

auxiliary and marginal particle filters

the why, how, and how much

sam power, thursday 16 april 2020, straight outta quarantine

overview

- review of HMMs (set notation)
- general particle filtering
 - bootstrap PF, guided PF, auxiliary PF
- marginal particle filtering
 - aside: multiple importance sampling
 - standard MargPF
 - auxiliary MargPF

hidden markov models

$$\mu_0(dx_0)$$

prior on location at $t = 0$

$$f_t(x_{t-1} \rightarrow x_t)$$

transition kernel / propagation / dynamics / ...

$$g_t(x_t, y_t)$$

emission / observation / potential / weights / ...

recipe for a particle filter

(based on presentation by N. Chopin)

- a base HMM (Feynman-Kac model')
- fake prior w/ same support as the real prior (simulate, evaluate density)
- fake dynamics w/ same support as the real dynamics (simulate, density)
- weights (*usually* specified by other stuff)
- everything you would need for (*sequential*) importance sampling

pf1 - bootstrap

(various authors)

- fake prior = real prior
- fake dynamics = real dynamics
- weights = original weights
- requires that real dynamics are still a good proposal under filtering distribution
- \sim importance sampling the posterior, using the prior

pf2 - guided

(don't know source)

- fake prior \neq real prior
- fake dynamics \neq real dynamics
- weights \neq original weights
- idea: use dynamics that push particles into good regions

$$w_t(x_{t-1}, x_t) = \frac{f_t(x_{t-1} \rightarrow x_t)}{\tilde{f}_t(x_{t-1} \rightarrow x_t)} \cdot g_t(x_t, y_t)$$

pf3 - auxiliary

(pitt-shephard; johansen-doucet)

- different prior, dynamics
- also different *target*
- idea: select particles with promising future, then propagate

$$\gamma_t(x_{0:t}) = \mu_0(x_0) \cdot \prod_{s=1}^t f_s(x_{s-1} \rightarrow x_s) \cdot \hat{p}(y_{t+1} | x_t)$$

some comments

- for { guided, auxiliary } PF, there are (locally) `optimal' choices
 - usually (not always though!) intractable, but a useful abstraction (c.f. IS)
 - nested SMC: use *SMC sampler* to approximate optimal proposal
- c.f. lookahead schemes, { twisted / controlled / ... } SMC
- **can** still be used in particle MCMC (Finke-Doucet-Johansen)
 - ~ just need the IS argument to work

multiple importance sampling

(veach, guibas)

- suppose we do IS targeting p , using q_1, \dots, q_N .
 - which of the following should we use?

$$\mathbf{E}_p [f(x)] \approx \frac{1}{N} \sum_{i=1}^N \frac{p(x_i)}{q_i(x_i)}$$

$$\mathbf{E}_p [f(x)] \approx \frac{1}{N} \sum_{i=1}^N \frac{p(x_i)}{\frac{1}{N} \sum_{j=1}^N q_j(x_i)}$$

marginal particle filtering

(klaas, doucet, de Freitas)

- roughly: same idea as MIS, but for particle filters

$$\pi(x_{t-1} | y_{0:t}) \approx \sum_{i=1}^N w_{t-1}^i \delta(x_{t-1}^i, dx_{t-1}) \qquad \pi(x_t | y_{0:t}) \approx \sum_{i=1}^N w_{t-1}^i f_t(x_{t-1}^i \rightarrow x_t) \cdot g_t(x_t, y_t)$$

$$Q_t(x_t | y_{0:t}) = \sum_{i=1}^N w_{t-1}^i q_t(x_{t-1}^i \rightarrow x_t | y_t)$$

weights for standard marginal PF

$$w_t^i = \frac{\sum_{j=1}^N w_{t-1}^j f_t(x_{t-1}^j \rightarrow x_t^i) \cdot g_t(x_t^i, y_t)}{\sum_{j=1}^N w_{t-1}^j q_t(x_{t-1}^j \rightarrow x_t^i | y_t)}$$

- things to consider
 - cost of evaluating weights
 - (optimal?) choice of q
 - what if $q = f$?

auxiliary marginal particle filter

$$\pi(x_{t-1} | y_{0:t}) \approx \sum_{i=1}^N w_{t-1}^i \delta(x_{t-1}^i, dx_{t-1})$$

$$\pi(x_t | y_{0:t}) \approx \sum_{i=1}^N w_{t-1}^i f_t(x_{t-1}^i \rightarrow x_t) \cdot g_t(x_t, y_t)$$

$$\pi(x_t | y_{0:t}) \approx \sum_{i=1}^N w_{t-1}^i \hat{g}_t(x_{t-1}^i, y_t) \cdot \hat{f}_t(x_{t-1}^i \rightarrow x_t | y_t)$$

$$Q_t(x_t | y_{0:t}) = \sum_{i=1}^N \hat{w}_{t-1}^i q_t(x_{t-1}^i \rightarrow x_t | y_t)$$

some more comments

- can show that marginal APF has `better' weights than standard APF
- can (sometimes) reduce $O(N^2)$ cost to $O(N * \log N)$, $O(N * \log(1/\epsilon))$
 - usually: incur some bias, via \sim low-rank approximation
 - can be worthwhile, useful technique for many-body systems in general
- extension to non-markovian models not totally clear
- not clear whether it can be used in PMCMC