Detecting Overfitting of Deep Generative Networks via Latent Recovery

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with

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Context

• **Deep Learning** is a powerful framework for computer vision and signal processing fields

• **Convolutional Neural Networks** (CNNs) allows for extremely **fast** execution and state-of-the-art **performance** in many applications

• Example: impressive results in image classification VGG [Simonyan’14], Inception Network [Szegedy’15]

• In this talk: focus on **Image Generation**
Generative Networks

• **Objective**: synthesize images that are perceptually similar (yet different) from examples from a dataset

• **Principle**: train a CNN $G$ to generate such image samples; Various (unsupervised) strategies during training to compare samples with examples from the dataset

• **Synthesis**: generated images $G(z)$ are obtained by feeding the network with (random) latent codes $z$

• **Remark**: no optimization required during synthesis (only $\sim 20$ ms with a GPU, $<10$ s with a CPU)
A recent and popular approach is Generative Adversarial Networks [Goodfellow’14], or GANs.

Incredible improvement in the last few years! 

Source: Ian Goodfellow
Examples of image synthesis

- **DC-GAN** [Radford’16] (trained on ~350k images for face)

  Face (350k ex.)

  Bedrooms (3M ex.)

  ???
Examples of image synthesis

- PG-GAN [Karras’18] (trained on ~30k images)
Examples of image synthesis

- PG-GAN [Karras’18] (trained on ~100k images/categories)
Examples of image synthesis

- BIG-GAN [Brock’19] (trained on ~292M images with 8.5K categories)

https://ganbreeder.app/
Examples of image synthesis

• Style-GAN [Karras et al.’19] (trained on ~80k images)

https://thispersondoesnotexist.com/
Motivation

• Deep Learning Paradigm: the **bigger** (= deeper/wider networks), the **better** (e.g. BIG-GAN [Brock’19])

• … but requires a lot of (offline) intensive computations and (most of the time) a **large dataset**

• Very strong suspicion of **overfitting** and **memorization** of generator networks, but difficult to investigate

• … although supported by **some evidence** in the literature
Reported limitations

• Classification Networks with random labels/images [Zang’17]
  « *The effective capacity of neural networks is sufficient for memorizing the entire data set* »
  « Explicit regularization may improve generalization performance, but is [not] by itself sufficient »

• Successful membership inference attack on Classification Networks [Shokri’17]

• Generative Networks (AutoEncoder) for disk generation [Newson’18]
  - Approximate the training examples with a template model
  - Failure in generalization capacity for data interpolation and role of regularization

• Discriminator in GANs can memorize the training dataset [Hayes’17] [Brock’19]
**Question**: How to evaluate Generative Networks regarding memorization?

- **training image (LSUN tower)**
- **generated image (WGAN)**
- **training image (CelebA HQ)**
- **generated image (PGGAN)**

**Related problem**: How to ensure privacy of the training data?
A short review of generative networks
Generative Architecture

- **Typical architecture**: fully convolutional neural network

- uses a (batch of) *iid* random vectors $z$ as the input

- starts with a fully connected layer

- followed by blocks of small upsampling convolutions and ReLU activations (until reaching the desired resolution)

Source: DC-GAN [Radford’16]
Many different approaches to train a generative network:

- As a decoder: **Auto-encoder** (AE) [LeCun’87], and **Variational Auto-Encoder** (VAE) [Kingma’14] (for sampling)
- **Generative Adversarial Network (GAN)** [Goodfellow’14]
- **Generative Latent Optimization** network (GLO) [Bojanowski’18]
- **Flow-based** generative model (GLOW) [Kingma and Dhariwal, 18]
- **Generative Moment Matching networks** (GMMNs)
- **Hybrid methods** (Cycle-GAN [Chen’18], AE-GAN [Li’17], …)
Auto-Encoder

- **Principle:** Encode an input image $x$ into a **latent code** $z = E(x)$ and decode with the generator $G(z)$.

- **Optimization problem:**

\[
\min_{G,E} \sum_{x_i \in \mathcal{D}} \| G(E(x_i)) - x_i \|^2_2
\]

- **Variant:** Variational Auto-Encoder ($z$ is a sampled from a pdf parametrized by $E$)
Generative Latent Optimization

- **Principle:** Both optimize latent codes $\{z_i\}$ and the generator $G$

- **Optimization problem:**
  $$\min_{G,\{z_i\}} \sum_{(z_i, x_i)} \|G(z_i) - x_i\|_2^2$$

- **Synthesis:** sampling from a pdf fitted on latent codes
Generative Adversarial Networks

- **Principle** [Goodfellow’14]: Adversarial optimization strategy between a generator $G$ and a **Discriminator** $D$ detecting real from fake images.

$$
\max_D \min_G \mathbb{E}_{z \sim p_Z, x \sim p_D} \log(D(x)) + \log(1 - D(G(z)))
$$

- **Optimization:**

- **Synthesis:** $G(z)$ computed from a sample $z$ from the training pdf $p_Z$
Generative Network Evaluation
Generative Network Evaluation

« One of the most important research topics in generative modeling is therefore not just how to improve generative models, but in fact, designing new techniques to measure our progress. » Deep Learning Book [Goodfellow et al. 2016]

- In theory, one would like to measure the discrepancy between the data distribution $p_D$ and the generated distribution $p_G$

- In practice, a lot of restrictions prevent from doing so (images in high dimensional space $\sim 10^6$, empirical approximation of unknown distribution $p_D$, metric between images, etc)

- State of the art approach: Fréchet Inception Distance (FID) [Heusel’17] is the distance between Inception Network features from image from $D$ and $G$, represented as Gaussian Density.
Memorization & Overfitting

• Mostly studied for classification networks:

  • **Generalization** is the capability of a classification network trained on an empirical training set to perform as well on unseen data (in practice, a **test set**);

  • **Overfitting** happens when the objective loss function is much **lower for the training set than the test set**

Memorization is when the loss is **arbitrarily small**
Memorization & Overfitting

- For *generative* networks, it is much less clear in the literature; by analogy, the consensus is that
  - **Memorization** is verbatim copy of (some) training data;
  - **Overfitting** is when synthesized images are « too close » from training examples

- How to evaluate overfitting and detect memorization in practice?
Overfitting Evaluation

• Mostly by visual inspection ([Radford'16], Birthday paradox [Arora’17])

• Nearest Neighbor search in the training dataset of generated images (PGGAN [Karras’18], BigGAN [Brock’19] …)

• Comparison of the estimated distributions of generated images and training images (e.g. with kernel density estimation) for low dimensional data [Wu’17]
Nearest Neighbor search

- Nearest Neighbor search in dataset

\[
\text{NN}_D(G(z)) = \arg \min_{y \in D} \| \phi(G(z)) - \phi(y) \|_2^2
\]

where \( \phi \) extracts features (pixels, patches, CNN \ldots)

- Example from BigGAN [Brock’19]

\[
G(z) \quad \text{NN}_D(G(z))
\]

with \( \phi = \text{Id} \)

with \( \phi = \text{VGG} \)
Nearest Neighbor search

- Nearest Neighbor search in dataset

\[ \text{NN}_D(G(z)) = \arg \min_{y \in D} \| \phi(G(z)) - \phi(y) \|^2 \]

where \( \phi \) extracts features (pixels, patches, CNN …)

- … is not reliable !

\[ \text{NN}_D(x) \]
Nearest Neighbor search

• Nearest Neighbor search in dataset

\[
\text{NN}_D(G(z)) = \arg \min_{y \in D} \| \phi(G(z)) - \phi(y) \|_2^2
\]

where \( \phi \) extracts features (pixels, patches, CNN …)

• … is not reliable!

\[x \quad \text{NN}_D(x)\]

\[y \in D\]

with \( \phi = \text{Id} \)

with \( \phi = \text{VGG} \)
Latent recovery
Latent recovery

**Idea:** for images \( y \) in the training dataset, search the nearest neighbor in the manifold of generated images

\[
\text{NN}_G(y) = G(z^*(y))
\]

\[
z^*(y) \in \arg \min_z \| \phi(G(z)) - \phi(y) \|_2^2
\]

... is surprisingly **much more reliable**!
- for various choice of \( \phi \): downsampling, masking, color and spatial distorsion, ...
- for other metrics
- for various optimization algorithms
Latent recovery with PG-GAN

Recovery is almost perfect for generated images!
Recovery of generated images

- For generated images, optimization is surprisingly robust!

\[
G(z) \quad G(z_0) \quad \text{Ground Truth}
\]
\[
y = \varphi(G(z)) \quad \text{Query (after masking)}
\]
\[
G(z*(y)) \quad \text{Recovered image}
\]
Latent Optimization

• Non-convex optimization problem

• Only a few iterations required with L-BFGS algorithm and L2 loss function (even for images outside the training and the generated sets)

Assessing overfitting
Latent recovery for overfitting

- **Proposed definition for overfitting**: discrepancy measure of latent recovery error between test and train datasets

- **Protocol**: (for instance on CelebA-HQ with 28k images)
  1) Dataset is divided into a test set $T$ (2k) and train set $D$ (26k)
  2) Generative model is trained on $D$
  3) Compute latent recovery errors for test and train set (2 x 2k)

$$\forall y \in D \cup T, \|G(z^*(y)) - y\|_2^2 \text{ where } z^*(y) \in \arg \min_z \|\phi(G(z)) - \phi(y)\|_2^2$$
Experimental Setup

- **Tested Generative models:**
  - **AE** and **GLO:** used for baseline, models trained to memorize
  - **GANs:** DC-GAN, PG-GAN and MESCH [Mescheder’17] (based on ResNet [He’18] and WGAN-GP [Gulrajani’18])
  - **Hybrid GANs:** Auto-Encoder GAN [Choi’18] [Li’17], Cycle-GAN [Zhu’18]

- **Datasets:** CelebA-HQ, LSUN (tower and bedrooms), MNIST, CIFAR, Yosemite

- **Various datasize** (for all but pure GANs, that fail with small datasets)
Latent recovery on CelebA-HQ

- Various generative models on CelebA-HQ

\[ y \in D \text{ (train)} \quad y \in T \text{ (validation)} \]
Latent recovery on CelebA-HQ

- Histograms of quadratic recovery error (MSE)

- Legend: Train, Test, Generated, and Distorted

- GANs are not memorizing

- For other models, overfitting depends on the data size (here 128, 1024 and 8192)
Statistical analysis

Measure of overfitting as the difference of test and train errors:

- **Median Recovery Error**
  \[ \text{MRE}_G(\mathcal{Y}) = \text{median} \left\{ \min_z \| y_i - G(z) \|^2 \right\}_{y_i \in \mathcal{Y}} \]

- **Normalization**
  \[ \text{MRE-gap}_G = \frac{(\text{MRE}_G(\mathcal{T}) - \text{MRE}_G(\mathcal{D}))}{\text{MRE}_G(\mathcal{T})} \]

- **Hypothesis testing:** \( p\)-value of the Kolmogorov-Smirnov (KS) test (probability of larger difference)

Detection of overfitting using either

- above **10% threshold** on MRE Gap
- below **1% threshold** on \( p\)-value of KS test
## Statistical results

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<th>CelebA-HQ</th>
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</table>
Local overfitting of GAN

• One could wonder if overfitting occurs only in small parts of the image.

• Tests on mouth and eye regions: still no overfitting detected for PG-GAN!
Comparison with FID

• FID doesn’t detect overfitting (for **Train** and **Test** images)
Applications
Application of latent recovery

- Most approaches in the literature use hybrid approaches mixing Adversarial and Auto-Encoder training strategies that have been shown to be prone to overfitting.

- **Idea:** combine pure GAN method and latent recovery to prevent overfitting and identity preserving without requiring training.

- We already demonstrate its practical interest for face de-identification.
Super-Resolution

• Generative Network [Dahl'17]

8 × 8 input  32 × 32 samples  ground truth

• Using PG-GAN and pooling for latent recovery
Face Completion

- Hybrid AE-GAN [Li’17]
- Hybrid PG-GAN [Chen’18]
- Latent recovery (without post-processing for blending)
Conclusion
Conclusion

- A simple **definition** for overfitting & memorization for generative networks
- Overfitting is evaluated using **latent recovery**
- Proof that overfitting can happen in Generative Networks, especially for popular hybrid GAN approaches
- FID does not detect overfitting
- Interesting applications to face processing (de-identification, completion, super-resolution) preserving the privacy of the training set
- Future work: faster latent recovery, improving optimization for non registered dataset

Thank you!
Miscellaneous

- Preprint: arxiv.org/abs/1901.03396
- Code: GitHub.com/ryanwebster90