

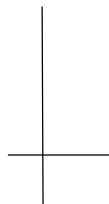
Deep Active Learning with a Neural Architecture Search

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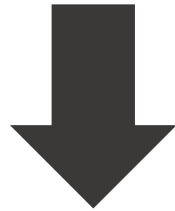
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Conclusion

Problem setting

- AL usually depends on the model output, while many real tasks does not have a off-the-shelf working model architecture.
- **Expressive architecture** will tend to **overfit** when trained over a small sample (early stage in AL).




The model architecture should be optimized
along with the AL process.



Motivation

- Complex models require more training data
- When the training data is limited, we should use a simple model to avoid over fitting.

The capacity of the architectural should:

- Start small.
 - Monotonically increasing along the active learning process.
- 

Algorithm 2 Deep Active Learning with iNAS

```
1: active-iNAS( $U, A_0, \mathcal{A}, Q, b, k$ )
2:  $t \leftarrow 1$ 
3:  $S_t \leftarrow$  Sample  $k$  points from  $U$  at random
4:  $U_0 \leftarrow U \setminus S_1$ 
5: while true do
6:    $A_t \leftarrow$  iNAS( $S, A_{t-1}, \mathcal{A}$ )
7:   train  $f_\theta \in A_t$  using  $S$ 
8:   if budget exhausted or  $U_t = \emptyset$  then
9:     Return  $f_\theta$ 
10:  end if
11:   $S' \leftarrow Q(f_\theta, S_t, U_t, b)$ 
12:   $S_{t+1} \leftarrow S_t \cup S'$ 
13:   $U_{t+1} \leftarrow U_t \setminus S'$ 
14:   $t \leftarrow t + 1$ 
15: end while
```

- Search model
- Query based on the current model

Methodology

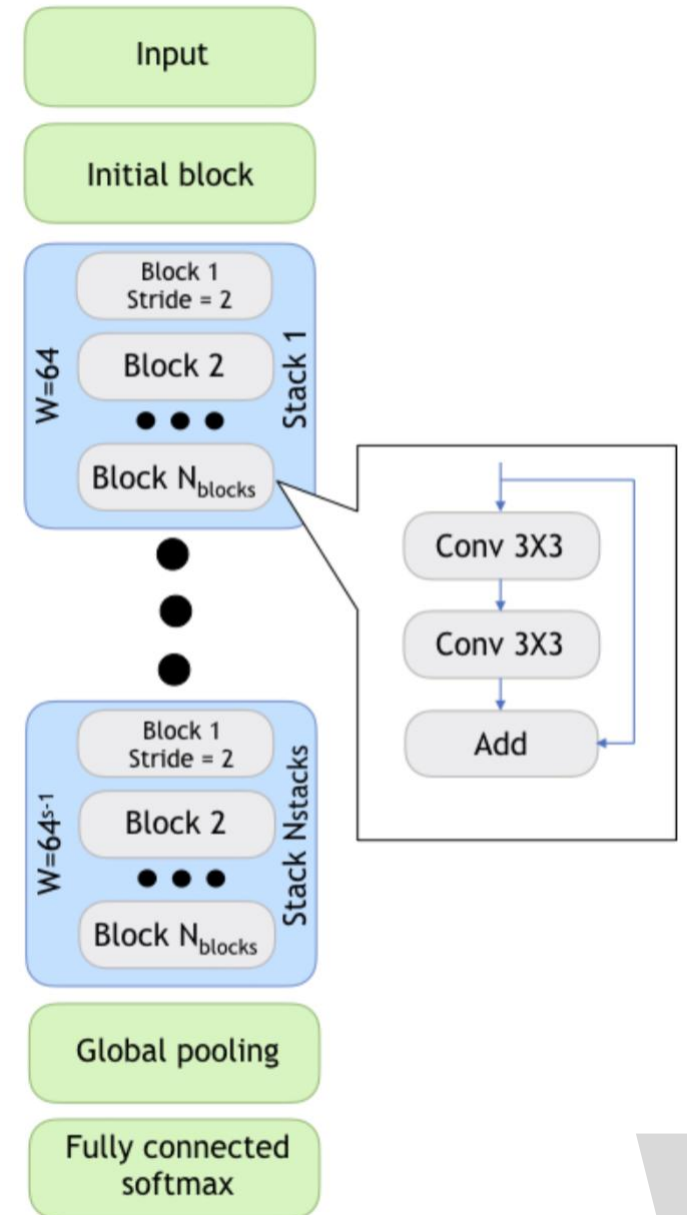
How to estimate the model complexity?

- Use the **depth** of the network.

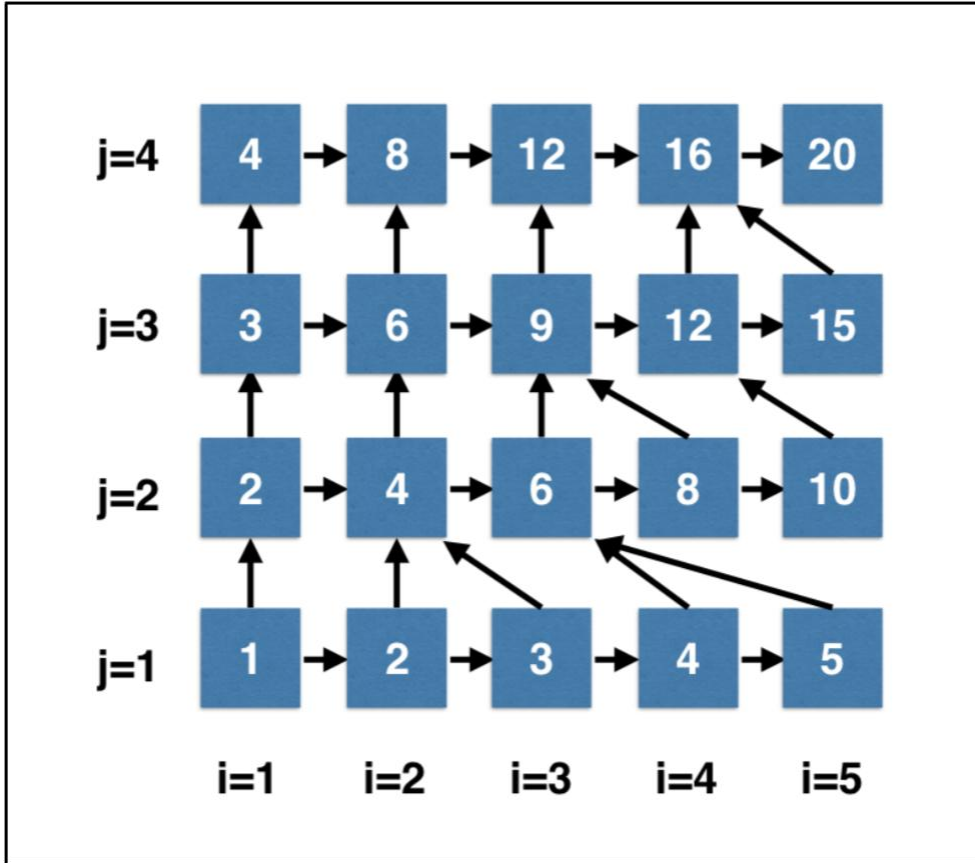
“homogenous” model architectures

- architectures composed of a **single block type** and with **each stack containing the same number of blocks**.
- Denoted as $A(B, \underbrace{N_{blocks}}, \underbrace{N_{stacks}})$

Search



Search Space as an Acyclic Directed Graph (DAG)



A search space up to $A(B, 5, 4)$ plotted on a grid.

Algorithm 1 iNAS

- 1: **iNAS**($S, A(B, i_0, j_0), \mathcal{A}, T_{iNAS}$)
 - 2: Let S', V' be an train-test random split of S
 - 3: **for** $t=1:T_{iNAS}$ **do**:
 - 4: $i \leftarrow i_{t-1}; j \leftarrow j_{t-1}$
 $\mathcal{A}' = \{ A(B, i, j),$
 $A(B, \lfloor \frac{ij}{j+1} \rfloor + 1, j + 1),$
 $A(B, i + 1, j) \}$
 - 5: $\mathcal{A}' = \mathcal{A}' \cap \mathcal{A}$
 - 6: $A(B, i_t, j_t) =$
 $= \operatorname{argmin}_{A \in \mathcal{A}'} \hat{r}_{V'}(\operatorname{argmin}_{f_\theta \in A} \hat{r}_{S'}(f_\theta))$
 - 7: **if** $A(B, i_t, j_t) = A(B, i_{t-1}, j_{t-1})$ **then**
 - 8: **break**
 - 9: **end if**
 - 10: **end for**
 - 11: **end for**
 - 12: Return $A(B, i_t, j_t)$
-

Experiments

- Resnet-18 ($A(B_r, 2, 4)$)
- $A(B_r, 1, 2)$
- Active-iNAS ($A(B_r, 1, 1) \rightarrow A(B_r, 12, 5)$)

- CIFAR-10
- CIFAR-100
- SVNH

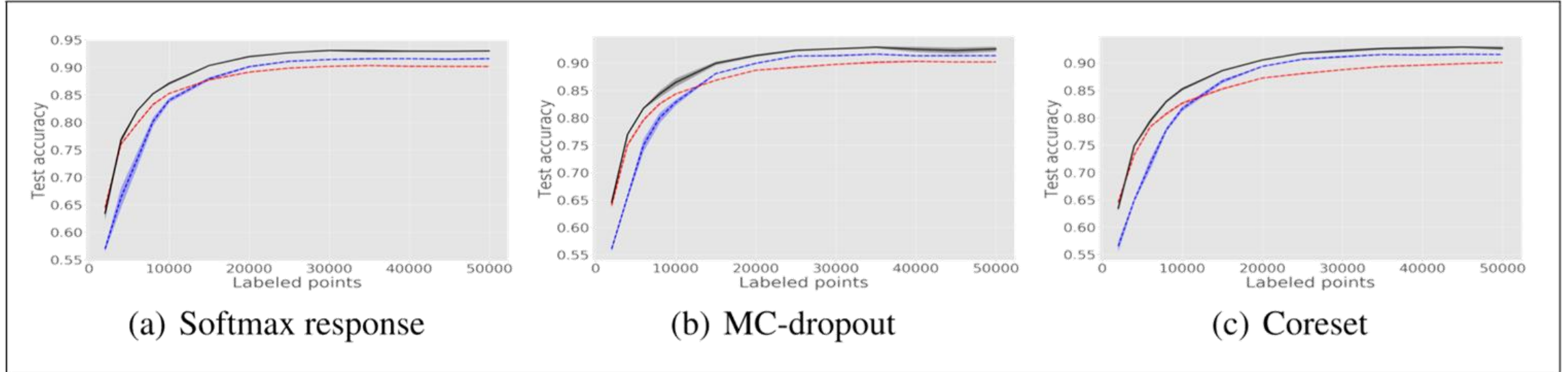


Figure 2: Active learning curves for CIFAR-10 dataset using various query functions, (a) softmax response, (b) MC-dropout, (c) coreset. In black (solid) – Active-iNAS (ours), blue (dashed) – Resnet-18 fixed architecture, and red (dashed) – $A(B_r, 1, 2)$ fixed.

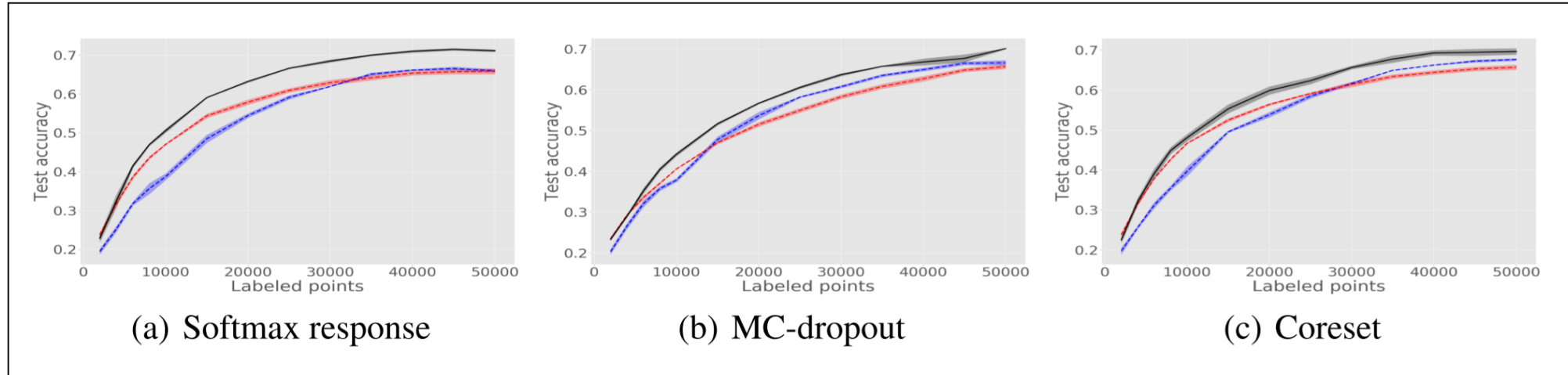


Figure 3: Active learning curves for CIFAR-100 dataset using various query functions, (a) softmax response, (b) MC-dropout, (c) coreset. In black (solid) – Active-iNAS (ours), blue (dashed) – Resnet-18 fixed architecture, and red (dashed) – $A(B_r, 1, 2)$ fixed.

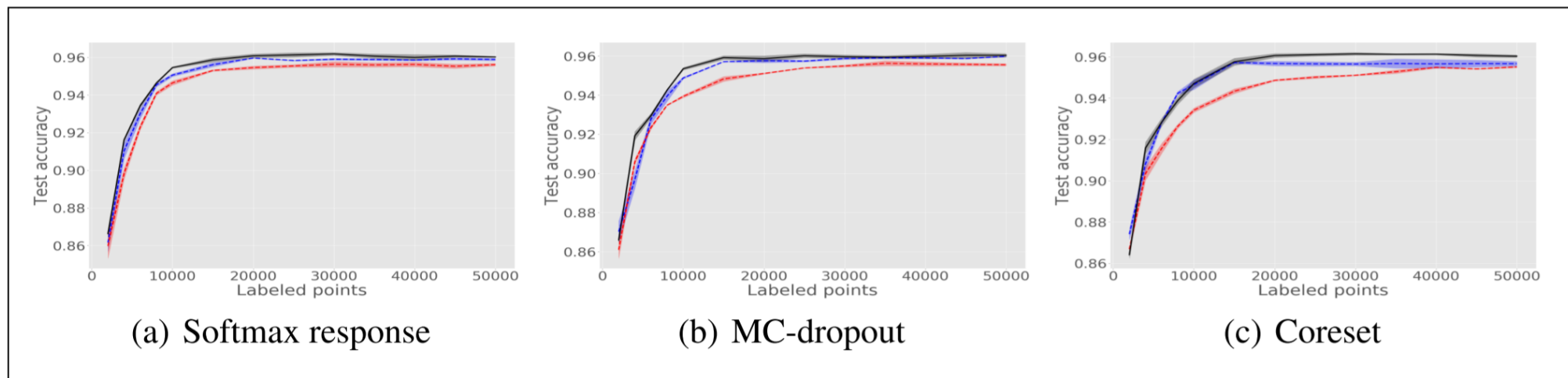


Figure 4: Active learning curves for SVHN dataset using various query functions, (a) softmax response, (b) MC-dropout, (c) coreset. In black (solid) – Active-iNAS (ours), blue (dashed) – Resnet-18 fixed architecture, and red (dashed) – $A(B_r, 1, 2)$ fixed.

Comparison of active-iNAS for various query functions

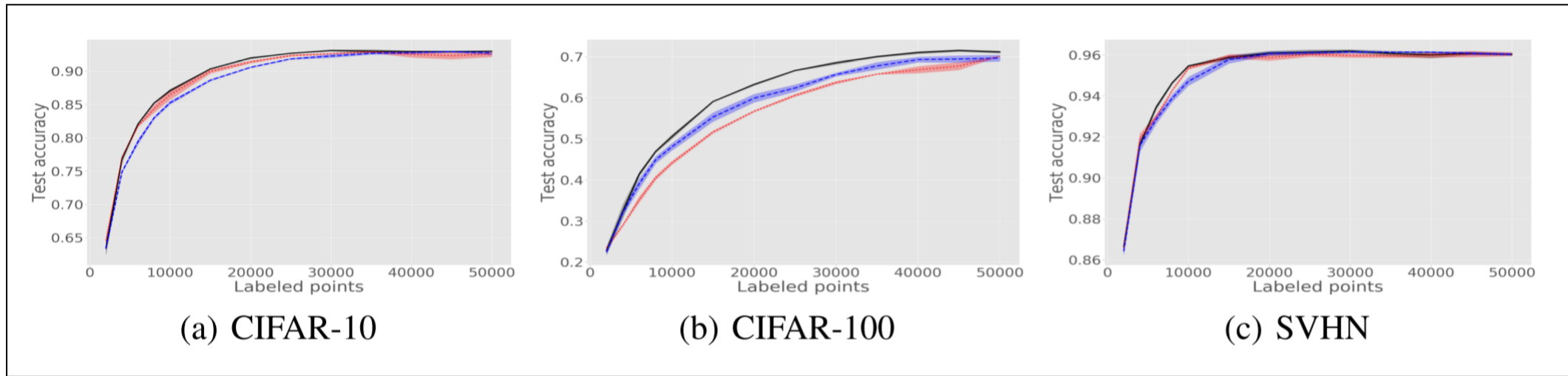
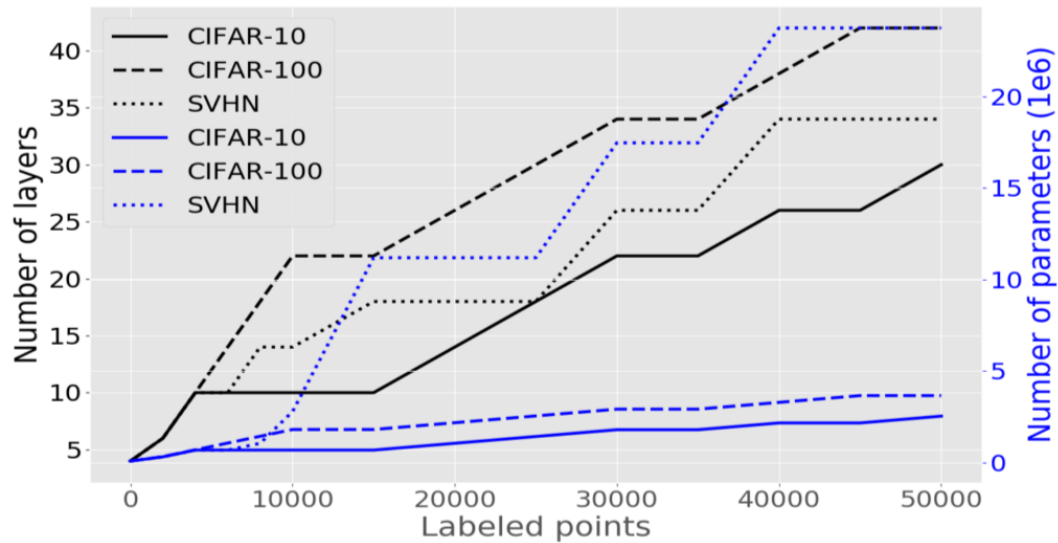
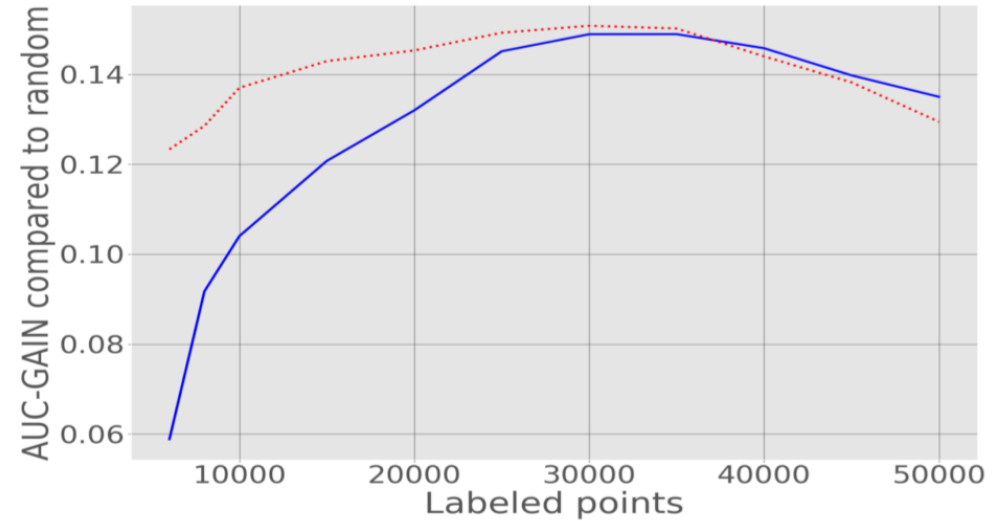


Figure 5: Comparison of active-iNAS for various query functions across three datasets, (a) CIFAR10, (b) CIFAR-100, (c) SVHN. In black (solid) – softmax response, red (dashed) – MC-dropout, and blue (dashed) – coresnet.

Model complexity



(a)



(b)

(b) Comparison of AUC-GAIN for softmax response active learning over CIFAR-10 for two architectures. In red (solid), the small architecture (A(Br, 1, 2)) and in blue (dashed) the Resnet-18 architecture (A(Br, 2, 4)).

感谢聆听！

