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UNIVERSIDAD DE LA REPÚBLICA URUGUAY

Spatial Coevolutionary Deep Neural Networks Training

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Outline

1. Motivation
2. Generative Adversarial Networks
3. Coevolutionary System Design
4. Experimental Analysis
5. Summary

Motivation

Generating Data

Figure 7: Generated samples

Motivation

Generative Models

Generative models map **from a latent input space to a specific output distribution**, e.g. certain images

Generative Adversarial Networks (GANs) are **unsupervised learning** algorithms and do not rely on direct mappings from input data to a latent space

- The **generative** model **never sees** the input data
- Training is only done by receiving adversarial feedback

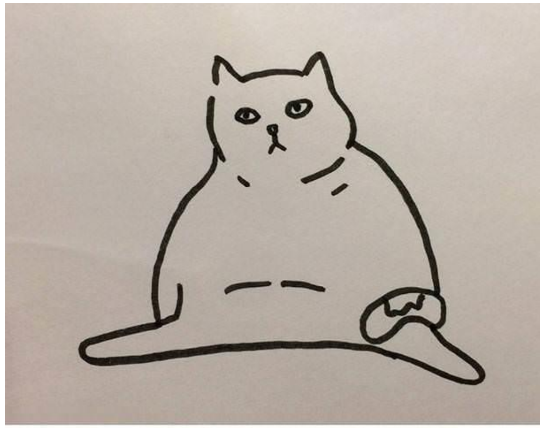
Motivation

Discriminative Models

Discriminative models classify between real and fake inputs

GANs create discriminative models from <u>unlabeled</u> data

- Image Classification
- Malware Detection
- …



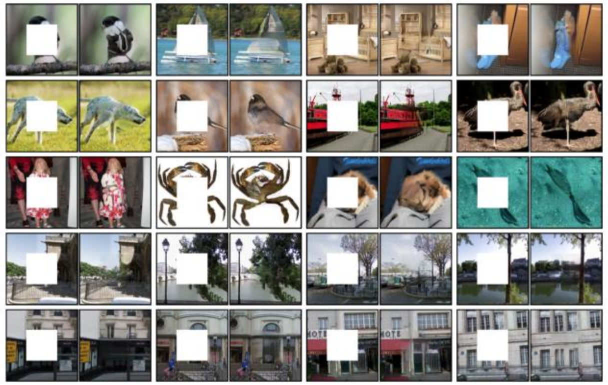
Which cat is real?

Motivation

Image generation

Figure 7: Generated samples

Image reparation



Music generation

Figure 3. Example result of the melodies (of 8 bars) generated by different implementations of MidiNet.

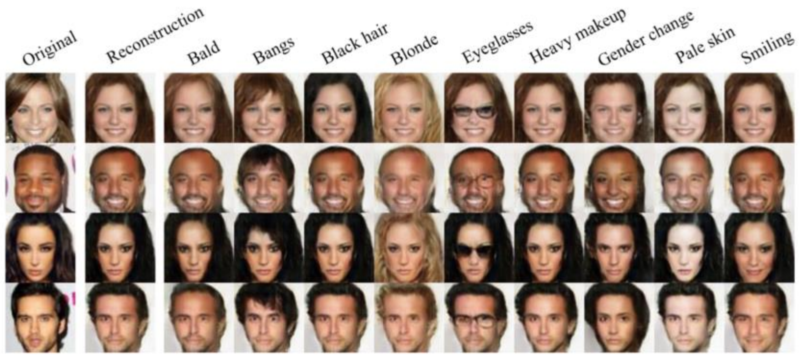
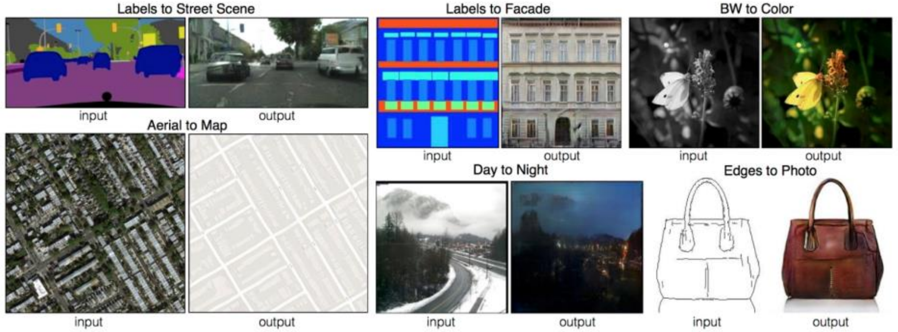
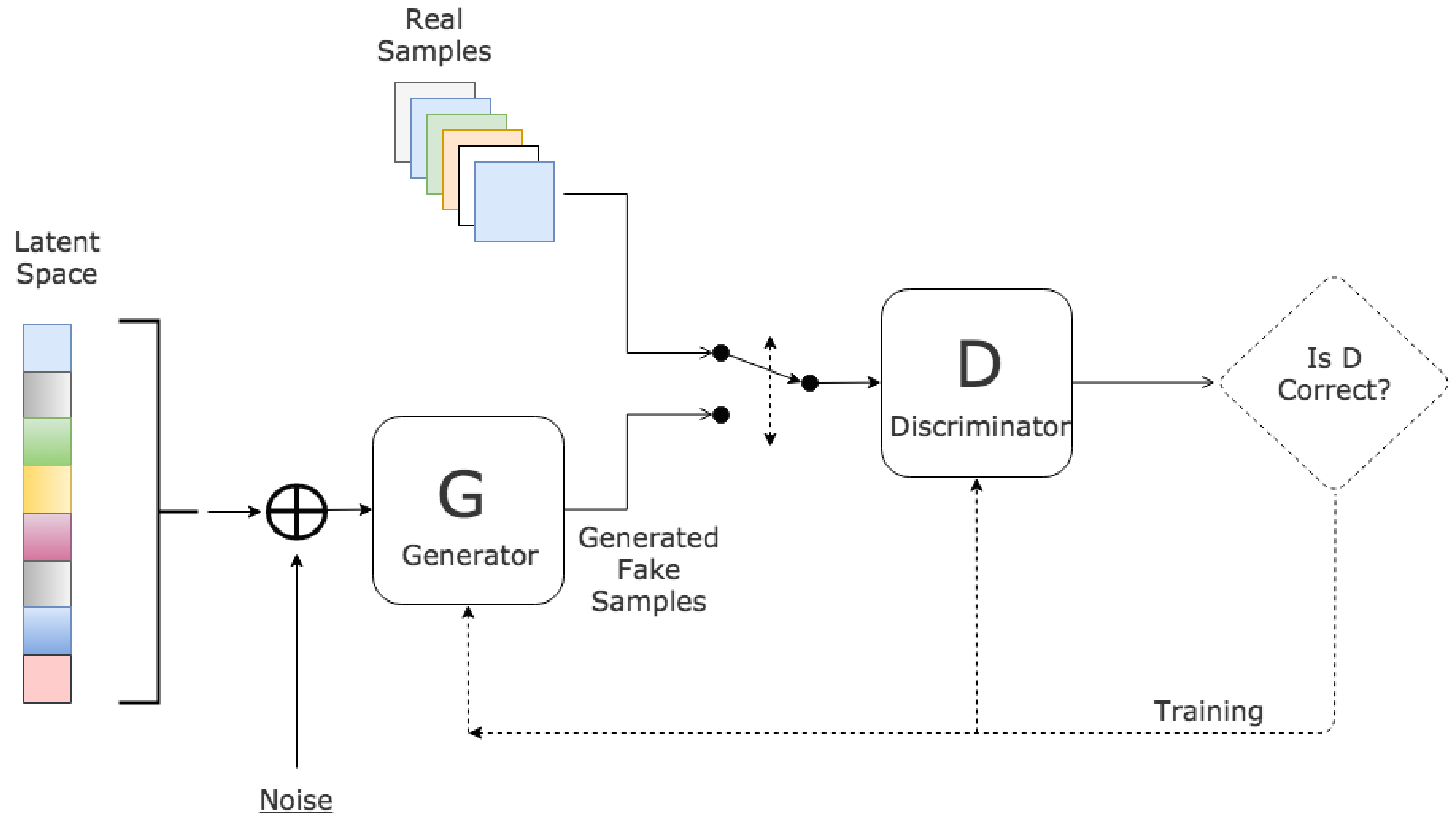


Image edition

Img-to-img translation



Generative Adversarial Networks

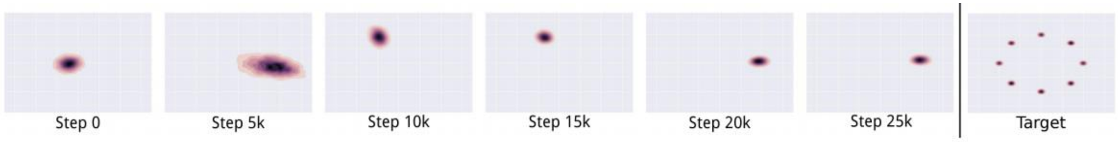


Mode Collapse

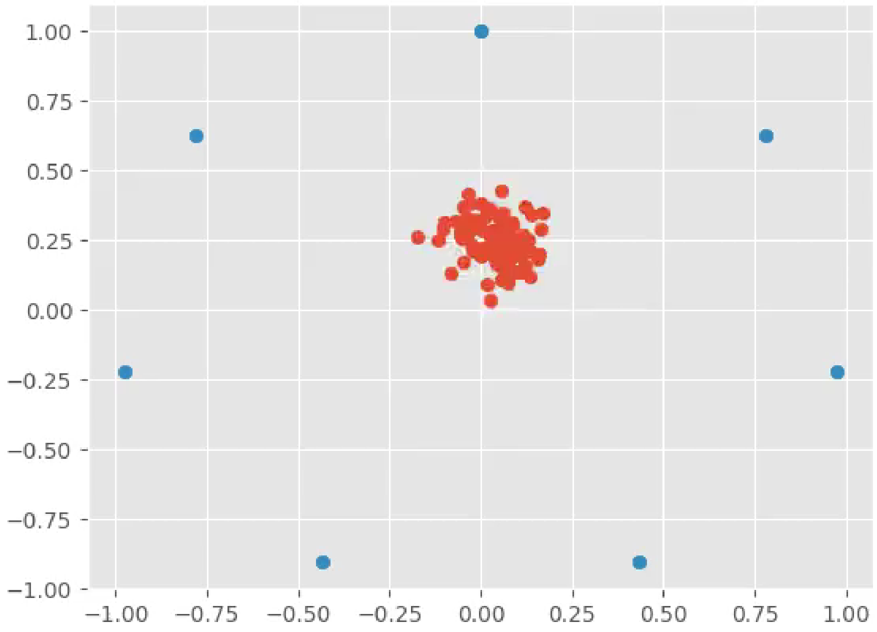
GAN Pathologies

Non-convergence: the model parameters oscillate, destabilize and never converge

Mode collapse: the generator collapses which produces limited varieties of samples



Diminished gradient: the discriminator gets too successful that the generator gradient vanishes and learns nothing



Focusing on different modes

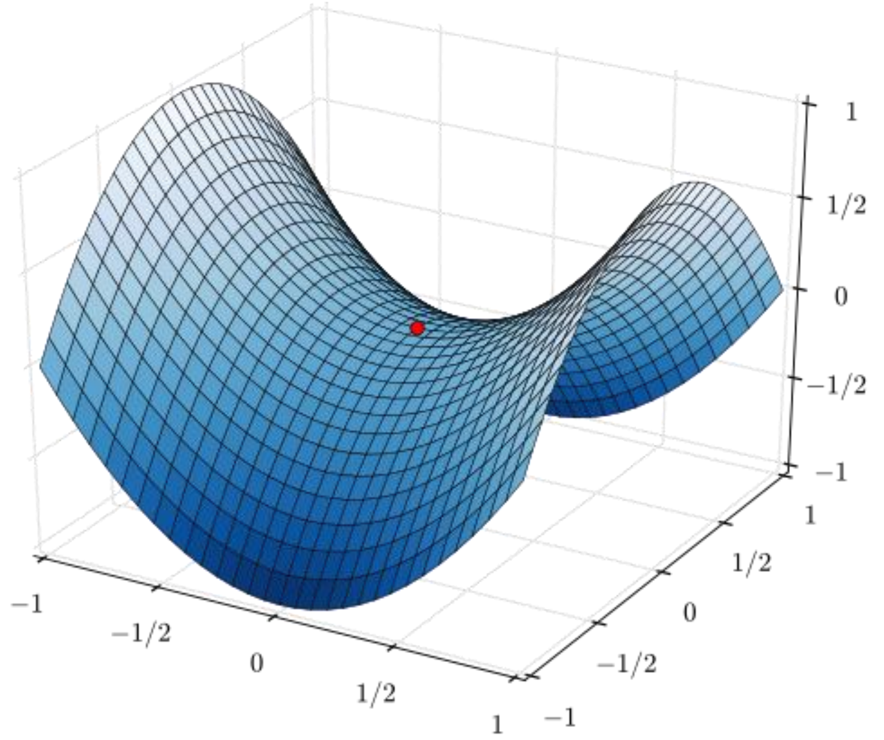
Relation between GANs and Coev

<u>Both are Minimax Problems</u>

(z) sample from latent space
(x) sample from real data

The ***generator's*** objective is to **minimize $\boldsymbol{D(G(z))}$**

The *discriminator's* objective is to **maximize $\boldsymbol{D(G(z))}$, while minimizing $\boldsymbol{D(x)}$**



Relation between GANs and Coev

Nature inspired coevolution

Biological arms races can provide adaptation
- Nature displays multiple adversaries and robustness

Can coevolution help to improve robustness in other adversarial settings?
- Multiple comparisons can aid **robustness**
- Multiple variations based on quality measurements improve **diversity**

Mustangs: Gradient-based Coevolution

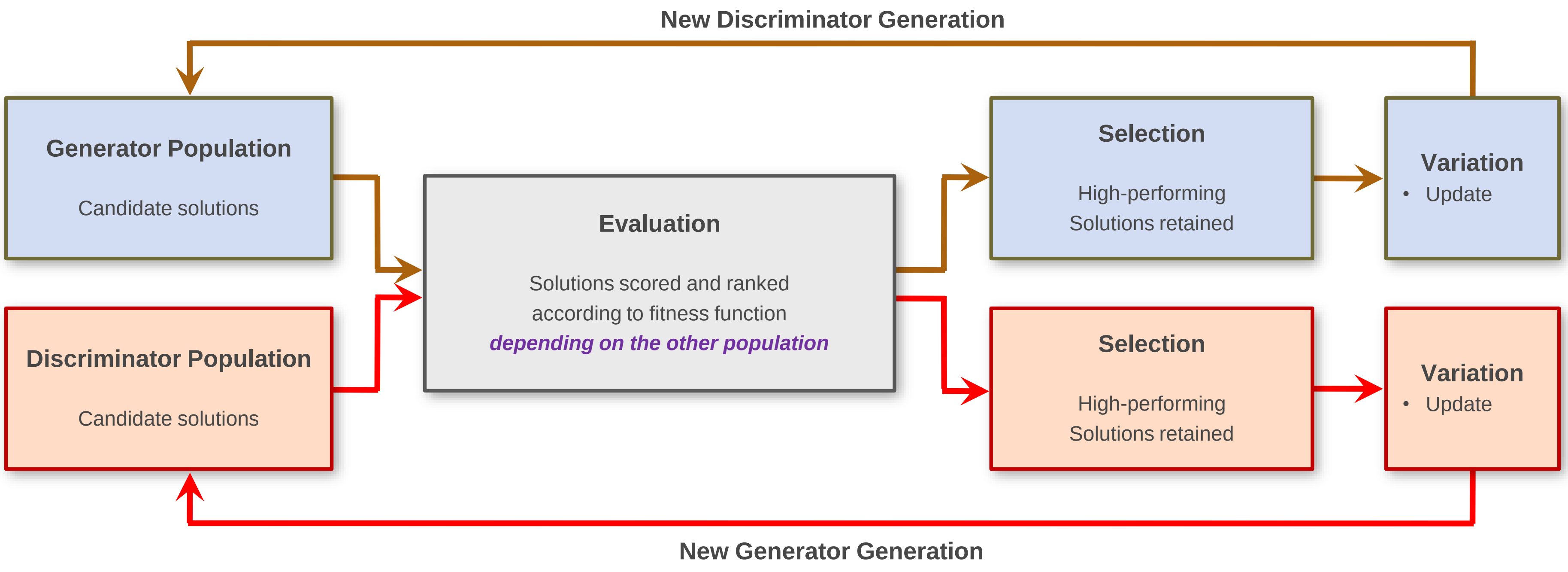
Combining the Advantages of both Techniques

A distributed, coevolutionary framework to train GANs with gradient-based optimizers

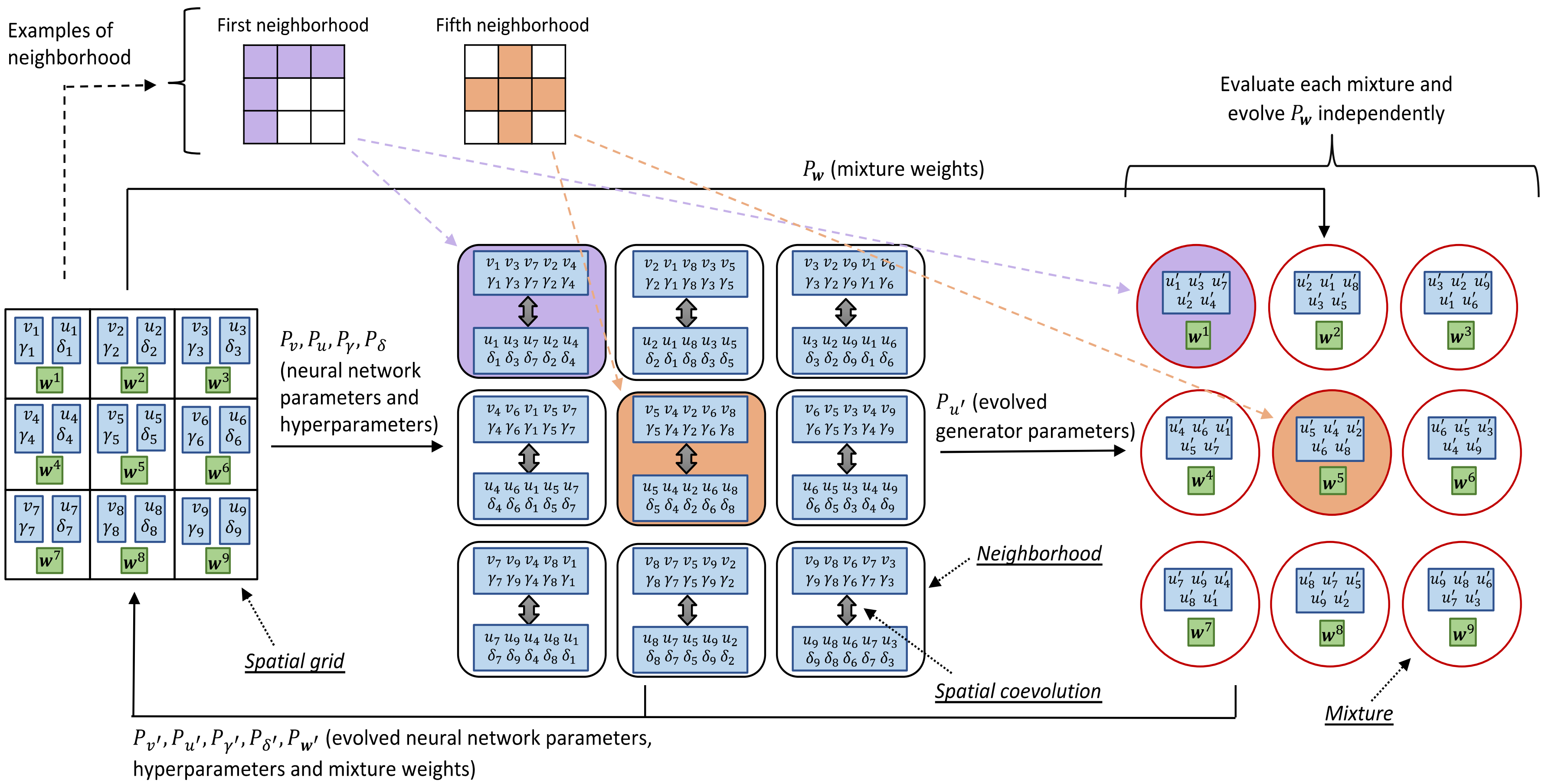
- Fast convergence due to gradient-based steps
- Robustness due to coevolution
- Improved convergence due to hyperparameter evolution
- Diverse solutions due to mixture evolution
- Scalability due to spatial distribution topology

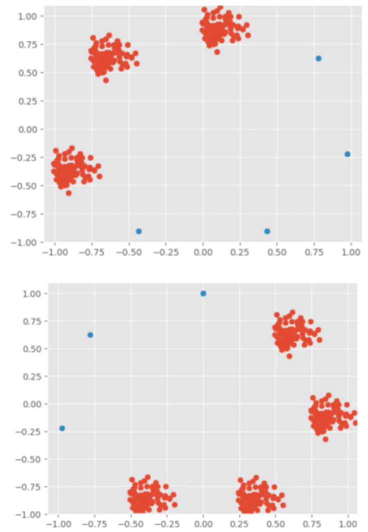
Mustangs: Gradient-based Coevolution

General Idea



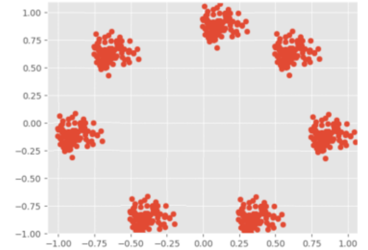
Mustangs: Gradient-based Coevolution





ω^a=0.43

ω^b=0.57

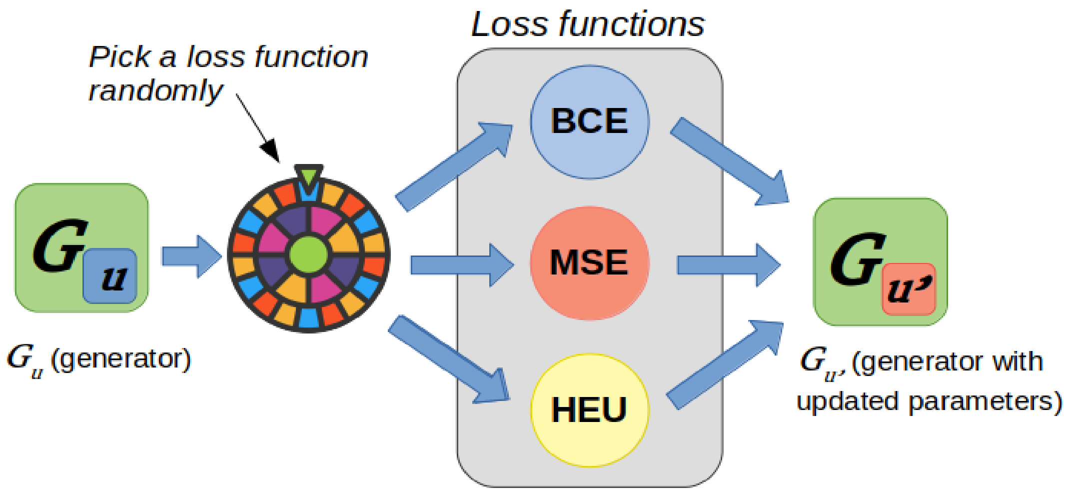


Mustangs: Gradient-based Coevolution

Loss Based Diversity

Mustangs randomly picks a loss function with different minimization objectives to improve the diversity

- Minmax loss
- Least-square loss
- Heuristic loss



Experiments

Evaluating Mustangs against other methods that provides diversity (population or loss based)

- E-GAN
- Lip-BCE
- Lip-MSE
- Lip-Heu
- GAN-BCE

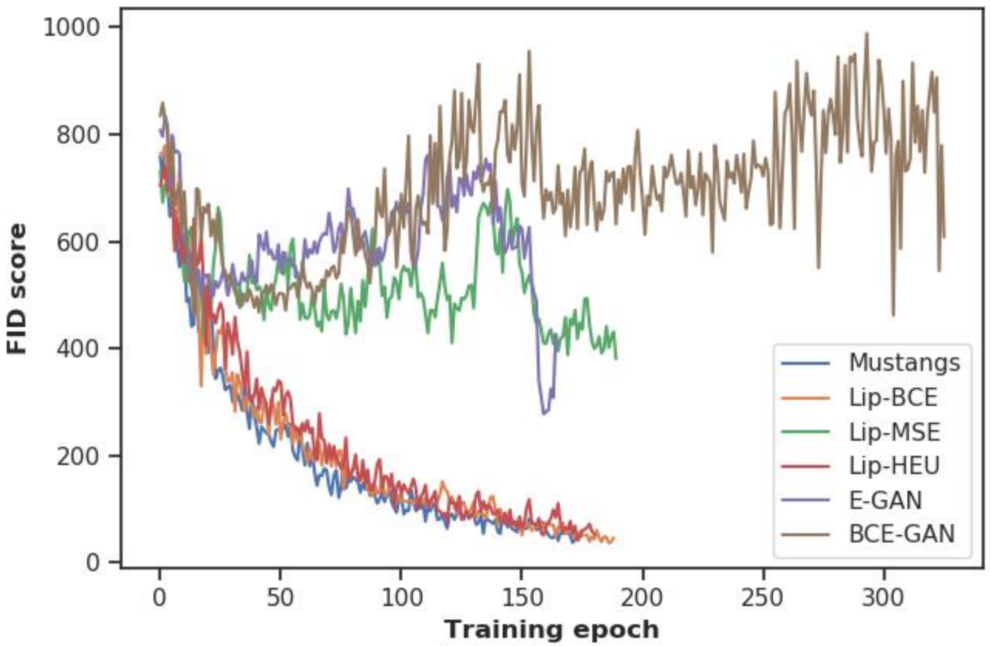
MNIST

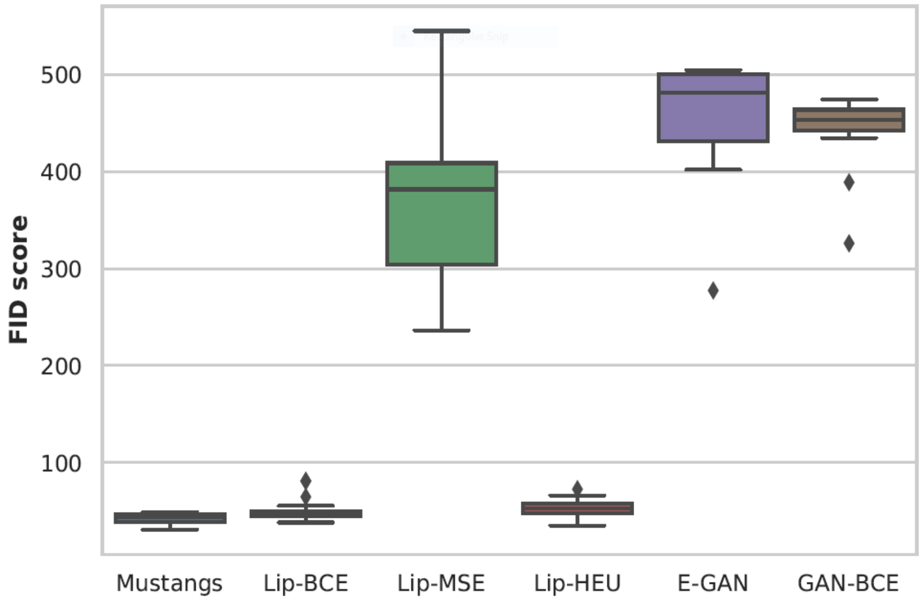
CelebA

CelebA

Experiments: MNIST

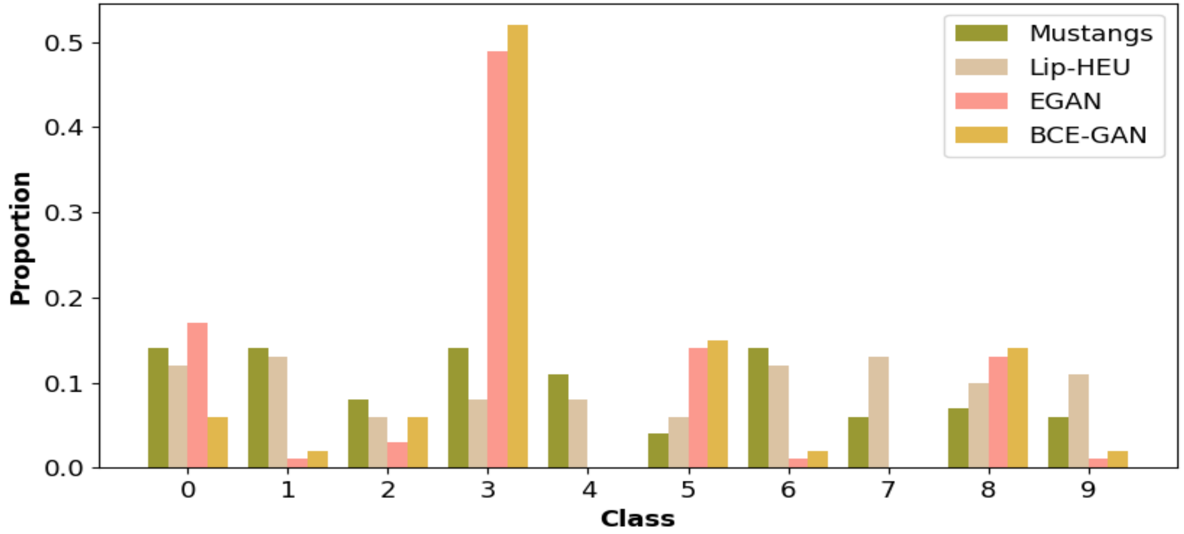
FID score: The lower, the better

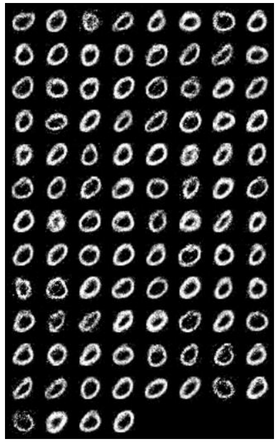




Experimental Results: MNIST

Generator Output Diversity




Mode collapse

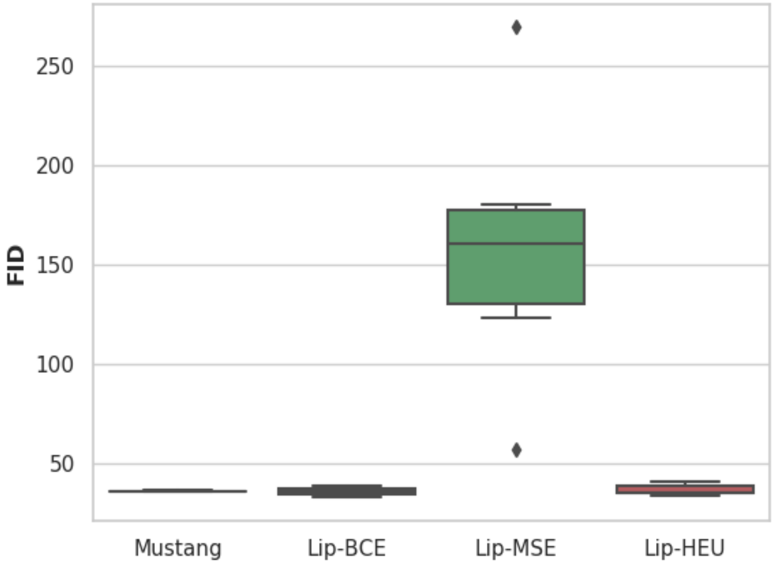

Mustangs

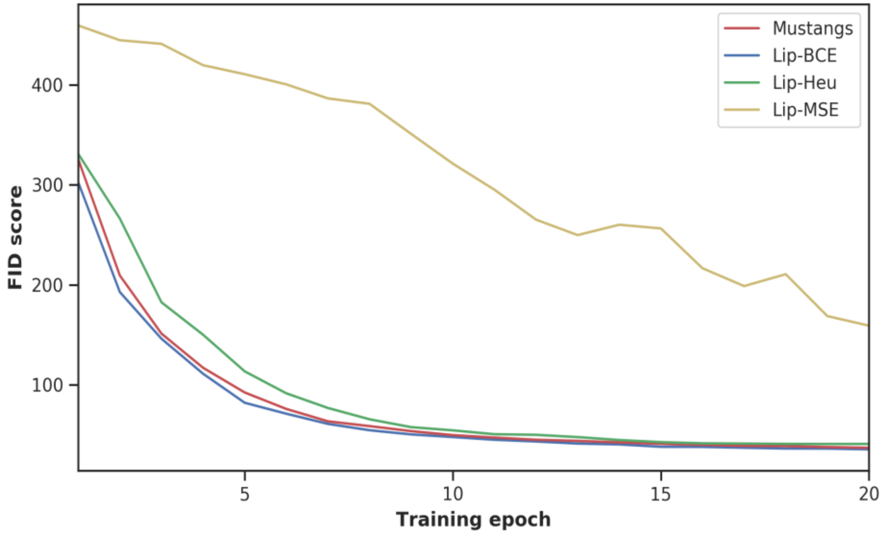

Lip-BCE

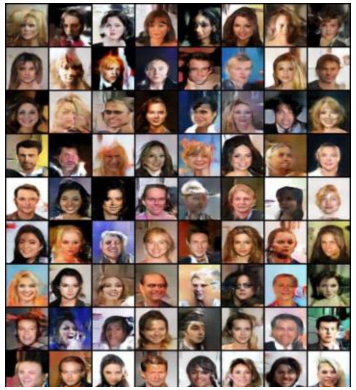

E-GAN

Experimental Results: CelebA

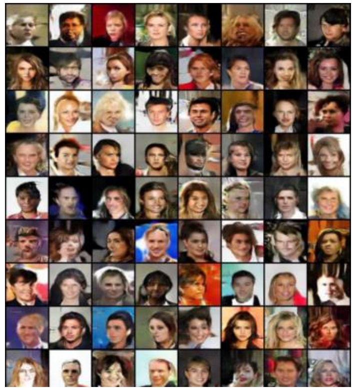
FID score: The lower, the better







Mustangs



Lip-BCE

Summary

- We have empirically showed that GAN training can be improved by boosting **diversity** (preventing critical GAN pathologies)
- We enhanced an existing spatial evolutionary GAN training framework that promoted genomic diversity by probabilistically choosing one of three loss functions
- **Work in progress** imply scaling works well
- https://github.com/mustang-gan

Comments?

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