Data Augmentation Generative Adversarial Networks

Antreas Antoniou, Amos Storkey, Harrison Edwards

Institute for Adaptive and Neural Computation

Arxiv

https://arxiv.org/abs/1711.04340

Presenter: Minho Park

Motivation

- Standard data augmentation produces only limited plausible alternative data.
- Generative models generate plausible data and much broader set of augmentations.
- Design and train a generative model to do data augmentation.

Motivation

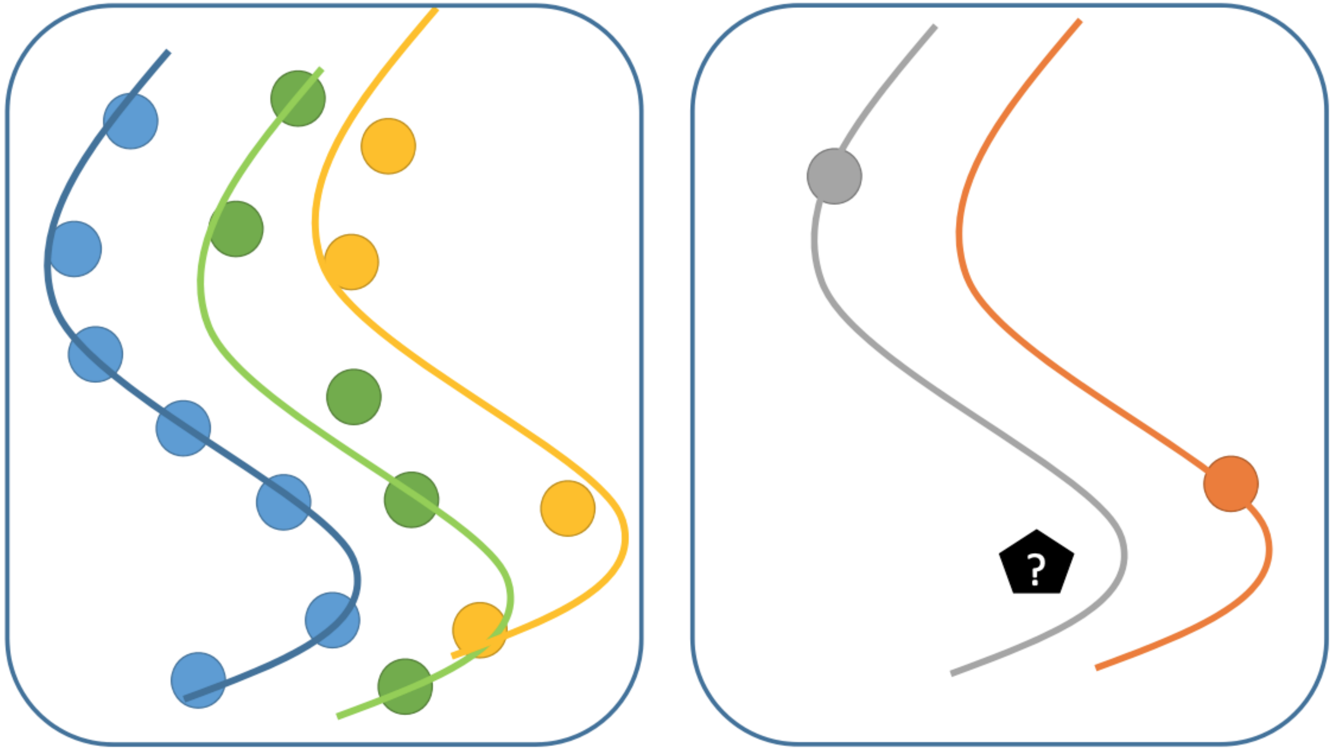


Figure 1: Learning a generative manifold for the classes in the source domain.

Contributions

* Meta-learning: Learning to learn

- Using a novel Generative Adversarial Network to learn a representation and process for a data augmentation.
- Demonstrate realistic data-augmentation samples.
- Demonstrating significant improvements in the generalization performance on standard classifier in the low-data regime.
- The application of DAGAN in the meta-learning space, SOTA.
- Efficient one shot augmentation of matching networks by learning a network to generate only the most salient augmentation examples for any given test case.

Transfer Learning and Dataset Shift

- Shift in the class distributions.
- One shot: extreme shift in the class distributions – two distribution share no support.
- However, the class conditional distribution share commonality and so information can be transferred.

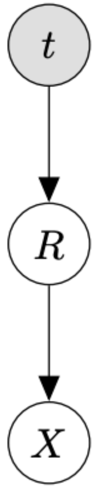


Figure 2: Graphical model for dataset shift in the one-shot setting: the distribution over class label t changes in an extreme way, affecting the distribution over latent R. However the generating distribution $P(X|R)$ does not change.

Generative Adversarial Networks

- GAN approaches can learn complex joint densities.
  - DCGANs use discriminate between true and generated examples as an objective.

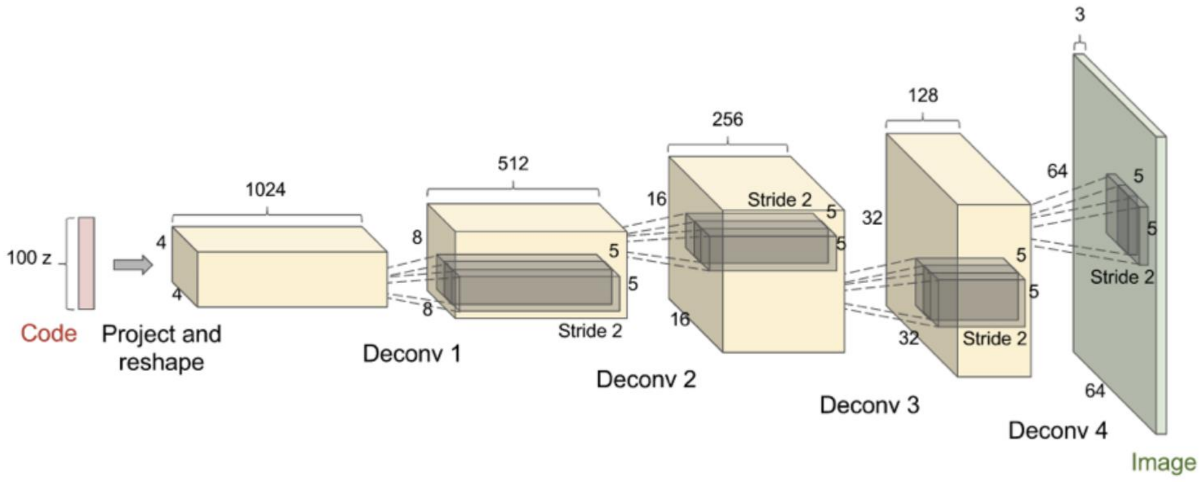


Figure 17: The generator network used by a DCGAN. Figure reproduced from Radford *et al.* (2015).

NIPS 2016 Tutorial: Generative Adversarial Networks, Ian Goodfellow, Arxiv, https://arxiv.org/abs/1701.00160
Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks, Alec Redford et al., ICLR 2016, https://arxiv.org/abs/1511.06434

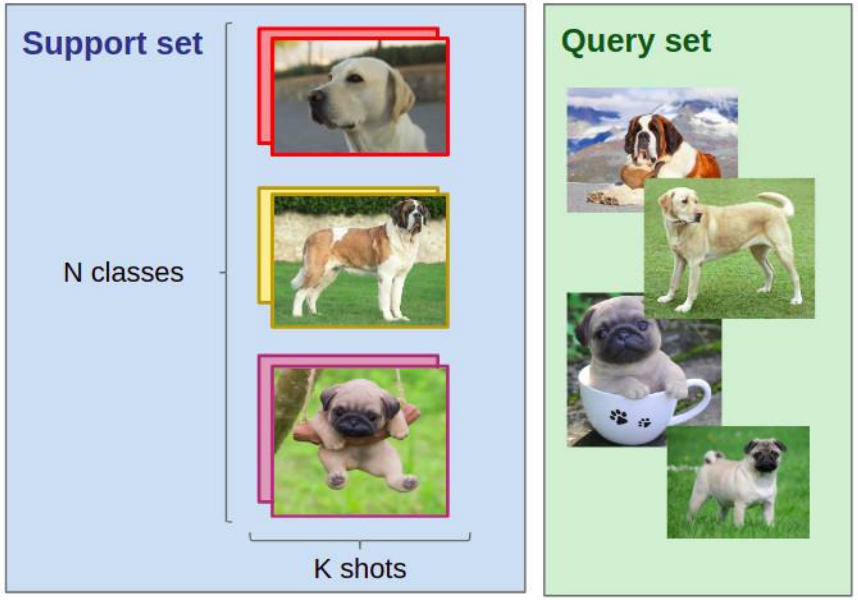
Data Augmentation

- Often it is non-trivial to encode known invariances in a model.
- Learn those trivial invariances by generating additional data items through transformations from existing data items.

Albumentations: Fast and Flexible Image Augmentations, Alexander Buslaev et al., Information 2020, https://github.com/albumentations-team/albumentations

Few-Shot Learning and Meta-Learning

- N-way K-shot problem
- Support set: e.g. N classes, K images classification
- Query set: e.g. Q images

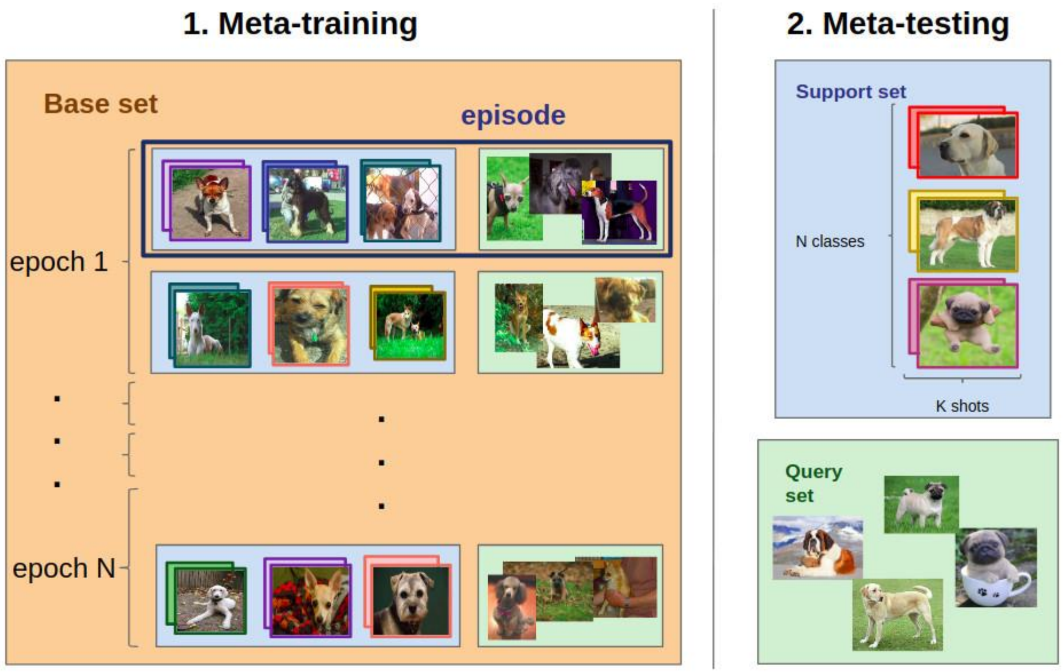


N(3)-way K(2)-shot image classification

Few-Shot Image Classification with Meta-Learning, Etienne Bennequin, https://www.kdnuggets.com/2020/03/few-shot-image-classification-meta-learning.html

Few-Shot Learning and Meta-Learning

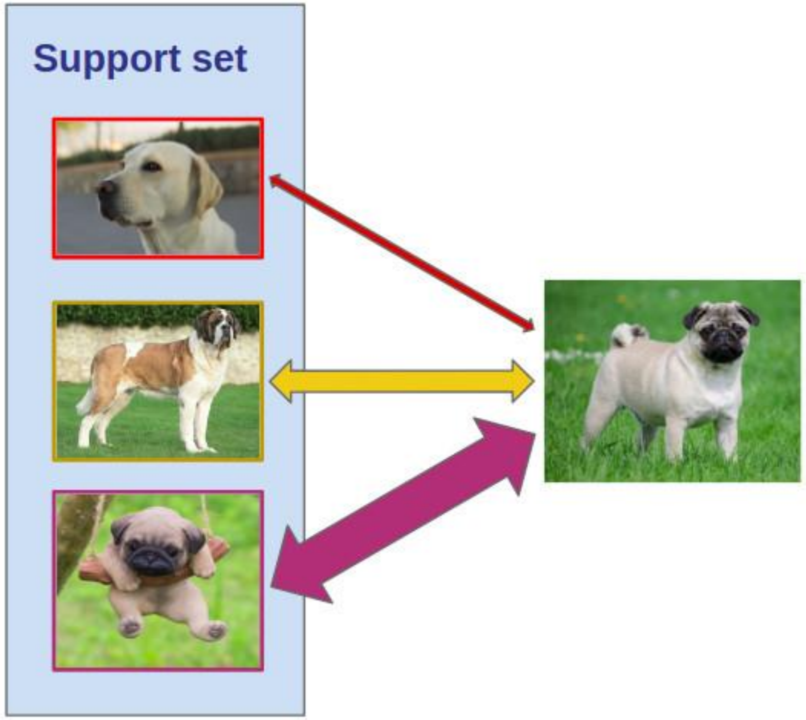
- Episodic training
  - Solve the ultimate task T
  - Using batch of training tasks $\{T_i\}$
- Each time it learns a new task, it becomes better at learning new tasks: it learns to learn.



Meta-training and Meta-testing

Few-Shot Learning and Meta-Learning

- Metric Learning
  - Obvious choice
- Can’t compare images pixel by pixel.
- Compare images in a relevant feature space.



The query (on the right) is compared to each image of the support set

DAGAN

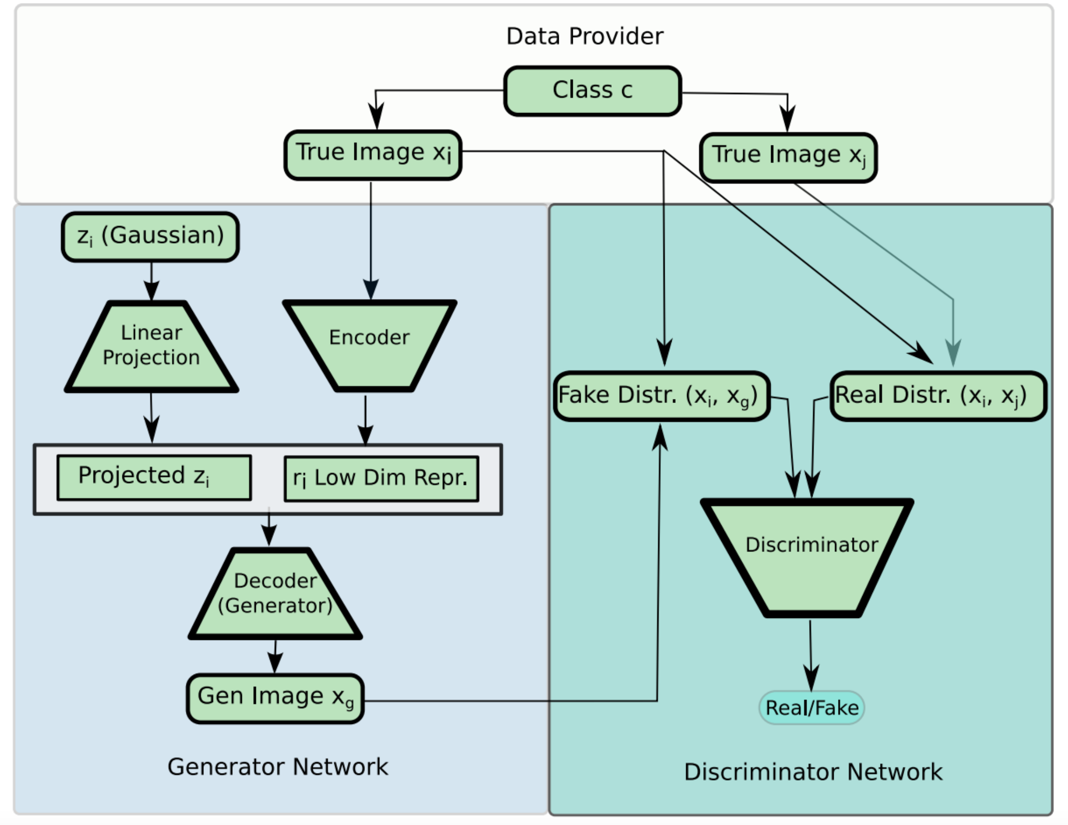


Figure 3: DAGAN Architecture.

DAGAN

- In same class c,
- GANs learn by minimizing a distri bution discrepancy measure betw een the generated data and the tr ue data.

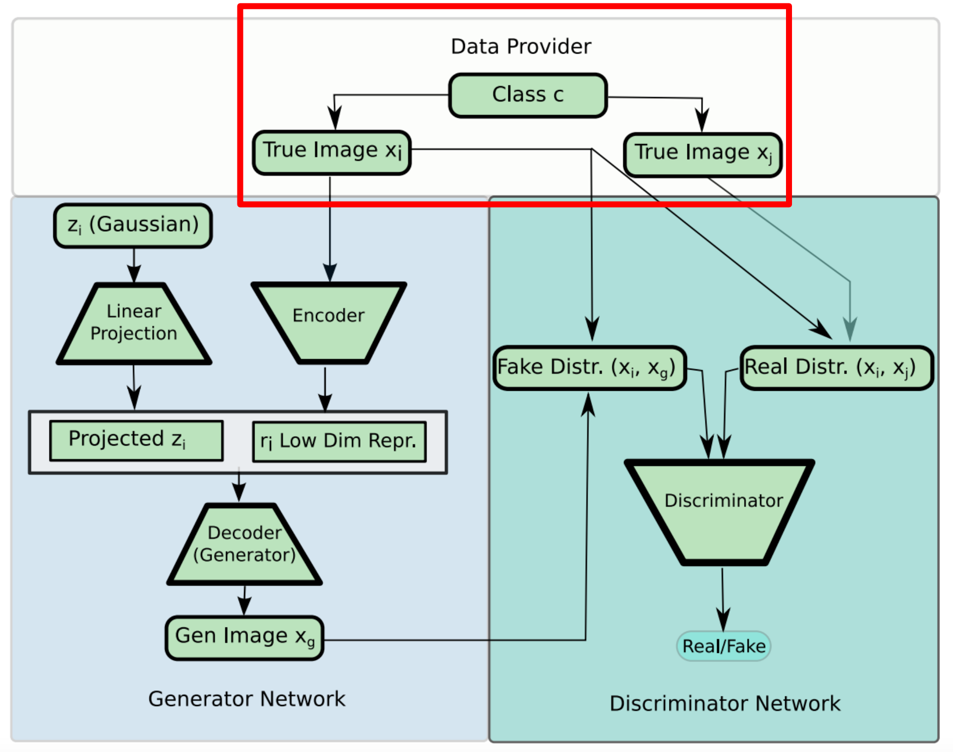


Figure 3: DAGAN Architecture.

DAGAN

- Conditional GAN (class c)
- $r = g(x)$
- $z = \mathcal{N}(0, I)$
- $x^* = f(z, r)$

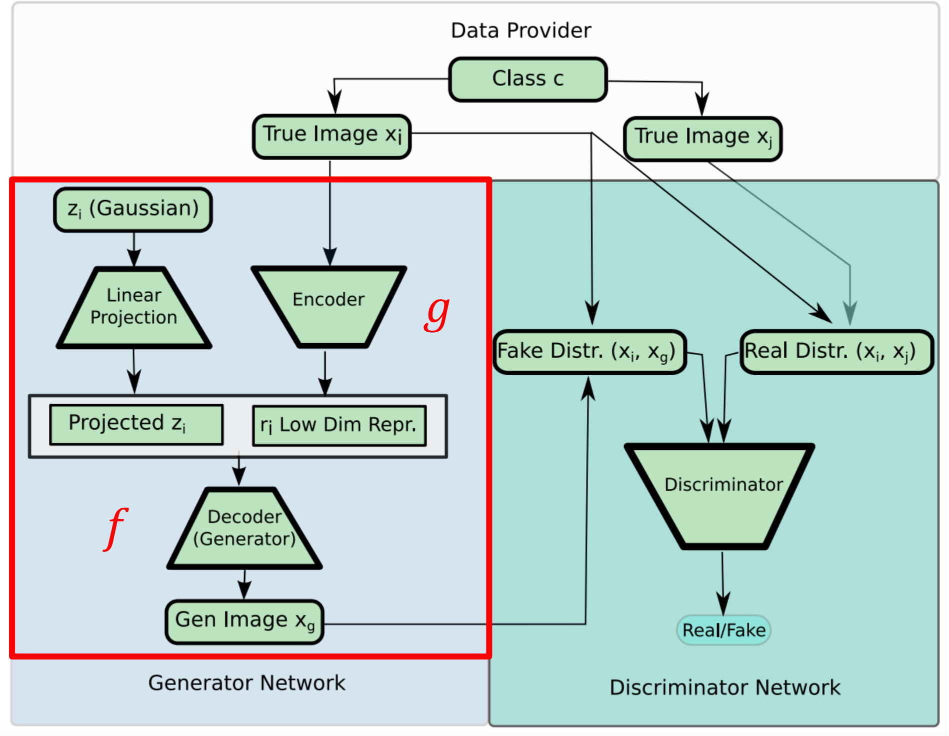


Figure 3: DAGAN Architecture.

DAGAN

- Use an improved WGAN critic.

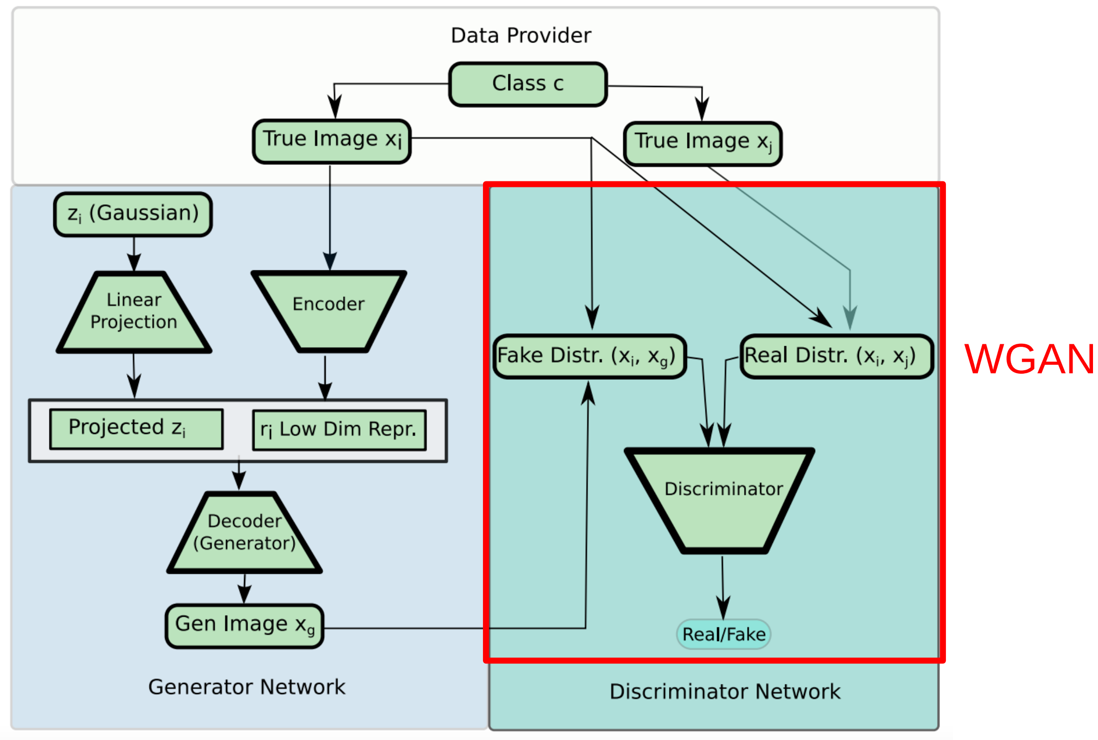


Figure 3: DAGAN Architecture.

Experiments

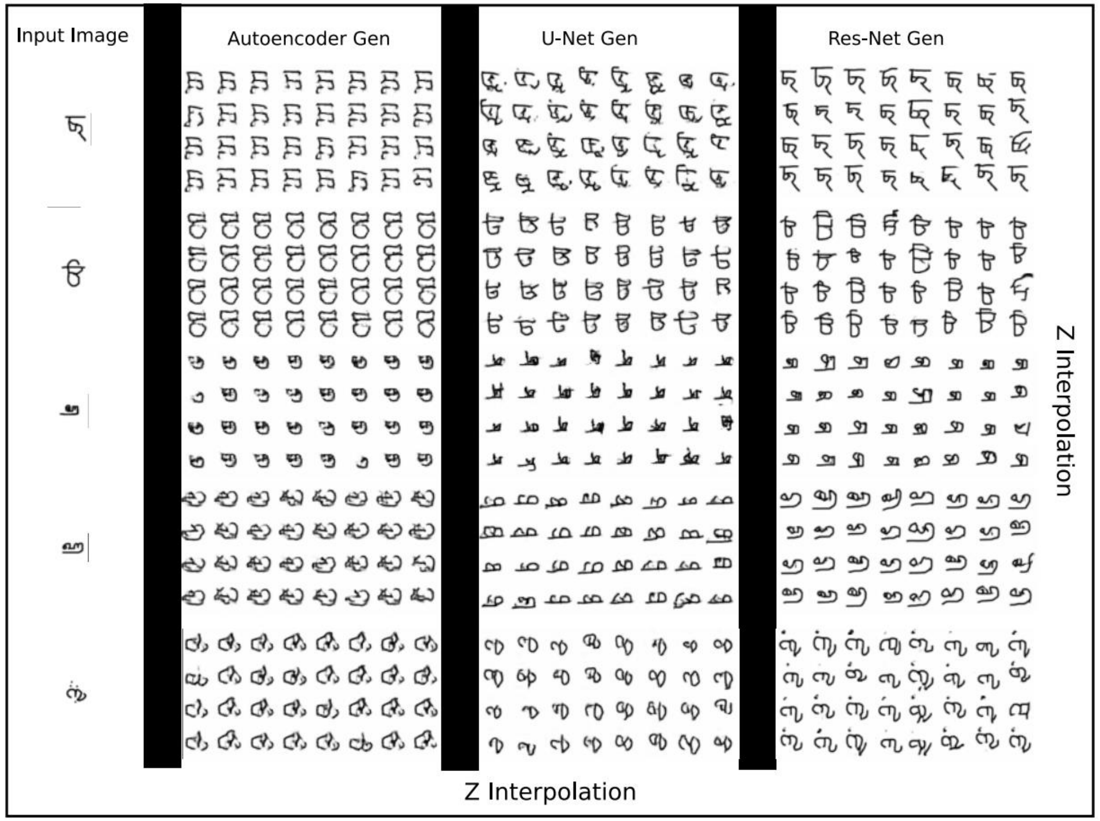
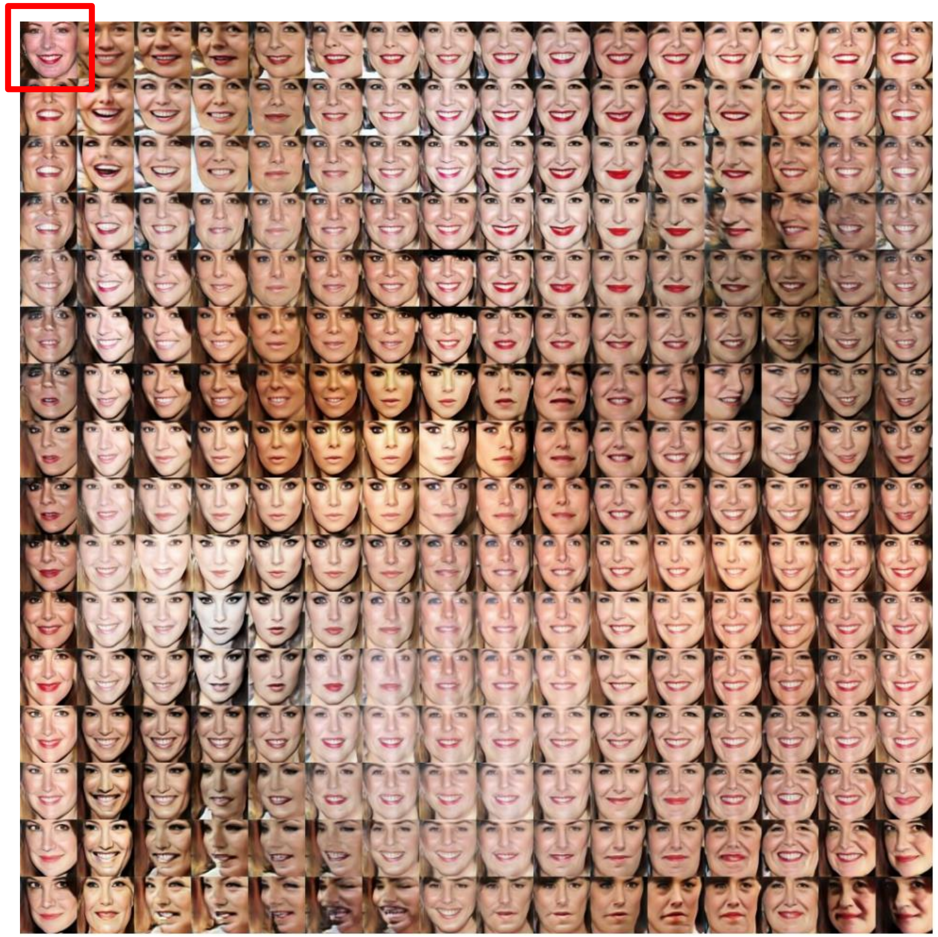


Figure 4: Omniglot DAGAN generations with different architectures.

Experiments

The only real image

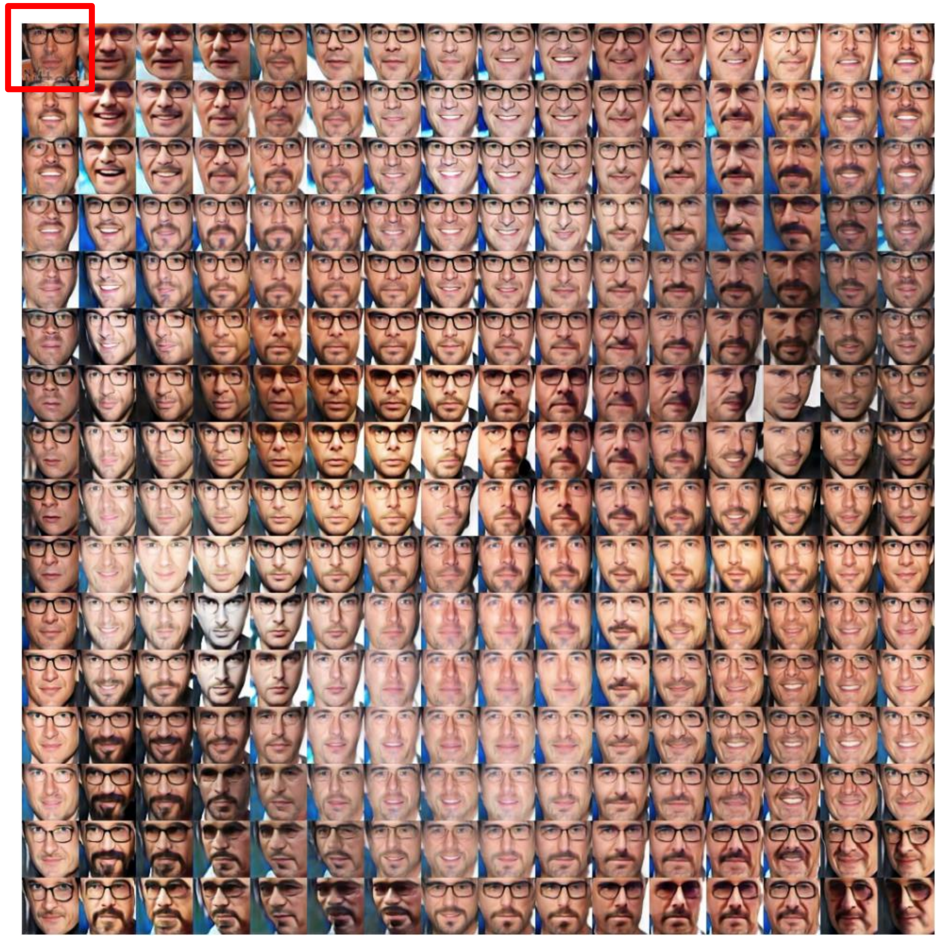


Generated images

Experiments

The only real image

Generated images



Experiments

Omniglot DAGAN Augmented Classification		
Experiment ID	**Samples Per Class**	**Test Accuracy**
Omni_5_Standard	5	0.689904
Omni_5_DAGAN_Augmented	5	**0.821314**
Omni_10_Standard	10	0.794071
Omni_10_DAGAN_Augmented	10	**0.862179**
Omni_15_Standard	15	0.819712
Omni_15_DAGAN_Augmented	15	**0.874199**
EMNIST DAGAN Augmented Classification		
Experiment ID	**Samples Per Class**	**Test Accuracy**
EMNIST_Standard	15	0.739353
EMNIST_DAGAN_Augmented	15	**0.760701**
EMNIST_Standard	25	0.783539
EMNIST_DAGAN_Augmented	25	**0.802598**
EMNIST_Standard	50	0.815055
EMNIST_DAGAN_Augmented	50	**0.827832**
EMNIST_Standard	100	0.837787
EMNIST_DAGAN_Augmented	100	**0.848009**
Face DAGAN Augmented Classification		
Experiment ID	**Samples Per Class**	**Test Accuracy**
VGG-Face_Standard	5	0.0446948
VGG-Face_DAGAN_Augmented	5	**0.125969**
VGG-Face_Standard	15	0.39329
VGG-Face_DAGAN_Augmented	15	**0.429385**
VGG-Face_Standard	25	0.579942
VGG-Face_DAGAN_Augmented	25	**0.584666**

Table 1: Vanilla Classification Results: All results are averages over 5 independent runs. The DAGAN augmentation improves the classifier performance in all cases. Test accuracy is the result on the test cases in the test domain

One Shot Learning With DAGAN

Technique Name	**Test Accuracy**
Pixel Distance	0.267
Pixel Distance + DAGAN Augmentations	**0.60515**
Matching Nets	0.938
Neural Statistician	0.931
Conv. ARC	**0.975**
Prototypical Networks	0.96
Siam-I	0.884
Siam-II	0.92
GR + Siam-I	0.936
GR + Siam-II	0.912
SRPN	0.948
Matching Nets (Local Reproduction)	**0.969**
Matching Nets + DAGAN Augmentations	**0.974**

Table 2: Omniglot One Shot Results: All results are averages over 3 independent runs. Note that our own local implementation of matching networks substantially outperform the matching network results presented in the original paper, However DAGAN augmentation takes matching networks up to the level of Conv-ARC (Shyam et al., 2017). Note DAGAN augmentation can even increase a simple pixel distance nearest neighbour model up to non-negligible levels.