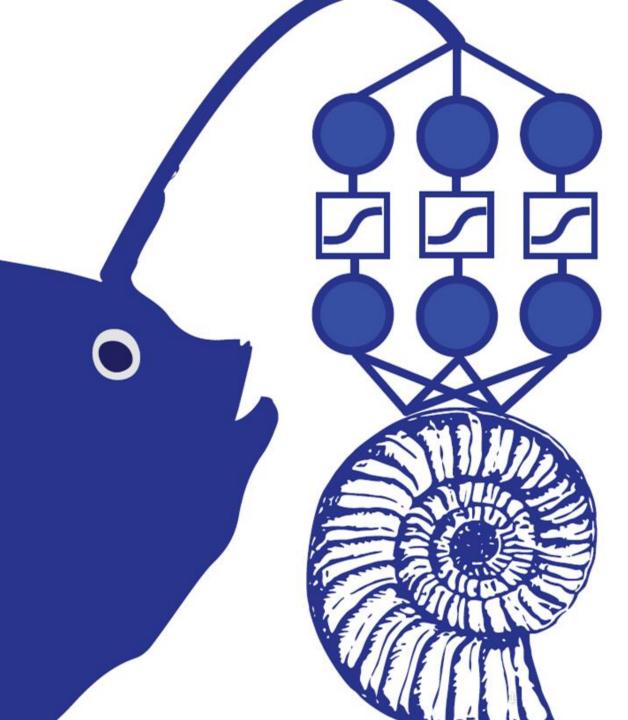
Introduction

DeepDive: Deep learning Diversity Estimation

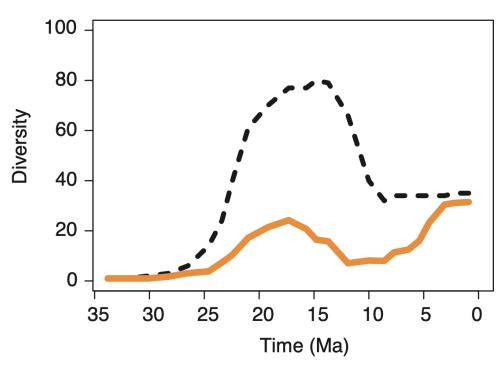
CPEG 2025



Estimating biodiversity from fossil data

- Fossils are our only direct evidence of past biodiversity.
- Non-random biases at spatial, taxonomic and temporal scales.
- Available methods are based on rarefaction or simple models assuming random sampling.

True vs observed diversity



Alroy 2010 Science; Starrfelt & Liow 2016 Phil Trans B; Flannery-Sutherland et al. 2022 Nature Comm

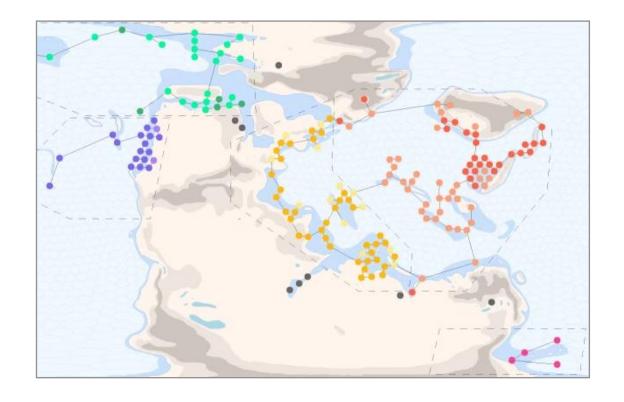
Problems in estimating biodiversity from fossils

 Spatial biases make global biodiversity patterns unidentifiable using the current methods.



PROCEEDINGS B

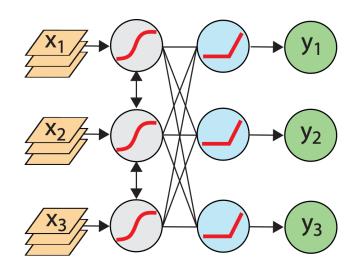
The apparent exponential radiation of Phanerozoic land vertebrates is an artefact of spatial sampling biases



Alroy 2010 Science; Starrfelt & Liow 2016 Phil Trans B; Flannery-Sutherland et al. 2022 Nature Comm

DeepDive: deep learning estimation of biodiversity through time

Input: fossil distribution in space and time



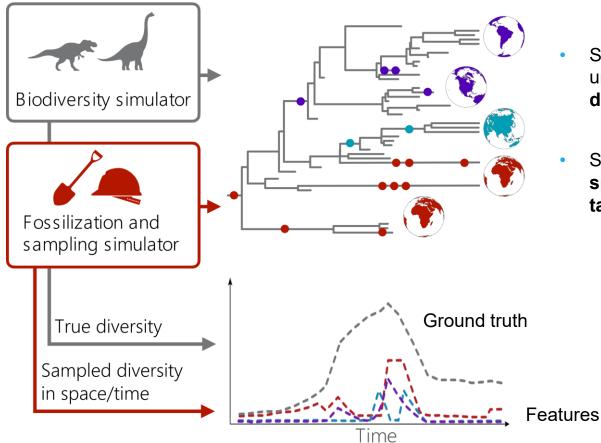
Output: diversity estimates through time

nature communications	8				
Article	https://doi.org/10.1038/s41467-024-48434-7				
DeepDive: estimating global biodiversity patterns through time using deep learning					

Cooper et al. 2024 Nature Comms Cooper et al. 2024 biorXiv



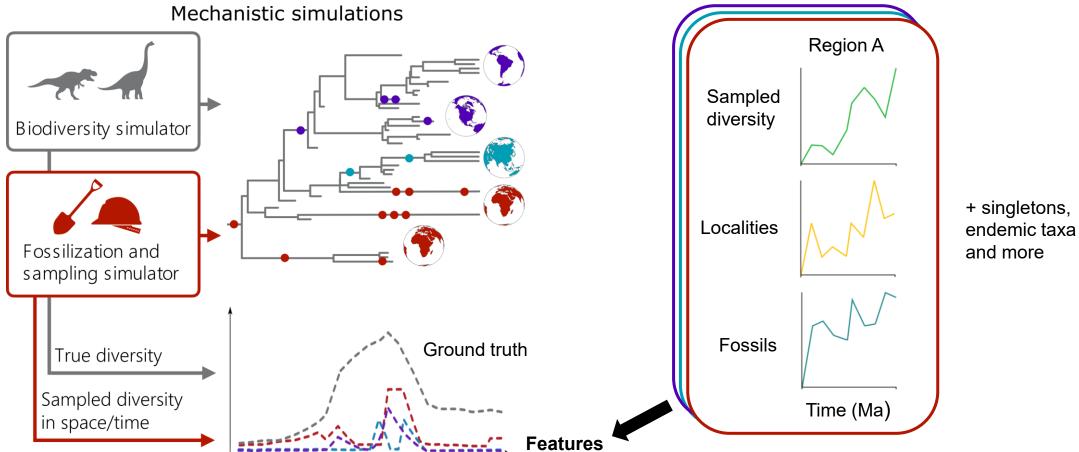
Mechanistic simulations



- Simulating clade evolution under spatial-explicit **birth- death processes**
- Simulating fossil data with spatial, temporal, and taxonomic biases

Cooper et al. 2024 Nature Communications

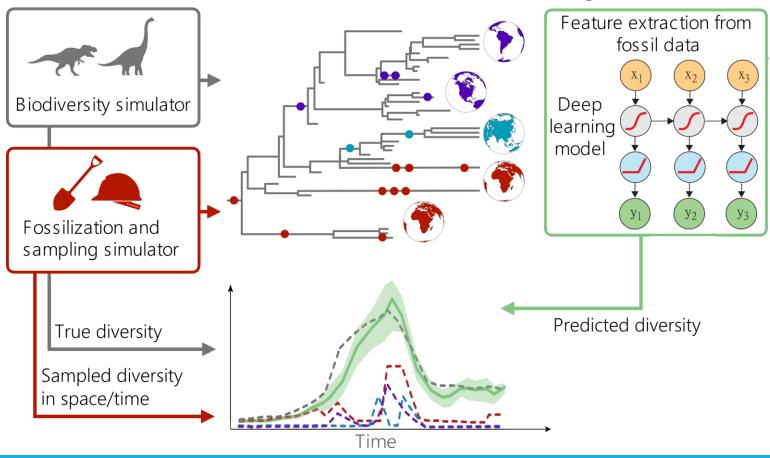




Time



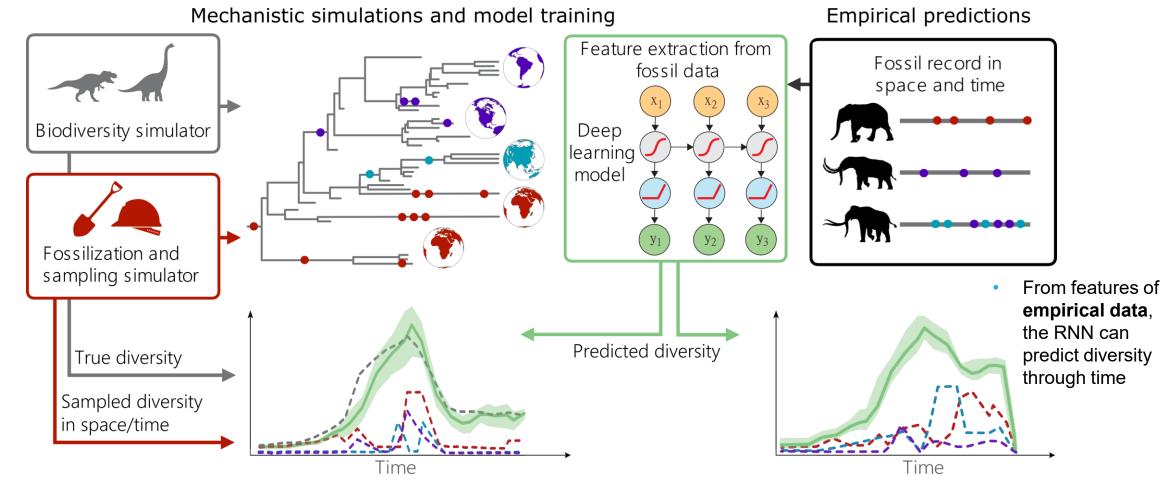
Mechanistic simulations and model training



Deep learning models for diversity estimation

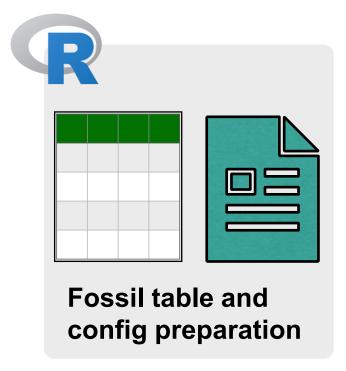
Training a Recurrent
 Neural Network to predict true diversity from sparse fossil data



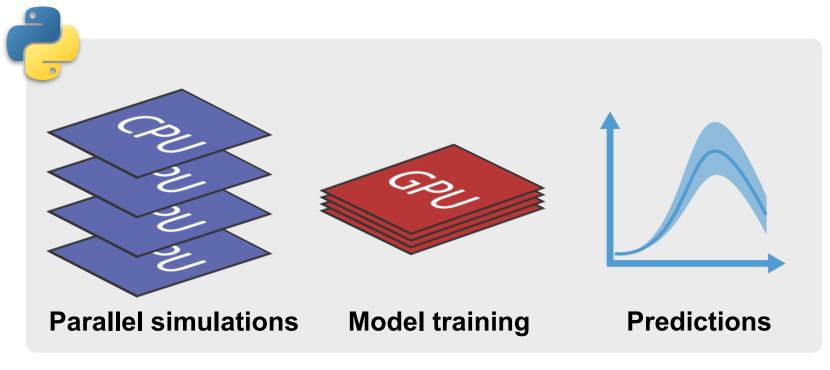




DeepDiveR



DeepDiveR



DeepDive

github.com/DeepDive-project

Data preparation

 Occurrence data e.g. from the Paleobiology Database can be formatted as input for DeepDive using the function prep_dd_input()

Taxon	Region	MinAge	MaxAge	Locality
Ailurus	Asia	0.6	1.3	1
Ailurus	Asia	9.5	10.35	2
Alopecocyon	Asia	9.5	10.35	2
Alopecocyon	Europe	9.7	11.11	3
				•••

	Α	В	C	D	Е	F
1	Replicate	Type	Region	t1	t2	t3
2	1	bin_start	NA	66.043	65	64
3	1	bin_mid	NA	65.5215	64.5	63.5
4	1	bin_dur	NA	1.043	1	1
5	1	locs	Africa	0	0	0
6	1	locs	Asia	1	0	0
7	1	locs	Europe	0	0	0
8	1	locs	NorthAme	0	2	1
9	1	locs	SouthAme	0	0	0
10	1	occs	Africa	0	0	0
11	1	occs	Africa	0	0	0
12	1	occs	Africa	0	0	0

Configuration



1. General:

Settings called at every stage of the analysis.



2. Simulations:

Settings for generating training and test data sets.



3. Regional constraints:

The ages at which regions become available or unavailable.



4. Model training:

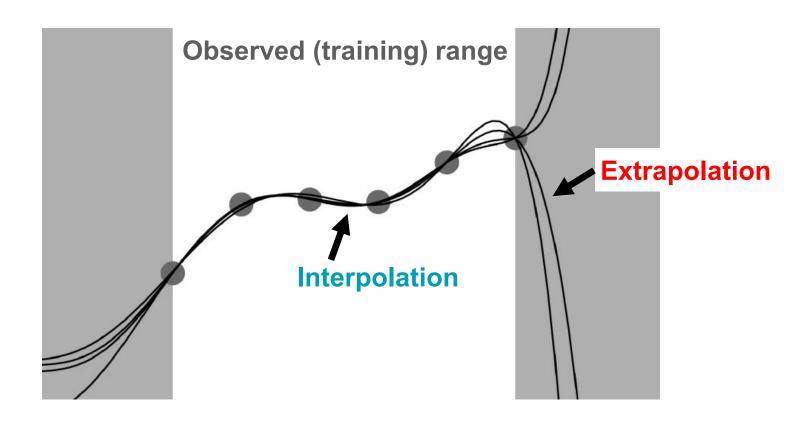
Specification of deep learning models to be trained.



5. Empirical predictions:

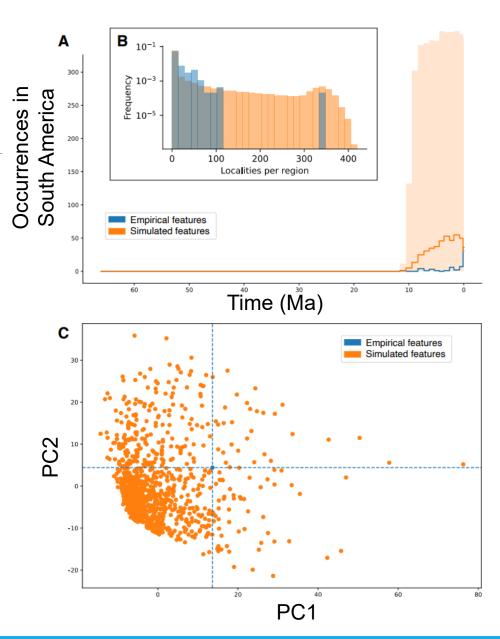
Settings for generating predictions from empirical data.

Training simulations must reflect the data

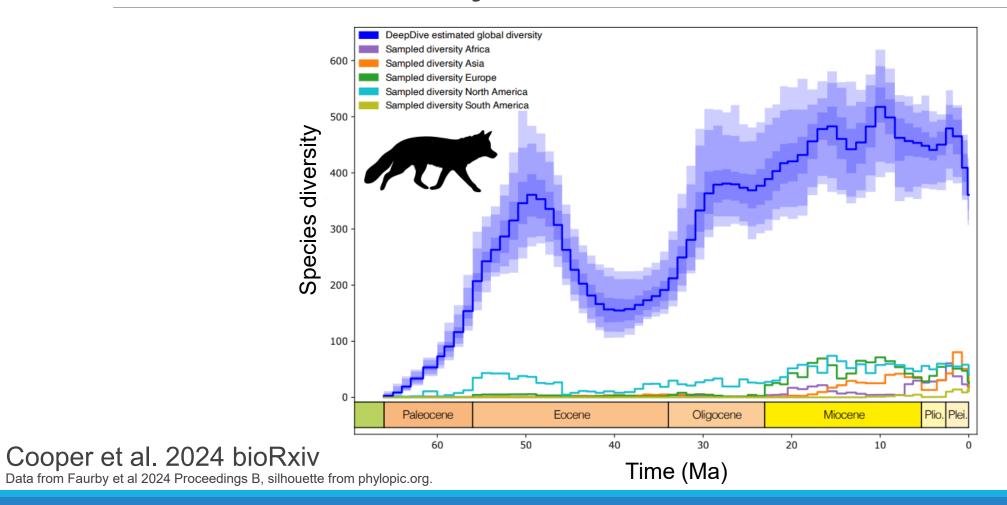


Autotune adjusts simulations to reflect empirical data

- Parameters with default NA are adjusted automatically and a new configuration saved unless user specified
- E.g. Across each region:
 - Sampled species
 - Longevity
 - Singletons
 - Gaps in data
 - Occurrences



Inferred diversity curve





Let's get started!

You can access the next tutorial at:

https://github.com/thauffe/cpeg25/tree/main/deepdive_analysis

or by following the QR code









CPEG 2025

Practical

DeepDive and DeepDiveR

Rebecca B. Cooper

