

IBM Research AI Δ -encoder: An effective sample synthesis method for few-shot object recognition

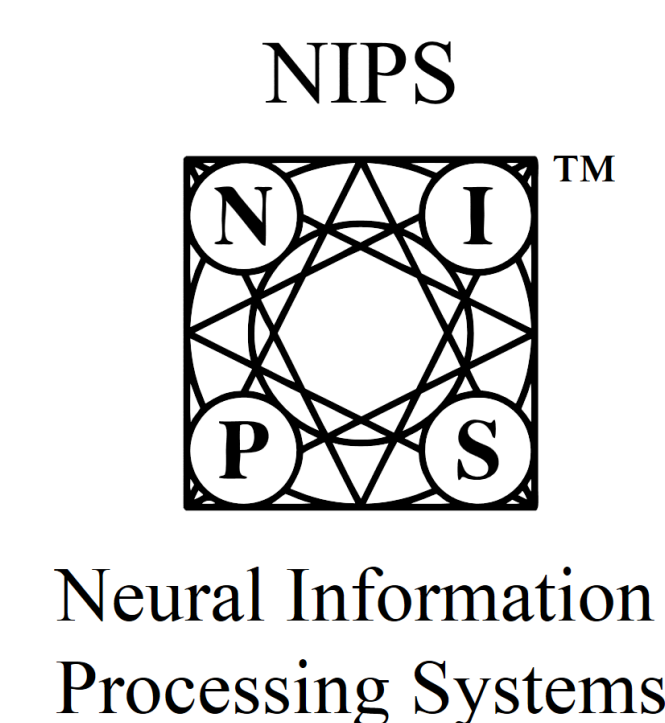


Eli Schwartz^{*1,2}, Leonid Karlinsky^{*1}, Joseph Shtok¹, Sivan Harary¹, Mattias Marder¹, Abhishek Kumar¹, Rogerio Feris¹, Raja Giryes², Alex M. Bronstein³

1 - IBM Research AI; 2 - School of Electrical Engineering, Tel-Aviv University, Tel-Aviv, Israel; 3 - Department of Computer Science, Technion, Haifa, Israel



see our
3-minutes pitch



Few-shot classification problem: presented with a few samples of K novel categories, produce a classifier for the K categories
Generative approach: synthesize new samples from the few available examples to improve the classifier training

Training data – 1 sample per category



Query image



Classifier

chimpanzee
dog
human
griffin
crocodile

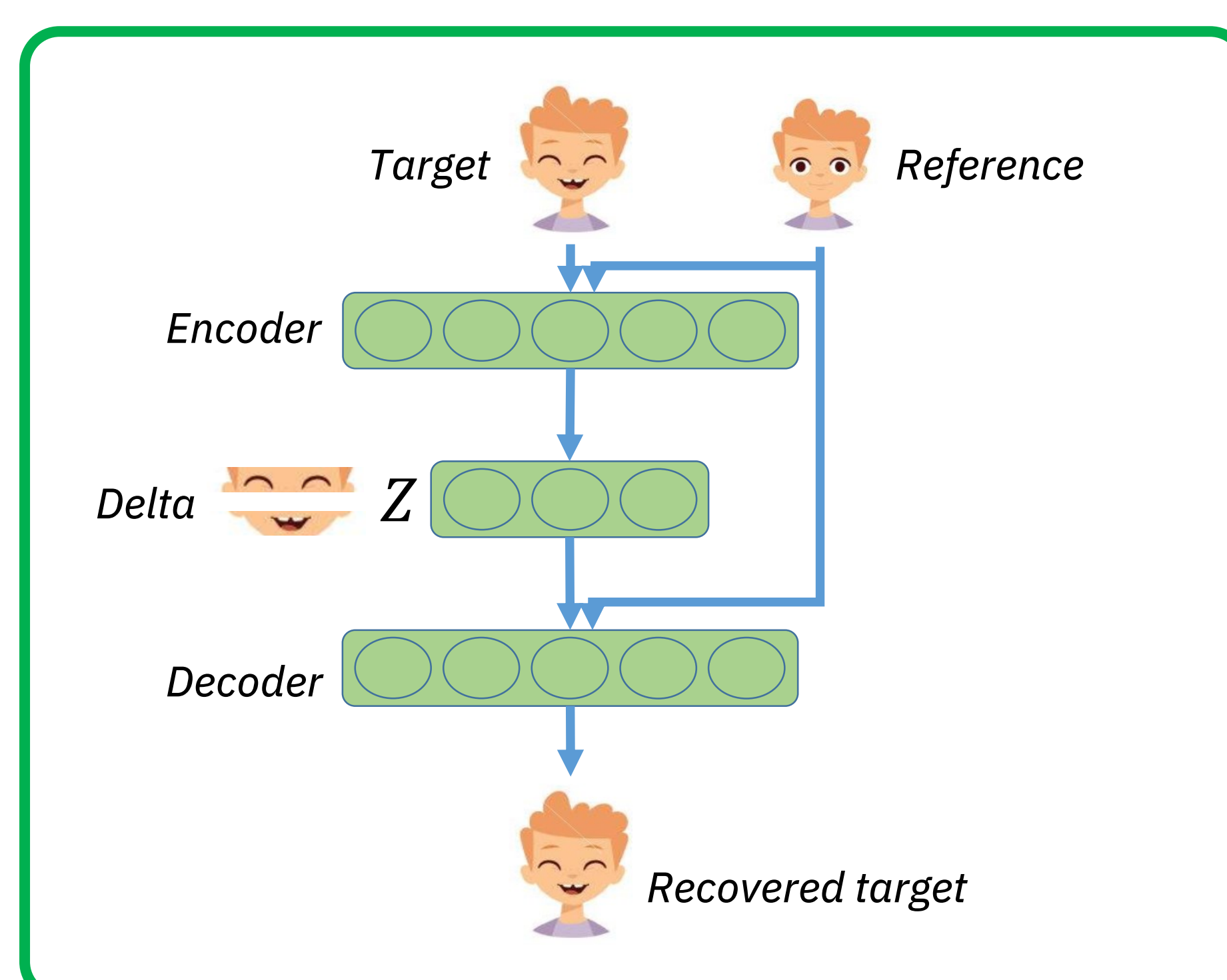
Data synthesis –
thousands of samples

Classifier training

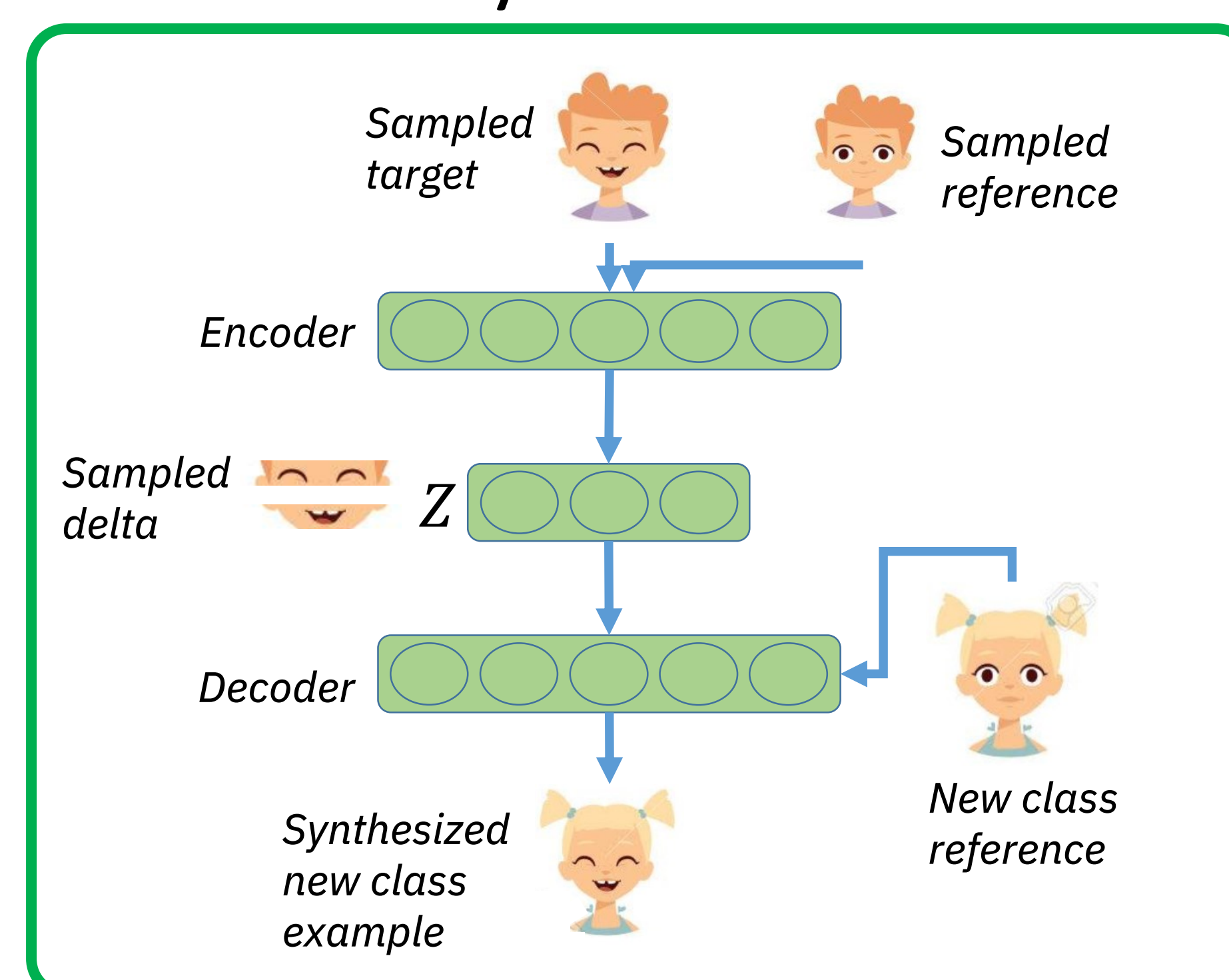
Our main idea

1. Learn to recover the relative transformation (the delta) between pairs of samples from the same category
2. Sample from a distribution of such transformations within the set of known categories
3. Learn to re-apply the transformations to examples of novel categories to produce additional samples thereof

Training



Synthesis



- A variant of an auto-encoder operating in feature space
- Network learns to encode the Δ between reference and target images
- This Δ is used to recover the target image as a (non-linear) combination of the reference and Δ

- At test time encoded Δ s are sampled from random training image pairs belonging to the same category
- Sampled Δ s are used to create samples for the new categories by combining them with the new category reference examples

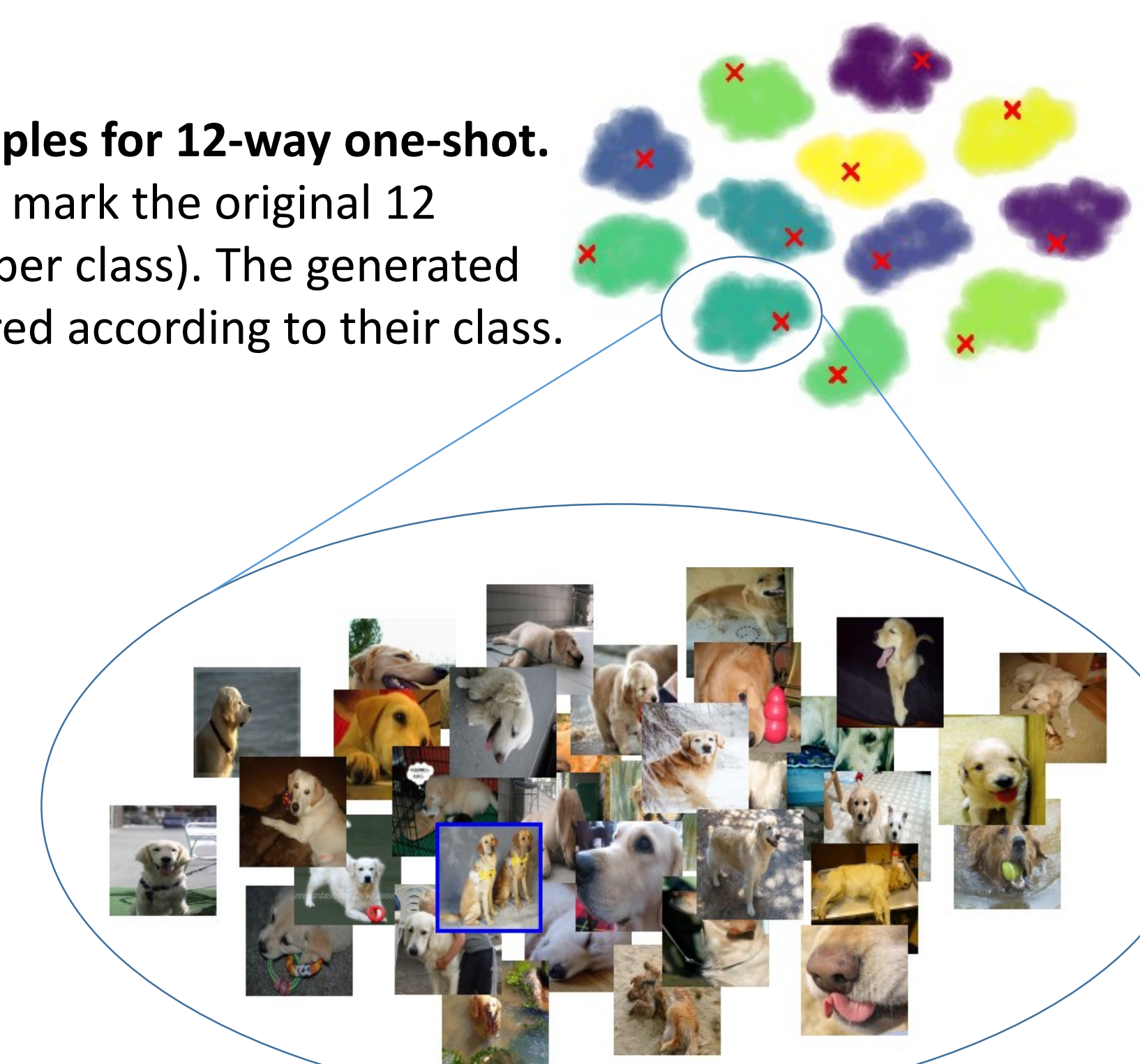


Visualization of two-way one-shot classification trained on synthesized examples. *Correctly* classified images are framed in **magenta (Golden retriever)** and **yellow (African wild dog)**. The only two images seen at training time and used for sample synthesis are framed in **blue**. Note the non-trivial relative arrangement of examples belonging to different classes handled successfully by our approach. Plotted using t-SNE applied to image features.

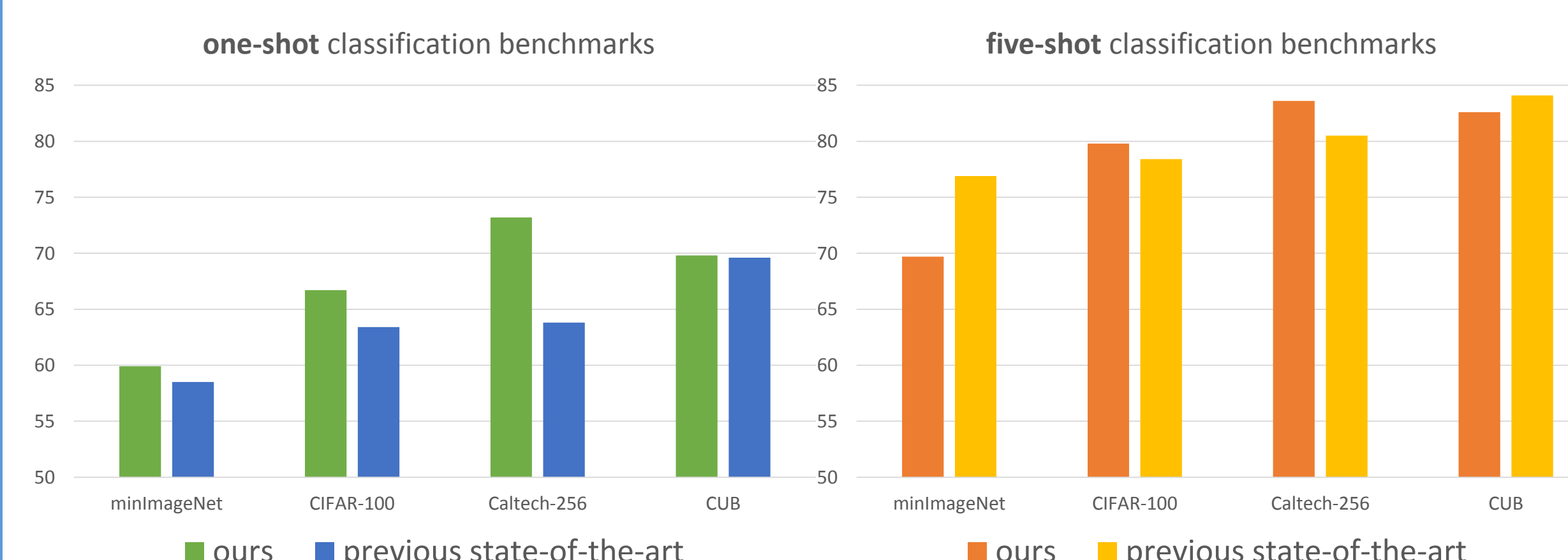
Dataset	Previous SOA 1-shot/5-shot	Ours 1-shot/5-shot
miniImageNet	58.5 / 76.9	59.9 / 69.7
CIFAR-100	63.4 / 78.4	66.7 / 79.8
Caltech-256	63.8 / 80.5	73.2 / 83.6
CUB	69.6 / 84.1	69.8 / 82.6

Generated samples for 12-way one-shot.

The **red** crosses mark the original 12 examples (one per class). The generated points are colored according to their class.



Synthesized samples visualization. The single example image is framed in **blue**. All other images represent the synthesized samples visualized using their nearest "real image" neighbors in the feature space. The two-dimensional embedding was produced by t-SNE.



1-shot/5-shot 5-way accuracy using features externally pre-trained on a non-overlapping set of ImageNet categories

Method	AWA2	APY	SUN	CUB
Nearest neighbor (baseline)	65.9 / 84.2	57.9 / 76.4	72.7 / 86.7	58.7 / 80.2
Prototypical Networks	80.8 / 95.3	69.8 / 90.1	74.7 / 94.8	71.9 / 92.4
Δ -encoder	90.5 / 96.4	82.5 / 93.4	82.0 / 93.0	82.2 / 92.6

