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Some contributions to sequential Monte Carlo methods for option pricing

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ABSTRACT

Pricing options is an important problem in financial engineering. In many scenarios of practical interest, financial option prices associated with an underlying asset reduces to computing an expectation w.r.t. a diffusion process. In general, these expectations cannot be calculated analytically, and one way to approximate these quantities is via the Monte Carlo (MC) method; MC methods have been used to price options since at least the 1970s. It has been seen in Del Moral P, Shevchenko PV. [Valuation of barrier options using sequential Monte Carlo. 2014. arXiv preprint] and Jasra A, Del Moral P. [Sequential Monte Carlo methods for option pricing. Stoch Anal Appl. 2011;29:292–316] that Sequential Monte Carlo (SMC) methods are a natural tool to apply in this context and can vastly improve over standard MC. In this article, in a similar spirit to Del Moral and Shevchenko (2014) and Jasra and Del Moral (2011), we show that one can achieve significant gains by using SMC methods by constructing a sequence of artificial target densities over time. In particular, we approximate the optimal importance sampling distribution in the SMC algorithm by using a sequence of weighting functions. This is demonstrated on two examples, barrier options and target accrual redemption notes (TARNs). We also provide a proof of unbiasedness of our SMC estimate.

KEYWORDS:

Diffusions | sequential Monte Carlo | option pricing

AMS SUBJECT CLASSIFICATION:

91G60 (primary) | 65C05 (secondary)

Disclosure statement

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Notes

1. We have a slight abuse of notation in the above, wherein we have used $\mu(n,S_n)$ and $\sigma(n,s_n)$ to denote $\mu(t_n,R_{t_n})$ and $\sigma(t_n,R_{t_n})$ respectively.

2. If μ is a constant other than 0, then it is trivial to extend the methods we propose. If it is a function of the asset value, we could do things similar to what we do in the local volatility model considered later.

3. We have assumed here that the interest rate is 0. If the interest rate was r, then there would be a factor of $e^{\int_0^T r(t)dt}$ multiplied with Q_D. This is a constant and affects the variance of the estimate only up to a (known) scale factor.

4. Path degeneracy is when repeated resampling steps lead to many multiple copies of the same particle $X_{1:N}$. This causes estimates based on the entire paths being unreliable.

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