Neural Dynamic N-mixture Model

A deep learning framework for inferring demographic rates from count data

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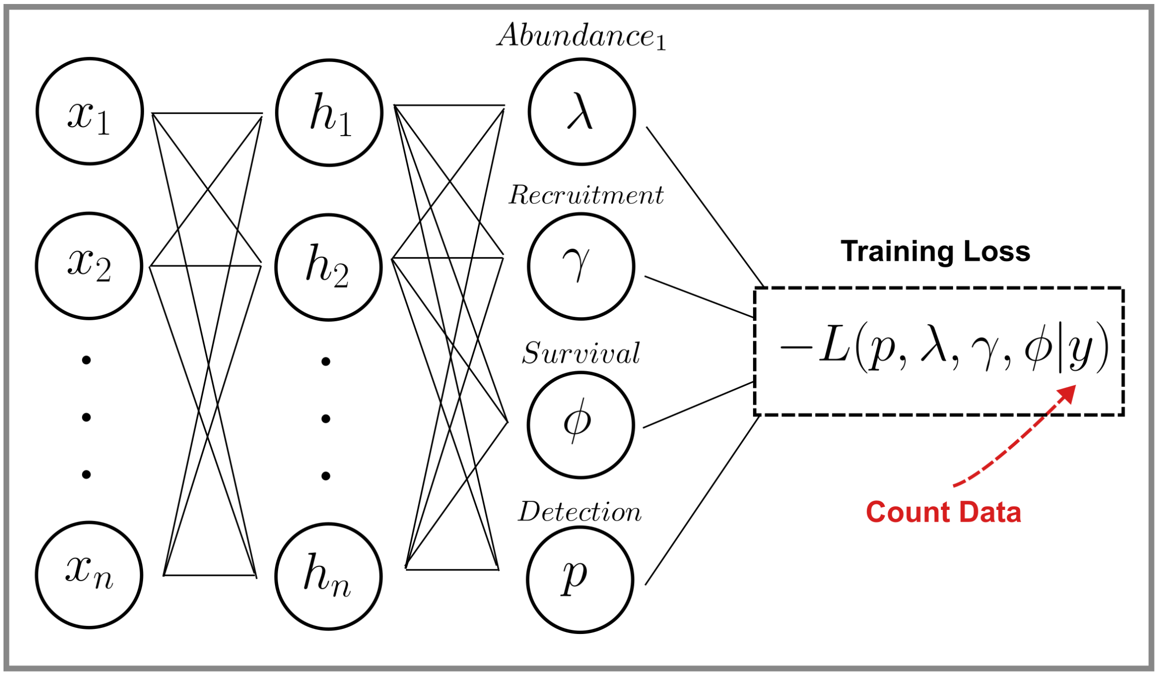

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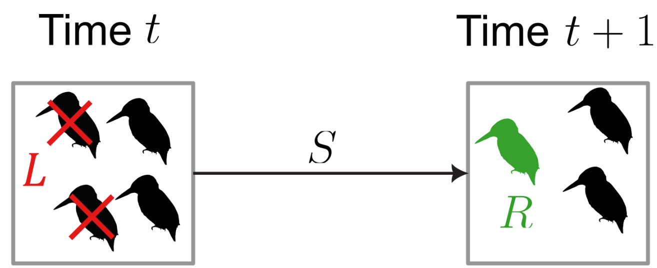
Beyond abundance change

Demographic rates

- Changes in abundance are valuable, but demographic mechanisms offer deeper ecological insights
- Species' extinctions event are the result of increasing difference between birth and loss
- Demographic rates can be early warnings of species extinction
- Monitoring survival and recruitment can help anticipate species' extinction and understand better the current biodiversity crisis



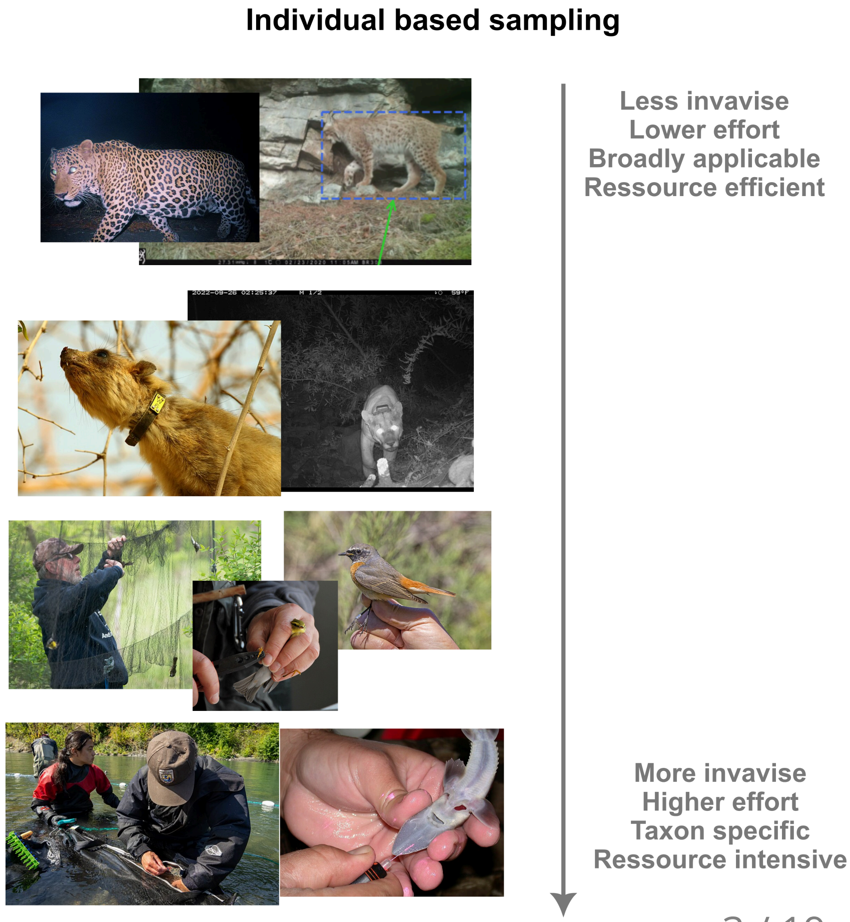
$$N_t = L + S \qquad N_{t+1} = S + R$$

$$\Delta N = N_{t+1} - N_t = R - L$$

Beyond abundance change

Problem

- Data for demographic rates models are individual based (i.e. *individual encounter history data*)
- They are costly in resources and time
- Individual identification is not equal for all taxa
- Can be invasive/traumatic
- Limited spatial and temporal extent



Beyond abundance change

Using abundance to infer demographic rates

- However, abundance data are available at large spatial and temporal scale
- The idea of inferring birth/immigration (μ) and death/emigration (λ) from experimental data is not new
- While overall change in abundance gives information about $\lambda - \mu$, the volatility of the time-series provide information about $\lambda + \mu$ making λ and μ identifiable

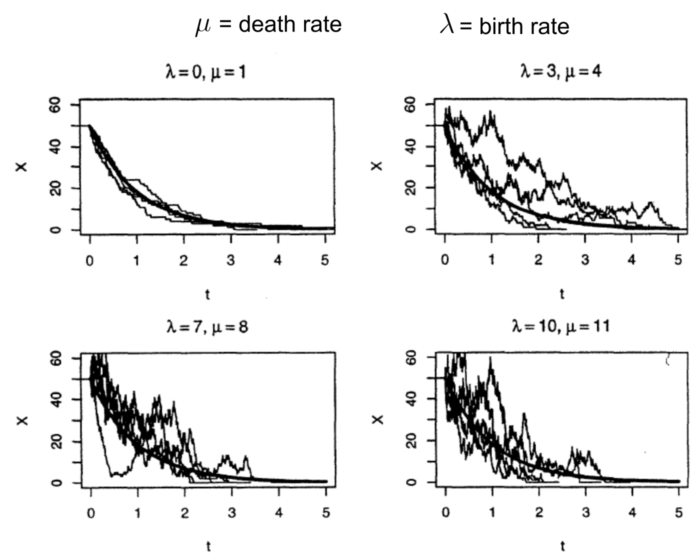


Figure 1.3 *Five realisations of a stochastic linear birth-death process together with the continuous deterministic solution for four different* (λ, μ) *combinations, each with* $\lambda - \mu = -1$ *and* $x_0 = 50$

Wilkinson, 2011

Dynamic N-mixture model

Hierarchical Model

Observation process

$$y_{i,j,t} \sim Binomial(N_{i,t}, p)$$

$y =$ observed abundance
$p =$ detection probability

State process

$$N_{i,1} \sim Poisson(\lambda)$$

$\lambda =$ abundance at $t = 1$

$$S_{i,t+1} \sim Binomial(N_{i,t}, \phi_{i,t})$$
$$R_{i,t+1} \sim Poisson(\gamma_{i,t})$$
$$N_{i,t+1} = S_{i,t+1} + R_{i,t+1}$$

$\phi =$ survival probability
$\gamma =$ number of recruits

Dail & Madsen, 2011

Neural hierarchical model

Limitations of hierarchical framework

- Linear or simple polynomial effects of covariates, even though true ecological responses are often unknown *a priori*
- MCMC algorithm scales poorly because inherently sequential, little possibility of parallelization
- Sensitive to priors and initial values

Limitations of Neural Networks

- Usually lack inferential power, making it less relevant for ecological insights
- Doesn't distinguish between ecological process and imperfect detection

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METHODS

Neural hierarchical models of ecological populations

Maxwell B. Joseph*

Abstract
Neural networks are increasingly being used in science to infer hidden dynamics of natural systems from noisy observations, a task typically handled by hierarchical models in ecology. This

Neural hierarchical model

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METHODS

Neural hierarchical models of ecological populations

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Abstract

Neural networks are increasingly being used in science to infer hidden dynamics of natural systems from noisy observations, a task typically handled by hierarchical models in ecology. This

- Combines flexibility and scalability of neural networks with the inferential power of hierarchical models
- Output activation function according to the parameter to infer (sigmoid for probability, exponential for counts)
- Loss function: tailored from the model specific negative log-likelihood
- Combines decades of development in hierarchical modelling for ecological data with the flexibility and predictive power of Neural Networks

Neural Dynamic N-mixture model

Deep Markov Model*

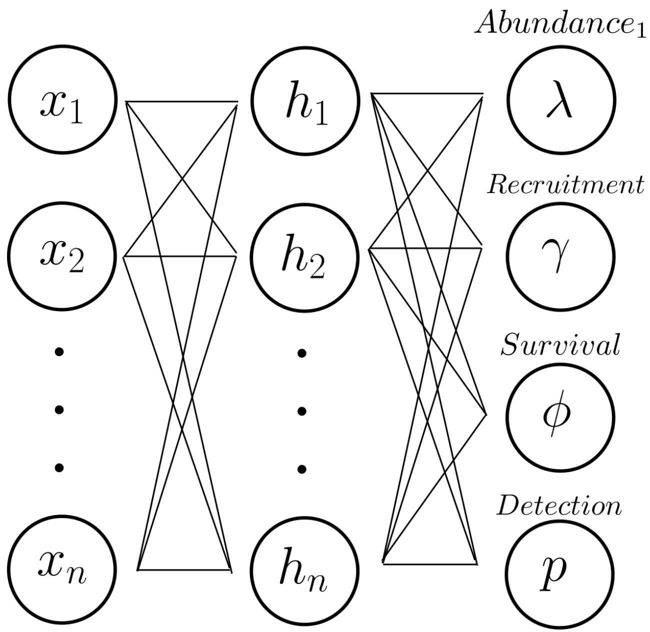
State process

$$N_{i,1} \sim Poisson(\lambda)$$

$$R_{i,t+1} \sim Poisson(\gamma_{i,t})$$
$$S_{i,t+1} \sim Binomial(N_{i,t}, \phi_{i,t})$$
$$N_{i,t+1} = S_{i,t+1} + R_{i,t+1}$$

Observation process

$$y_{i,j,t} \sim Binomial(N_{i,t}, p)$$



$$\lambda = exp(\mathbf{w}_\lambda \cdot \mathbf{x}_h + b_\lambda)$$

$$\gamma = exp(\mathbf{w}_\gamma \cdot \mathbf{x}_h + b_\gamma)$$

$$\phi = \sigma(\mathbf{w}_\phi \cdot \mathbf{x}_h + b_\phi)$$

$$p = \sigma(\mathbf{w}_p \cdot \mathbf{x}_h + b_p)$$

* Krishnan et al. 2017

Neural Dynamic N-mixture model

Deep Markov Model*

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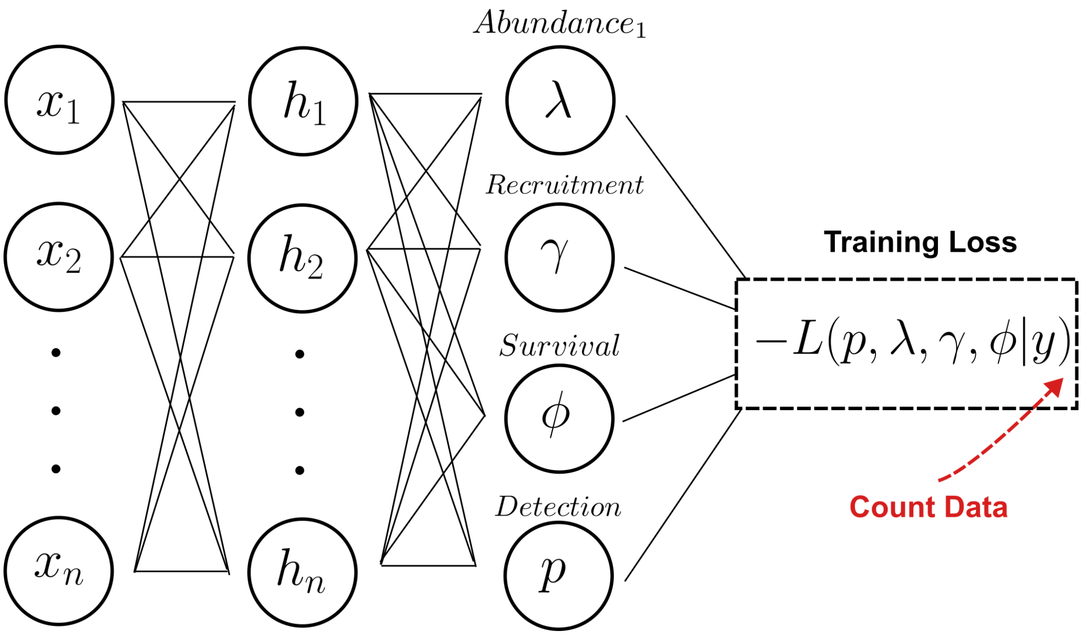

* Krishnan et al. 2017

Example with the N-mixture model

Observation process

$$y_{i,j,t} \sim Binomial(N_{i,t}, p)$$

State process

$$N_i \sim Poisson(\lambda)$$

Integrated likelihood:

$$L(p, \lambda \mid y_{it}) = \prod_{i=1}^{R} \left(\sum_{N_i=0}^{\infty} \left(\prod_{t=1}^{T} Bin(y_{it}; N_i, p) \right) Pois(N_i; \lambda) \right)$$

Example with the N-mixture model

Observation process

$$y_{i,j,t} \sim Binomial(N_{i,t}, p)$$

State process

$$N_i \sim Poisson(\lambda)$$

Integrated likelihood:

$$L(p, \lambda \mid y_{it}) = \prod_{i=1}^{R} \left(\sum_{N_i=0}^{K} \left(\prod_{t=1}^{T} Bin(y_{it}; N_i, p) \right) Pois(N_i; \lambda) \right)$$

- Marginalize over $K >> y_{it}$

Dynamic N-mixture model

State process

$$\begin{aligned} N_{i,1} &\sim Poisson(\lambda) \\ R_{i,t+1} &\sim Poisson(\gamma_{i,t}) \\ S_{i,t+1} &\sim Binomial(N_{i,t}, \phi_{i,t}) \\ N_{i,t+1} &= S_{i,t+1} + R_{i,t+1} \end{aligned}$$

Observation process

$$y_{i,j,t} \sim Binomial(N_{i,t}, p)$$

Integrated likelihood

$$\begin{aligned} \mathcal{L}(p, \lambda, \gamma, \phi \mid y_{it}) = \prod_{i=1}^{R} \Bigg[\sum_{N_{i1}=0}^{\infty} \cdots \sum_{N_{iT}=0}^{\infty} \Bigg\{ \Bigg(\prod_{t=1}^{T} Bin(y_{it}; N_{it}, p) \Bigg) \\ \times Pois(N_{i1}; \lambda) \cdot \prod_{t=2}^{T} P_{N_{it-1}, N_{it}} \Bigg\} \Bigg] \end{aligned}$$

The transition matrix

- As it it a Hidden Markov Model, the likelihood involves a transition between time t and $t + 1$
- This is the bottleneck

Optimization

- Hidden Markov Model $\Rightarrow$ Deep Markov Model (Krishnan et al., 2017)
- Trade-off between memory use and speed
- I choose fast implementation with heavy memory use

Simulated data

Results of the simulation

Fitting on real data

Next step

- So far it is a simple MLP
- Promising to use a CNN

Limitations