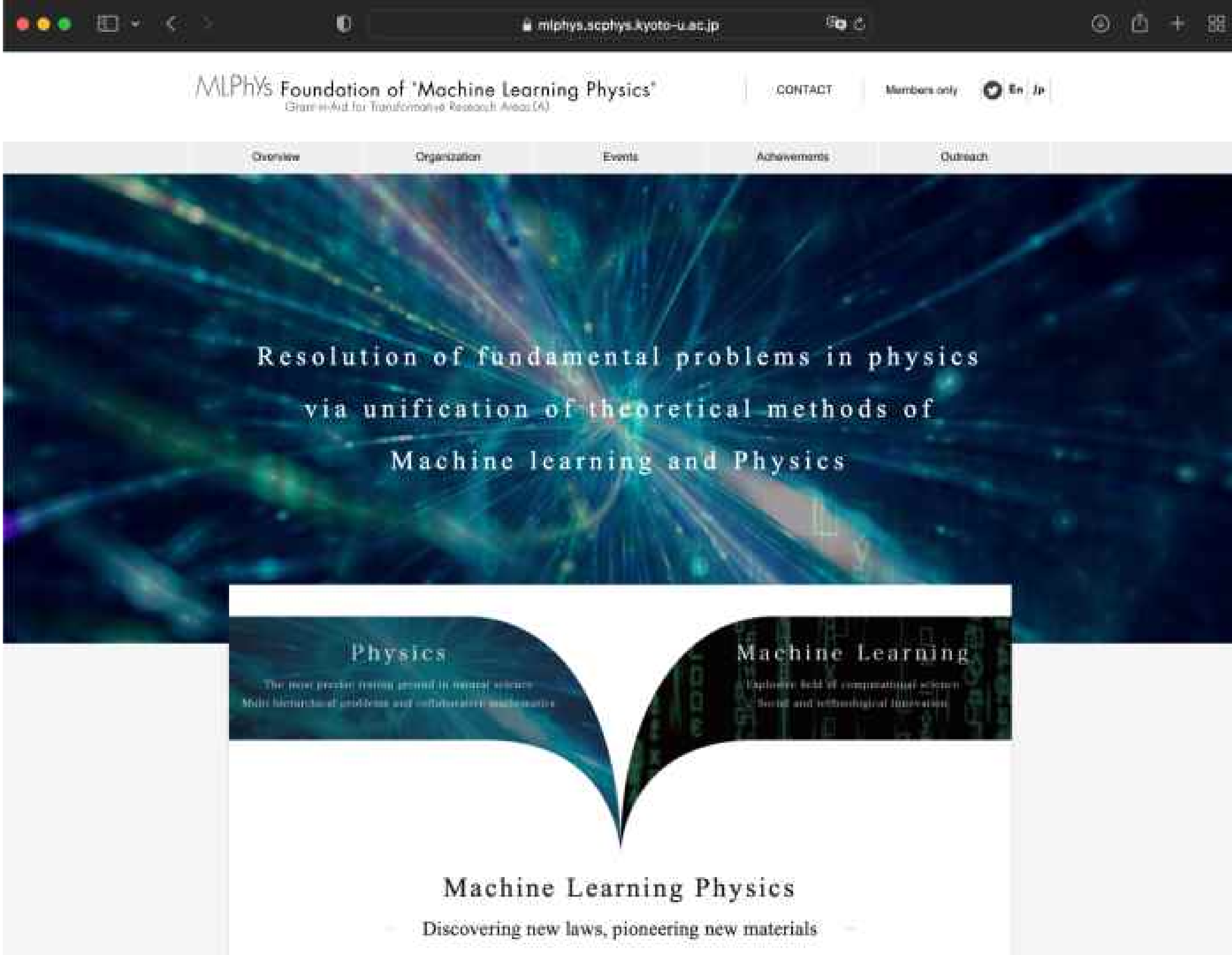
ipi seminar, univ. Tokyo, online, 10 Nov 2022

Deep Learning and Emergent Spacetime

Koji Hashimoto (Kyoto U.)

Based on:
- "Deriving dilaton potential in improved holographic QCD from chiral condensate" 2209.04638
  "Deriving dilaton potential in improved holographic QCD from meson spectrum" 2108.08091
  w/ K.Ohashi (Keio), T.Sumimoto (Osaka u)
- "Neural ODE and Holographic QCD" 2006.00712 w/ H.Y.Hu, Y.Z.You (UCSD)
- "Deep Learning and AdS/QCD" 2005.02636 w/ T. Akutagawa, T. Sumimoto (Osaka u)
- "Deep Boltzmann Machine and AdS/CFT" 1903.04951
- "Deep Learning and Holographic QCD" 1809.10536
  w/ S. Sugishita (Kentucky), A. Tanaka, A. Tomiya (RIKEN)
- "Deep Learning and AdS/CFT" 1802.08313 w/ S. Sugishita (Kentucky), A. Tanaka, A. Tomiya (RIKEN)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MLPhys Foundation of "Machine Learning Physics"
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Overview
Organization
Events
Achievements
Outreach
Resolution of fundamental problems in physics
via unification of theoretical methods of
Machine learning and Physics
Physics
Machine Learning
Machine Learning Physics
Discovering new laws, pioneering new materials

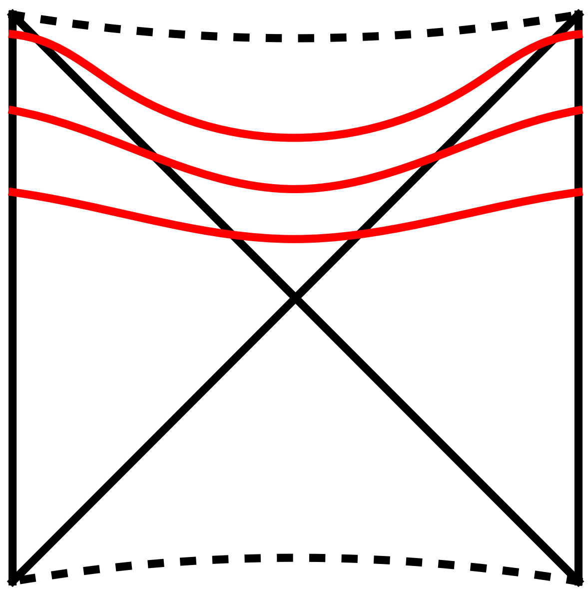
> Osaka CTSR – RIKEN iTHES/iTHEMS - Kavli IPMU
> Joint symposium

Deep learning and physics

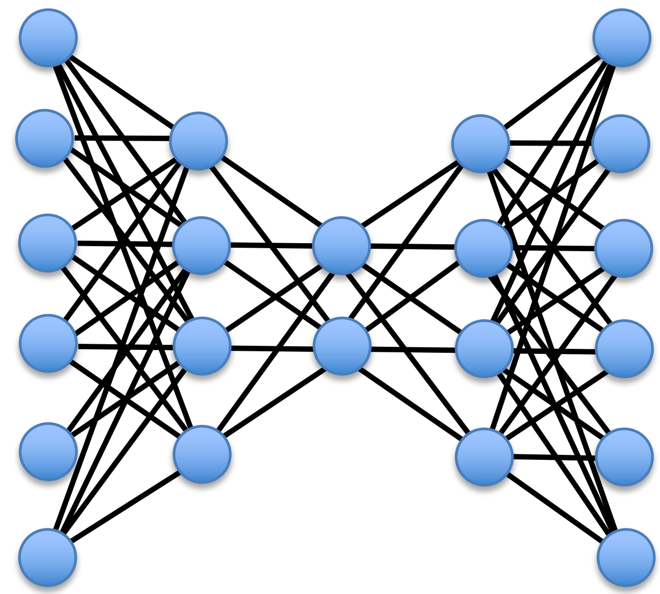
> Venue: Nambu hall, Osaka university
> Date: June 5 (Mon), 2017, 13:00-18:00
> Invited speakers :
> S. Amari (RIKEN)
> S. Ikeda (ISM / Kavli IPMU)
> Y. Kawahara (Osaka U. / RIKEN)
> M. Taki (RIKEN)
> A. Tanaka (RIKEN)
> T. Ohtsuki (Sophia U.)
> N. Suzuki (Kavli IPMU)

> Organizers:
> K. Hashimoto (Osaka U.)
> T. Hatsuda (RIKEN iTHES/iTHEMS)
> H. Murayama (Kavli IPMU)

Similarity!?



Wormholes in Penrose diagram
of maximally extended eternal
AdS Schwarzschild black hole
[Iizuka, Sugishita, KH `17]



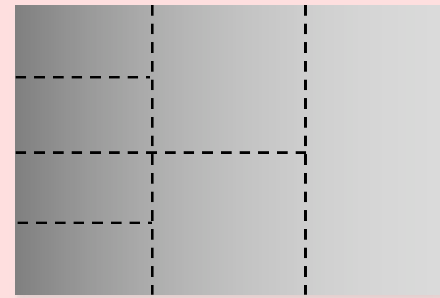
Deep Autoencoder

Roadmap

Quantum gravity in (d+1)-dim.

General spacetime

Anti de Sitter spacetime



‘tHooft `93
Susskind `94
Maldacena `97

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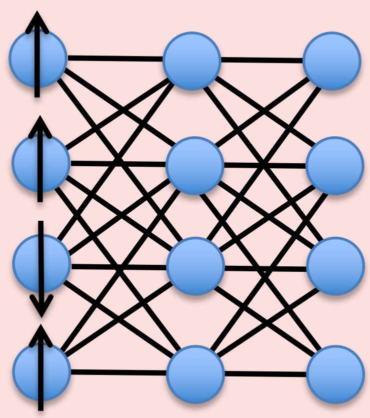
|| ?

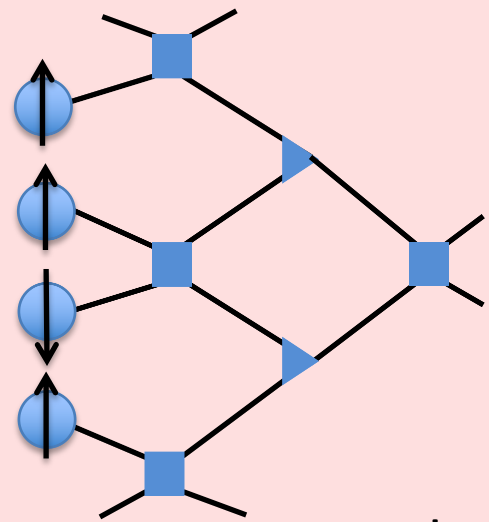
|| Swingle `10

Quantum mechanics in d-dim.



Neural network

Carleo, Troyer `17



Tensor network

Roadmap

1.

Quantum gravity in (d+1)-dim.

'tHooft `93
Susskind `94
Maldacena `97

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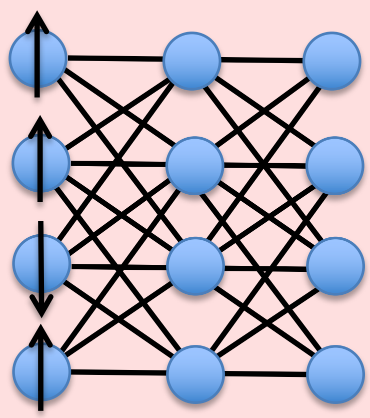
Quantum mechanics in d-dim.

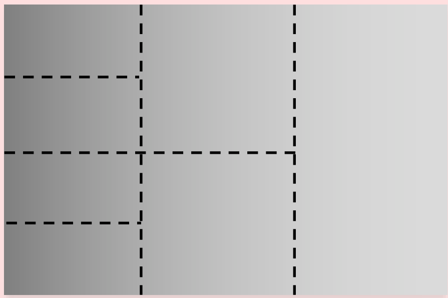
General spacetime

|| ?



Neural network

Anti de Sitter spacetime



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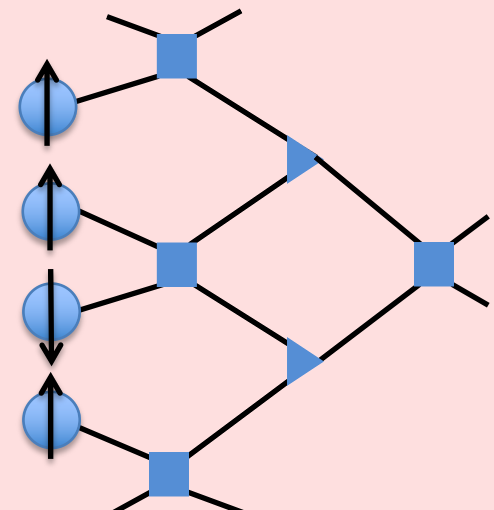

Tensor network

Carleo, Troyer `17

Roadmap

Quantum gravity in (d+1)-dim.

'tHooft `93
Susskind `94
Maldacena `97

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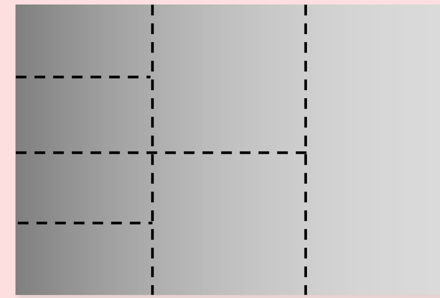
Quantum mechanics in d-dim.

General spacetime

|| ?

Anti de Sitter spacetime



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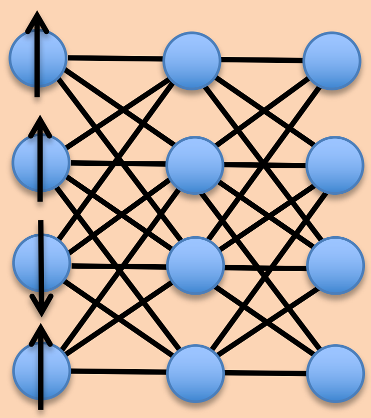
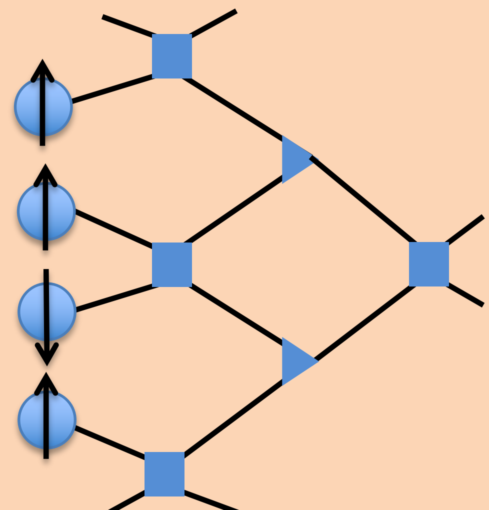
2.



Neural network

Carleo, Troyer `17



Tensor network

Roadmap

Quantum gravity in (d+1)-dim.

‘tHooft `93
Susskind `94
Maldacena `97

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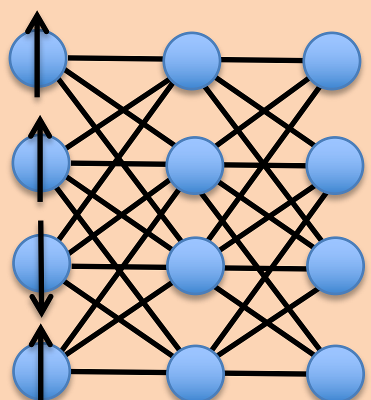
Quantum mechanics in d-dim.

3\. General spacetime

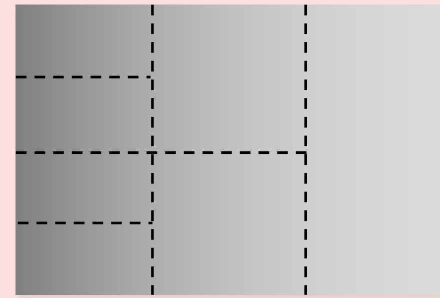
|| ?



Neural network

Carleo, Troyer `17

Anti de Sitter spacetime



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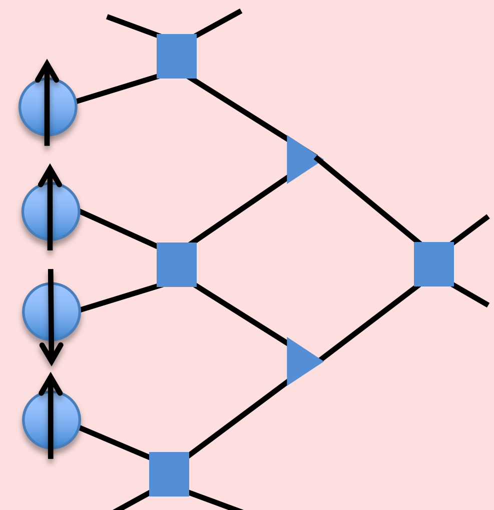


Tensor network

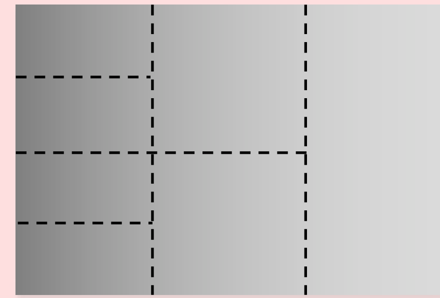
Roadmap

4.

Quantum gravity in (d+1)-dim.

General spacetime

Anti de Sitter spacetime



'tHooft `93
Susskind `94
Maldacena `97

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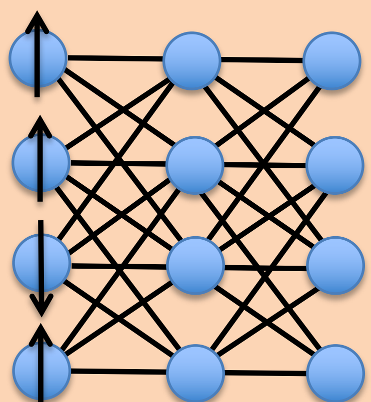
|| ?

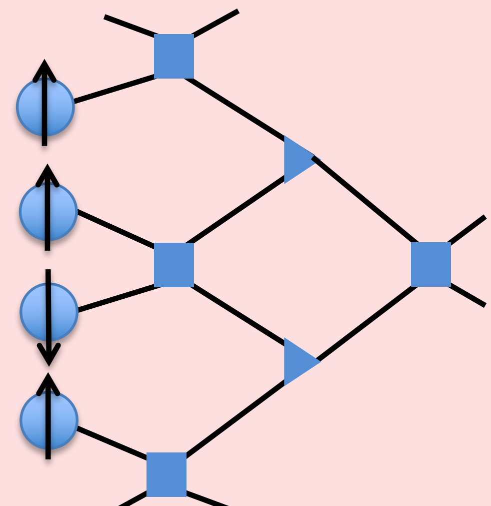
|| Swingle `10

Quantum mechanics in d-dim.



Neural network

Carleo, Troyer `17



Tensor network

Deep Learning and Quantum Gravity

1. Quantum gravity — 4 pages
2. Neural network quantum states — 6 pages
3. When is NN a spacetime? — 5 pages
4. Spacetime emergent from data — 7 pages

Discussion: Quantum gravity $\subset$ ML ?

Roadmap

1.

Quantum gravity in (d+1)-dim.

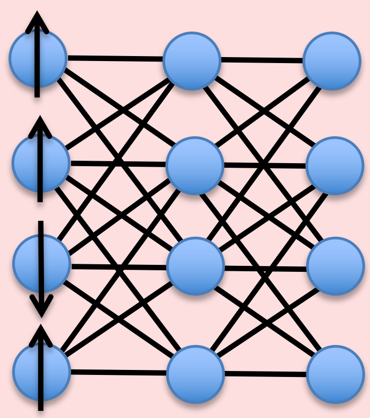
'tHooft `93
Susskind `94
Maldacena `97

||

Quantum mechanics in d-dim.

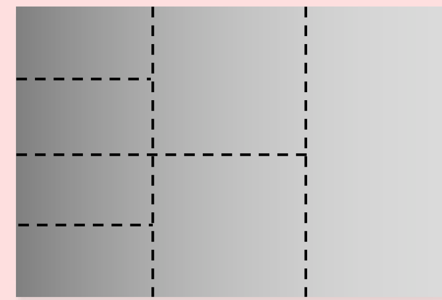
General spacetime

|| ?



Neural network

Anti de Sitter spacetime



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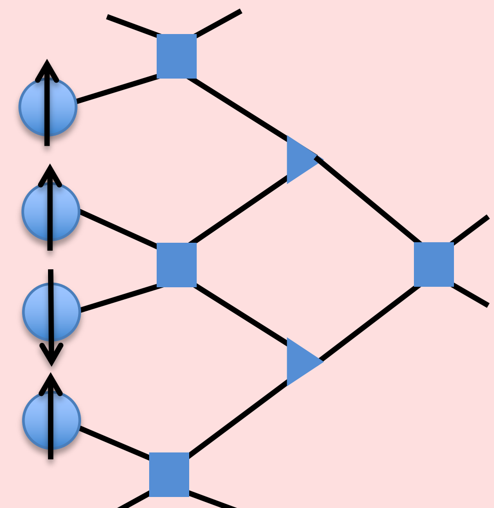


Carleo, Troyer `17

Tensor network

1. Quantum Gravity

Brief History of quantum gravity

1974 'tHooft, Veltman:
Perturbation fails in Einstein gravity.

1970 Nambu, Susskind, Nielsen:
String theory of hadrons.

1974 Yoneya, Scherk, Schwarz:
String is quantum gravity.

1971 Bekenstein:
Black hole entropy.

1993 'tHooft, Susskind:
Holographic principle.

1997 Maldacena:
AdS/CFT correspondence.

① Quantum Gravity

AdS/CFT correspondence, no proof

[Maldacena, Adv.Theor.Math.Phys. 2 (1998) 231]

"CFT"		"AdS"
"Large N" Quantum mechanics in d-dim. spacetime	=	Classical ~~Quantum~~ gravity in (d+1)-dim. spacetime

- Vast amount of examples known
- No proof!
- How does it work?
- Given Left, how can one get Right?

① Quantum Gravity

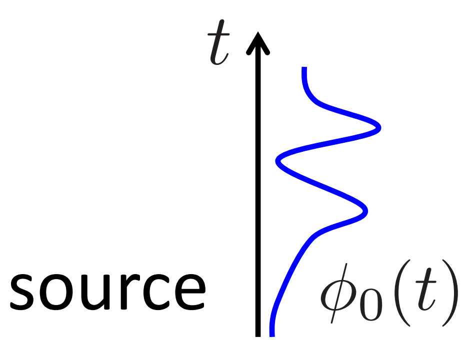
Dictionary : equating partition functions

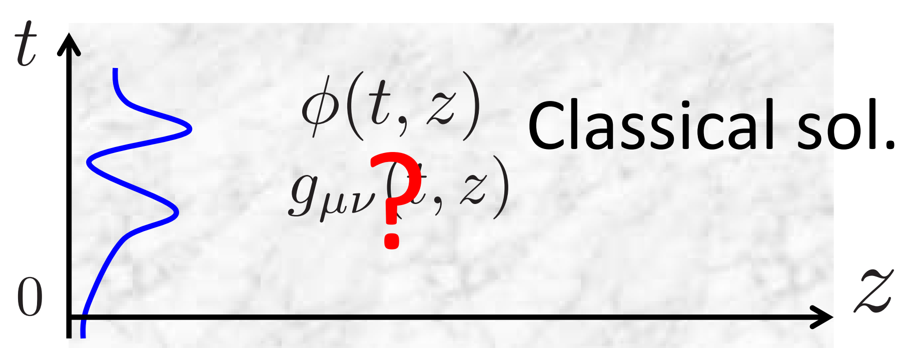
[Gubser, Klebanov, Polyakov, Phys.Lett.B428(1998)105]
[Witten, Adv.Theor.Math.Phys. 2 (1998) 253]

Partition function of Quantum mechanics **=** Partition function of Classical gravity

$$Z[\phi_0] = \int [\mathcal{D}q(t)] e^{-\int dt (\mathcal{L}[q,\dot{q}] + \phi_0(t)\mathcal{O}[q])}$$

$$Z[\phi_0] = e^{-\int dt dz \sqrt{-g}(R[g] + \mathcal{L}[\phi] + \cdots)}$$





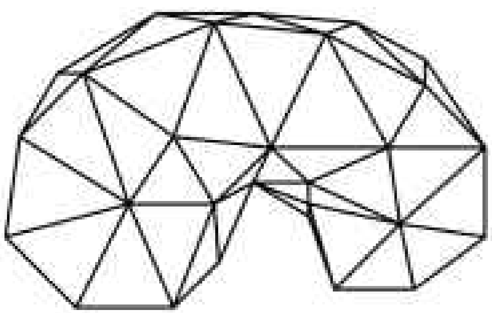
$\phi_0(t) = \phi(t, z = 0)$

① Quantum Gravity

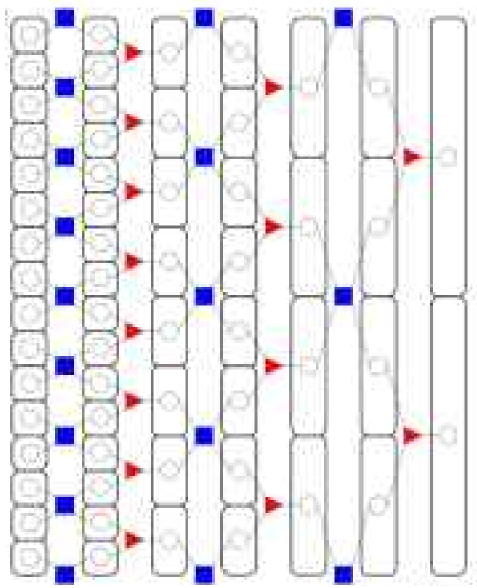
Quantum geometry is a network

Regge calculus
[Regge 1961]

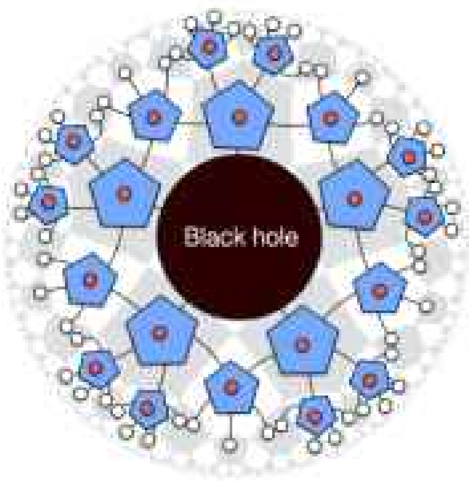
Causal dynamical triangulation
[Ambjorn, Loll 1998]



AdS/MERA (Tensor Network)
[Swingle `09]



Quantum codes for holography
[Pastawski, Yoshida, Harlow, Preskill `15]



Deep Learning and Quantum Gravity

Discussion: Quantum gravity $\subset$ ML ?

Roadmap

Quantum gravity in (d+1)-dim.

‘tHooft `93
Susskind `94
Maldacena `97

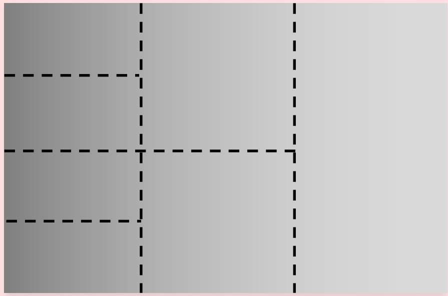
||

Quantum mechanics in d-dim.

General spacetime

|| ?

Anti de Sitter spacetime



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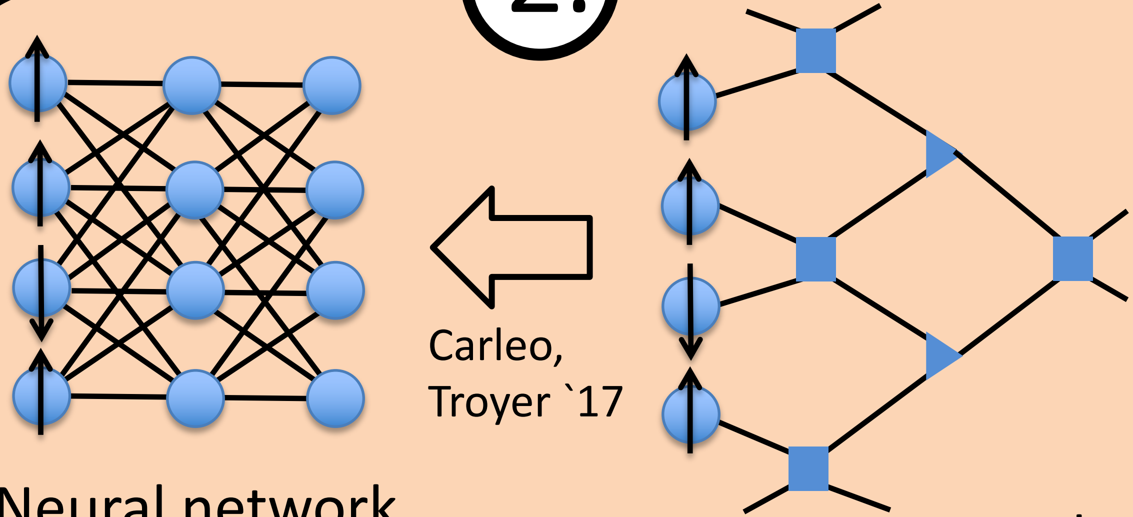
2.



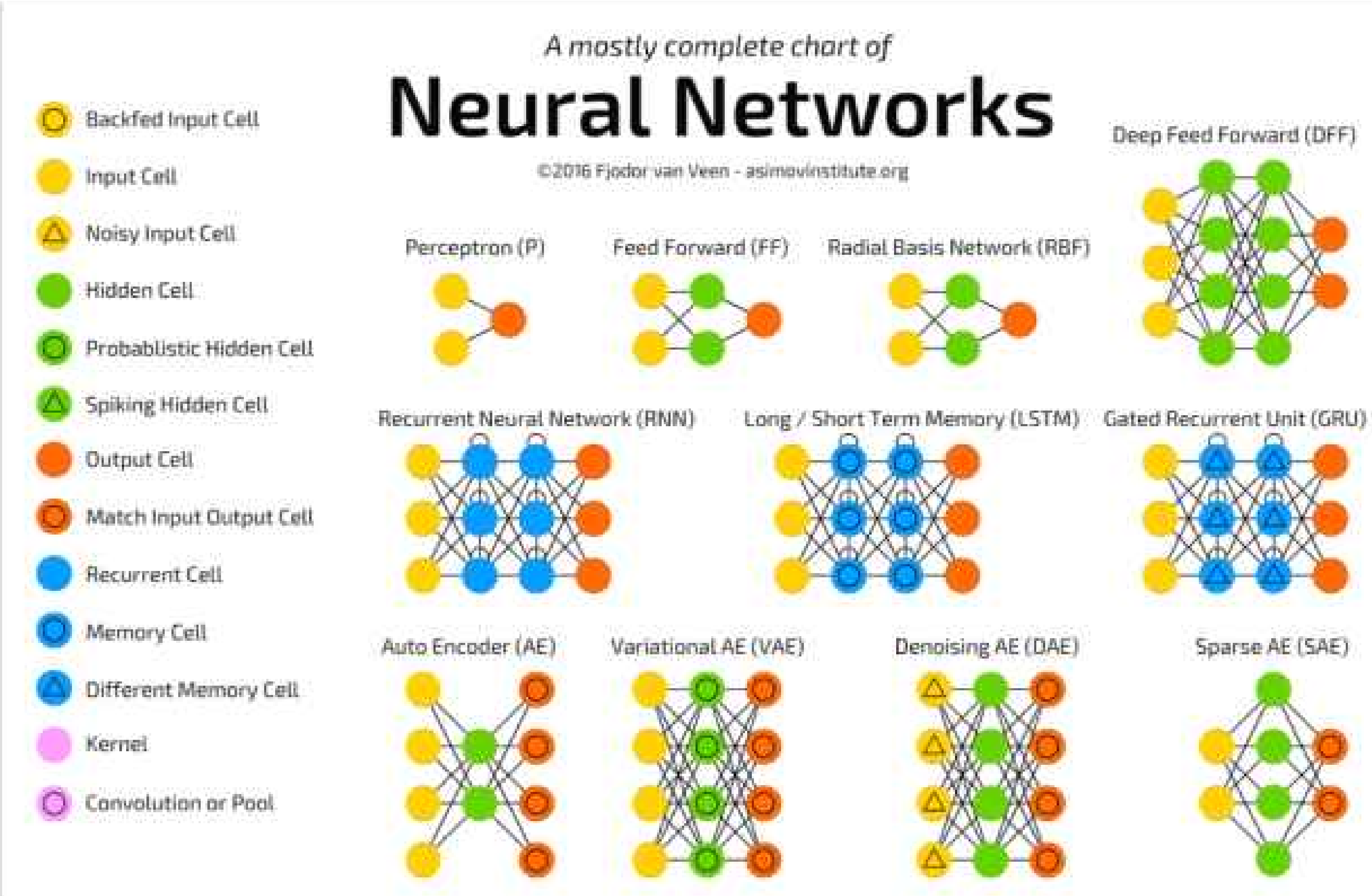
Carleo, Troyer `17

Neural network

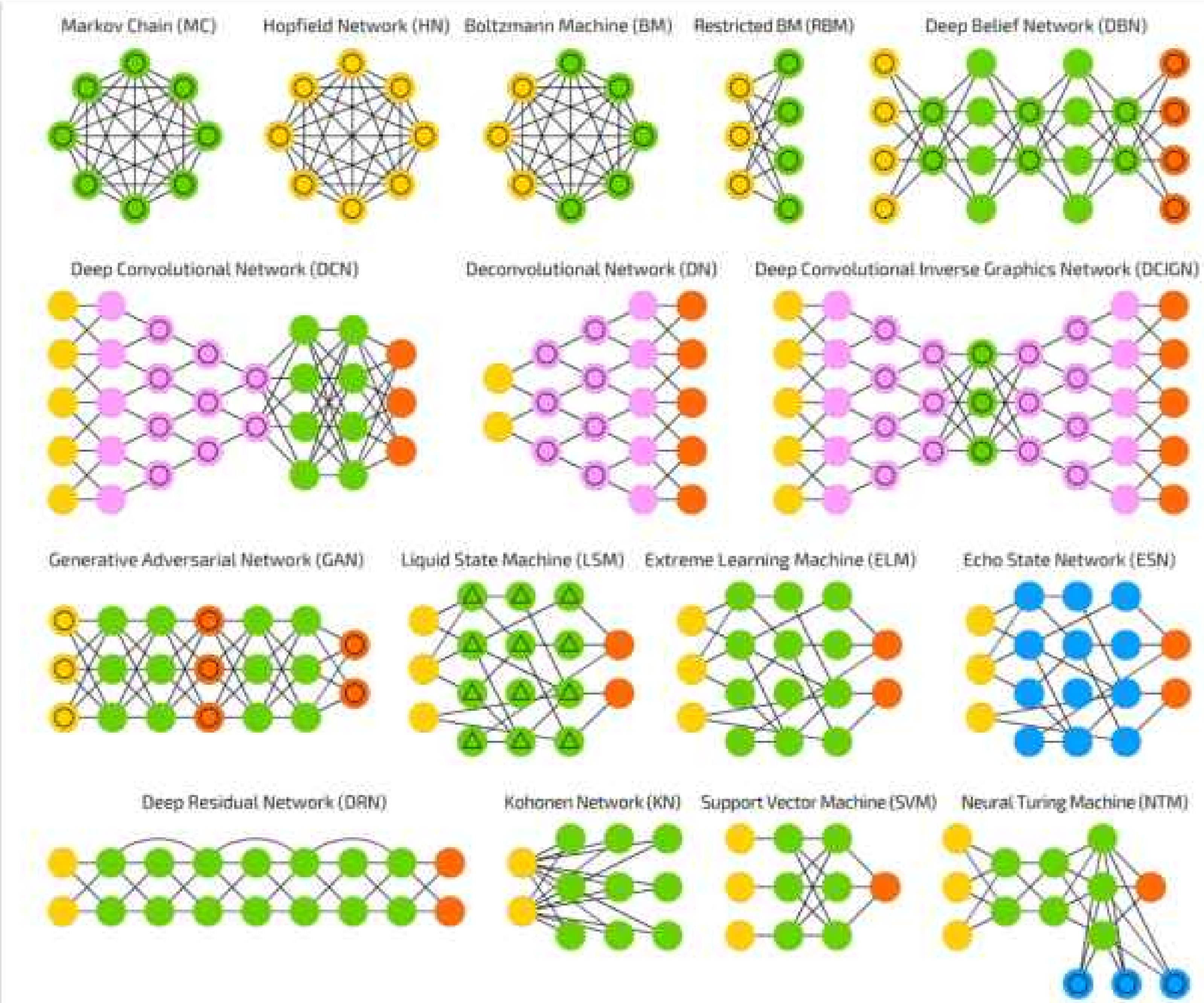
Tensor network

② Neural Network Quantum States

Various neural networks were invented



http://www.asimovinstitute.org/neural-network-zoo/

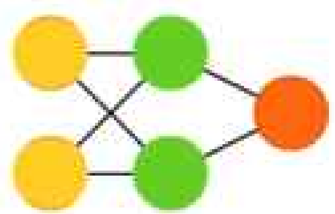

Markov Chain (MC)
Hopfield Network (HN)
Boltzmann Machine (BM)
Restricted BM (RBM)
Deep Belief Network (DBN)
Deep Convolutional Network (DCN)
Deconvolutional Network (DN)
Deep Convolutional Inverse Graphics Network (DCIGN)
Generative Adversarial Network (GAN)
Liquid State Machine (LSM)
Extreme Learning Machine (ELM)
Echo State Network (ESN)
Deep Residual Network (DRN)
Kohonen Network (KN)
Support Vector Machine (SVM)
Neural Turing Machine (NTM)

② Neural Network Quantum States

Machine learning = function approximator

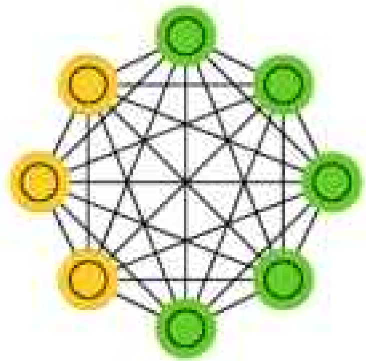
Input: a vector $(x_1, x_2, x_3, \cdots)$
Output: a value $f(x_1, x_2, x_3, \cdots)$

Network architecture is the function ansatz



Perceptron model
[Rosenblatt 1958]
[Rumelhart, McClelland 1986]

$$f = W_i^{(2)} \varphi \left(W_{ij}^{(1)} x_j \right)$$

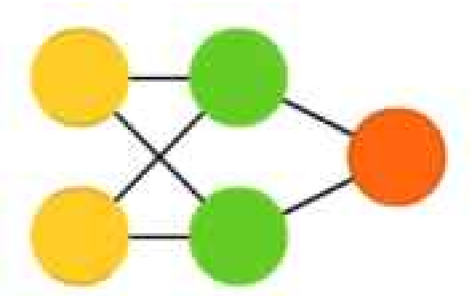


Boltzmann machine
[Ackley, Hinton, Sejnowski 1985]

② Neural Network Quantum States

Neural network for classification

Perceptron model



$$f = W_i^{(2)} \varphi\left(W_{ij}^{(1)} x_j\right)$$

"Unit" (circle) : Vector component

"Weight" (line) : Linear transformation to be optimized

"Activation function" (hidden line-end) : Nonlinear component-wise transf.

$$\varphi(x) \equiv \frac{1}{1+e^{-x}}$$

- Training protocol :

1) Prepare many sets $\{(x_j, f)\}$: (input, output)
2) Train the network (adjust W) by lowering "Loss function" $E \equiv \sum_{\text{data}} \left| f - W_i^{(2)} \varphi\left(W_{ij}^{(1)} x_j\right)\right|$

② Neural Network Quantum States

Find ground state wave function $\psi(s_1, s_2, \cdots, s_N)$

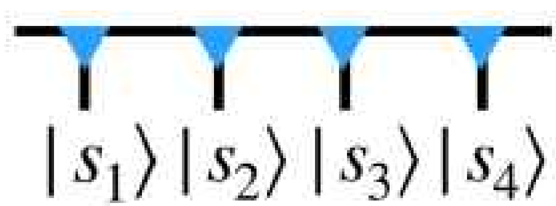
Q : Minimize its energy *E* for a given Hamiltonian *H*,

$$E = \frac{\sum_{s_1,\cdots s_N, s'_1,\cdots,s'_N} \psi^\dagger(s'_1,\cdots,s'_N)\hat{H}_{s'_1,\cdots s'_N,s_1,\cdots,s_N}\psi(s_1,\cdots,s_N)}{\sum_{s_1,\cdots s_N}\psi^\dagger(s_1,\cdots,s_N)\psi(s_1,\cdots,s_N)}$$

A : Use ansatz and optimize parameters!

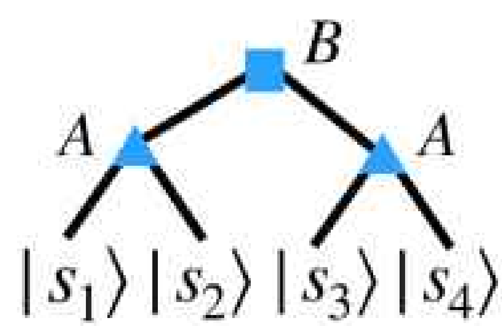
- Matrix product states

$$\psi(s_1, s_2, \cdots) = \mathrm{tr}[A^{(s_1)}A^{(s_2)}\cdots]$$



- Tensor network states

$$\psi(s_1, s_2, \cdots) = \sum_{m,n} B_{mn}A_{ms_1s_2}A_{ns_3s_4}$$

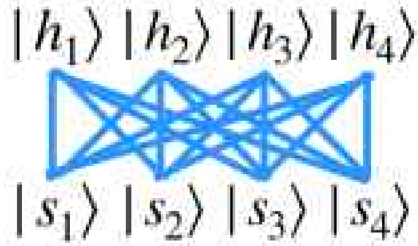


② Neural Network Quantum States

Neural network can be wave functions

- Boltzmann machine states

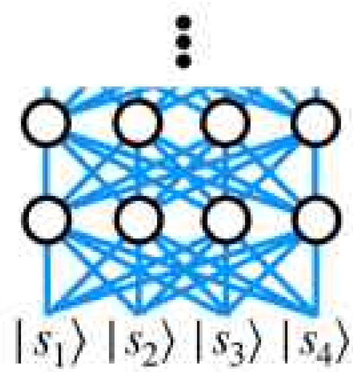
  [Carleo, Troyer `17],
  [Nomura, Darmawan, Yamaji, Imada `17], ..



$$\psi(s_1, \cdots, s_N) = \sum_{h_A} \exp\left[\sum_a a_a s_a + \sum_A b_A h_A + \sum_{a,A} J_{aA} s_a h_A\right]$$

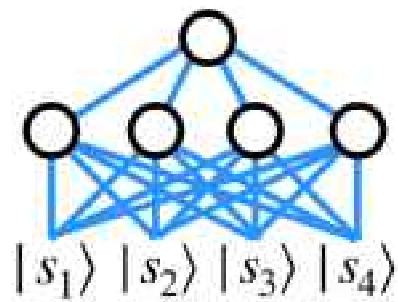
- Deep Boltzmann machine states

  [Carleo, Nomura, Imada `18], ..



- Feedfoward network states [Saito `18], ..

$$\psi(s_1, \cdots, s_N) = \sum_i f_i \, \sigma\left(\sum_j W_{ij} s_j + b_i\right)$$



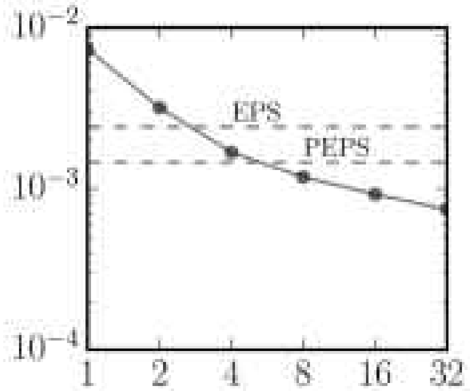
② Neural Network Quantum States

Better? and Why?

Neural states may beat conventional ones.

Ex) 2-dimensional antiferromagnetic Heisenberg model [Carleo, Troyer `17]

Energy with RBM states



# of hidden units

Discovered intimate relations are there.

1) Boltzmann machine states are tensor network states [Chen, Cheng, Xie, Wang, Xiang `18]

2) Tensor states are deep Boltzmann [Gao, Duan `17] [Huang, Moore `17]

3) Tensor states are feedforward with "product pooling" [Cohen, Shashua `18]

Ex) Unified approach: MPO-Net [Gao, Cheng, He, Xie, Zhao, Lu, Xiang `19]

Deep Learning and Quantum Gravity

Roadmap

Quantum gravity in (d+1)-dim.

‘tHooft `93
Susskind `94
Maldacena `97

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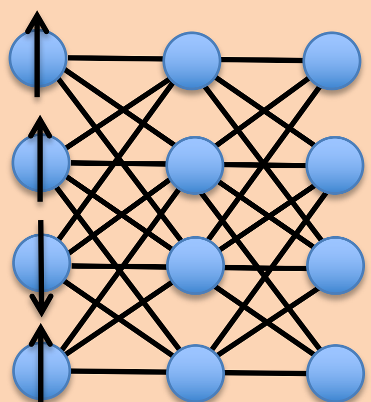
Quantum mechanics in d-dim.

3. General spacetime

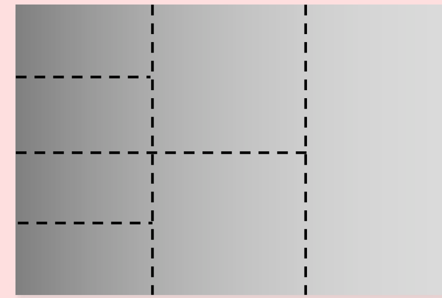
|| ?



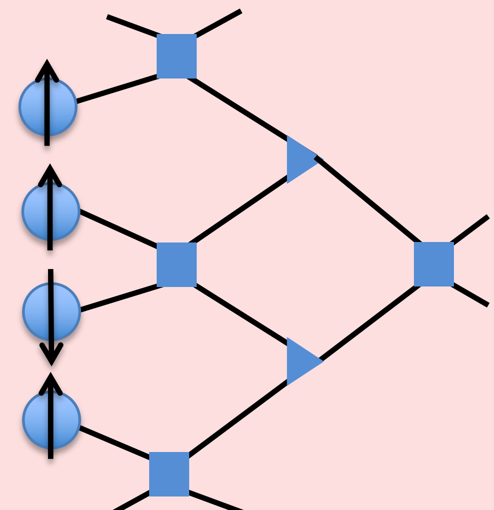
Neural network

Carleo, Troyer `17

Anti de Sitter spacetime



|| Swingle `10

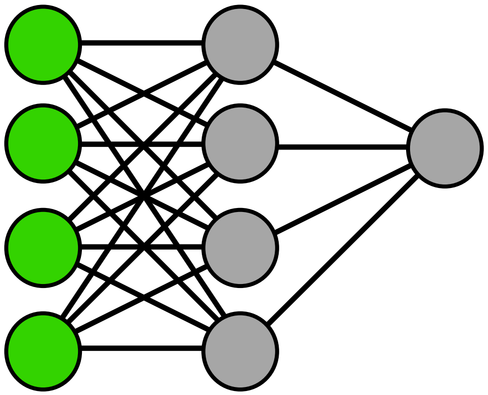


Tensor network

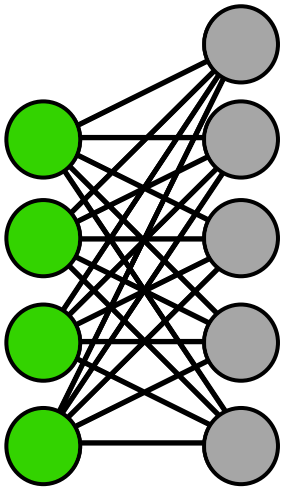
③ When is NN a spacetime?

General NN is not a space

No notion of which unit is close to which



Perceptron model
[Rosenblatt 1958]
[Rumelhart, McClelland 1986]

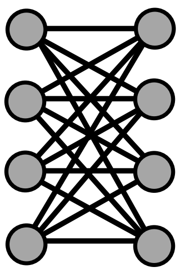


Boltzmann machine
[Ackley, Hinton, Sejnowski 1985]

③ When is NN a spacetime?

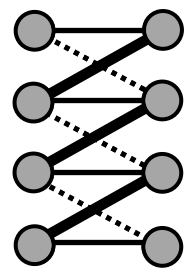
Sparsity + weight sharing, for NN to be a space

No locality



Fully connected

Locality imposed



Convolutional layer

[Fukushima `80]

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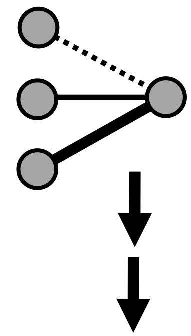


Parallelly translated

Input: $\phi(n\Delta x)$

Output:

$$a\phi(n\Delta x) + b\partial_x\phi(n\Delta x) + c\partial_x^2\phi(n\Delta x) + \cdots$$

③ When is NN a spacetime?

NN depth as time

Dynamical system

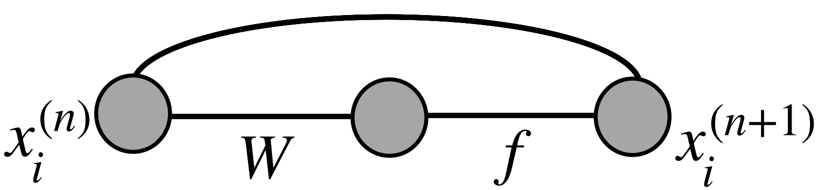
$$\dot{x}_i = f_i(x(t)) \quad \Longrightarrow \quad x_i(t_{n+1}) = \underline{x_i(t_n)} + \Delta t \cdot f_i(x(t_n))$$

$$t_{n+1} = t_n + \Delta t$$

Discretized time

ResNET (Residual network) : easily trained deep model

[K.He et al.,1512.03385]



$$x_i^{(n+1)} = f(W_{ij} x_j^{(n)}) + \underline{x_i^{(n)}}$$

Skip connection

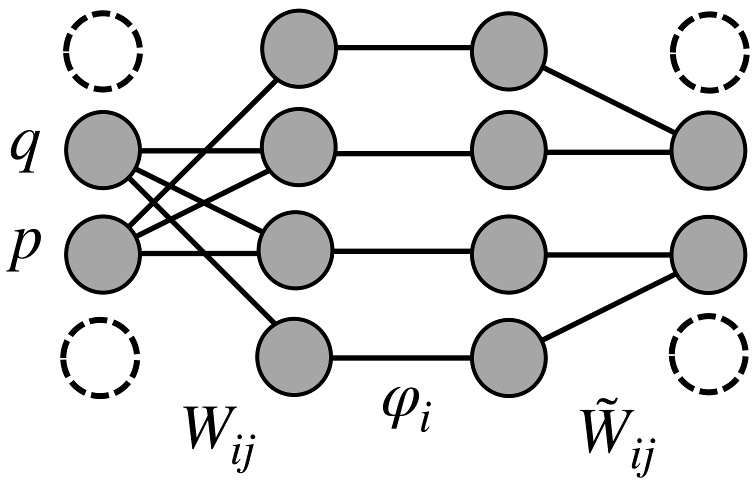
③ When is NN a spacetime?

Hamilton dynamics is a NN

1802.08313

$$\dot{q} = \frac{\partial H}{\partial p}, \qquad \dot{p} = -\frac{\partial H}{\partial q}$$

Time-dependent Hamiltonian = weights/activation



$$W = \begin{pmatrix} 0 & 0 & v & 0 \\ 0 & 1 + \Delta t w_{11} & \Delta t w_{12} & 0 \\ 0 & \Delta t w_{21} & 1 + \Delta t w_{12} & 0 \\ 0 & u & 0 & 0 \end{pmatrix}$$

$$\varphi_i = \begin{pmatrix} \Delta t f(x) \\ 1 \\ 1 \\ \Delta t g(x) \end{pmatrix} \qquad \tilde{W} = \begin{pmatrix} 0 & 0 & 0 & 0 \\ \lambda_1 & 1 & 0 & 0 \\ 0 & 0 & 1 & \lambda_2 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$H = w_{11} p q + \frac{1}{2} w_{12} p^2 - \frac{1}{2} w_{21} q^2 + \frac{\lambda_1}{v} F(vp) - \frac{\lambda_2}{u} G(uq)$$

$$(F' = f, \quad G' = g)$$

③ When is NN a spacetime?

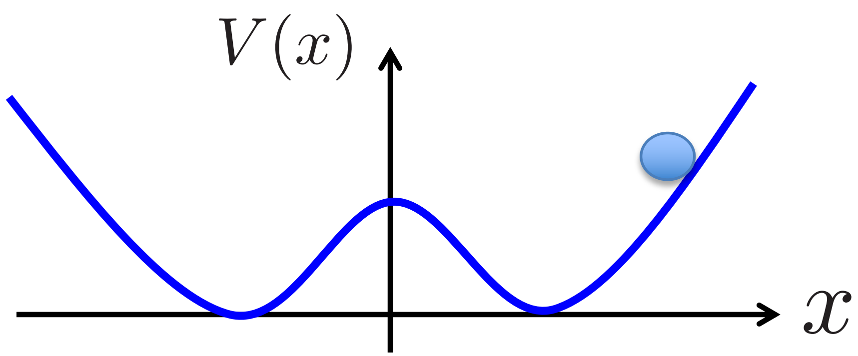
Q. Find a Hamiltonian

Consider a particle motion $x(t)$ in a given potential $V(x)$ in 1 dimension, with unknown time-dependent friction force $h(t)\dot{x}$.

One tried many initial conditions $(x(t=0), \dot{x}(t=0))$ and collected those which stop at $t=10$.

Q. From given data of the initial conditions, find $h(t)$.

$$m\ddot{x} = h(t)\dot{x} + \frac{\partial V(x)}{\partial x}$$



Deep Learning and Quantum Gravity

1. Quantum gravity — 4 pages
2. Neural network quantum states — 6 pages
3. When is NN a spacetime? — 5 pages
4. Spacetime emergent from data — 7 pages

Discussion: Quantum gravity $\subset$ ML ?

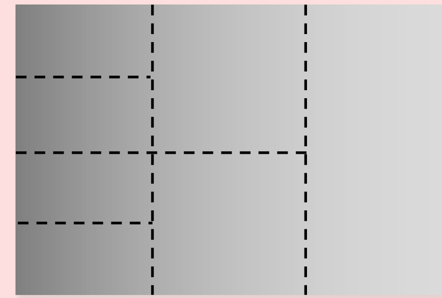
Roadmap

4.

General spacetime

Anti de Sitter spacetime

Quantum gravity in (d+1)-dim.



'tHooft `93
Susskind `94
Maldacena `97

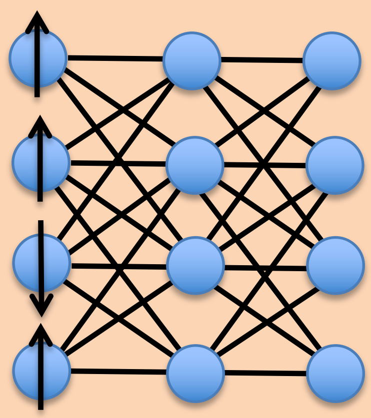
||

|| ?

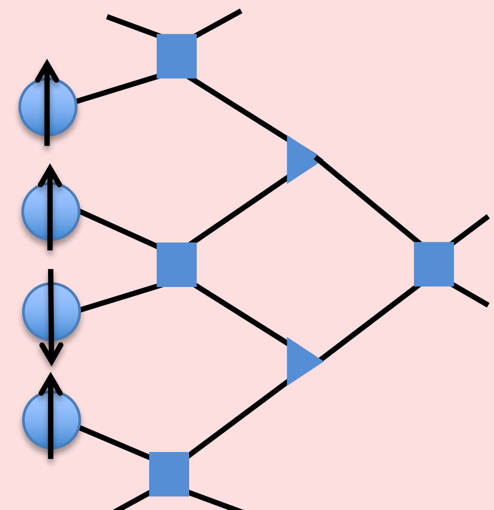
||

Swingle `10

Quantum mechanics in d-dim.

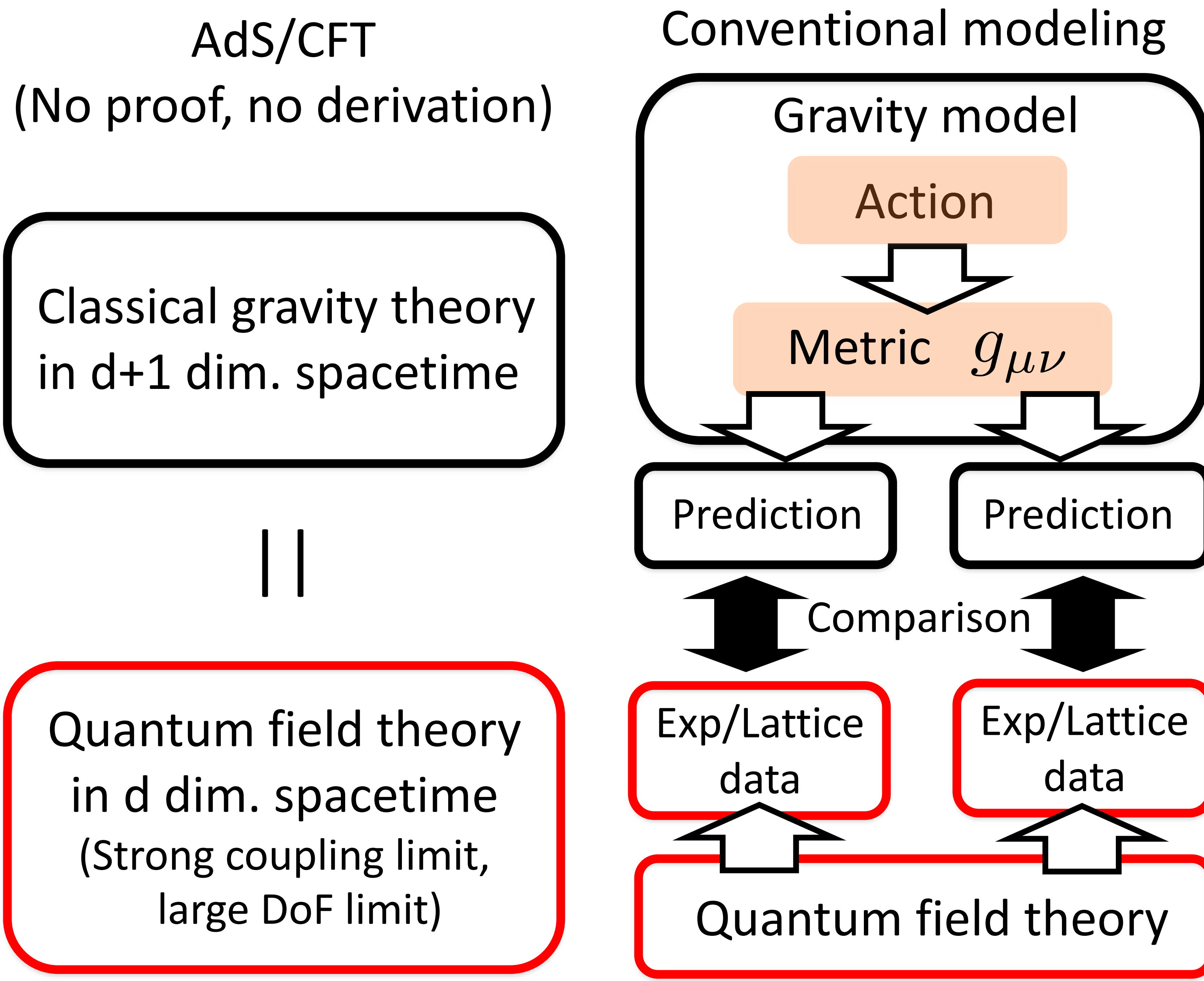


Carleo, Troyer `17

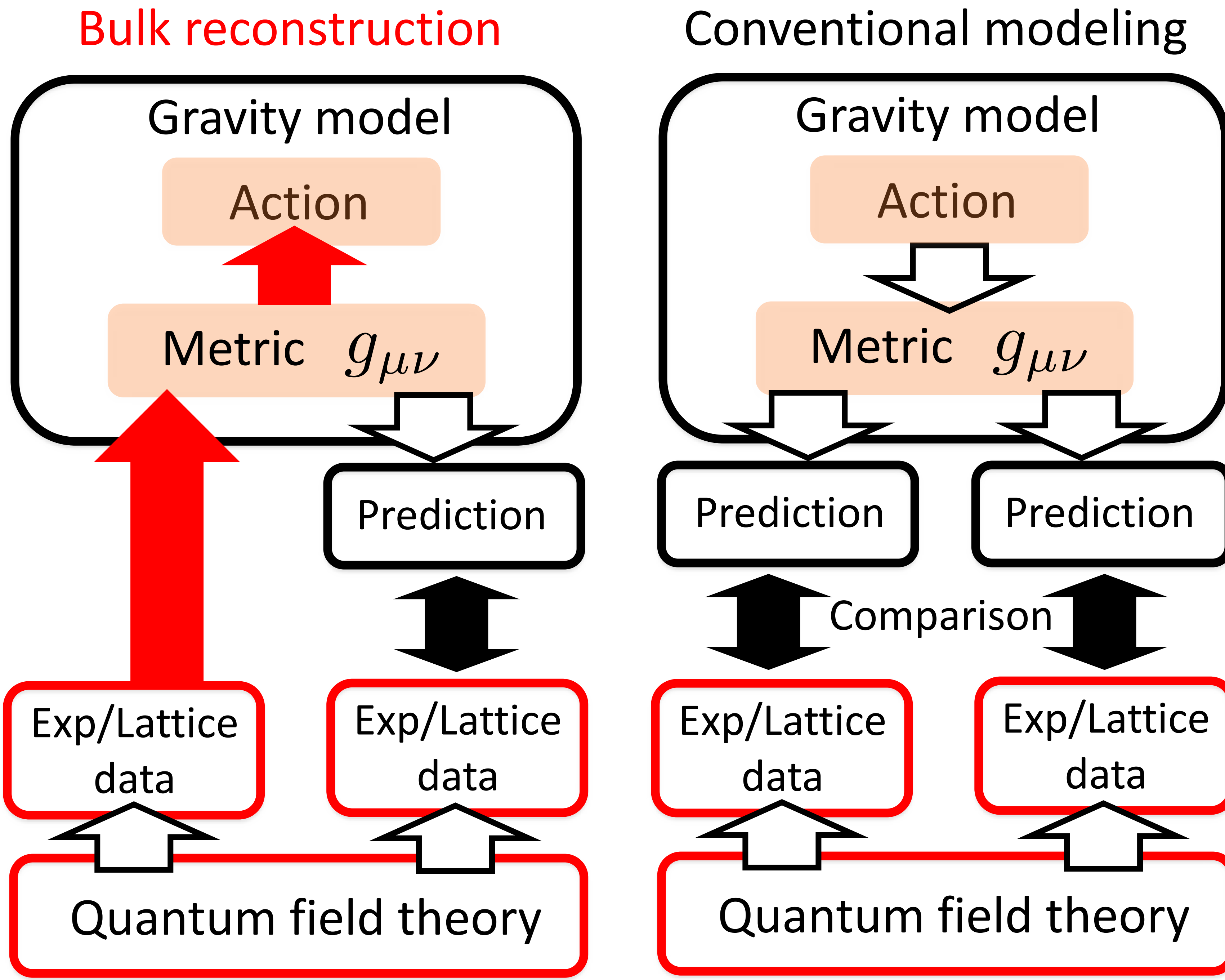


Neural network

Tensor network



AdS/CFT
(No proof, no derivation)
Classical gravity theory
in d+1 dim. spacetime
||
Quantum field theory
in d dim. spacetime
(Strong coupling limit,
large DoF limit)
Conventional modeling
Gravity model
Action
Metric $g_{\mu\nu}$
Prediction
Prediction
Comparison
Exp/Lattice
data
Exp/Lattice
data
Quantum field theory


Bulk reconstruction
Gravity model
Action
Metric $g_{\mu\nu}$
Prediction
Exp/Lattice data
Exp/Lattice data
Quantum field theory
Conventional modeling
Gravity model
Action
Metric $g_{\mu\nu}$
Prediction
Prediction
Comparison
Exp/Lattice data
Exp/Lattice data
Quantum field theory

④ Spacetime emergent from data

Gravity side

Classical scalar field theory in unknown 5-dim. spacetime

1802.08313
1809.10536

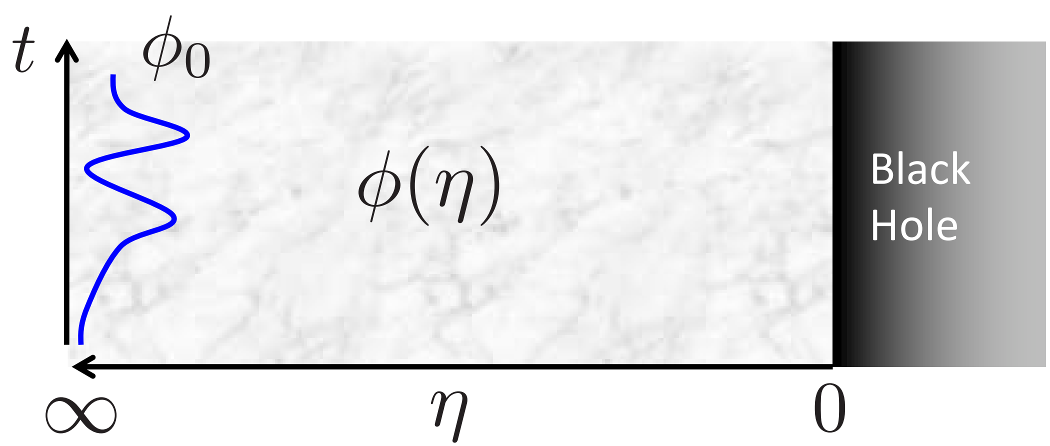
$$S = \int d\eta d^4x \sqrt{\det g}\,\left[(\partial_\eta \phi)^2 - V(\phi)\right]$$

$$\begin{cases} ds^2 = -f(\eta)dt^2 + d\eta^2 + g(\eta)(dx_1^2 + \cdots + dx_{d-1}^2) \\ V[\phi] = -\dfrac{3}{L^2}\phi^2 + \dfrac{\lambda}{4}\phi^4 \end{cases}$$

Data: $(\phi_0, Z[\phi_0])$

$\Updownarrow$

$(\phi|_{\eta=\infty}, \partial_\eta \phi|_{\eta=\infty}, \partial_\eta \phi|_{\eta=0})$



④ Spacetime emergent from data

Equation of motion as a feedforward NN

Eq. of motion $\partial_\eta^2 \phi + h(\eta) \partial_\eta \phi - \dfrac{\delta V[\phi]}{\delta \phi} = 0$

metric $h(\eta) \equiv \partial_\eta \left[\log \sqrt{f(\eta) g(\eta)^{d-1}} \right]$

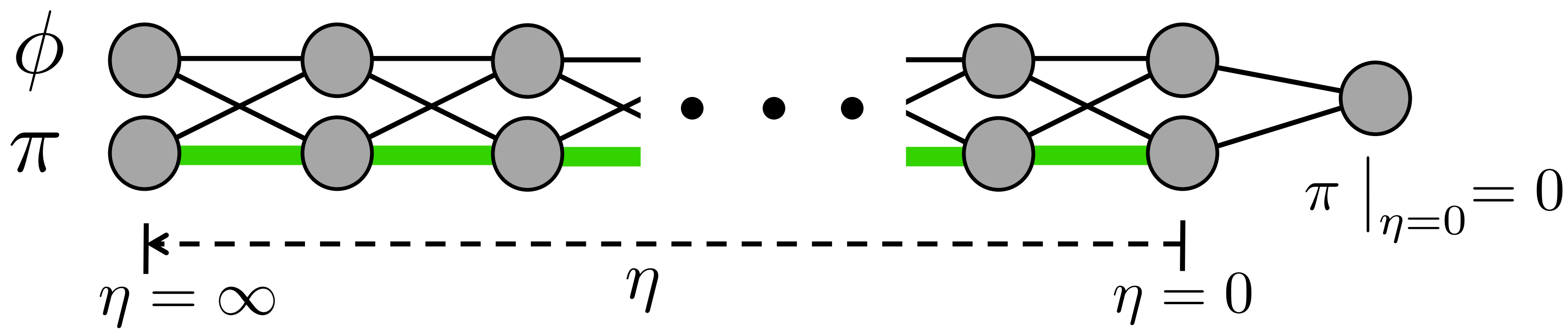
⇩

Discretization
Hamilton form

$$\begin{cases} \phi(\eta + \Delta\eta) = \phi(\eta) + \Delta\eta \, \pi(\eta) \\ \pi(\eta + \Delta\eta) = \pi(\eta) + \Delta\eta \left(h(\eta) \pi(\eta) - \dfrac{\delta V(\phi(\eta))}{\delta \phi(\eta)} \right) \end{cases}$$

⇩

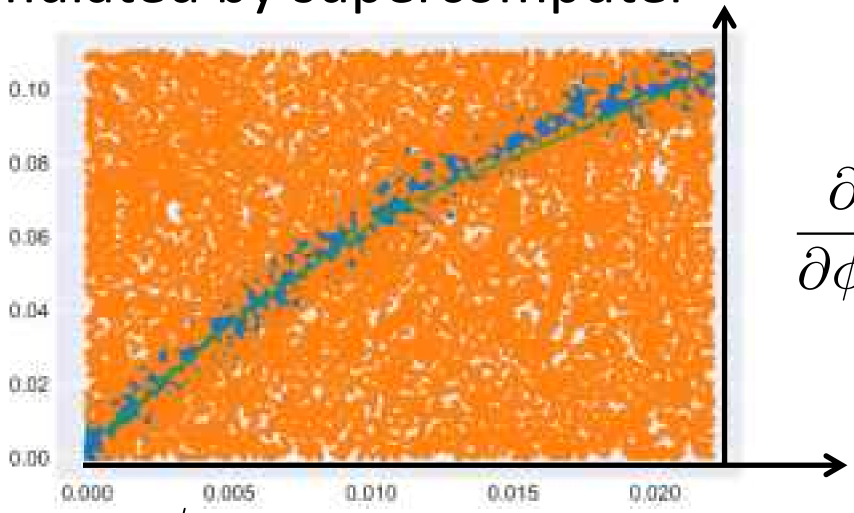
Feedfoward neural network for classification



④ Spacetime emergent from data

Training with data of quark condensate

Data of quantum chromodynamics
simulated by supercomputer

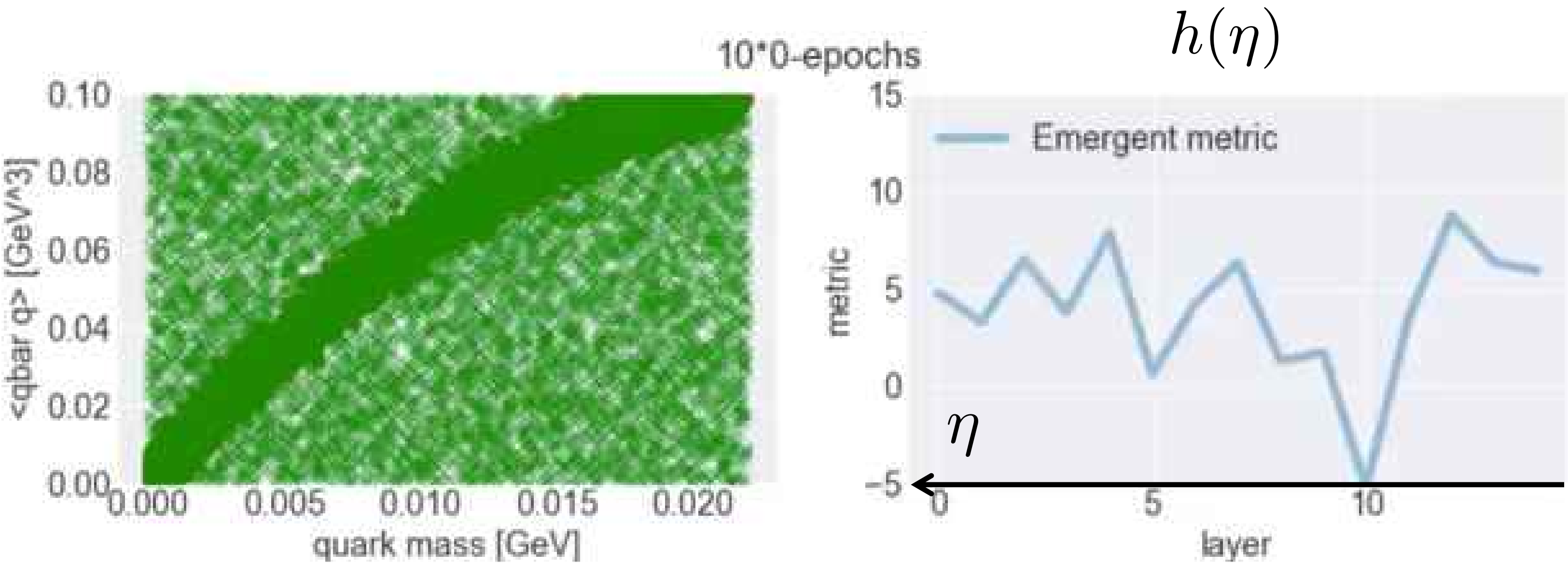


$\frac{\partial}{\partial \phi_0} Z[\phi_0]$: Quark condensate

ϕ_0 : Quark mass

④ Spacetime emergent from data

Spacetime metric emergent as NN

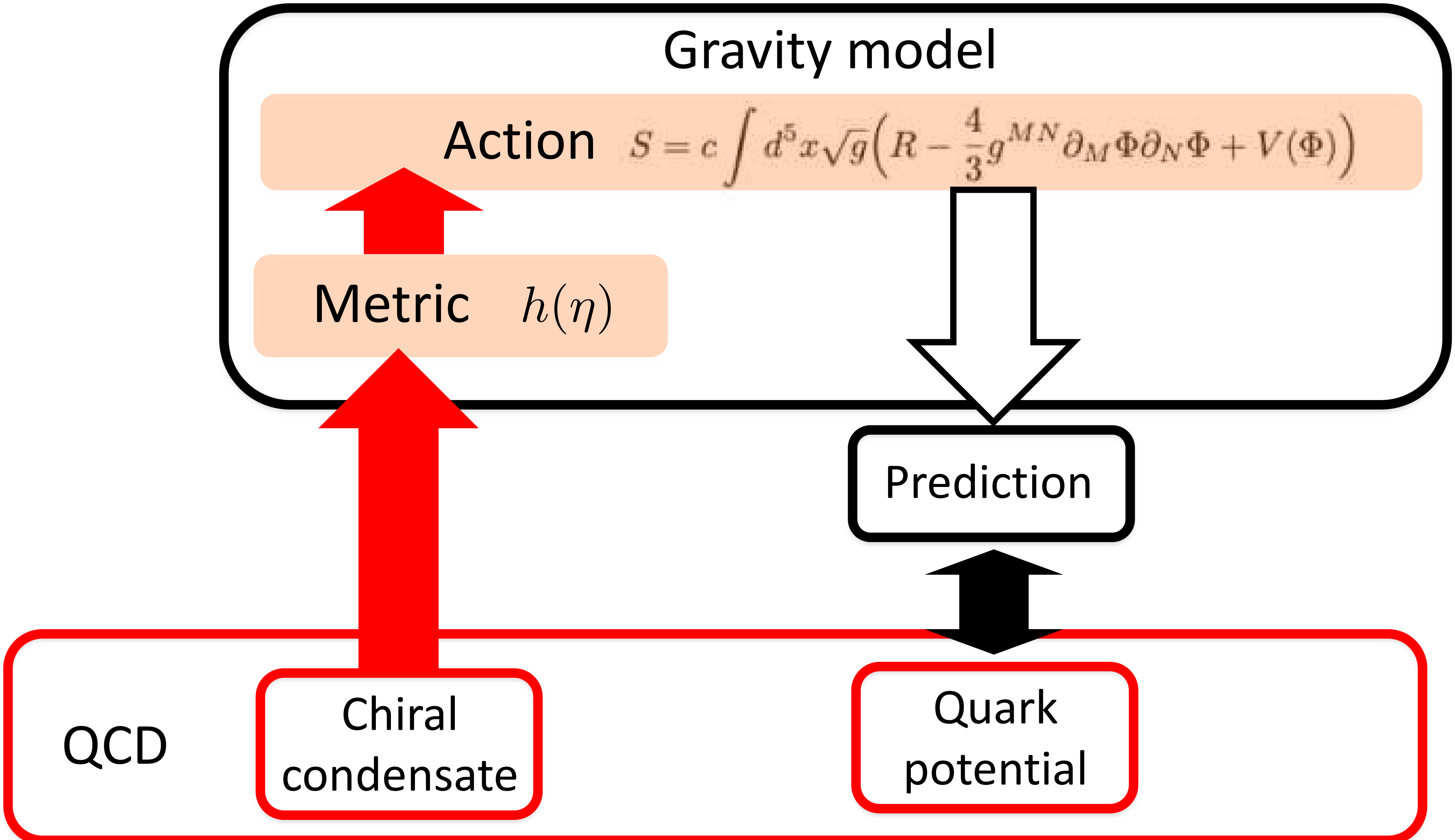


Trained values of potential :

1/L = 237(3)[MeV] ,   λ/L = 0.0127(6)

4. Spacetime emergent from data

Reconstructing gravity model dual to QCD



4. Spacetime emergent from data

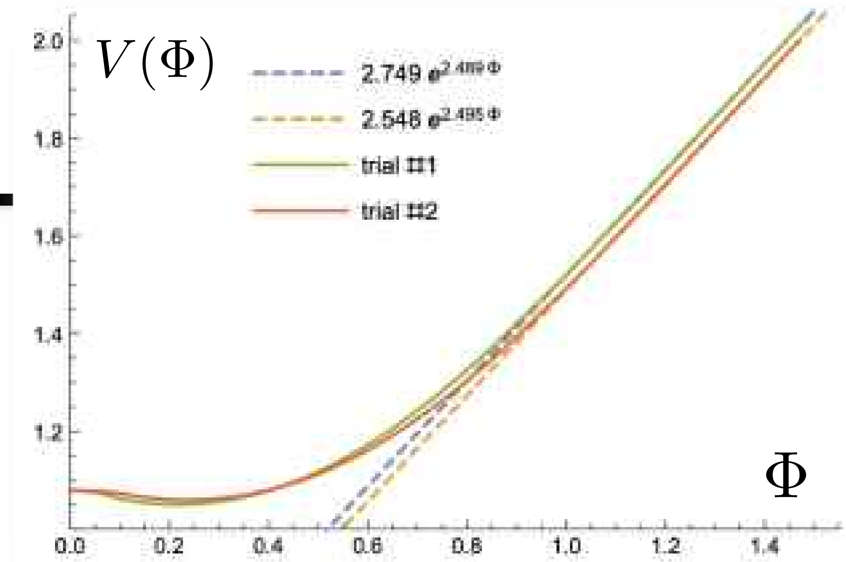
Deriving the dilaton potential

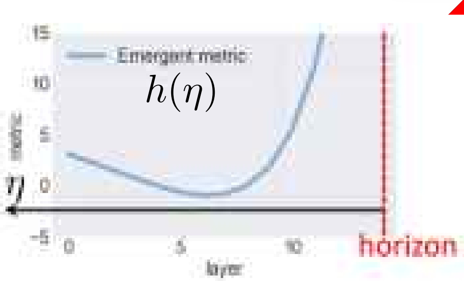
Gravity model

Action $S = c\int d^5x\sqrt{g}\left(R - \frac{4}{3}g^{MN}\partial_M\Phi\partial_N\Phi + V(\Phi)\right)$

2209.04638

Metric $h(\eta)$





Chiral condensate

4. Spacetime emergent from data

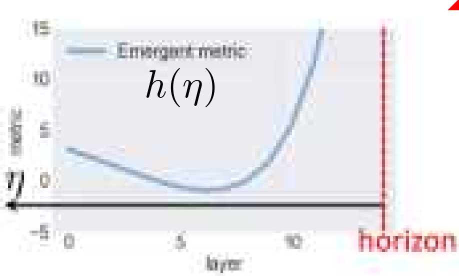
Prediction of QCD string breaking

Gravity model

Action $S = c\int d^5x\sqrt{g}\left(R - \frac{4}{3}g^{MN}\partial_M\Phi\partial_N\Phi + V(\Phi)\right)$

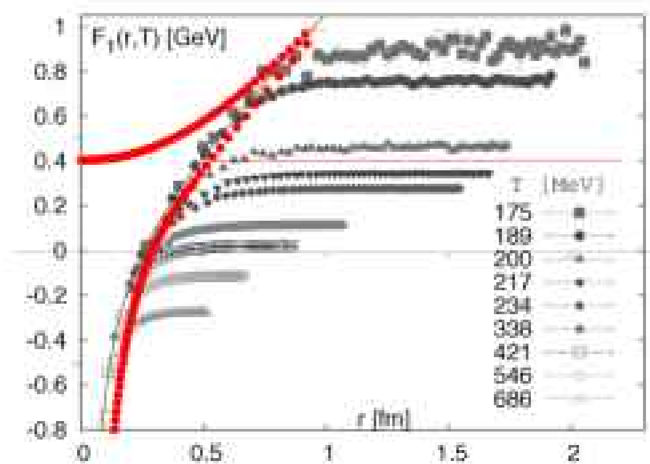
Metric $h(\eta)$

Prediction



Chiral condensate

Quark potential



Roadmap

4.

Quantum gravity in (d+1)-dim.

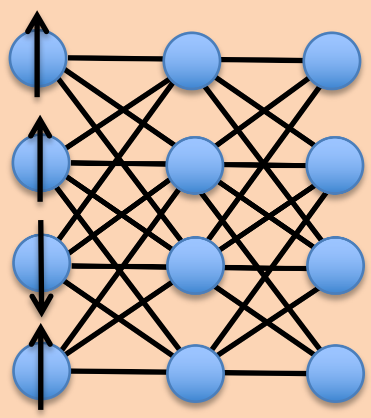
'tHooft `93
Susskind `94
Maldacena `97

||

Quantum mechanics in d-dim.

General spacetime

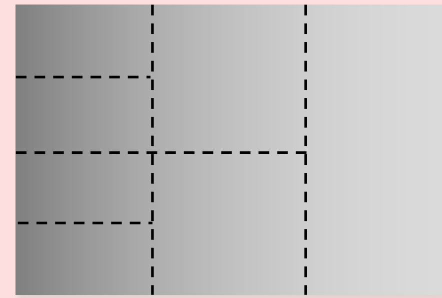
|| ?



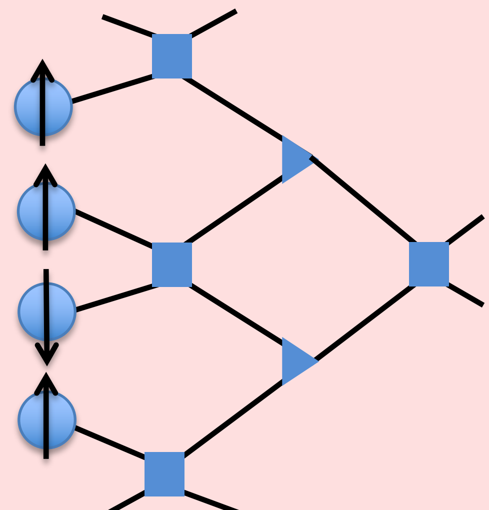
Neural network

Carleo, Troyer `17

Anti de Sitter spacetime



|| Swingle `10



Tensor network

Deep Learning and Quantum Gravity

Discussion: Quantum gravity $\subset$ ML ?

Discussion: Quantum gravity ⊂ ML ?

3 steps for quantum gravity

Quantum Mechanics side
Large DoF limit
Large DoF expansion
Finite DoF

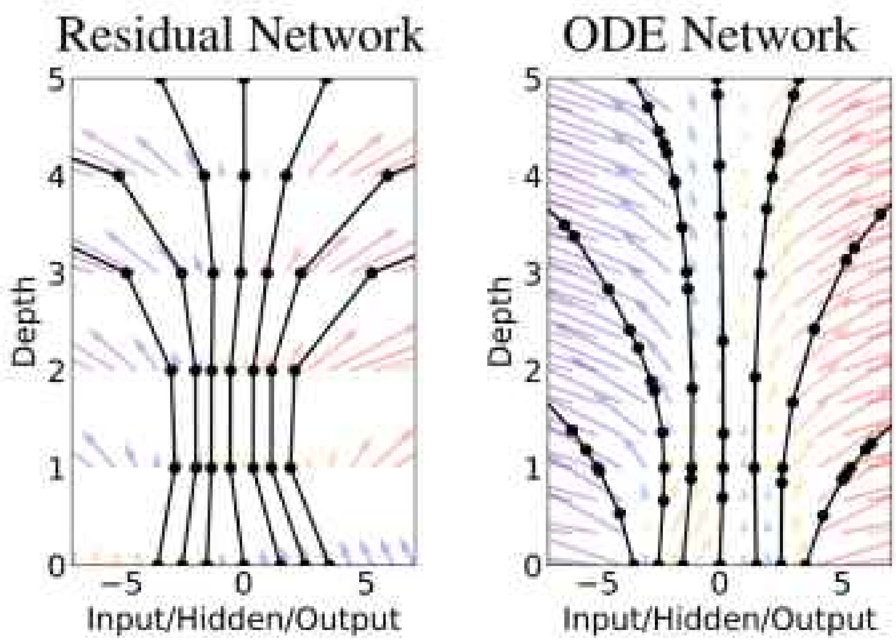
Gravity side		Architecture
metric $g_{\mu\nu}$	field ϕ	
Classical	Classical	Feedforward NN
Classical	Quantum	Deep Boltzmann
Quantum	Quantum	?

- Neural ODE : free from discretization
- Quantum AdS/CFT ⊂ Deep Boltzmann machine
- Which part of geometry is the neurons?

Discussion: Quantum gravity ⊂ ML ?

Neural ODE : free from discretization

2006.00712



Neural ODE [R.T.Q.Chen, Y.Rubanova, J.Bettencourt, D.Duvenaud 1806.07366]

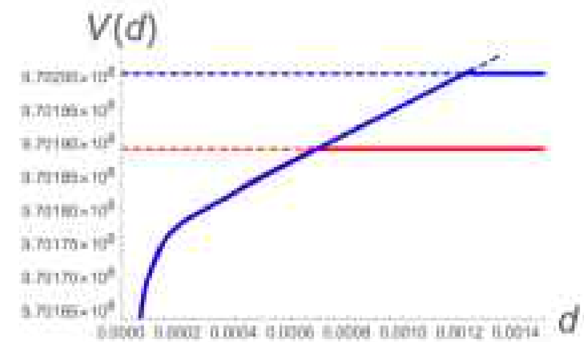
$$\frac{d\phi(\eta)}{d\eta} = f(\phi(\eta), \eta, h(\eta))$$

Emergent metric

$$h(\eta) = 8.2351\tilde{\eta}^8 + 8.0108\tilde{\eta}^7 + 7.6071\tilde{\eta}^6 + 6.9468\tilde{\eta}^5 + 150.8853\tilde{\eta}^4 - 130.8117\tilde{\eta}^3 + 55.5384\tilde{\eta}^2 - 2.22235\tilde{\eta}^1 + 3.7719.$$

$$\tilde{\eta} = 1 - \eta$$

Q Qbar potential

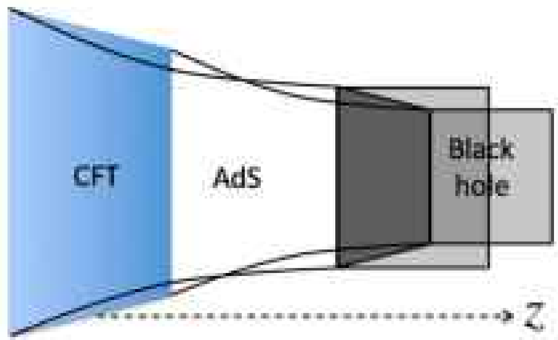


Discussion: Quantum gravity ⊂ ML ?

Quantum AdS/CFT ⊂ Deep Boltzmann

AdS/CFT

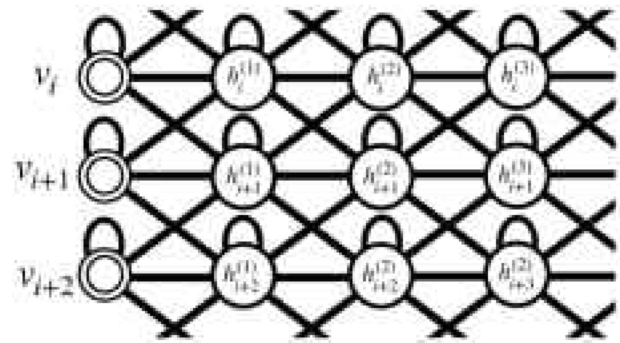
[Maldacena 1997]



$$Z_{\mathrm{QFT}}[J] = \int_{\phi(z=0)=J} \mathcal{D}\phi \, \exp\left(-S_{\mathrm{gravity}}[\phi]\right)$$

Deep Boltzman machine

[Salakhutdinov, Hinton 2009]



$$P(v_i) = \sum_{h_i \in \{0,1\}} \exp\left[-\mathcal{E}(v_i, h_i)\right]$$

[KH `19] [You,Yang,Qi `18] (See also [Gan,Shu `17][Howard `18])

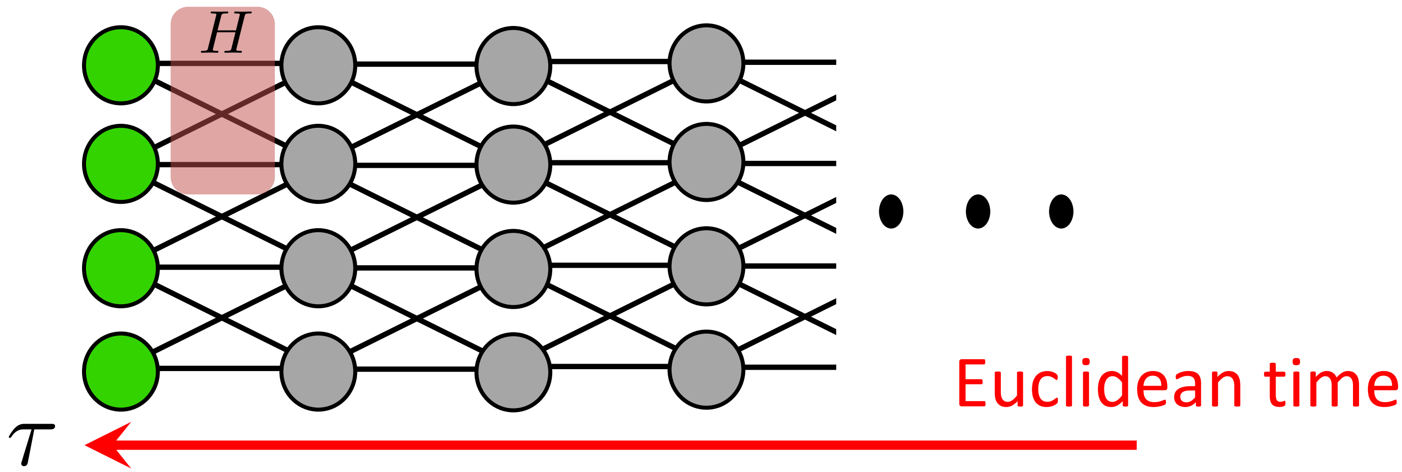
Discussion: Quantum gravity ⊂ ML ?

Physical picture of Deep Boltzmann

Ground state wave function for given Hamiltonian is identified as a deep Boltzmann machine

[Carleo, Nomura, Imada `18], ..

$$|\psi\rangle = \lim_{\tau\to\infty} e^{-\tau H}|\mathrm{any}\rangle = e^{-\Delta\tau H}e^{-\Delta\tau H}\cdots|\mathrm{any}\rangle$$



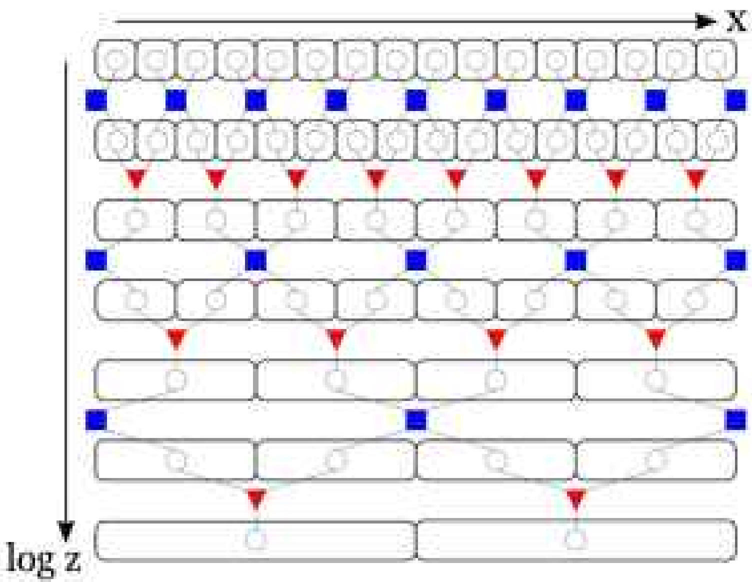
$$\psi(x_i) = \sum_{h_j^{(n)}\in\{0,1\}} \exp\left[-\sum_{ij} w_{ij}^{(0)} x_i h_j - \sum_n \sum_{ij} w_{ij}^{(n)} h_i^{(n)} h_j^{(n+1)}\right]$$

Discussion: Quantum gravity ⊂ ML ?

AdS/CFT discretized the bulk, but fixed

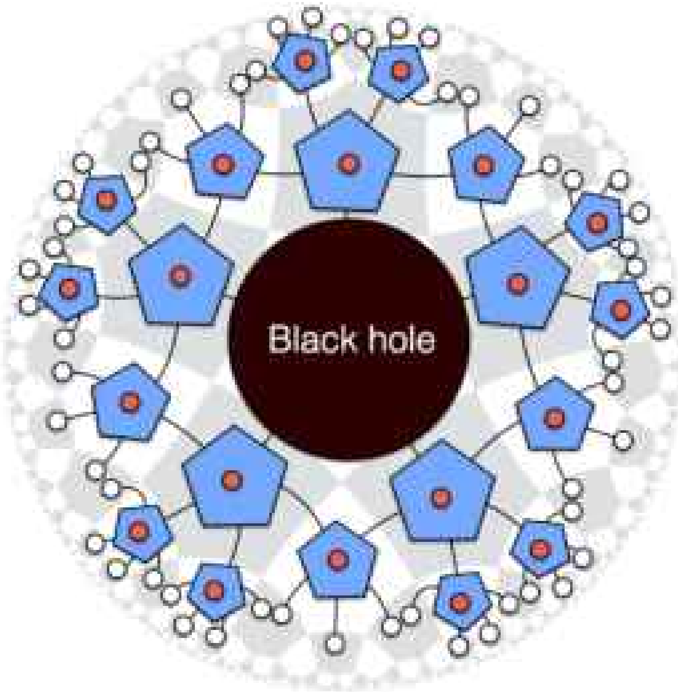
AdS/MERA

[Swingle `09]



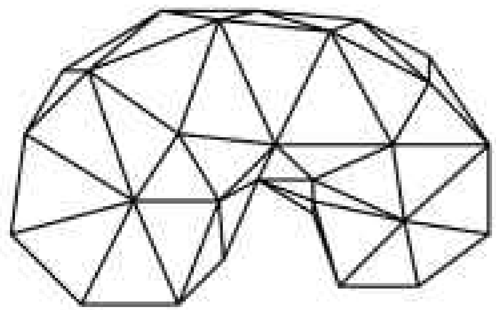
Quantum codes for holography

[Pastawski, Yoshida, Harlow, Preskill `15]



Discussion: Quantum gravity ⊂ ML ?

Quantum spacetime? Regge vs Matrix



Regge calculus
[Regge `61]

Fixed lattice architecture, variable lengths

Suits conventional NN

Dynamical triangulation
[Ambjorn, Loll `98]

Randomly generated lattice architecture, fixed lengths

Novel "QG NN"

③ When is NN a spacetime?

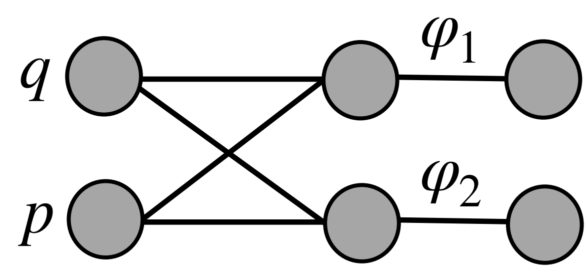
Hamilton dynamics is a NN

1802.08313

$$\dot{q} = \frac{\partial H}{\partial p}, \qquad \dot{p} = -\frac{\partial H}{\partial q}$$

Trial NN representation:

$$\begin{cases} q(t+\Delta t) = \varphi_1(W_{11}q(t) + W_{12}p(t)) \\ p(t+\Delta t) = \varphi_2(W_{21}q(t) + W_{22}p(t)) \end{cases}$$



$\Delta t \to 0$

Consistency requires

$$\begin{cases} W_{ij} = \delta_{ij} + \Delta t w_{ij} \\ \varphi_i(x) = x + \Delta t g_i(x) \end{cases}$$

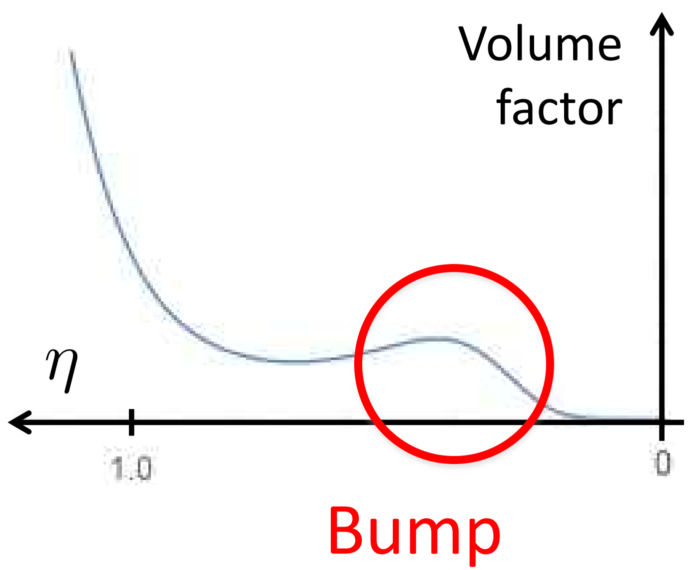
$$\begin{cases} \dot{q} = w_{11}q + w_{12}p + g_1(q) \\ \dot{p} = w_{21}q + w_{22}p + g_2(p) \end{cases}$$

Trivial linear Hamiltonian...

④ Spacetime emergent from data

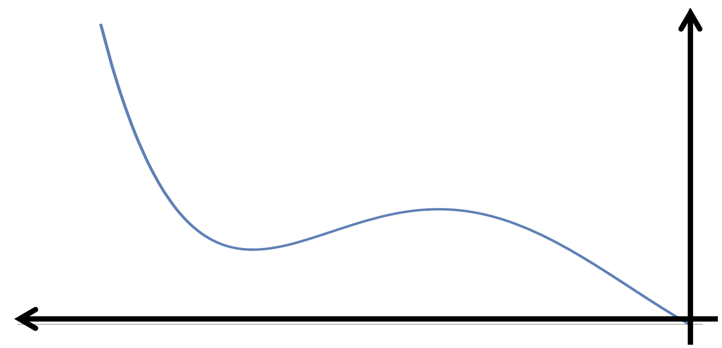
Emergent metric can predict physics

Emergent metric



Cf) Bottom-up model

$$ds^2 = \frac{e^{cz^2/2}}{z^2}\left((1-z^4)dt^2 + dx_i^2 + \frac{1}{1-z^4}dz^2\right)$$

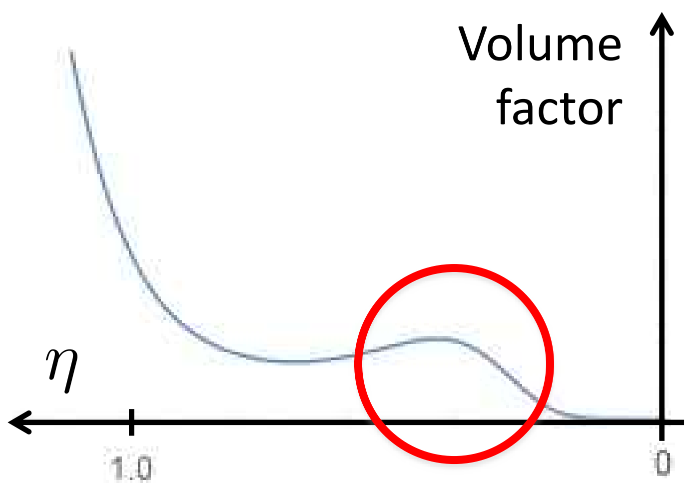


[Andreev, Zakharov, `06, `07]

④ Spacetime emergent from data

Emergent metric can predict physics

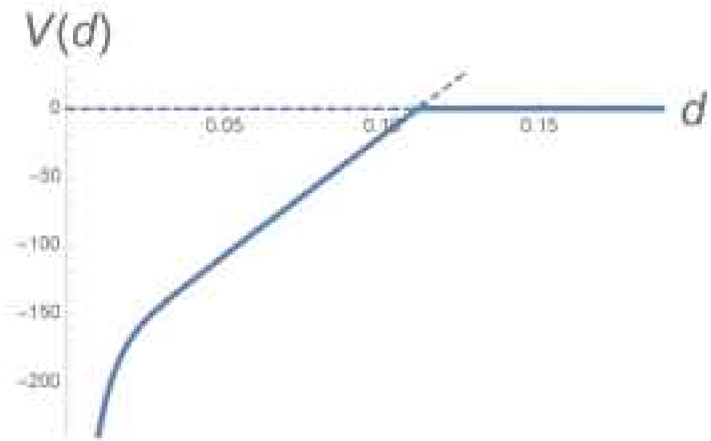
Emergent metric

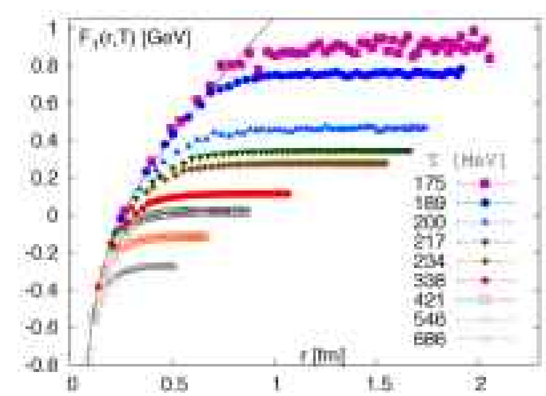


Bump

Procedures based on [Maldacena] [Rey,Theisen,Yee]

Q Qbar potential





[Petreczky, `10]

3. Holography is a NN

Detailed mapping possible

Scalar field theory in curved spacetime

$$S = \int d^d x dz \frac{1}{2} \left[a(z)(\partial_z \phi)^2 + b(z) \sum_{I=1}^{d-1} (\partial_I \phi)^2 + d(z)(\partial_\tau \phi)^2 + c(z) m^2 \phi^2 \right]$$

Proper discreti-zation

$$(\partial_z \phi)^2 = \lim_{\Delta z \to 0} \frac{(\phi(z_{k+1}) - \phi(z_k))^2}{(\Delta z)^2}$$

$$(\partial_\tau \phi)^2 = \lim_{\Delta\tau, \Delta z \to 0} \left[\frac{\phi(x_{i,l+1}, z_k) - \phi(x_{i,l}, z_k)}{\Delta\tau} \cdot \frac{\phi(x_{i,l+1}, z_{k+1}) - \phi(x_{i,l}, z_{k+1})}{\Delta\tau} \right]$$

$$h_{i,l}^{(k)} \equiv \phi(x_{i,l}, z_k)$$

Energy function of deep Boltzmann

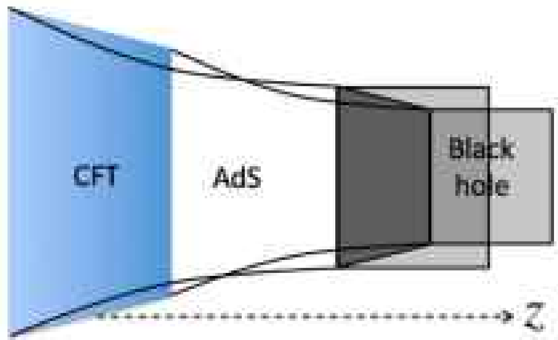
$$S = \mathcal{E} \equiv \sum_k \left[\sum_{i,j} \sum_{l,m} \left\{ w_{ij,lm}^{(k)} h_{i,l}^{(k)} h_{j,m}^{(k+1)} + \tilde{w}_{ij,lm}^{(k)} h_{i,l}^{(k)} h_{j,m}^{(k)} \right\} \right]$$

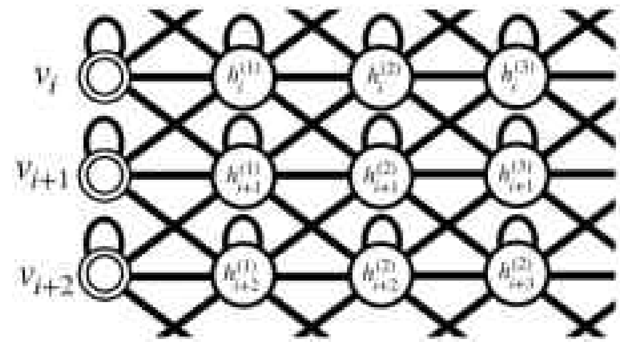
$$w_{ij,lm}^{(k)} \equiv -\frac{a_k}{(\Delta z)^2} \delta_i^j \delta_l^m + \frac{b_k}{2(\Delta x)^2} \left(2\delta_i^j \delta_l^m - \delta_{i+1}^j \delta_l^m - \delta_i^{j+1} \delta_l^m \right) + \frac{d_k}{2(\Delta\tau)^2} \left(2\delta_i^j \delta_l^m - \delta_i^j \delta_{l+1}^m - \delta_i^j \delta_l^{m+1} \right)$$

$$\tilde{w}_{ij,lm}^{(k)} \equiv \left(\frac{a_k + a_{k-1}}{2(\Delta z)^2} + m^2 \frac{c_k}{2} \right) \delta_i^j \delta_l^m$$

3. Holography is a NN

Dictionary: Spacetime is a NN





AdS/CFT	Deep Boltzmann machine
Bulk coordinate z	Hidden layer label k
QFT source $J(x)$	Input value v_i
Bulk field $\phi(x, z)$	Hidden variables $h_i^{(k)}$
QFT generating function $Z[J]$	Provability distribution $P(v_i)$
Bulk action $S[\phi]$	Energy function $\mathcal{E}(v_i, h_i^{(k)})$

5. Holographic spacetime is a NN

Algebraize PDE by Fourier transformation

[Karch, Kaz, Son, Stephanov `06]

Classical gauge theory in 5-d dilaton gravity background

$$S = \int d^4x dz\, e^{-\Phi} \sqrt{-g}\, \left(F_{MN}\right)^2$$

Dilaton $\Phi(z)$, metric $ds^2 = e^{2A(z)} \left(dz^2 + \eta_{\mu\nu} dx^\mu dx^\nu\right)$

AdS boundary ($z \sim 0$) : $B(z) \equiv \Phi(z) - A(z) \sim \log z$

Solve EoM for gauge field $A_\mu(z, x^\mu) = v_n(z) \rho_\mu(x^\mu)$

$$\frac{\partial}{\partial z}\left(e^{-B} \frac{\partial}{\partial z} v_n\right) + \omega^2 e^{-B} v_n = 0$$

When frequency takes a proper discrete value $\omega^2 \sim m_n^2$, gauge field is normalizable : vector meson spectra.

5. Holographic spacetime is a NN

Algebraize PDE by Fourier transformation

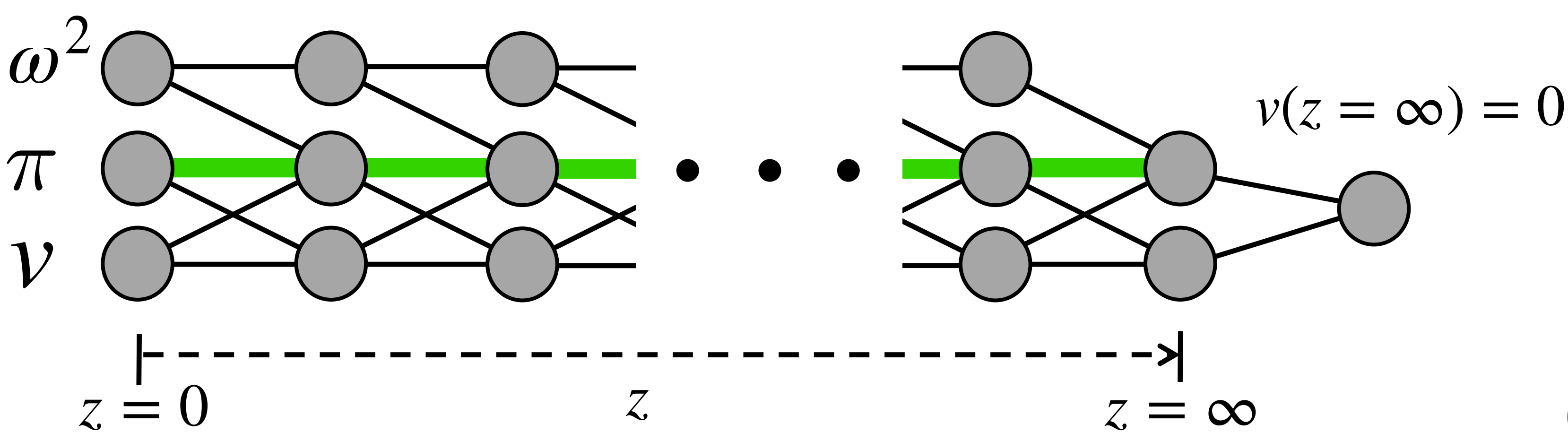
Bulk EoM $$\frac{\partial}{\partial z}\left(e^{-B}\frac{\partial}{\partial z}v_n\right)+\omega^2 e^{-B}v_n=0$$

⇩

Discretization
Hamilton form
$$\begin{cases} v_n(z+\Delta z)=v_n(z)+\Delta z\,\pi_n(z) \\ \pi_n(z+\Delta z)=\pi_n(z)+\Delta z\left(B'(z)\pi_n(z)-\omega^2 v_n(z)\right)\end{cases}$$

⇩

Neural-Network representation

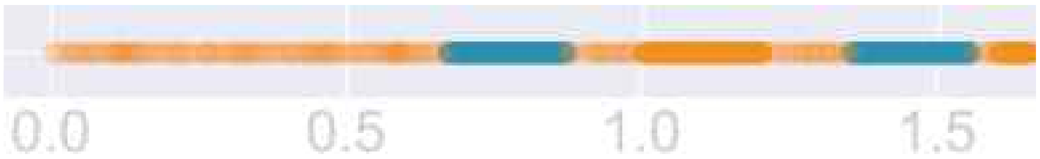


5. Holographic spacetime is a NN

Training with QCD data: hadron spectra

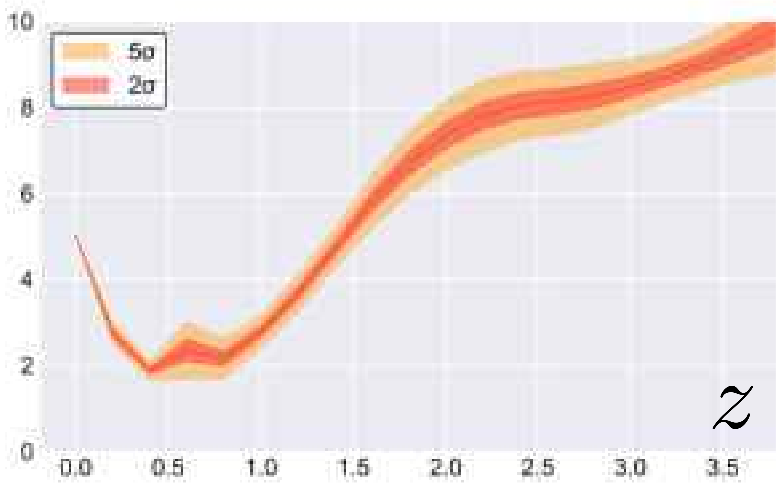
PDG data for rho meson mass :

$$m_\rho^{(1)} = 0.77 \text{ GeV}, \; m_\rho^{(2)} = 1.45 \text{ GeV}$$



● Positive
● Negative

$$B'(z) = \Phi'(z) - A'(z)$$



5. Holographic spacetime is a NN

Training with QCD data: hadron spectra

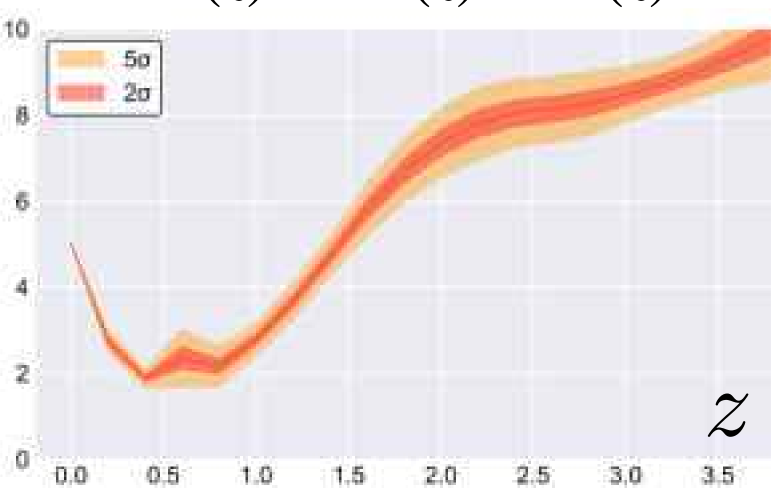
PDG data for rho meson mass :

$$m_\rho^{(1)} = 0.77 \text{ GeV}, m_\rho^{(2)} = 1.45 \text{ GeV}$$

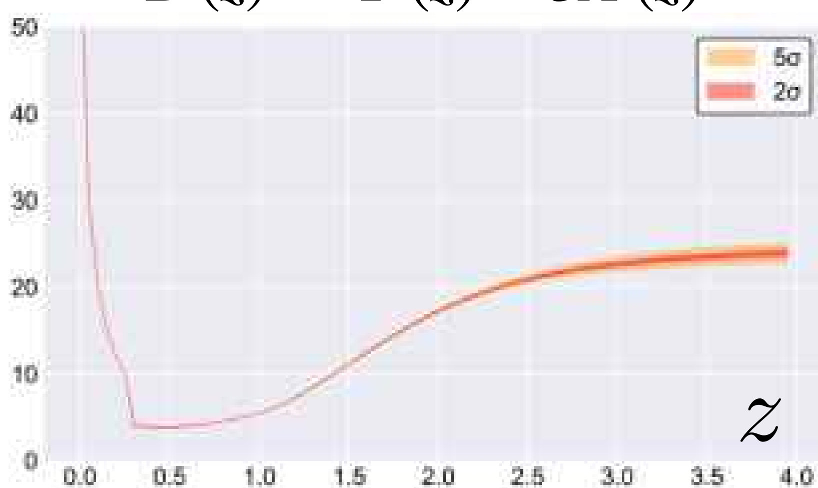
PDG data for a_2 meson mass :

$$m_{a_2}^{(1)} = 1.32 \text{ GeV}, m_{a_2}^{(2)} = 1.70 \text{ GeV}$$

$$B'(z) = \Phi'(z) - A'(z)$$



$$\tilde{B}'(z) = \Phi'(z) - 3A'(z)$$

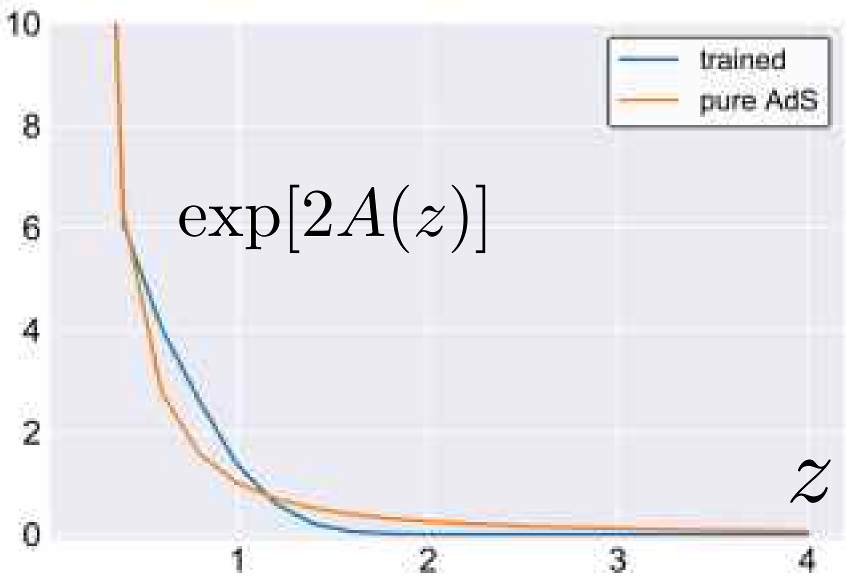


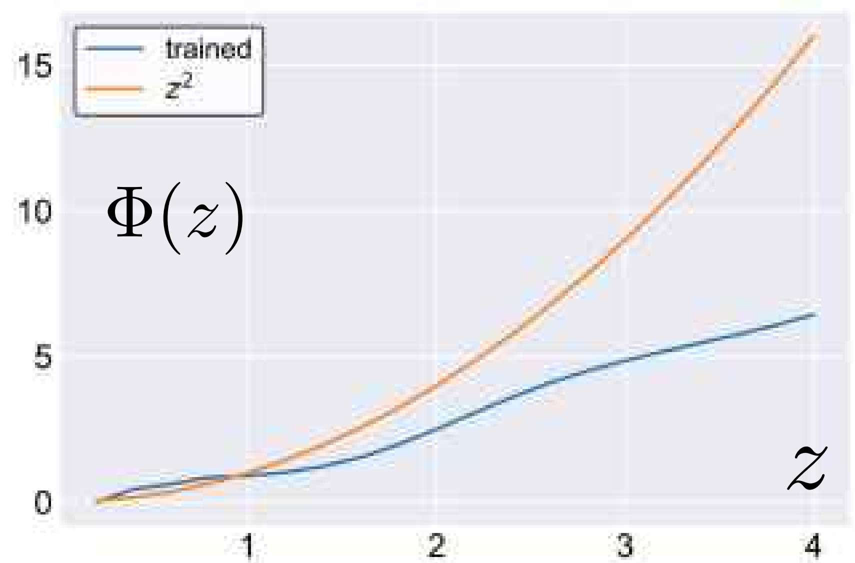
5. Holographic spacetime is a NN

Neural geometry emergent in the bulk

Metric
- consistent with pure AdS

Dilaton
- grows at IR,
  like QCD running coupling





4. Spacetime emergent from data

Simplest holographic model

Classical scalar field probing 5-dim. curved spacetime

$$S = \int d\eta d^4x \sqrt{\det g} \left[(\partial_\eta \phi)^2 - V(\phi) \right]$$

1802.08313
1809.10536

$$ds^2 = -f(\eta)dt^2 + d\eta^2 + g(\eta)(dx_1^2 + \cdots + dx_{d-1}^2)$$

- AdS boundary ($\eta \sim \infty$) : $f \sim g \sim \exp[2\eta/L]$
- Black hole horizon ($\eta \sim 0$) : $f \sim \eta^2, \ g \sim \text{const.}$

Solve eq. of motion to get response $\langle \bar{\psi}\psi \rangle_{m_q}$. [Klebanov, Witten `98]

- AdS boundary ($\eta \sim \infty$) : $\phi = m_q e^{-\eta} + \langle \bar{\psi}\psi \rangle e^{-3\eta}$
- Black hole horizon ($\eta \sim 0$) : $\partial_\eta \phi \Big|_{\eta=0} = 0$

1. Quantum Gravity

Brief History of quantum gravity

1970 Nambu, Susskind, Nielsen: String theory of hadrons.

1971 Bekenstein: Black hole entropy is area.

Bekenstein, Lettere al Nouvo Cimento 4(1972)737.

1974 Yoneya, Scherk, Schwarz: String is quantum gravity.

Yoneya, Prog.Theor.Phys. 51 (1974) 1907.
Scherk, Schwarz, Nucl.Phys. B81 (1974) 118.

1974 'tHooft, Veltman: Perturbation fails in gravity.

'tHooft, Verltman, Ann.Inst.Henri Poincare A20 (1974) 69.

1993 'tHooft, Susskind: Holographic principle.

'tHooft, Conf.Proc.C930308 (1993)284.
Susskind, J.Math.Phys.36(1995)6377.

1997 Maldacena: Discovery of AdS/CFT correspondence.

Maldacena, Adv.Theor.Math.Phys. 2 (1998) 231.

1-1 Is deep learning useful? 3 reasons.

1. Holographic QCD is an inverse problem,
   and the deep learning is good at it.

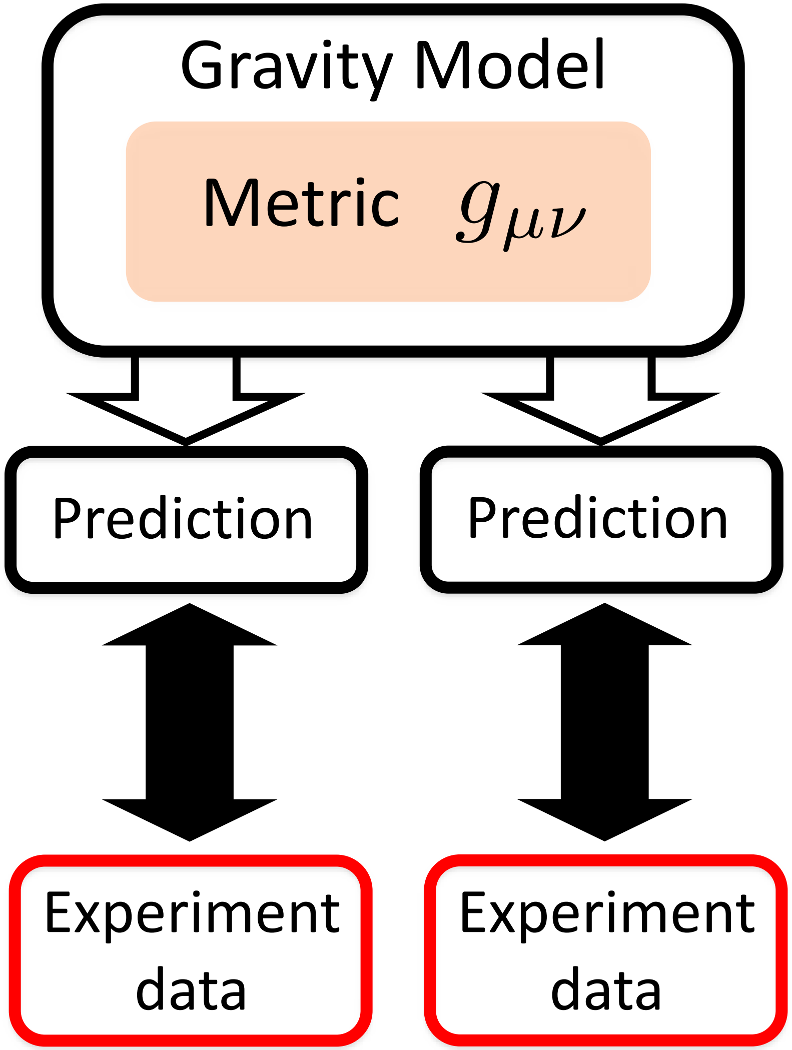
$$A = f(B)$$

Normal problem:
  System “f” given, calculate A for given B.
Inverse problem:
  For given many data (A,B), find “f”.

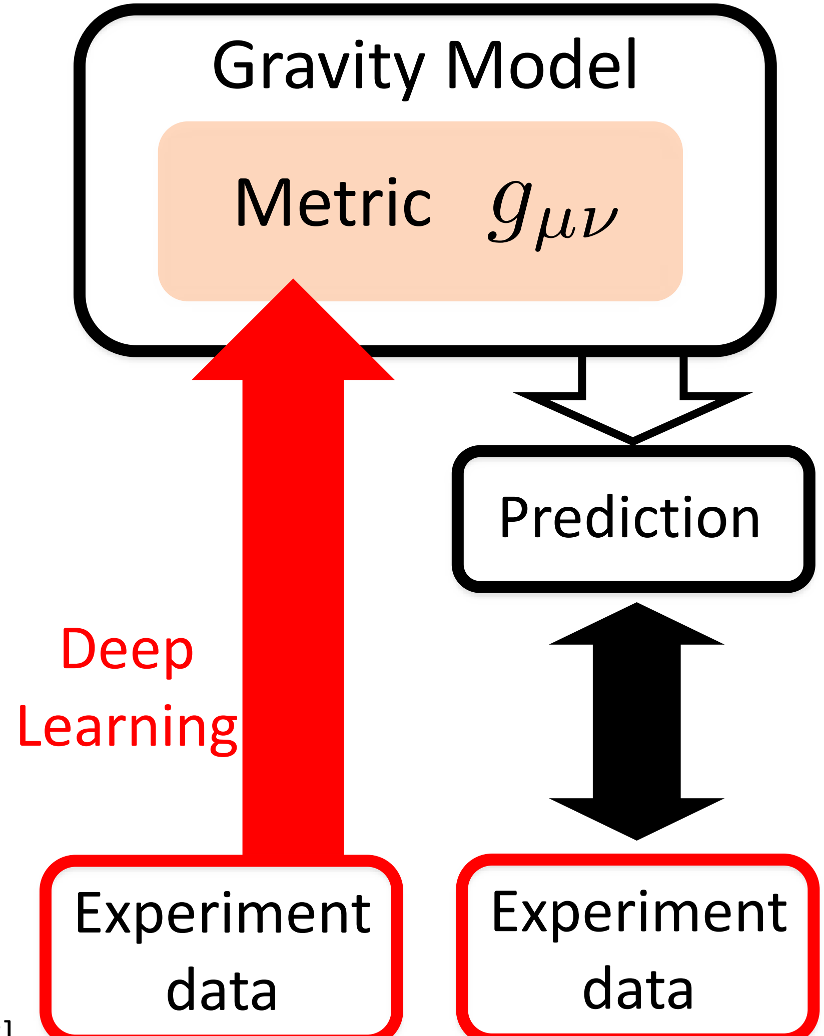
2. Discrete gravity is a network optimization,
   and so is the deep learning.

3. Deep learning architecture resembles holography.

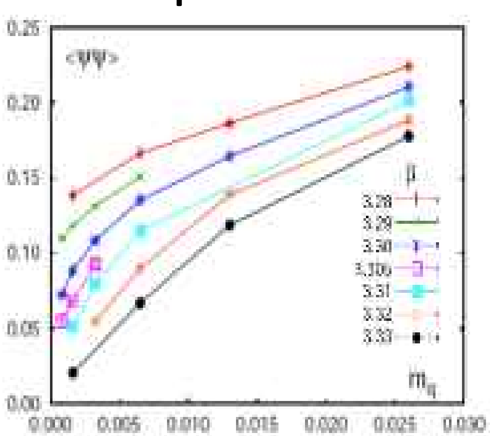
1-2 Holographic QCD is an inverse problem



1-2 Holographic QCD is an inverse problem

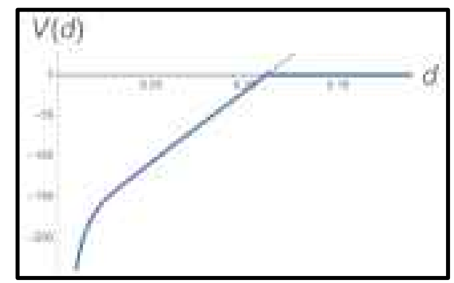


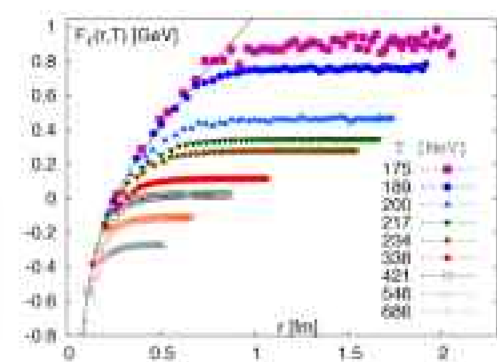
Lattice QCD data:
chiral condensate
VS quark mass



[RBC-Bielefeld collaboration, 2008]
(Courtesy of W.Unger)

Q Qbar potential





[Petreczky, 2010]

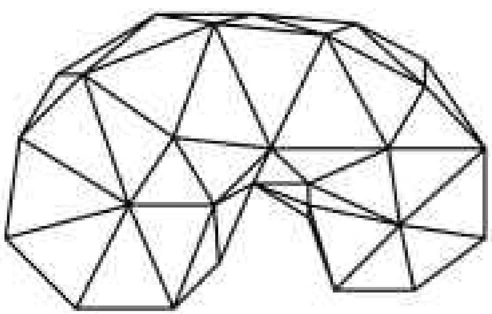
1-3 Discrete gravity = Network optimization?

Regge calculus

[Regge 1961]

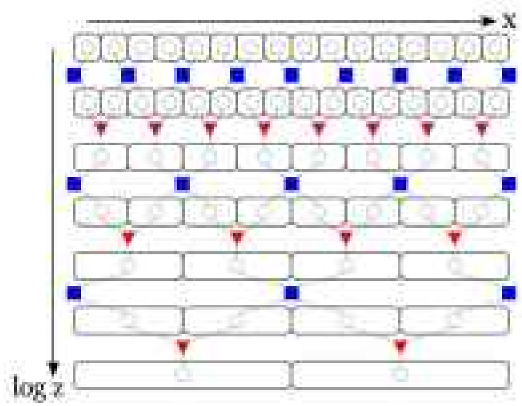
Causal dynamical triangulation

[Ambjorn, Loll 1998]



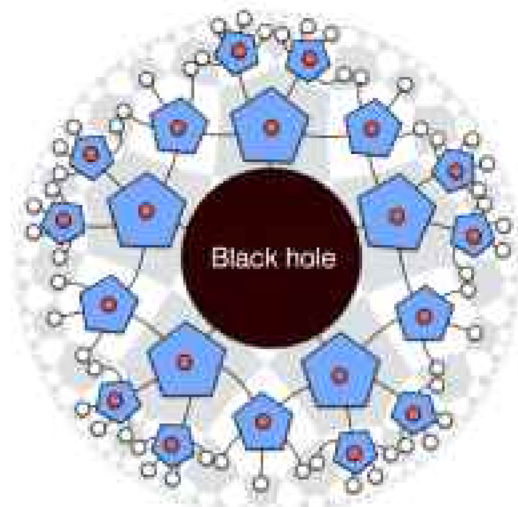
AdS/MERA

[Swingle `09]

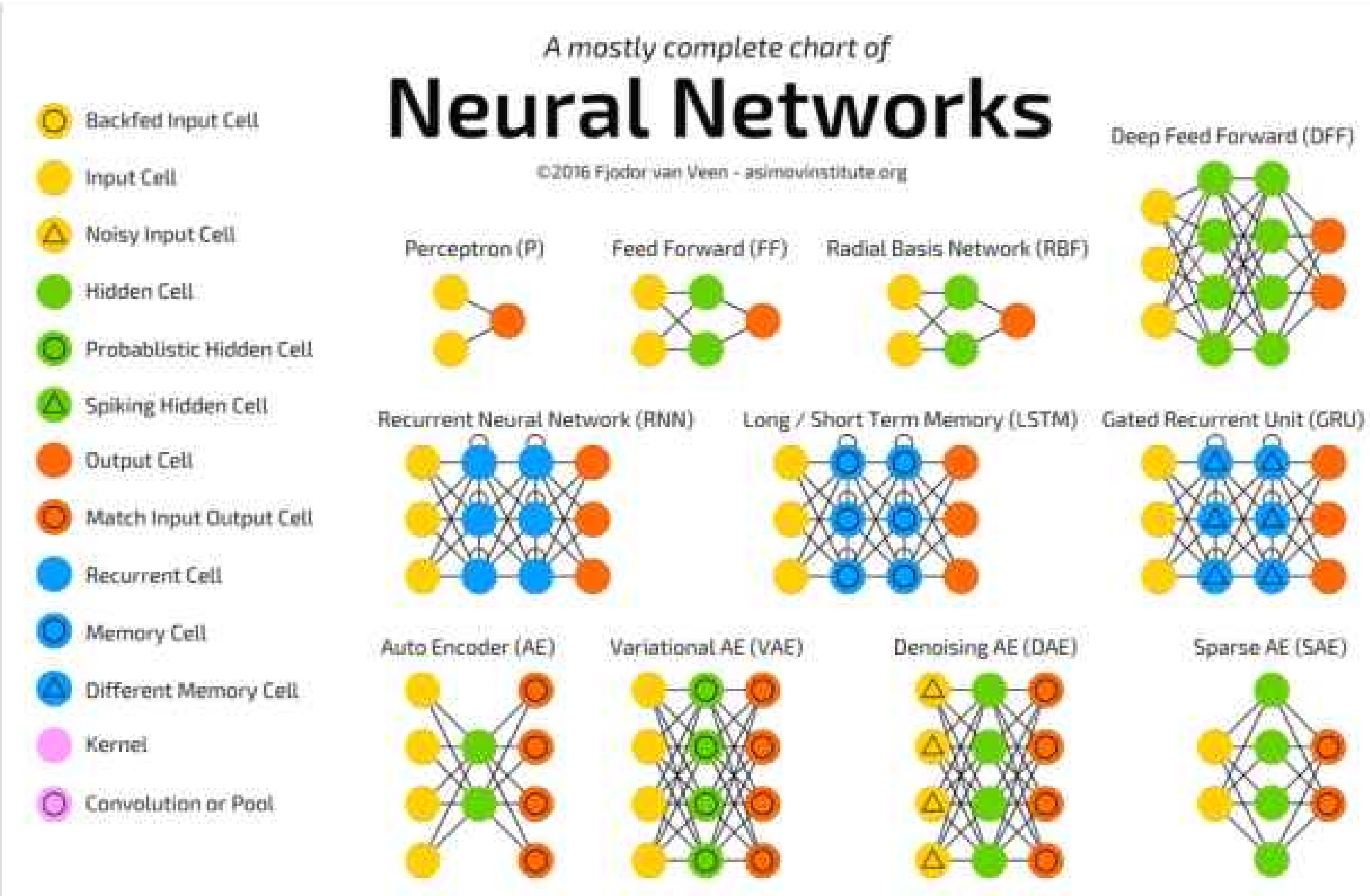


Quantum codes for holography

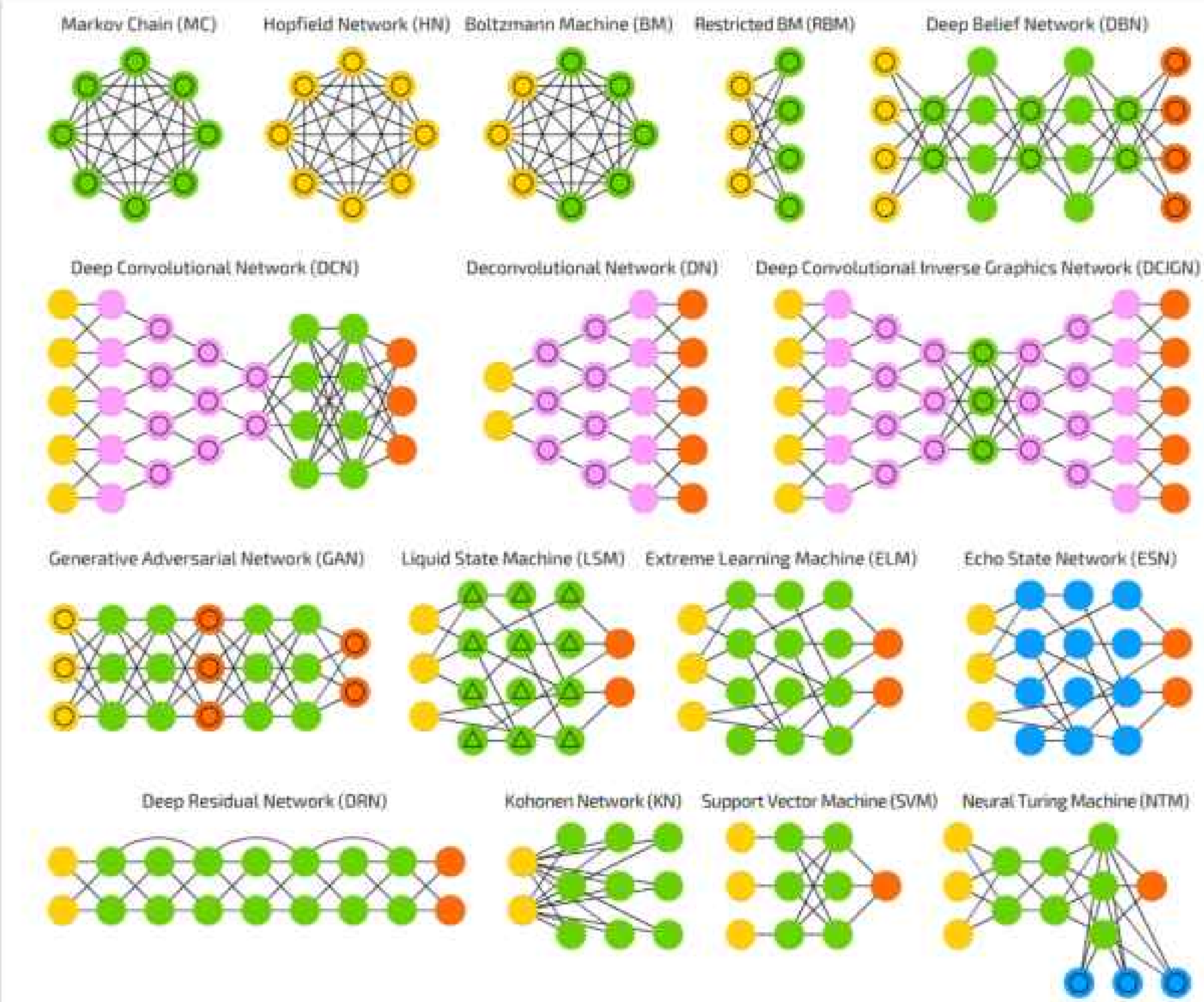
[Pastawski, Yoshida, Harlow, Preskill `15]



1-4 Machine learning = Optimizing networks



http://www.asimovinstitute.org/neural-network-zoo/

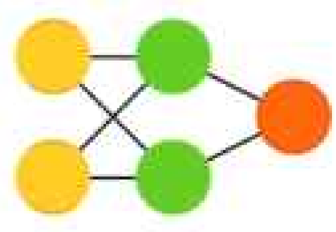


Markov Chain (MC)
Hopfield Network (HN)
Boltzmann Machine (BM)
Restricted BM (RBM)
Deep Belief Network (DBN)
Deep Convolutional Network (DCN)
Deconvolutional Network (DN)
Deep Convolutional Inverse Graphics Network (DCIGN)
Generative Adversarial Network (GAN)
Liquid State Machine (LSM)
Extreme Learning Machine (ELM)
Echo State Network (ESN)
Deep Residual Network (DRN)
Kohonen Network (KN)
Support Vector Machine (SVM)
Neural Turing Machine (NTM)

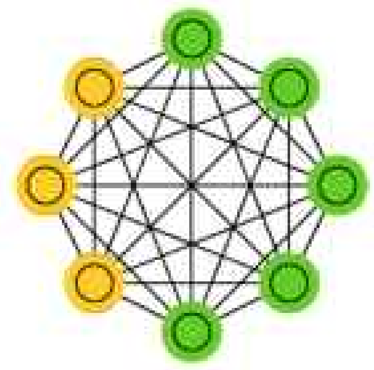
1-5 Machine learning = function approximator

Input: a vector $(v_1, v_2, v_3, \ldots)$
Output: a value $f(v_1, v_2, v_3, \ldots)$

Network architecture = Function ansatz



Perceptron model
[Rosenblatt 1958]
[Rumelhart, McClelland 1986]

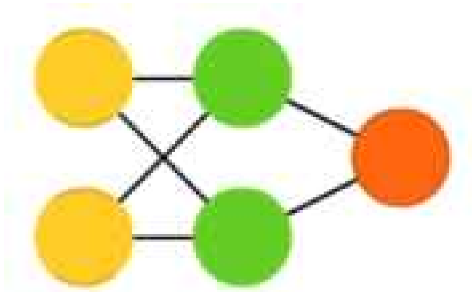


Boltzmann machine
[Ackley, Hinton, Sejnowski 1985]

Universal approximation theorem :
Any function can be approximated with more hidden units [Cybenko 1989] [Roux, Bengio 2008]

1-6 Neural network for classification

Perceptron model



$$f = W^{(2)}_i \varphi\left(W^{(1)}_{ij} x_j\right)$$

“Unit” (circles) : Vector components

“Weight” (lines) : Linear transformation to be optimized

“Activation function” (hidden line-end) : Nonlinear component-wise transf.

$$\varphi(x) \equiv \frac{1}{1+e^{-x}}$$

- Training protocol :

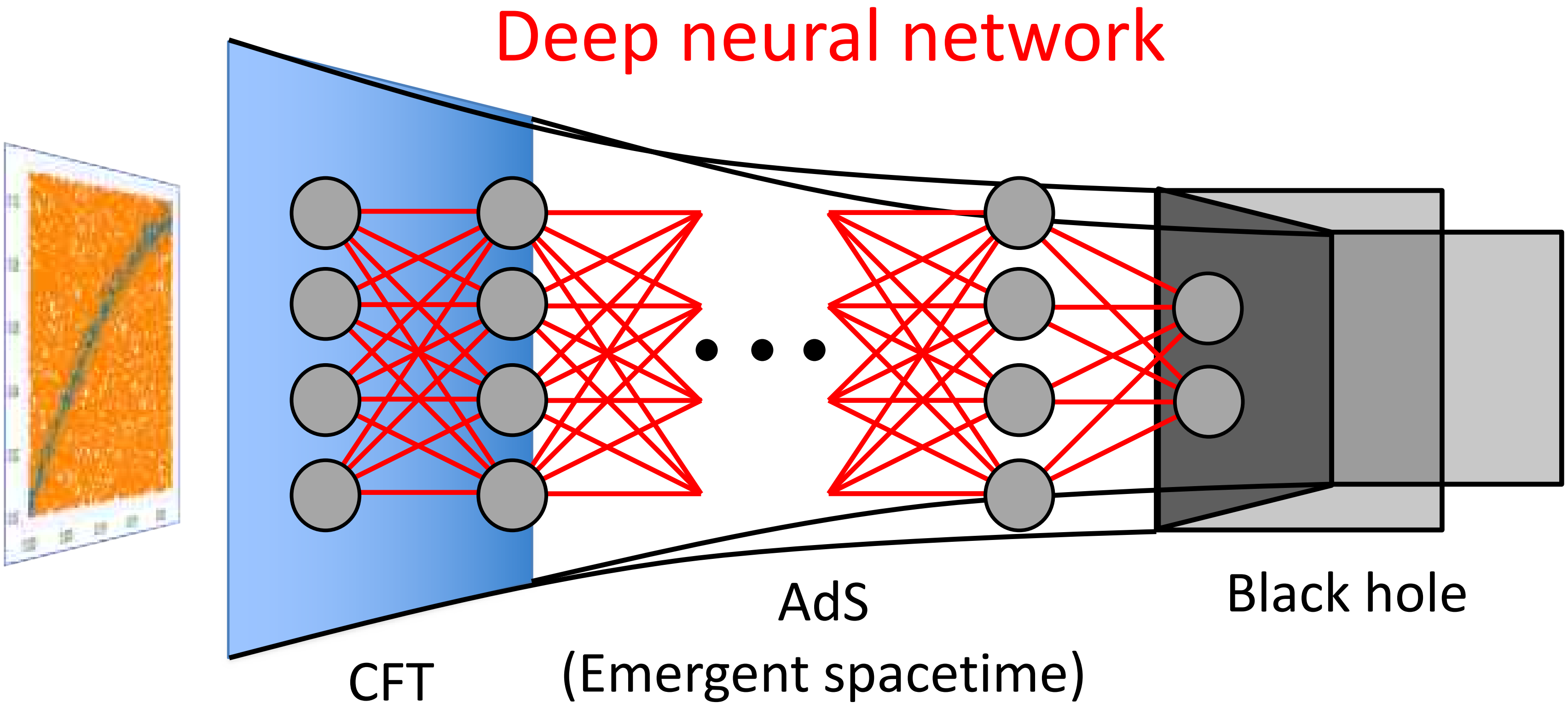
1) Prepare many sets $\{(x_j, f)\}$: input + output
2) Train the network (adjust W) by lowering “Loss function” $E \equiv \sum_{\text{data}} \left| f - W^{(2)}_i \varphi\left(W^{(1)}_{ij} x_j\right) \right|$

1-7

Holography as a classifier

AdS/CFT

[Maldacena ‘97]



7 pages

1. Is deep learning useful?

ArXiv:1903.04951

8 pages

2. Deeply learning QCD chiral condensate

ArXiv:1802.08313, 1809.10536 w/ S. Sugishita, A. Tanaka, A. Tomiya

4 pages

3. Deeply learning QCD hadron spectra

ArXiv:1909.????? w/ T.Akutagawa, T. Sumimoto

2-1 AdS/CFT: quantum response from geometry

[Klebanov, Witten]

Classical scalar field theory in (d+1) dim. geometry

$$S = \int d^{d+1}x \sqrt{-\det g}\left[(\partial_\eta \phi)^2 - V(\phi)\right]$$

$$ds^2 = -f(\eta)dt^2 + d\eta^2 + g(\eta)(dx_1^2 + \cdots + dx_{d-1}^2)$$

- AdS boundary ($\eta \sim \infty$) : $f \sim g \sim \exp[2\eta/L]$
- Black hole horizon ($\eta \sim 0$) : $f \sim \eta^2, \; g \sim \text{const.}$

Solve EoM, get response $\langle \mathcal{O} \rangle_J$. Boundary conditions:

- AdS boundary ($\eta \sim \infty$) :

$$\phi = J e^{-\Delta_- \eta} + \frac{1}{\Delta_+ - \Delta_-}\langle \mathcal{O} \rangle e^{-\Delta_+ \eta}$$

- Black hole horizon ($\eta \sim 0$) : $\partial_\eta \phi \,\Big|_{\eta=0} = 0$

2-2 Neural network of AdS scalar

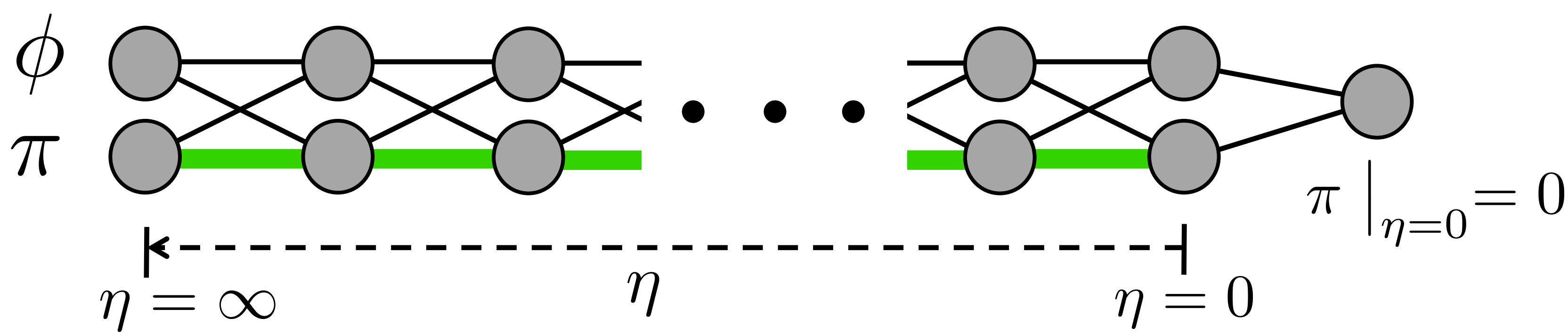
Bulk EoM $$\partial_\eta^2 \phi + \underline{\underline{h(\eta)}} \partial_\eta \phi - \frac{\delta V[\phi]}{\delta \phi} = 0$$

metric $$h(\eta) \equiv \partial_\eta \left[\log \sqrt{f(\eta) g(\eta)^{d-1}} \right]$$

Discretization, Hamilton form

$$\begin{cases} \phi(\eta + \Delta\eta) = \phi(\eta) + \Delta\eta \, \pi(\eta) \\ \pi(\eta + \Delta\eta) = \pi(\eta) + \Delta\eta \left(h(\eta)\pi(\eta) - \frac{\delta V(\phi(\eta))}{\delta \phi(\eta)} \right) \end{cases}$$

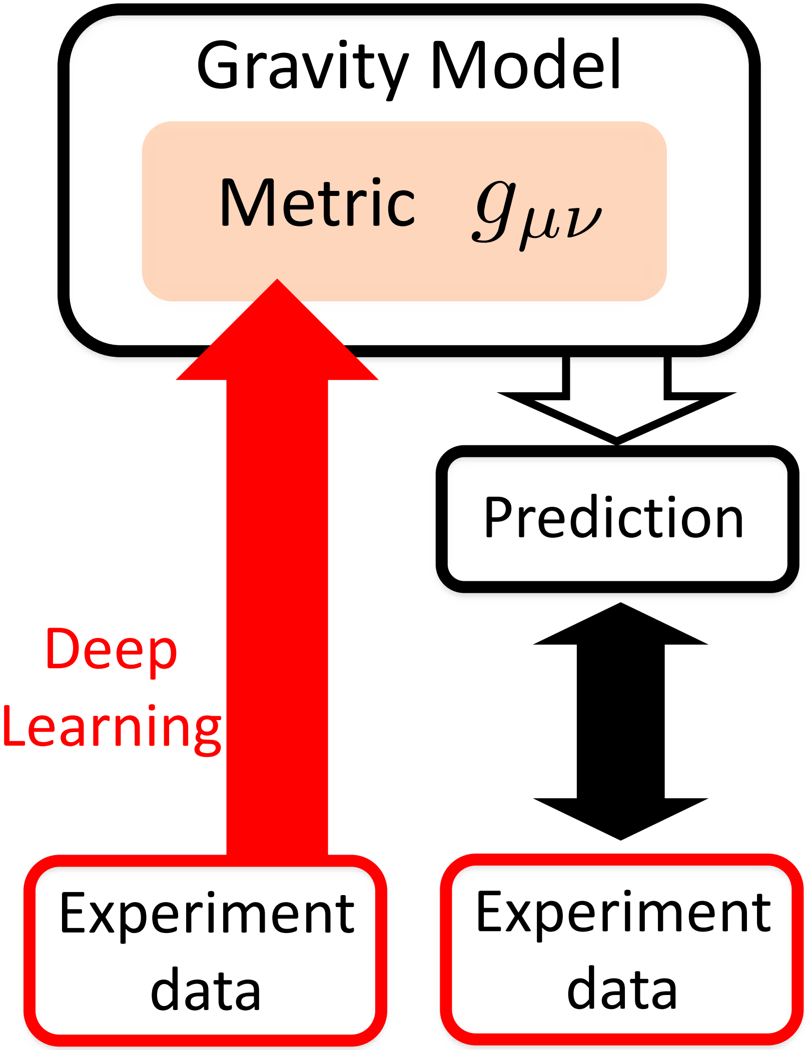
Neural-Network representation



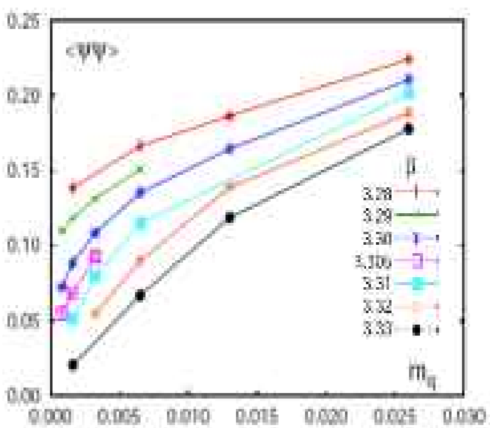
2-3 Dictionary of AdS/DL correspondence

AdS/CFT	Deep learning
Emergent space $\infty > \eta \geq 0$	Depth of layers $i = 1, 2, \cdots, N$
Bulk gravity metric $h(\eta)$	Network weights $W_{ij}^{(a)}$
Nonlinear response $\langle \mathcal{O} \rangle_J$	Input data $x_i^{(1)}$
Horizon condition $\partial_\eta \phi \big|_{\eta=0} = 0$	Output data F
Interaction $V(\phi)$	Activation function $\varphi(x)$

Holographic QCD is an inverse problem

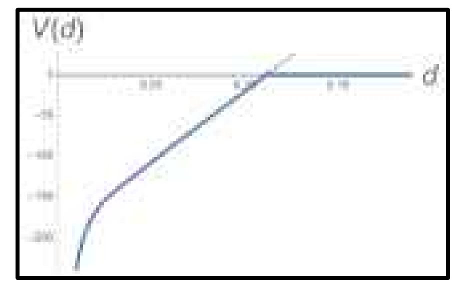


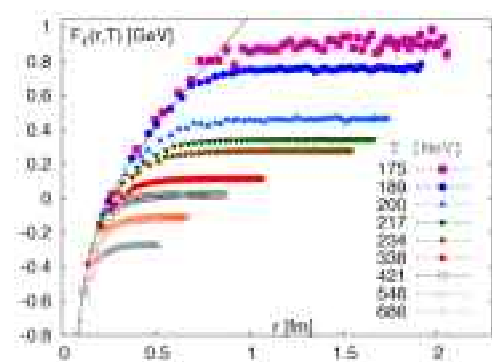
Lattice QCD data:
chiral condensate
VS quark mass



[RBC-Bielefeld collaboration, 2008]
(Courtesy of W.Unger)

Q Qbar potential



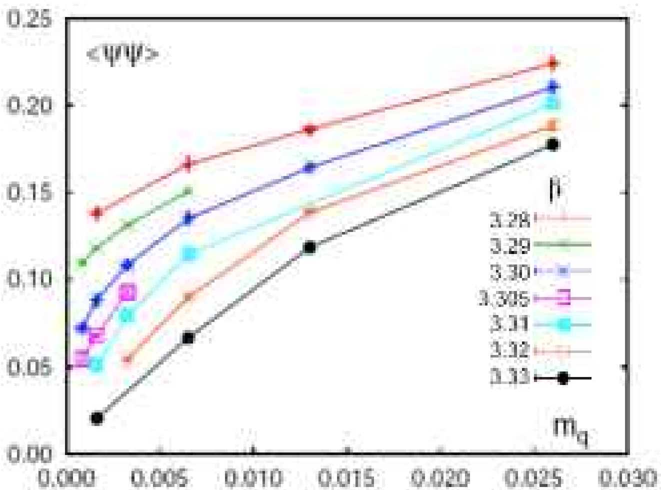


[Petreczky, 2010]

2-4

QCD data as a classification

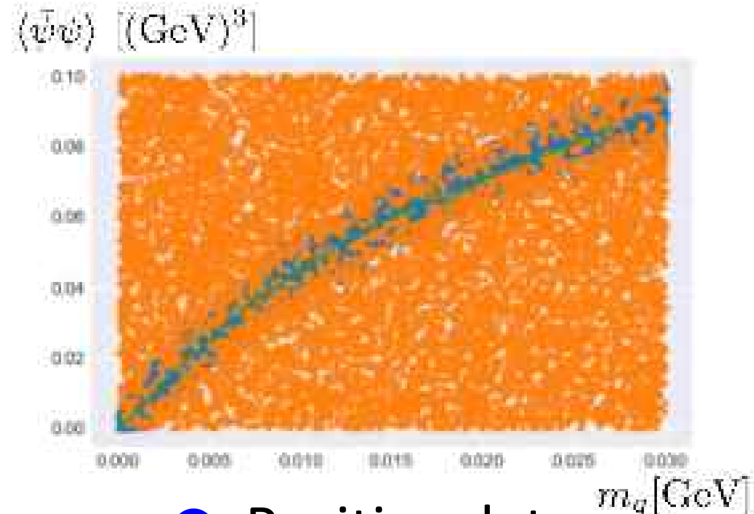
Chiral condensate VS quark mass.



β=3.30 ⇔ T=196[MeV]
[RBC-Bielefeld collaboration, 2008]
(Courtesy of W.Unger)

Pick up

β=3.33 data



- Positive data
- Negative data

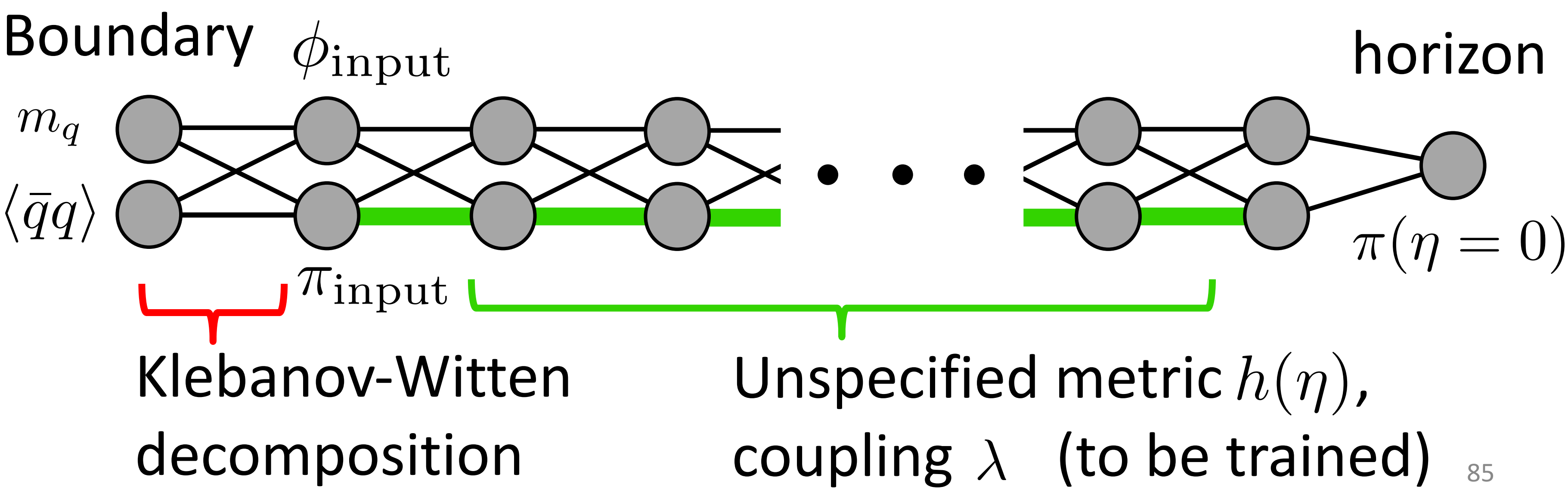
2-5

Map data to asymptotic scalar

[Klebanov, Witten] [DaRold,Pomarol][Karch,Katz,Son,Stephanov] [Cherman,Cohen,Werbos]

$$\phi = \frac{\sqrt{N_c}}{4\pi} m_q e^{-\eta} + \frac{\pi}{2\sqrt{N_c}} \langle \bar{q}q \rangle e^{-3\eta} - \frac{\lambda}{2} \left(\frac{\sqrt{N_c}}{4\pi} m_q \right)^3 \eta e^{-3\eta}$$

- Conformal dimension of $\langle \bar{q}q \rangle$ is 3.
- Sub-leading contribution, present.
- Everything measured in unit of AdS radius.



2-5 Map data to asymptotic scalar

[Klebanov, Witten] [DaRold,Pomarol][Karch,Katz,Son,Stephanov] [Cherman,Cohen,Werbos]

$$\phi = \frac{\sqrt{N_c}}{4\pi} m_q e^{-\eta} + \frac{\pi}{2\sqrt{N_c}} \langle \bar{q} q \rangle e^{-3\eta} - \frac{\lambda}{2} \left(\frac{\sqrt{N_c}}{4\pi} m_q \right)^3 \eta e^{-3\eta}$$

- Conformal dimension of $\langle \bar{q} q \rangle$ is 3.
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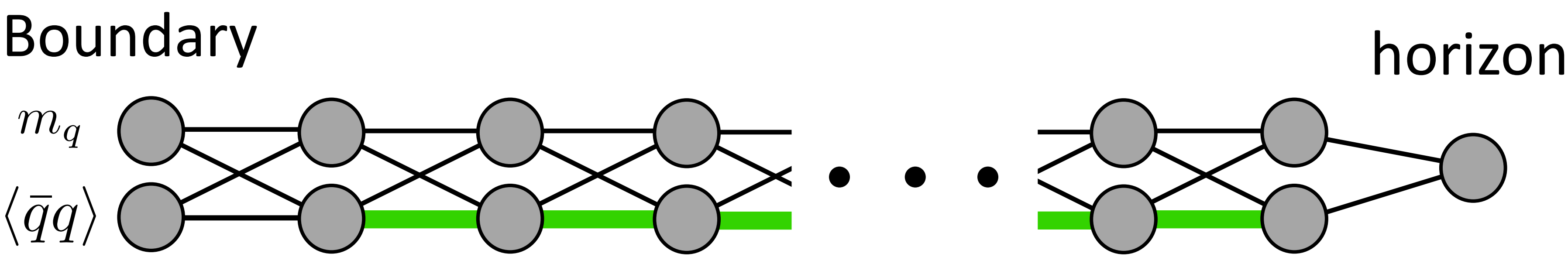
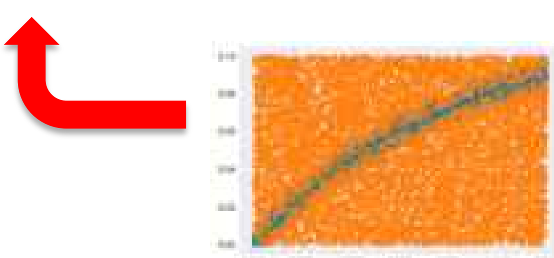
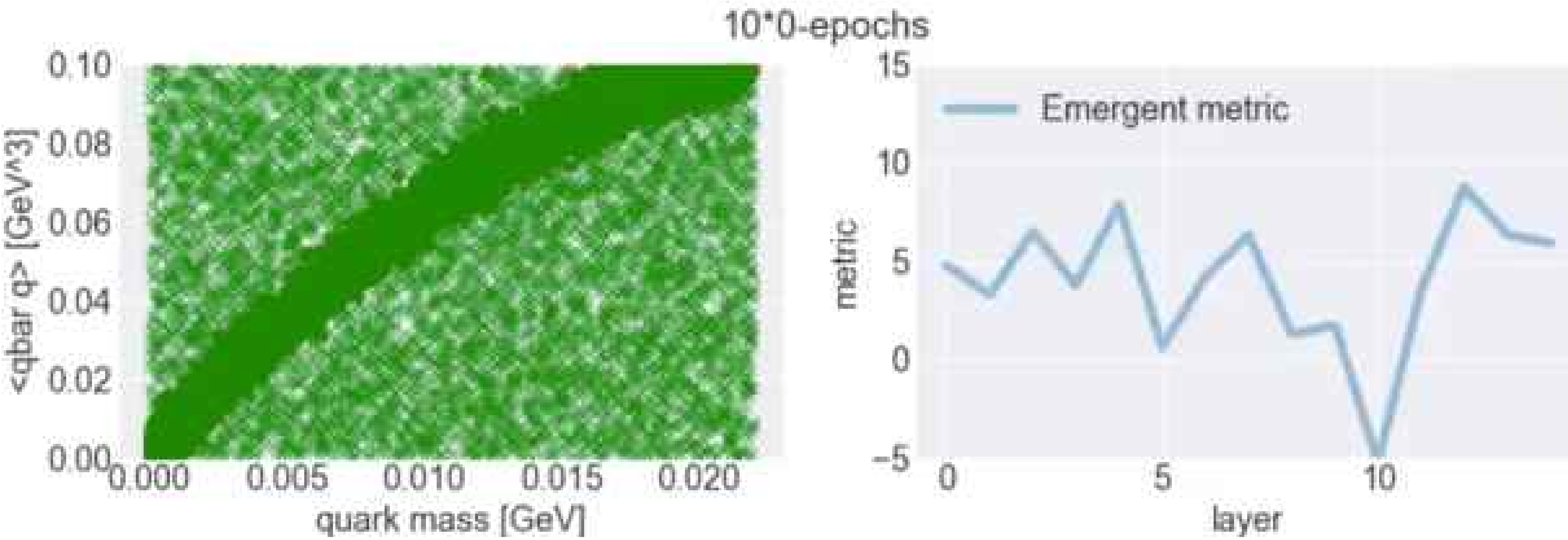




QCD lattice data

2-6 Machine learns QCD data, metric emerges

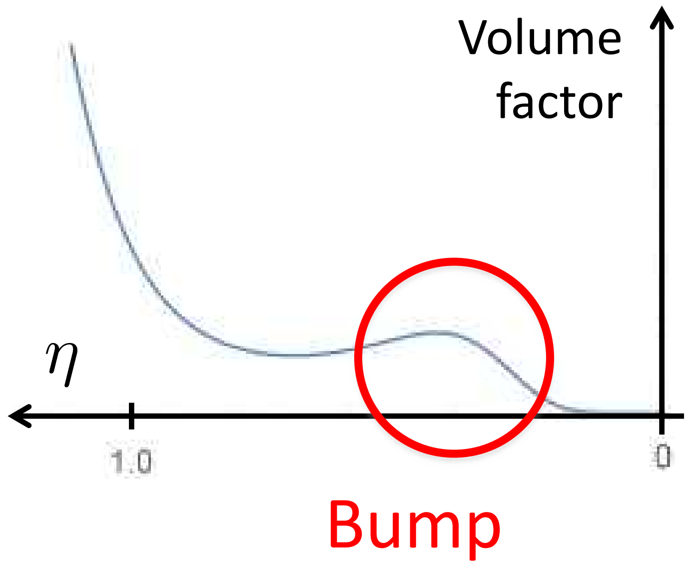


Learned value of (AdS radius)$^{-1}$: $1/L$ = 237(3)[MeV]

bulk scalar self coupling : λ/L = 0.0127(6)

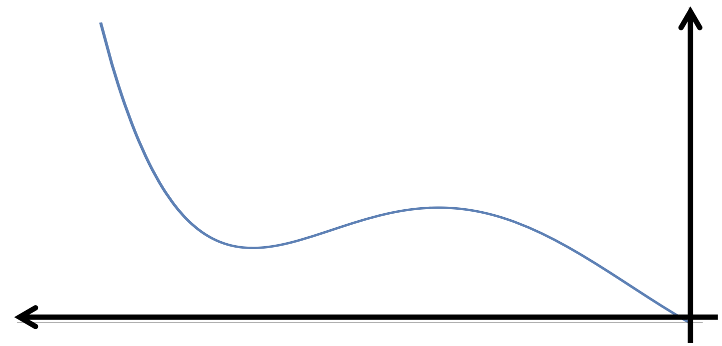
2-7 Machine learned a bottom-up model

Learned metric



Cf) Bottom-up model

$$ds^2 = \frac{e^{cz^2/2}}{z^2}\left((1-z^4)dt^2 + dx_i^2 + \frac{1}{1-z^4}dz^2\right)$$



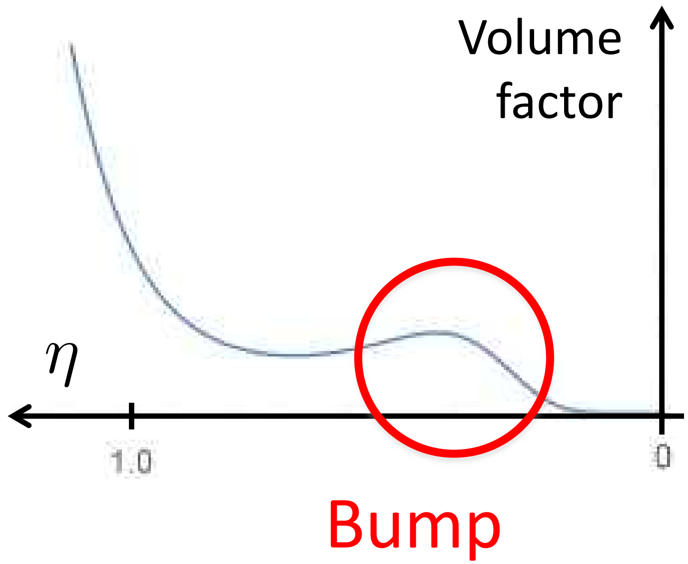
[Andreev, Zakharov, `06, `07]

Quantum gravity effect? Cf [Hyakutake `14]

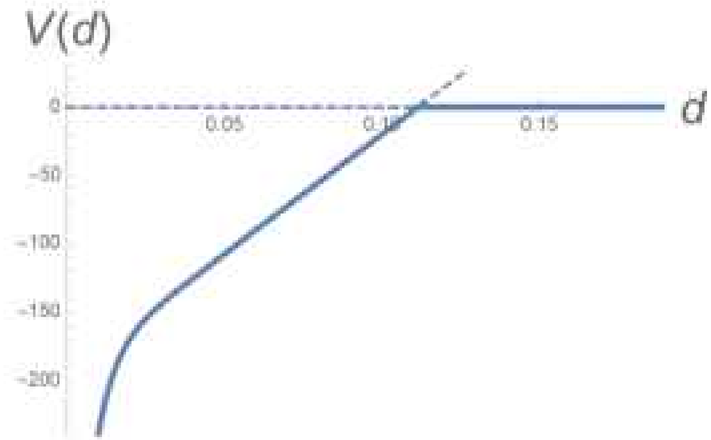
Coexistence of { Confinement / Deconfinement

2-8 Machine predicts a Q Qbar potential

Learned metric



Q Qbar potential



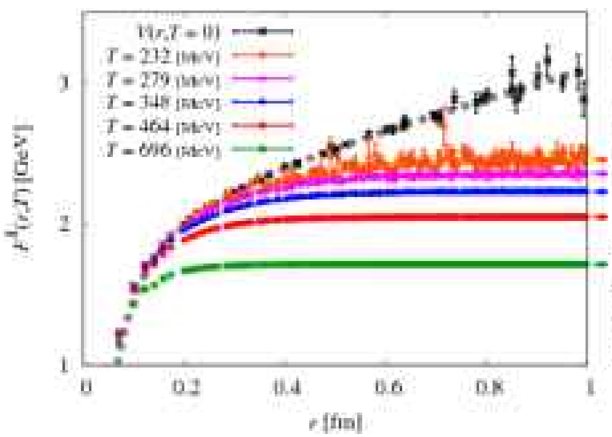
Procedures
based on
[Maldacena]
[Rey,Theisen,Yee]

Coexistence of

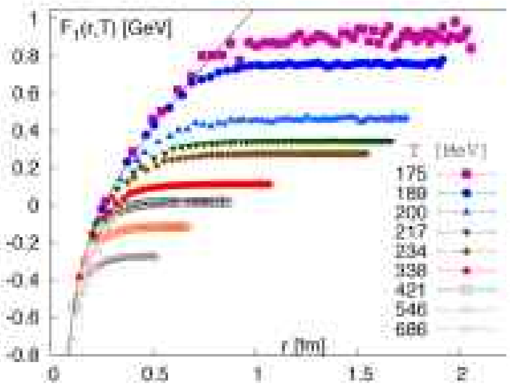
- Confinement → Linear potential
- Deconfinement → Debye screening

2-8 Machine predicts a Q Qbar potential

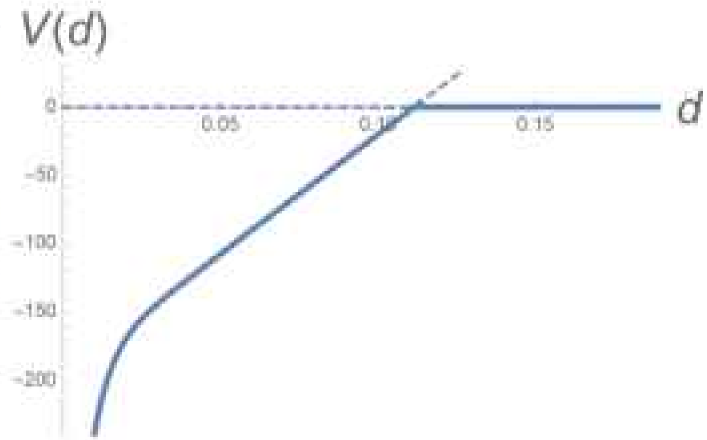
Q Qbar potential



[T.Ishikawa et al., `08,
CPPACS + JLQCD collaboration]



[Petreczky, `10]



Coexistence of
- Confinement → Linear potential
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4 pages

3. Deeply learning QCD hadron spectra

ArXiv:1909.????? w/ T.Akutagawa, T. Sumimoto

3-1 Hadron spectra from geometry

[Karch, Kaz, Son, Stephanov `06]

Classical gauge theory in 5-d dilaton gravity background

$$S = \int d^4x dz \, e^{-\Phi} \sqrt{-g} \left(F_{MN}\right)^2$$

Dilaton $\Phi(z)$, metric $ds^2 = e^{2A(z)} \left(dz^2 + \eta_{\mu\nu} dx^\mu dx^\nu \right)$

AdS boundary ($z \sim 0$) : $B(z) \equiv \Phi(z) - A(z) \sim \log z$

Solve EoM for gauge field $A_\mu(z, x^\mu) = v_n(z) \rho_\mu(x^\mu)$

$$\frac{\partial}{\partial z} \left(e^{-B} \frac{\partial}{\partial z} v_n \right) + \omega^2 e^{-B} v_n = 0$$

When frequency takes a proper discrete value $\omega^2 \sim m_n^2$, gauge field is normalizable : vector meson spectra.

3-2 Neural network of AdS scalar

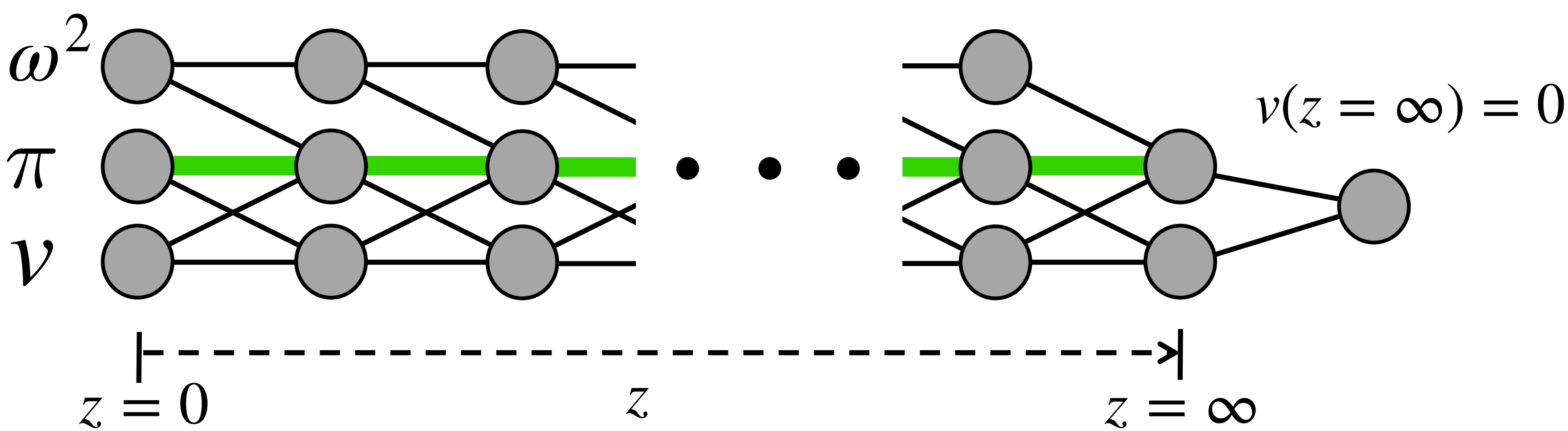
Bulk EoM

$$\frac{\partial}{\partial z}\left(e^{-B}\frac{\partial}{\partial z}v_n\right) + \omega^2 e^{-B} v_n = 0$$

Discretization, Hamilton form

$$\begin{cases} v_n(z+\Delta z) = v_n(z) + \Delta z\, \pi_n(z) \\ \pi_n(z+\Delta z) = \pi_n(z) + \Delta z \left(B'(z)\pi_n(z) - \omega^2 v_n(z)\right) \end{cases}$$

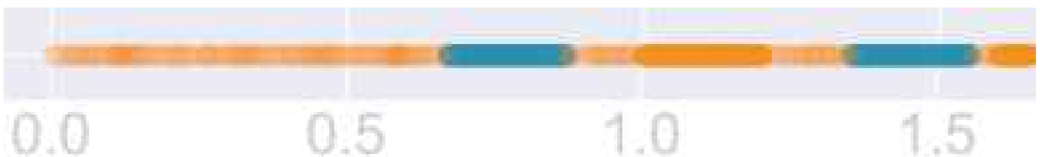
Neural-Network representation



3-3 QCD data as a classification

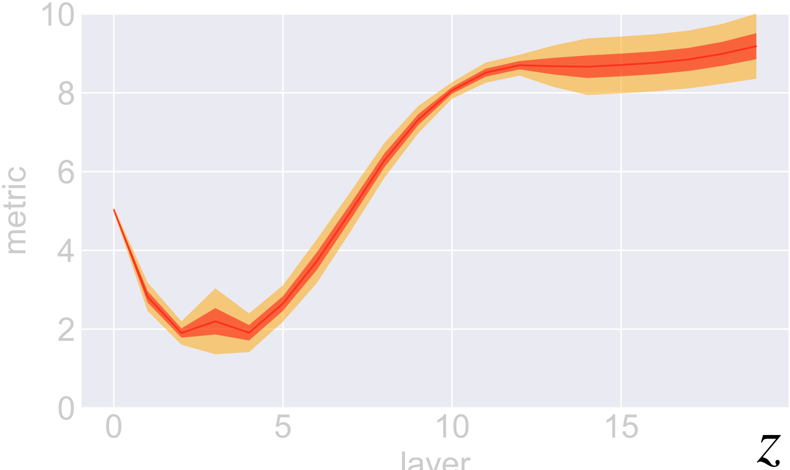
PDG data for rho meson mass :

$$m_\rho^{(1)} = 0.77 \text{ GeV}, m_\rho^{(2)} = 1.45 \text{ GeV}$$



- Positive
- Negative

$$B'(z) = \Phi'(z) - A'(z)$$



3-3 QCD data as a classification

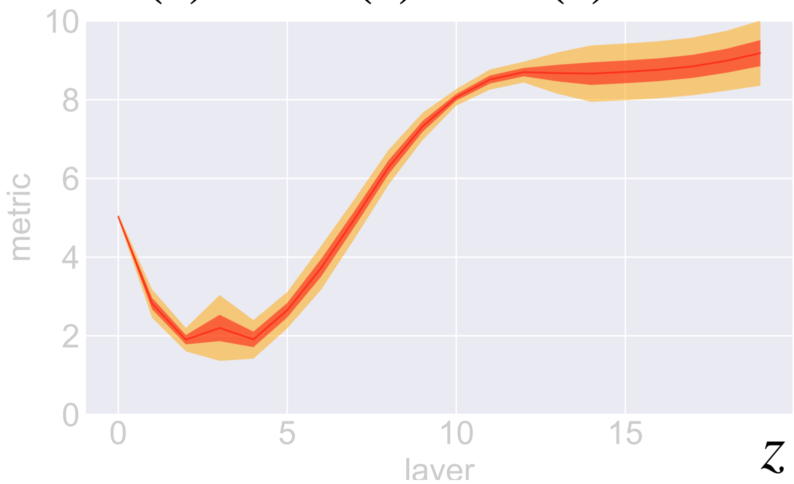
PDG data for rho meson mass :

$$m_\rho^{(1)} = 0.77 \text{ GeV}, \ m_\rho^{(2)} = 1.45 \text{ GeV}$$

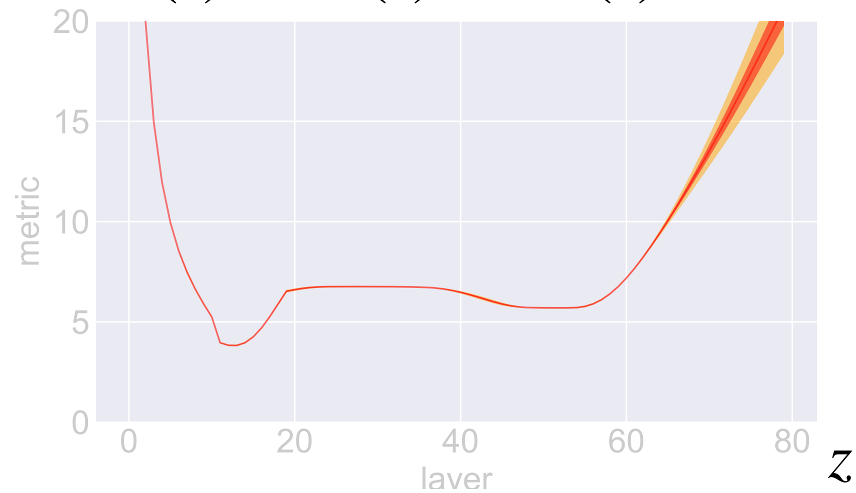
PDG data for a_2 meson mass :

$$m_{a_2}^{(1)} = 1.32 \text{ GeV}, \ m_{a_2}^{(2)} = 1.70 \text{ GeV}$$

$$B'(z) = \Phi'(z) - A'(z)$$

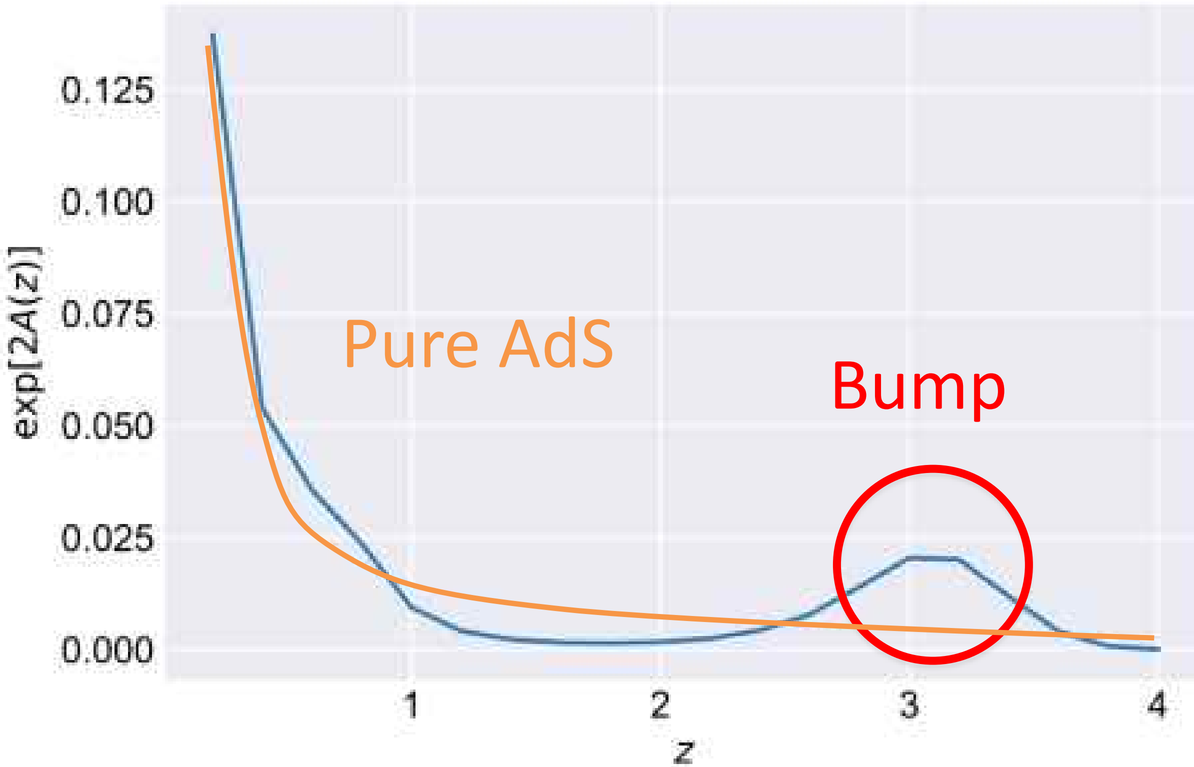


$$\tilde{B}'(z) = \Phi'(z) - 3A'(z)$$



3-4

Emergent spacetime is confining



Confining geometry emerged

…… consistent with Wilson loop

7 pages

1. Is deep learning useful?

ArXiv:1903.04951

8 pages

2. Deeply learning QCD chiral condensate

ArXiv:1802.08313, 1809.10536 w/ S. Sugishita, A. Tanaka, A. Tomiya

4 pages

3. Deeply learning QCD hadron spectra

ArXiv:1909.????? w/ T.Akutagawa, T. Sumimoto

A

What do we learn?

Strategy for a universal modeling?

- Consistency with more observables:
  1-pt, 2-pt, 3-pt, … and spacetime dependence?
- More hadron spectroscopy.
- Rather, observable-oriented modeling?

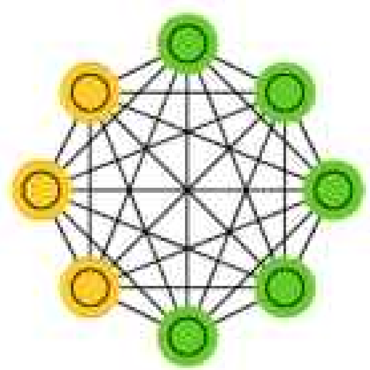
Consistency with top-down approach?

- Supergravity as a regularization for learning

Quantum gravity path-integral?

A-1 Neural network for probability distribution

Boltzmann machine



"Unit" (circles) : Spins
"Visible units" (yellow)
"Hidden units" (green)

"Weight" (lines) : Spin-spin coupling to be optimized

$$P(v_i) = \sum_{h_i \in \{0,1\}} \exp[-\mathcal{E}(v_i, h_i)] \qquad \mathcal{E}(v_i, h_i) \equiv \sum_{ij} w_{ij} v_i h_j$$

- Training protocol :

1) Prepare many sets $\{(v_i, P_{\mathrm{ex}}(v_i))\}$: input + output
2) Train the network (adjust W) by lowering "Loss function" $E \equiv D_{\mathrm{KL}}\left(P_{\mathrm{ex}}(v_i) \,||\, P(v_i)\right)$

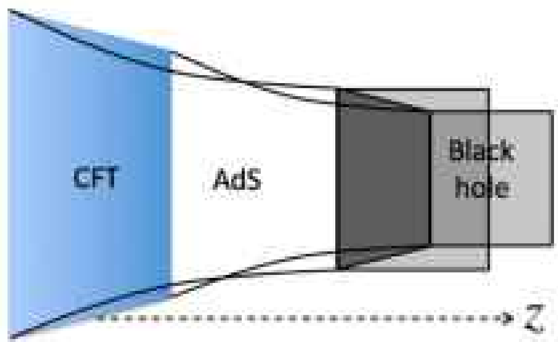
A-2

QFT on AdS as a Boltzmann machine

[KH `19] [You,Yang,Qi `18] (See also [Gan,Shu `17][Howard `18])

AdS/CFT

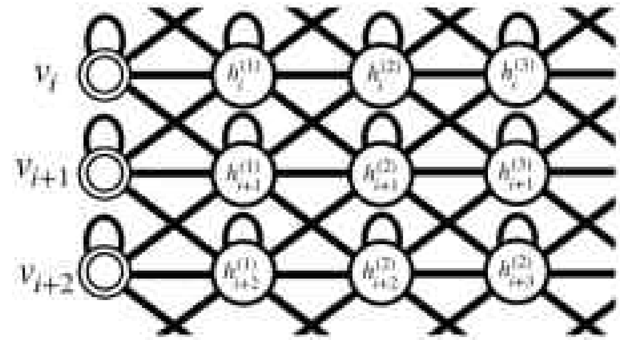
[Maldacena 1997]



$$Z_{\mathrm{QFT}}[J] = \int_{\phi(z=0)=J} \mathcal{D}\phi \, \exp\left(-S_{\mathrm{gravity}}[\phi]\right)$$

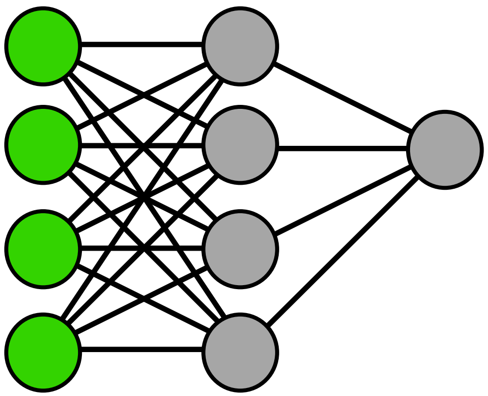
Deep Boltzmann machine

[Salakhutdinov, Hinton 2009]

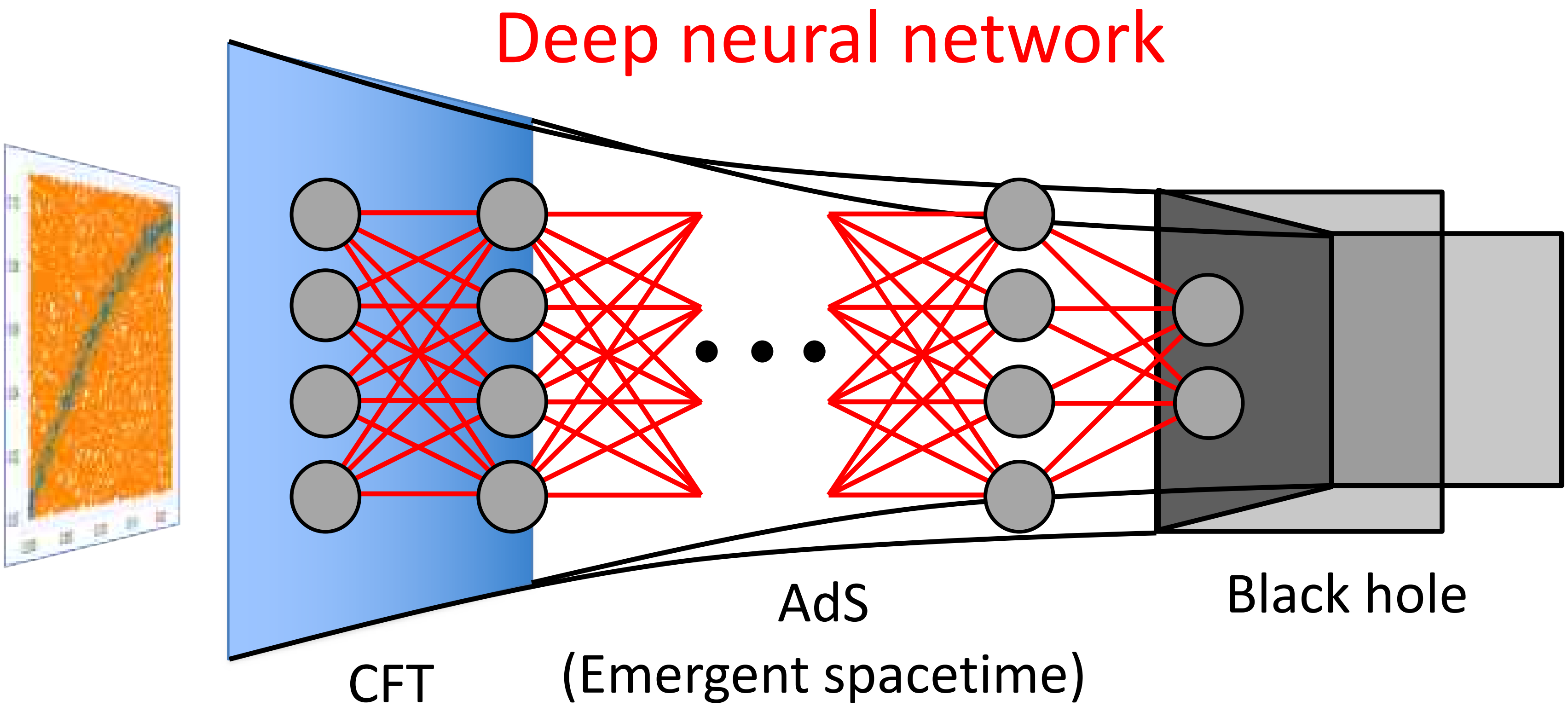


$$P(v_i) = \sum_{h_i \in \{0,1\}} \exp\left[-\mathcal{E}(v_i, h_i)\right]$$

AdS/CFT	Deep Boltzmann machine
Bulk coordinate z	Hidden layer label k
QFT source $J(x)$	Input value v_i
Bulk field $\phi(x,z)$	Hidden variables $h_i^{(k)}$
QFT generating function $Z[J]$	Provability distribution $P(v_i)$
Bulk action $S[\phi]$	Energy function $\mathcal{E}(v_i, h_i^{(k)})$



Summary: Neural network as a spacetime



A

Emergent geometry?

Emergence of AdS radial direction?

Bulk reconstruction and locality.

[Heemskerk, Penedones, Polchinski, Sully 09]

Entanglement entropy reconstruction.

[Balasubramanian, Chowdhury, Czech, de Boer, Heller 13]
[Myers, Rao, Sugishita 14]

Optimization of boundary path integral.

[Caputa,Kundu,Miyaji,Takayanagi,Watanabe 17]

Renormalization and effective LG theory.

[Ki-Seok Kim, Chanyong Park 16]

AdS/MERA. [Swingle 12]

Emergence of smooth neural network space?

Statistical neural network. [Amari et al.]

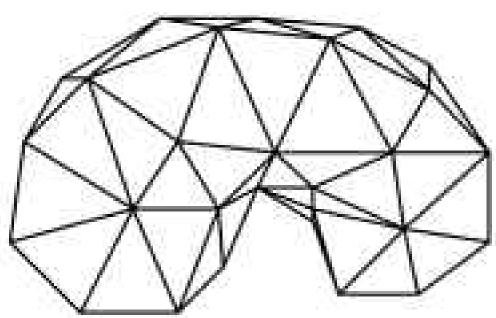
1-3 Quantum gravity = Network optimization

Regge calculus

[Regge 1961]

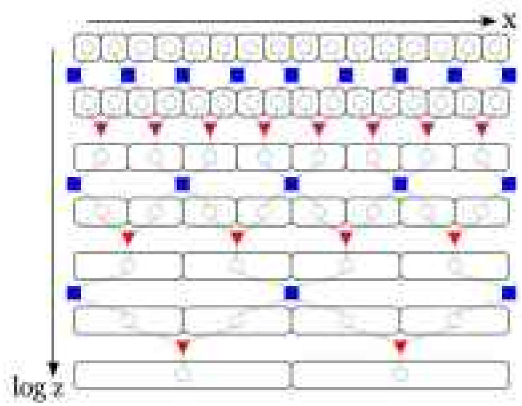
Causal dynamical triangulation

[Ambjorn, Loll 1998]



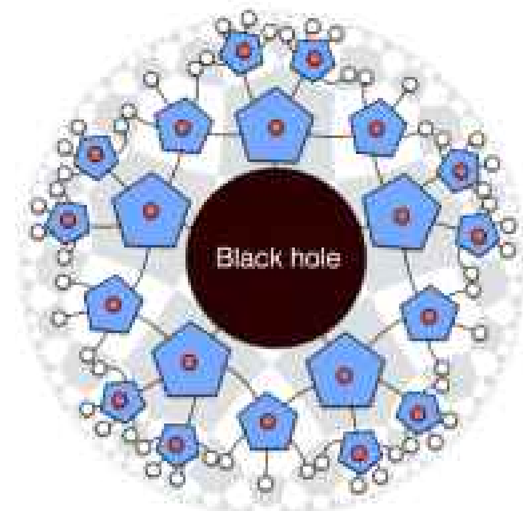
AdS/MERA

[Swingle `09]

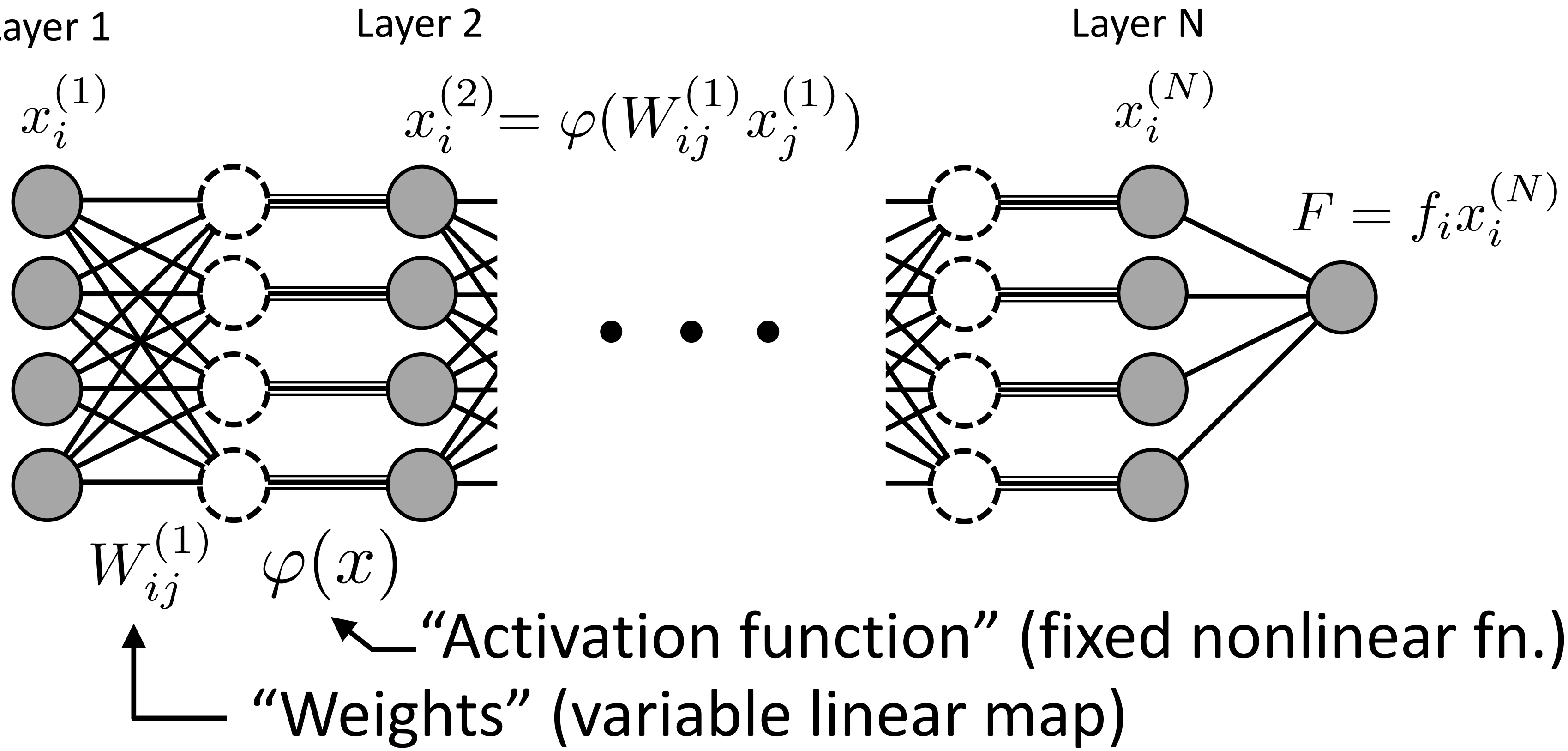


Quantum codes for holography

[Pastawski, Yoshida, Harlow, Preskill `15]



2-2 Deep learning : optimized sequential map



1) Prepare many sets $\{x_i^{(1)}, F\}$: input + output
2) Train the network (adjust W_{ij}) by lowering "Loss function" $E \equiv \sum_{\text{data}} \left| f_i(\varphi(W_{ij}^{(N-1)} \varphi(\cdots \varphi(W_{lm}^{(1)} x_m^{(1)})))) - F \right|$

Deep Learning And Physics

DLAP2019

> Yukawa Institute for Theoretical Physics
> Kyoto, Japan
> 31 Oct - 2 Nov 2019

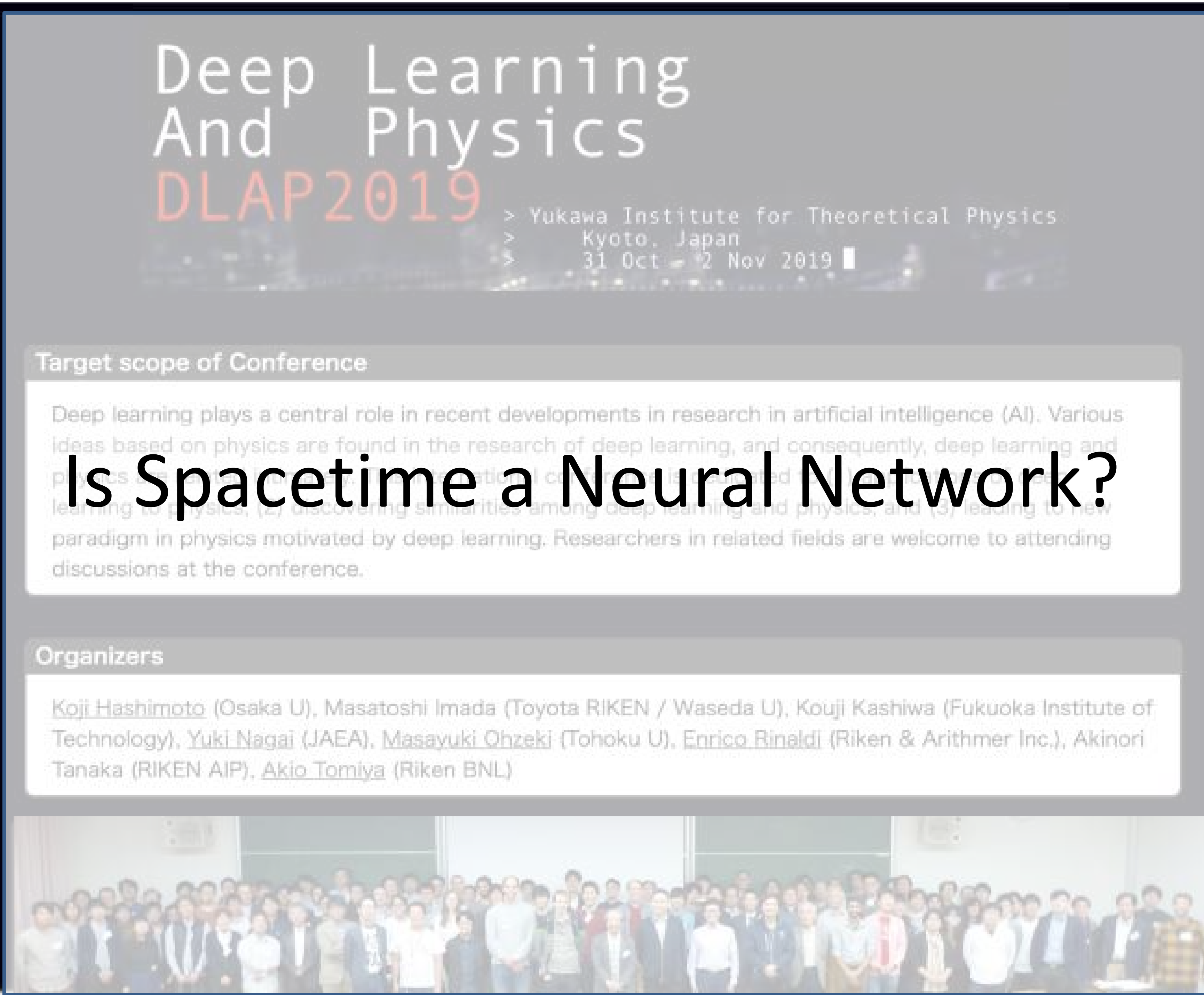
Target scope of Conference

Deep learning plays a central role in recent developments in research in artificial intelligence (AI). Various ideas based on physics are found in the research of deep learning, and consequently, deep learning and physics are related intimately. This international conference is dedicated to (1) applications of deep learning to physics, (2) discovering similarities among deep learning and physics, and (3) leading to new paradigm in physics motivated by deep learning. Researchers in related fields are welcome to attending discussions at the conference.

Organizers

Koji Hashimoto (Osaka U), Masatoshi Imada (Toyota RIKEN / Waseda U), Kouji Kashiwa (Fukuoka Institute of Technology), Yuki Nagai (JAEA), Masayuki Ohzeki (Tohoku U), Enrico Rinaldi (Riken & Arithmer Inc.), Akinori Tanaka (RIKEN AIP), Akio Tomiya (Riken BNL)

Is Spacetime a Neural Network?



Spacetime is a Neural Network

1. Space is a NN
2. Time is a NN 1802.08313
3. Holography is a NN 1903.04951
4. Holographic space is a NN 1802.08313 1809.10536
5. Holographic spacetime is a NN 2001.?????
6. Quantum spacetime is a NN?