

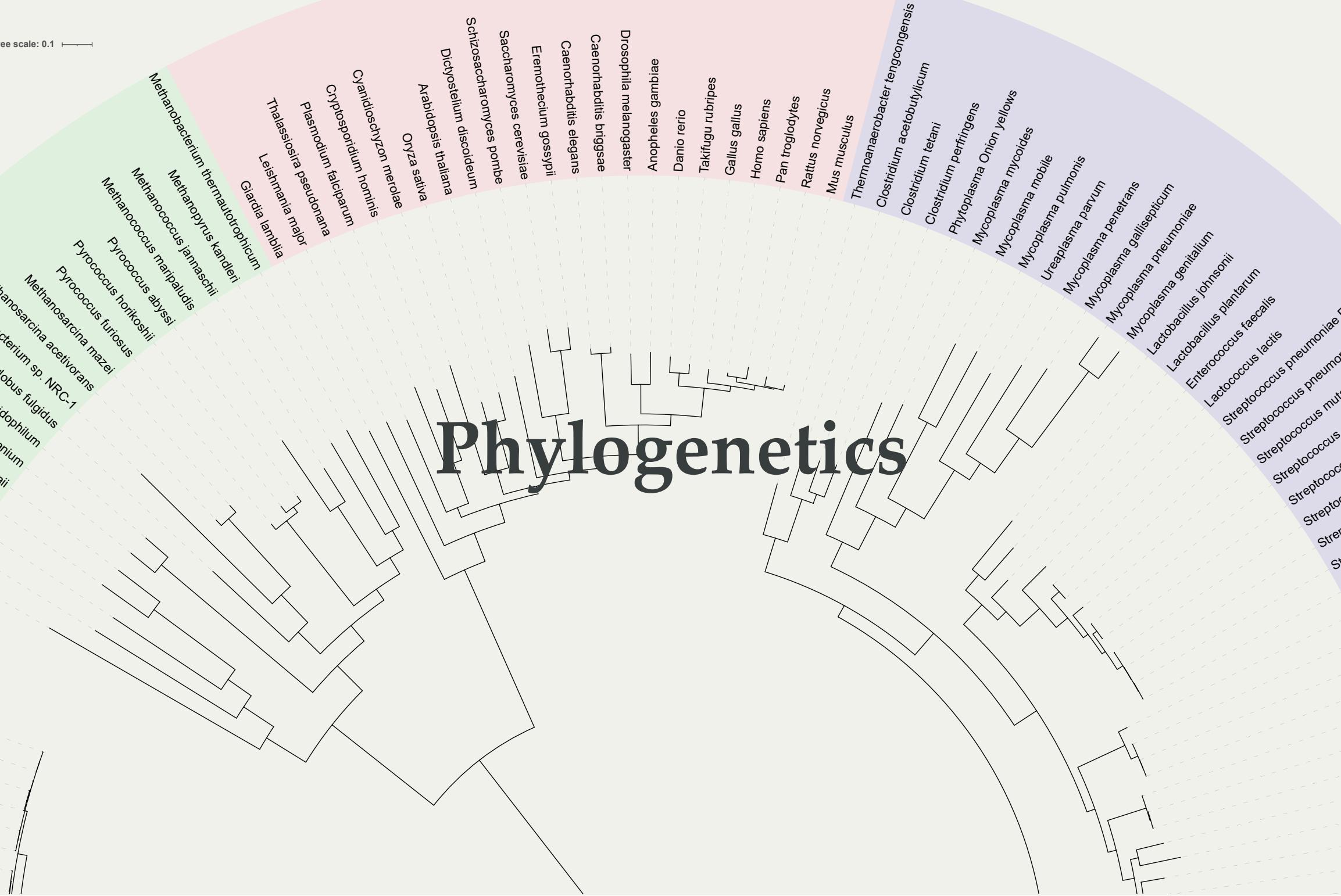
TreePPL – a new DSL in Miking for Phylogenetics

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Miking team

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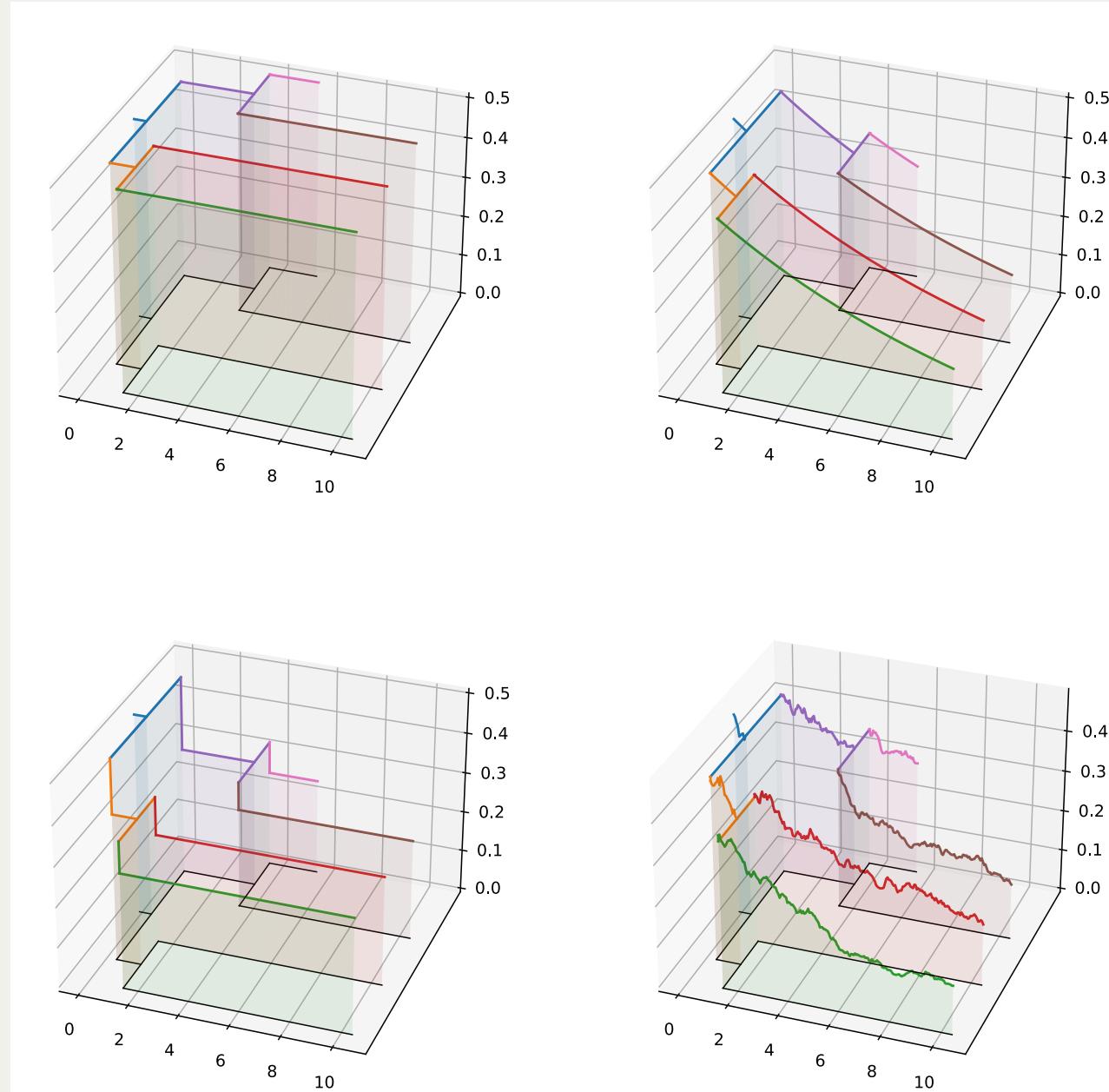
Contents

1. A few words about our domain, phylogenetics
2. Probabilistic programming languages
3. TreePPL demo



Phylogenetics discussion

- Problems that phylogenetics deals with
 - Reconstructing phylogenetic trees
 - Using phylogenetic trees to understand evolution and ecology



Diversification models on a phylogenetic tree

What can the users do?

- Methods of phylogenetics
 - Parsimony
 - Statistical methods: ML and Bayesian
- Software for phylogenetics
 - monolithic software: e.g. MrBayes, RAxML
 - extensible software: e.g. BEAST, BEAST2, RevBayes
- Write the model yourself
 - implement in a general-purpose language: e.g. C, Java, Python, or R
 - implement in a probabilistic programming language: e.g. WebPPL, Birch
 - implement in a phylogenetic PPL: TreePPL

Probabilistic Programming Languages



Bayes theorem

Let x be some observed data and θ be an unobserved parameter in whose value we are interested in.

$$\widehat{p(\theta|x)} = \frac{\overbrace{p(x|\theta)}^{\text{likelihood}} \overbrace{p(\theta)}^{\text{prior distribution}}}{\underbrace{p(x)}_{\text{normalizing constant}}}$$

data distribution/

Bayes theorem

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observe/factor
data distribution/ assume/sample

Coin example

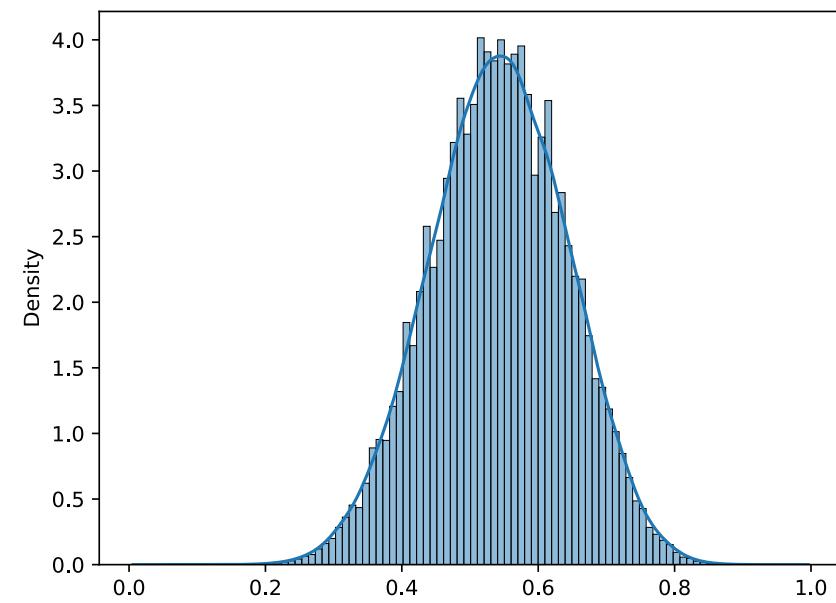
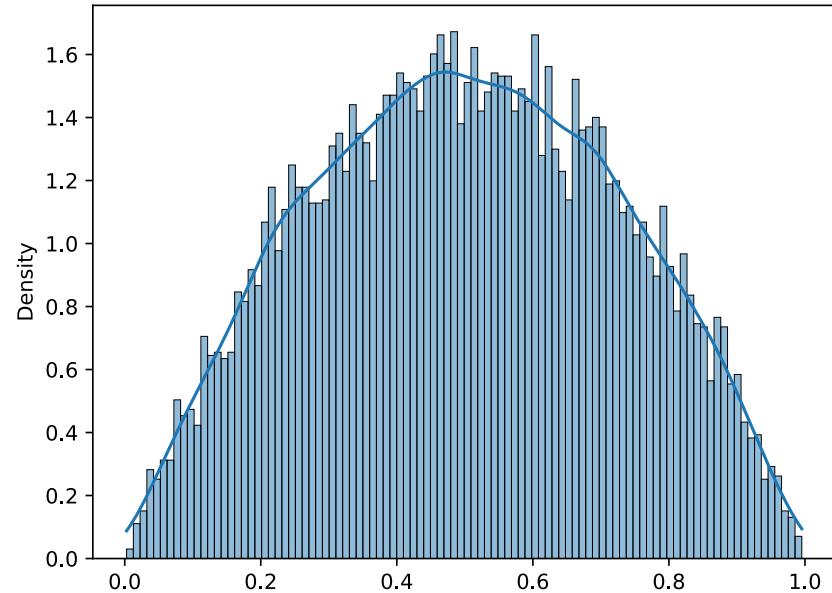
```
1 outcomes=[True, True, True, False, True, False, True, True, True, True, False,  
2     False, True, True, False, True, False, False, True, False, False]
```

Define prior

```
assume p ~ Beta(2.0, 2.0);
```

Condition on data

```
for i in 1 to (length(outcomes)) {  
    observe outcomes[i] ~  
    Bernoulli(p);  
}
```

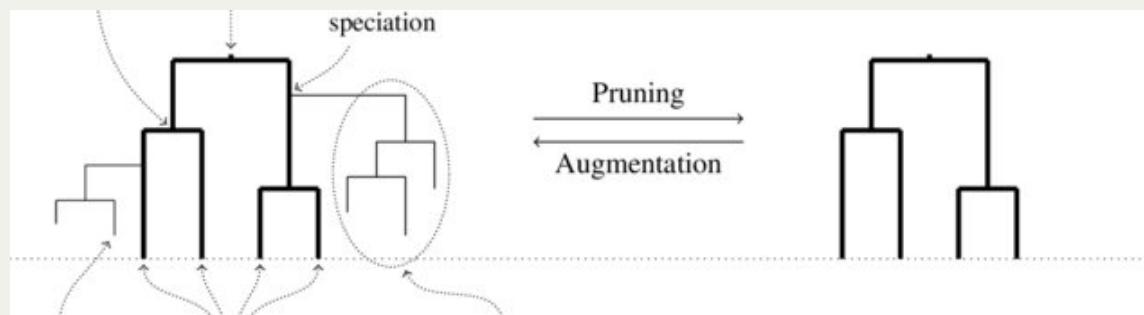


The complete coin example in TreePPL using Python as a wrapper.

```
1 source = """\
2 model function coin(outcomes: Bool[]): Real {
3     assume p ~ Beta(2.0, 2.0);
4     for i in 1 to (length(outcomes)) {
5         observe outcomes[i] ~ Bernoulli(p);
6     }
7     return(p);
8 }
9 """
10
11 with treeppl.Model(source=source, samples=10_000, method="is-lw") as coin:
12     res = coin(
13         outcomes=outcomes
14     )
15     sns.histplot(
16         x=res.samples, weights=res.nweights, bins=100, stat="density", kde=
17     )
18     plt.show()
```

Universal PPLs

```
1 function simulateSubtree(time: Real, lambda: Real, mu: Real) {  
2     assume waitingTime ~ Exponential(lambda + mu);  
3     if waitingTime > time {  
4         weight 0.0;  
5         resample;  
6     } else {  
7         assume isSpeciation ~ Bernoulli(lambda / (lambda + mu));  
8         if isSpeciation {  
9             simulateSubtree(time - waitingTime, lambda, mu);  
10            simulateSubtree(time - waitingTime, lambda, mu);  
11        }  
12    }  
13 }
```

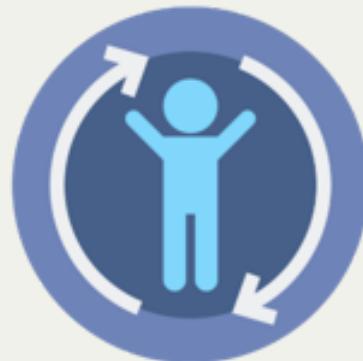


Simulating unobserved evolutionary lineages



Phylogenetic Data

Supports natively the PhyJSON format for evolutionary trees



Simplicity

Designed to meet the needs of computational biologists

TreePPL



Rich Model Library

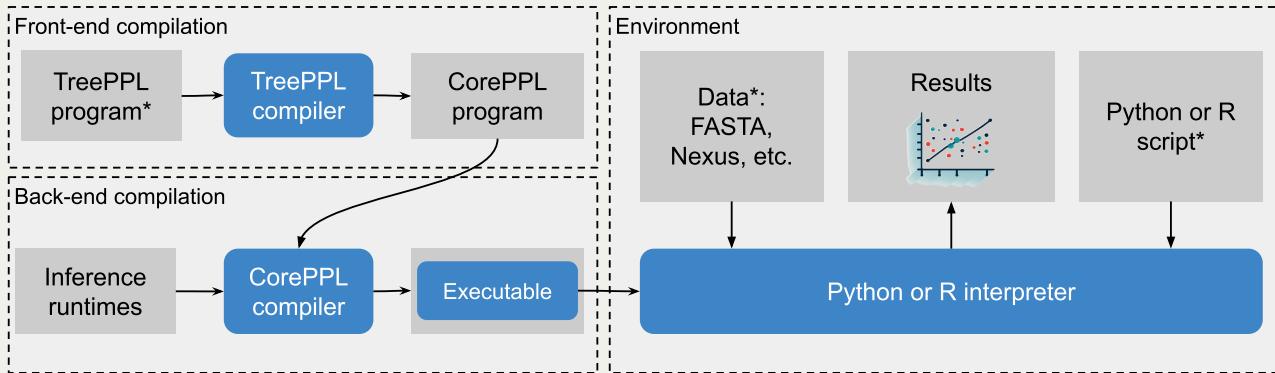
Offers state-of-the art diversification models as templates



Powerful Statistical Inference

Sequential Monte-Carlo (SMC) and Markov-chain Monte-Carlo (MCMC) inference

Architecture



Optimizations

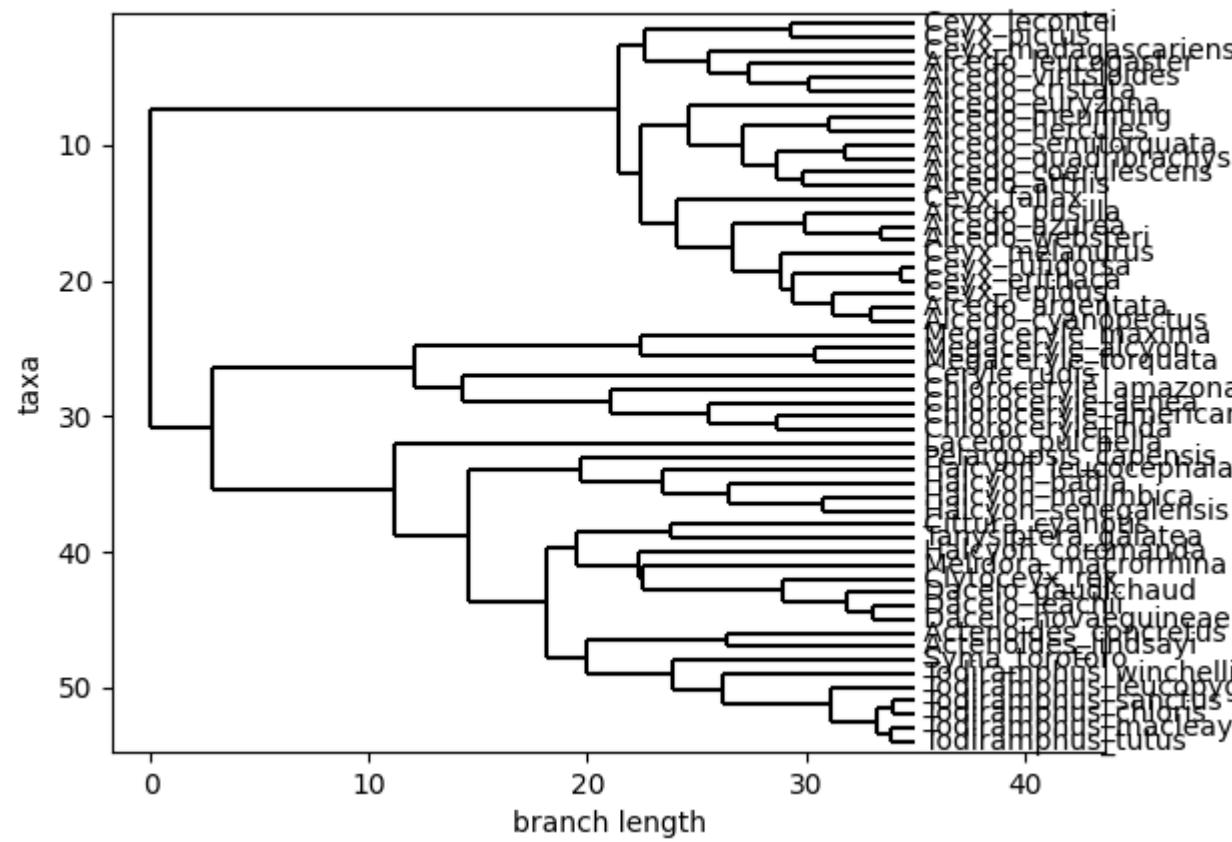
- Partial CPS transformation
- Automatic alignment
- (Delayed sampling/ conjugacy analysis)

Inference strategies

- Lightweight importance sampling
- Sequential Monte Carlo: Bootstrap Particle Filter,
- Sequential Monte Carlo: Alive particle filter
- Lightweight MCMC
- Trace MCMC
- Particle MCMC

Write a program that infers the bifurcation rate λ and the extinction rate μ under the assumption that they are constant for a given binary evolutionary tree.

UNTITLED





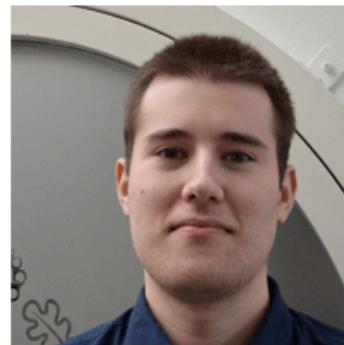
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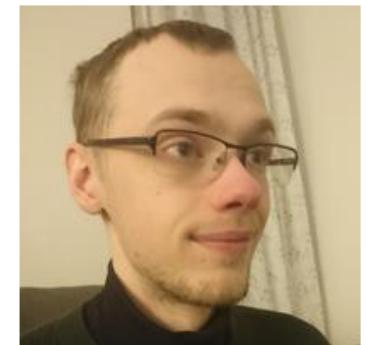
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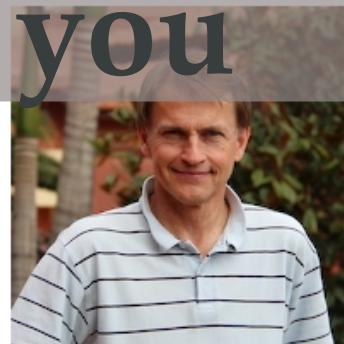
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- Slides have been designed using images from Flaticon.com as well DALL-E

Downloading

Project homepage: <https://treeppl.org>

Main repo: <https://github.com/treeppl/treeppl>

Python library: <https://github.com/treeppl/treeppl-python>

Paper:

<https://www.biorxiv.org/content/10.1101/2023.10.10.561673v1>

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Bonus material

Discussion of PPLs

- PPL semantics
 - Usual language: *input* → *output* + *side effects*
 - PPL: *each program trace describes a sample from a probability distribution*
- Advantages of PPLs
 - natural and generative way of encoding a posterior distribution
 - no need to implement inference
 - enables model comparison as estimation of normalizing constant possible

