Processing ddRAD for population history inference

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• Reduced-representation genomic method

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- Cheap

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- Lots of data returned

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- Cheap
- Lots of data returned
- Stable software pipelines for using these data

A Quick Note

Slides that contain ddRAD specific info will be noted. Some steps can be used with multiple data sources.

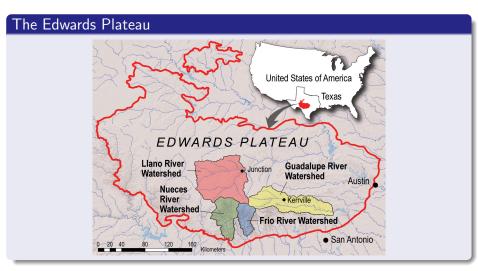
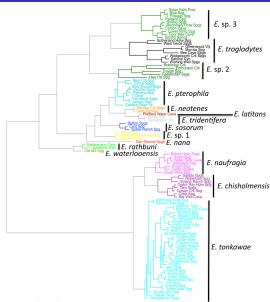


Image: AGU



13 putative species of $\it Eurycea$

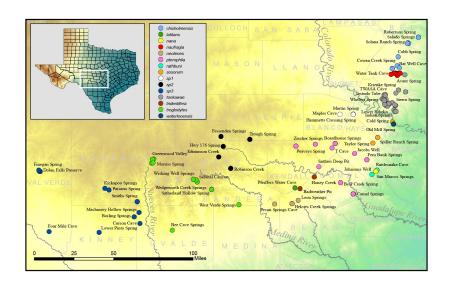
13 putative species of *Eurycea* All of which are fairly threatened by development

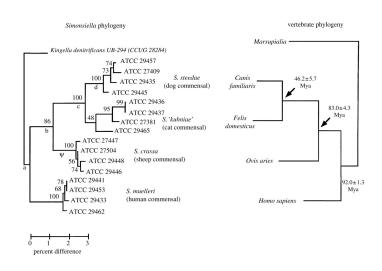


- 100 nucleotide changes

How many species of ${\it Eurycea}$ are there, really?

How many species of *Eurycea* are there, really? And is there introgression between them?





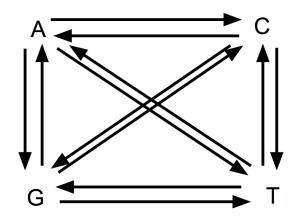
JP Staley, 2006. Figure 2

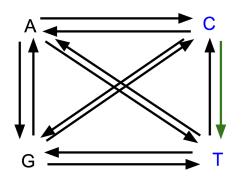
Maximum likelihood

Maximum likelihood is a framework for estimating phylogeny by modeling the process of evolution that generated our sequence data

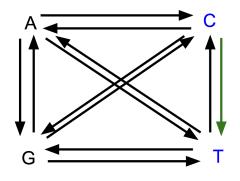
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Probability of C to T change Equilibrium frequency of C 0 * .25 = 0



Probability of C to T change Equilibrium frequency of C .75 * .25 = .1875

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 - And because we are making mathematically-defined assumptions, we can use model-fitting to find the "true" model

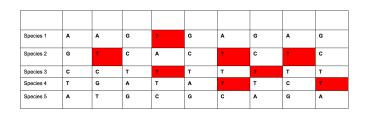
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Problems

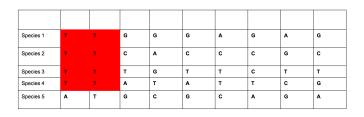
- Problems
- Missing data

- Problems
- Biased Missing data

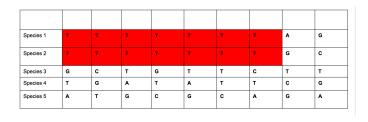


- Problems
- Biased Missing data

• Missing data concentrated in specific individuals



- Missing data concentrated in specific individuals
- Missing data concentrated in certain loci in your data matrix



- Problems
- Model misspecification

Problems

 Model misspecification: when your data are not adequately described by your model

Today, we'll be visualizing our data at every step to try and minimize a bias in which individuals have missing data

Phylogenetics

We'll also look at ways to make sure we aren't overly-conservative in our choosing of SNPs (i.e., biasing our collection towards sites that exhibit little change)

One of the things that makes RADseq, and especially ddRADseq, so cheap is the pooling of samples

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The way we recover individual samples is via demultiplexing

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This allows for the cost-saving properties of batching, without the cost-increasing properties of synthesizing oligonucleotides.

The STACKS step for this is called Process RAD Tags

Output

• FASTQ files

Let's look at the output

- FASTQ files
- Reads, grouped by individual

Let's look at the output

- FASTQ files
- Reads, grouped by individual
- We haven't done any SNP calling. This is just the step that gets our data ready to do that

The STACKS step for this is called ustacks

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Key Parameters

- -m: Minimum stack depth
- -M: Maximum mismatches allowed between reads in a stack

Other Parameters

• -i: ID for this sample

Exercise

One of the issues we discussed was biased missing data

Catalog Building

Once we have our within-individual stacks, we build a catalog of loci across individual catalogs (cstacks)

Catalog Building

Key Parameters

• -n: number of mismatches to allow between a putative tag, and a tag in the catalog

Outputting Data for Phylogenetics

The STACKS step for this is called populations

Outputting Data for Phylogenetics

A new file is needed, here: the population map

Outputting Data for Phylogenetics

Key Parameters

- -r: Percentage of individuals in a population that must have a locus to output it
- -m: Minimum stack depth at a locus

Exercise

Let's look at this output

Exercise

Let's look at this output But we can also look in a more complex way: countPhyloMissing.sh and plotPhyloMissing.py

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RAxML approximate likelihoods

RAxML

Dataset	L score
323320	-288336.664115
323340	-84377.460743
323360	-27407.770692
323380	-10281.525371
323390	-1699.210794
	'

RAxML Approximate final L scores

Garli

Garli

Dataset	L score
323320	-287898.7874
323340	-84289.0263
323360	-27384.6012
323380	-10273.63021
323390	-1697.6284

Why

Tips	Number of unrooted (binary) trees	
4	3	
5	15	
6	105	
7	945	
8	10,395	
9	135,135	
10	2,027,025	
11	34,459,425	
12	654,729,075	
13	13,749,310,575	
14	316,234,143,225	
15	7,905,853,580,625	
16	213,458,046,676,875	
17	6,190,283,353,629,375	
18	191,898,783,962,510,625	
19	6,332,659,870,762,850,625	
20	22,164,309,5476,699,771,875	
21	8,200,794,532,637,891,559,375	
22	319,830,986,772,877,770,815,625	
23	13,113,070,457,687,988,603,440,625	>21 moles of trees
24	563,862,029,680,583,509,947,946,875	

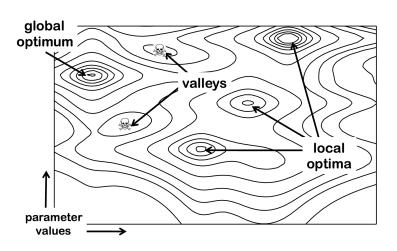


Image stolen, shamelessly, from Derrick Zwickl

Garli can take an input tree and optimize phylogenetic parameter estimates.

We actually had fantastic results doing this in a large scale phylogenetics paper (Wright et al. 2015)

Second-round optimization

Dataset	L score	
323320	-287897.3609	
323340	-84281.7290	
323360	-27384.6012	
323380	-10273.6302	
323390	-1697.6283	