

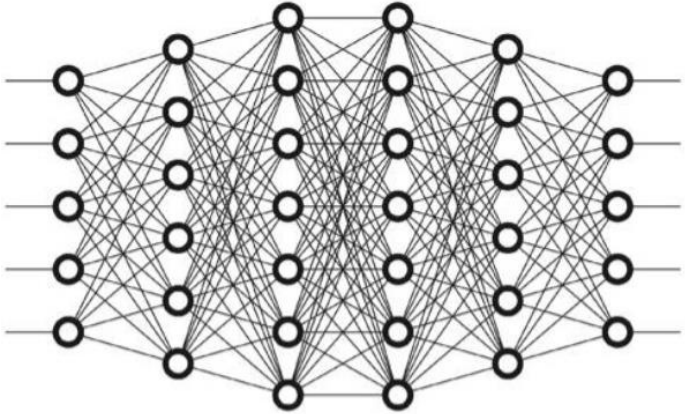
Part III: Effective Complexity of Deep Learning Models

Presenter: Xia Hu

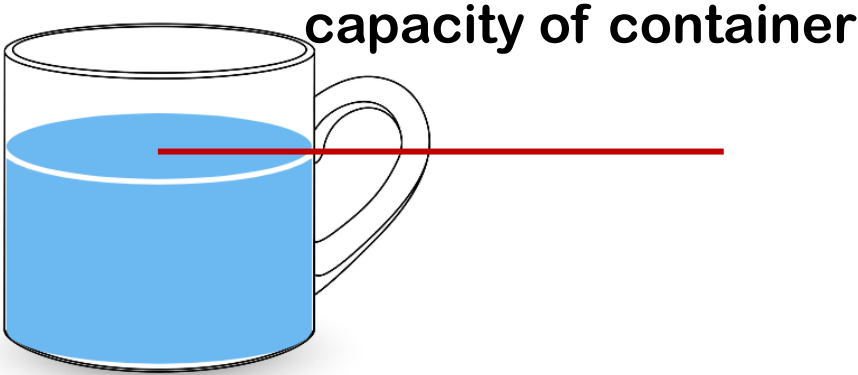
Outline

- **Introduction**
- Measure of Effective Model Complexity
- High Capacity Low Reality Phenomenon
- Discussion

Effective Model Complexity reflects the complexity of the function represented by deep models with specific parameterizations



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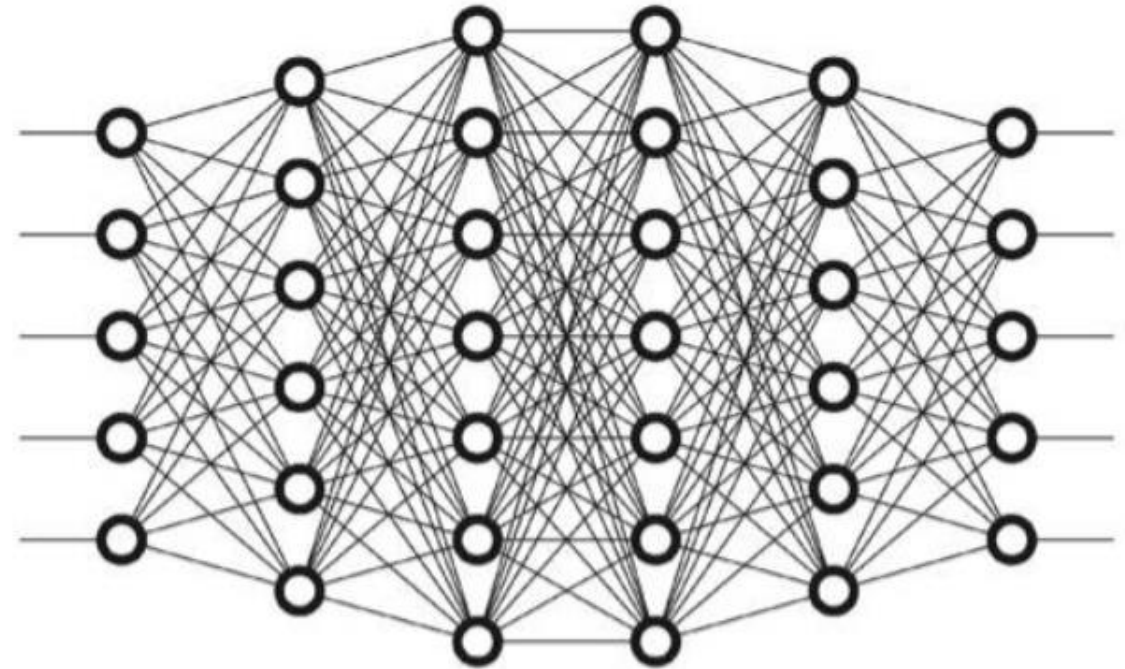
If we informally regard a deep learning model as a “container”.

Effective Model Complexity is affected by ...

- Model framework
- Model size
- Optimization process
- Data complexity

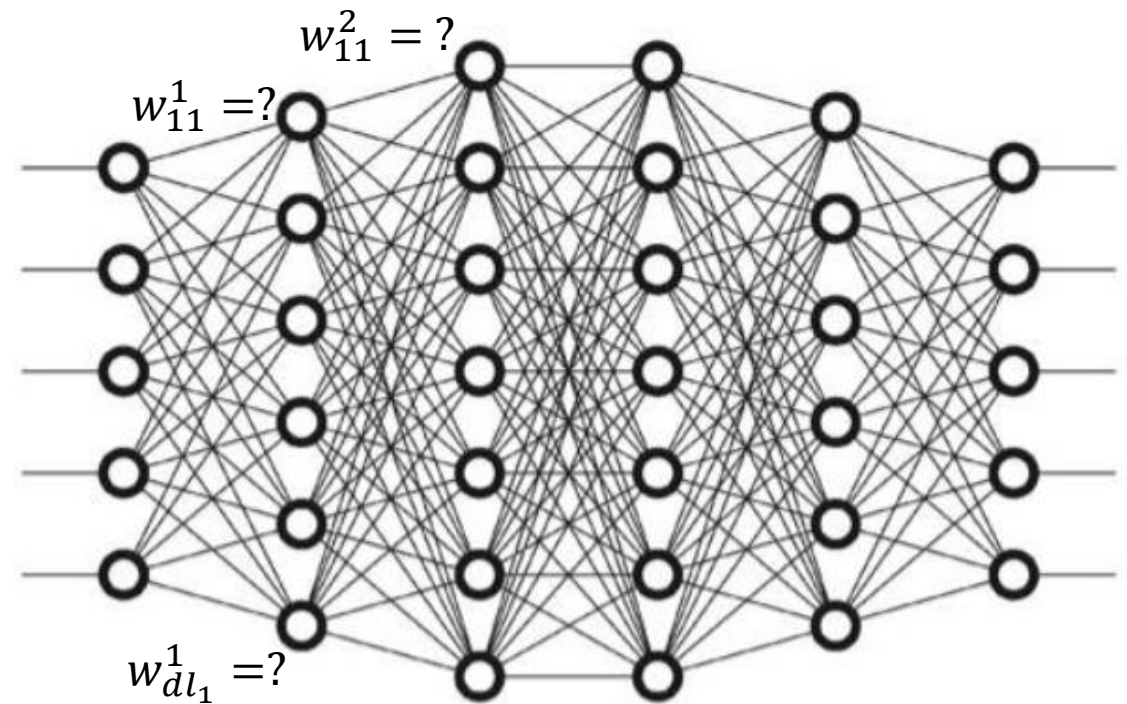
Effective Model Complexity is affected by ...

- Model framework
 - Model type? FCNN, CNN, RNN, ResNet ...
 - Activation function? Tanh, ReLU ...
- Model size
 - Number of hidden layers = ?
 - Width of each layer = ?
 - Number of filters = ?
 - Number of trainable parameters = ?
 - ...



Effective Model Complexity is affected by ...

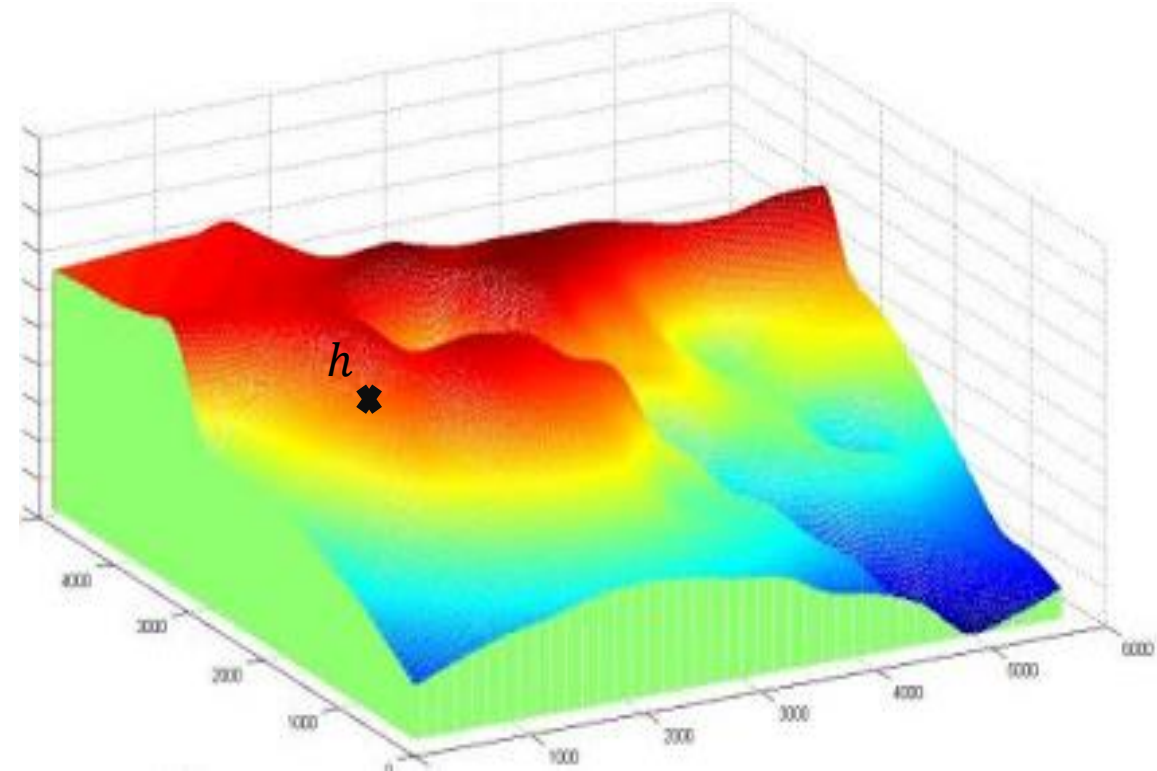
- Optimization process
 - What is the objective function?
 - What is the optimization algorithm?
 - The setting of hyper-parameters
- Data complexity
 - Data dimensionality
 - Number of class labels
 - Data distribution
 - ...



Reflected in the values of model parameters

Effective Model Complexity is affected by ...

- Model framework and size fixed
 - Model N
 - Corresponding hypothesis space H
- Model parameters fixed
 - A specific $h \in H$

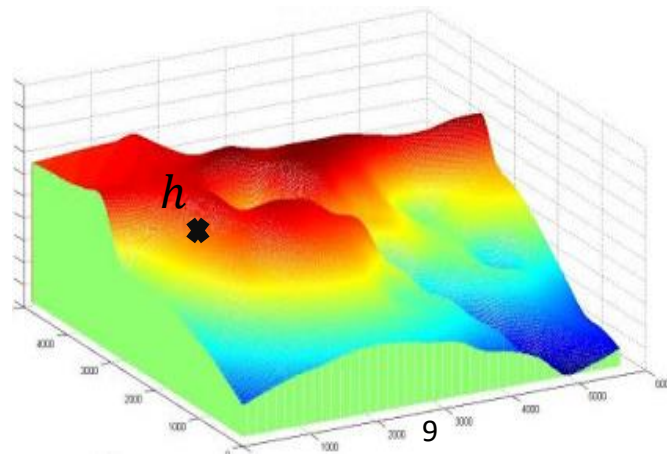


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Measure of Effective Complexity

- Necessity to design quantitative measures for effective complexity of deep learning models.
 - Effective complexity cannot be directly derived from the model structure alone.
 - Different parameter values lead to different effective complexity.
 - Be sensitive to distinguish between models with the same structure but different parameter values.



What is the model complexity of h ?

Measure by Piecewise Linear Property

- Piecewise linear property
 - A finite number of linear regions
 - Local linear model
- Deep neural networks with piecewise linear activation functions
 - ReLU
 - Hard Tanh
 - Maxout
 - ...

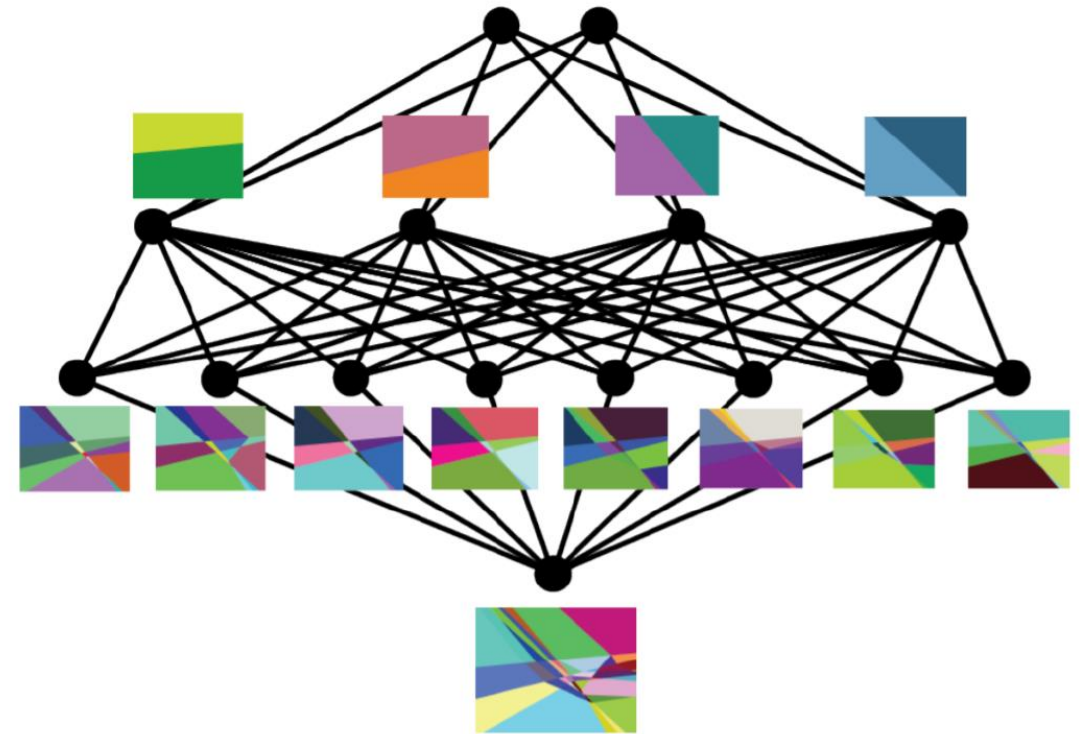


Figure from [Hanin and Rolnick, 2019]

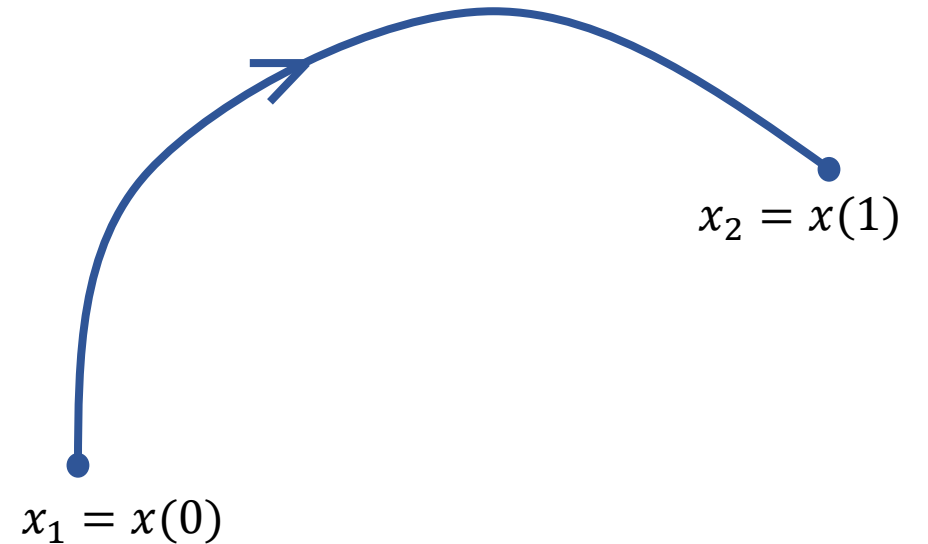
Measure by Piecewise Linear Property

- Trajectory path

$$x(t), t \in [0, 1]$$

- Number of linear regions through trajectory path

$$\Gamma(N(x(t); W))$$



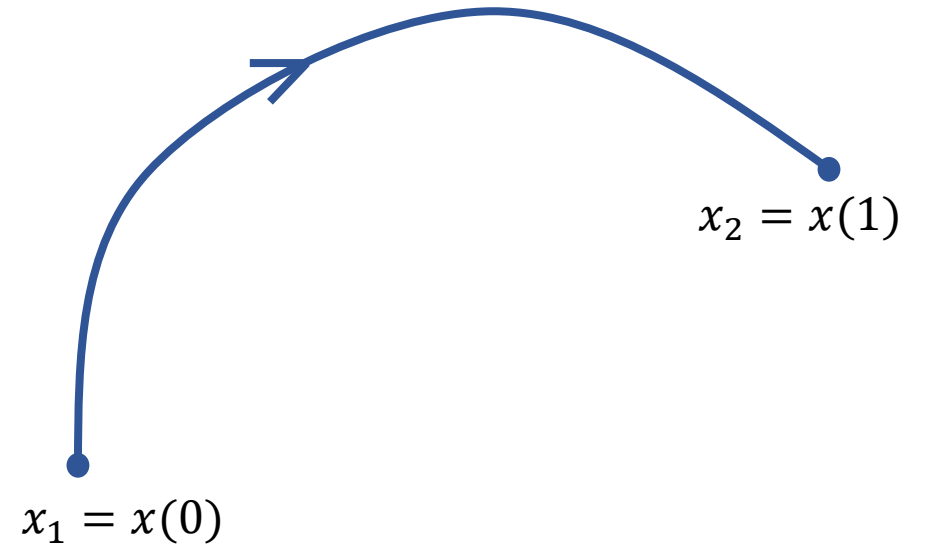
Measure by Piecewise Linear Property

- Trajectory path

$$x(t), t \in [0, 1]$$

- Length of trajectory path

$$l(x(t)) = \int \left\| \frac{dx(t)}{dt} \right\| dt$$



Measure by Piecewise Linear Property

- A deep ReLU neural network

$$E \left[l \left(z^{(i)}(x(t)) \right) \right] \geq O \left(\frac{\sigma_w \sqrt{m}}{\sqrt{m+1}} \right)^i l(x(t))$$



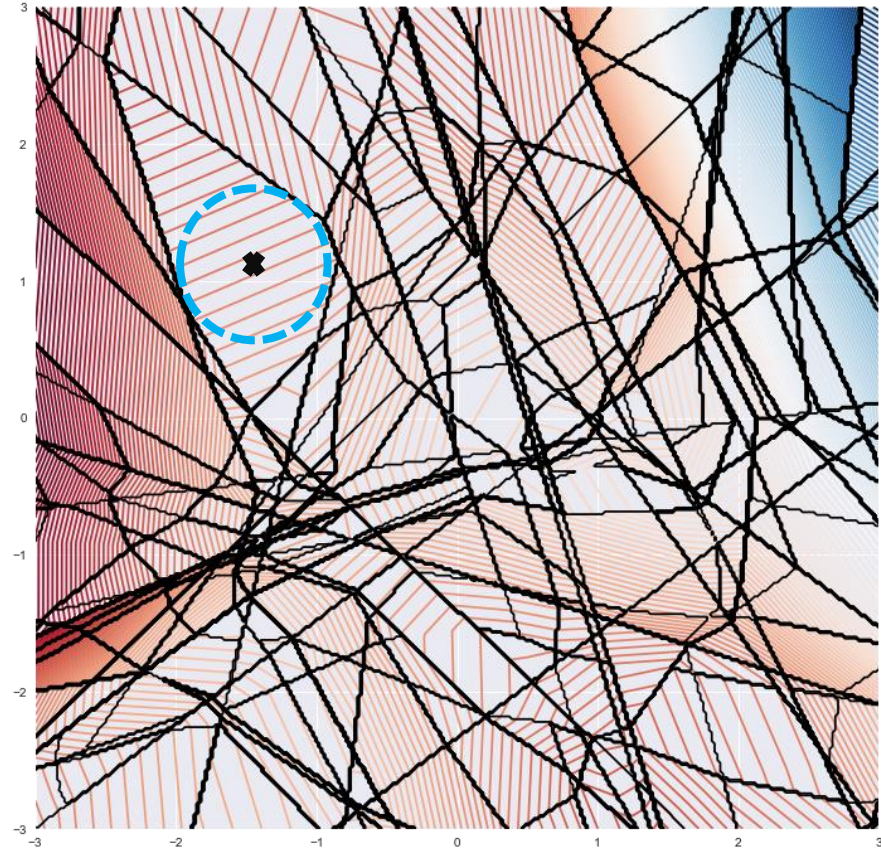
Figure from [Raghu et al., 2019]

Measure by Piecewise Linear Property

- Local sensitivity measure

$$E_{x \in D} [\|J(x)\|_F]$$

- An input is perturbed within the same linear region



Measure by Piecewise Linear Property

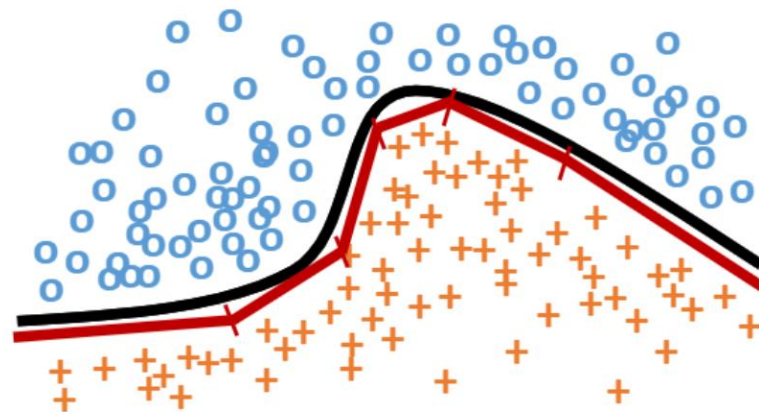
- The volume of boundaries between linear regions

$$E \left[\frac{\text{volume}_{d-1}(B_N \cap K)}{\text{volume}_d(K)} \right] \approx T \cdot M$$

- Given a ReLU neural network $N: \mathbb{R}^d \rightarrow \mathbb{R}, d > 1$

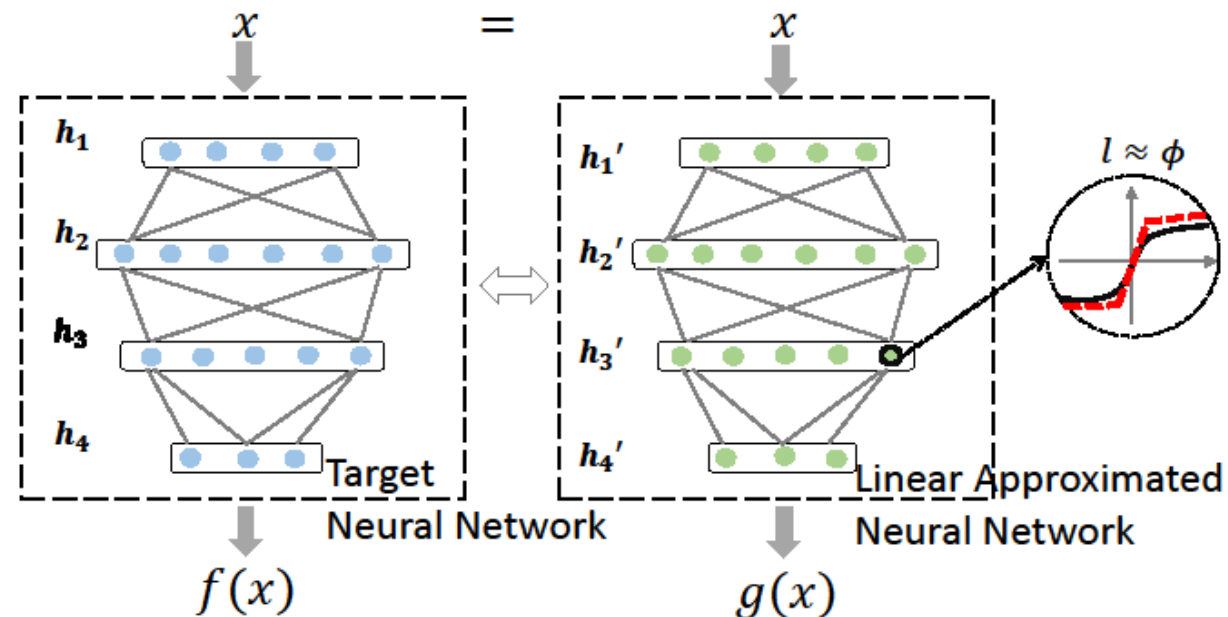
Measure by Piecewise Linear Property

- Deep neural networks with non-piecewise linear activation functions
 - Sigmoid, Tanh, ...
- Make them benefit from the piecewise linear property.



Measure by Piecewise Linear Property

- Linear approximation neural network $g(x)$
 - Piecewise linear approximation with as small number of linear regions as possible



Measure by Piecewise Linear Property

- Number of linear regions of the piecewise linear approximation

$$d \sum_i \log \left(\sum_j k_{i,j} - m_i + 1 \right)$$

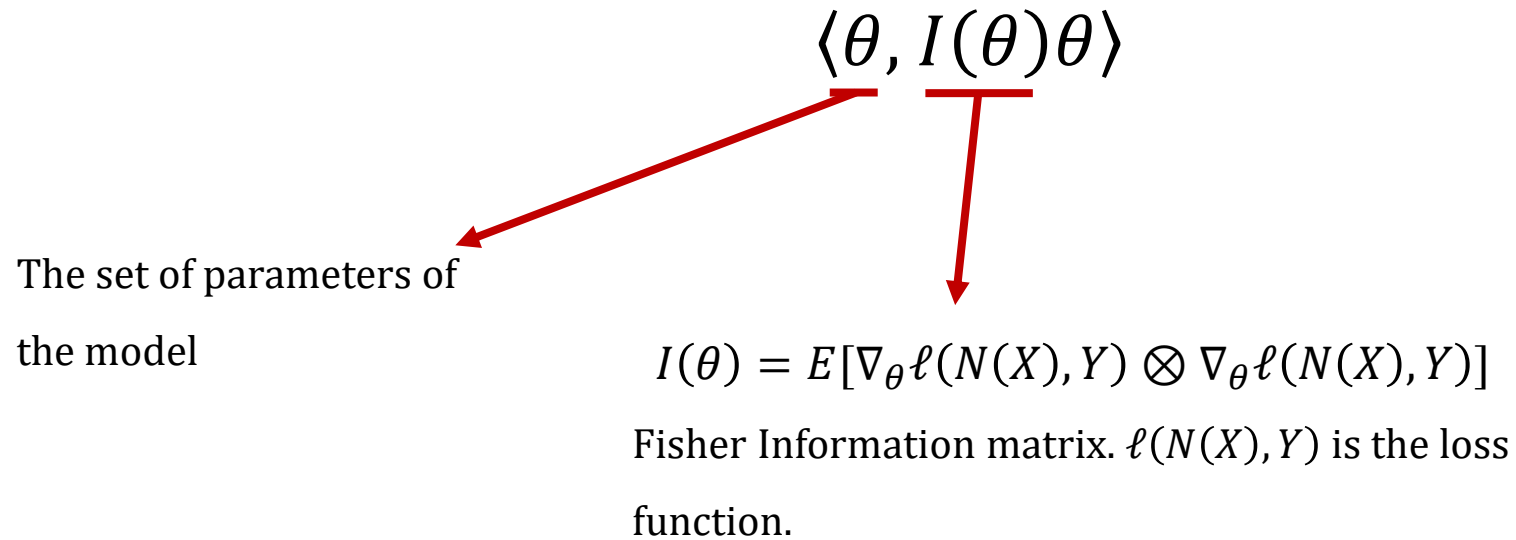
Other Measure Metrics

- Number of samples with non zero training error

$$\max\{n \mid E_{S \sim D}[\text{Error}_S(\Gamma(S))] \leq \epsilon\}$$

Other Measure Metrics

- Fisher-Rao Information

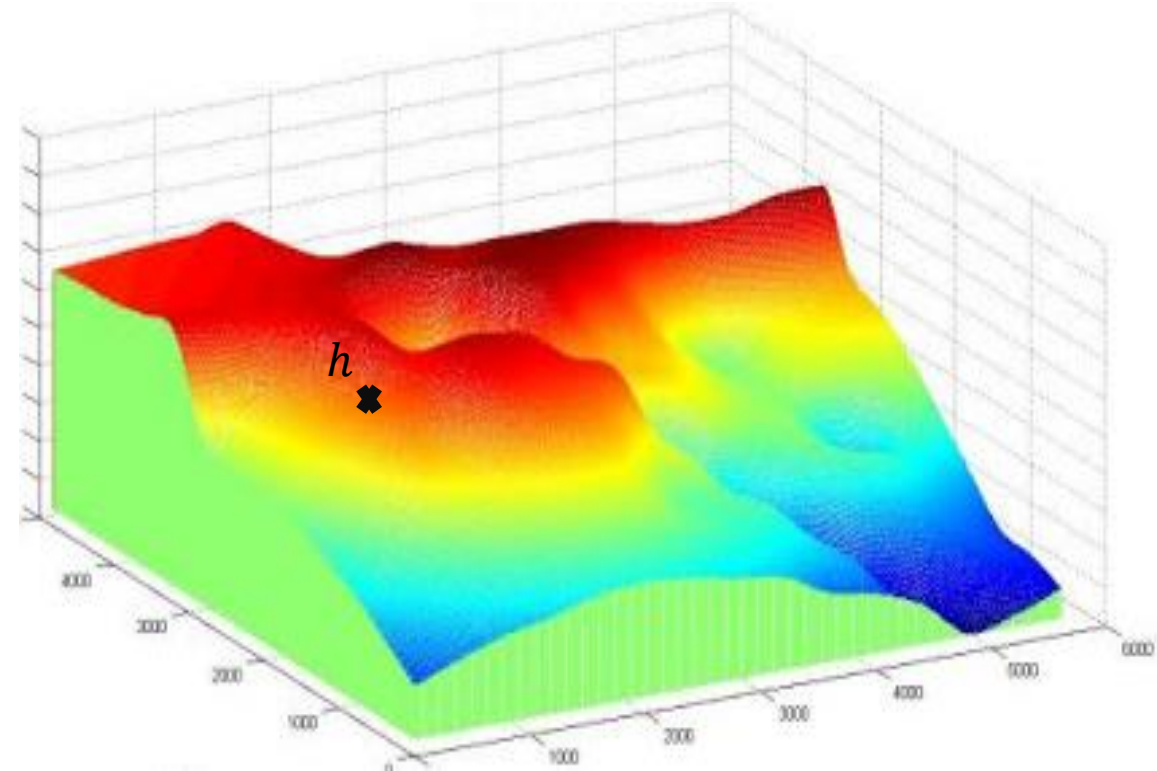


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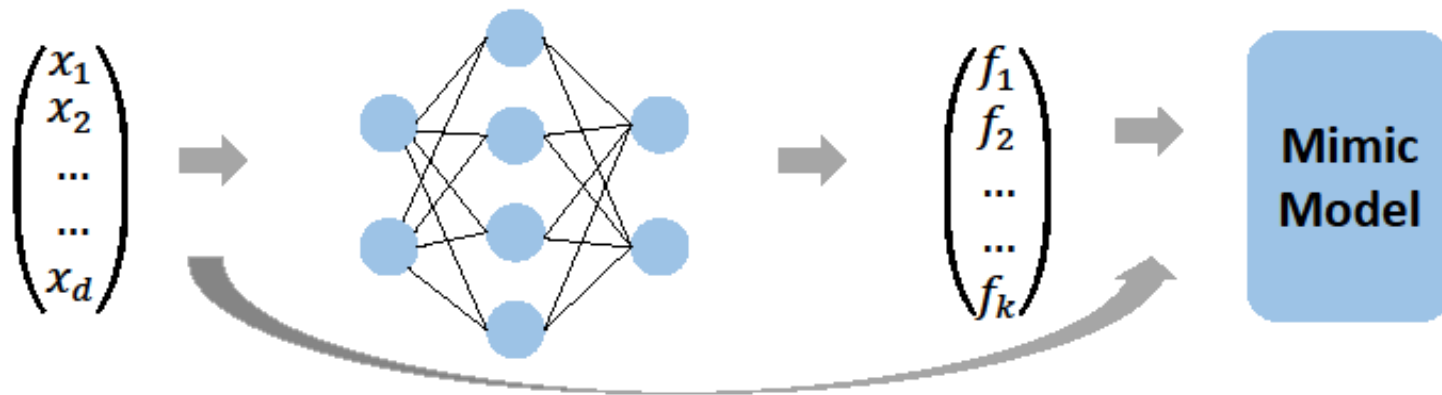
High Capacity Low Reality Phenomenon

- Expressive capacity is high
 - Deep learning models are always highly over-parameterized.
- Effective complexity of learned model is found to be low
- There might be a huge gap!



High Capacity Low Reality Phenomenon

- Given a well-trained deep model
- A shallow model
 - Can mimic the deep model to as high accuracy as the deep one
 - Sometimes only requires the same number of parameters



High Capacity Low Reality Phenomenon

- The effective complexity of the trained deep model might not be very high
 - It can be mimicked by a shallow one
- The strength of deep learning may arise in part from a good match between deep architecture and current training algorithms
 - Deep architectures might be easier to train by current optimization algorithms.

High Capacity Low Reality Phenomenon

- Given a ReLU neural network $N: \mathbb{R} \rightarrow \mathbb{R}$

$$E[\#\{\text{linear regions in } S\}] \approx |S| \cdot T \cdot M$$

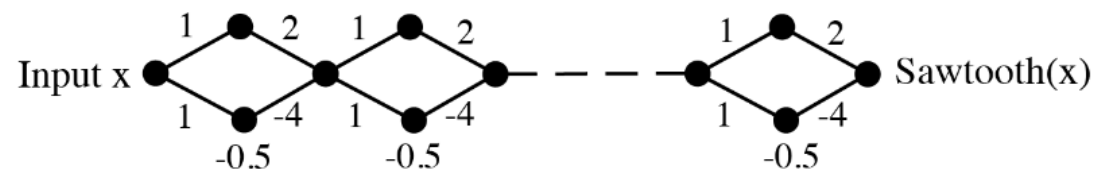
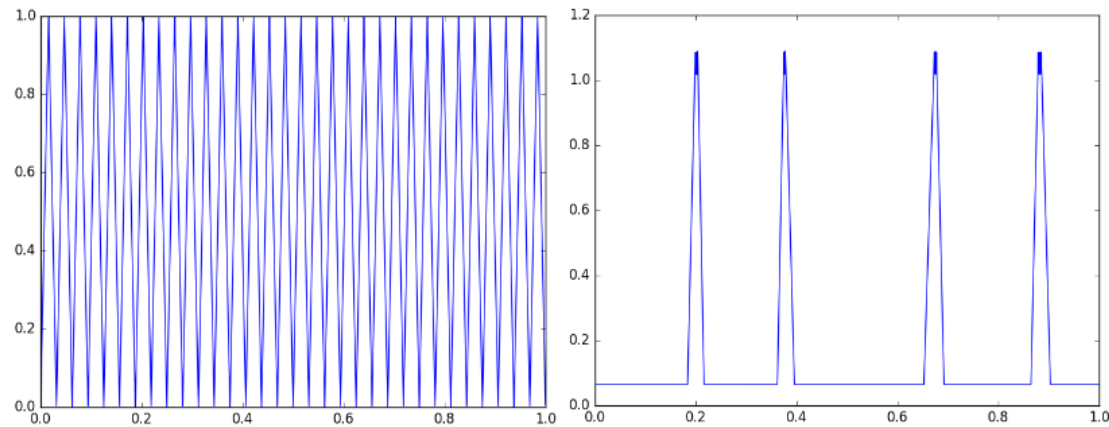


Figure from [Hanin and Rolnick, 2019]

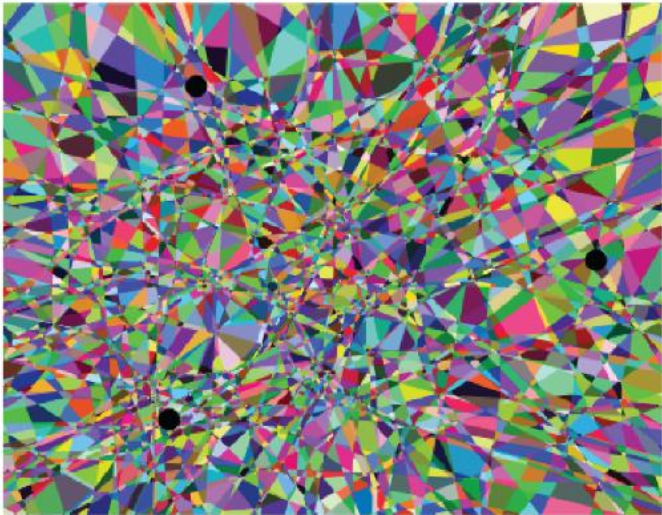
High Capacity Low Reality Phenomenon

- Given a ReLU neural network $N: \mathbb{R}^d \rightarrow \mathbb{R}, d > 1$

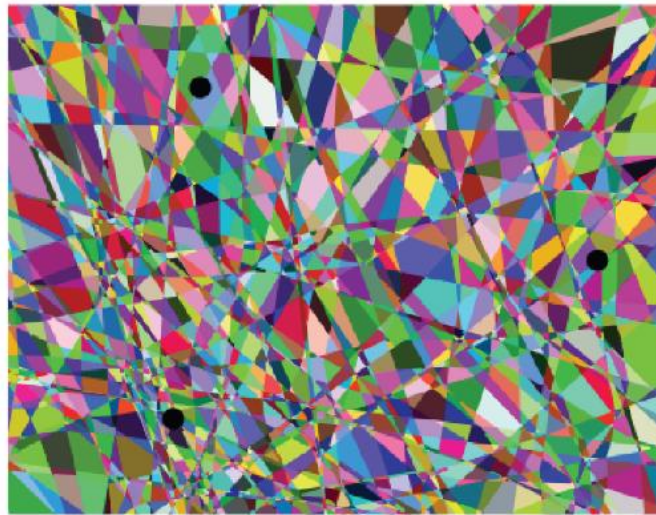
$$E \left[\frac{\text{volume}_{d-1}(B_N \cap K)}{\text{volume}_d(K)} \right] \approx T \cdot M$$

High Capacity Low Reality Phenomenon

Epoch 0: 9744 regions



Epoch 1: 4196 regions



Epoch 20: 8541 regions

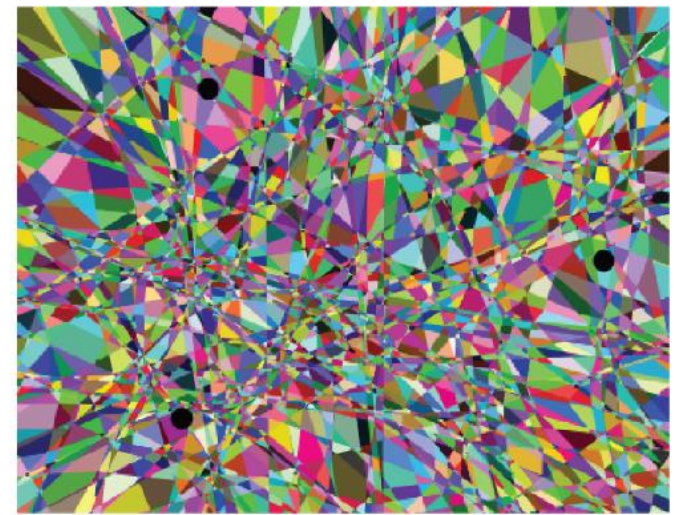


Figure from [Hanin and Rolnick, 2019]

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Discussion

- Effective model complexity is a relatively new, promising and useful problem in deep learning
 - Investigate the usefulness of optimization algorithms
 - Study the rule of regularizations
 - Develop new regularization approaches
 -

Discussion

- Other interesting problems
 - Cross-model comparison
 - Specify granularity of effective complexity measures