

## Problem:

Given unlabeled data in training, classify a query image into one of the classes defined by a few support images per class. The unlabeled and support images do not share the same object classes.

## Challenge:

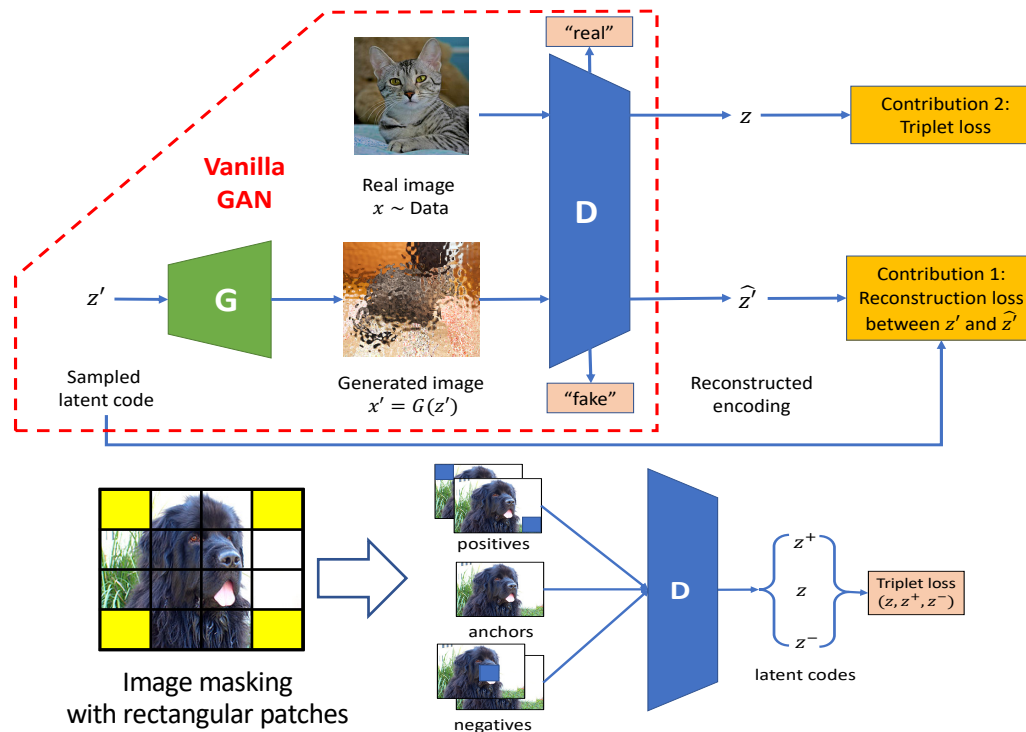
No access to a large set of labeled images to enable the episodic training of standard few-shot classification.

## Contribution 1:

A GAN architecture with reconstruction loss for the discriminator to explicitly capture the most relevant latent codes that generate “fake” images.

## Contribution 2:

Enforce the discriminator to produce image encodings that respect similarity of images via self-supervised learning which uses image masking.



**Table:** Unsupervised few-shot classification on Mini-Imagenet and Tiered-Imagenet

| Unsupervised Methods                        | Mini-Imagenet, 5-way               |                                    | Tiered-Imagenet, 5-way             |                                    |
|---|------------------------------------|------------------------------------|------------------------------------|------------------------------------|
|   | 1-shot                             | 5-shot                             | 1-shot                             | 5-shot                             |
| SN-GAN (Miyato et al., ICLR 2018)           | 34.84 $\pm$ 0.68                   | 44.73 $\pm$ 0.67                   | 35.57 $\pm$ 0.69                   | 49.16 $\pm$ 0.70                   |
| AutoEncoder (Vincent et al., JMLR 2010)     | 28.69 $\pm$ 0.38                   | 34.73 $\pm$ 0.63                   | 29.57 $\pm$ 0.52                   | 38.23 $\pm$ 0.72                   |
| Rotation (Gidaris et al., ICLR 2018)        | 35.54 $\pm$ 0.47                   | 45.93 $\pm$ 0.62                   | 36.90 $\pm$ 0.54                   | 51.23 $\pm$ 0.72                   |
| BiGAN kNN (Donahue et al., ICLR 2017)       | 25.56 $\pm$ 1.08                   | 31.10 $\pm$ 0.63                   | -                                  | -                                  |
| AAL-ProtoNets (Antonios et al., Arxiv 2019) | 37.67 $\pm$ 0.39                   | 40.29 $\pm$ 0.68                   | -                                  | -                                  |
| CACTUs-ProtoNets (Hsu et al., ICLR 2019)    | 39.18 $\pm$ 0.71                   | 53.36 $\pm$ 0.70                   | -                                  | -                                  |
| Our GdBt2                                   | <b>48.28 <math>\pm</math> 0.77</b> | <b>66.06 <math>\pm</math> 0.70</b> | <b>47.86 <math>\pm</math> 0.79</b> | <b>67.70 <math>\pm</math> 0.75</b> |
| Fully-supervised Methods                    |                                    |                                    |                                    |                                    |
| ProtoNets (Snell et al., NeurIPS 2017)      | 46.56 $\pm$ 0.76                   | 62.29 $\pm$ 0.71                   | 46.52 $\pm$ 0.72                   | 66.15 $\pm$ 0.74                   |

**Figure:** Every row shows images in the descending order from left to right by their estimated distance to the original (unmasked) image.

