

Accelerating Access to Life-Saving  
Treatments to Patients

pumas<sup>AI</sup>



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



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



We humanize technology to provide personalized treatments for patients



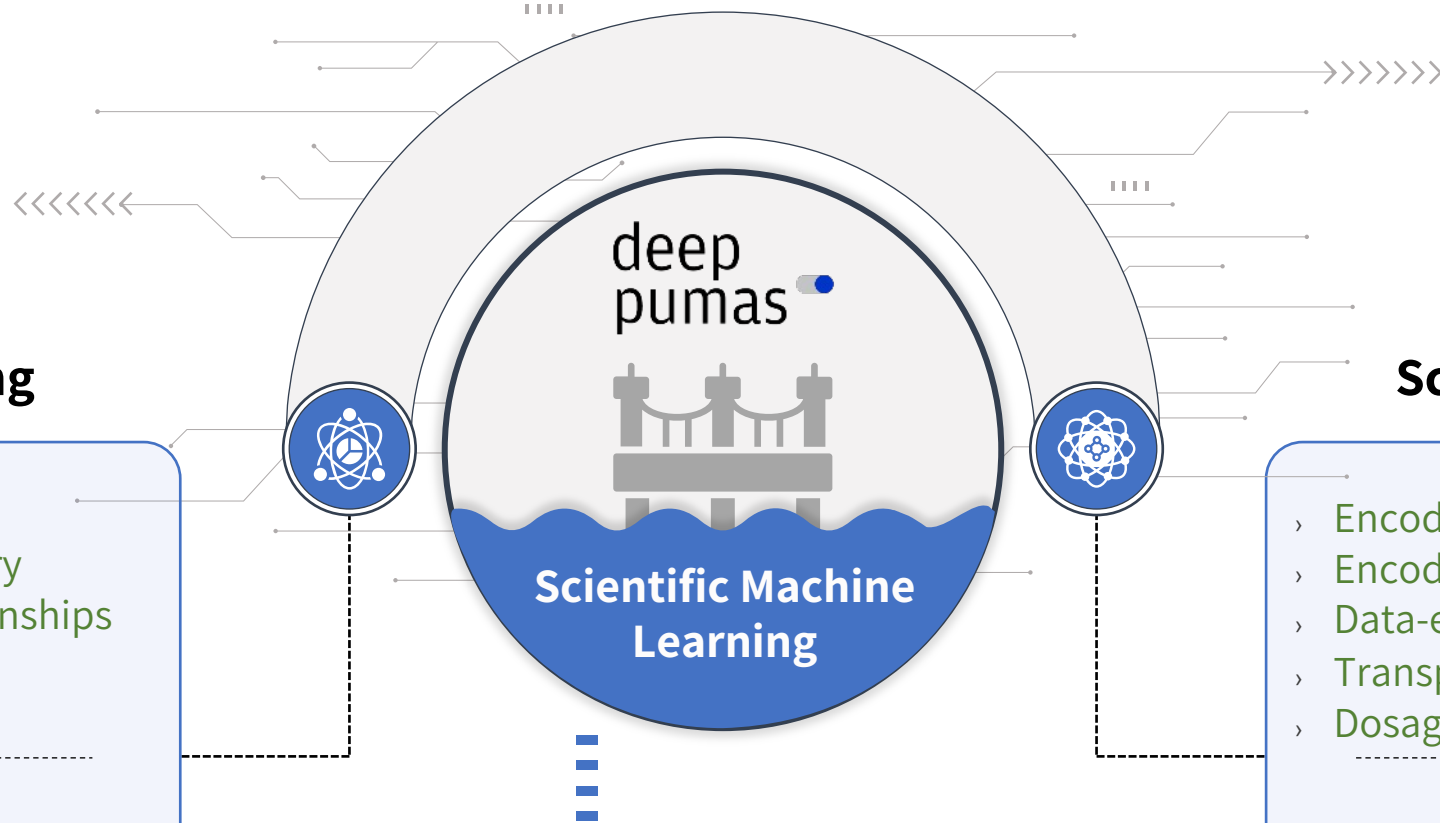
Find the shortest development path for regulatory approval, with us



pumas<sup>AI</sup>

## DeepPumas Introduction

Niklas Korsbo



## Machine Learning

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

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

## Scientific Modeling

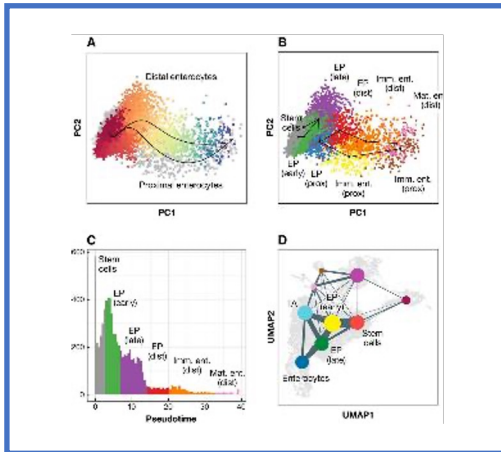
- › Encoding scientific understanding
- › Encoding information hierarchies
- › Data-efficient
- › Transparent and interpretable
- › Dosage optimization, etc.

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



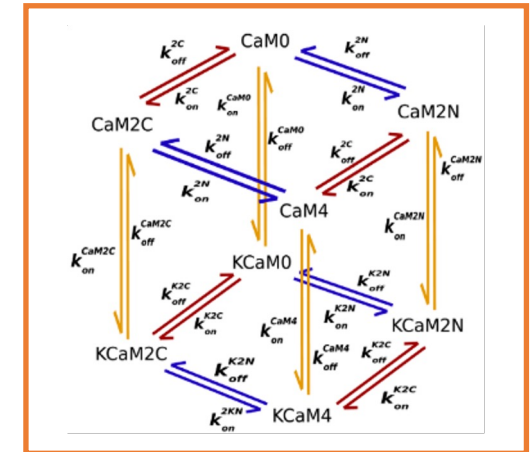
# DeepPumas – simple and effective utilization of both knowledge and data

## 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



»



»



»



»



**Lead  
Generation**

**Clinical  
Research**

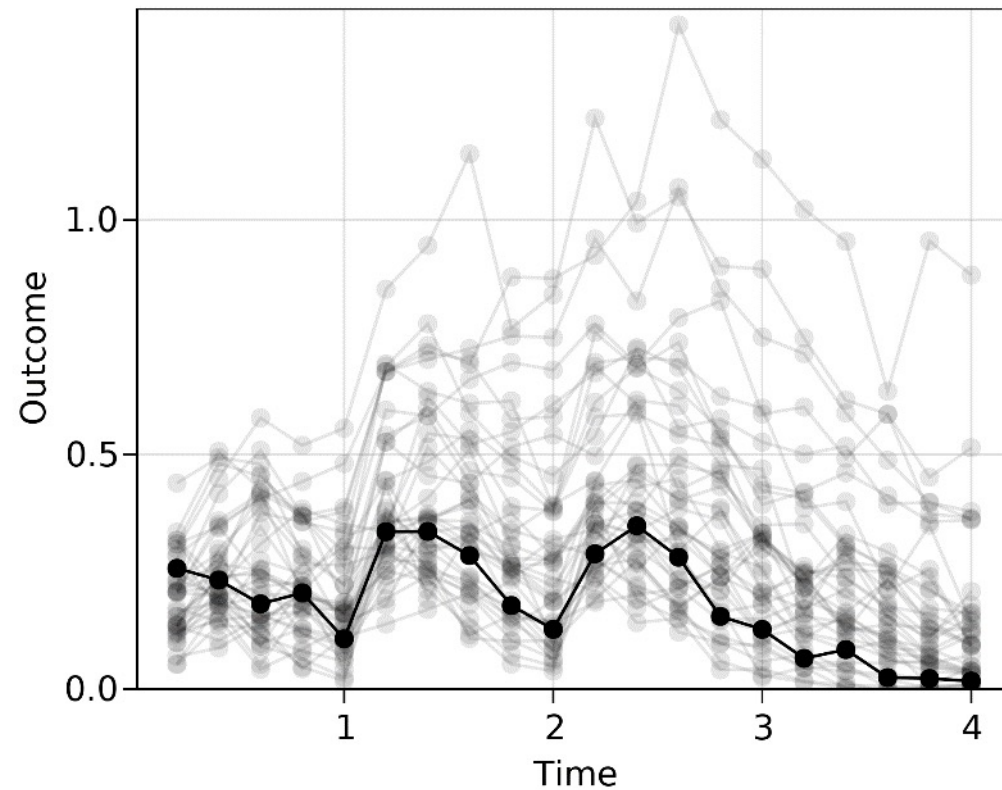
**Market  
Research**

**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

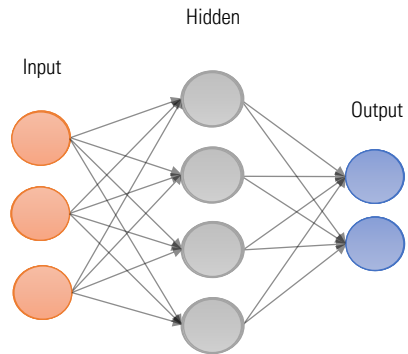
$$\text{Outcome} \sim \text{Normal}(\text{Central}, \sqrt{\text{Central}} \cdot \sigma)$$

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# WHAT IS A NEURAL NETWORK (NN)?

Information processing mechanism

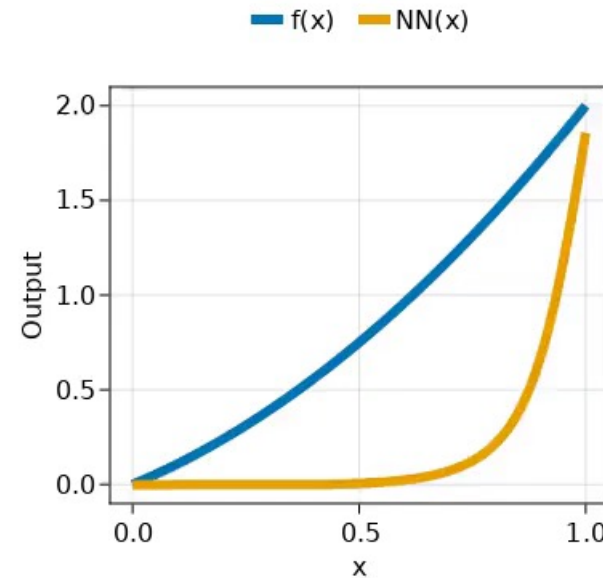
Loosely based on neurons



Mathematically: Just a function!

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

Universal approximators!

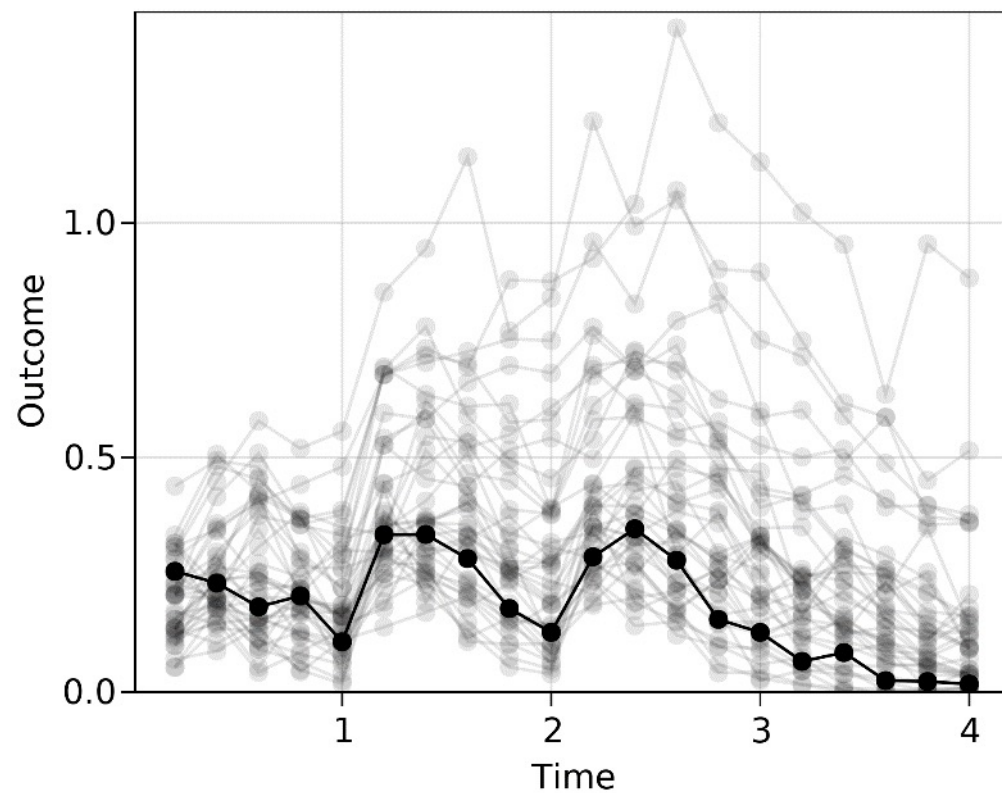


- Approximate any function
- Functional form tuned by parameters
- Parameter tuning can be linked to observed patient outcomes

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



# NLMF WITH DEEP PUMAS



Typical values

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

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

Patient data

Age  
Weight



Random effects

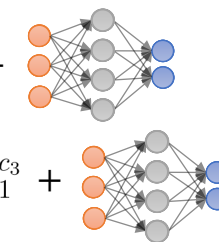
$$\eta \sim \text{MvNormal}(\Omega)$$

Individual parameters

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

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

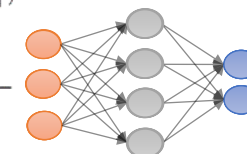
$$V_i = \theta_3 \cdot e^{\eta_{i,3}} + c_2 \cdot Weight_i^{c_3}$$



Dynamics

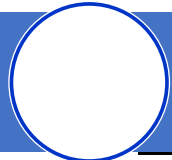
$$\frac{d[\text{Depot}]}{dt} = -Ka[\text{Depot}],$$

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



Error model

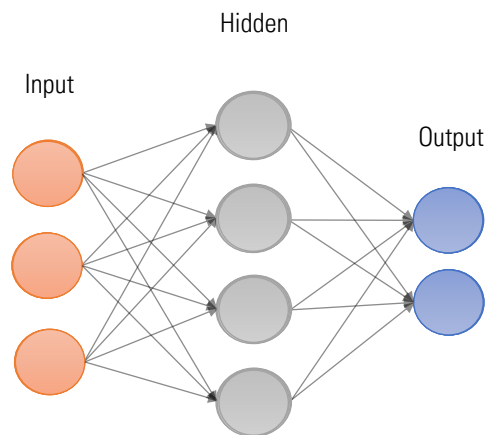
$$Outcome \sim \text{Normal}\left(Central, \sqrt{Central} \cdot \sigma\right)$$



# 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

