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A Survey of Sequential Monte Carlo Methods for Economics and Finance

Drew Creal

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Abstract

This article serves as an introduction and survey for economists to the field of sequential Monte Carlo methods which are also known as particle filters. Sequential Monte Carlo methods are simulation-based algorithms used to compute the high-dimensional and/or complex integrals that arise regularly in applied work. These methods are becoming increasingly popular in economics and finance; from dynamic stochastic general equilibrium models in macro-economics to option pricing. The objective of this article is to explain the basics of the methodology, provide references to the literature, and cover some of the theoretical results that justify the methods in practice.

Keywords:

Kalman filter | Markov chain Monte Carlo | Particle filter | Sequential Monte Carlo | State space models

JEL Classification:

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Notes

[1]The residual and systematic resampling schemes are also known in the genetic algorithm literature under alternative names, see Whitley (1994).

[2]Matlab code for each of the resampling algorithms can be found at Nando de Freitas' webpage at http://www.cs.ubc.ca/ ~nando/software.html.

[3]The squared coefficient of variance CV^2 is equal to the estimator of the asymptotic variance for the self-normalized IS estimator (see Geweke, 1989, 2005), where the function being integrated is equal to one, i.e., $f(x_{0:n}) = 1$.

[4]Keep in mind that the estimator may be poor in some time periods when $g_n(x_n \mid x_{n-1}, y_n; \theta)$ is a poor approximation of $p(y_n \mid x_n; \theta)p(x_n \mid x_{n-1}; \theta)$.

[5]For example, Theorem 5 of Chopin (2004) states that the asymptotic variance (42) will remain bounded if there exist constants C, , such that for any $n \geq 0$:

a. For any x, x′, x″ ∈X, the transition density satisfies ;
b. For any x, x′, x″ ∈X, the incremental importance density satisfies ;

c. For any $x \in X$, $y \in Y$, the observation density satisfies ;

where X and Y are the state spaces of the Markov chain.

[6] In a standard particle filter from Section 2, the joint smoothing densities are analagous to the artificial joint densities described here.