

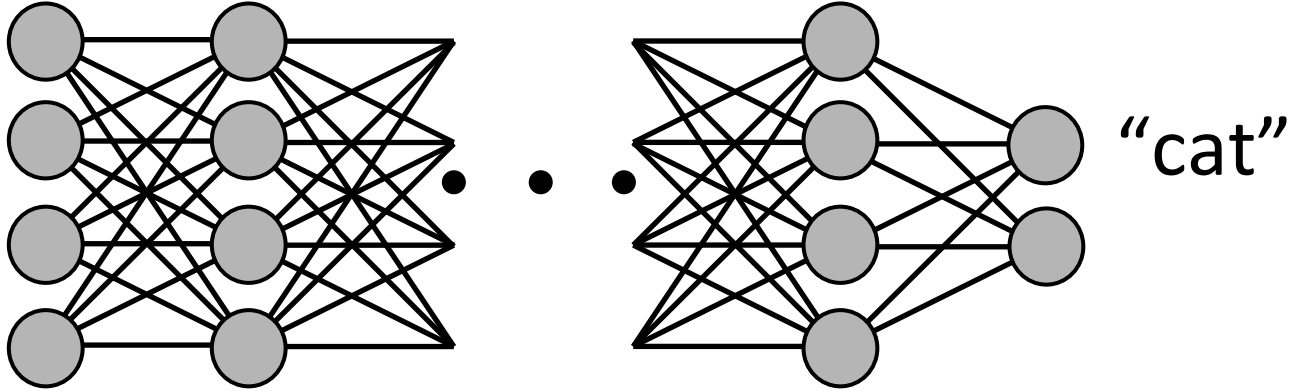
# Deep Learning and AdS/CFT

Koji Hashimoto (Osaka u)

ArXiv:1802.08313, 1809.10536

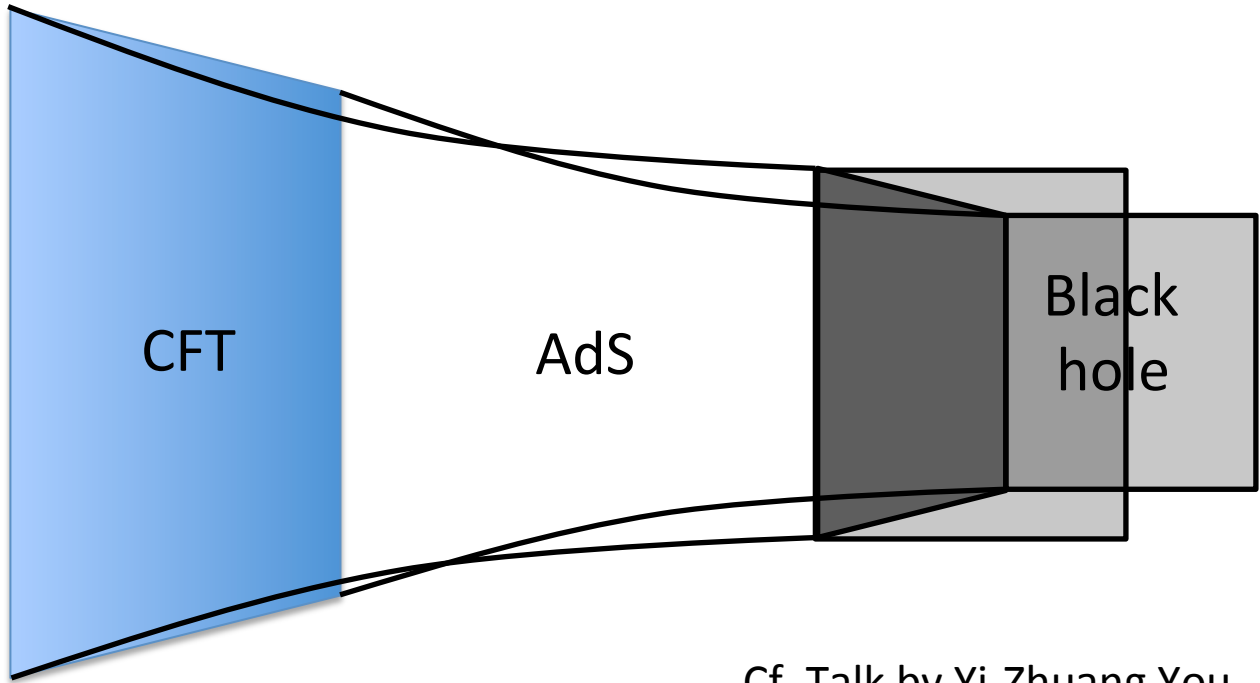
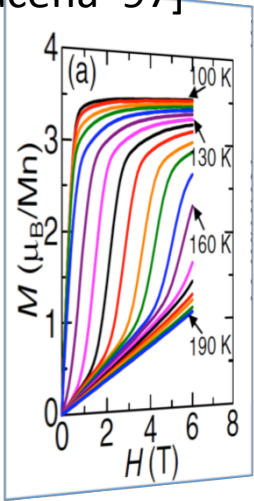
w/ S. Sugishita (Osaka),  
A. Tanaka (RIKEN AIP),  
A. Tomiya (RIKEN BNL)

# Deep Learning



# AdS/CFT

[Maldacena '97]



Cf. Talk by Yi-Zhuang You

1. Formulation of  
AdS/DL correspondence

2. Deeply learning QCD

# 1. Formulation of AdS/DL correspondence

1-1

**Three motivations**

review

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

review

**Deep learning: optimized sequential map**

1-2

**From AdS to DL**

1-3

**Dictionary of AdS/DL correspondence**

1-1

## (1) Brief history of quantum gravity

1974 Yoneya, Scherk-Schwarz: String = quantum gravity.

Yoneya, Prog.Theor.Phys. 51 (1974) 1907.

Scherk, Schwarz, Nucl.Phys. B81 (1974) 118.

1976 Hawking: Information loss problem of black holes.

Hawking, Phys.Rev.D14(1976)2460.

1997 Maldacena: Discovery of AdS/CFT.

A quantum gravity is nonperturbatively defined.

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

2002 Holographic QCD. Karch, Katz, JHEP 0206:043.

Kruczenski, Mateos, Myers, Winters JHEP 0405:041.

Sakai, Sugimoto, PTP 113 (2004) 843.

2008 Holographic superconductor.

Hartnoll, Herzog, Horowitz, PRL 101(2008)031601.

2009 Bulk reconstruction.

Heemskerk, Penedones, Polchinski, Sully, JHEP 0910:079.

1-1

## 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?

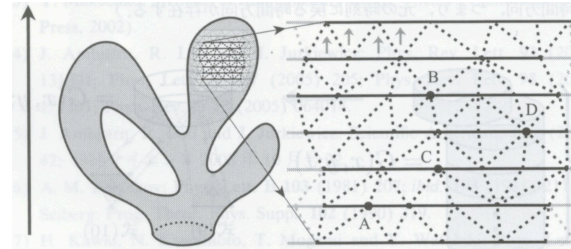
Statistical neural network. [Amari et al.]

1-1

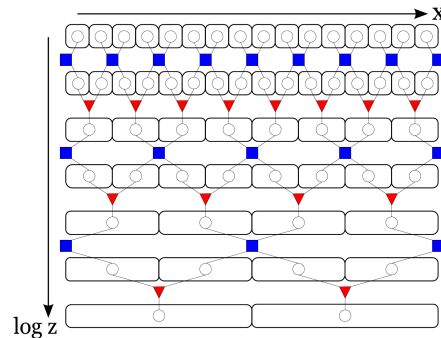
# Discretized QG spacetime?

Quantum gravity, discretized

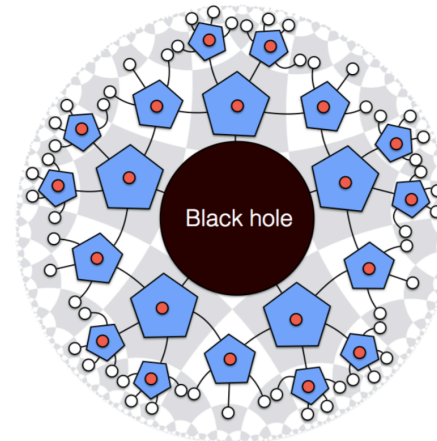
Causal dynamical  
triangulation [Ambjorn, Loll 1998]



AdS/MERA  
[Swingle 2009]



HaPPY code  
[Pastawski, Yoshida, Harlow, Preskill 2015]



1-1

## (2) Solving inverse problem

AdS/CFT  
(No proof, no derivation)

Classical gravity  
in  $d+1$  dim. spacetime

||

Quantum field theory  
in  $d$  dim. spacetime  
(Strong coupling limit,  
large DoF limit)

Conventional  
holographic modeling

Model  
Metric  $g_{\mu\nu}$

Prediction

Prediction

Comparison

Experiment  
data

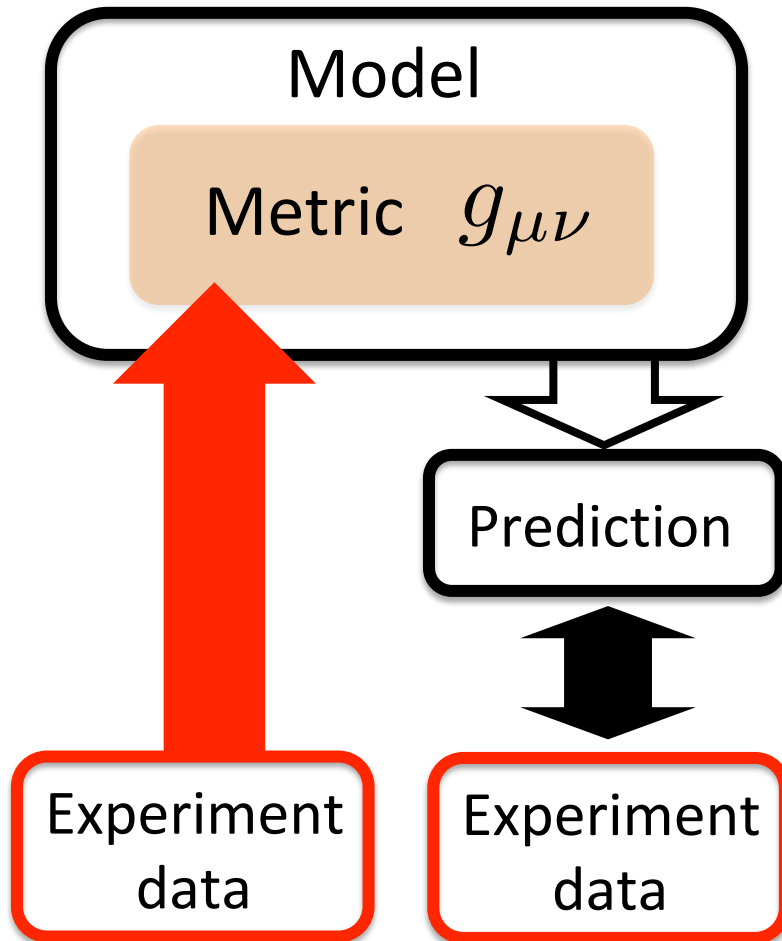
Experiment  
data



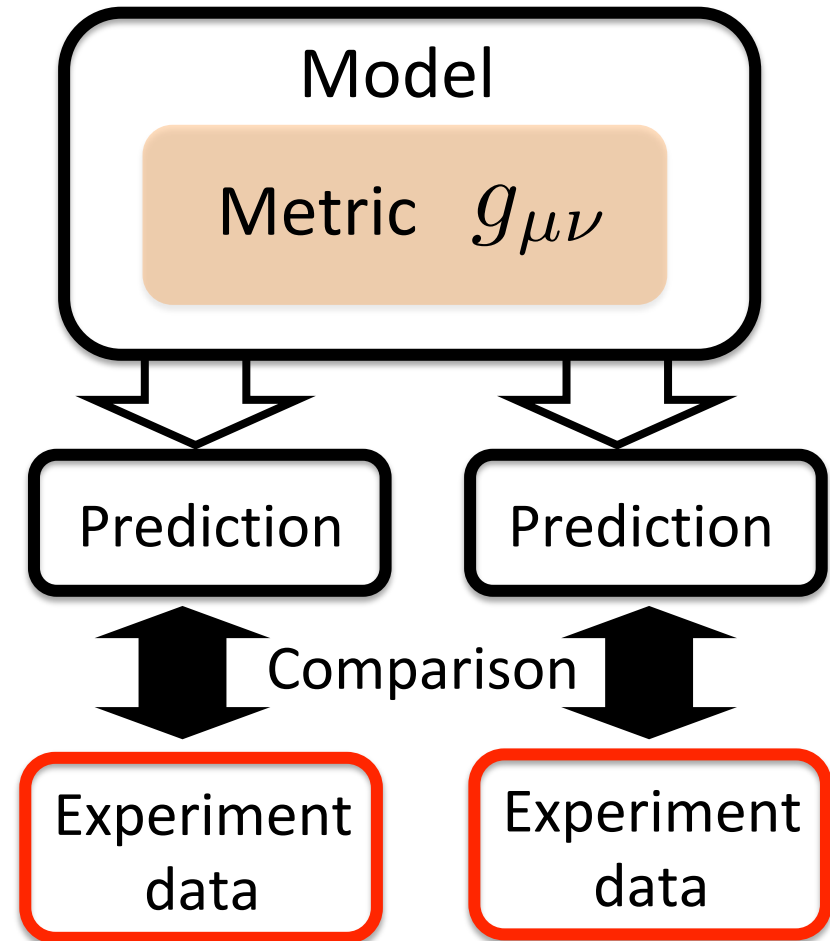
1-1

## (2) Solving inverse problem

Our deep learning  
holographic modeling



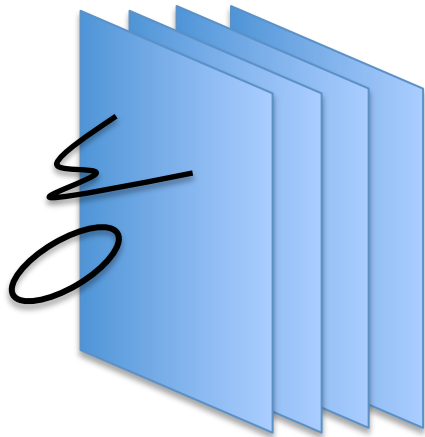
Conventional  
holographic modeling



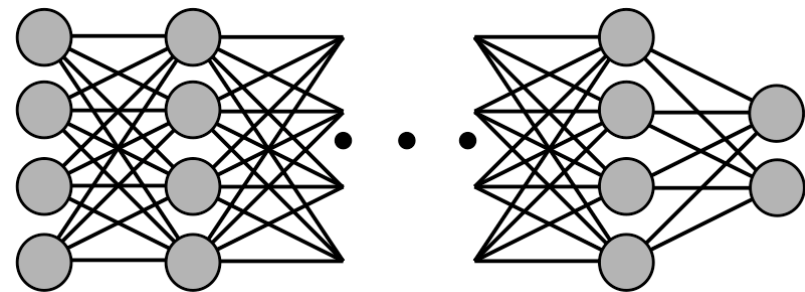
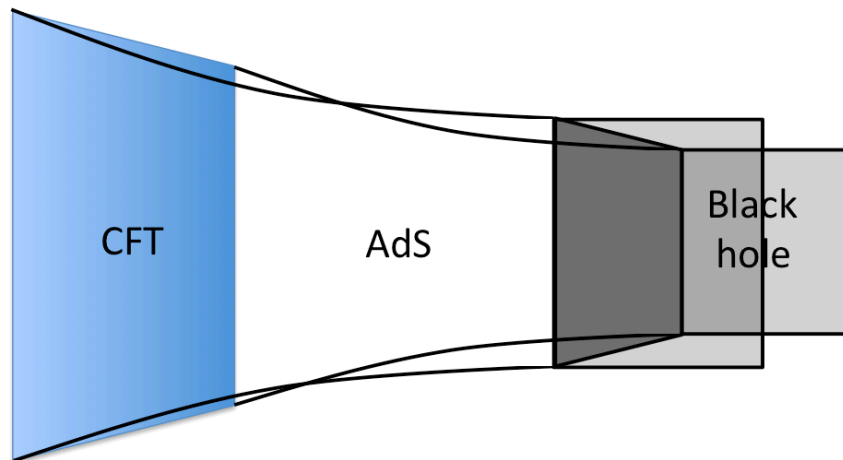
1-1

### (3) Most fundamental principle?

Brane  
(Superstring theory)



Brain  
(Neuroscience)



review

# AdS/CFT: quantum response from geometry

[Klebanov, Witten]

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

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

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

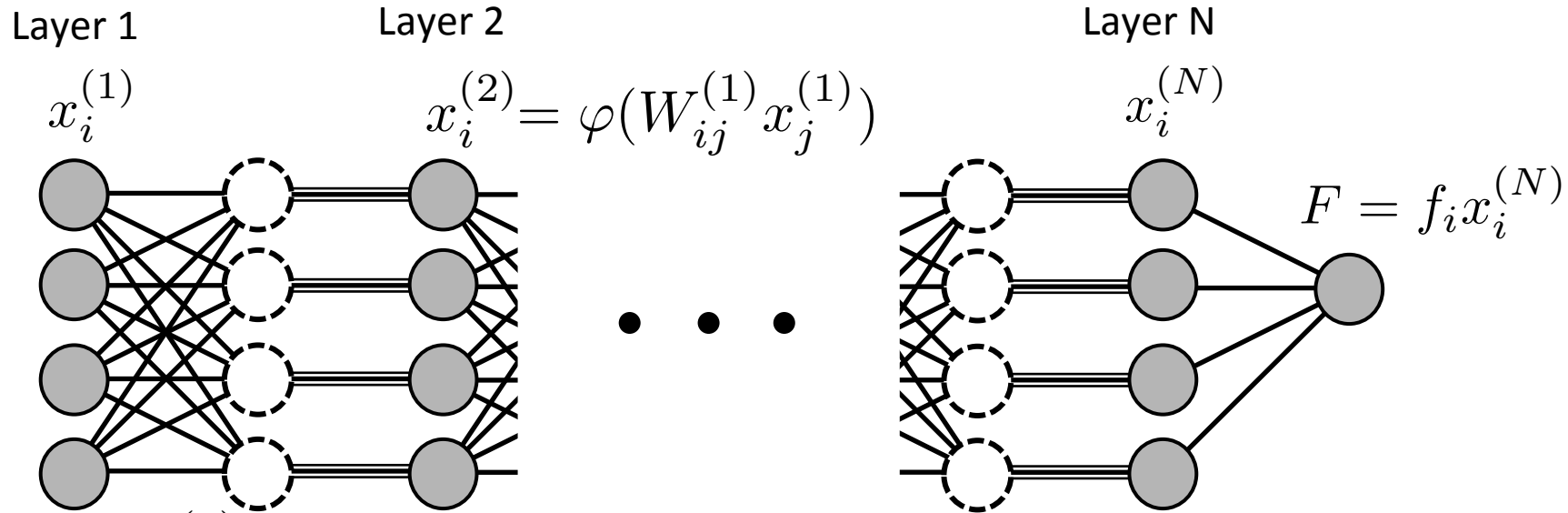
$$\left[ \begin{array}{l} \text{AdS boundary } (\eta \sim \infty) : f \sim g \sim \exp[2\eta/L] \\ \text{Black hole horizon } (\eta \sim 0) : f \sim \eta^2, g \sim \text{const.} \end{array} \right.$$

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

$$\left[ \begin{array}{l} \text{AdS boundary } (\eta \sim \infty) : \\ \phi = J e^{-\Delta_- \eta} + \frac{1}{\Delta_+ - \Delta_-} \langle \mathcal{O} \rangle e^{-\Delta_+ \eta} \\ \text{Black hole horizon } (\eta \sim 0) : \partial_\eta \phi \Big|_{\eta=0} = 0 \end{array} \right.$$

review

# Deep learning : optimized sequential map



$W_{ij}^{(1)}$

$\varphi(x)$

“Weights” (variable linear map)

“Activation function” (fixed nonlinear fn.)

- 1) Prepare many sets  $\{x_i^{(1)}, F\}$  : input + output
- 2) Train the network (adjust  $W_{ij}$ ) by lowering

“Loss function”  $E \equiv \sum_{\text{data}} \left| f_i(\varphi(W_{ij}^{(N-1)} \varphi(\dots \varphi(W_{lm}^{(1)} x_m^{(1)}))) - F \right|$

# 1-2

## From AdS to DL

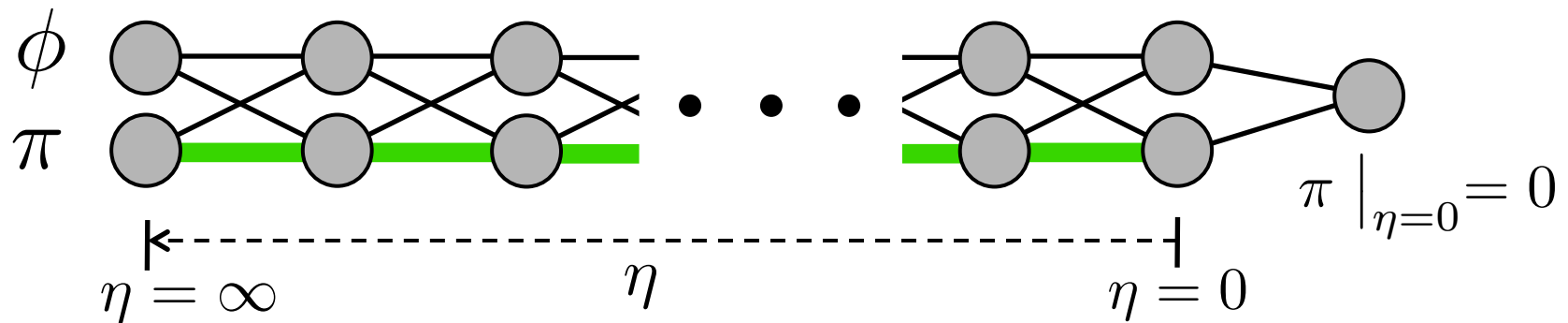
Bulk EoM  $\partial_\eta^2 \phi + \underbrace{h(\eta)}_{\text{metric}} \partial_\eta \phi - \frac{\delta V[\phi]}{\delta \phi} = 0$

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

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



1-3

## Dictionary of AdS/DL correspondence

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

# 1. Formulation of AdS/DL correspondence

1-1

**Solving inverse problem**

review

**Deep learning : optimized sequential map**

review

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

1-2

**From AdS to DL**

1-3

**Dictionary of AdS/DL correspondence**

1. Formulation of  
AdS/DL correspondence

2. Deeply learning QCD



## 2. Deeply learning QCD

2-1

Demonstration of holographic modeling

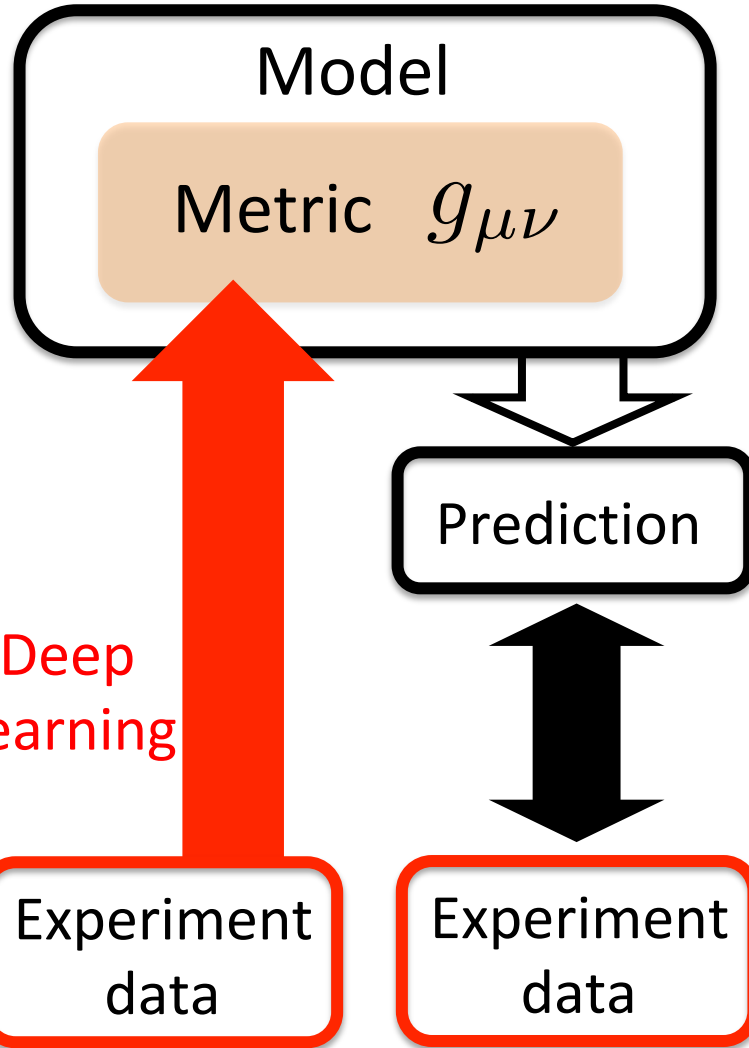
2-2

**Deeply learning QCD**

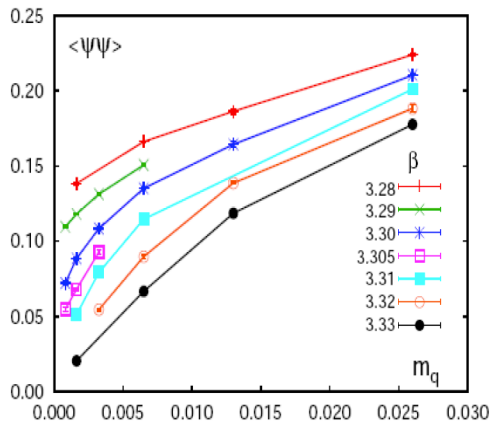
- 1) Use a QCD data.
- 2) Let the network learn the metric.
- 3) Calculate other physical quantities.

# 2-1

## Demonstration of holographic modeling

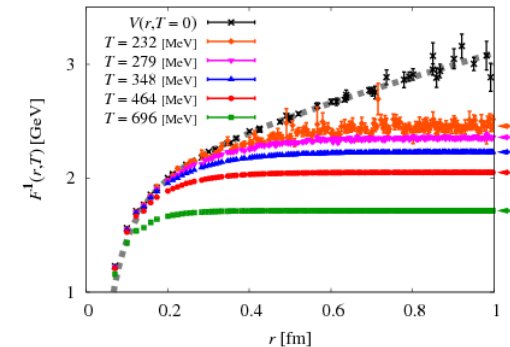
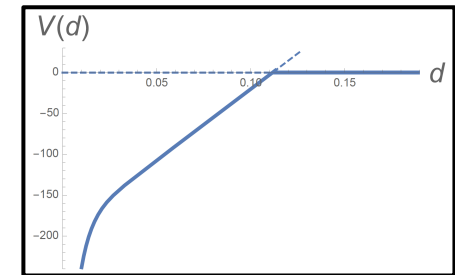


Lattice QCD data:  
chiral condensate  
VS quark mass



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

Q Qbar potential



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

2-2

## Deeply learning QCD

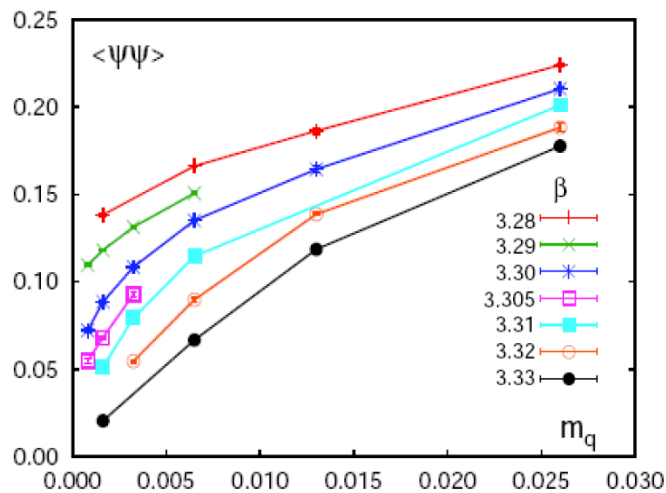
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# 2-2

## Deeply learning QCD

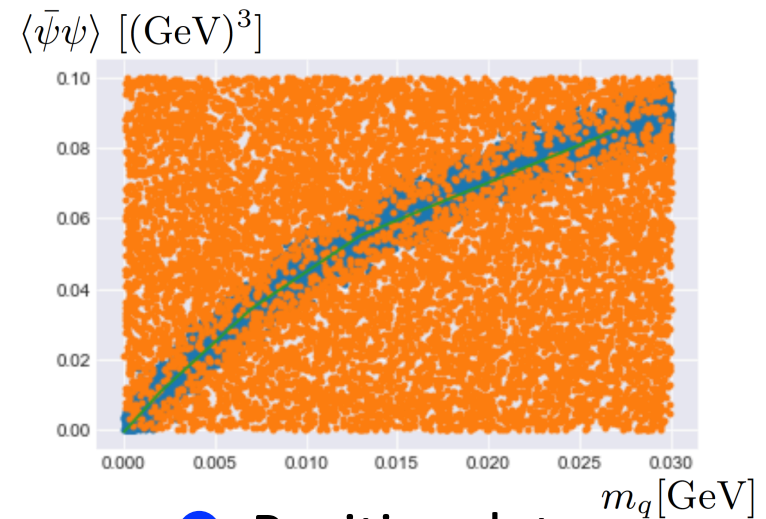
- 1) Use a QCD data.
- 2) Let the network learn the metric.
- 3) Calculate other physical quantities.

Chiral condensate VS quark mass.



$\beta=3.30 \Leftrightarrow T=196[\text{MeV}]$   
 [RBC-Bielefeld collaboration, 2008]  
 (Courtesy of W.Unger)

Pick up  
 →  
 $\beta=3.33$   
 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]

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

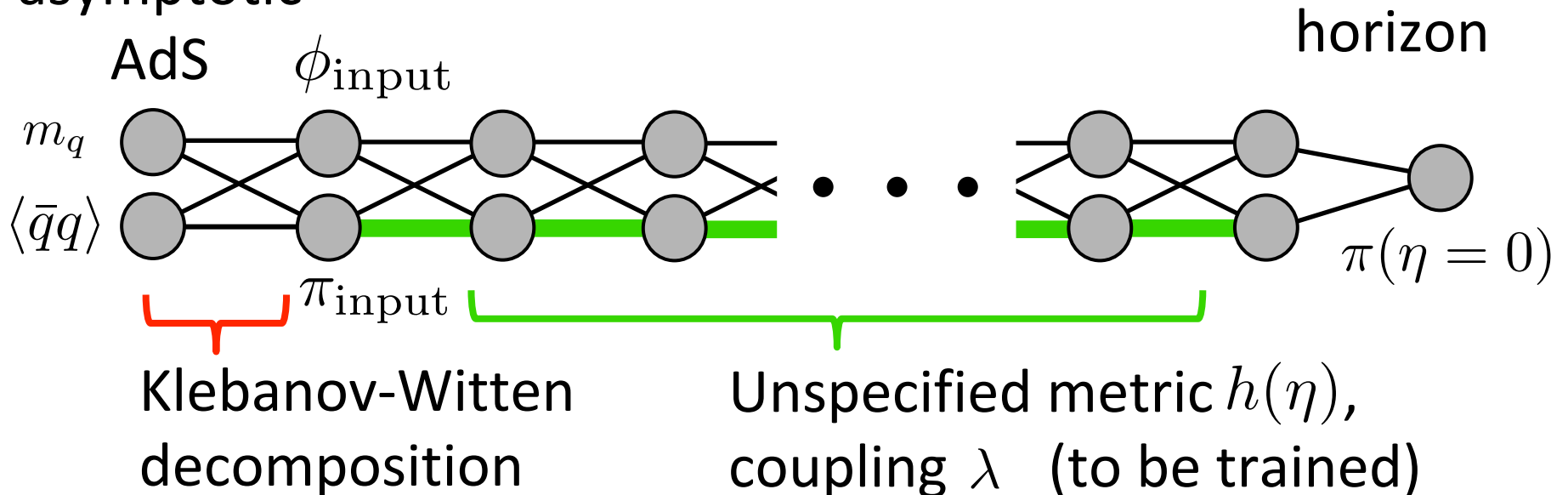
- Conformal dimension of  $\langle \bar{q}q \rangle$  is 3.
- Sub-leading contribution, present.
- Everything measured in unit of AdS radius.

# 2-2

## Deeply learning QCD

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

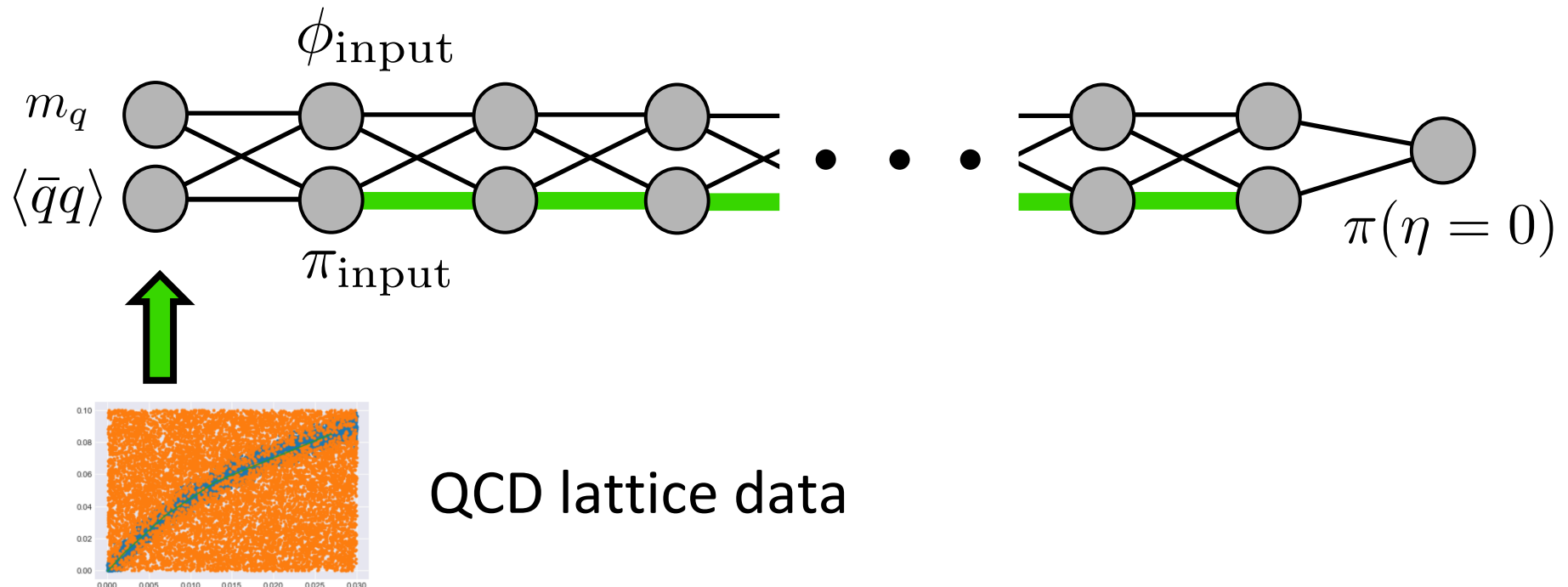
asymptotic



# 2-2

## Deeply learning QCD

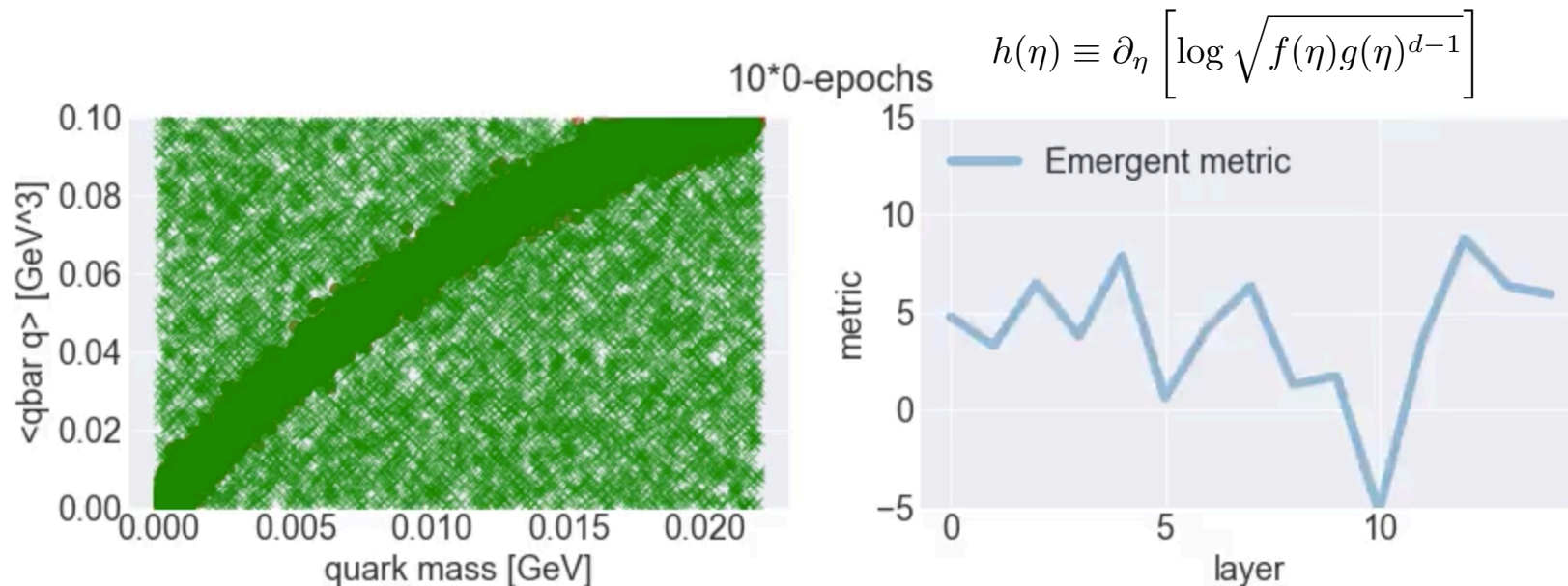
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- 3) Calculate other physical quantities.



# 2-2

## Deeply learning QCD

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



Learned value of (AdS radius)<sup>-1</sup> :  $1/L = 237(3)[MeV]$   
 bulk coupling :  $\lambda/L = 0.0127(6)$

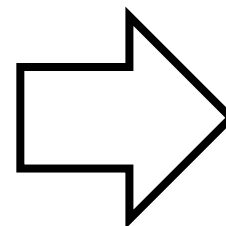
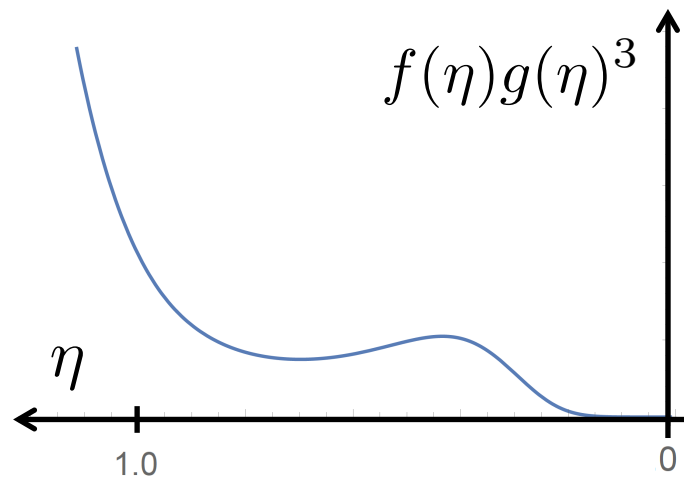


# 2-2

## Deeply learning QCD

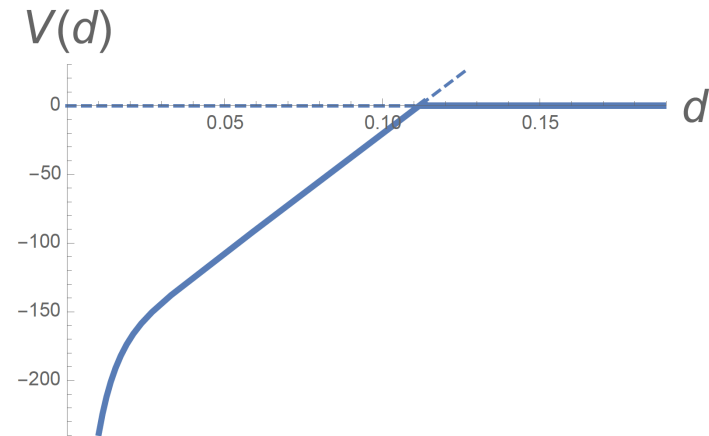
- 1) Use a QCD data.
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Learned metric



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

Q Qbar potential

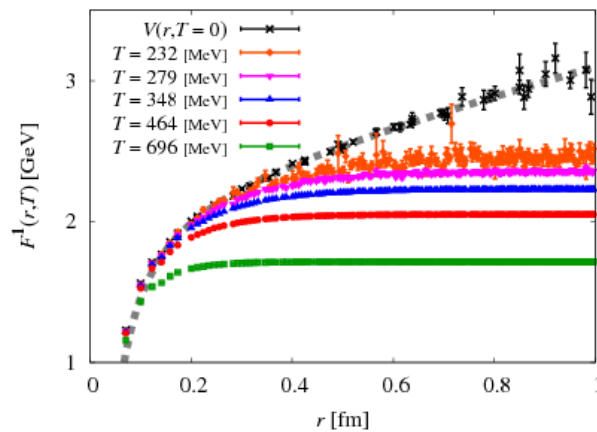


# 2-2

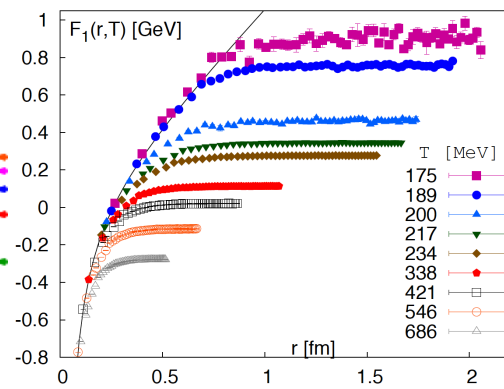
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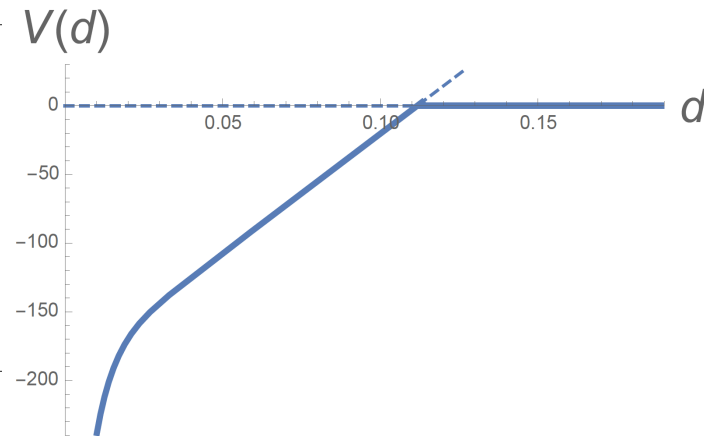
### Q Qbar potential



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

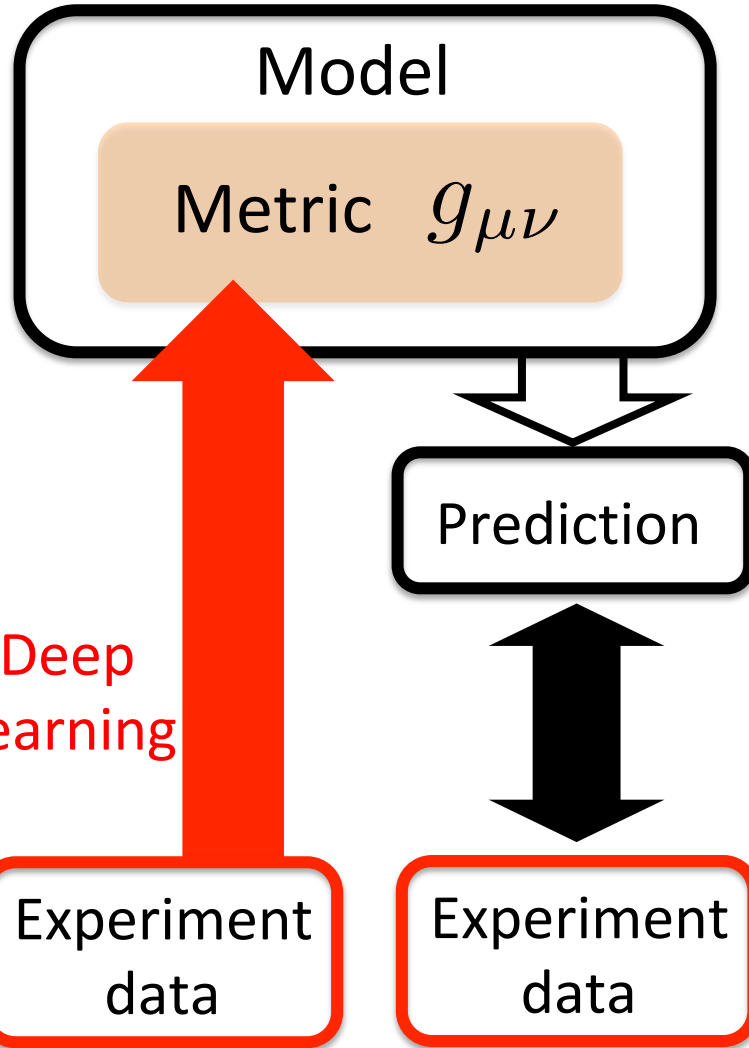


[Petreczky, 2010]

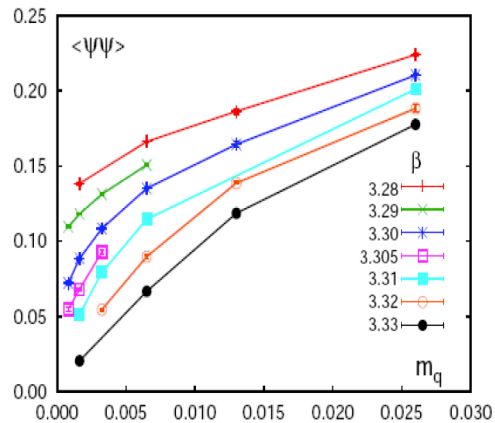


# 2-1

## Demonstration of holographic modeling

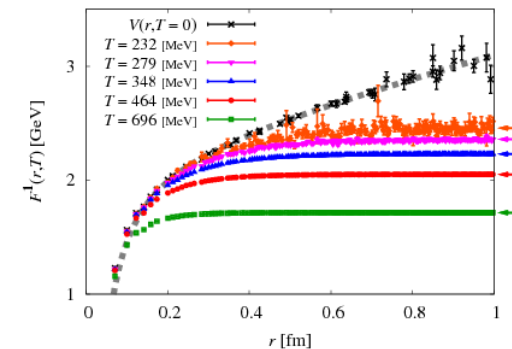
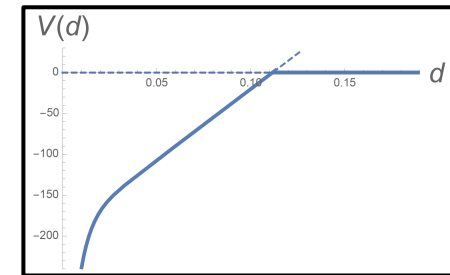


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