

A Criterion for Invariant Measures of Markov Processes

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Summary. Using the martingale formulation for Markov processes introduced by Stroock and Varadhan, we develop a criterion for checking if a measure happens to be invariant.

0. Introduction

Let S be a compact metric space or a locally compact separable metric space. Let $x(t)$ be a homogeneous Markov process with state space S and transition probability function

$$P(t, x, A) = P_x(x(t) \in A).$$

As usual $B(S)$ will denote the bounded measurable functions on S . Let $\{T_t: t > 0\}$ be the associated semigroup i.e.

$$(T_t f)(x) = \int f(y) P(t, x, dy) \quad \text{for all } f \in B(S).$$

The infinitesimal generator L is defined by the formula

$$Lf = s\text{-}\lim_{t \downarrow 0} \frac{T_t f - f}{t}$$

and its domain $D(L)$ consists of all those $f \in B(S)$ for which the above limit exists. If μ is an invariant measure for this Markov process i.e.

$$\mu(A) = \int P(t, x, A) d\mu(x) \quad \text{for all } t > 0$$

and for all Borel sets A , one can check that

$$\int Lf(x) d\mu(x) = 0 \quad \text{for all } f \in D(L).$$

And conversely, if $\int Lf(x) d\mu(x) = 0$ for all $f \in D(L)$ then μ is an invariant measure. Notice that in order to apply this criterion one has to compute $D(L)$

which is hard to do. The result of this work is that you do not have to check that $\int Lf(x) d\mu(x)=0$ for all $f \in D(L)$ in order to see if μ is an invariant measure. It turns out that it suffices to check $\int Lf(x) d\mu(x)=0$ for f varying over the subclass of $D(L)$ consisting of the functions such that the martingale problem is well-posed (for information about the martingale problem, see [2]).

For future use, we recall the minimum principle: let $H: B(S) \rightarrow B(S)$ be an operator then H satisfies the minimum principle if $f(x) \geq f(x_0)$ for all $x \in S$ implies that $Hf(x_0) \geq 0$.

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1. Statement of the Basic Result

Theorem. *Let S be a compact metric space and $C(S)$ be the class of continuous functions defined on S or let S be a locally compact separable metric space and $C(S)$ be the class of bounded continuous functions which have a limit at infinity. Let $D([0, \infty), S)$ denote the space of right-continuous trajectories. Let M be a dense subset of $C(S)$ and $L: M \rightarrow C(S)$ an operator which satisfies the minimum principle and the following convexity property: for each integer $p > 0$ and $\theta: \mathbb{R}^p \rightarrow \mathbb{R}$ a smooth convex function (smooth means at least twice differentiable) and for $f_1, f_2, \dots, f_p \in M$, we have $\theta(f_1, \dots, f_p) \in D(L)$.*

For $w \in D([0, \infty), S)$ define $x(t, w) = w(t)$.

We assume that for each $x \in S$ the martingale problem is well-posed i.e. there is a unique probability measure P_x on $D([0, \infty), S)$ such that

- i) $P_x(x(0) = x) = 1$
- ii) $f(x(t)) - \int_0^t Lf(x(s)) ds$

is a P_x -martingale for each $f \in M$.

Let μ be a probability measure on S such that $\int Lf(x) d\mu(x) = 0$ for all $f \in M$, then μ is an invariant measure.

Remark. Under previous assumptions the following inequality holds:

$$L\theta(f_1, \dots, f_p) \geq \sum_{k=1}^p \frac{\partial \theta}{\partial x_k}(f_1, \dots, f_p) \cdot Lf_k.$$

Because the martingale problem is well posed, the process $x(t)$ is Markovian and so we have an associated semigroup $\{T_t: t > 0\}$ and an infinitesimal generator \bar{L} which is an extension of L . Since $\theta(f_1, \dots, f_p) \in D(L)$ we can take point-wise limit in order to compute $L\theta(f_1, \dots, f_p)$ and recalling Jensen's inequality, we have:

$$\begin{aligned}
& \lim_{t \rightarrow 0} \frac{E_x \theta(f_1(x(t)), \dots, f_p(x(t))) - \theta(f_1(x), \dots, f_p(x))}{t} \\
& \geq \lim_{t \rightarrow 0} \frac{\theta(E_x f_1(x(t)), \dots, E_x f_p(x(t))) - \theta(f_1(x), \dots, f_p(x))}{t} \\
& = \frac{d}{dt} \theta(E_x f_1(x(t)), \dots, E_x f_p(x(t)))|_{t=0} \\
& = \sum_{k=1}^p \frac{\partial \theta}{\partial x_k} (f_1(x), \dots, f_p(x)) \left(\frac{d}{dt} E_x f_k(x(t)) \right) \Big|_{t=0}
\end{aligned}$$

$$\text{i.e. } L\theta(f_1, \dots, f_p) \geq \sum_{k=1}^p \frac{\partial \theta}{\partial x_k} (f_1, \dots, f_p) Lf_k.$$

2. Proof of Compact Case

Lemma 1. *Let us consider $C(S)$ and $W = \{f \in C(S) : f \geq 0\}$. Let V be a subspace of $C(S)$ such that the constant function $1 \in V$. Then each monotone linear functional on V can be extended to $C(S)$ in such a way that the extension is a monotone linear functional on $C(S)$.*

Proof. W is clearly a convex set and $tW \subseteq W$ for all $t \geq 0$ i.e. W is a wedge in $C(S)$. For $f \in C(S)$ we have

$$f(x) \geq \inf f > -\infty \quad \text{for all } x \in S$$

hence for a suitable constant α :

$$f(x) + \alpha \geq 0 \quad \text{for all } x \in S.$$

But constants are in V , thus

$$(f + V) \cap W \neq \emptyset \quad \text{for each } f \in C(S)$$

and so

$$(f + V) \cap W \neq \emptyset \quad \text{if and only if } (-f + V) \cap W \neq \emptyset.$$

Therefore by the Krein extension theorem for non-negative linear functionals (see [1]), any monotone linear functional on V can be extended to a monotone linear functional on $C(S)$.

Lemma 2. *Let S be a compact metric space and μ a probability measure on S . Let V be a linear subspace of $C(S)$ such that the constant function $1 \in V$. Assume we have a linear operator $\pi: V \rightarrow C(S)$ such that*

- i) $\pi 1 = 1$
- ii) $\pi f \geq 0$ if $f \geq 0$
- iii) $\int \pi f(x) d\mu(x) = \int f(x) d\mu(x)$.

Assume for each integer $p > 0$ and any $f_1, \dots, f_p \in V$ and for any convex function $\theta: \mathbb{R}^p \rightarrow \mathbb{R}$ that the following convexity inequality holds:

$$\int \theta(\pi f_1(x), \dots, \pi f_p(x)) d\mu(x) \leq \int \theta(f_1(x), \dots, f_p(x)) d\mu(x).$$

Then we can find a Borel set Δ such that $\mu(\Delta)=0$ and we can find an operator $\bar{\pi}: C(S) \rightarrow B(S)$ such that

- i) if $f \in V$, then $(\bar{\pi}f)(x) = (\pi f)(x)$ for $x \notin \Delta$
- ii) if $f \in C(S)$ and $f \geq 0$, then $(\bar{\pi}f)(x) \geq 0$ for $x \notin \Delta$
- iii) $\int \bar{\pi}f(x) d\mu(x) = \int f(x) d\mu(x)$ for each $f \in C(S)$.

Proof. Let us construct a probability measure λ on $S \times S$ with marginals μ and such that

$$\int_{S \times S} f(y) d\lambda(x, y) = \int_S f(y) d\mu(y)$$

and

$$\int_{S \times S} g(x) h(y) d\lambda(x, y) = \int_S g(x)(\pi h)(x) d\mu(x)$$

where $f \in C(S)$, $g \in C(S)$ and $h \in V$.

If Y is a random variable on the product space $S \times S$, then $E^\lambda\{Y|x\}$ is the random variable such that

$$\int_{A \times S} Y(x, y) d\lambda(x, y) = \int_A E^\lambda\{Y(x, y) | p_1(x, y) = x\} d\mu(x)$$

for all Borel sets A (here p_1 is the canonical projection).

Hence, the probability measure λ that we want is such that

$$E^\lambda\{h(y) | x\} = (\pi h)(x)$$

for a.e. $-d\lambda(x, y)$ and for $h \in V$. To do this, let $W \subseteq C(S) \times V$ be the linear subspace

$$W = \left\{ v \left| \begin{array}{l} v(x, y) = \sum_{i=1}^n g_i(x) h_i(y) + f(y) \\ \text{where } g_i \in C(S), h_i \in V \text{ and } f \in C(S) \end{array} \right. \right\}$$

and consider the linear functional $A: W \rightarrow R$ defined by

$$A(v) = \int \left(\sum_{i=1}^n g_i(x) \pi h_i(x) + f(x) \right) d\mu(x).$$

A is a non-negative functional i.e.

$$A(v) \geq 0 \quad \text{if } v \geq 0.$$

To check this: the function $\Phi^{g_1, \dots, g_n}: R^n \rightarrow R$ defined by

$$\Phi^{g_1, \dots, g_n}(z_1, \dots, z_n) = -\inf_x \left(\sum_{i=1}^n g_i(x) z_i \right)$$

is a convex function, then using the convexity inequality

$$\int \inf_x \left(\sum_{i=1}^n g_i(x) \pi h_i(y) \right) d\mu(y) \geq \int \inf_x \left(\sum_{i=1}^n g_i(x) h_i(y) \right) d\mu(y)$$

and so

$$\int \left(\sum_{i=1}^n g_i(y) \pi h_i(y) \right) d\mu(y) \geq \int \inf_x \left(\sum_{i=1}^n g_i(x) h_i(y) \right) d\mu(y).$$

But $v \geq 0$ implies

$$\inf_x \left(\sum_{i=1}^n g_i(x) h_i(y) \right) + f(y) \geq 0$$

and then

$$A(v) = \int \left(\sum_{i=1}^n g_i(y) \pi h_i(y) + f(y) \right) d\mu(y) \geq 0.$$

By Lemma 1, we can extend this functional A to a non-negative linear functional \bar{A} on $C(S \times S)$. And by Riesz theorem

$$\bar{A}(v) = \int_{S \times S} v(x, y) d\lambda(x, y)$$

where λ is a positive measure. Since

$$\lambda(C(S \times S)) = \int_{S \times S} 1 d\lambda(x, y) = \int_S 1 d\mu(x) = 1$$

we get that λ is a probability measure. By the properties of λ , we see that for $h \in V$ we have

$$E^\lambda \{h(y) | x\} = (\pi h)(x) \quad \text{for } x \notin N$$

where $\mu(N) = 0$ and N depends on h .

Since S is a compact metric space, we can find a sequence $h_n \in V$ such that the h_n 's are dense in V . For each n , we find a Borel set A_n such that $\mu(A_n) = 0$ and

$$E^\lambda \{h_n(y) | x\} = (\pi h_n)(x) \quad \text{for } x \notin A_n.$$

Let $N_1 = \bigcup_{n=1}^{\infty} A_n$, then $\mu(N_1) = 0$ and for each n

$$E^\lambda \{h_n(y) | x\} = (\pi h_n)(x) \quad \text{for } x \notin N_1.$$

Given any $h \in V$, we pick a subsequence h_{n_k} such that $\sup_{x \in S} |h(x) - h_{n_k}(x)| \rightarrow 0$ as $k \uparrow \infty$. Then

$$E^\lambda \{h_{n_k}(y) | x\} = (\pi h_{n_k})(x) \quad \text{for } x \notin N_1$$

implies that $E^\lambda \{h(y) | x\} = (\pi h)(x)$ for $x \notin N_1$.

Again, since S is a compact metric space, we can find a sequence $f_n \in C(S)$ such that $f_n \geq 0$ and the f_n 's are dense in $\{f \in C(S) : f \geq 0\}$. For each n , we find a Borel set B_n such that $\mu(B_n) = 0$ and

$$E^\lambda \{f_n(y) | x\} \geq 0 \quad \text{for } x \notin B_n.$$

Let $N_2 = \bigcup_{n=1}^{\infty} B_n$, then $\mu(N_2) = 0$ and for each n :

$$E^\lambda \{f_n(y) | x\} \geq 0 \quad \text{for } x \notin N_2.$$

Given any $f \in C(S)$ such that $f \geq 0$, we pick a subsequence f_{n_j} such that

$$\sup_{x \in S} |f(x) - f_{n_j}(x)| \rightarrow 0 \quad \text{as } j \uparrow \infty.$$

Then $E^\lambda \{f_{n_j}(y) | x\} \geq 0$ for $x \notin N_2$ implies that $E^\lambda \{f(y) | x\} \geq 0$ for $x \notin N_2$.

Let $\Delta = N_1 \cup N_2$, then obviously $\mu(\Delta) = 0$. Let us define

$$(\bar{\pi}f)(x) = E^\lambda \{f(y) | x\} \quad \text{for } f \in C(S)$$

and check that it has the desired properties

i) if $h \in V$, then

$$E^\lambda \{h(y) | x\} = (\pi h)(x) \quad \text{for } x \notin N_1$$

and so

$$E^\lambda \{h(y) | x\} = (\pi h)(x) \quad \text{for } x \notin \Delta$$

i.e. $(\bar{\pi}h)(x) = (\pi h)(x)$ for $x \notin \Delta$.

ii) if $f \in C(S)$ and $f \geq 0$, then

$$E^\lambda \{f(y) | x\} \geq 0 \quad \text{for } x \notin N_2$$

and so

$$E^\lambda \{f(y) | x\} \geq 0 \quad \text{for } x \notin \Delta$$

i.e. $(\bar{\pi}f)(x) \geq 0$ for $x \notin \Delta$.

iii) for any $f \in C(S)$

$$\int_S \bar{\pi}f(x) d\mu(x) = \int_S E^\lambda \{f(y) | x\} d\mu(x) = \int_{S \times S} f(y) d\lambda(x, y) = \int_S f(y) d\mu(y)$$

i.e. $\int \bar{\pi}f(x) d\mu(x) = \int f(x) d\mu(x)$.

Lemma 3. Let S be a locally compact separable metric space. Let $Y_0, Y_1, \dots, Y_n, \dots$ be a time-homogeneous Markov chain with transition probability function $g(y, A)$ and state space S . Let

$$G(y) = (\pi_g - I)H(y) = \int (H(x) - H(y))g(y, dx)$$

then $Z_n = H(Y_n) - \sum_{j=0}^{n-1} G(Y_j)$ is a F_n -martingale where F_n is the σ -algebra generated by Y_0, Y_1, \dots, Y_n .

Proof. Just check that $E(Z_{n+1} | F_n) = Z_n$.

Proof of the theorem in the compact case:

Step 1. Let $\lambda > 0$ and consider the operator $I - \lambda L: M \rightarrow C(S)$. Let $N_\lambda = \text{Range}(I - \lambda L)$ and let

$$\pi_\lambda = (I - \lambda L)^{-1}: N_\lambda \rightarrow M.$$

To see that π_λ is well-defined, let us check that the null space of $I - \lambda L$ is trivial: let $f = \lambda Lf$, then for some $x_0 \in S$ $f(x) \geq f(x_0)$ and thus by the minimum principle $f(x_0) = \lambda Lf(x_0) \geq 0$ i.e. $f(x) \geq 0$; but

$$\int f(x) d\mu(x) = \lambda \int Lf(x) d\mu(x) = 0$$

and this implies that $f \equiv 0$.

π_λ has the following properties.

i) π_λ is a non-negative operator: let $f \in N_\lambda$ be such that $f \geq 0$, since S is a compact space for some $x_0 \in S$ we have

$$\pi_\lambda f(x) \geq \pi_\lambda f(x_0) \quad \text{for all } x \in S$$

then by the minimum principle, we have

$$L\pi_\lambda f(x_0) \geq 0$$

and so

$$\pi_\lambda f(x_0) \geq \pi_\lambda f(x_0) - \lambda L\pi_\lambda f(x_0) = f(x_0) \geq 0.$$

This implies:

$$\pi_\lambda f(x) \geq 0 \quad \text{for all } x \in S$$

i.e. $\pi_\lambda f \geq 0$.

ii) $\pi_\lambda 1 = 1$. To see this, notice that if C is constant function then $LC = 0$ because C maximum implies $LC \leq 0$ and C minimum implies $LC \geq 0$. Hence the operator $I - \lambda L$ leaves constants invariant, in particular

$$(I - \lambda L)1 = 1.$$

Then

$$\pi_\lambda 1 = \pi_\lambda (I - \lambda L)1 = 1.$$

iii) $\int \pi_\lambda f(x) d\mu(x) = \int f(x) d\mu(x)$ for all $f \in N_\lambda$. To see this: $f \in N_\lambda$ implies $f = (I - \lambda L)g$ for some $g \in M$, thus

$$\int f(x) d\mu(x) = \int g(x) d\mu(x) - \lambda \int Lf(x) d\mu(x) = \int g(x) d\mu(x)$$

but $\pi_\lambda f = \pi_\lambda (I - \lambda L)g = g$ and so

$$\int f(x) d\mu(x) = \int \pi_\lambda f(x) d\mu(x).$$

We must show that π_λ can be extended from N_λ to all $C(S)$ as $\bar{\pi}_\lambda$ such that

i) $\bar{\pi}_\lambda 1 = 1$

ii) $\bar{\pi}_\lambda f \geq 0$ if $f \geq 0$

iii) $\int \bar{\pi}_\lambda f(x) d\mu(x) = \int f(x) d\mu(x)$ for all $f \in C(S)$. Let $\theta: R^p \rightarrow R$ be a convex function. Since any pointwise limit of convex functions is a convex function we can find a smooth convex function which approximates θ by taking the convolution of θ with a test function. Hence we can assume that θ is a smooth convex function. Let $f_1, f_2, \dots, f_p \in N_\lambda$ and consider

$$\Phi(\lambda) = \int (\theta(f_1, \dots, f_p) - \theta(f_1 - \lambda Lf_1, \dots, f_p - \lambda Lf_p)) d\mu.$$

Since θ is convex, we have that Φ is a concave function.

Differentiating

$$\Phi'(\lambda) = \int \sum_{k=1}^p \frac{\partial \theta}{\partial x_k} (f_1 - \lambda Lf_1, \dots, f_p - \lambda Lf_p) Lf_k d\mu$$

and so

$$\Phi'(0) = \int \sum_{k=1}^p \frac{\partial \theta}{\partial x_k} (f_1, \dots, f_p) Lf_k d\mu$$

then

$$\Phi'(0) \leq \int L\theta(f_1, \dots, f_p) d\mu = 0.$$

But Φ is a concave function and $\Phi(0) = 0$ hence $\Phi(\lambda) \leq 0$ for all $\lambda > 0$.

$$\text{i.e.} \quad \int \theta(f_1, \dots, f_p) d\mu \leq \int \theta(f_1 - \lambda Lf_1, \dots, f_p - \lambda Lf_p) d\mu$$

$$\text{i.e.} \quad \int \theta(\pi_\lambda g_1, \dots, \pi_\lambda g_p) d\mu \leq \int \theta(g_1, \dots, g_p) d\mu$$

for $g_1, \dots, g_p \in M$.

By Lemma 2, we have a Borel set A_λ such that $\mu(A_\lambda) = 0$ and an operator $\pi_\lambda^{(1)}: C(S) \rightarrow B(S)$ such that

- i) if $f \in N_\lambda$ then $\pi_\lambda^{(1)} f(x) = \pi_\lambda f(x)$ for $x \notin A_\lambda$
- ii) if $f \in C(S)$ and $f \geq 0$, then $\pi_\lambda^{(1)} f(x) \geq 0$ for $x \notin A_\lambda$
- iii) $\int \pi_\lambda^{(1)} f(x) d\mu(x) = \int f(x) d\mu(x)$ for all $f \in C(S)$.

Since the solution of the martingale problem is unique, we have a Markov process $x(t)$ and hence a semigroup $\{T_t: t > 0\}$.

Let $\{R_\alpha: \alpha > 0\}$ be the resolvent associated with this semigroup and consider the operator

$$\pi_\lambda^{(2)} = \frac{1}{\lambda} R_\lambda^1: C(S) \rightarrow B(S).$$

$\pi_\lambda^{(2)}$ has the properties

- i) $\pi_\lambda^{(2)} 1 = \frac{1}{\lambda} R_\lambda^1 1 = \frac{1}{\lambda} \lambda = 1$
- ii) if $f \in C(S)$ and $f \geq 0$, then $\pi_\lambda^{(2)} f = \frac{1}{\lambda} R_\lambda^1 f \geq 0$
- iii) $\pi_\lambda^{(2)} f = \pi_\lambda f$ for $f \in N_\lambda$.

To check this, since $f(x(t)) - \int_0^t Lf(x(s)) ds$ is a martingale, we have

$$E_x(f(x(t)) - \int_0^t Lf(x(s)) ds) = f(x)$$

then

$$T_t f(x) - \int_0^t T_s Lf(x) ds = f(x)$$

$$\frac{1}{\lambda} R_\lambda^1 f(x) - \frac{1}{\lambda} \int_0^\infty e^{-\frac{t}{\lambda}} \int_0^t T_s Lf(x) ds dt = f(x)$$

and integrating by parts

$$\frac{1}{\lambda} R_{\lambda}^1 f(x) - \int_0^{\infty} e^{-t/\lambda} T_t Lf(x) dt = f(x)$$

i.e. $\frac{1}{\lambda} R_{\lambda}^1 f(x) - R_{\lambda}^1 Lf(x) = f(x)$

i.e. $\frac{1}{\lambda} R_{\lambda}^1 (I - \lambda L) f(x) = f(x)$

i.e. $\pi_{\lambda}^{(2)} = (I - \lambda L)^{-1}$ on N_{λ} .

Let us define the extension

$$\bar{\pi}_{\lambda}: C(S) \rightarrow B(S).$$

For each $f \in C(S)$, we define

$$\bar{\pi}_{\lambda} f(x) : \begin{cases} \pi_{\lambda}^{(1)} f(x) & \text{if } x \notin A_{\lambda} \\ \pi_{\lambda}^{(2)} f(x) & \text{if } x \in A_{\lambda}. \end{cases}$$

It is easy to check that $\bar{\pi}_{\lambda}$ has the desired properties.

Step 2. Consider the operators

$$\pi_{\lambda}: N_{\lambda} \rightarrow M \text{ and their extension}$$

$$\bar{\pi}_{\lambda}: C(S) \rightarrow B(S). \text{ Using the invariance principle let us show that}$$

$$(\bar{\pi}_{\lambda})^n \rightarrow T_t \quad \text{when } \lambda \rightarrow 0, n \rightarrow \infty, \lambda n \rightarrow t;$$

where $(T_t f)(x) = E_x(f(x(t)))$ is the semigroup corresponding to the unique solution of the martingale problem. Then since

$$\int (\bar{\pi}_{\lambda})^n f(x) d\mu(x) = \int f(x) d\mu(x)$$

taking limits, we get $\int T_t f(x) d\mu(x) = \int f(x) d\mu(x)$ for all $f \in C(S)$, in other words: $\mu T_t = \mu$ i.e. μ is an invariant measure.

The proof of step 2 goes as follows: For each $\lambda > 0$ consider the Markov chain

$$X_0^{(\lambda)}, X_1^{(\lambda)}, \dots, X_n^{(\lambda)}, \dots$$

with stationary transition probability function $\bar{\pi}_{\lambda}$. Therefore, for $f \in M$ and $g_{\lambda} = f - \lambda Lf \in N_{\lambda}$ we have

$$(\bar{\pi}_{\lambda} - I) g_{\lambda} = \bar{\pi}_{\lambda} (I - \lambda L) f - (I - \lambda L) f = \lambda Lf$$

and by Lemma 3

$$g_{\lambda}(X_n^{(\lambda)}) - \lambda \sum_{j=0}^{n-1} Lf(X_j^{(\lambda)}) \quad \text{is a martingale.}$$

Construct the process

$$Y_t^{(\lambda)} = X_{\lfloor \frac{t}{\lambda} \rfloor}^{(\lambda)}$$

(here $\lfloor \cdot \rfloor$ is the usual integer part function).

We see that $Y_t^{(\lambda)}$ has right-continuous trajectories. Let $Q_x^{(\lambda)}$ be the probability measure on $S \times S \times S \times \dots$ induced by the process $\{X_n^{(\lambda)}: n > 0\}$ conditioned to start at x i.e. for any Borel sets $\Gamma_0, \Gamma_1, \dots, \Gamma_m$ and any $k > 0$

$$\begin{aligned} Q_x^{(\lambda)}(X_k^{(\lambda)} \in \Gamma_0, \dots, X_{k+m}^{(\lambda)} \in \Gamma_m) \\ = \int_{\Gamma_m} \dots \int_{\Gamma_0} \delta_x(dy_0) \pi_\lambda(y_0, dy_1) \dots \pi_\lambda(y_{m-1}, dy_m). \end{aligned}$$

Let $P_x^{(\lambda)}$ be the probability measure on $D([0, \infty), S)$ defined by

$$P_x^{(\lambda)}(x(t_1) \in \Gamma_1, \dots, x(t_n) \in \Gamma_n) = Q_x^{(\lambda)}(Y_{t_1}^{(\lambda)} \in \Gamma_1, \dots, Y_{t_n}^{(\lambda)} \in \Gamma_n)$$

where $\Gamma_1, \dots, \Gamma_n$ are Borel sets in S . We want to see that $P_x^{(\lambda)}$ as $\lambda \rightarrow 0$ is weakly compact in $D([0, \infty), S)$. Let $\psi(\lambda, x, \delta, t) = P_x^{(\lambda)}(\tau_\delta < t)$ where $\delta > 0$ and τ_δ is the exit time from the open ball $B(x, \delta)$. To prove compactness of the sequence $\{P_x^{(\lambda)}: \lambda > 0\}$ it suffices to see that for each $\delta > 0$:

$$\lim_{t \rightarrow 0} \limsup_{\lambda \rightarrow 0} \sup_{x \in S} \psi(\lambda, x, \delta, t) = 0.$$

Since the state space is compact, it suffices to check

$$\lim_{t \rightarrow 0} \limsup_{\lambda \rightarrow 0} \sup_{x \in B(x_0, \delta)} \psi(\lambda, x, \delta, t) = 0$$

for some fixed $x_0 \in S$ (but arbitrary). By Urysohn's lemma there is $\theta \in C(S)$ such that $\theta = 0$ on $B(x_0, \delta)$, $\theta = 1$ on $B(x_0, 2\delta)^c$ and $0 < \theta < 1$ in the remaining annulus. Since M is dense in $C(S)$ given a number $0 < \rho < 1$ we can find $0 < \theta_\rho \in M$ such that

$$\sup_{x \in S} |\theta_\rho(x) - \theta(x)| < \rho$$

then

$$\sup \{\theta_\rho(x): d(x, x_0) < \delta\} < \rho$$

and

$$\inf \{\theta_\rho(x): d(x, x_0) > 2\delta\} > 1 - \rho.$$

Let $\phi_{\rho, \lambda} = (I - \lambda L)\theta_\rho$. This implies

$$\bar{\pi}_\lambda(\phi_{\rho, \lambda}) = \theta_\rho \quad \text{and so} \quad \bar{\pi}_\lambda(\phi_{\rho, \lambda}) - \phi_{\rho, \lambda} = \lambda L\theta_\rho.$$

Since θ_ρ is a nice bounded function, we can find A^ρ such that $|L\theta_\rho| < A^\rho$ and hence

$$|\phi_{\rho, \lambda}(x)| = |\theta_\rho(x) - \lambda L\theta_\rho(x)| \leq \rho + \lambda A^\rho \quad \text{for } x \in B(x_0, \delta)$$

and

$$|\phi_{\rho, \lambda}(x)| \geq \theta_\rho(x) - \lambda |L\theta_\rho(x)| \geq 1 - \rho - \lambda A^\rho \quad \text{for } x \in B(x_0, 2\delta)^c.$$

By what we said before

$$\phi_{\rho, \lambda}(Y_{(n\lambda)}^{(\lambda)}) - \lambda \sum_{j=0}^{n-1} L\theta_\rho(Y_{(j\lambda)}^{(\lambda)})$$

is a martingale, and the fact that $|L\theta_\rho| < A^\rho$ obviously implies that $\phi_{\rho, \lambda}(Y_{(n\lambda)}^{(\lambda)}) - n\lambda A^\rho$ is a supermartingale. Since $\{\phi_{\rho, \lambda}(x(t \wedge \tau_\delta)) - A^\rho(t \wedge \tau_\delta)\}$ is uniformly bounded, we can apply Doob's stopping time theorem.

Let $x \in B(x_0, \delta)$

$$E_x^{(\lambda)}[\phi_{\rho, \lambda}(x(t \wedge \tau_{3\delta})) - A^\rho(t \wedge \tau_{3\delta})] \leq E_x^{(\lambda)}[\phi_{\rho, \lambda}(x(0 \wedge \tau_{3\delta})) - A^\rho(0 \wedge \tau_{3\delta})]$$

that is

$$E_x^{(\lambda)}[\phi_{\rho, \lambda}(x(t \wedge \tau_{3\delta})) - A^\rho(t \wedge \tau_{3\delta})] \leq \phi_{\rho, \lambda}(x) \leq \rho + \lambda A^\rho.$$

Now, since $d(x, x_0) < \delta$, $\tau_{3\delta} \leq t$ implies that $Y_{(t \wedge \tau_{3\delta})}^{(\lambda)} \in B(x_0, 2\delta)^c$ so

$$\begin{aligned} E_x^{(\lambda)}[\phi_{\rho, \lambda}(x(t \wedge \tau_{3\delta}))] &= E_x^{(\lambda)}[\phi_{\rho, \lambda}(x(\tau_{3\delta}), \tau_{3\delta} \leq t] \\ &+ E_x^{(\lambda)}[\theta_\rho(x(t)), \tau_{3\delta} > t] + E_x^{(\lambda)}[-\lambda L\theta_\rho(x(t)), \tau_{3\delta} > t] \\ &\geq (1 - \rho - \lambda A^\rho) P_x^{(1)}(\tau_{3\delta} \leq t) - \lambda A^\rho P_x^{(\lambda)}(\tau_{3\delta} > t) \\ &= (1 - \rho - \lambda A^\rho) P_x^{(\lambda)}(\tau_{3\delta} \leq t) - \lambda A^\rho + \lambda A^\rho P_x^{(\lambda)}(\tau_{3\delta} \leq t) \\ &= (1 - \rho) P_x^{(\lambda)}(\tau_{3\delta} \leq t) - \lambda A^\rho \end{aligned}$$

and clearly

$$E_x^{(\lambda)}[A^\rho(t \wedge \tau_{3\delta})] \leq t A^\rho.$$

Then

$$\begin{aligned} (1 - \rho) P_x^{(\lambda)}(\tau_{3\delta} \leq t) - \lambda A^\rho - t A^\rho &\leq E_x^{(\lambda)}[\phi_{\rho, \lambda}(x(t \wedge \tau_{3\delta})) - A^\rho(t \wedge \tau_{3\delta})] \\ &\leq \rho + \lambda A^\rho \end{aligned}$$

i.e. $(1 - \rho) P_x^{(\lambda)}(\tau_{3\delta} \leq t) \leq \rho + 2\lambda A^\rho + t A^\rho$ for $x \in B(x_0, \delta)$.

Then

$$\lim_{t \rightarrow 0} \limsup_{\lambda \rightarrow 0} \sup_{x \in B(x_0, \delta)} P_x^{(\lambda)}(\tau_{3\delta} \leq t) \leq \frac{\rho}{1 - \rho}$$

and since ρ is arbitrary

$$\lim_{t \rightarrow 0} \limsup_{\lambda \rightarrow 0} \sup_{x \in B(x_0, \delta)} P_x^{(\lambda)}(\tau_{3\delta} \leq t) = 0.$$

Therefore, for some subsequence λ_j

$$P_x^{(\lambda_j)} \Rightarrow Q_x \quad \text{as } \lambda_j \rightarrow 0.$$

It remains to identify the limit Q_x .

Let $f \in M$ and $g_\lambda = f - \lambda Lf$, then $(\bar{\pi}_\lambda - I)g_\lambda = \lambda Lf$ and we know

$$g_\lambda(x(n\lambda)) - \lambda \sum_{j=0}^{n-1} Lf(x(j\lambda))$$

is a $P_x^{(\lambda)}$ -martingale.

Notice that

$$g_{\lambda_j}(x(n_j \lambda_j)) - \frac{\lambda_j n_j}{n_j} \sum_{k=0}^{n_j-1} Lf(x(k \lambda_j))$$

tends to

$$f(x(t)) - \int_0^t Lf(x(s)) ds \quad \text{as } \lambda_j \rightarrow 0, n_j \rightarrow \infty, \lambda_j n_j \downarrow t.$$

And since $P_x^{(\lambda_j)} \Rightarrow Q_x$, we can easily conclude that $f(X(t)) - \int_0^t Lf(x(s)) ds$ is a Q_x -martingale, but we assumed that P_x is the unique solution to the martingale problem, hence $Q_x = P_x$ and so $P_x^{(\lambda_j)} \Rightarrow P_x$ as $\lambda_j \rightarrow 0$.

3. Proof of Non-Compact Case

From now on, we assume that the state space S is a locally compact separable metric space.

Lemma 4. *Let S_1 and S_2 be locally compact separable metric spaces. Let \hat{S}_1 and \hat{S}_2 be the one-point compactifications of S_1 and S_2 respectively. Let Λ_1 be a non-negative linear functional on $C(\hat{S}_1)$ and Λ_2 a non-negative linear functional on $C(\hat{S}_2)$. Assume there are probability measures μ_1 on S_1 and μ_2 on S_2 such that $\Lambda_1 f = \int f d\mu_1$ and $\Lambda_2 g = \int g d\mu_2$. Let Λ be a non-negative linear functional on $C(\hat{S}_1 \times \hat{S}_2)$ such that $\Lambda f = \Lambda_1 f$ for $f \in C(\hat{S}_1)$ and $\Lambda g = \Lambda_2 g$ for $g \in C(\hat{S}_2)$. Then there is a probability measure μ on $S_1 \times S_2$ such that*

$$\Lambda h = \int h d\mu \quad \text{for all } h \in C(\hat{S}_1 \times \hat{S}_2).$$

Proof. Since $\hat{S}_1 \times \hat{S}_2$ is a compact metric space, by Riesz theorem there is a measure μ on $\hat{S}_1 \times \hat{S}_2$ such that $\Lambda h = \int h d\mu$ for all $h \in C(\hat{S}_1 \times \hat{S}_2)$. Since $\Lambda l = \Lambda_1 l = 1$ we have that μ is a probability measure. And since $\Lambda f = \Lambda_1 f$ for $f \in C(\hat{S}_1)$ and $\Lambda g = \Lambda_2 g$ for $g \in C(\hat{S}_2)$, we have that μ has marginals μ_1 and μ_2 . Now

$$\begin{aligned} \mu(S_1 \times \{\infty\}) &= \mu_2(\{\infty\}) = 0 \\ \mu(\{\infty\} \times S_2) &= \mu_1(\{\infty\}) = 0 \end{aligned}$$

hence μ is concentrated on $S_1 \times S_2$ and thus μ is the desired probability measure.

Lemma 5. *Let S be a locally compact separable metric space and μ a probability measure on S . Let M be a linear subspace of $C(S)$ (the class of bounded continuous functions on S which have a limit at infinity) such that the constant function $1 \in M$. Assume we have an operator $\pi: M \rightarrow C(S)$ such that*

- i) $\pi 1 = 1$
- ii) $\pi f \geq 0$ if $f \geq 0$
- iii) $\int \pi f(x) d\mu(x) = \int f(x) d\mu(x)$.

Assume that for each integer $p > 0$ and any $f, \dots, f_p \in M$ and for any convex function $\theta: \mathbb{R}^p \rightarrow \mathbb{R}$, the following convexity inequality holds

$$\int \theta(\pi f_1(x), \dots, \pi f_p(x)) d\mu(x) \leq \int \theta(f_1(x), \dots, f_p(x)) d\mu(x).$$

Then we can find a Borel set Δ such that $\mu(\Delta) = 0$ and we can find an operator $\bar{\pi}: C(S) \rightarrow B(S)$ such that

- i) if $f \in M$, then $\bar{\pi}f(x) = \pi f(x)$ for $x \notin \Delta$
- ii) if $f \in C(S)$ and $f \geq 0$, then $\bar{\pi}f(x) \geq 0$ for $x \notin \Delta$
- iii) $\int \bar{\pi}f(x) d\mu(x) = \int f(x) d\mu(x)$ for all $f \in C(S)$.

Proof. Notice that $C(S)$ is isomorphic to $C(\hat{S})$. Let $W \subseteq C(\hat{S}) \times M$ be the linear subspace defined as

$$W = \left\{ v \left| \begin{array}{l} v(x, y) = \sum_{i=1}^n g_i(x) h_i(y) + f(y) \\ \text{where } g_i \in C(\hat{S}), h_i \in M \text{ and } f \in C(\hat{S}) \end{array} \right. \right\}$$

and consider the linear functional

$$A: W \rightarrow \mathbb{R} \text{ defined by } A(v) = \int \left(\sum_{i=1}^n g_i(x) \pi h_i(x) + f(x) \right) d\mu(x).$$

Just as we did before, we can see that A is a non-negative linear functional. By Lemma 1 we can extend A to a non-negative linear functional \bar{A} on $C(\hat{S} \times \hat{S})$. But for $f \in C(\hat{S})$, since $f(x)1 \in W$ we have

$$\bar{A}f = \bar{A}(f1) = \int f(x) d\mu(x).$$

Hence by Lemma 4, there is a probability measure λ on $S \times S$ such that

$$Av = \int v(x, y) d\lambda(x, y) \quad \text{for all } v \in C(S \times S).$$

Since S is locally compact separable metric space, the space $C(S)$ is a complete separable metric space. And by a previous reasoning the lemma follows.

Proof of the theorem in the non-compact case:

Step 1. Same as before.

Step 2. Consider the operator $\pi_\lambda: N_\lambda \rightarrow M$ and its extension $\bar{\pi}_\lambda: C(S) \rightarrow B(S)$.

As before, to see that μ is an invariant measure it suffices to see that $(\bar{\pi}_\lambda)^n \rightarrow T_t$ when $\lambda \rightarrow 0$, $n \rightarrow \infty$, $\lambda n \rightarrow t$ where T_t is the associated semigroup with the unique solution to the martingale problem.

The proof of step 2 goes as follows:

As before we want to see that $P_x^{(\lambda)}$ as $\lambda \rightarrow 0$ is weakly compact in $D([0, \infty), S)$ where $x \in S$ is fixed but arbitrary. Since S is a locally compact separable metric space, we have that S is σ -compact i.e. there is a sequence D_k of compact subsets of S such that

$$S = \bigcup_{k=1}^{\infty} D_k.$$

Clearly, we can assume that

$$D_k \subseteq \text{Interior}(D_{k+1}).$$

Let $x \in D_k$ and consider

$$\theta_k: S \rightarrow [0, 1]$$

such that

$$\theta_k(y) = \begin{cases} 1 & \text{for } y \in D_k \\ 0 & \text{for } y \notin D_{k+1}. \end{cases}$$

For any Borel set A , we define

$$\pi_{\lambda,k}(y, A) = \theta_k(y) \pi_\lambda(y, A) + (1 - \theta_k(y)) I_A(y).$$

Let $P_x^{\lambda,k}$ be defined in terms of $\pi_{\lambda,k}$ as $P_x^{(\lambda)}$ was already defined in terms of π_λ . Let $G_t = \{x(s): 0 < s < t\}$ and define

$$\tau_k = \inf\{t: G_t \cap D_k^c \neq \emptyset\}.$$

Then since the process $x(t)$ is a jump Markov process the τ_k are lower semicontinuous stopping times. By the definition of the Kernel $\pi_{\lambda,k}$ we see that the process is not altered until it leaves for the first time the set D_k , thus $P_x^{\lambda,k} = P_x^{(\lambda)}$ on F_{τ_k} . Also by the definition of $\pi_{\lambda,k}$ we see that the process is slowed down in the set $(D_{k+1} - D_k)$ and there is no motion outside the set D_{k+1} , therefore, by a procedure analogous to the compact case, we can see that the sequence $\{P_x^{\lambda_j,k}: \lambda_j > 0\}$ is weakly compact i.e. for some subsequence $P_x^{\lambda_j,k} \Rightarrow Q_x^k$ as $\lambda_j \rightarrow 0$. Moreover for events in F_{τ_k} the limit Q_x^k is clearly identified as P_x the unique solution to the martingale problem i.e. $Q_x^k = P_x$ on F_{τ_k} . Also notice that by the definition of the Kernel $\pi_{\lambda,k}$ we have

$$P_x^{\lambda,k} = P_x^{(\lambda)} \quad \text{on } F_{\tau_k}.$$

Applying the Lemma 11.1.1 of reference [2] we have that $P_x^{(\lambda_j)} \Rightarrow P_x$ as $\lambda_j \rightarrow 0$.

4. Applications

Let $S = \mathbb{R}^d$ be the state space and let us look at some examples to see the scope of application of the previous theorem.

i) Consider the operator

$$L = \frac{1}{2} \sum_{i,j=1}^n a_{ij} \frac{\partial^2}{\partial x_i \partial x_j} + \sum_{j=1}^n b_j \frac{\partial}{\partial x_j}$$

where the coefficients $a_{ij}(x)$ and $b_j(x)$ are smooth enough. Then for $f \in C^2(\mathbb{R}^d)$ the initial value problem

$$\frac{\partial u}{\partial t} = Lu, \quad u(0, x) = f(x)$$

has a unique solution $u \in C^2(\mathbb{R}^d)$. Thus differentiating under the integral sign

$$\frac{\partial}{\partial t} \int u(t, x) d\mu(x) = \int Lu(t, x) d\mu(x) = 0$$

i.e.

$$\int u(t, x) d\mu(x) = \int u(0, x) d\mu(x)$$

but we know $u(t, x) = T_t f(x)$, so

$$\int T_t f(x) d\mu(x) = \int f(x) d\mu(x)$$

i.e. μ is an invariant measure. In this case, the previous theorem was not necessary to check that μ is an invariant measure.

ii) Let $w(t)$ be the Brownian motion in R^d and consider the stochastic differential equation

$$dx(t) = \sigma(x(t)) dw(t) + b(x(t)) dt.$$

Assume that for some constant $K > 0$ the matrix $\sigma = (\sigma_{ij})$ and the vector $b = (b_j)$ satisfy

$$\begin{aligned} |\sigma_{ij}(x) - \sigma_{ij}(y)| + |b_j(x) - b_j(y)| &\leq K|x - y| \\ |\sigma_{ij}(x)| + |b_j(x)| &\leq K(1 + |x|) \end{aligned}$$

for all $x, y \in R^d$ and $1 \leq i, j \leq n$. Then by the standard theory of Itô we have a unique Markovian solution of this stochastic differential equation which has the infinitesimal generator

$$L = \frac{1}{2} \sum_{i,j=1}^n a_{ij} \frac{\partial^2}{\partial x_i \partial x_j} + \sum_{j=1}^n b_j \frac{\partial}{\partial x_j}.$$

Here $(a_{ij}) = a = \sigma \sigma^*$.

Let M consist of the class of functions $f = g + C$ where $g \in C_0^\infty(R^d)$ and C is a constant function. We see that L maps M into $C(R^d)$ and L satisfies the minimum principle.

If $f_1, \dots, f_p \in M$ and $\theta: R^p \rightarrow R$ is a smooth convex function, then

$$L\theta(f_1, \dots, f_p) \in C(R^d)$$

and so the convexity inequality holds. Since the theory of Itô applies the martingale problem is well-posed (see reference [2]). Thus if μ is a probability measure on R^d such that $\int Lf(x) d\mu(x) = 0$ for all $f \in M$, then by the previous theorem, we conclude that μ is an invariant measure. In this case the procedure outlined in (i) no longer applies, however, the previous theorem does.

iii) Let $L = \frac{1}{2} \sum_{i,j=1}^n a_{ij} \frac{\partial^2}{\partial x_i \partial x_j} + \sum_{j=1}^n b_j \frac{\partial}{\partial x_j}$.

We assume that the matrix $a = (a_{ij})$ is bounded, continuous and positive definite, and we also assume that the vector $b = (b_j)$ is bounded and continuous. In this case neither the procedure outlined in (i) nor in (ii) applies but (see reference [2]) by the theory of Stroock and Varadhan, we can associate with L a unique Markov process $x(t)$ with infinitesimal generator L . Taking as M the class of functions $f = g + C$ where $g \in C_0^\infty(R^d)$ and C is a constant function, we can check that our theorem applies.

5. Application to Infinite Particle Systems

Let P be a countable set, let F be a finite set and consider

$$S = \prod_{i \in P} F.$$

Endow F with the discrete metric and S with the product topology. Then S is a compact metric space. For any N finite subset of P let

$$S_N = \prod_{i \in N} F$$

and let $\tau_N: S \rightarrow S_N$ be the natural projection. A function $\phi: S \rightarrow \mathbb{R}$ is said to be a tame function if there is a finite subset N of P and a function $f: S_N \rightarrow \mathbb{R}$ such that $\phi(x) = f(\tau_N(x))$ for all $x \in S$, in other words, ϕ depends only on a finite number of variables.

Let M be the class of tame functions, it is clear that M is dense in $C(S)$. Let $G: M \rightarrow C(S)$ be a nice pregenerator (we mean: G satisfies the minimum principle and the martingale problem is well-posed). If $f_1, f_2, \dots, f_p \in M$ and $\theta: \mathbb{R}^p \rightarrow \mathbb{R}$ is a smooth convex function, then obviously $\theta(f_1, \dots, f_p) \in M$ and so, the convexity inequality holds.

If μ is a probability measure such that

$$\int Gf(x) d\mu(x) = 0 \quad \text{for all } f \in M$$

by the previous theorem, we can conclude that μ is an invariant measure.

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