

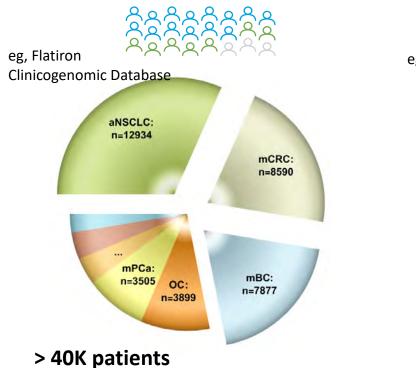
Neural-PK/PD as Pharmacology-Informed Deep Learning Architecture

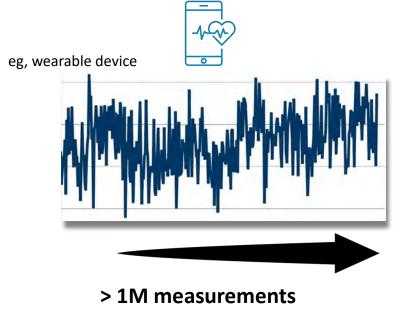
James Lu, Genentech

IQ Workshop on Machine Intelligence for Quantitative Modeling in Drug Discovery & Development Applications
15-16 September 2022

Motivation: the Data Challenge in the Digital Age

- Current trends in technology & digitization generate growth across:
 - the number of patients
 - the number of longitudinal measurements
 - the dimensionality of data





eg, gene expression

> 10K genes

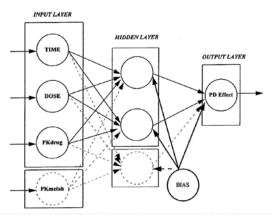
Cancer Genome Atlas Network, Nature (2012)



A Brief History of Neural Networks for PK & PK/PD Modeling

earning-

Feed-Forward Network



Artificial Neural Networks As a Novel Approach to Integrated Pharmacokinetic—Pharmacodynamic Analysis

JOGARAO V. S. GOBBURU'X AND EMILE P. CHENT

Received October 11, 1995, from the "Department of Pharmaceutical Sciences, North Dakota State University, Fargo, ND 58105, and *Department of Drug Metabolism and Pharmacokinetics, Hoffmann-La Roche, Nutley, NJ 07110. Accepted for publication. February 19, 1996.

INPUT

ILLNESS

HIDDEN

Recurrent Neural Network

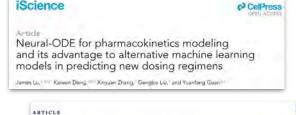


ARTICLE Introduction of an artificial neural network-based method for concentration-time predictions

Dominic Stefan Bräm120 | Neil Parrott | Lucy Hutchinson | Bernhard Steiert |

Neural-ODE Chen et al, NeurIPS (2018)





Deep compartment models: A deep learning approach for the reliable prediction of time-series data in pharmacokinetic modeling Alexander Janssen¹ | Frank W. G. Leebeek² | Marjon H. Cnossen³

Ron A. A. Mathôt | for the OPTI-CLOT study group and SYMPHONY consortium

OUTPUT

Mapping the Dose-Effect Relationship of Orbofiban from Sparse Data with an Artificial Neural Network

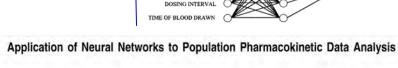
DONALD E. MAGER, JASON D. SHIREY, DERMOT COX, DESMOND J. FITZGERALD, DARRELL R. ABERNETHY ¹Laboratory of Clinical Investigation, National Institute on Aging, Gerontology Research Center, Baltimore, Maryland ²Department of Clinical Pharmacology, Royal College of Surgeons in Ireland, Dublin, Ireland University College Dublin, Dublin, Ireland

Population pharmacokinetic and pharmacodynamic models of remifentanil in healthy volunteers using artificial neural network analysis

S. H. Kang, M. R. Poynton, K. M. Kim, H. Lee, D. H. Kim, S. H. Lee, K. S. Bae, O. Linares, S. E. Kern' & G. J. Nohi

ARTICLE An artificial neural network-pharmacokinetic model and its interpretation using Shapley additive explanations Chika Ogami^{1,2} | Yasuhiro Tsuji² | Hiroto Seki³ | Hideaki Kawano⁴ | Hideto To¹ | Yoshiaki Matsumoto⁵ | Hiroyuki Hosono

> Genentech A Member of the Roche Group



HSIAO-HUI CHOWTX, KRISTIN M. TOLLET, DENISE J. ROES, VICTOR ELSBERRYT, AND HSINCHUN CHENT

Received September 24, 1996, from the *Department of Pharmacy Practice and Science, *Department of Management Information Systems, and Arizona Cancer Center, University of Arizona, Tucson, AZ 85721. Accepted for publication March 24, 1997

PK and PK/PD Modeling from the Dynamical Systems Perspective

- Two distinct types of Dynamical Systems
 - Autonomous:

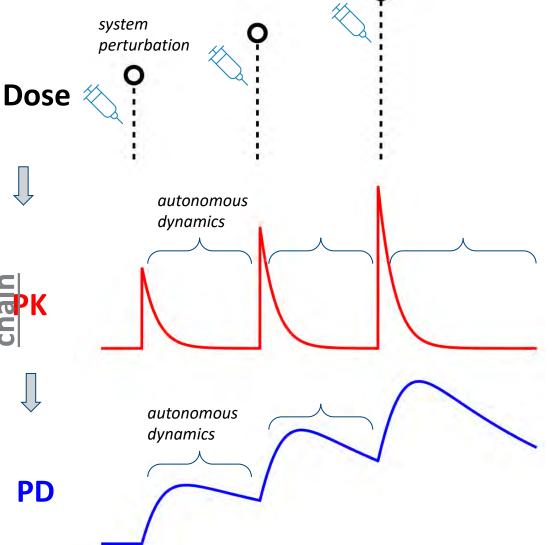
$$y'(t) = f(y(t), p)$$

Non-autonomous:

$$y'(t) = f(y(t), t, p)$$

PK and PK/PD models are piecewise autonomous systems with dosing introducing time-dependent perturbations:

$$y'(t) = \sum_{i=1}^{n} \operatorname{dose}(i) \, \delta(t - T_i) + f(y(t), p)$$



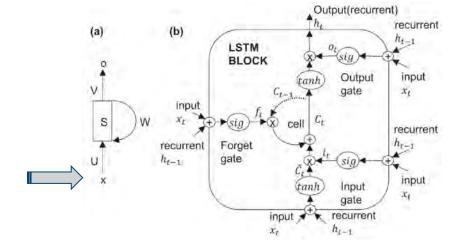
Distinctions with alternative Deep Learning Models for Time Series Data

Standard DL architectures for Time Series data (such as LSTM) do not explicitly encode causality relationships between **Dose**, **PK** and **PD**

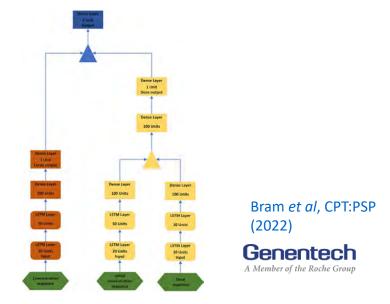
- All input data (x) enters the neural net at an equal footing
- Potentially challenging to perform counterfactual ("whatif") simulations

Necessitated the development of architectures that separates out:

- Concentration sequence data
- Dose sequence data



Liu *et al*, IJCPT (2021)



The Merging of Deep Learning with Dynamical Systems

Deep Learning

- Excels in approximating high dimensional/nonlinear functions
- Learn to improve model as data increases

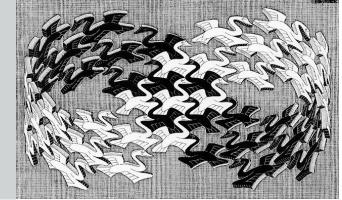
Dynamical Systems

- Enables assumption of causal dynamical relationships
- Enables dosing implementation as perturbation in the system state:

$$\frac{dy(t)}{dt} = \sum_{i=1}^{n} \operatorname{dose}(i) \, \delta(t - T_i) + f(y(t), p)$$

$$\frac{d y(t)}{d t} = \sum_{i=1}^{n} \operatorname{dose}(i) \, \delta(t - T_i) + \left(\sum_{i=1}^{n} \operatorname{dose}(i) + \left(\sum_{i=1}^{n} \operatorname{dose}(i) + \left(\sum_{i=1}^{n} \operatorname$$



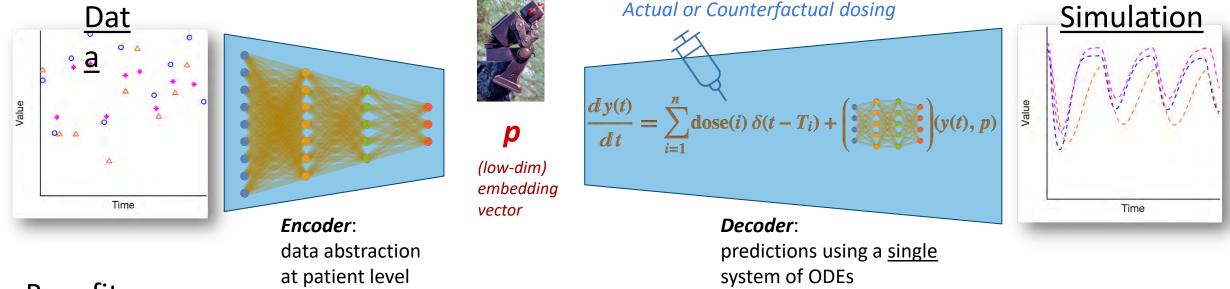


A pharmacology-informed dynamical system that learns from data and enables counterfactual dosing simulations



The Architecture of Neural-PK/PD enhances Interpretability

Pharmacology-Informed Encoder-Decoder Architecture



Benefits:

- Explicit control on the parameter dimension for characterizing inter-individual variability
- Explicit control on the state dimension for reproducing observed dynamics
- Explicit dosing port enables counterfactual simulations under different dosing regimens

Formulations of Population-PK/PD vs Neural-PK/PD

Human Generated Model

Equations based on human experience & data fit

DADT(1)=K21*A(2)-K12*A(1)-K10*A(1)

DADT(2)=K12*A(1)-K21*A(2)

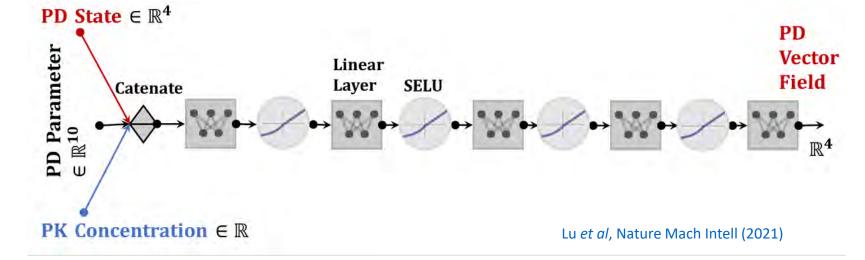
DADT(3)=KEO*CP-KEO*A(3)

DADT(4)=-KTR*A(4)+KTR*A(4)*(1-EFFPLT)*(BT/A(8))**GAM

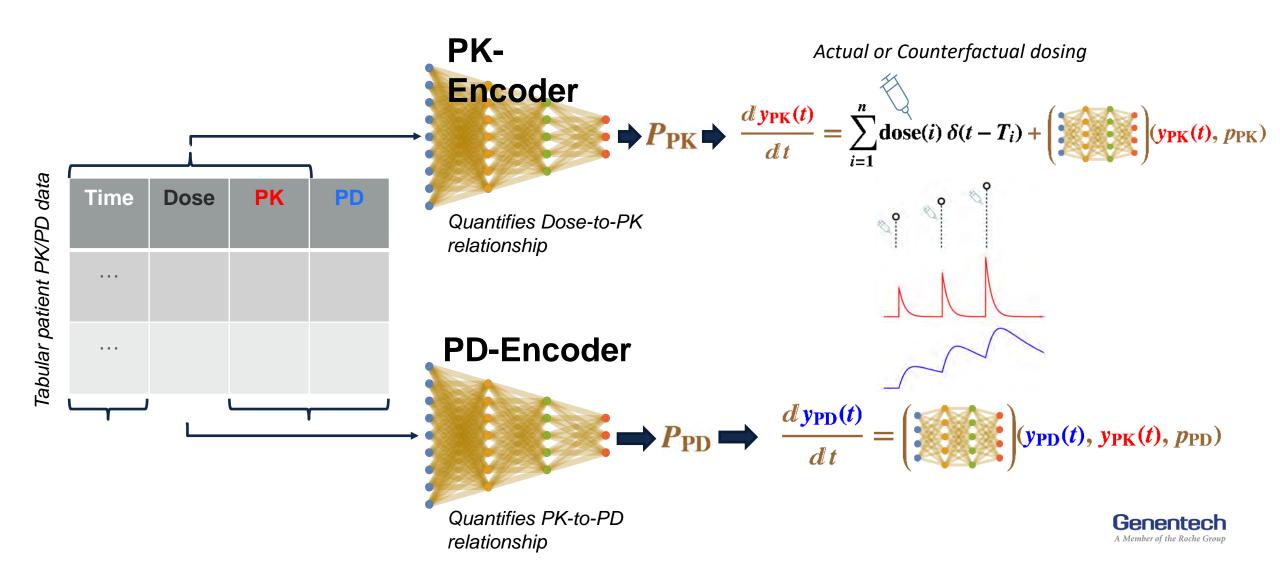
DADT(5)=-KTR*A(5)+KTR*A(4)

Neural Network Generated Model

Neural network learned from PK & PD data

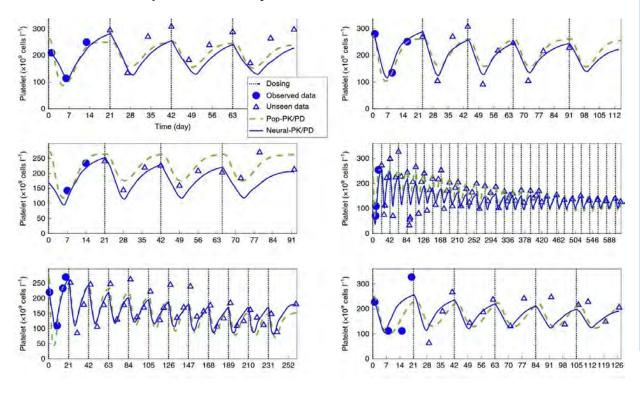


Encoding Causality Assumption into Neural-PK/PD Architecture



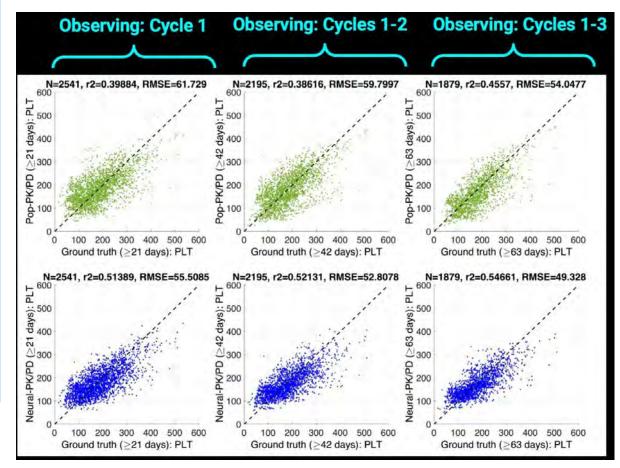
Neural-PK/PD Enables Accurate Predictions in Time

Learned model demonstrates qualitatively similar dynamics but more precise predictions as compared to the state-of-the-art pop-PK/PD model for platelet dynamics



Lu et al, Nature Mach Intell (2021)

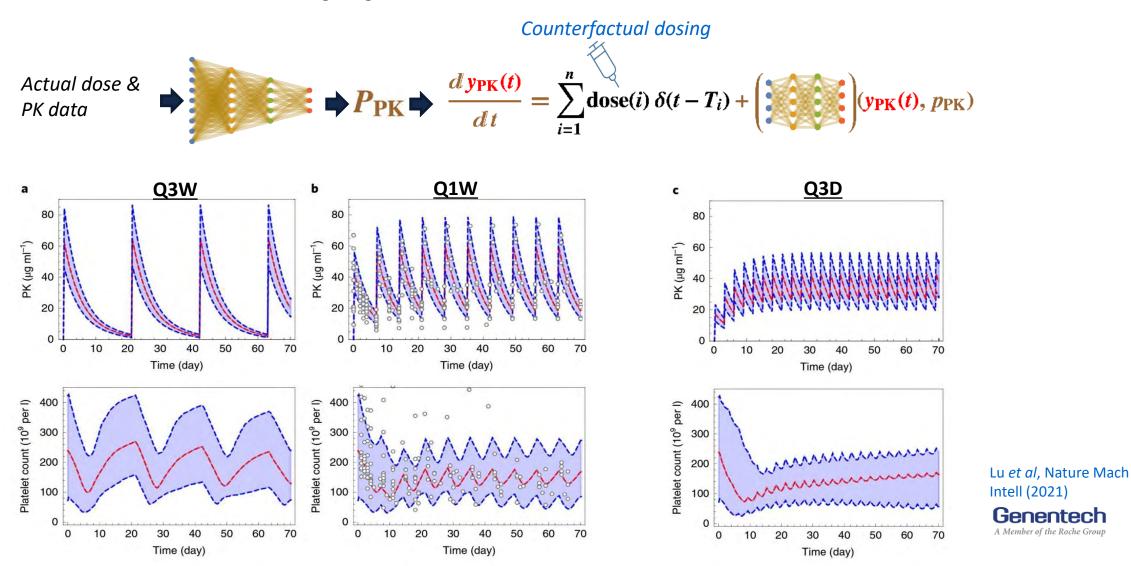
Model demonstrates superior predictive performance



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Neural-PK/PD Enables Predictions for Alternate Dosing Regimens

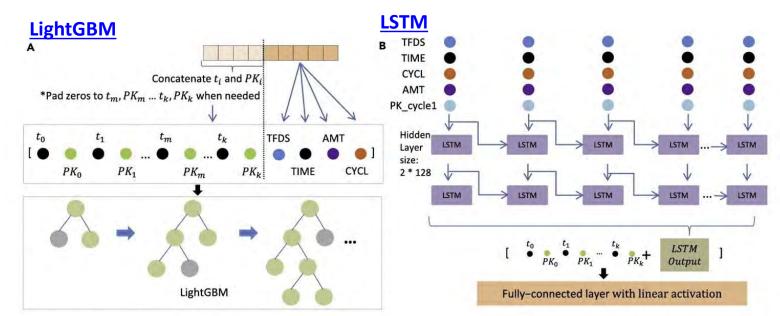
Simulations of counterfactual dosing regimens shown to be consistent with data

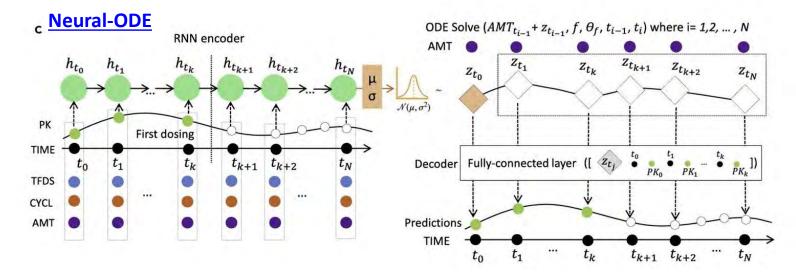


The Importance of the Architecture Choice in Generalizability

 Comparison of Neural-ODE based architecture vs alternate models:



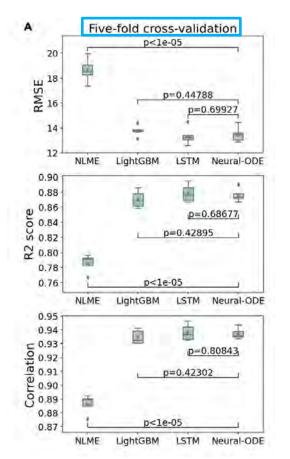


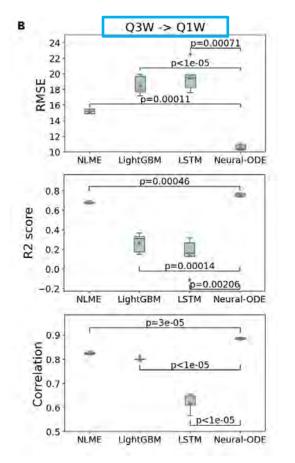


The Importance of the Architecture Choice in Generalizability

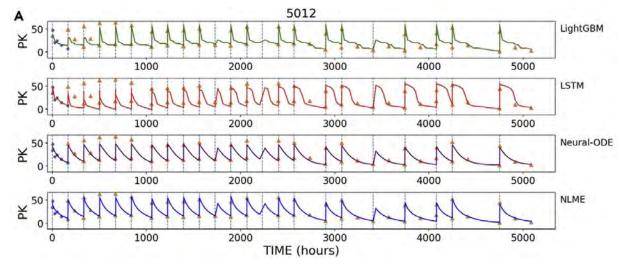
ML/DL models exhibit similar performance when train and test sets are from the same distribution

Models such as LightGBM and LSTM do not generalize well across dosing regimens

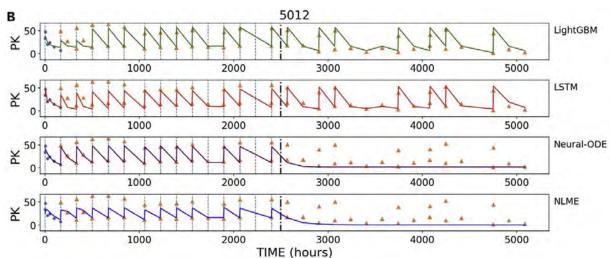




Comparison of model predictions for a patient



Comparison of model predictions with dosing stopped @ t=2500 hour



Conclusion

- The rise of complex, high volume PK/PD data in the Digital Age necessitates the development of AI methodologies
- Neural-PK/PD is a pharmacology-informed DL model that encapsulates dose-concentration-effect relationship within an encoder-decoder architecture:
 - leverages dynamical systems concepts
 - encoder bottleneck may improve better generalization from limited data
 - decoder enables counterfactual simulations

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Kaiwen Deng, Xinyuan Zhang, Yuanfang Guan



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