

The consequences of approximate  
conditional independence of subtrees  
on phylogeny estimation

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# Cats and Dogs Example

- ◆ Consider a data set from 12 species, closely related to domestic cats and dogs.
- ◆ The alignment is the 1545 base pair mitochondrial COX I gene.

# Partial Alignment

Cat	ATGTTCATAAACCGGTGACTATTTCAACTAATCACAAAGATATTGGTACTCTTACCTT...
Cheetah	ATGTTCATAAACCGCTGATTATTTCAACTAATCATAAAGATATCGGTACTCTTACCTC...
Clouded Leopard	ATGTTCATAAACCGCTGACTATTTCAACTAACCATAAAGATATTGGAACCTTTACCTT...
Snow Leopard	ATGTTCATAAACCGCTGACTATTTCAACCAATCACAAAGATATTGGAACCTTTACCTT...
Leopard	ATGTTCATAAACCGCTGACTATTTCAACCAATCACAAAGATATTGGAACCTTTACCTT...
Tiger	ATGTTCATAAACCGCTGACTATTTCAACCAATCACAAGGATATTGGAACCTTTACCTT...
Dog	ATGTTCATTAACCGATGATTGTTCTCCACTAATCACAAGGATATTGGTACTTTATACTTA...
Gray Wolf	ATGTTCATTAACCGATGATTGTTCTCCACTAATCACAAGGATATTGGTACTTTATACTTA...
Coyote	ATGTTCATTAACCGATGATTGTTCTCTACTAATCACAAAGATATTGGTACTTTATATCTA...
Dhole	ATGTTCATTAACCGATGGTTATTCTCTACTAATCACAAAGATATTGGGACTTGTATCTA...
Red Fox	ATGTTCATTAATCGATGATTATTCTCTACTAACCAACAAAGACATCGGTACTTTATATTG...
Raccoon Dog	ATGTTCATTAACCGATGACTATTCTCTACTAACCAACAAAGACATTGGCACTTTATATTTA...

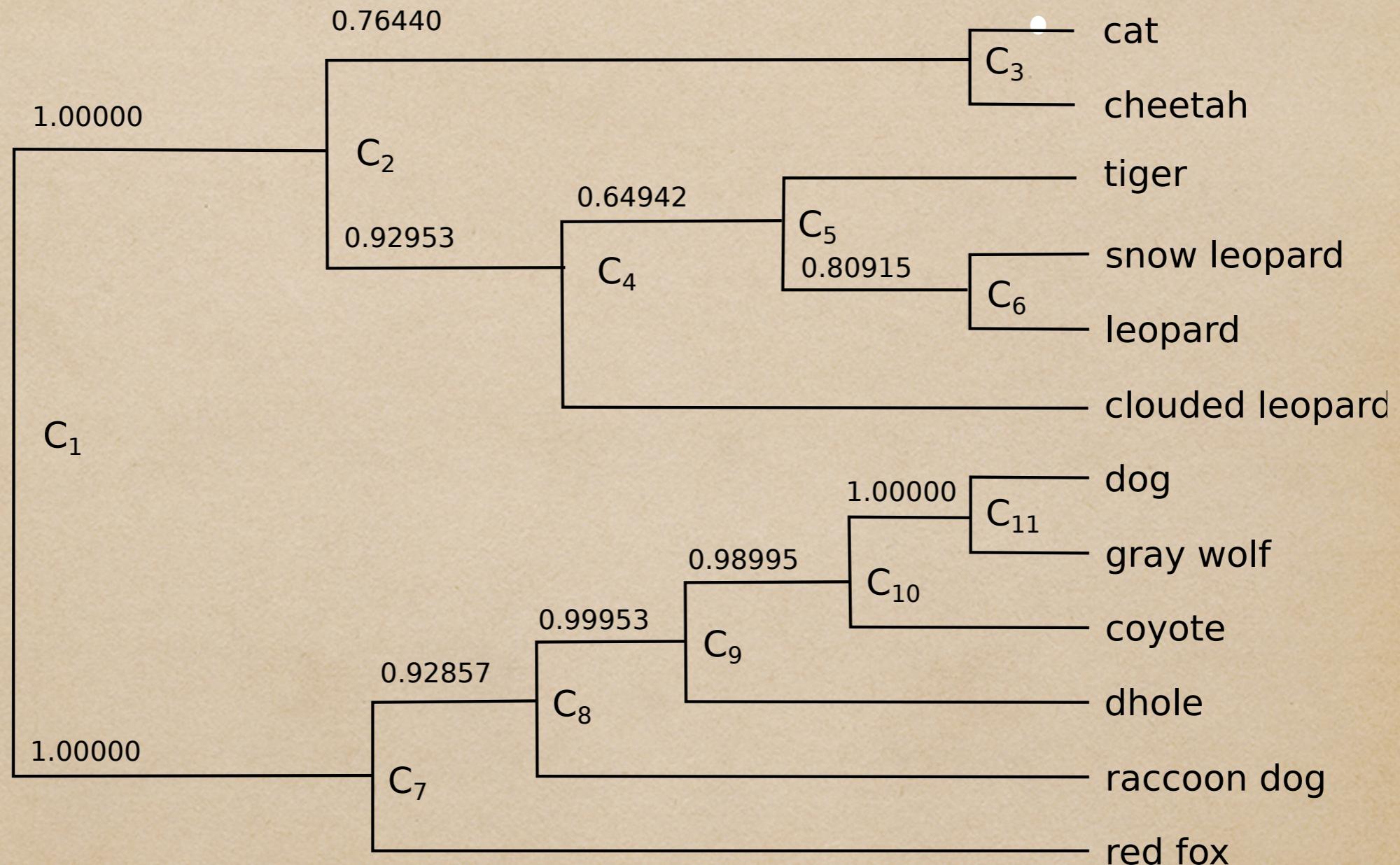
# MCMC Samples

- ◆ Statisticians develop MCMC methods to sample trees from the posterior distribution.
- ◆ The posterior distribution of each topology  $T$  is estimated with its simple relative frequency in this sample.

# Cat/Dog Example

- ◆ For a given likelihood model, one MCMC sample of 100,000 trees includes 229 unique trees.
- ◆ With a rooting that separates the dog-like and cat-like species, the following display shows the tree and the estimated probability of each of its clades.

# A Probable Tree



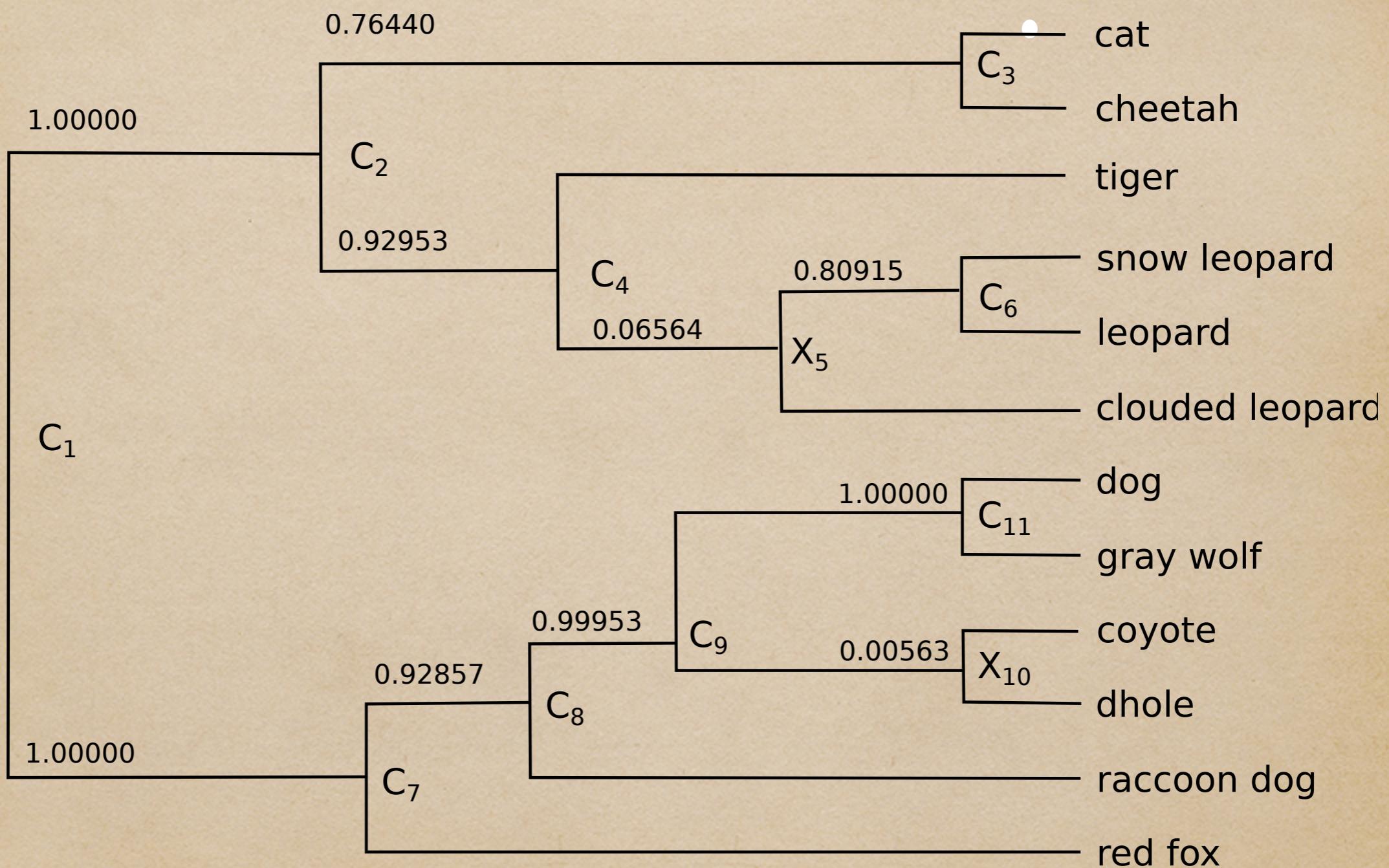
# MCMC Summary

- ◆ There were 229 unique trees among the 100,000 sampled trees.
- ◆ 50 of these trees were sampled once.
- ◆ Different MCMC samples would contain slightly different sets of trees.
- ◆ Some unsampled trees are much more probable than others.

# Trees as Intersections of Clades

- ◆ The tree is equivalent to its collection of clades.
- ◆  $P(T_1) = P(C_2 \cap C_3 \cap \dots \cap C_{11})$
- ◆ However, the clades are not independent of each other.
- ◆  $P(T_1) \neq P(C_2) \times \dots \times P(C_{11})$

# A Less Probable Tree

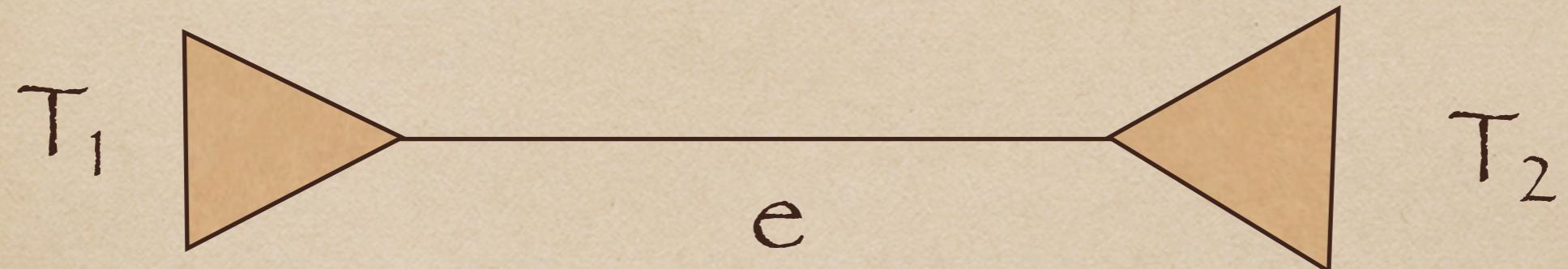


# Simple Relative Frequencies

- ◆ The most probable tree had estimated probability 0.33925.
- ◆ The less probable tree had estimated probability 0, even though each of its clades had appeared multiple times in the sample.

# Conditional Independence of Separated Subtrees

- ◆ A new alternative method to estimate the probabilities of trees from MCMC samples depends on the principle of the (approximate) conditional independence of separated subtrees.



Given  $e$ , the subtrees  $T_1$  and  $T_2$  are conditionally independent.

# General Principle

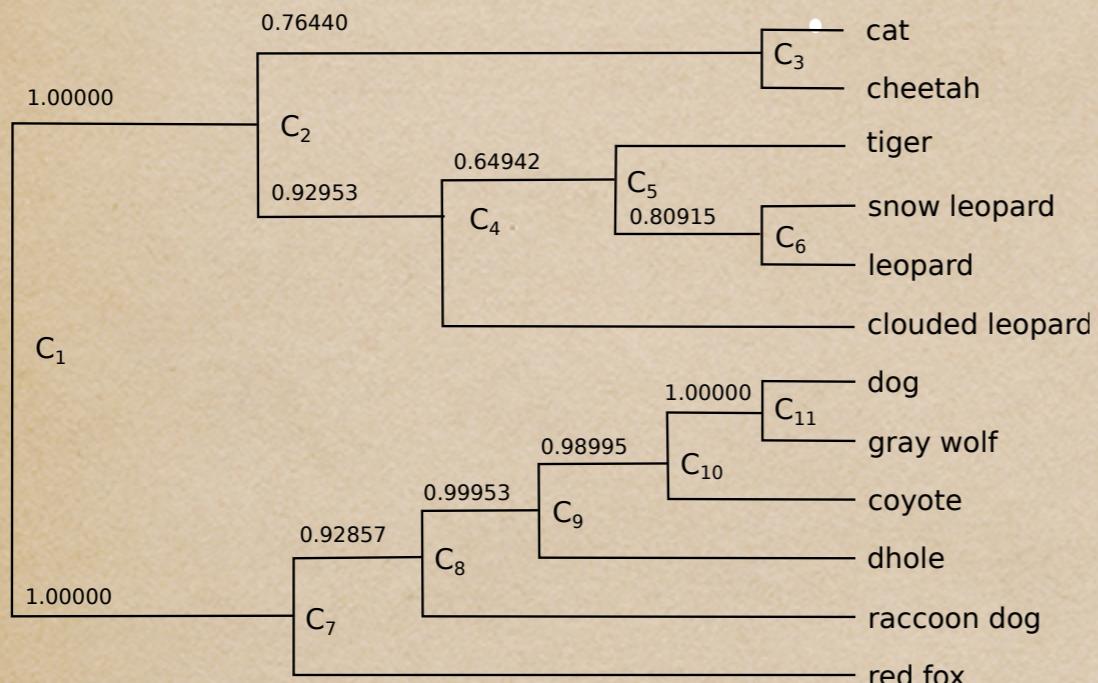
- ◆ Let  $s = A|B$  be a partition of the species set into two nonempty sets,  $A$  and  $B$ .
- ◆ Let  $A_1, \dots, A_m \subset A$  and  $B_1, \dots, B_n \subset B$  and let each subset also denote the existence of an edge in the tree that splits all species into itself and its complement.
- ◆ We say that  $s$  separates  $\{A_i\}$  from  $\{B_j\}$ .
- ◆ Then,  $P(A_1 \cap \dots \cap A_m \cap B_1 \cap \dots \cap B_n | s)$

$$\approx P(A_1 \cap \dots \cap A_m | s) \times P(B_1 \cap \dots \cap B_n | s)$$

# Algorithm

- ◆ The principle of conditional independence of separated subtrees leads to an algorithm to approximate the probabilities of trees.
- ◆ This approximate probability is the product over nontrivial clades of the conditional probabilities of their subclades given the clade.

# Example Calculation



$$\begin{aligned}
 P(T_1) &\approx \\
 P(C_2 \cap C_7 | C_1) & \\
 \times P(C_3 \cap C_4 | C_2) & \\
 \times P(C_5 \cap \text{clouded leopard} | C_4) & \\
 \times P(C_6 \cap \text{tiger} | C_5) & \\
 \times P(C_8 \cap \text{red fox} | C_7) & \\
 \times P(C_9 \cap \text{raccoon dog} | C_8) & \\
 \times P(C_{10} \cap \text{dhole} | C_9) & \\
 \times P(C_{11} \cap \text{coyote} | C_{10}) &
 \end{aligned}$$

$$\frac{100000}{100000} \times \frac{69393}{100000} \times \frac{63655}{92953} \times \frac{50827}{64942} \times \frac{92857}{100000} \times \frac{92857}{92857} \times \frac{98948}{99953} \times \frac{98995}{98995} \doteq 0.3419$$

Compare to SRF estimate 0.3393

# Calculation Details

- ◆ Each conditional probability takes the form:

$$P(C_i \cap C_j | C_k) = P(C_i \cap C_j \cap C_k) / P(C_k)$$

- ◆ Note that  $P(C_i \cap C_j \cap C_k)$  is the probability that the unrooted tree contains a node that partitions the species into three groups and  $P(C_k)$  is the probability of an edge.

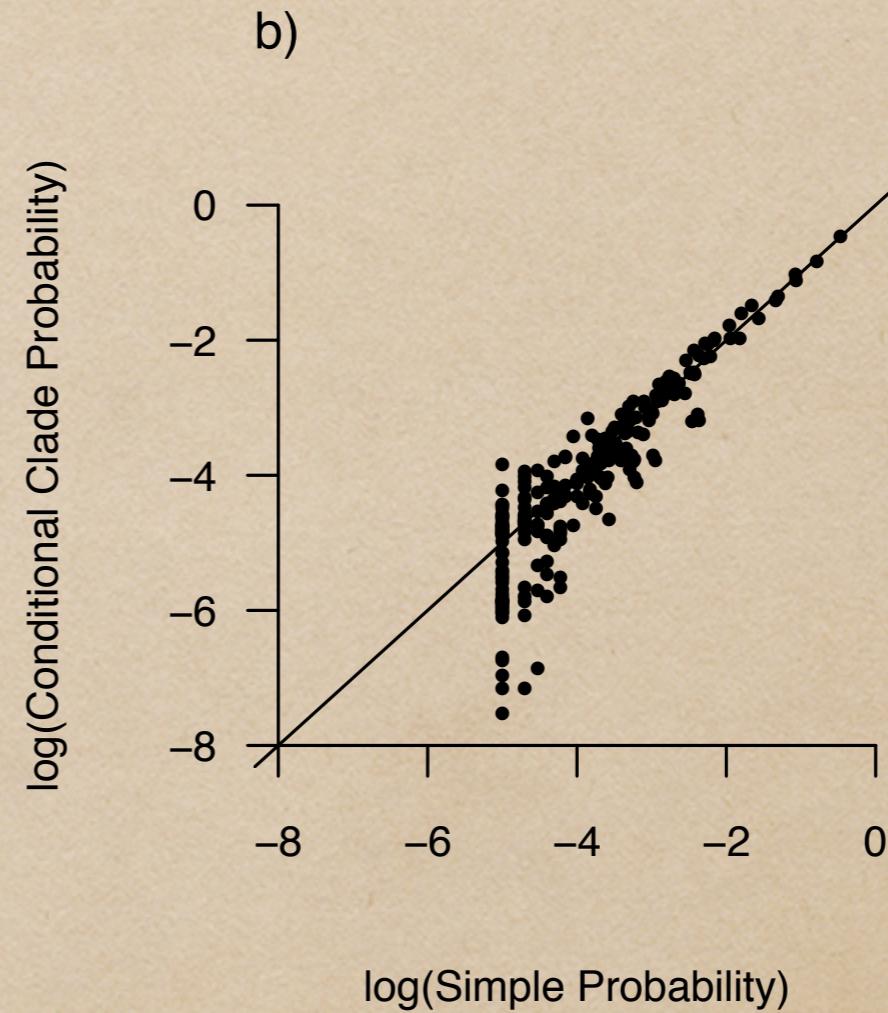
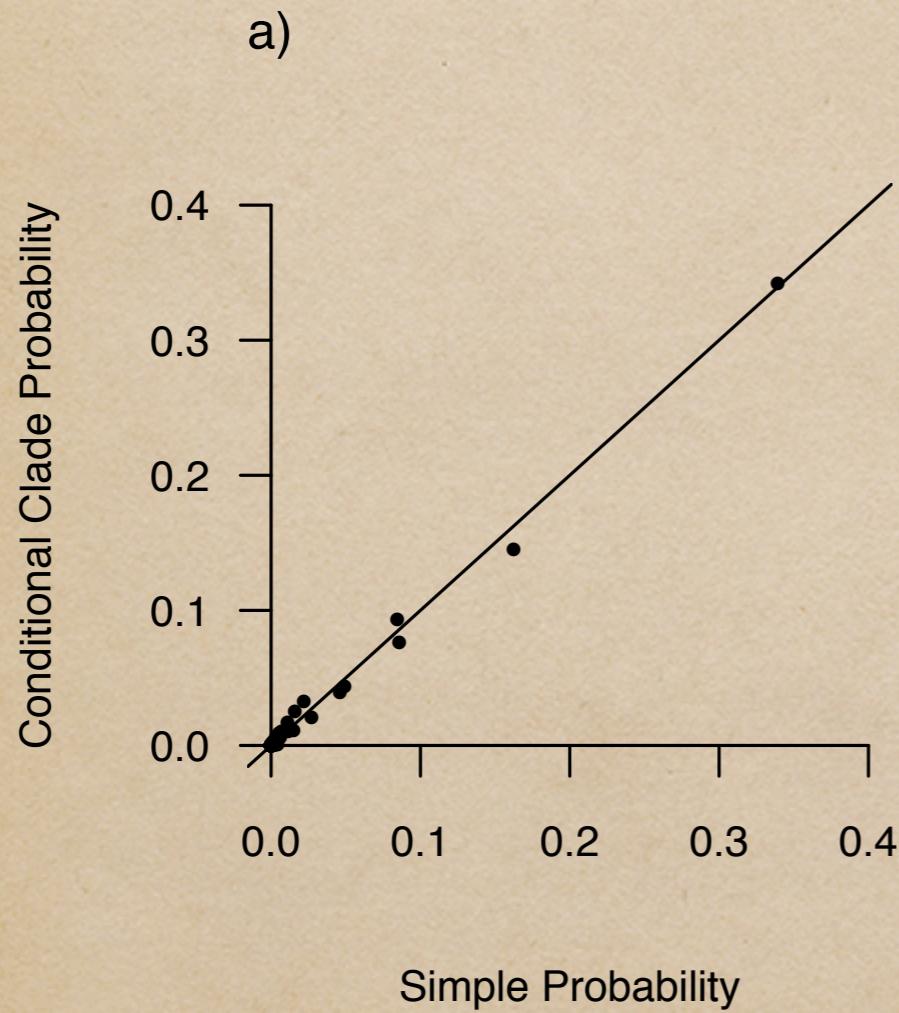
# Unrooted Tree Version

$$\diamond P(T) \approx \frac{\prod_{n \in \text{internal}(T)} \{ P(\text{triple split } (n)) \}}{\prod_{e \in \text{edges}(T)} \{ P(\text{edge } e) \}}$$

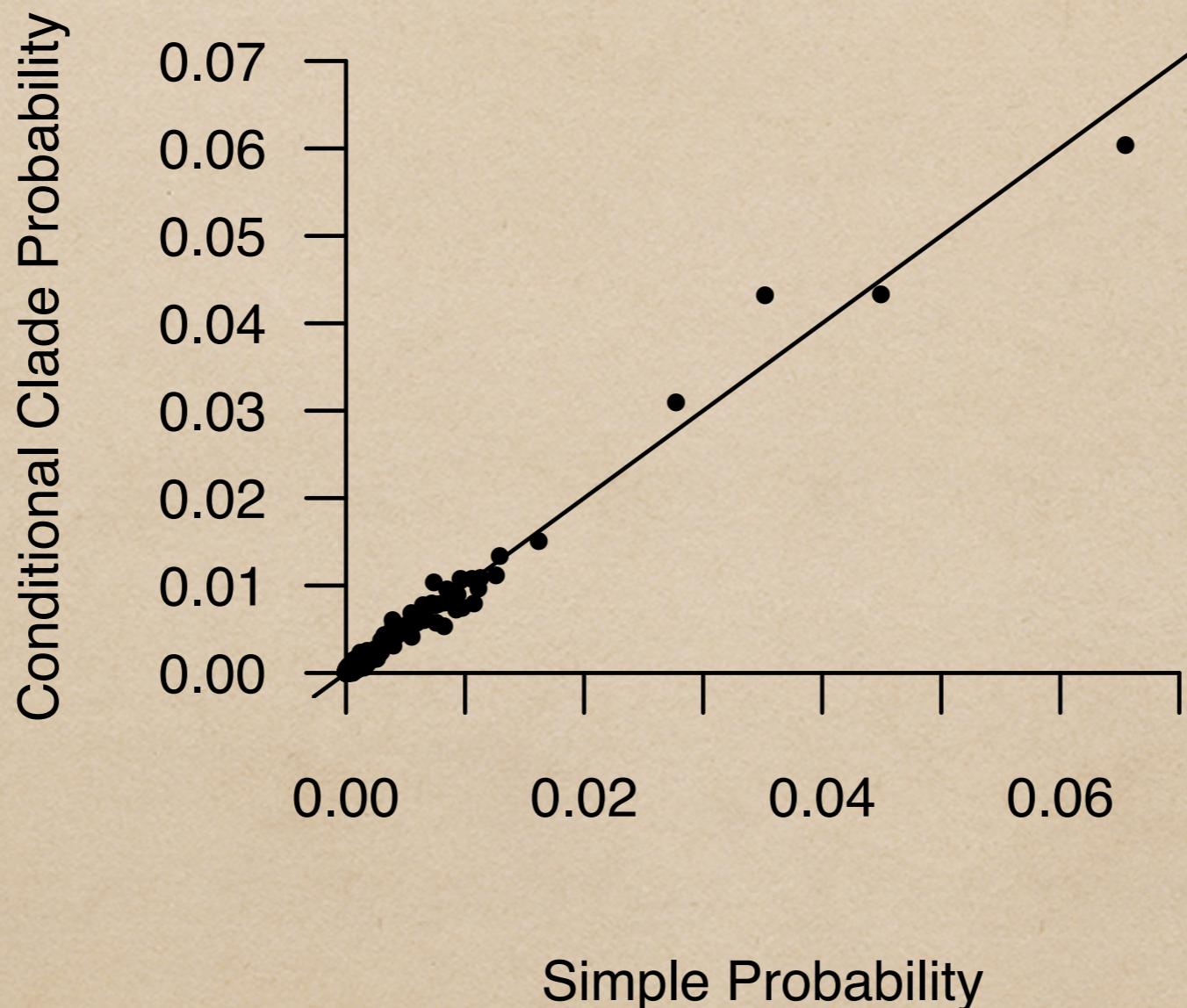
# Estimating Conditional Probabilities

- ◆ Take an MCMC sample of trees.
- ◆ For each sampled tree, increment counters for each clade (edge partition) it contains and for each triple (internal node partition).
- ◆ Estimated conditional probabilities are ratios of node counts over edge counts.

# Estimates for Cat/Dog Trees



# Larger 62-species Example

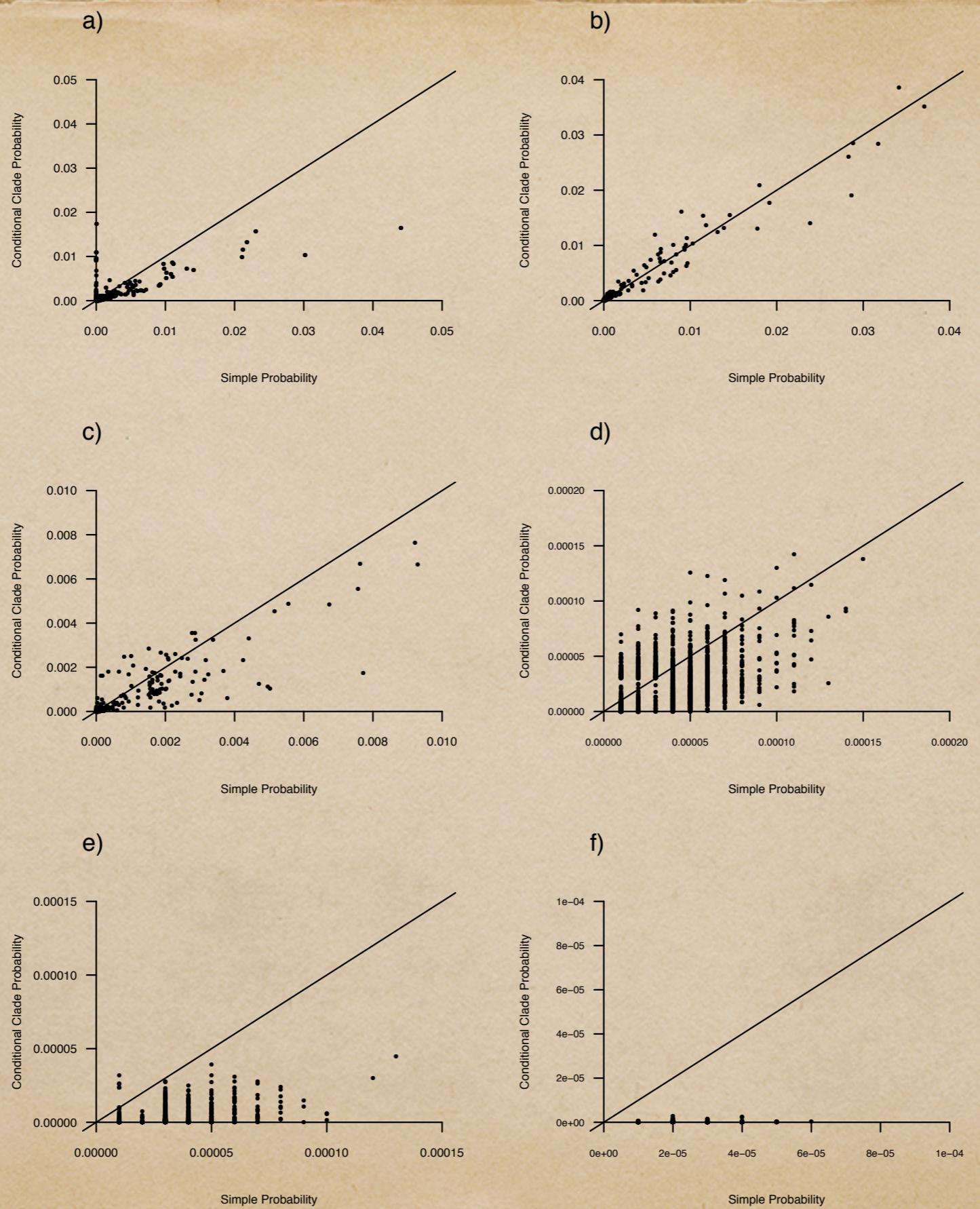


# Coverage

- ◆ The sum of estimated probabilities taken over the entire MCMC sample is an estimate of the coverage of the sample.
- ◆ In the cat and dog example, the 229 trees in the sample are estimated to represent about 99.8 % of the total probability.

# Coverage for 11 Data Sets

Data Set	sampled trees <sup>a</sup>	coverage <sup>b</sup>	corr. <sup>c</sup>	max.	abs. diff. <sup>d</sup>	max CCD <sup>e</sup>	max SRF <sup>f</sup>
DS 1	8,333	0.654	0.777		0.02760	0.01741	0.04407
DS 2	3,473	0.979	0.973		0.00979	0.03857	0.03707
DS 3	2,861	0.984	0.995		0.01601	0.17888	0.16880
DS 4	18,680	0.683	0.867		0.00598	0.00762	0.00930
DS 5	96,608	$7.45 \times 10^{-5}$	0.047		0.00004	$5.64 \times 10^{-7}$	0.00004
DS 6	81,218	0.187	0.606		0.00010	0.00014	0.00015
DS 7	30,537	0.749	0.972		0.00034	0.00245	0.00241
DS 8	84,629	0.021	0.273		0.00010	0.00005	0.00013
DS 9	99,209	$3.70 \times 10^{-12}$	0.006		0.00003	$1.18 \times 10^{-13}$	0.00003
DS 10	89,811	$1.23 \times 10^{-3}$	0.066		0.00006	$3.61 \times 10^{-6}$	0.00006
DS 11	99,791	$1.40 \times 10^{-15}$	0.0003		0.00002	$1.18 \times 10^{-16}$	0.00002



# Faster Sampling

- ◆ MCMC sampling produces highly dependent samples (millions of trees have the same information as a few hundred from an independent sample)
- ◆ The posterior approximation is one key step to a new sampling paradigm.

# Importance Sampling

1. Determine conditional clade distributions.
2. Sample a tree topology.
  - 2.1. Sample branch lengths to complete the tree.
  - 2.2. Find the sampling probability density of the tree.
  - 2.3. Find the (unnormalized) posterior density of the tree.
  - 2.4. Give the sampled tree weight (posterior/sampling density).

# Importance Sampling (continued)

3. Take weighted average of sampled trees for estimates (of clade probabilities, branch lengths, et. cetera).

# Importance Sampling (continued)

- ◆ If the incomplete steps can be finished and if the sampling distribution approximates well the actual posterior distribution, then independent sampling from a complicated high-dimensional posterior distribution will be possible.
- ◆ This may mean orders of magnitude less computational effort for Bayesian inference with large trees.

# Approximation

- ◆ The true posterior distribution which sits in a huge parameter space is estimated to be close to one in a much smaller parameter space.

# Number of Parameters

This table compares the number of free parameters for general tree distributions and distributions that satisfy conditional independence among separated subtrees.

$n$	$r_n - 1$	$c_n$
2	0	0
3	2	2
4	14	14
5	104	64
6	944	244
7	10,394	846
8	135,134	2,778
9	2,027,024	8,828
10	34,459,424	27,488

# Summary

- ◆ The new method provides a means to estimate probabilities of rare trees much more accurately than simple sample averages.
- ◆ The new method is one key step in a new paradigm for computation in Bayesian phylogenetic inference.

# Acknowledgments

- ◆ Thanks to Cécile Ané!
- ◆ Funding from NSF and NIH.