The empirical mean position
of a branching Lévy process

David Cheek*    Seva Shneer†

Abstract

We consider a supercritical branching Lévy process on the real line. Under mild
moment assumptions on the number of offspring and their displacements, we
prove a second-order limit theorem on the empirical mean position.

1 Introduction

A branching Lévy process describes a population of particles undergoing spatial
movement, death, and reproduction. It can be defined informally as follows (for
a formal definition, see Section 2). Initially there is one particle located at the
origin of the real line. The particle lives for an exponentially-distributed time.
During this time it moves according to a Lévy process. At the time of death,
the particle is replaced by a random number of new particles, displaced from
the parent particle’s death position according to a point process. All particles
move, die, and reproduce in a statistically identical manner, independently of
every other particle. We are only concerned with the supercritical case. That
is, each particle gives birth to more than one particle on average, and thus the
total number of particles grows to infinity with positive probability.

The empirical distribution of the particle positions is of key interest. This
distribution has received considerable attention, especially for branching random
walks and branching Brownian motion, which are special cases of the model.
There are many results on the empirical distribution’s maximum [5, 4, 10], as
well as on large deviations [12] and on the almost-sure weak convergence to a
Gaussian distribution [3, 11].

The empirical mean position, which is simple and important for applications,
has received relatively little attention. For specific branching random walks,
[13] shows that the empirical mean position almost surely grows asymptotically
linearly with time, while [7] shows that the empirical mean position’s variance

*Harvard University
†Heriot-Watt University
converges. These results combined raise the question of characterising a second-order limit term.

For branching Lévy processes, under some mild moment assumptions on the offspring number and their displacements, we provide a second-order limit theorem for the empirical mean position. Namely, we show that the difference between the empirical mean position at time $t$ and $rt$, for some constant $r$, converges almost surely to a random variable.

Before proceeding with the remainder of the paper, we discuss some special cases of the model and some applications.

First, consider that particles do not move during their lifetime and that each particle is displaced by +1 from its parent. The empirical distribution of particle positions is just the empirical distribution of generations in a branching process. Our result describes the average generation, complementing results of [13, 6].

We also refer the reader to [13] for an extensive discussion of applications of such limit theorems in biology. Second, consider instead that displacement sizes are Poisson distributed. One recovers a popular model for cancer evolution [9]. Here particles are cells, and the spatial position of a cell corresponds to its number of mutations. Our result gives the average number of mutations per cell. Third, consider that particles are not displaced from their parent but during their lifetime move according to a Poisson counting process. One recovers a model seen in phylogenetics. The branching process represents speciation for example [1], while the position counts the number of mutations which arise according to the infinite-sites model [8].

The remainder of the paper is organised as follows. We introduce the model in Section 2 formulate our main result in Section 3 and prove it in Section 4.

## 2 Model

Initially there is a single particle named $\emptyset$ which moves according to a Lévy process $(Z_{\emptyset,s})_{s \geq 0}$, with $Z_{\emptyset,0} = 0$ and $\mathbb{E}[Z_{\emptyset,1}^2] < \infty$. After an exponentially distributed waiting time $A_\emptyset$, the particle dies and is replaced by a random number $N_\emptyset$ of new particles with $\mathbb{E}[N_\emptyset] > 1$ and $\mathbb{E}[N_\emptyset^2] < \infty$. The new particles are born at positions $(Z_{\emptyset,A_\emptyset} + D_i)_{i=1}^{N_\emptyset}$. The $D_i$ are $\mathbb{R}$-valued random variables with

$$\mathbb{E}\left[\left(\sum_{i=1}^{N_\emptyset} D_i\right)^2\right] < \infty.$$  

Independence is assumed between $(Z_{\emptyset,s})_{s \geq 0}$ and $A_\emptyset$ and $(D_i)_{i=1}^{N_\emptyset}$ (but the $D_i$ need not be independent of each other nor of $N_\emptyset$). All particles independently follow the initial particle’s behaviour.

To denote particles we follow standard notation. Let

$$\mathcal{T} = \bigcup_{n \in \mathbb{N} \cup \{0\}} \mathbb{N}^n.$$
Here $\mathbb{N}^0 = \{\emptyset\}$ contains the initial particle. For $v = (v_1, ..., v_n) \in \mathcal{T}$ and $i \in \mathbb{N}$ write $vi = (v_1, ..., v_n, i)$, where $v$ is the parent of $vi$. To describe genealogical relationships, the set $\mathcal{T}$ is endowed with a partial ordering $\prec$, defined by

$$(u_i)_{i=1}^m \prec (v_i)_{i=1}^n \iff m < n \text{ and } (u_i)_{i=1}^m = (v_i)_{i=1}^m.$$  

Write $\preceq$ for $\prec$ or $\preceq$.

Now let

$$[(Z_{v,s})_{s \geq 0}, A_v, (D_{vi})_{i=1}^{N_v}]$$

for $v \in \mathcal{T}$ be i.i.d. copies of

$$[(Z_{\emptyset,s})_{s \geq 0}, A_{\emptyset}, (D_i)_{i=1}^{N_{\emptyset}}].$$

The set of all particles to ever exist is

$$\mathcal{T}^* = \{(v_i)_{i=1}^n \in \mathcal{T} : v_{m+1} \leq N_{(v_i)_{i=1}^m}, \text{ for } m = 0, 1, .., n-1\}.$$  

The particles alive at time $t \geq 0$ are

$$\mathcal{T}_t = \left\{ v \in \mathcal{T}^* : \sum_{u < v} A_u \leq t < \sum_{u \leq v} A_u \right\}.$$  

Particle $v$ at time $t$, if it is alive, has position

$$X_{v,t} = \sum_{\emptyset < u \leq v} D_u + \sum_{\emptyset \leq u < v} Z_{u,A_u} + Z_{v,t} - \sum_{\emptyset \leq u < v} A_u.$$  

### 3 Main result

Write $\lambda = \mathbb{E}[A_{\emptyset}]^{-1}$ for the branching rate. Write

$$r = \mathbb{E}[Z_{\emptyset,1}] + \lambda \mathbb{E}\left[\sum_{i=1}^{N_{\emptyset}} D_i\right]$$

for the movement rate.

**Theorem 3.1.** Conditional on the event $\{\lim_{t \to \infty} |\mathcal{T}_t| = \infty\}$, the limit

$$\lim_{t \to \infty} \left( \frac{1}{|\mathcal{T}_t|} \sum_{v \in \mathcal{T}_t} X_{v,t} - rt \right)$$

exists and is finite almost surely.
4 Proof of Theorem 3.1

Our proof will involve conditioning on whether branching occurs during the time interval $[0, h]$ for some small $h > 0$. Write

$$J_{0,h} = \{ A_0 > h \}$$

for the event that the first branching occurs after time $h$. Write

$$J_{1,h} = \{ A_0 \leq h < A_0 + \min_{i=1,\ldots,N_0} A_i \}$$

for the event that the first branching occurs before time $h$ and the second branching occurs after time $h$. Write

$$J_{2,h} = \{ A_0 + \min_{i=1,\ldots,N_0} A_i \leq h \}$$

for the event that the second branching occurs before time $h$. Note the probabilities

$$P[J_{0,h}] = 1 - h\lambda + o(h),$$
$$P[J_{1,h}] = h\lambda + o(h),$$
$$P[J_{2,h}] = o(h),$$
as $h \downarrow 0$. Observe the conditional distribution

$$\left( \sum_{v \in T_t} (X_{v,t+h} - r(t+h)) \mid J_{0,h} \right) \overset{d}{=} \sum_{v \in T_t'} (Z_{0,h} + X'_{v,t} - r(t+h)), \quad (1)$$

where $(X'_{v,t})_{v \in T_t'} \overset{d}{=} (X_{v,t})_{v \in T_t}$, and $(X'_{v,t})_{v \in T_t'}$ is independent of $Z_{0,h}$. Meanwhile

$$\left( \sum_{v \in T_t} (X_{v,t+h} - r(t+h)) \mid J_{1,h} \right) \overset{d}{=} \sum_{i=1}^{N_0} \sum_{v \in T_t'} (Z_i + X'_{v,t} - r(t) + \eta) + \eta_h, \quad (2)$$

where $(X'_{v,t})_{v \in T_t'} \overset{d}{=} (X_{v,t})_{v \in T_t}$ for $i = 1, \ldots, N_0$, the $(X'_{v,t})_{v \in T_t'}$ are independent of each other and of $(D_i)_{i=1}^{N_0}$, and $\eta$ is a random variable whose first and second moments converge to 0 as $h \downarrow 0$.

Lemma 4.1.

$$E \left[ \sum_{v \in T_t} (X_{v,t} - r t) \right] = 0.$$

Proof. From (1),

$$E \left[ \sum_{v \in T_t} (X_{v,t+h} - r(t+h)) \mid J_{0,h} \right] = E \left[ \sum_{v \in T_t} (X_{v,t} - r t) \right] + h (E[Z_{0,1}] - r) E[|T_t'|].$$
From (2),

\[
E \left[ \sum_{v \in T_{t+h}} (X_{v,t+h} - r(t+h)) | J_{1,h} \right] = E[N_0]E \left[ \sum_{v \in T_t} (X_{v,t} - rt) \right] + E \left[ \sum_{i=1}^N D_i \right] E[|T_t|] + o(1).
\]

Taking the unconditional expectation,

\[
E \left[ \sum_{v \in T_{t+h}} (X_{v,t+h} - r(t+h)) \right] = (1 - h\lambda)E \left[ \sum_{v \in T_{t+h}} (X_{v,t+h} - r(t+h)) | J_{0,h} \right]
\]

\[+ h\lambda E \left[ \sum_{v \in T_{t+h}} (X_{v,t+h} - r(t+h)) | J_{1,h} \right] + o(h)
\]

\[= E \left[ \sum_{v \in T_t} (X_{v,t} - rt) \right] (1 + h\lambda E[N_0 - 1]) + o(h).
\]

Rearranging and taking \( h \downarrow 0 \),

\[
\frac{d}{dt} E \left[ \sum_{v \in T_t} (X_{v,t} - rt) \right] = \lambda E[N_0 - 1] E \left[ \sum_{v \in T_t} (X_{v,t} - rt) \right].
\]

The statement of the lemma for any \( t \) now follows from the above and the fact that it clearly holds for \( t = 0 \). \( \square \)

Next we provide a bound for second moments.

**Lemma 4.2.**

\[
\sup_{t \geq 0} \left\{ e^{-2\lambda E[N_0 - 1] t} E \left[ \left( \sum_{v \in T_t} (X_{v,t} - rt) \right)^2 \right] \right\} < \infty.
\]

**Proof.** From (1),

\[
E \left[ \left( \sum_{v \in T_{t+h}} (X_{v,t+h} - r(t+h)) \right)^2 | J_{0,0} \right] = E \left[ \left( \sum_{v \in T_t} (X_{v,t} - rt) \right)^2 \right]
\]

\[+ 2h (E[Z_{0,1}] - r) E \left[ \sum_{v \in T_t} (X_{v,t} - rt) \right] + hE[Z_{0,1}^2]E[|T_t|^2] + o(h).
\]

\[= \lambda E[N_0 - 1] E \left[ \sum_{v \in T_t} (X_{v,t} - rt) \right] + o(h).
\]
From (2),
\[
E \left[ \left( \sum_{v \in T_{t+h}} (X_{v,t+h} - r(t+h)) \right)^2 \right]_{J_{h,1}}
\]
\[
= E \left[ \left( \sum_{i=1}^{N_\emptyset} \sum_{v \in T_i^t} (X_{v,t} - rt) \right)^2 \right] + 2E \left[ \sum_{i=1}^{N_\emptyset} D_i|T_i^t| \sum_{v \in T_i^t} (X_{v,t} - rt) \right]
+ 2E \left[ \sum_{i,j=1}^{N_\emptyset} D_i|T_i^t| \sum_{v \in T_j^t} (X_{v,t} - rt) \right] + E \left[ \left( \sum_{i=1}^{N_\emptyset} D_i|T_i^t| \right)^2 \right] + o(1)
\]
\[
= E[N_\emptyset]|E \left[ \left( \sum_{v \in T_i^t} (X_{v,t} - rt) \right)^2 \right] + E \left[ \sum_{i=1}^{N_\emptyset} D_i \right] E \left[ |T_i^t| \sum_{v \in T_i^t} (X_{v,t} - rt) \right]
+ E \left[ \left( \sum_{i=1}^{N_\emptyset} D_i \right)^2 \right] E[|T_i^t|^2] + o(1).
\]

But \(E[|T_i^t|]\) and \(E[|T_i^t|^2]\) are just linear combinations of \(e^{\lambda t}\) and \(e^{2\lambda t}\) [2]. Therefore

\[
E \left[ \left( \sum_{v \in T_{t+h}} (X_{v,t+h} - r(t+h)) \right)^2 \right]
\]
\[
= (1 - \lambda h)E \left[ \left( \sum_{v \in T_{t+h}} (X_{v,t+h} - r(t+h)) \right)^2 \right]_{J_{h,0}}
+ h\lambda E \left[ \left( \sum_{v \in T_{t+h}} (X_{v,t+h} - r(t+h)) \right)^2 \right]_{J_{h,1}} + o(h)
\]
\[
= (1 + h\lambda E[N_\emptyset - 1])E \left[ \left( \sum_{v \in T_i^t} (X_{v,t} - rt) \right)^2 \right] + hce^{2\lambda E[N_\emptyset - 1]} + hde^{\lambda E[N_\emptyset - 1]} + o(h),
\]
for some constants $c, d$. Rearranging and taking $h \downarrow 0$,

$$
\frac{d}{dt} \mathbb{E} \left[ \left( \sum_{v \in T_t} (X_{v,t} - rt) \right)^2 \right] = \lambda \mathbb{E} [N_0 - 1] \mathbb{E} \left[ \left( \sum_{v \in T_t} (X_{v,t} - rt) \right)^2 \right] + ce^{2\lambda \mathbb{E}[N_0 - 1]} + de^{\lambda \mathbb{E}[N_0 - 1]}.
$$

We now present a martingale result for which a filtration $(\mathcal{F}_t)_{t \geq 0}$ needs to be defined:

$$
\mathcal{F}_t = \sigma \left( (X_{v,s})_{v \in T_s} : 0 \leq s \leq t \right).
$$

**Lemma 4.3.**

$$
\left( e^{-\lambda t} \sum_{v \in T_t} (X_{v,t} - rt) \right)_{t \geq 0}
$$

is a martingale with respect to $(\mathcal{F}_t)_{t \geq 0}$.

**Proof.** Write

$$
T_{u,t} = \{ v \in T_t : u \preceq v \}
$$

for the particles alive at time $t$ which are descendants of $u \in T$. Let $0 \leq s \leq t$. Then

$$
e^{-\lambda t} \sum_{v \in T_t} (X_{v,t} - rt) = e^{-\lambda t} \sum_{u \in T_s} \sum_{v \in T_{u,t}} (X_{v,t} - X_{u,s} - r(t - s))
$$

$$
+ e^{-\lambda t} \sum_{u \in T_s} |T_{u,t}| (X_{u,s} - rs).
$$

Taking conditional expectations,

$$
\mathbb{E} \left[ e^{-\lambda t} \sum_{v \in T_t} (X_{v,t} - rt) \mid \mathcal{F}_s \right] = e^{-\lambda s} \mathbb{E} \left[ \sum_{v \in T_{t-s}} (X_{v,t-s} - r(t-s)) \right] + e^{-\lambda t} \sum_{u \in T_s} e^{\lambda(t-s)} (X_{u,s} - rs)
$$

$$
= e^{-\lambda s} \sum_{u \in T_s} (X_{u,s} - rs),
$$

where the last equality is due to Lemma 4.1.
Proof of Theorem 3.1. By Lemmas 4.2 and 4.3 and the martingale convergence theorem, there is a $\mathbb{R}$-valued random variable $V$ with

$$\lim_{t \to \infty} e^{-\lambda t} \sum_{v \in T_t} (X_{v,t} - rt) = V$$

(3)

almost surely. But conditioned on the event $\{\lim_{t \to \infty} |T_t| = \infty\}$, there is a positive random variable $W$ with

$$\lim_{t \to \infty} e^{-\lambda t} |T_t| = W$$

(4)

almost surely [2]. Combine (3) and (4) to conclude the proof.

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