# The Feynman-Kac representation 

Jason Swanson

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## 1 Introduction

Suppose that $b: \mathbb{R}^{d} \rightarrow \mathbb{R}^{d}$ and $\sigma: \mathbb{R}^{d} \rightarrow \mathbb{R}^{d} \times \mathbb{R}^{d}$ are continuous functions that satisfy the linear growth condition

$$
|b(x)|+|\sigma(x)| \leq K(1+|x|)
$$

for some constant $K$ and all $x \in \mathbb{R}^{d}$. Consider the stochastic differential equation

$$
\begin{equation*}
X(t)=X(0)+\int_{0}^{t} \sigma(X(s)) d B(s)+\int_{0}^{t} b(X(s)) d s \tag{1.1}
\end{equation*}
$$

We shall assume that for each $x \in \mathbb{R}^{d}$, there exists a pair of $\mathbb{R}^{d}$-valued processes, $X$ and $B$, defined on some probability space $(\Omega, \mathcal{F}, P)$, such that $P(X(0)=x)=1, B$ is a standard $d$-dimensional Brownian motion under $P$, and (1.1) is satisfied. We also assume that the law of $(X, B)$ is uniquely determined.

Let $L$ denote the generator of $X$. That is, $L$ is the differential operator

$$
L f(x)=\frac{1}{2} \sum_{i, j} a_{i j}(x) \partial_{i j}^{2} f(x)+b(x)^{T} \nabla f(x)
$$

where $f \in C^{2}\left(\mathbb{R}^{d}\right)$ and $a(x)=\sigma(x) \sigma(x)^{T}$.
The Feynman-Kac representation asserts that, under appropriate conditions, the solution to the initial value problem

$$
\begin{equation*}
\partial_{t} u=L u, \quad u(0, x)=f(x) \tag{1.2}
\end{equation*}
$$

is given by

$$
\begin{equation*}
u(t, x)=E^{x}[f(X(t))] . \tag{1.3}
\end{equation*}
$$

We will first present a heuristic derivation of this result, and then state the full theorem, whose proof can be found in the references.

Suppose that (1.2) has a solution $u(t, x)$. Fix $T>0$ and define $v(t, x)=u(T-t, x)$. Then $\partial_{t} v=-L v$. Define $Y(t)=v(t, X(t))$. By Itô's rule,

$$
Y(t)=Y(0)+M(t)+\int_{0}^{t}\left(\partial_{t} v(s, X(s))+L v(s, X(s))\right) d s=Y(0)+M(t)
$$

where $M(t)$ is a local martingale. Hence,

$$
u(T-t, X(t))=u(T, X(0))+M(t)
$$

If $M$ is in fact a martingale, then taking expectations gives

$$
E^{x}[u(T-t, X(t))]=u(T, x) .
$$

Assuming that we can justify letting $t \rightarrow T$ under the expectation, this gives

$$
E^{x}[u(0, X(T))]=u(T, x)
$$

Since $u(0, x)=f(x)$ and since this is true for all $T>0$, we have derived (1.3).

## 2 The Feynman-Kac representation theorem

The full theorem is more general than what is described in the introduction. We will actually consider the initial value problem

$$
\begin{equation*}
\partial_{t} u=L u-k u+g, \quad u(0, x)=f(x), \tag{2.1}
\end{equation*}
$$

where $k, g:[0, \infty) \times \mathbb{R}^{d} \rightarrow \mathbb{R}$ are continuous. We assume that $k \geq 0$ and that $g$ satisfies the following growth condition: for each $T>0$, there exist constants $L$ and $r$ such that

$$
\sup _{0 \leq t \leq T}|g(t, x)| \leq L\left(1+|x|^{r}\right)
$$

for all $x \in \mathbb{R}^{d}$.
Theorem 2.1 Assume that $u(t, x)$ is continuous on $[0, \infty) \times \mathbb{R}^{d}$, and that $\partial_{t} u$ and $\partial_{i j}^{2} u$ are continuous on $(0, \infty) \times \mathbb{R}^{d}$ for all $i$ and $j$. Assume that $u$ satisfies (2.1), and that $u$ satisfies the same growth condition as $g$. Let

$$
Z(t)=\exp \left\{-\int_{0}^{t} k(s, X(s)) d s\right\}
$$

Then

$$
\begin{equation*}
u(t, x)=E^{x}\left[f(X(t)) Z(t)+\int_{0}^{t} g(s, X(s)) Z(s) d s\right] . \tag{2.2}
\end{equation*}
$$

In particular, such a solution to (2.1) is unique.
This is a special case of Theorem 5.7.6 in [1]. (The full result in [1] concerns the case when $b$ and $\sigma$ also depend on $t$.) Note that when $k=0$, we have $Z(t)=1$ and (2.2) reduces to

$$
u(t, x)=E^{x}\left[f(X(t))+\int_{0}^{t} g(s, X(s)) d s\right] .
$$

In particular, if $k=g=0$, then (2.2) reduces to (1.3).

## 3 The killed process

The process $X(t)$ can be thought of as representing the location of a particle which is moving about randomly in $\mathbb{R}^{d}$. In this section, we modify the process $X$ so that the particle is "killed" at a random time $\rho$. Specifically, we define

$$
\begin{equation*}
\rho=\inf \left\{t \geq 0: \int_{0}^{t} k(s, X(s)) d s \geq \tau\right\} \tag{3.1}
\end{equation*}
$$

where $\tau$ is independent of $X$ and is exponentially distributed with mean 1. The killed process is defined as

$$
\tilde{X}(t)= \begin{cases}X(t) & \text { if } t<\rho  \tag{3.2}\\ \Delta & \text { if } t \geq \rho\end{cases}
$$

where $\Delta$ is a so-called "cemetery" state which is outside of $\mathbb{R}^{d}$.
The function $k(t, x)$ is interpreted as the killing rate. Informally, this means that if, at time $t$, the particle is alive and is situated at the point $x$, then the probability that it dies in the next $h$ units of time is approximately $k(t, x) h$ when $h$ is small. Symbolically,

$$
\begin{equation*}
P(\rho \leq t+h \mid \rho>t, X(t)=x) \approx k(t, x) h \tag{3.3}
\end{equation*}
$$

To see this more formally, first recall that $X$ is a Markov process with respect to a filtration $\mathcal{F}_{t}$. Since $\tau$ and $X$ are independent,

$$
P\left(\rho>t+h \mid \mathcal{F}_{\infty}\right)=P\left(\int_{0}^{t+h} k(s, X(s)) d s<\tau \mid \mathcal{F}_{\infty}\right)=Z(t+h)
$$

where $Z$ is defined as in Theorem 2.1. Hence,

$$
\begin{aligned}
P\left(\rho>t+h \mid \mathcal{F}_{t}\right) & =E\left[Z(t+h) \mid \mathcal{F}_{t}\right] \\
& =Z(t) E\left[\exp \left\{-\int_{t}^{t+h} k(s, X(s)) d s\right\} \mid \mathcal{F}_{t}\right] \\
& =Z(t) E^{X(t)}\left[\exp \left\{-\int_{0}^{h} k(t+s, X(s)) d s\right\}\right],
\end{aligned}
$$

where we have used the Markov property in the last equality. Finally, then,

$$
\begin{aligned}
P(\rho>t+h \mid X(t)) & =E\left[Z(t) E^{X(t)}\left[\exp \left\{-\int_{0}^{h} k(t+s, X(s)) d s\right\}\right] \mid X(t)\right] \\
& =E^{X(t)}\left[\exp \left\{-\int_{0}^{h} k(t+s, X(s)) d s\right\}\right] E[Z(t) \mid X(t)]
\end{aligned}
$$

Therefore,

$$
\begin{aligned}
P(\rho \leq t+h \mid \rho>t, X(t)=x) & =1-P(\rho>t+h \mid \rho>t, X(t)=x) \\
& =1-\frac{P(\rho>t+h \mid X(t)=x)}{P(\rho>t \mid X(t)=x)} \\
& =1-E^{x}\left[\exp \left\{-\int_{0}^{h} k(t+s, X(s)) d s\right\}\right] .
\end{aligned}
$$

Under suitable conditions on $k$ and $X$, we may differentiate under the expectation, which yields (3.3) as the first order linear approximation.

The connection between the killed process and the Feynman-Kac representation is given by the following theorem.

Theorem 3.1 Suppose that (2.1) has a solution $u$ which satisfies the assumptions of Theorem 2.1. Let $X$ denote the solution to (1.1) and let $\widetilde{X}$ be the killed process given by (3.1) and (3.2). Then

$$
u(t, x)=E^{x}\left[f(\widetilde{X}(t))+\int_{0}^{t} g(s, \widetilde{X}(s)) d s\right]
$$

where $f$ and $g$ are extended so that $f(\Delta)=0$ and $g(t, \Delta)=0$.
Proof. Let $\varphi(t, x)$ be a measurable function such that $E^{x}[\varphi(t, X(t)) Z(t)]$ exists. Extend $\varphi$ so that $\varphi(t, \Delta)=0$. Then

$$
\begin{aligned}
E^{x}[\varphi(t, X(t)) Z(t)] & =E^{x}\left[\varphi(t, X(t)) P\left(\int_{0}^{t} k(s, X(s)) d s<\tau \mid \mathcal{F}_{\infty}\right)\right] \\
& =E^{x}\left[\varphi(t, X(t)) P\left(t<\rho \mid \mathcal{F}_{\infty}\right)\right] \\
& =E^{x}\left[\varphi(t, X(t)) 1_{\{t<\rho\}}\right] \\
& =E^{x}[\varphi(t, \widetilde{X}(t))] .
\end{aligned}
$$

The theorem now follows directly from Theorem 2.1.

## References

[1] Ioannis Karatzas and Steven E. Shreve. Brownian Motion and Stochastic Calculus. Springer, 1991.

