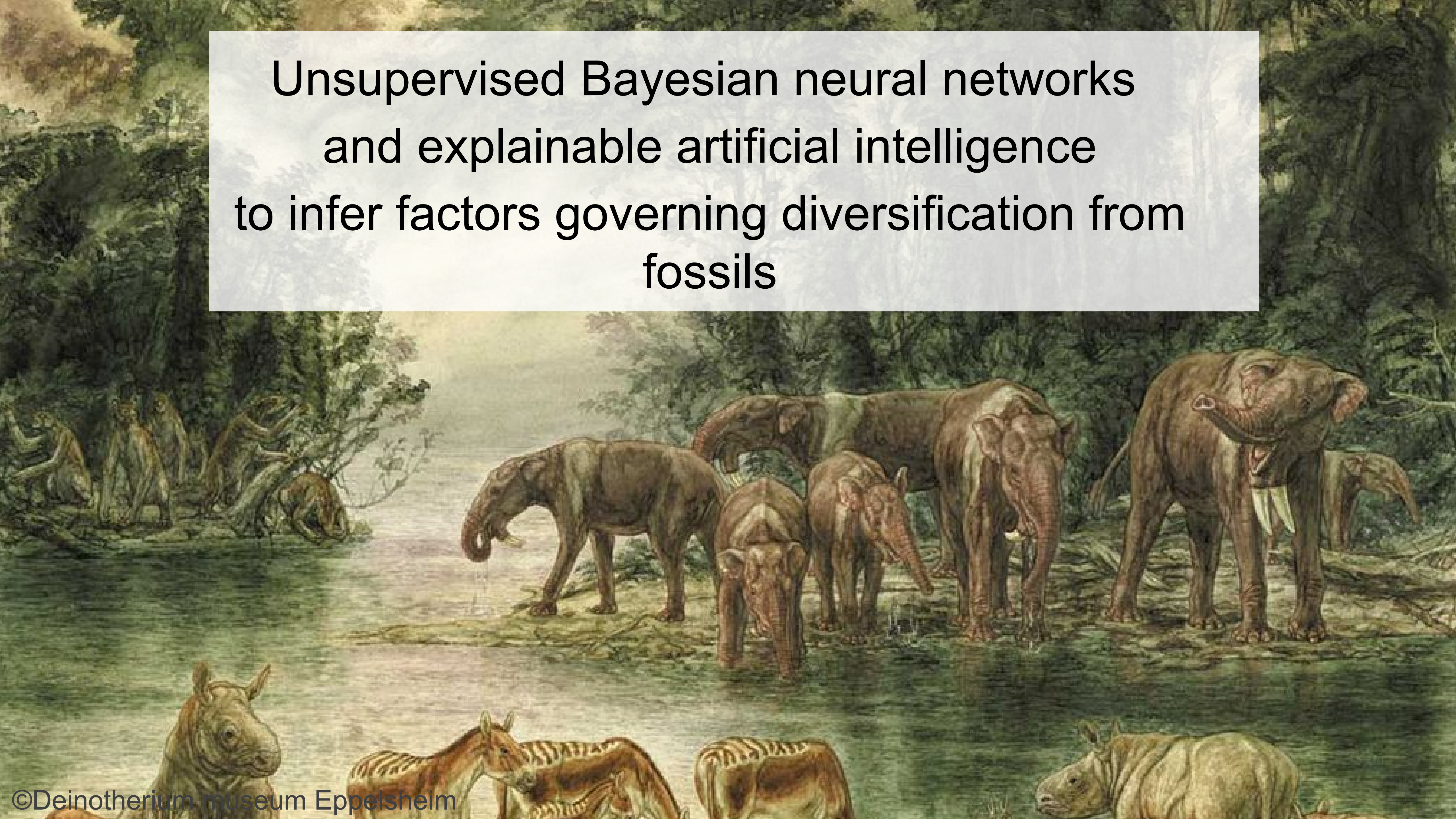
Unsupervised Bayesian neural networks and explainable artificial intelligence to infer factors governing diversification from fossils



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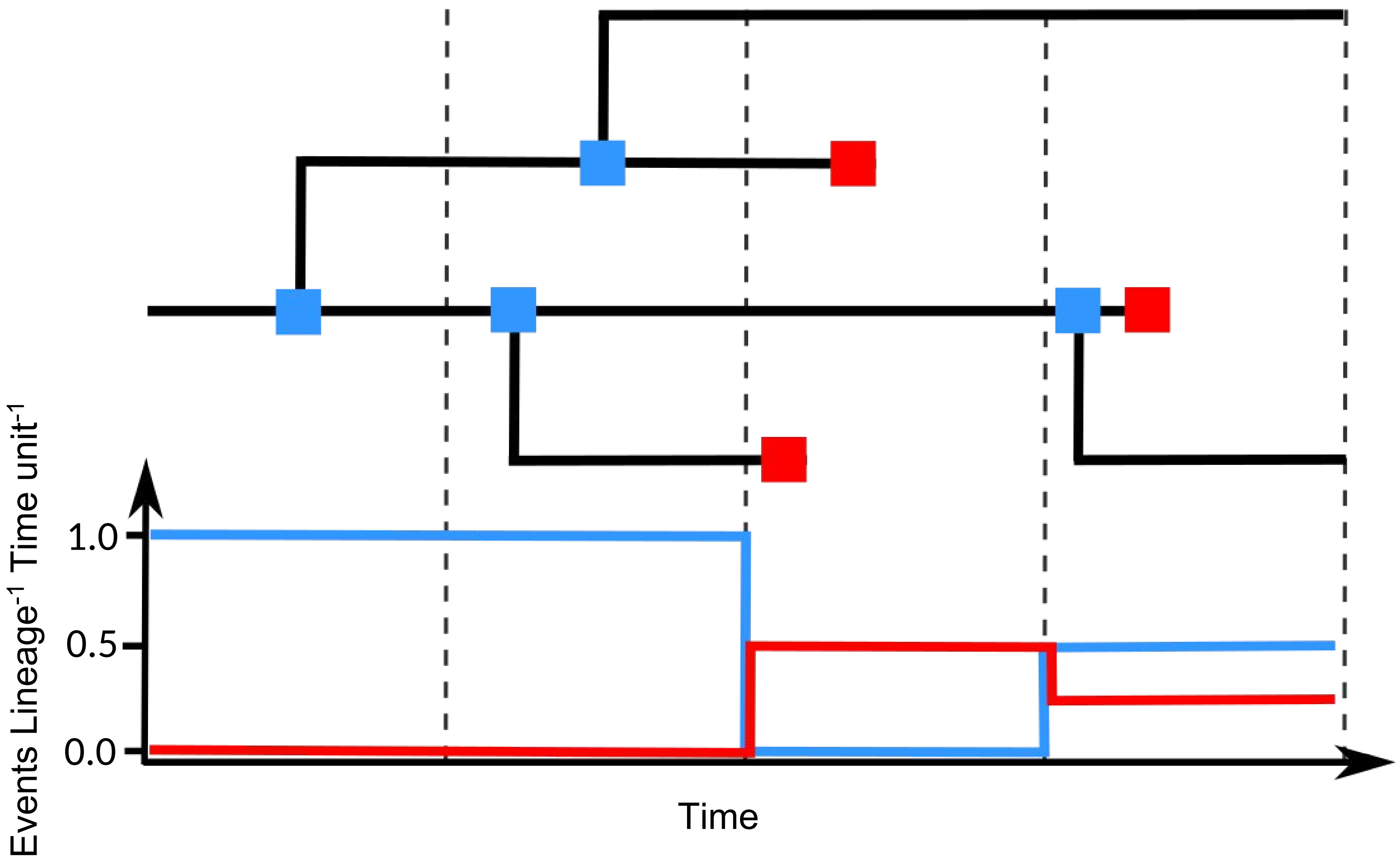
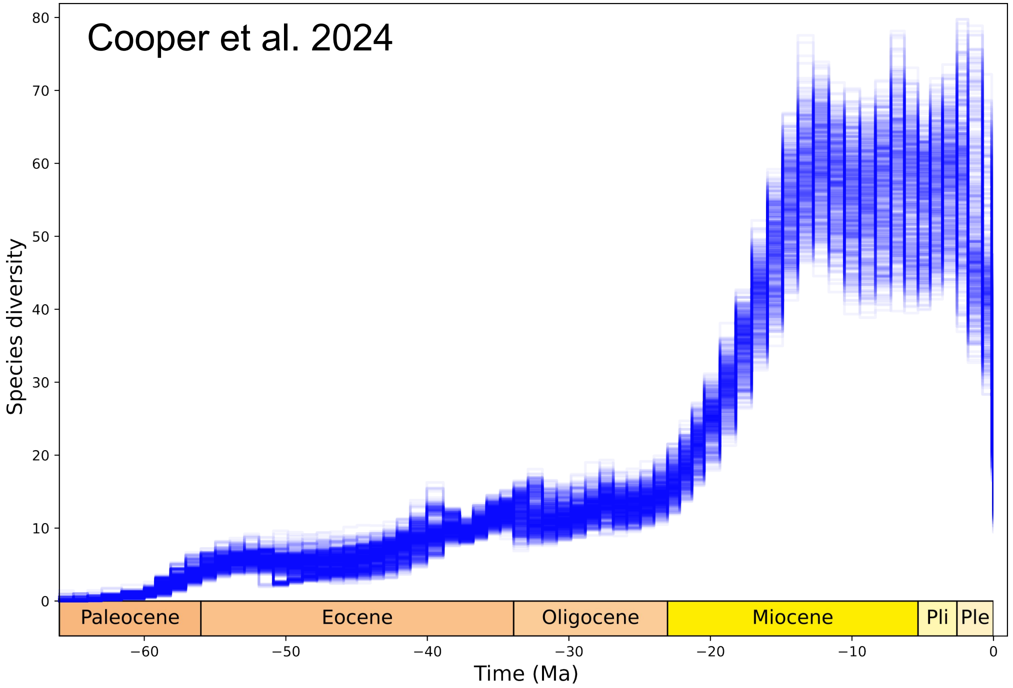
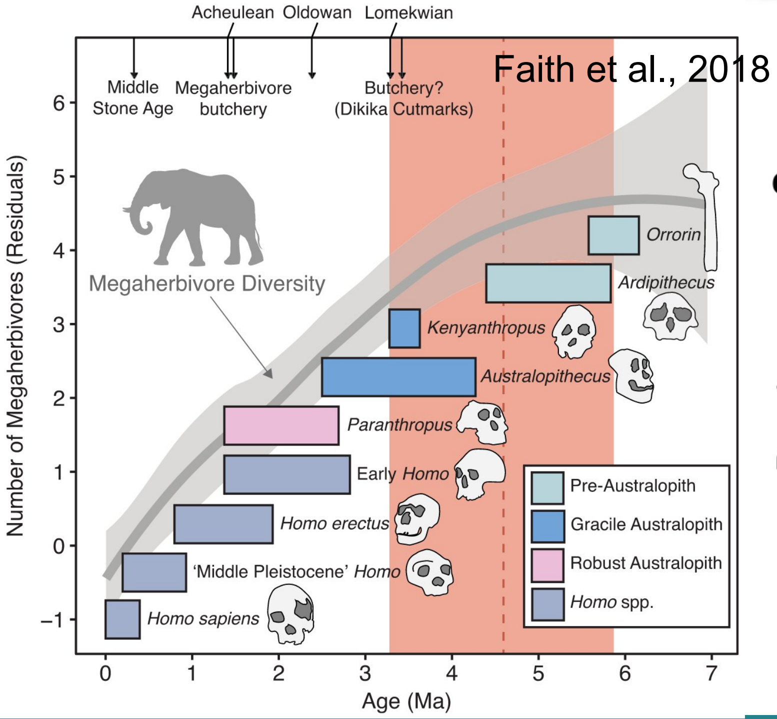
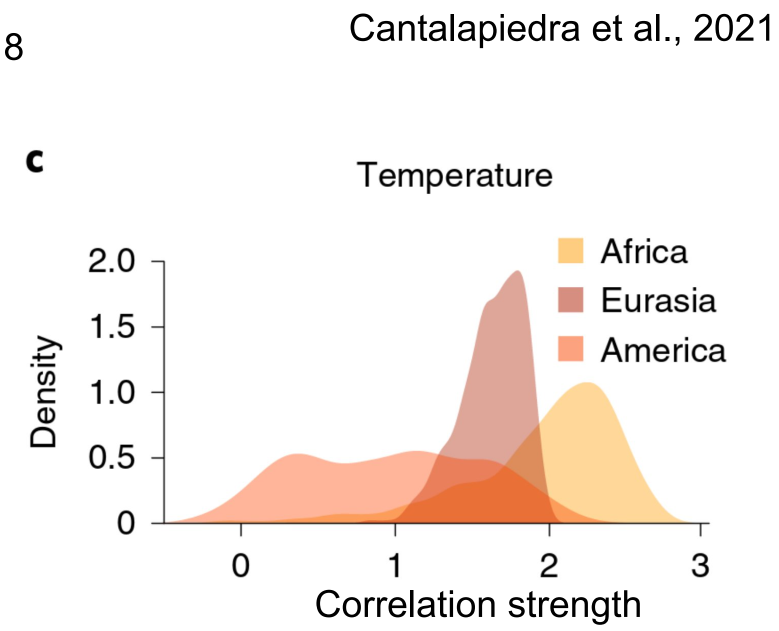
Speciation and extinction rates



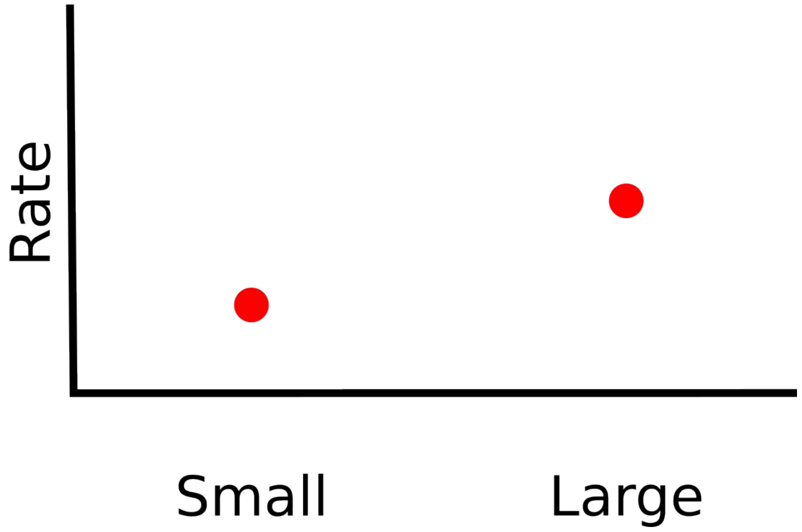
What caused the demise of elephants and their extinct relatives?







Limitations to infer factors governing diversification – unifactorial & monotonic



Higher origination and extinction rates in larger mammals

Lee Hsiang Liow*, Mikael Fortelius†‡, Ella Bingham§, Kari Lintulaakso†, Heikki Mannila§¶, Larry Flynn‖, and Nils Chr. Stenseth*,**

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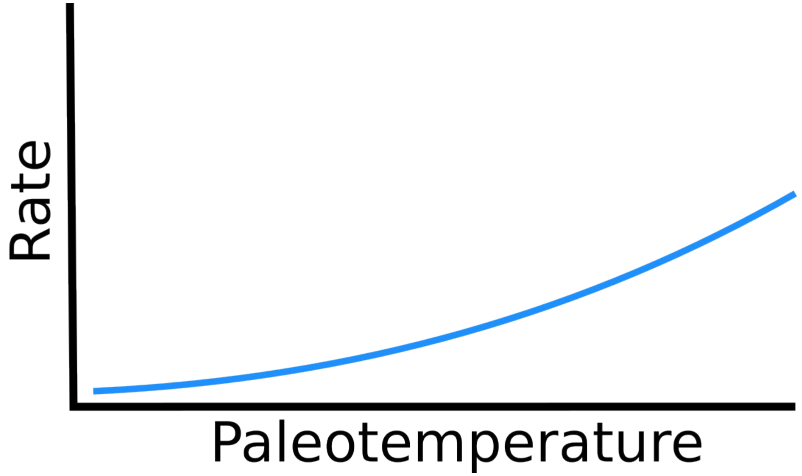


ECOLOGY LETTERS

Ecology Letters, (2013) **16**: 72–85 doi: 10.1111/ele.12062

IDEA AND PERSPECTIVE

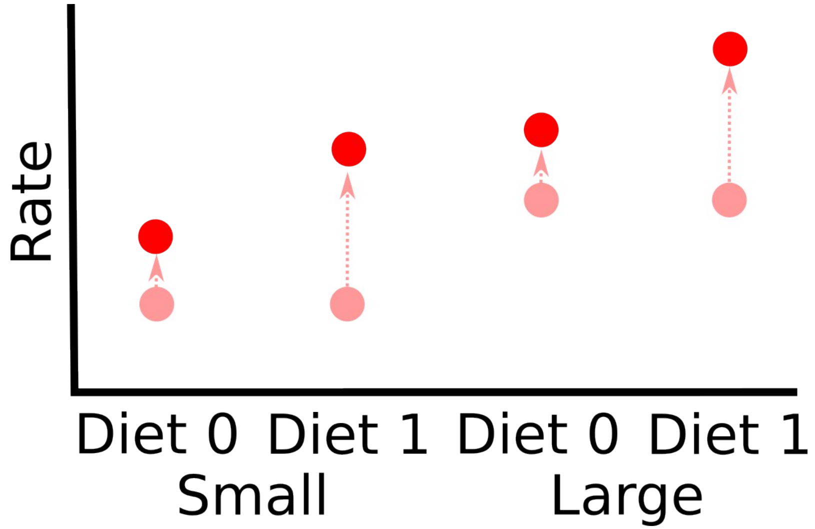
Macroevolutionary perspectives to environmental change

Fabien L. Condamine[1]* Jonathan Rolland[1] and Hélène Morlon[1]*

Abstract

Predicting how biodiversity will be affected and will respond to human-induced environmental changes is one of the most critical challenges facing ecologists today. Here, we put current environmental changes and their effects on biodiversity in a macroevolutionary perspective. We build on research in palaeontology and recent developments in phylogenetic approaches to ask how macroevolution can help us understand how environmental changes have affected biodiversity in the past, and how they will affect biodiversity in the future. More and more paleontological and phylogenetic data are accumulated, and we argue that much of the potential these data have for understanding environmental changes remains to be explored.

Limitations to infer factors governing diversification – additive



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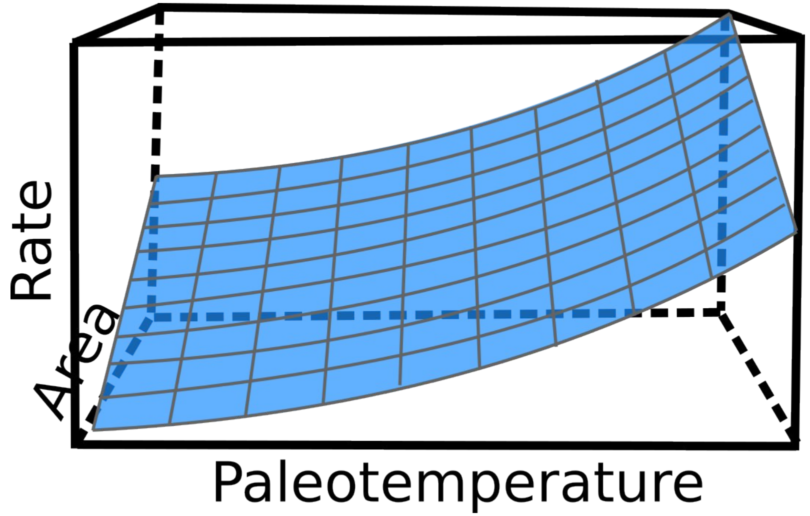
Research

Selective extinction against redundant species buffers functional diversity

Catalina Pimiento[1,2,†], Christine D. Bacon[3,4,†], Daniele Silvestro[3,4,5], Austin Hendy[6], Carlos Jaramillo[2,7,8], Alexander Zizka[4,9], Xavier Meyer[5,10] and Alexandre Antonelli[3,4,11]



SCIENTIFIC REPORTS

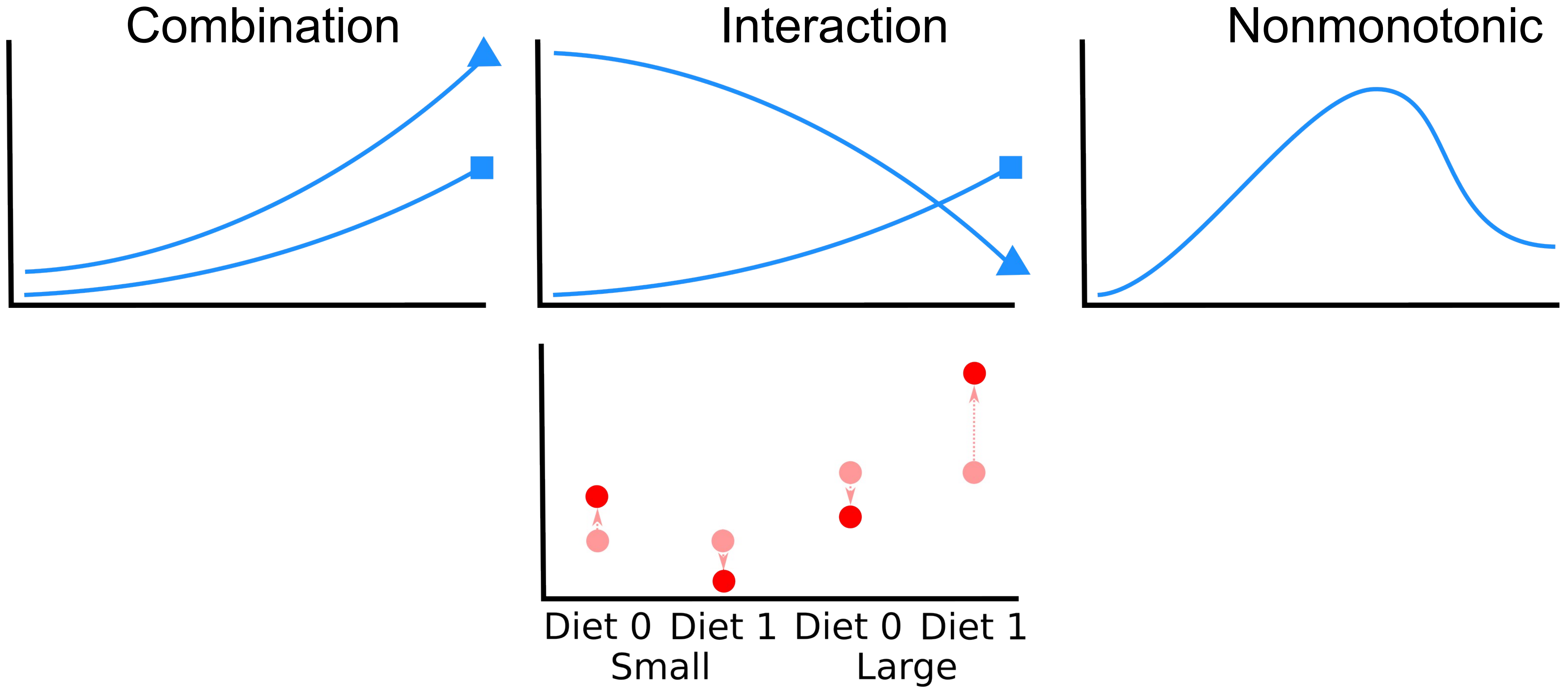
OPEN

Environmentally driven extinction and opportunistic origination explain fern diversification patterns

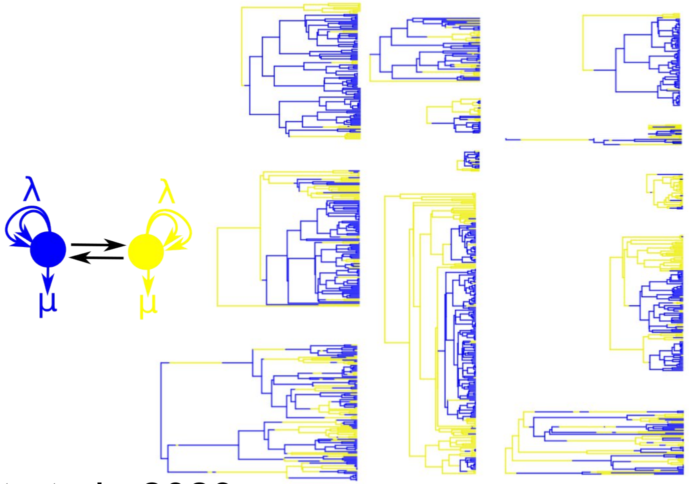
Received: 18 January 2017
Accepted: 25 May 2017
Published online: 06 July 2017

Samuli Lehtonen[1,2], Daniele Silvestro[3,4,5,6], Dirk Nikolaus Karger[2,7], Christopher Scotese[8], Hanna Tuomisto[2], Michael Kessler[7], Carlos Peña[2], Niklas Wahlberg[2,9] & Alexandre Antonelli[3,4,10]

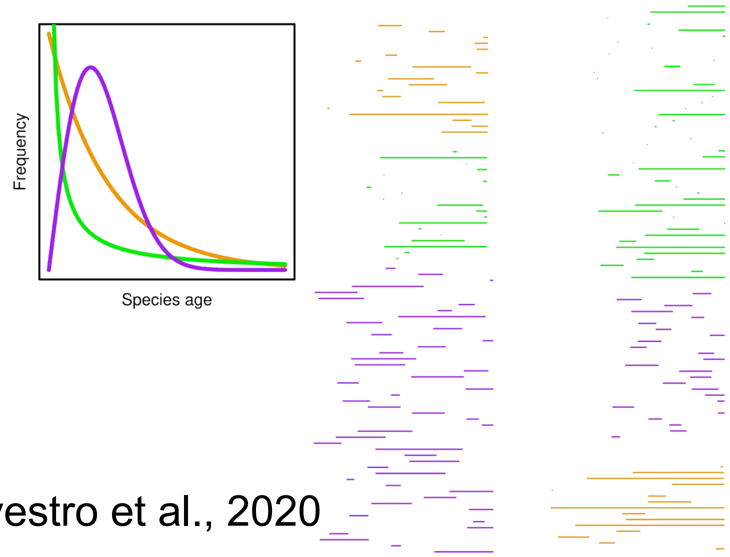
Improvements to infer factors governing diversification



1. Simulate data under known rates



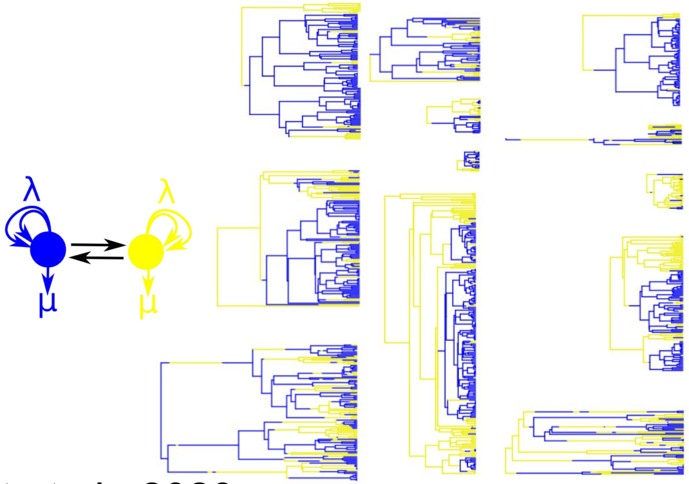
Lambert et al., 2023



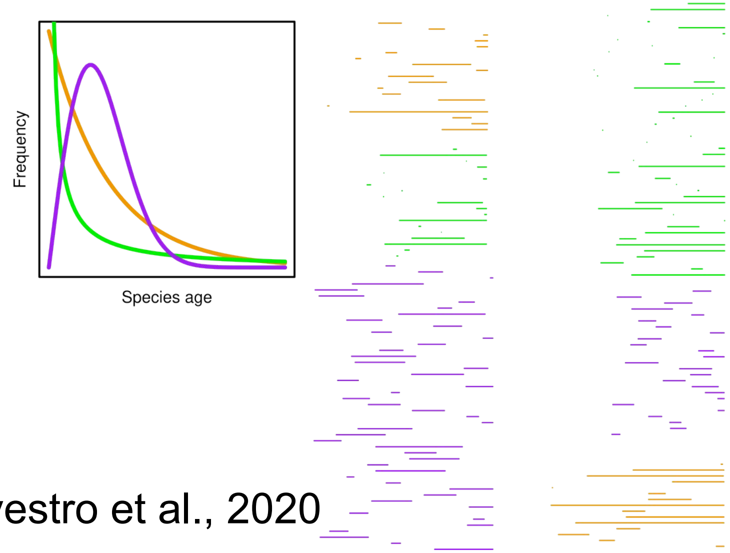
Silvestro et al., 2020

Unsupervised Bayesian neural networks and xAI to infer factors governing diversification

1. Simulate data under known rates

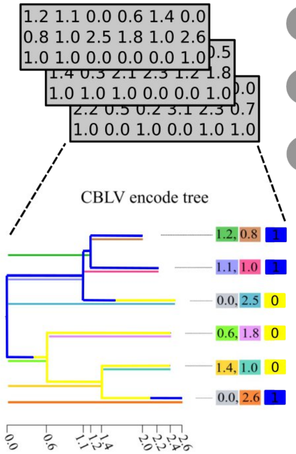


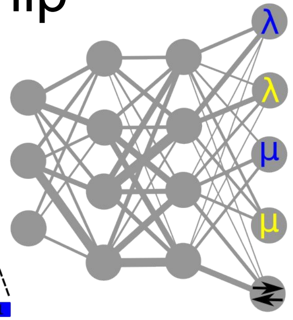
Lambert et al., 2023



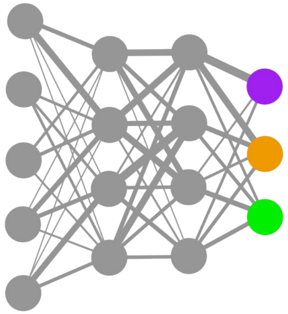
Silvestro et al., 2020

2. Learn data-rates relationship





Summary statistics
- -Preservation
- -Duration
- -Count frequency
- -...



Unsupervised Bayesian neural networks and xAI to infer factors governing diversification

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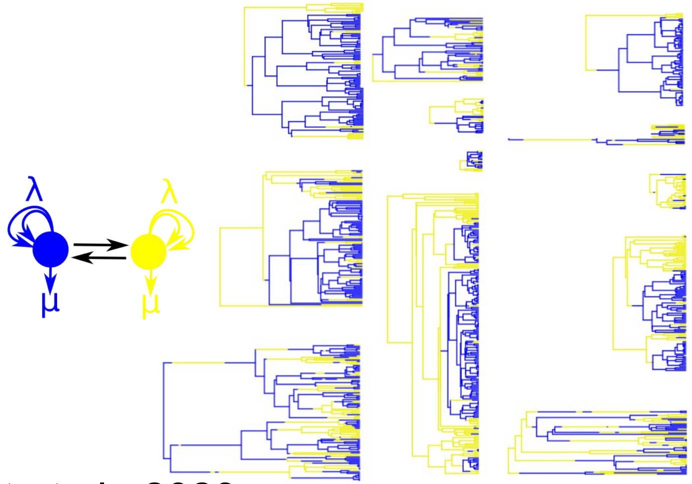
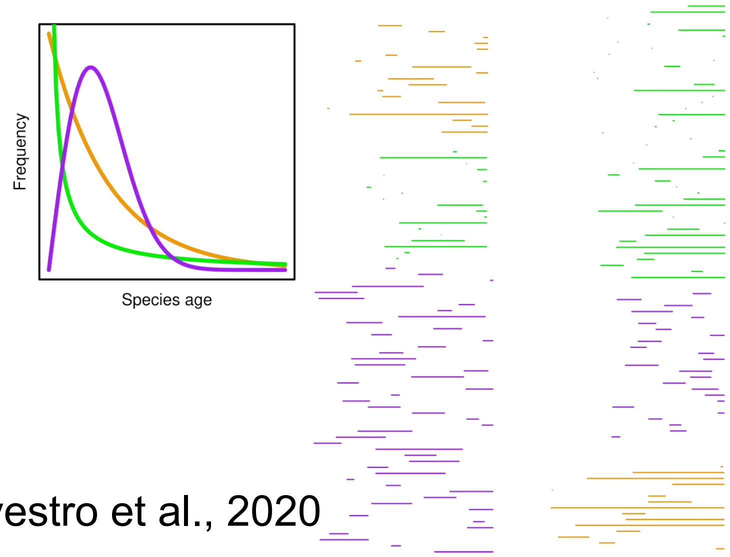


Lambert et al., 2023



Silvestro et al., 2020

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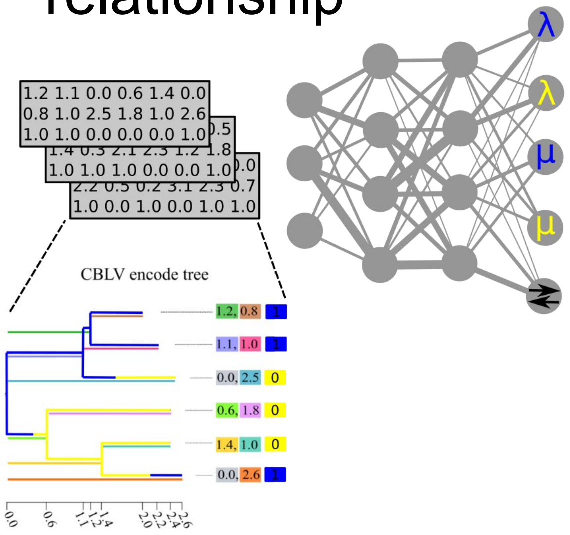

Summary statistics
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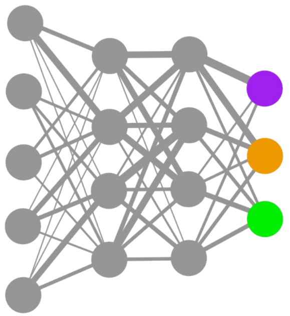
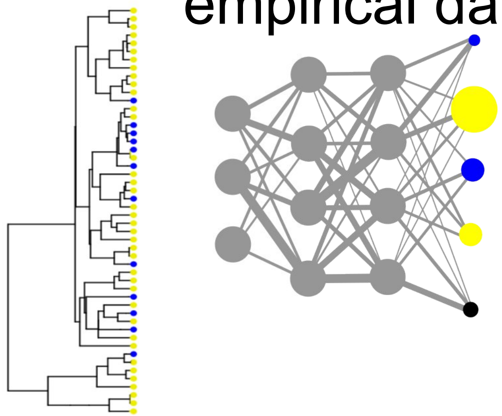
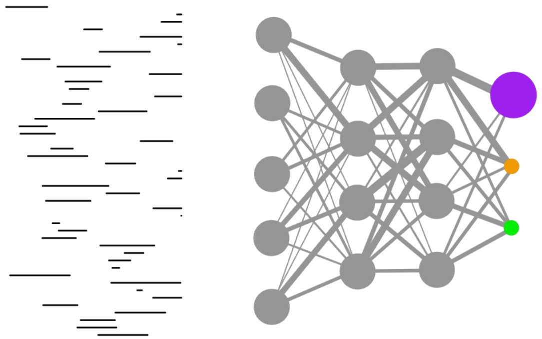
-Duration
-Count frequency
-...



3. Predict rates from empirical data





Unsupervised Bayesian neural networks and xAI to infer factors governing diversification

1. Simulate data under known rates

2. Learn data-rates relationship

3. Predict rates from empirical data

- Once trained, fast rate inference
- Rate estimates often more accurate than with Bayesian Inference or Maximum Likelihood

- Many simulations needed to train
- We can only infer factors that we have simulated
- Increasing complexity with more factors
- Were simulated data similar to the empirical ones?

Lambert et al., 2023

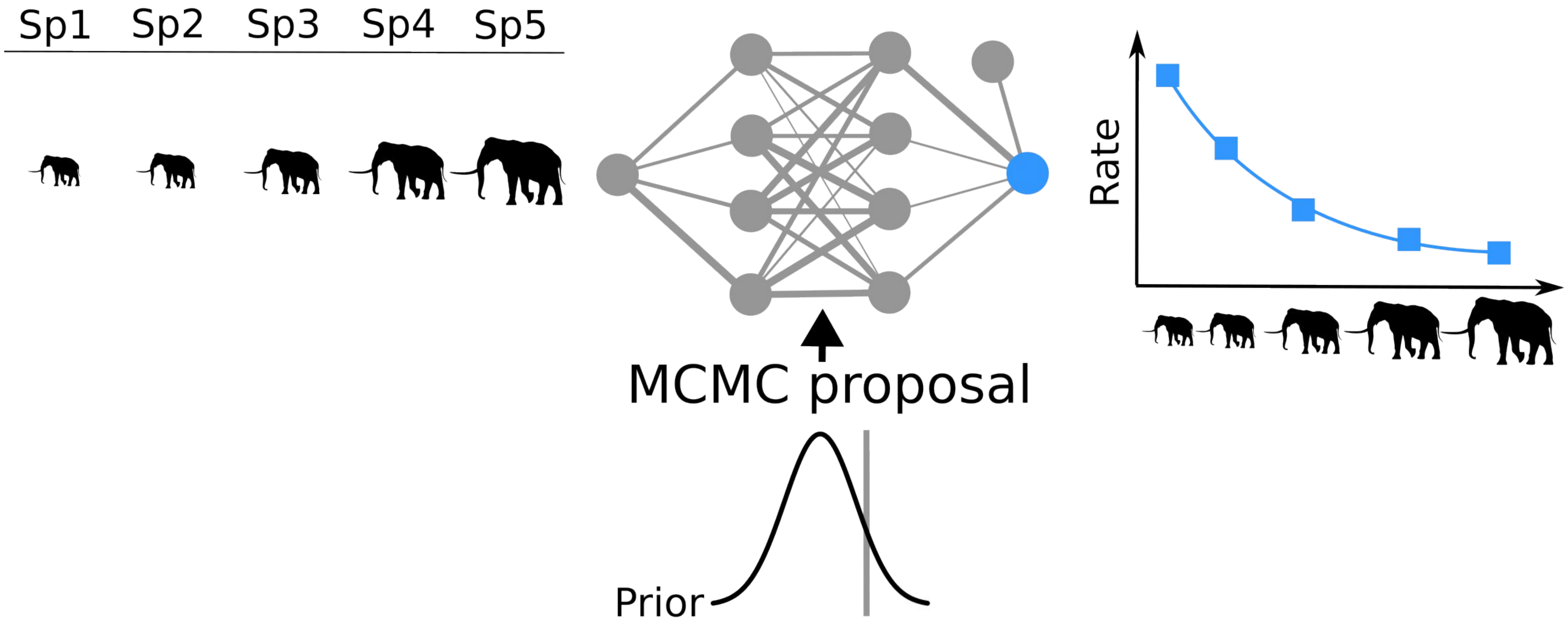
Summary statistics
-Preservation
-Duration
-Count frequency
-...

Silvestro et al., 2020

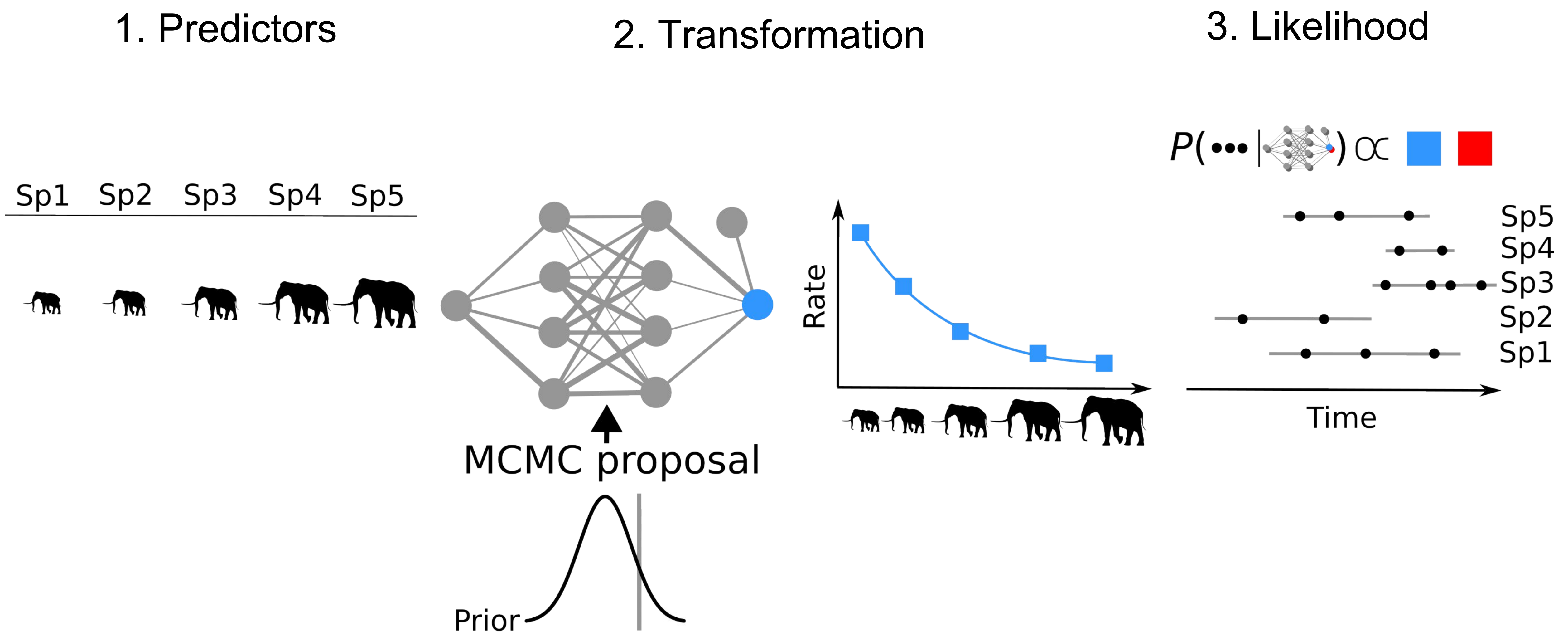
Unsupervised Bayesian neural networks and xAI to infer factors governing diversification

1. Predictors

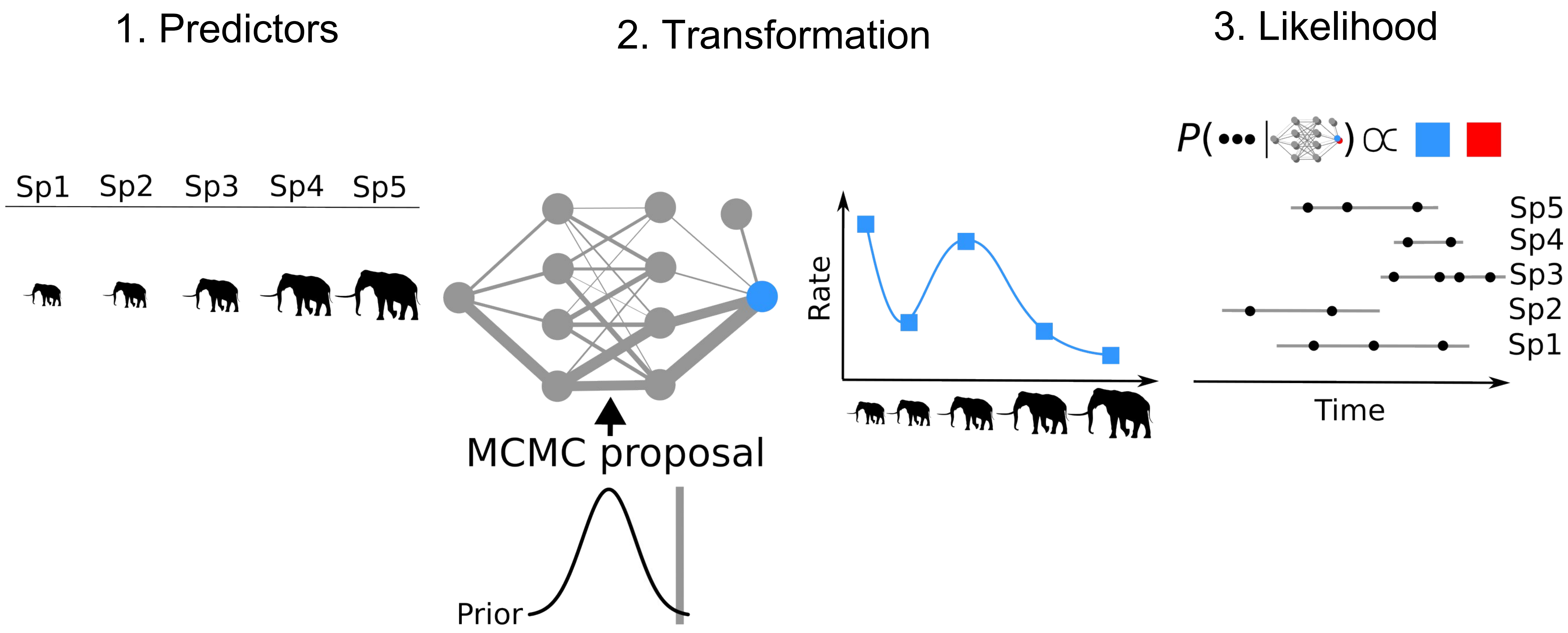
2. Transformation



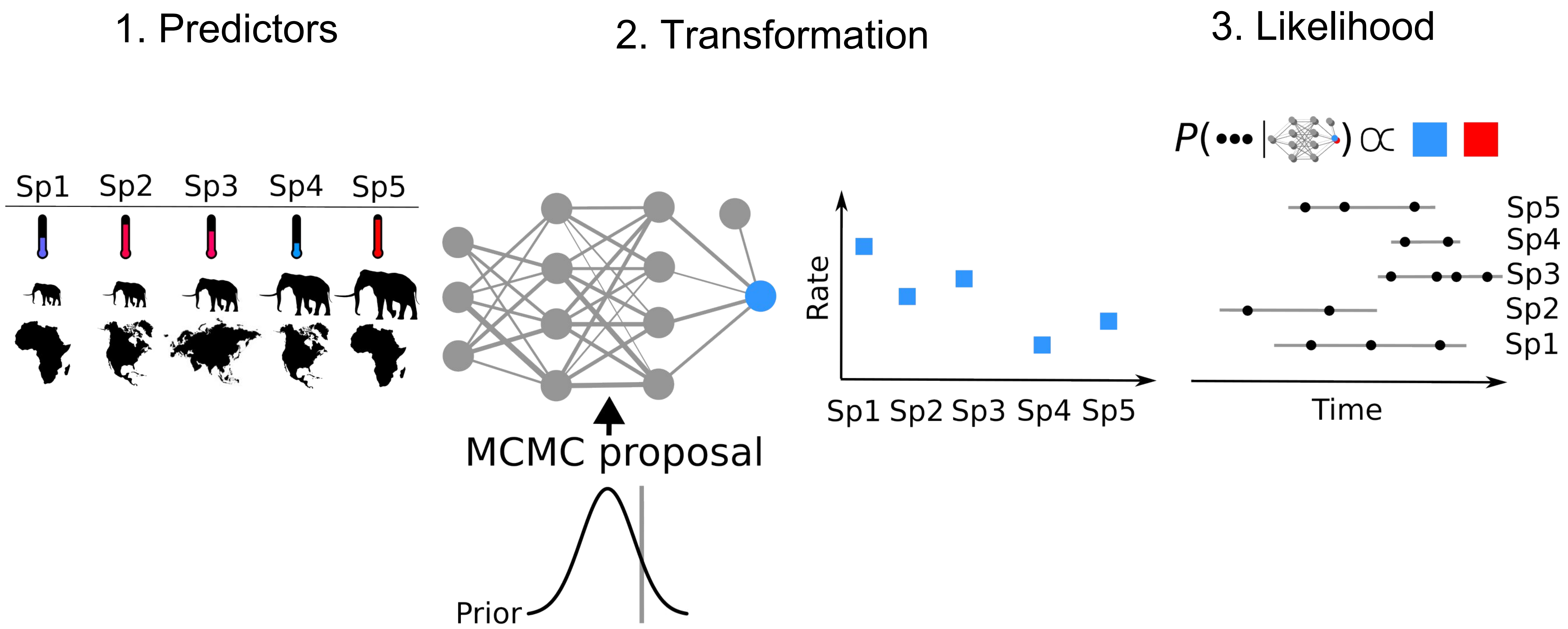
Unsupervised Bayesian neural networks and xAI to infer factors governing diversification



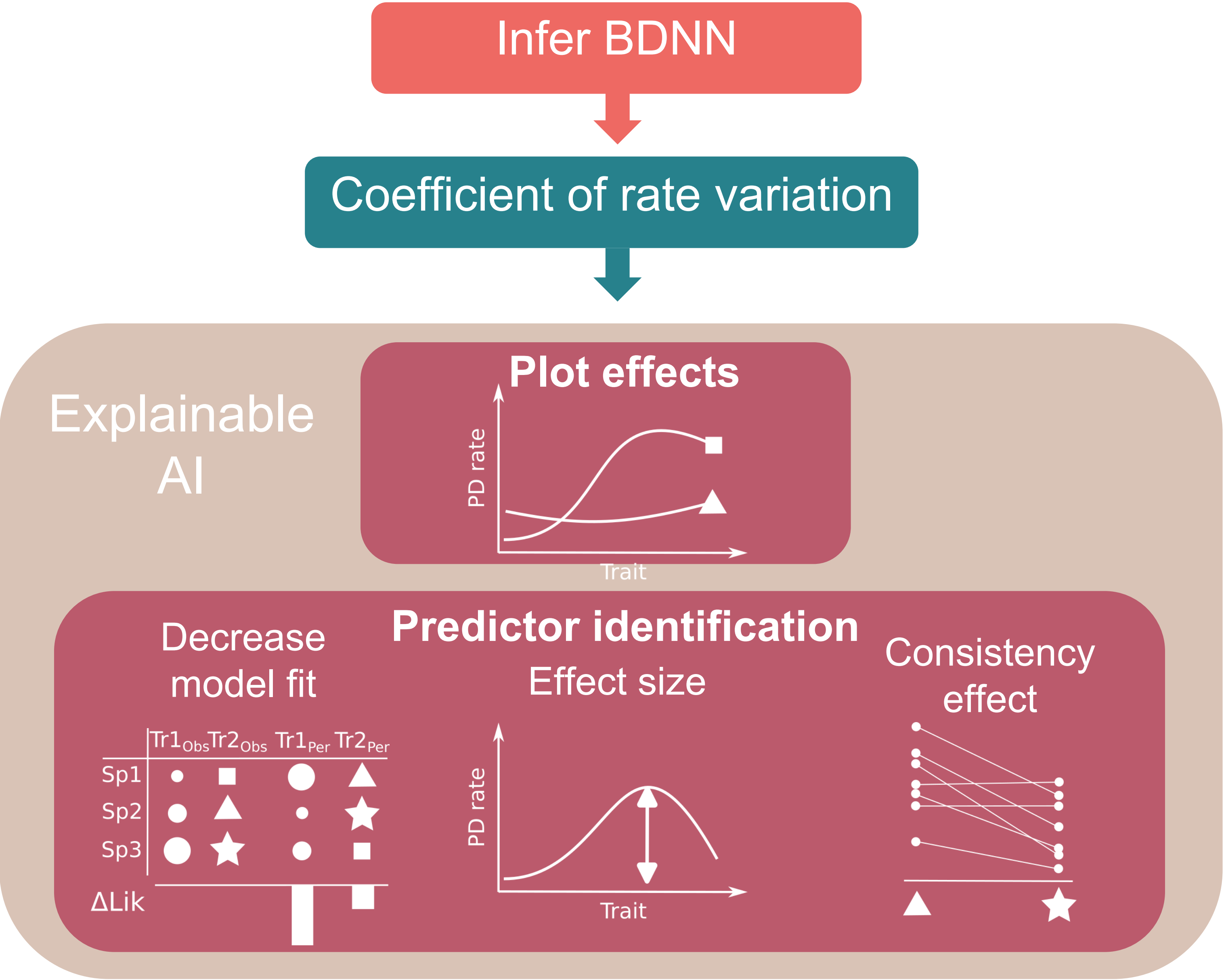
Unsupervised Bayesian neural networks and xAI to infer factors governing diversification



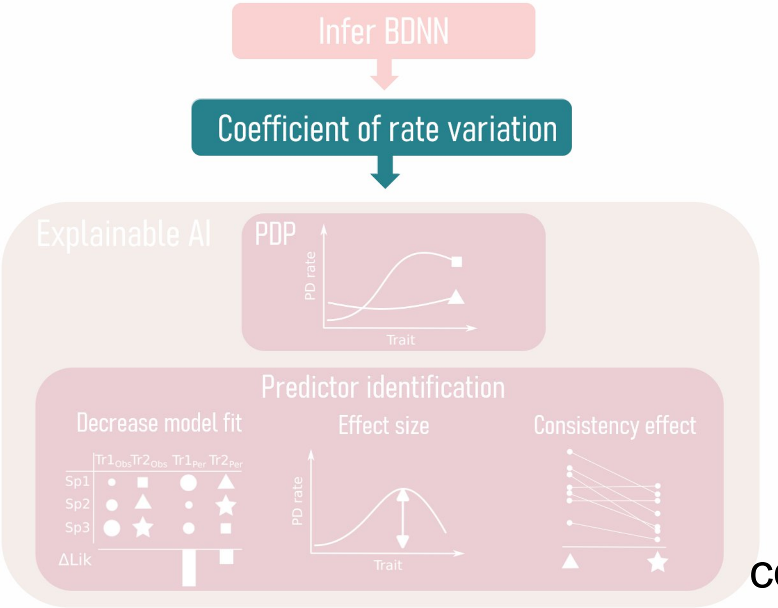
Unsupervised Bayesian neural networks and xAI to infer factors governing diversification

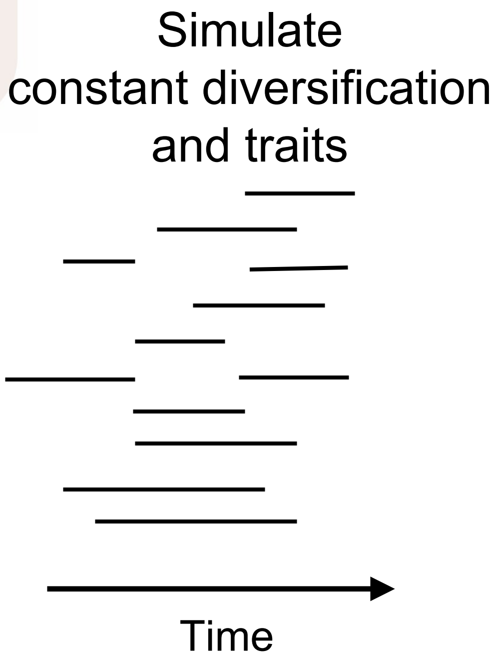


Unsupervised Bayesian neural networks **and xAI** to infer factors governing diversification



Should we dig deeper into factors? Threshold for variation in species-specific rates





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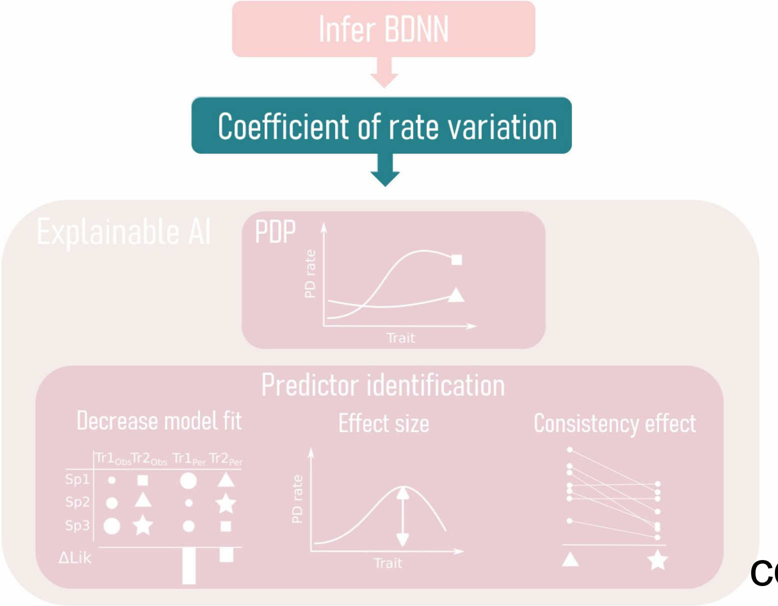

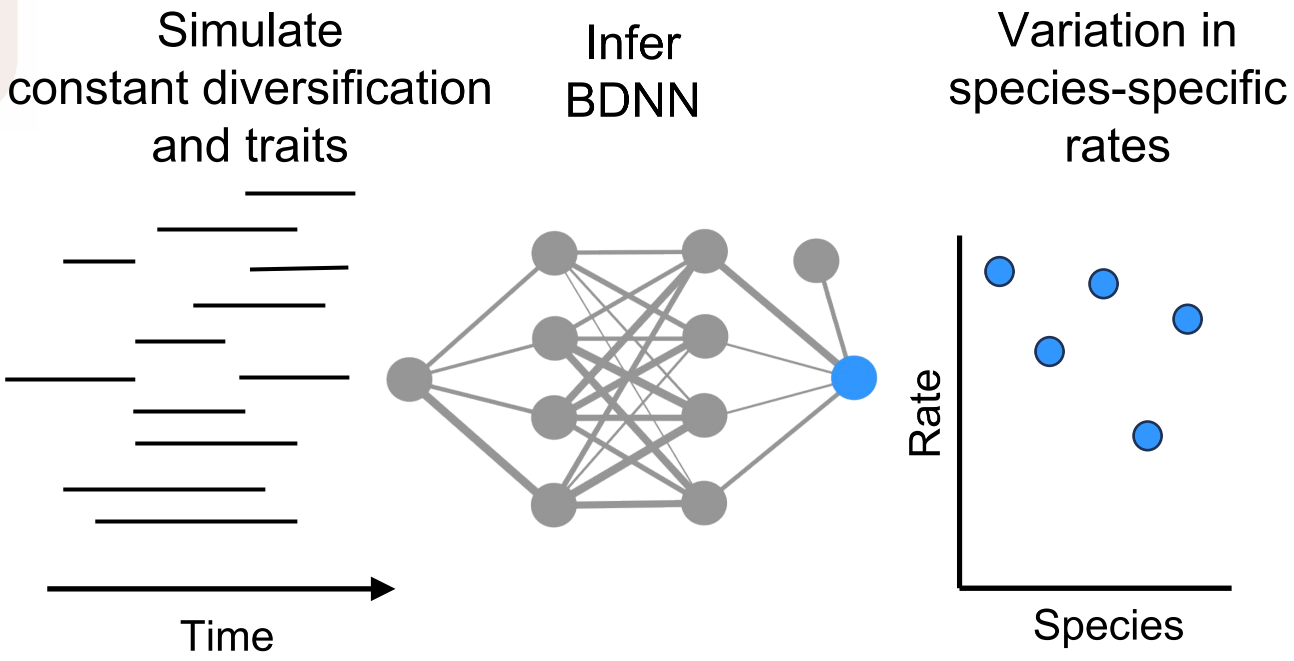

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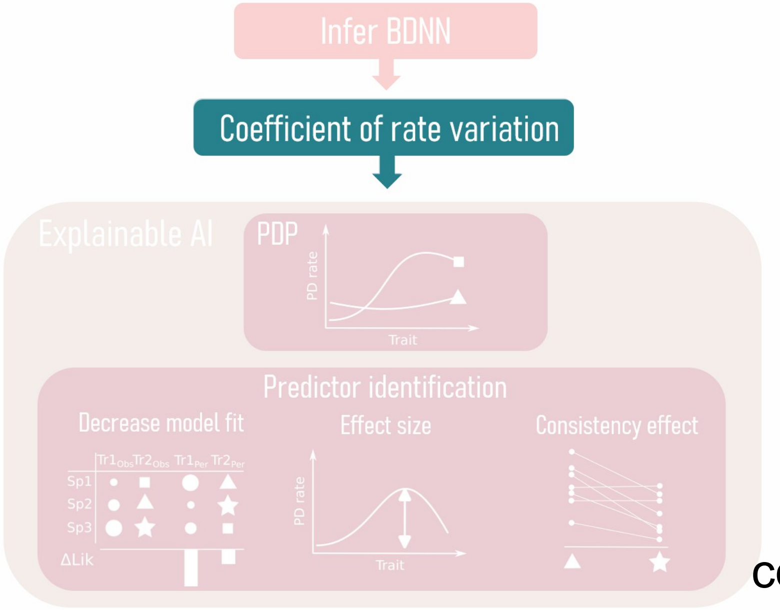
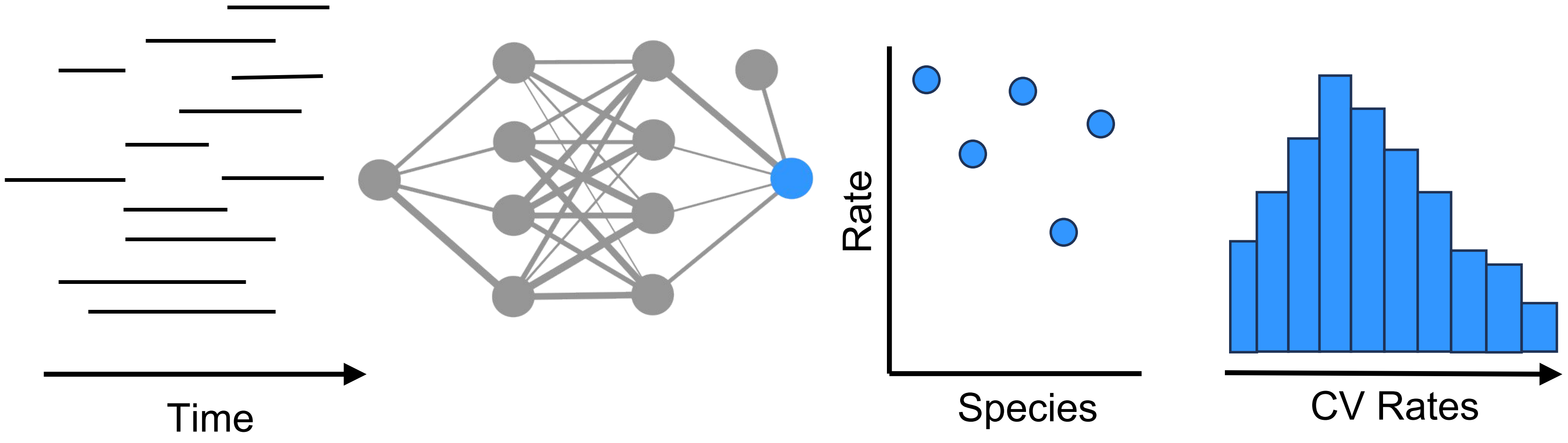


Simulate constant diversification and traits

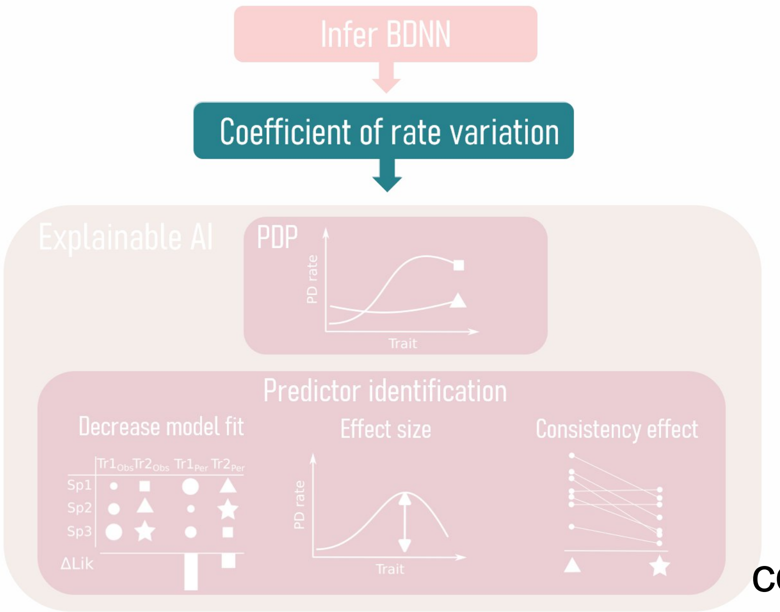
Infer BDNN

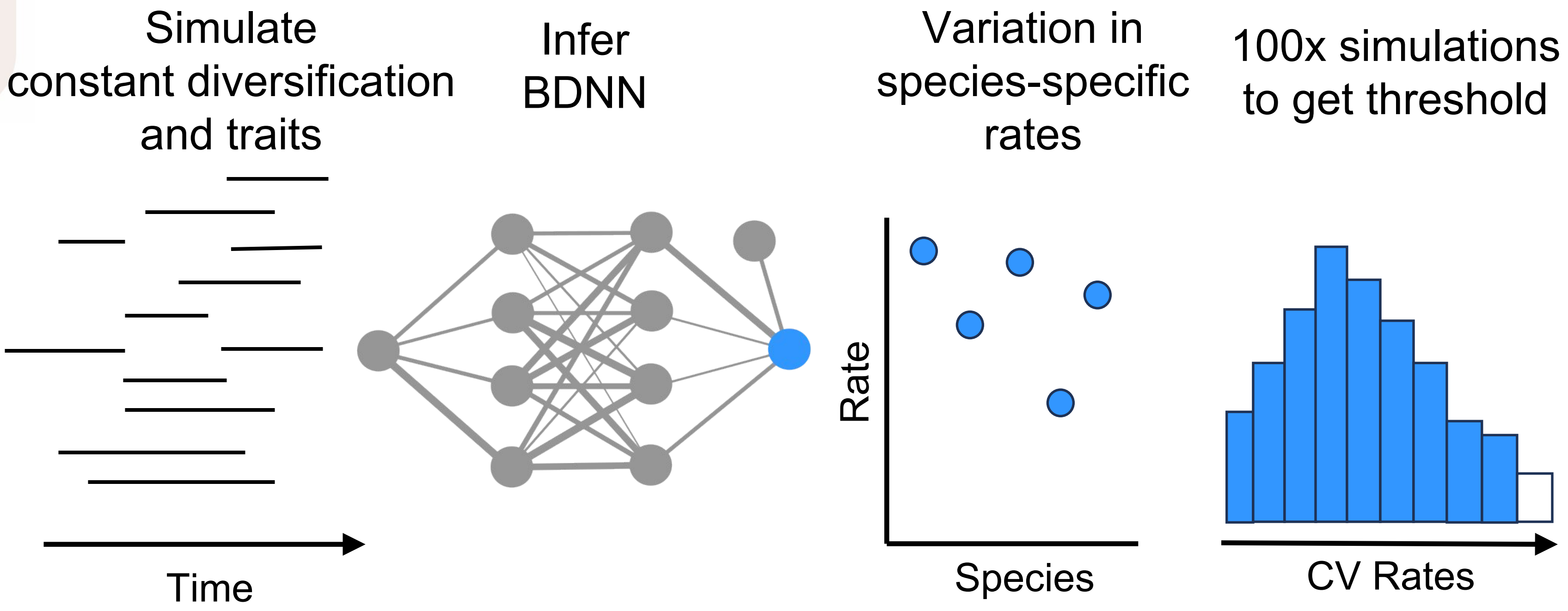
Variation in species-specific rates

100x simulations



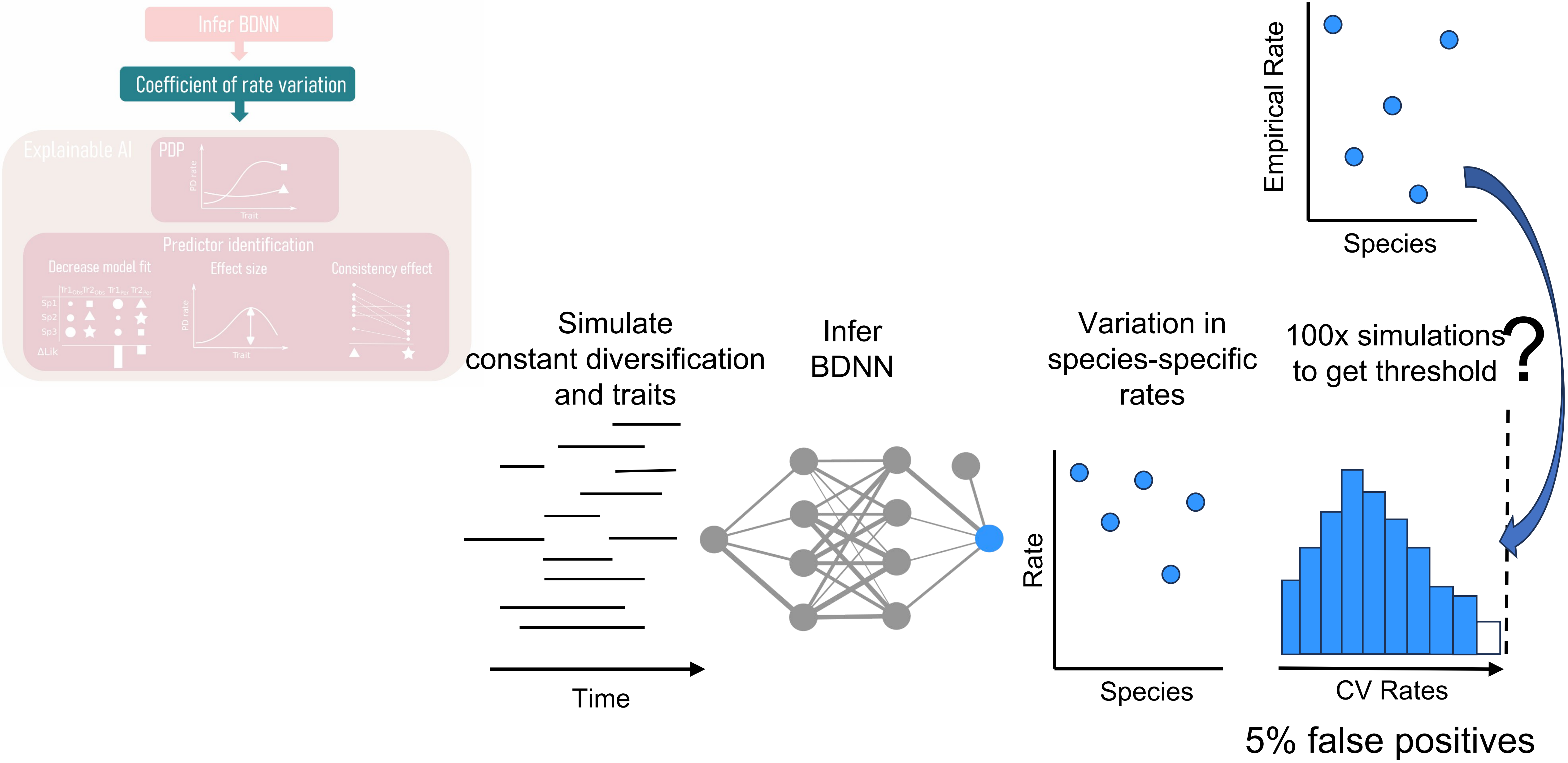
Should we dig deeper into factors? Threshold for variation in species-specific rates



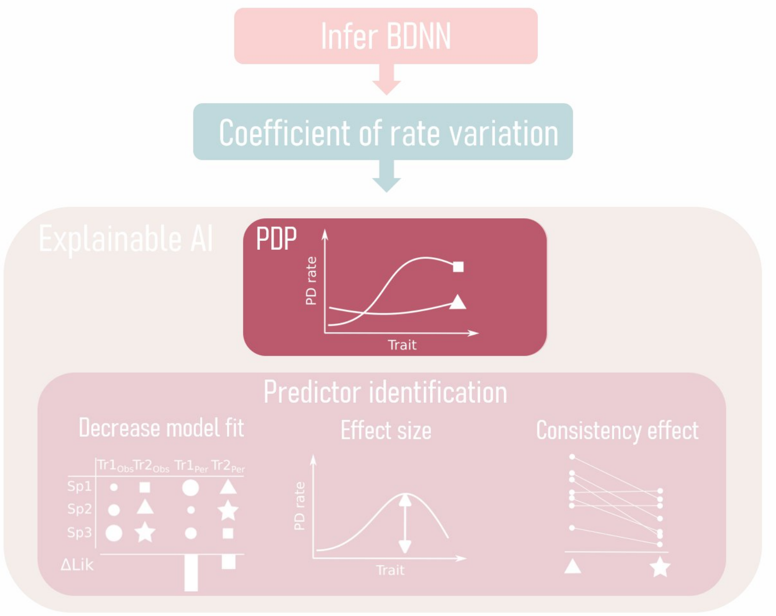


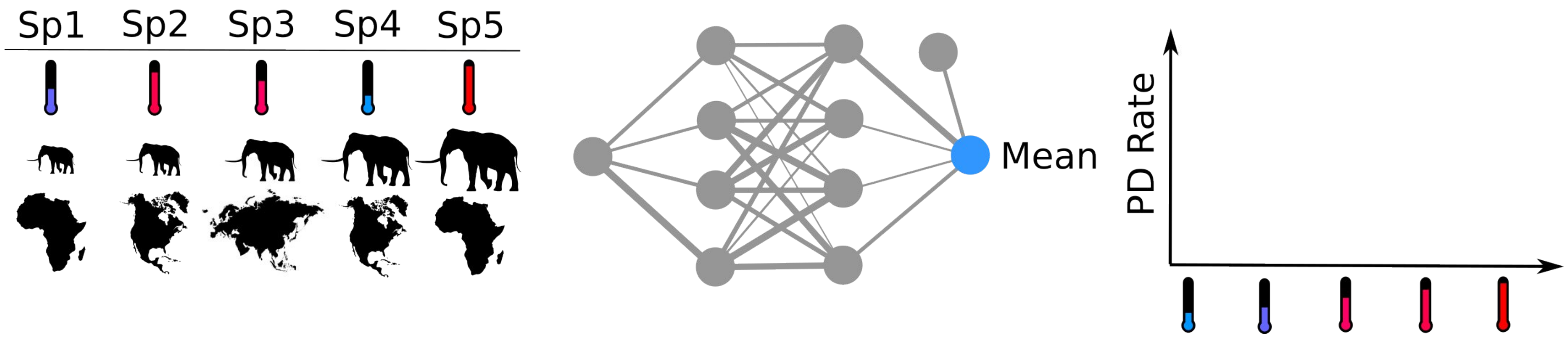
5% false positives

Should we dig deeper into factors? Threshold for variation in species-specific rates



Visualize effect on rates





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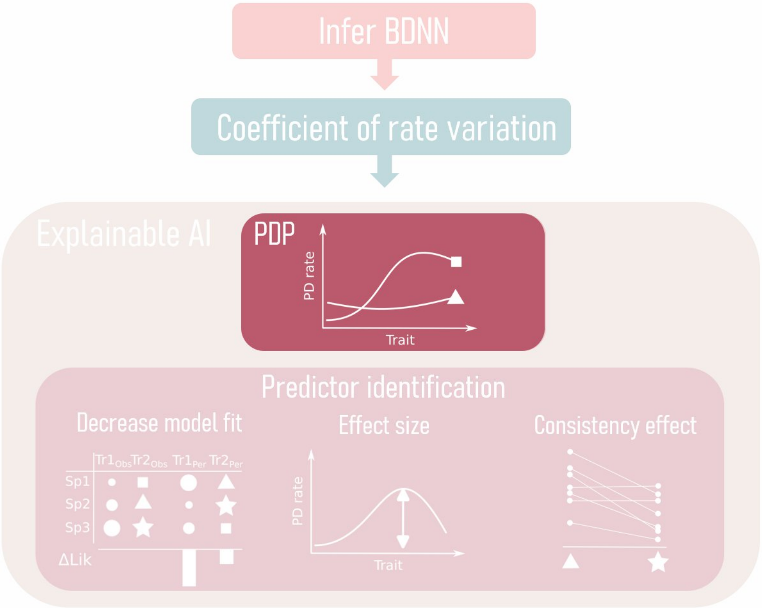

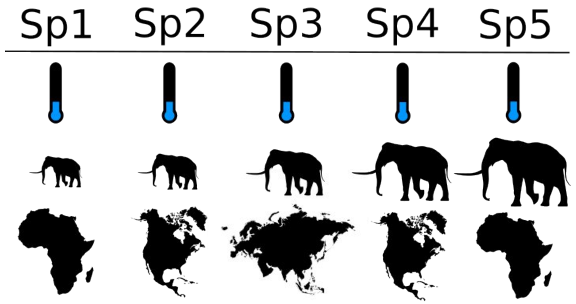

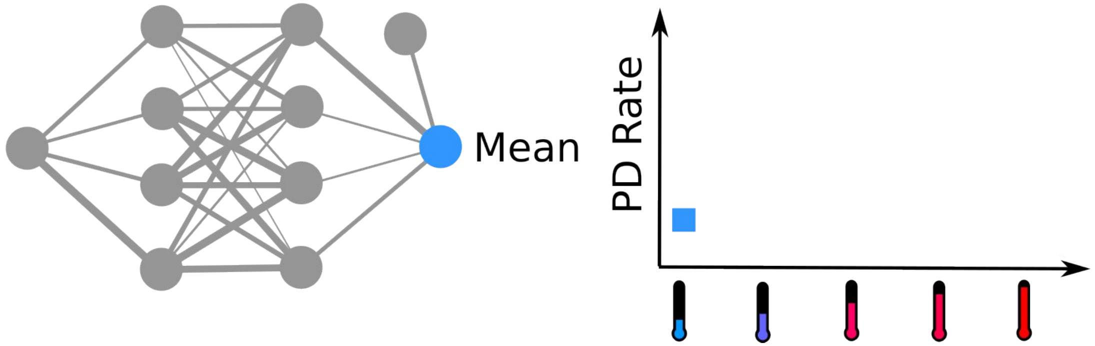

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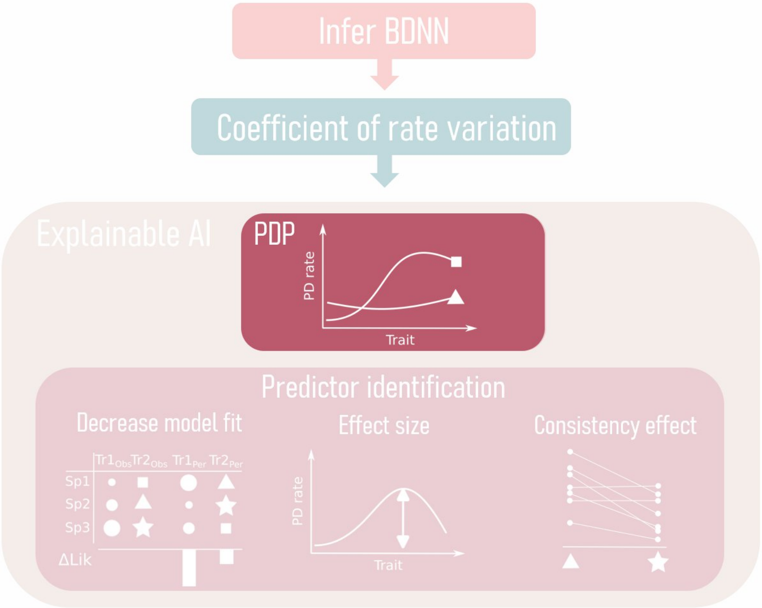

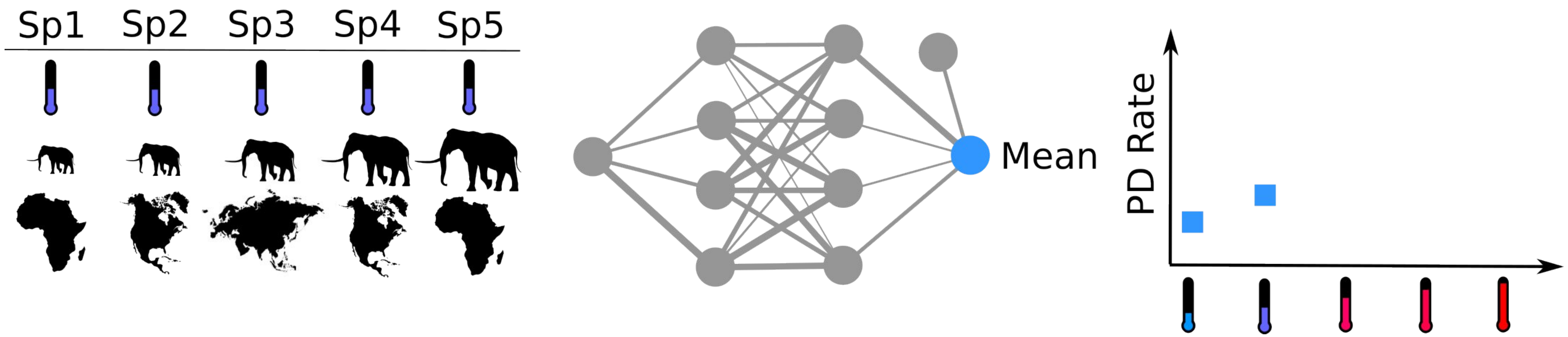

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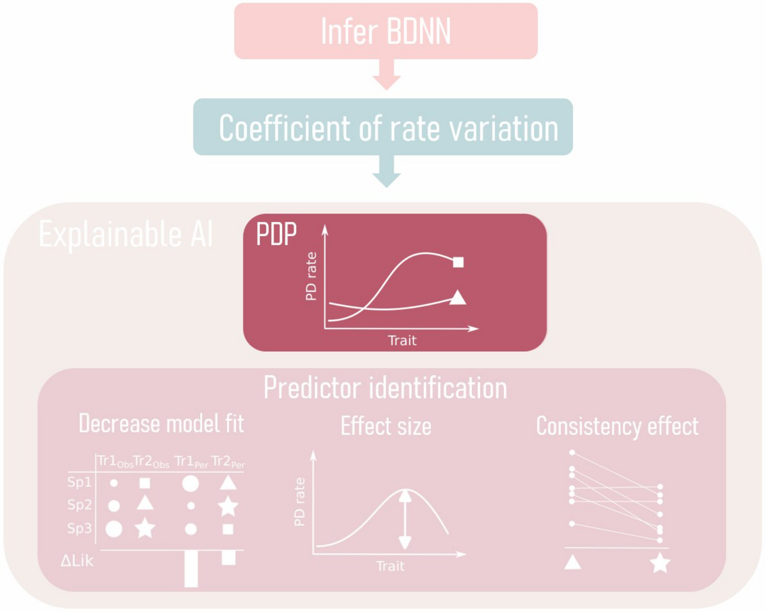
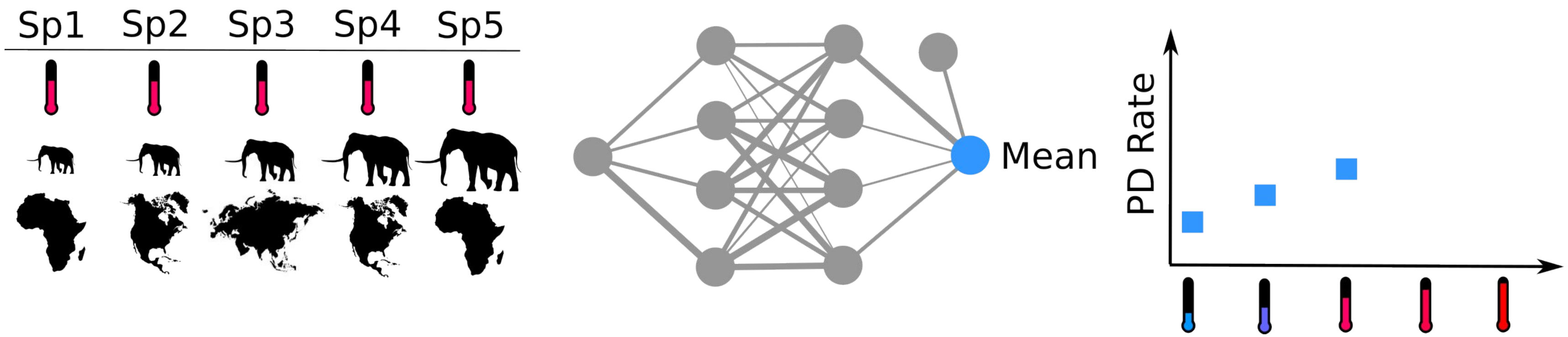
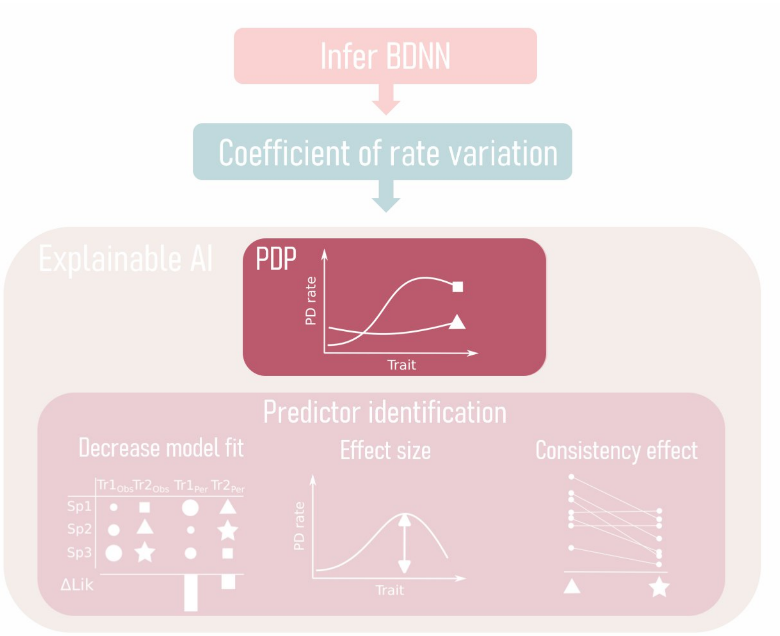
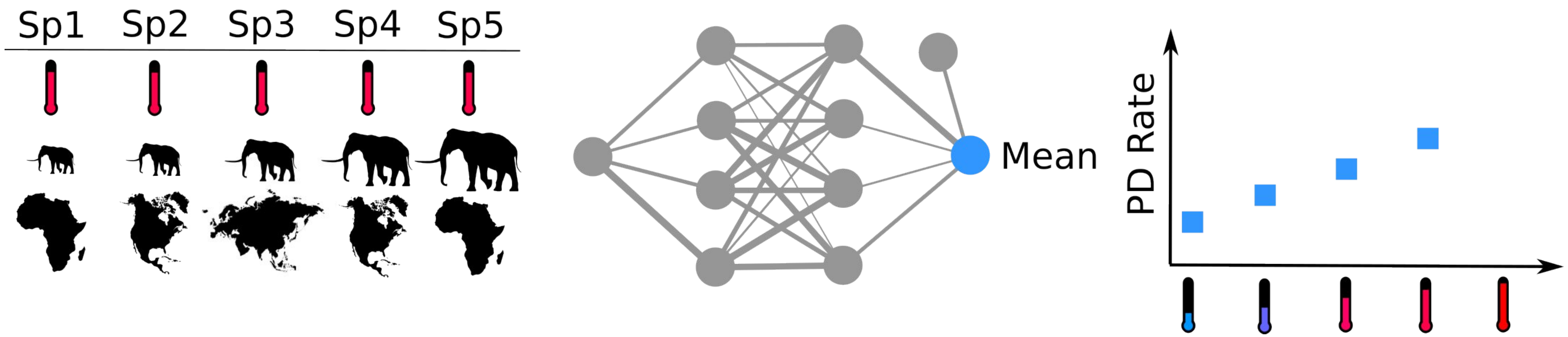




Visualize effect on rates





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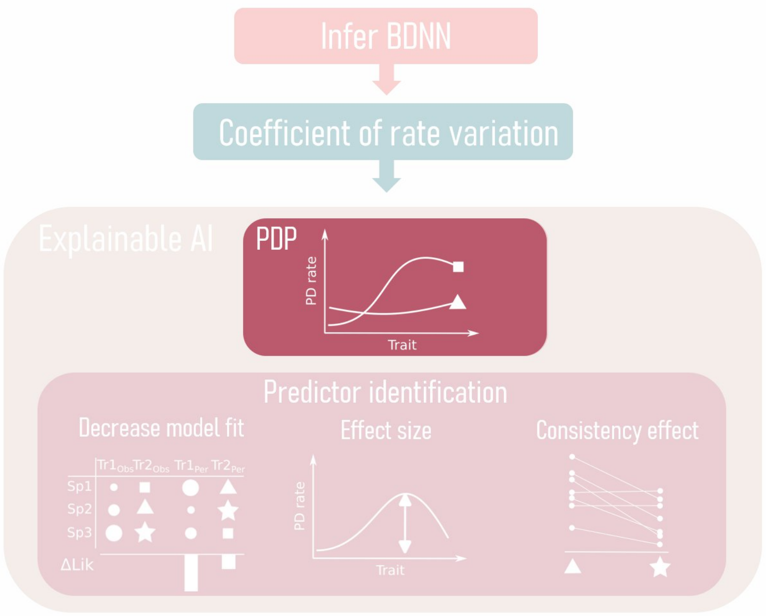
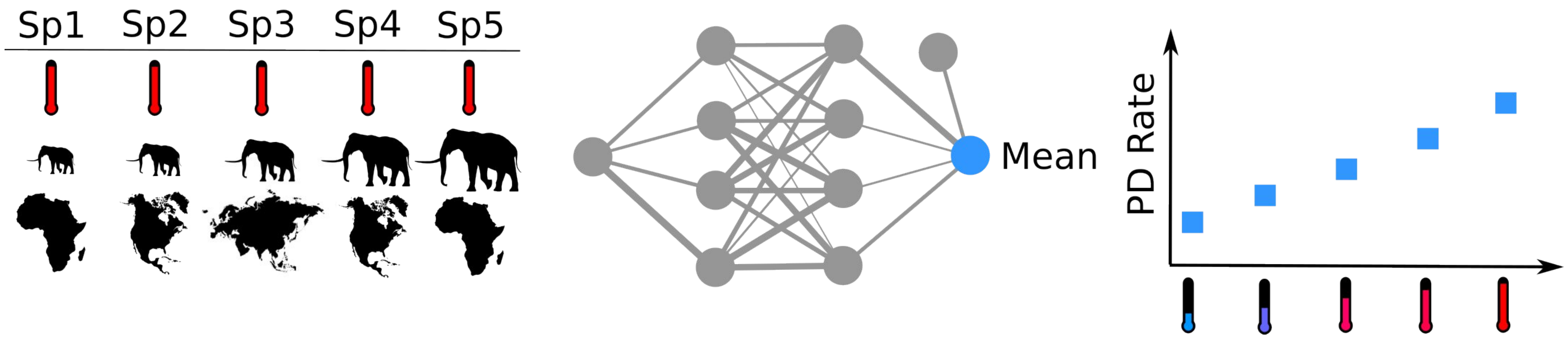
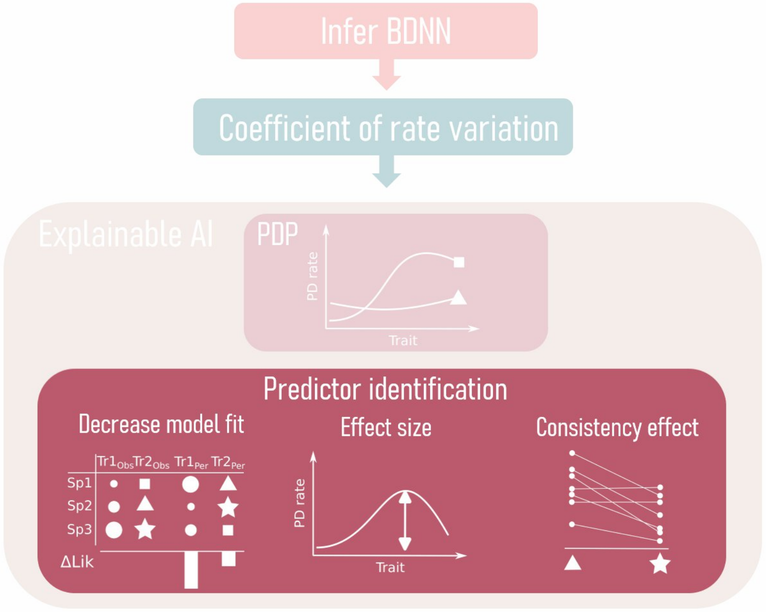
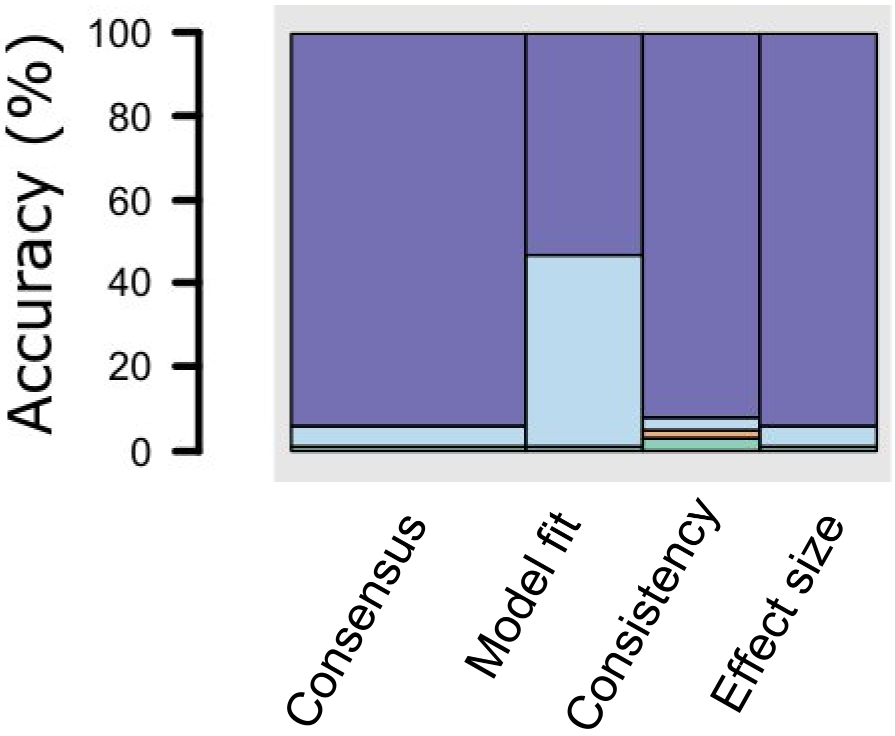


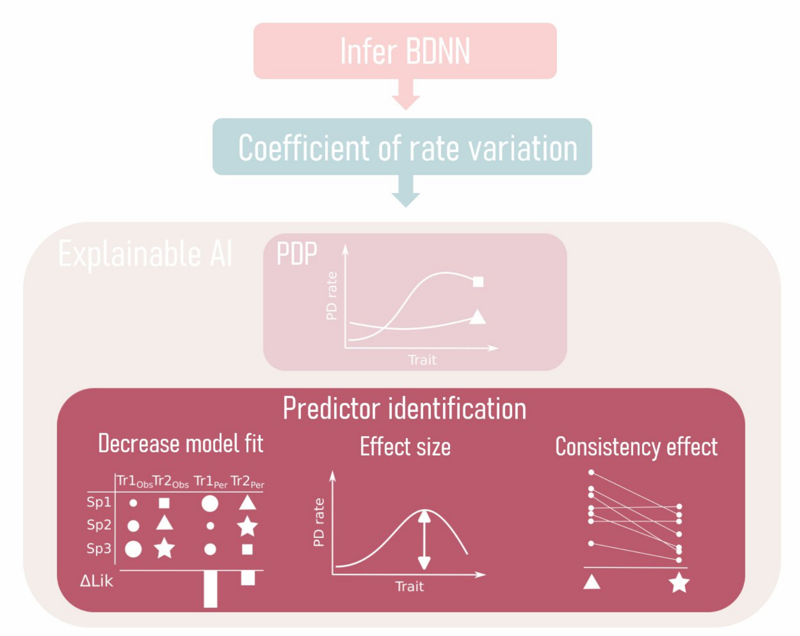


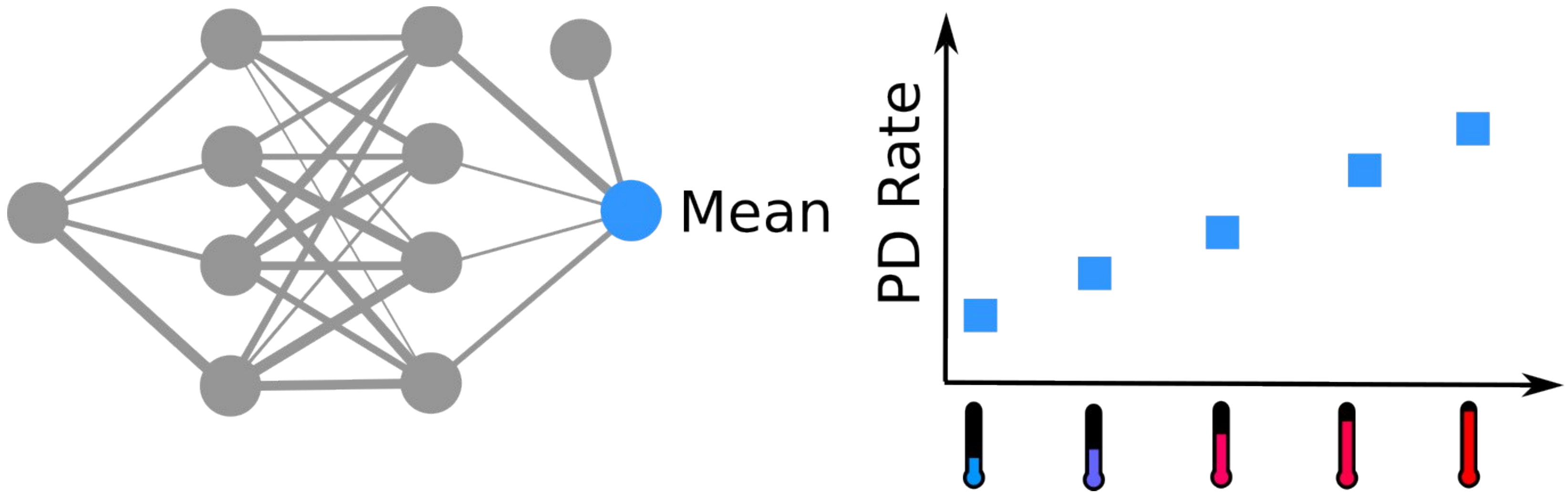
Identify rate predictors with consensus among xAI approaches





xAI: Consistency through posterior probability





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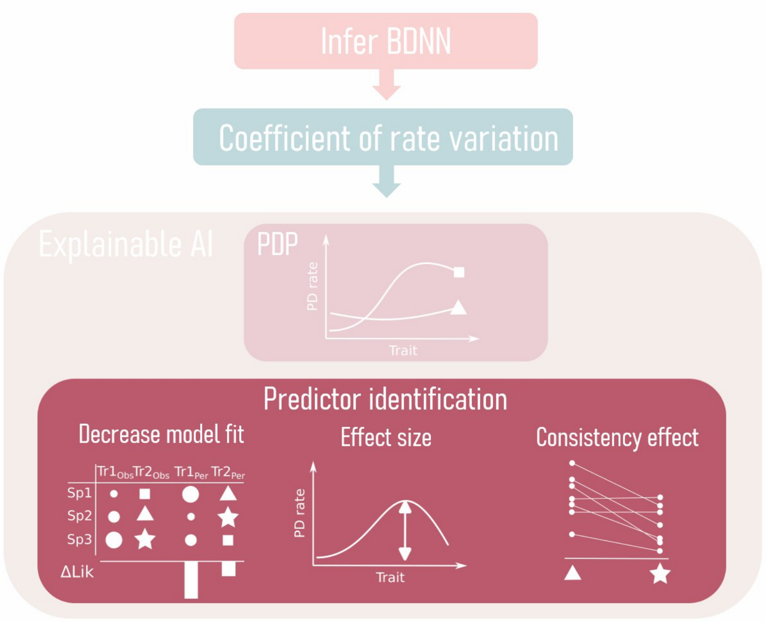

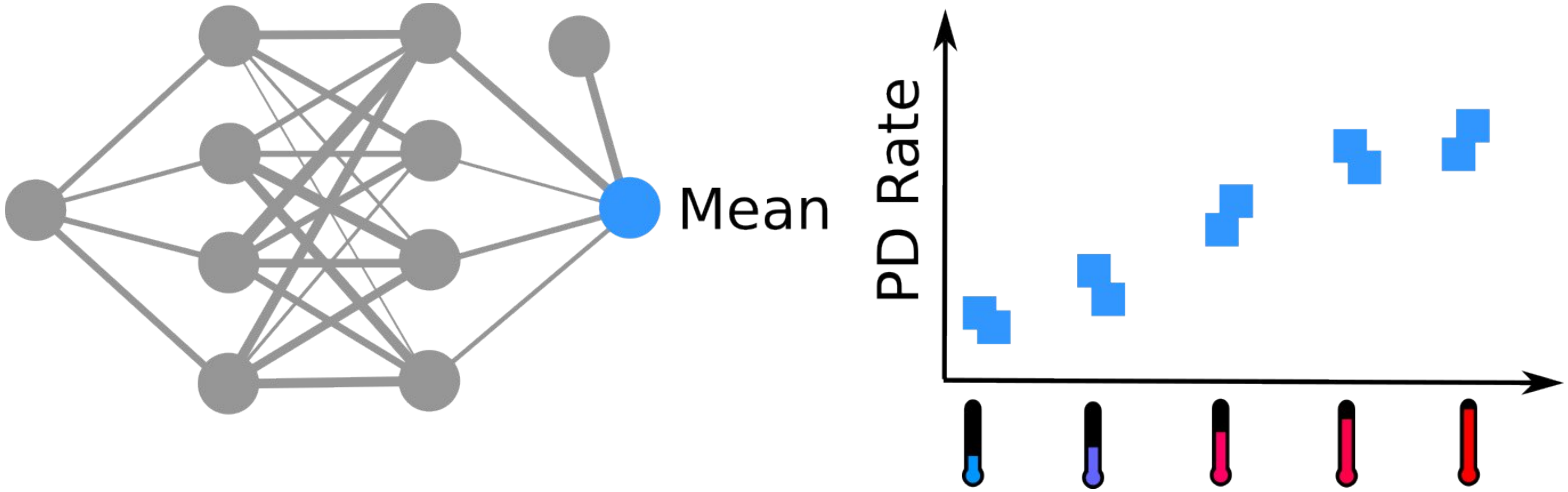

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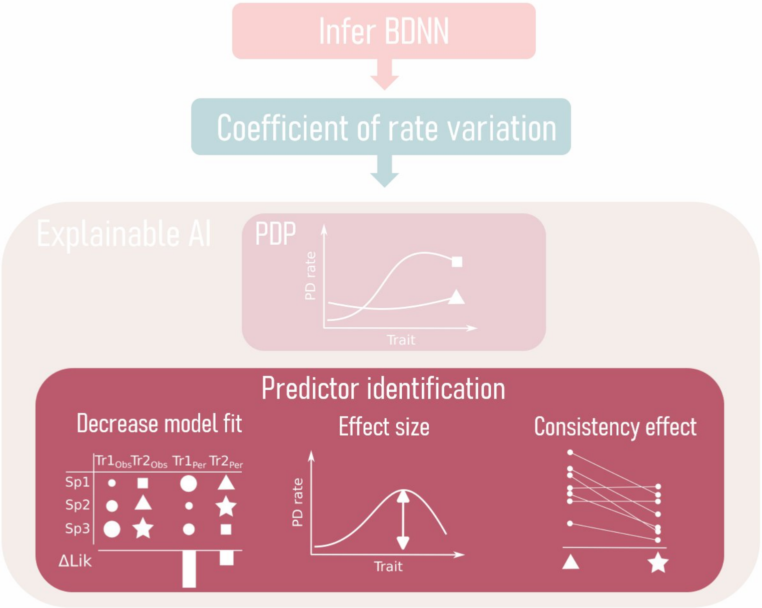
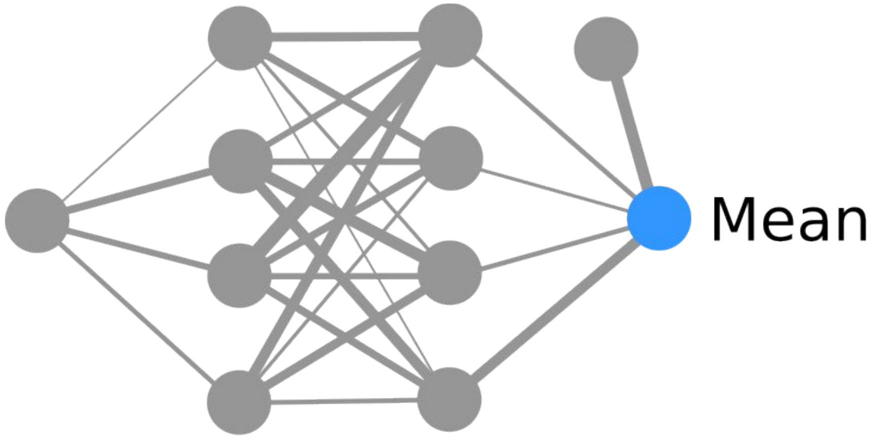
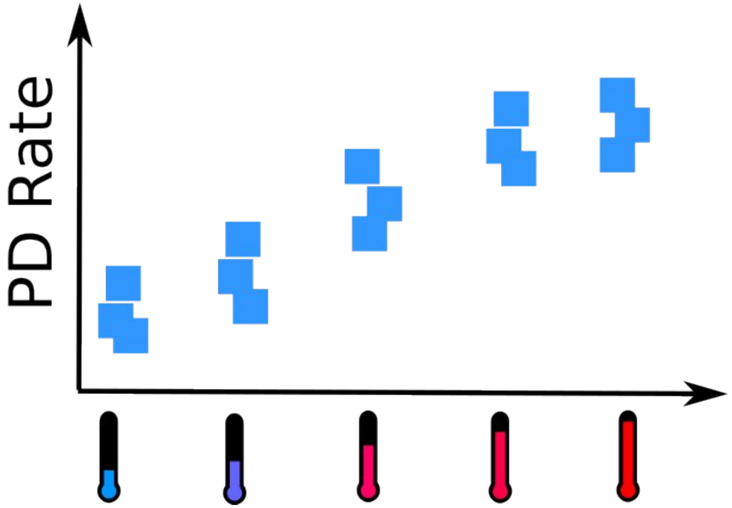
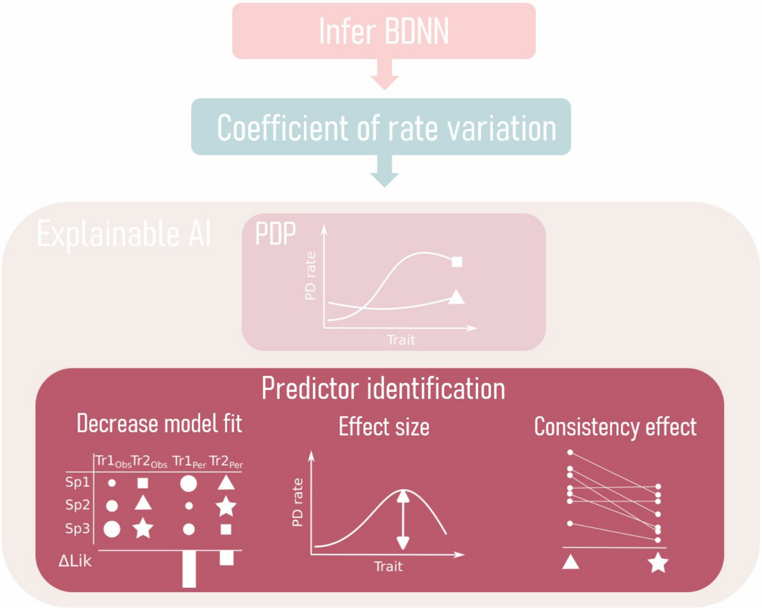
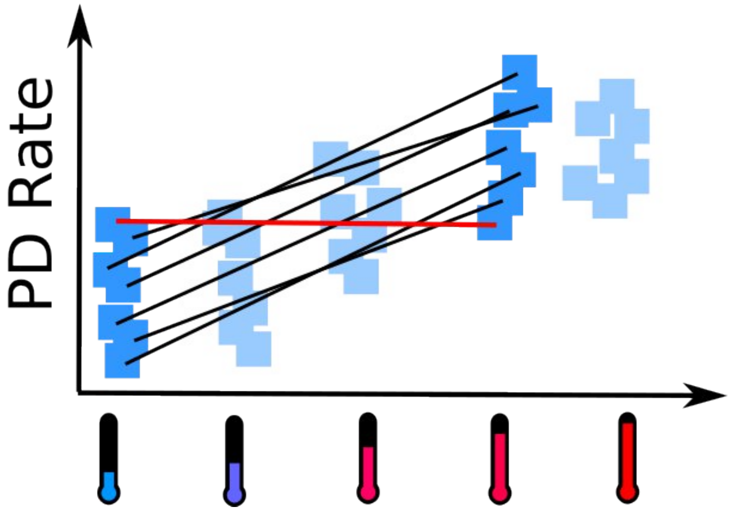






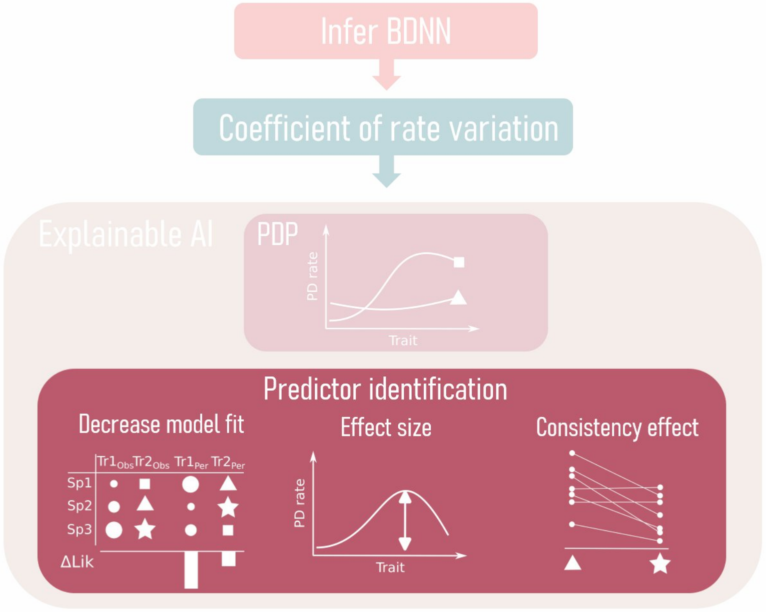
xAI: Consistency through posterior probability

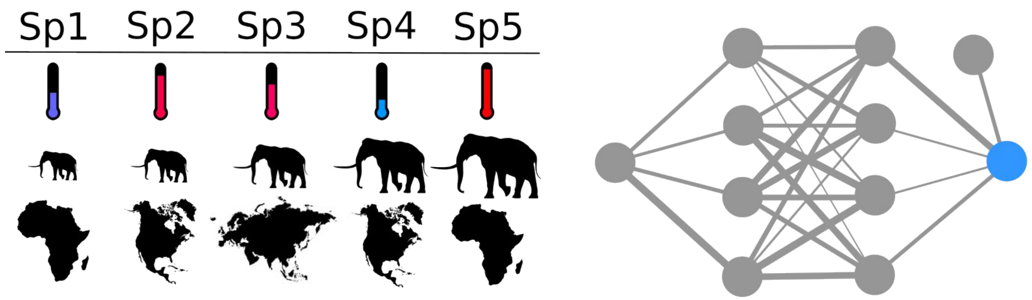


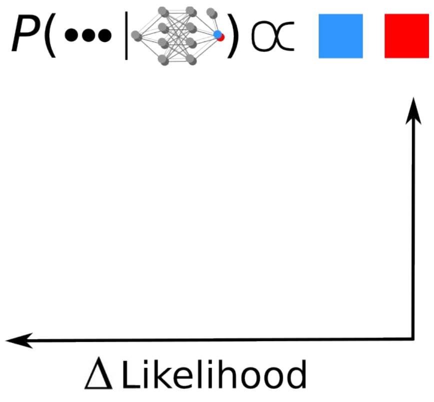


85 % of PD rates are greater than comparative temperature

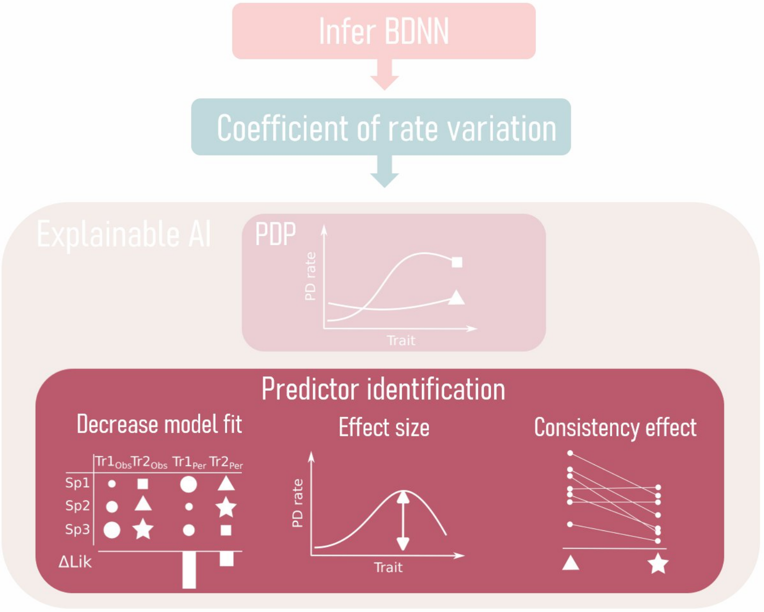
xAI: Decrease in model likelihood when permuting features

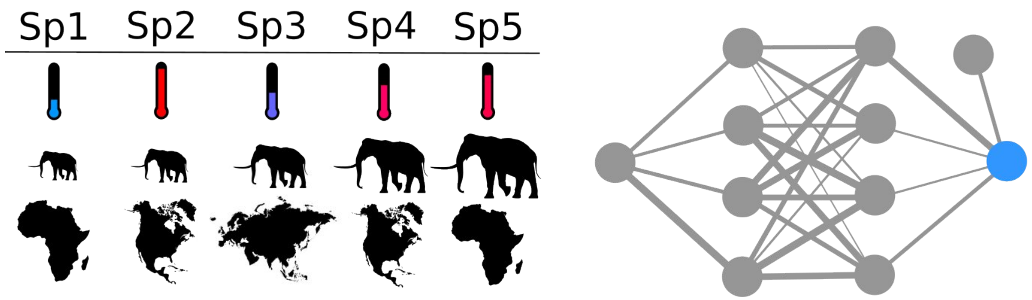


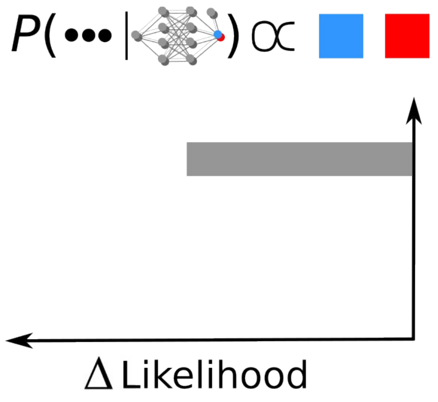




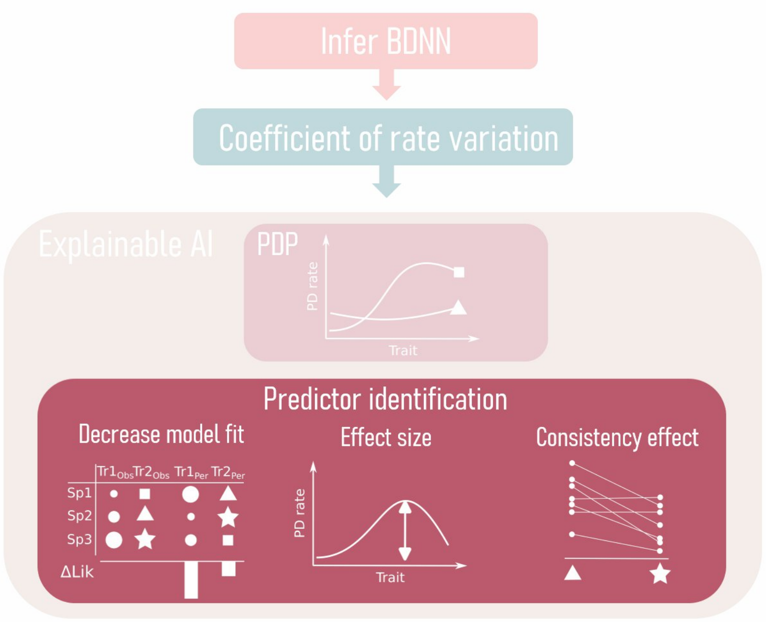
xAI: Decrease in model likelihood when permuting features

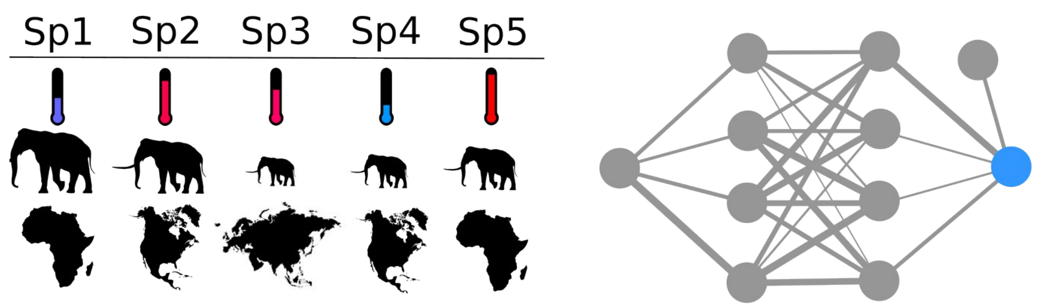


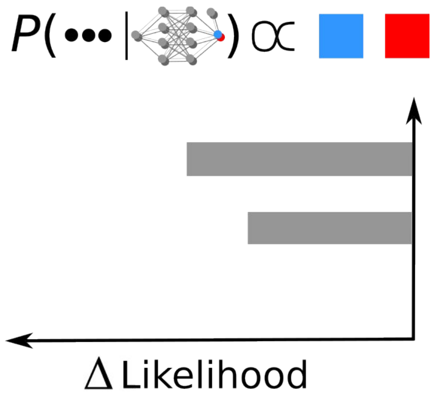




xAI: Decrease in model likelihood when permuting features







xAI: Decrease in model likelihood when permuting features