

Importance sampling in the neighborhood of a stable equilibrium point

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RESIM

26 June 2012

Problem of interest

Consider a process model such as

$$dX^\varepsilon(t) = b(X^\varepsilon(t))dt + \sqrt{\varepsilon}\sigma(X^\varepsilon(t))dW(t)$$

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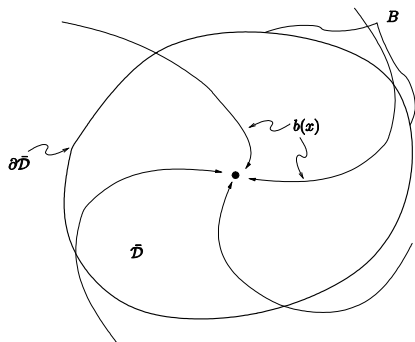
Example.

$$p_T^\varepsilon \doteq P \{ X^\varepsilon(t) \text{ exits } \bar{\mathcal{D}} \text{ through } B \text{ before time } T \mid X^\varepsilon(0) = 0 \},$$

where $B \subset \partial\bar{\mathcal{D}}$ and $\bar{\mathcal{D}} \subset \mathcal{D}$, and T is large.

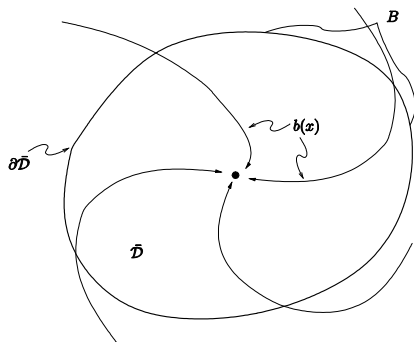
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Also of interest: other process models, e.g., jump Markov. We focus on diffusion.

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Note the distinction in comparison to canonical problem studied in rare event simulation: the problem is time dependent and the stable point is in the domain of the event.

One possible approach

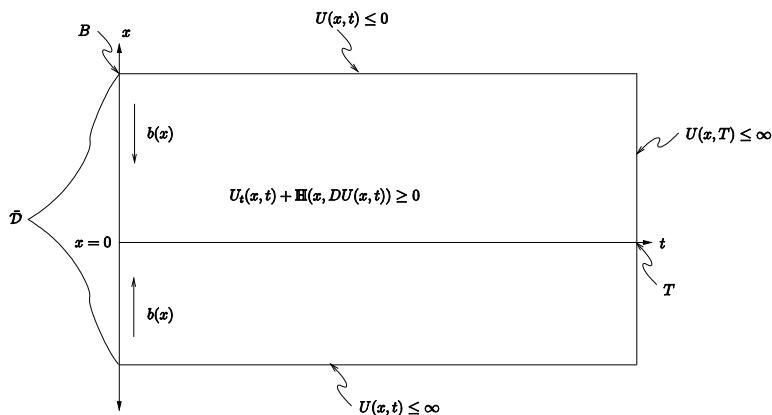
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PDE/subsolutions approach to the design of importance sampling. Let

$$\mathbb{H}(x, p) = \langle p, b(x) \rangle - \frac{1}{2} \|\sigma(x)^T p\|^2$$

and let $U(x, t)$ satisfy



One possible approach

Theorem. Let $U(x, t)$ be a subsolution. Simulate

$$d\bar{X}^\varepsilon(t) = b(\bar{X}^\varepsilon(t))dt - \sigma(\bar{X}^\varepsilon(t))^T DU(\bar{X}^\varepsilon(t), t)dt + \sqrt{\varepsilon}\sigma(\bar{X}^\varepsilon(t))dW(t)$$

with $\bar{X}^\varepsilon(0) = 0$ and use samples

$$1_{\{\bar{\tau}^\varepsilon \leq T, \bar{X}^\varepsilon(\bar{\tau}^\varepsilon) \in B\}} R^\varepsilon(\bar{X}^\varepsilon),$$

where $\bar{\tau}^\varepsilon$ is time of escape from \bar{D} and $R^\varepsilon(\bar{X}^\varepsilon)$ is likelihood ratio of distribution of X^ε w.r.t \bar{X}^ε .

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$$\limsup_{\varepsilon \rightarrow 0} \varepsilon \log E [1 \{ \bar{\tau}^\varepsilon \leq T, \bar{X}^\varepsilon(\bar{\tau}^\varepsilon) \in B \} R^\varepsilon(\bar{X}^\varepsilon)]^2 \leq -U(0, 0) - \gamma_T.$$

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First question: Where to get good subsolutions?

One possible approach

When T is large the Freidlin-Wentzell quasipotential provides a *nearly optimal, time independent* subsolution. Let

$$Q(x) = \inf \left\{ \int_0^\tau \frac{1}{2} \left(\dot{\phi} - b(\phi) \right)^T \left[\sigma(\phi) \sigma(\phi)^T \right] \left(\dot{\phi} - b(\phi) \right) dt \right. \\ \left. : \phi(0) = 0, \phi(\tau) = x, \tau < \infty \right\}.$$

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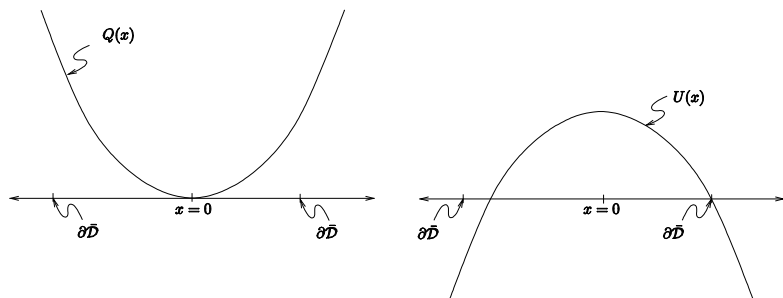
Then Q is available in explicit form for important classes of problems, and

$$U(x) = -Q(x) + \inf_{y \in B} Q(y)$$

is a subsolution with $U(0)$ slightly smaller than γ_T for T large.

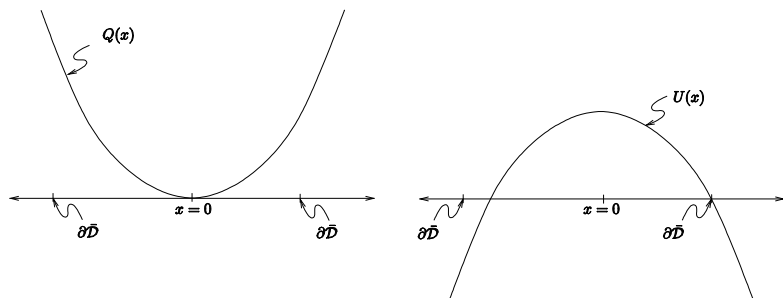
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Easy to check that $Q(0) = 0$ and $\mathbb{H}(x, -DQ(x)) = 0$. Then adding $\inf_{y \in B} Q(y)$ maximizes $U(0)$ subject to boundary conditions:



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$$\gamma_T - U(0) = (\text{inf over } [0, T]) - (\text{inf over } [0, \infty)).$$

Problem with the quasipotential subsolution

The induced importance sampling scheme has the proper decay rate $U(0) + \gamma_T$, but performance not as good as one expects. Reason for poor performance: dual exponential scalings, one in $1/\varepsilon$, one in T .

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Example. 1D Gauss-Markov with $\bar{D} = [-1, 1]$, $B = \partial\bar{D}$, $c = 1$, $\bar{\sigma} = 1$:

$$dX^\varepsilon(t) = -cX^\varepsilon(t)dt + \sqrt{\varepsilon}\bar{\sigma}dW(t).$$

Relative errors:

T vs ε	0.25	0.5	1	1.5	2.5	10	14	18
0.20	91	7	2	1	1	10	51	179
0.16	253	10	2	1	1	10	48	139
0.13	748	16	3	1	1	9	48	378
0.11	1594	26	3	1	1	10	42	272
0.09	–	49	4	2	1	9	43	357
0.07	–	127	5	2	1	8	47	251
0.05	–	714	8	2	1	8	42	145

Problem with the quasipotential subsolution

A non-asymptotic representation for the 2nd moment. Given control process v let $\hat{X}^\varepsilon(0) = 0$ and

$$d\hat{X}^\varepsilon(t) = -c\hat{X}^\varepsilon(t)dt + \bar{\sigma}DU(\hat{X}^\varepsilon(t))dt + v(t)dt + \sqrt{\varepsilon}\bar{\sigma}dW(t).$$

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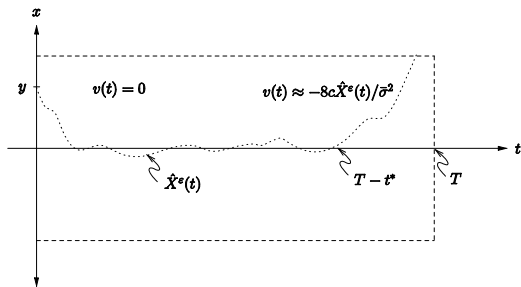
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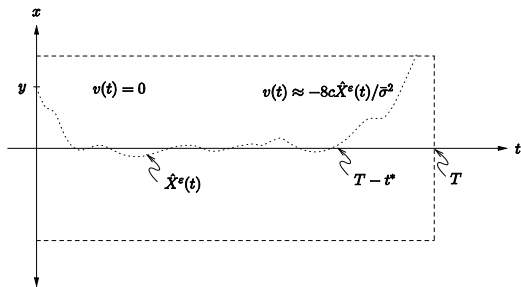
Based on a representation theorem (Boué-D, *Annals of Probability*, 1998) we have the *non-asymptotic* bound

$$\begin{aligned} & -\varepsilon \log E \left[1_{\{\bar{\tau}^\varepsilon \leq T, \bar{X}^\varepsilon(\bar{\tau}^\varepsilon) \in B\}} R^\varepsilon(\bar{X}^\varepsilon) \right]^2 \\ &= \inf_v E \left[\frac{1}{2} \int_0^{\hat{\tau}^\varepsilon} |v(s)|^2 ds - \int_0^{\hat{\tau}^\varepsilon} |DU(\hat{X}^\varepsilon(s))|^2 ds + \infty 1_{\{\hat{\tau}^\varepsilon > T\}} \right]. \end{aligned}$$

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Using the control above one obtains

$$E \left[\frac{1}{2} \int_0^{\hat{\tau}^\epsilon} |v(s)|^2 ds - \int_0^{\hat{\tau}^\epsilon} |DU(X^\epsilon(s))|^2 ds + \infty 1 \{ \hat{\tau}^\epsilon > T \} \right] \leq -\epsilon C_1 [T - t^*] + C_2,$$

and thus

$$E [1 \{ \bar{\tau}^\epsilon \leq T, \bar{X}^\epsilon(\bar{\tau}^\epsilon) \in B \} R^\epsilon(\bar{X}^\epsilon)]^2 \geq e^{C_1 [T - t^*]} e^{-\frac{1}{\epsilon} C_2}.$$

Resolution of the problem

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$$U_t^\varepsilon(x, t) + \langle DU^\varepsilon(x, t), b(x) \rangle - \frac{1}{2} \|\sigma(x) DU^\varepsilon(x, t)\|^2 + \frac{\varepsilon}{2} \text{tr} \left[\sigma(x) \sigma^T(x) D^2 U^\varepsilon(x, t) \right] = 0.$$

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- Combine quasipotential subsolution away from rest point with explicit solution to an approximating problem near rest point (linear quadratic regulator).

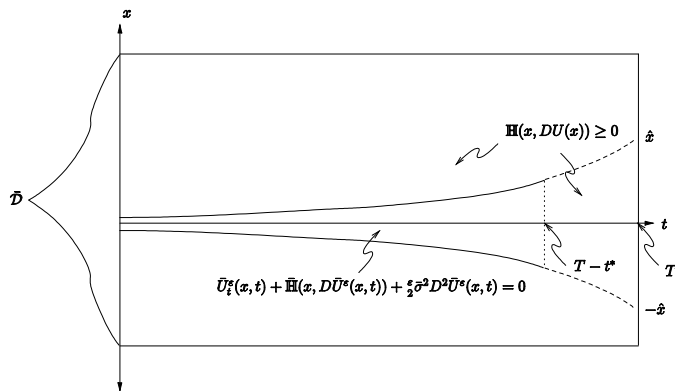
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Resolution:

- Combine quasipotential subsolution away from rest point with explicit solution to an approximating problem near rest point (linear quadratic regulator).
- Construct time and ε -dependent subsolution with bounds that are (proveably) uniform in T .

Construction of a time-dependent subsolution

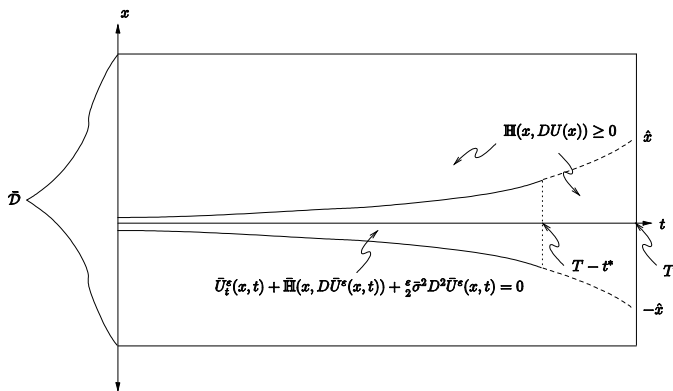
Basic form of the partition:



$\bar{\mathbf{H}}$ is the Hamiltonian of the *linearized* system.

Construction of a time-dependent subsolution

Basic form of the partition:



$\bar{\mathbf{H}}$ is the Hamiltonian of the *linearized* system. A heuristic motivation: better approximation to the zero-variance scheme for the time dependent problem, which previously was poorly approximated near $x = 0$.

Construction of a time-dependent subsolution

Consider one-dimensional problem, with linearization $c = b'(0)$, $\bar{\sigma} = \sigma(0)$. For $0 \leq x \leq e^{c(t-T)}$, let $\bar{U}^\varepsilon(x, t)$ be solution to linear quadratic regulator with terminal condition $\bar{U}^\varepsilon(x, T) = M(x - \hat{x})^2 / 2 + U(\hat{x})$.

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$$\begin{aligned}\bar{U}^\varepsilon(x, t) &= a^M(t) \left(x - \hat{x} e^{-c(t-T)} \right)^2 + U(\hat{x}) \\ &\quad - \frac{\varepsilon}{2} \log \left((2c/M + \bar{\sigma}^2) - \bar{\sigma}^2 e^{2c(t-T)} \right), \\ a^M(t) &= \frac{ce^{2c(t-T)}}{(2c/M + \bar{\sigma}^2) - \bar{\sigma}^2 e^{2c(t-T)}} > 0.\end{aligned}$$

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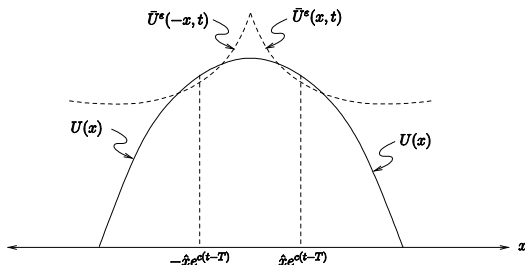
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For $-e^{c(t-T)} \leq x \leq 0$ have $\bar{U}^\varepsilon(x, t) = \bar{U}^\varepsilon(-x, t)$. Here \hat{x} and M parameters used in the design to control region where $\bar{U}^\varepsilon(x, t)$ will define subsolution.

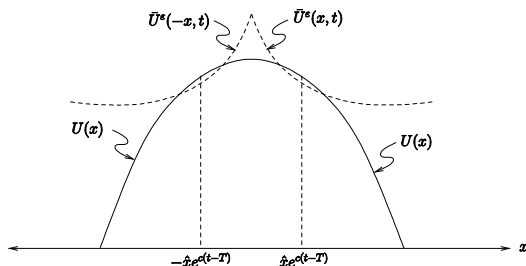
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Number of details in merging various functions. *Most important issue:* need to assemble time dependent subsolution as minima of several functions.



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Second derivatives are $-\infty$ at handoff between functions. Causes problems and needs to be avoided.

Construction of a time-dependent subsolution

We use the *exponential mollification*

$$\bar{U}^\delta(t, x) = -\delta \log \left(\sum_{i=1}^K e^{-\frac{1}{\delta} F^i(t, x)} \right)$$

for various F^i ($= \bar{U}^\varepsilon(x, t), \bar{U}^\varepsilon(-x, t)$, etc.).

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First introduced for importance sampling in (D. and Wang, *Mathematics of Operations Research*, 2007), and to obtain non-asymptotic bounds in (Blanchet, Glynn and Leder, *TOMACS*, 2011).

Construction of a time-dependent subsolution

Lemma. We have the bounds

$$\wedge_{i=1}^K F^i(t, x) \geq \bar{U}^\delta(t, x) \geq \wedge_{i=1}^K F^i(t, x) - \delta \log K.$$

Suppose

$$\begin{aligned} F_t^i(x, t) + \langle DF^i(x, t), b(x) \rangle - \frac{1}{2} \left\| \sigma(x) DF^i(x, t) \right\|^2 + \frac{\varepsilon}{2} \operatorname{tr} \left[\sigma(x) \sigma^T(x) D^2 F^i(x, t) \right] \\ \geq \gamma^i(x, t, \varepsilon) \end{aligned}$$

and let

$$\rho^j(x, t; \delta) = e^{-\frac{1}{\delta} F^j(t, x)} \left/ \sum_{j=1}^K e^{-\frac{1}{\delta} F^j(t, x)} \right.$$

Then for $\delta \geq \varepsilon$

$$\begin{aligned} \bar{U}_t^\delta(x, t) + \langle D\bar{U}^\delta(x, t), b(x) \rangle - \frac{1}{2} \left\| \sigma(x) D\bar{U}^\delta(x, t) \right\|^2 + \frac{\varepsilon}{2} \operatorname{tr} \left[\sigma(x) \sigma^T(x) D^2 \bar{U}^\delta(x, t) \right] \\ \geq \sum_{i=1}^K \rho^i(x, t; \delta) \gamma^i(x, t, \varepsilon). \end{aligned}$$

Properties of the time-dependent subsolution

Using the mollification with $\delta = \varepsilon$ to construct the subsolution and then applying a verification argument, we get the *non-asymptotic* bound

$$\begin{aligned} & \left(1 - \frac{\varepsilon \bar{\sigma}^2}{4c \hat{x}^2} e^{2ct^*} \right) \left[U(0) - \frac{4c}{\bar{\sigma}^2} \hat{x}^2 e^{-2ct^*} \right] - \varepsilon \log 2 \\ & + \frac{\varepsilon}{4\bar{\sigma}} \left[\log \left(\frac{2c}{M} + \sigma^2 - \frac{\sigma^2 c}{2c + M\bar{\sigma}^2} \right) - \log \left(\frac{2c}{M} + \sigma^2 \right) \right] \\ & + \frac{\varepsilon}{4} \log \left(\frac{c}{2(2c + M\bar{\sigma}^2)} \right). \end{aligned}$$

Properties of the time-dependent subsolution

Previous example with $M = 1$, $t^* = 0.9$, $\delta = \varepsilon$, and $\hat{x} \approx .5$:

T vs ε	1	1.5	2.5	10	14	18
0.20	2	2	2	1	1	1
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Ongoing work

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- Extension to the non-Gaussian case.