KIAS, 26 March, 2018
CQuest, Sogang u., 29 March, 2018
MIT, CTP, 4 Apr, 2018
MPI, AEI, 13 Apr, 2018
HET group, Osaka, 30 May, 2018
DLAP2018 workshop, Osaka, 1 June, 2018
Paris QCD workshop, 11 June, 2018
Machine learning workshop, TSiMF, China, 15 June, 2018
Workshop "Strings and Fields", YITP, Kyoto, 31 July, 2018
APCTP focus program, Hanyang u. Seoul, 15 Aug, 2018
Workshop "QG meets lattice QCD", ECT*, Trento, 3 Sep, 2018

Deep Learning and AdS/QCD

Koji Hashimoto (Osaka u)

ArXiv:1802.08313 + 1809.?????

w/ S. Sugishita (Osaka), A. Tanaka (RIKEN AIP),
A. Tomiya (CCNU)

0. Bulk emergence?

1. Formulation of AdS/DL

2. Deeply learning QCD

0-1

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.

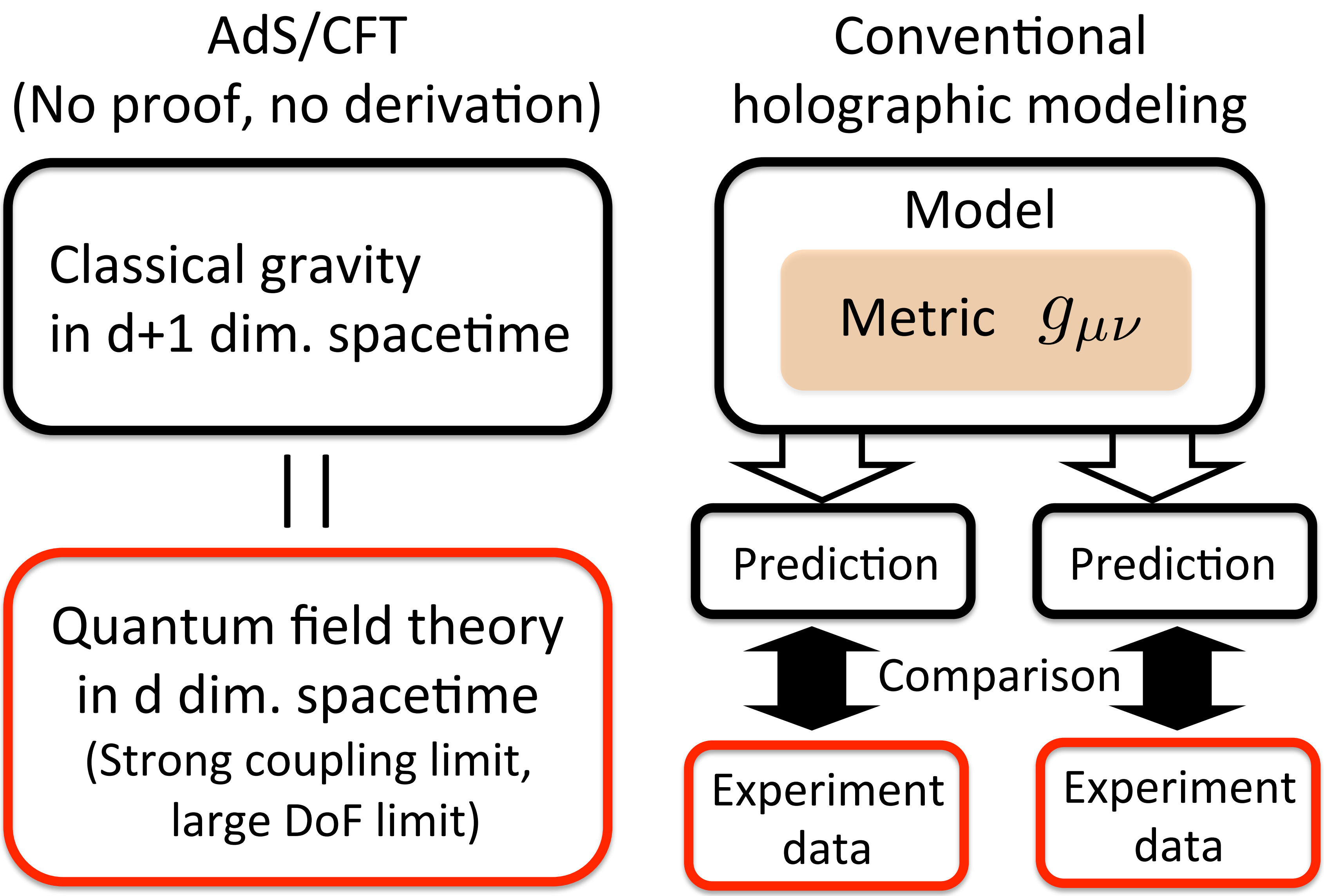
[Ki-Seok Kim, Chanyong Park 16]

AdS/MERA. [Swingle 12]

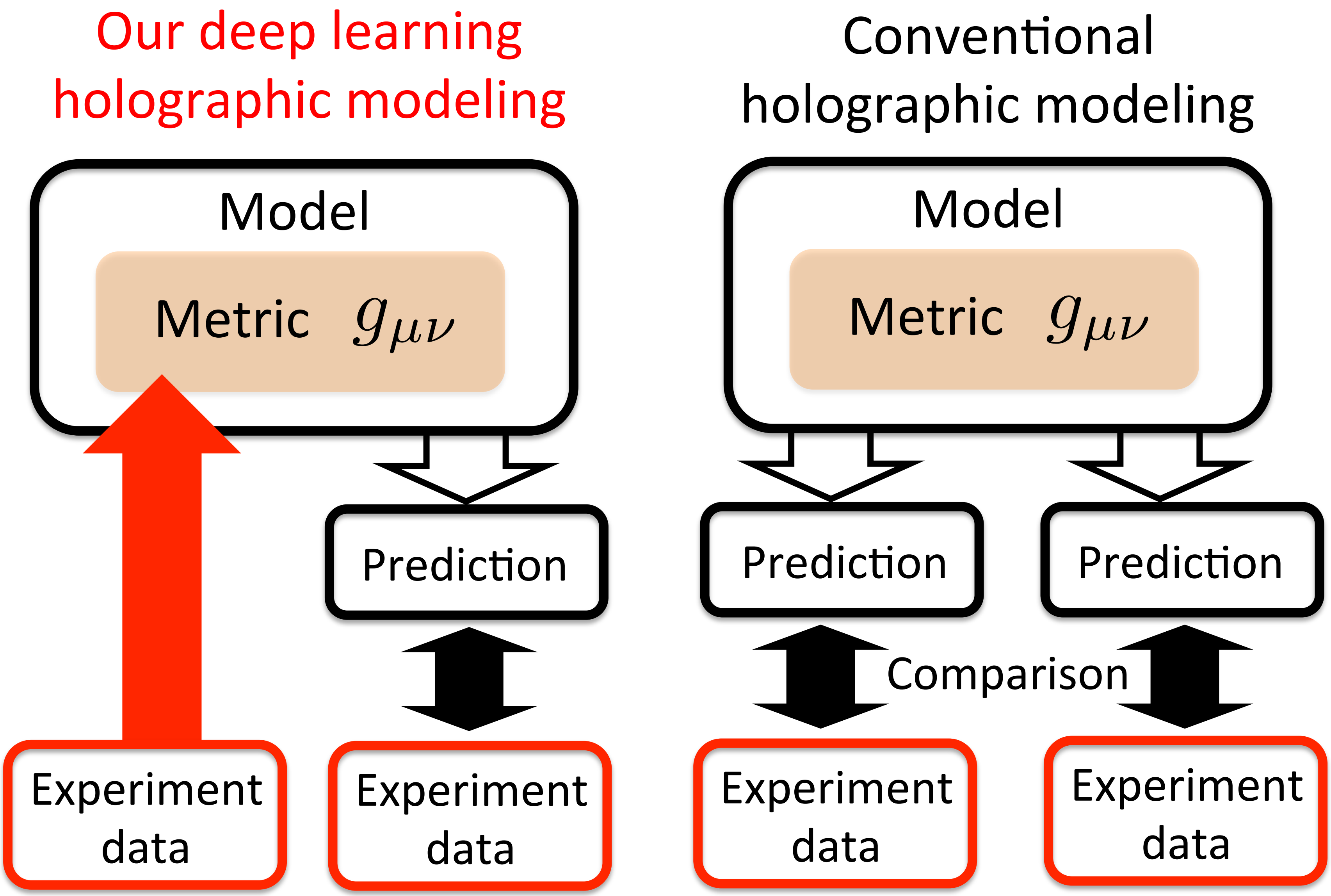
Emergence of smooth neural network space?

Statistical neural network. [Amari et al.]

0-2 Solving inverse problem



0-2 Solving inverse problem



0. Bulk emergence?

1. Formulation of AdS/DL

2. Deeply learning QCD

1. Formulation of AdS/DL

review **AdS/CFT: quantum response from geometry**

review **Deep learning: optimized sequential map**

1-1 **From AdS to DL**

1-2 **Dictionary of AdS/DL correspondence** review

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 ($\eta \sim 0$) : $f \sim \eta^2,\ g \sim \mathrm{const.}$

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

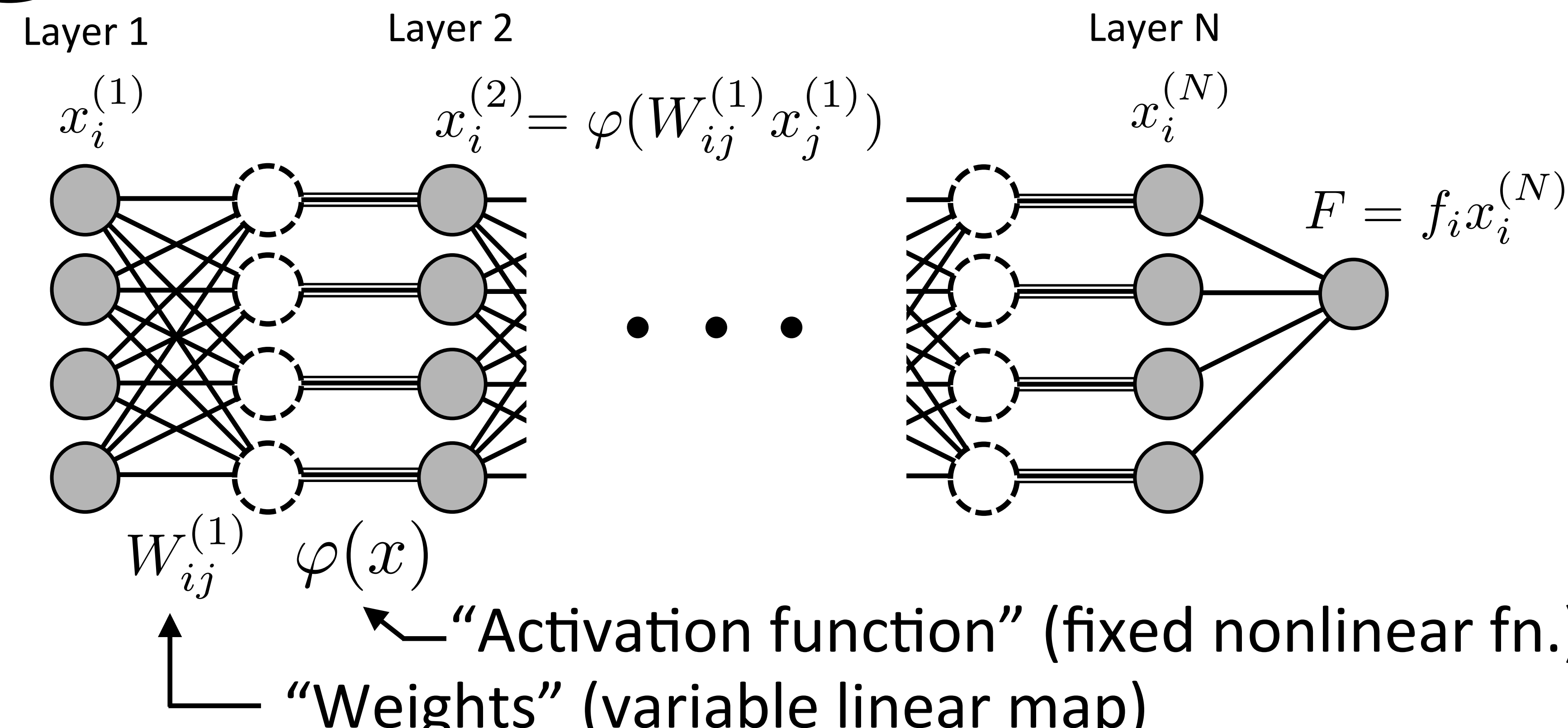
- AdS boundary ($\eta \sim \infty$) :

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

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

review

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" $E \equiv \sum_{\text{data}} \left| f_i(\varphi(W_{ij}^{(N-1)} \varphi(\cdots \varphi(W_{lm}^{(1)} x_m^{(1)})))) - F \right|$

1-1 From AdS to DL

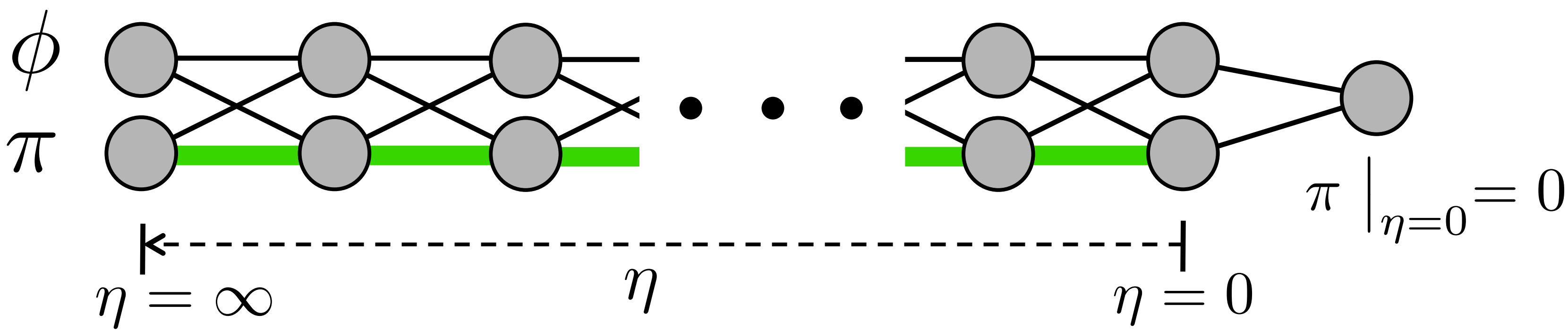
Bulk EoM $$\partial_\eta^2\phi + \underbrace{h(\eta)}_{\text{metric}}\partial_\eta\phi - \frac{\delta V[\phi]}{\delta\phi} = 0$$

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

Discretization, Hamilton form

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

Neural-Network representation



1-2 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 $\varphi(x)$

1. Formulation of AdS/DL

review **AdS/CFT: quantum response from geometry**

review **Deep learning: optimized sequential map**

1-1 **From AdS to DL**

1-2 **Dictionary of AdS/DL correspondence**

0. Bulk emergence?

1. Formulation of AdS/DL

2. Deeply learning QCD

2. Deeply learning QCD

2-1 **Demonstration of holographic modeling**

2-2 **Deeply learning QCD**

1) Use a QCD data.
2) Let the network learn the metric.
3) Calculate other physical quantities.

2-1 Demonstration of holographic modeling

Model

Metric $g_{\mu\nu}$

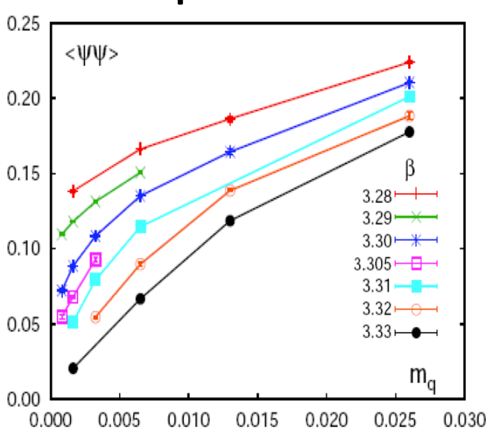
Deep Learning

Prediction

Experiment data

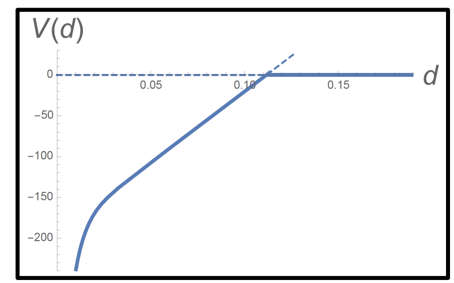
Experiment data

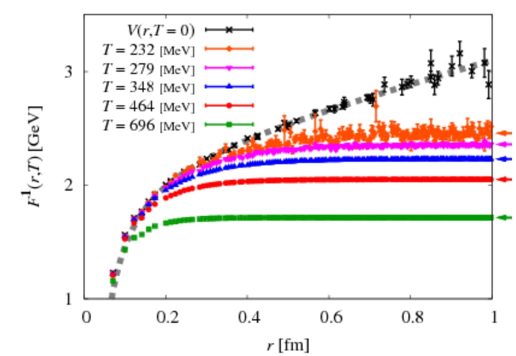
Lattice QCD data:
chiral condensate
VS quark mass



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

Q Qbar potential





[T.Ishikawa et al., 2008,
CPPACS + JLQCD collaboration]

2-2

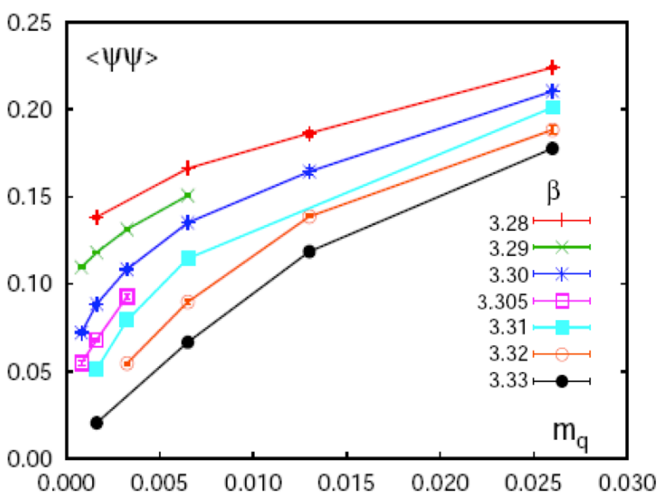
Deeply learning QCD

1) Use a QCD data.
2) Let the network learn the metric.
3) Calculate other physical quantities.

2-2 Deeply learning QCD

1) Use a QCD data.
2) Let the network learn the metric.
3) Calculate other physical quantities.

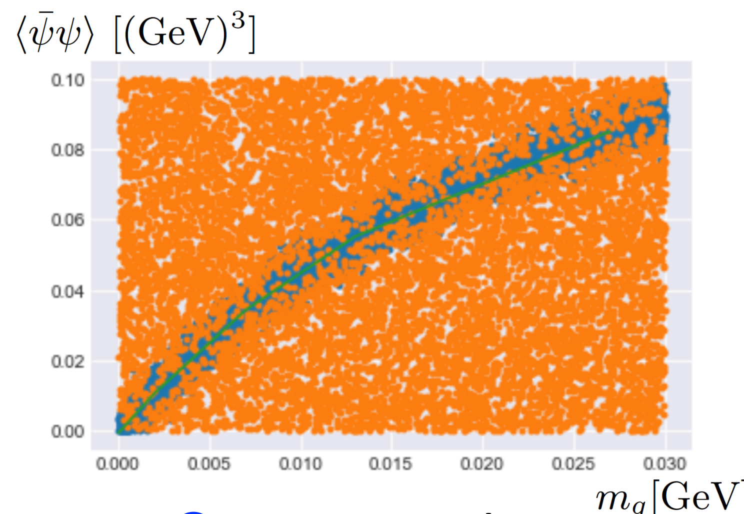
Chiral condensate VS quark mass.



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

Pick up

β=3.33
data



Positive data
Negative data

2-2

Deeply learning QCD

1) Use a QCD data.
2) Let the network learn the metric.
3) Calculate other physical quantities.

Map it to asymptotic scalar configuration. [Klebanov, Witten]
[DaRold,Pomarol][Karch,Katz,Son,Stephanov] [Cherman,Cohen,Werbos]

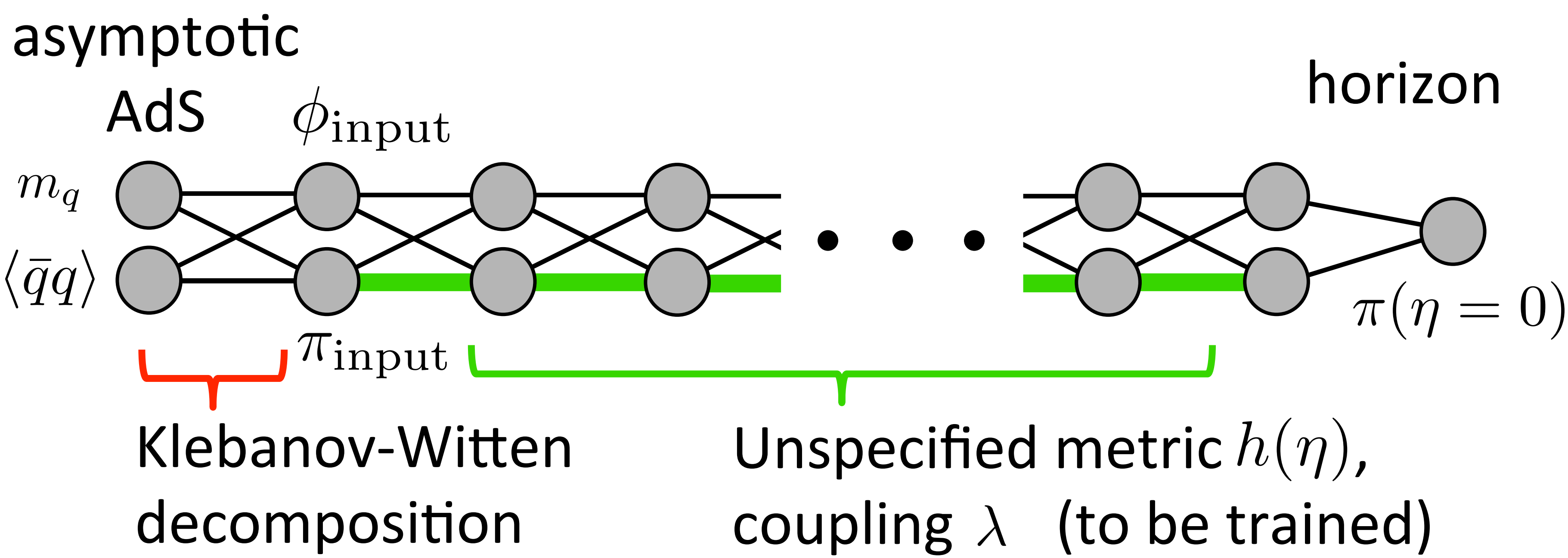
$$\phi = \frac{\sqrt{N_c}}{4\pi} m_q e^{-\eta} + \frac{\pi}{2\sqrt{N_c}} \langle \bar{q} q \rangle e^{-3\eta} - \frac{\lambda}{2} \left(\frac{\sqrt{N_c}}{4\pi} m_q \right)^3 \eta e^{-3\eta}$$

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

2-2

Deeply learning QCD

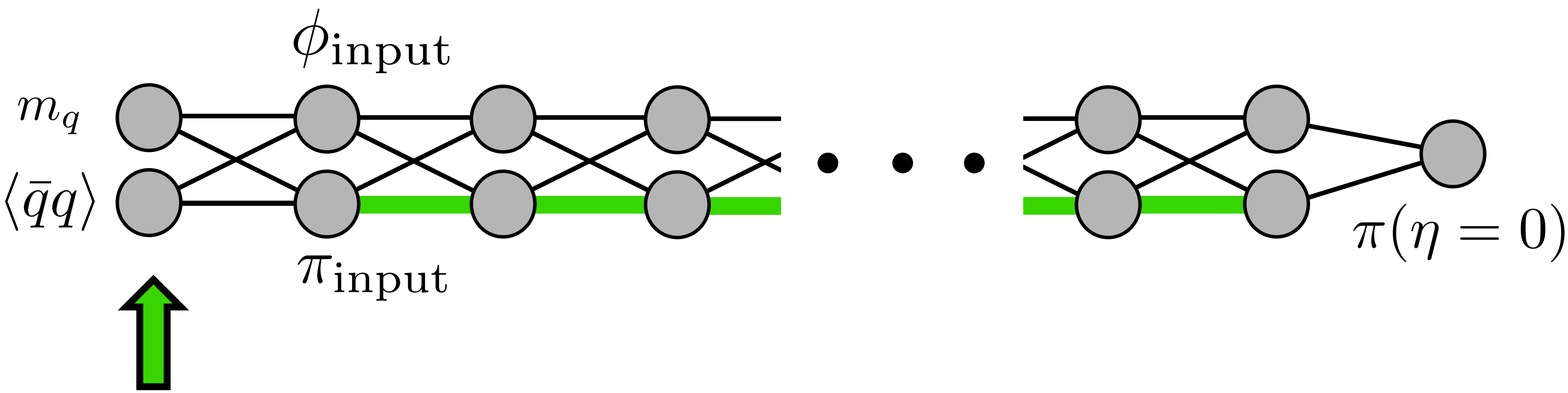
1) Use a QCD data.
2) Let the network learn the metric.
3) Calculate other physical quantities.

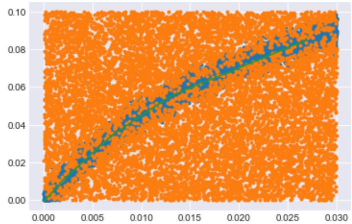


2-2

Deeply learning QCD

1) Use a QCD data.
2) Let the network learn the metric.
3) Calculate other physical quantities.

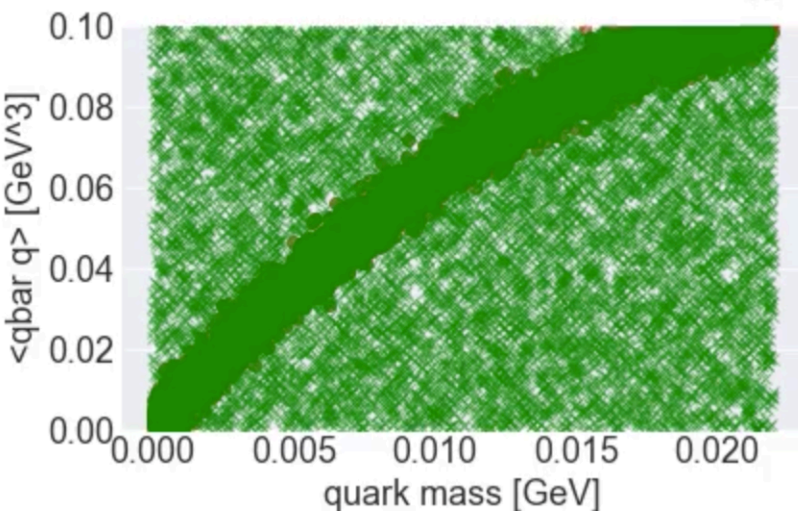




QCD lattice data

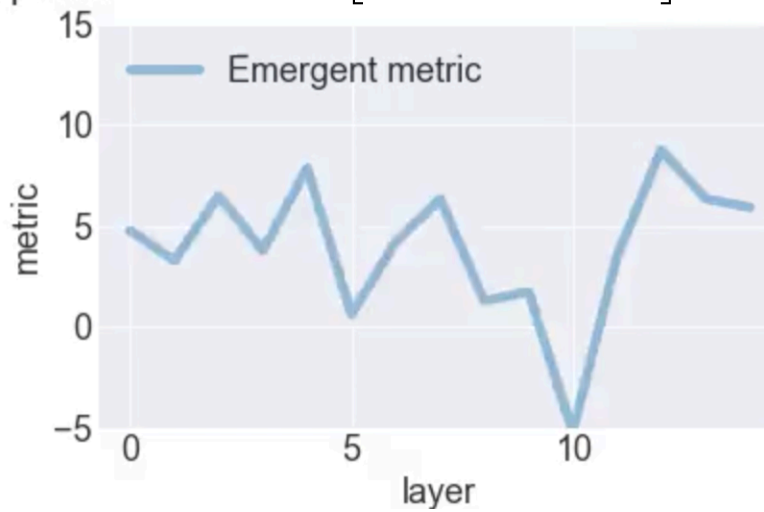
2-2 Deeply learning QCD

1) Use a QCD data.
2) Let the network learn the metric.
3) Calculate other physical quantities.



10*0-epochs

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



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

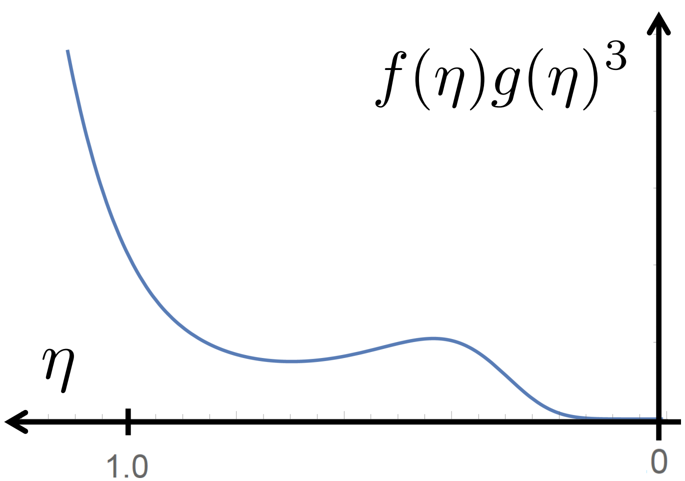
bulk coupling : λ/L = 0.0127(6)

2-2

Deeply learning QCD

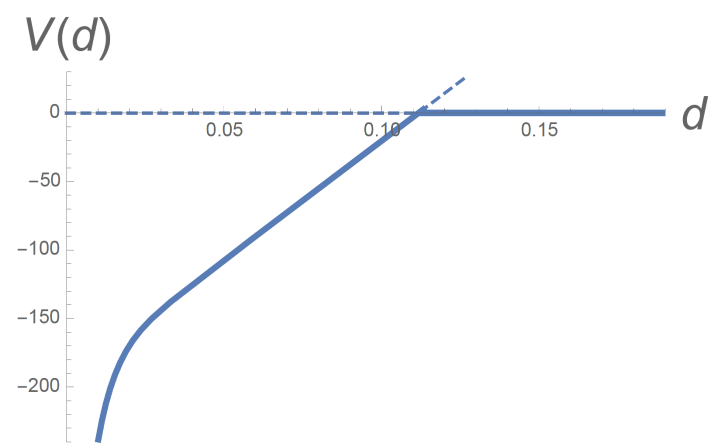
1) Use a QCD data.
2) Let the network learn the metric.
3) Calculate other physical quantities.

Learned metric



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

Q Qbar potential

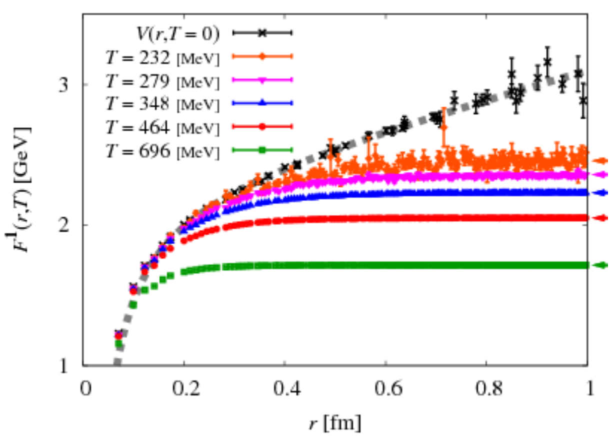


2-2

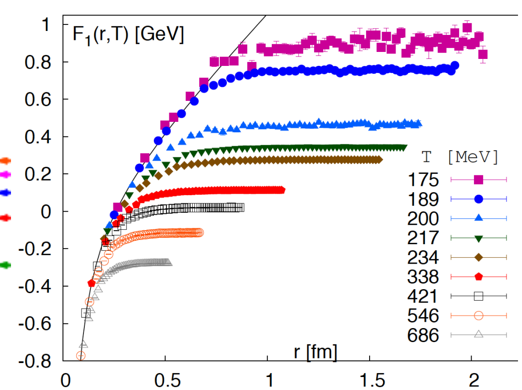
Deeply learning QCD

1) Use a QCD data.
2) Let the network learn the metric.
3) Calculate other physical quantities.

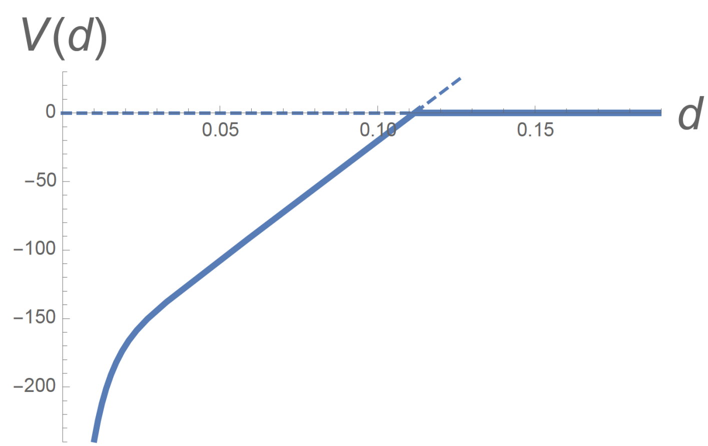
Q Qbar potential



[T.Ishikawa et al., 2008,
CPPACS + JLQCD collaboration]



[Petreczky, 2010]



2-1 Demonstration of holographic modeling

Model

Metric $g_{\mu\nu}$

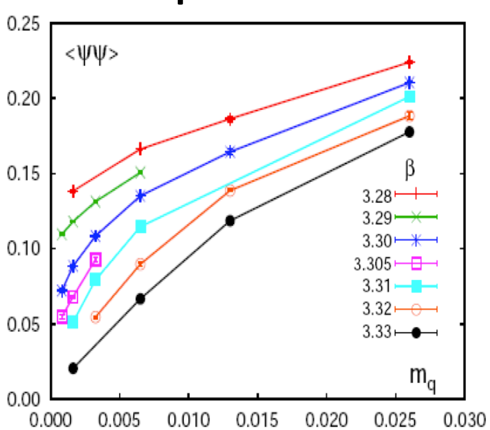
Prediction

Deep Learning

Experiment data

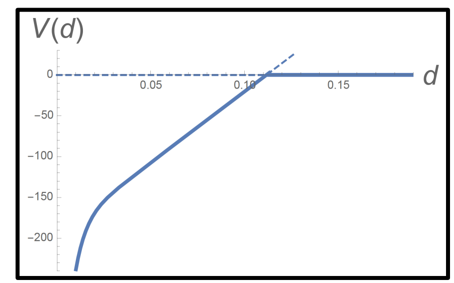
Experiment data

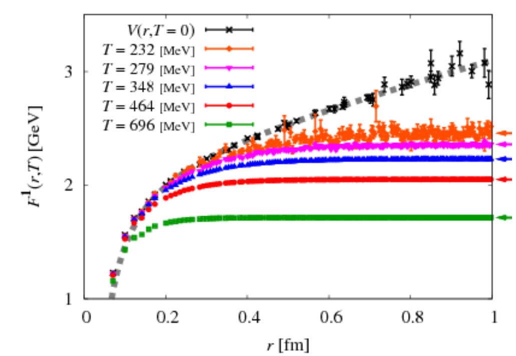
Lattice QCD data: chiral condensate VS quark mass



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

Q Qbar potential





[T.Ishikawa et al., 2008, CPPACS + JLQCD collaboration]

0. Bulk emergence?

1. Formulation of AdS/DL

2. Deeply learning QCD

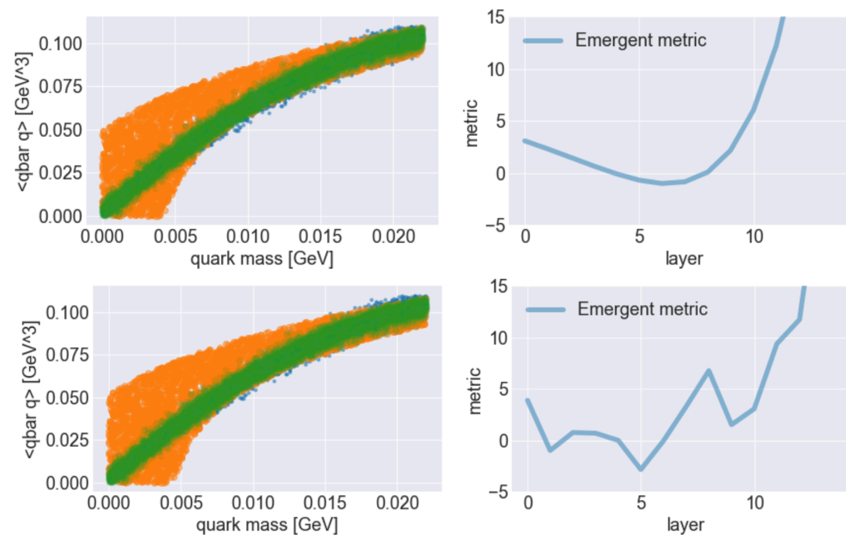
Q Machines learn…, what do we learn?

- Physics message :
  Emergent metric has a bump.
  → No chiral symmetry breaking while “confinement”

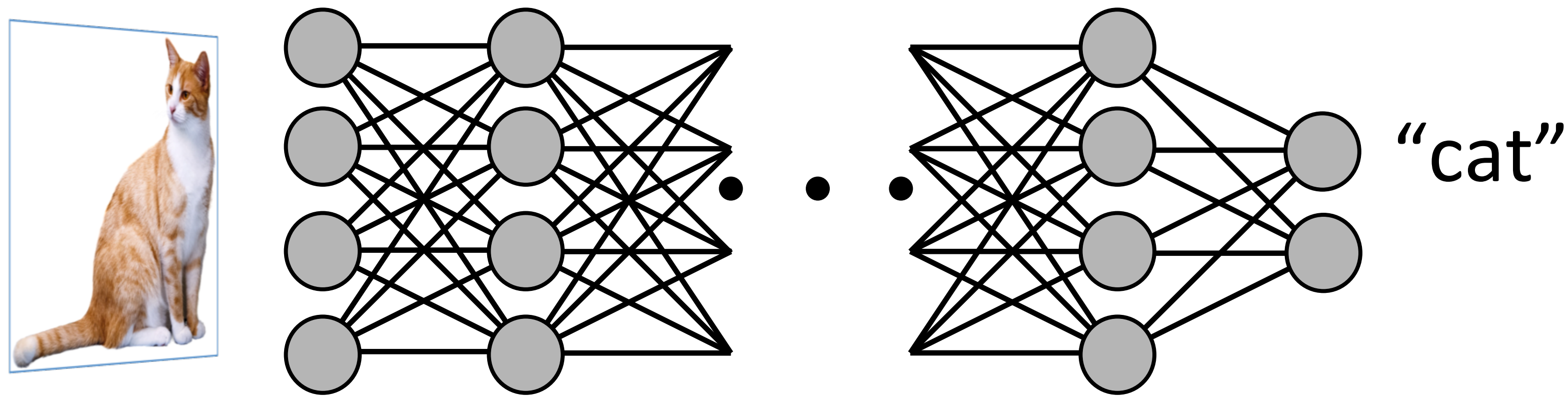
- Toward a quantum gravity :
  Finite Nc, finite coupling
  → Need of path integral of many emergent metrics

Emergent metric
-with regularization

-without regularization



Deep Learning



AdS/CFT

[Maldacena '97]