

A functional central limit theorem  
for branching random walks,  
with applications to Quicksort asymptotics

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Strobl, AofA 2015

## Background and history

Let  $X_n$  be the number of comparisons needed by QUICKSORT to sort the first  $n$  in a sequence  $(U_m)_{m \in \mathbb{N}}$  of independent uniforms, using the respective first element of the list as a pivot.

- Régnier (1989) 'found the martingale',

$$Y_n := (X_n - EX_n)/(n + 1) \rightarrow Y_\infty \text{ almost surely, as } n \rightarrow \infty,$$

- Rösler (1989) characterized  $\mathcal{L}(Y_\infty)$  as a fixed point of a contraction,
- Neininger (2014) obtained an associated second order result,

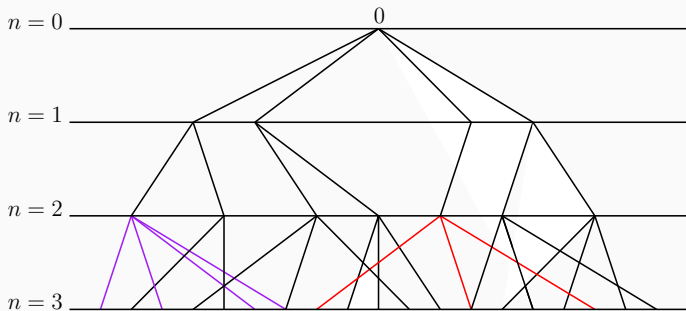
$$\sqrt{n/(2 \log n)}(Y_n - Y_\infty) \rightarrow N(0, 1) \text{ in distribution,}$$

using the contraction method. (Fuchs (2015): Method of moments)

We will use the well-established link to branching random walks (Biggins, Chauvin, Devroye, Marckert, Roualt and others) to obtain

- yet another proof, indeed: of a stronger result,
- similar results for other (tree) models.

## BRW: Basics



Combines splitting (branching) and shifting (random walk).

Basic **parameter**: (distribution of) a point process

$$\zeta = \sum_{i=1}^N \delta_{z_i}, \quad \text{where } \begin{cases} N & : \text{ (random) no. of children,} \\ z_1, \dots, z_N & : \text{ (random) location shifts,} \end{cases}$$

with i.i.d. copies of  $\zeta$  for the separate individuals.

## BRW: The Biggins martingale

- $(Z_n)_{n \in \mathbb{N}_0}$ : a BRW with parameter  $\mathcal{L}(\eta)$ ,
- $\nu$  with  $\nu(A) := \mathbb{E}\zeta(A)$  is the **intensity measure** of  $\zeta$ ,
- $\nu_n(A) := \mathbb{E}Z_n(A)$  is the intensity measure of  $Z_n$ ,
- by construction,  $Z_1 = \eta$  and  $\nu_1 = \nu$ .

Let ' $\hat{\cdot}$ ' denote the resp. **moment generating function**,

$$\hat{\zeta}(\theta) = \int e^{\theta x} \zeta(dx), \quad \hat{Z}_n(\theta) = \int e^{\theta x} Z_n(dx), \quad \hat{\nu}_n(\theta) = \int e^{\theta x} \nu_n(dx).$$

Fundamental observation:

$$\nu_n = \nu^{*n}, \quad \hat{\nu}_n(\theta) = \nu(\theta)^n.$$

As a consequence,

$$W_n(\theta) := \hat{\nu}(\theta)^{-n} \hat{Z}_n(\theta), \quad n \in \mathbb{N},$$

is a **martingale**.

## BRW: Assumptions

(A)  $P(\zeta(\mathbb{R}) = 0) = 0$ ,  $P(\zeta(\mathbb{R}) < \infty) = 1$ ,  $P(\zeta(\mathbb{R}) = 1) < 1$ .

(B) For some  $p_0 > 2$ ,  $\theta_0 > 0$ ,

$$\mathbb{E}(\hat{\zeta}(\theta))^{p_0} < \infty \text{ for all } \theta \in (-\theta_0, \theta_0).$$

Let  $N_n := Z_n(\mathbb{R})$  be the (random) number of particles in generation  $n$ .

(A) implies  $m := \mathbb{E}\zeta(\mathbb{R}) > 1$ , hence  $(N_n)_{n \in \mathbb{N}_0}$  is **supercritical**, so that

$$m^{-n} N_n \rightarrow N_\infty \text{ almost surely.}$$

(A) and (B) also imply that  $W_n(\theta) \rightarrow W_\infty(\theta)$  almost surely, which we regard as a **strong law of large numbers** for the Biggins martingale.

We will need

$$\sigma^2 := \text{var}(N_\infty), \quad \tau^2 := (\log \hat{\nu})''(0).$$

## BRW: A functional central limit theorem

Fix  $R > 0$  and let  $\mathbb{D} := \{z \in \mathbb{C} : |z| \leq R\}$ . Regard

$$D_n(u) := m^{n/2} \left( W_\infty \left( \frac{u}{\sqrt{n}} \right) - W_n \left( \frac{u}{\sqrt{n}} \right) \right)$$

as a random element of the space  $\mathbb{A}$  of continuous function  $f : \mathbb{D} \rightarrow \mathbb{C}$  that are analytic on  $\mathbb{D}^\circ$ . Endow  $\mathbb{A}$  with uniform convergence.

### Theorem

As  $n \rightarrow \infty$ ,  $D_n$  converges in distribution to a limit process  $D_\infty$ . The distribution of  $D_\infty$  is the same as the distribution of

$$\mathbb{D} \ni u \mapsto \sigma \sqrt{N_\infty} \xi(\tau u),$$

with  $N_\infty$ ,  $\xi$  independent and  $\xi$  the *random analytic function*

$$\xi(u) := \sum_{k=1}^{\infty} \xi_k \frac{u^k}{\sqrt{k!}}, \quad (\xi_k)_{k \in \mathbb{N}} \text{ i.i.d. } N(0, 1).$$

## From BRW to Quicksort

- Switch to **continuous time**: particles have independent and exponentially distributed lifetimes.
- Generalize the FCLT from fixed times  $n = 1, 2, \dots$  to **stopping times**  $\tau_1, \tau_2, \dots$  with  $\tau_n \uparrow \infty$ .
- Use the continuous time BRW with  $\eta := 2\delta_1$ .
- With  $\tau_n$  the time of birth of the  $n$ th particle,  $Z_{\tau_n}$  is the **profile of the Quicksort tree** of sublists.
- The **punchline**:
  - the quantity of interest is the mean of the profile,
  - on the transform side, mean means taking the derivative,
  - the functional  $\mathbb{A} \ni \phi \mapsto \phi'(0)$  is **continuous**.

Now use the FCLT and the Continuous Mapping Theorem.

## The strengthening

- We may regard Neinger's result as a **martingale CLT**.
- It is known that these often hold in the stronger sense of **stable convergence** (Rényi).

Let  $(\mathcal{F}_n)_{n \in \mathbb{N}}$  be the martingale filtration.

Basic idea:

Instead of  $\mathcal{L}(D_n)$  consider  $\mathcal{L}[D_n | \mathcal{F}_n]$ .

- These conditional distributions are **random variables with values in a space probability measures**.
- The space of probability measures on the topological space  $\mathbb{A}$  of analytic functions is itself a topological space  $\mathcal{M}$  if endowed with weak convergence.

### Theorem

*In  $\mathcal{M}$ ,  $\mathcal{L}[D_n | \mathcal{F}_n]$  converges almost surely to  $\mathcal{L}(D_\infty)$ .*



## Back to basics: the Pólya urn

- Start with one black and one white ball. In each step, select one ball u.a.r., and add one ball of the same colour. Let  $X_n$  be the number of white balls added after  $n$  steps,  $X = (X_n)_{n \in \mathbb{N}}$ .
- $Y_n := X_n / (n + 2)$ ,  $n \in \mathbb{N}$ , is a bd. **martingale**, hence  $Y_n \rightarrow Y_\infty$  a.s..
- **Boundary theory** (or direct calculation) says that  $X$ , given  $Y_\infty = \theta$ , is a simple random walk on  $\mathbb{Z}$ , with  $\theta$  the probability for a move to the right.
- Let  $W_n := \sqrt{n}(Y_\infty - Y_n)$ . Standard CLT gives

$$\mathcal{L}[W_n | Y_\infty = \theta] \rightarrow N(0, \theta(1 - \theta)) \text{ in distribution.}$$

- We may rewrite this as a.s. convergence of the random p.m.  $\mathcal{L}[W_n | Y_\infty]$  to the random (!) p.m.  $N(0, Y_\infty(1 - Y_\infty))$ .

### Theorem

$\mathcal{L}[W_n | X_1, \dots, X_n]$  converges a.s. to  $N(0, Y_\infty(1 - Y_\infty))$ .

(Proof uses some beta-gamma algebra.)