Neuron Campaign for Initialization Guided by Information Bottleneck Theory

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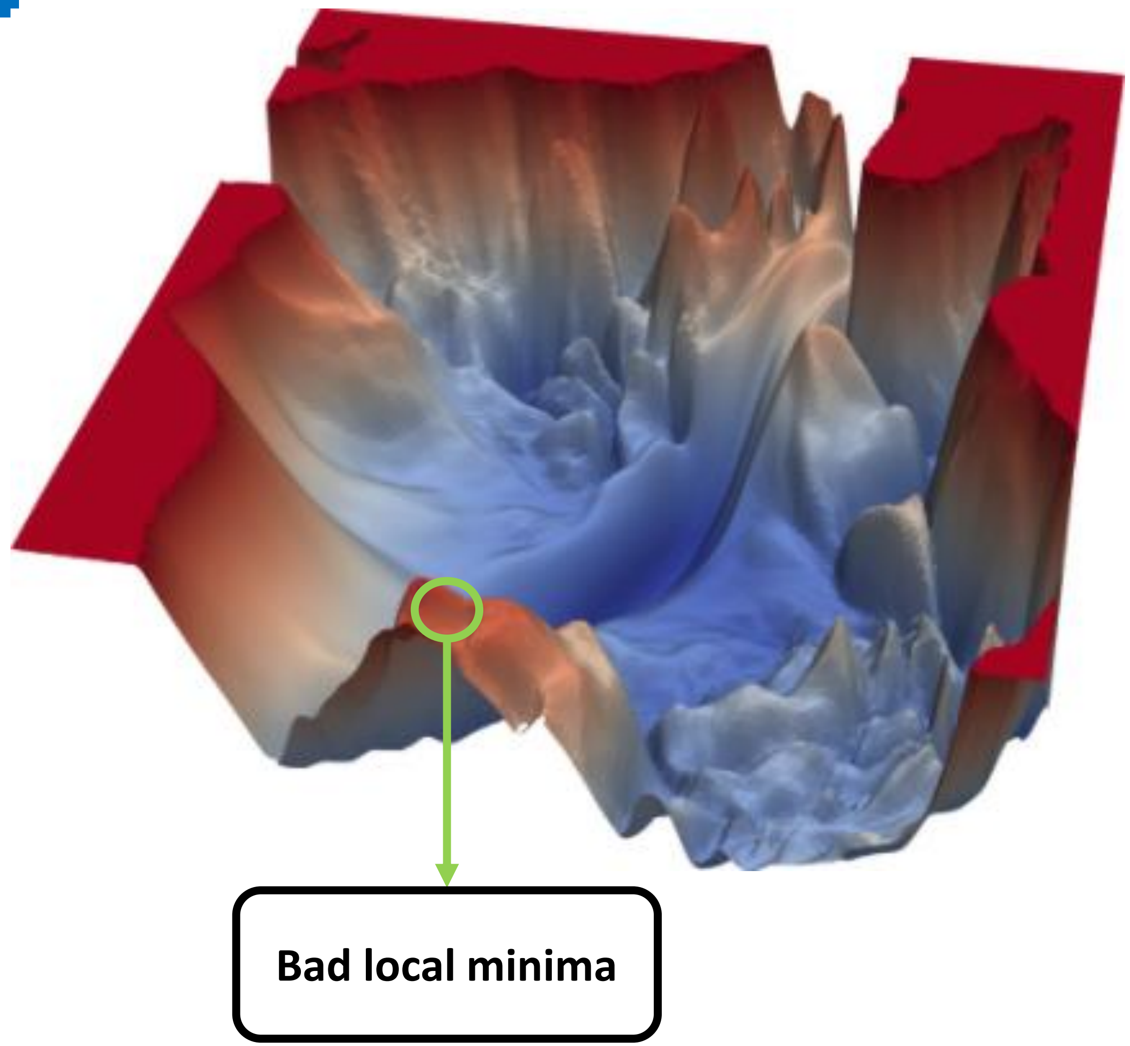
Background

Background



- Training a DNN is to find a good local minima.
- A bad initialization may lead to stuck in a bad local minima.

Related work & Limitation

Traditional Initialization strategy

- Random Initialization

$$W \sim N\left(0, 0.01^2\right)$$

- Gradient Exposure and vanish
  - Forward

$$y = W_3 * W_2 * W_1 * x$$

  - Backward

$$\nabla W_1 = \boxed{\frac{\partial Loss}{\partial f_3}} * \boxed{\frac{\partial f_3}{\partial z_3} * \frac{\partial f_2}{\partial z_2} * \frac{\partial f_1}{\partial z_1}} * \boxed{W_3 * W_2} * X$$

Variance scaling Initialization strategy

- Xavier Initialization (for linear and sigmoid activation function)

$$W \sim U\left[-\frac{\sqrt{6}}{\sqrt{n_j + n_{j+1}}}, \frac{\sqrt{6}}{\sqrt{n_j + n_{j+1}}}\right]$$

- He initialization (for Relu activation function)

$$W \sim N\left(0, \sqrt{\frac{2}{n_j}}\right)$$

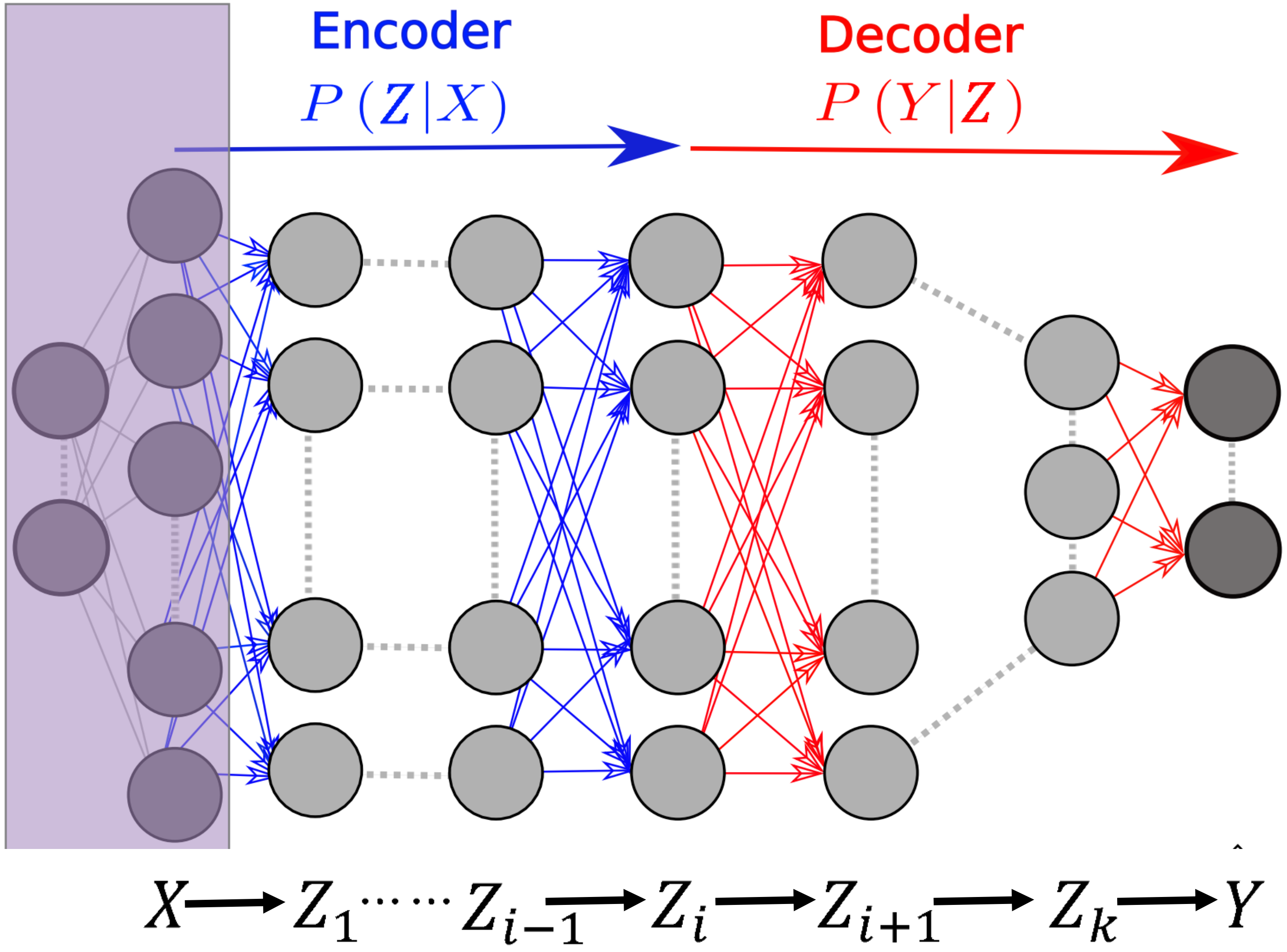
- LSUV (Layer Sequential Unit-Variance initialization)

$$\mathrm{W}_L = \mathrm{W}_L / \sqrt{var(Z_i)}$$

Approach

- **Identify the desire initialization strategy leading to better generalization**
- **Two criteria guided by the Information Bottleneck Theory**
- **Neuron Campaign Initialization algorithm**

Information Bottleneck Theory and measurement



- Input information maintenance:
  $$I(X; Z_i)$$
- Target-related information enhancement
  $$I(Z_i; Y)$$
- Criterion:
  $$\alpha I(X; Z_i) + (1 - \alpha) I(Z_i; Y)$$
- The front layer should focus more on input information maintenance

Criteria Simplification with High Efficiency

- $I(X; Z_i)$ input information maintenance criterion

$$tr(\Sigma_i)$$

  where Σ_i is the covariance matrix of Z_i

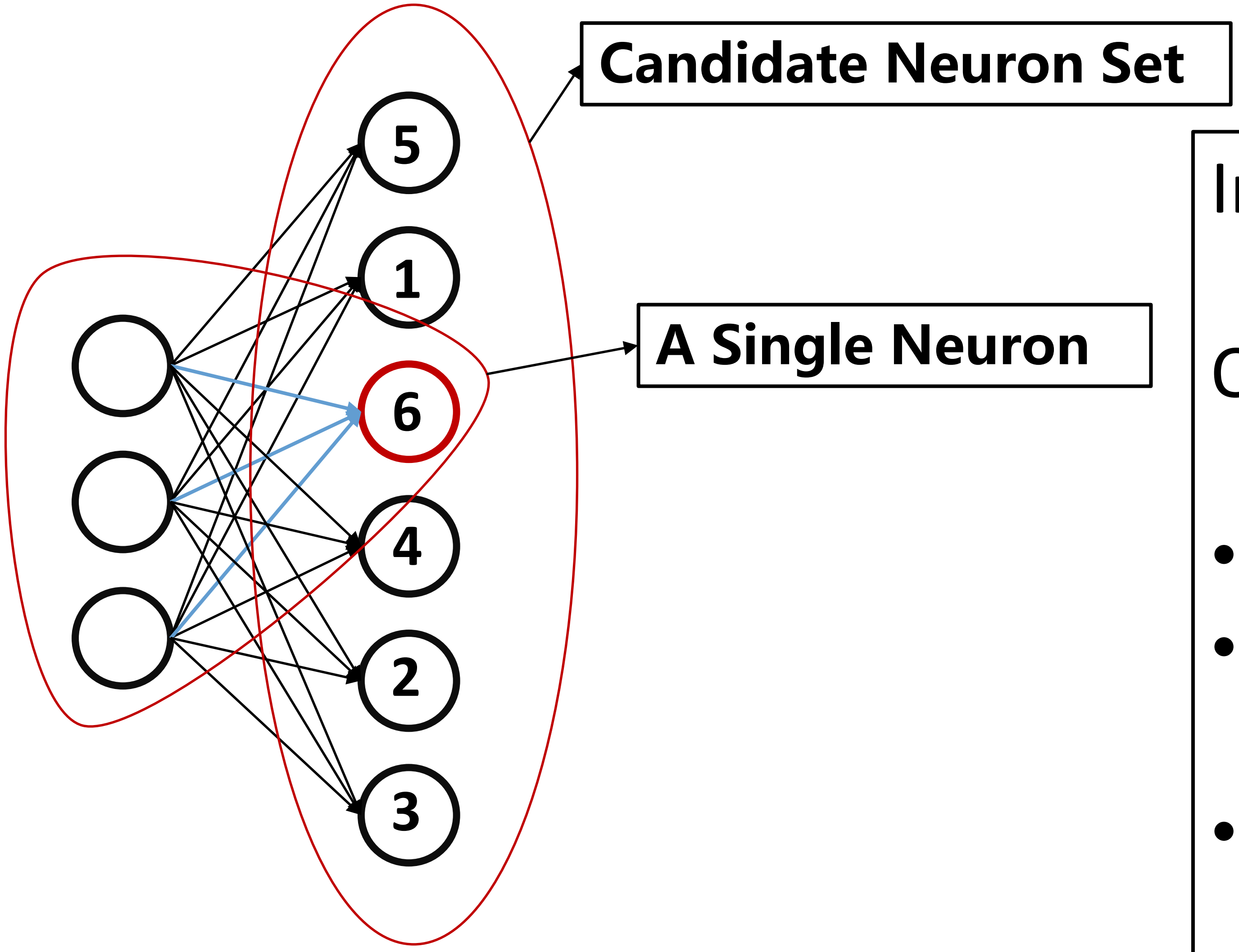
- $I(Z_i; Y)$ target-related maintenance criterion

$$tr\left(\widehat{H}\widehat{H}^T\right) - \frac{1}{N}\sum_{j=0}^{N} tr\left(\hat{Z}_i^T \Pi^j \hat{Z}_i\right)$$

Inter-class variance

Intra-class variance

Neuron Campaign Initialization algorithm



Input: weight with size [3, 6]

Output: weight with size [3, 3]

- Pre-Initialize a large neuron set
- Select neuron with well-designed criteria (based on IB)
- Combine neurons as initial weight

Algorithm details

Algorithm 1 Neuron Campaign initialization algorithm

Input: Candidate weight matrix $\mathbf{W}$

1: **for** t=1 to T **do**

2: Update generalized orthnormalization matrix at t steps: $\mathbf{A}_t = (\mathbf{A}_{t-1}, \mathbf{a}_t^T)^T$

3: Calculate the null space projection by $\mathbf{P}_t = \mathbf{P}_{t-1} - \mathbf{a}_t \mathbf{a}_t^T \mathbf{W}$

4: Select optimal neuron whose index is chosen by $i = \max_i s_i \frac{||\mathbf{p}_t^i||}{||\mathbf{W}_i||}$

5: Update $\mathbf{w}^* = \mathbf{W}_{\cdot,i}$

6: Normalize basis of the generalized orthnormalization matrix as $\mathbf{a}_{t+1} = \mathbf{p}_t^i / ||\mathbf{p}_t^i||$

7: **end for**

Output: Winning neurons formed weight matrix $\mathbf{W}'$

Ensure orthogonality of the selected neurons

Select the neuron with largest score

Evaluation

Experimental details

Table 1: minimal error rate and corresponding epoch comparison of IBCI with baseline methods on MNIST.

Strategy	Layers	Vanilla	LSUV	**IBCI**
Xavier	2	2.04 ± 0.03 (75)	2.05 ± 0.06 (51)	**1.93 ± 0.06 (60)**
	3	1.82 ± 0.05 (52)	1.80 ± 0.07 (63)	**1.71 ± 0.09 (36)**
	5	2.83 ± 0.16 (98)	3.13 ± 0.17 (69)	**2.53 ± 0.09 (78)**
He	2	2.03 ± 0.03 (65)	2.00 ± 0.04 (70)	**1.93 ± 0.07 (57)**
	3	1.83 ± 0.05 (54)	1.86 ± 0.07 (71)	**1.73 ± 0.04 (35)**
	5	2.76 ± 0.07 (80)	2.90 ± 0.12 (77)	**2.62 ± 0.08 (73)**

Hidden layer dimension setting

layers	Hidden Layer Dimension
2	784, 100, 10
3	784, 256, 100, 10
5	784, 32, 32, 32, 32, 10

Ablation Study

Table 2: minimal error rate and corresponding epoch comparison of IBCI with methods with only one criterion.

Strategy	Layers	IBCI	TIE	IIM
Xavier	2	**1.93 ± 0.06 (60)**	2.04 ± 0.07 (58)	2.07 ± 0.09 (84)
	3	**1.71 ± 0.09 (36)**	1.82 ± 0.03 (43)	1.82 ± 0.05 (52)
	5	**2.53 ± 0.09 (78)**	2.68 ± 0.05 (82)	2.57 ± 0.09 (84)
He	2	**1.93 ± 0.07 (57)**	2.07 ± 0.06 (59)	2.034 ± 0.09 (62)
	3	**1.73 ± 0.04 (35)**	1.83 ± 0.07 (42)	1.856 ± 0.05 (55)
	5	**2.62± 0.08 (73)**	2.89 ± 0.11 (74)	2.67 ± 0.12 (86)

Target Information Enhancement, i.e., IBCI without IIM

Input Information Maximization , i.e., IBCI without TIE

Conclusion & Future work

Conclusion & Future Work

Conclusion

- Introduce the Information Bottleneck Theory into practice use.
- Propose a novel and interesting neuron campaign initialization algorithm.

Future work

- Introduce to broader neural network architectures.
- Can we help to understand the recent popular initialization with pretrain?

Reference

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Thanks & QA