BIG4: Biosystematics, informatics and genomics of the big 4 insect groups- training tomorrow's researchers and entrepreneurs

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Statistical Phylogenetics

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Statistical Phylogenetics

- Despite the computational complexity, statistical approaches are becoming increasingly important in phylogenetics:
 - Difficult problems requiring accurate and unbiased inference (e.g., structure of rapid radiations)
 - More aspects of molecular evolution being examined (structural dependencies, positive selection etc)
 - Combination of background knowledge and sequence information (e.g., divergence time estimation)
 - Rich evolutionary models (e.g., biogeography)

Infer relationships among three species:







Outgroup:



Three possible trees (topologies):



Maximum likelihood inference



probability

Likelihood function

Bayesian inference



Bayesian or ML?

- Maximum likelihood
 - Can be fast
 - Background knowledge ignored
 - No natural way of measuring uncertainty
 - Difficult to extend to complex models
 - Assessing quality of results from ML algorithms difficult
- Bayesian inference
 - May be slower
 - Possible to incorporate background knowledge
 - Natural measure of uncertainty (posterior probability distribution)
 - Standard computational machinery (Markov chain Monte Carlo), which can easily be extended to complex models
 - Convergence diagnostics for MCMC well developed

"My" Bayesian Software

MrBayes

- Large model space (but ~ fixed)
- Robust and reliable
- RevBayes
 - Flexible model specification using graphical models concepts
 - Clunky but pretty competent
- Rev
 - Completely flexible graphical model specification
 - Programmable
 - Work in progress...

Software challenges

- Modeling explosion, especially in the Bayesian context
- Challenging for empiricists to communicate and correctly understand models
- Challenging for developers of inference software to cope with expanding model universe
- Addressed using switches and the like
- Can we develop more generic computational machinery?



Probabilistic Graphical Models

- Theoretical framework for specifying dependencies in complex statistical models
- Allows a complex model to be broken down into conditionally independent distributions
- Closely related to standard statistical model formulae:

 $x \sim \operatorname{Norm}(\mu, \sigma)$

 Extensive literature on generic algorithms that apply to model graphs





Hierarchical Graphical Model



RevBayes Project

- Interactive computing environment intended primarily for Bayesian phylogenetic inference
- Uses a special language, Rev, for constructing probabilistic phylogenetic and evolutionary graphical models interactively, step by step
- Rev is similar to R and the BUGS modeling language
- RevBayes provides generic computing machinery for simulation, inference and model testing





A complete MCMC analysis in Rev

```
a <- -1.0
b <- 1.0
mu ~ dnUnif(a, b)
sigma ~ dnExp(1.0)
for (i in 1:10) {
    x[i] ~ dnNorm(mu, sigma)
    x[i].clamp(0.5)
}
mymodel = model(mu) # Any stochastic node in the model works
mymcmc = mcmc(mymodel)
mymcmc.run(1000)</pre>
```

```
# definition of the myGTR function ("Ziheng's favorite")
function model myGTR (CharacterMatrix data) {
   # describe Q matrix
   pi ~ dflatdir(4);
   r \sim dflatdir(6);
   Q := gtr(pi, r);
   # describe tree
   tau ~ dtopuni(data.taxa(), rooted=false);
   # gamma shape
   al pha ~ duni f(0, 0, 50, 0);
   # discrete gamma mixture
   for (i in 1:4)
       catRate[i] := qgamma(i*0.25-0.125, alpha, alpha);
   for (i in 1: data. size())
       ratecat[i] ~ dcat(simplex(0.25, 0.25, 0.25, 0.25));
   # associate distributions with tree parts
   for (i in 1: data. size()) {
       for (n in 1:tau.numNodes()) {
              if (tau.isTerminal(n)) {
                   tau.length[n] ~ \exp(1.0);
                   tau.state[n] ~ ctmc(Q, e.length*catRate[ratecat[i]],
                       tau.state[tau.parent(n));
                   tau.state[n] <- data[i][tau.tipIndex(n)];</pre>
              }
              else {
                   tau.length[n] ~ \exp(10.0);
                   tau.state[n] ~ ctmc(Q, e.length*catRate[ratecat[i]],
                       tau. state[n]);
              }
        }
   }
   # return model
   return model ( Q );
```

Definition of a new phylogenetic model

Appr. 20 lines

Complexity hidden from normal user

```
# Read in data
myData <- read( "data.nex" )
# Apply model
myModel = zihengGTR( myData )
# Construct mcmc
myMCMC = mcmc( myModel )
# Run mcmc
myMCMC.run(10000)</pre>
```

The Canary Islands



Dolichoiulus (Diplopoda)



Dolichoiulus (Diplopoda, Julida, Julidae, Pachyulinae)







Inference

Bayesian inference using MCMC sampling, accommodating uncertainty in all model parameters

Canary Islands: 3-island model



Mainland

Ecological zones

- Coastal belt
- Open habitat
- Thermophilous forest
- Laurisilva
- Pine forest
- Sub-alpine



Ten island-habitat types

- M1 Other Mainland
- E2 Eastern-Open
- C2 Central-Open
- W2 Western Open
- C3 Central-laurel forest
- W3 Western-laurel forest
- C4 Central-pine forest
- W4 Western-pine forest
- C5 Central-alpine vegetation
- W5 Western-alpine vegetation

Separating island-hopping and niche-shift rates

$$r = \begin{bmatrix} r_i & \text{Shift between islands} \\ r_e & \text{Shift between niches} \\ r_i r_e & \text{Shift between islands and niches} \end{bmatrix}$$

Standard biogeography model:

r ~ dirichlet(1, 1, 1, ...)

Islands-ecology model:

mu ~ dirichlet(1, 1)

```
r := simplex( mu[1], mu[2], mu[1] * mu[2], ...)
```

