ICML
International Conference
On Machine Learning

WEIZMANN INSTITUTE OF SCIENCE

Pure Noise to the Rescue of Insufficient Data:
Improving Imbalanced Classification by Training on Random Noise Images

Shiran Zada

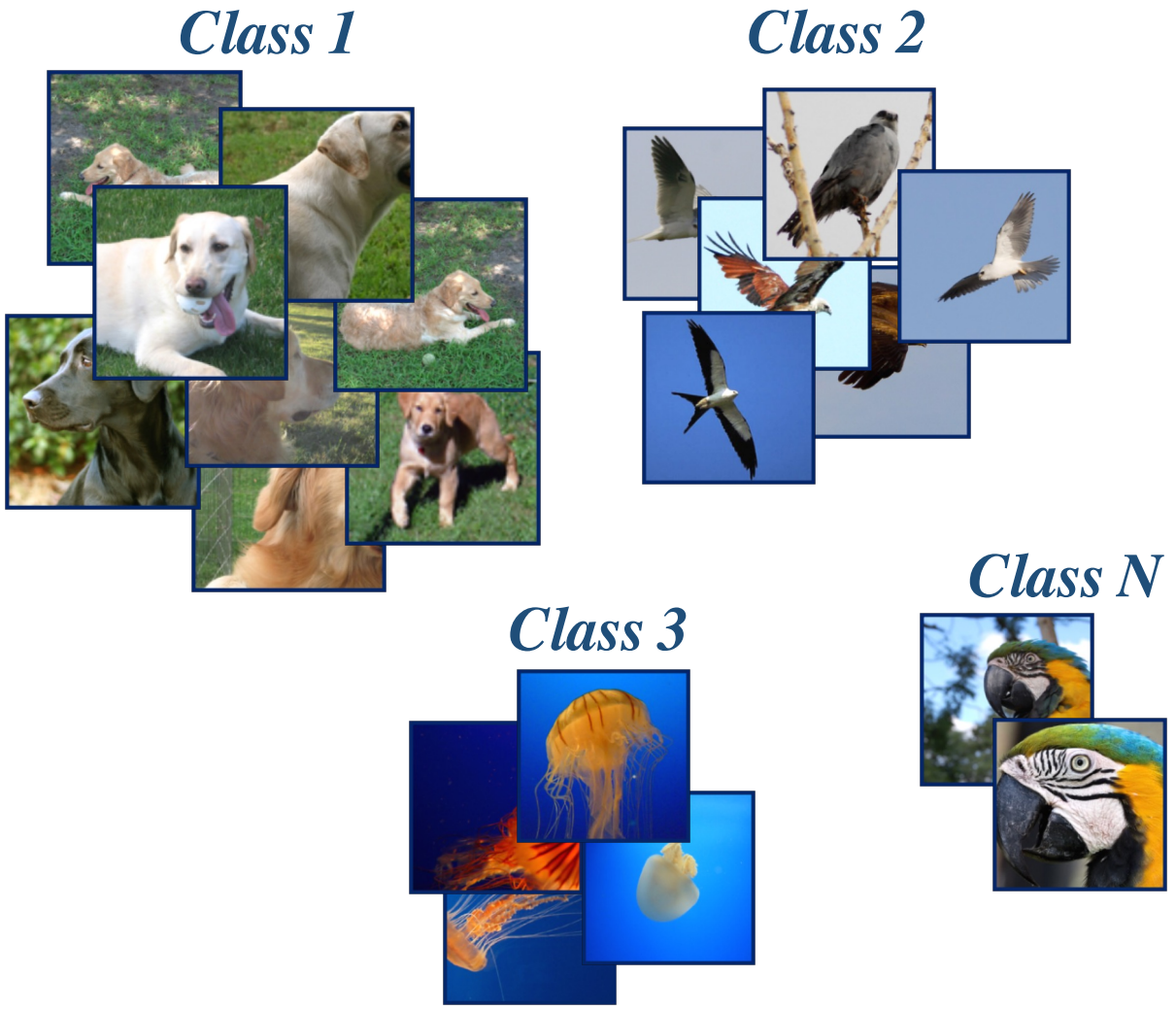
Itay Benou

Michal Irani

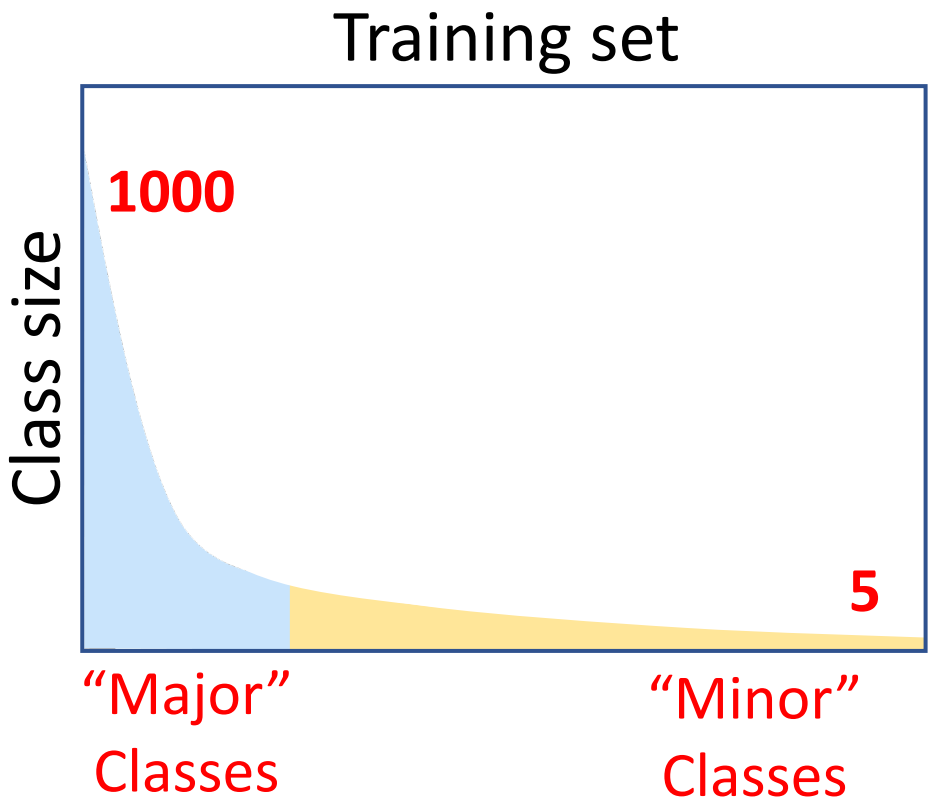
Weizmann Institute of Science, Israel

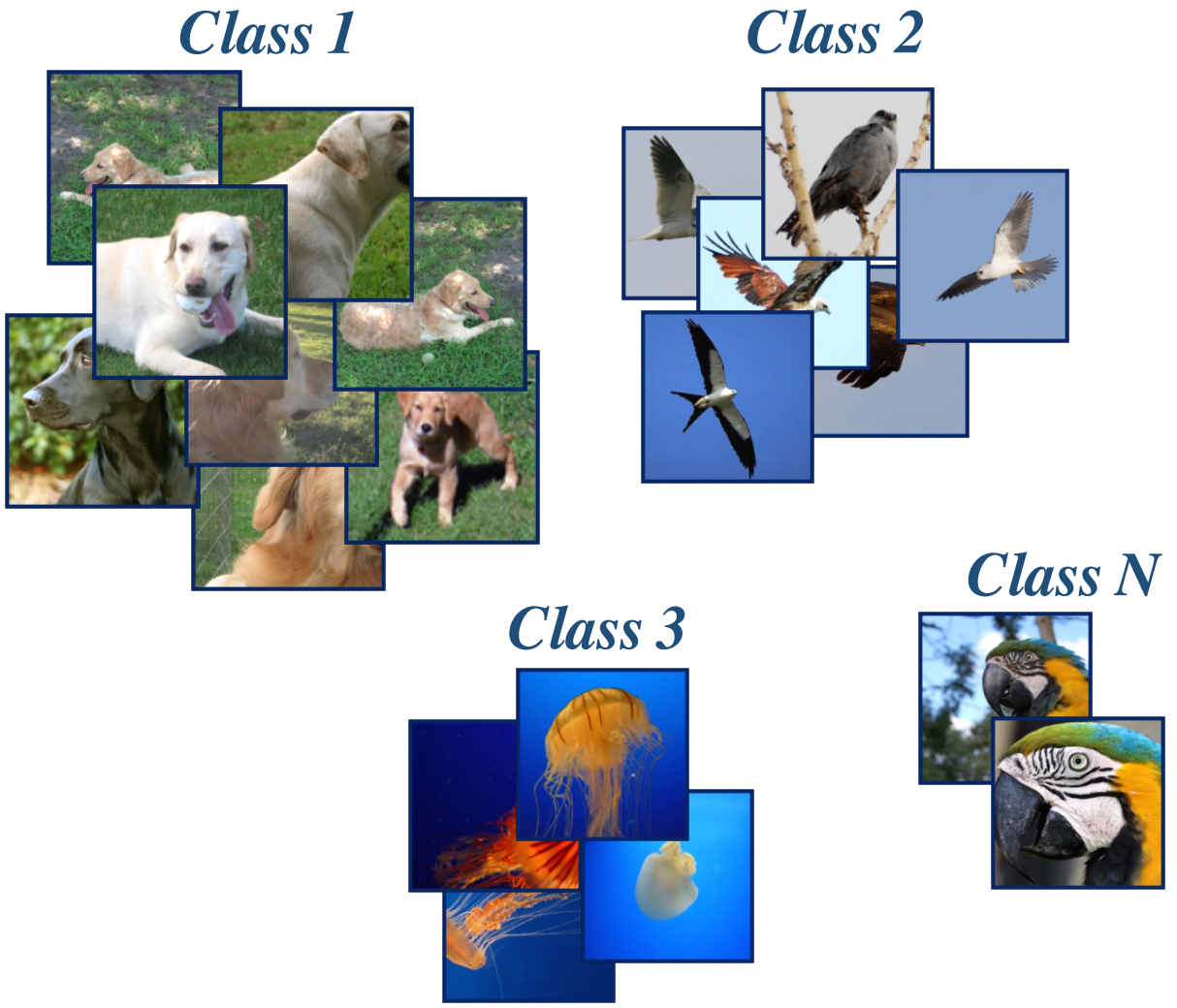
What is “Imbalanced Classification”?

What is “Imbalanced Classification”?



What is “Imbalanced Classification”?





Prior Work

Prior Work

- Oversampling minor classes

  (e.g., [Shen et al., 2016], [Kim et al., 2020], [Mullick et al., 2019])

Prior Work

- Oversampling minor classes

  (e.g., [Shen et al., 2016], [Kim et al., 2020], [Mullick et al., 2019])

- Loss re-weighting

  (e.g., [Huang et al. 2016], [Cui et al., 2019], [Ren et al., 2020], [Hong et al., 2021])

Prior Work

- Oversampling minor classes

  (e.g., [S… …2016], [Kim et al., 2020], [Mullick et al., 2019])

- Loss re-weighting

  (e.g., [Huang et al. 2016], [Cui et al., 2019], […et al., 2020], [Hong et al., 2021])

Overfit minor classes

Prior Work

- Oversampling minor classes

  (e.g., [S… …2016], [Kim et al., 2020], [Mullick et al., 2019])

- Loss re-weighting

  (e.g., [Huang et al. 2016], [Cui et al., 2019], […et al., 2020], [Hong et al., 2021])

Overfit minor classes

In this work:

Extend "Oversampling" using PURE-NOISE IMAGES

Prior Work

- Oversampling minor classes

  (e.g., [S… 2016], [Kim et al., 2020], [Mullick et al., 2019])

- Loss re-weighting

  (e.g., [Huang et al. 2016], [Cui et al., 2019], […et al., 2020], [Hong et al., 2021])

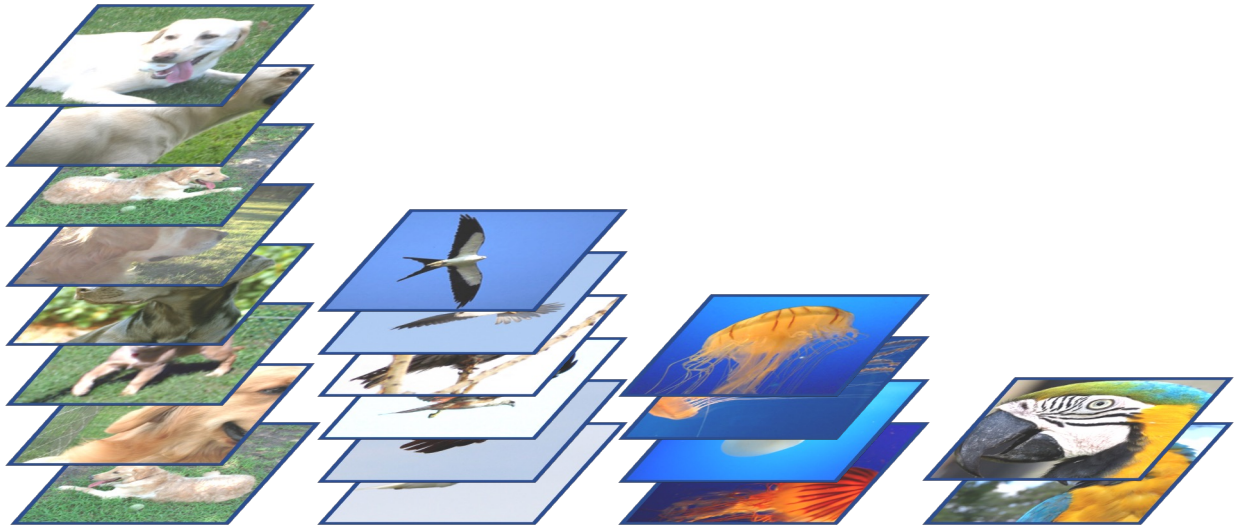
Overfit minor classes

In this work:

Extend "Oversampling" using PURE-NOISE IMAGES

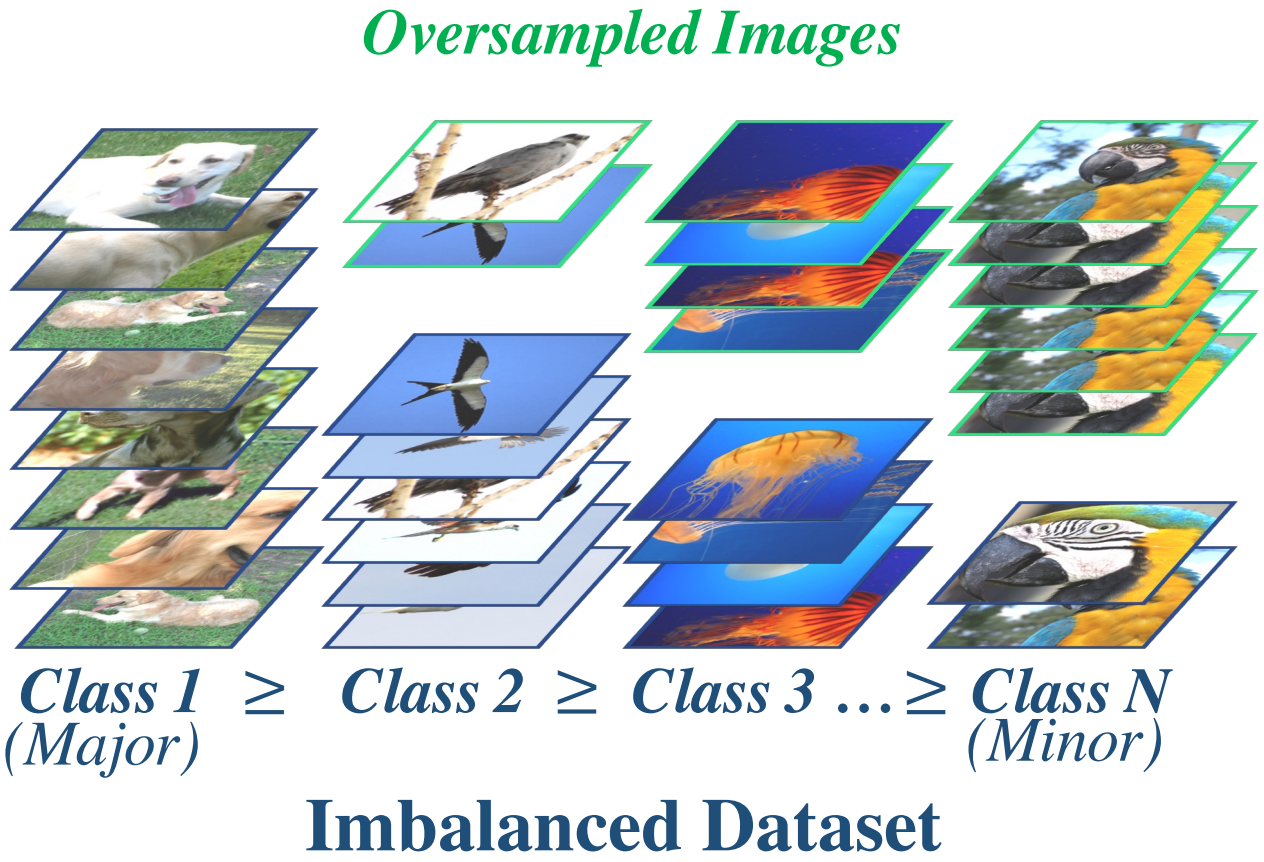
➔ SOTA results in Imbalanced classification

Vanilla Oversampling

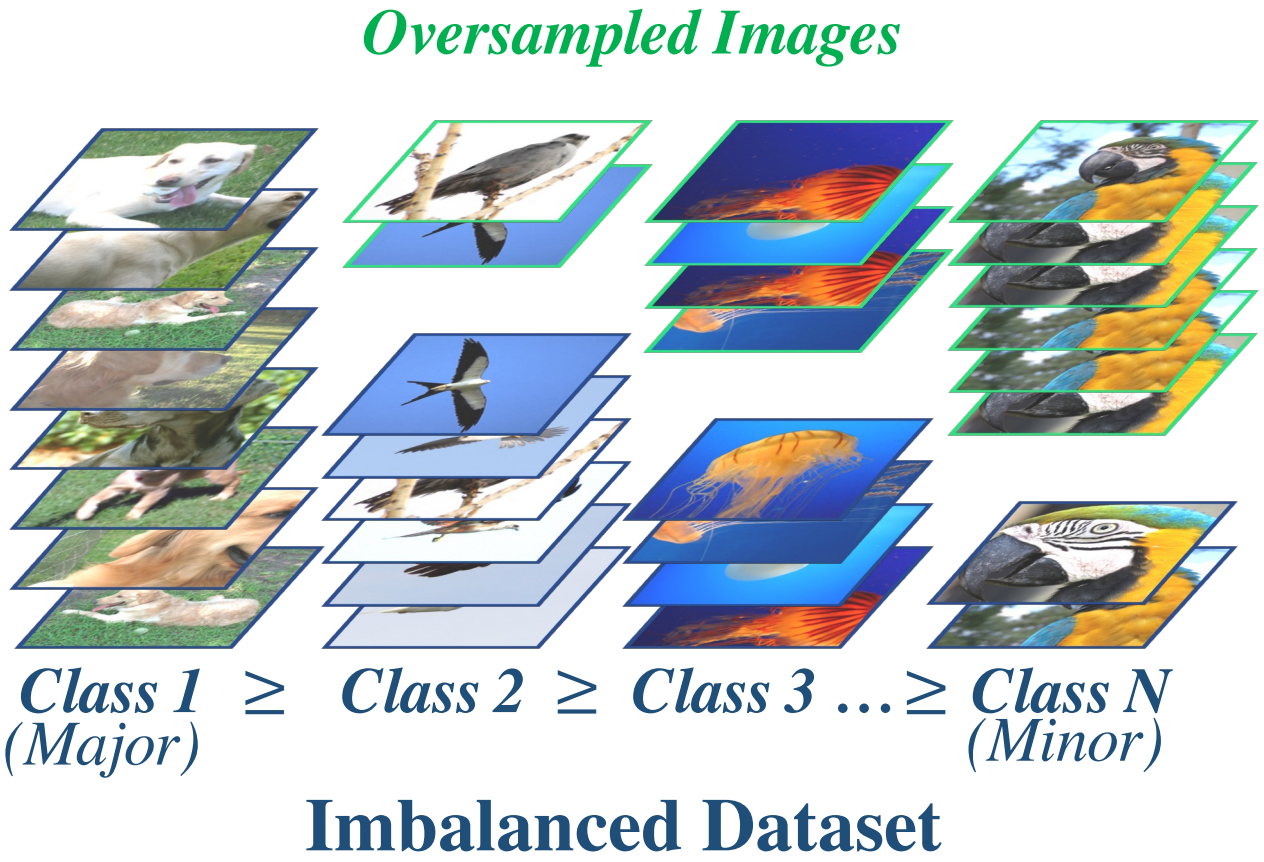


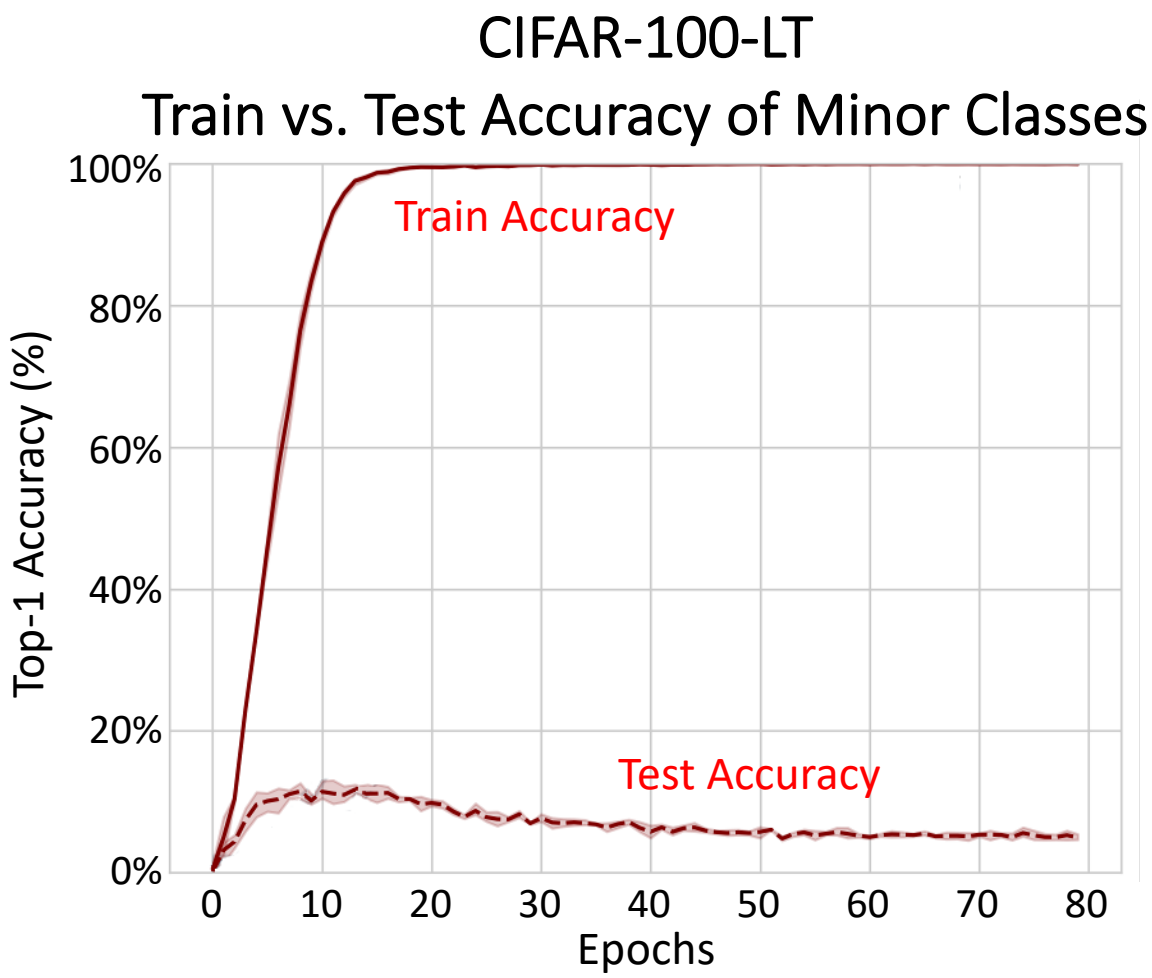
Imbalanced Dataset

Vanilla Oversampling

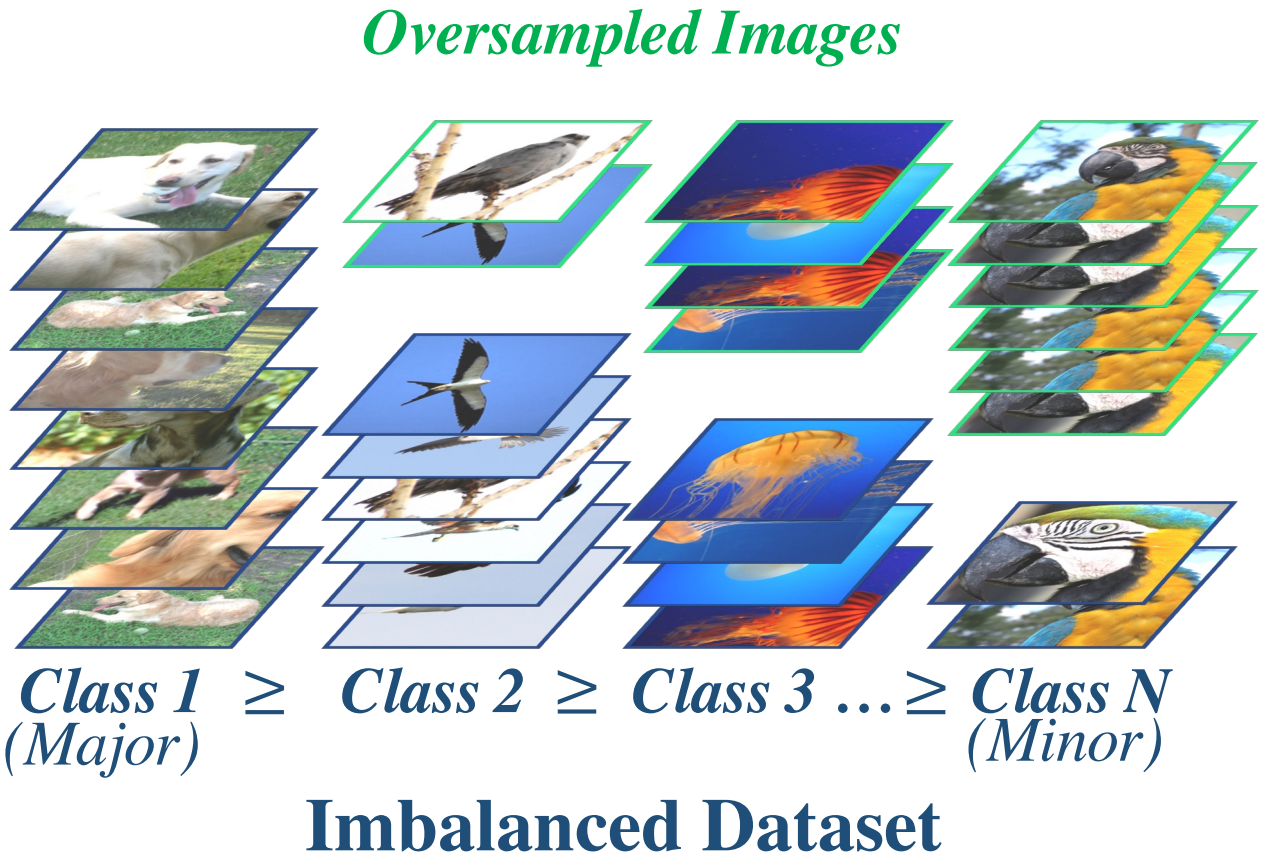


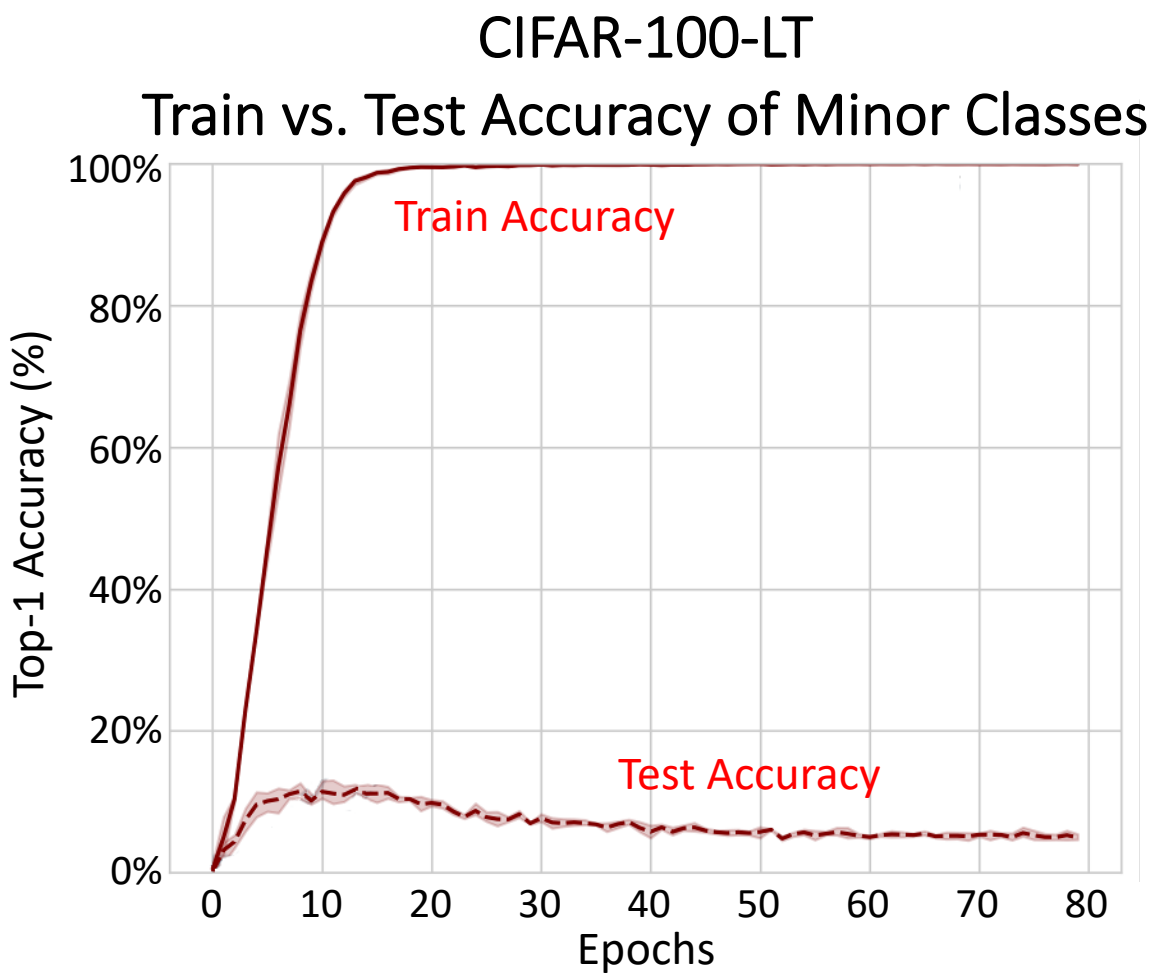
Vanilla Oversampling





Vanilla Oversampling

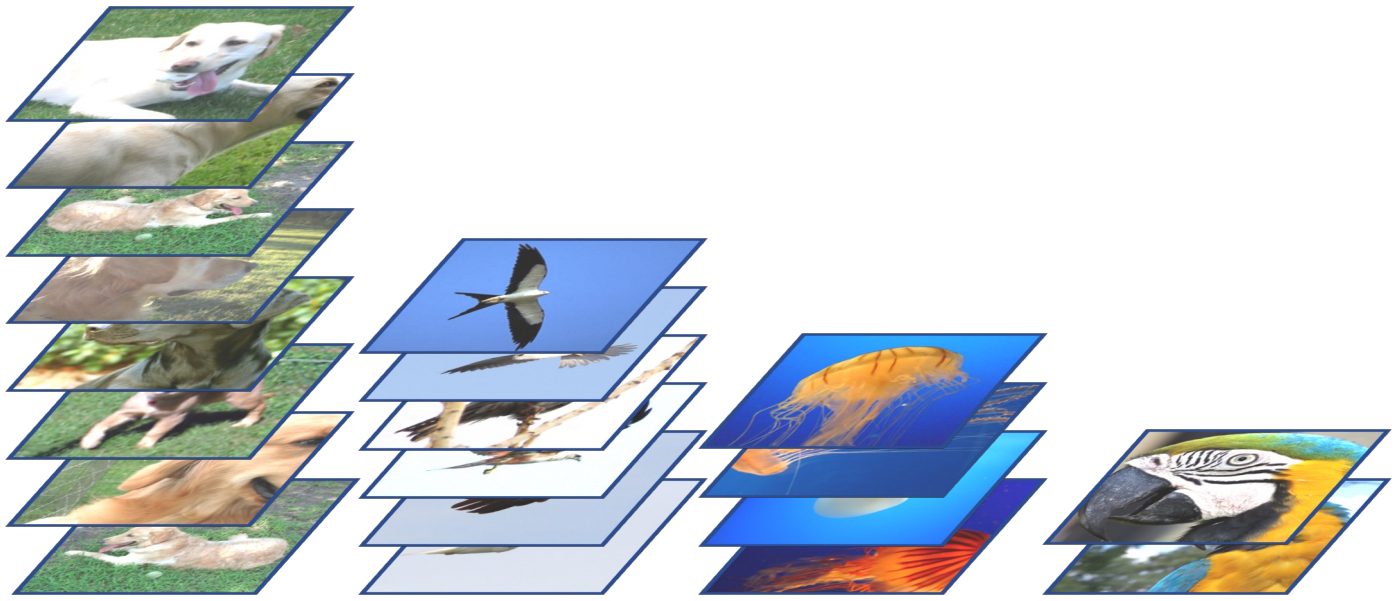




Overfits minor classes

Our Approach

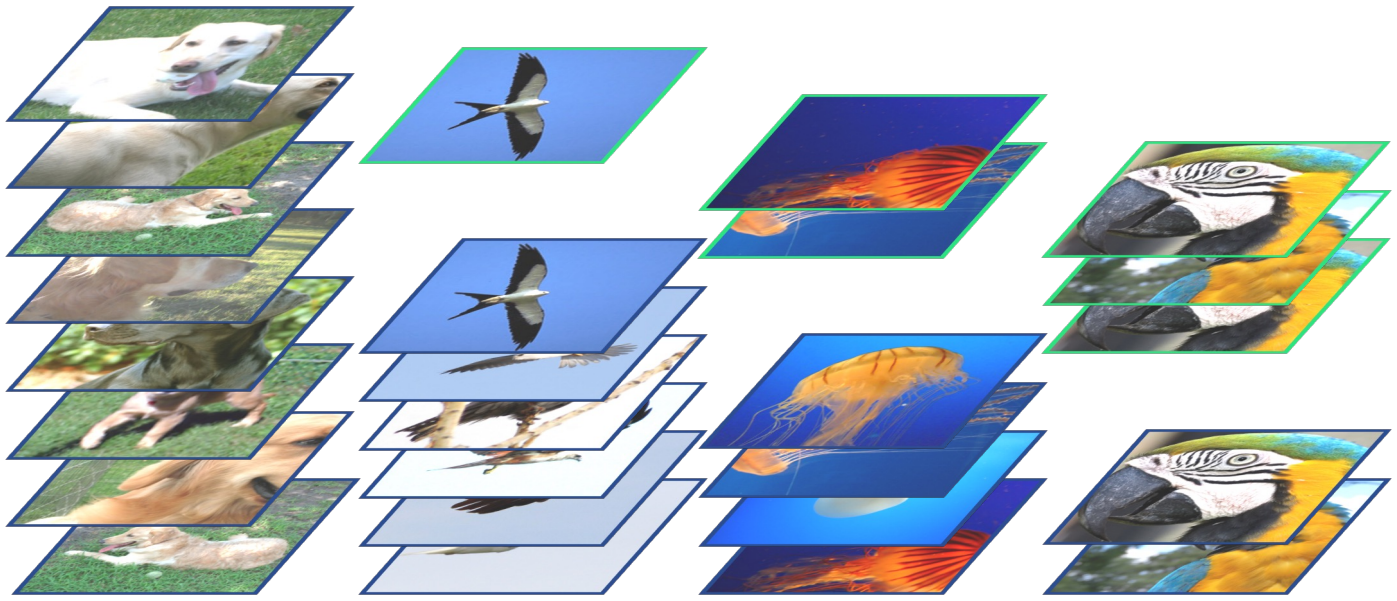
Oversampling with Pure Noise Images (OPeN)



Our Approach

Oversampling with Pure Noise Images (OPeN)

Oversampled images



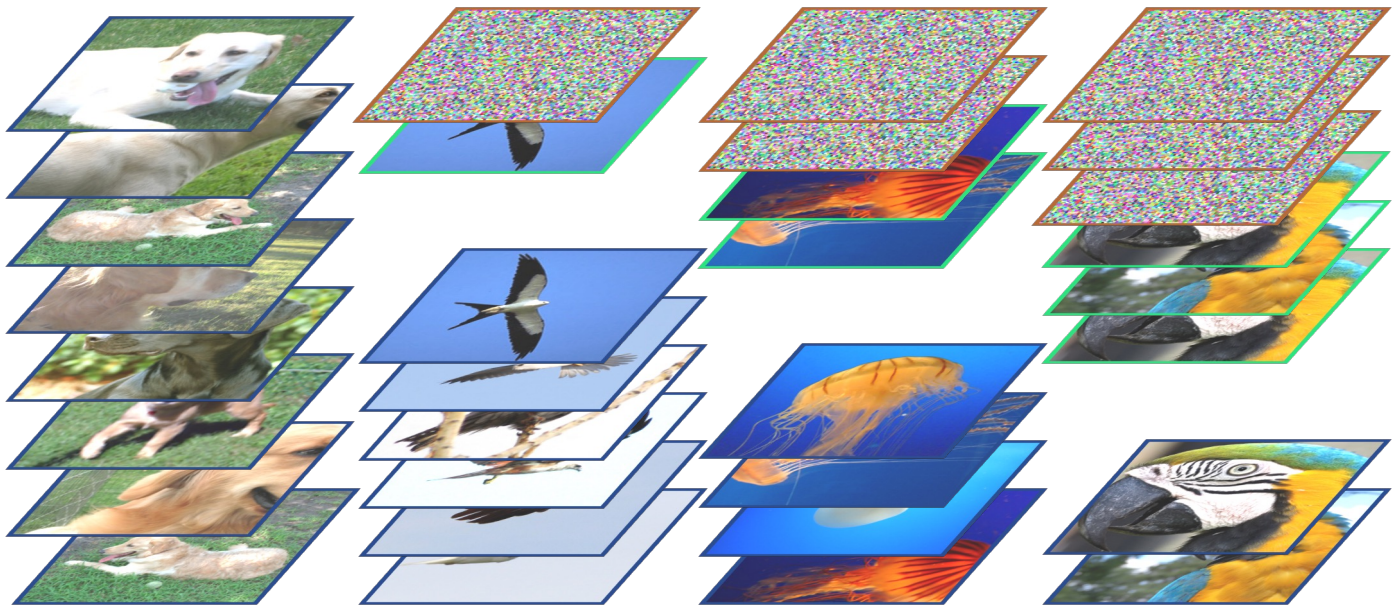
Class 1 *(major)* ≥ ***Class 2*** ≥ ***Class 3*** …≥ ***Class N*** *(minor)*

Imbalanced Dataset

Our Approach

Oversampling with Pure Noise Images (OPeN)

Oversampled images + ***Pure Noise Images***



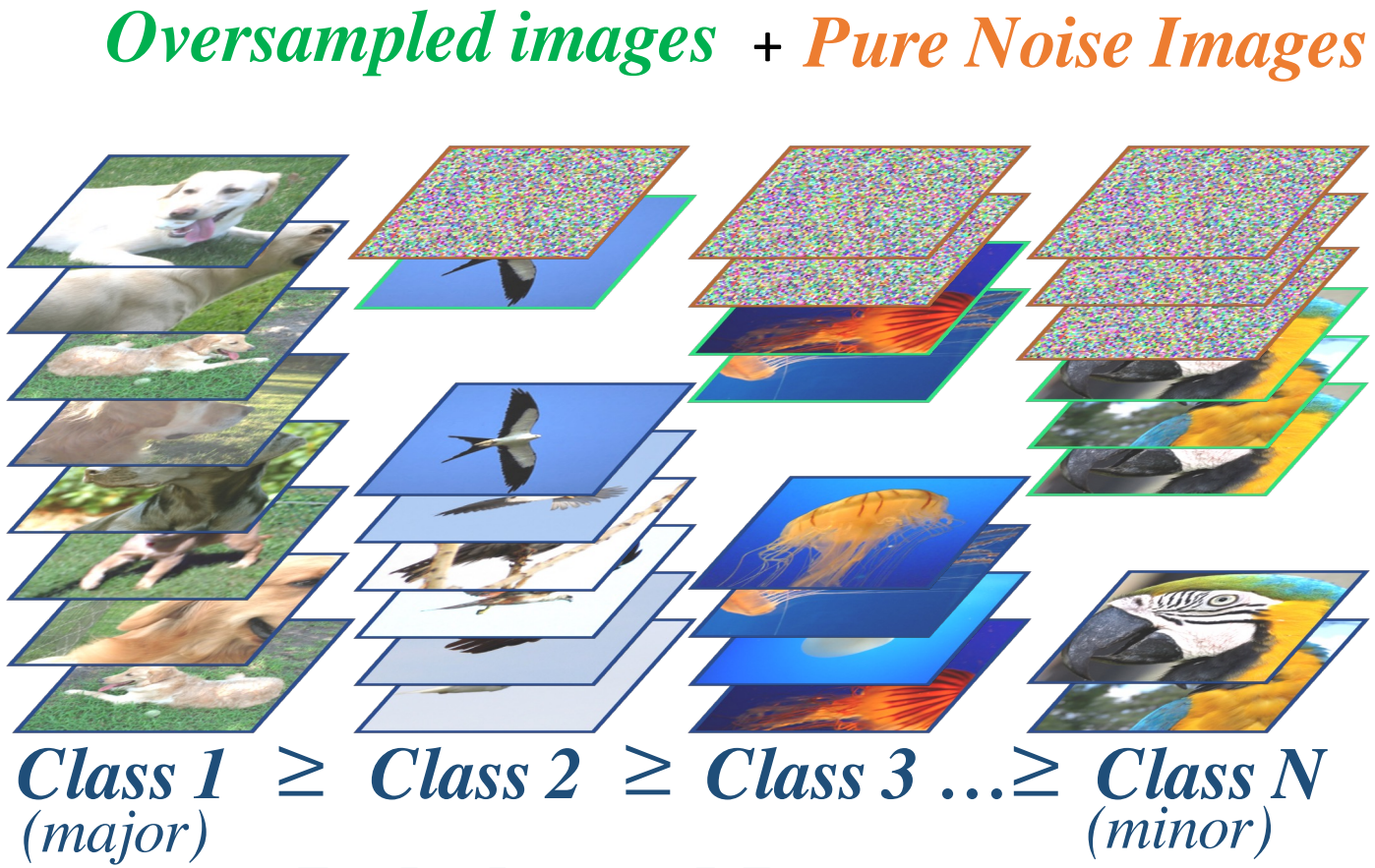
Class 1 ≥ ***Class 2*** ≥ ***Class 3*** …≥ ***Class N***

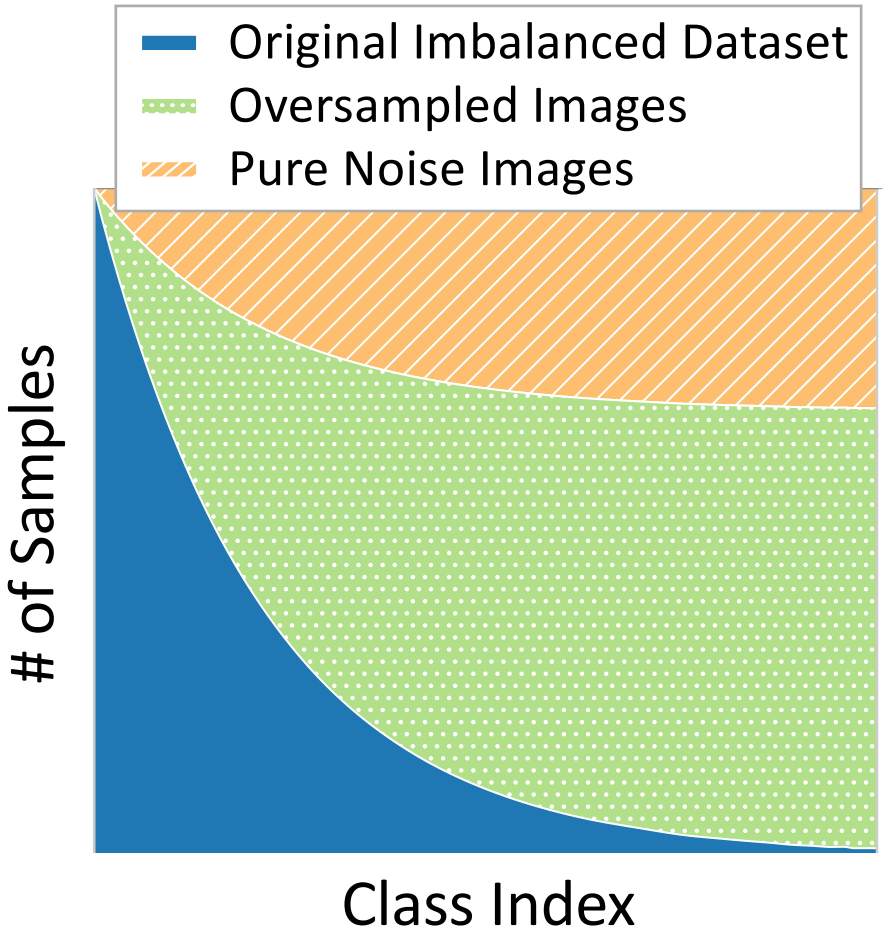
(major) *(minor)*

Imbalanced Dataset

Our Approach

Oversampling with Pure Noise Images (OPeN)





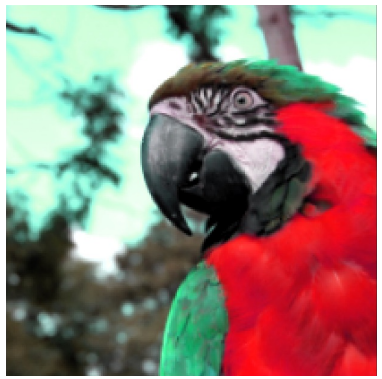
Why Does this Help?

- Augmentations are in close vicinity to the original images

Original Image

Geometric

Color



Additive Noise

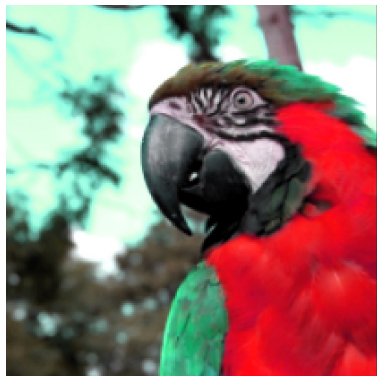
Why Does this Help?

- Augmentations are in close vicinity to the original images

Original Image

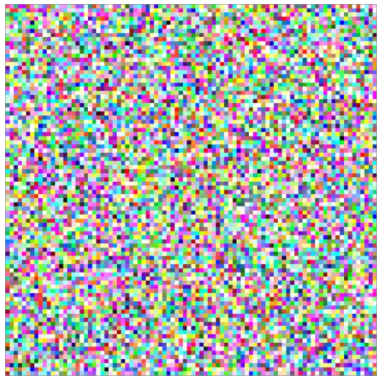
Geometric

Color



Additive Noise

Pure Noise



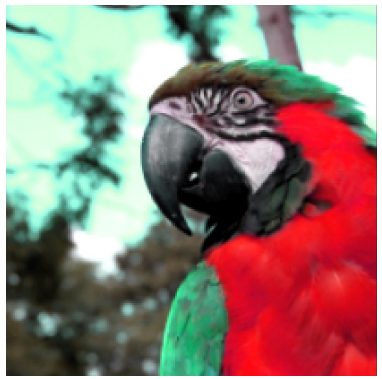
Why Does this Help?

- Augmentations are in close vicinity to the original images

Original Image

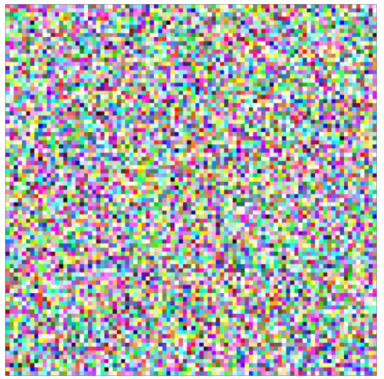
Geometric

Color



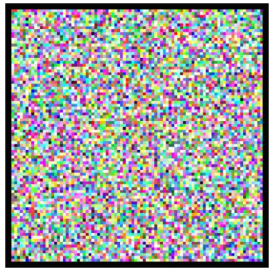
Additive Noise

Pure Noise

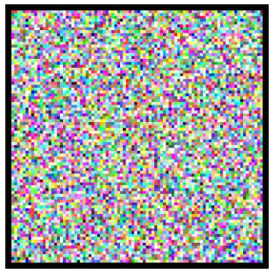


- Teaches to expect uncertainty in <u>minor-classes</u> at test-time.

Distribution shift – Natural Vs. Noise

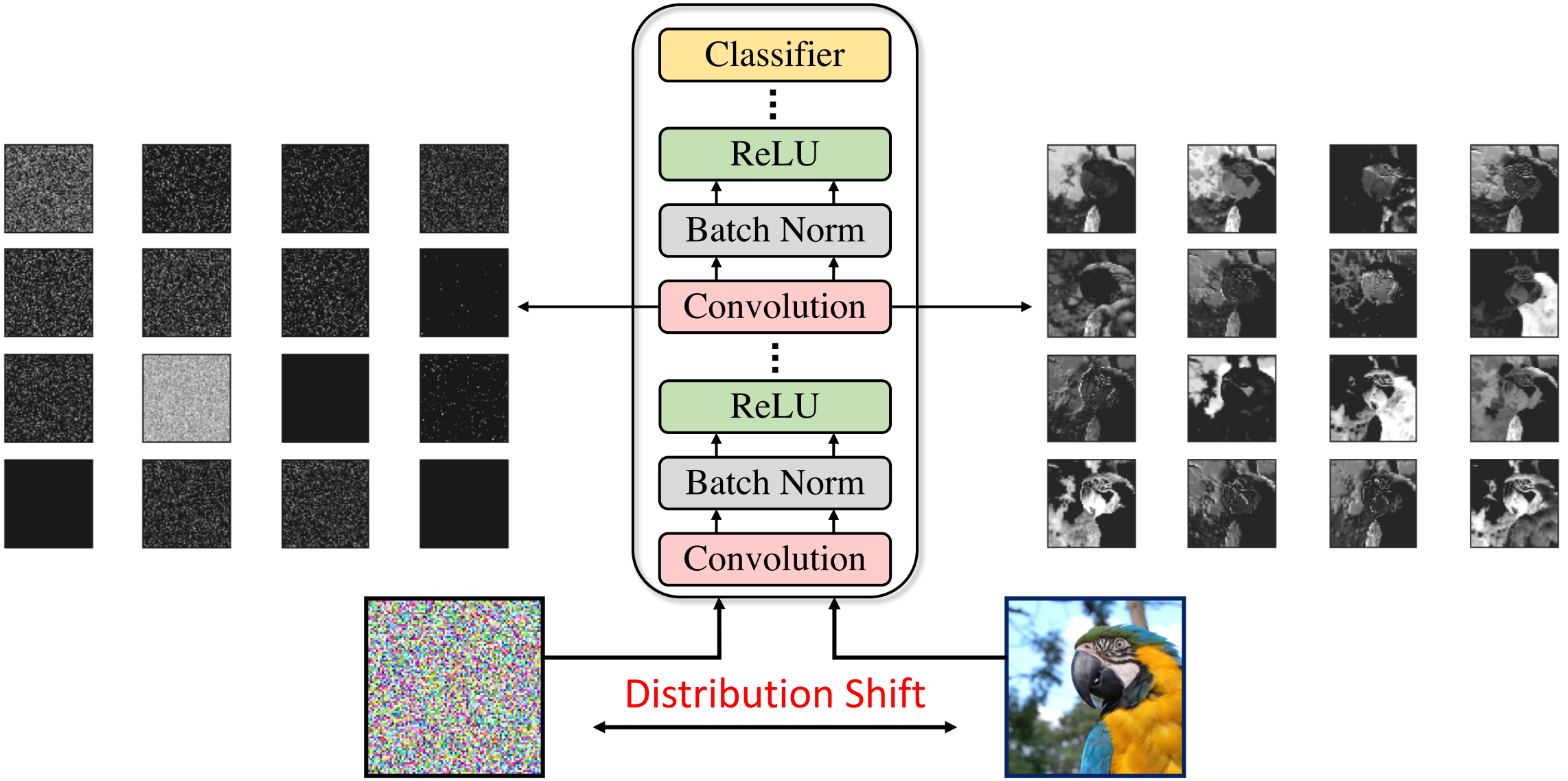


Distribution shift – Natural Vs. Noise

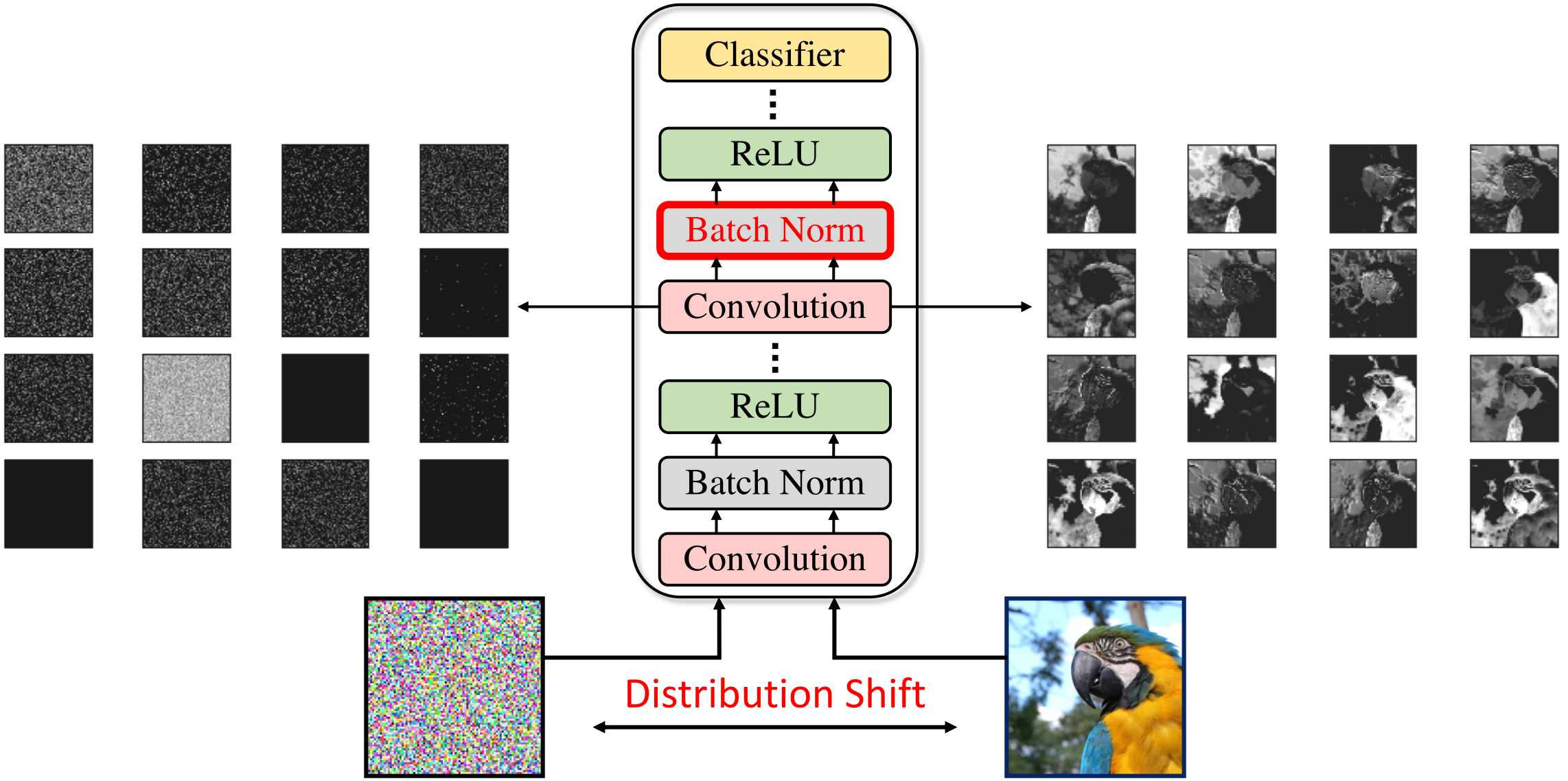


Distribution Shift

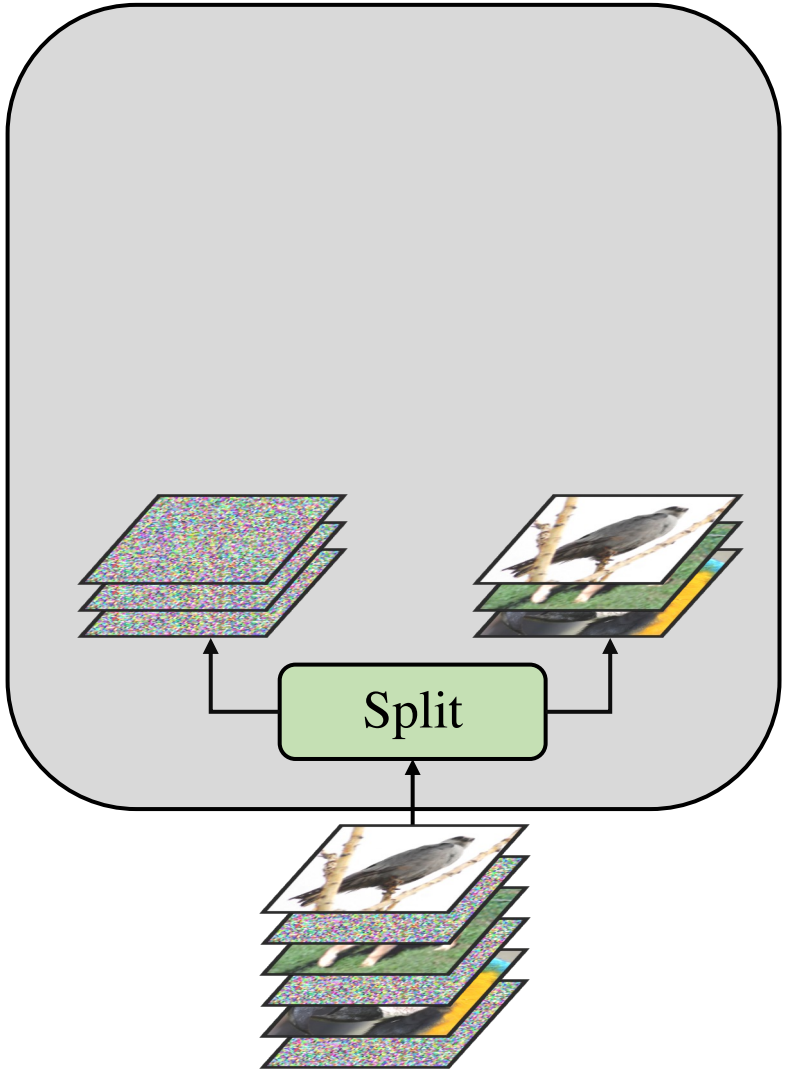
Distribution shift – Natural Vs. Noise



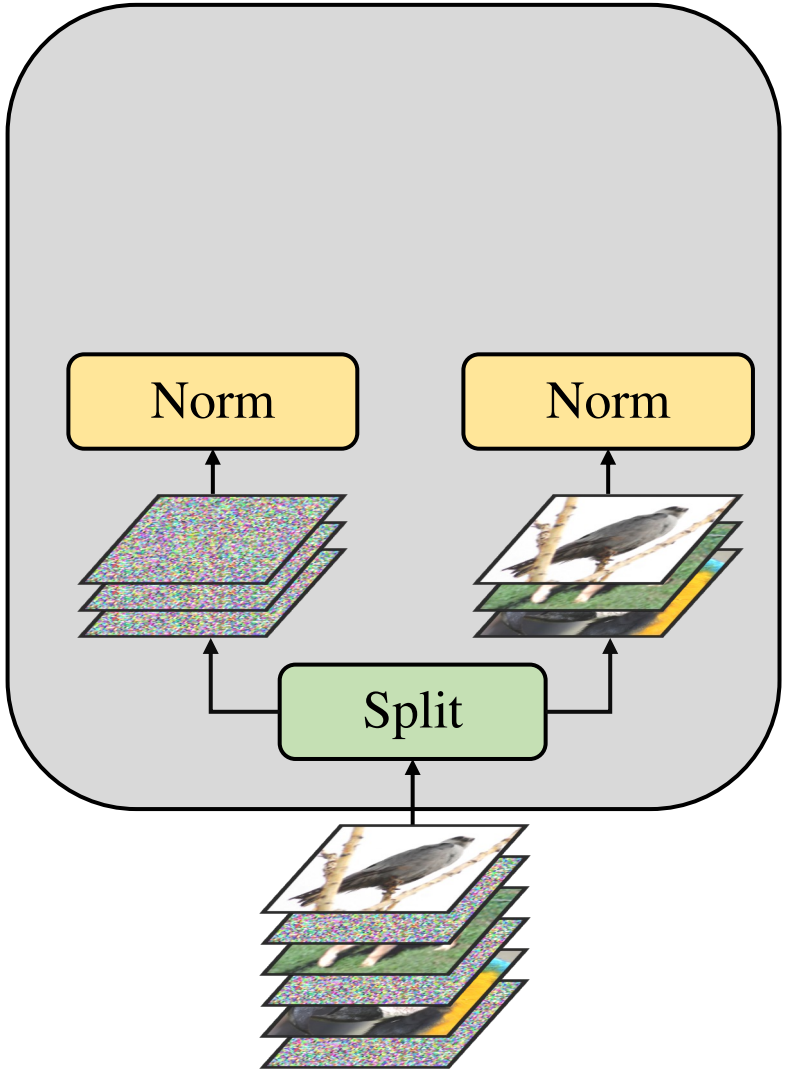
Distribution shift – Natural Vs. Noise



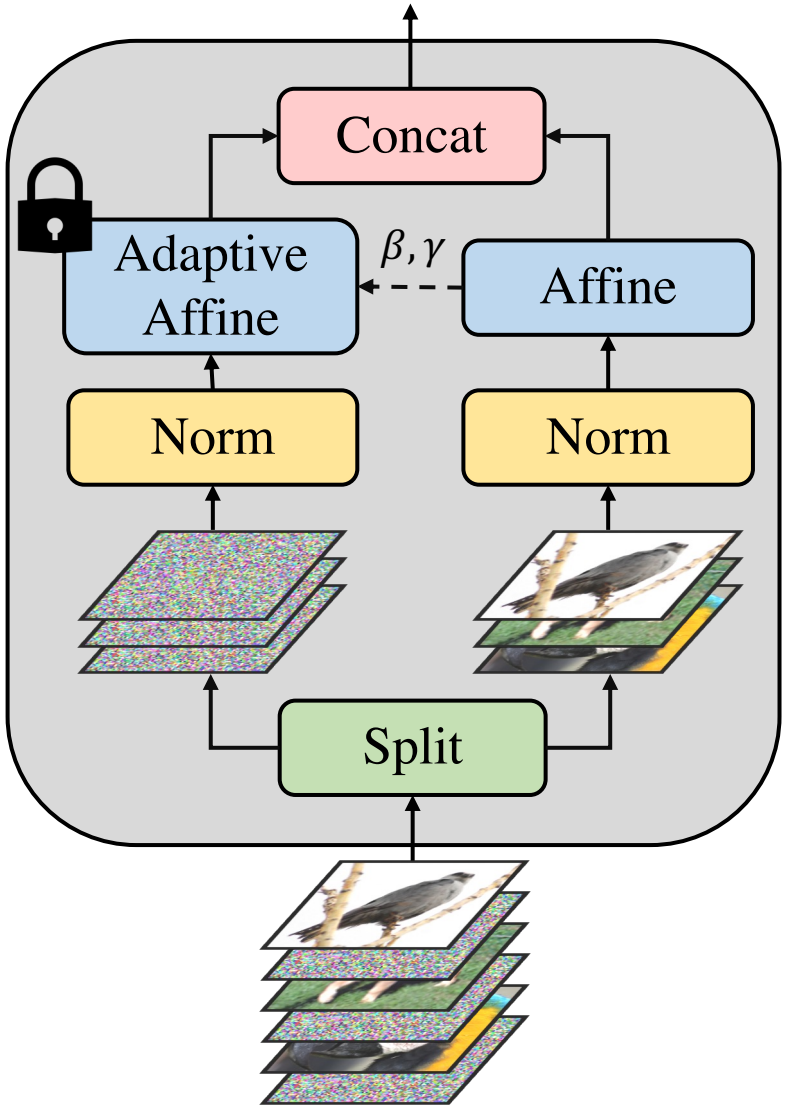
Distribution Aware Routing BN (DAR-BN)



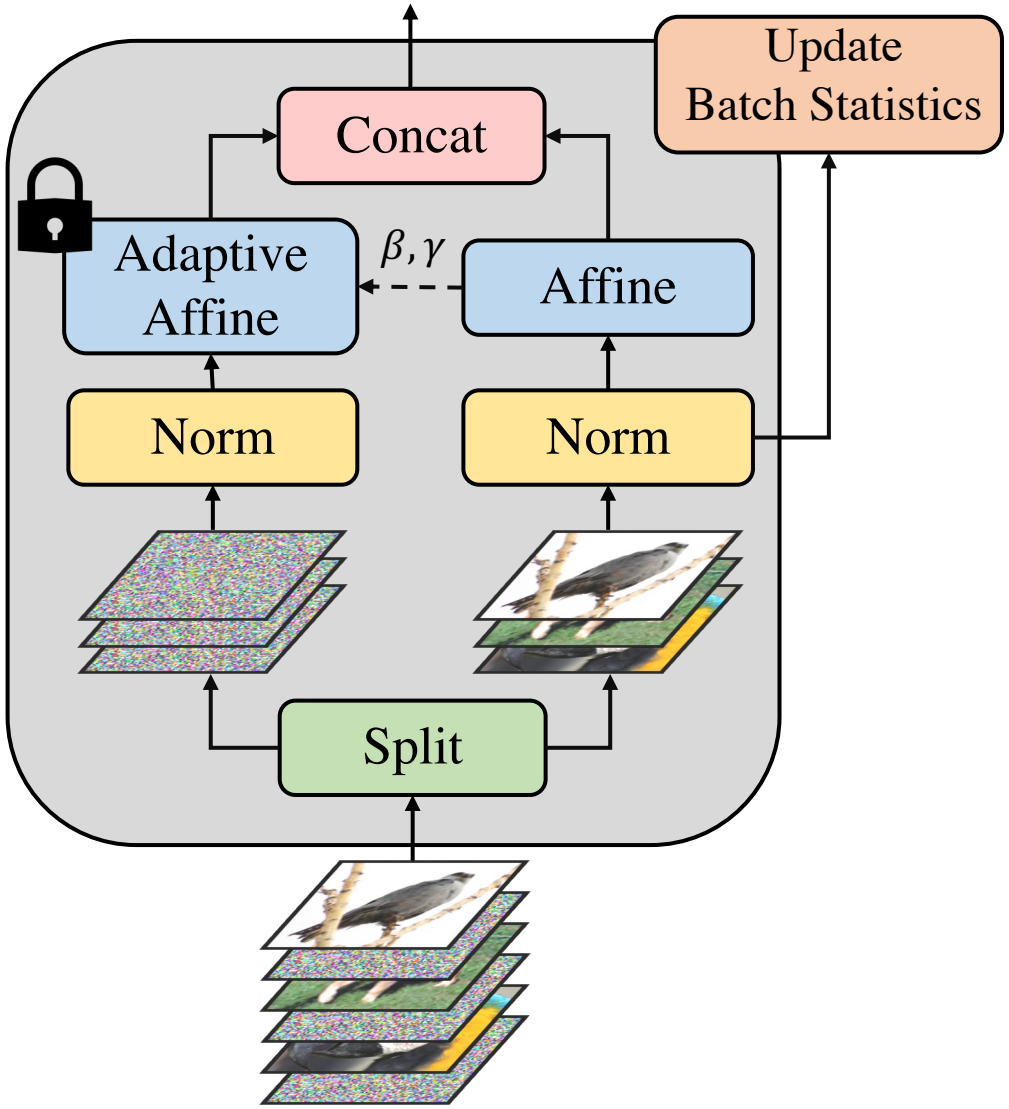
Distribution Aware Routing BN (DAR-BN)



Distribution Aware Routing BN (DAR-BN)



Distribution Aware Routing BN (DAR-BN)



Results

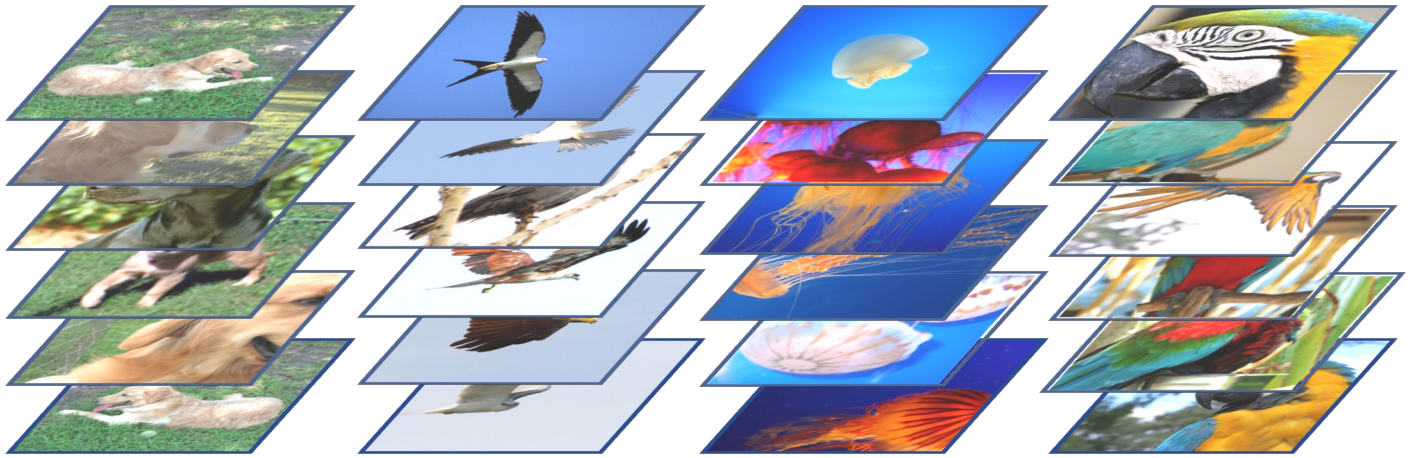
State of The Art:

- CIFAR-10-LT
- CIFAR-100-LT
- ImageNet-LT
- Places-LT
- CelebA-5

Top-1 Test Accuracy

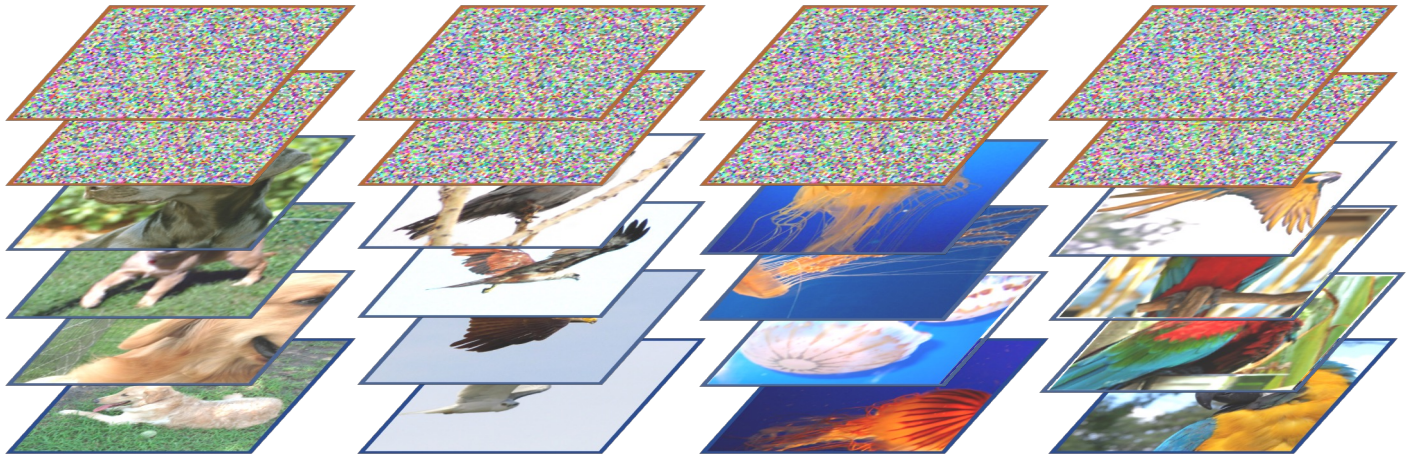
Methods	ImageNet-LT
ERM	51.1
Oversampling	49.0
BALMS	52.1
LADE	53.0
MisLAS	52.7
OPeN	**55.1**

Balanced Classification



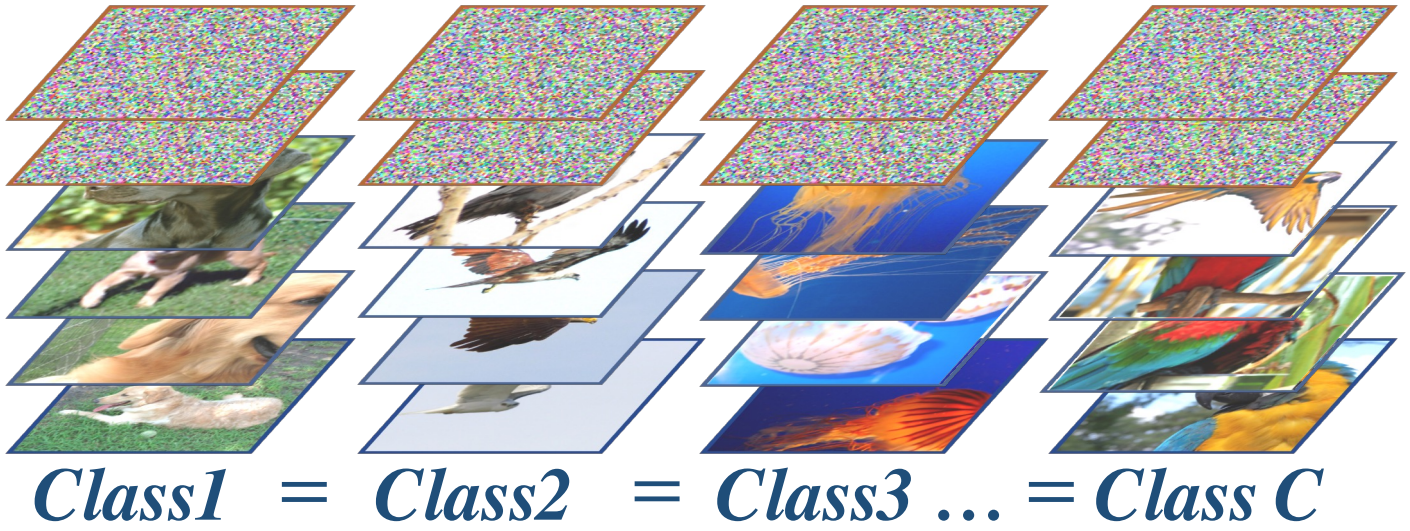
Class1 = Class2 = Class3 … = Class C

Balanced Classification



Class1 = Class2 = Class3 … = Class C

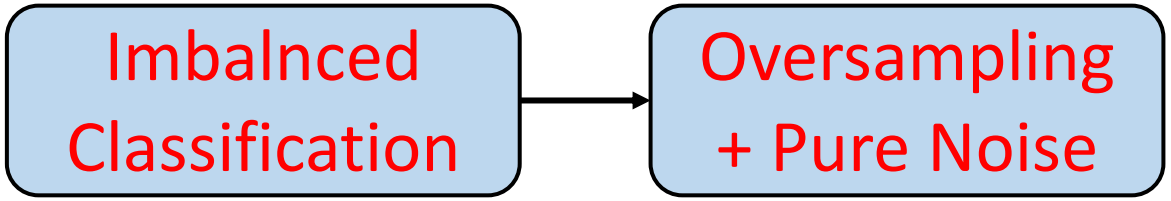
Balanced Classification



Method	CIFAR-10	CIFAR-100
Baseline	94.62	74.96
AutoAugment[1]	+1.49	+4.88
AutoAugment + Ours	**+2.38**	**+6.35**

1 [Cubuk et al., 2019]

Summary

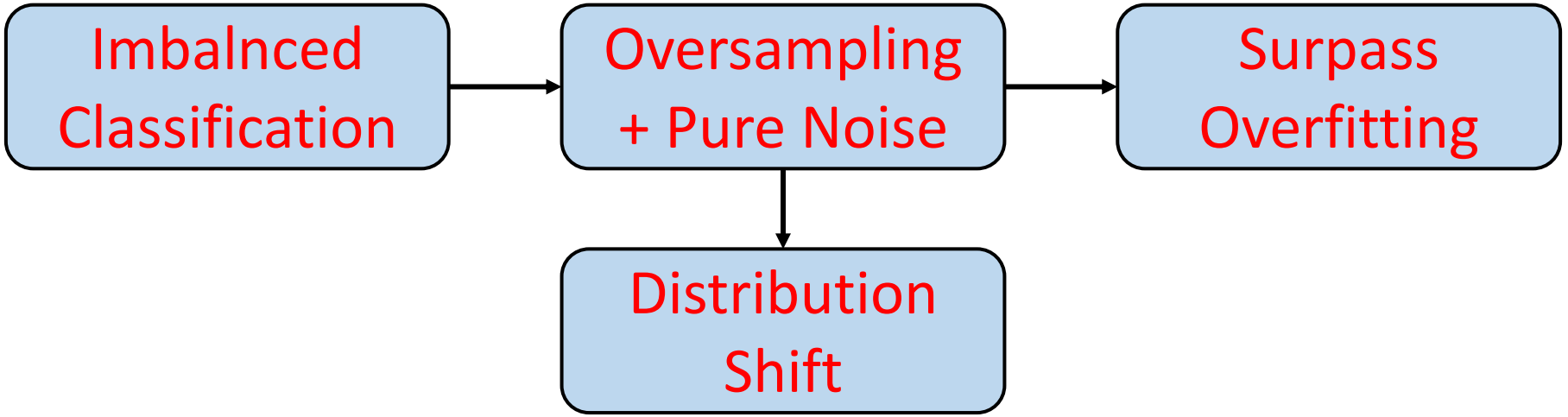


https://github.com/shiranzada/pure-noise

Summary

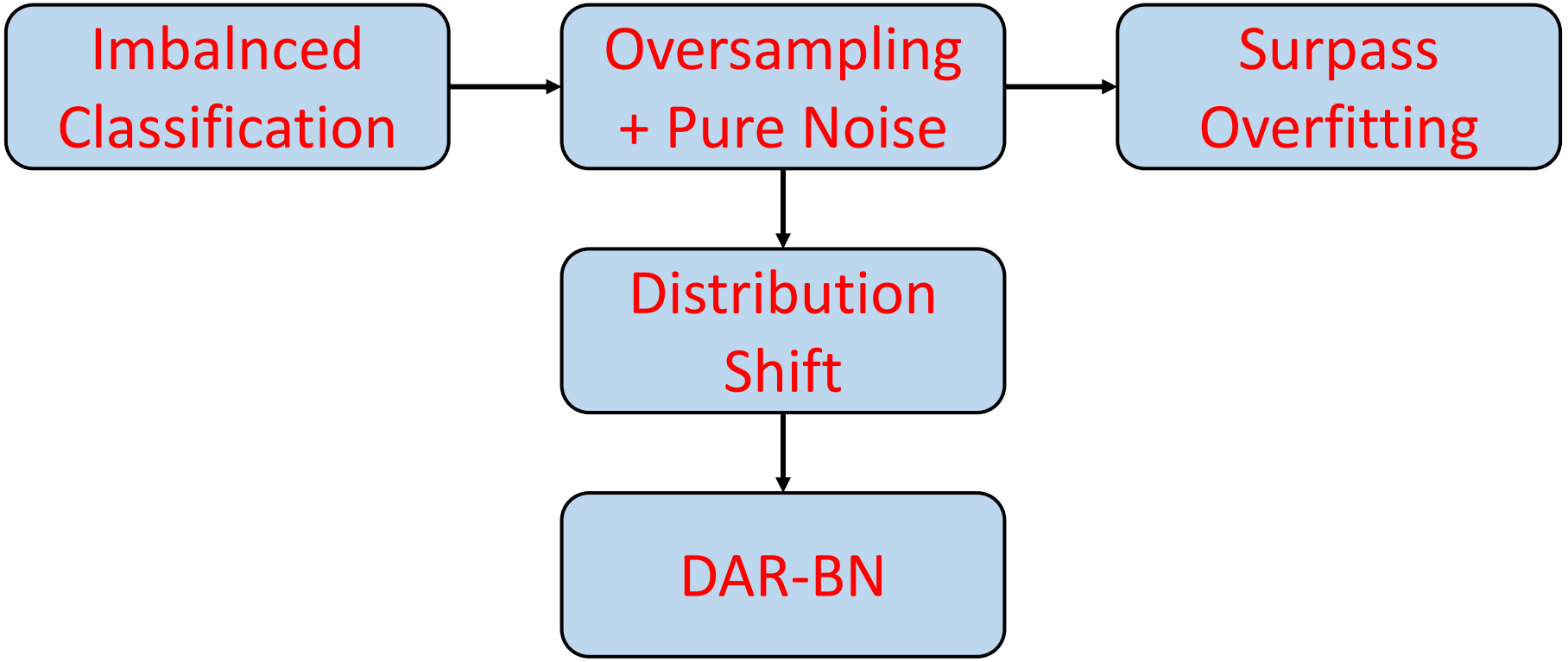
https://github.com/shiranzada/pure-noise

Summary



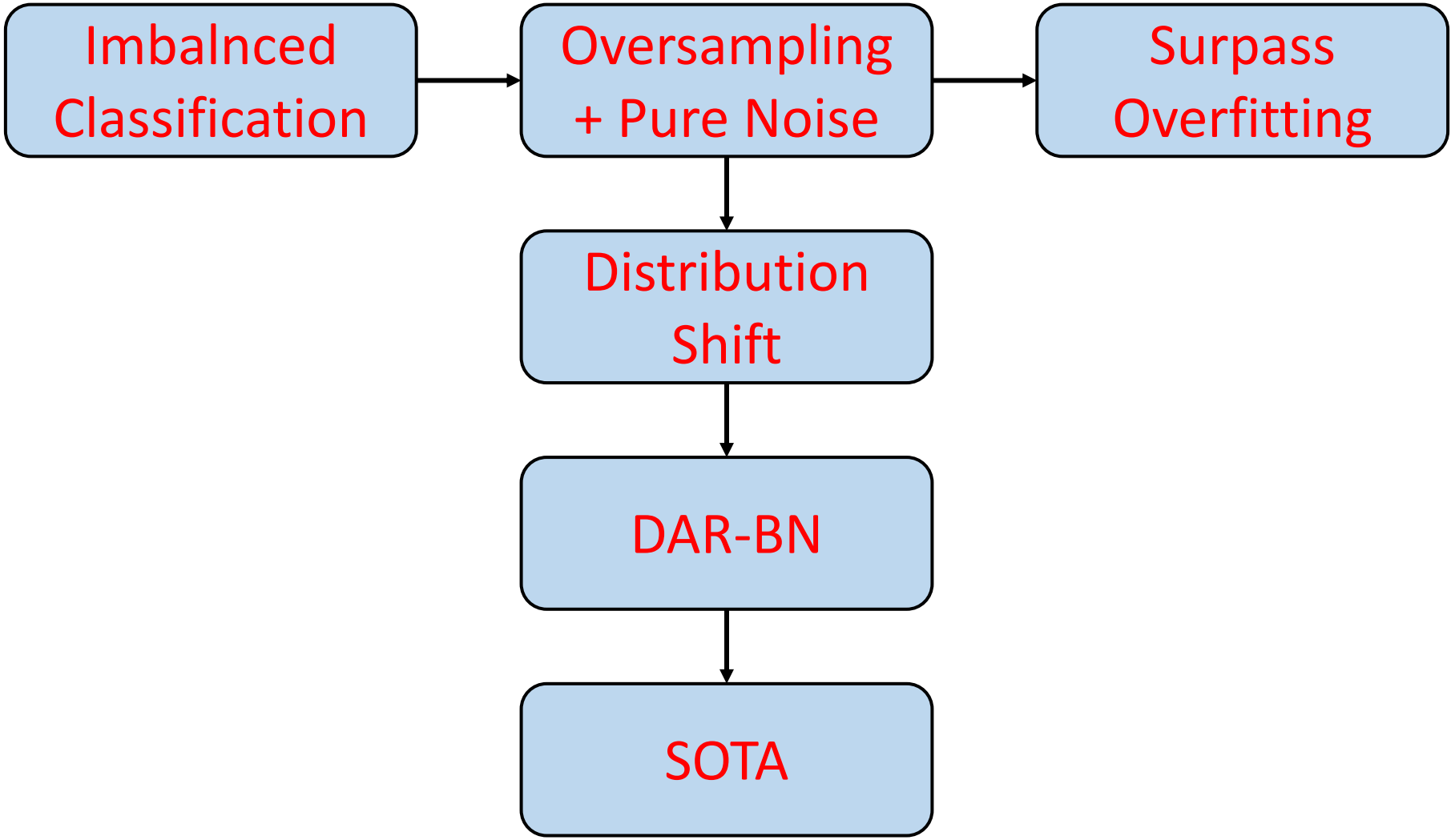
https://github.com/shiranzada/pure-noise

Summary



https://github.com/shiranzada/pure-noise

Summary



https://github.com/shiranzada/pure-noise