### **Comparative Genomic Analyses**

Rui Borges Vetmeduni Vienna

# Bayesian inference

Bayesian inference: way to reason about probabilities.

- nothing more than a probability analysis
- a mathematical formalization of a decision process
- constitutes a different interpretation of probability

### Thomas Bayes (1702-1761)



## Bayesian inference

Bayesian approach to probability has some unique aspects.

- prior beliefs
- ▶ information from the data
- ▶ the idea of updated probability

# Bayesian inference

The Bayes' theorem or Bayes' rule is the fundamental formula of Bayesian inference.

$$p(\theta|D) \propto p(\theta)p(D|\theta)$$

 $\triangleright$   $p(\theta)$ : prior distribution

 $ightharpoonup p(D|\theta)$ : likelihood

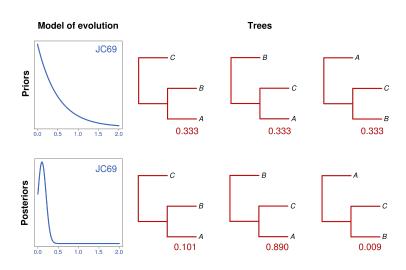
 $\triangleright$   $p(\theta|D)$ : posterior distribution

The posterior distribution specifies the the probability after the prior has been updated with the available data.

The Bayes' theorem translates straightforwardly to tree inference problems.

$$p(\tau, \theta|D) \propto p(\tau, \theta)p(D|\tau, \theta)$$

- D is the molecular sequence alignment
- ightharpoonup au and heta represent the tree and the model of evolution parameters

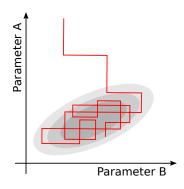


Estimating the posterior distribution in a phylogenetic context can be difficult.

- ▶ impossible to derive  $p(\tau, \theta|D)$  analytically
- concentrated in a small part of a vast parameter space

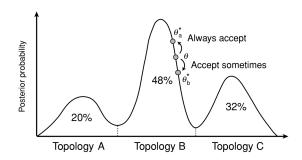
The posterior distribution is estimated using Markov chain Monte Carlo (or **MCMC**) sampling.

- set up a Markov chain that converges to the posterior probability distribution
- MCMC represents random samples from the posterior



Metropolis-Hastings algorithm is an MCMC method.

- make small random changes on the parameter values
- accept or reject those changes according to the appropriate probabilities



An MCMC run is a random sample of the posterior distribution.

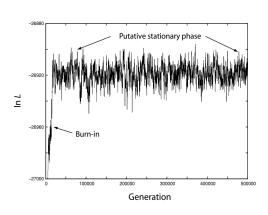
- ▶ the amount of time it spends sampling a particular region is proportional to the posterior probability of that region given that it converged to the target distribution
- convergence needs to be monitored

#### Burn-in:

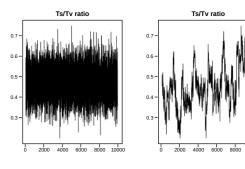
- early phase of the run
- heavily influenced by the starting points
- likelihood increases very rapidly

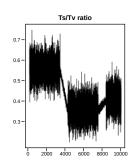
### Stationary phase:

- the chain approaches its stationary distribution
- the likelihood values reach a plateau



### Checking the convergence of MCMC with trace plots:





# Summarizing the posterior distribution

The model parameters and the tree are summarized differently:

- model parameters are usually continuous and can be summarized as any usual statistics: means, median, the credibility interval
- trees are more difficult to summarize
- posterior clade probabilities: the sum of the posterior probabilities of all trees that contain that clade

# Summarizing the posterior distribution

#### **Exercise**

Bayesian phylogenetic inference in a sequence alignment with five species returned the three topologies with the following posterior probabilities (P.p.):

```
Topology P.p. (((Human,Dog),(Chicken,Lizard)),Frog) 0.76 ((((Human,Dog),Chicken),Lizard),Frog) 0.17 (((Human,Dog),Chicken),(Lizard,Frog)) 0.07
```

What is the posterior probability of the following clades: (Chicken,Frog), (Chicken lizard), ((Human,Dog),Chicken) and (Human,Dog)?

## Bayesian versus maximum likelihood trees

#### Maximum-Likelihood trees

- $ightharpoonup p(D|\tau,\theta)$
- Maximum likelihood tree
- ▶ ignores pre-existing information
- bootstrapping
- resample characters

### Bayesian trees

- $ightharpoonup p(\tau,\theta|D)$
- Maximum a-posteriori tree
- considers pre-existing information
- MCMC
- resample parameters

### Literature

**The Phylogenetic Handbook** by Lemey, Salemi and Vandamme (2009) Cambridge University Press

► Chapter 7: sections 7.1, 7.2 and 7.3, 7.4, 7.6, 7.7 and 7.9