



18<sup>th</sup> ICC - INTERNATIONAL  
CONGRESS ON CATALYSIS

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# ACCELERATING MULTI-SCALE MODELING OF CATALYTIC DEVICES THROUGH MACHINE LEARNING SURROGATES

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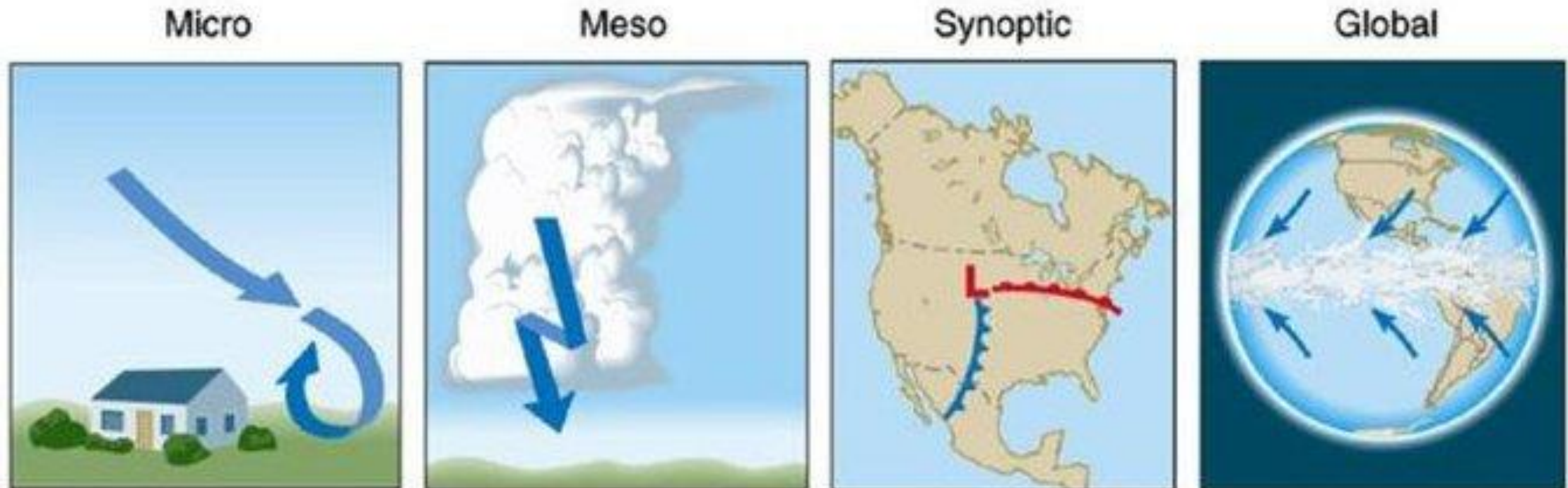
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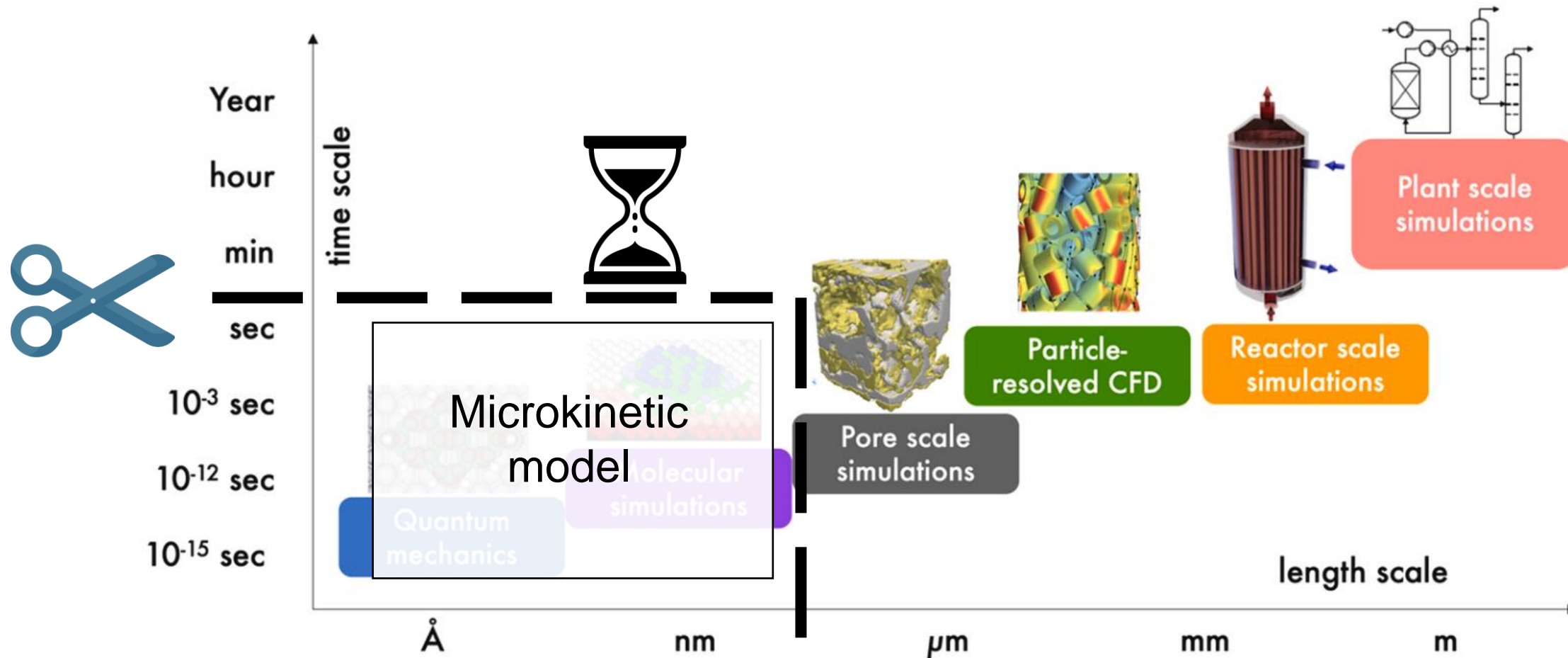


# Real life problems are multi scale



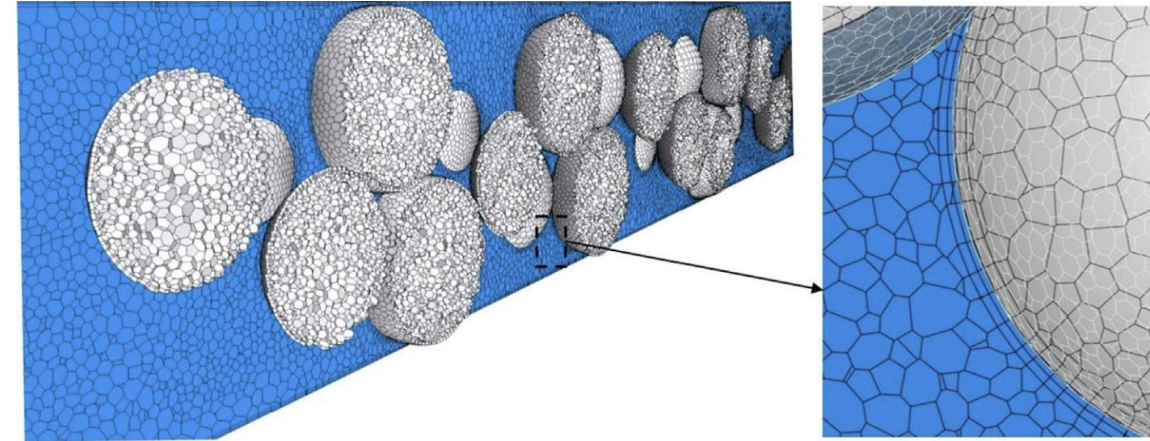
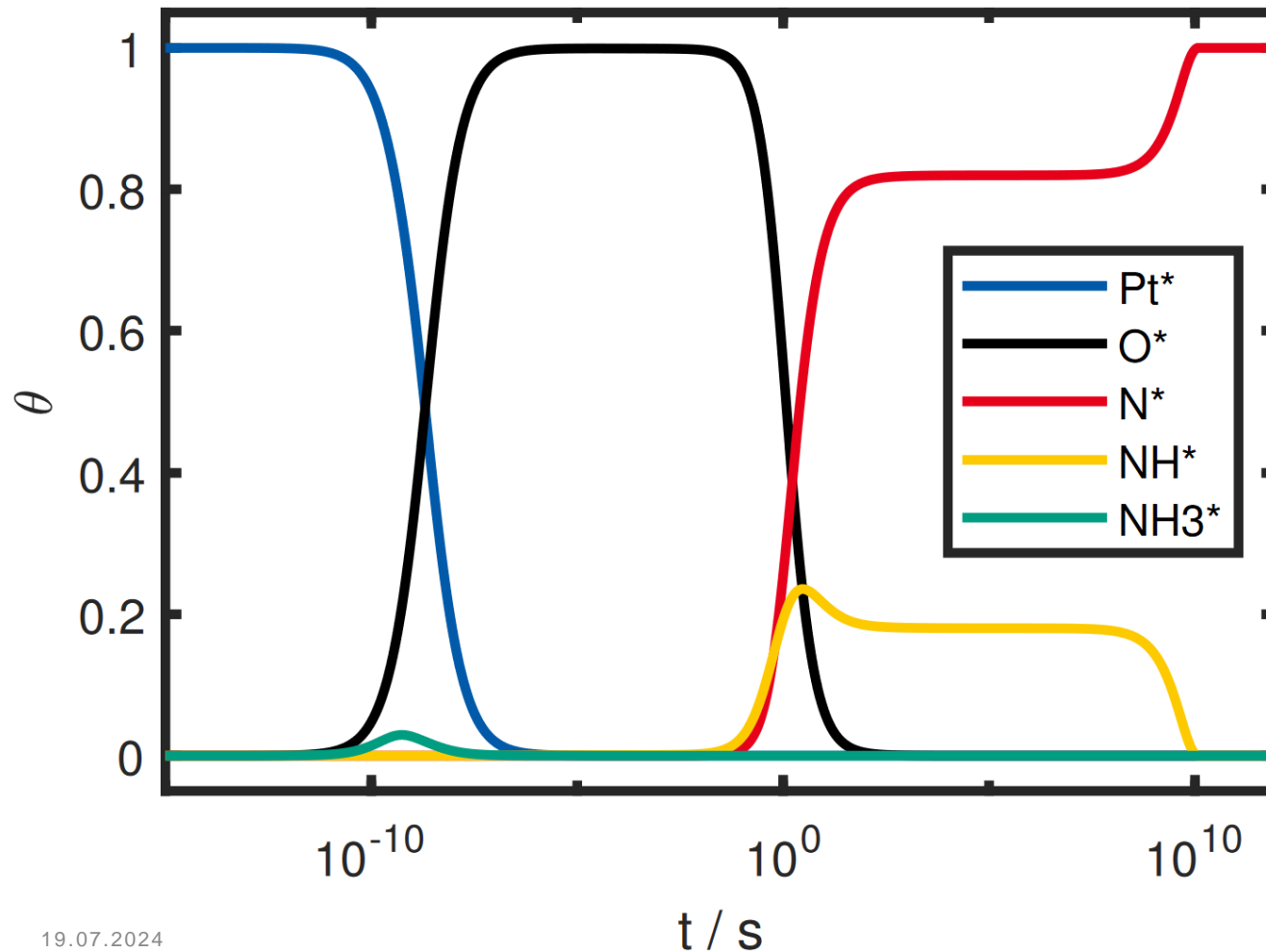
„Scales of atmospheric motion“  
Florida State University - Neil O'Brien'

# Real life problems are multi scale



Chemical Engineering Research and Design 184 (2022) 39–58

# Solving microkinetics is slow



Chemical Engineering Science, 250, 117408

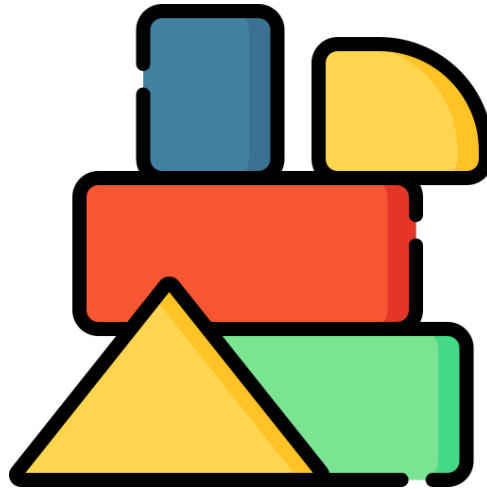
- 70-90%<sup>[1]</sup>
- ~ 90%<sup>[2]</sup>
- > 99%<sup>[3]</sup>

[1] Bracconi, M., et al. (2017), AIChE Journal, 63(1), 95–104.

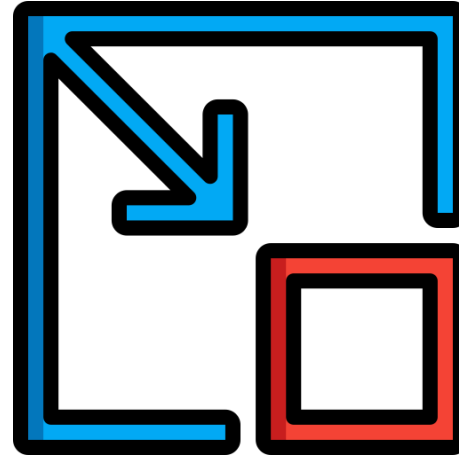
[2] Nikitin, V. F., et al. (2021), Acta Astronautica, 194, 376–382.

[3] Brown, T. S., et al. (2021), In Lecture Notes in Computer Science:  
Vol. 12761 LNCS (pp. 23–39)

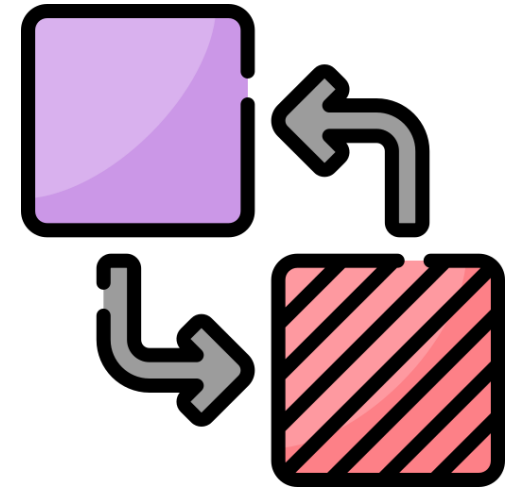
# Speed-up strategies



Simplify



Reduce<sup>[1,2]</sup>



Replace

# Types of surrogates

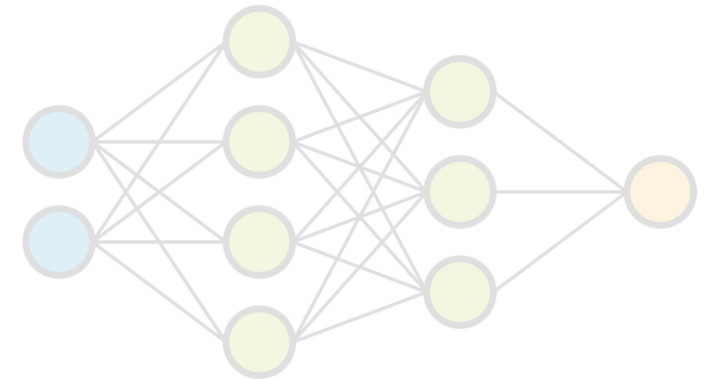
Splines<sup>[1-5]</sup>

up to 7 parameters<sup>[6]</sup>

Random Forests<sup>[7,8]</sup>

Neural Networks

# Physics?



[1] Chemical Engineering Science 2009, 64, 1384–1389.

[2] Catalysis Today 2010, 151, 271–277.

[3] Applied Catalysis B: Environmental 2012, 111-112, 445–455.

[4] Computers & Chemical Engineering 2016, 88, 126–134.

[5] AIChE Journal 2017, 63, 87–94.

[6] Computers & Chemical Engineering 2017, 98, 21–30.

[7] Computers & Chemical Engineering 2018, 115, 286–294.

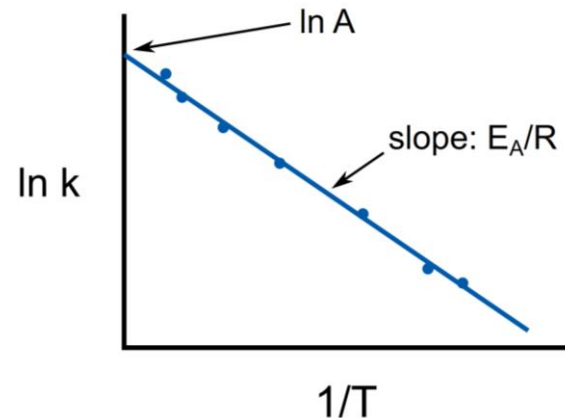
[8] Chemical Engineering Journal 2020, 400, 125469..

# Arrhenius & mass action law

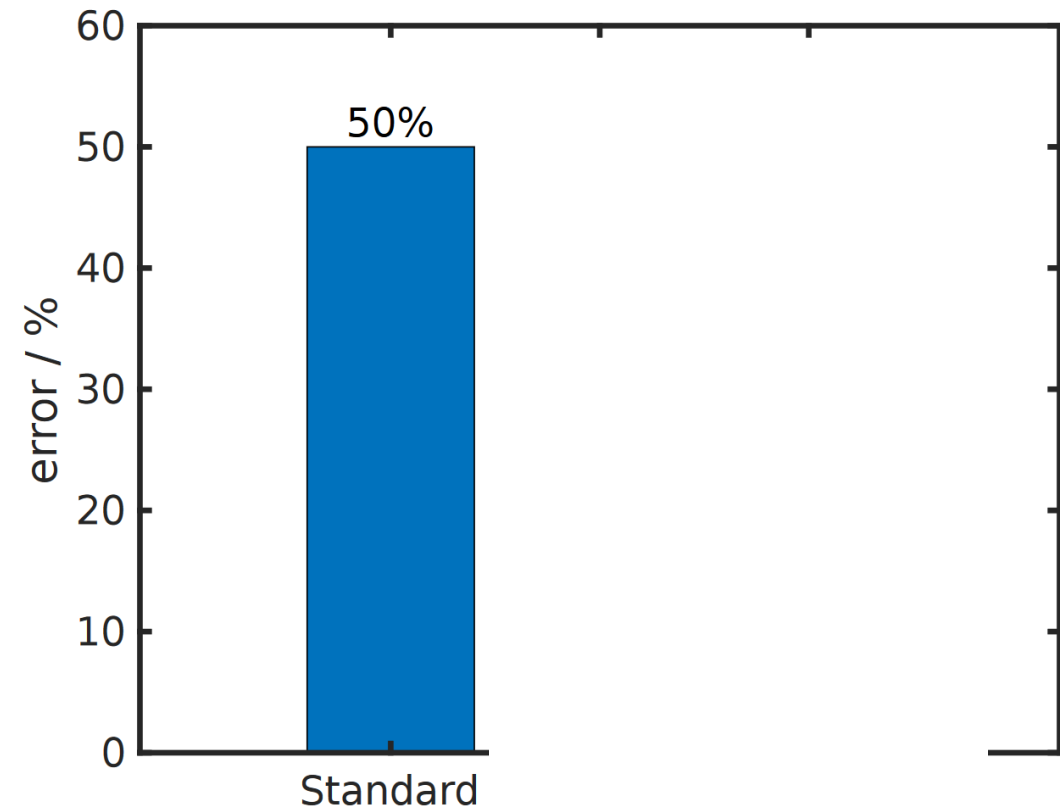
$$r = k_0 \cdot \exp\left(-\frac{E_A}{R T}\right) \cdot \prod_{i \in \text{reac.}} a_i^{-\nu_{i,j}}$$

$$\ln r = \ln k_0 - \frac{E_A}{R} \cdot \frac{1}{T} - \sum_{i \in \text{reac.}} \ln a_i$$

$$\begin{aligned} \dot{S} &= r_{\text{ads}} - r_{\text{des}} \\ &= r_{\text{RDS}}^+ - r_{\text{RDS}}^- \end{aligned}$$

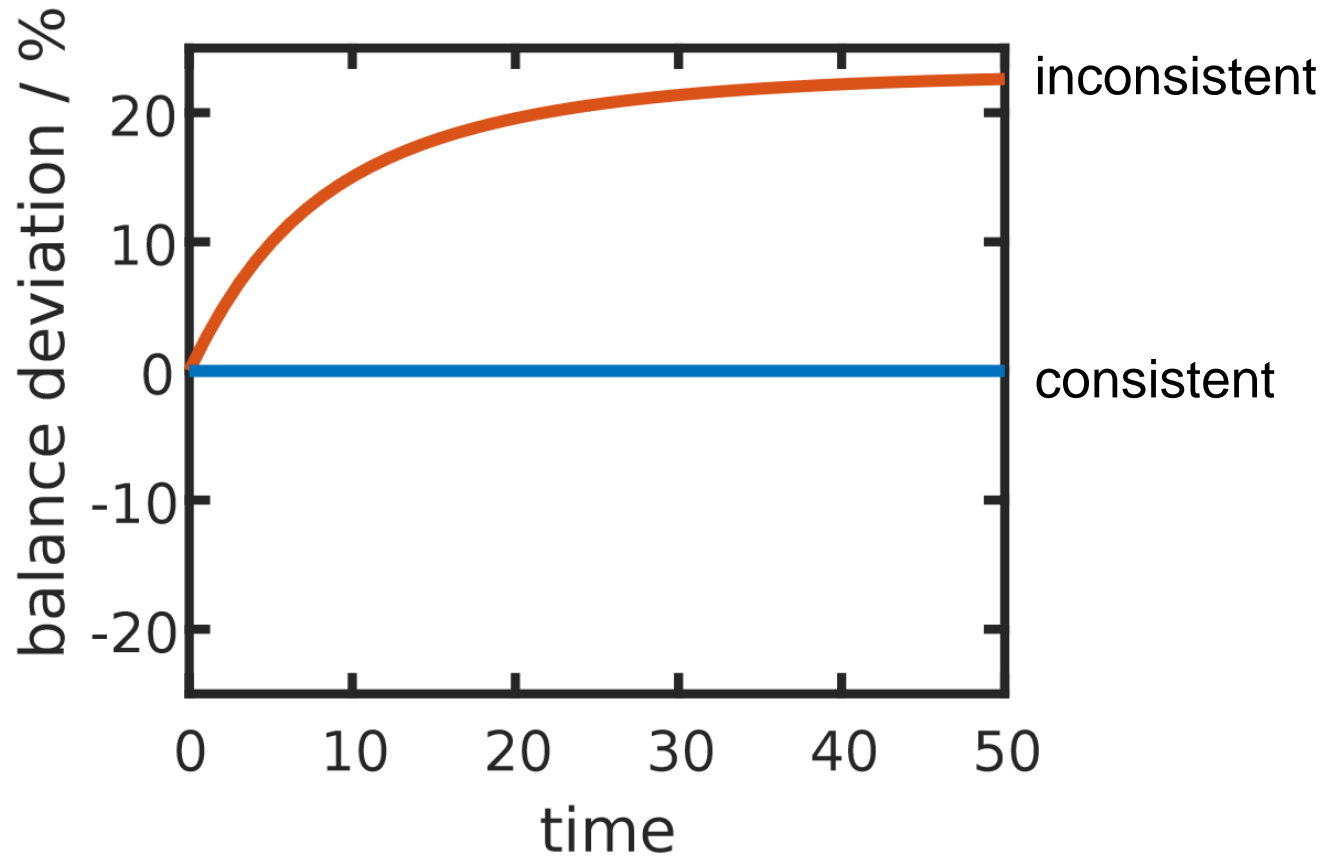


Preferential oxidation of CO on Pt<sup>[1,2]</sup>



Döppel and Votsmeier, Chem. Eng. Sci. 2022, 262, 117964

# Atom balance

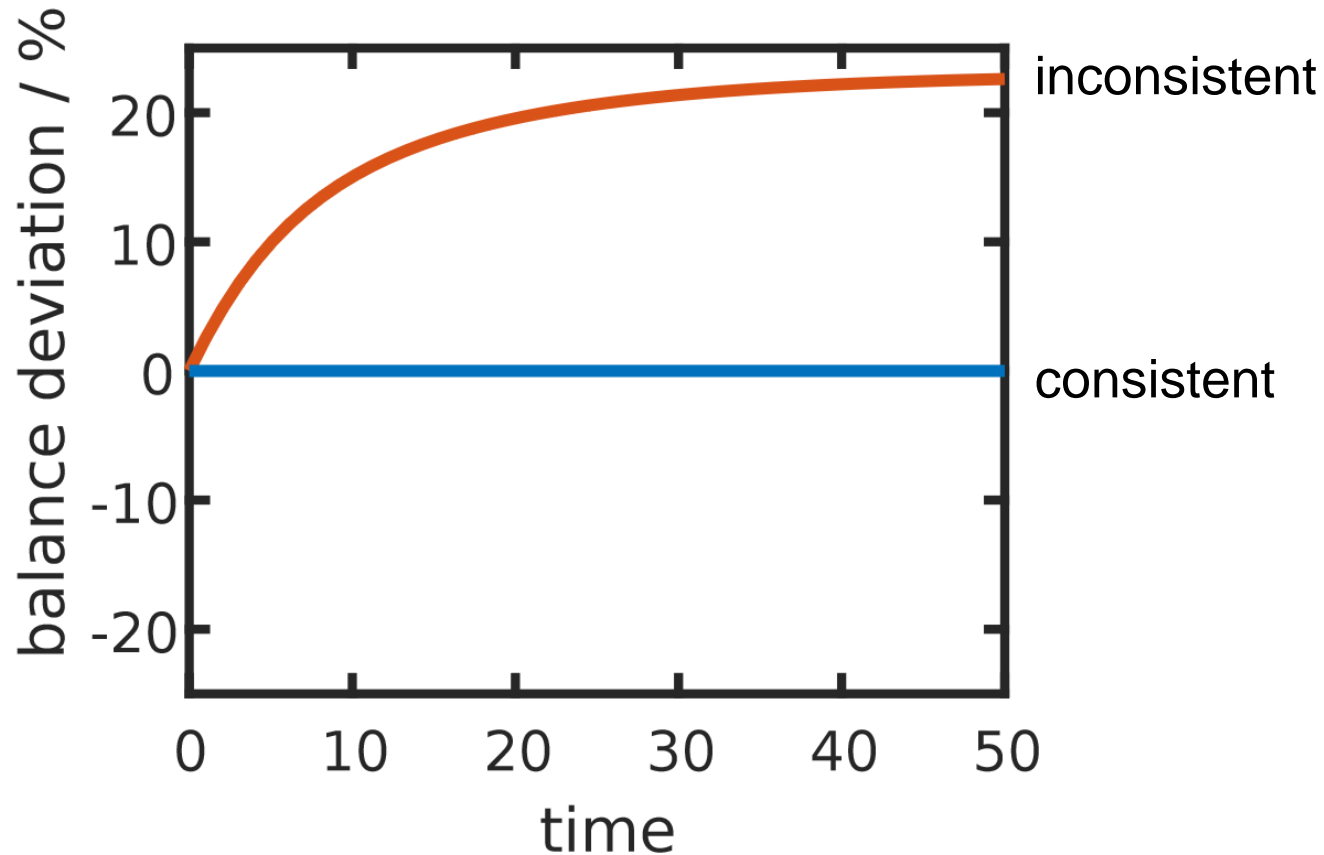


Via key species:  
5 species  
– 3 elements  
= 2 unknowns

Döppel and Votsmeier, Proceedings of the Combustion institute, 2024, in production



# Atom balance



Via global reactions:

$$R_{\text{CO-ox}} = \dots$$

$$R_{\text{H}_2\text{-ox}} = \dots$$

$$R_{\text{WGS}} = \dots$$

$$\dot{s} = \sum_j v_{i,j} R_j$$

Döppel and Votsmeier, Proceedings of the Combustion institute, 2024, in production



# Thermodynamics

De Donder relation<sup>[1]</sup>

$$r_{\text{eff}} = r^+ - r^-$$
$$= r^+ \cdot \left( 1 - \frac{\prod_i a_i^{v_{i,j}}}{K_{\text{eq}}} \right)$$

- Fewer rates to model
- Progress towards correct equilibrium

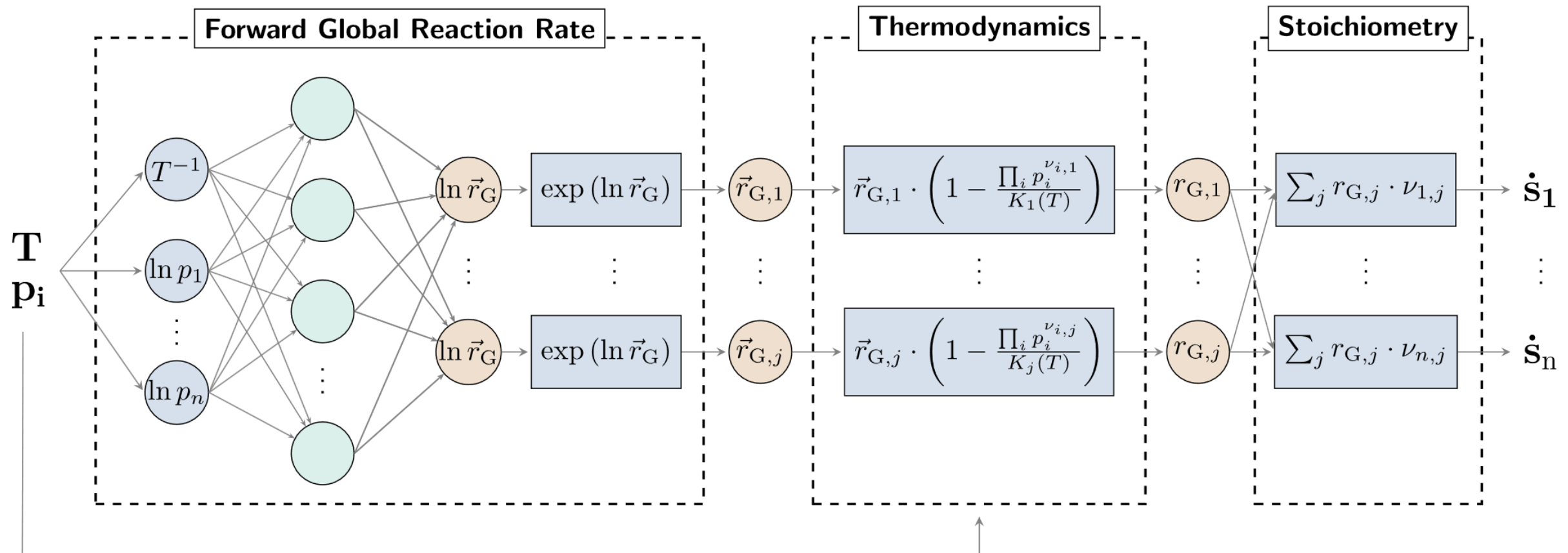


# Physics checklist

- ✓ Arrhenius law
- ✓ Law of mass action
- ✓ Atom balance
- ✓ Thermodynamics
- Butler-Volmer expression?
- Charge balance?
- Symmetry?



# Global Reaction Neural Network



Kircher, Döppel, and Votsmeier, Chem. Eng. J., 2024, 485, 149863



# Applications

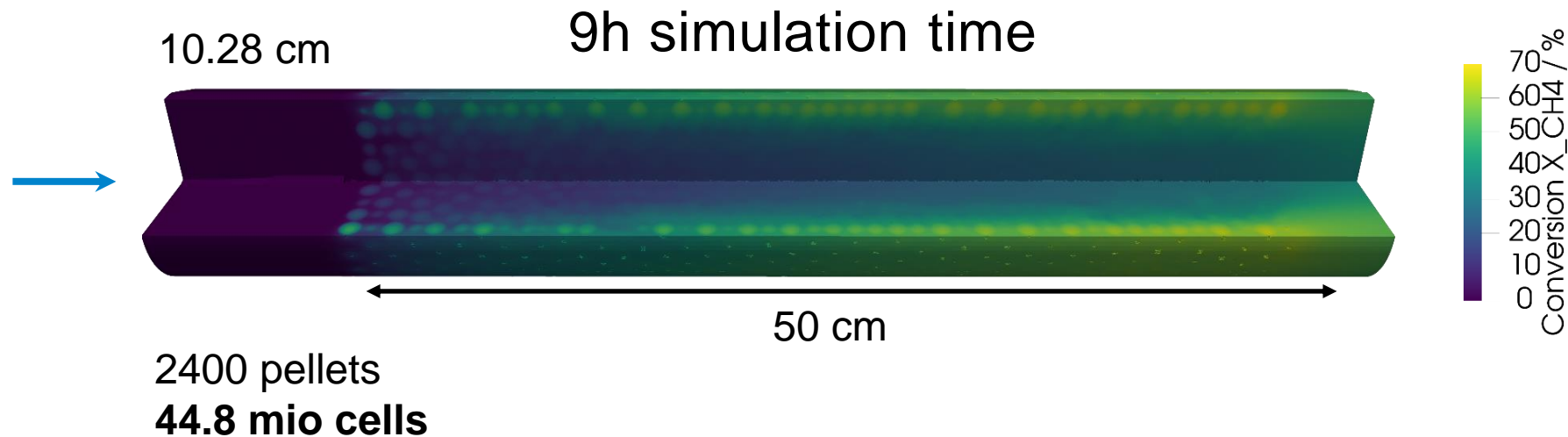
- Preferential oxidation of CO on Pt<sup>[1]</sup>
- Methane steam reforming on Rh<sup>[1]</sup>
- Methanol synthesis on Cu/Zn<sup>[2]</sup>
- Ammonia synthesis on Ru<sup>[3]</sup>
- Methane non-oxidative coupling over single atom Fe/SiO<sub>2</sub><sup>[3]</sup>

# Reactor Simulation Packed Bed Steam Reforming

Biermann, Uglietti, Döppel, Kircher, Votsmeier, Braconi, Maestri, Manuscript in preparation

Catalytic Foam<sup>[1]</sup> Interface 

- 2D validation: 120x speed-up
- 3D simulation:

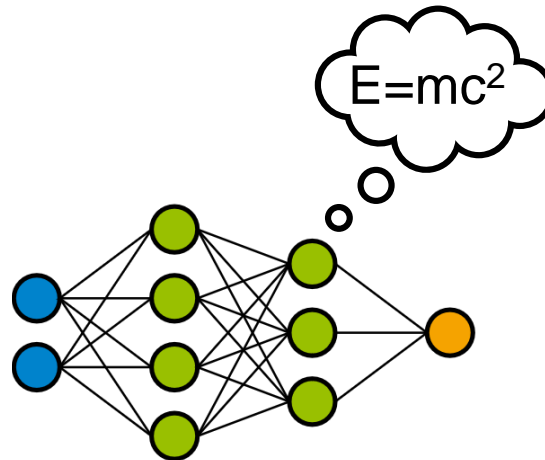
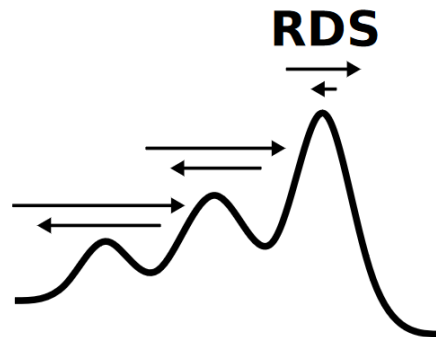




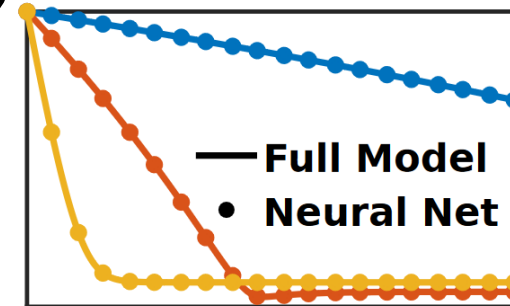
# Summary

- Machine learning surrogates enable detailed reactor simulations
- Embedding physics leads to reliable results

## Microkinetics



## Reactor Simulation

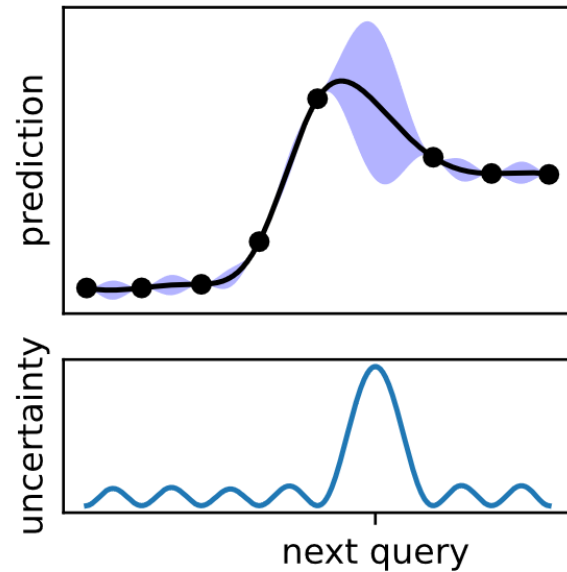


## Machine Learning

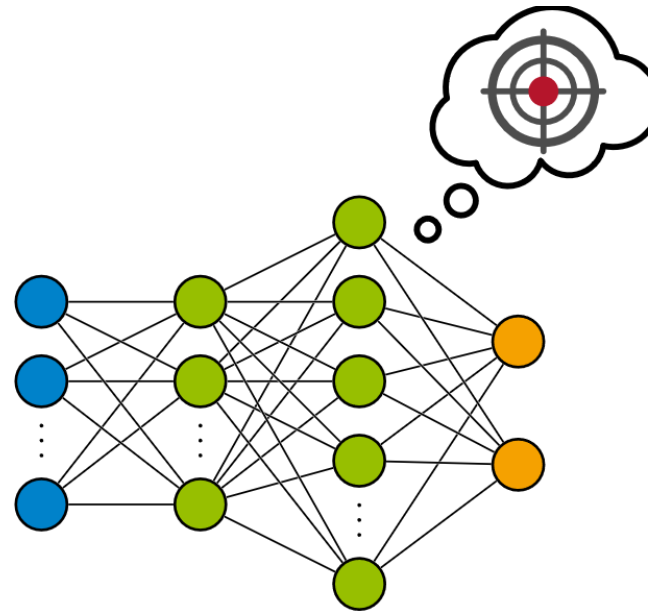


Scan for slides!

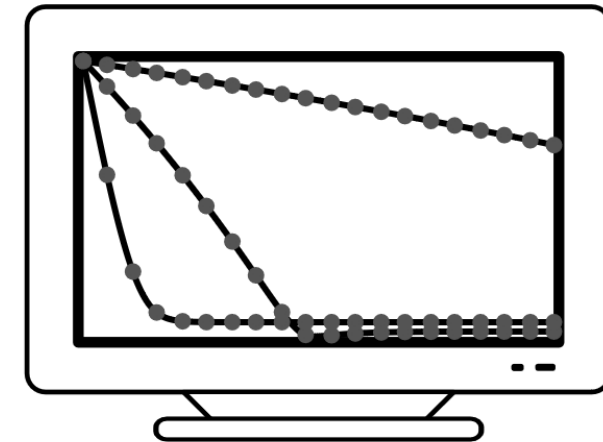
# Automated surrogates



automated training  
set design



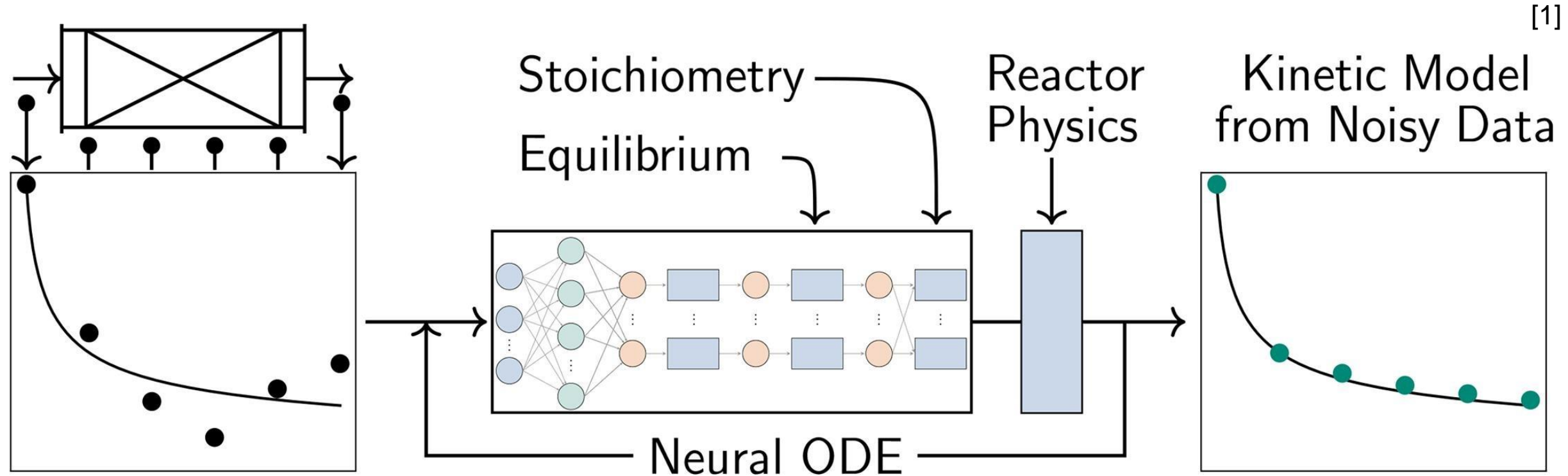
goal-oriented  
kernel model



fast & accurate  
reactor simulations

Döppel et al., Chem. Ing. Tech. 2024, 96, 6, 759-768

# Model discovery from integral data



- Methane steam reforming on Rh<sup>[1]</sup>
- Preferential oxidation of CO on Pt<sup>[2]</sup>
- CO<sub>2</sub> Fischer Tropsch<sup>[3]</sup>





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# Acknowledgements



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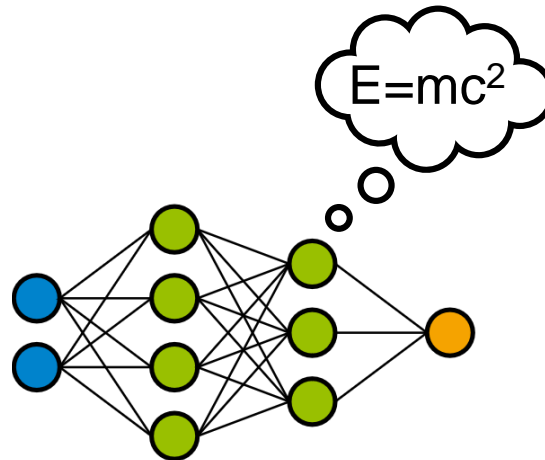
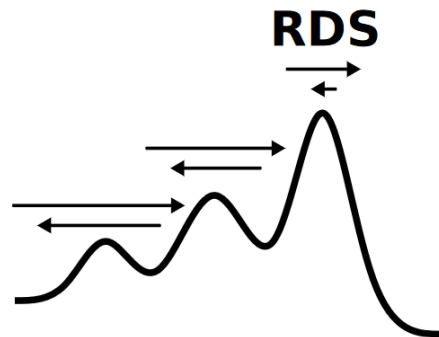


Prof. M. Bracconi

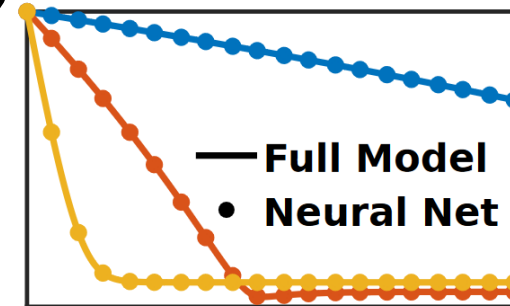
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## Microkinetics



## Reactor Simulation



## Machine Learning



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