Bayesian Tree Sampling

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CIBIV

December 3, 2007

Outline

1. Bayes Theorem
   - Bayes Theorem

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2. Markov Chains
   - definition
   - Properties

Outline

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The difference

> *The Bayesian approach asks the right question in a hypothesis testing procedure, namely, "What is the probability that this hypothesis is true, given the data?" rather than the classical approach, which asks a question like, "Assuming that this hypothesis is true, what is the probability of the observed data?"*
>
> *–Statistical Methods in Bioinformatics*

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Therefore

$$\Pr(A|B)\Pr(B) = \Pr(B|A)\Pr(A)$$
$$\Pr(A|B) = \frac{\Pr(B|A)\Pr(A)}{\Pr(B)}.$$

This is Bayes formula or theorem.

Bayes Theorem

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$$\underbrace{\Pr(A|B)}_{\text{Posterior Density}} \propto \overbrace{\mathrm{L}(A,B)}^{\text{Likelihood}}\ \overbrace{\Pr(A)}^{\text{Prior}}$$

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- Bayesian, flips the probability around.
- It is easy to include prior information which is often available.
- The Bayesian conditional probability is perhaps more intuitive.

Making formulas tangible

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- In words: The likelihood is the probability of the DNA data given the Tree and the model parameters.
- The Prior is $\Pr(T, M)$ and indicates any information we already know. i.e. The root is not older than 10 million years.
- The Posterior density is $\Pr(T, M|D)$ the probability of the tree and model parameters given the sequence data.

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- Therefore MHMCMC must be used, this means it will take a lot of computer resources.
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- It will always be slower than ML.

Outline

Markov Chains

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- We don't care about the whole sequence, just the last output which is 3.
- The next item has a 50% chance that it will be a 4, and a 50% chance that it will be a 2.
- This is a Markov Chain.

Definition of a Markov Chain

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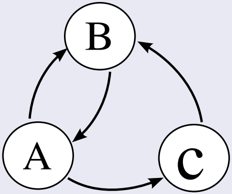
Rough Math definition

$$\Pr(X_n | X_{n-1}, X_{n-2}, \ldots) = \Pr(X_n | X_{n-1})$$

Markov Chain Graph

State Graph



- Simple Markov Chains can be represented as a graph.

Markov Chain Graph

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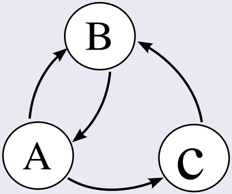

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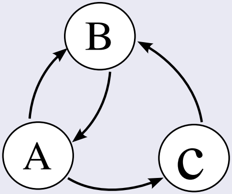

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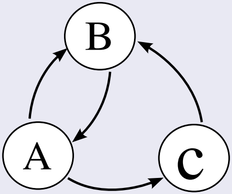

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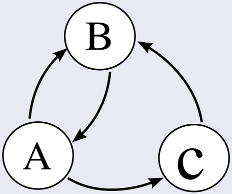

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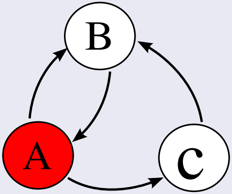
- For clarity, when transitions are equiprobable we omit the transition probabilities.

Markov Chain Graph
Example

State Graph



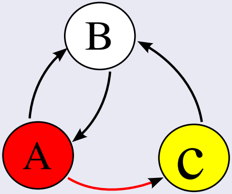
Output

A

Markov Chain Graph

Example

State Graph

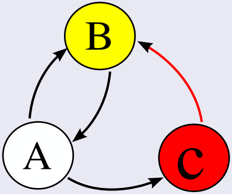


Output

A C

Markov Chain Graph
Example

State Graph

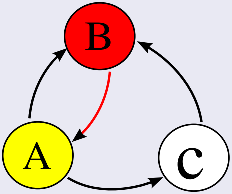


Output

A C B

Markov Chain Graph
Example

State Graph

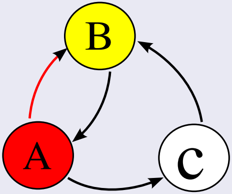


Output

A C B A

Markov Chain Graph
Example

State Graph

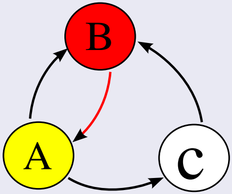


Output

A C B A B

Markov Chain Graph
Example

State Graph



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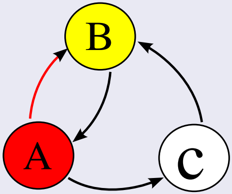

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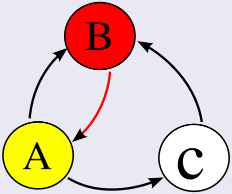

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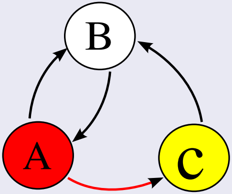

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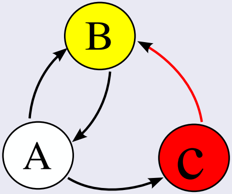

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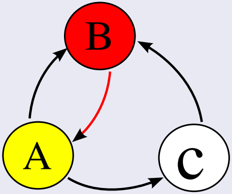

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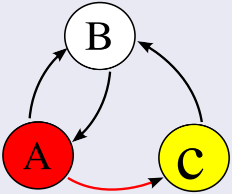

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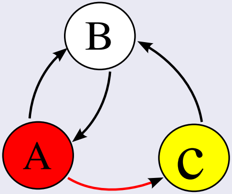


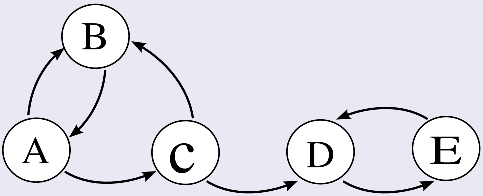
Output

A C B A B A B A C B A C

- Note that the states can be anything. ie different trees

Extra Markov Chain Properties
Irreducibility

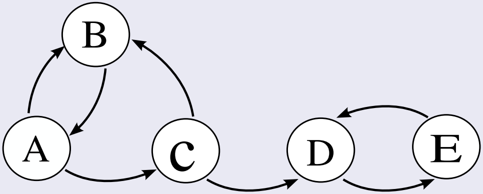
Reducible state diagram



Extra Markov Chain Properties

Irreducibility

Reducible state diagram



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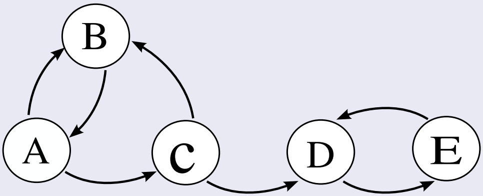

Definition

A Markov Chain is Irreducible if and only if the chain can get from any possible state to any other possible state eventually.

Extra Markov Chain Properties

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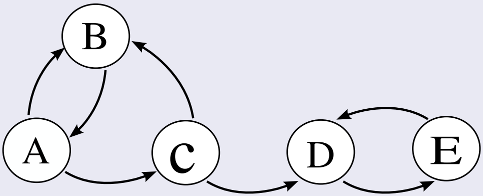

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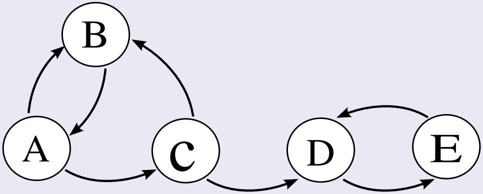

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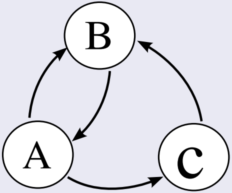
- The above state diagram is NOT irreducible.
- Adding a transition from $D \rightarrow C$ it would make this irreducible

Extra Markov Chain Properties

Reversibility



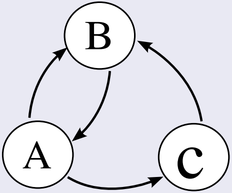
Is this output reversed?

C A B C A B A B A B C

- Note that there is no $C \longrightarrow B$ transition or $C \longrightarrow A$ transition.

Extra Markov Chain Properties

Reversibility



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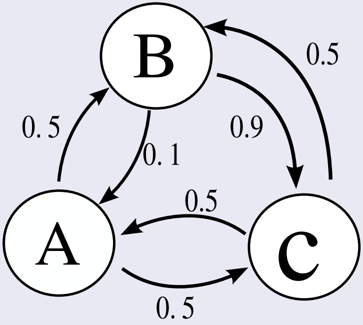
- Therefore we can tell that this output sequence is reversed.

Extra Markov Chain Properties
Reversibility

Tricky Example



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- The transition $B \rightarrow A$ is much less likely than $B \rightarrow C$ in the forward direction.

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Reversibility

Is this output reversed?

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- The transition $B \rightarrow A$ is much less likely than $B \rightarrow C$ in the forward direction.
- In this example there are 7 $B \rightarrow C$ transitions and only 1 $B \rightarrow A$ transition in the forward direction.

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- It seems we can guess that this output is not reversed.
- But we stick to simple definitions for this course.

Extra Markov Chain Properties
Reversibility

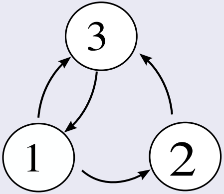
Definition

A Markov Chain is reversible if we cannot detect whether or not the chain is running in “reverse”. That is the output is statistically identicle in both directions.

Extra Markov Chain Properties

Aperiodic

Periodic-Aperiodic



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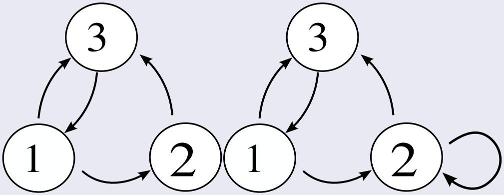

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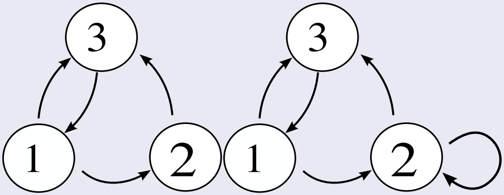

Definition

A Markov Chain is periodic if there is some fixed “cycle” of states, and it is aperiodic otherwise.

Extra Markov Chain Properties

Why do we care?

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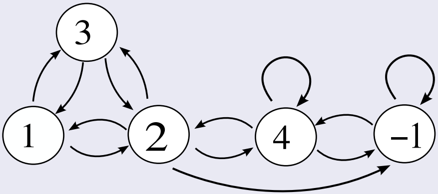
- If a MCMC chain has these 3 properties (reversible, irreducible and aperiodic), then it is also ergodic.

Extra Markov Chain Properties

Stationary distribution



output

1 3 2 4 4 2 1 2 -1 -1 4 2 3 1 3 2 4 4 4 -1 -1 -1 4 2 3 1 2 3 -1

- We can calculate statistics on the output, like mean and standard deviation. Also we can plot histograms etc.

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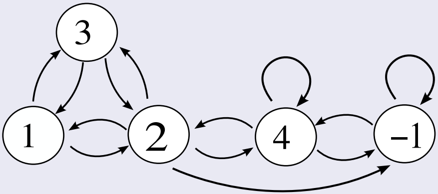
Stationary distribution



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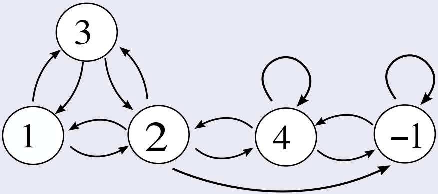
Stationary distribution



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- We can calculate statistics on the output, like mean and standard deviation. Also we can plot histograms etc.
- Consider the distribution of the output.
- What about the start state. That is if the chain is started in state 1, will the distribution be different from starting in 2.

Extra Markov Chain Properties
Ergodic

Definition

If we can start from any state, and if we take samples for long enough, and we end up with the same distribution, that distribution is the stationary distribution of the Markov Chain, and the Markov Chain is said to be ergodic

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Definition

If a Markov Chain is reversible, irreducible and aperiodic then it is also ergodic.

- So we can know that a chain will converge to the stationary distribution without testing every state.

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Extra Markov Chain Properties
Ergodic

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- So we can know that a chain will converge to the stationary distribution without testing every state.
- Usually the symbol π denotes the stationary distribution.
- Note that we have not said anything about how many samples we need to get an accurate distribution.

Outline

Metropolis Hastings MCMC

Algorithm

- Start in state X_n

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- Accept the new state with that probability.
- If we accept, then $X_{n+1} = X'$, otherwise $X_{n+1} = X_n$.

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The Key Idea

The stationary distribution is the posterior distribution of interest. That is the MHMCMC chain is sampling the Bayesian posterior distribution.

Example

- Start with tree $T = (a, b|c, d)$.

Output

$(a, b|c, d)$

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- The new state is $T = (a, d|b, c)$
- We continue $T' = (a, c|b, d)$ ($c \rightleftharpoons d$), and accept.

Output

$(a, b|c, d)$ $(a, b|c, d)$ $(a, d|b, c)$ $(a, c|b, d)$

Die example

Wiki Formula

$$\Pr(k|i,s) = \frac{1}{s^i}\sum_{n=0}^{\lfloor\frac{k-i}{s}\rfloor}(-1)^n\binom{i}{n}\binom{k-sn-1}{i-1}$$

Die MHMCMC

- Formula looks too complicated!

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Die MHMCMC

- Formula looks too complicated!
- Use a simple MHMCMC instead.
- Just pick one die at random and re-throw.
- This is reversible and the acceptance ratio is 1. i.e we always accept.

Die example

3 die

1	1	1

Output

3

Die example

3 die

1	1	1
4	1	1

Output

3 6

Die example

3 die

1	1	1
4	1	1
4	1	6

Output

3 6 11

Die example

3 die

1	1	1
4	1	1
4	1	6
2	1	6

Output

3 6 11 9

Die example

3 die

1	1	1
4	1	1
4	1	6
2	1	6
3	1	6

Output

3 6 11 9 10

Die example

3 die

1	1	1
4	1	1
4	1	6
2	1	6
3	1	6
3	1	4

Output

3 6 11 9 10 8

Die example

3 die

1	1	1
4	1	1
4	1	6
2	1	6
3	1	6
3	1	4
3	5	4

Output

3 6 11 9 10 8 12

Die example

3 die

1	1	1
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2	1	6
3	1	6
3	1	4
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- If we have 100 die and start at all ones, it will take a long time to get to the “equilibrium”.
- On the other hand we could roll *every die at each step.*
- In this case we get to equilibrium in just a single step but must generate 100 random numbers per step.

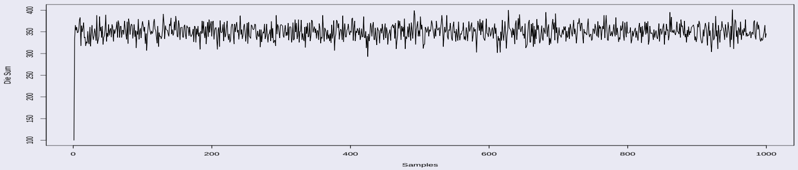
More Die

100 die, rolling 1 dice per step

More Die

100 die, rolling 1 dice per step

100 die, rolling all per step



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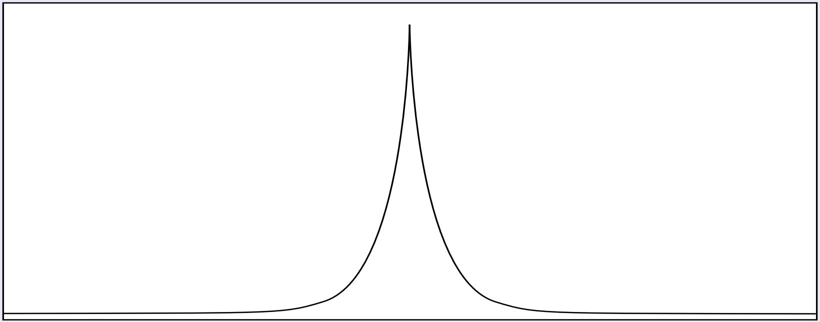
- Due to the correlations between samples we don’t really need every sample from the MCMC chain and instead only collect every 100’th sample or so.
- Performance should be measured in the number of effective samples per CPU cycle.

Witch's Hat



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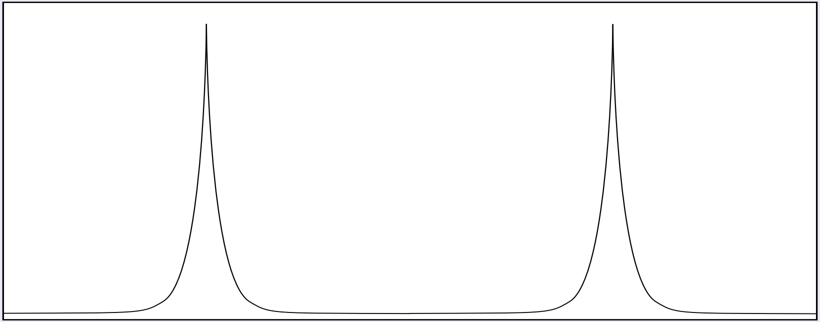

- Consider all non tree like signals.
- Recombination, Horizontal Gene Transfer and other effects could contribute to a lot of witch's hats.

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- Multiple runs from random starting locations

Outline

Posterior

$$\Pr(T, M|D) \propto \Pr(D|T, M)\Pr(T, M)$$

- The likelihood is $\mathrm{L}(T, D, M) = \Pr(D|T, M)$
- T is the tree.
- D is the DNA/Protein etc sequence data.
- M is the model parameters, like GTR.

Warning

Trees Make Life Difficult

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- The wrong choice of moves could make the chain run very slowly.
- Examples of real output.

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- The idea is that we won’t get stuck.
- Generally not as effective as just developing some better moves.

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- Priors should be considered with respect to the hypothesis that will be tested.

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- For rooted topologies, a simple bounded uniform prior is sufficient.
- Even if the max root height is 100 expected substitutions per site, the posterior can now be normalized.

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  - Support values are easier to interpret.
  - Can incorporate prior information easily.