

**Exit Problem.** Consider

$$x_\epsilon(t) = x + \int_0^t b(x_\epsilon(s))ds + \sqrt{\epsilon}\beta(t)$$

and let  $Q_{x,\epsilon}$  be the distribution of the solution  $x_\epsilon$ . As  $\epsilon \rightarrow 0$  the measure  $Q_{x,\epsilon}$  concentrates on the trajectory which is the solution of

$$x(t) = x + \int_0^t b(x(s))ds$$

There is a large deviation principle for  $\{Q_{x,\epsilon}\}$  on  $C[[0, T]; R^d]$ .

$$Q_{x,\epsilon}(A) = \exp\left[-\inf_{\substack{f(\cdot) \in A \\ f(0)=x}} \frac{1}{2\epsilon} \int_0^T \|f'(t) - b(f(t))\|^2 dt + o\left(\frac{1}{\epsilon}\right)\right]$$

More precisely for closed sets  $C$

$$\limsup_{\substack{y \rightarrow x \\ \epsilon \rightarrow 0}} \epsilon \log Q_{y,\epsilon}(C) \leq -\inf_{\substack{f(\cdot) \in C \\ f(0)=x}} \frac{1}{2} \int_0^T \|f'(t) - b(f(t))\|^2 dt$$

and for open sets  $G$ ,

$$\liminf_{\substack{y \rightarrow x \\ \epsilon \rightarrow 0}} \epsilon \log Q_{y,\epsilon}(G) \leq -\inf_{\substack{f(\cdot) \in G \\ f(0)=x}} \frac{1}{2} \int_0^T \|f'(t) - b(f(t))\|^2 dt$$

Let  $G$  be an open set containing a unique stable equilibrium point  $x_0$  for the ODE

$$\dot{x}(t) = b(x(t))$$

i.e. any solution of the ODE starting from any point in the closure  $\bar{G}$  tends to  $x_0$  as  $t \rightarrow \infty$ , remaining in  $G$  for all  $t > 0$ . For instance assume that  $G$  is smooth and  $b \neq 0$  on the boundary  $\delta G$  and points inward at every point. For any  $x \in G$  and  $z \in \delta G$  let

$$U(T, x, z) = \inf_{\substack{f: f(0)=x, f(T)=z \\ f(t) \in G \text{ for } t < T}} \frac{1}{2} \int_0^T \|f'(t) - b(f(t))\|^2 dt$$

and

$$U(x, z) = \inf_{T > 0} U(T, x, z)$$

Let  $z_0 \in \delta G$  be such that  $U(x_0, z_0) < U(x_0, z)$  for all  $z \in \delta G, z \neq z_0$ . If  $\tau$  is the exit time and  $x(\tau)$  is the exit place from  $G$ , then for any  $x \in G$  and any neighborhood  $N$  of  $z_0$ ,

**Theorem:**

$$\lim_{\epsilon \rightarrow 0} Q_{x,\epsilon}[x(\tau) \notin N] \rightarrow 0$$

**Remark.** No matter where the process starts inside  $G$  intially it will follow the ODE, be driven towards  $x_0$ , slow down as it reaches  $x_0$  and hang around there for a very long time.

Let us take two neighborhoods  $S_1, S_2$  around  $x_0$ , with  $x_0 \in S_1 \subset \bar{S}_1 \subset S_2$ . It is not hard to see that  $U(x, z)$  is a continuous function of  $x$  and  $z$ , and given  $N$ , we can pick  $S_1, S_2$  such that

$$\inf_{x \in \delta S_2} \inf_{z \in N^c} U(x, z) \geq \sup_{x \in \delta S_2} U(x, z_0) + \eta$$

We will estimate the following probabilities: if  $\tau'$  be the exit time from  $G \cap \bar{S}_1^c$

$$\limsup_{\epsilon \rightarrow 0} \epsilon \sup_{x \in \delta S_2} \log Q_{x, \epsilon}[x(\tau') \in N^c] \leq - \inf_{x \in \delta S_2} \inf_{z \in N^c} U(x, z)$$

and

$$\liminf_{\epsilon \rightarrow 0} \epsilon \inf_{x \in \delta S_2} \log Q_{x, \epsilon}[x(\tau') \in N] \geq - \sup_{x \in \delta S_2} U(x, z_0)$$

This will do it. The picture is the process will sooner or later exit from  $\bar{S}_1^c$ . But most of the time it will be pulled back to  $x_0$ . There is a very small chance that it will exit in  $N$  and even smaller chance of exiting from  $N^c$ . So it is most likely to exit from  $N$ .

First we estimate the probability that exit from  $\bar{S}_1^c$  takes too long.

$$\limsup_{T \rightarrow \infty} \limsup_{\epsilon \rightarrow 0} \epsilon \log \sup_{x \in \bar{S}_1^c} Q_{x, \epsilon}[\tau' \geq T] = -\infty$$

Otherwise there will be paths with  $\int_0^T \|f'(t) - b(f(t))\|^2 dt$  bounded and  $T$  large. This means there will be paths with  $\int_0^T \|f'(t) - b(f(t))\|^2 dt$  small and  $T$  large. This in turn means solutions of ODE remaining in  $\bar{S}_1^c$  for too long. If the paths do not hang around for too long, the large deviation estimate applies and it is much more likely to exit from  $N$ , than from  $N^c$ .

A special case is the gradient flow, where  $b(x) = -(\nabla V)(x)$ .  $x_0$  is a local minimum of  $V$ . Then it is not hard to see that  $U(x_0, z) = 2[V(z) - V(x_0)]$ .

**Invariant distributions.**

$$\mathcal{L} = \frac{1}{2} \sum_{i,j} a_{i,j}(x) D_{i,j} + \sum_j b_j(x) D_j$$

$\mu$  is probability measure on  $R^d$  such that

$$\int (\mathcal{L}u)(x) d\mu(x) = 0$$

for all smooth  $u$  with compact support. Suppose there is a unique process corresponding to  $\mathcal{L}$ , is  $\mu$  an invariant distribution fro the process? Proof depends on duality and consequently finding enough classical solutions for the equation

$$u_t = \mathcal{L}u$$

or the resolvent equation

$$\lambda u - \mathcal{L}u = f$$

which require ellipticity and Hölder continuity. Assume only that the coefficients are continuous, but the process is unique. If we know that  $d\mu = \phi dx$  with  $\phi \in L_q$  we can use the  $L_p$  theory in the elliptic case. To prove it in general requires several steps.

**Invariance Principle.**

**Theorem:** Suppose  $\pi_h(x, dy)$  is a Markov Chain such that, for every smooth  $u$  with compact support

$$\frac{1}{h} \int [u(y) - u(x)] \pi_h(x, dy) \rightarrow (\mathcal{L}u)(x)$$

uniformly on compact sets, and there exists a unique process with out explosion for  $\mathcal{L}$ , then the interpolated Markov Chain converges to the process. In particular

$$\lim_{\substack{h \rightarrow 0 \\ nh \rightarrow t}} \int f(y) \pi_h^n(x, dy) \rightarrow (T_t f)(x) = \int f(y) p(t, x, dy)$$

where  $p$  is the transition probability of the process corresponding to  $\mathcal{L}$ .

**Proof: Step 1.** Let us interpolate the Markov chain and call the process  $P_h$ . Let us take smooth cut off function  $\phi^R(x)$  and define

$$\pi_h^R(x, y) = \phi^R(x) \pi_h(x, dy) + (1 - \phi^R(x)) \delta_x(dy)$$

It is easy to see that

$$\frac{1}{h} \int [u(y) - u(x)] \pi_h^R(x, dy) \rightarrow (\mathcal{L}^R u)(x) = \phi^R(x) (\mathcal{L}u)(x)$$

uniformly in  $x$ . We will prove that the processes  $P_{h,x}^R$  are tight. Let  $\tau_\epsilon$  be the exit time from the ball of radius  $\epsilon$  for the process starting from  $x$ . We want to estimate

$$\sup_x \sup_{h \leq 1} P_{h,x}^R[\tau_\epsilon \leq \delta] = F(\epsilon, \delta)$$

If  $u_\epsilon$  is a smooth function that is 1 in a ball of radius  $\frac{\epsilon}{2}$  and 0 outside a ball of radius  $\epsilon$ ,  $\|\mathcal{L}^R u_\epsilon(x)\| \leq C_\epsilon$  and

$$\int [u(y) - u(x)] \pi_h^R(x, dy) \leq C_\epsilon h$$

In particular

$$u(X(nh)) - u(x) - nhC_\epsilon$$

is a super-martingale under  $P_{x,h}^R$  and

$$P_{x,h}^R[\tau_\epsilon \leq \delta] \leq E[u(\tau_\epsilon \wedge \delta)] \leq \delta C_\epsilon$$

Let  $\tau_1, \tau_2, \dots, \tau_N$  be the successive times at which  $X(nh)$  gets away a distance  $\epsilon$  from the previous  $x(\tau_i)$ . We proceed till  $\tau_N > T$ . We estimate the following.

$$\sup_{\omega, h} E[e^{-\tau_{i+1}} | \mathcal{F}_{\tau_i}] \leq \rho < 1$$

$$P[N \geq k] \leq P[\tau_1 + \dots + \tau_k \leq T] \leq e^T E[e^{-(\tau_1 + \dots + \tau_k)}] \leq e^T \rho^k$$

and

$$P[\min(\tau_1, \dots, \tau_k) \leq \delta] \leq k\delta C_\epsilon$$

From the locality of  $\mathcal{L}$ , it follows that

$$\pi_h^R(x, B(x, \epsilon)^c) = o(h)$$

Therefore

$$\sup_x P_{x,h}^R \left[ \sup_{0 \leq j \leq n} |X((j+1)h) - X(jh)| \geq \epsilon \right] \rightarrow 0$$

as  $h \rightarrow 0$ . This is enough to control the oscillations. We can use the control on the modulus of continuity to prove tightness. If  $P_x^R$  is any limit it is a solution to the martingale problem for  $\mathcal{L}^R$ . This agrees with  $\mathcal{L}$  until the exit time from  $B_R$  the ball of radius  $R$ . Since there is no explosion if  $R$  is large  $\tau_R$  is large, is bigger than  $T$ , with probability nearly one and so  $P_{x,h}^R$  and  $P_{x,h}$  are close and the limit of  $P_{x,h}$  as  $h \rightarrow 0$  is  $P_x$ .

Finally to prove that  $\mu$  is the invariant measure we will construct a Markov Chain  $\{\pi_h(x, dy)\}$ , for which  $\mu$  is invariant and which converges to  $\{P_x\}$ . Given  $\mathcal{L}$ , we construct the resolvent

$$\Pi_h = (I - h\mathcal{L})^{-1}$$

on the range of  $D_h$  of bounded functions with two bounded derivatives under  $(I - h\mathcal{L})$ . The maximum principle guarantees that  $\Pi_h$  is well defined and is positivity preserving. We define a linear functional  $\Lambda$  on functions of two variables of the form

$$g(x, y) = v_0(y) + \sum_i u_i(x) w_i(y)$$

with  $u, w$  being bounded continuous functions and  $w_i = v_i - h\mathcal{L}v_i \in D_h$ , by

$$\Lambda(g) = \int v_0(y) d\mu(y) + \sum_{i=1}^n \int u_i(x) v_i(x) d\mu(x)$$

Suppose  $\Lambda$  is nonnegative and we extend it as a non negative linear functional. Then both the marginals of  $\Lambda$  are  $\mu$ . [Note that we can take  $v_1 = 1$  and the remaining  $v$  as 0. Then  $g(x, y) = u_1(x)$ ]. If we take the r.c.p.d  $\pi_h(x, dy)$ ,  $\mu\pi_h = \mu$  and

$$\pi_h(v - h\mathcal{L}v) = v$$

for smooth  $v$  we have

$$\frac{1}{h}(\pi_h v - v) = \pi_h \mathcal{L}v \rightarrow \mathcal{L}v$$

for  $v$  with compact support.

Suppose  $g(x, y) \geq 0$ . Then consider the function

$$\inf_x \sum_{i=1}^n u_i(x)v_i = \Phi(\mathbf{v})$$

defined for  $\mathbf{v} = (v_1, \dots, v_n) \in R^n$ .  $\Phi$  is concave and

$$\Phi(\mathbf{v}(x) - t(\mathcal{L}\mathbf{v})(x))$$

is a convex function of  $t$  for all  $x$ . So is the integral

$$\psi(t) = \int \Phi(\mathbf{v}(x) - t(\mathcal{L}\mathbf{v})(x))d\mu(x)$$

$$\psi'(0) = - \int \sum_i \Phi_{u_i}(\mathbf{v}(x))(\mathcal{L}v_i)(x)d\mu(x) \leq \int [\mathcal{L}\Phi(\mathbf{v})](x)d\mu(x) = 0$$

Therefore for  $h \geq 0$ ,

$$\psi(h) = \int \Phi(\mathbf{v}(x) - h(\mathcal{L}\mathbf{v})(x))d\mu(x) \leq \int \Phi(\mathbf{v}(x))d\mu(x)$$

We can approximate  $\Phi$  by smooth convex functions. Denote  $v_i - h\mathcal{L}v_i = w_i$ . Then

$$\begin{aligned} \int [v_0(x) + \sum u_i(x)v_i(x)]d\mu(x) &\geq \int [v_0(x) + \Phi(\mathbf{v}(x))]d\mu(x) \\ &\geq \int [v_0(x) + \Phi(\mathbf{w}(x))]d\mu(x) \end{aligned}$$

But

$$[v_0(y) + \Phi(\mathbf{w}(y))] = \inf_x [v_0(y) + \sum_i u_i(x)w_i(y)] = \inf_x g(x, y) \geq 0$$