Outline

Model comparison

Further methods

Further packages

1. Model comparison

DIC and Bayes Factor

- DIC is a popular and useful method for comparing models; it can be calculated form MCMC samples
- Bayes Factor takes into account more information, but can be harder to calculate

$$\frac{\Pr(D|M_1)}{\Pr(D|M_2)} = \frac{\int \Pr(\theta_1|M_1)\Pr(D|\theta_1, M_1)\, d\theta_1}{\int \Pr(\theta_2|M_2)\Pr(D|\theta_2, M_2)\, d\theta_2}$$

- Harmonic mean estimator (HME): take the inverse of the mean of the inverse likelihood (using MCMC samples) – heavily criticised (google “worst Monte Carlo ever”), but some claim it works (Rasmussen et al., 2014).

MCMC / ABC

Reversible-jump MCMC

- extend MCMC to jump between models – take samples from

$$p(\text{Model } M|\text{Data}) \propto p(M)p(\text{Data}|M)$$

- First propose to jump between models, then jump between parameter spaces (possibly of different size)

ABC

- similar; but: a summary statistic which is sufficient for parameter estimation is not necessarily sufficient for model selection (Didelot et al., 2011)

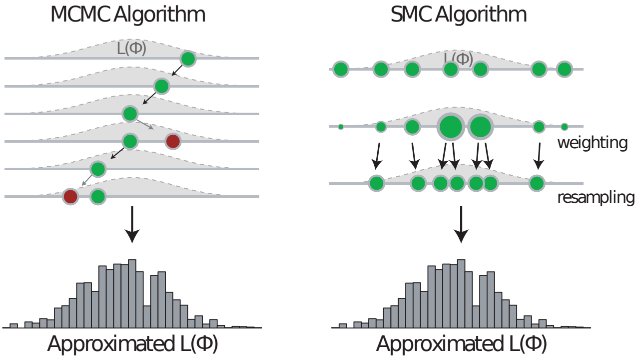
2. Further methods

Sampling from the posterior

Estimating the likelihood

	MCMC	SMC
SMC	PMCMC ✓	SMC^2
ABC	ABC-MCMC ✓	ABC-SMC

SMC vs MCMC



MCMC Algorithm

1) Draw new parameter Φ' close to the old Φ
2) Calculate L(Φ')
3) Jump proportional to L(Φ')/L(Φ)

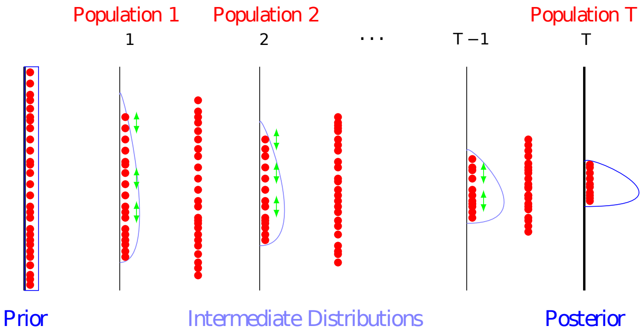
SMC Algorithm

1) Last set of parameters $\{\Phi_i\}$
2) Assign weight ω_i proportional to $L(\Phi_i)$
3) Draw new $\{\Phi_i\}$ based on the ω_i

- Other forms of MCMC exist, e.g. Gibbs Sampler
- can use SMC for sampling from posterior, but must combat particle depletion

- use N_θ particles for parameters, each with N_X particles for the trajectories
- each θ-particle has its own particle filter
- rejuvenation: after every step, propose a Metropolis-Hastings step

ABC-SMC



(Toni and Stumpf, 2009)

Iterated Filtering

- similar: particles take a random walk
- multiple iterations of SMC; at each iteration, make random walk step size smaller
- King et al., 2008

Gaussian Process Emulation

- Instead of defining an acceptance window (ABC), evaluate summary statistics at test points, and fit a Gaussian process to this
- can use this to define implausibility regions
- more later
- similar approach: Synthetic likelihoods (Wood, 2010)

3. Further packages

MCMC

- `LaplacesDemon`
  - > 20 MCMC algorithms (including Metropolis-Hastings)
- `MHadaptive`
  - seems to incorrectly calculate DIC
- both are quite general, similar approach to our functions

ABC

- `EasyABC`
  - implements various ABC methods, including
    - ABC-MCMC (as used here)
    - improved ABC-MCMC (Wegmann et al., 2009)
    - ABC-SMC (Toni, Welch, et al., 2009)
  - only uses Euclidean distance
- `abc`
  - package for analysing ABC output, similar to `coda`

libbi

- `http://libbi.org/`
- not an *R* package, written using a mixture of *C* and *perl*.
- very fast, very up-to-date; implements PMCMC and SMC^2.
- uses its own syntax for model structure
- doesn't easily run on Windows

SSM

- `https://github.com/standard-analytics/ssm`
- not an *R* package, written using a mixture of *C* and *python*.
- very fast, very up-to-date
- uses inference chains; start with simple methods, home in on parameter space of interest
- uses its own syntax for model structure
- doesn't easily run on Windows

POMP

- R package

```
install.packages("pomp")
```

- implements many up-to-date methods
- interfaces with ***C*** for speed