

# THE BINARY SEARCH TREE EQUATION

**Michael Drmota** \*

Inst. of Discrete Mathematics and Geometry

Vienna University of Technology, A 1040 Wien, Austria

[michael.drmota@tuwien.ac.at](mailto:michael.drmota@tuwien.ac.at)

[www.dmg.tuwien.ac.at/drmota/](http://www.dmg.tuwien.ac.at/drmota/)

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Workshop on Branching Random Walks and Searching in Trees

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# Outline of the Talk

- The “Binary Search Tree Equation”
- 3 Motivations
- Left/Right-most Particle in Branching Random Walks
- Height of Binary Search Trees
- Profile of Binary Search Trees
- Intersection Property

# The “Binary Search Tree Equation”

$$\Phi'(u) = -\frac{1}{\alpha^2} \Phi\left(\frac{u}{\alpha}\right)^2$$

$$\alpha > 0, u > 0$$

Laplace transform:  $\Phi(u) = \int_0^\infty \Psi(y) e^{-uy} dy$ :

$$y \Psi(y/\alpha) = \int_0^y \Psi(w) \Psi(y-w) dw$$

$$\Psi(y/\alpha) = \int_0^1 \Psi(yt) \Psi(y(1-t)) dt = \mathbb{E}[\Psi(yU) \Psi(y(1-U))]$$

Additive version:  $w(x) = \Psi(e^x)$ ,  $\gamma = \log \alpha$ ,  $X_1 = \log \frac{1}{U}$ ,  $X_2 = \log \frac{1}{1-U}$ :

$$w(x - \gamma) = \mathbb{E}[w(x - X_1) w(x - X_2)]$$

# The “Binary Search Tree Equation”

## Trivial Solutions

- $\Phi(u) = \frac{1}{u}$  (for all  $\alpha > 0$ ),  $\Psi(y) = 1$

- $\Phi(u) = \frac{1}{1+u}$  (for  $\alpha = 1$ ),  $\Psi(y) = e^{-y}$

## Non-trivial solution

- $\Phi(u) = \frac{1 + u^{1/4}}{u} e^{-u^{1/4}}$  (for  $\alpha = 16$ ),  $\Psi(y) = e^{-y/4}$

# The “Binary Search Tree Equation”

First attempt for a solution

$$\Phi(u) = \sum_{n \geq 1} c_n u^n$$

$$c_{n+1} = -\frac{\alpha^{-n-2}}{n+1} \sum_{k=0}^n c_k c_{n-k}, \quad c_0 = \Phi(0) = 1$$

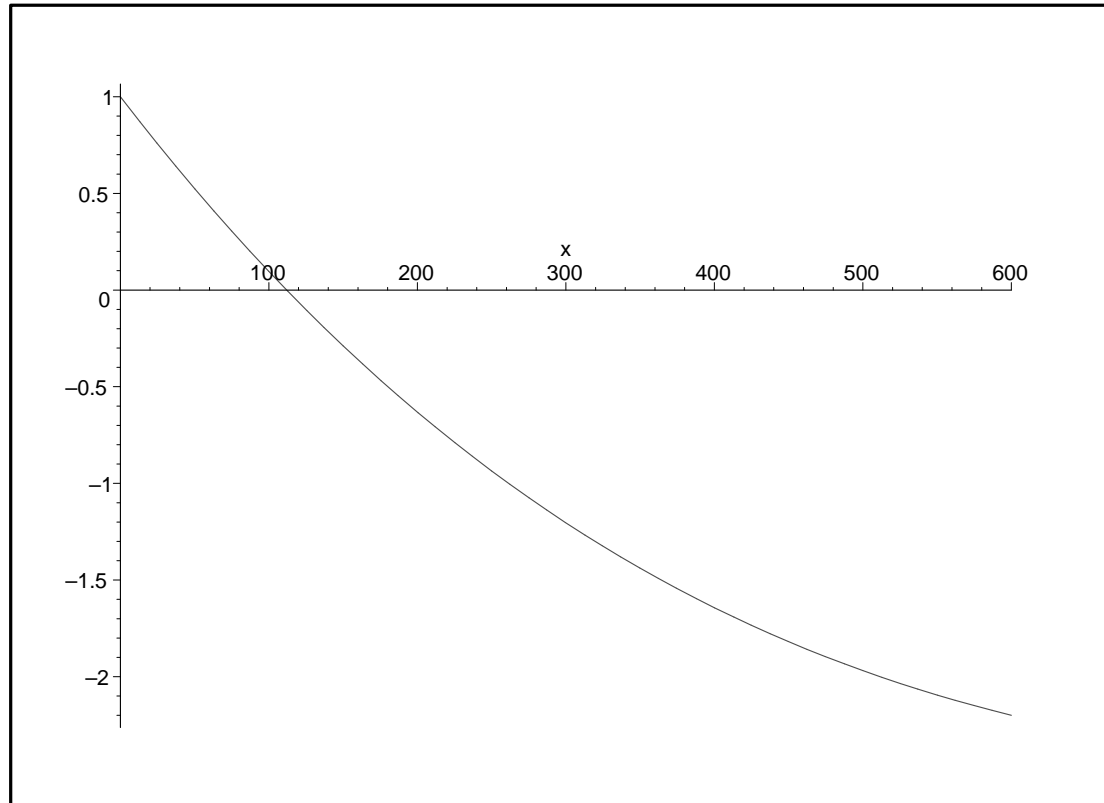
This provides a (unique) and **entire** solution for  $\boxed{\alpha > 1}$ .

**Remark.** ( $c = 4.31107 \dots$  and  $c' = 0.3733 \dots$  satisfy  $c \log\left(\frac{2e}{c}\right) = 1$ )

- $\alpha \in (0, e^{1/c}] = (0, 1.26 \dots]$ :  $\Phi(u) \sim \frac{1}{u}$  ( $u \rightarrow \infty$ )
- $\alpha \in [e^{1/c'}, \infty) = [14.56 \dots, \infty)$ :  $\Phi(u) \sim \frac{1}{u}$  ( $u \rightarrow 0$ )

# The “Binary Search Tree Equation”

**Out of Range:** e.g.  $\alpha = 10$ :  $\Phi(u) \not\sim 1/u$   
(no Laplace transform of a (tail) distribution function  $\Psi(y)$ )



# Motivation 1: Branching Random Walk

Random point measure

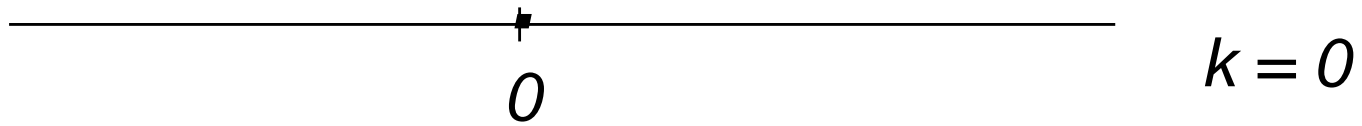
$$Z = \delta_{X_1} + \delta_{X_2}$$

For example:  $X_1 = \log(1/U)$ ,  $X_2 = \log(1/(1 - U))$ .

**Branching Random Walk:** Sequence  $Z_k$  of random point measures:

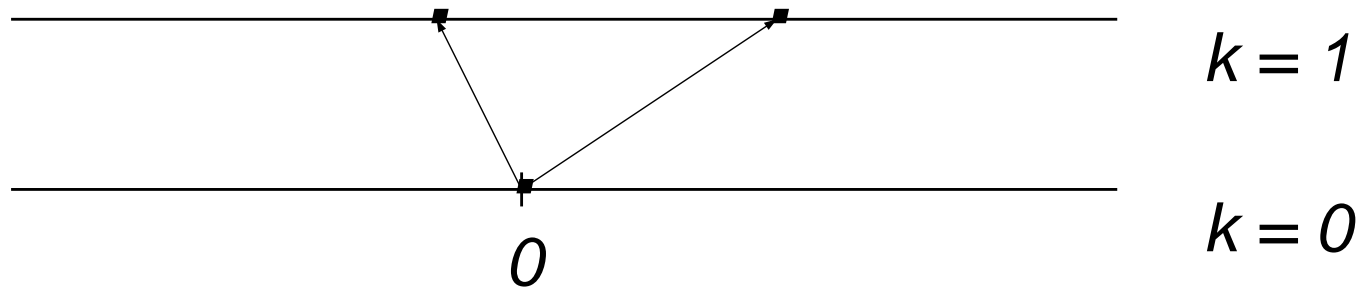
- $Z_0 = \delta_0$ .
- $Z_{k+1}$  is induced by  $Z_k$  by adding independent copies of  $Z$  to all points of  $Z_k$ .

# Motivation 1: Branching Random Walk

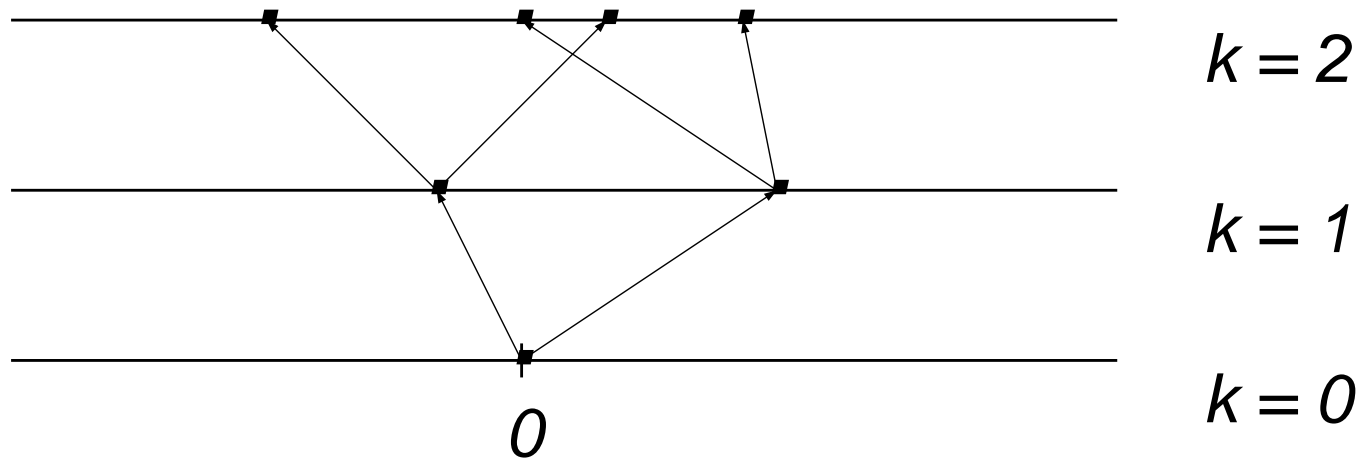




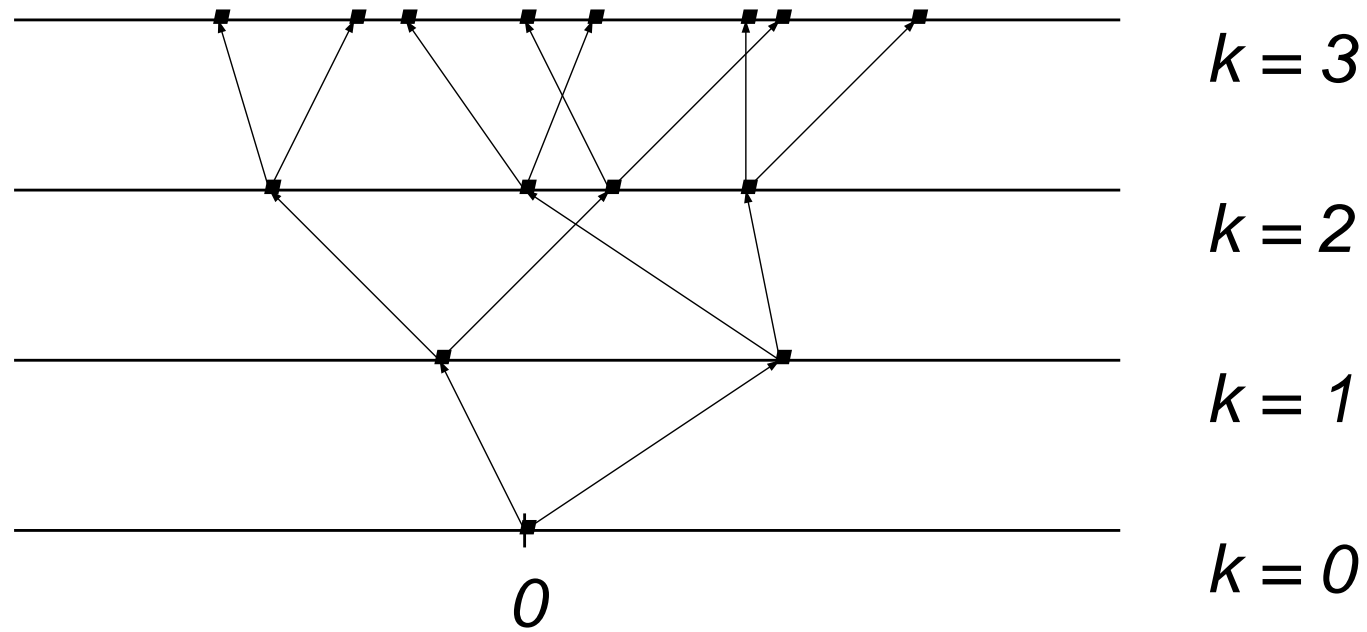
# Motivation 1: Branching Random Walk



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# Motivation 1: Branching Random Walk



# Motivation 1: Branching Random Walk

$L_k$  ... Position of the **leftmost** point (after  $k$  steps)

$$w_k(x) = \mathbb{P}\{L_k > x\}$$

$R_k$  ... Position of the **rightmost** point (after  $k$  steps)

$$\bar{w}_k(x) = \mathbb{P}\{L_k \leq x\}$$

$$w_{k+1}(x) = \mathbb{E} [w_k(x - X_1) w_k(x - X_2)]$$

$$\bar{w}_{k+1}(x) = \mathbb{E} [\bar{w}_k(x - X_1) \bar{w}_k(x - X_2)]$$

**Travelling wave:**  $w_k(x) = w(x - k\gamma)$ :

$$\boxed{w(x - \gamma) = \mathbb{E} [w(x - X_1) w(x - X_2)]}$$

# Motivation 1: Branching Random Walk

Special case:  $X_1 = \log(1/U)$ ,  $X_2 = \log(1/(1 - U))$

- Iteration

$$Y_k(u) := \int_0^\infty w_k(\log y) e^{-uy} dy$$

$$\boxed{Y'_{k+1}(u) = Y_k(u)^2}$$

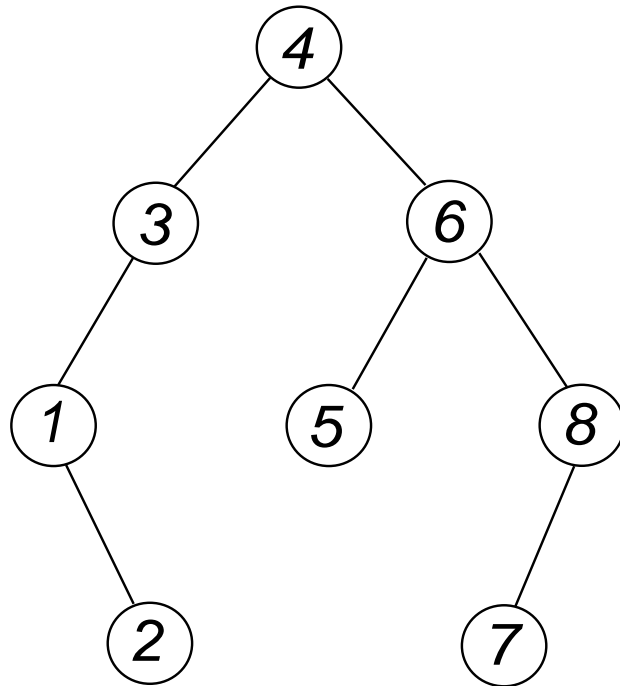
- Travelling wave:  $w_k(x) = w(x - k\gamma)$ ,  $\alpha = e^\gamma$

$$\Phi(u) = \int_0^\infty w(\log y) e^{-uy} dy$$

$$\boxed{\Phi'(u) = -\alpha^{-2} \Phi(u/\alpha)^2}$$

# Motivation 2: Binary Search Trees

Vertex labelled binary tree:



# Motivation 2: Binary Search Trees

Storing Data:

4,6,3,5,1,8,2,7

# Motivation 2: Binary Search Trees

Storing Data:

6,3,5,1,8,2,7

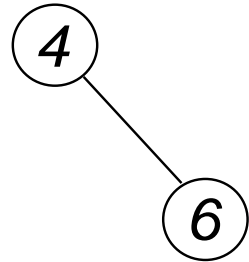
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# Motivation 2: Binary Search Trees

Storing Data:

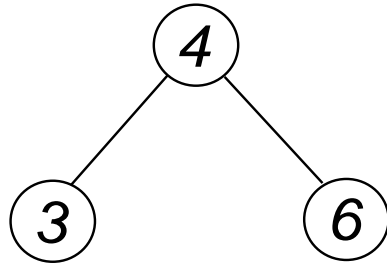
3,5,1,8,2,7



# Motivation 2: Binary Search Trees

Storing Data:

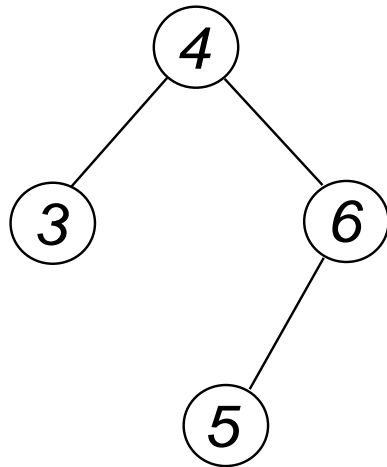
5,1,8,2,7



# Motivation 2: Binary Search Trees

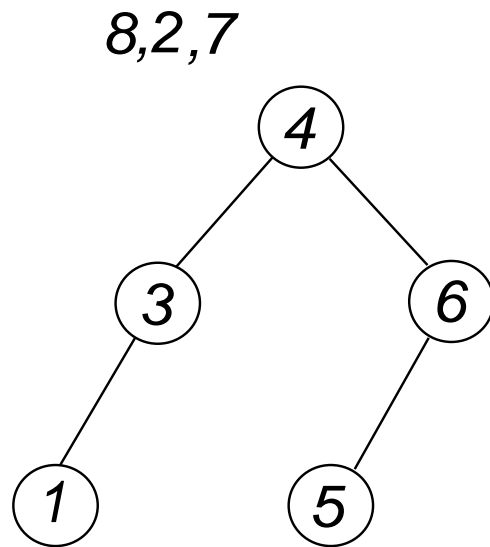
Storing Data:

1,8,2,7



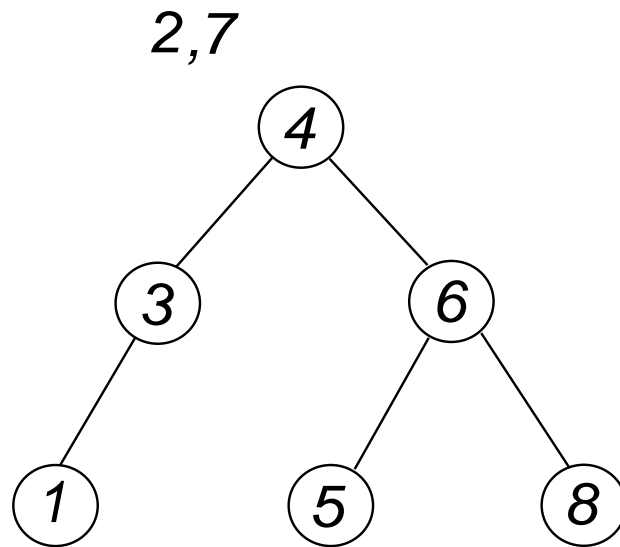
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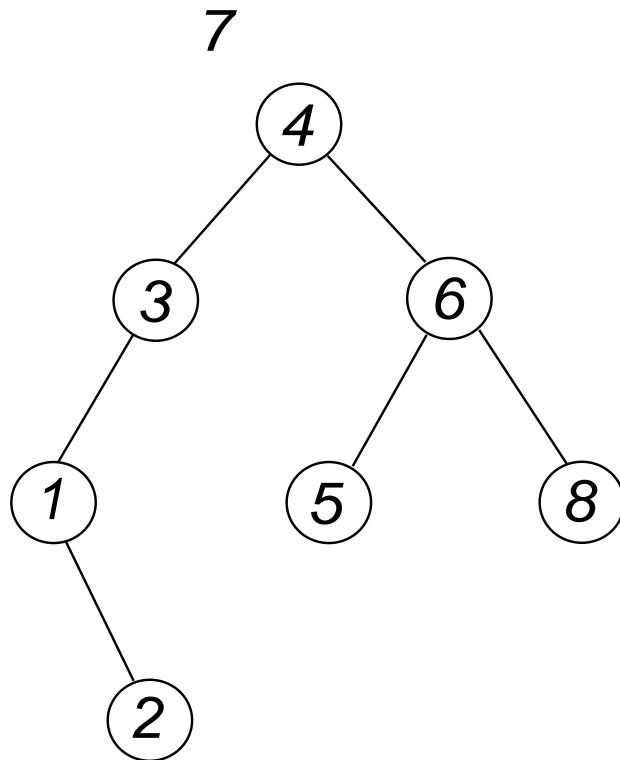
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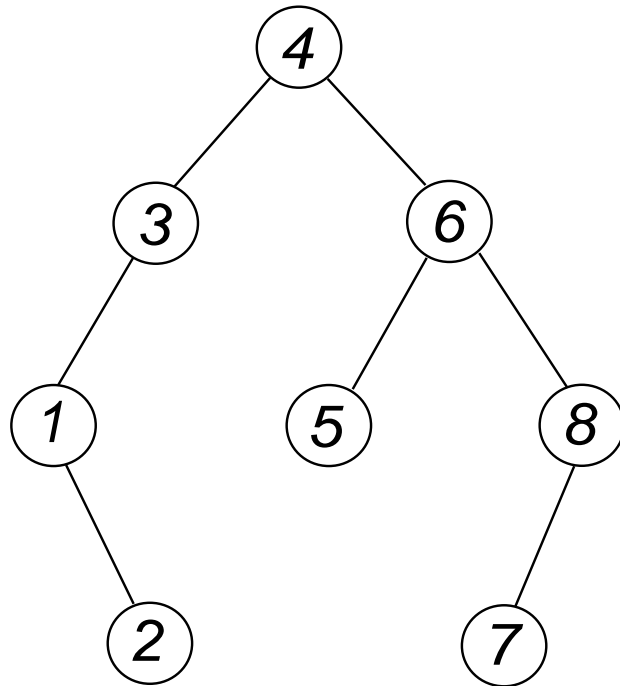
# Motivation 2: Binary Search Trees

Storing Data:



# Motivation 2: Binary Search Trees

Storing Data:



# Motivation 2: Binary Search Trees

## Probabilistic Model:

Every permutation of  $\{1, 2, \dots, n\}$  is equally likely.

→ probability distribution on binary trees of size  $n$

→ every parameter on trees is a **random variable**

## Notation

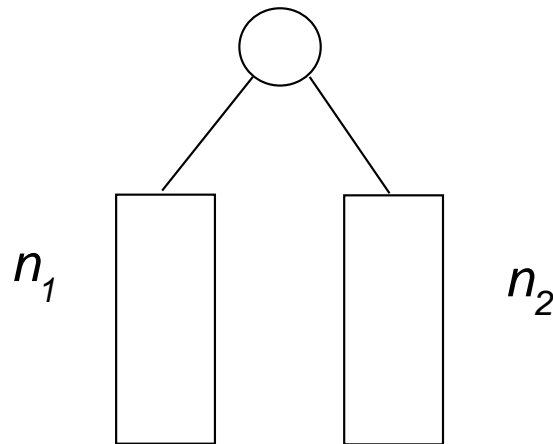
$H_n$  ... **height** of trees (of size  $n$ )



## Motivation 2: Binary Search Trees

**Observation:** Subtrees of the root are also binary search trees, the splitting probabilities are  $\frac{1}{n}$ .

$$\mathbb{P}\{H_{n+1} \leq k + 1\} = \frac{1}{n} \sum_{n_1+n_2=n} \mathbb{P}\{H_{n_1} \leq k\} \cdot \mathbb{P}\{H_{n_2} \leq k\}$$



# Motivation 2: Binary Search Trees

Generating Functions:

$$y_k(x) = \sum_{n \geq 0} \mathbb{P}\{H_n \leq k\} \cdot x^n$$

$$y'_{k+1}(x) = y_k(x)^2$$

with initial conditions  $y_1(x) = 1$ ,  $y_k(0) = 1$ .

# Motivation 2: Binary Search Trees

Generating Functions:

Special solution of the recurrence  $y'_{k+1}(x) = y_k(x)^2$ :

$$y_k(x) = \alpha^k \Phi(\alpha^k(1-x))$$

where  $\Phi'(u) = -\alpha^{-2}\Phi(u/\alpha)^2$ .

Analogue of the **travelling wave solution** in BRW's.

# Motivation 2: Binary Search Trees

## Profile of Binary Search Trees

$X_{n,k}$  ... number of nodes at level  $k$  (in a BST with  $n$  vertices)

$$X_k(x, u) = \sum_{n \geq 0} \mathbb{P}\{X_{n,k} = \ell\} x^n u^\ell:$$

$$\frac{\partial}{\partial x} X_{k+1}(x, u) = X_k(x, u)^2.$$

# Motivation 3: Stochastic Fixed Point Equations

$$Y \equiv V_1 Y^{(1)} + V_2 Y^{(2)}$$

$Y^{(1)}, Y^{(2)}$  copies of  $Y$ ,  $((V_1, V_2), Y^{(1)}, Y^{(2)})$  independent.

$$G(x) = \mathbb{E} e^{-xY}$$

$$G(x) = \mathbb{E} [G(xV_1) G(xV_2)]$$

# Motivation 3: Stochastic Fixed Point Equations

Special case:  $z > 0, z \neq \frac{1}{2}$

$$Y \equiv zU^{2z-1}Y^{(1)} + z(1-U)^{2z-1}Y^{(2)}$$

$$G(x) = \mathbb{E} e^{-xY}$$

$$G(x) = \mathbb{E} \left[ G(xzU^{2z-1}) G(xz(1-U)^{2z-1}) \right]$$

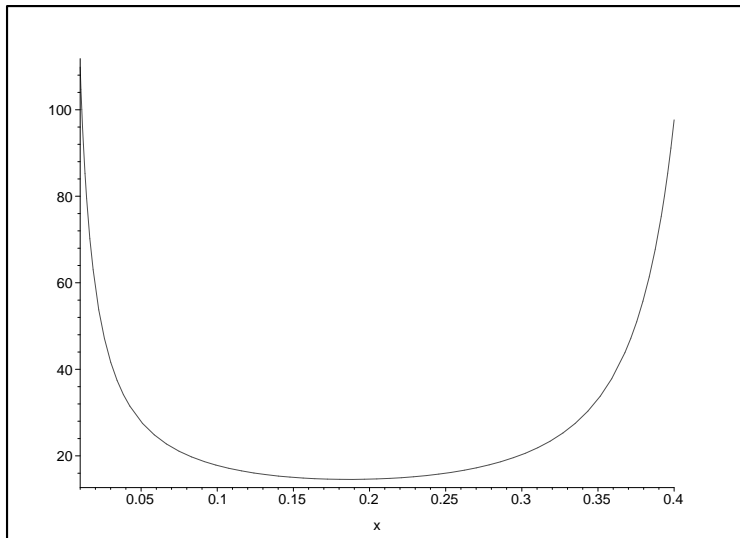
$$\Psi(y) = G(y^{2z-1}) = \mathbb{E} \left( e^{-y^{2z-1}Y} \right)$$

$$\Psi \left( y/z^{2z-1} \right) = \mathbb{E} [\Psi(yU) \Psi(y(1-U))]$$

$$\alpha = \alpha(z) = z^{\frac{1}{2z-1}}$$

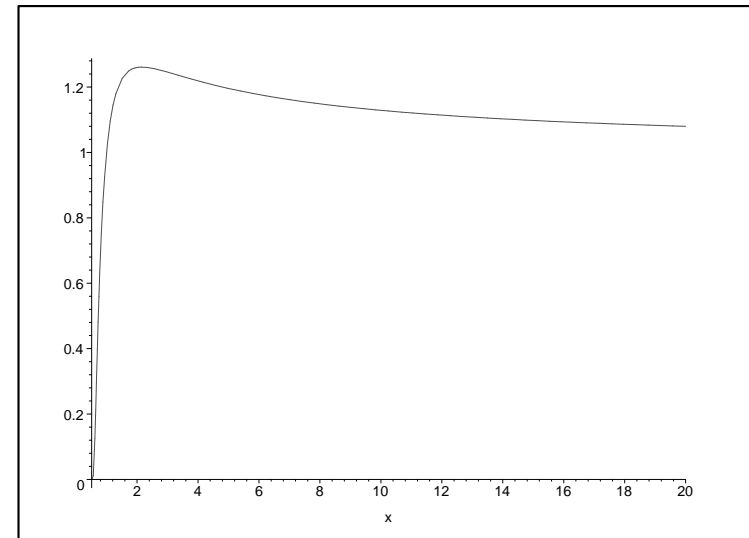
# Motivation 3: Stochastic Fixed Point Equations

Behaviour of  $\alpha(z) = z^{2z-1}$ :



$$0 < z < \frac{1}{2}$$

$$\alpha(z) \geq e^{1/c'} = 14.56 \dots$$



$$\frac{1}{2} < z < \infty$$

$$0 \leq \alpha(z) \leq e^{1/c} = 1.26 \dots$$

# Motivation 3: Stochastic Fixed Point Equations

Existence of solutions: [Biggins + Kyprianou, Liu]

$$G(x) = \mathbb{E} \left[ \prod_j G(xV_j) \right]$$

$$v(\gamma) = \log \left( \mathbb{E} \left[ \sum_j V_j^\gamma \right] \right), \quad v(0) > 0, \quad v(1 \pm \varepsilon) < \infty$$

- $v(1) = 0, v'(1) = 0$ :  $\frac{1 - G(x)}{-x \log x} \rightarrow c_1 \quad (x \rightarrow 0)$

- $v(1) = 0, v'(1) < 0$ :  $\frac{1 - G(x)}{x} \rightarrow c_2 \quad (x \rightarrow 0)$



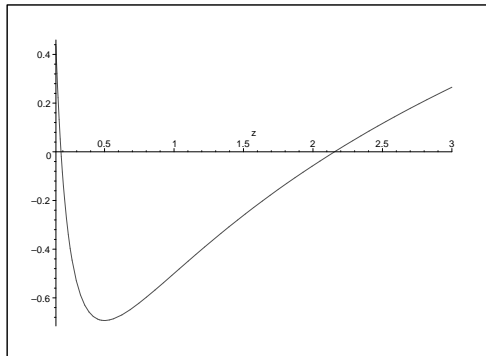
# Motivation 3: Stochastic Fixed Point Equations

Special case:  $V_1 = zU^{2z-1}$ ,  $V_2 = z(1-U)^{2z-1}$

$$v(\gamma) = \log \frac{2z^\gamma}{(2z-1)\gamma + 1}$$

$$v(1) = 0, \quad v'(1) = \log z + \frac{1}{2z} - 1$$

$$v'(1) \leq 0 \quad \iff \quad \boxed{\frac{c'}{2} \leq z \leq \frac{c}{2}}$$



# Motivation 3: Stochastic Fixed Point Equations

$$\Psi(y/\alpha) = \mathbb{E}[\Psi(yU) \Psi(y(1 - U))]$$

**Case 1.**  $0 < \alpha \leq e^{1/c} = 1.26 \dots$ ,  $2\alpha^\beta = \beta + 1$

$$1 - \Psi(y) \sim c_1 y^\beta \quad (y \rightarrow 0) \quad \text{for } 0 < \alpha < e^{1/c}$$

$$1 - \Psi(y) \sim c_1 y^{c-1} \log y \quad (y \rightarrow 0) \quad \text{for } \alpha = e^{1/c}$$

$\Psi(u)$  is monotonely decreasing (tail distribution function).

**Case 2.**  $e^{1/c'} \leq \alpha < \infty$ ,  $2\alpha^\beta = \beta + 1$

$$1 - \Psi(y) \sim c_1 y^\beta \quad (y \rightarrow \infty) \quad \text{for } e^{1/c'} < \alpha < \infty$$

$$1 - \Psi(y) \sim c_1 y^{c'-1} \log y \quad (y \rightarrow \infty) \quad \text{for } \alpha = e^{1/c'}$$

$\Psi(u)$  is monotonely increasing (distribution function).

# Motivation 3: Stochastic Fixed Point Equations

## Notation

- $\alpha = e^{1/c} = 1.26 \dots$  (or  $z = c/2$ ):

$$\Psi_c(y), \quad w_c(x) = \Psi_c(e^x)$$

- $\alpha = e^{1/c'} = 14.56 \dots$  (or  $z = c'/2$ ):

$$\Psi_{c'}(y), \quad w_{c'}(x) = \Psi_{c'}(e^x)$$

# Left/Right-most Point in BRW's

**Theorem** [Chauvin + D.]

$Z_k$  ... BRW with  $Z_0 = \delta_0$  and increments  $X_1 = \log(1/U)$ ,  $X_2 = \log(1/(1-U))$ .

$L_k, R_k$  ... position of the left/right-most particle (after  $k$  steps)  
 $m_1(k), m_2(k)$  ... median of the distributions of  $L_k, R_k$ , resp.

$$\mathbb{P}\{L_k > x\} = w_c(x - m_1(k)) + o(1)$$

$$\mathbb{P}\{R_k \leq x\} = w_{c'}(x - m_2(k)) + o(1)$$

$$m_1(k) = \frac{1}{c}k + \Theta(\log k) \quad m_2(k) = \frac{1}{c'}k + \Theta(\log k) \quad (k \rightarrow \infty),$$

$$\mathbb{P}\{|L_k - m_1(k)| > x\} \leq Ce^{-\eta x}, \quad \mathbb{P}\{|R_k - m_2(k)| > x\} \leq Ce^{-\eta x}.$$

# Left/Right-most Point in BRW's

## Extensions

$m \geq 2$ ,  $(V_1, \dots, V_m)$  r.v.'s with  $V_1 + \dots + V_m = 1$  and density

$$f(x_1, \dots, x_m) = \frac{(m(t+1) - 1)!}{(t!)^m} (x_1 x_2 \cdots x_m)^t$$

on the simplex  $x_1 + \dots + x_m = 1$ ,  $0 \leq x_j \leq 1$   
( $t \geq 0$  is a integer parameter.)

$Z_k$  BRW with increments  $X_j = \log(1/V_j)$  ( $1 \leq j \leq m$ ).

Then there exist functions  $w_1(x)$  and  $w_2(x)$  such that

$$\mathbb{P}\{L_k > x\} = w_1(x - m_1(k)) + o(1)$$

$$\mathbb{P}\{R_k \leq x\} = w_2(x - m_2(k)) + o(1)$$

with medians

$$m_1(k) = k \log \rho_1 + \Theta(\log k), \quad m_2(k) = k \log \rho_2 + \Theta(\log k) \quad (k \rightarrow \infty).$$

# Height of Binary Search Trees

$$y'_{k+1}(x) = y_k(x)^2, \quad y_1(x) = 1, \quad y_k(0) = 1.$$

## Theorem

$H_n$  ... height of binary search trees with  $n$  nodes.

$$\mathbb{P}\{H_n \leq k\} = \Psi_c(n/y_k(1)) + o(1)$$

$$\log y_k(1) = \frac{k}{c} + \frac{3c}{2(c-1)} \log k + O(1)$$

$$\mathbb{E} H_n = \max\{k \geq 0 : y_k(1) \leq n\} + O(1) = c \log n - \frac{3c}{2(c-1)} \log \log n + O(1)$$

$$\mathbb{P}\{|H_n - \mathbb{E} H_n| > y\} = O(e^{-\eta y})$$

**Remark.** The function  $\Psi_c(y)$  describes the distribution of the saturation level (up to this level the tree is a complete binary trees).

# Height of Binary Search Trees

## Extensions

- $m$ -ary search trees (also fringe-balanced versions)
- recursive trees
- plane oriented recursive trees
- $m$ -ary recursive trees
- ...

# Height of Binary Search Trees

## History

- $\text{Var } H_n = O(1)$  ??? [Robson 1979] (**Robson's conjecture**)
- $\mathbb{E} H_n \sim c \log n$  [Devroye 1986]
- $\mathbb{E} H_n = c \log n + O(\log \log n)$  [Devroye+Reed 1995]
- $\mathbb{E} H_n = c \log n - \frac{3c}{2(c-1)} \log \log n + O(1)$  [Reed 2003]
- $\text{Var } H_n = O(1)$  [Reed 2003] [D. 2003]



# Height of Binary Search Trees

More on the variance  $\text{Var } H_n$ :

$$V(x) := \sum_{k \geq 0} (2k + 1) \left( 1 - \Psi_c \left( \frac{x}{y_k(1)} \right) \right) - \left( \sum_{k \geq 0} \left( 1 - \Psi_c \left( \frac{x}{y_k(1)} \right) \right) \right)^2$$

$$V(e^{1/c}x) = V(x) + o(1) \quad (x \rightarrow \infty).$$

$$\boxed{\text{Var } H_n = V(n) + o(1) \quad (n \rightarrow \infty)}$$

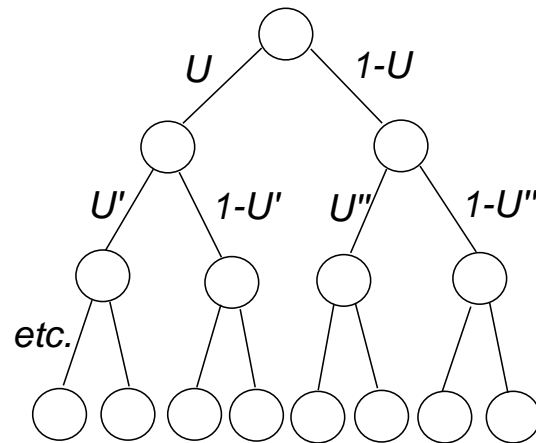
$$\boxed{\max_{n \geq n_1} |\text{Var } H_n - v_0| \leq 10^{-3}}$$

$$v_0 = c \int_0^\infty (E(u) + E(ue^{-1/c})) \Psi_c(u) \frac{du}{u} = 2.085687 \dots$$

$$E(u) := \sum_{k \geq 0} \left( 1 - \Psi_c(ue^{-k/c}) \right).$$

# Height of Binary Search Trees

Direct relation between BST's and BRW's [Devroye]



$x$  ... vertex of (infinite) binary tree (at level  $k$ )

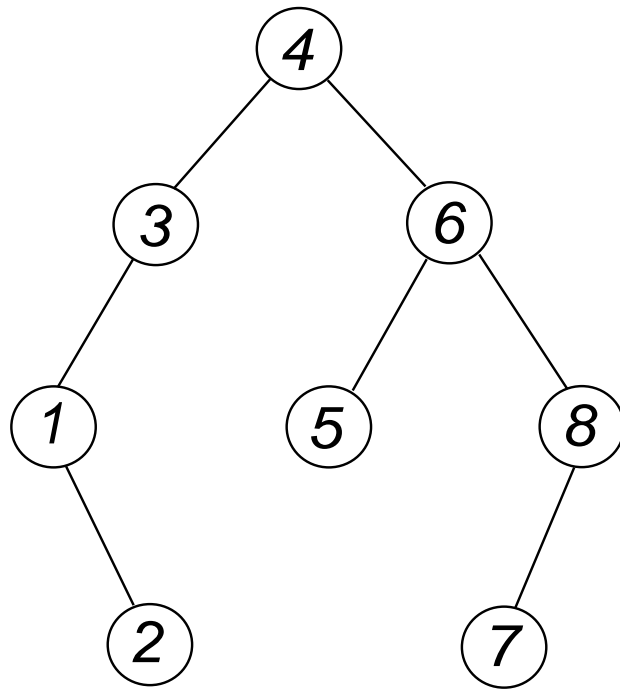
$U_1, U_2, \dots, U_k$  ... r.v.'s on the path from the root to  $x$

$$h_n(x) = \lfloor U_k \lfloor \dots \lfloor U_2 \lfloor U_1 n \rfloor \dots \rfloor \rfloor$$

$$BST_n = \{x : h_n(x) \geq 1\}$$

# Profile of Binary Search Trees

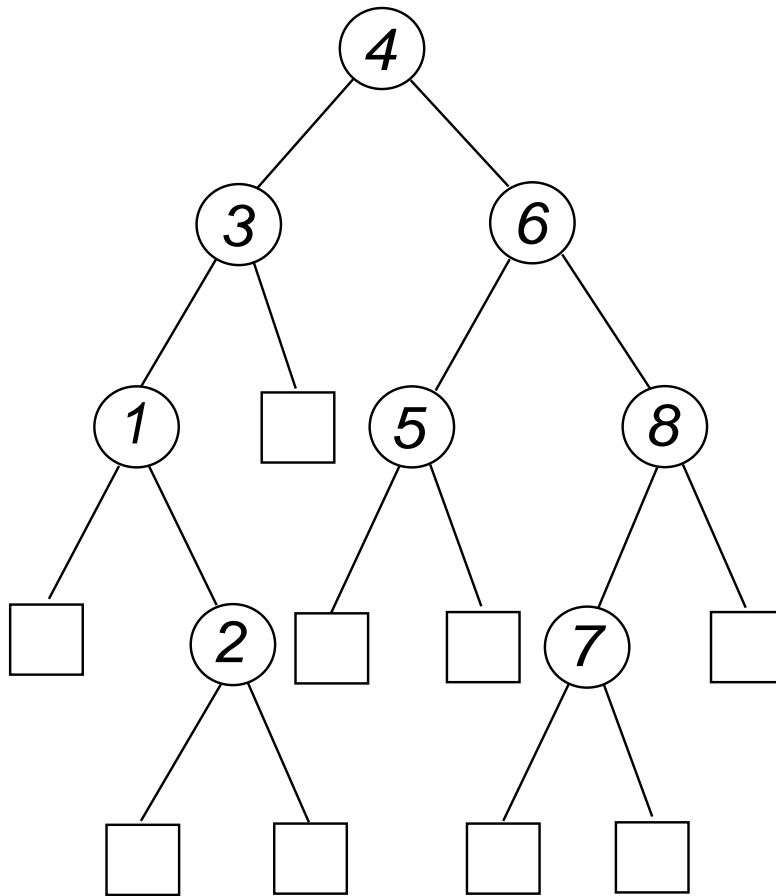
Internal and external profile:



Including “free” places

# Profile of Binary Search Trees

Internal and external profile:



□ ... “free” place

# Profile of Binary Search Trees

Internal and external profile:

$X_{n,k}$  ... number of **internal** vertices at level  $k$

$Y_{n,k}$  ... number of **external** vertices at level  $k$

$$X_{n,k} = \sum_{j>k} 2^{k-j} Y_{n,j}$$

# Profile of Binary Search Trees

## A stochastic process of analytic functions

$(M(z), z \in B)$  stochastic process of analytic functions that is defined by  $\mathbb{E} M(z) = 1$  and the **stochastic fixed point equation**:

$$M(z) \equiv zU^{2z-1}M^{(1)}(z) + z(1-U)^{2z-1}M^{(2)}(z)$$

$B$  ... domain in  $\mathbb{C}$  with  $B \cap \mathbb{R} = (\frac{c'}{2}, \frac{c}{2}) =: I$

# Profile of Binary Search Trees

**Theorem** [Chauvin+D.+Jabbour, Chauvin+Klein+Marckert+Rouault]

$Y_{n,k}$  ... number of **external** vertices at level  $k$

$$\left( \frac{Y_{n, \lfloor 2z \log n \rfloor}}{\mathbf{E} Y_{n, \lfloor 2z \log n \rfloor}}, z \in I \right) \rightarrow (M(z), z \in I).$$

(almost surely!!)

$X_{n,k}$  ... number of **internal** vertices at level  $k$

$$\left( \frac{X_{n, \lfloor 2z \log n \rfloor}}{\mathbf{E} X_{n, \lfloor 2z \log n \rfloor}}, z \in I' \right) \rightarrow (M(z), z \in I').$$

$$I' = \left( \frac{1}{2}, \frac{c}{2} \right)$$

# Profile of Binary Search Trees

## Extensions:

- $m$ -ary search trees (also fringe balanced) [D.+Janson+Neininger]
- recursive trees, plane oriented recursive trees [Schopp]



# Profile of Binary Search Trees

## Profile polynomials

$$W_n(z) = \sum_{k \geq 0} Y_{n,k} z^k$$

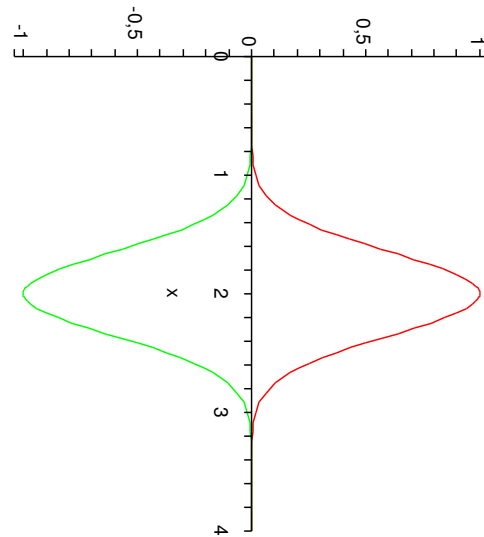
$$M_n(z) = \frac{W_n(z)}{\mathbb{E} W_n(z)} \text{ is a martingale}$$

$$\boxed{M_n(z) \rightarrow M(z)}$$

# Profile of Binary Search Trees

Expected profile

$$\mathbf{E} Y_{n,k} \sim \frac{(2 \log n)^k}{k! n \Gamma(k / \log n)}$$



# Profile of Binary Search Trees

Fixed point equation

$$Y_{n,k+1} \equiv Y_{\lfloor Un \rfloor, k}^{(1)} + Y_{n-1-\lfloor Un \rfloor, k}^{(2)}$$

If the limit

$$\frac{Y_{n, \lfloor 2z \log n \rfloor}}{\mathbb{E} Y_{n, \lfloor 2z \log n \rfloor}} \rightarrow M(z)$$

exists then

$$M(z) \equiv zU^{2z-1}M^{(1)}(z) + z(1-U)^{2z-1}M^{(2)}(z).$$

# Intersection Property

Point process:

$$Z = \sum_{j=1}^N \delta_{X_j},$$

Example:  $N = 2$ ,  $X_1 = \log(1/V)$ ,  $X_2 = \log(1/(1 - V))$ .

**Transform  $\mathbf{T}$**  (for distributions functions):

$$(\mathbf{T}G)(x) = \mathbf{E} \left( \prod_{j=1}^N G(x - X_j) \right).$$

Example:  $G(x) = F(e^{-x})$ :  $F(x) = \mathbf{E}(F(xV)F(x(1 - V)))$ .

# Intersection Property

**Intersection property:**

*Suppose that  $F(x)$  and  $G(x)$  are continuous distribution functions such that the difference  $F(x) - G(x)$  has exactly **one zero**. Then the difference  $(\mathbf{T} F)(x) - (\mathbf{T} G)(x)$  has at most **one zero**.*

# Intersection Property

Lemma.

Suppose that  $V$  is  $t$ -beta distributed and  $\mathbf{T}$  is defined by  $(\mathbf{T}F)(x) = \mathbf{E}(F(xV)F(x(1 - V)))$ .

Then the Laplace transforms  $\Phi(u) = \int_0^\infty F(x)e^{-xu} dx$  satisfy an *intersection property*.

This property is the **key property** for the proof of the travelling wave property for the **left/right-most particle of BRW's** and also for the distribution of the **height of binary search trees**.

It is not clear whether this is also true on the level of distributions functions?

# Intersection Property

## Theorem

Let  $G_0(x) = 0$  for  $x < 0$  and  $G_0(x) = 1$  for  $x \geq 0$  and set  $G_{k+1} = \mathbf{T} G_k$ , that is,

$$G_{k+1}(x) = \mathbf{E} \left( \prod_{j=1}^N G_k(x - X_j) \right).$$

If  $\mathbf{T}$  satisfies the *intersection property* then there exists  $w(x)$  such that (uniformly for real  $x$  as  $k \rightarrow \infty$ )

$$\boxed{G_k(x) = w(x - m(k)) + o(1)},$$

where  $m(k)$  is defined by  $G_k(m(k)) = \frac{1}{2}$ .

More precisely, we have

$$m(k) = kc + o(k).$$

for some constant  $c > 0$  and  $w(x)$  satisfies

$$w(x) = \mathbf{E} \left( \prod_{j=1}^N w(x + c - X_j) \right).$$



**Thank You!**