

Accelerating Access to Life-Saving Treatments to Patients

pumas^{AI}



Augmenting healthcare intelligence with predictive analytics that turn data into life-saving decisions



Our data-analytical tools help make data-driven decisions more efficiently



PumasCP



DeepPumas



Pumas



We humanize technology to provide personalized treatments for patients



Lyv



Find the shortest development path for regulatory approval, with us

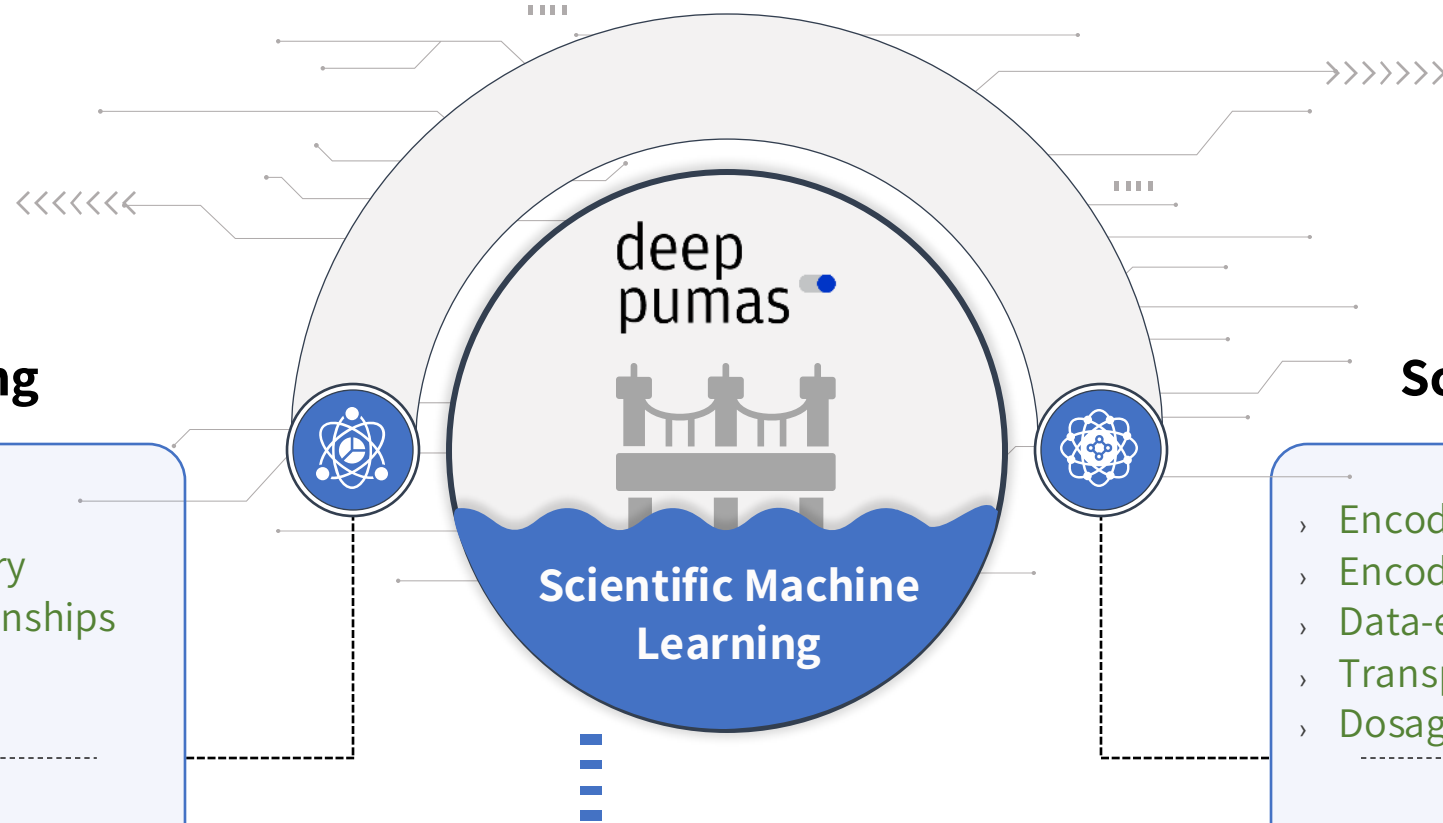


Scientific &
Strategic Consulting

pumas^{AI}

DeepPumas Introduction

Niklas Korsbo



Machine Learning

- › Automatic model discovery
- › Finding unintuitive relationships
- › Handling complex data

- › Lacks scientific understanding
- › Requires big data
- › Inscrutable

Scientific Modeling

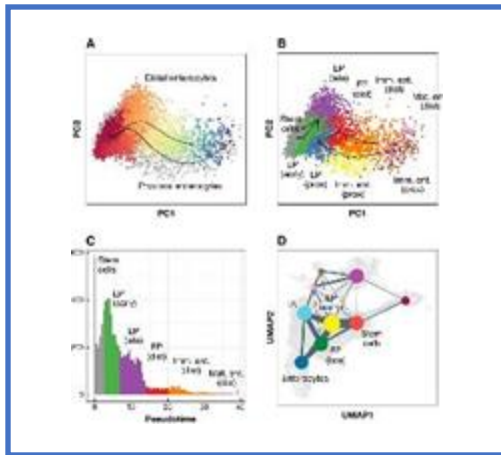
- › Encoding scientific understanding
- › Encoding information hierarchies
- › Data-efficient
- › Transparent and interpretable
- › Dosage optimization, etc.

- › Labor intensive
- › Misses unintuitive relationships
- › Hard to utilize complex data



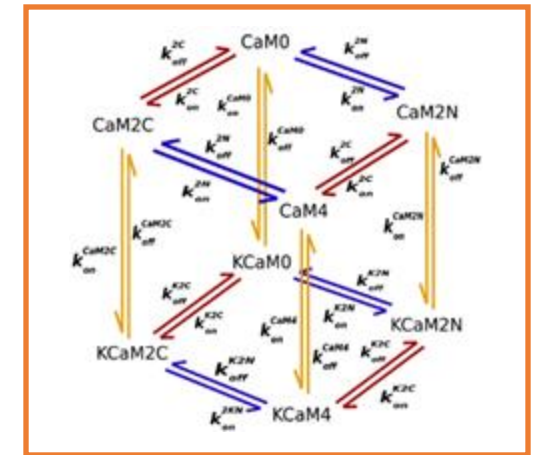
DeepPumas – simple and effective utilization of both knowledge and data

Data



Good Predictions

Models



Clinical
Tests



Medical
Images



Measured
Outcomes



Monitoring
Devices



Omics



Wearables



Known Molecular
Interactions



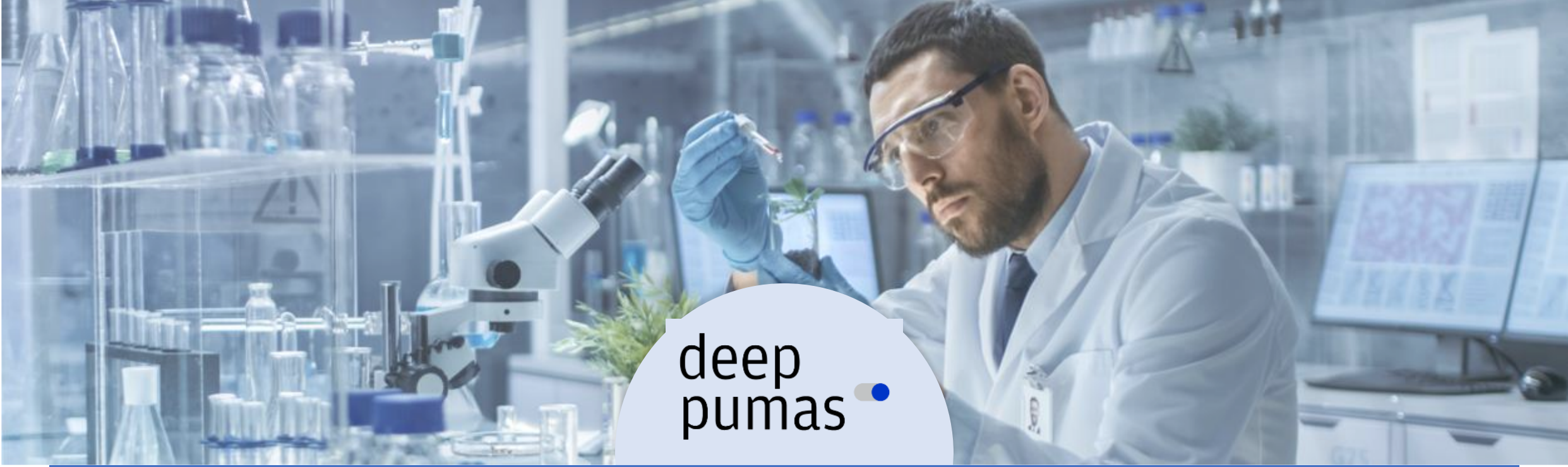
Known Cell
Interactions



Known Drug
Properties



Known Prognostic
Factors



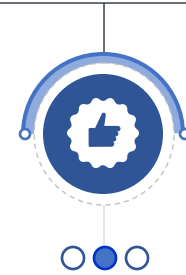
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**Lead
Generation**

**Clinical
Research**

**Market
Research**

**Quality-by-design
Manufacturing**

**Individualized
Patient Management**

NLME

Typical values

$$\theta \in \mathbb{R}_+^3$$

$$\Omega \in \mathbb{R}_+^3$$

Patient data

Age
Weight

Random effects

$$\eta \sim \text{MvNormal}(\Omega)$$

Individual parameters

$$Ka_i = \theta_1 \cdot e^{\eta_{i,1}} + c_1 \cdot \text{Age}_i$$

$$CL_i = \theta_2 \cdot e^{\eta_{i,2}}$$

$$V_i = \theta_3 \cdot e^{\eta_{i,3}} + c_2 \cdot \text{Weight}_i^{c_3}$$

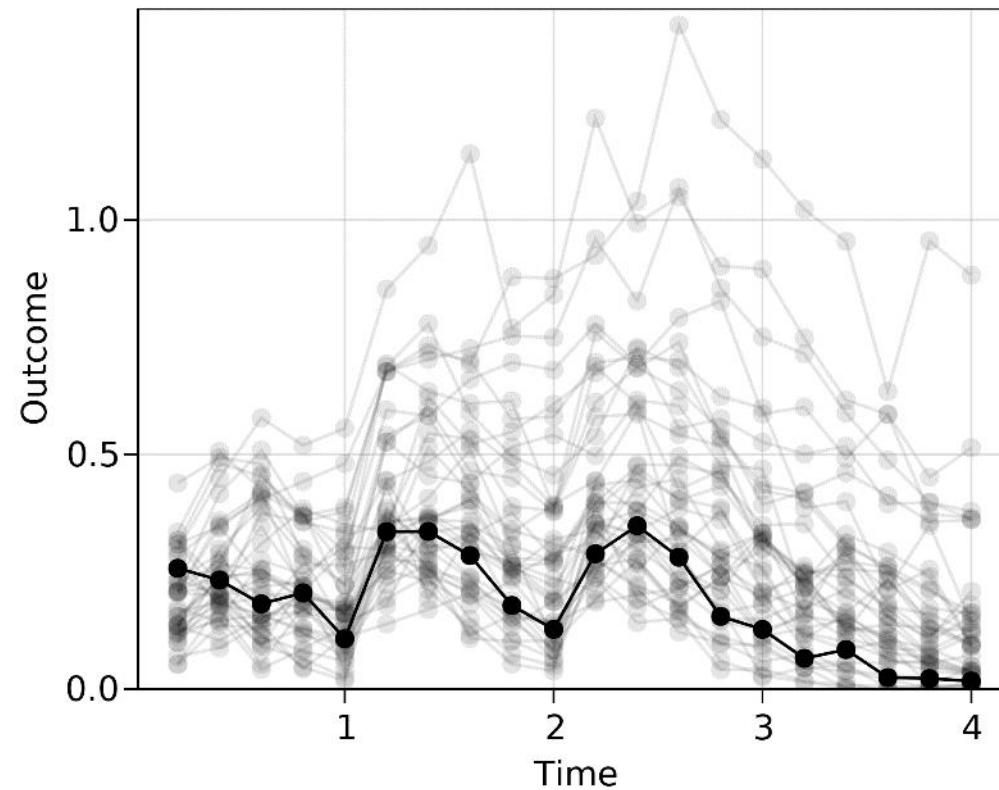
Dynamics

$$\frac{d[\text{Depot}]}{dt} = -Ka[\text{Depot}],$$

$$\frac{d[\text{Central}]}{dt} = Ka[\text{Depot}] - \frac{CL}{V}[\text{Central}].$$

Error model

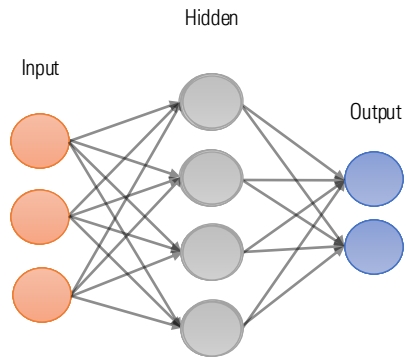
$$\text{Outcome} \sim \text{Normal}(\text{Central}, \sqrt{\text{Central}} \cdot \sigma)$$



WHAT IS A NEURAL NETWORK (NN)?

Information processing mechanism

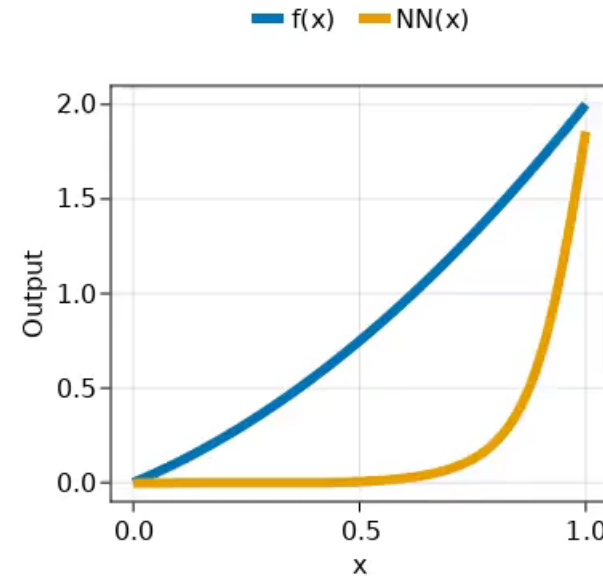
Loosely based on neurons



Mathematically: Just a function!

NNs are useable anywhere where you'd use a function!

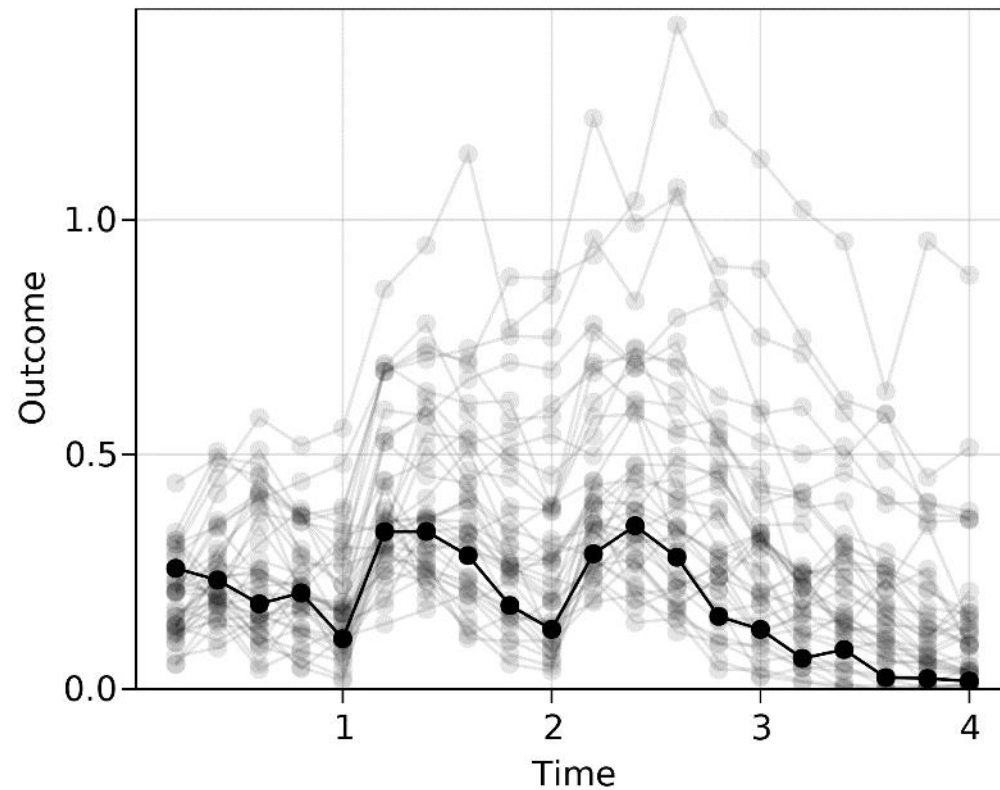
Universal approximators!



- Approximate any function
- Functional form tuned by parameters
- Parameter tuning can be linked to observed patient outcomes

Use **data** to automatically discover **relationships**

NLMF WITH DEEPPUMAS



Typical values

$$\theta \in \mathbb{R}_+^3$$

$$\Omega \in \mathbb{R}_+^3$$

Patient data

Age
Weight



Random effects

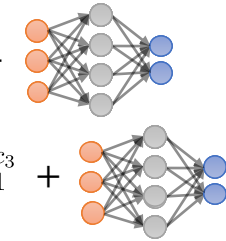
$$\eta \sim \text{MvNormal}(\Omega)$$

Individual parameters

$$Ka_i = \theta_1 \cdot e^{\eta_{i,1}} + c_1 \cdot Age_i$$

$$CL_i = \theta_2 \cdot e^{\eta_{i,2}}$$

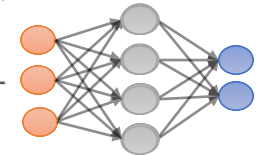
$$V_i = \theta_3 \cdot e^{\eta_{i,3}} + c_2 \cdot Weight_i^{c_3}$$



Dynamics

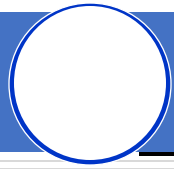
$$\frac{d[\text{Depot}]}{dt} = -Ka[\text{Depot}],$$

$$\frac{d[\text{Central}]}{dt} = Ka[\text{Depot}] -$$



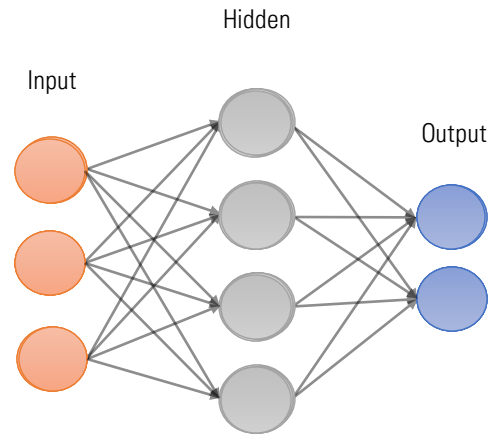
Error model

$$Outcome \sim \text{Normal}\left(Central, \sqrt{Central} \cdot \sigma\right)$$



DeepNLME – Flexible local information processing

Covariate data
Dynamic variables
Random effects
Time
Drug PK



Individualized parameters
Outcome transformations
Longitudinal biomarkers
DiffEQ terms

Image  Parameter contribution

Time after first dose
Random effects  Individualizable longitudinal biomarkers

Receptor drug occupancy
Random effect  Pain score

Dynamic variables
Random effects  Individualizable dynamics term

Data

- Primary outcomes
- Longitudinal biomarkers
- Images
- Omics
- EHRs

