A Large-Scale Study on Regularization and Normalization in GANs

Google Research Brain Team
Which *model* achieves a given level of *sample quality* the *fastest*?
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**Model**

- Loss + regularization + normalization + neural architectures

- **Non-saturating**
  - Gradient penalty
  - L2 regularization
  - Spectral normalization
  - Layer normalization
  - Batch normalization

- **Wasserstein**

- **Least-squares**

- **RESNET**

- **DCGAN/SNDCGAN**

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Which *model* achieves a given level of *sample quality* the *fastest*?

Sample quality: measured by

(a) Frechet Inception Distance
(b) Inception Score
Which \textit{model} achieves a given level of \textit{sample quality} the \textit{fastest}?

Fastest: minimizes the number of hyperparameter settings needed

Reported in the literature + sequential Bayesian optimization
Experimental protocol

1. Pick a **dataset** (CelebA-HQ, LSUN Bedrooms, CIFAR10)
2. Pick a **model** (>15,000)
3. Train it on **more than 260 hyperparameter settings**
4. Plot the **best score** for a given budget of hyperparameters
Study: Regularization and normalization

1. **Improved Training of Wasserstein GANs**

2. **On Convergence and Stability of GANs**

3. **Spectral Normalization for Generative Adversarial Networks**

4. **Layer Normalization**

5. **Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift**
Results: Regularization and normalization study

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Results: Regularization and normalization study

Non-saturating loss, LSUN Bedroom

FID

\[ 10^0 \quad 10^1 \quad 10^2 \]

\# Hyperparameter settings

\[ 10^0 \quad 10^1 \quad 10^2 \]
Results: Regularization and normalization study

Non-saturating loss, LSUN Bedroom

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Results: Regularization and normalization study

Non-saturating loss, LSUN Bedroom

- No regularization and normalization
- Gradient penalty

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Results: Regularization and normalization study

Without Gradient penalty

DRAGAN

L2

LSUN Bedroom

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Results: Regularization and normalization study

1. Optimization remains a key challenge

2. Spectral normalization is the most effective technique
   ○ No dataset-specific hyperparameter tuning is required
   ○ Per-iteration overhead is minimal

3. Gradient-based regularization from Gulrajani et al.
   ○ Useful, but necessitates hyperparameter tuning
   ○ Has a significantly higher per-iteration cost than spectral normalization

Many Paths to Equilibrium: GANs do not Need to Decrease a Divergence at Every Step

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Varying losses and neural architectures

1. **Insights transfer across loss functions**
   - Wasserstein GAN
     Arjovsky, M., Chintala, S., & Bottou, L. (2017)
   - Least squares Generative Adversarial Networks.

2. **Insights transfer across neural architectures**
   - (SN)-DCGAN
   - Deep Residual Learning for Image Recognition
     He, K., Zhang, X., Ren, S., & Sun, J. (2016)
Summary

There is a lot of room for progress -- optimization remains a key challenge.

Spectral normalization is currently the most effective technique.

Gradient-based regularization is useful, but necessitates more tuning.
Future work

1. Customized architectures (e.g. BigGAN, StyleGAN)
2. Self-attention and self-modulation mechanisms
3. Improved quantitative evaluation measures
   - *Assessing Generative Models via Precision and Recall*
     Sajjadi, M. S., Bachem, O., Lucic, M., Bousquet, O., & Gelly, S. (2018)
   - *Improved Precision and Recall Metric for Assessing Generative Models*
Resources

Code, pretrained models and Colab available at:

github.com/google/compare_gan

Check out our poster #9 tonight (Jun 12th) 6:30-9:00 pm!