流模型：计算物理视角

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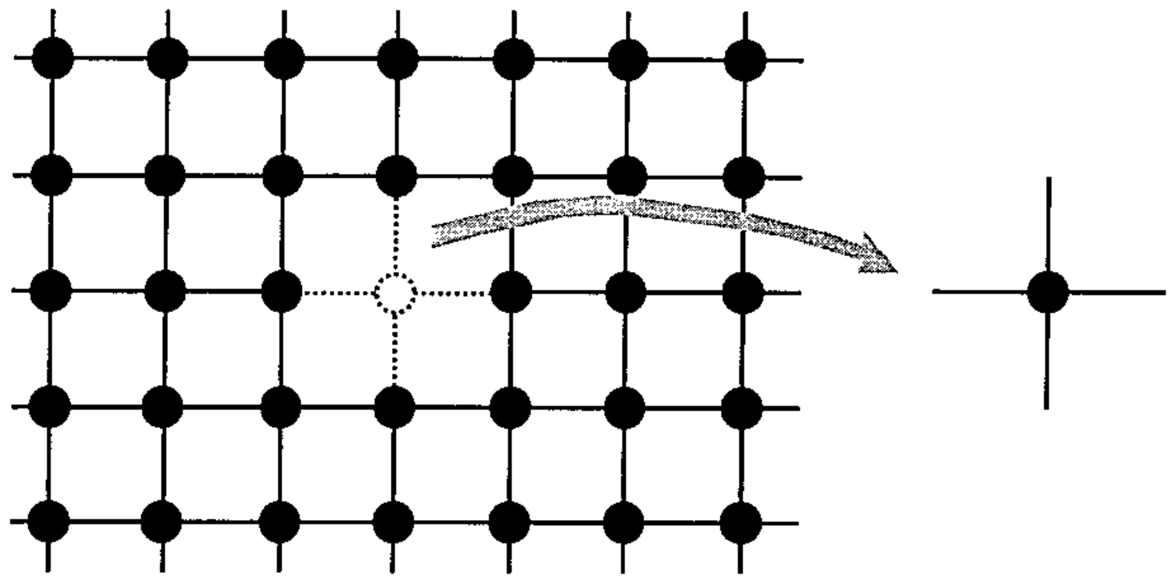
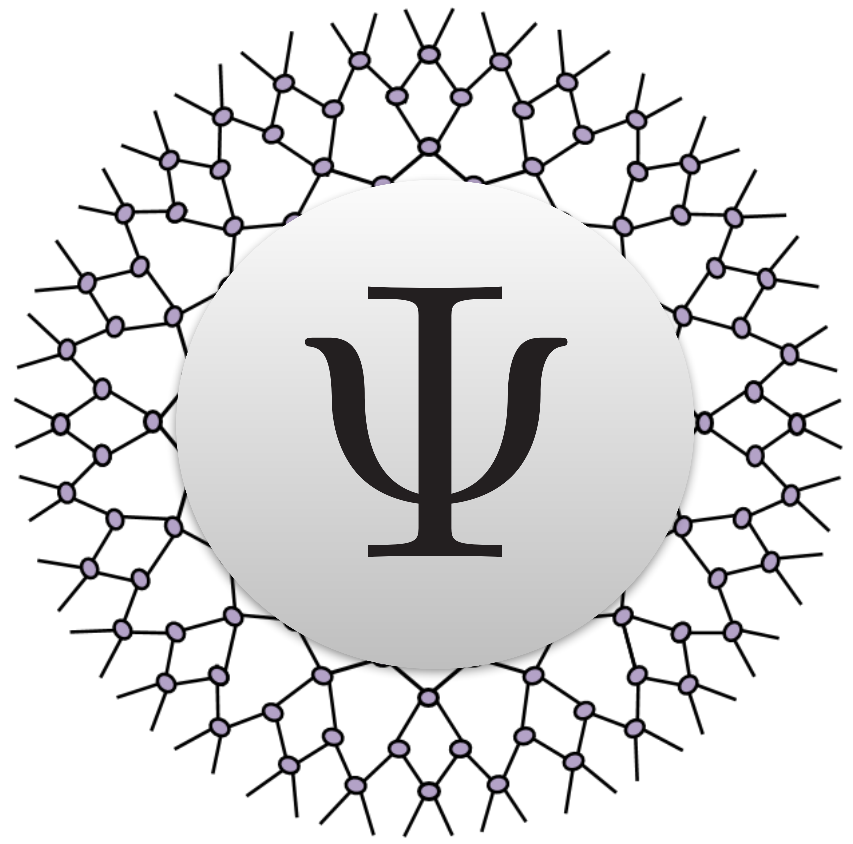
https://wangleiphy.github.io

Physicists' gifts to Machine Learning

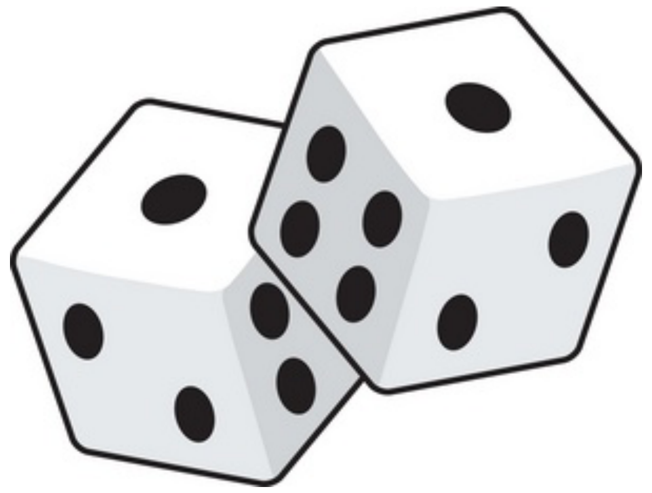
Mean Field Theory



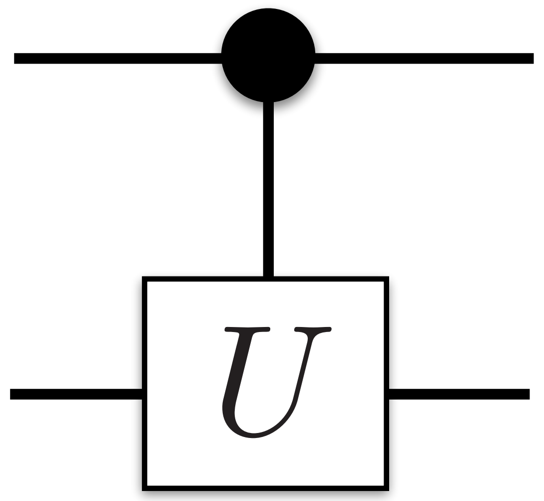
Tensor Networks



Monte Carlo Methods



Quantum Computing



Deep learning is more than fitting functions

Discriminative learning

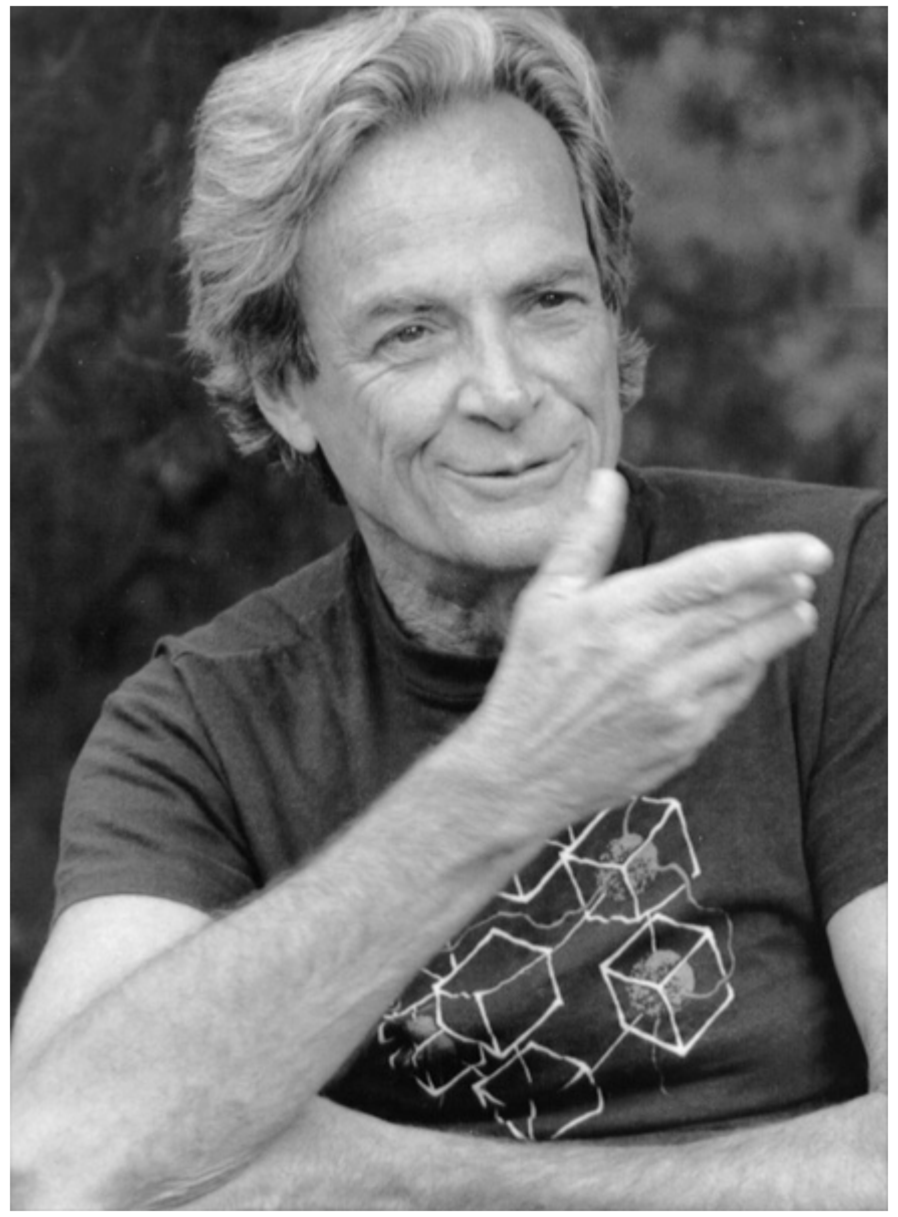
$$y = f(\boldsymbol{x})$$

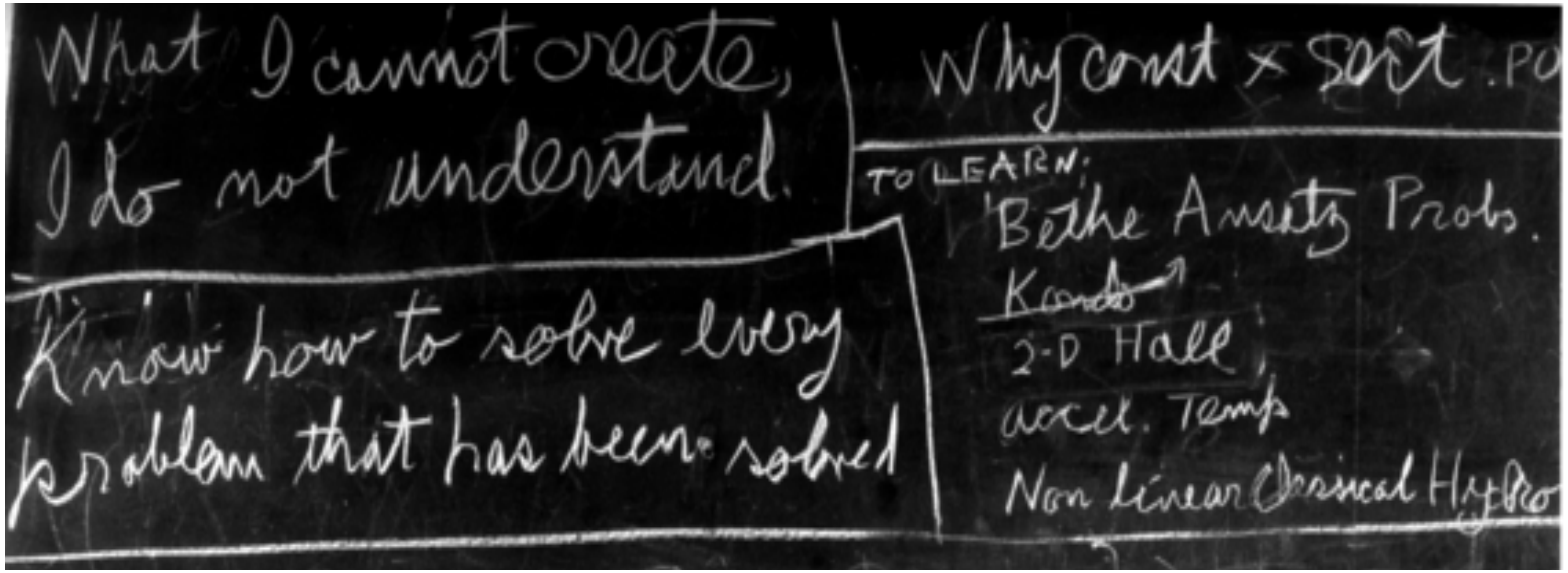
or $p(y|\boldsymbol{x})$

Generative learning

$$p(\boldsymbol{x}, y)$$

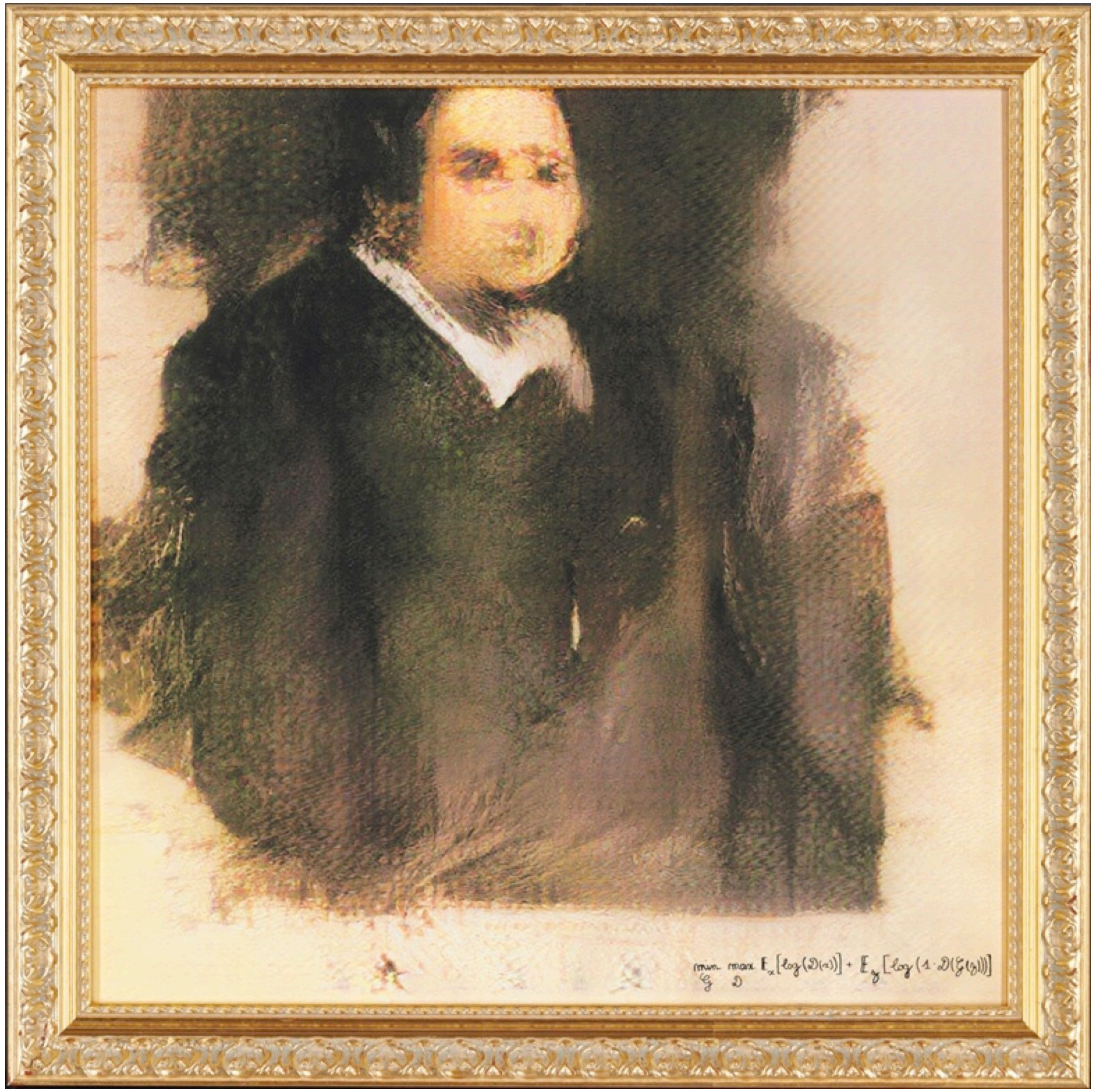
Deep learning is more than fitting functions





“What I can not create, I do not understand”

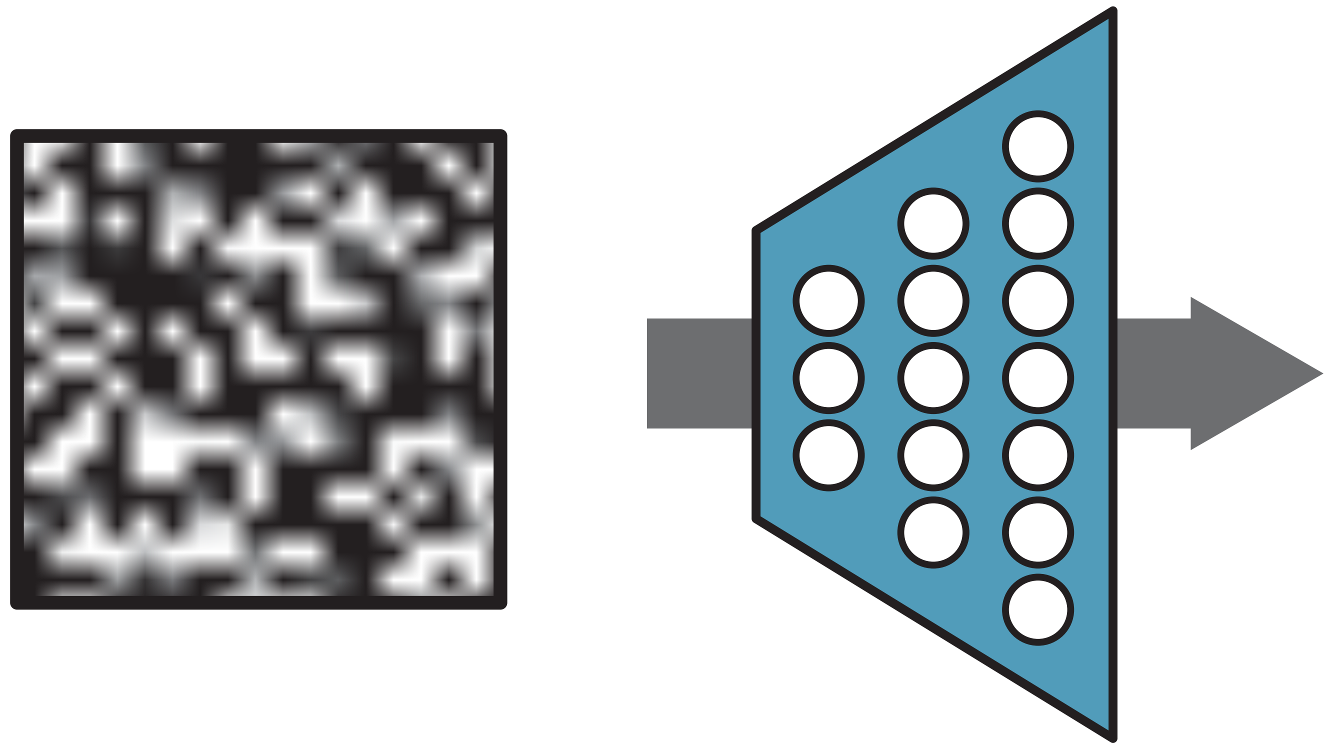
Generated Arts

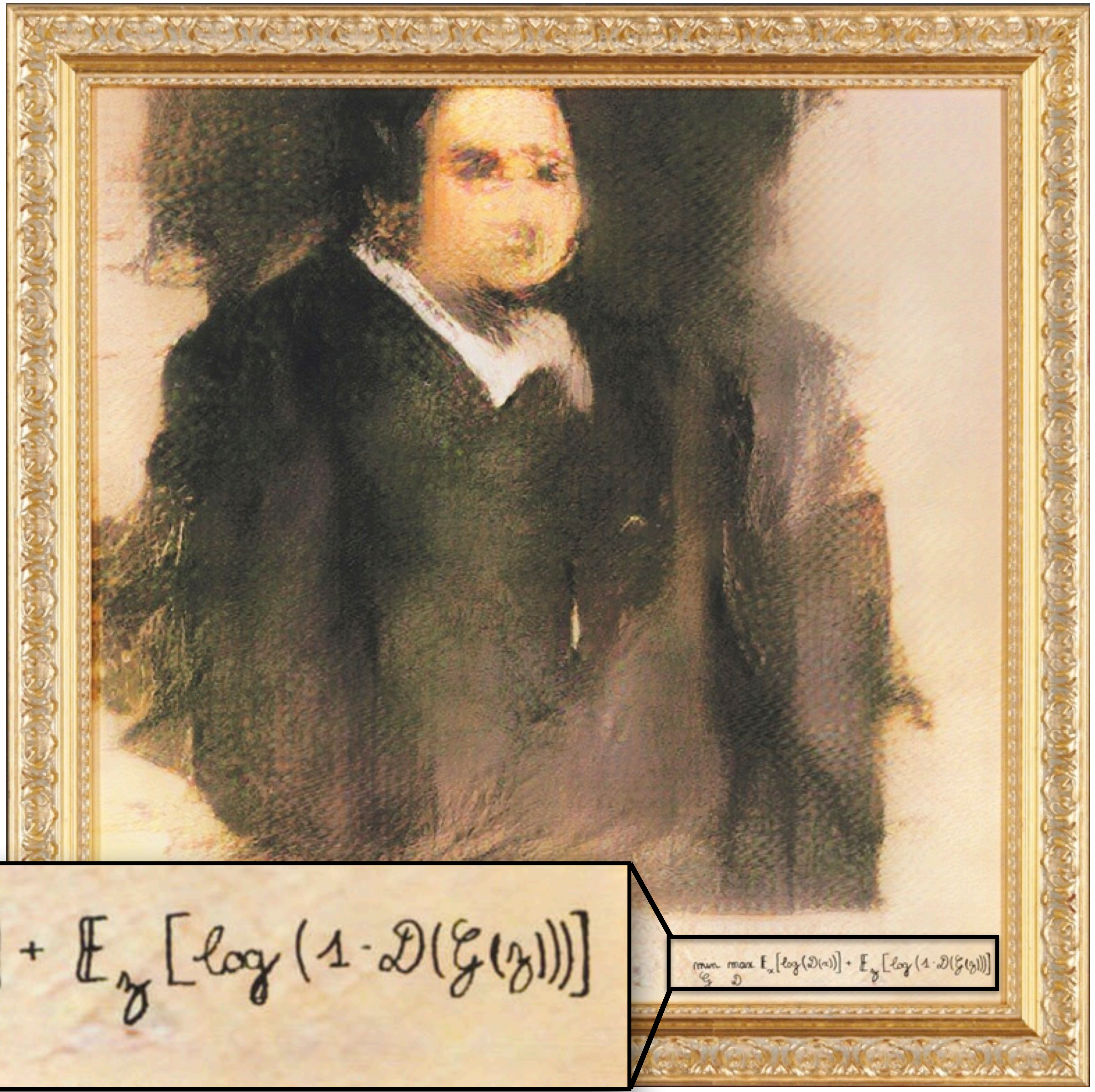


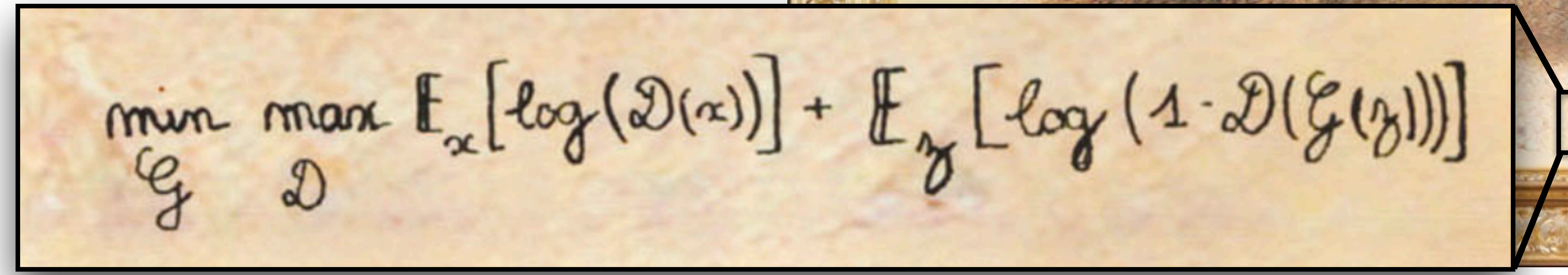
$432,500
25 October 2018
Christie's New York

https://www.christies.com/Features/A-collaboration-between-two-artists-one-human-one-a-machine-9332-1.aspx

Generated Arts





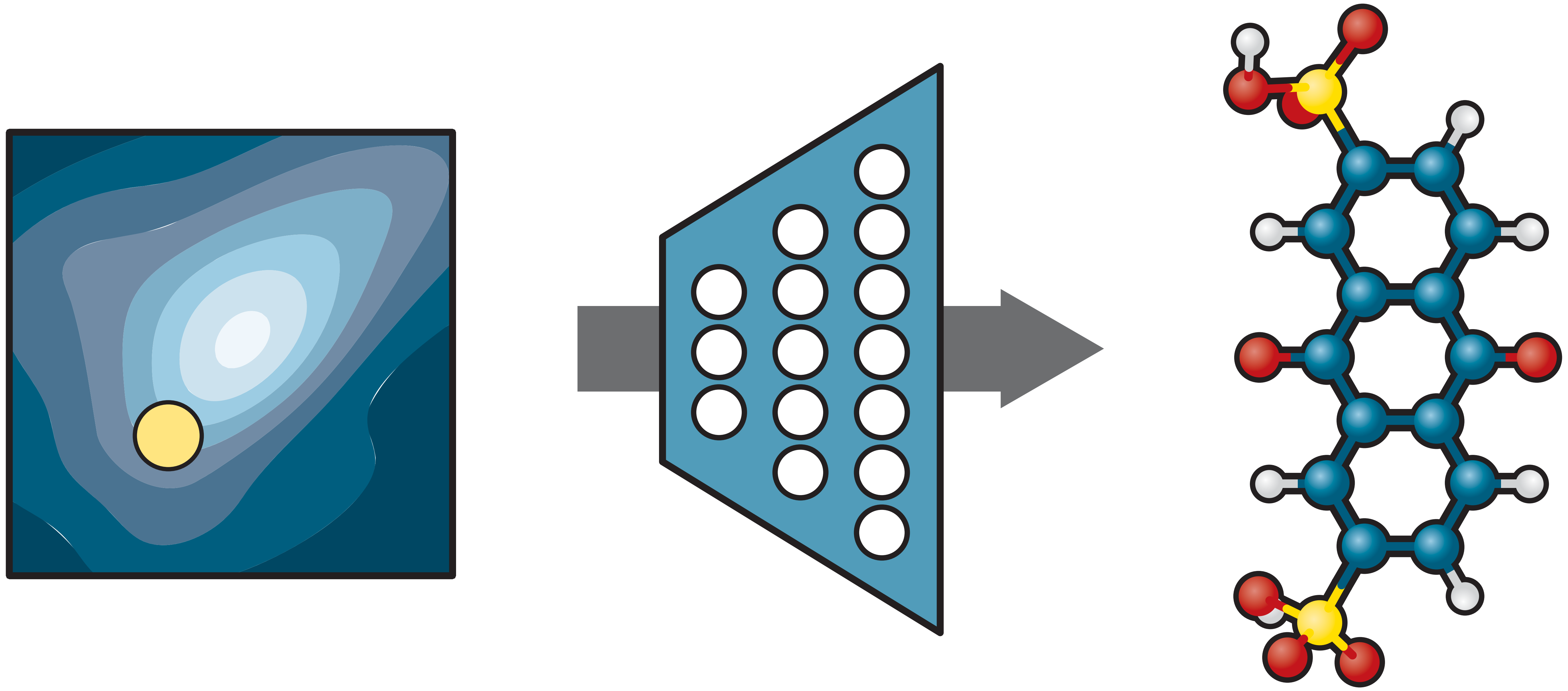


$432,500
25 October 2018
Christie's New York

https://www.christies.com/Features/A-collaboration-between-two-artists-one-human-one-a-machine-9332-1.aspx

Generating molecules

Latent attributes



Physical configurations

Math behind: Probability Transformation

Simple Distributions

Generate →

← Inference

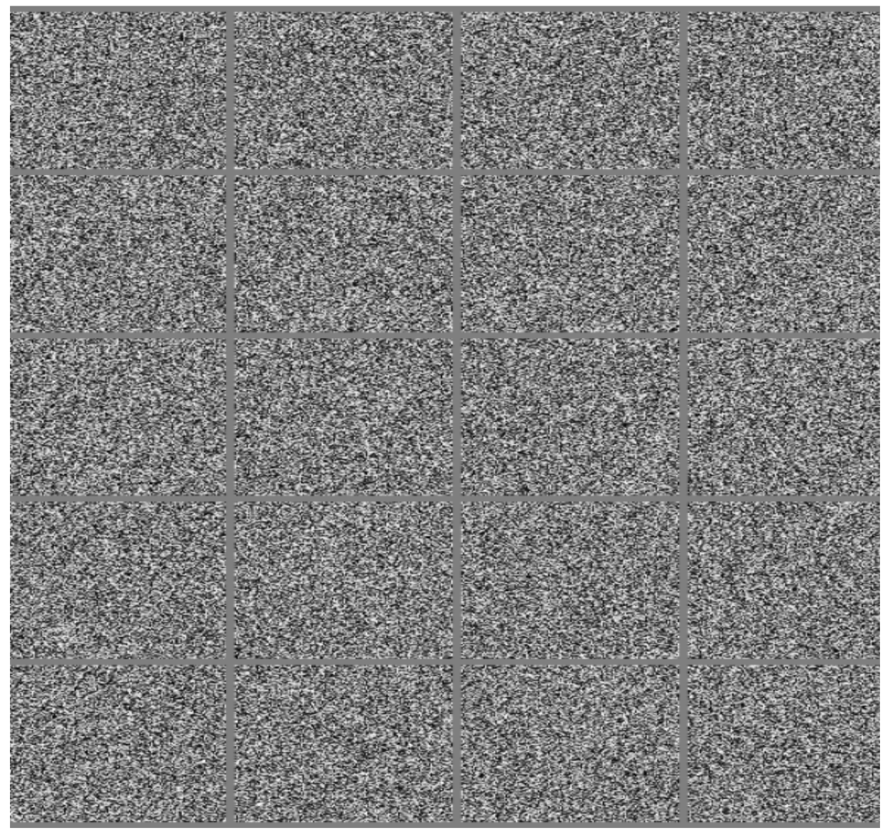
Complex Distribution

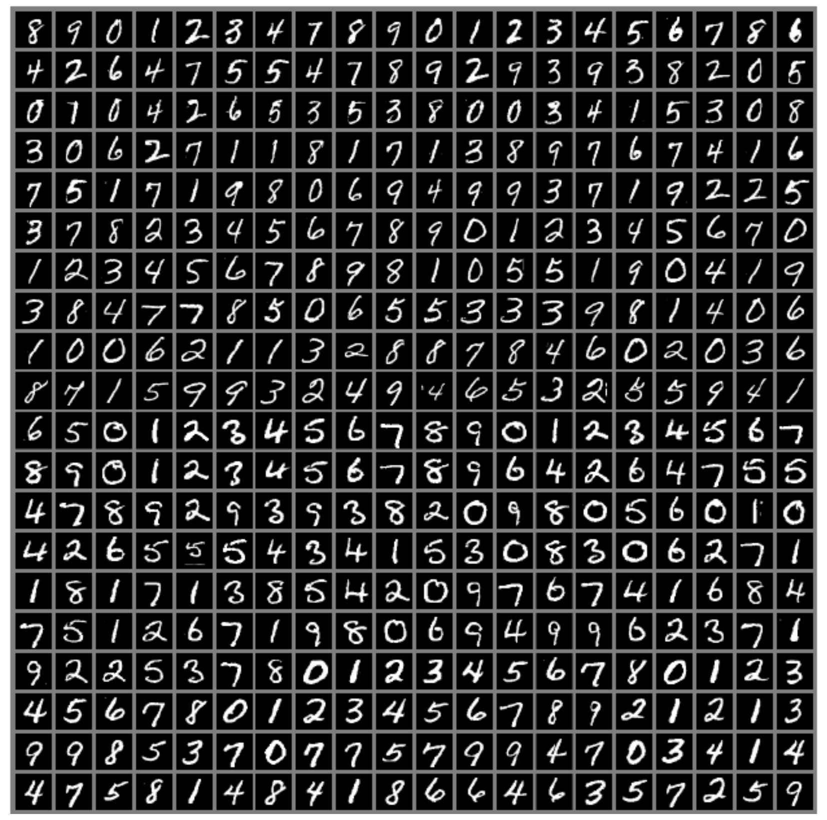
Sanchez-Lengeling & Aspuru-Guzik,
Inverse molecular design using machine learning:
Generative models for matter engineering, Science ‘18

Probabilistic Generative Modeling

$$p(\boldsymbol{x})$$

How to express, learn, and sample from a high-dimensional probability distribution ?



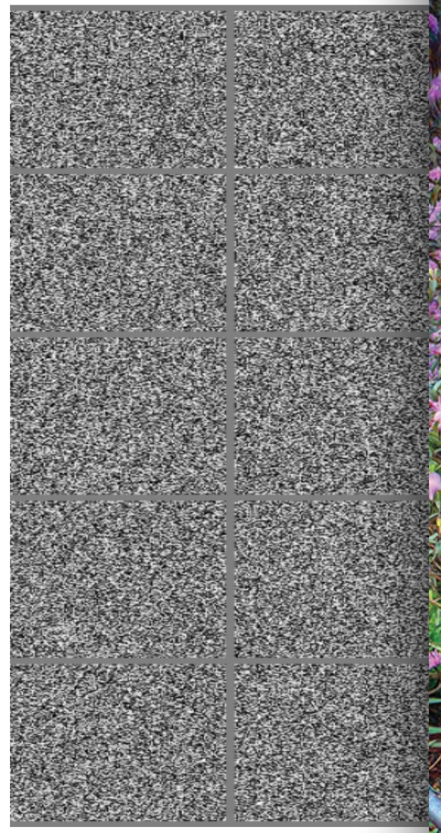


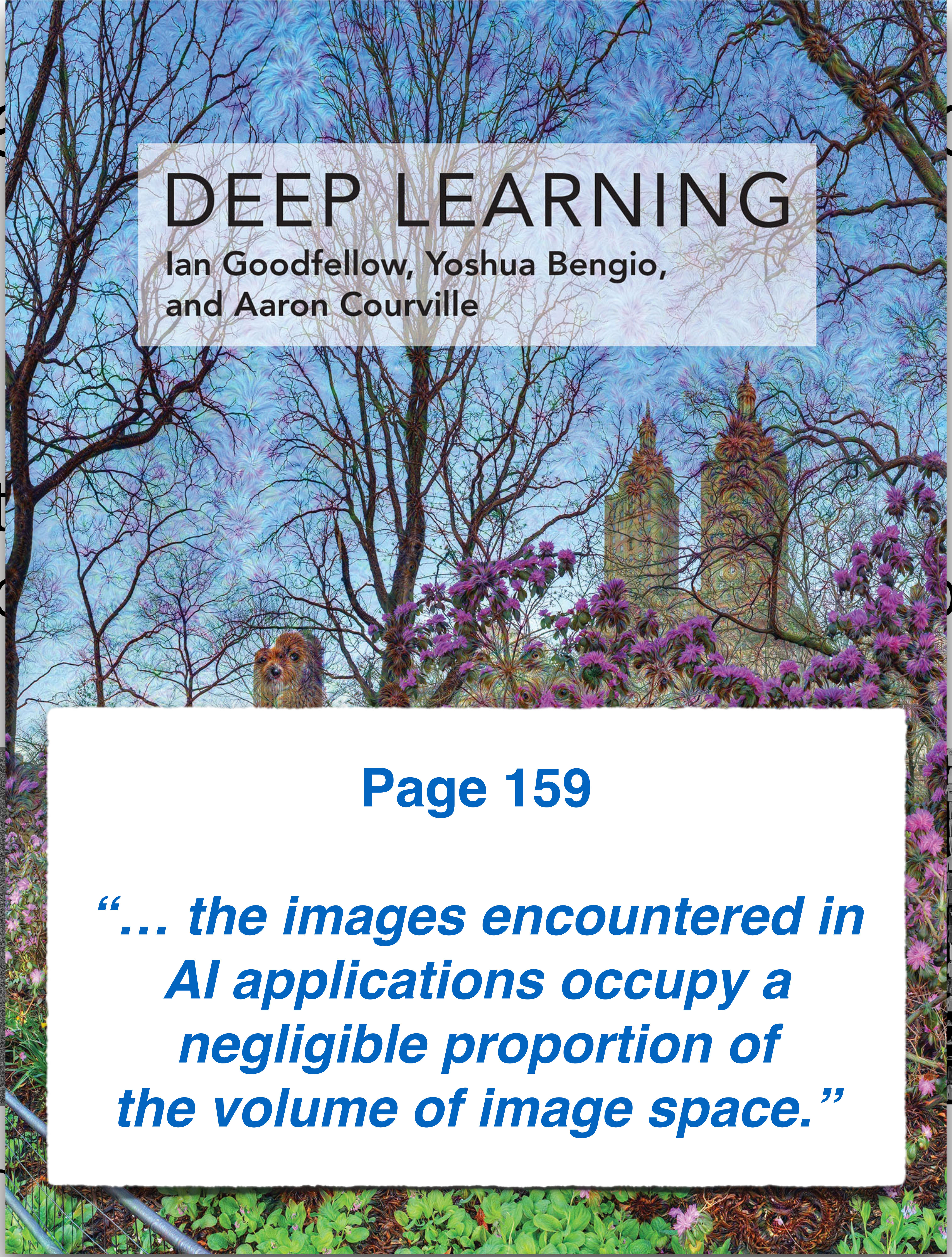
“random” images

“natural” images

Proba… odeling

How t… from a
high-… ution ?





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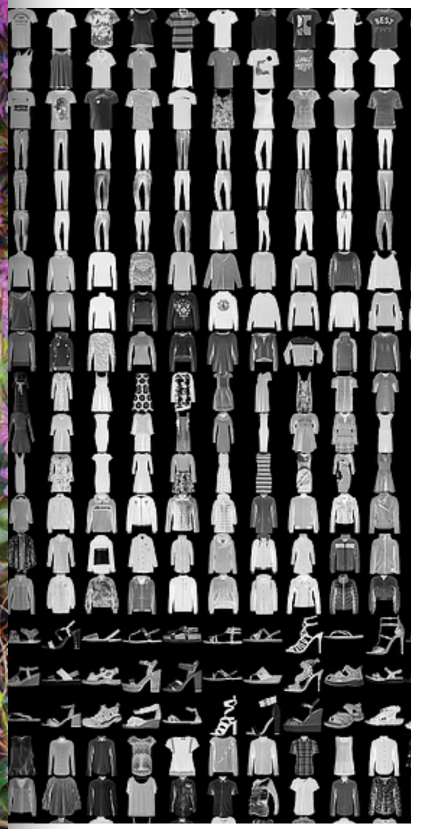
"… the images encountered in AI applications occupy a negligible proportion of the volume of image space."

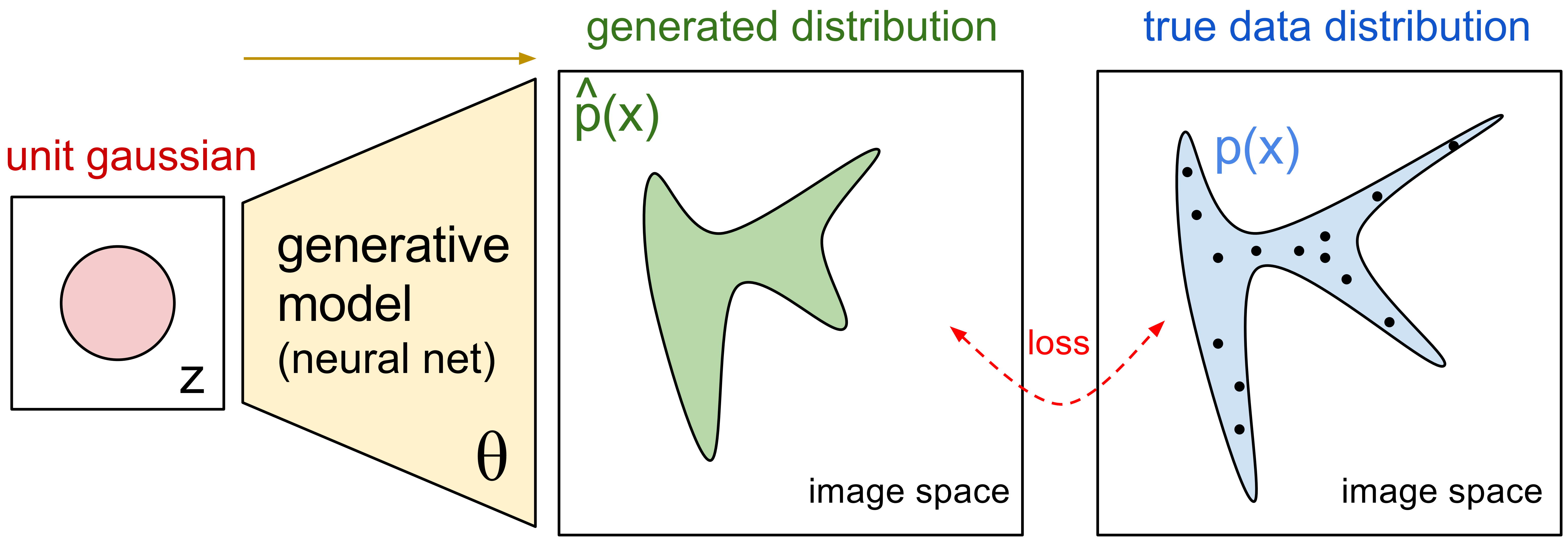


"random

Probabilistic Generative Modeling

$$p(\boldsymbol{x})$$

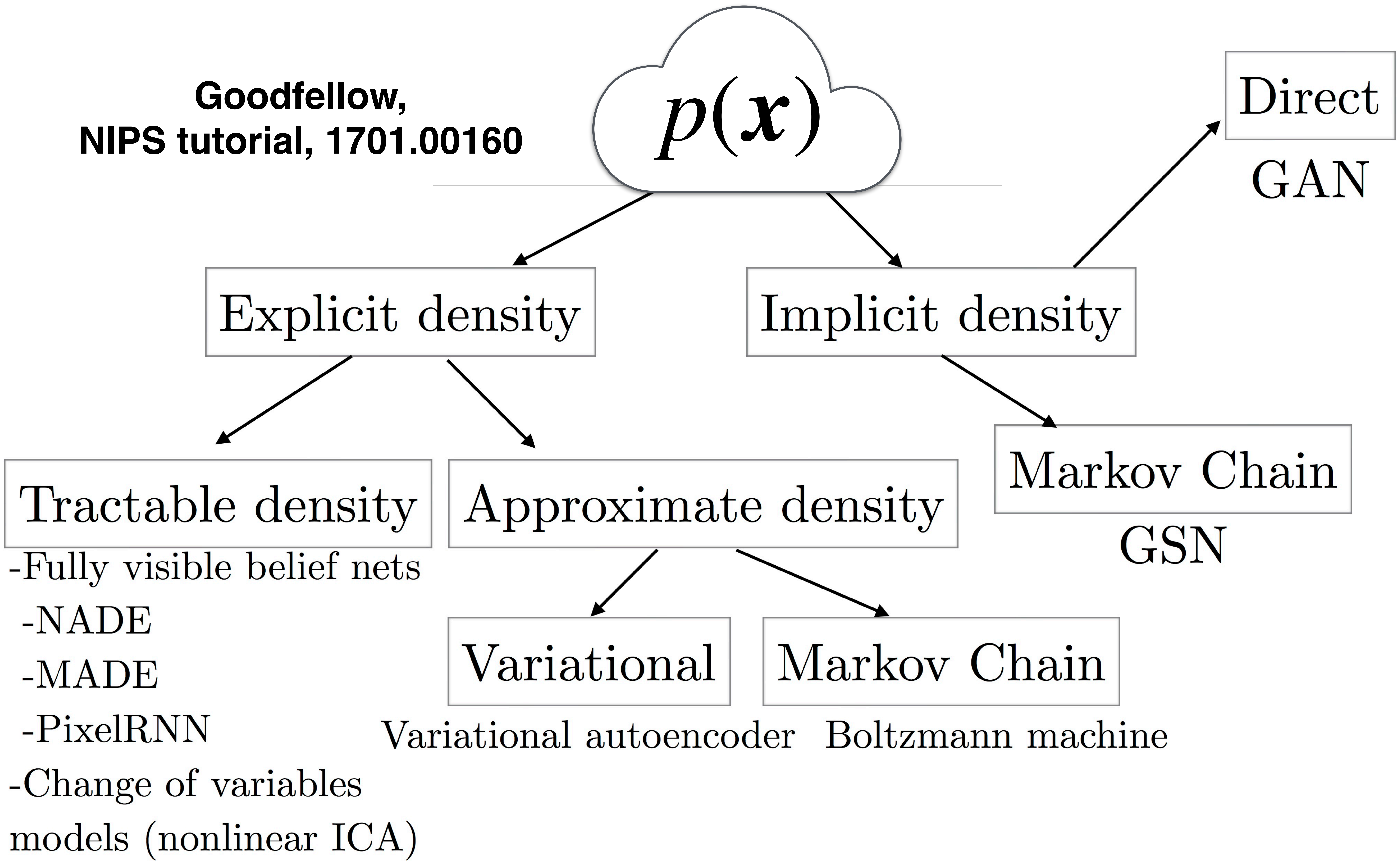
How to express, learn, and sample from a high-dimensional probability distribution ?



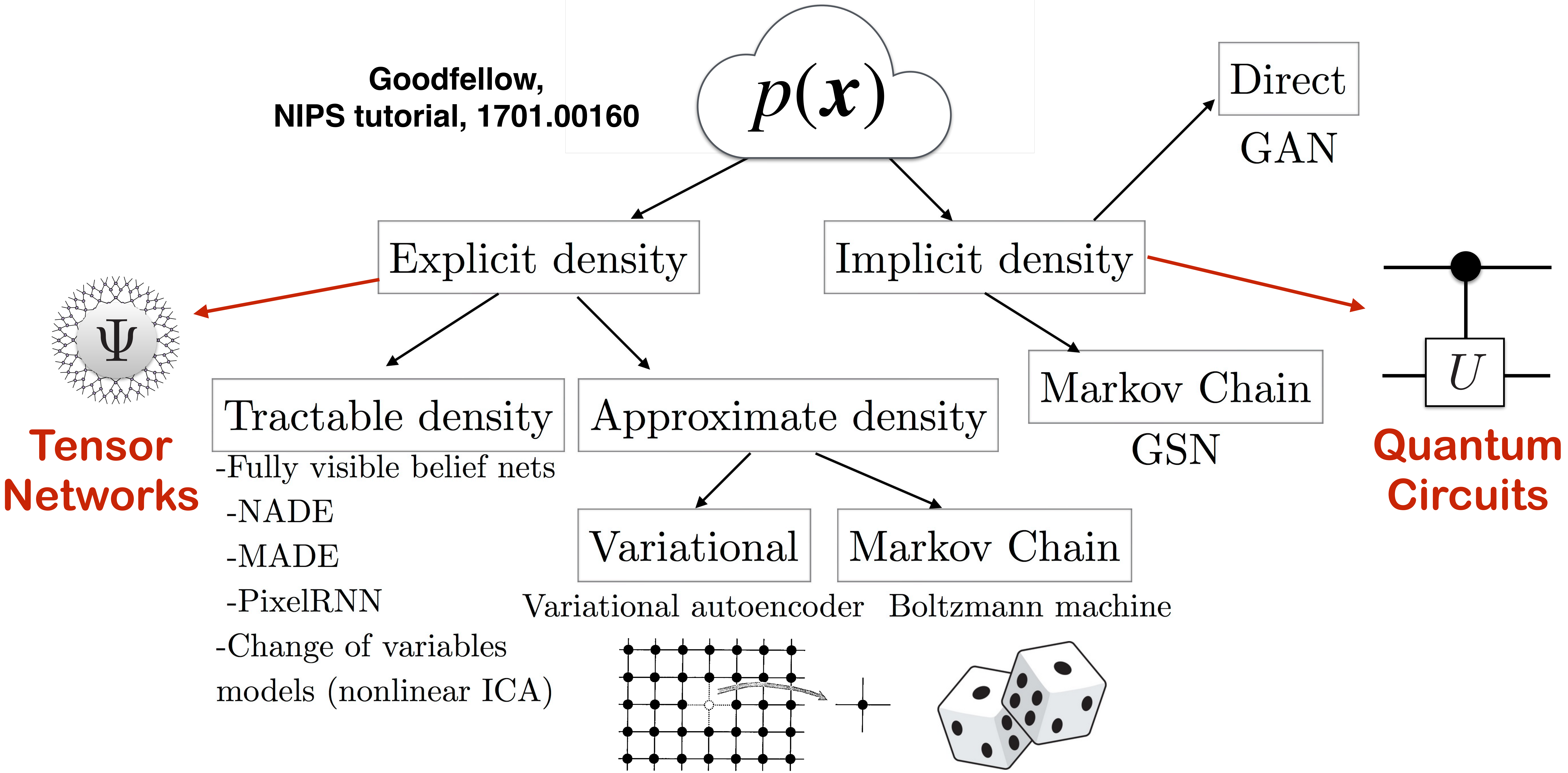
https://blog.openai.com/generative-models/

Physics genes of generative models

Goodfellow,
NIPS tutorial, 1701.00160



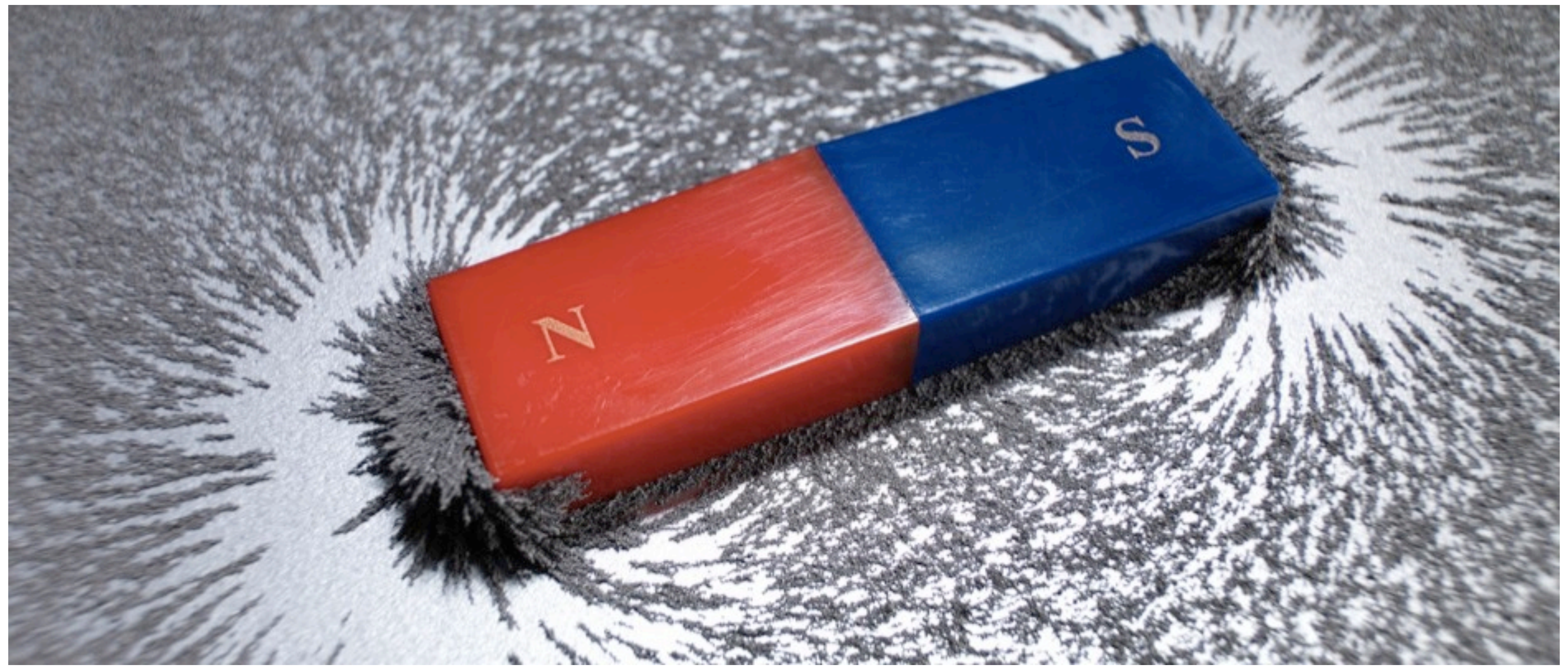
Physics genes of generative models



Generative modeling

Known: samples
Unknown: generating distribution

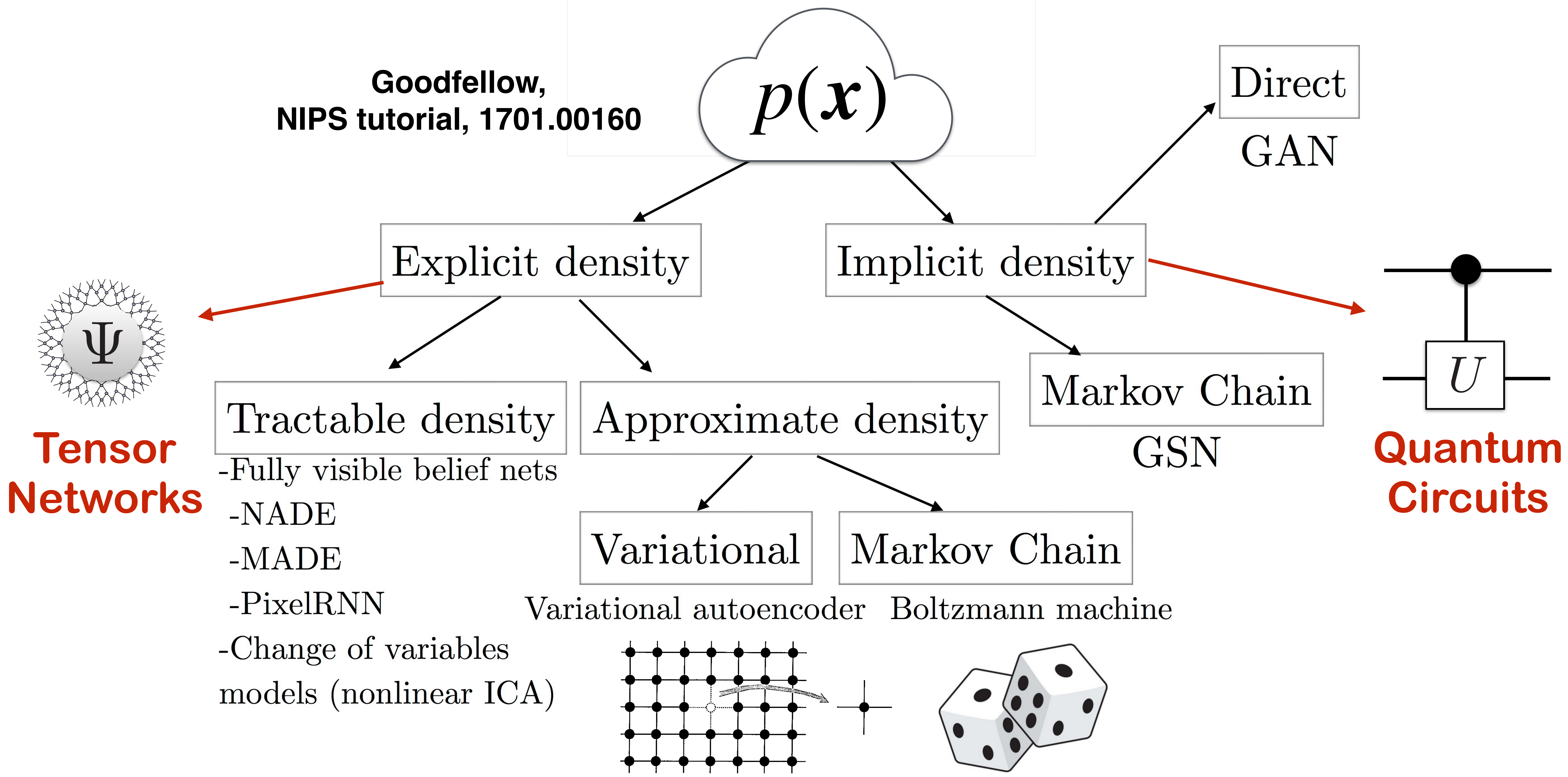
Physics



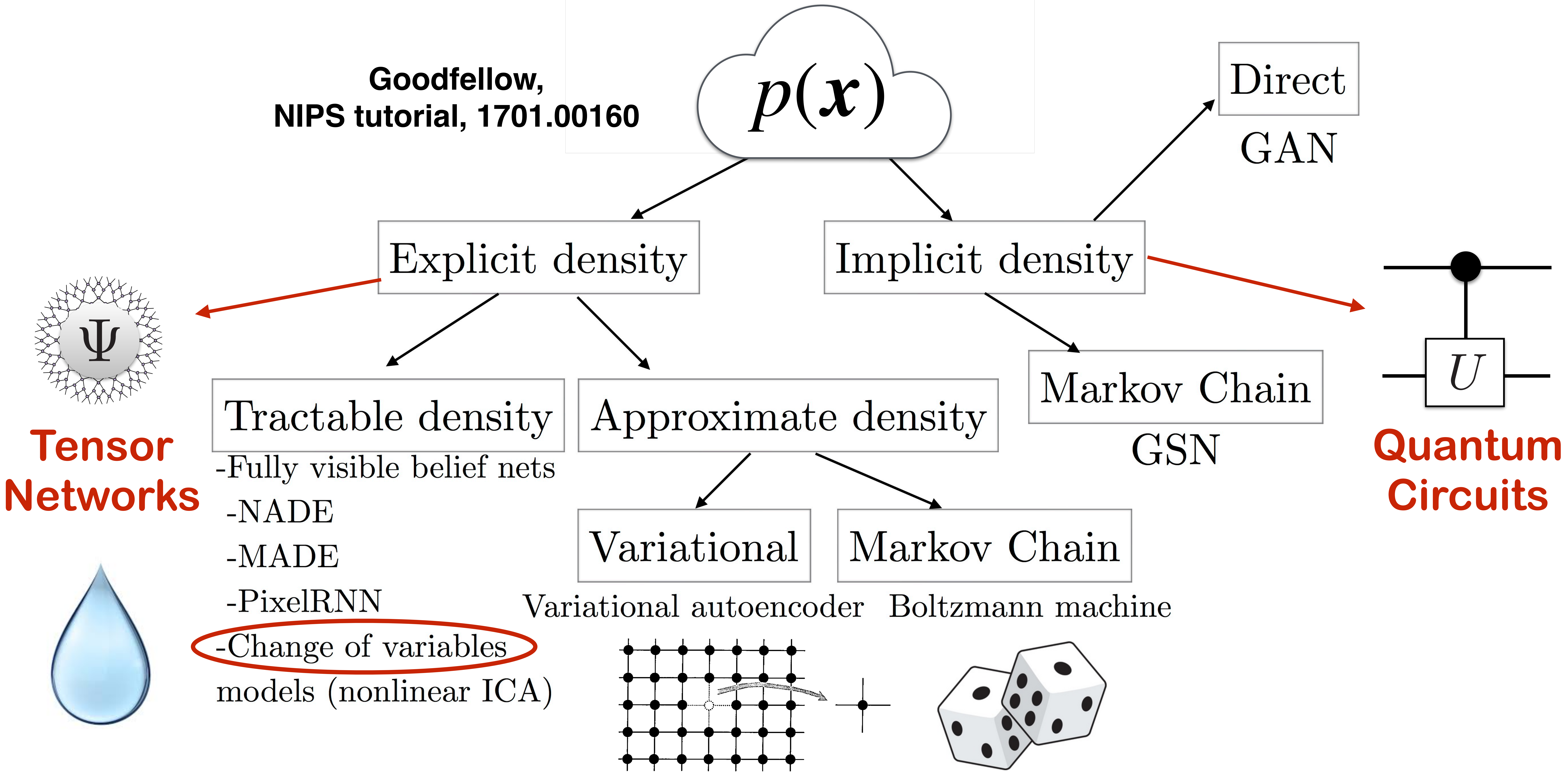
Known: energy function
Unknown: samples, partition function

Modern generative models for physics
Physics of and for generative modeling

Physics genes of generative models



Physics genes of generative models



Lecture Note http://wangleiphy.github.io/lectures/PILtutorial.pdf

Generative Models for Physicists

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Institute of Physics, Chinese Academy of Sciences
Beijing 100190, China

October 28, 2018

Abstract

Generative models generate unseen samples according to a learned joint probability distribution in the high-dimensional space. They find wide applications in density estimation, variational inference, representation learning and more. Deep generative models and associated techniques (such as differentiable programing and representation learning) are cutting-edge technologies physicists can learn from deep learning.

This note introduces the concept and principles of generative modeling, together with applications of modern generative models (autoregressive models, normalizing flows, variational autoencoders etc) as well as the old ones (Boltzmann machines) to physics problems. As a bonus, this note puts some emphasize on physics-inspired generative models which take insights from statistical, quantum, and fluid mechanics.

The latest version of the note is at http://wangleiphy.github.io/. Please send comments, suggestions and corrections to the email address in below.

CONTENTS

Generative modeling with normalizing flows

Wavenet 1609.03499 1711.10433

https://deepmind.com/blog/wavenet-generative-model-raw-audio/
https://deepmind.com/blog/high-fidelity-speech-synthesis-wavenet/

Glow 1807.03039

https://blog.openai.com/glow/

Generative modeling with normalizing flows

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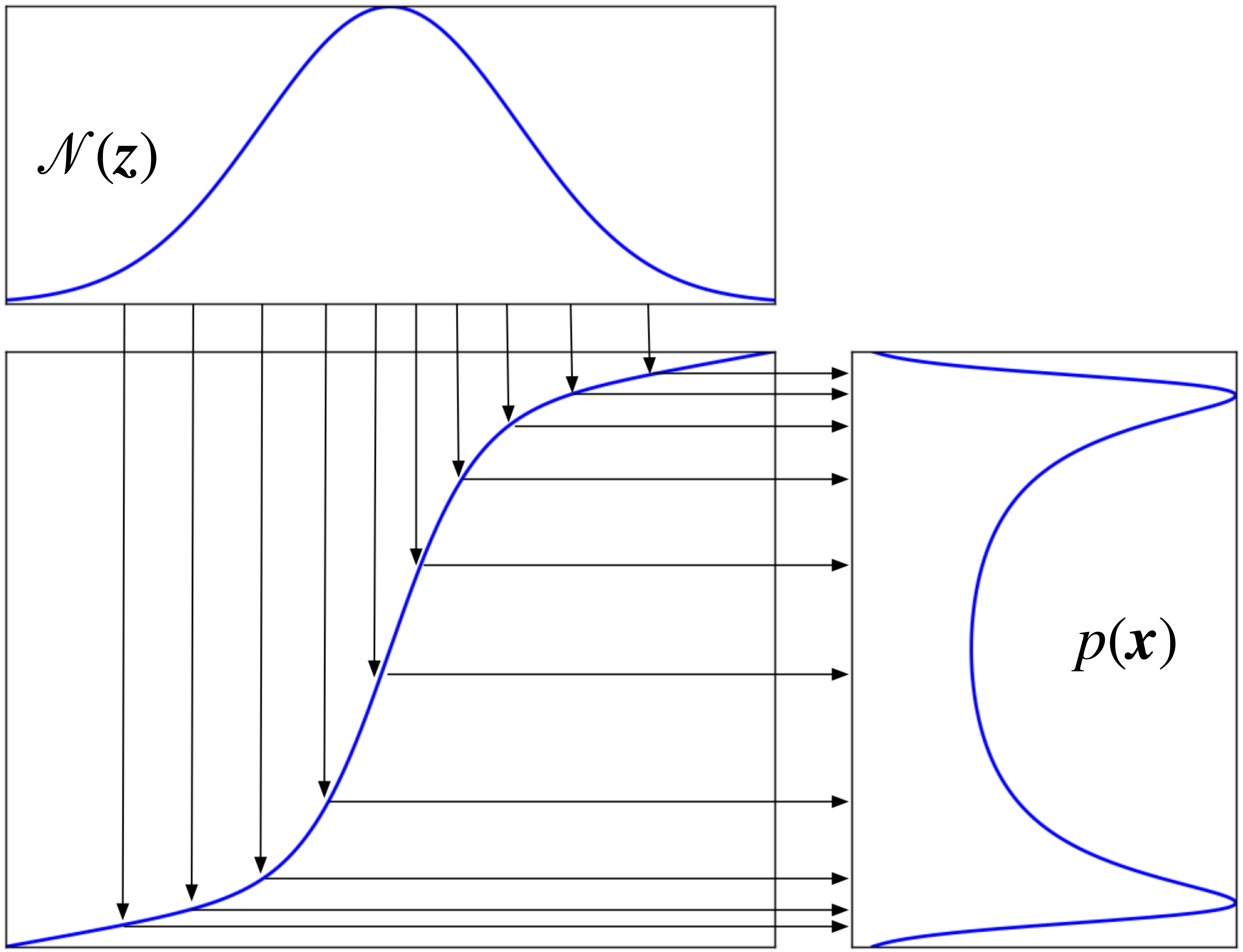
Glow 1807.03039

https://blog.openai.com/glow/

Normalizing flow in a nutshell

latent space



"neural net" with 1 neuron

physical space

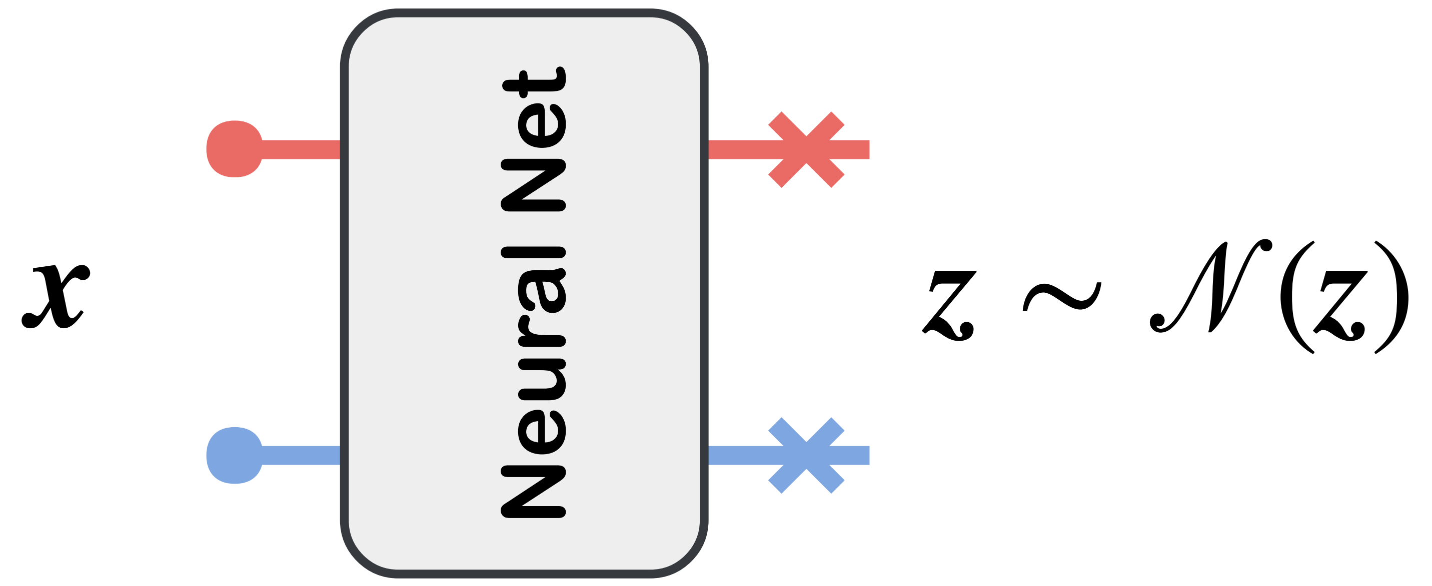
Normalizing Flows

Change of variables $x \leftrightarrow z$ **with deep neural nets**

$$p(\boldsymbol{x}) = \mathcal{N}(z) \left| \det \left(\frac{\partial z}{\partial \boldsymbol{x}} \right) \right|$$

Review article 1912.02762
Tutorial https://iclr.cc/virtual_2020/speaker_4.html

composable, differentiable, and invertible mapping between manifolds



Learn probability transformations with normalizing flows

Got this name in Tabak & Vanden-Eijnden, Commun. Math. Sci. '10

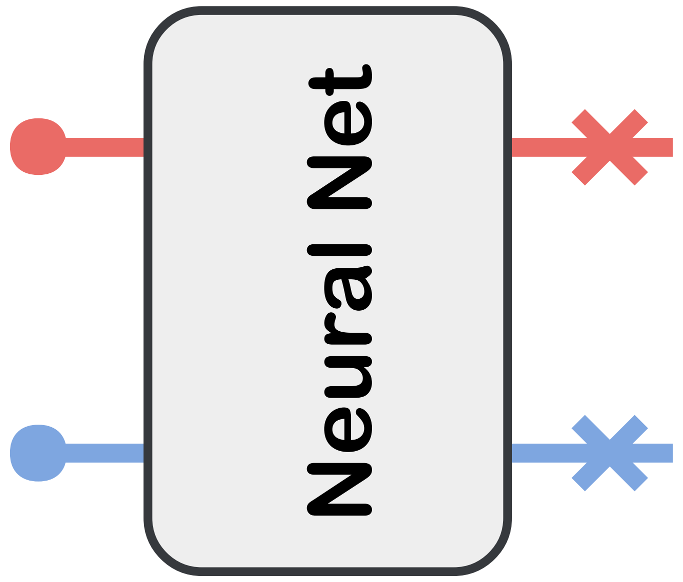
Training approaches

Density estimation

"learn from data"

$$\mathscr{L} = -\mathbb{E}_{\boldsymbol{x}\sim\text{dataset}}\left[\ln p(\boldsymbol{x})\right]$$

$\boldsymbol{x} \sim \text{dataset}$



$\boldsymbol{z}$

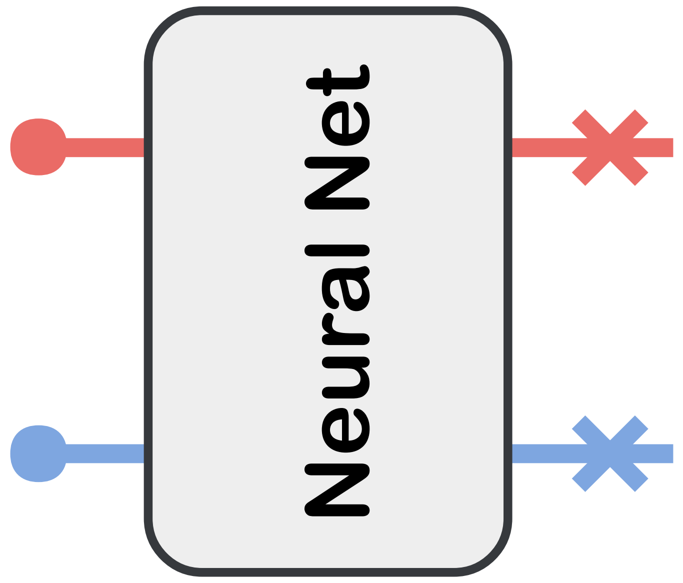
Sample from dataset in the physical space

Variational calculation

"learn from Hamiltonian"

$$\mathscr{L} = \int d\boldsymbol{x}\, p(\boldsymbol{x})\left[\ln p(\boldsymbol{x}) + \beta H(\boldsymbol{x})\right]$$

$\boldsymbol{x}$



$\boldsymbol{z} \sim \mathcal{N}(\mathbf{0}, \Sigma)$

Sample in the latent space

Training approaches

Density estimation

"learn from data"

$$\mathscr{L} = -\mathbb{E}_{\boldsymbol{x}\sim\text{dataset}}\left[\ln p(\boldsymbol{x})\right]$$

$$\mathbb{KL}(\pi||p) = \sum_{\boldsymbol{x}} \pi \ln \pi - \underbrace{\sum_{\boldsymbol{x}} \pi \ln p}_{\mathscr{L}}$$

Sample from dataset in the physical space

Variational calculation

"learn from Hamiltonian"

$$\mathscr{L} = \int d\boldsymbol{x}\, p(\boldsymbol{x})\left[\ln p(\boldsymbol{x}) + \beta H(\boldsymbol{x})\right]$$

$$\mathscr{L} + \ln Z = \mathbb{KL}\left(p||\frac{e^{-\beta H}}{Z}\right) \geq 0$$

Sample in the latent space

Forward KL or Reverse KL ?

Maximum Likelihood Estimation

$$q^* = \text{argmin}_q D_{\text{KL}}(p\|q)$$

Variational Free Energy

$$q^* = \text{argmin}_q D_{\text{KL}}(q\|p)$$

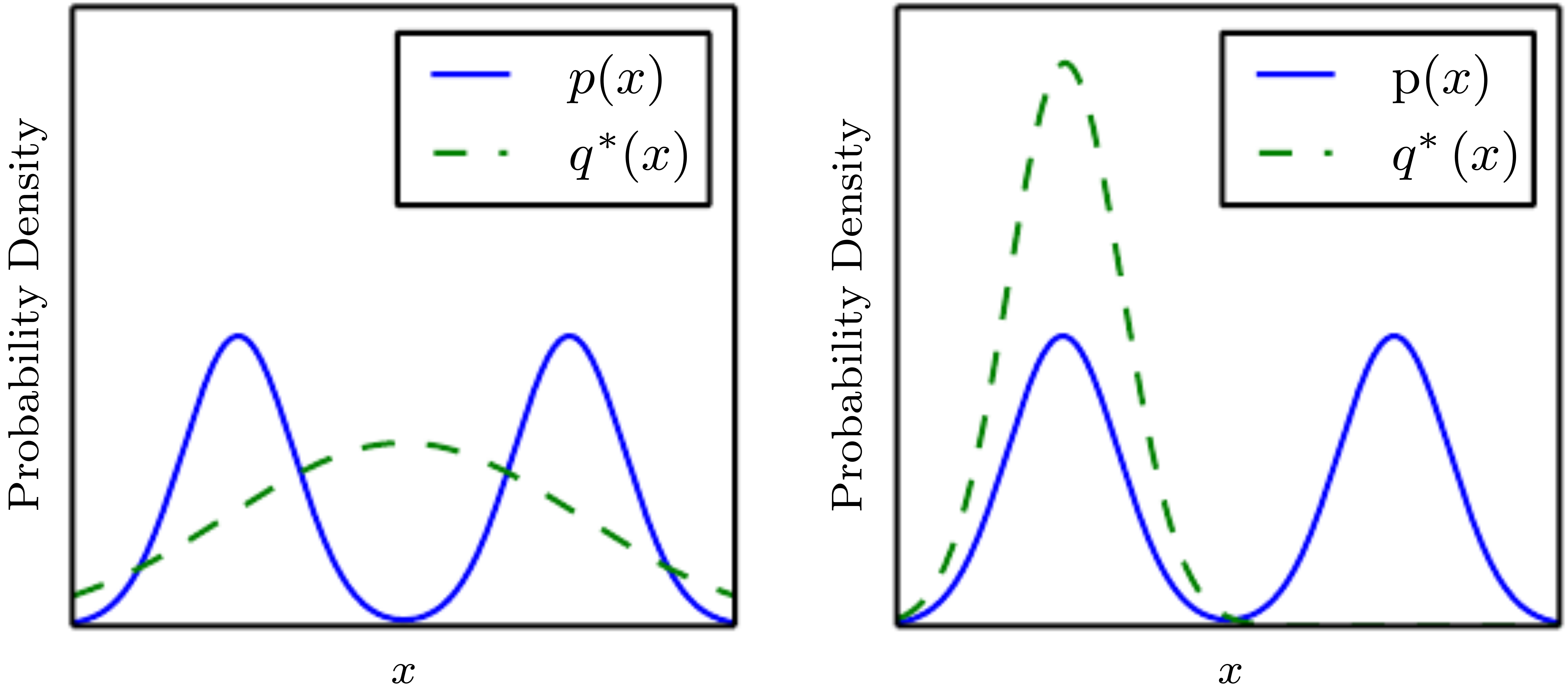


Fig. 3.6, Goodfellow, Bengio, Courville, http://www.deeplearningbook.org/

Monte Carlo Gradient Estimators

Review: 1906.10652

$$\nabla_{\boldsymbol{\theta}} \mathbb{E}_{\boldsymbol{x} \sim p_{\boldsymbol{\theta}}} \left[f(\boldsymbol{x}) \right]$$

Reinforcement learning
Variational inference
Variational Monte Carlo
Variational quantum algorithms
…

Score function estimator (REINFORCE)

$$\nabla_{\theta} \mathbb{E}_{\boldsymbol{x} \sim p_{\theta}} \left[f(\boldsymbol{x}) \right] = \mathbb{E}_{\boldsymbol{x} \sim p_{\theta}} \left[f(\boldsymbol{x}) \, \nabla_{\theta} \ln p_{\theta}(\boldsymbol{x}) \right]$$

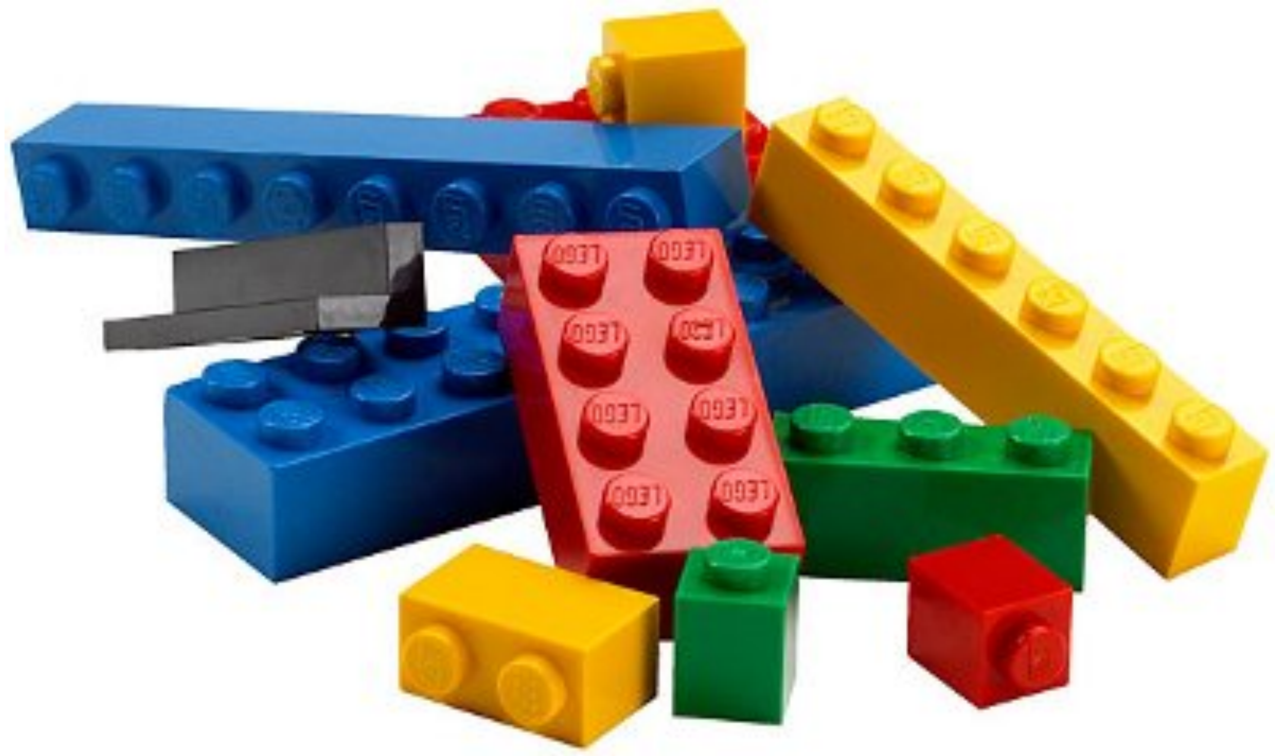
Pathwise estimator (Reparametrization trick) $\boldsymbol{x} = g_{\theta}(\boldsymbol{z})$

$$\nabla_{\theta} \mathbb{E}_{\boldsymbol{x} \sim p_{\theta}} \left[f(\boldsymbol{x}) \right] = \mathbb{E}_{\boldsymbol{z} \sim \mathcal{N}(\boldsymbol{z})} \left[\nabla_{\theta} f(g_{\theta}(\boldsymbol{z})) \right]$$

Choose the one with the lowest variance

Design principles

Composability

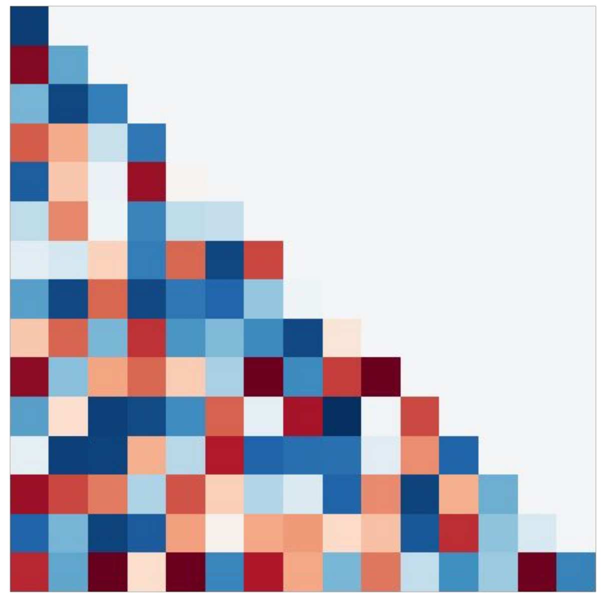


$$z = \mathscr{T}(x)$$

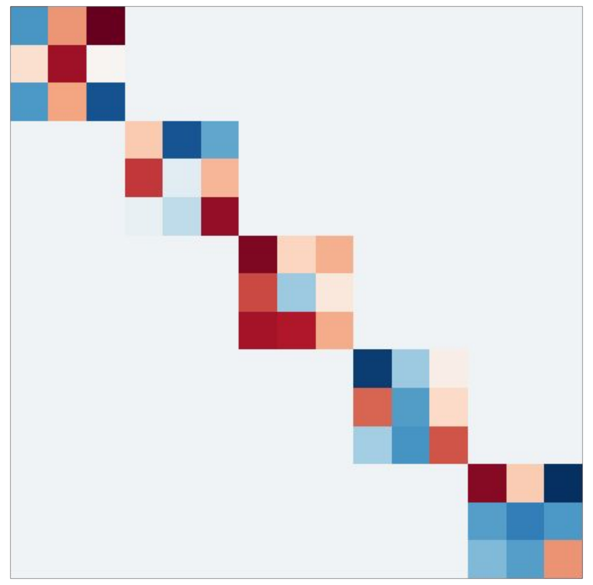
$$\mathscr{T} = \mathscr{T}_1 \circ \mathscr{T}_2 \circ \mathscr{T}_3 \circ \cdots$$

Balanced efficiency & inductive bias

$$\left|\det\left(\frac{\partial z}{\partial x}\right)\right|$$



Autoregressive



Neural RG

$$\frac{\partial \rho(x,t)}{\partial t} + \nabla \cdot \left[\rho(x,t)v\right] = 0$$

Continuous flow

Example of a building block

Forward

arbitrary neural nets

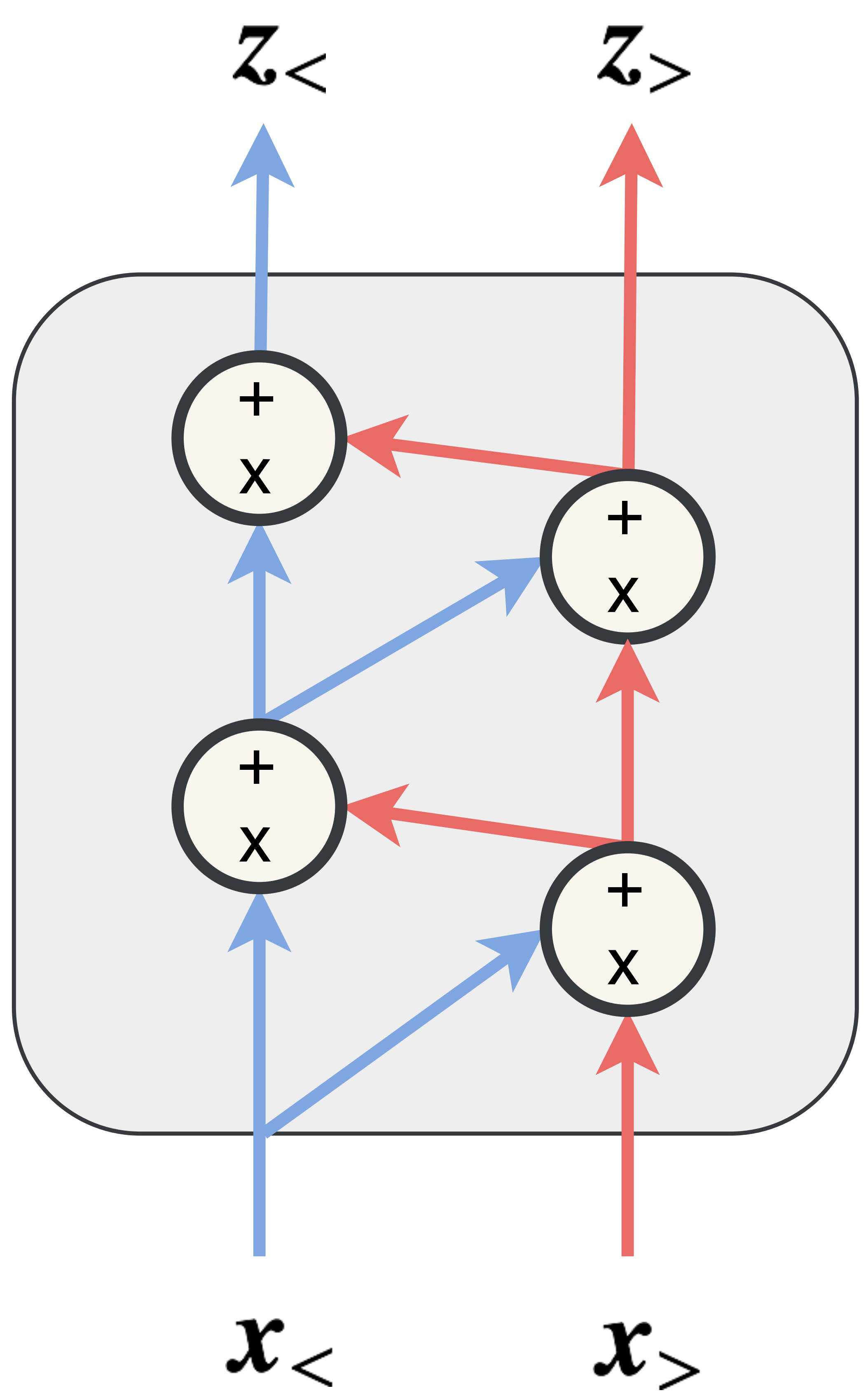
$$\begin{cases} \boldsymbol{x}_< = \boldsymbol{z}_< \\ \boldsymbol{x}_> = \boldsymbol{z}_> \odot e^{s(\boldsymbol{z}_<)} + t(\boldsymbol{z}_<) \end{cases}$$

Inverse

$$\begin{cases} \boldsymbol{z}_< = \boldsymbol{x}_< \\ \boldsymbol{z}_> = (\boldsymbol{x}_> - t(\boldsymbol{x}_<)) \odot e^{-s(\boldsymbol{x}_<)} \end{cases}$$

Log-Abs-Jacobian-Det

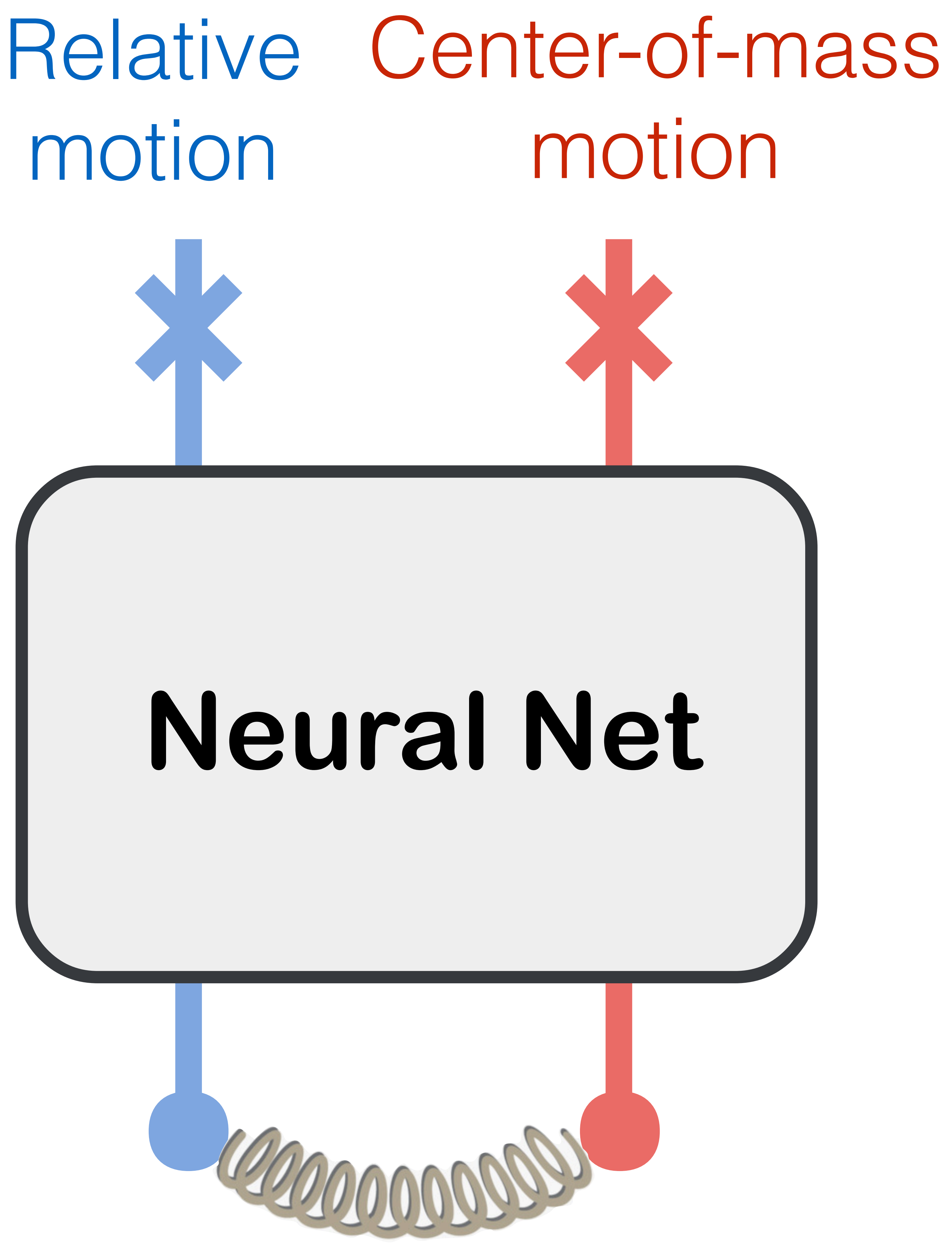
$$\ln\left|\det\left(\frac{\partial x}{\partial z}\right)\right| = \sum_i [s(\boldsymbol{z}_<)]_i$$



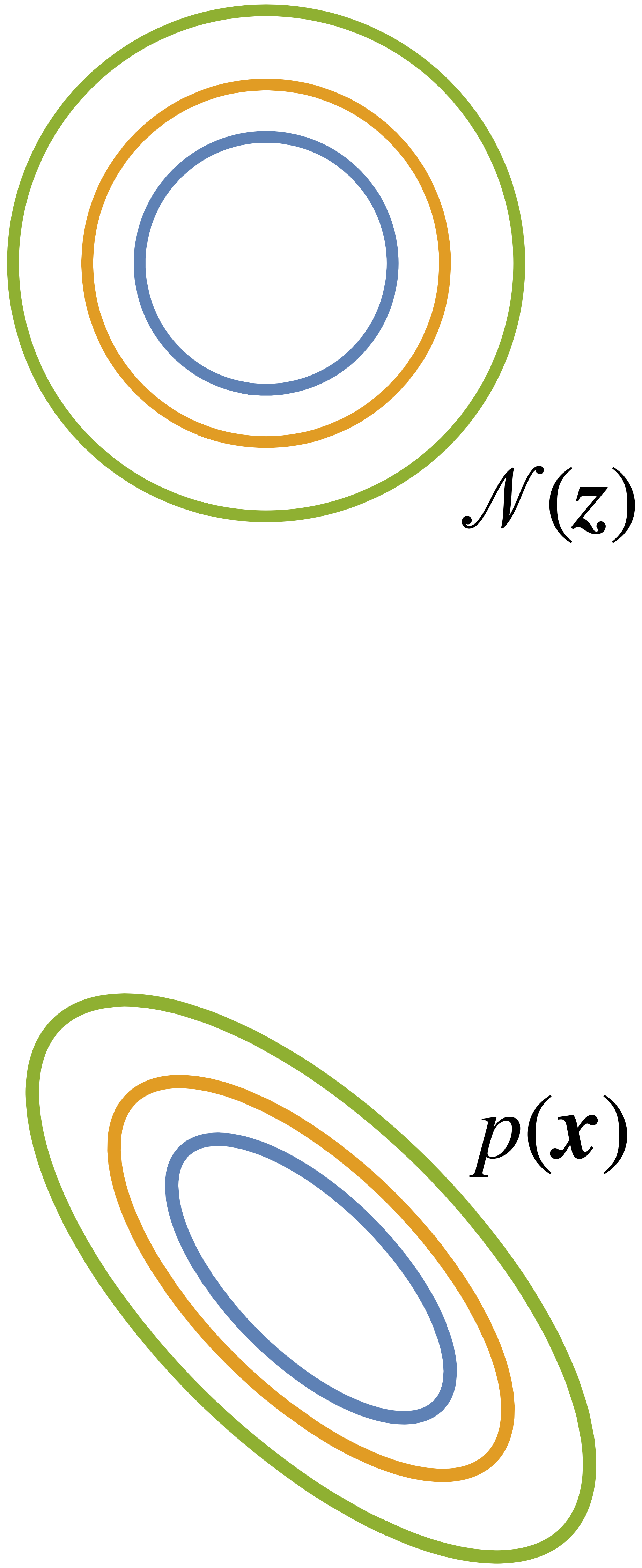
Real NVP, Dinh et al,1605.08803

Turns out to have surprising connection Störmer–Verlet integration (later)

How it can be useful in physics ?

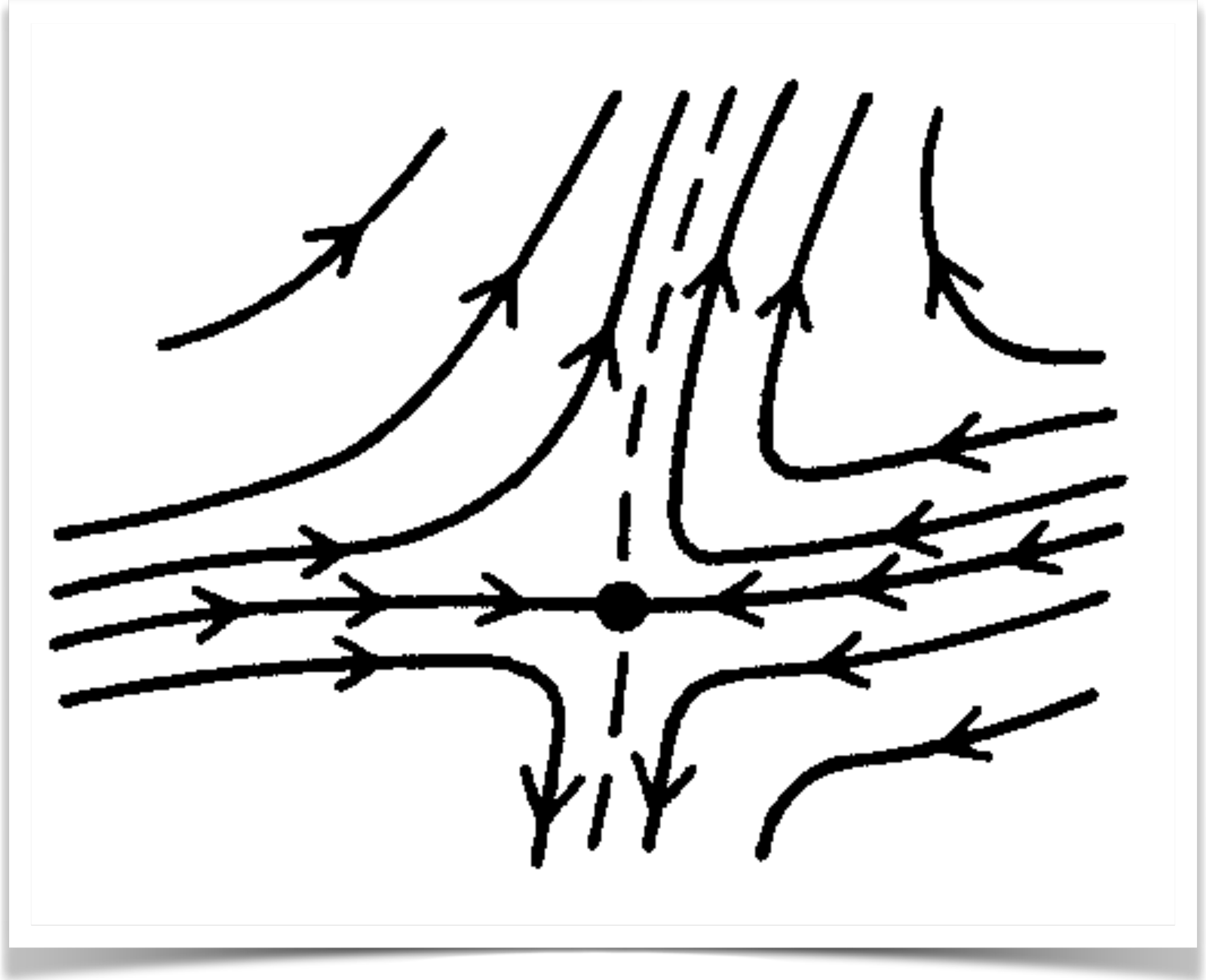


Coupled harmonic oscillator



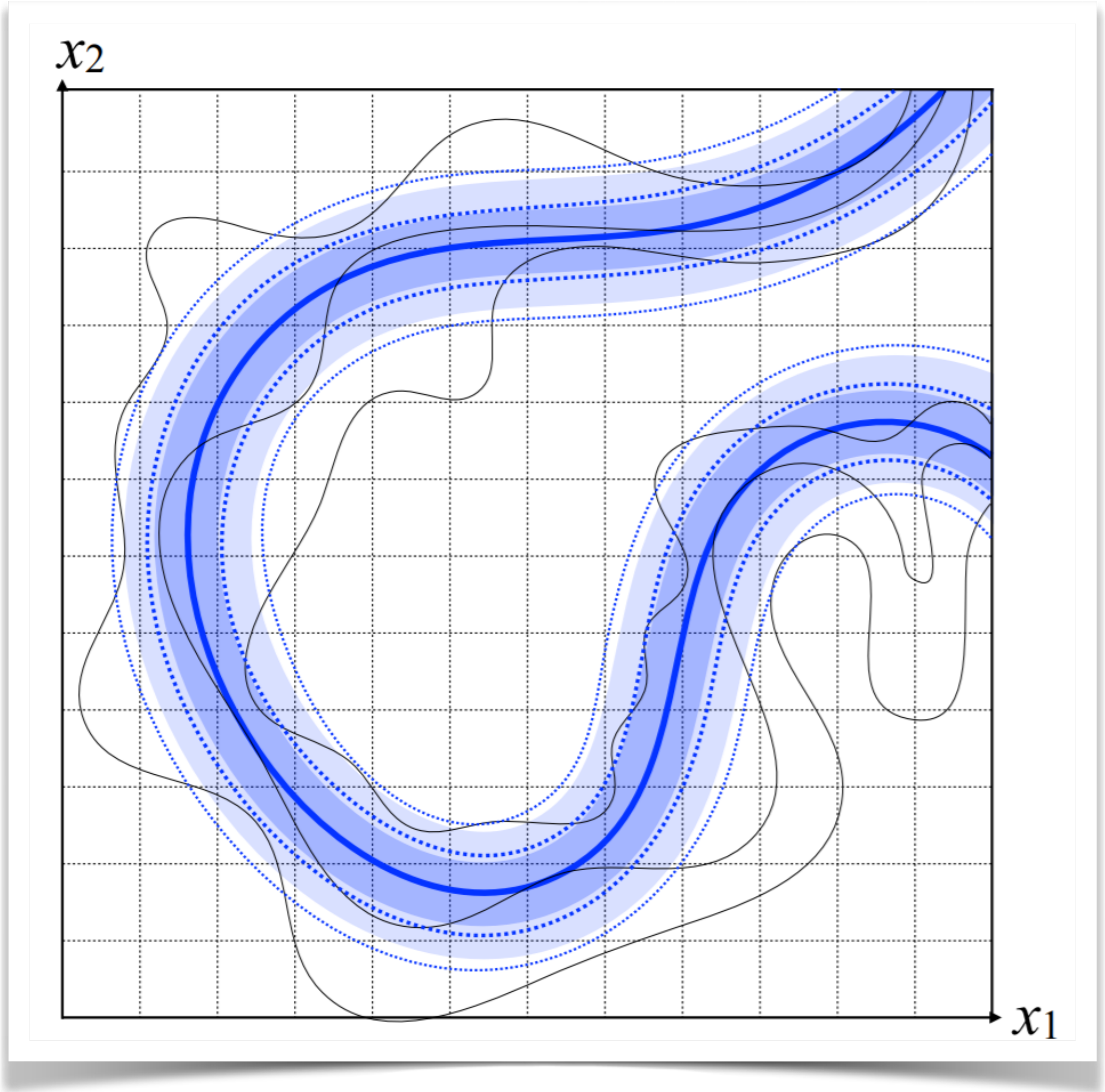
How it can be useful in physics ?

Renormalization group



Effective theory emerges upon transformation of the variables

Monte Carlo update

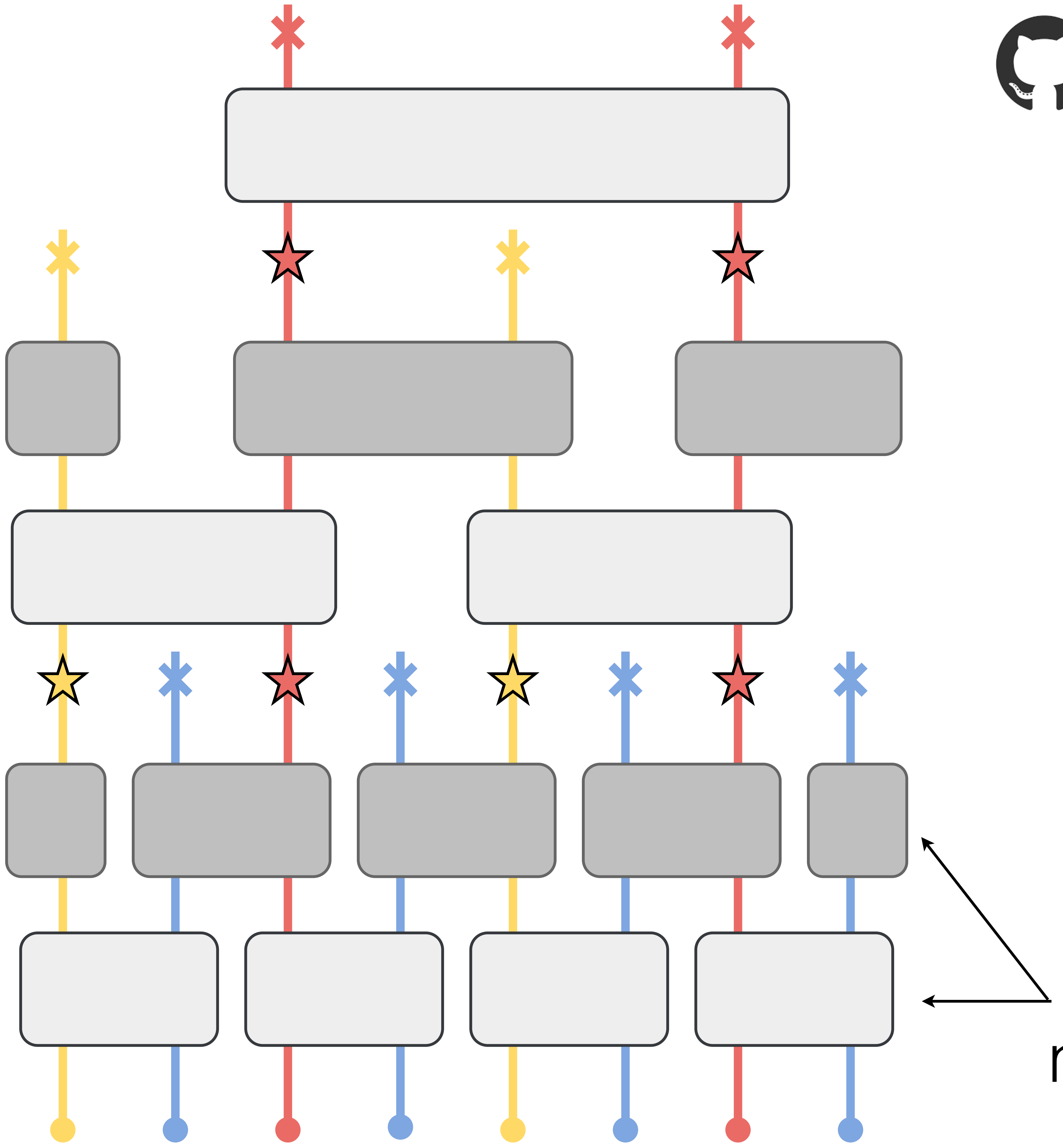


Physics happens on a manifold
Learn neural nets to unfold that manifold

Neural Network Renormalization Group

Li, LW, PRL ‘18

li012589/NeuralRG



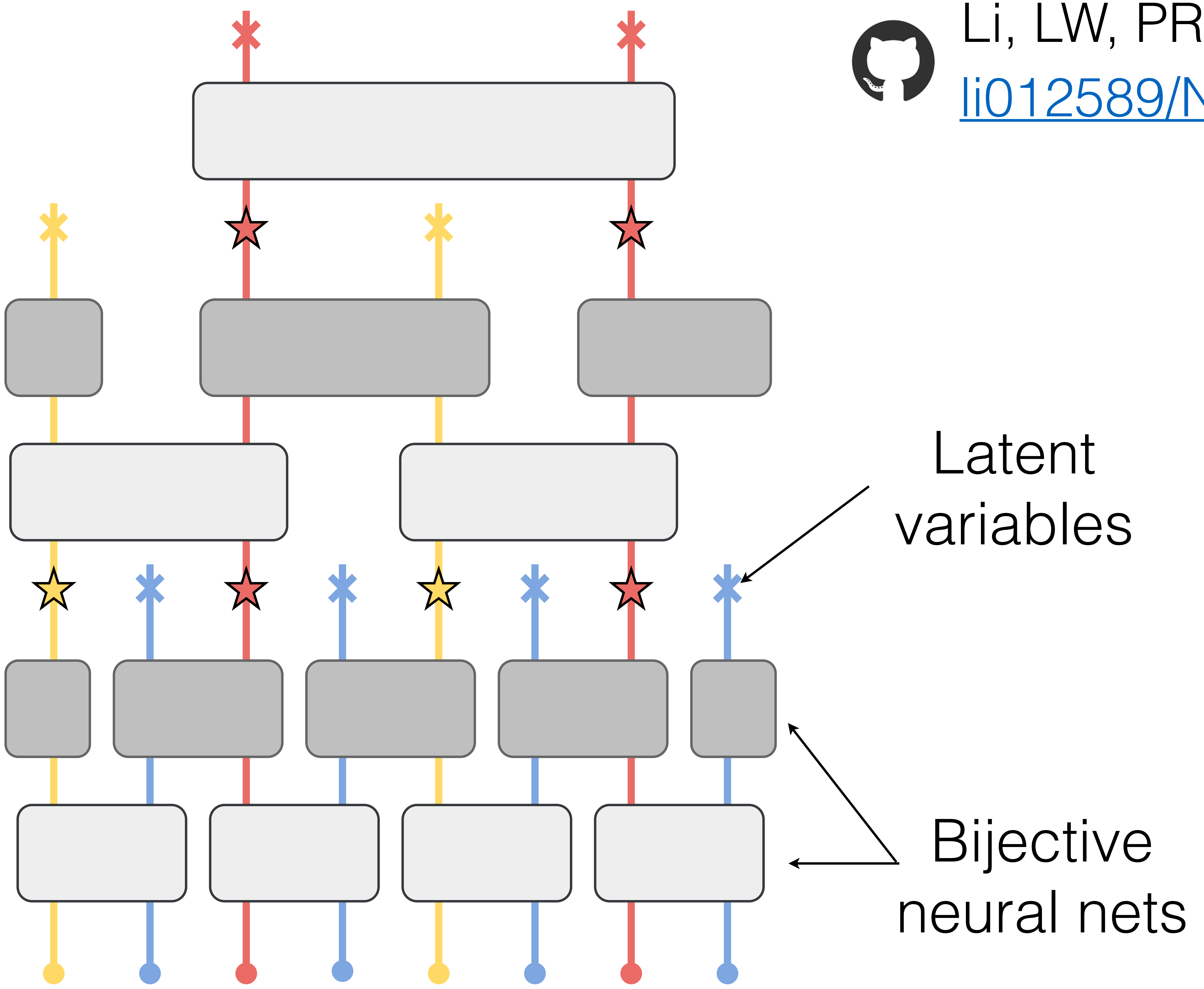
Bijective neural nets

Correlated classical variables

Neural Network Renormalization Group

Li, LW, PRL '18

li012589/NeuralRG

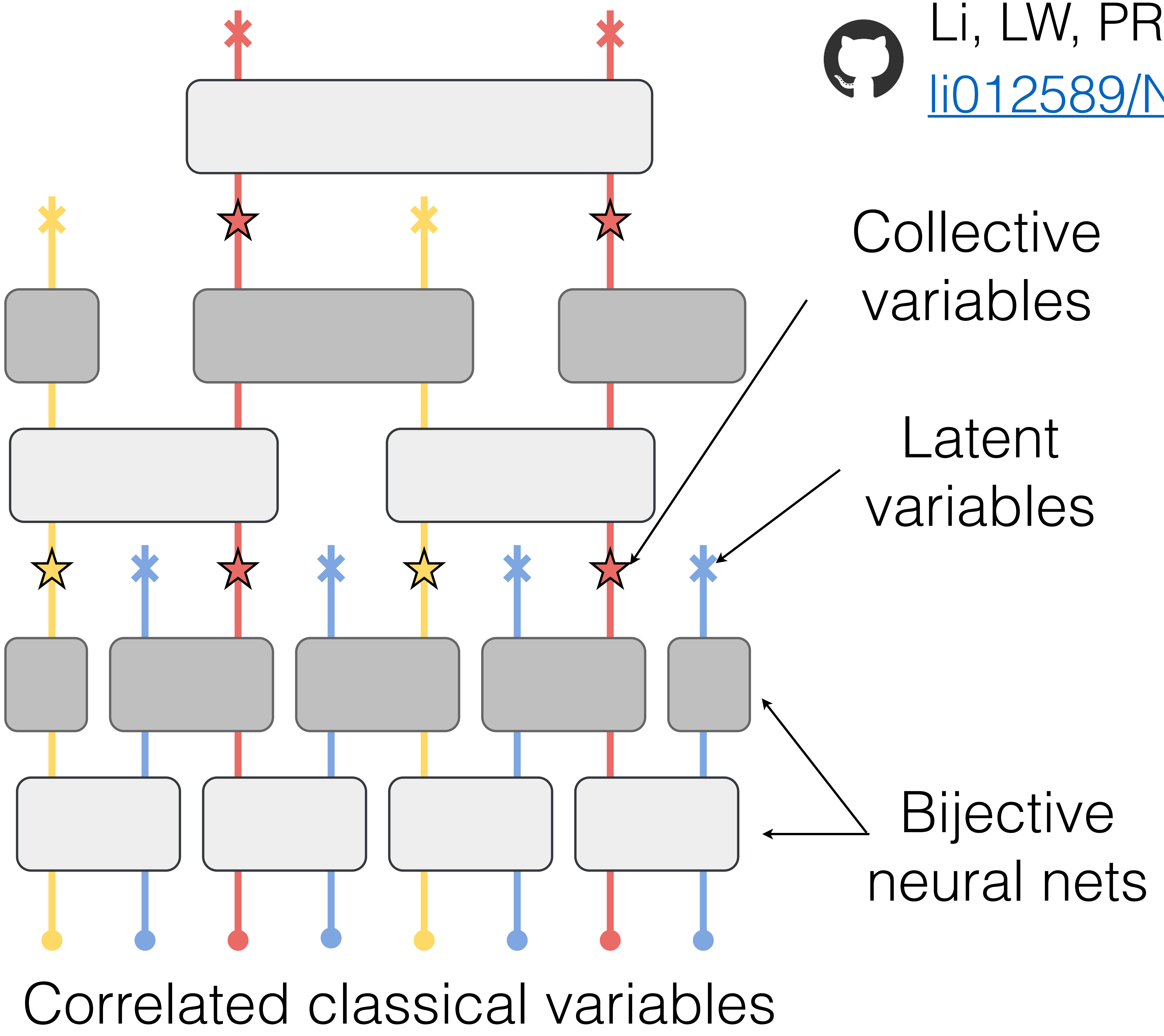


Correlated classical variables

Neural Network Renormalization Group

Li, LW, PRL '18

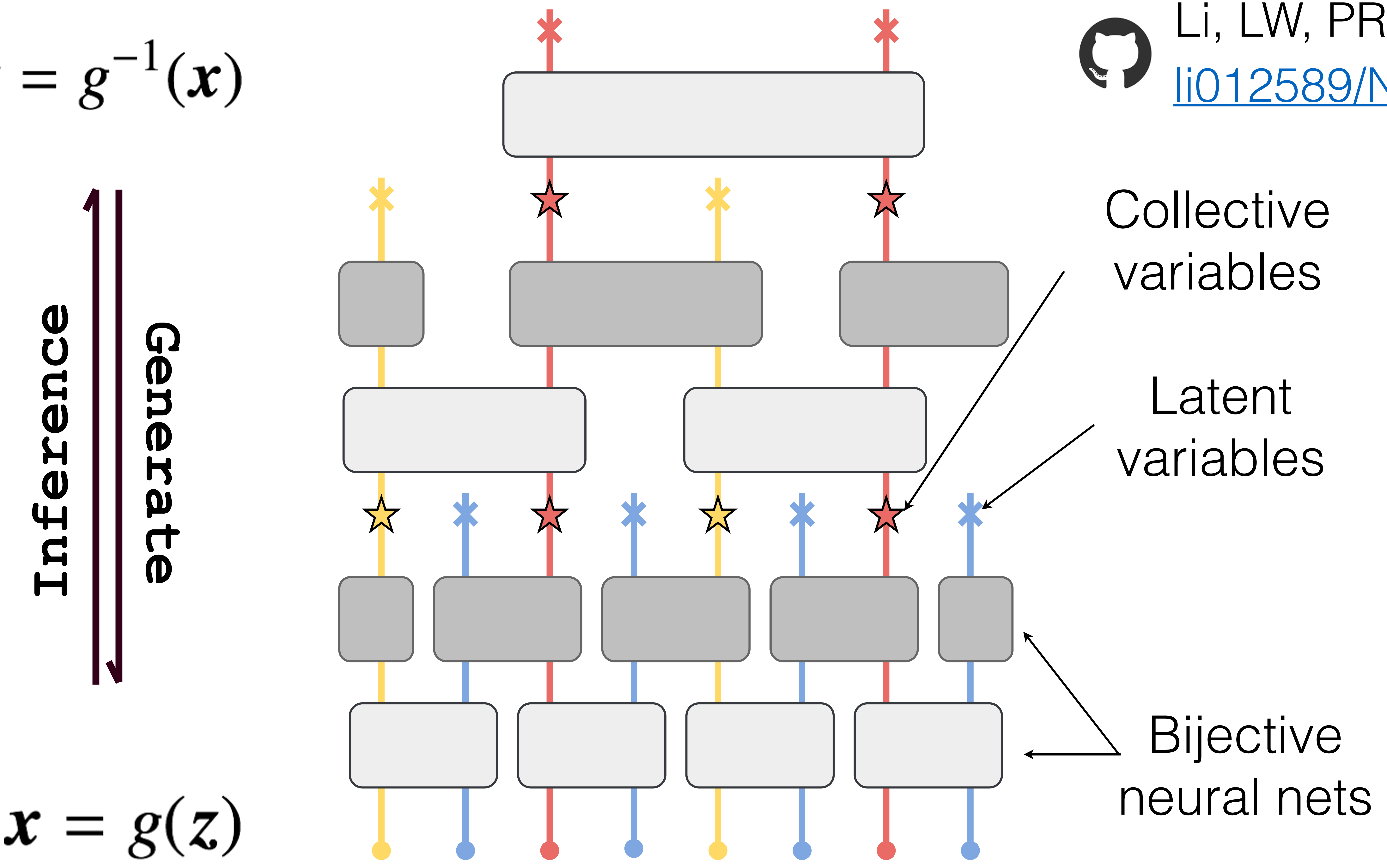
li012589/NeuralRG



Neural Network Renormalization Group

Li, LW, PRL '18
li012589/NeuralRG

$$z = g^{-1}(x)$$



$$x = g(z)$$

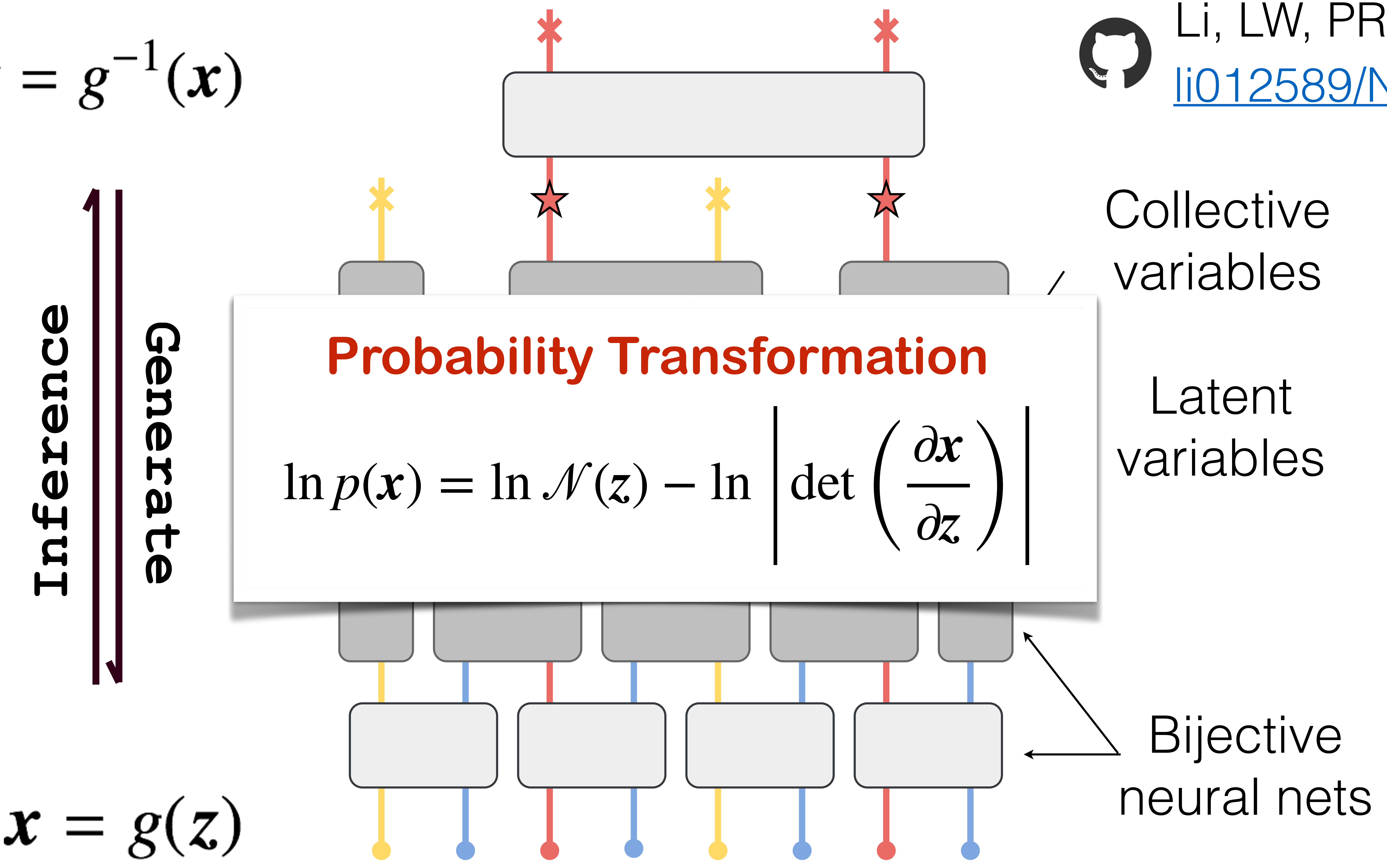
Correlated classical variables

Neural Network Renormalization Group

Li, LW, PRL ‘18

li012589/NeuralRG

$$z = g^{-1}(x)$$



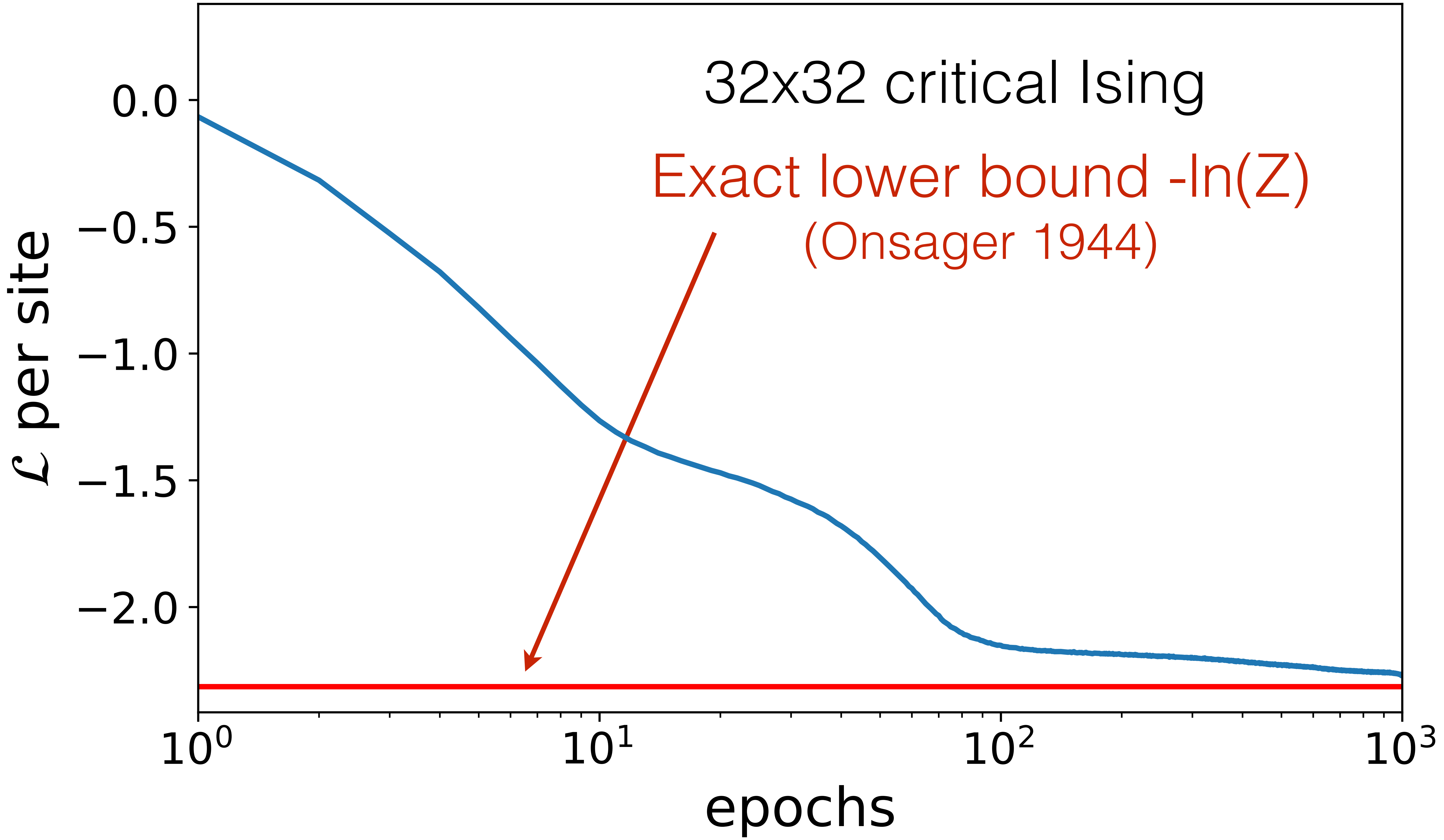
Probability Transformation

$$\ln p(x) = \ln \mathcal{N}(z) - \ln \left| \det \left(\frac{\partial x}{\partial z} \right) \right|$$

$$x = g(z)$$

Correlated classical variables

Variational Loss

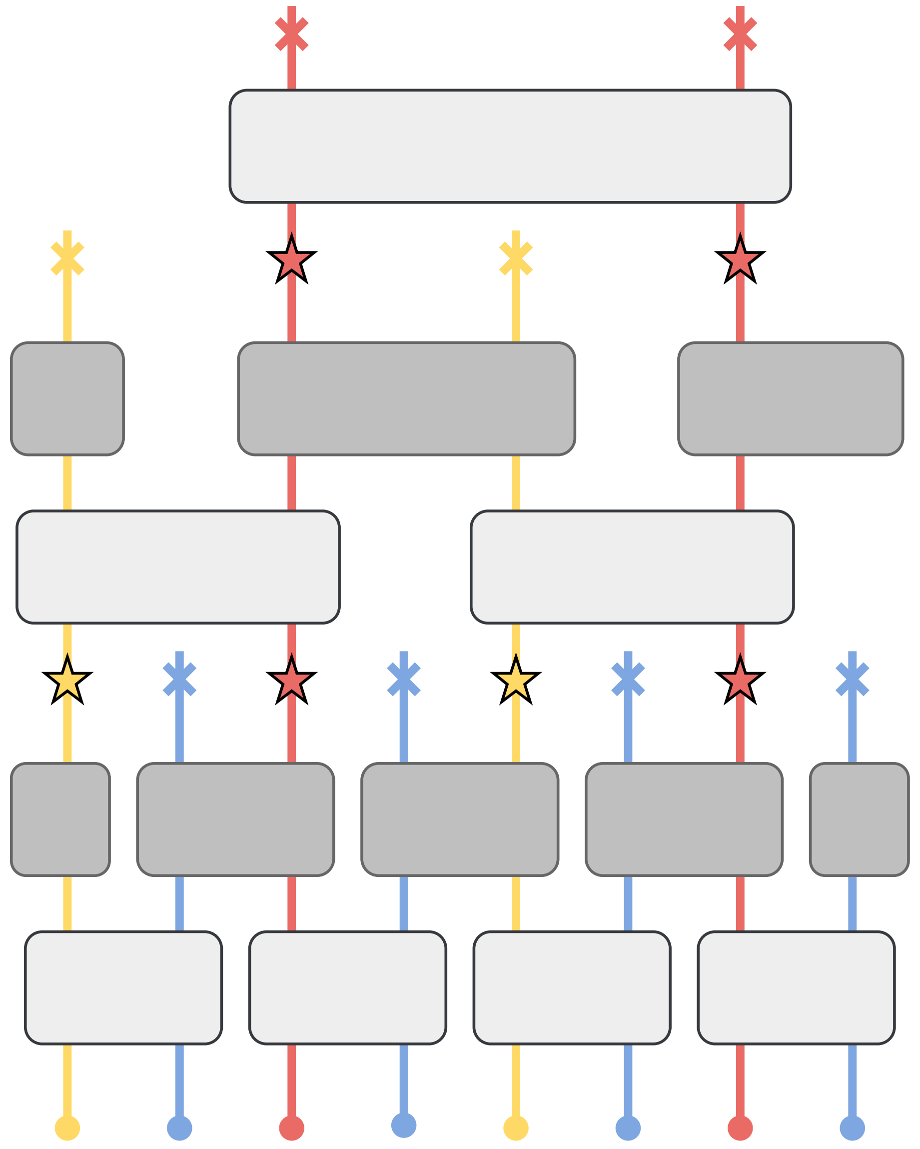


Training = Variational free energy calculation

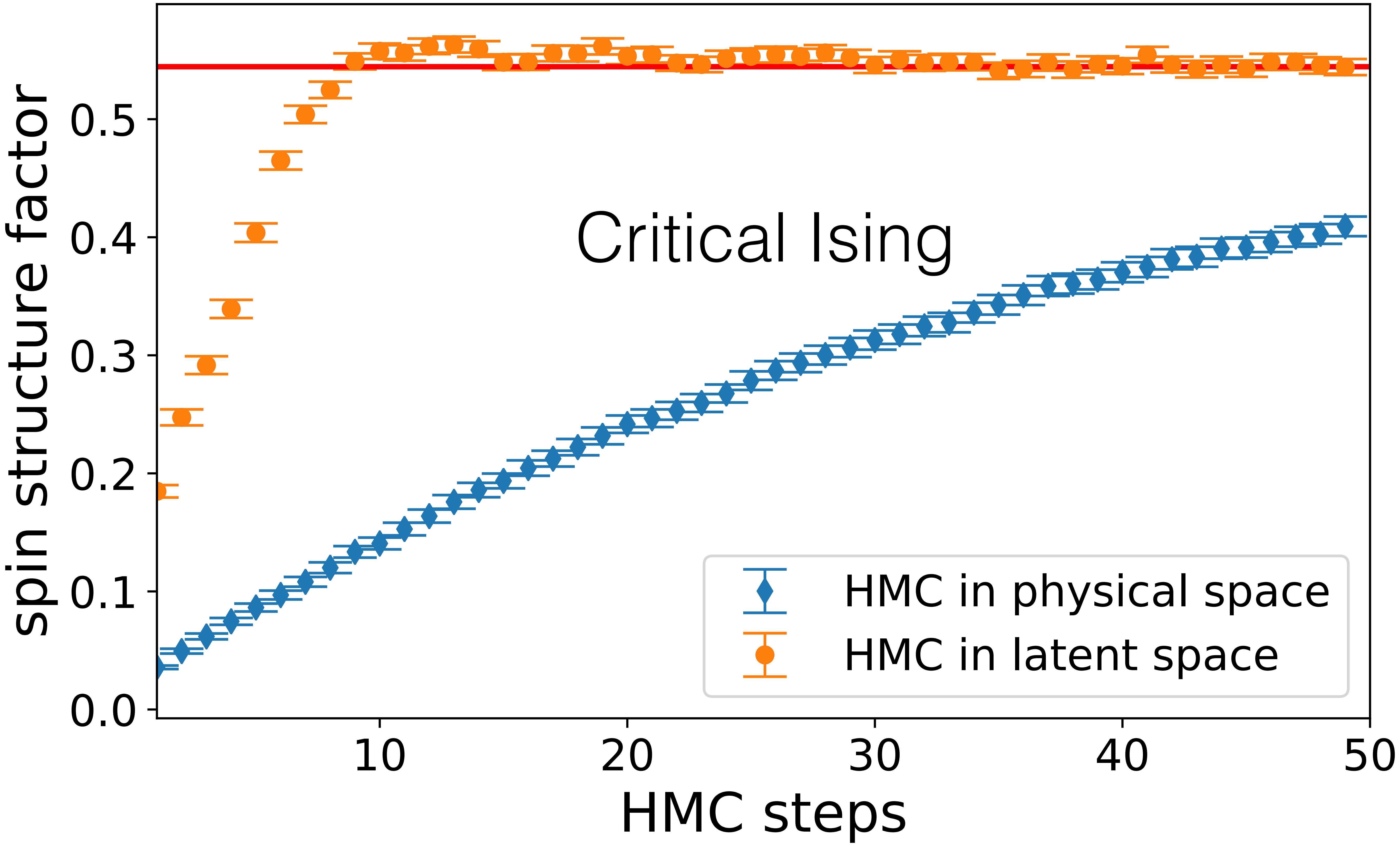
Sampling in the latent space

Latent space energy function

$E_{\text{eff}}(z) = E(g(z)) + \ln p(g(z)) - \ln \mathcal{N}(z)$



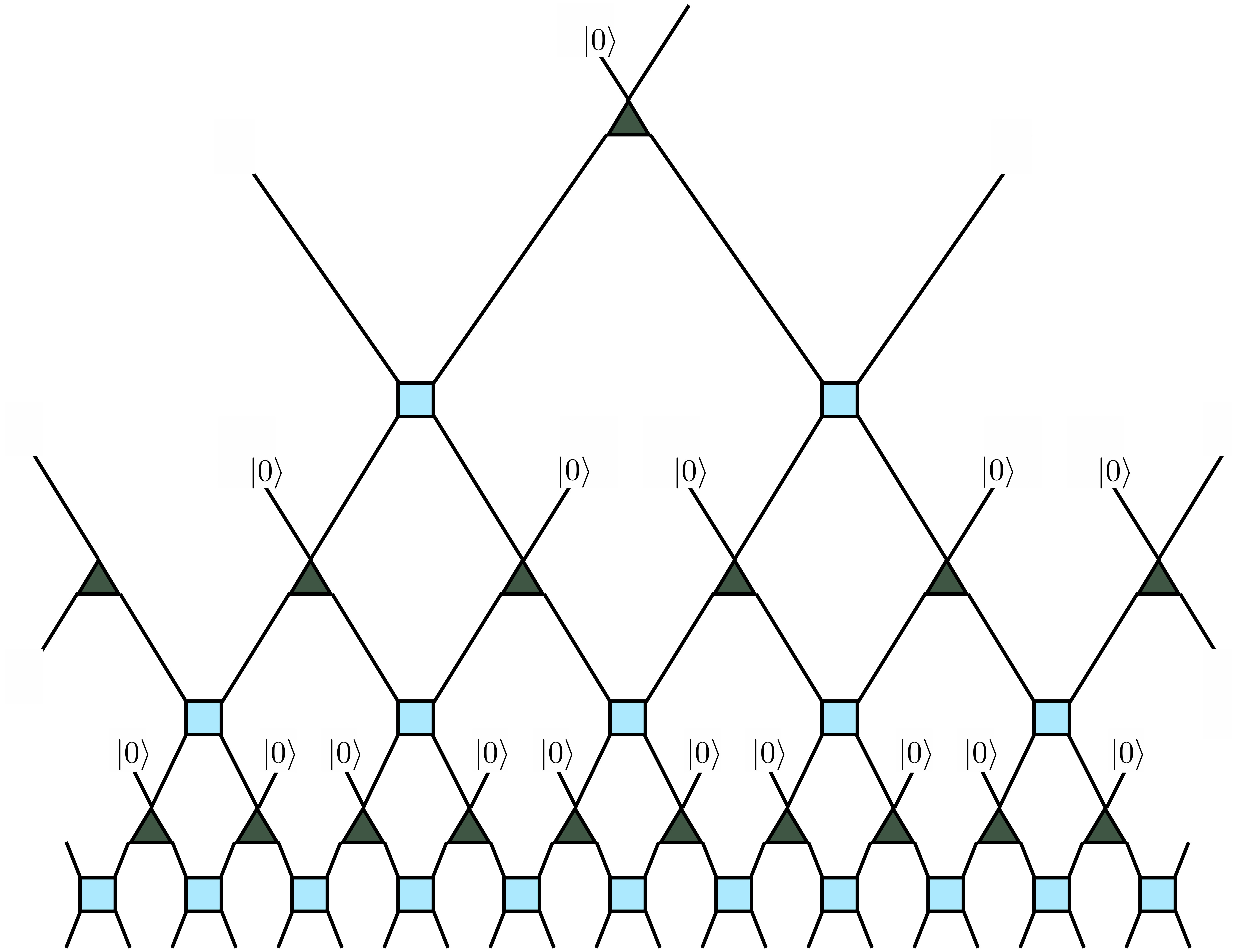
Physical energy function $E(\boldsymbol{x})$

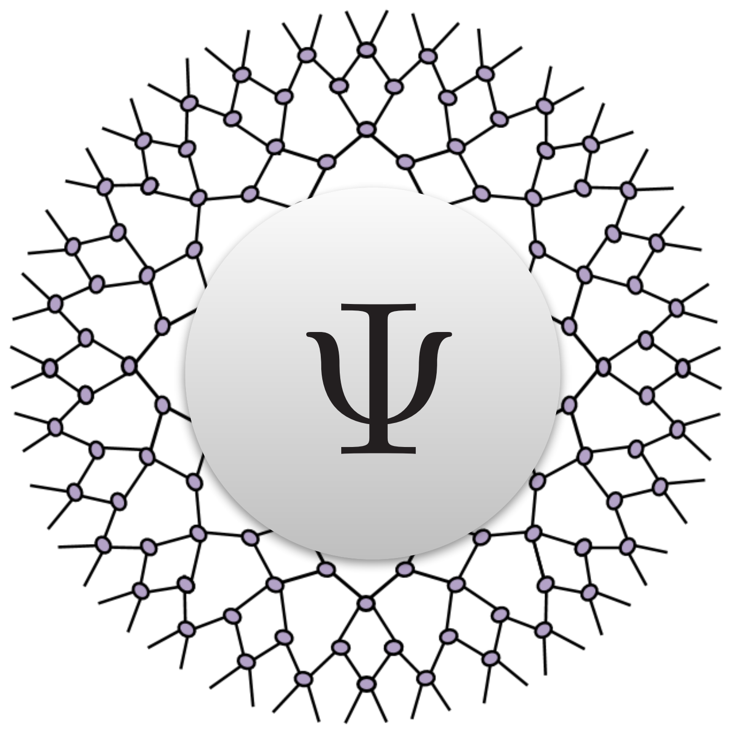


HMC thermalizes faster in the latent space

Other ways to de-bias: neural importance sampling, Metropolis rejection of flow proposal …

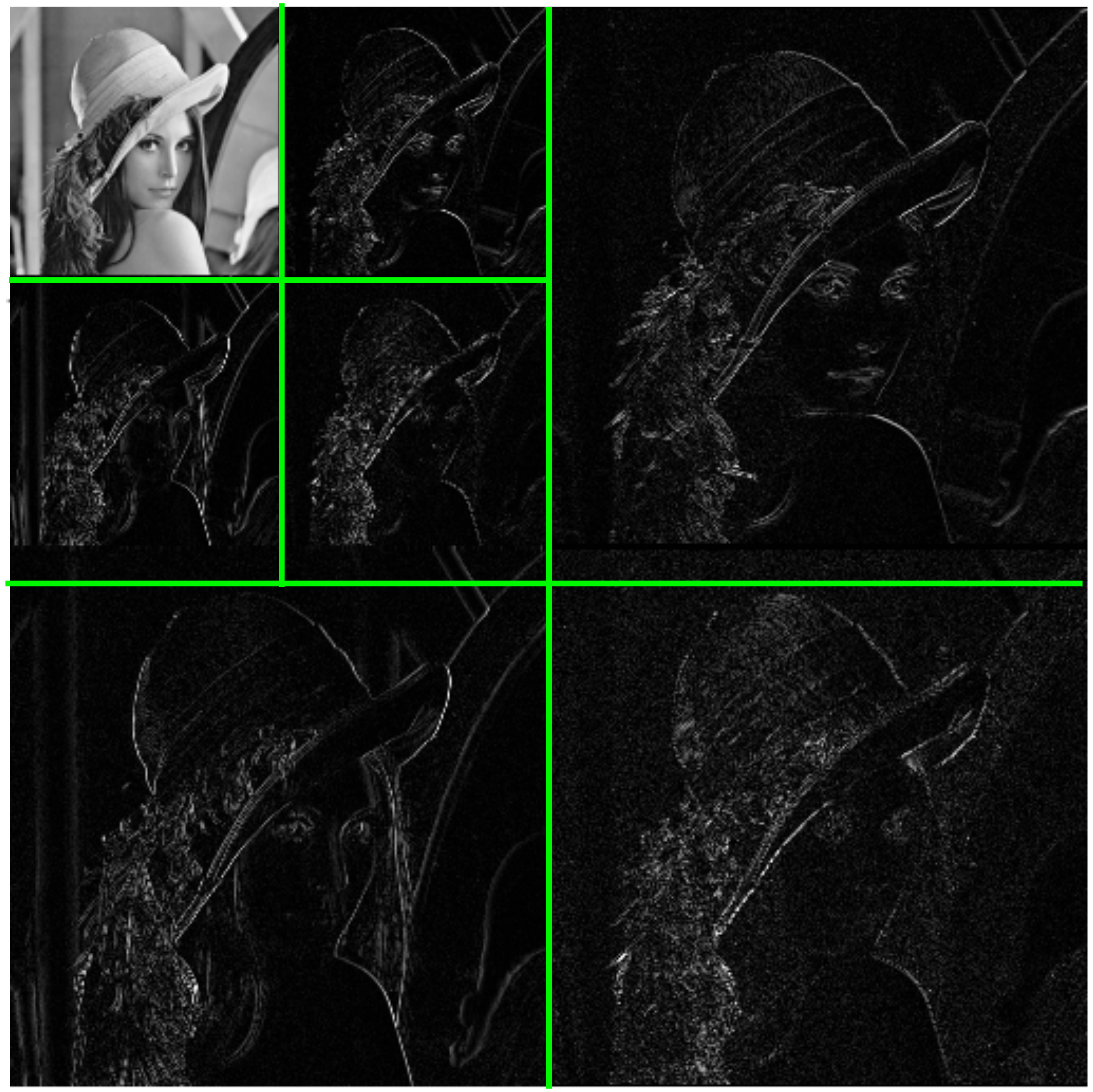
Quantum origin of the architecture

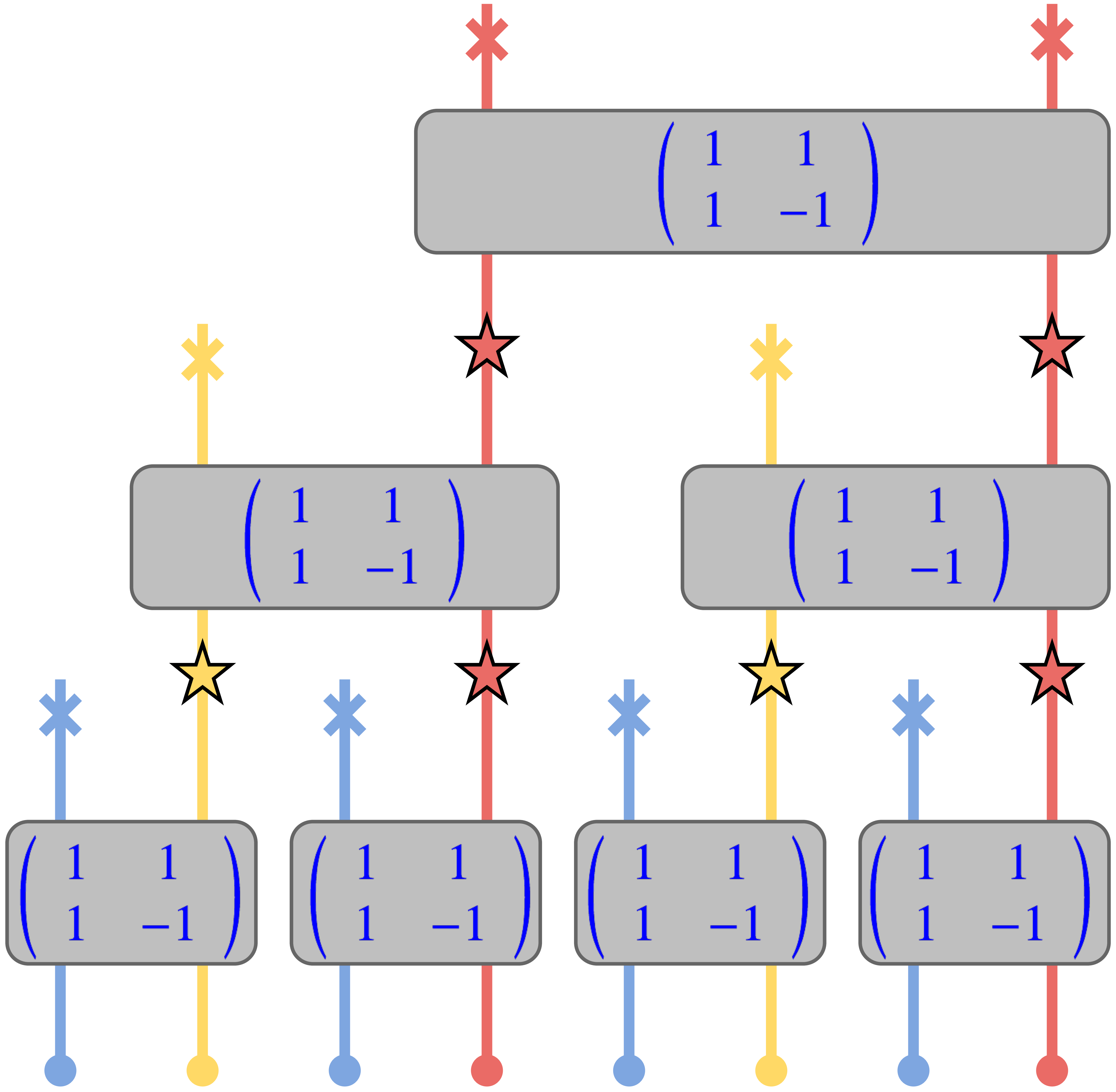




Multi-Scale
Entanglement
Renormalization
Ansatz

Connection to wavelets





Nonlinear & adaptive generalizations of wavelets

Guy, Wavelets & RG1999+ White, Evenbly, Qi, Wavelets, MERA, and holographic mapping 2013+

Continuous normalizing flows

$$\ln p(\boldsymbol{x}) = \ln \mathcal{N}(\boldsymbol{z}) - \ln \left| \det \left(\frac{\partial \boldsymbol{x}}{\partial \boldsymbol{z}} \right) \right|$$

Consider infinitesimal change-of-variables Chen et al 1806.07366

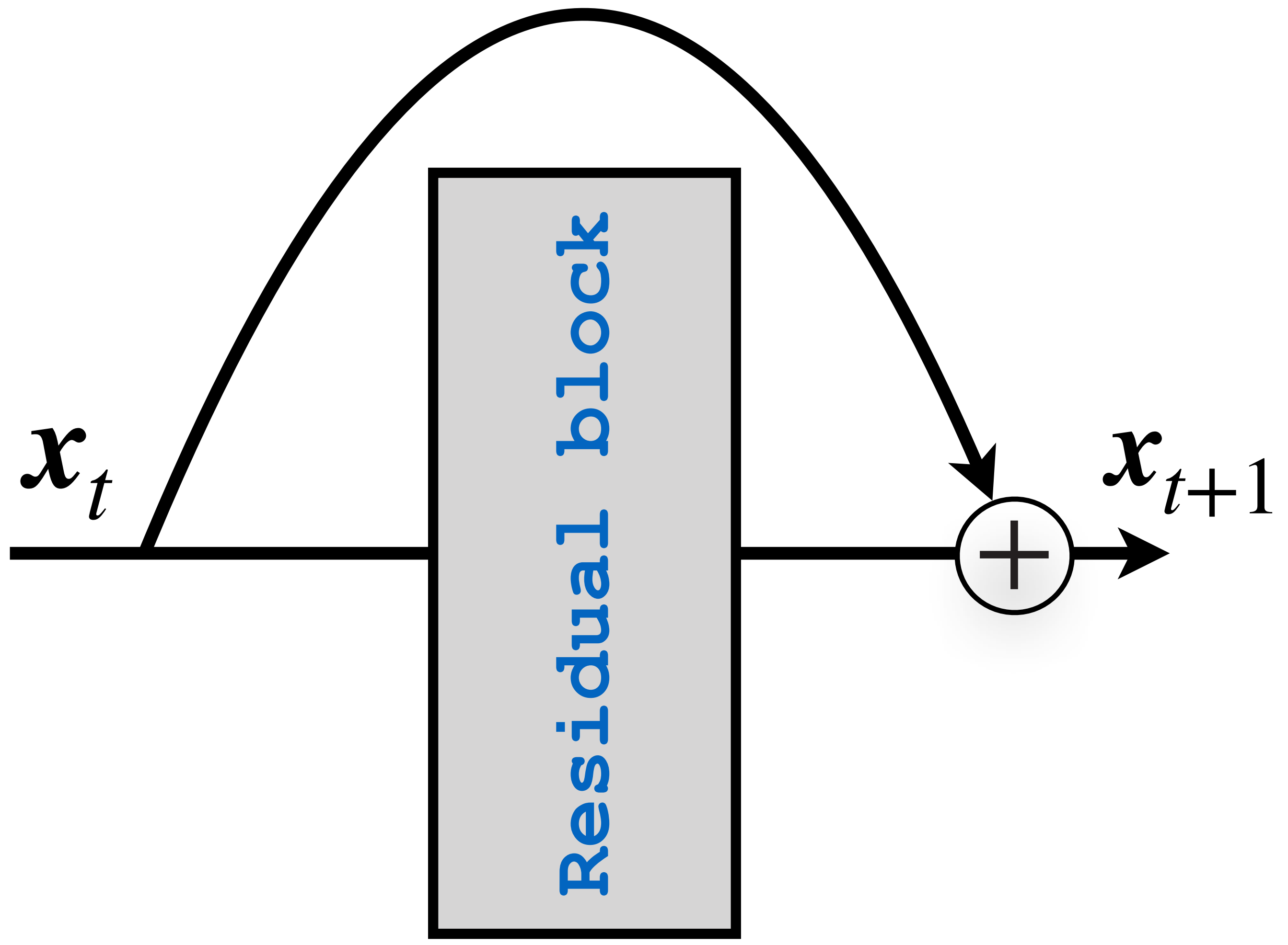
$$\boldsymbol{x} = \boldsymbol{z} + \varepsilon \boldsymbol{v} \qquad \ln p(\boldsymbol{x}) - \ln \mathcal{N}(\boldsymbol{z}) = -\ln \left| \det \left(1 + \varepsilon \frac{\partial \boldsymbol{v}}{\partial \boldsymbol{z}} \right) \right|$$

$\varepsilon \to 0$

$$\frac{d\boldsymbol{x}}{dt} = \boldsymbol{v} \qquad \frac{d \ln \rho(\boldsymbol{x}, t)}{dt} = -\nabla \cdot \boldsymbol{v}$$

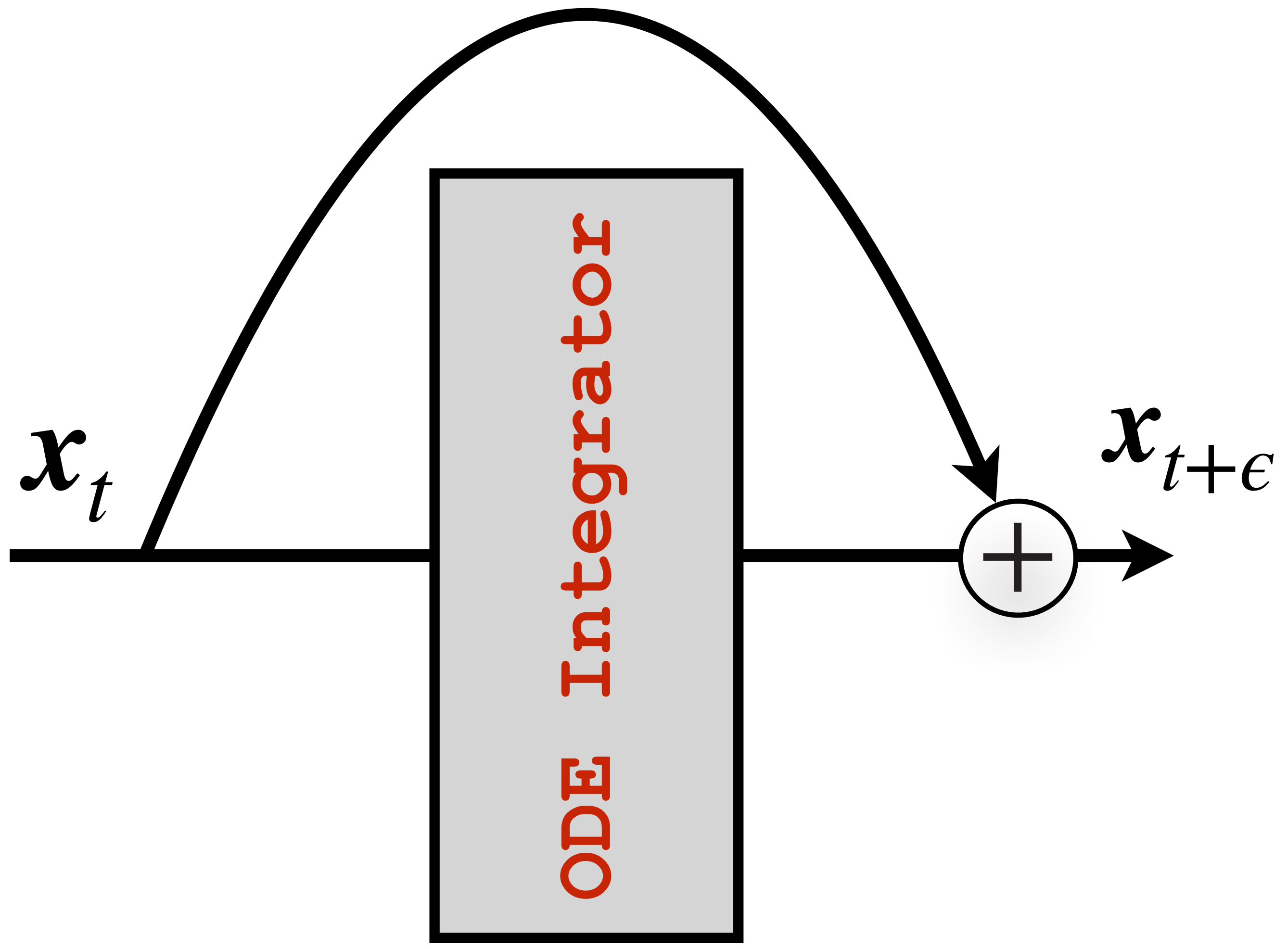
Neural Ordinary Differential Equations

Residual network



$$x_{t+1} = x_t + f(x_t)$$

ODE integration

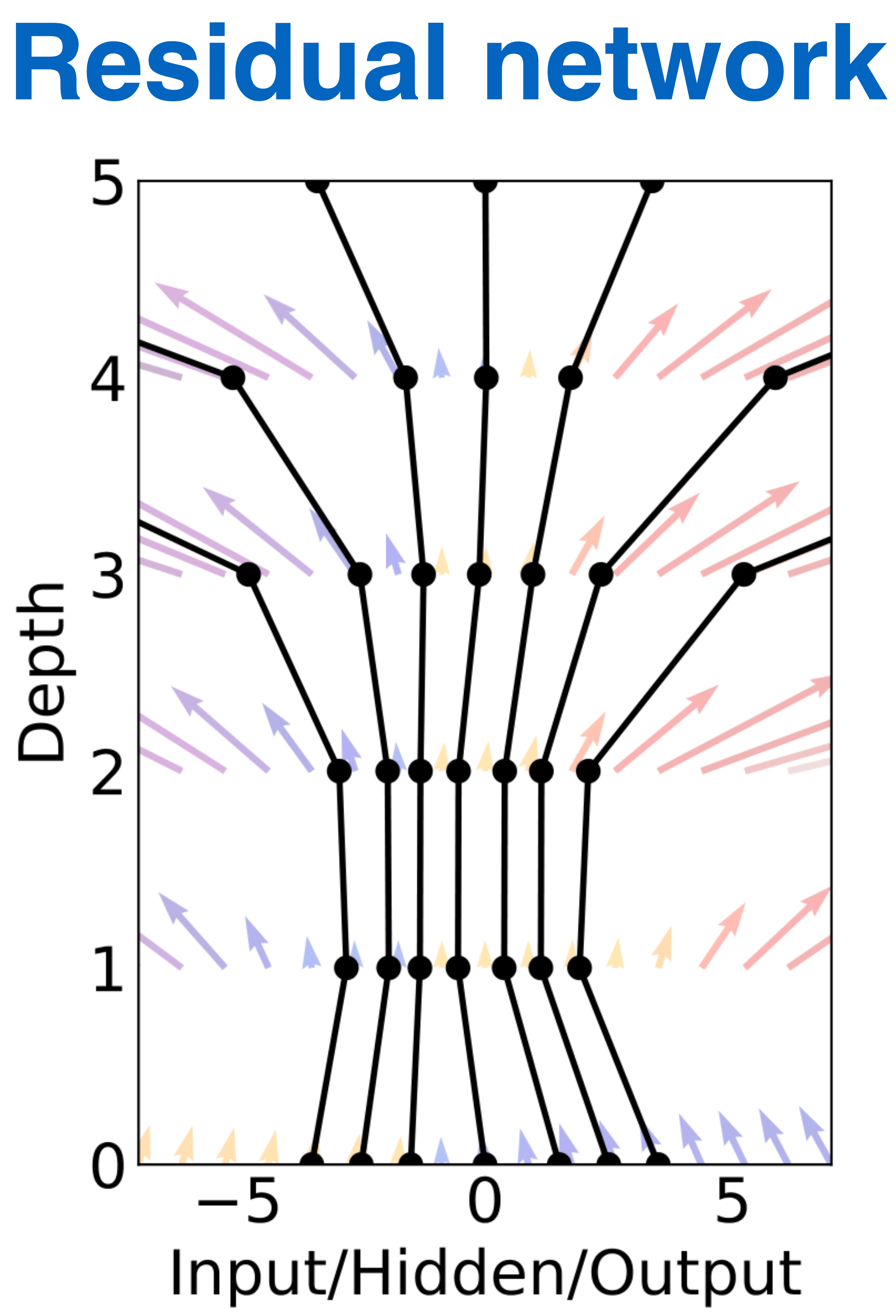


$$dx/dt = f(x)$$

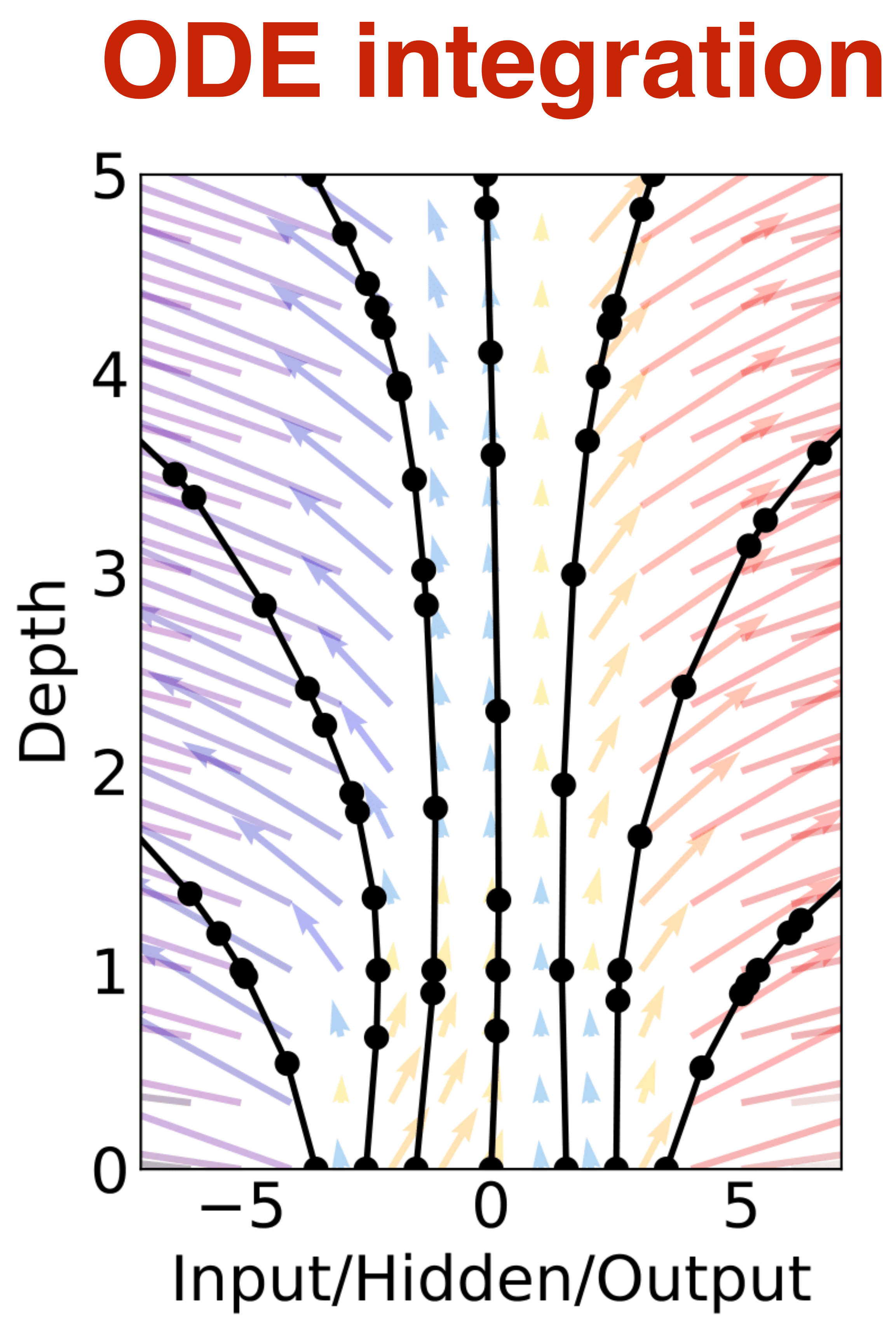
Chen et al, 1806.07366

Harbor el al 1705.03341
Lu et al 1710.10121,
E Commun. Math. Stat 17'…

Neural Ordinary Differential Equations



$$x_{t+1} = x_t + f(x_t)$$



$$dx/dt = f(x)$$

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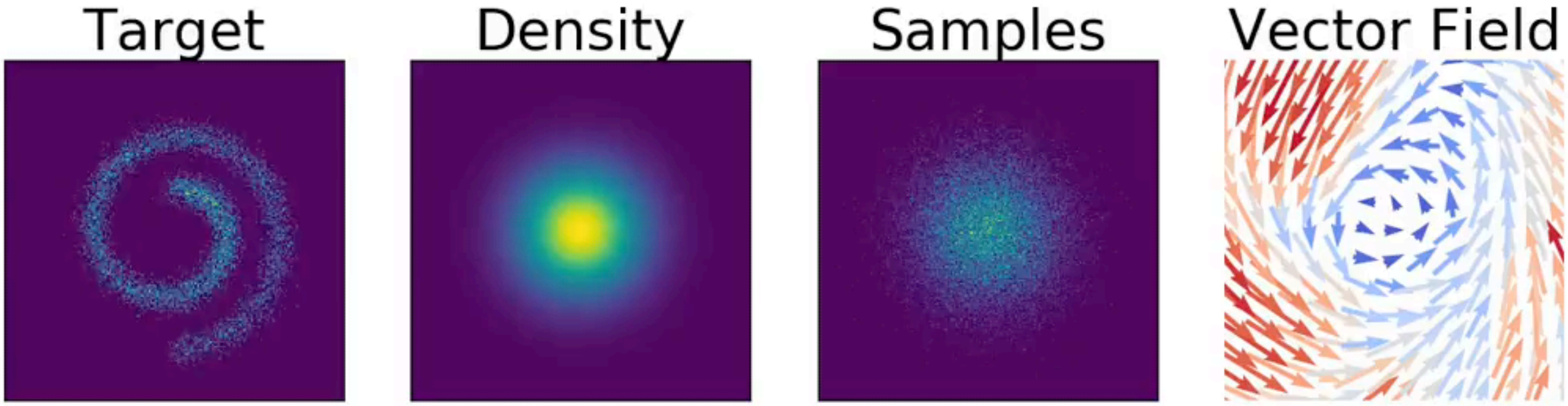
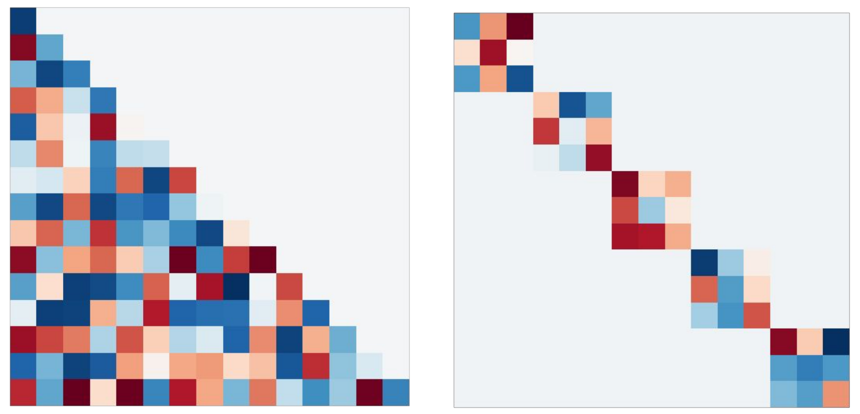
E Commun. Math. Stat 17'…

Neural Ordinary Differential Equations

Chen et al, 1806.07366, Grathwohl et al 1810.01367

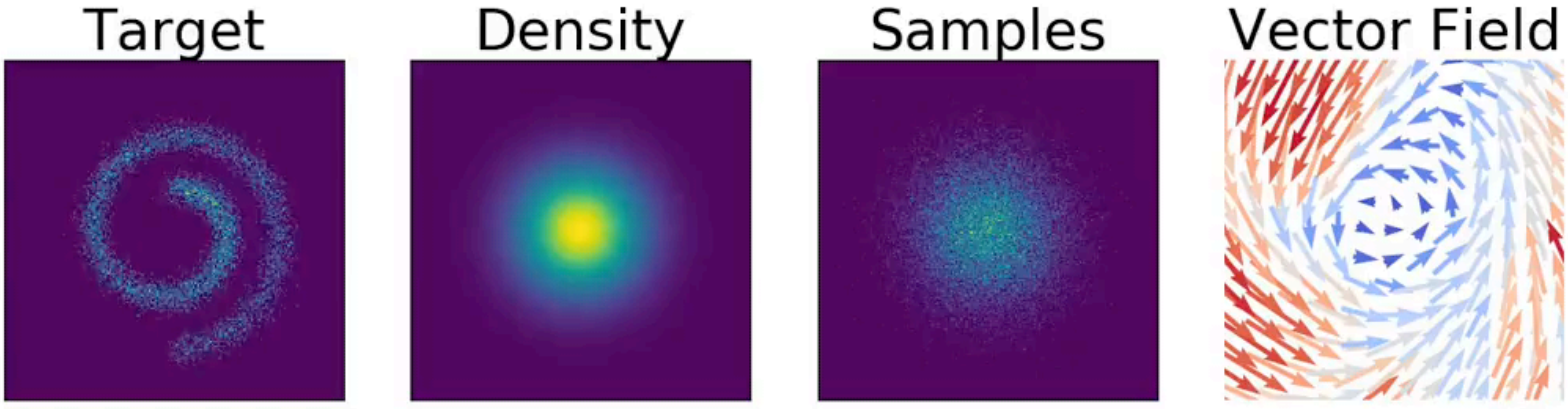


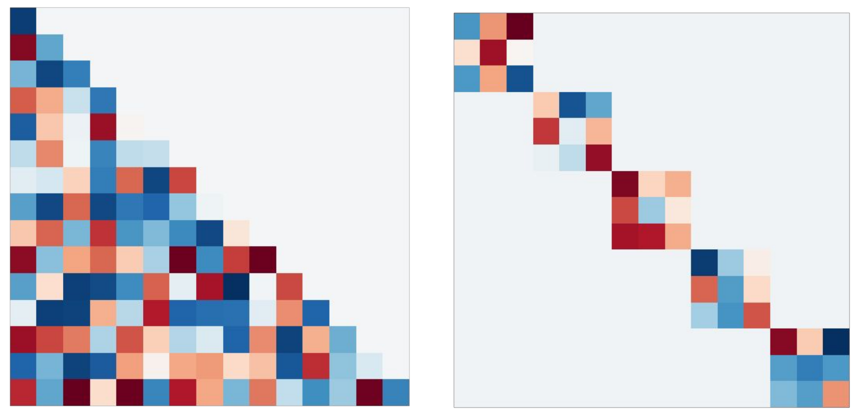


Continuous normalizing flow have no structural constraints on the transformation Jacobian

Neural Ordinary Differential Equations

Chen et al, 1806.07366, Grathwohl et al 1810.01367



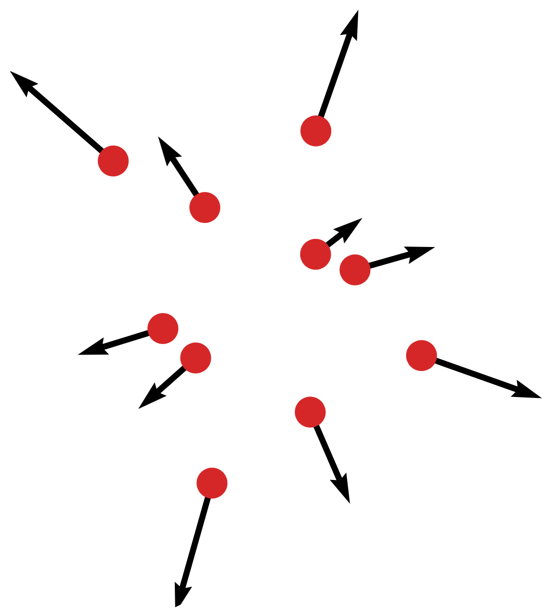


Continuous normalizing flow have no structural constraints on the transformation Jacobian

Fluid physics behind flows

Zhang, E, LW 1809.10188
wangleiphy/MongeAmpereFlow

$$\frac{d\boldsymbol{x}}{dt} = \boldsymbol{v}$$

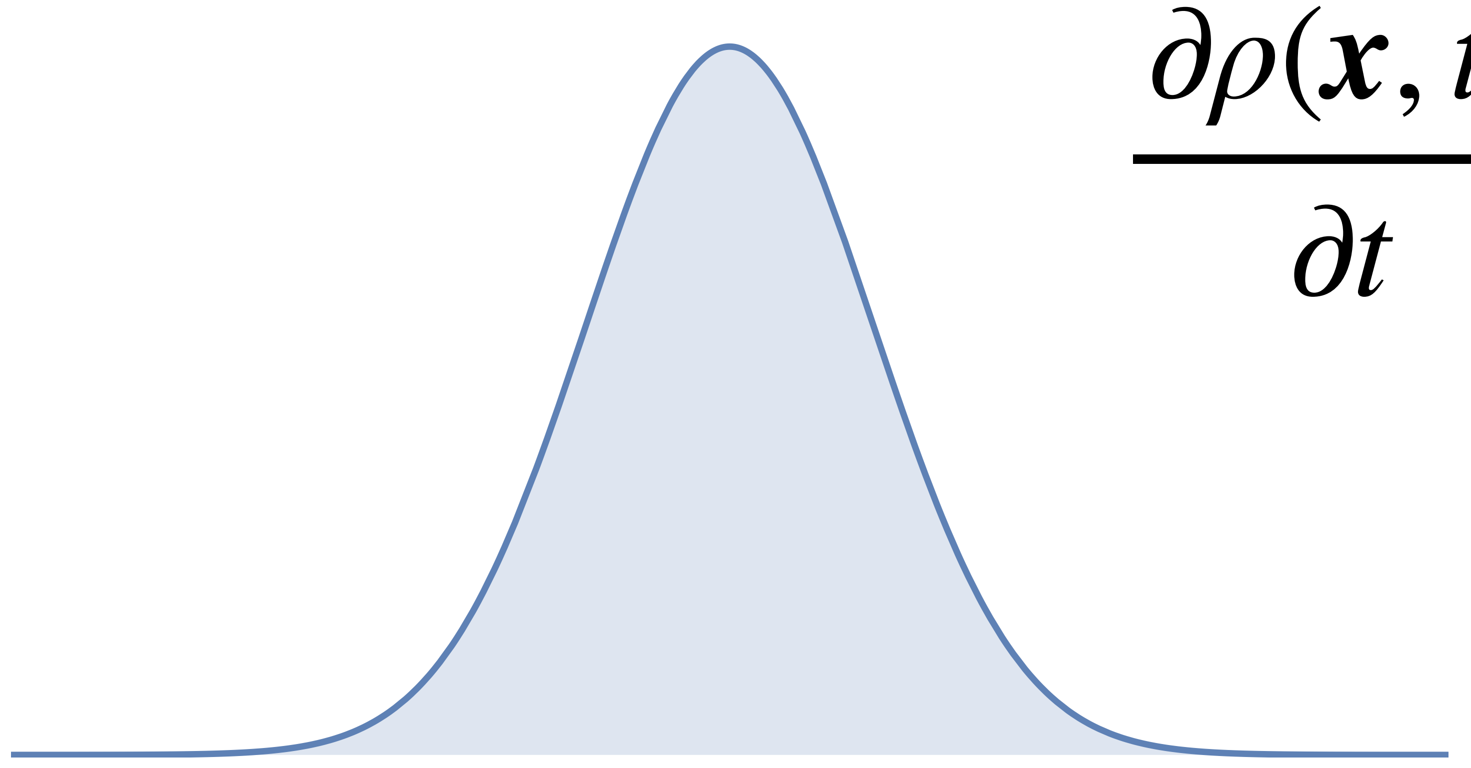


$$\frac{d \ln \rho(\boldsymbol{x}, t)}{dt} = - \nabla \cdot \boldsymbol{v}$$

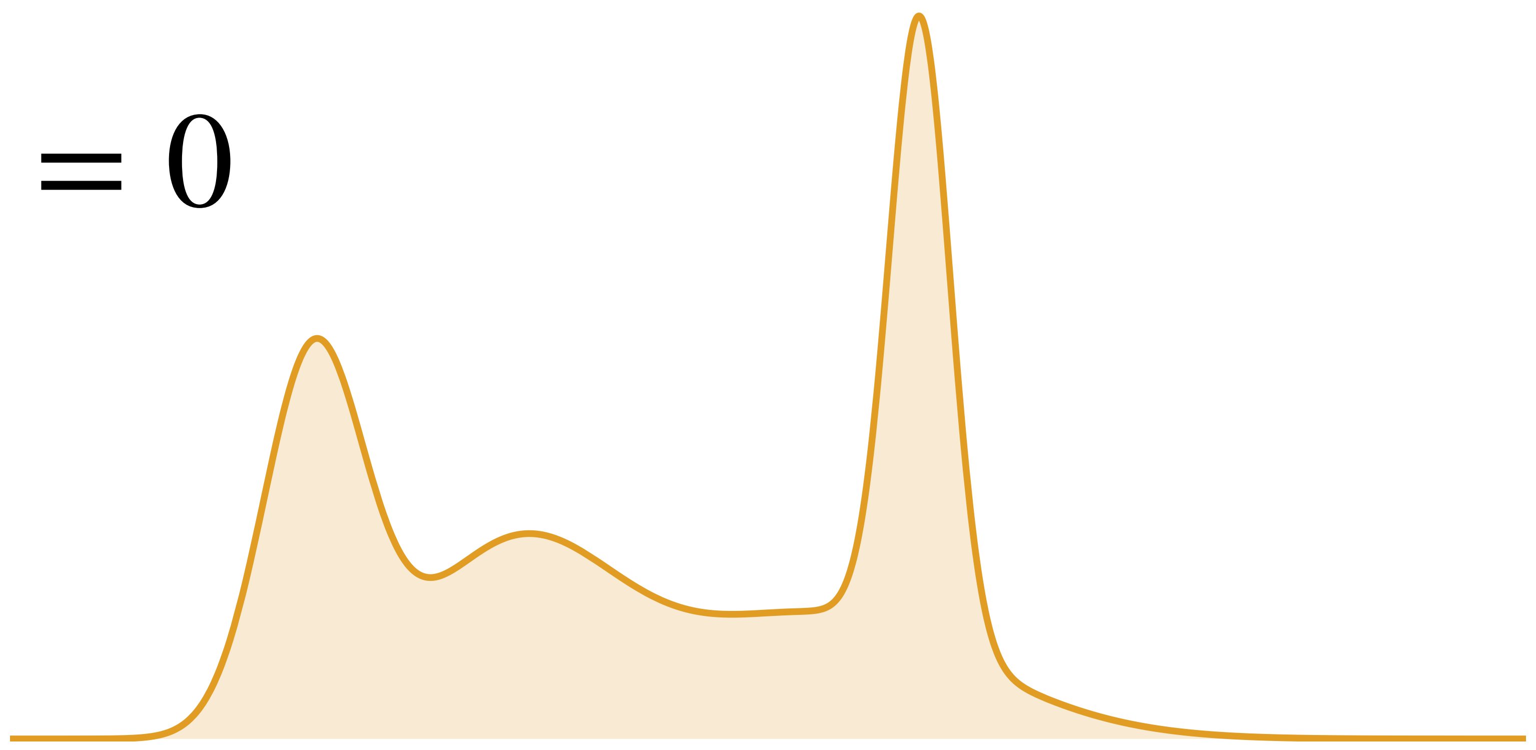
$$\frac{d}{dt} = \frac{\partial}{\partial t} + \boldsymbol{v} \cdot \nabla$$

"material derivative"

$$\frac{\partial \rho(\boldsymbol{x}, t)}{\partial t} + \nabla \cdot \left[\rho(\boldsymbol{x}, t)\boldsymbol{v}\right] = 0$$



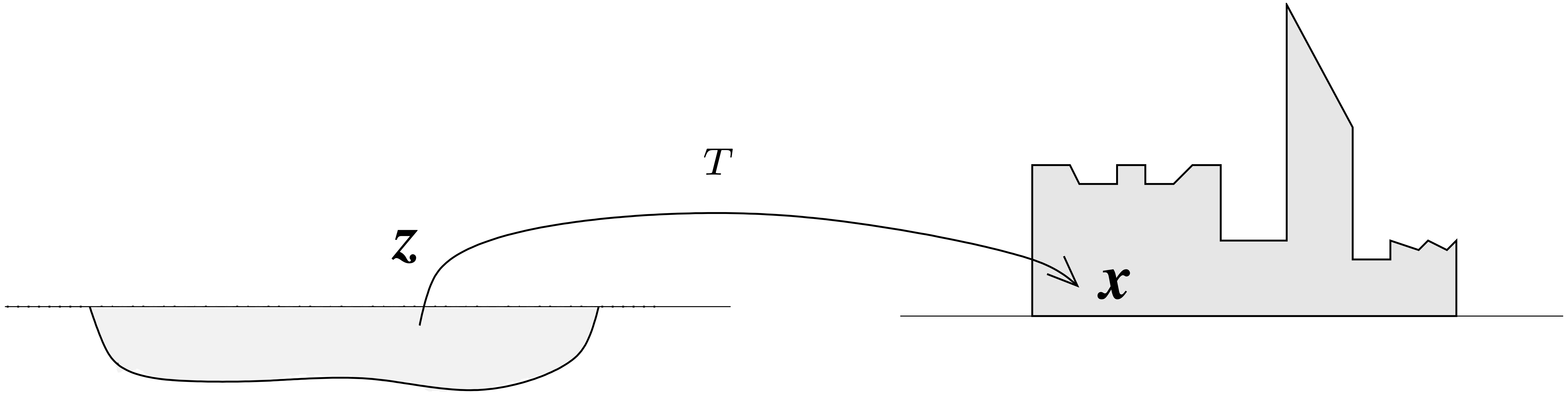
Simple density



Complex density

Optimal Transport Theory

Monge problem (1781): How to transport earth with optimal cost ?



Monge Kantorovich Koopmans Dantzig Brenier Otto McCann Villani Figalli

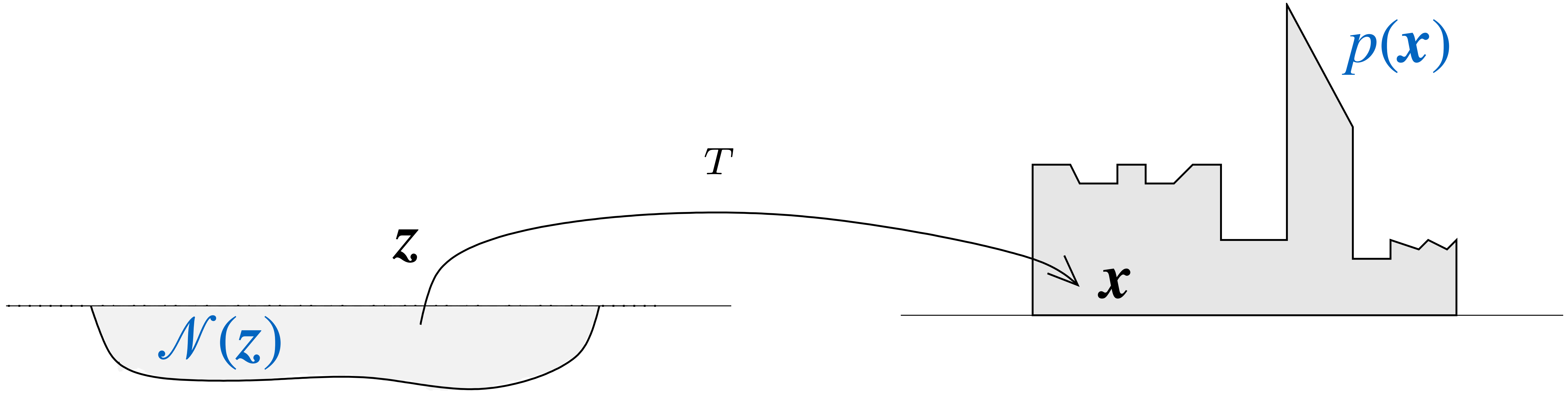
Nobel Prize in Economics '75

Fields Metal '10 **Fields Metal '18**

from Cuturi, Solomon NISP 2017 tutorial

Optimal Transport Theory

Monge problem (1781): How to transport earth with optimal cost ?




Monge


Kantorovich


Koopmans


Dantzig


Brenier


Otto


McCann


Villani


Figalli

Nobel Prize in Economics ’75

Fields Metal ’10

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from Cuturi, Solomon NISP 2017 tutorial

Optimal Transport Theory

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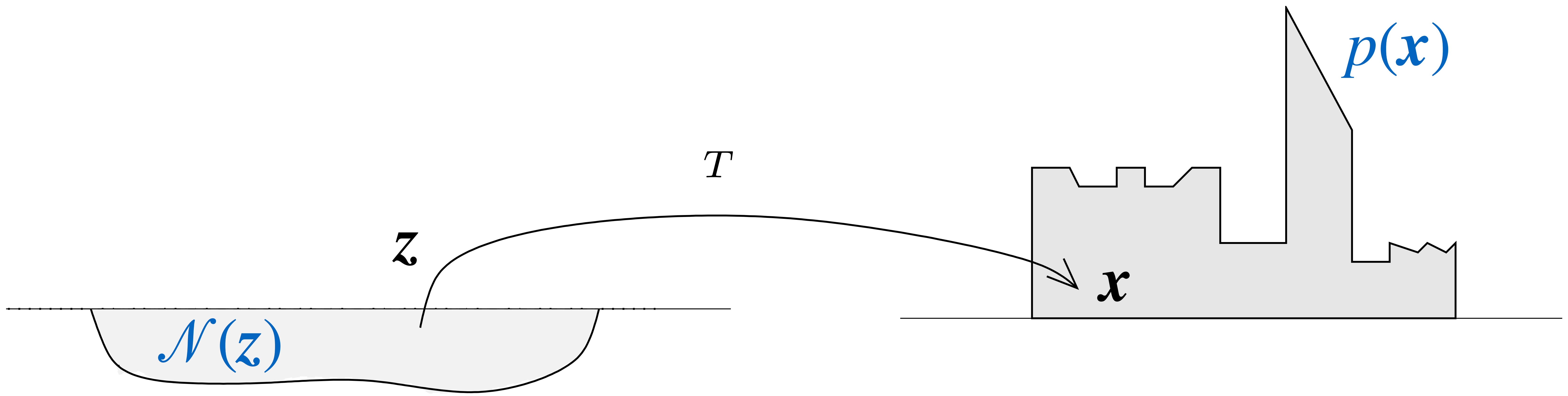


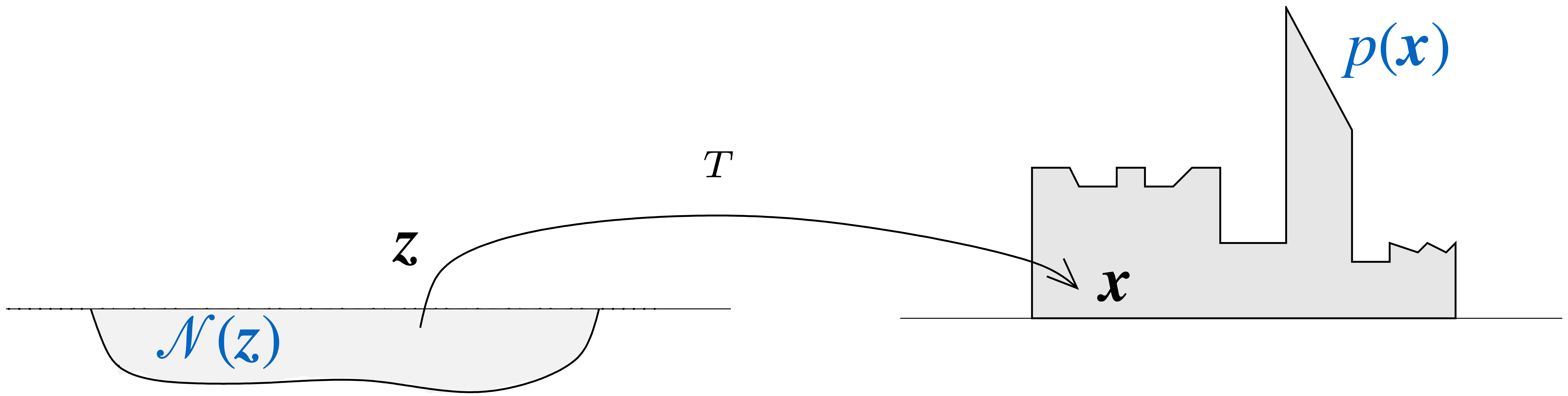
★ Brenier theorem (1991)

Under certain conditions
the optimal map is

$$z \mapsto x = \nabla u(z)$$

Optimal Transport Theory

Monge problem (1781): How to transport earth with optimal cost ?



Brenier theorem (1991)

Under certain conditions
the optimal map is

$$z \mapsto x = \nabla u(z)$$

Monge-Ampère Equation

$$\frac{\mathcal{N}(z)}{p(\nabla u(z))} = \det\left(\frac{\partial^2 u}{\partial z_i \partial z_j}\right)$$

Monge-Ampère Flow

Zhang, E, LW 1809.10188

[wangleiphy/MongeAmpereFlow]

$$\frac{\partial \rho(\boldsymbol{x}, t)}{\partial t} + \nabla \cdot \left[\rho(\boldsymbol{x}, t) \nabla \varphi \right] = 0$$

1. **Drive the flow with an "irrotational" velocity field**
2. **Impose symmetry to the scalar valued potential for symmetric generative model**

$$\varphi(g\,\boldsymbol{x}) = \varphi(\boldsymbol{x}) \quad \Longrightarrow \quad \rho(g\,\boldsymbol{x}) = \rho(\boldsymbol{x})$$

Hamiltonian dynamics: phase space flow

Hamiltonian equations

$$\begin{cases} \dot{p} = -\dfrac{\partial H}{\partial q} \\ \dot{q} = +\dfrac{\partial H}{\partial p} \end{cases}$$

Hamiltonian dynamics: phase space flow

Hamiltonian equations

$$\begin{cases} \dot{p} = -\dfrac{\partial H}{\partial q} \\ \dot{q} = +\dfrac{\partial H}{\partial p} \end{cases}$$

Phase space variables

$$\boldsymbol{x} = (p, q)$$

Symplectic metric

$$J = \begin{pmatrix} & I \\ -I & \end{pmatrix}$$

Hamiltonian dynamics: phase space flow

Hamiltonian equations

$$\begin{cases} \dot{p} = -\dfrac{\partial H}{\partial q} \\ \dot{q} = +\dfrac{\partial H}{\partial p} \end{cases}$$

Phase space variables

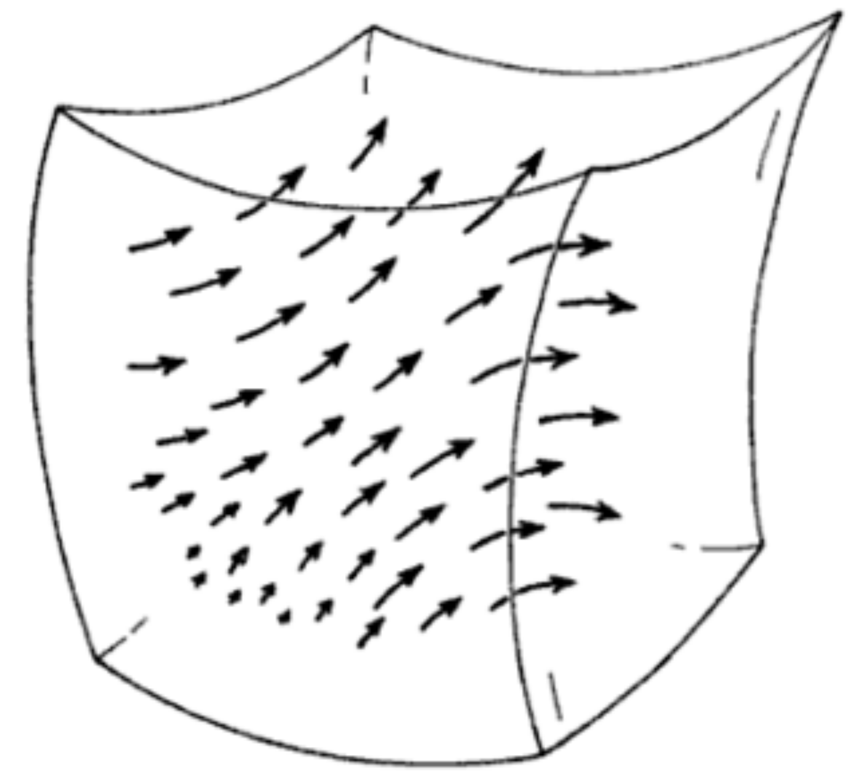
$$\boldsymbol{x} = (p, q)$$

Symplectic metric

$$J = \begin{pmatrix} & I \\ -I & \end{pmatrix}$$

Symplectic gradient flow

$$\dot{\boldsymbol{x}} = \nabla_{\boldsymbol{x}} H(\boldsymbol{x}) J$$



Hamiltonian dynamics: phase space flow

Hamiltonian ec **pace va** **ic gradient flow**

$= (p, q$

$\nabla_x H(x) J$

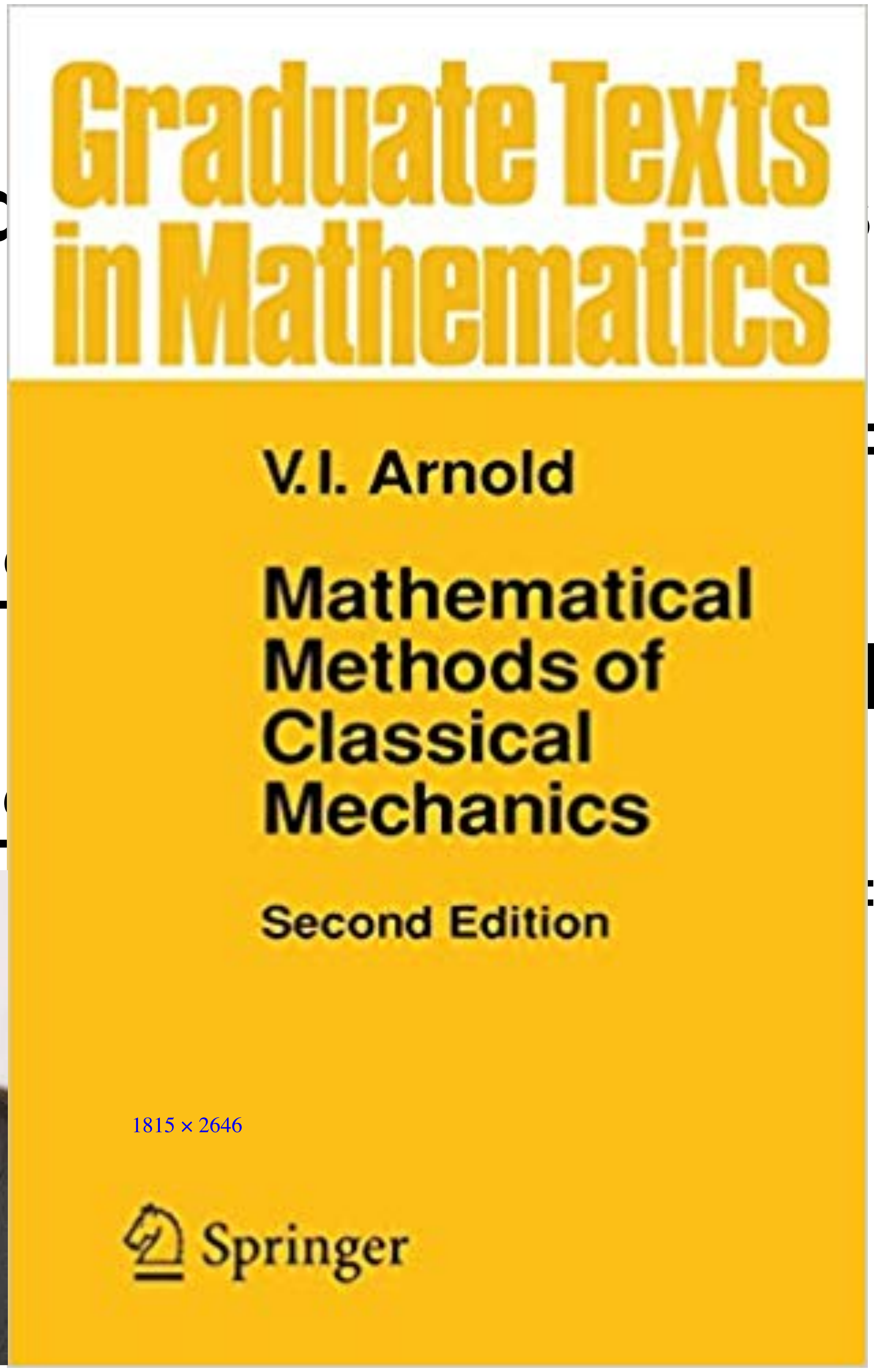
$\dot{p} = -$

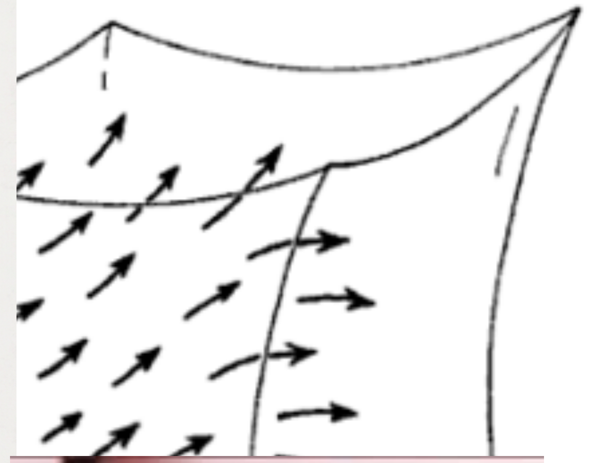
$\dot{q} = +$

lectic m

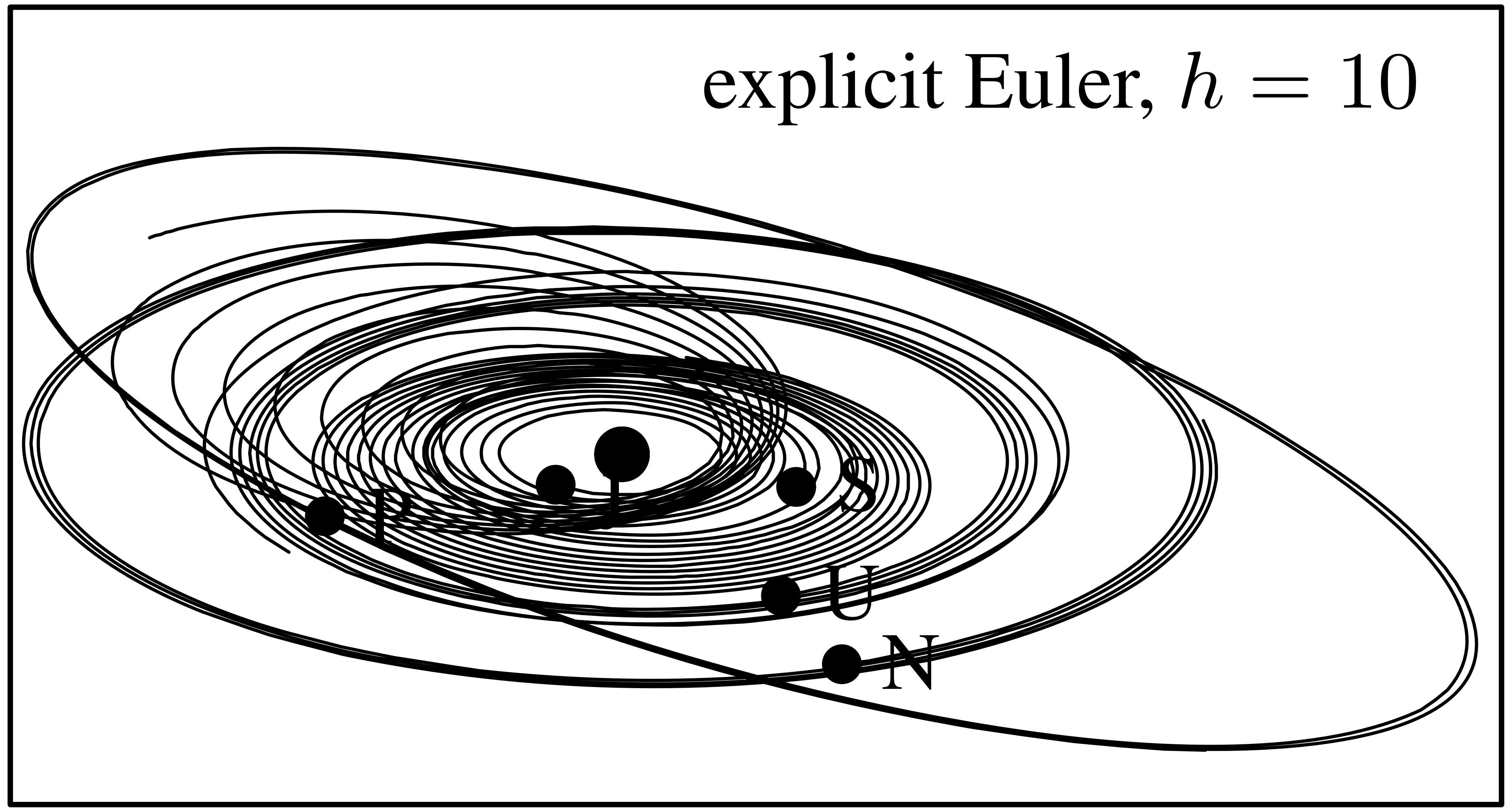
I

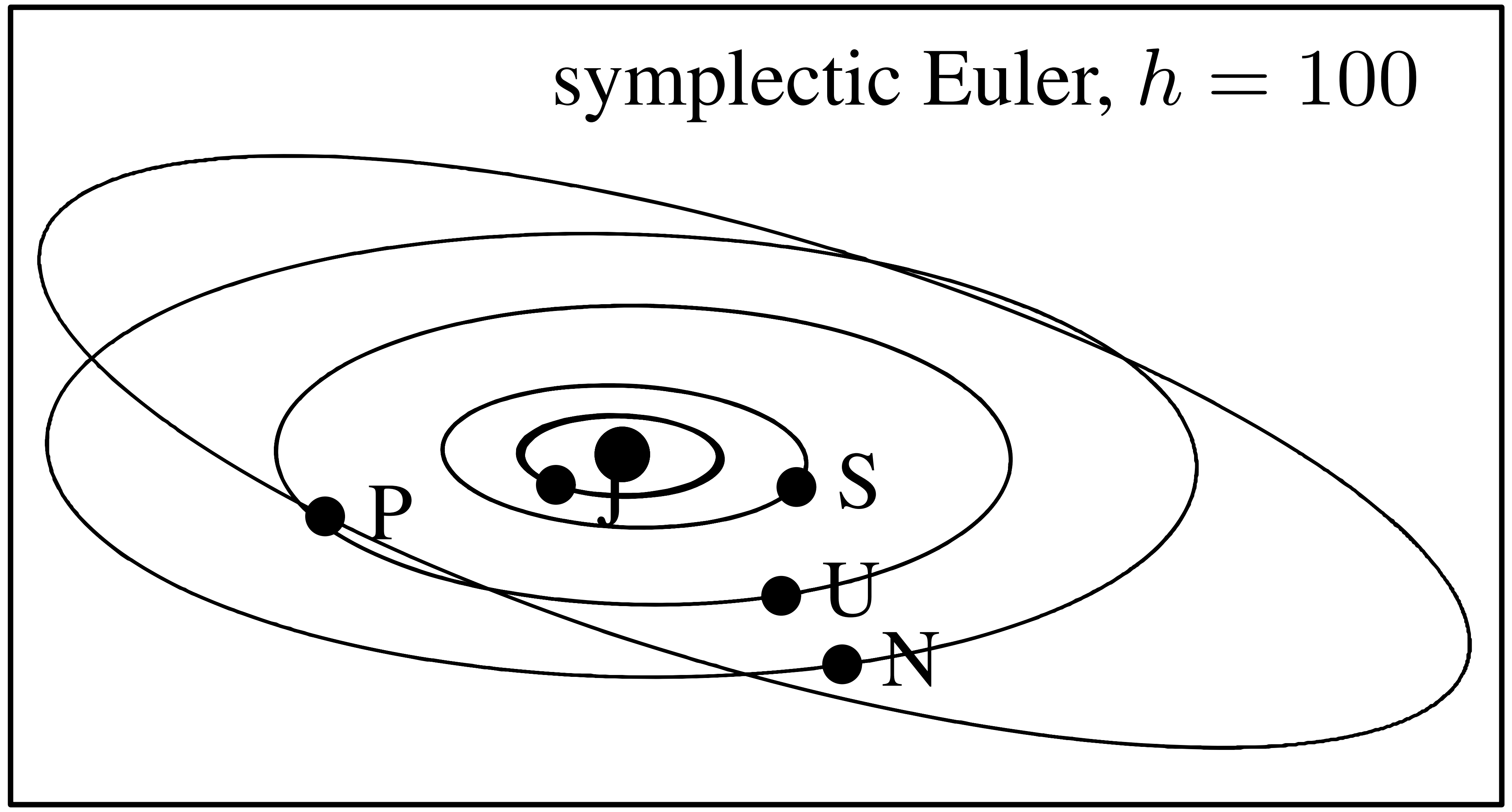
$\Big(-I$





Symplectic Integrators





from Hairer et al, Geometric Numerical Integration

Canonical Transformations

Change of variables

$$\boldsymbol{x} = (p, q) \longleftrightarrow \boldsymbol{z} = (P, Q)$$

which satisfies $\left(\nabla_{\boldsymbol{x}} \boldsymbol{z}\right) J \left(\nabla_{\boldsymbol{x}} \boldsymbol{z}\right)^T = J$ symplectic condition

Canonical Transformations

Change of variables

$$\boldsymbol{x} = (p, q) \longleftrightarrow \boldsymbol{z} = (P, Q)$$

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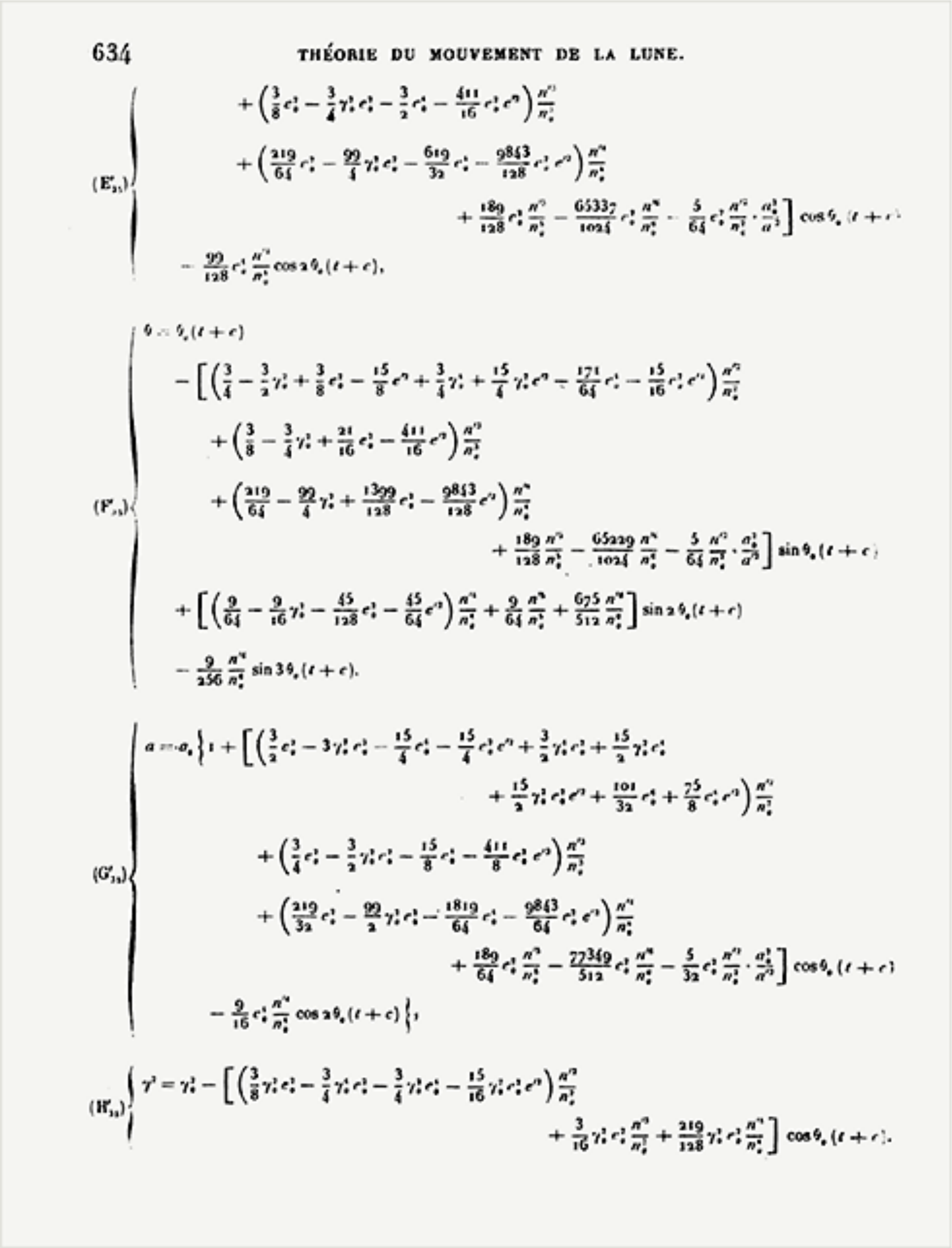
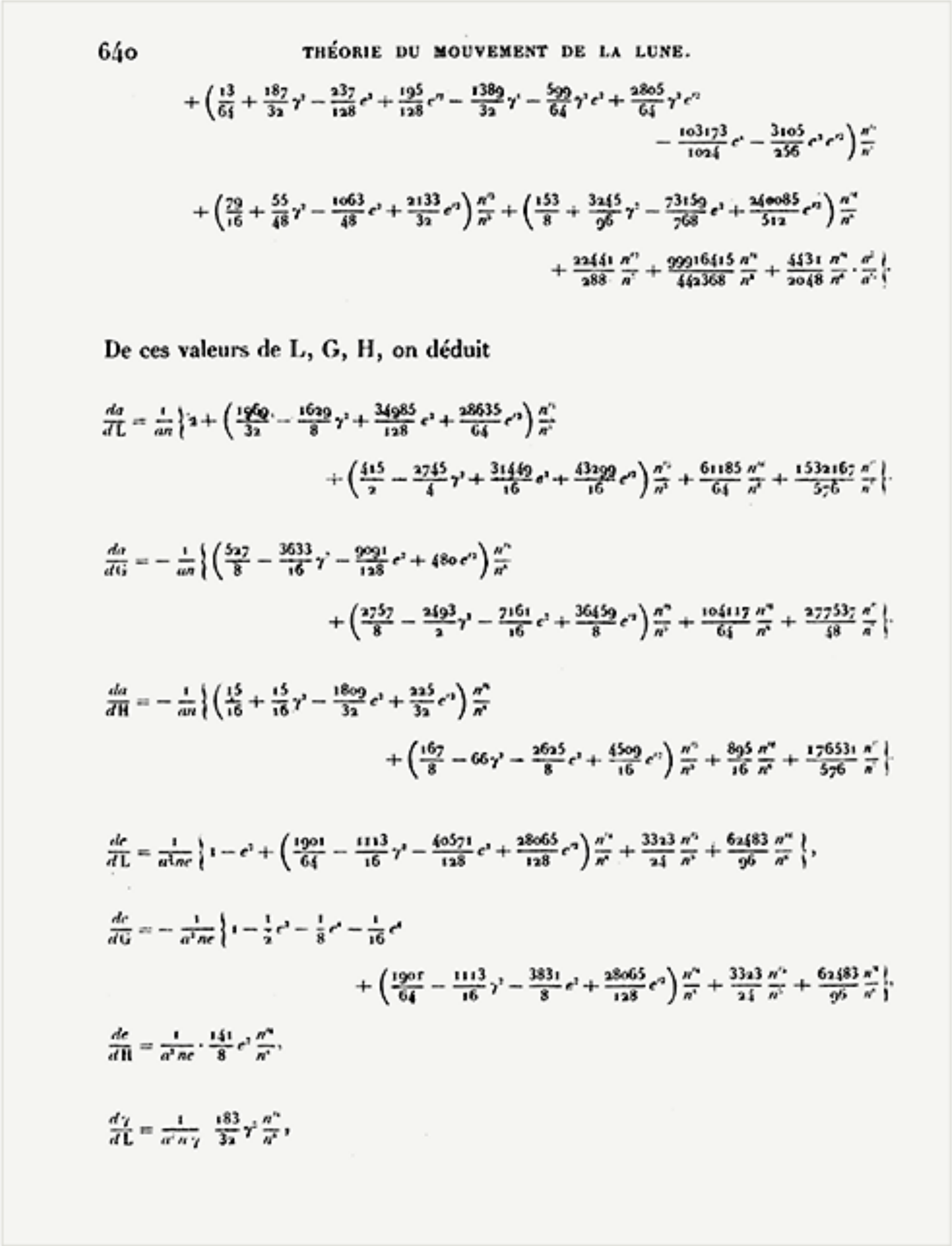
one has $\dot{\boldsymbol{z}} = \nabla_{\boldsymbol{z}} K(\boldsymbol{z}) J$ where $K(\boldsymbol{z}) = H \circ \boldsymbol{x}(\boldsymbol{z})$

Preserves Hamiltonian dynamics in the “latent phase space”

Canonical transformation for Moon-Earth-Sun 3-body problem

Gutzwiller, RMP, '98


634 THÉORIE DU MOUVEMENT DE LA LUNE.


640 THÉORIE DU MOUVEMENT DE LA LUNE.

De ces valeurs de L, G, H, on déduit

↑

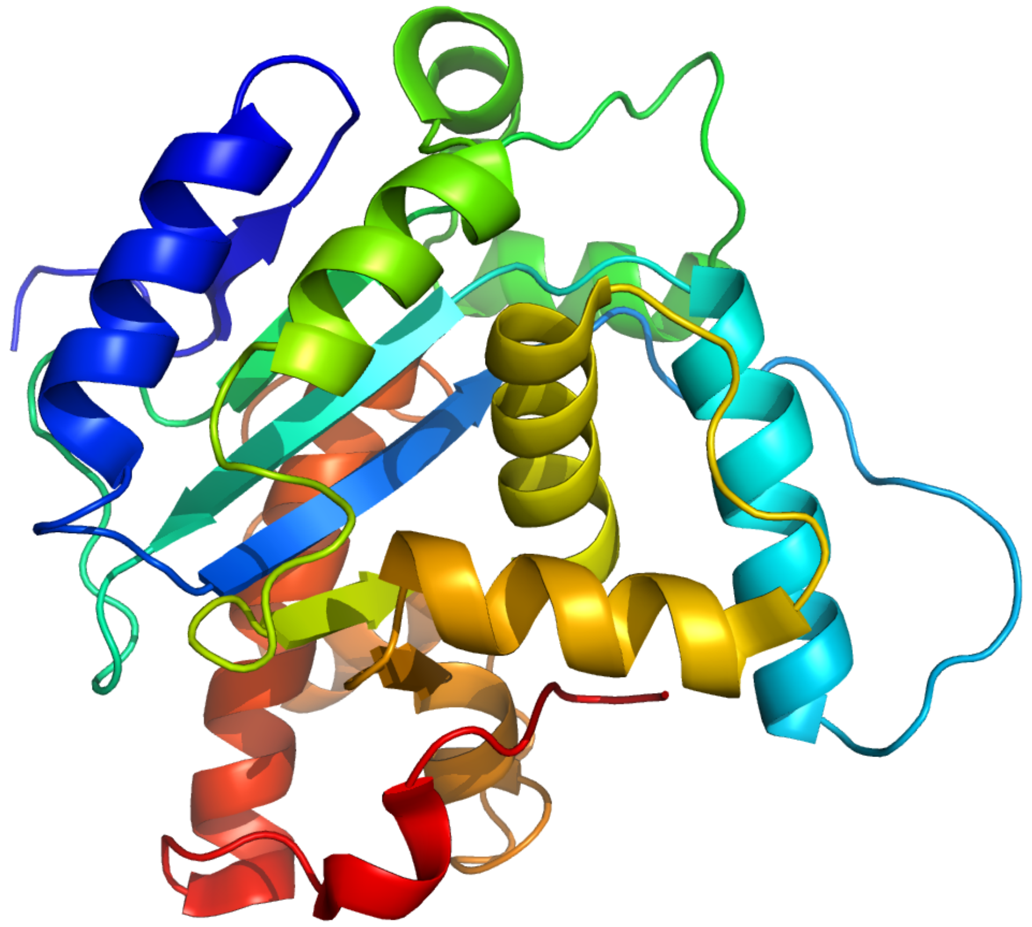
Charles Delaunay

More than 1800 pages of this, ~20 years of efforts (1846-1867)

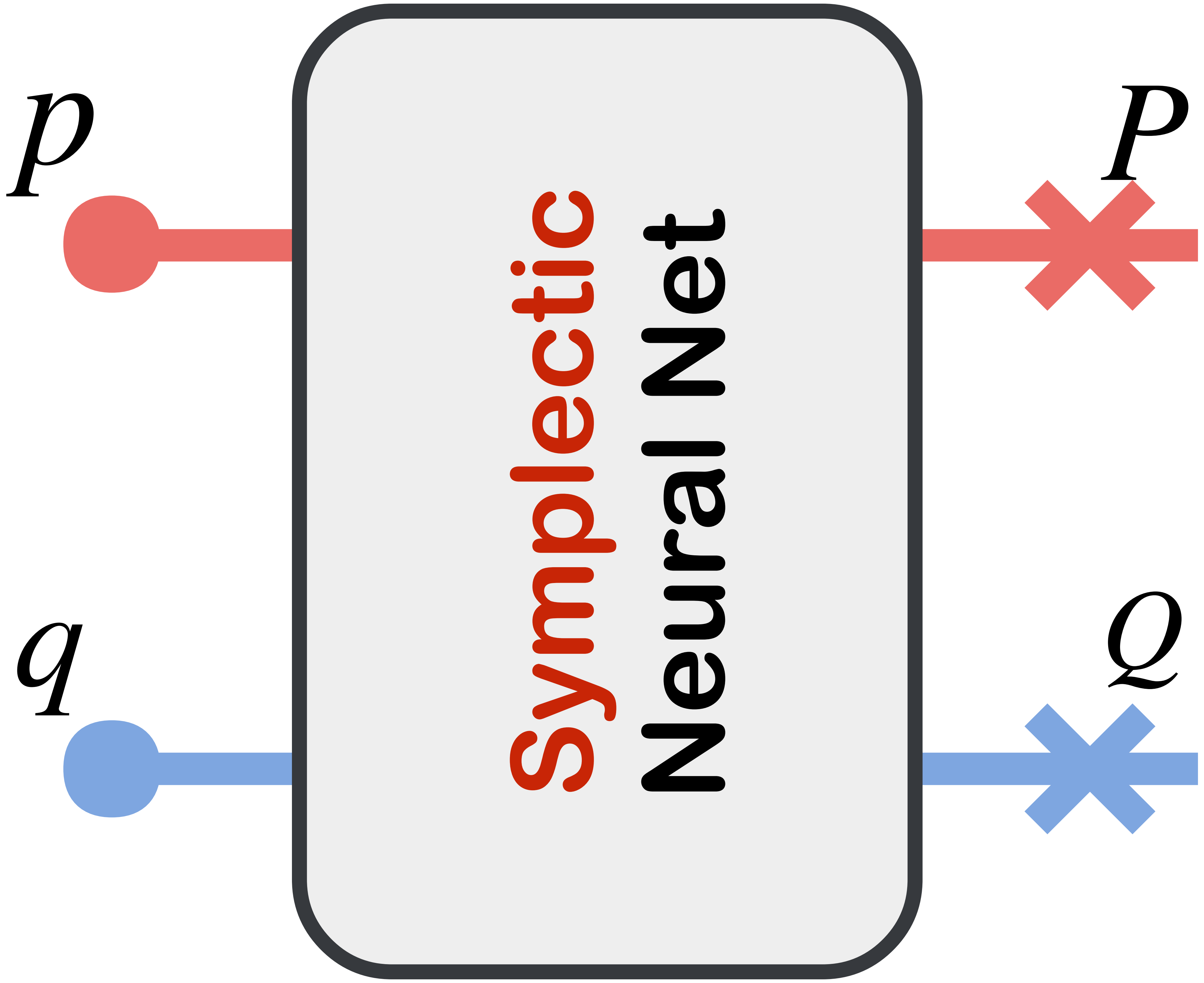
Neural Canonical Transformations

Li, Dong, Zhang, LW, PRX '20 li012589/neuralCT

$H(p, q)$



physical space

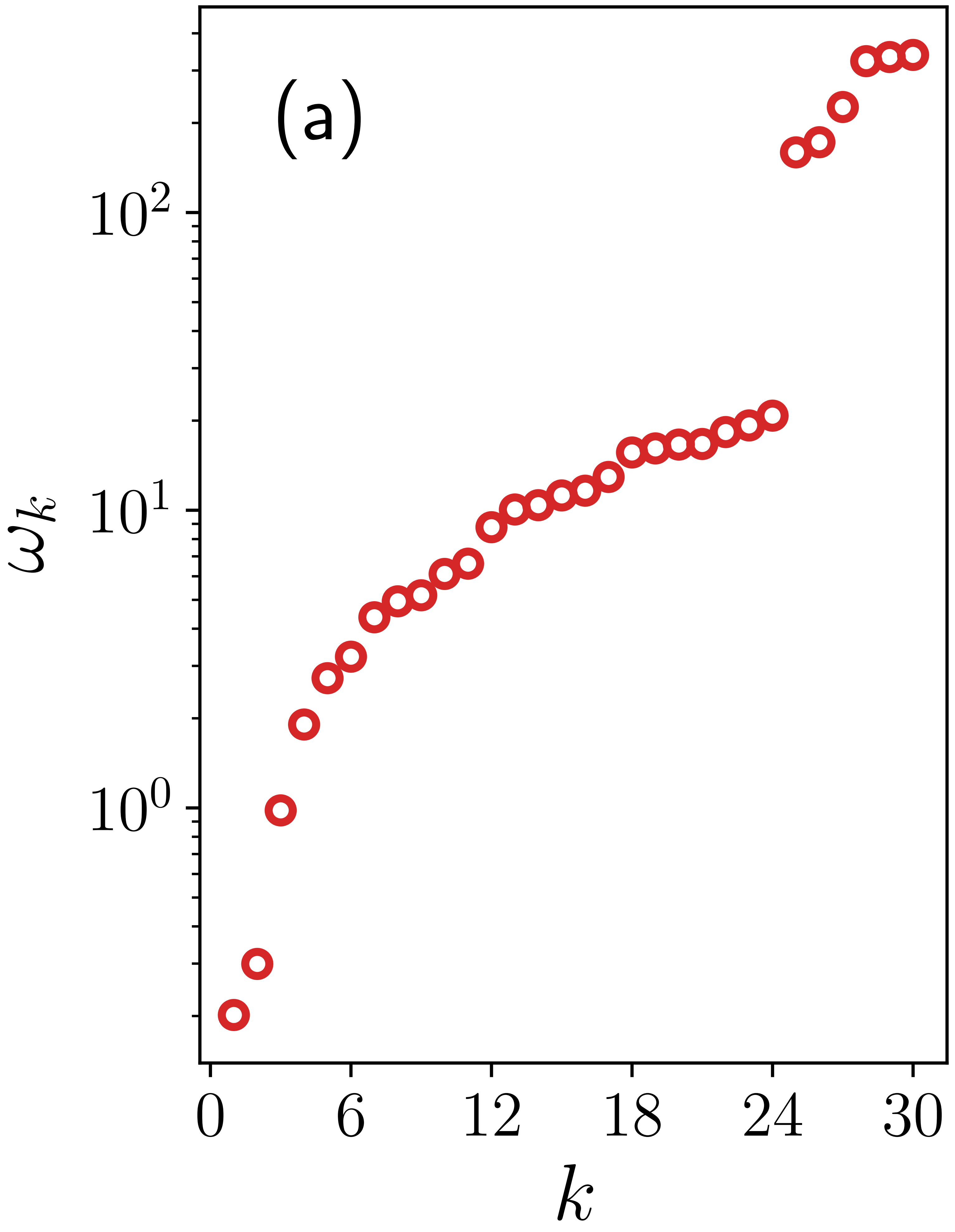


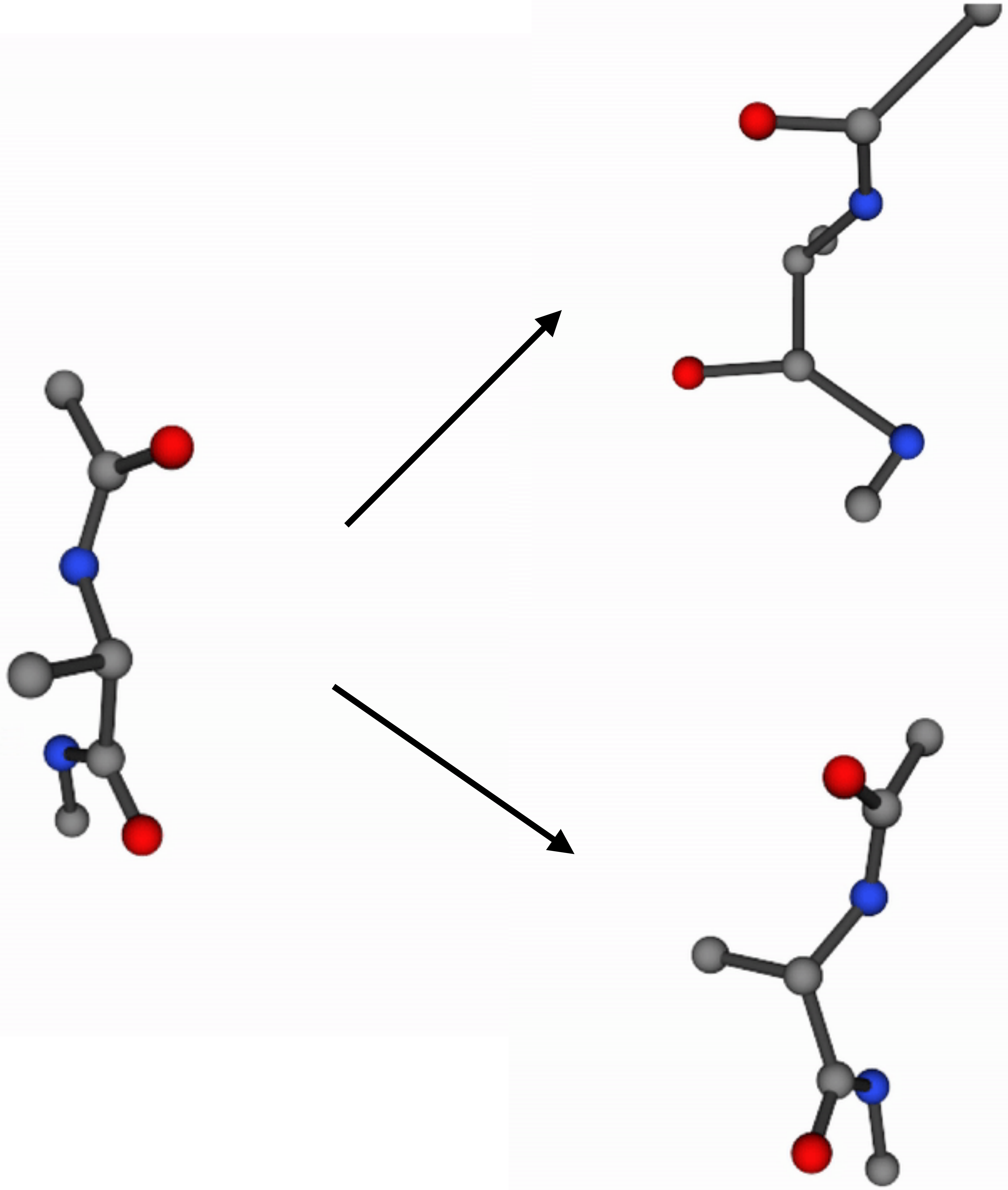
$$K(P, Q) = \sum_k \frac{P_k^2 + \omega_k^2 Q_k^2}{2}$$

latent space

Learn the network parameter and the latent harmonic frequency

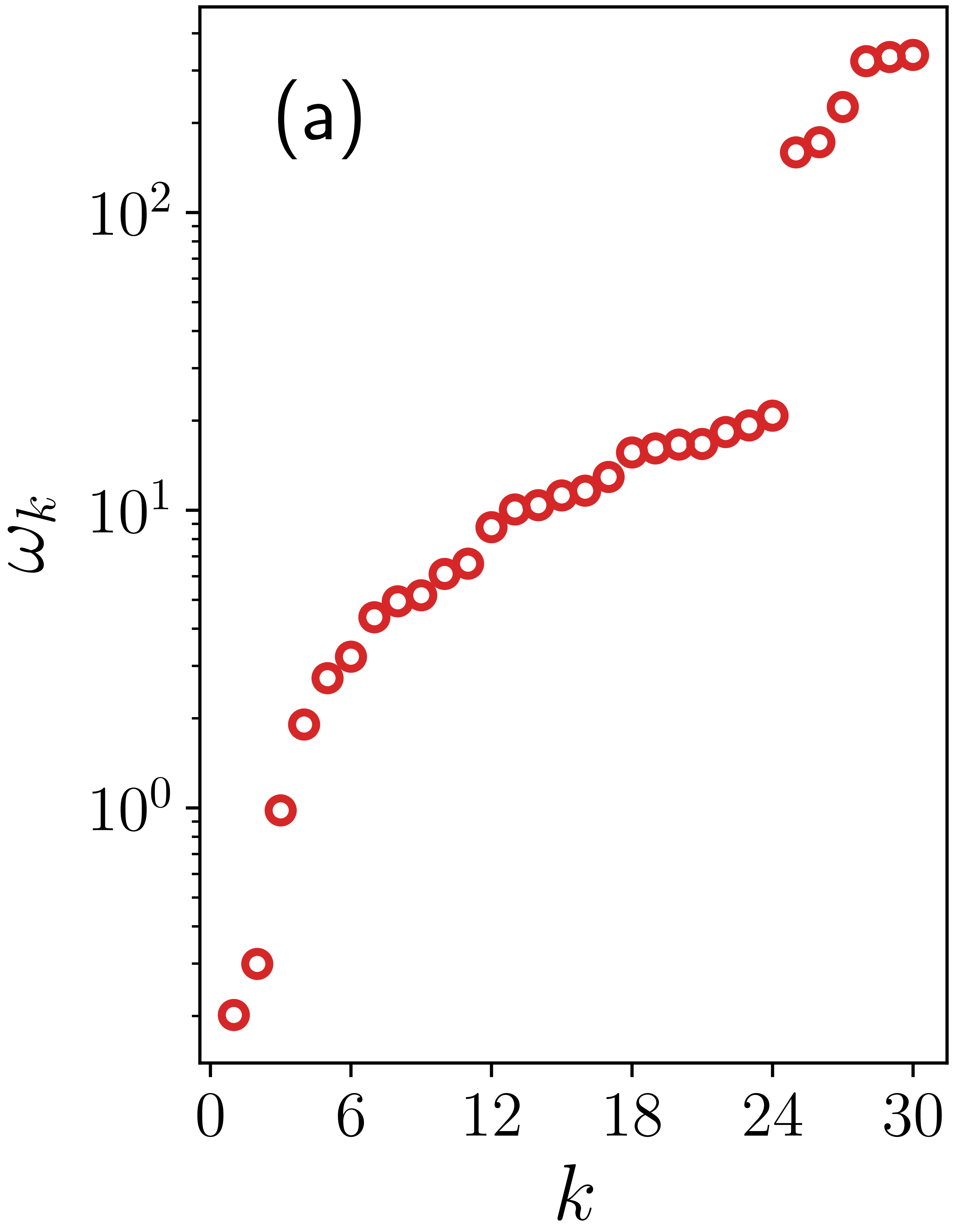
Alanine dipeptide slow modes

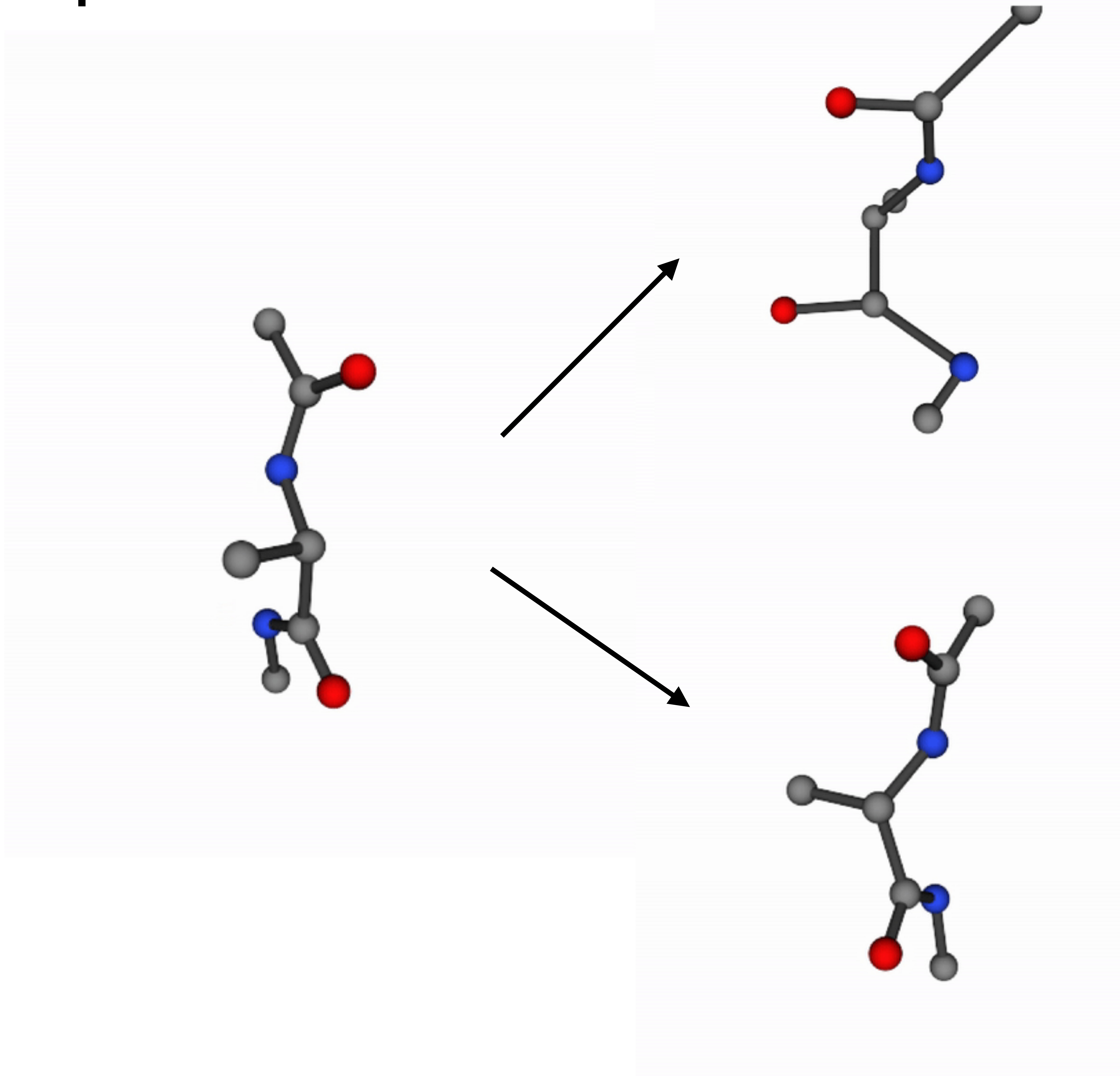




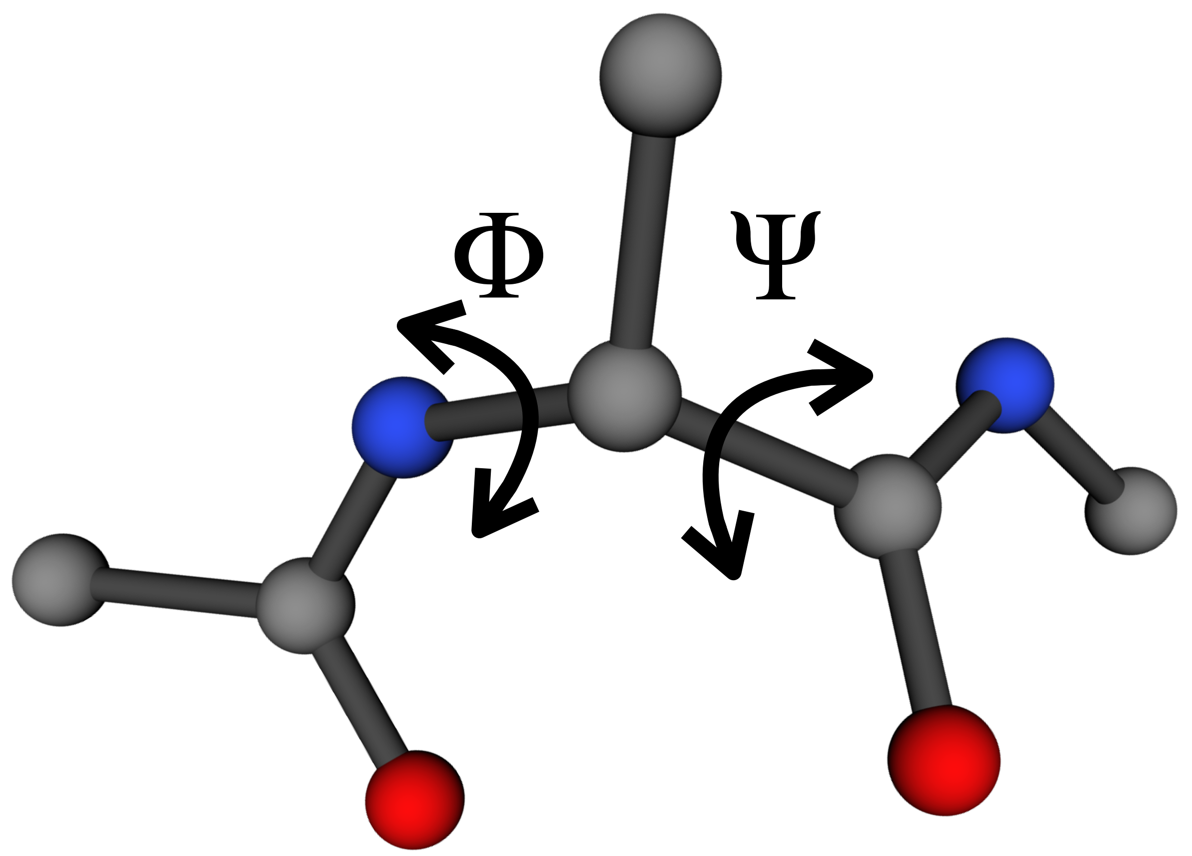
Neural canonical transformation identifies nonlinear slow modes!

Alanine dipeptide slow modes

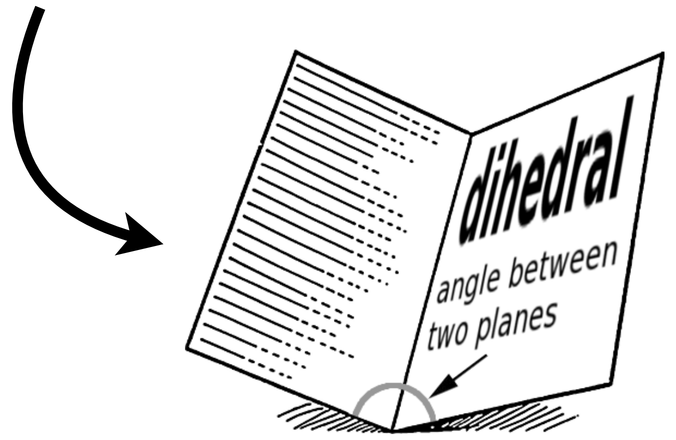


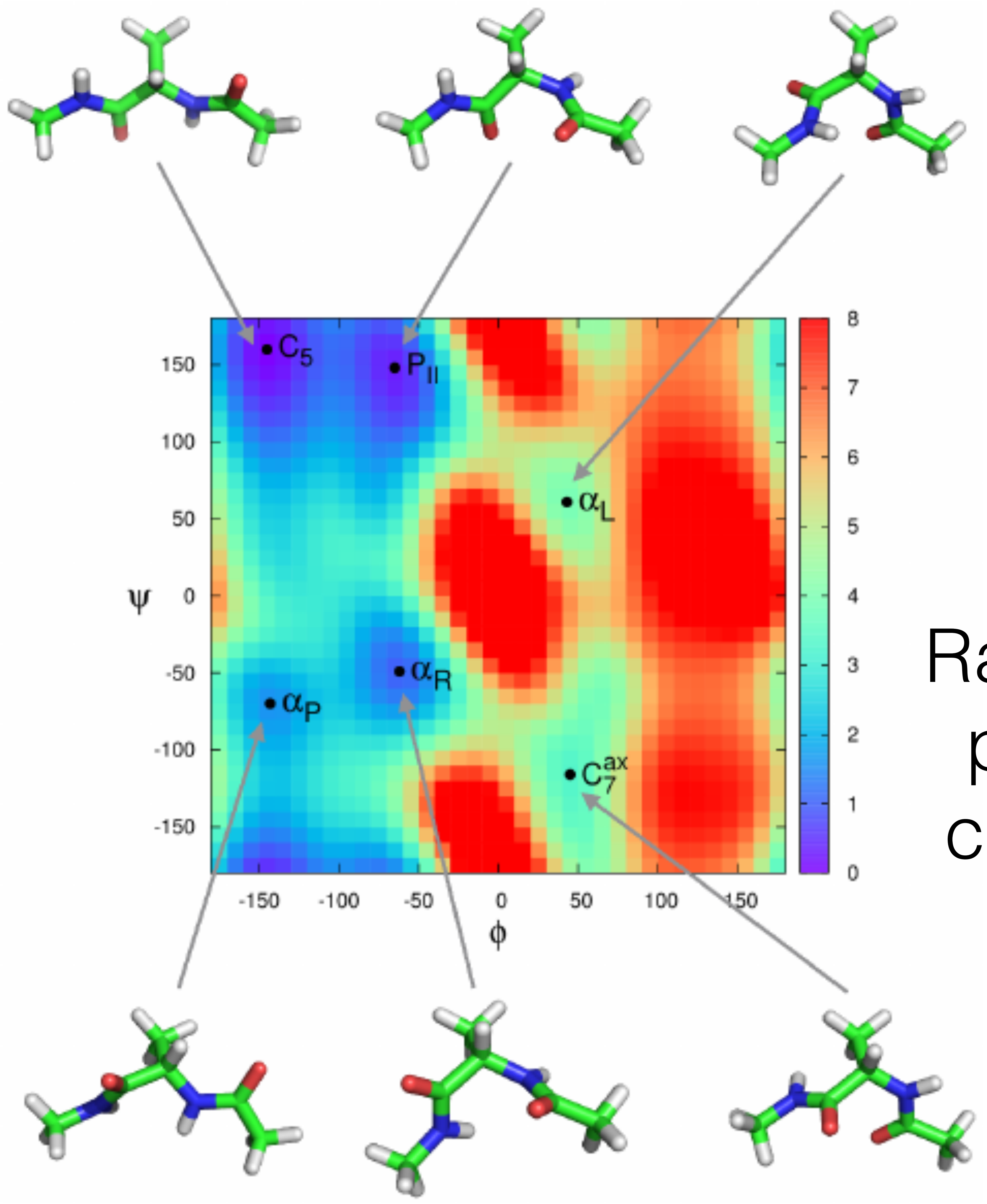


Neural canonical transformation identifies nonlinear slow modes!



slow motion of the
two torsion angles





Ramachandran
plot of stable
conformations

Dimensional reduction to slow collective variables useful for control, prediction, enhanced sampling…

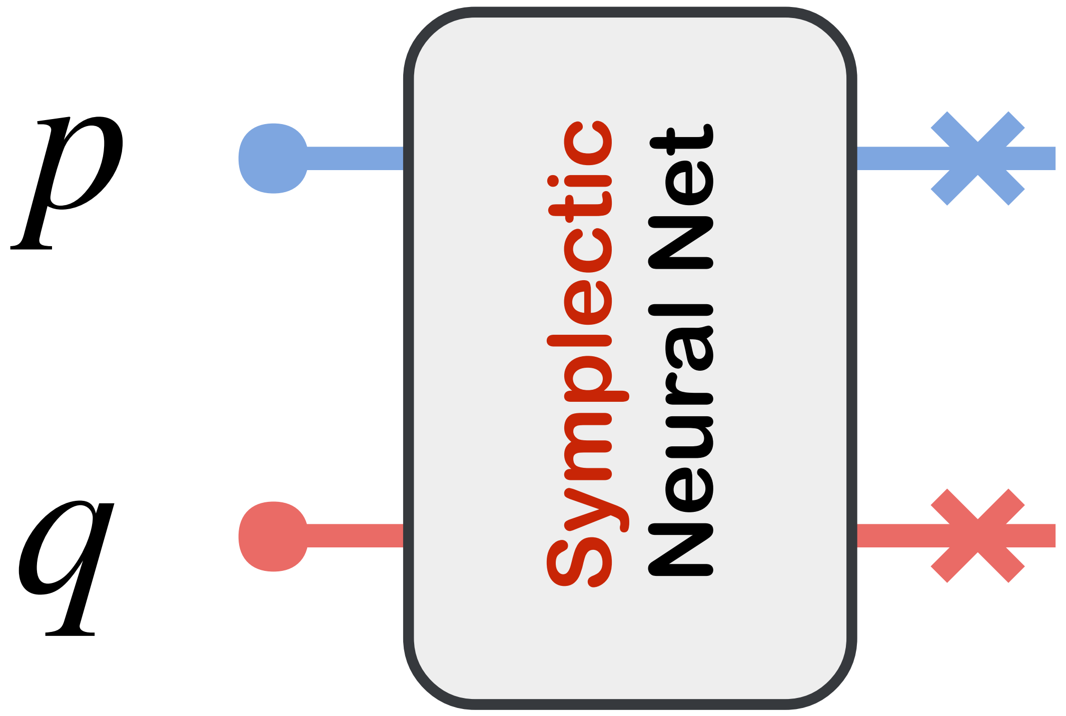
check the paper 1910.00024, PRX ’20 for more examples & applications

Symplectic primitives

- Linear transformation: Symplectic Lie algebra
- Continuous-time flow: Symplectic generating functions

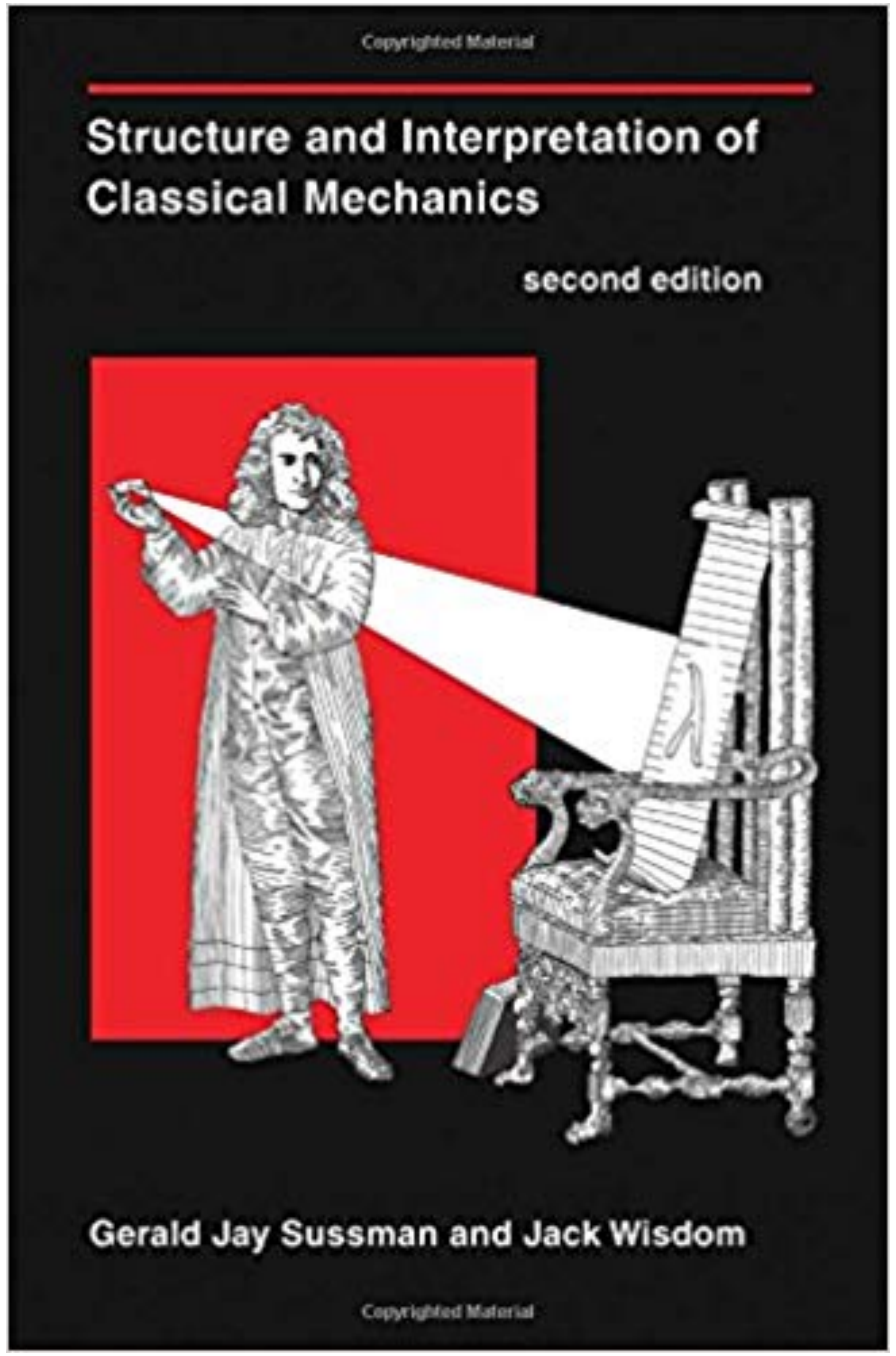
Symplectic integrator of neural ODE, Chen et al 1806.07366

- **Neural point transformation**



$$P = p\left(\nabla_Q q\right)$$

$$Q = f(q)$$ invertible neural net



"A Hamiltonian Extravaganza"

—Danilo J. Rezende@DeepMind

Sep 25 **ICLR 2020 paper submission deadline**

Sep 26 *Symplectic ODE-Net,* 1909.12077 SIEMENS

Sep 27 *Hamiltonian Graph Networks with ODE Integrators*, 1909.12790 NYU

Sep 29 *Symplectic RNN*, 1909.13334 NYU

Sep 30 *Equivariant Hamiltonian Flows*, 1909.13739

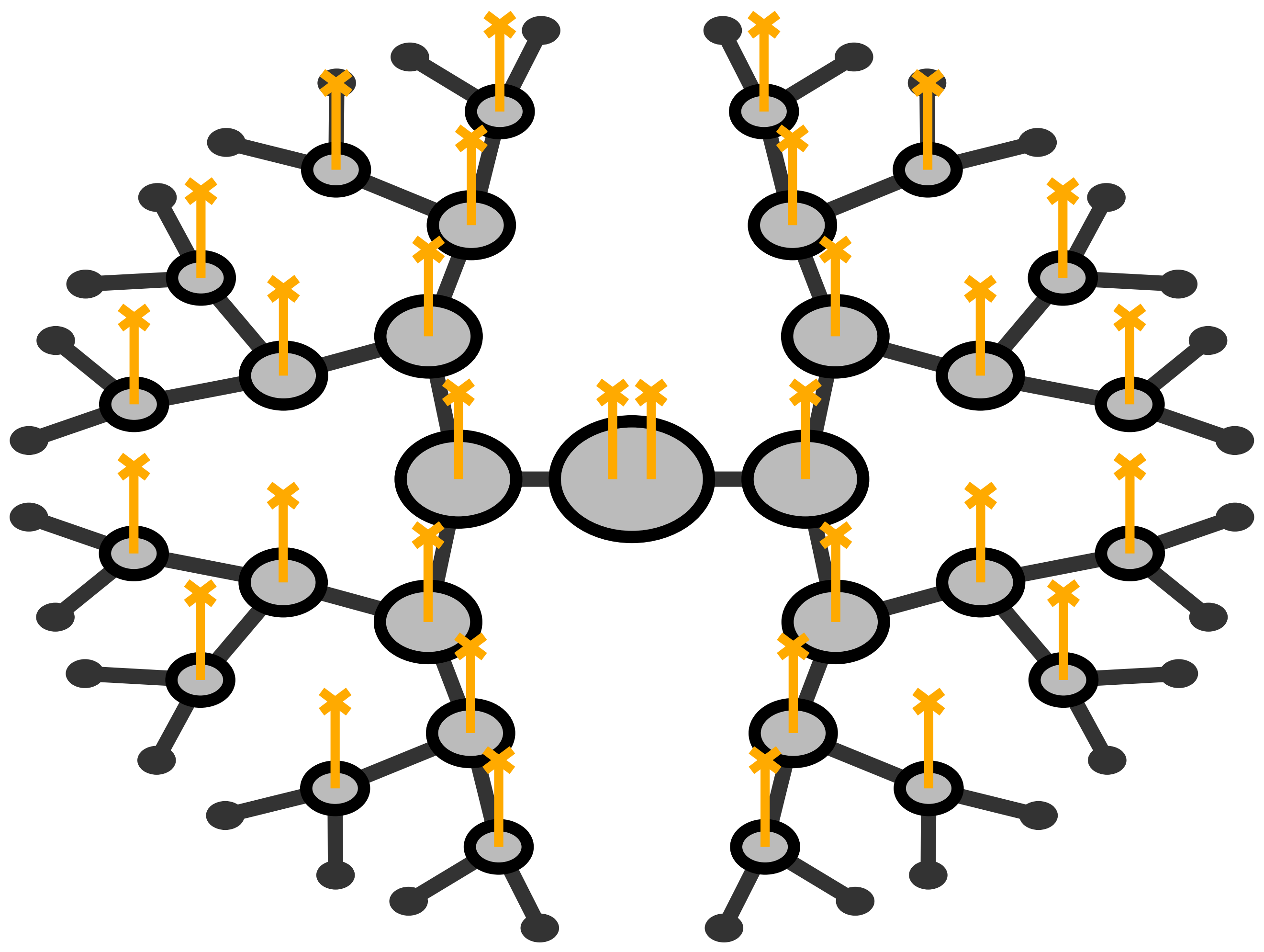
Hamiltonian Generative Network, 1909.13789 http://tiny.cc/hgn

Neural Canonical Transformation with Symplectic Flows, 1910.00024

See also Bondesan & Lamacraft, *Learning Symmetries of Classical Integrable Systems*,1906.04645

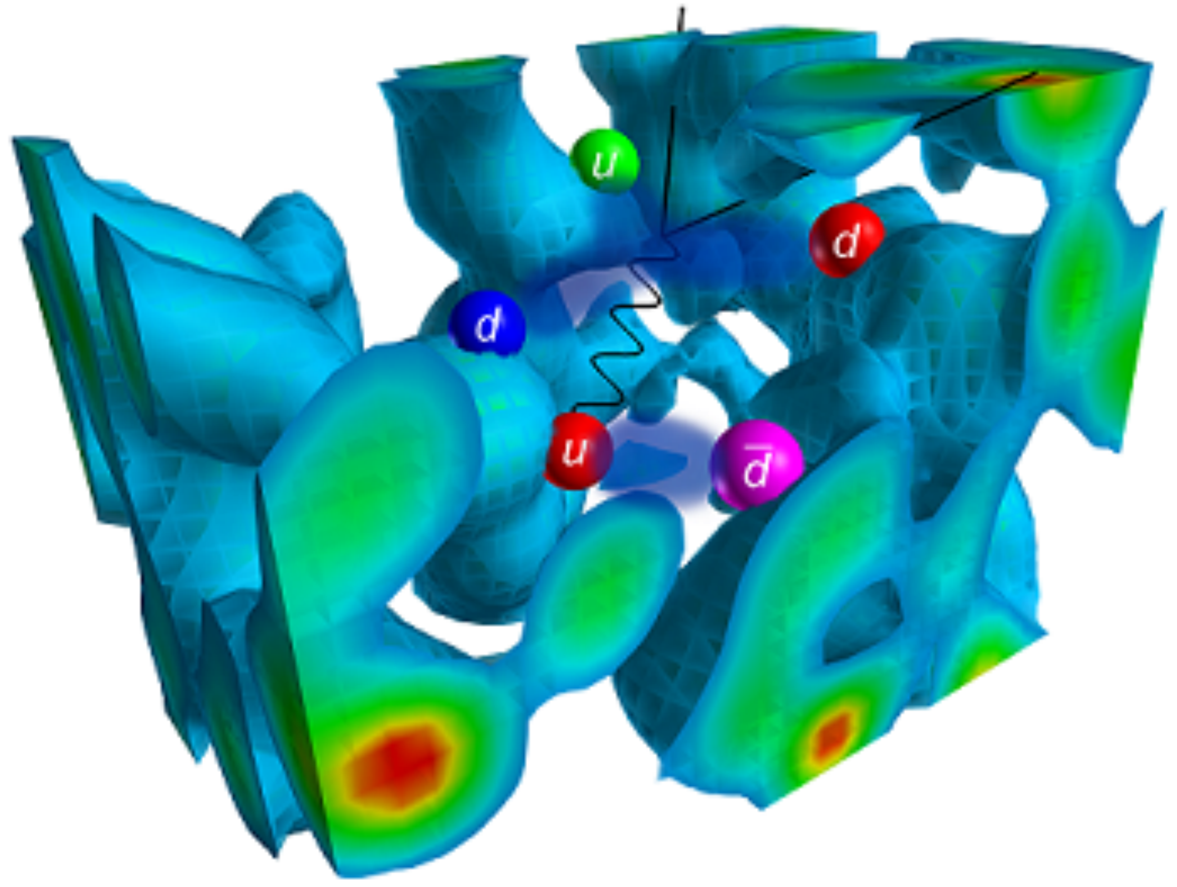
Killer application in science ?

Renormalization group



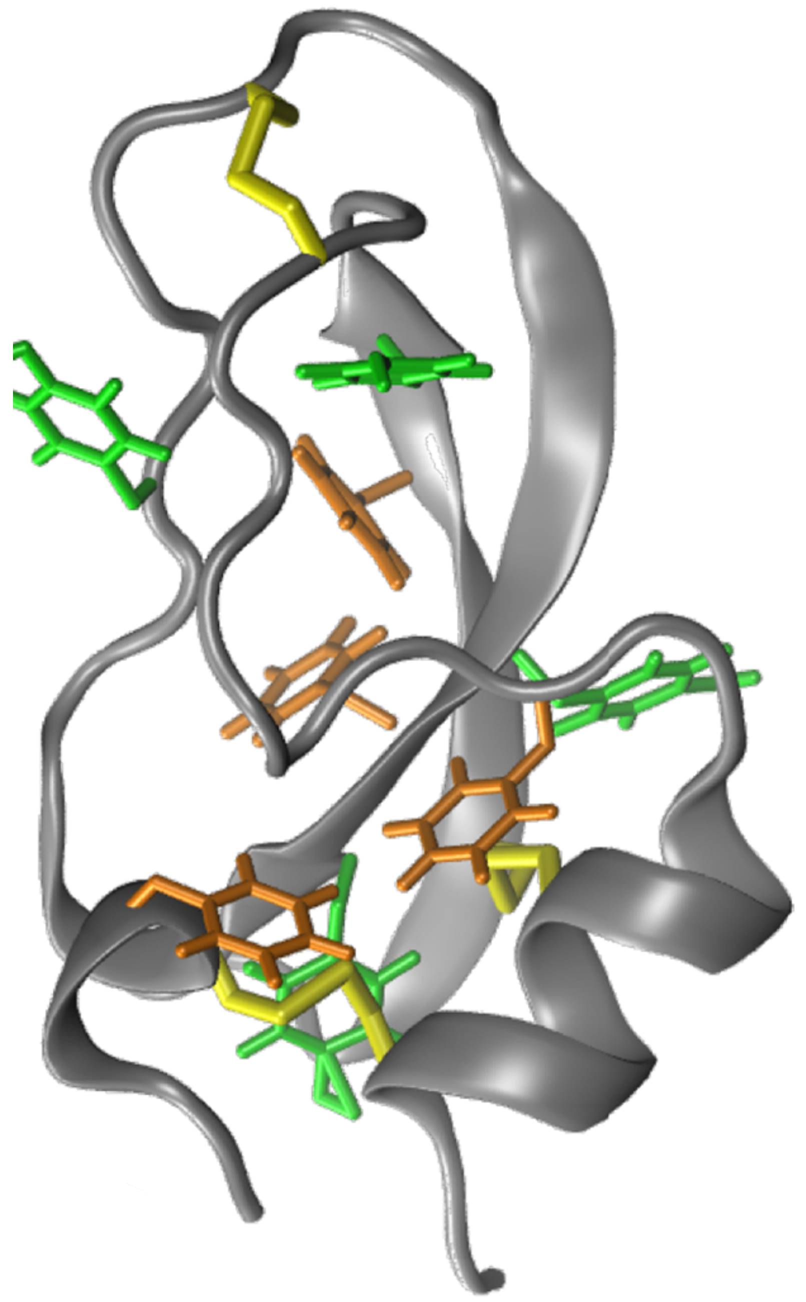
Li and LW, PRL '18
Hu et al, PRResearch '20

Lattice field theory



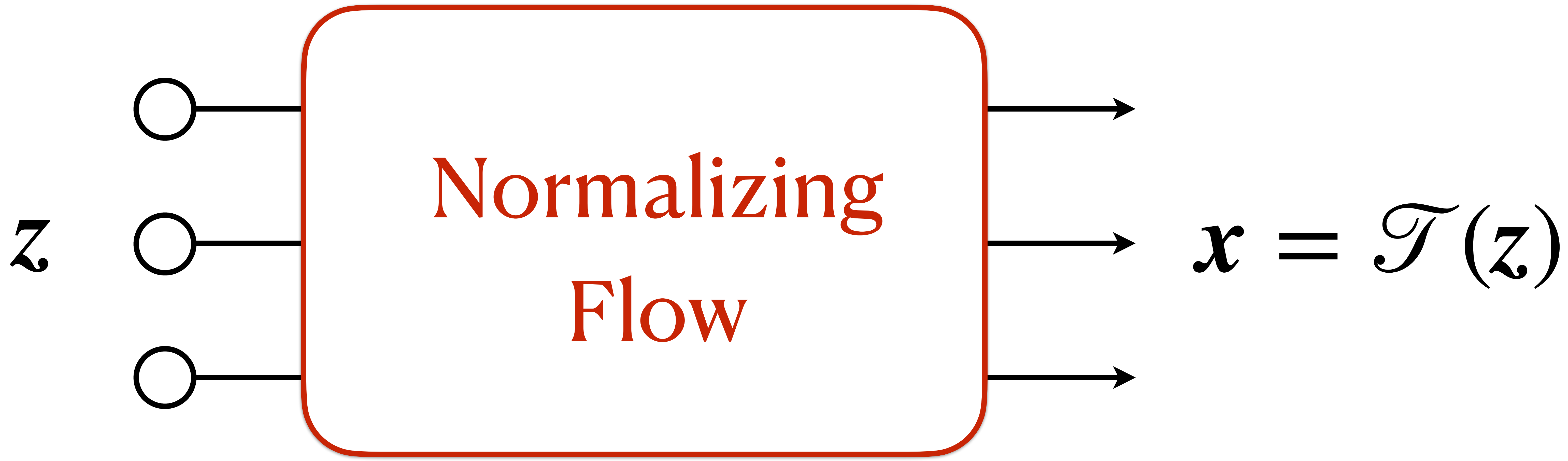
Albergo et al, PRD '19
Kanwar et al, PRL '20

Molecular simulation



Noe et al, Science '19
Wirnsberger et al, JCP '20

Symmetries



Invariance

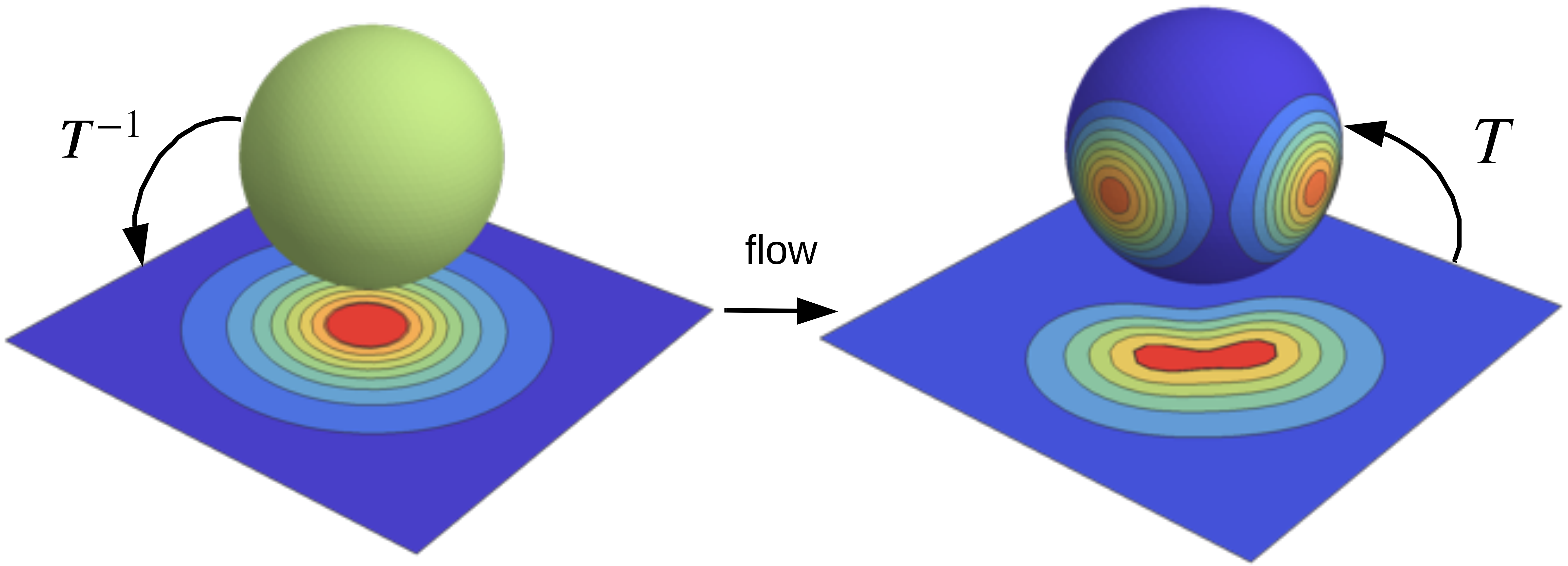
$$\rho(g\,\boldsymbol{x}) = \rho(\boldsymbol{x})$$

Equivariance

$$\mathscr{T}(g\,z) = g\mathscr{T}(z)$$

Spatial symmetries, permutation symmetries, gauge symmetries…

Flow on manifolds

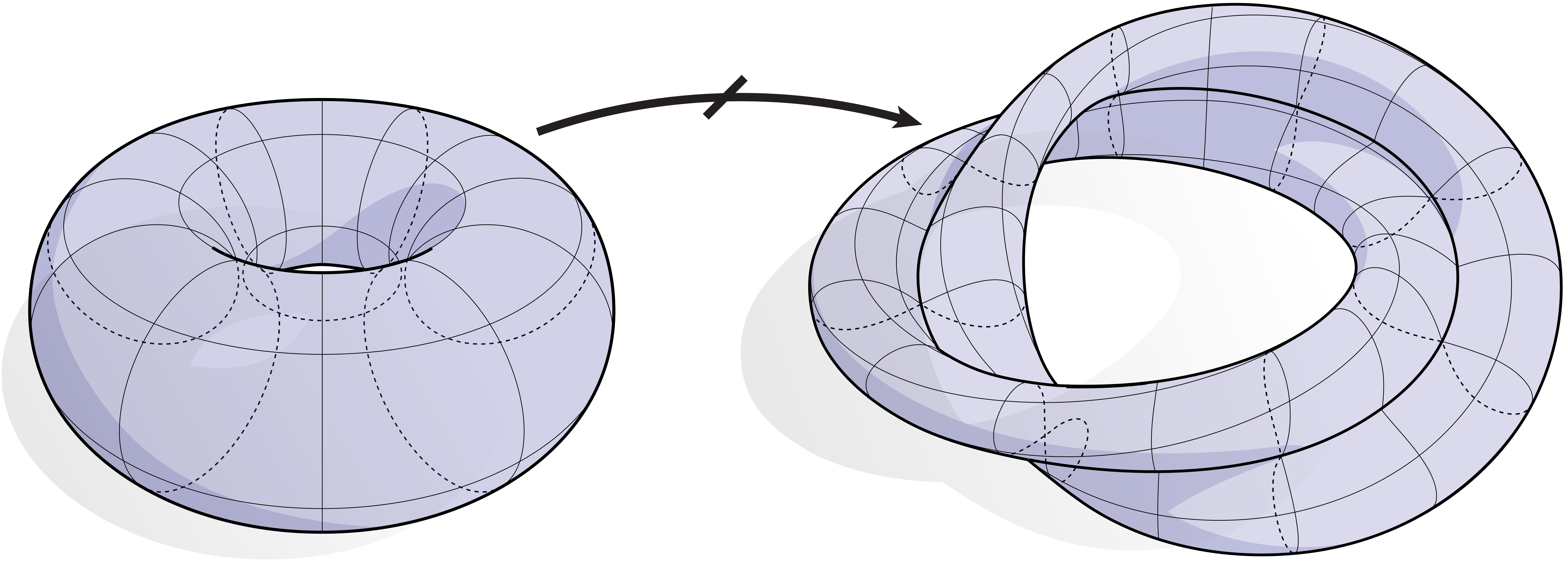


Periodic variables, gauge fields, …

Gemici et al 1611.02304, Rezende et al, 2002.02428, Boyda et al, 2008.05456

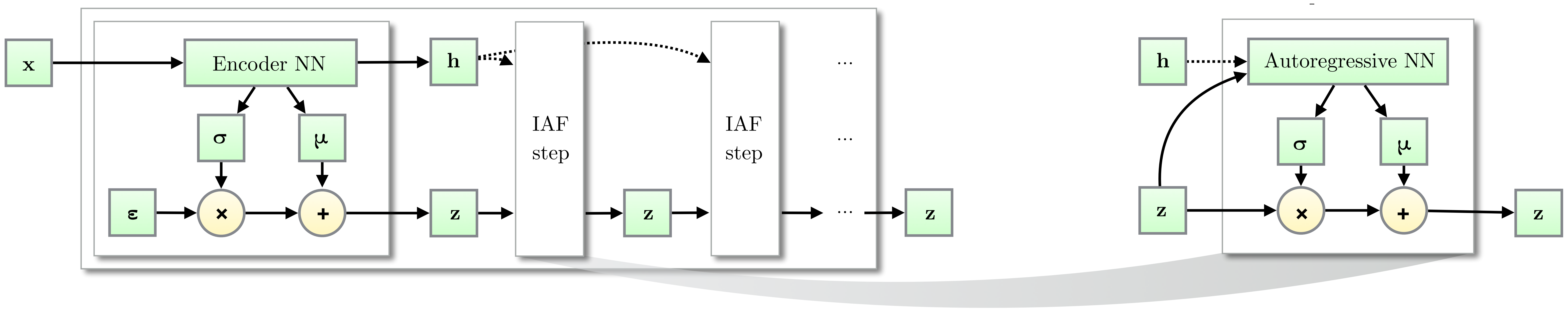
Neural ODE on manifolds, Falorsi et al, 2006.06663, Lou et al, 2006.10254, Mathieu et al, 2006.10605

Obstructions

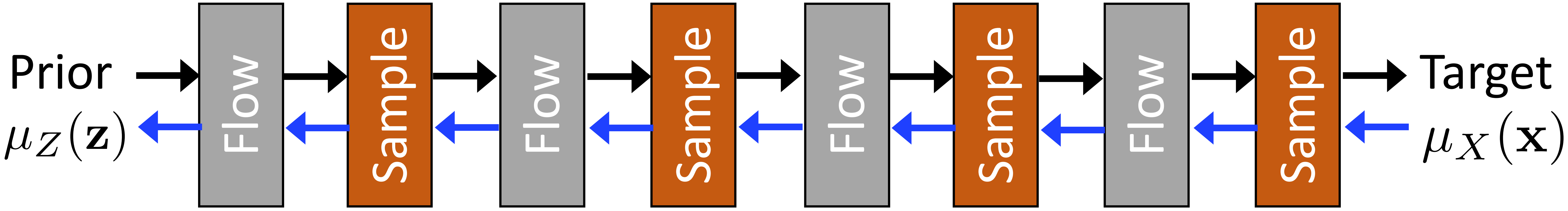


Dupont et al 1904.01681, Cornish et al, 1909.13833, Zhang et al, 1907.12998, Zhong et al, 2006.00392…

Mix with other approaches



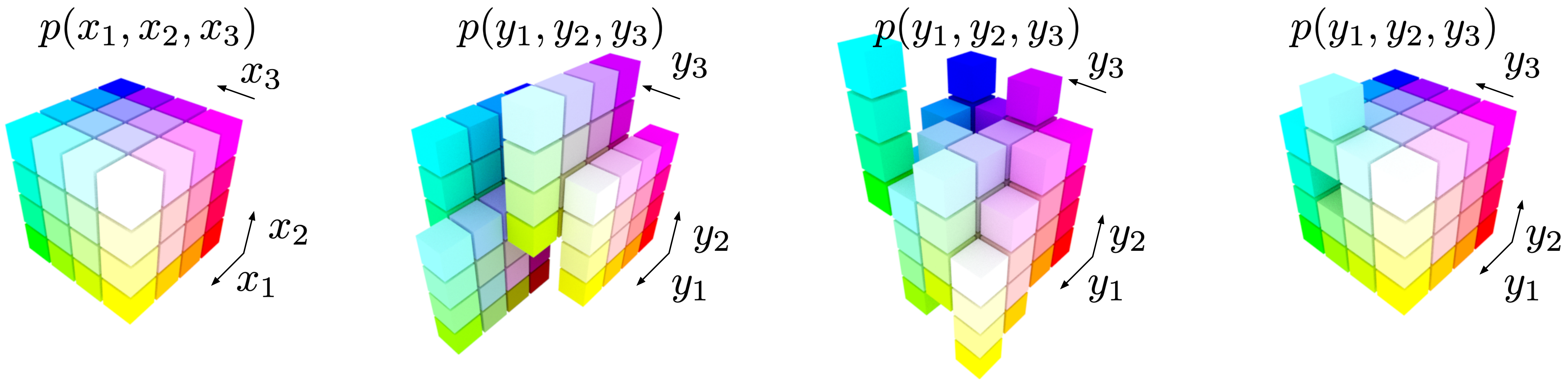
Kingma et al, 1606.04934,…



Levy et al, 1711.09268, Wu et al 2002.06707, …

Discrete flows

$$p(\boldsymbol{x}) = p(\boldsymbol{y} = \mathcal{T}(\boldsymbol{x}))$$



Tran et al, 1905.10347, Hoogeboom et al, 1905.07376, van den Berg 2006.12459

Representation learning: what and how ?

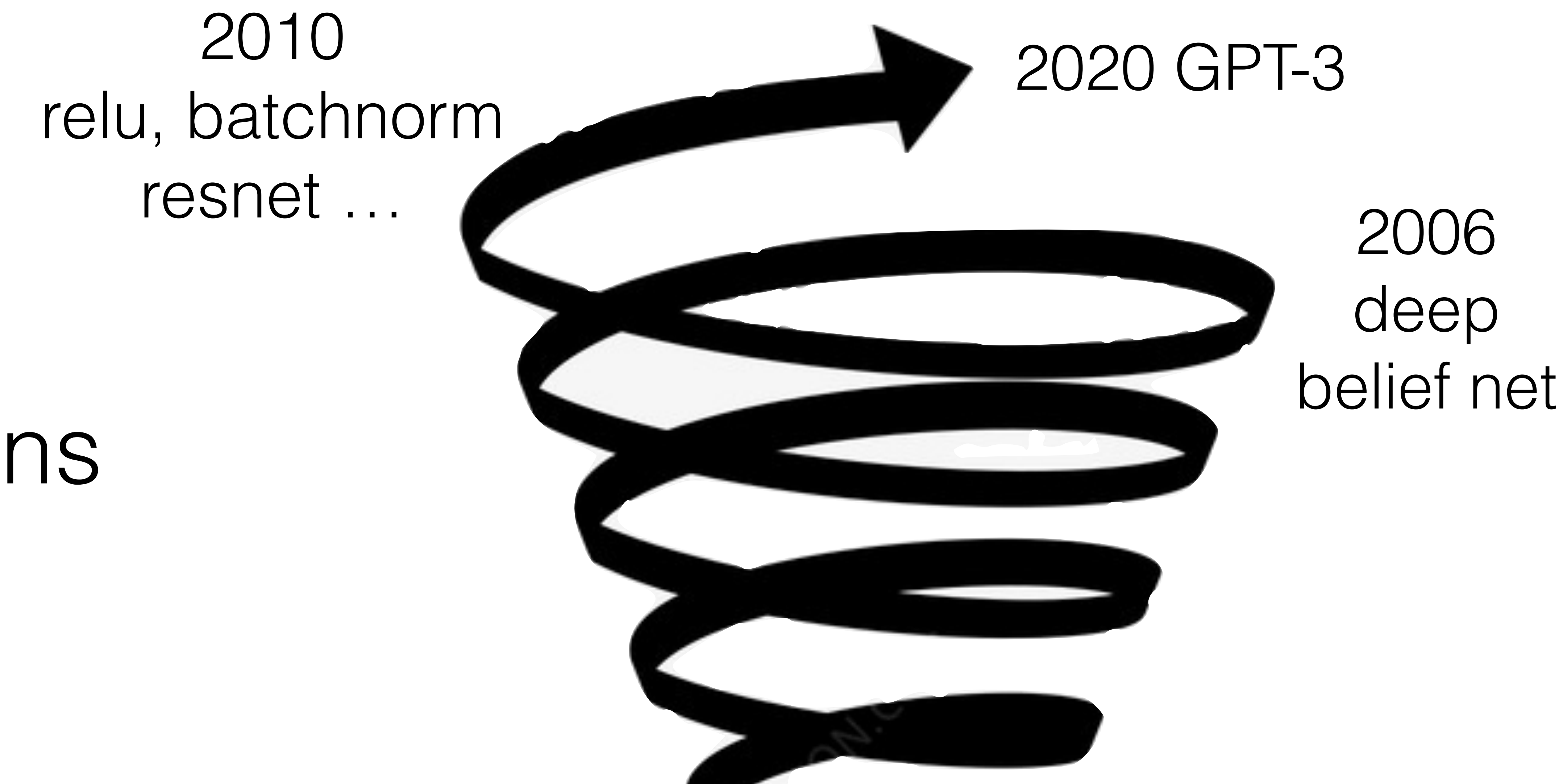
What is a good representation ?

1812.02230

Towards a Definition of Disentangled Representations

Irina Higgins*, David Amos*, David Pfau, Sebastien Racaniere, Loic Matthey, Danilo Rezende, Alexander Lerchner
DeepMind

Generative **P**re-**T**raining appears to be a successful way in learning good representations



Thank You!

Explore more in the interface of machine learning & physics

量子纠缠：从量子物质态到深度学习

程 嵩[1,2] 陈 靖[1,2] 王 磊[1,†]

(1 中国科学院物理研究所 北京 100190)

(2 中国科学院大学 北京 100049)

《物理》2017年7月

微分万物：深度学习的启示*

王 磊[1,2,†] 刘金国[3]

(1 中国科学院物理研究所 北京 100190)

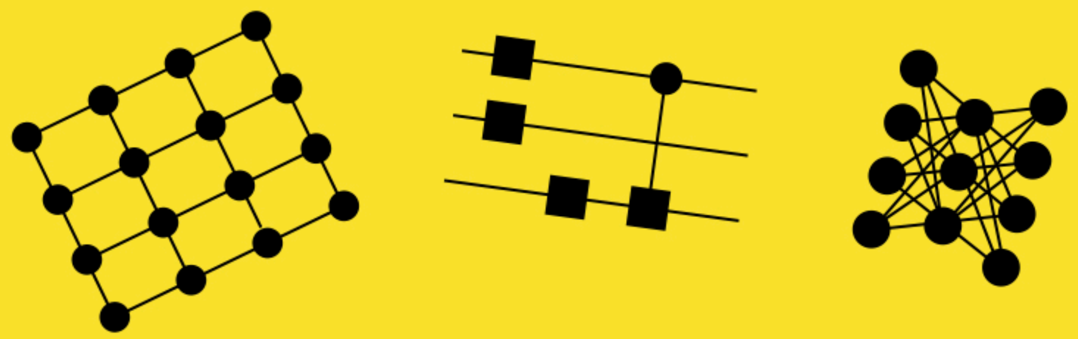
(2 松山湖材料实验室 东莞 523808)

(3 哈佛大学物理系 剑桥 02138)

《物理》2021年2月

Spring School

深度学习&量子编程



王磊

深度学习：从理论到实践

以微分编程和表示学习为重点介绍深度学习技术，并讲解它们在统计物理和量子多体计算中的应用实例

张潘

从机器学习角度理解张量网络

从表述，优化，学习与泛化这四个角度介绍张量网络及其在应用数学和机器学习中的应用

罗秀哲

面向物理学家的Julia编程实践

以量子物理的工程实践为重点介绍Julia语言，量子计算的基础概念，Julia语言中的CUDA编程和量子物理工具链

刘金国

量子编程实践

介绍量子机器学习，量子优化算法和量子化学中的研究前沿，基于Julia量子计算库Yao.jl实现这些算法，介绍自动微分与GPU编程在量子编程中的应用

报名方式： https://bit.ly/2CE5J8H

教学资料： https://github.com/QuantumBFS/SSSS

授课形式：

中文授课+程序演示+Hackathon (有奖品)

时间：2019年5月6-10日

地点：广东东莞

松山湖材料实验室

粤港澳交叉科学中心

Quantum Hackathon：

学员将通过组队的形式，完成一个量子物理相关的编程挑战。我们将评出表现突出的团队，给予奖励。

Contact: wanglei@iphy.ac.cn

QuantumBFS Yao Framework

julia

SONGSHAN LAKE MATERIALS LABORATORY 松山湖材料实验室