

# Probabilistic analysis of a search tree problem

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joint work with Nicolas Broutin and Ralph Neininger

# Partial match retrieval

A classical combinatorial problem is to perform a search in a multidimensional database where the record to be retrieved is either *fully* or *partially* specified. The latter is called a *Partial match query*.

$n$ -dim. domain:  $S = S_1 \times \cdots \times S_n$

set of data  $S' \subseteq S$  with  $|S'| < \infty$ .

Problem: For a fixed query  $q = (q_1, \dots, q_n)$  with  $q_i \in S_i \cup \{*\}$ , find all elements  $s = (s_1, \dots, s_n) \in S'$  such that

$$s_i = q_i, \quad \text{if} \quad q_i \neq *.$$

# Data structures

Comparison-based structures - search trees:

- Quadtrees (Finkel and Bentley '74),
- $K$ -d-trees (Bentley '75)

Several variants are known in the literature.

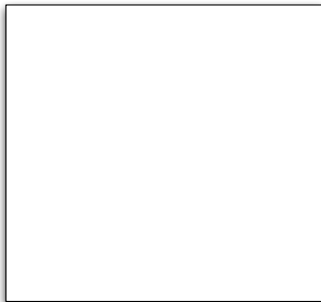
Digital structures:

- $K$ -d-tries (Rivest '76)

# The Quadtree - Construction

Model:  $S_i = [0, 1]$  for all  $i$ .

Dimension:  $n = 2$

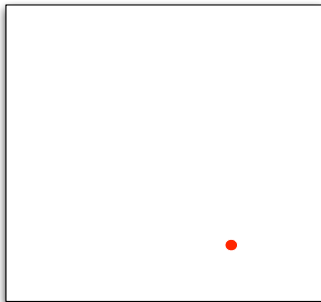


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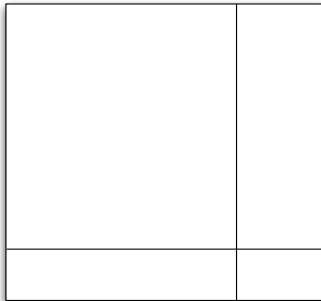
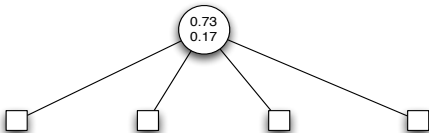
0.73, 0.17



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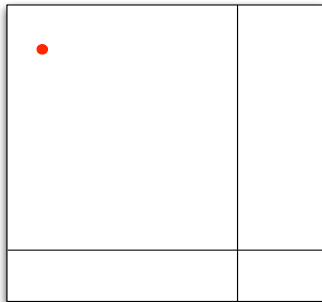
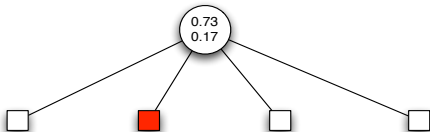


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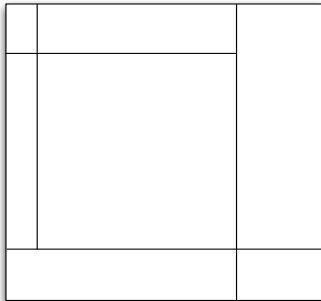
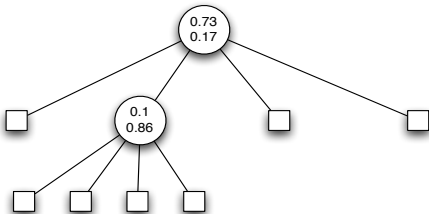
0.1, 0.86



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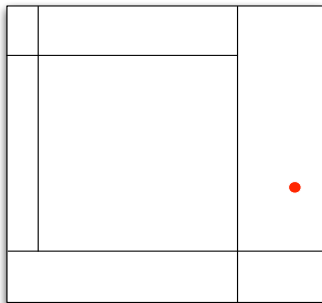
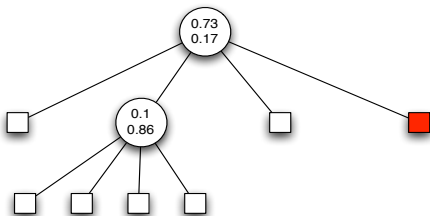


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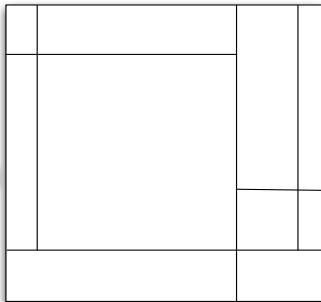
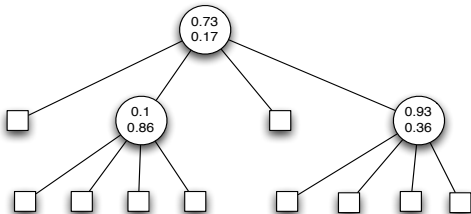
0.93, 0.36



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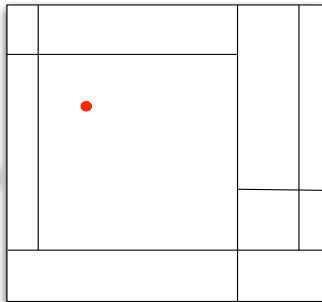
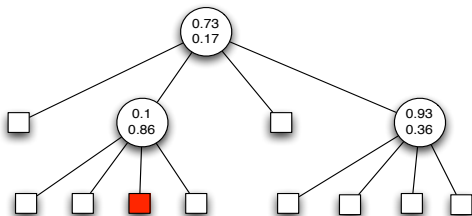


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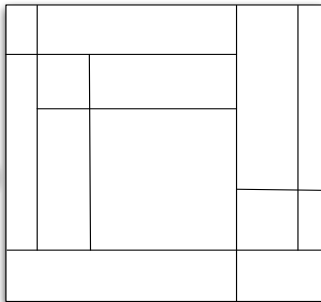
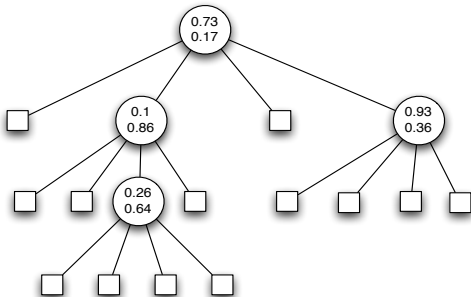
0.26, 0.64



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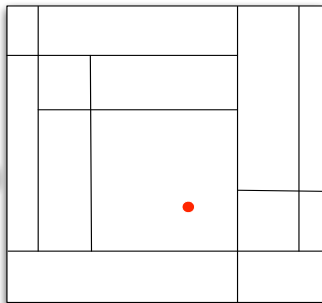
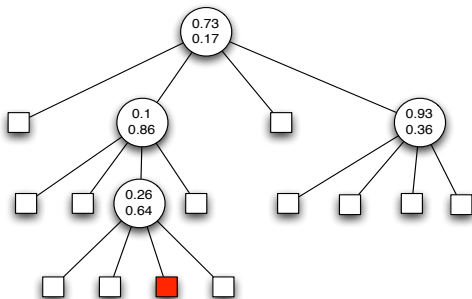


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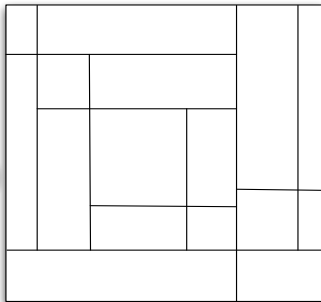
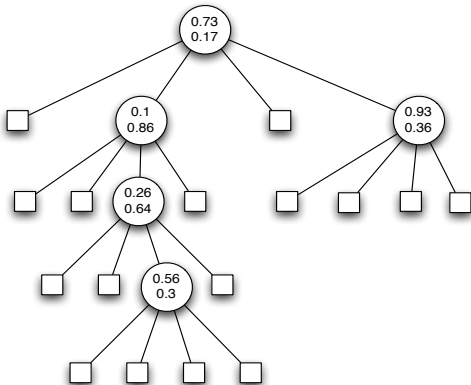
0.56, 0.3



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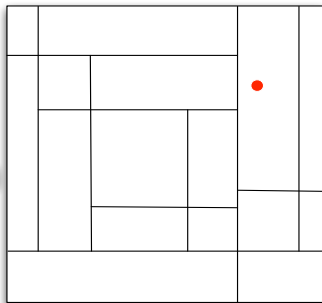
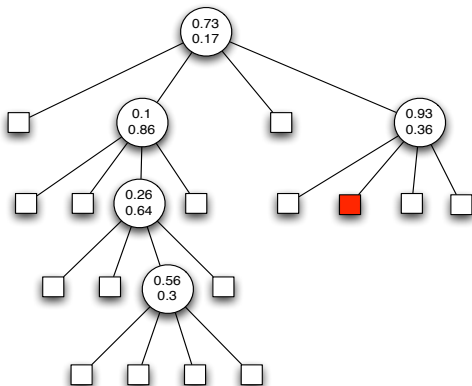


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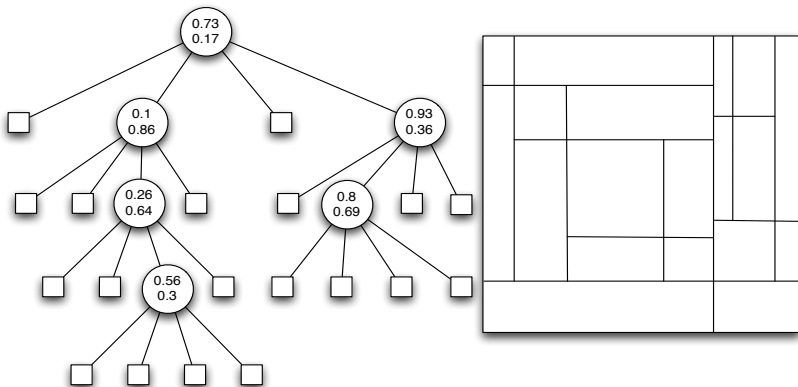
0.8, 0.69



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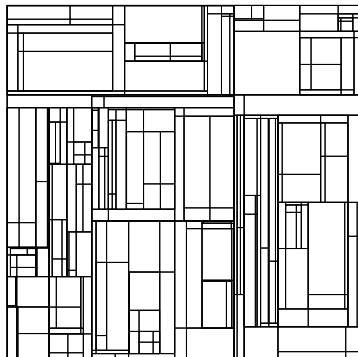
Quadtree:  $n = 2$





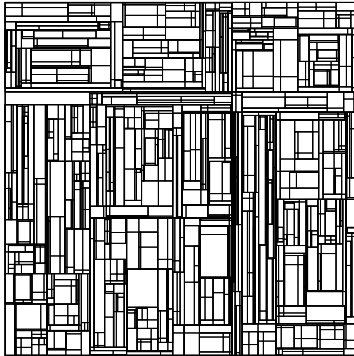
# Simulation - Quadtree

$n = 100$



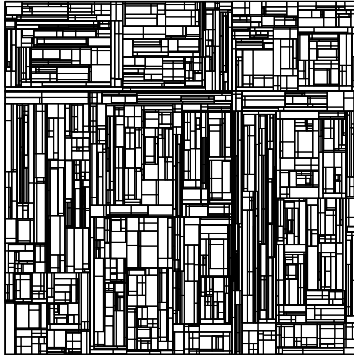
# Simulation - Quadtree

$n = 500$



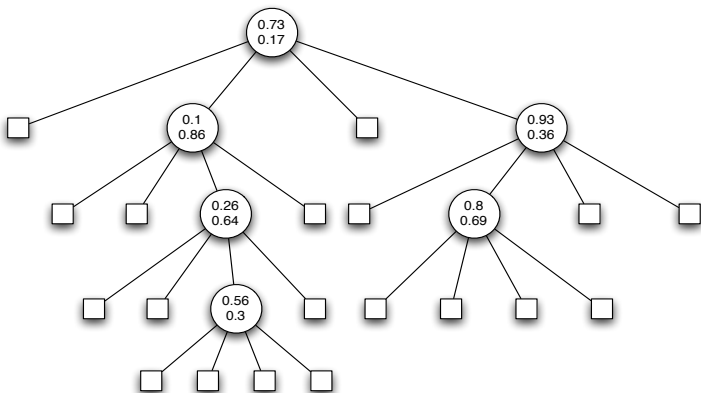
# Simulation - Quadtree

$n = 1000$



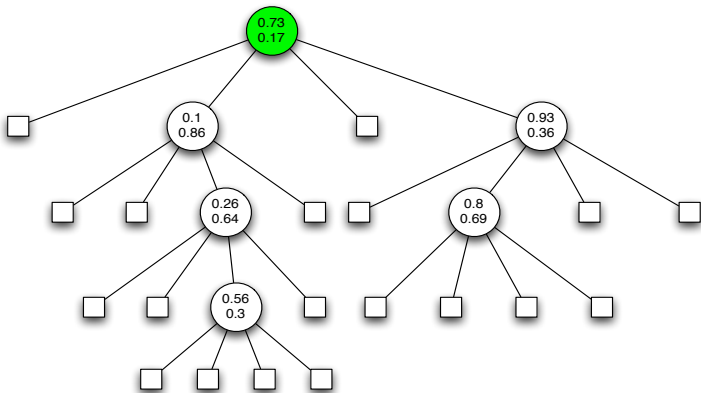
# A partial match query

Query:  $q = \{s, *\}$ ,  $s = 0.2$



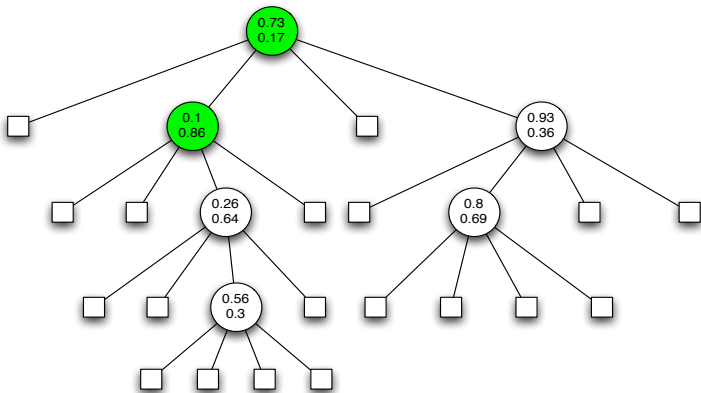
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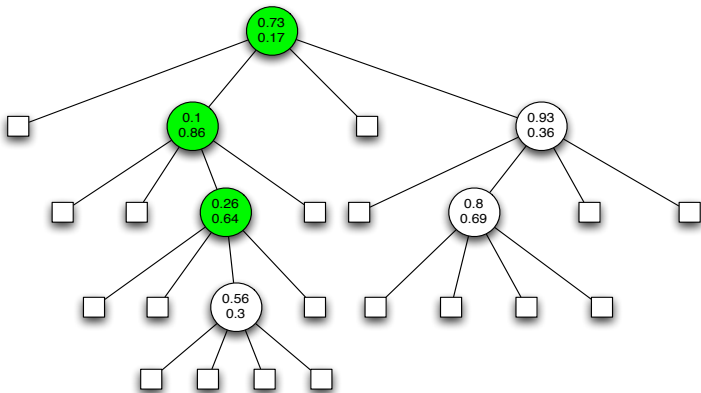
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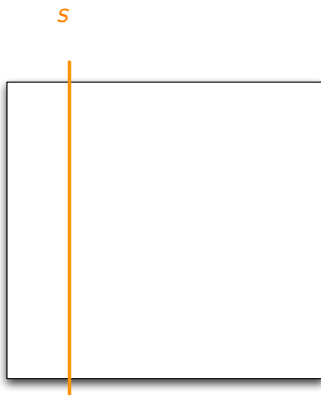
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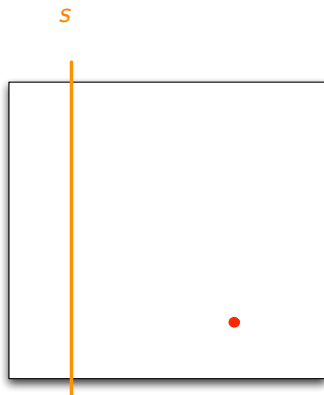
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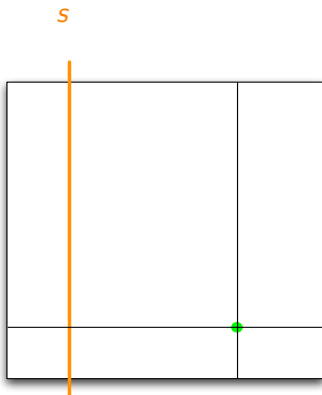
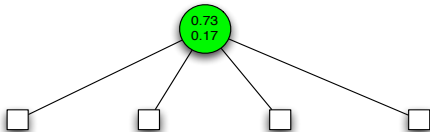
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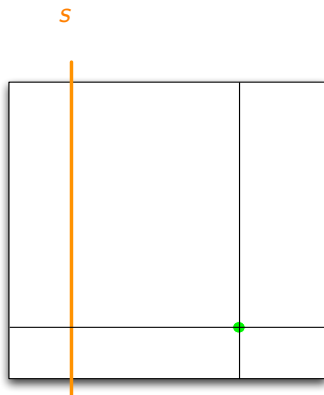
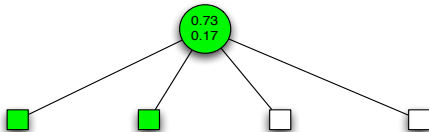
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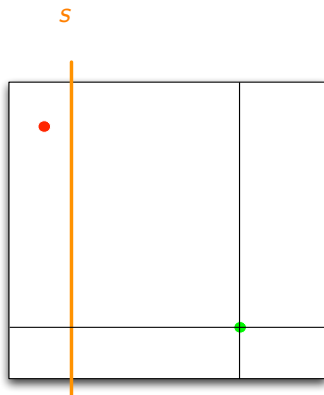
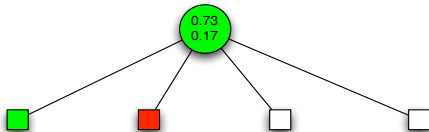
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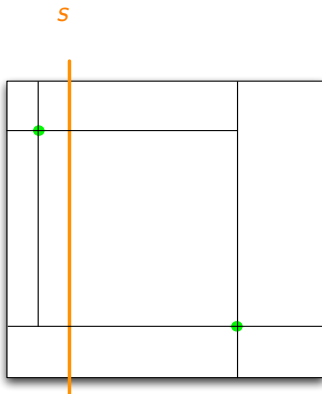
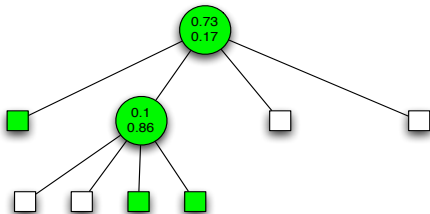
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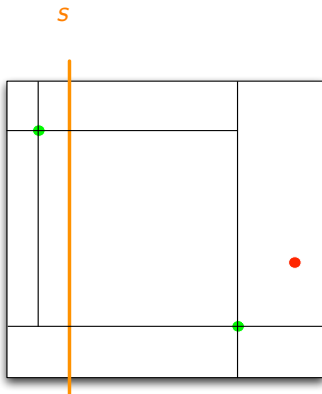
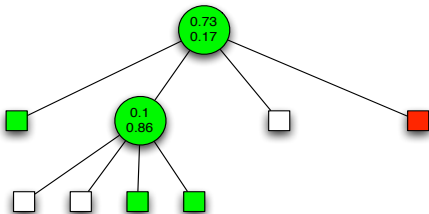
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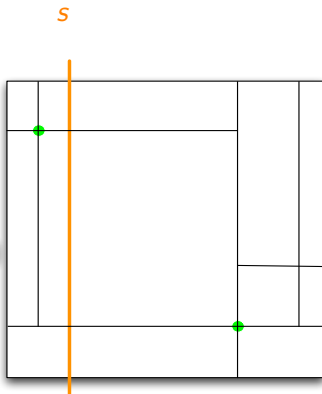
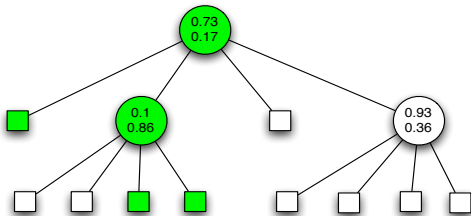
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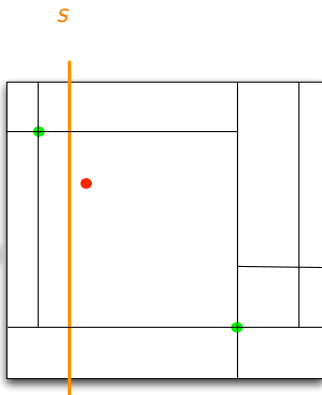
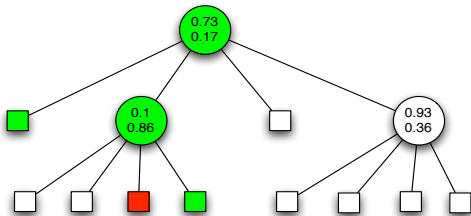
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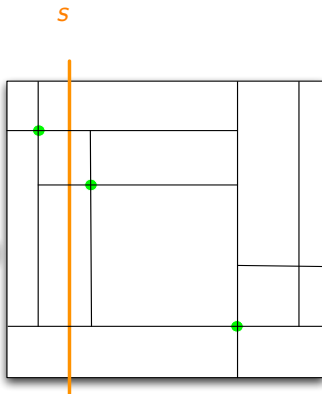
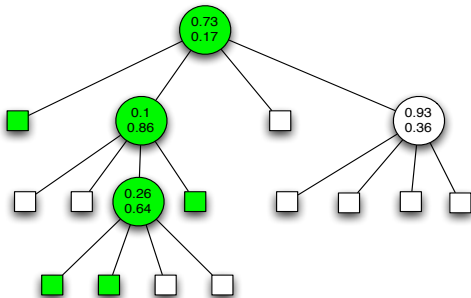
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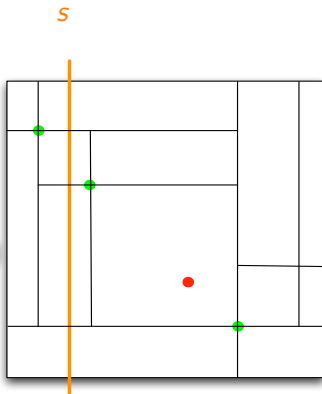
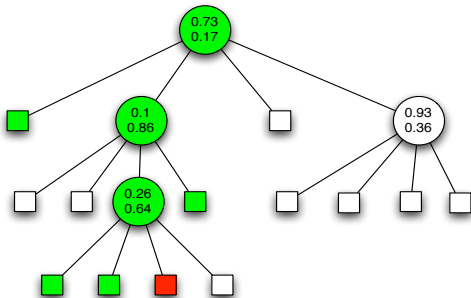
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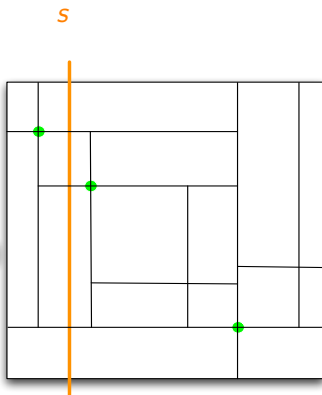
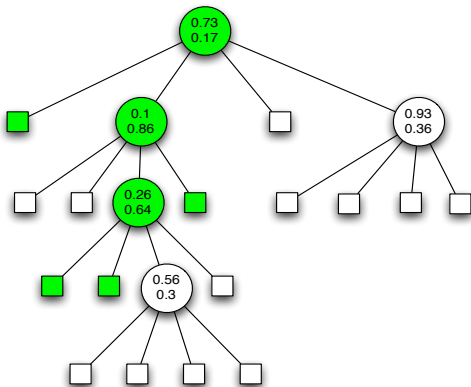
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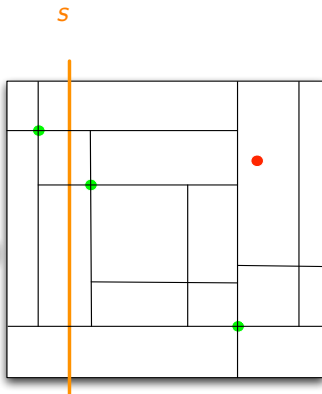
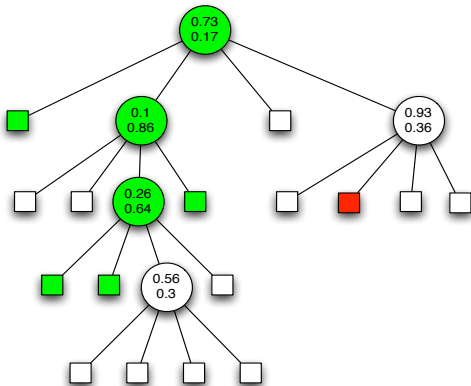
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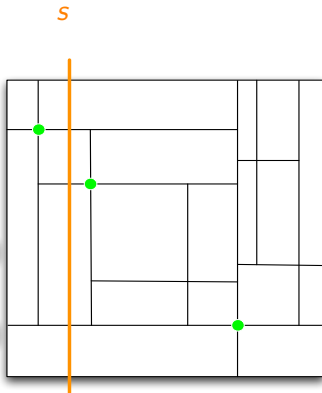
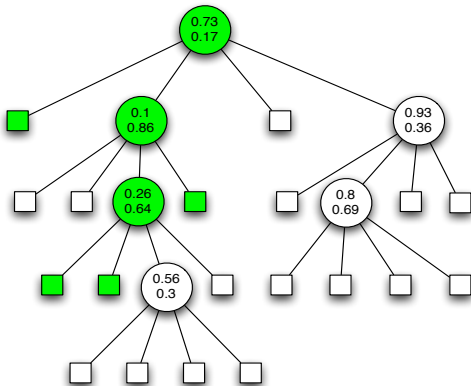
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# A problem of stochastic geometry

Performing a partial match query with  $q = \{s, *\}$ , a node is visited *if and only if* it is inserted in a subregion that intersects the vertical line  $x = s$ .

This is equivalent to an intersection of its horizontal line and the line  $x = s$ .

# Probabilistic model

For the analysis of the complexity of information retrieval we *always* assume the components of elements in the database  $S'$  to be *independent* and *uniform* on  $[0, 1]^2$ .

$C_n(s)$ : number of nodes visited by a partial match query with  $q = \{s, *\}$  in a random two-dimensional quadtree of size  $n$ .

# Probabilistic analysis of the complexity

Theorem (Flajolet, Gonnet, Puech, Robson '93)

*Let  $\xi$  be uniform on  $[0, 1]$ , independent of the quadtree. For  $n \rightarrow \infty$ , it holds*

$$\mathbb{E}[C_n(\xi)] \sim \kappa n^\beta$$

*with*

$$\kappa = \frac{\Gamma(2\beta + 2)}{2\Gamma^3(\beta + 1)} \approx 1.59, \quad \beta = \frac{\sqrt{17} - 3}{2} \approx 0.56.$$

The variance or a distributional limit theorem remained open problems.



# Asymptotic results for fixed $s$

Theorem (Curien, Joseph '11)

For fixed  $s \in [0, 1]$  and  $n \rightarrow \infty$ , it holds

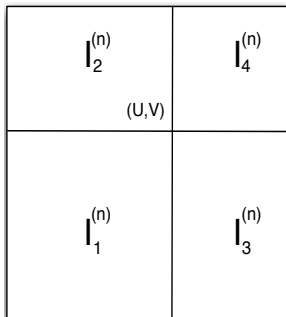
$$\mathbb{E}C_n(s) \sim K_1 n^\beta (s(1-s))^{\beta/2},$$

where

$$K_1 \int_0^1 (s(1-s))^{\beta/2} ds = \kappa.$$

# The main idea - Decomposing at the root

$U, V$  : components of the first inserted point,  
 $l_1^{(n)}, \dots, l_4^{(n)}$  : number of points in the subregions.



Given  $U, V$ , we have

$$\mathcal{L}(l_1^{(n)}, l_2^{(n)}, l_3^{(n)}, l_4^{(n)}) = \text{Mult}(n-1; UV, U(1-V), (1-U)V, (1-U)(1-V)).$$

# The main idea - Decomposing at the root

For any  $s \in [0, 1]$ ,

$$C_n(s) \stackrel{d}{=} 1 + 1_{\{s < U\}} \left( C_{I_1^{(n)}}^{(1)} \left( \frac{s}{U} \right) + C_{I_2^{(n)}}^{(2)} \left( \frac{s}{U} \right) \right) \\ + 1_{\{s \geq U\}} \left( C_{I_3^{(n)}}^{(3)} \left( \frac{s - U}{1 - U} \right) + C_{I_4^{(n)}}^{(4)} \left( \frac{s - U}{1 - U} \right) \right),$$

where  $(C_n^{(1)}), (C_n^{(2)}), (C_n^{(3)}), (C_n^{(4)})$  are ind. copies of  $(C_n)$ , ind. of  $(U, V, I_1^{(n)}, I_2^{(n)}, I_3^{(n)}, I_4^{(n)})$ .

This does **not** imply a recurrence for  $C_n(s)$ , neither for fixed  $s$  nor for  $s = \xi$ . It is due to this fact that the problem remained unsolved for many years.

# The recursion on the process level

The recursion

$$C_n(s) \stackrel{d}{=} 1 + 1_{\{s < U\}} \left( C_{I_1^{(n)}}^{(1)} \left( \frac{s}{U} \right) + C_{I_2^{(n)}}^{(2)} \left( \frac{s}{U} \right) \right) \\ + 1_{\{s \geq U\}} \left( C_{I_3^{(n)}}^{(3)} \left( \frac{s - U}{1 - U} \right) + C_{I_4^{(n)}}^{(4)} \left( \frac{s - U}{1 - U} \right) \right),$$

remains valid on the level of càdlàg functions,  $(C_n(s))_{s \in [0,1]}$  is a random stepfunction!

# The recursion on the process level

Scaling gives

$$\begin{aligned} \frac{C_n(s)}{n^\beta} &\stackrel{d}{=} n^{-\beta} + 1_{\{s < U\}} \left( \left( \frac{l_1^{(n)}}{n} \right)^\beta \frac{C_{l_1^{(n)}}^{(1)}\left(\frac{s}{U}\right)}{\left(l_1^{(n)}\right)^\beta} + \left( \frac{l_2^{(n)}}{n} \right)^\beta \frac{C_{l_2^{(n)}}^{(2)}\left(\frac{s}{U}\right)}{\left(l_2^{(n)}\right)^\beta} \right) \\ &\quad + 1_{\{s \geq U\}} \left( \left( \frac{l_3^{(n)}}{n} \right)^\beta \frac{C_{l_3^{(n)}}^{(3)}\left(\frac{s-U}{1-U}\right)}{\left(l_3^{(n)}\right)^\beta} + \left( \frac{l_4^{(n)}}{n} \right)^\beta \frac{C_{l_4^{(n)}}^{(4)}\left(\frac{s-U}{1-U}\right)}{\left(l_4^{(n)}\right)^\beta} \right). \end{aligned}$$

# Fixed-point equation

Assuming  $n^{-\beta} C_n(s) \rightarrow Z(s)$  uniformly in  $s \in [0, 1]$  for  $n \rightarrow \infty$ , suggests that  $Z$  satisfies

$$\begin{aligned} Z(s) \stackrel{d}{=} & 1_{\{s < U\}} \left( (UV)^{\beta} Z^{(1)} \left( \frac{s}{U} \right) + (U(1-V))^{\beta} Z^{(2)} \left( \frac{s}{U} \right) \right) \\ & + 1_{\{s \geq U\}} \left( (1-U)V^{\beta} Z^{(3)} \left( \frac{s-U}{1-U} \right) \right. \\ & \left. + 1_{\{s \geq U\}} \left( (1-U)(1-V)^{\beta} Z^{(4)} \left( \frac{s-U}{1-U} \right) \right), \right. \end{aligned}$$

where  $Z^{(1)}, Z^{(2)}, Z^{(3)}, Z^{(4)}$  are ind. copies of  $Z$ , ind. of  $(U, V)$ .

# A functional limit law

Theorem (Broutin, Neininger, S. '12)

*There exists a random continuous process  $Z$  on the unit interval such that*

$$\left( \frac{C_n(s)}{K_1 n^\beta} \right)_{s \in [0,1]} \rightarrow (Z(s))_{s \in [0,1]}, \quad n \rightarrow \infty,$$

*in distribution in  $(\mathcal{D}[0,1], d_{sk})$  where  $d_{sk}$  denotes the Skorohod metric.*

# Characterization of $Z$

Theorem (Broutin, Neininger, S. '12)

$Z$  is the unique solution in  $(\mathcal{D}[0, 1], d_{sk})$  of the fixed-point equation

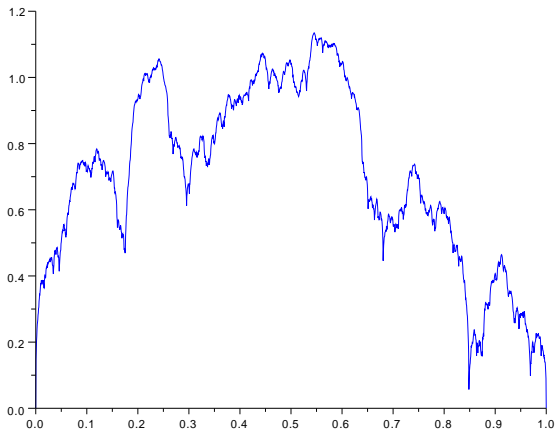
$$\begin{aligned} Z(s) \stackrel{d}{=} & 1_{\{s < U\}} \left( (UV)^{\beta} Z^{(1)}\left(\frac{s}{U}\right) + (U(1-V))^{\beta} Z^{(2)}\left(\frac{s}{U}\right) \right) \\ & + 1_{\{s \geq U\}} ((1-U)V)^{\beta} Z^{(3)}\left(\frac{s-U}{1-U}\right) \\ & + 1_{\{s \geq U\}} ((1-U)(1-V))^{\beta} Z^{(4)}\left(\frac{s-U}{1-U}\right), \end{aligned}$$

with  $\mathbb{E}\|Z\|^2 < \infty$  and  $\mathbb{E}Z(\xi) = B(\beta/2 + 1, \beta/2 + 1)$ .  
Here,  $Z^{(1)}, Z^{(2)}, Z^{(3)}, Z^{(4)}$  are independent copies of  $Z$ ,  
independent of  $(U, V)$ .



# A Simulation

by Nicolas Broutin



# The marginals of $Z$

Theorem (Broutin, Neininger, S. '12)

For all  $s \in [0, 1]$ , we have

$$Z(s) \stackrel{d}{=} Z \cdot (s(1-s))^{\beta/2},$$

where  $Z$  is the unique solution of

$$Z \stackrel{d}{=} V^{\beta} U^{\beta/2} Z + (1-V)^{\beta} U^{\beta/2} Z'$$

with  $\mathbb{E}Z = 1$  and  $\mathbb{E}Z^2 < \infty$ . Again,  $Z'$  is an independent copy of  $Z$  and  $(Z, Z')$  is independent of  $(U, V)$ .

## Back to the uniform case

Theorem (Broutin, Neininger, S. '12)

*We have*

$$\frac{C_n(\xi)}{\kappa n^\beta} \xrightarrow{d} Z \cdot \frac{(\xi(1-\xi))^{\beta/2}}{B(\beta/2 + 1, \beta/2 + 1)}$$

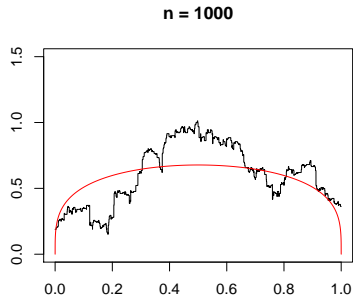
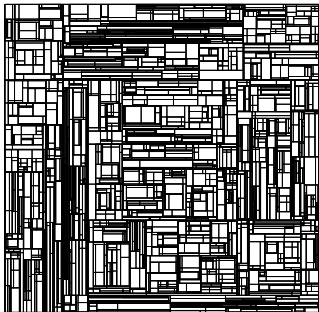
*with convergence of all moments , in particular*

$$\text{Var}[C_n(\xi)] \sim K_2 n^{2\beta},$$

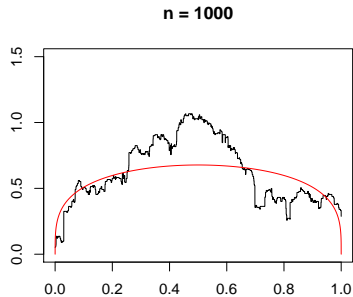
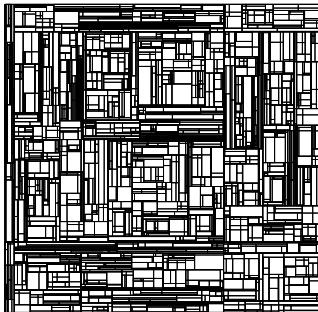
*where*

$$K_2 = K_1^2 \left[ \frac{2(2\beta + 1)}{3(1 - \beta)} B^2(\beta + 1, \beta + 1) - B^2\left(\frac{\beta}{2} + 1, \frac{\beta}{2} + 1\right) \right] = 0.44736 \dots$$

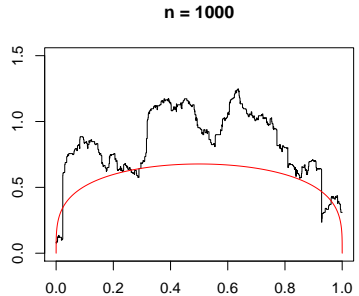
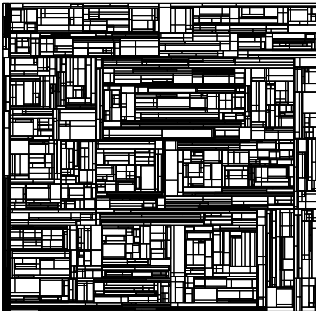
# Simulations



# Simulations



# Simulations



# The proof - Functional contraction method

Solutions to the fixed-point equation of interest, or more generally of type

$$Z \stackrel{d}{=} \sum_{i=1}^K A_i Z_i + b,$$

with conditions as in our case and random linear operators  $A_1, \dots, A_K$  are considered as fixed-points of the map

$$\begin{aligned} T : \mathcal{M}(\mathcal{D}[0, 1]) &\rightarrow \mathcal{M}(\mathcal{D}[0, 1]), \\ T(\mu) &= \mathcal{L} \left( \sum_{i=1}^K A_i Z_i + b \right), \end{aligned}$$

where  $Z_1, \dots, Z_r$  are independent with common distribution  $\mu$ , independent of  $(A_1, \dots, A_K, b)$ .

# The proof - Functional contraction method

- Choose a suitable subset of  $\mathcal{M}(\mathcal{D}[0, 1])$  and endow it with some appropriate metric  $d$  that turns  $T$  into a contraction. Here, the crucial condition turns out to be

$$\sum_{l=1}^K \mathbb{E} \|A_l\|_{\text{op}}^s < 1,$$

for  $s < 1$ .

- Construct a solution of the fixed-point equation by hand.
- Show  $d(C_n^*, Z) \rightarrow 0$  and infer distributional convergence for the rescaled quantity  $C_n^*$ .



# The why of $\beta$ - Size-biasing!

Let  $X_n = C_n(\xi)$ . On the level of expectations,

$$\mathbb{E}[X_n] = 1 + 2\mathbb{E}\left[1_{\{\xi < U\}}X_{I_1^{(n)}}^{(1)} + 1_{\{\xi \geq U\}}X_{I_3^{(n)}}^{(3)}\right].$$

This allows to compute  $\beta$ :

$$\mathbb{E}[X_n] = 1 + 2\mathbb{E}[X_{L_n}]$$

with  $L_n \stackrel{d}{=} \text{Bin}(n-1, \sqrt{UV})$ . Scaling gives

$$n^{-\gamma}\mathbb{E}[X_n] \sim 2\mathbb{E}\left[\left(\frac{L_n}{n}\right)^{\gamma} \frac{X_{L_n}}{L_n^{\gamma}}\right].$$

Hence  $1 = 2\mathbb{E}[(\sqrt{UV})^{\gamma}] \Rightarrow \gamma = \beta$ .

The constant  $\beta$  appears in several other contexts, e.g. as the Hausdorff dimension of the random Cantor set.

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