Stochastic Simulation Microprojects

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Please look through some of the papers, choose one and engage with it. If it is a methodology paper (most of them are) then you should implement the methodology as part of the process of reviewing and assessing the paper. If it is a more theoretical paper, then it would still be sensible for you to implement the method to investigate and illustrate the behaviour studied.

If there is something you want to do instead, just ask one of us if it is suitable — the papers below constitute only a tiny fraction of what could have been suggested .

1. Gerber, Matthieu, & Chopin, Nicolas. Sequential quasi Monte Carlo. "Journal of the Royal Statistical Society: Series B (Statistical Methodology)", 77(3), 509-579 (2015).
   Quasi Monte Carlo provides a deterministic alternative to Monte Carlo methods which employ *low discrepancy sequences* in place of (pseudo)random ones; this paper enables their use in a sequential Monte Carlo context by considering a marginal construction.

2. Gonçalves, Flávio B., Krzysztof Łatuszyński, and Gareth O. Roberts. "Barker's algorithm for Bayesian inference with intractable likelihoods." Brazilian Journal of Probability and Statistics 31(4): 732-745 (2017).
   There has been much recent interest in the development of algorithms for problems in which the likelihood cannot be evaluated, even pointwise. This paper combines a technique known as the Bernoulli factory with a smooth alternative to the Metropolis-Hastings acceptance probability to allow the construction of MCMC algorithms in this setting.

3. Ionides, E. L., Nguyen, D., Atchadé, Y., Stoev, S., & King, A. A. (2015). "Inference for dynamic and latent variable models via iterated, perturbed Bayes maps." Proceedings of the National Academy of Sciences, 112(3), 719-724.
   This paper introduces a particular iterative scheme for parameter inference in latent variable models, such as hidden Markov models.

4. Jacob, Pierre E., Fredrik Lindsten, and Thomas B. Schön. "Smoothing with couplings of conditional particle filters." arXiv preprint arXiv:1701.02002 (2017).
   This paper provides a novel approach to the smoothing problem in state space models by combining a coupling construction with the conditional particle filter algorithm initially introduced in the context of Particle MCMC.

5. Jacob, Pierre E., John O'Leary, and Yves F. Atchadé. "Unbiased Markov chain Monte Carlo with couplings." arXiv preprint arXiv:1708.03625 (2017).
   This paper demonstrates that it is possible to eliminate the initialization bias of MCMC in some settings by a clever coupling construction.

6. Jacob, Pierre E., Lawrence M. Murray, and Sylvain Rubenthaler. "Path storage in the particle filter." Statistics and Computing 25(2): 487-496 (2015).
   This paper considers the issue of path degeneracy in sequential Monte Carlo from an unusual perspective, providing bounds on the coalescence time and providing an efficient method for storing the full history of this type of particle system.

7. Lee, Anthony, and Nick Whiteley. "Variance estimation in the particle filter." arXiv preprint arXiv:1509.00394 (2015).
This paper provides schemes for estimating the variance and asymptotic variance associated with a sequential Monte Carlo from the output of a single instance of that algorithm by exploiting a particular representation of that variance in terms of the genealogy of the particle system.

8. Olsson, Jimmy, and Johan Westerborn. "Efficient particle-based online smoothing in general hidden Markov models: the PaRIS algorithm." Bernoulli 23.3 (2017): 1951-1996.
An approach to smoothing in HMMs which employs a Monte Carlo approximation of a forward-only representation of the forward filtering backward smoothing recursions to provide an computationally efficient approach to approximating the smoothing distribution.

9. Shestopaloff, Alexander Y., and Radford M. Neal. "Sampling latent states for high-dimensional non-linear state space models with the embedded HMM method." Bayesian Analysis (2017), to appear.
This paper introduces a class of algorithms which have a close connection to particle filters but which employ MCMC approximations where standard particle filters use conditionally independent simulations from a proposal distribution.

10. Zanella, Giacomo, Informed proposals for local MCMC in discrete spaces. arXiv prepint arxiv: 1711.07424 (2017).
Locally-informed proposals within Metropolis-Hastings proposals owe much of their success in continuous spaces to the topological structure: it is clear what a *local* proposal means in this context and for smooth targets gradient information can be exploited in the Metropolis-adjusted Langevin Algorithm or (less locally) Hamiltonian Monte Carlo. This paper develops and investigates an approach to making efficient local proposals in discrete spaces.