Annotated Bibliography

Suzie Brown

SEQUENTIAL MONTE CARLO

Gordon, Salmond, and Smith, 1993, "Novel Approach to Nonlinear/Non-Gaussian Bayesian State Estimation"

Original reference for SMC.

Kitagawa, 1996, "Monte Carlo Filter and Smoother for Non-Gaussian Nonlinear State Space Models"

Nice introduction to SMC. Review of other nonlinear filtering techniques: extensions to Kalman filtering.

Del Moral, 2013, *Mean Field Simulation for Monte Carlo Integration*

Loads of rigorous results about SMC e.g. convergence, rates, CLTs.

Doucet and Johansen, 2011, "A Tutorial on Particle Filtering and Smoothing: Fifteen Years Later"

Andrieu, Doucet, and Holenstein, 2010, "Particle Markov Chain Monte Carlo Methods"

Introduces particle MCMC methods, including particle Gibbs with conditional SMC.

RESAMPLING

Kitagawa, 1996, "Monte Carlo Filter and Smoother for Non-Gaussian Nonlinear State Space Models"

Comparison of multinomial, stratified & systematic resampling. And the effect of presorting. [in appendix]

Douc, Cappé, and Moulines, 2005, "Comparison of Resampling Schemes for Particle Filtering"

Comparison of Monte Carlo variance between mutli, res-multi, strat, syst. CLTs for resampled particles.

Lee, Murray, and Johansen, 2019, "Resampling in Conditional SMC Algorithms"

Implementation of lowvariance resampling within conditional SMC.

Murray, Lee, and Jacob, 2016, "Parallel Resampling in the Particle Filter"

Whitley, 1994, "A Genetic Algorithm Tutorial"

Carpenter, Clifford, and Fearnhead, 1999, "Improved Particle Filter for Nonlinear Problems"

Gerber, Chopin, and Whiteley, 2019, "Negative Association, Ordering and Convergence of Resampling Methods"

Li et al., 2020, *Stratification and Optimal Resampling for Sequential Monte Carlo*

Del Moral, Doucet, and Jasra, 2012, "On Adaptive Resampling Strategies for Sequential Monte Carlo Methods"

BACKWARD SIMULATION

Kitagawa, 1996, "Monte Carlo Filter and Smoother for Non-Gaussian Nonlinear State Space Models"

Some solutions to ancestral degeneracy: fixed lag smoother, forward-backward-type algorithm.

Doucet and Johansen, 2011, "A Tutorial on Particle Filtering and Smoothing: Fifteen Years Later"

Lindsten and Schön, 2013, "Backward Simulation Methods for Monte Carlo Statistical Inference"

A whole book on backward simulation. [Chapter 5] describes backward simulation and ancestor sampling in particle MCMC.

whiteley2010

In the discussion, Nick Whiteley introduces (remarkably briefly) the idea of ancestor sampling in particle Gibbs.

CONVERGENCE OF GENEALOGIES

Also consider looking at: Donnelly Tavaré 1995 "Coalescents and genealogical structure under neutrality"; Griffiths Tavaré 1994 "Sampling theory for neutral alleles in a varying environment"; Marjoram 1992 "Correlation structures in applied probability" (PhD thesis, UCL).

Kingman, 1982, "On the Genealogy of Large Populations"

- Introduces the n-coalescent (in a very nice clear way) with the sam enotation we still use
- **Theorem:** suppose $\nu_{1:N}$ are exchangeable and independent across generations and $\mathrm{Var}[\nu_1] \to \sigma^2 \in (0,\infty)$ and $\mathbb{E}[\nu_1^m] \leq M_m$ for all $m \in \mathbb{N}$. Then the n-genealogies scaled by $\lfloor N\sigma^{-2}t \rfloor$ converge to the n-coalescent in the sense of FDDs.
- n-coalescent also applies for models where ν_j are not exchangeable or independent across generations, as long as the genealogies are Markov at least up to error $O(N^{-1})$ and the transitions satisfy $p_{\xi\eta} = q_{\xi\eta}\sigma^2 N^{-1} + o(N^{-1})$, where q's are transition probs of n-coalescent
- The n-coalescent is a good robust model for *large neutral* populations

- Genealogy decouples into a jump chain and a pure death process
- There exists the Kingman coalescent as infinite-dimensional embedding of the n-coalescents

Kingman, 1982, "The Coalescent"

Broadly, this paper introduces the Kingman coalescent (as opposed to n-coalescent) and proves some properties

Möhle, 1998, "Robustness Results for the Coalescent"

Necessary & sufficient conditions for convergence of Cannings model to a coalescent process more general than Kingman. Allowing large mergers but not simultaneous mergers.

- Population size can vary over time, but only deterministically
- Offspring counts must be independent but not necessarily identically distributed across generations
- This means time scale must be allowed to vary over time: τ_N becomes $\tau_N(t)$ and c_N becomes $c_N(t)$, or $c(t)$ in Möhle's notation
- Only proves convergence of FDDs
- Conditions of theorem are still very strong, requiring infinitely many moments to be bounded. There is now a condition on one mixed moment that wasn't needed in Kingman1982.
- The conditions are sufficient but not necessary
- Time scale $\tau_N(t)$ is allowed to be chosen freely, but the theorem only holds when it is an appropriate function (i.e. an inverse of c_N similar to the usual) so this is not a very great generalisation over defining τ in the usual way.

Möhle and Sagitov, 1998, "A Characterization of Ancestral Limit Processes Arising in Haploid Population Genetics Models"

- Assume $\nu_{1:N}$ are exchangeable, and i.i.d. across generations, and the population size N is constant
- Necessary & sufficient conditions are given for (FDD) convergence of the genealogies to a Λ-coalescent, and the correct measure Λ is uniquely constructed from infinitely many moment limits. (Note: Möhle's notation uses μ for the measure rather than Λ.)
- The conditions are: (I) infinitely many pure moment limits exist, slightly different from the condition 2a of Möhle1998; (II) the exchangeable version of the mixed moment condition 2b of Möhle1998.
- Under the additional condition $c_N \to 0$ we also get weak convergence to the Λ-coalescent, although the proof is not explicit in this paper (it just refers to the methods of another work).

Sagitov, 1999, "The General Coalescent with Asynchronous Mergers of Ancestral Lines"

- Assume $\nu_{1:N}$ are exchangeable, and i.i.d. across generations, and the population size N is constant
- k-mergers (but not simultaneous mergers) are allowed
- 3 necessary conditions are given for FDD convergence to some limit of the form $p_{\xi\eta} = \delta_{\xi\eta} + V_N q_{\xi\eta} + o(V_N)$, where $Q = (q_{\xi\eta})$ is some Markov generator, and $V_N \to 0$.
- Additionally, a subset of the necessary conditions are shown to be sufficient for the above asymptotic relation to hold with specific Q corresponding to a Λ-coalescent, on the (constant, deterministic) time scale $T_N^{-1} \sim V_N$.

- Unfortunately I didn't really understand the second and third conditions...
- As one would expect, the necessary conditions can be shown to hold when Kingman's condition $\sup_N \mathbb{E}[\nu_1^k] < \infty \forall k \geq 2$ applies (see Remark 1)

Möhle, 1999, "Weak Convergence to the Coalescent in Neutral Population Models"

Möhle, 2000, "Total Variation Distances and Rates of Convergence for Ancestral Coalescent Processes in Exchangeable Population Models"

Möhle and Sagitov, 2001, "A Classification of Coalescent Processes for Haploid Exchangeable Population Models"

Even more general result than Möhle, 1998, "Robustness Results for the Coalescent", giving necessary & sufficient conditions for convergence to a process allowing large and simultaneous mergers. I hope to adapt this result to prove necessity of our Theorem 1 conditions.

Möhle and Sagitov, 2003, "Coalescent Patterns in Exchangeable Diploid Population Models"

SMC GENEALOGIES

Jacob, Murray, and Rubenthaler, 2015, "Path Storage in the Particle Filter"

Description of ancestries as trunk+crown. Upper bound on storage cost via an approximate multinomial resampling scheme that is independent of weights. Numerical simulations suggesting similar results for stratified and systematic resampling (including an ordering on the schemes?).

Koskela et al., 2018, *Asymptotic genealogies of interacting particle systems with an application to sequential Monte Carlo*

VARIANCE ESTIMATION

Chan and Lai, 2013, "A General Theory of Particle Filters in Hidden Markov Models and some Applications"

Lee and Whiteley, 2018, "Variance Estimation in the Particle Filter"

Olsson and Douc, 2019, "Numerically Stable Online Estimation of Variance in Particle Filters"