

Unsupervised NAS

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Neural Architecture Search: Unsupervised Learning of Features and Neural Architectures.

- There is work on learning visual features by exploiting a range of signals of techniques –rotation, colorization, jigsaw puzzle.
- Unsupervised features are very useful. E.g., (i) to enable a simple classifier for classification given these features as input, (ii) to perform domain transfer, (iii) even to model how an infant learns image features?
- But what about learning the neural architecture? There is much recent work on Neural Architecture Search (NAS). But can this be learnt in an unsupervised manner?
- Yes! Chenxi Liu et al. “Are Labels Necessary for Neural Architecture Search”? Arxiv. 2020.



Signals to Exploit of Unsupervised Learning

In this project, we rely on **self-supervised objectives**

- We will use “unsupervised” and “self-supervised” interchangeably
- These objectives were originally developed to transfer **learned weights**
- We study their ability to transfer **learned architecture**

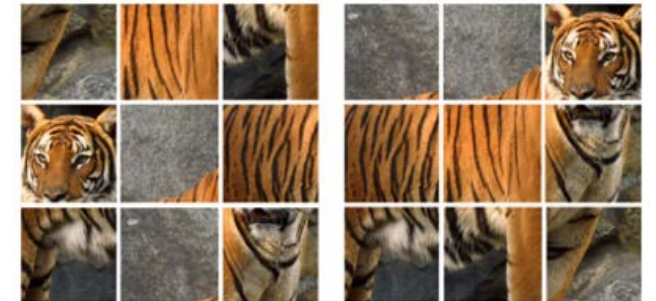
Rotation



Colorization



Jigsaw Puzzle



Gidaris, Spyros, Praveer Singh, and Nikos Komodakis. "Unsupervised representation learning by predicting image rotations." In ICLR. 2018.

Zhang, Richard, Phillip Isola, and Alexei A. Efros. "Colorful image colorization." In ECCV. 2016.

Noroozi, Mehdi, and Paolo Favaro. "Unsupervised learning of visual representations by solving jigsaw puzzles." In ECCV. 2016.

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Using these self-supervised objectives, we conduct [two sets of experiments](#) of complementary nature

- Sample-Based
- Search-Based

Sample-Based Experiments

Experimental design:

- Sample 500 unique architectures from a search space
- Train them using **Rotation**, **Colorization**, **Jigsaw Puzzle**, and **(supervised) Classification**
- Measure rank correlation between pretext task accuracy and target task accuracy

Advantage:

- Each network is trained and evaluated individually

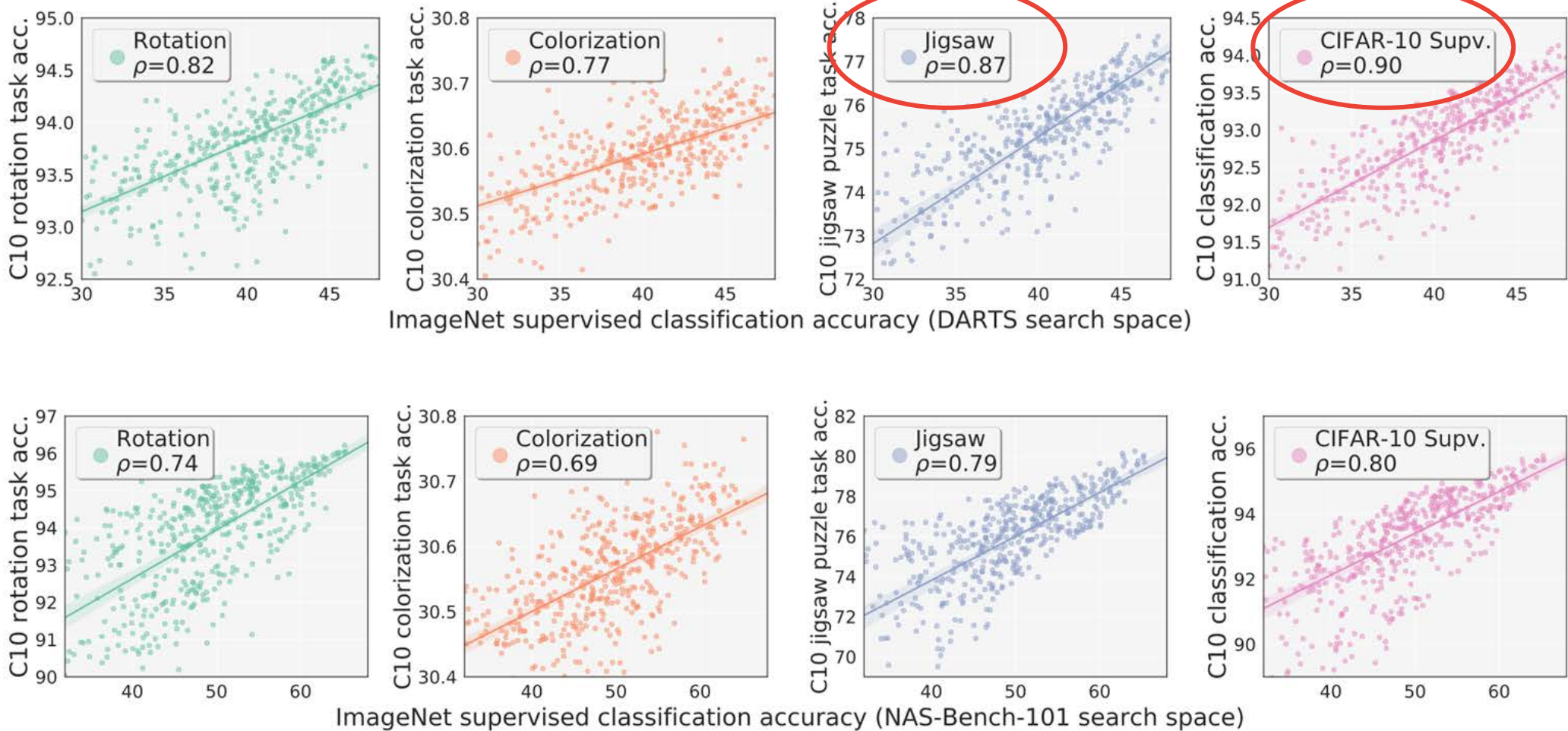
Disadvantage:

- Only consider a small, random subset of the search space

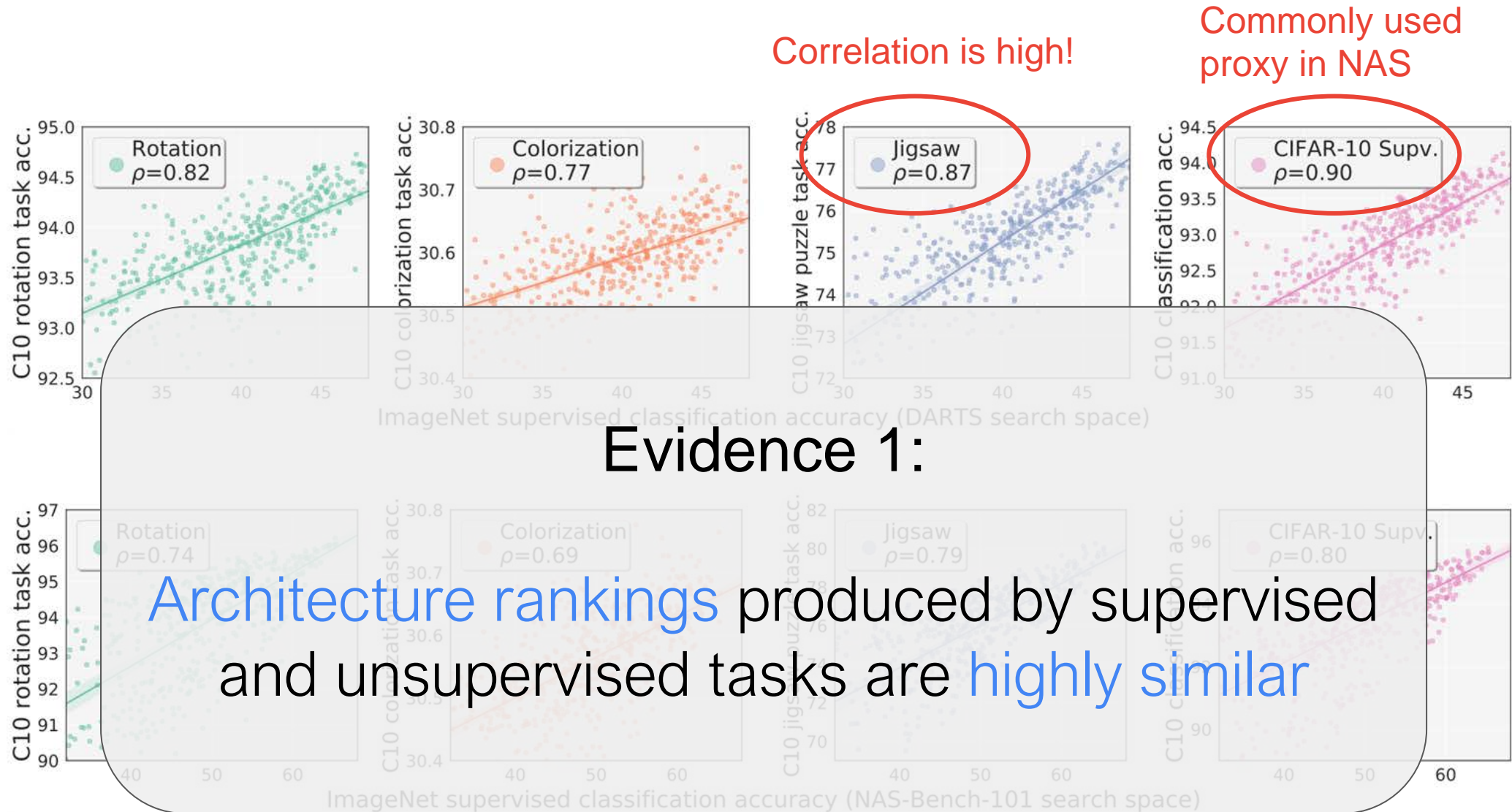
Sample-Based Experiments

Correlation is high!

Commonly used proxy in NAS



Sample-Based Experiments



Search-Based Experiments

Experimental design:

- Take a well-established NAS algorithm (DARTS)
- Replace its search objective with Rotation, Colorization, Jigsaw Puzzle
- Train from scratch the searched architecture on target data and task

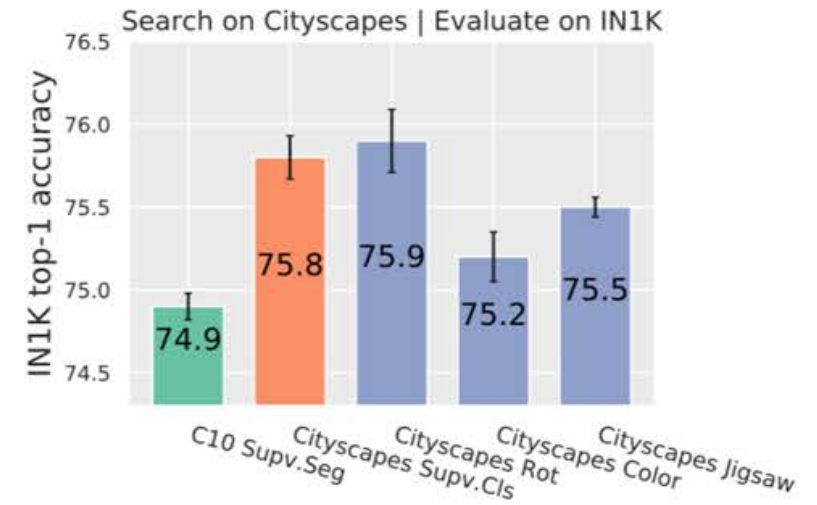
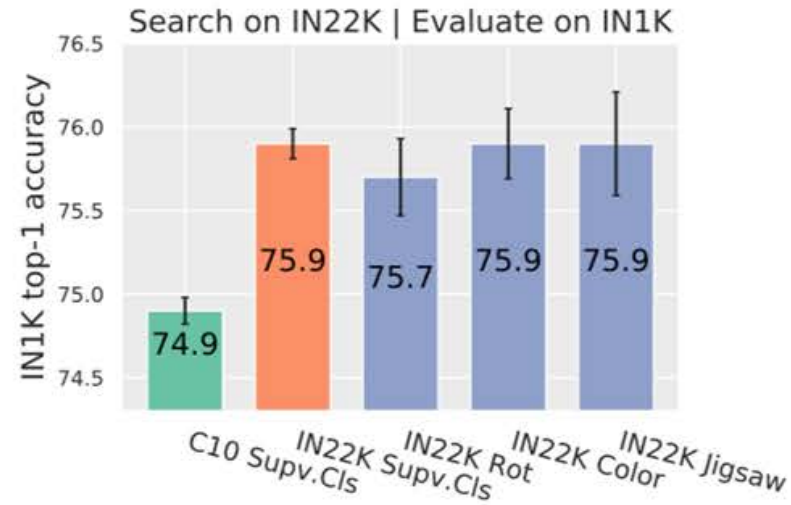
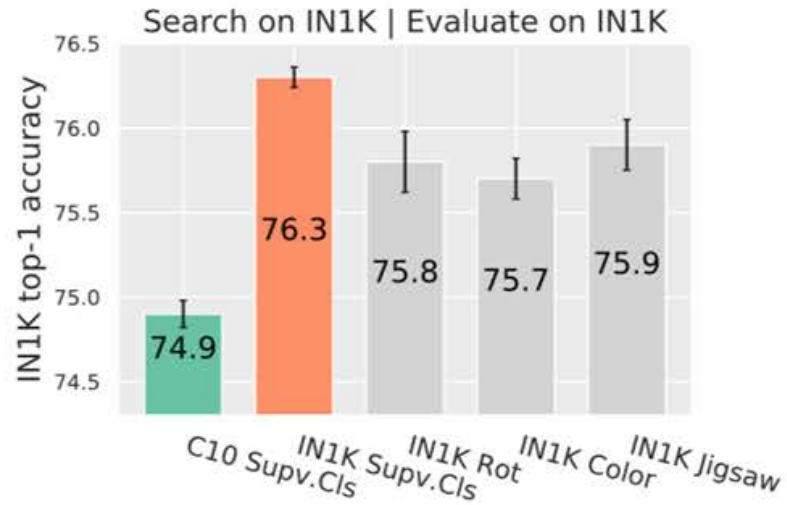
Advantage:

- Explore the entire search space

Disadvantage:

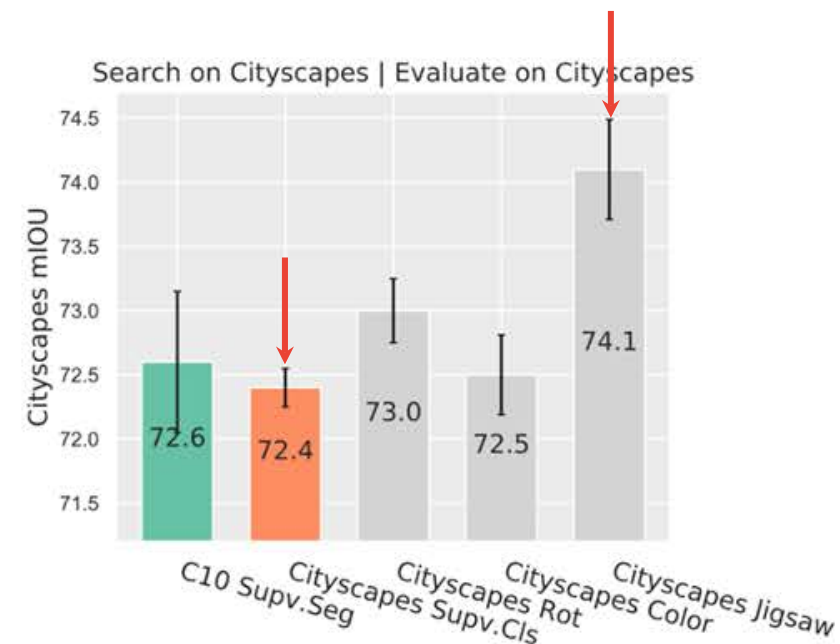
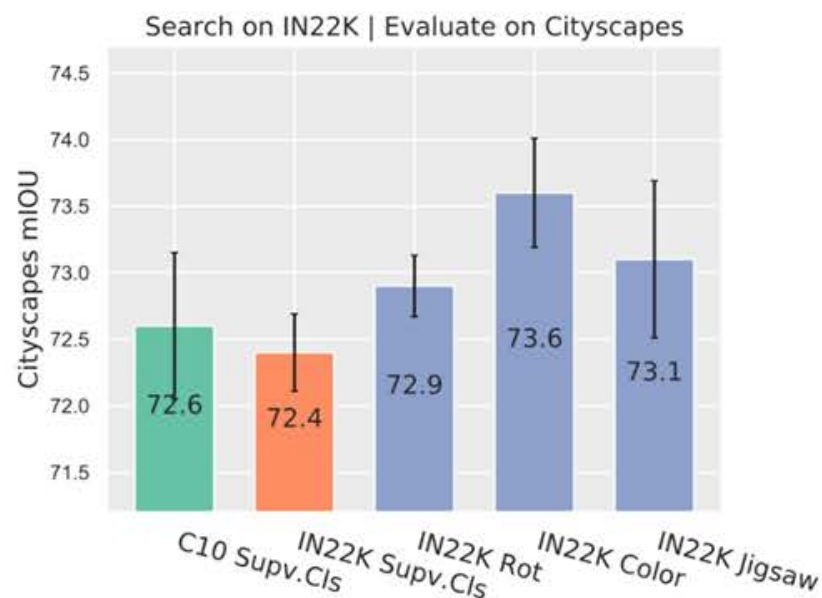
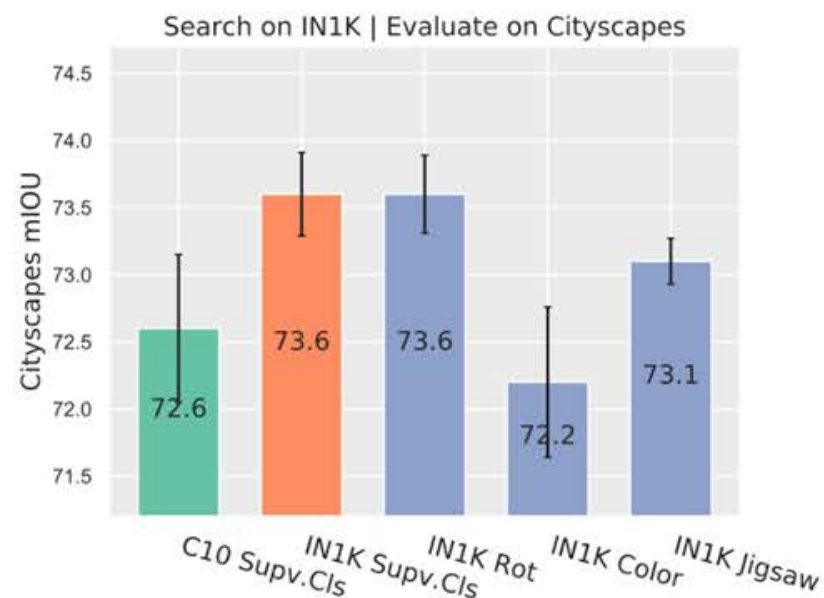
- Training dynamics mismatch between search phase and evaluation phase

Search-Based Experiments: ImageNet Classification



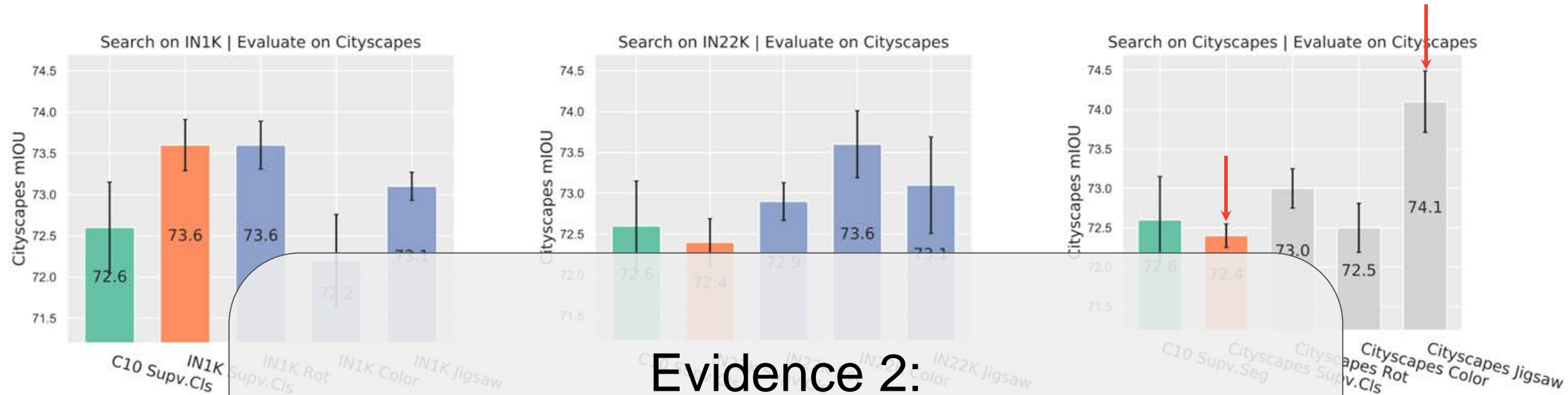
- UnNAS is better than the commonly used **CIFAR-10 supervised proxy**
- UnNAS is comparable to **(supervised) NAS** across search tasks and datasets
- UnNAS even outperforms the state-of-the-art (75.8) which uses a more sophisticated algorithm

Search-Based Experiments: Cityscapes Sem. Seg.



- UnNAS is better than the commonly used **CIFAR-10 supervised proxy**
- UnNAS is comparable to **(supervised) NAS** across search tasks and datasets
- Even a case where UnNAS is **clearly better** than supervised NAS

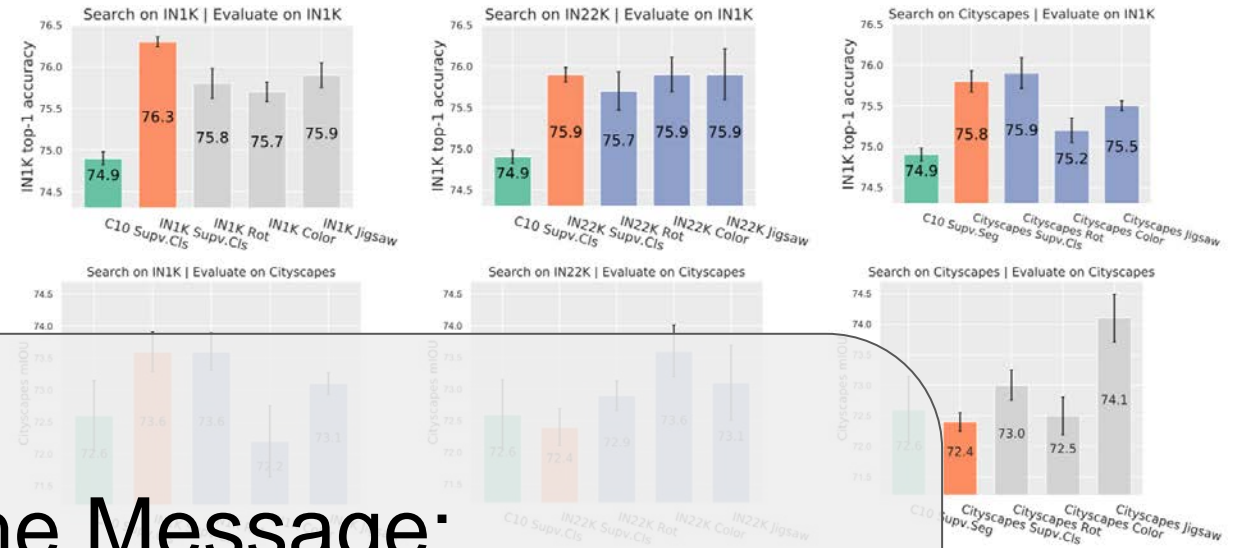
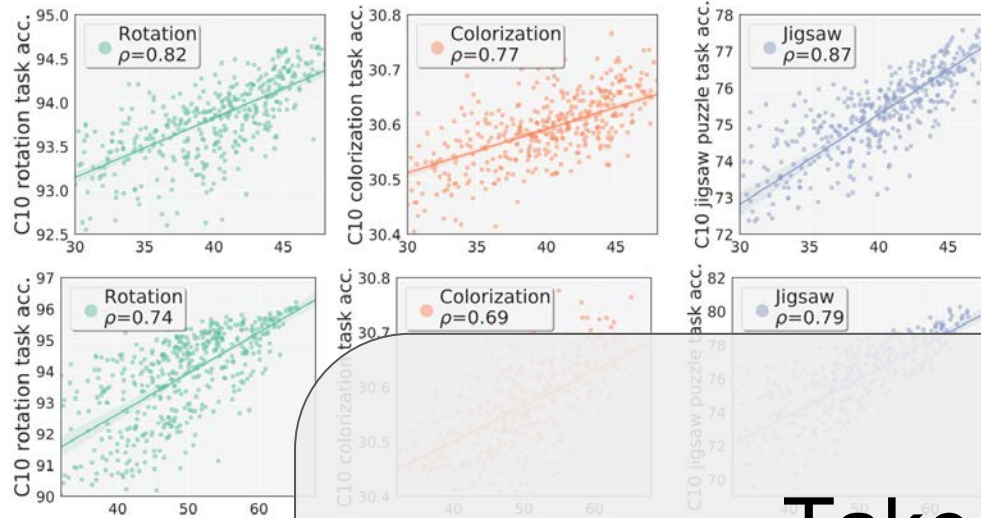
Search-Based Experiments: Cityscapes Sem. Seg.



Evidence 2:

- UnNAS is better than the commonly used CIFAR-10 supervised proxy
 - UnNAS is comparable to (supervised) NAS across search tasks and datasets
 - Even a data-mine-free UnNAS can clearly outperform NAS
- UnNAS architectures are comparable in performance to their supervised counterpart

Evidence 1 + Evidence 2



Take-Home Message:

To perform NAS *successfully*,
labels are *not necessary*