第十七届全国核物理大会

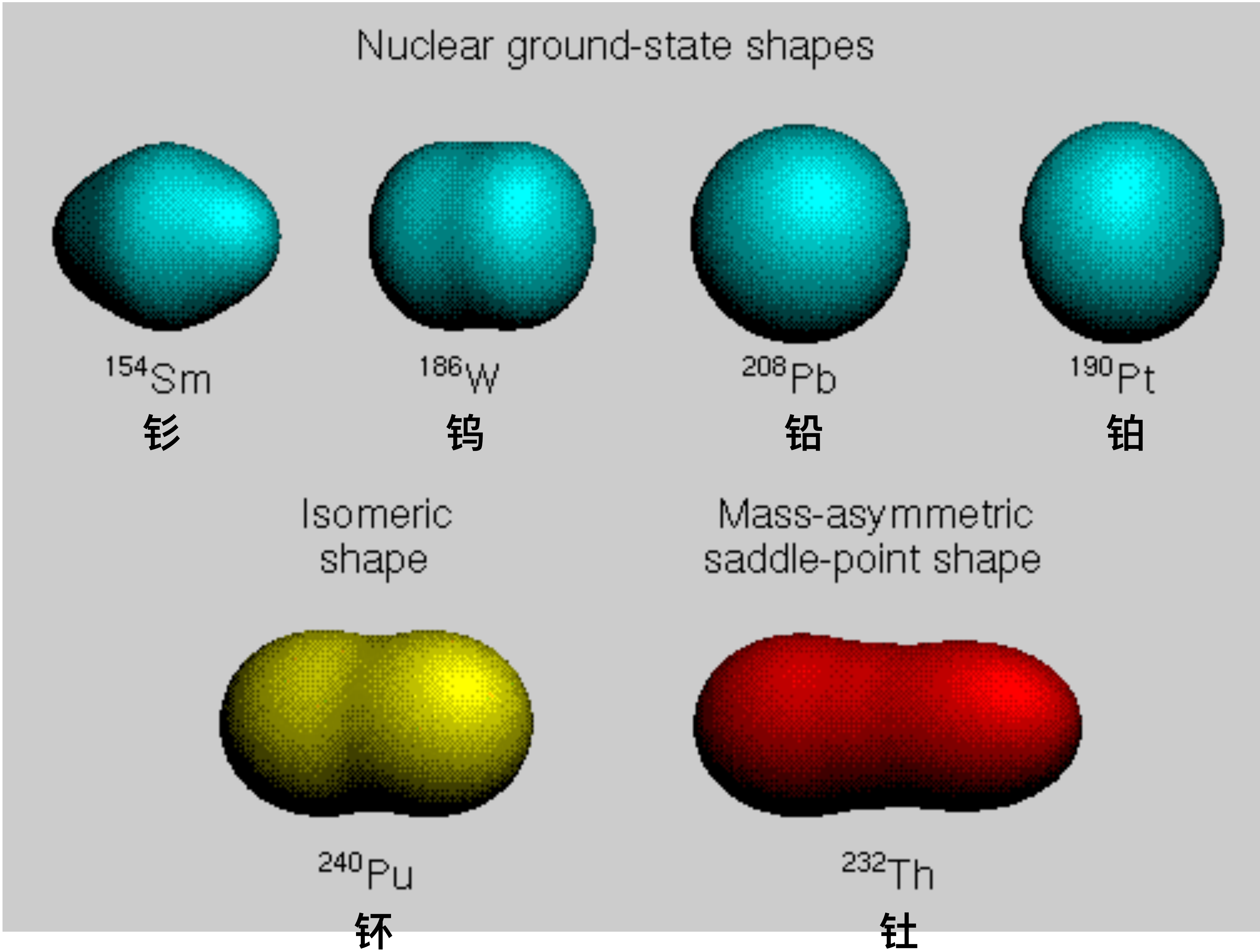
深度学习核变形因子

Deep learning nuclear shape deformation

Long-Gang Pang
with Kai Zhou and Xin-Nian Wang

Based on arXiv:1906.06429

Nuclear shape deformation



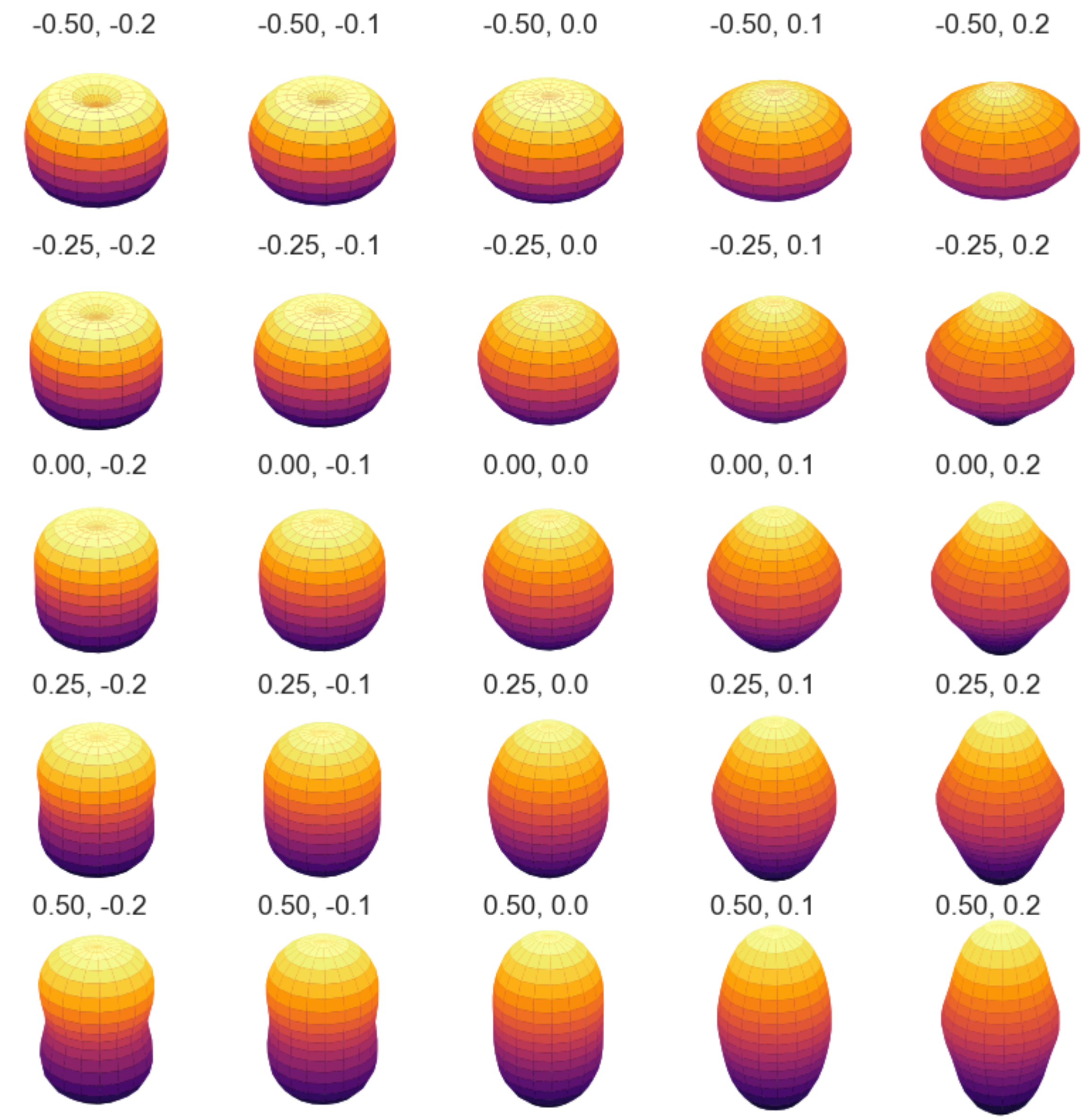
credit: Los Alamos National Lab

Deformed Woods-Saxon

$$\rho(r,\theta,\phi) = \frac{\rho_0}{1+e^{(r-R_0(1+\beta_2 Y_{20}(\theta)+\beta_4 Y_{40}(\theta)))/a}}$$

- Deformed Woods-Saxon can parameterize shape deformation using 2 parameters
- $Y_{20} = \frac{\sqrt{5}}{4\sqrt{\pi}}\left(3\cos^2\theta - 1\right)$

  $Y_{40} = \frac{3}{16\sqrt{\pi}}\left(35\cos^4\theta - 30\cos^2\theta + 3\right)$
- β_2 changes shapes vertically, from oblate (pumpkin-like) to prolate (egg-like)
- β_4 changes shapes horizontally, from dips to bumps

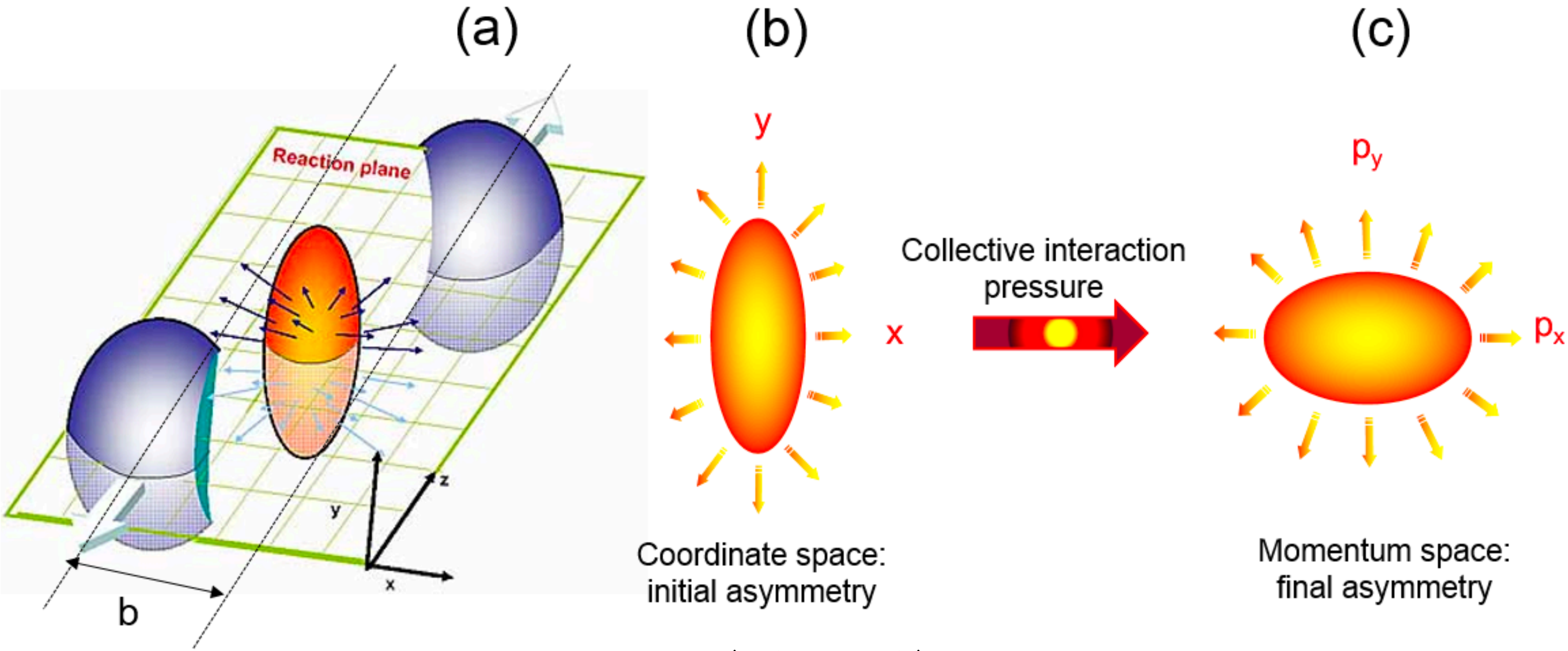


The motivation

- Nuclear structure plays an important role in explaining the experimental data of heavy ion collisions
  - Ultra-central puzzle for anisotropic flow
  - Chiral magnetic effect by isobaric collisions $^{96}_{40}\text{Ziconium vs }^{96}_{44}\text{Ruthenium}$
  - Mechanism of initial state entropy deposition

Nuclear structure from heavy ion collisions?

Anisotropic flow of heavy ion collisions

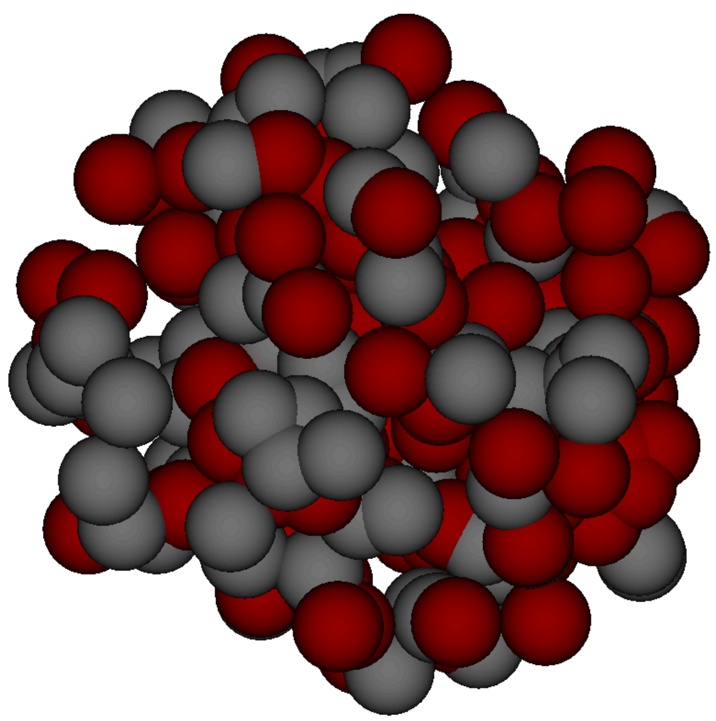


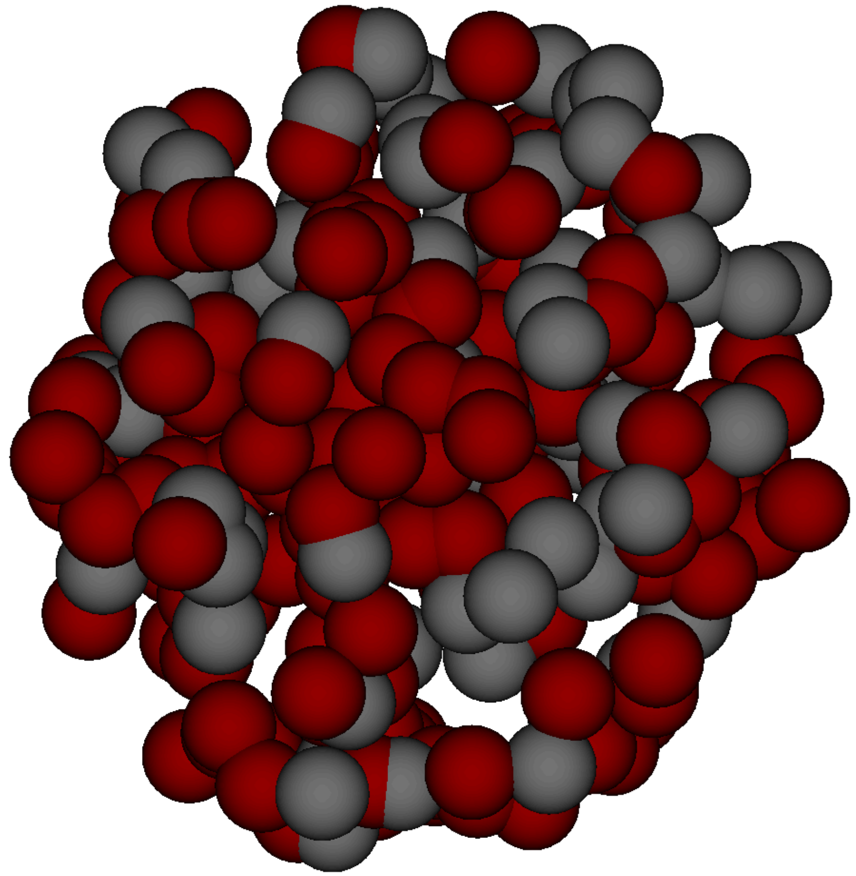
$$\varepsilon_2 = \frac{\langle y^2 - x^2 \rangle}{\langle y^2 + x^2 \rangle}$$

$$v_2 = \langle \cos 2\phi_p \rangle$$

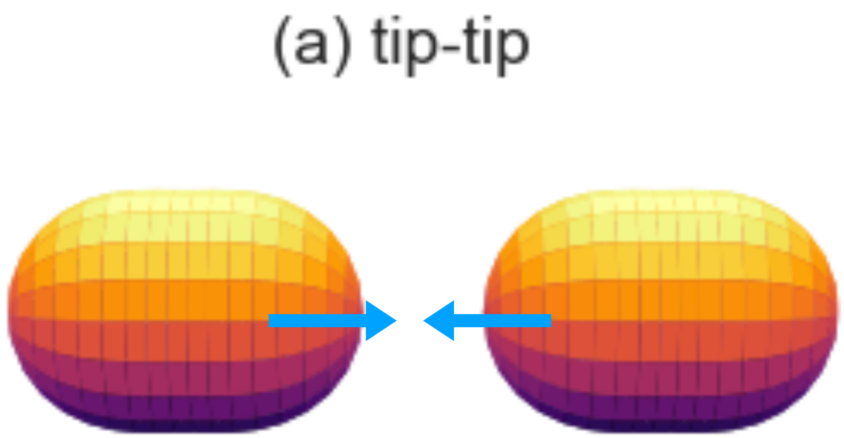
Fig from: Phenomenological Review on Quark–Gluon Plasma: Concepts vs. Observations, By Roman Pasechnik and Michal Sumbera

Fluctuations from nucleon distributions

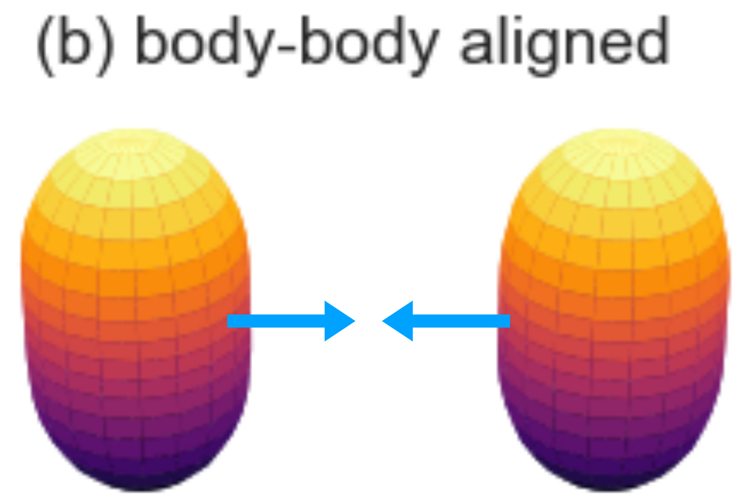

Au


U

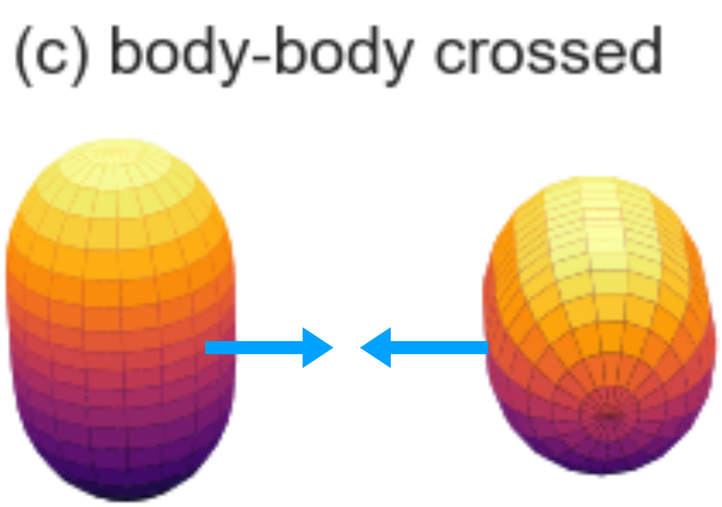
Fluctuations from Euler Rotations



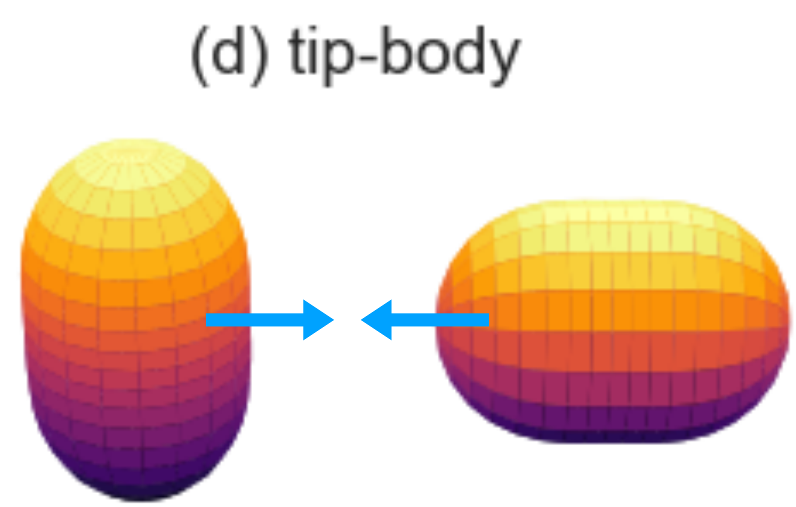
high multiplicity, small v_2



high multiplicity, large v_2

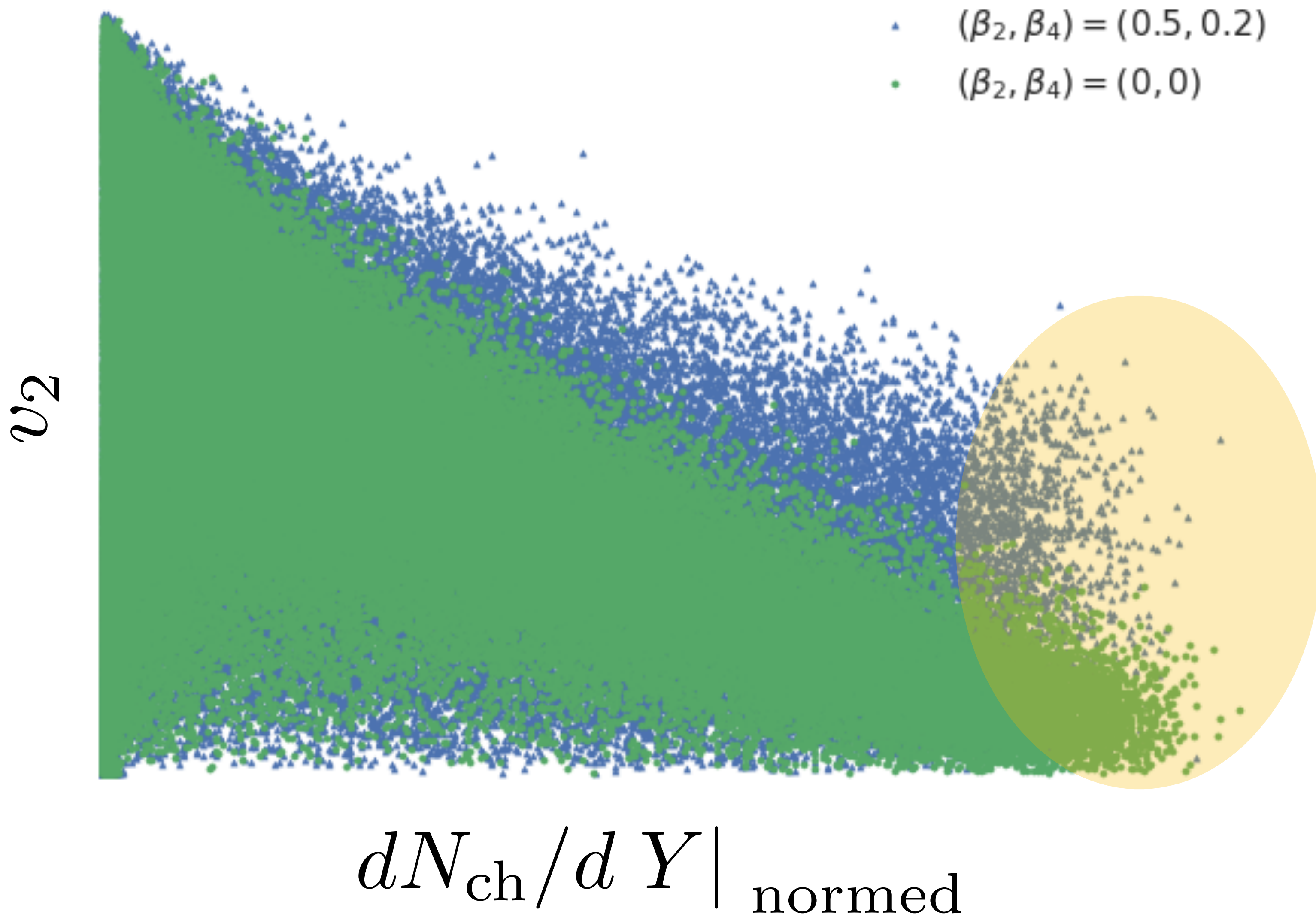


low multiplicity, small v_2

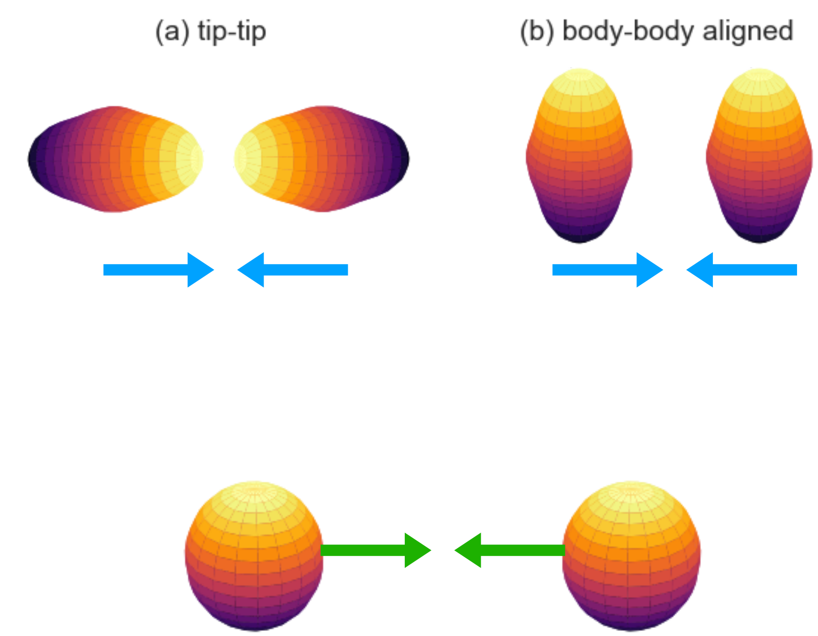


low multiplicity, small v_2

Training data from Trento + mapping



fully overlapped collisions

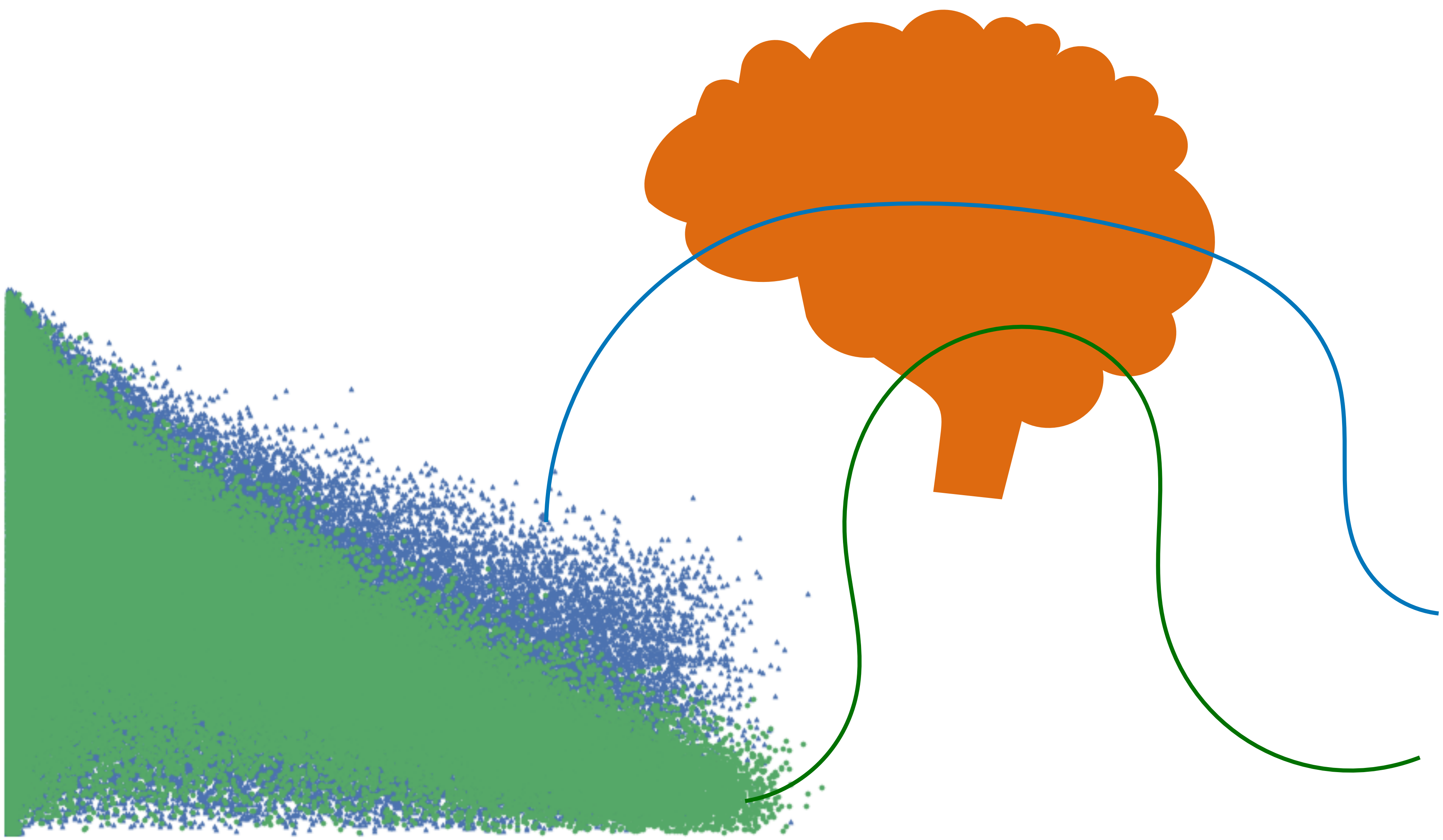


$v_2 = k_2\varepsilon_2 + k_2'\varepsilon_2^3 + \delta_2$ where $k_2 = 0.2,\ k_2' = 0.1$ and δ_2 provides 10% residual fluctuations

$dN_{\mathrm{ch}}/d\,Y|_{\mathrm{normed}} = \dfrac{dN_{\mathrm{ch}}/dY}{\langle dN_{\mathrm{ch}}/dY\rangle_{\mathrm{most\ central}}} \approx \dfrac{s_0}{\langle s_0\rangle_{\mathrm{most\ central}}}$ at mid-rapidity.

Key idea: regression task that maps image to parameters

Deep neural network



$$(\beta_2, \beta_4) = (0.5, 0.2)$$

$$(\beta_2, \beta_4) = (0, 0)$$

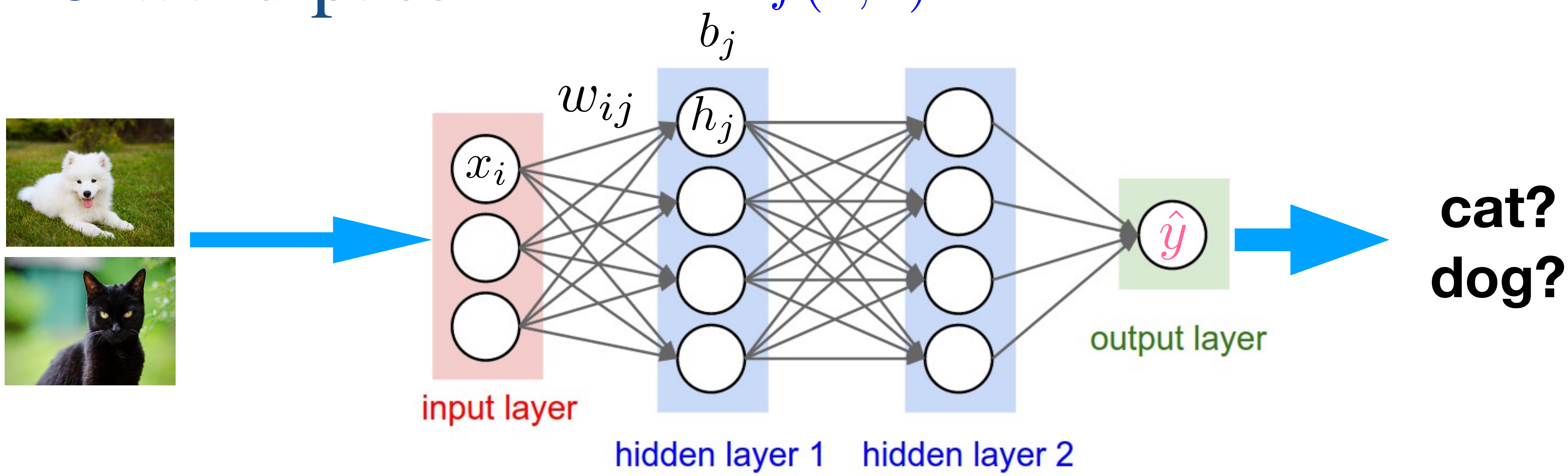
inputs

outputs

Forward pass

$f(x,\theta)$

Fig from CS231N, Stanford



Linear operation

$$z_j = \sum_{i=1}^{N} x_i w_{ij} + b_j$$

where $\theta = \{w_{ij}, b_j\}$

Non-linear activation function $h_j = \sigma(z_j)$

(a) Sigmoid

$$\sigma(z) = \frac{1}{1+\exp(-z)}$$

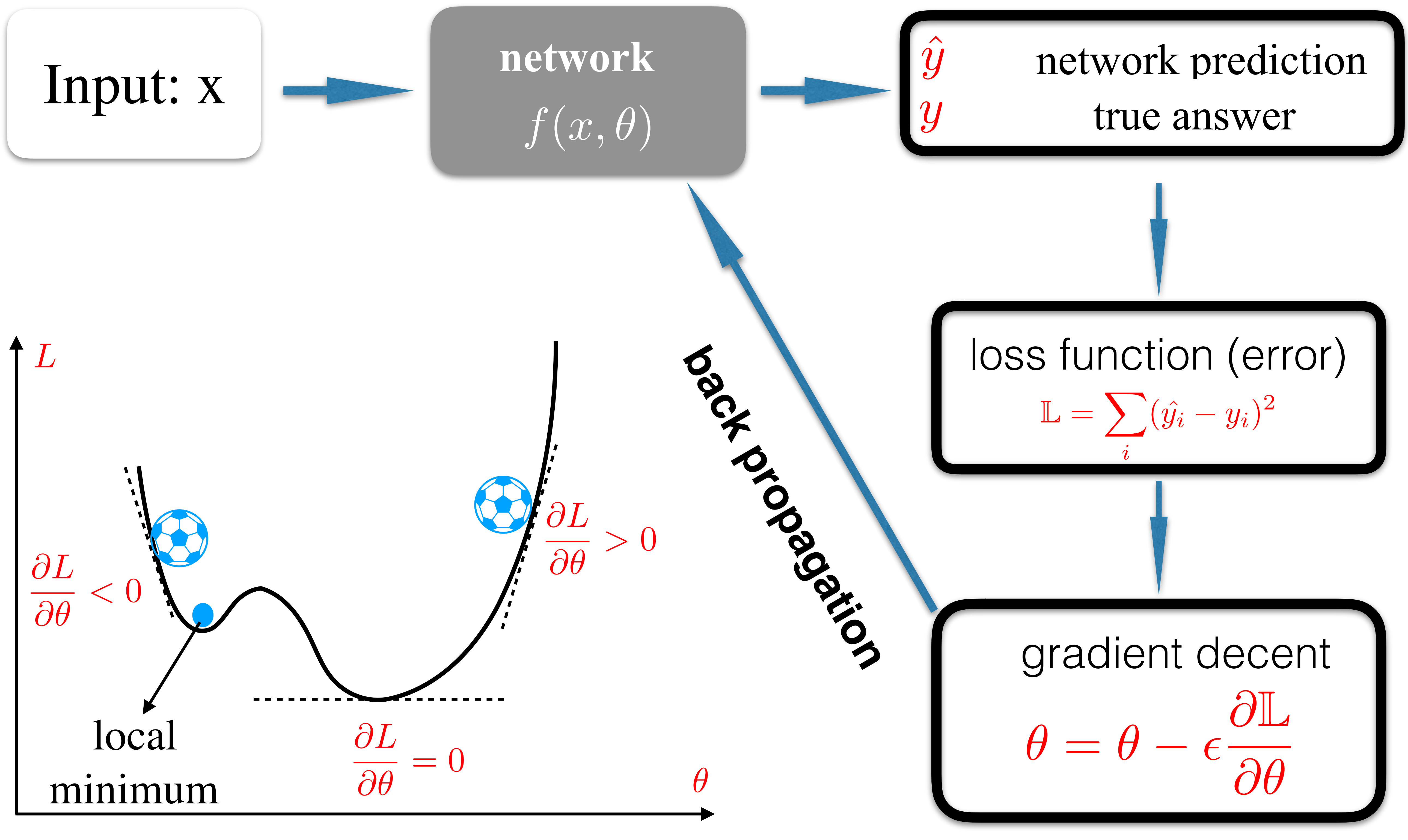
(b) ReLU

$$\sigma(z) = \begin{cases} z, & z > 0 \\ 0, & z \leq 0 \end{cases}$$

(c) PReLU

$$\sigma(z) = \begin{cases} z, & z > 0 \\ az, & z \leq 0 \end{cases}$$

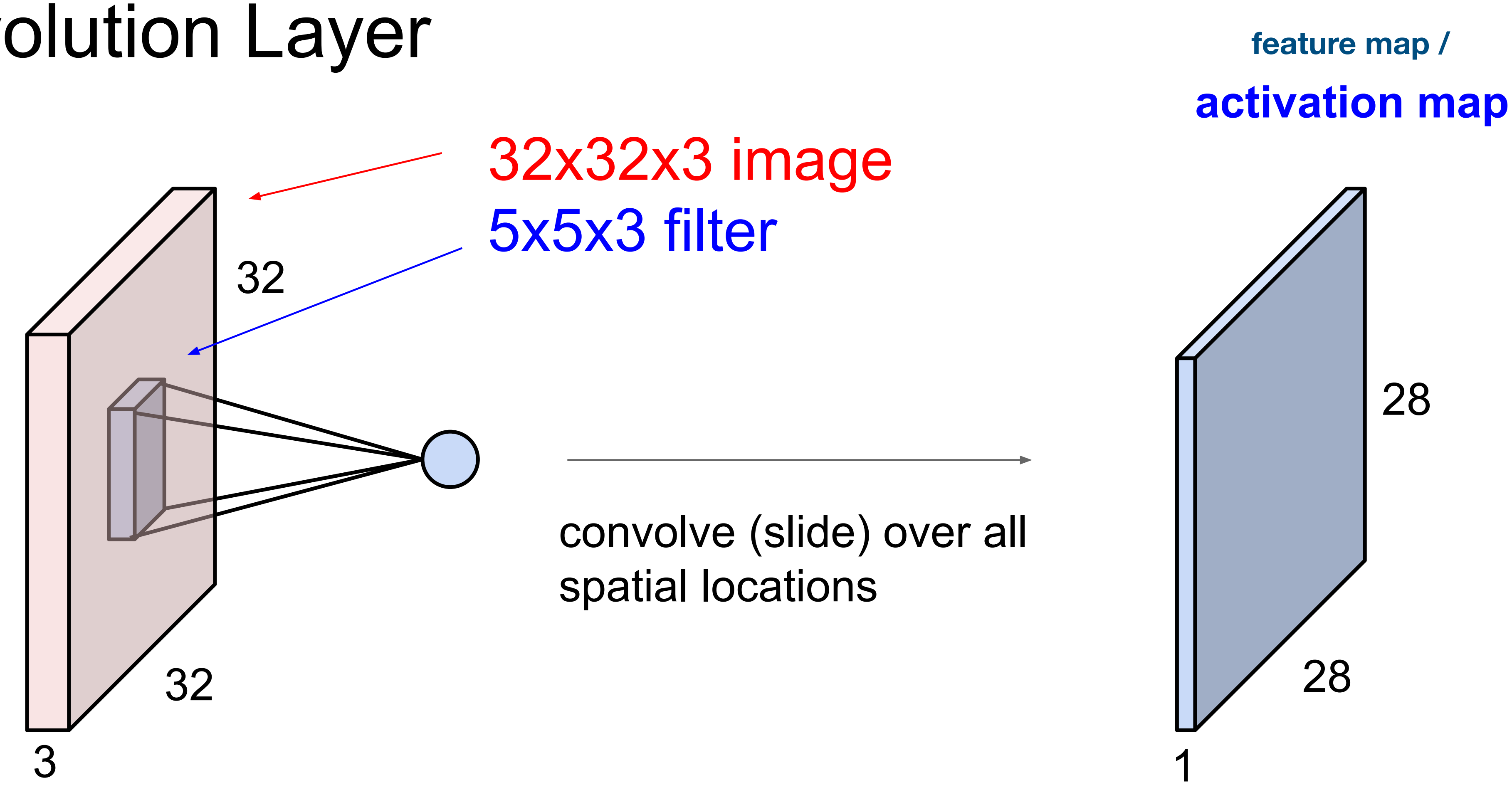
Deep neural network

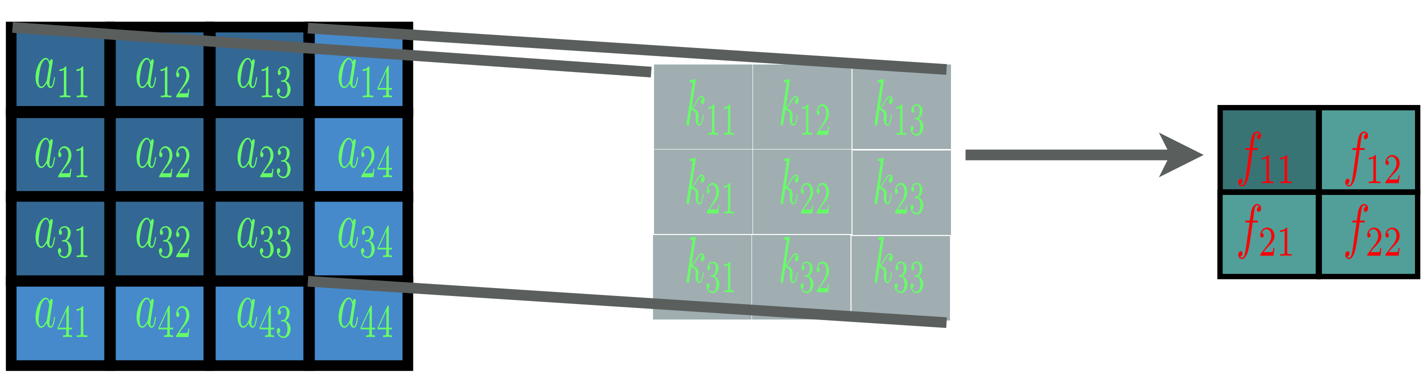


State-of-the-art pattern recognition

Deep convolution neural network + Residual Block + Squeeze Excitation block

Convolution Layer

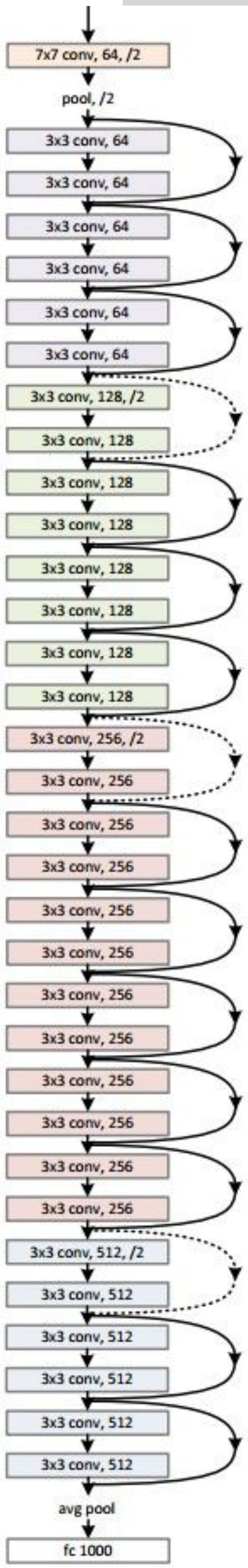


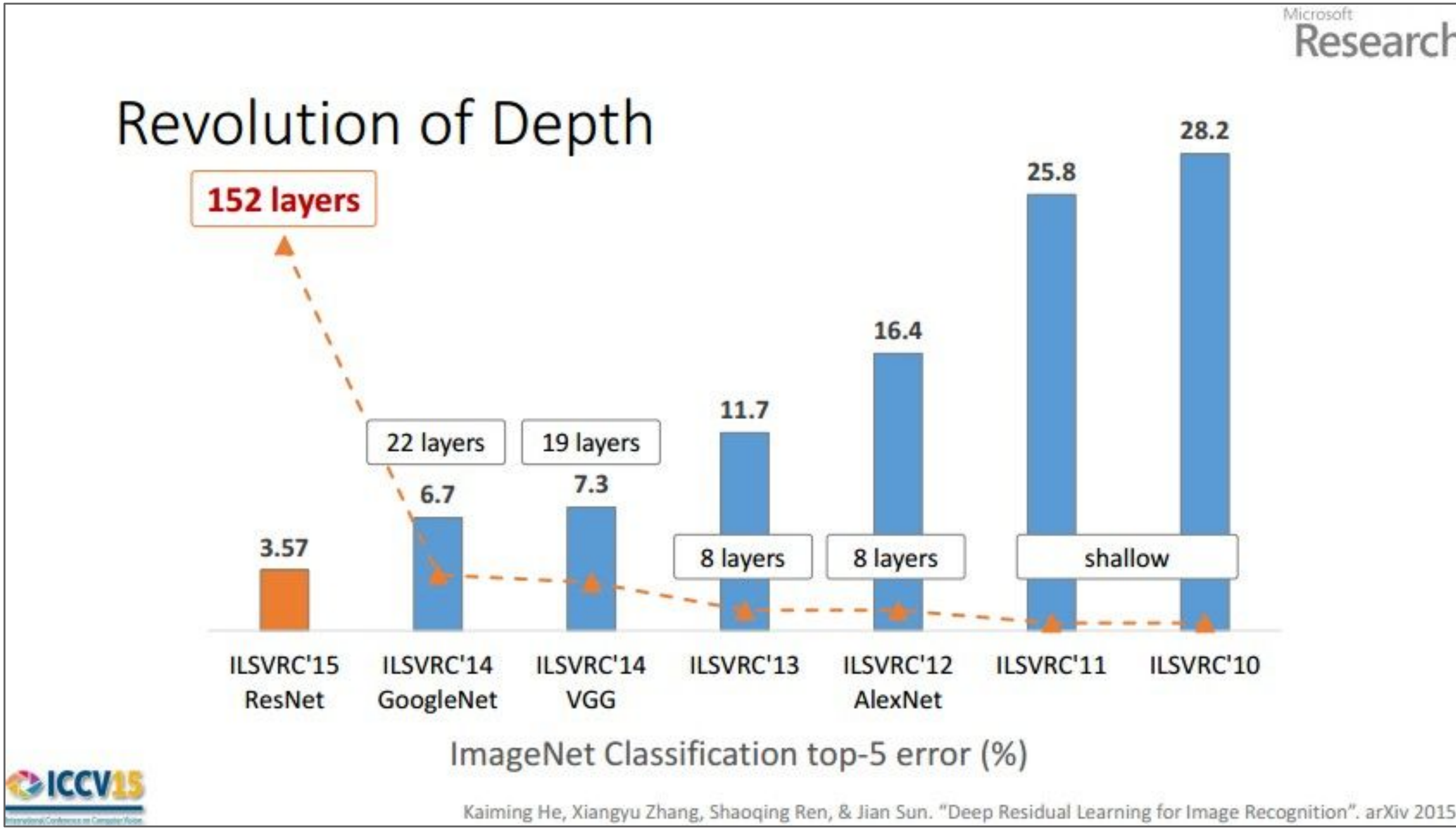


$$
\begin{aligned}
f_{11} = {} & a_{11}k_{11} + a_{12}k_{12} + a_{13}k_{13} \\
& a_{21}k_{21} + a_{22}k_{22} + a_{23}k_{23} \\
& a_{31}k_{31} + a_{32}k_{32} + a_{33}k_{33}
\end{aligned}
$$

State-of-the-art pattern recognition

Deep convolution neural network + Residual Block + Squeeze Excitation block

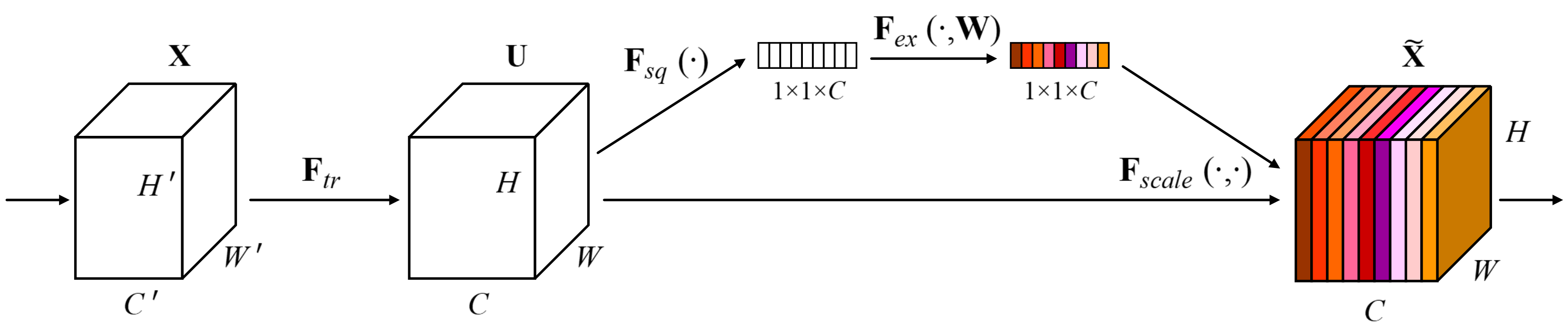


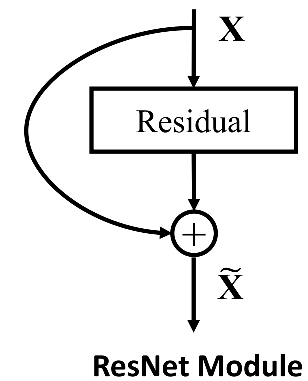


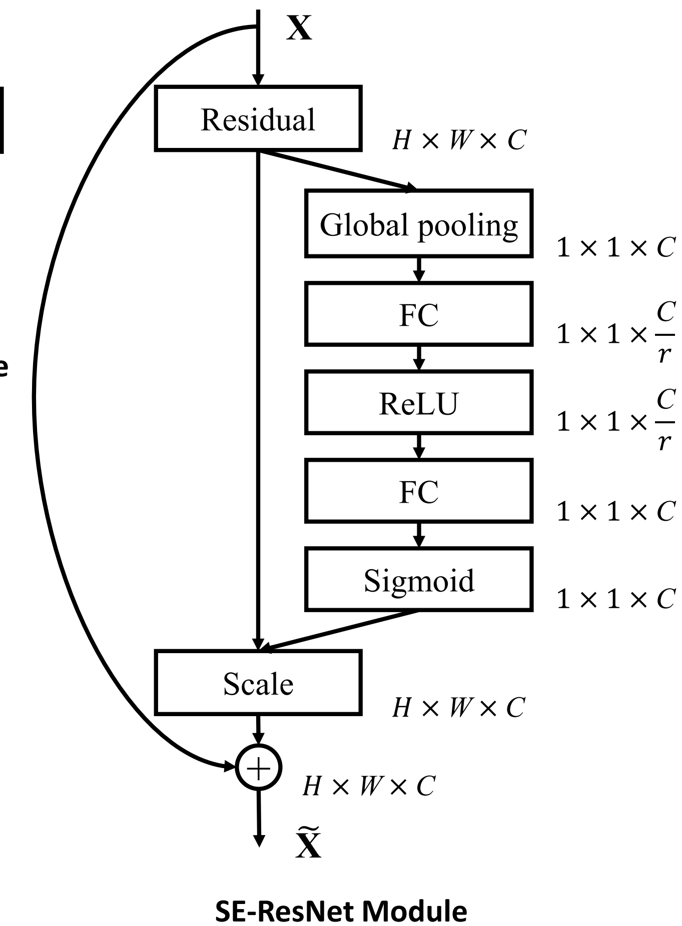
(slide from Kaiming He's recent presentation)

State-of-the-art pattern recognition

Deep convolution neural network + Residual Block + Squeeze Excitation block

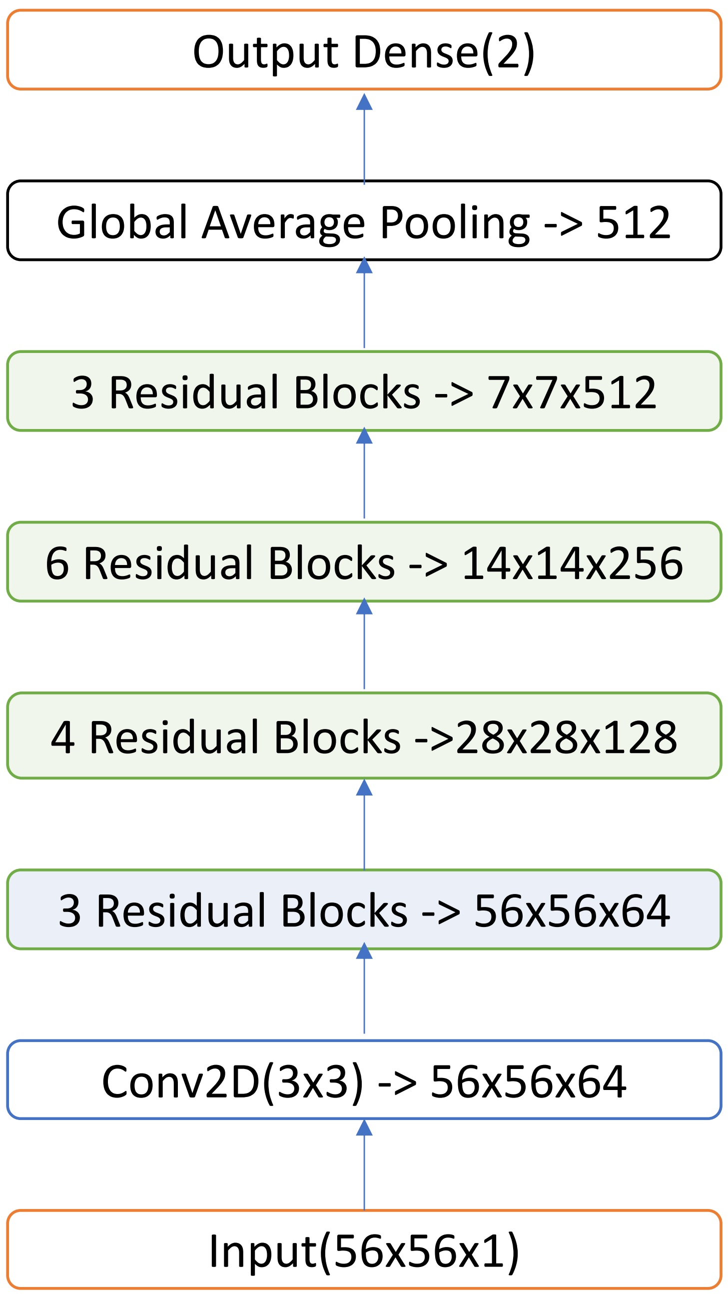




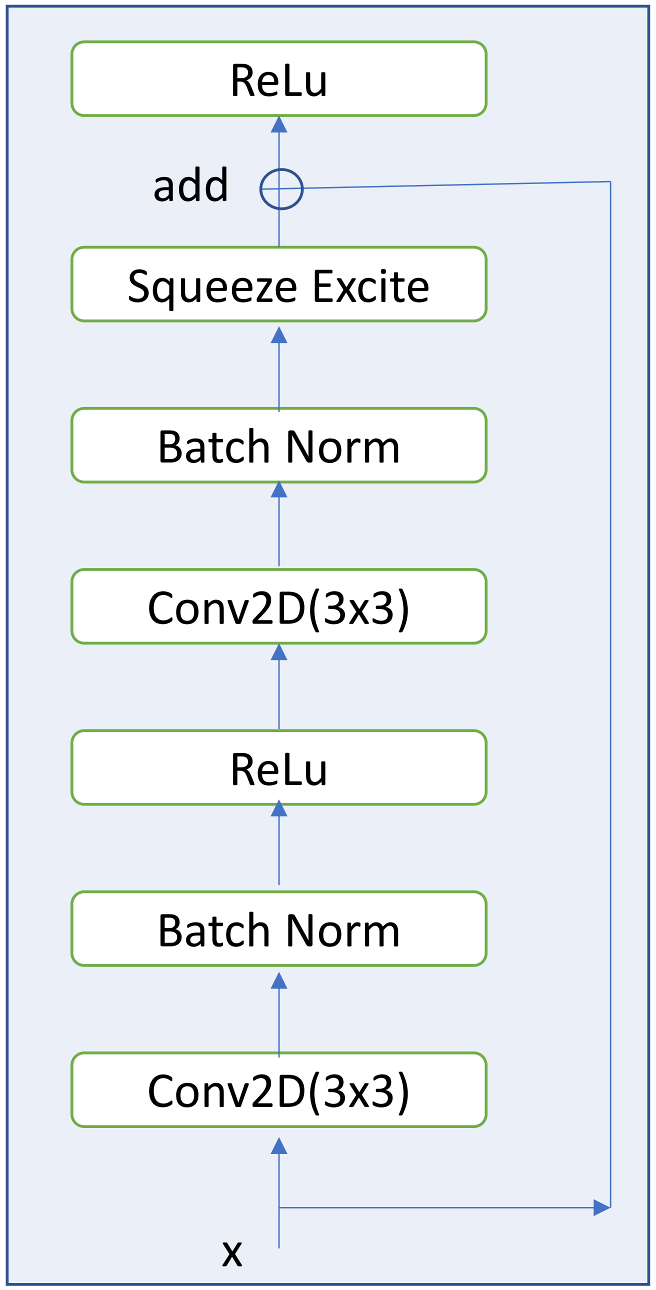


- Global average pooling and dot product to provide extra correlation between different channels.
- Improve relatively 2-8% over residual network.

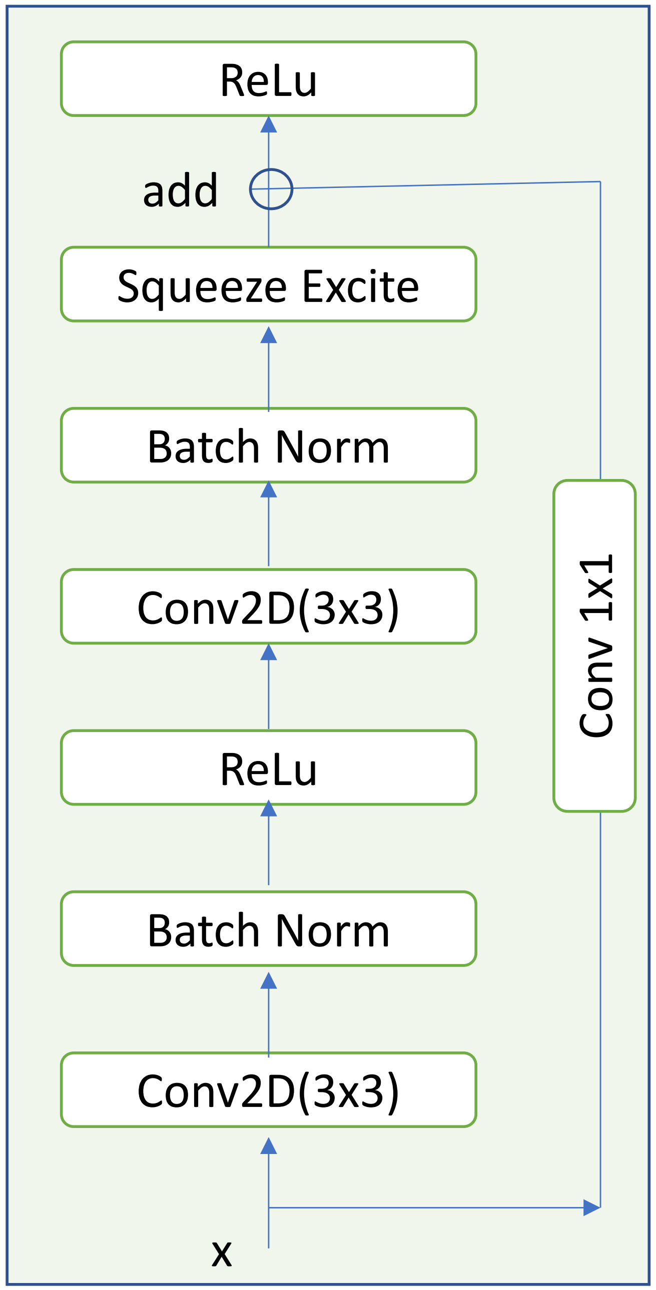
Network structure for nuclear deformation



Regression Network

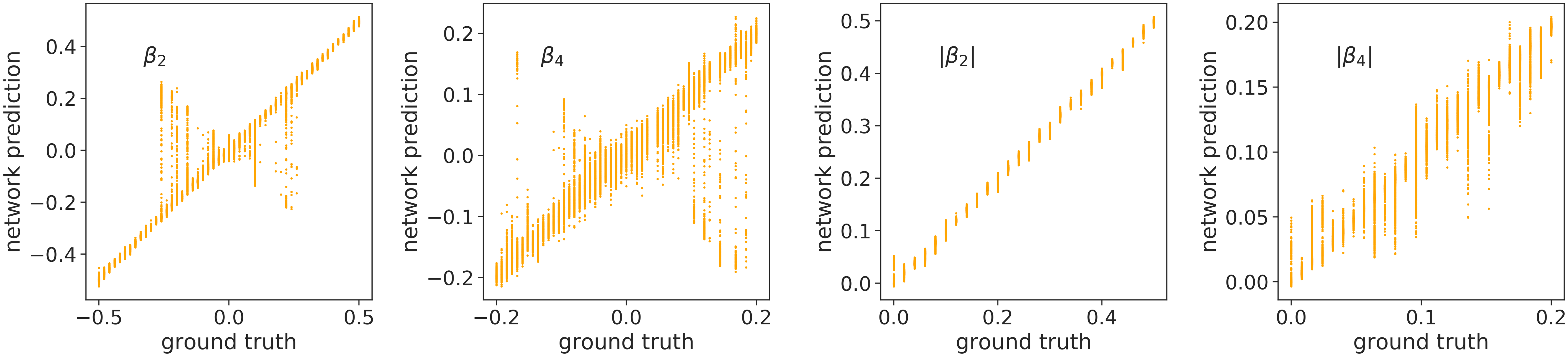


1 Blue Residual Block



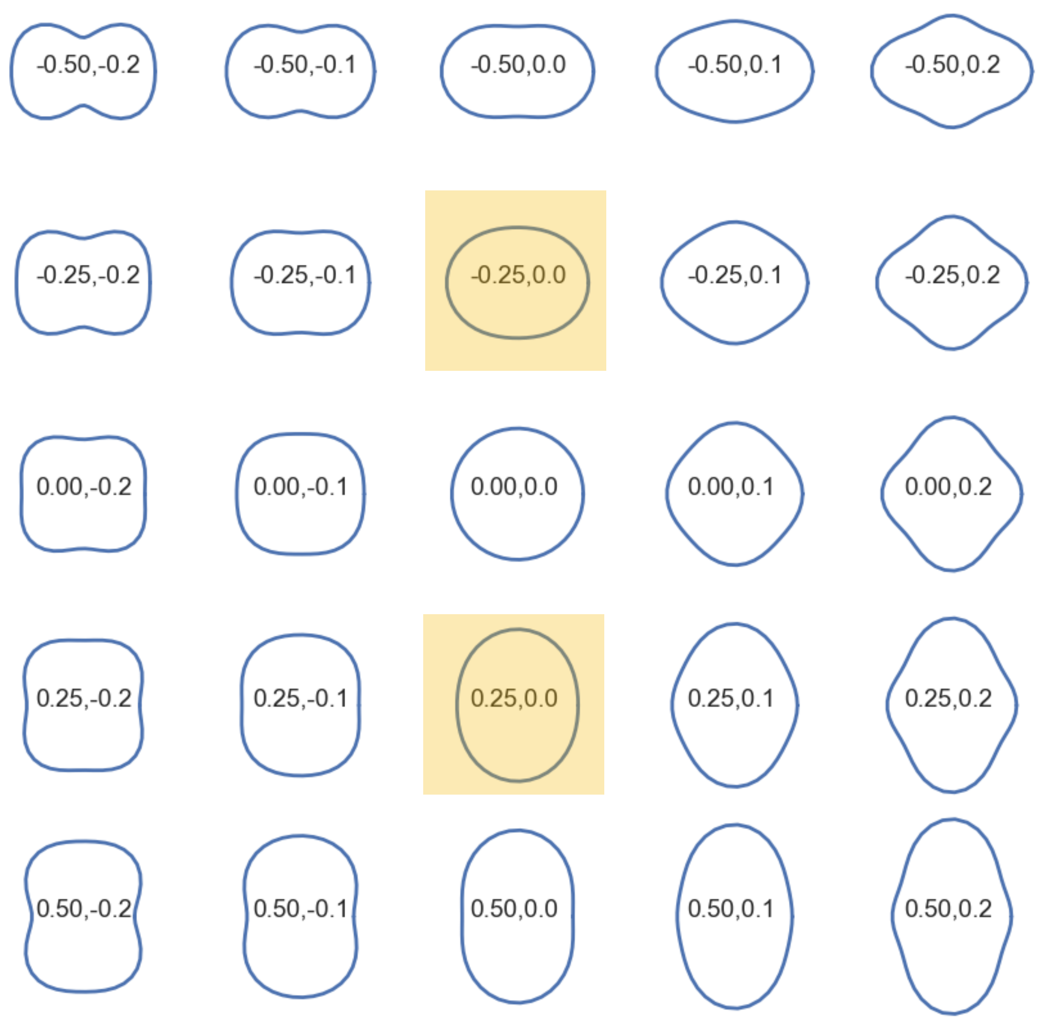
1 Green Residual Block

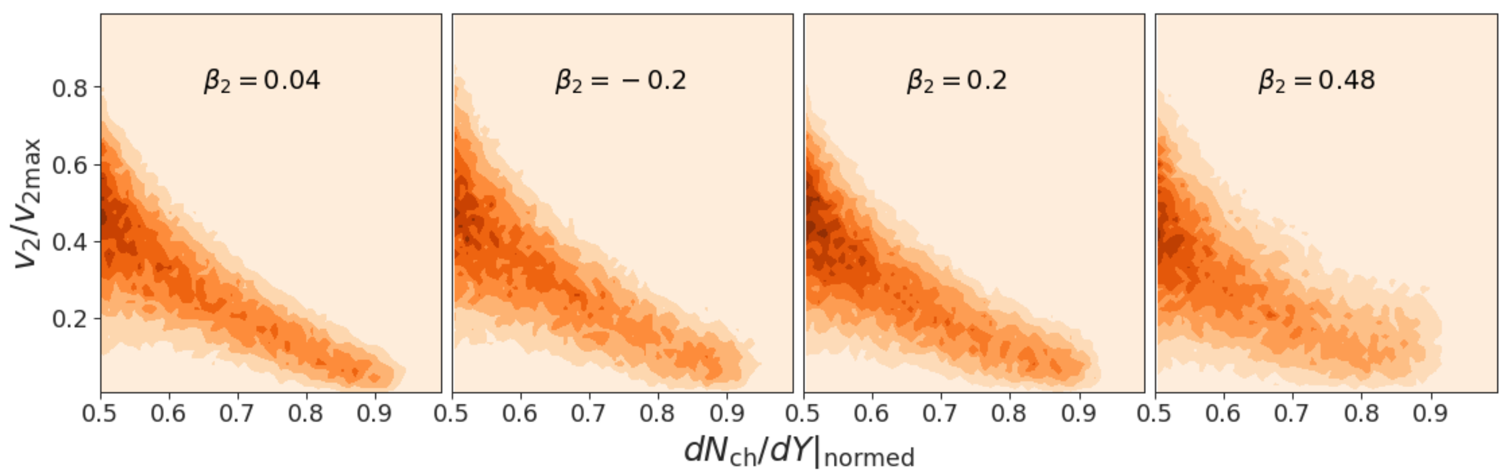
Results



- Predict well for $|\beta_2|$
- Not possible to constrain the sign of β_2 from $(v_2, dN/dY_{\text{norm}})$
- Results from deep learning implies degeneracy for β_2 with the same $|\beta_2|$

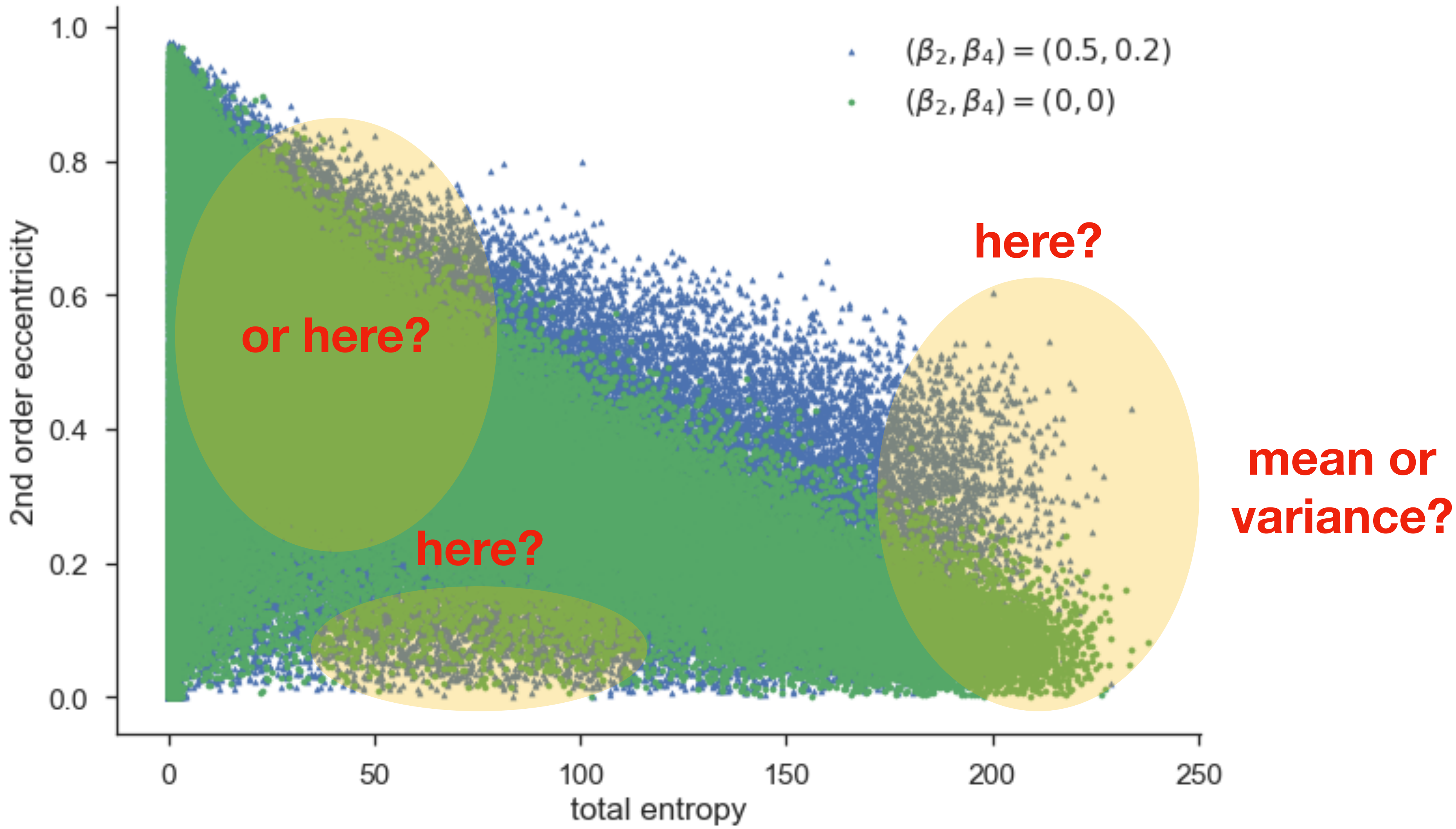
Reason for degeneracy visualized by 2d projection





- Degenerate due to strong Lorentz contraction at high energy collisions.

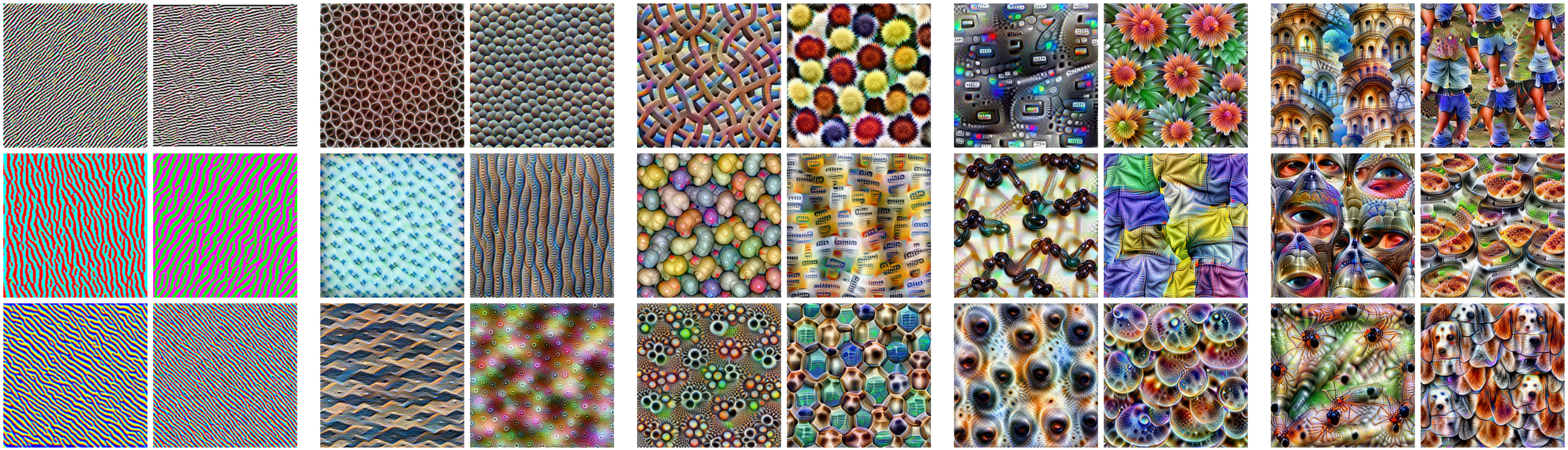
What has been learned by the network?



- Use regions visually attractive to humans?
- Or did it find new features?

Global explanation: what has been learned by each neuron?

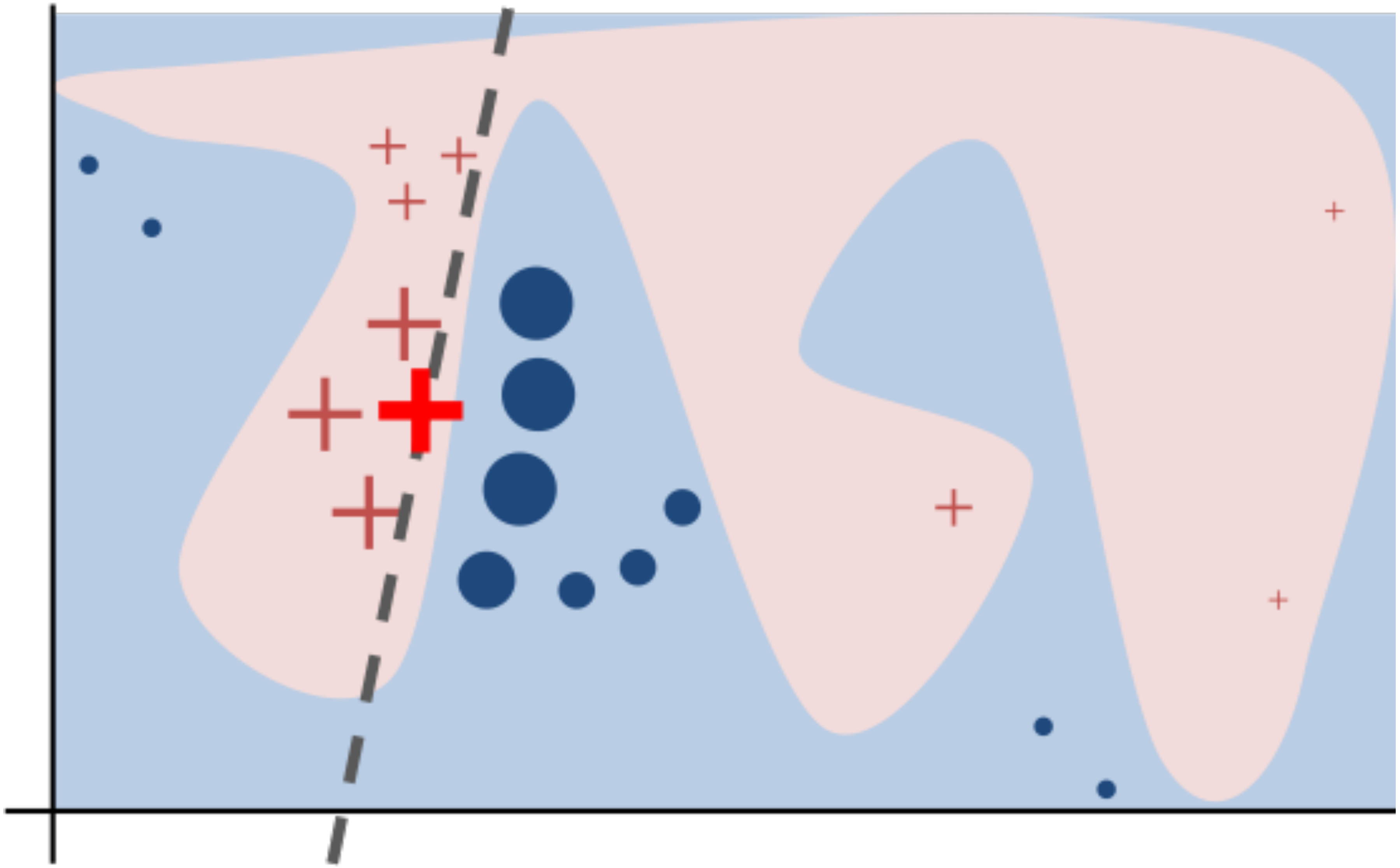
Olah, et al., "Feature Visualization", Distill, 2017.



Edges (layer conv2d0) **Textures** (layer mixed3a) **Patterns** (layer mixed4a) **Parts** (layers mixed4b & mixed4c) **Objects** (layers mixed4d & mixed4e)

- Shallow layers learn edges, textures
- Intermediate layers learn patterns
- Deep layers learn parts and objects

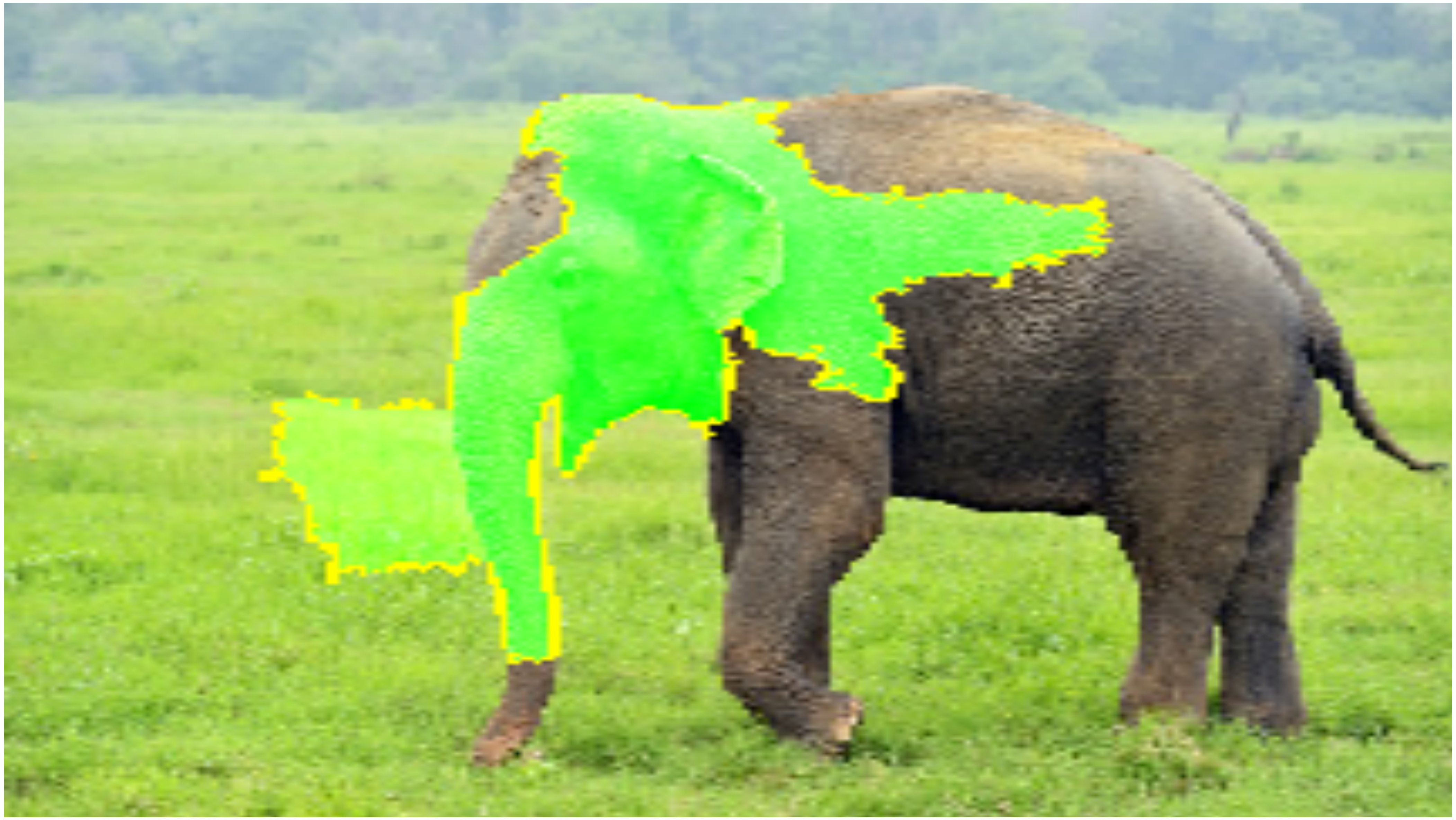
Local explanations



- LIME: perturbs input image by masking super pixels (with similar color), to check the prediction difference

- Class activation map: maps the discriminative regions learned by deep layers to the input image

Explanations from LIME



- LIME: occlude super-pixels (pixels with similar color)

Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. "why should I trust you?"

Explanations from class activation map (CAM)

B. Zhou, A. Khosla, Lapedriza. A., A. Oliva, and A. Torralba. Learning Deep Features for Discriminative Localization. *CVPR*, 2016.

- CAM captures roughly the discriminative region for classification.

Regression activation mask

2D feature maps

weights

$$\text{GradCam} = \frac{1}{c \times k \times k} \sum_{n=1}^{c} A^n \boxed{\sum_{i,j=1}^{k} \frac{\partial f}{\partial A_{ij}^n}}$$

- c: number of channels
- k: transverse size of the feature map
- A_{ij}^n: the value at site (i, j) for the nth feature map before the final output layer.

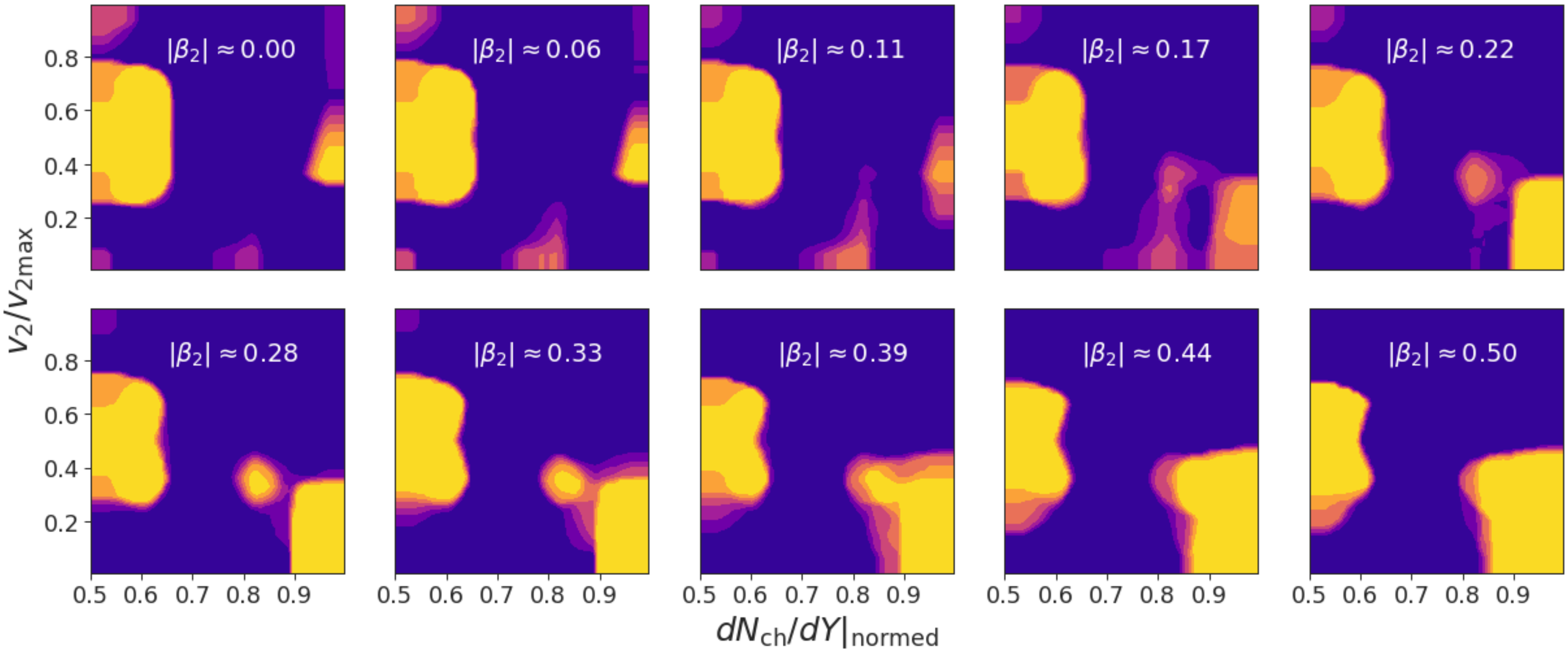
Regression attention mask

$$m = \sum_i \omega_i m_i, \text{ where } m_i = \text{Gradcam}(x_i) > T$$

$$w_i = \frac{\exp\left[-\sigma_i\right]}{\sum_j \exp\left[-\sigma_j\right]}, \qquad \sigma_i = ||f(m_i \circ x_i) - f(x_i)||,$$

- m: regression attention mask (for aligned inputs)
- ω_i: importance weight for the ith mask
- σ_i : the prediction difference between original image and the masked image (discard unimportant regions using $m_i \circ x_i$).

Regression attention mask



- Neural network pays attention to fully overlapped collisions and semi-peripheral collisions.

Conclusion

- Deep neural network is efficient in verifying whether nuclear shape deformation is encoded in the complex output of heavy ion collisions, and it is also successful in decoding it.
- First interpretation model for regression task.
- Helps to locate the most relevant features — open the black-box for knowledge discovery.
- One can apply the same idea to electric/weak charge distribution, neutron skin and short range correlations.