GAN-Based Image Data Augmentation  
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**Introduction**  
- Generative Adversarial Networks (GANs) are powerful generative models introduced by (Goodfellow et al.) [7] and can be trained on as little data as a single image [5].  
- Lack of data makes ML hard -- data augmentation  
- Prior work:  
  - “Translating” images [3]  
  - Generating numeric data [1]  
- Motivation: Explore using these super powerful generative models to augment more complex data sets  
- Classic Problem: Image classification of numbers in the MNIST database.

**Direct Data Augmentation**  
- Trained the classifier on purely GAN-generated data for GANs of various sizes  
- Pure synthetic data comparable to pure real data in training classifier

<table>
<thead>
<tr>
<th>Train Size</th>
<th>α = 1</th>
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</thead>
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<tr>
<td>250</td>
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**Recursive GAN Training**  
- Repeatedly use GANs to augment the dataset of images then used to train more GANs  
- Classifier performance shows oscillating accuracies before long-term drop in performance

**Model Architectures**  
- GAN Loss is like a Two-Player Game:  
  \[
  \min_{G} \max_{D} V(D, G) = \mathbb{E}_{x \sim p_{data}(x)} \left[ \log D(x) \right] + \mathbb{E}_{z \sim p_z(z)} \left[ \log (1 - D(G(z))) \right]
  \]
- The classifier used cross entropy loss with regularization

**Summary and Future Work**  
- Summary:  
  - We achieved comparable performance when training only on GAN-generated data and significant performance increases when using GAN-generated data and real data.  
  - Adding GAN generated data can be more beneficial than adding more original data, and leads to more stability in training  
  - Recursive training of GANs failed to yield performance increase  
- Future work:  
  - More fine tuning of hyperparameters when training GANs  
  - Exploring other classifier architectures and generative models  
  - More complex image classification tasks, ex. CIFAR 100

**References:**  

**Future work:**  
- More complex image classification tasks, ex. CIFAR 100

**Train Size**
- RecTrain Accuracies
- 250: 0.641 0.422 0.615 0.709 0.696
- 500: 0.648 0.611 0.741 0.763 0.710
- 1000: 0.683 0.670 0.694 0.756 0.738
- 2000: 0.788 0.687 0.680 0.793 0.781

**Model Architectures**
- GAN Architecture
- Generator and Discriminator
- The classifier used cross entropy loss with regularization

**Figure:**
- 500 Real, 500 Synthetic
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UNSURE IF BAD MODEL
OR INSUFFICIENT DATA
Enlarge your Dataset
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- Trained classifier on mixed synthetic data + real data in various ratios
- Mixed data outdoes pure real data; more noticeable for small datasets
- Unstable training losses suggest higher variance in real data
Recursive GAN Training

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![Graph showing RecTrain Accuracies](image)
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- RecTrain Accuracies

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### Figure

- GAN Architecture
- Classifier

Recursive GAN Training

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