The Fisher-KPP equation and related topics References: Bramson. Convergence of solutions of the Kolmogorov equation to travelling waves. Etheridge. An introduction to superprocesses. Durrett. Stochastic calculus: a practical introduction. <u>Branching Brownian motion</u>

<u>Defn</u> (BBM) Branching Brownian motion has three ingredients:

- (i) The spatial motion During its lifetime, each particle moves in IR according to a Brownian motion.
- (ii) The branching rate, V Each particle has a lifetime with distribution Exp(V).
- (iii) The branching mechanism, $\overline{\Phi}$ When it dies, a particle leaves behind (at the location where it died) a random number of offspring particles with probability generating function $\overline{\Phi}$. Conditional on their time and place of birth, offspring particles behave independently of each other.

Notation

- N(t) is the number of particles alive at time t.
- $X_1(t), ..., X_{N(t)}(t)$ are the locations of the particles alive at time t (e.g. in Ulam-Harris ordering)
- P_{∞} is law of BBM starting with a single particle at ∞ . $P := P_0$.
- $\cdot \mathbf{E}_{\mathbf{x}}$ is corresponding expectation. $\mathbf{E} = \mathbf{E}_{\mathbf{0}}$.

Important properties

- 1. Markov property. BBM is a Markov process (since Exp r.v.s are memoryless and BMs are Markov processes.
- 2. Branching property. Conditional on $(X_1(t), X_2(t), ..., X_{N(t)}(t))$, the descendants of each particle alive at time t evolve according to independent BBMs.

The rightmost particle Let $\overline{\phi}(u) = u^2$, V = 1 (i.e. branch into two particles at rate 1). Let $M(t) = \max_{i \in \{1,...,N(t)\}} X_i(t)$. Let $m(t) = \sup \{ x \in \mathbb{R} : \mathbb{P}(M(t) \le x) \le \frac{1}{2} \}$, the median of M(t). Theorem (Branson, 1978) $m(t) = \sqrt{2}t - \frac{3}{2\sqrt{2}}\log t + O(1)$ as $t \to \infty$. See Roberts (2013) for a simpler proof. Notation • For se [0,t], $X_{i,t}(s) =$ location of ancestor of $X_i(t)$ at time s. • For $x \in \mathbb{R}$, P_x is probability measure under which $(B_t)_{t \ge 0}$ is a BM started at x, and E_{x} is corresponding expectation.

Lemma (Many-to-one lemma) Suppose
$$F: C[0,t] \rightarrow \mathbb{R}$$
 is measurable. Then

$$\mathbb{E}_{\infty}\left[\sum_{i=1}^{N(t)} F((X_{i,t}(s), 0 \le s \le t))\right] = e^{t} \mathbb{E}_{\infty}\left[F((B_{s})_{0 \le s \le t})\right].$$

Lemma (Many-to-one lemma) Suppose
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Proof: Conditional on the set of branching events, each path $(X_{i,t}(s), 0 \le s \le t)$ is a BM. So LHS = $\mathbb{E}_{x}[N(t)] \mathbb{E}_{x}[F((B_{s})_{0 \le s \le t})]$.

Since each particle branches into two particles at rate 1, $\frac{d}{dt} \mathbb{E}[N(t)] = \mathbb{E}[N(t)]$ and so $\mathbb{E}[N(t)] = e^{t}$. \Box .

First noment calculation
Lemma (Gaussian tail estimates) if
$$Z \sim N(0,1)$$
, then for $x > 0$,
 $P(Z > x) \leq e^{-\frac{1}{2}x^2}$ and $P(Z > x) \leq \frac{1}{\sqrt{2\pi}} \frac{1}{x} e^{-\frac{1}{2}x^2}$.
By the many-to-one lemma, for $y > 0$ with $y < \sqrt{t}$,
 $E\left[\#\{i \leq N(t): X_i(t) > \sqrt{2t} - y\}\right] = e^t E_0\left[1 + \frac{8}{8t^2}\sqrt{2t} - \frac{1}{\sqrt{t}}\right]$
 $= e^t P(Z > \sqrt{2t} - \frac{1}{\sqrt{t}})$ where $Z \sim N(0,1)$
 $\sim e^t \frac{1}{\sqrt{2t}} \frac{1}{\sqrt{2t}} e^{-\frac{1}{2}(\sqrt{2t} - \frac{1}{\sqrt{t}})^2}$
 $= e^t \frac{1}{\sqrt{2t}} e^{-\frac{1}{2}(2t - 2\sqrt{2}y + o(1))}$
 $\sim \frac{1}{2\sqrt{\pi t}} e^{\sqrt{2}y}$ as $t \to \infty$.

$$\begin{split} \mathbb{E}\left[\#\{i \le N(t): X_{i}(t) \ge \sqrt{2}t - y\}\right] &\sim \frac{1}{2\sqrt{\pi t}} e^{\sqrt{2}t} \quad \text{as } t \to \infty. \\ \text{So } \mathbb{E}\left[\#\{i \le N(t): X_{i}(t) \ge \sqrt{2}t - y\}\right] = \Theta(1) \quad \text{as } t \to \infty \quad \text{iff } y = \frac{1}{2\sqrt{2}} \log t + O(1). \\ (\text{Roberts: } \#\{i \le N(t): X_{i}(t) \ge \sqrt{2}t - \frac{3}{2\sqrt{2}} \log t, X_{i,t}(s) \le \xi(s) \quad \forall s \le t\}). \end{split}$$

$\frac{McKean \ representation}{Back \ to \ general \ V, \Phi}.$ $\frac{Theorem}{Leorem} (McKean (1975), Skorohod (1964))$ $Suppose \ \Phi'(1) < \infty. \ Suppose \ \Psi \in C^{2}(\mathbb{R}) \ with \ O \leq \Psi(\infty) \leq 1 \ \forall x \in \mathbb{R}.$ For $t > 0, x \in \mathbb{R}, \ let$ $u(t, x) = \mathbb{E}_{x} \left[\prod_{i=1}^{N(t)} \Psi(X_{i}(t)) \right].$ Then u solves the PDE $\frac{\partial u}{\partial t} = \frac{1}{2} \Delta u + V(\Phi(u) - u), \quad u(0, x) = \Psi(x). \quad (1)$

Proof: Assume that u(t, oc) is twice continuously differentiable in oc at time t. (Once we have shown that u solves (1) under this assumption, regularity theory for the heat semigroup implies that u is smooth.)

Proof ctd:
$$u(t,x) = \mathbb{E}_{x} \left[\prod_{i=1}^{N(t)} \Psi(X_{i}(t)) \right].$$

Let $S = time$ of first branching event.
 $B_{s} = location of original particle at time S.$
 $K = # offspring particles at time S.$
Then for $\delta > 0$,
 $u(t+\delta, x) = \mathbb{E}_{x} \left[\prod_{j=1}^{N(t+\delta)} \Psi(X_{j}(t+\delta)) | S \le \delta \right] \mathbb{P}(S \le \delta)$
 $+ \mathbb{E}_{x} \left[\prod_{j=1}^{N(t+\delta)} \Psi(X_{j}(t+\delta)) | S > \delta \right] \mathbb{P}(S > \delta)$
 $= \sum_{k=0}^{\infty} \mathbb{E}_{x} \left[\prod_{j=1}^{N(t+\delta)} \Psi(X_{j}(t+\delta)) | S \le \delta, K = k] \mathbb{P}(S \le \delta, K = k)$
 $+ \mathbb{E}_{x} \left[\mathbb{E}_{B_{s}} \left[\prod_{j=1}^{N(t)} \Psi(X_{j}(t)) \right] \mathbb{P}(S > \delta).$
(2)

For the first term on the RHS, for 1≤i≤K, let Ni = set of particles at time t+S which are descended from particle i at time S. For s≤S and i≤k, Ex[TT Y(Xi(t+S))|(S,Bs,K)=(s,y,k)] = Ey[u(t,Bs-s)] + O(S) since particle i branches before time S w.p. Hence by our assumption that u(t,·) is C²,

$$\mathbb{E}_{x}\left[\prod_{j\in N_{i}}^{l} \Psi(X_{j}(t+\delta)) \right] \le \delta, K=k] = u(t,x) + O(\delta).$$

Proof ctd:
$$u(t,x) = \mathbb{E}_{x} \left[\prod_{i=1}^{N(t)} \Psi(X_{i}(t)) \right].$$

Hence by our assumption that $u(t, \cdot)$ is C^{2} ,
 $\mathbb{E}_{x} \left[\prod_{i \neq N_{i}} \Psi(X_{i}(t+\delta)) | S \leq \delta, K = k \right] = u(t,x) + O(\delta).$
By the branching property,
 $\mathbb{E}_{x} \left[\prod_{i=1}^{N} \Psi(X_{i}(t+\delta)) | S \leq \delta, K = k \right] = (u(t,x) + O(\delta))^{k}.$
Since $S \sim \exp(V)$,
 $\sum_{k=0}^{\infty} \mathbb{E}_{x} \left[\prod_{i=1}^{V(t+\delta)} \Psi(X_{i}(t+\delta)) | S \leq \delta, K = k \right] \mathbb{P}(S \leq \delta, K = k)$
 $= \sum_{k=0}^{\infty} (u(t,x)^{k} + kO(\delta)) (V\delta + O(\delta^{2})) \mathbb{P}(K = k)$
 $= V\delta \Phi(u(t,x)) + O(\delta^{2}) \quad \text{since } \Phi^{1}(1) < \infty.$
Since $\frac{1}{2}\Delta$ is the infinitesimal generator of BM,
 $\mathbb{E}_{x} \left[\mathbb{E}_{B_{S}} \left[\prod_{i=1}^{T} \Psi(X_{i}(t)) \right] \right] \mathbb{P}(S > \delta) = \mathbb{E}_{x} \left[u(t, 8_{\delta}) \right] \mathbb{P}(S > \delta)$
 $= (u(t,x) + \delta \frac{1}{2}\Delta u(t,x) + o(\delta))(1 - V\delta + O(\delta^{2})).$
Substituting into (2),
 $u(t+\delta,x) = V\delta \Phi(u) + u + \delta \frac{1}{2}\Delta u - V\delta u + o(\delta).$
Hence $u(t+\delta,x) - u(t,x) = \frac{1}{2}\Delta u + V(\Phi(u) - u) + o(1)$ as $\delta \to 0. \Box$.

Then
$$u(t, zc) := \mathbb{P}_{zc}(\mathbb{V}_{nr}(X(t)) = 1)$$
 solves the PDE (3).
(depends on genealogy, not just locations of particles).

$$\frac{\text{Back to the rightmost particle}}{\mathbb{P}(M(t) \ge x) = 1 - \mathbb{P}(\underset{i=1}{\overset{\text{M(t)}}{1}} \mathbb{1}_{X_{i}(t) \le x} = 1)$$

$$= 1 - \mathbb{E}_{-\infty} \begin{bmatrix} \prod_{i=1}^{N(t)} \mathbb{1}_{X_{i}(t) \le 0} \end{bmatrix}$$

$$= 1 - v(t, -\infty), \quad \text{where } v \text{ solves } \begin{cases} \frac{\partial v}{\partial t} = \frac{1}{2} \Delta v + v^{2} - v \\ v(0, y) = \mathbb{1}_{y \le 0} \end{cases}$$

Back to the rightmost particle
$$\Phi(u) = u^2, V = 1.$$

$$P(M(t) \ge x) = 1 - P(\underset{i=1}^{M(t)} 1_{X_i(t) \le x} = 1)$$

$$= 1 - E_{-x} [\underset{i=1}^{M(t)} 1_{X_i(t) \le 0}]$$

$$= 1 - v(t, -x), \quad \text{where } v \text{ solves } \{ \frac{\partial v}{\partial t} = \frac{1}{2} \Delta v + v^2 - v \\ v(0, y) = 1 \\ y \le 0. \}$$
Hence $u(t, x) := 1 - v(t, -x)$ solves $\{ \frac{\partial u}{\partial t} = \frac{1}{2} \Delta u + u(1 - u) \\ u(0, y) = 1 \\ y \le 0. \}$
Fisher-KPP equation
So $P(M(t) \ge x) = u(t, x).$

 $\begin{array}{l} \hline Feynman-Kac formula\\ \underline{Proposition} & Suppose \ k: [0,\infty) \times \mathbb{R} \rightarrow \mathbb{R} \ \text{ is continuous and bounded, that } u: [0,\infty) \times \mathbb{R} \rightarrow \mathbb{R} \ \text{ is continuous and bounded, and smooth on } (0,\infty) \times \mathbb{R}, \ \text{ and that} \\ \hline \frac{\partial u}{\partial t} = \frac{1}{2} \Delta u + k(t,\infty) u \quad \forall t > 0, x \in \mathbb{R}. \\ \hline \text{ Then for } 0 \leq t' \leq t, x \in \mathbb{R}, \\ u(t,x) = \mathbb{E}_{x} \left[e^{\int_{0}^{t} k(t-s,8_{s}) ds} u(t-t',8_{t'}) \right]. \end{array}$