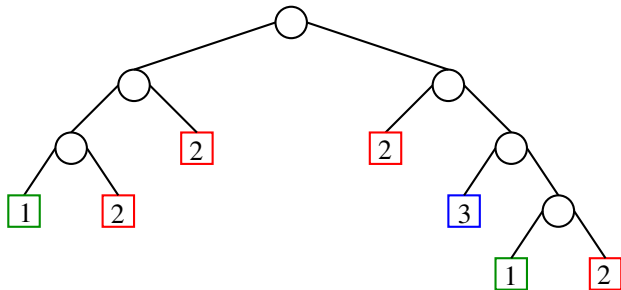
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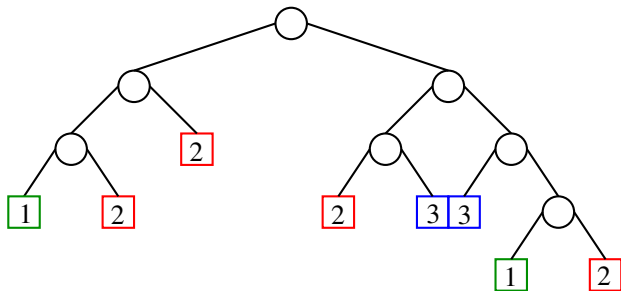
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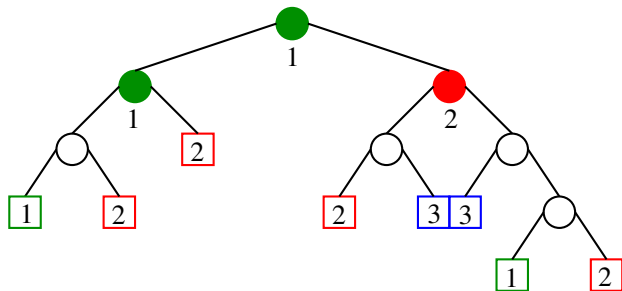
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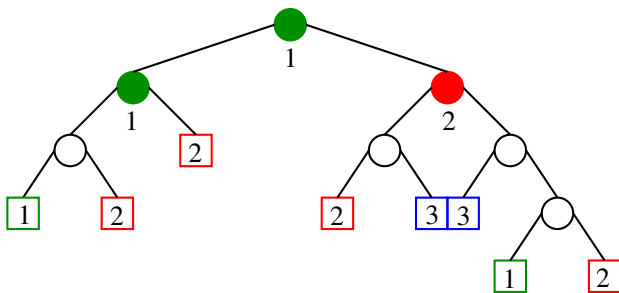
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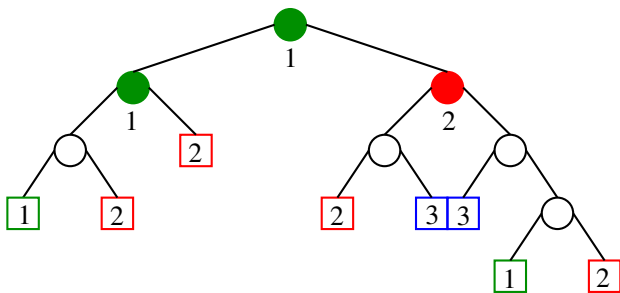


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$I_n$ : uniform on  $\{0, \dots, n-1\}$  and  $J_n = n-1-I_n$ .

# General recursion

$$X_n \stackrel{d}{=} \sum_{r=1}^K A_r(n) X_{I_r(n)}^{(r)} + b_n, \quad n > n_0.$$

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- $K \geq 1$  Number of subproblems (also  $K = K_n$ ).
- $X_n^{(r)} \stackrel{d}{=} X_n$  (recursive).
- $I^{(n)} = (I_1^{(n)}, \dots, I_K^{(n)})$  Sizes of subproblems.
- $(X_n^{(1)}, \dots, X_n^{(K)})$ ,  $(A_1(n), \dots, A_K(n), b_n, I^{(n)})$  independent.



# Contraction method

Rösler (1991, 1992)

Rachev and Rüschemdorf (1995)

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with

$$A_r^{(n)} = \frac{\sigma(I_r^{(n)})}{\sigma(n)} A_r(n),$$
$$b^{(n)} = \frac{1}{\sigma(n)} (b_n - \mu(n) + \sum_{r=1}^K A_r(n) \mu(I_r^{(n)})).$$

# Convergence

Idea:

$$\begin{array}{ccc} \gamma^n & \underline{\underline{d}} & \sum_{r=1}^K A_r^{(n)} \gamma_{I_r}^{(n)} + b^{(n)} \\ \downarrow & & \downarrow \quad \downarrow \quad \downarrow \\ \gamma & \underline{\underline{d}} & \sum_{r=1}^K A_r^* \gamma^{(r)} + b^* \end{array}$$

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 \end{array}$$

$$\left. \begin{array}{l}
 A_r^{(n)} \longrightarrow A_r^* \\
 \mathbf{b}^{(n)} \longrightarrow \mathbf{b}^*
 \end{array} \right\} \implies \mathbf{Y}^n \longrightarrow \mathbf{Y}.$$

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Limit map:

$$\begin{aligned}
 T: \mathcal{M} &\rightarrow \mathcal{M} \\
 \nu &\mapsto \mathcal{L}\left(\sum_{r=1}^K A_r^* Z^{(r)} + b^*\right)
 \end{aligned}$$

with  $(A_1^*, \dots, A_K^*, b^*), Z^{(1)}, \dots, Z^{(K)}$  independent,  $Z^{(r)} \stackrel{d}{=} \nu$ .

# The minimal $\ell_p$ metric



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**Definition:** The minimal  $\ell_p$  metric ( $p \geq 1$  fixed) is given by

$$\ell_p : \mathcal{M}_p \times \mathcal{M}_p \rightarrow [0, \infty)$$

$$(\mu, \nu) \mapsto \inf\{\|X - Y\|_p : \mathcal{L}(X) = \mu, \mathcal{L}(Y) = \nu\}$$

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Well-known fact: For a  $\text{unif}[0, 1]$  r.v.  $U$  we have

$$\mathcal{L}(F_X^{-1}(U)) = \mathcal{L}(X).$$

## The minimal $\ell_p$ metric — optimal couplings

2<sup>nd</sup> step: Use the same  $\text{unif}[0, 1]$  r.v.  $U$  for both, i.e.

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**Definition:** A vector  $(X, Y)$  with  $\mathcal{L}(X) = \mu$ ,  $\mathcal{L}(Y) = \nu$  and

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**Corollary:** We have

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$$\ell_p(\mu, \nu) = \|X - Y\|_p \leq \|X - Z\|_p + \|Z - Y\|_p = \ell_p(\mu, \nu) + \ell_p(\nu, \rho). \quad \clubsuit$$

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$\Rightarrow \mu_n \xrightarrow{\ell_p} \mathcal{L}(X) \in \mathcal{M}_p$ . ♣.

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**Corollary:** For  $\mu_n, \mu \in \mathcal{M}_p$  with  $\ell_p(\mu_n, \mu) \rightarrow 0$ :

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**Theorem:** Assume that  $(A_1, \dots, A_k, b)$  are  $L^p$ -integrable r.v.'s.,

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Lipschitz on  $(\mathcal{M}_2(0), \ell_2)$

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$$Y_n \stackrel{d}{=} \frac{I_n}{n} Y_{I_n} + \frac{n-1}{n}, \quad \mathcal{L}(I_n) = \text{unif}\{0, \dots, n-1\}$$

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We obtain  $\Delta(n) \rightarrow 0$ .

(E.g., for  $p = 1$  show  $\Delta(n) \leq (C \log n)/n$  by induction.)

## General theorem in $\mathcal{M}_p$

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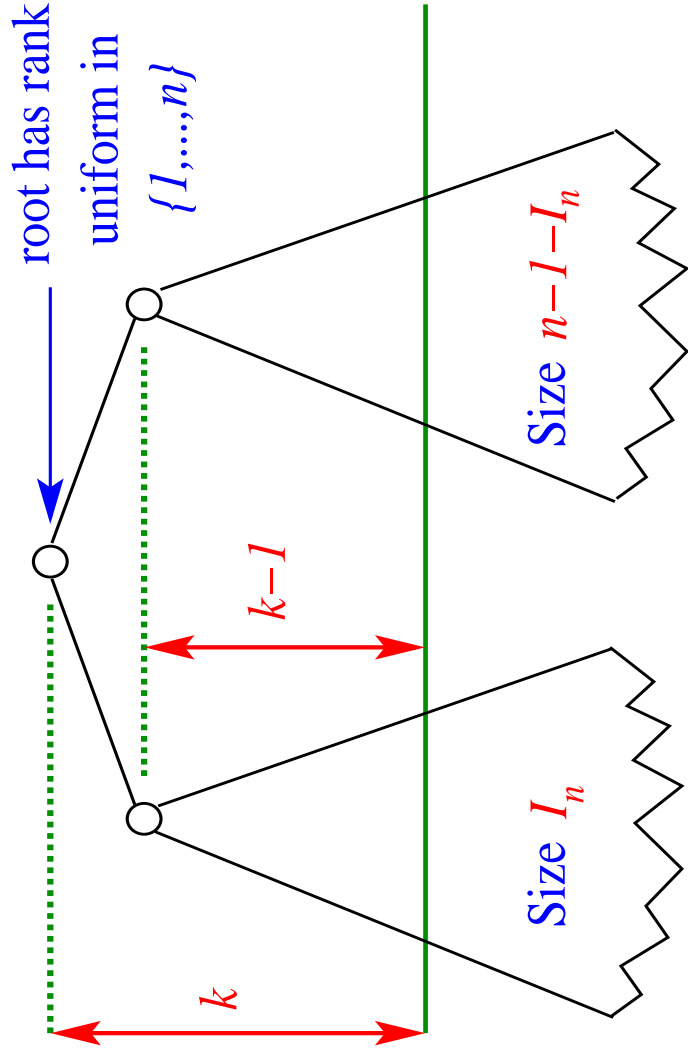
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$$\mathbb{E} \left[ (A_1^*)^2 \right] + \mathbb{E} \left[ (A_2^*)^2 \right] = \mathbb{E}u^2 + \mathbb{E}(1-u)^2 = \frac{2}{3} < 1.$$

# Recursive description of profile



$$Y_{n,k} \stackrel{d}{=} Y_{I_n, k-1}^{(1)} + Y_{n-1-I_n, k-1}^{(2)}$$

$Y_{0, k-1}^{(1)}, \dots, Y_{n-1, k-1}^{(1)}, Y_{0, k-1}^{(2)}, \dots, Y_{n-1, k-1}^{(2)}, I_n$  independent,

$I_n$  uniform distributed on  $\{0, \dots, n-1\}$ .

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**Thm:** (Lynch 1965)

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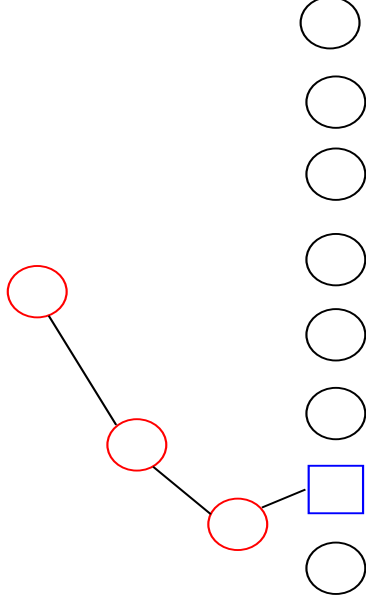
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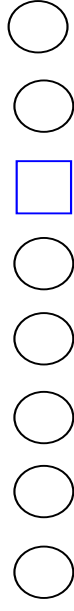
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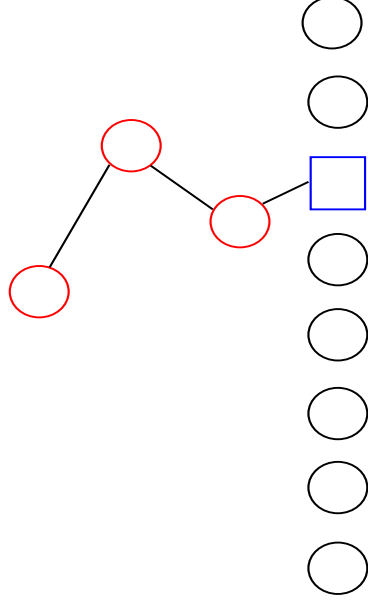
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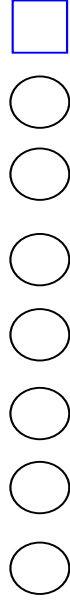
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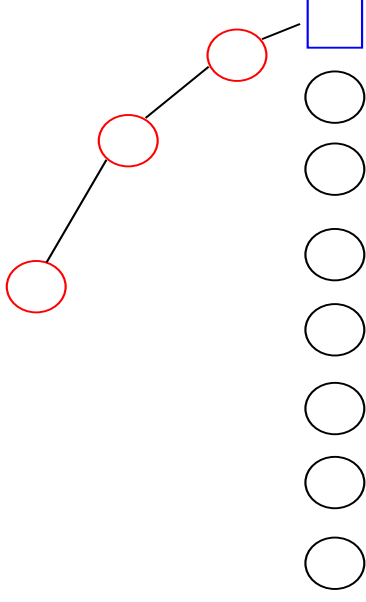
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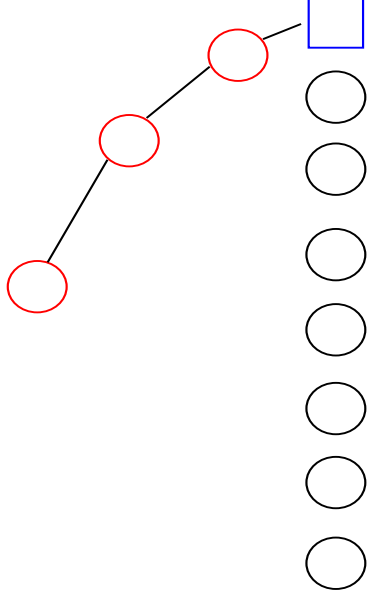
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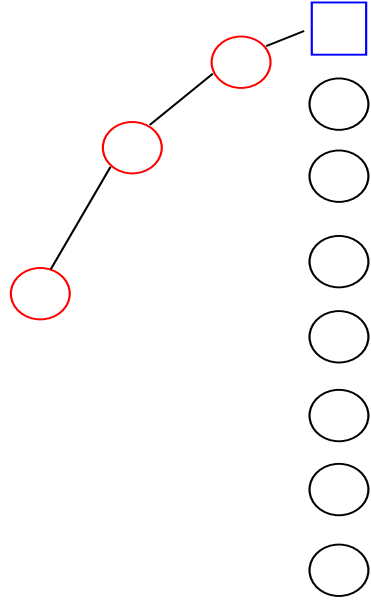
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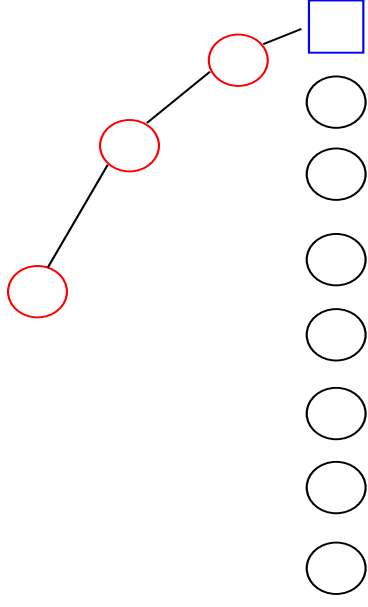
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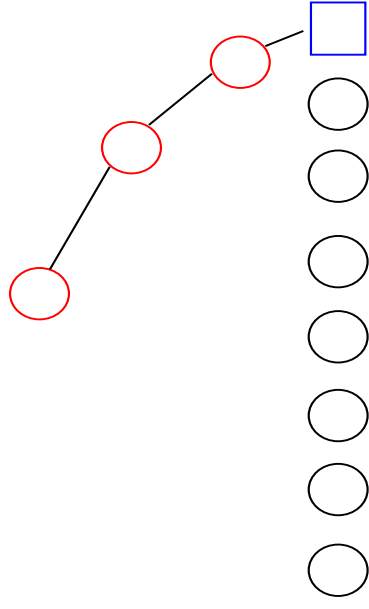


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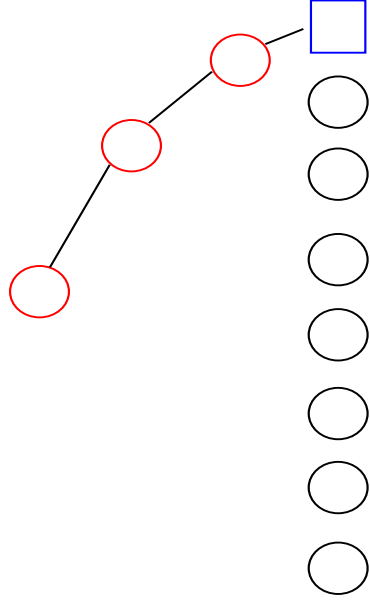
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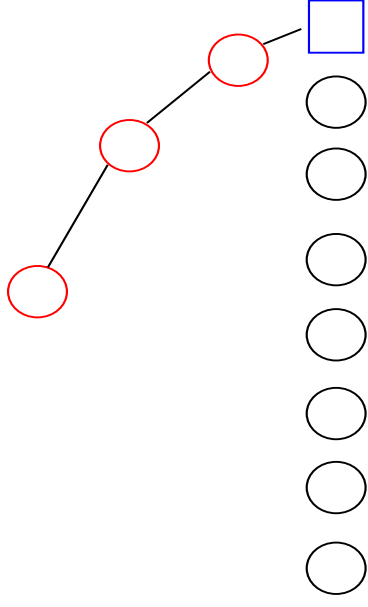
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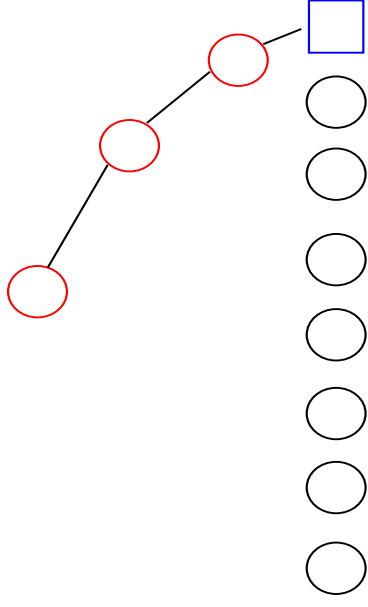


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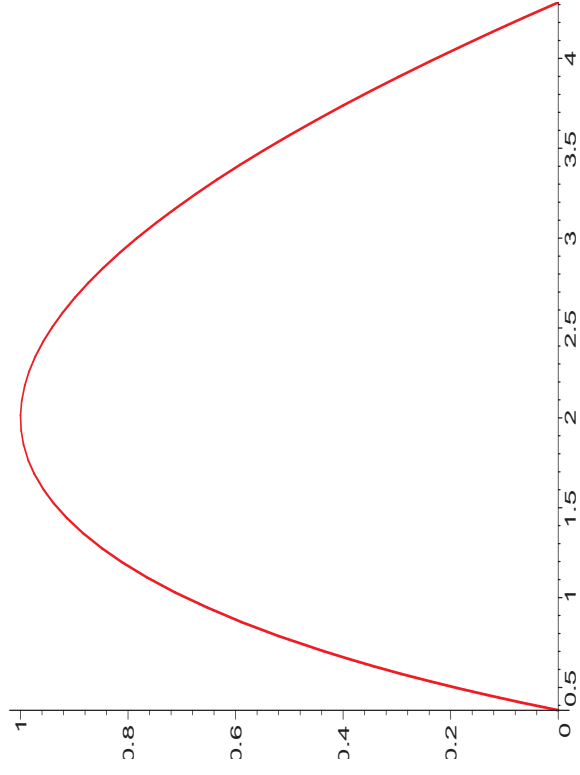
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Asymptotic: For all  $\beta > 0$  uniformly for  $k \leq \beta \log n$ :

$$\mathbb{E} Y_{n,k} = \frac{(2 \log n)^k}{k! n \Gamma\left(\frac{k}{\log n}\right)} (1 + o(1)) \quad (\text{H.-K. Hwang 1995})$$

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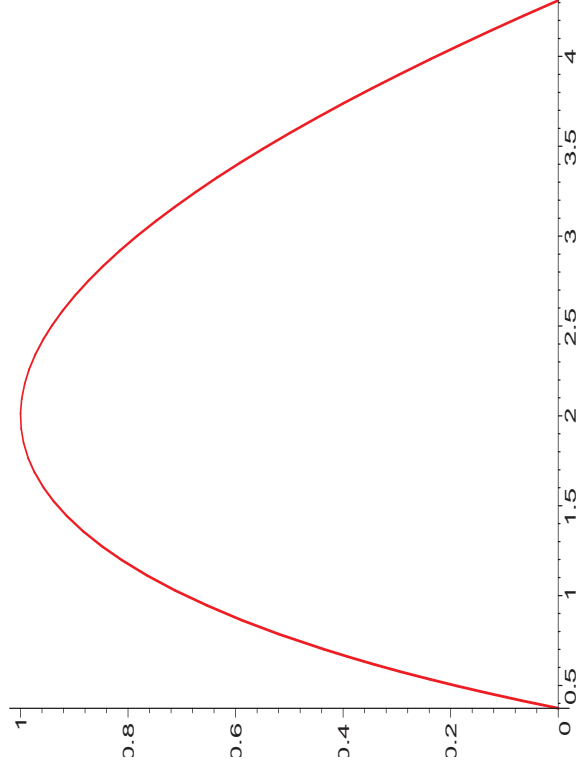


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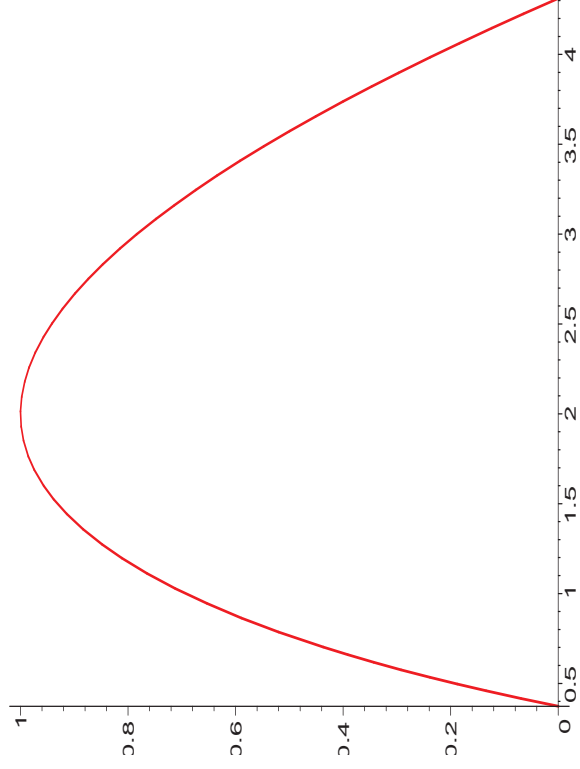


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Most nodes expected at  $k \sim 2 \log n$ :

$$\mathbb{E} Y_{n, \lfloor 2 \log n \rfloor} \sim \frac{n}{\sqrt{4\pi \log n}}$$

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Limit equation:

$$X_\alpha \stackrel{d}{=} \frac{\alpha}{2} u^{\alpha-1} X_\alpha^{(1)} + \frac{\alpha}{2} (1-u)^{\alpha-1} X_\alpha^{(2)}$$

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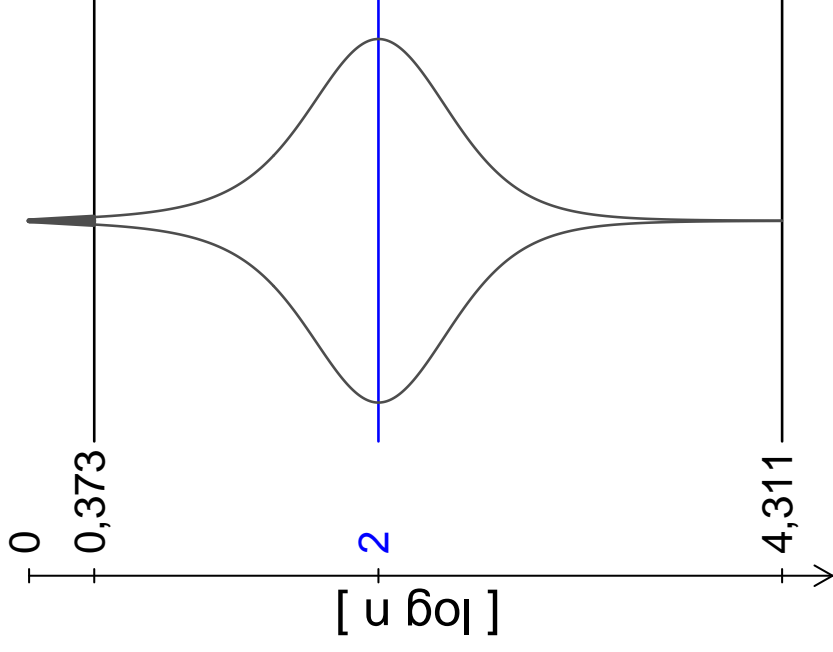
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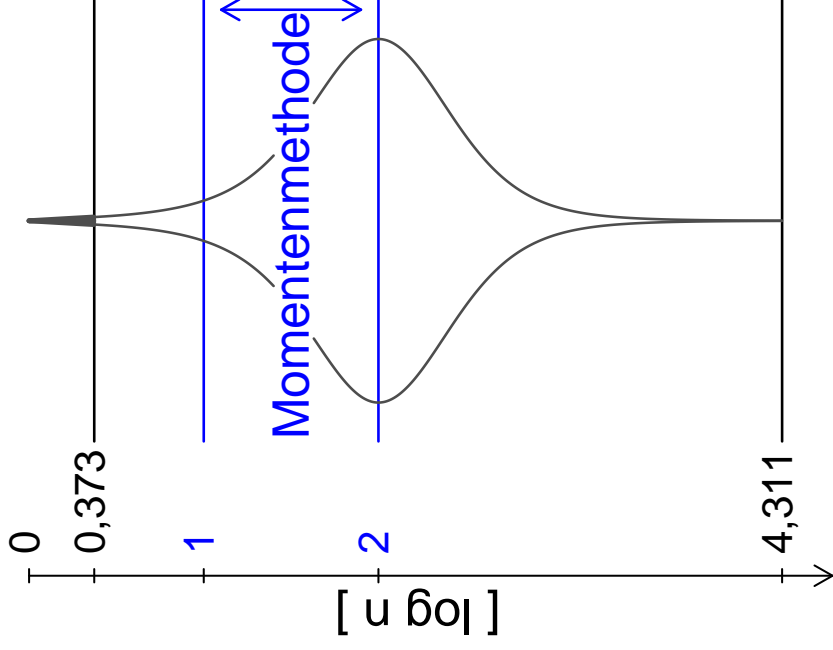
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# Techniques



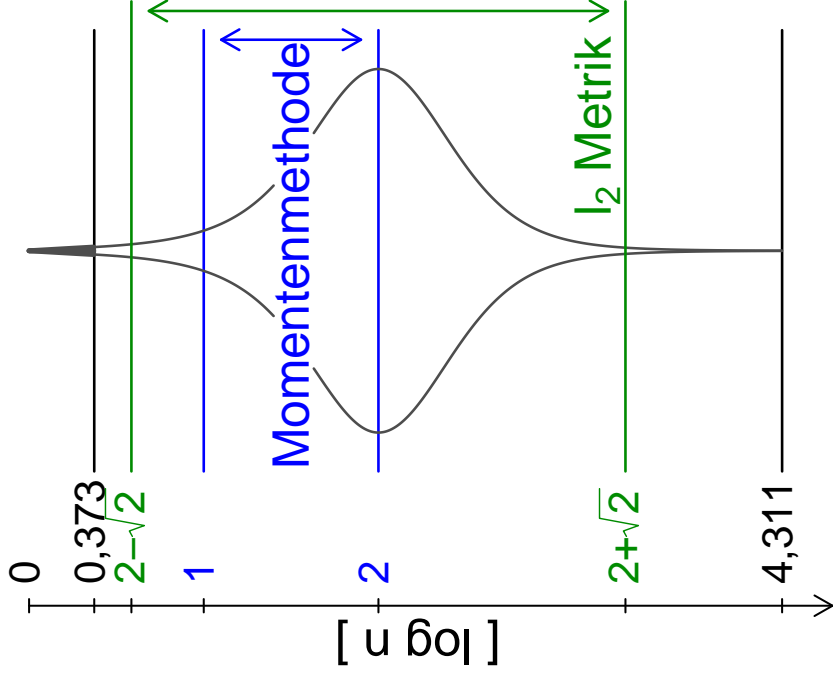
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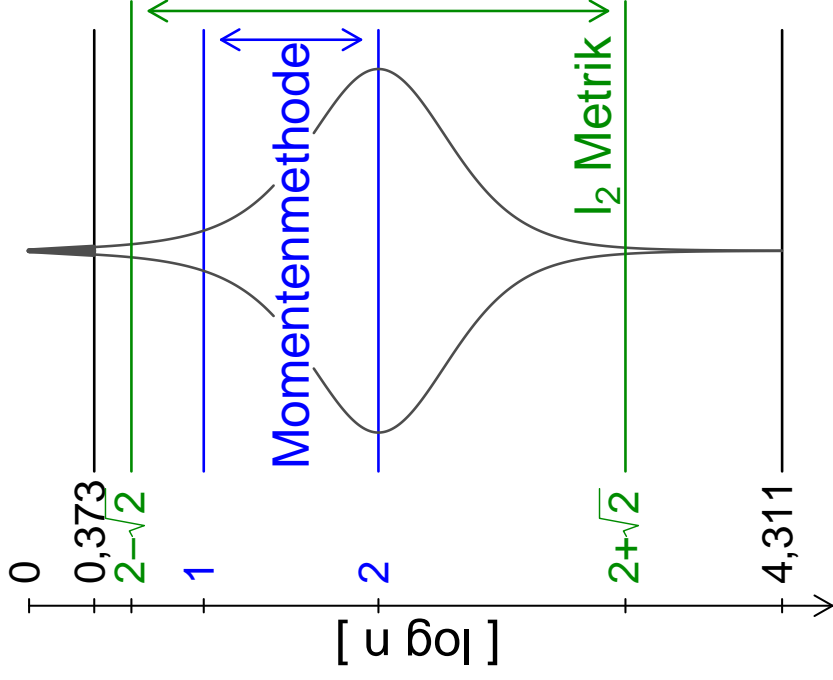
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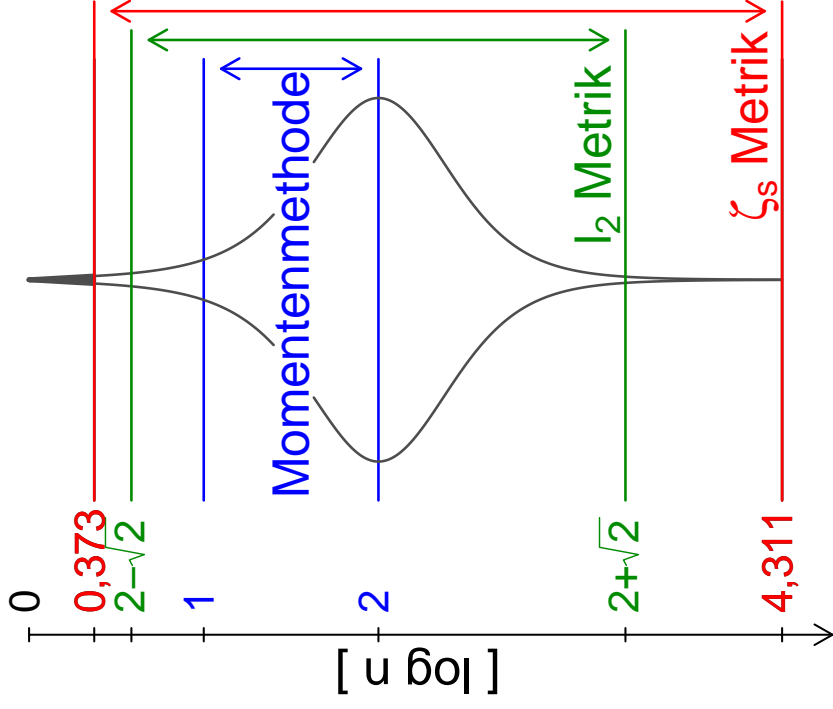


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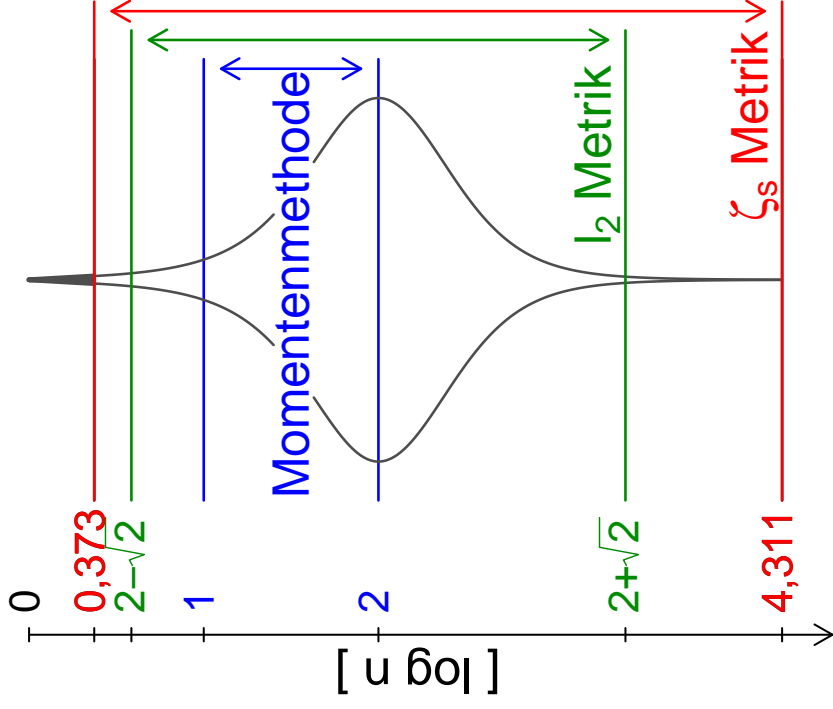


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For all  $\alpha \in (\alpha_-, \alpha_+)$  there exists  $s = s(\alpha)$ :

$$\zeta_s \left( \frac{X_{n,k}}{\mathbb{E} X_{n,k}}, X_\alpha \right) = O \left( \left| \frac{k}{\log n} - \alpha \right| \vee \frac{1}{\log n} \right)$$

(Fuchs, Hwang, N. 2005)

## Application: Central limit theorem

Let  $W_1, W_2, \dots$  be i.i.d.,  $L^p$ -integrable,  $p \geq 2$ ,  
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Limit equation:

$$Y \stackrel{d}{=} \frac{1}{\sqrt{2}} Y^* + \frac{1}{\sqrt{2}} Y^{**}.$$

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$$\sum_{r=1}^K (A_r^*)^2 = 1 \quad \text{almost surely.}$$

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## A general theorem: Periodicities

$$X_n \stackrel{d}{=} \sum_{r=1}^K X_{I_r^{(n)}}^{(r)} + b_n, \quad n \geq n_0, \quad (1)$$

all r.v.  $L_2$ -integrable with conditions as before. Assume

$$\mathbb{E}[X_n] = f(n) + \Re(\gamma n^\lambda) + o(n^\sigma), \quad (2)$$

with a function  $f : \mathbb{N}_0 \rightarrow \mathbb{R}$ ,  $\gamma \in \mathbb{C} \setminus \{0\}$ , and  $\lambda = \sigma + i\tau \in \mathbb{C}$  with  $\sigma > 0$ . We denote

$$A_r^{(n)} = \left( \frac{I_r^{(n)}}{n} \right)^\lambda, \quad r = 1, \dots, K, \quad (3)$$

$$b^{(n)} = \frac{1}{n^\sigma} \left( b_n - f(n) + \sum_{r=1}^K f(I_r^{(n)}) \right). \quad (4)$$

## A general theorem: Periodicities

Assume

$$(A_1^{(n)}, \dots, A_K^{(n)}) \xrightarrow{\ell_2} (A_1^*, \dots, A_K^*) \quad \text{and} \quad \|b^{(n)}\|_2 \rightarrow 0, \quad (5)$$

and furthermore

$$\mathbb{E} \sum_{r=1}^K |A_r^*|^2 < 1. \quad (6)$$

Then,

$$\ell_2 \left( \frac{X_n - f(n)}{n^\sigma}, \Re \left( e^{i\tau \ln n} Y \right) \right) \rightarrow 0, \quad (7)$$

where  $\mathcal{L}(Y)$  is the unique fixed point in  $\mathcal{M}_2^{\mathbb{C}}(\gamma)$  of

$$T : \mathcal{M}^{\mathbb{C}} \rightarrow \mathcal{M}^{\mathbb{C}}, \quad \eta \mapsto \mathcal{L} \left( \sum_{r=1}^K A_r^* Z^{(r)} \right), \quad (8)$$

where  $(A_1^*, \dots, A_K^*)$ ,  $Z^{(1)}, \dots, Z^{(K)}$  are independent and  $\mathcal{L}(Z^{(r)}) = \eta$  for  $r = 1, \dots, K$ .

# Applications

- ▶ # leaves in  $d$ -dim. quadtrees,  $d \geq 9$
- ▶ # nodes in  $m$ -ary search trees,  $m \geq 27$
- ▶ size of fragmentation trees
- ▶ composition of various urn models
- ▶ e.g. cyclic urns with at least 7 colors

# Proof

## Exercise:

The restriction of  $T$  to  $\mathcal{M}_2^{\mathbb{C}}(\gamma)$  maps into  $\mathcal{M}_2^{\mathbb{C}}(\gamma)$  and is Lipschitz in  $\ell_2$  with Lipschitz constant bounded by

$$\left( \mathbb{E} \sum_{r=1}^K |A_r^*|^2 \right)^{1/2} < 1.$$

**Comment:** The proof can be given along the lines for the corresponding result above in  $(\mathcal{M}_2(0), \ell_2)$ .

Thus, (6) implies the existence of a unique fixed-point  $\mathcal{L}(Y)$ .



## Proof

With  $Y_0 := 0$  and

$$Y_n := \frac{X_n - f(n)}{n^\sigma}, \quad n \geq 0$$

we obtain

$$Y_n \stackrel{d}{=} \sum_{r=1}^K \left( \frac{l_r^{(n)}}{n} \right)^\sigma Y_{l_r^{(n)}}^{(r)} + b^{(n)}, \quad n \geq n_0, \quad (9)$$

The fixed point property of  $\mathcal{L}(Y)$  implies

$$\frac{1}{n^\sigma} \mathfrak{R} \left( n^\lambda Y \right) \stackrel{d}{=} \frac{1}{n^\sigma} \mathfrak{R} \left( \sum_{r=1}^K n^\lambda A_r^* Y^{(r)} \right). \quad (10)$$

where  $(A_1^*, \dots, A_K^*)$ ,  $Y^{(1)}, \dots, Y^{(b)}$  are independent and  $\mathcal{L}(Y^{(r)}) = \mathcal{L}(Y)$  for  $r = 1, \dots, K$ .

## Construction on one probability space

We may assume, e.g. by taking optimal couplings, that

$$\|A_r^{(n)} - A_r^*\|_2 = \left\| \left( \frac{I_r^{(n)}}{n} \right)^\lambda - A_r^* \right\|_2 \rightarrow 0, \quad (n \rightarrow \infty).$$

We choose  $X_n^{(r)}$  as optimal couplings to  $\mathfrak{R}(n^{i\tau} X^{(r)})$  for  $n \geq 0$  and  $r = 1, \dots, K$ .

Clearly, we may assume that, as required,  $X_n^{(r)}$ ,  $r = 1, \dots, K$ , are independent of each other and of  $(I^{(n)}, b_n)_n$ .

## Bounding the $\ell_2$ -distance

We denote, for  $n \geq 1$ ,

$$\Delta(n) := \ell_2 \left( \frac{Y_n - f(n)}{n^\sigma}, \Re \left( X e^{i\tau \ln n} \right) \right) = \ell_2 \left( X_n, \frac{1}{n^\sigma} \Re \left( n^\lambda X \right) \right).$$

Using (9) and (10) we obtain, for  $n \geq n_0$ ,

$$\begin{aligned} \Delta(n) &= \ell_2 \left( \sum_{r=1}^K \left( \frac{l_r^{(n)}}{n} \right)^\sigma X_{l_r^{(n)}}^{(r)} + b^{(n)}, \frac{1}{n^\sigma} \Re \left( \sum_{r=1}^K n^\lambda A_r^* X^{(r)} \right) \right) \\ &\leq \left\| \sum_{r=1}^K \left( \left( \frac{l_r^{(n)}}{n} \right)^\sigma X_{l_r^{(n)}}^{(r)} - \frac{1}{n^\sigma} \Re \left( n^\lambda A_r^* X^{(r)} \right) \right) \right\|_2 + \|b^{(n)}\|_2 \\ &\leq \left\| \sum_{r=1}^K \left( \left( \frac{l_r^{(n)}}{n} \right)^\sigma X_{l_r^{(n)}}^{(r)} - \frac{1}{n^\sigma} \Re \left( (l_r^{(n)})^\lambda X^{(r)} \right) \right) \right\|_2 + \|b^{(n)}\|_2 \\ &\quad + \left\| \sum_{r=1}^K \left( \frac{1}{n^\sigma} \Re \left( (l_r^{(n)})^\lambda X^{(r)} \right) - \frac{1}{n^\sigma} \Re \left( n^\lambda A_r^* X^{(r)} \right) \right) \right\|_2. \end{aligned}$$

## Bounding the $\ell_2$ -distance

By (5) and (3) the second and third of the three latter summands tend to zero as  $n \rightarrow \infty$ . We abbreviate

$$W_r^{(n)} = \left( \frac{I_r^{(n)}}{n} \right)^\sigma X_{I_r^{(n)}}^{(r)} - \frac{1}{n^\sigma} \Re \left( (I_r^{(n)})^\lambda X^{(r)} \right). \quad (11)$$

Hence, the latter estimate implies

$$\begin{aligned} \Delta(n) &\leq \left( \mathbb{E} \left( \sum_{r=1}^K W_r^{(n)} \right)^2 \right)^{1/2} + o(1) \\ &= \left( \mathbb{E} \sum_{r=1}^K (W_r^{(n)})^2 + \mathbb{E} \sum_{\substack{r,s=1 \\ r \neq s}}^K W_r^{(n)} W_s^{(n)} \right)^{1/2} + o(1). \quad (12) \end{aligned}$$

## Bounding the $\ell_2$ -distance

Since  $X_n^{(r)}$  and  $\mathfrak{R}(n^{i\tau} X^{(r)})$  are optimal couplings for all  $n \geq 1$  and  $r = 1, \dots, K$  we obtain

$$\mathbb{E}(W_r^{(n)})^2 = \mathbb{E} \left[ \left( \frac{I_r^{(n)}}{n} \right)^{2\sigma} \Delta^2(I_r^{(n)}) \right]. \quad (13)$$

From (2) we obtain

$$\mathbb{E}[X_n] = \frac{1}{n^\sigma} \mathfrak{R}(\gamma n^\lambda) + R(n), \quad n \geq 1,$$

with  $R(n) \rightarrow 0$  as  $n \rightarrow \infty$ .

## Bounding the $\ell_2$ -distance

Since  $\mathbb{E}[X^{(r)}] = \gamma$  and by the independence conditions we obtain

$$\begin{aligned}\mathbb{E}W_r^{(n)} &= \mathbb{E}[(I_r^{(n)}/n)^\sigma R(I_r^{(n)})] \\ \mathbb{E}[W_r^{(n)}W_s^{(n)}] &= \mathbb{E}\left[\left(\frac{I_r^{(n)}}{n}\frac{I_s^{(n)}}{n}\right)^\sigma R(I_r^{(n)})R(I_s^{(n)})\right].\end{aligned}$$

Splitting the latter integral into the events  $\{I_r^{(n)} \leq n_1 \text{ or } I_s^{(n)} \leq n_1\}$  and  $\{I_r^{(n)} > n_1 \text{ and } I_s^{(n)} > n_1\}$  for some  $n_1 > 0$  we obtain, for every  $n_1 > 0$ ,

$$|\mathbb{E}[W_r^{(n)}W_s^{(n)}]| \leq \left(\frac{n_1}{n}\right)^\sigma \|R\|_\infty^2 + \sup_{n \geq n_1} R^2(n),$$

where  $\|R\|_\infty := \sup_{n \geq n_1} |R(n)| < \infty$ .

## Bounding the $\ell_2$ -distance

$$|\mathbb{E}[W_r^{(n)} W_s^{(n)}]| \leq \left(\frac{n_1}{n}\right)^\sigma \|R\|_\infty^2 + \sup_{n \geq n_1} R^2(n),$$

From this we obtain first, letting  $n \rightarrow \infty$ ,  
 $\limsup_{n \rightarrow \infty} |\mathbb{E}[W_r^{(n)} W_s^{(n)}]| \leq \sup_{n \geq n_1} R^2(n)$ , and then, letting  
 $n_1 \rightarrow \infty$ ,

$$\mathbb{E}[W_r^{(n)} W_s^{(n)}] \rightarrow 0 \quad \text{as } t \rightarrow \infty. \quad (14)$$

Now, (12), (13), and (14) imply, for  $n > n_0$ ,

$$\Delta(n) \leq \left( \mathbb{E} \left[ \sum_{r=1}^K \left( \frac{l_r^{(n)}}{n} \right)^{2\sigma} \Delta^2(l_r^{(n)}) \right] + R_1(n) \right)^{1/2} + R_2(n), \quad (15)$$

with  $R_1(n), R_2(n) \rightarrow 0$  as  $n \rightarrow \infty$

## Bounding the $\ell_2$ -distance

**First step:** Show  $\|\Delta\|_\infty < \infty$ .

Define  $\Delta^*(n) := \sup_{0 < j \leq n} \Delta(j)$ .

We have  $|R_1(n)| < 1$  and  $|R_2(n)| < 1$  for  $n \geq n_1$ . Then with (15) we obtain, for  $n \geq n_1$ ,

$$\Delta(n) \leq \left( \mathbb{E} \left[ \sum_{r=1}^K \left( \frac{l_r^{(n)}}{n} \right)^{2\sigma} (\Delta^*)^2(n) \right] + 1 \right)^{1/2} + 1.$$

By (3), (5) and (6)

$$\mathbb{E} \sum_{r=1}^K (l_r^{(n)} / n)^{2\sigma} \leq \xi < 1, \quad n \geq n_2 > n_1.$$



## Bounding the $\ell_2$ -distance

Thus, for all  $n \geq n_2$  we obtain, with  $\sqrt{a+b} \leq \sqrt{a} + \sqrt{b}$  for  $a, b \geq 0$ ,

$$\Delta(n) \leq \sqrt{\xi} \Delta^*(n) + 2,$$

and thus

$$\Delta^*(n) \leq \sqrt{\xi} \Delta^*(n) + 2 + \Delta^*(n_2),$$

which implies  $\|\Delta\|_\infty \leq 2 + \Delta^*(n_2)/(1 - \sqrt{\xi}) < \infty$ .

**Second step:**  $\Delta(n) \rightarrow 0$ .

$L := \limsup_{n \rightarrow \infty} \Delta(n) > 0$ . Let  $\varepsilon > 0$ . There exists an  $n_3 \geq n_2$  such that for all  $n \geq n_3$  we have  $\Delta(n) \leq L + \varepsilon$ . Then (15) implies

## Bounding the $\ell_2$ -distance

$$\begin{aligned} \Delta(n) &\leq \left( \mathbb{E} \left[ \sum_{r=1}^K \left( \frac{l_r^{(n)}}{n} \right)^{2\sigma} \left( \eta\{l_r^{(n)} < n_3\} + \eta\{l_r^{(n)} \geq n_3\} \right) \Delta^2(l_r^{(n)}) \right] + R_1 \right) \\ &\leq \left( \sum_{r=1}^K \left( \frac{n_3}{n} \right)^{2\sigma} \|\Delta\|_\infty^2 + \xi(L + \varepsilon)^2 + R_1(n) \right)^{1/2} + R_2(n). \end{aligned}$$

Hence,  $n \rightarrow \infty$  implies

$$L \leq \sqrt{\xi}(L + \varepsilon),$$

which if  $L > 0$  is a contradiction if we choose  $\varepsilon$  small enough. Consequently, we have  $L = 0$  yielding the assertion.