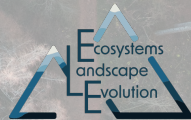


Interpretable machine learning for forecasting dynamical processes in ecosystems

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Motivation

In the context of intense disruptions, how to extrapolate beyond observations and anticipate ecosystem responses?

Mechanistic ecosystem models

explicit representation of ecological processes

- + Potential for extrapolation
- Hard to parametrise
- Inaccurate

Differential equations

$$\frac{1}{\text{plant}} \frac{d}{dt} \text{plant} = \overbrace{r(\text{sun}, \text{water})}^{\text{growth rate}} - \underbrace{b(\text{plant})}_{\text{Intra-specific competition}} - \overbrace{c(\text{insect}, \text{bird})}^{\text{Inter-specific competition}}$$

Can we improve the parametrization of ecosystem models?

Inverse ecosystem modelling

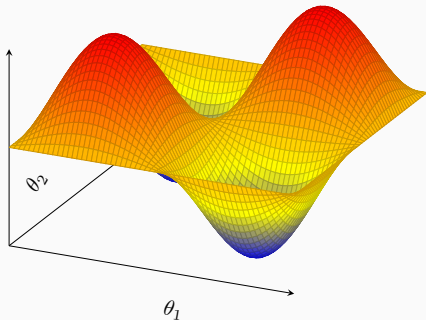
Direct measurement of parameter values is difficult and inaccurate $\Rightarrow$ **infer the parameters from observation data**

$L_{\mathcal{M}}(\theta)$ = Distance between **observations** and **simulations** (loss function)

Most probable parameters $\hat{\theta}$

$$\hat{\theta} = \arg \min_{\theta} L_{\mathcal{M}}(\theta)$$

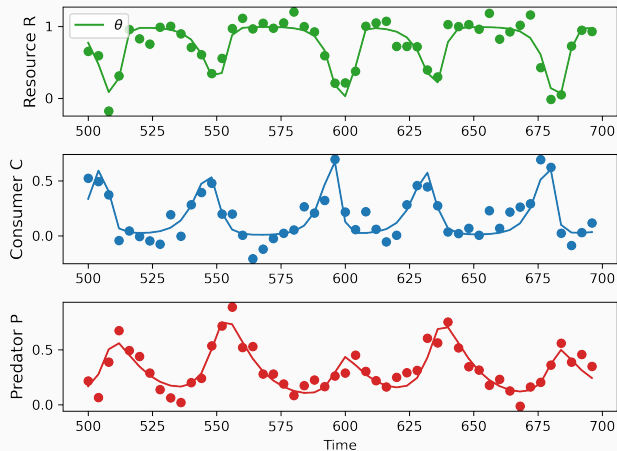
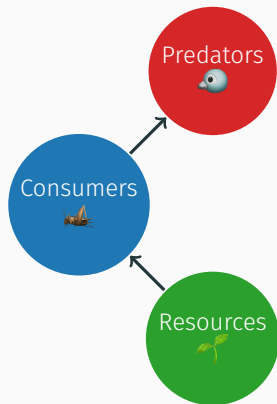
$$L_{\mathcal{M}}(\theta)$$



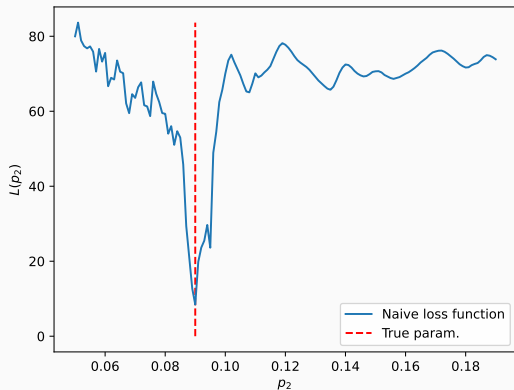
Problem: illustration with food web dynamics

Chaotic food web system

Hastings et al. 1991.



Problem: illustration with food web dynamics

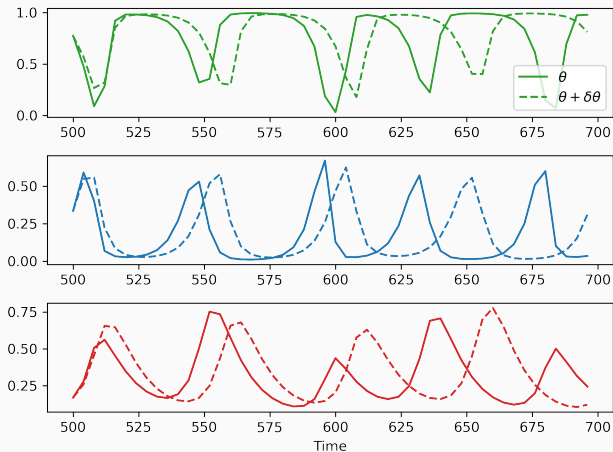


Problems

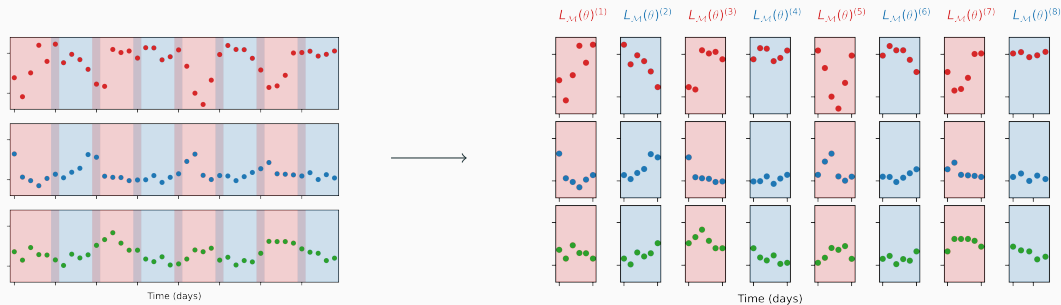
- Many local minima

Problem: illustration with food web dynamics

- Ecosystem models are **very sensitive to parameters and initial states**.



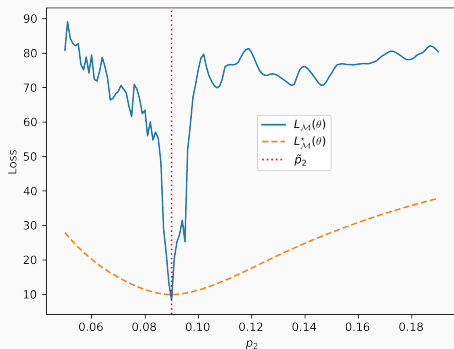
Learning from time series batches



$$L_{\mathcal{M}}^*(\theta) = L_{\mathcal{M}}^{(1)}(\theta) + L_{\mathcal{M}}^{(2)}(\theta) + \dots$$

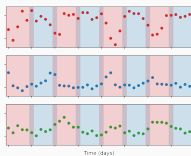
Loss function regularisation

The batch method **regularises** the loss function associated with **models showing complex dynamics** such as chaotic dynamics and limit cycles.



- Necessitate the sensitivity of the model to the parameters $\Rightarrow$ difficult to implement in practice

ML framework =

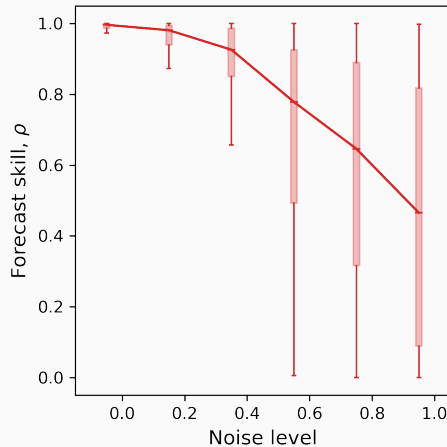
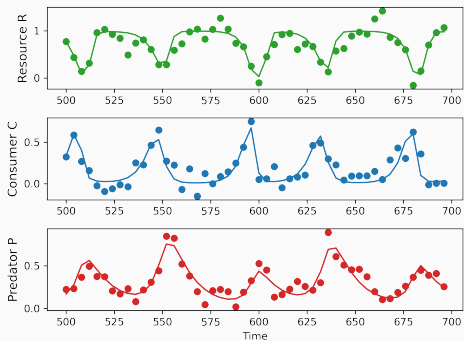


+ automatic differentiation ←

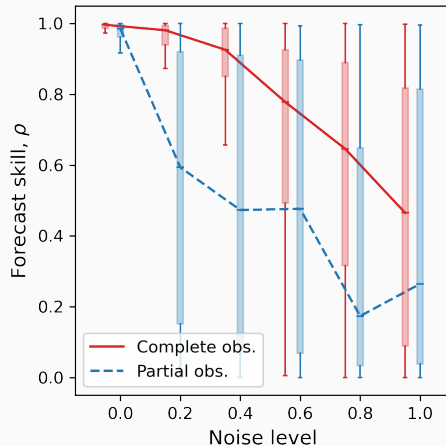
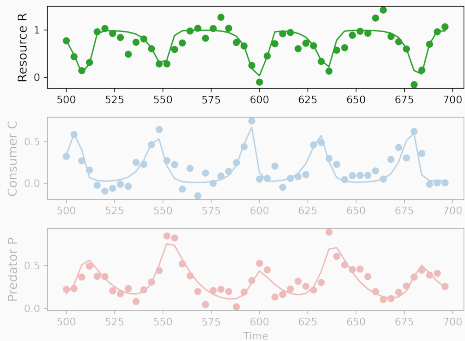
+ state of the art optimizers ←



Robustness of the ML framework to noise

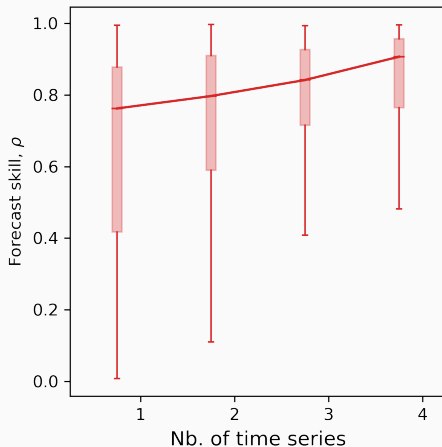


Robustness of the ML framework to partial observations

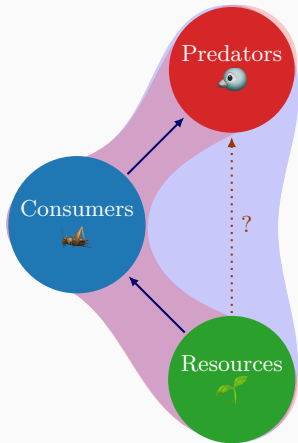


Performance of the ML framework in processing and combining the information of heterogeneous data sets

Batches are treated as **independent** time series
⇒ The batch method can **process and combine the information of independent time series!**



Contrasting different hypotheses



Two models

$\mathcal{M}_1$ Standard food web

$\mathcal{M}_2$ Omnivory variant

Fit those models to compare their probability given the data

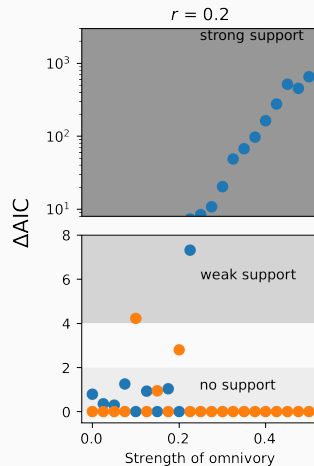
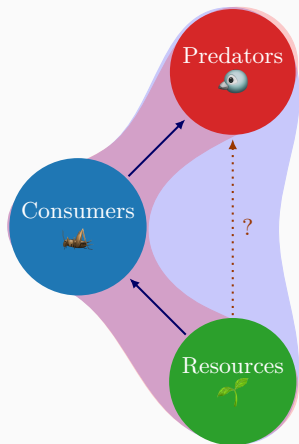
$$L_{\mathcal{M}_2} > L_{\mathcal{M}_1}?$$

$\mathcal{M}_1 \subseteq \mathcal{M}_2$: Need to penalize complexity

Aikake information criterion

$$\text{AIC}_{\mathcal{M}_2} > \text{AIC}_{\mathcal{M}_1}$$

Contrasting different hypotheses: results



The ML framework can provide support for the most accurate model given the data.

Summary and perspectives

- **Novel batch method** combined in a **ML framework with automatic differentiation** and **state of the art optimizers** to regularise the parametrization of complex ecosystem models.
- The batch methods **splits data** in batches with short time horizon, allowing to learn **from heterogeneous time series with partial and noisy observations**.
- The ML framework can **test ecological theory against data** and help **continuously improving ecosystem models**.
- We plan on utilising the ML framework **with real data**, for **investigating ecosystem responses to different climate scenarios**.

Boussange, V., Vilimelis-Aceituno, P., Pellissier, L., *Blending Machine Learning with mechanistic models to learn from ecological time series*, In prep.

Thanks for your attention!

Questions?

<https://vboussange.github.io>
to learn more about EcologyInformedML.jl.