Evaluation

Likelihood

Log Likelihood: \[ L = \frac{1}{N} \sum_{i} \log P_G(x^i) \]

We cannot compute \( P_G(x^i) \). We can only sample from \( P_G \).
Likelihood
- Kernel Density Estimation

- Estimate the distribution of $P_G(x)$ from sampling

Each sample is the mean of a Gaussian with the same covariance.

Now we have an approximation of $P_G$, so we can compute $P_G(x^i)$ for each real data $x^i$

Then we can compute the likelihood.
Likelihood v.s. Quality

• Low likelihood, high quality?
  Considering a model generating good images (small variance)

\[ P_G(x^i) = 0 \]

• High likelihood, low quality?

\[
L = \frac{1}{N} \sum_i \log P_G(x^i) = -\log 100 + \frac{1}{N} \sum_i \log P_G(x^i)
\]

\[ 0.99 \times X \quad 0.01 \times X \]
Objective Evaluation

Objective Evaluation

$\mathbf{x}$: image

$\mathbf{y}$: class (output of CNN)

Concentrated distribution means higher visual quality

Uniform distribution means higher variety

$P(\mathbf{y}|\mathbf{x})$

$P(\mathbf{y}) = \frac{1}{N} \sum_{n} P(\mathbf{y}^n | \mathbf{x}^n)$

Class 1

Class 2

Class 3

[Tim Salimans, et al., NIPS, 2016]
Objective Evaluation

\[ P(y|x) \]

\[ P(y) = \frac{1}{N} \sum_{n} P(y^n|x^n) \]

Inception Score

\[
= \sum_{x} \sum_{y} P(y|x) \log P(y|x) \\
- \sum_{y} P(y) \log P(y)
\]

Negative entropy of \( P(y|x) \)

Entropy of \( P(y) \)
Mario Lucic, Karol Kurach, Marcin Michalski, Sylvain Gelly, Olivier Bousquet, “Are GANs Created Equal? A Large-Scale Study”, arXiv, 2017

<table>
<thead>
<tr>
<th>GAN</th>
<th>Discriminator Loss</th>
<th>Generator Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>MM GAN</td>
<td>$L_{D}^{GAN} = -\mathbb{E}<em>{x \sim p_d}[\log(D(x))] + \mathbb{E}</em>{\hat{x} \sim p_g}[\log(1 - D(\hat{x}))]$</td>
<td>$L_{G}^{GAN} = -L_{D}^{GAN}$</td>
</tr>
<tr>
<td>NS GAN</td>
<td>$L_{D}^{NSGAN} = L_{D}^{GAN}$</td>
<td>$L_{G}^{NSGAN} = \mathbb{E}_{\hat{x} \sim p_g}[\log(D(\hat{x}))]$</td>
</tr>
<tr>
<td>WGAN</td>
<td>$L_{D}^{WGAN} = -\mathbb{E}<em>{x \sim p_d}[D(x)] + \mathbb{E}</em>{\hat{x} \sim p_g}[D(\hat{x})]$</td>
<td>$L_{G}^{WGAN} = -L_{D}^{WGAN}$</td>
</tr>
<tr>
<td>WGAN GP</td>
<td>$L_{D}^{WGAN} = L_{D}^{WGAN} + \lambda \mathbb{E}_{\hat{x} \sim p_g}[(|\nabla D(\alpha \hat{x} + (1 - \alpha) x)|_2 - 1)^2]$</td>
<td>$L_{G}^{WGAN} = -\mathbb{E}_{\hat{x} \sim p_g}[D(\hat{x})]$</td>
</tr>
<tr>
<td>LS GAN</td>
<td>$L_{D}^{LSGAN} = -\mathbb{E}<em>{x \sim p_d}[(D(x) - 1)^2] + \mathbb{E}</em>{\hat{x} \sim p_g}[D(\hat{x})^2]$</td>
<td>$L_{G}^{LSGAN} = -\mathbb{E}_{\hat{x} \sim p_g}[(D(\hat{x}) - 1)^2]$</td>
</tr>
<tr>
<td>DRAGAN</td>
<td>$L_{D}^{DRAGAN} = L_{D}^{GAN} + \lambda \mathbb{E}_{\hat{x} \sim p_d + \mathcal{N}(0,1)}[(|\nabla D(\hat{x})|_2 - 1)^2]$</td>
<td>$L_{G}^{DRAGAN} = -L_{D}^{NS GAN}$</td>
</tr>
<tr>
<td>BEGAN</td>
<td>$L_{D}^{BEGAN} = \mathbb{E}_{x \sim p_d}[(|x - AE(x)|<em>1) - k_t \mathbb{E}</em>{\hat{x} \sim p_g}[(|\hat{x} - AE(\hat{x})|_1]$</td>
<td>$L_{G}^{BEGAN} = \mathbb{E}_{\hat{x} \sim p_g}[(|\hat{x} - AE(\hat{x})|_1]$</td>
</tr>
</tbody>
</table>

Smaller is better
FIT:
We don’t want memory GAN.

- Using k-nearest neighbor to check whether the generator generates new objects
Missing Mode?

Mode collapse is easy to detect.