Stochastic Deconvolutional Neural Network Ensemble Training on Generative Pseudo-Adversarial Networks

A Method for Minimising the Mode Collapse Problem

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ABSTRACT

The training of Generative Adversarial Networks (GANs) is a difficult task mainly due to the nature of the networks. One such issue is when the generator and discriminator start oscillating, rather than converging to a fixed point. Another case can be when one agent becomes more adept than the other which results in the decrease of the other agent’s ability to learn, reducing the learning capacity of the system as a whole. Additionally, there exists the problem of ‘Mode Collapse’ which involves the generator’s output collapsing to a single sample or a small set of similar samples. To train GANs a careful selection of the architecture that is used along with a variety of other methods to improve training. Even when applying these methods there is low stability of training in relation to the parameters that are chosen. Stochastic ensembling is suggested as a method for improving the stability while training GANs.

In practice, however, GANs suffer from many issues, particularly during training. One common failure mode involves the generator collapsing to produce only a single sample or a small family of very similar samples. Another involves the generator and discriminator oscillating during training, rather than converging to a fixed point. In addition, if one agent becomes much more powerful than the other, the learning signal to the other agent becomes useless, and the system does not learn.

A lot of attempts have been made to minimise the mode-collapse problem and improve variety on the output [3, 4, 5, 6]. However, some solutions are computationally expensive and treated mode-collapse problem symptomatically.

The assumption behind the methodology described later is that the architecture of a typical GAN causes mode-collapse to occur. The Discriminator $D$ portion of the network constantly requires new samples from the Generator $G$ and due to how $D$ is defined, it never reaches a state for which the output of $G$ is satisfactory. This in turn results into two possible ways for the model to evolve. Firstly, in the case where $G$ is overly powerful the network can start oscillating. This is where even the slightest modification of parameters can result in significantly different outputs that the discriminator cannot “remember”. In this situation the output differs from epoch to epoch, at the cost of local variety inside of one epoch. We call this scenario the “soft-collapse” of a model.

However, if $G$ is weaker the oscillation scenario cannot occur. In this instance a situation called “hard-collapse” may manifest. This is where after a small number of attempts to significantly modify the output and go into oscillation mode, it fails. The discriminator becomes absolute certain that the all
samples are fake. This results with the loss of the generator being effectively infinite. This results in undefined gradients and it being impossible for the training to progress further.

As we believe that mode-collapse is unavoidable situation another, synthetic way of solving this issue, is suggested. Proposed is the simple idea of Stochastic Ensembling, which can be described as random shuffling of filters on deep levels of the generator. This is comparable to creating a set of weak generators that can still suffer from the mode-collapse problem, but still produce an acceptable output variety.

The efficiency of the described method is demonstrated on another, Pseudo-GAN, where the role of discriminator is played by any pre-trained image classifier. This can be seen as a state of absolute mode-collapse from the beginning of training.

**Methodology**

The main difference between standard GAN architecture and one using *Stochastic Ensembling* is in the way that the deep layers are constructed within the Generator. In these layers, stochastic deconvolution is applied, the main idea of which is to randomly select a set of filters from a fixed filter bank.

In this architecture a *stochastic deconvolution* layer is constructed using filters of size 4, applied with a stride of size 2. PReLU (Parameterised Leaky ReLU function initialised to 0.2) was applied to improve model fitting [7] and weight normalization was also used to improve stability [8].

The higher level layers are left as standard deconvolution layers so as to provide refinement for the network and can be reused between different combinations of deep layers. Meanwhile different combinations of deep layers are available for covering the different distributions in the training dataset. An architecture that could achieve the same effect as Stochastic Ensembling is to split the generator into an ensemble of generators with shared upper layers. This increases the size of the networks requirements making it computationally expensive to train. On the other hand stochastic deconvolutions create \(8^4 = 4096\) different ‘routes’ through the use of only 8 different filters in 4 deep layers.

From an intuitive point of view, the combination of paths covers different visual “topics” in the training distribution, for which high-level features are usually shared. This prevents the network from early collapse and describes the distribution more effectively. It does not guarantee that GANs based on stochastic deconvolution do not suffer from mode collapse, but does provide some redundancy. Even if each route of 4096 in the example above collapsed it would still provide some variety. Another benefit of using stochastic deconvolutional layers is that the size of filters can be kept smaller. This enables the discriminator to outperform each sub-generator and in the worst case scenario the sub-generator will start oscillations without experiencing hard mode collapse.

We believe that stochastic ensembling can be beneficial outside of GAN models and can be useful for any problem that involves generative models. The approach could offer an avenue of further research for the application in non-generative models as an easily implemented alternative to other ensemble techniques.

**Figure 1.** Example generator structure showing how at each ‘sdeconv’ (stochastic deconvolutional) layer the filters are being selected randomly.
Apart from the stochastic ensembling architecture the rest of GAN is built to standard approach with only usage of weight normalization [8] and parametric ReLU additions. For the training of the architecture the standard cGAN loss was used,

\[ L_{cGAN} = \mathbb{E}_{x,y} [\log D(y)] \\
+ \mathbb{E}_{x,z} [\log (1 - D \circ G(x, z))] \]

**Experiments**

Two experiments were performed to estimate the benefits of data variety with respect to the outputs of the model when using stochastic deconvolutional generator (SGAN). The comparison was made with an ‘adapted GAN’ described in ‘On the Effects of Batch and Weight Normalization in Generative Adversarial Networks’ [8] which is shown to be advantageous in regard to combating the mode collapse problem and increasing the variation within the output samples. The SGAN was constructed from the ‘adapted GAN’ by altering the first three generator layers. The layers were converted to stochastic deconvolutions with banks of 16 filters, which gave \(16^4 = 65536\) potential combinations of filters. With the absence of a common measurement technique the comparison was performed visually. However, the final results differed significantly when compared to the normal GAN approach that we believe no extra measurements were necessary.

The first experiment used the MNIST dataset. The first notable difference was during training. It was required to restart the training of the ‘adapted GAN’ multiple times due to immediate collapse of the network output. This was due to wrong weight initialisation. However, when using the SGAN architecture, immediate collapse was never observed during the training process, irrespective of the initialisation.

The main method for comparing the output of the networks was visually inspecting the outputs. The following table shows the period output during training. The larger state of the SGAN architecture required training for a much longer period of time.
Step 0

Step 50

Step 100

Step 250

Step 500
Initial signs of degradation occurs; model starts to decrease variety producing only “ones”

Step 1000
Majority of outputs are 1s

Step 1500

Step 2000

Step 2500

Step 2667
Model was not able to recover, training stopped

Step 0

Step 50

Step 250

Step 500
Recovered dead paths, no degradation observed

Step 1000

Step 1500
Degradation and collapse of sub-networks. Significantly better comparing to GAN

Step 2000

Step 2500

Step 2667
Last step of GAN model Still generating decent results with a minimal degradation

Step 3000
Slow degradation continues, however variety is not affected comparing to quality of the output
The difference in stability can be seen in the progression and volatility of loss during the training of the two architectures. The SGAN is more stable (Figure 6) while the ‘adapted GAN’ starts to reach the practical max and 0 already (Figure 5) around step 1100.

Tommy Hilfiger Instagram account

The SGAN architecture was also compared to the adapted GAN [8] over a dataset consisting of images scraped from the official Tommy Hilfiger Instagram account. The dataset consisted of 2350 images of all kinds of topics (Figure 4). No data argumentation was applied except random horizontal swaps. None of the known GAN architectures would be able to produce decent results based on such a small training set with such an input data variety.
‘Adapted GAN’ output

Step 0

Step 50

Step 100

Step 500
‘Best’ results achieved

Step 654
Mode collapse

Step 700
Decreased variety after recovering, started oscillating

Step 824
Mode collapse again

Step 871
Recovering with quality and variety degradation

Step 956
Collapsed

Step 1100
Recovering with a high level of variety and quality degradation

Step 1250
Collapsed

SGAN output

Step 0

Step 50
Greater variety observed

Step 100

Step 500
Some sub-networks collapsed, variety is still high

Step 654

Step 1000
Recovered collapsed paths, sub-network its own “topic”
Step 1426
Training ended, model not able to recover

Step 1500
Degradation of local variety, overall variety is still present

Step 2000
Sub-networks show signs of oscillation, overall variety still decent

Step 2380
Sub-networks degradation, overall quality is superior to adapted GAN

Generative Pseudo-Adversarial Network
GAN architectures where the role of discriminator is being played by a pre-trained image classifier, can be thought of as being ‘perfectly’ collapsed. For any generated image, the discriminator cannot be fooled. In practice, such a network is not adversarial hence it is referred to as a Generative Pseudo-Adversarial Network (GPAN).

Following the classic approach, such a model can never be trained and will become stuck at the very start with the theoretically infinite gradients of the generator. Suggested below is a model that behaves similarly to a typical adversarial model by applying stochastic ensembling and the ‘adapted PatchGAN’ described in ‘Another way of restoring distribution of an image classifier’ [9]. The suggested model follows the ‘adapted PatchGAN’, with minor modifications, applying stochastic ensembling on deep levels of the generator (Figure 7) and extending the output to a higher resolution of 1024.

In this architecture a stochastic deconvolution layer and convolutional layers are constructed using filters of size 4, applied with a stride of size 2. PReLU (Parameterised Leaky ReLU function initialised to 0.2) was applied to improve model fitting [7] unless

| Requested category vector 2x2x1 |
|---------------------------------|
| SDeconv(4), 520, 4x4            |
| SDeconv(4), 468, 8x8            |
| SDeconv(4), 416, 16x16          |
| SDeconv(4), 208, 32x32          |
| Conv, 16, 64x64                 |
| SDeconv(4), 104, 64x64          |
| Deconv, 208, 128x128            |
| Deconv, 104, 256x256            |
| Deconv, 52, 512x512             |
| Deconv, 3, 1024x1024            |

Figure 7. Generator part of GPAN architecture featuring 5 SDeconv layers
it was the last layer for which tanh function was used. Weight normalization was also used, so as to improve stability [8].

In the construction of the GPAN, the generator part (Figure 7) used 5 stochastic deconvolution layers with filter banks consisting of 4 sets of filters. This gives a theoretical maximum variety of 1024 combinations. The discriminator remained unchanged, but received a resized, 512 × 512, copy of the output produced by generator.

A few additions were made to the architecture to achieve better quality of the output. The importance regions, in accordance with the grad-cam methodology [10], of the pool5 layer in the VGG16 classifier were extracted and masked in a conditional GAN (cGAN) loss. The purpose of this was to allow the output to satisfy either the VGG or discriminator losses independently. In addition, to improve the output variety in each batch of images, B the constraint to contain only one set of wanted categories from the classifier was applied.

The same losses for the ‘adapted PatchGAN’ were used. For the cGAN part of the network,

\[ L_{cGAN} = \mathbb{E}_{x,y} \left[ \log D(x,y) \right] + \mathbb{E}_{x,z} \left[ \log \left( 1 - D(x,G(x,z)) \right) \right] \]

The masking loss was applied to keep the background of the image as white as possible,

\[ L_m = 1 - M(G) \] where \( M(G) \) is the masked output of the generator. The substrate loss to influence the model to generate an image \( G \) as similar to the substrate \( T \) as possible,

\[ L_{sub} = |T - G| - \log \left( 1 - \frac{|T - G|^2}{2} \right) \]

As well as the same loss for the output activating the VGG classifier,

\[ L_{VGG} = L_p + L_n \]

where \( L_p \) is the loss for required classes not appearing in the output and \( L_n \) is the loss associated with classes being identified that were not required [9].

Let, \( M_i(x) \), \( \forall i \in M = \{4,8,16,32,64\} \) be the feature map from each sdeconv layer, with shape \( i \times i \times \text{depth} \). Each feature map was compared between images in the same batch to construct a ‘Split Loss’. The purpose of this loss was to influence the network to develop different feature maps for each image in batch. Defining \( F: \mathbb{R}^3 \rightarrow \mathbb{R}^3 \) as the function which measures the element-wise difference between two 3-dimensional feature maps,

\[ F(a,b) = \frac{1}{|x|} \sum_x \tanh \left( \left( \frac{a_x - b_x}{25} \right)^4 \right) \]

For training with a batch \( B \) the split loss is defined as,

\[ L_{split} = \sum_{i \in M} \frac{2w_i}{|B| \cdot (|B| - 1)} \sum_{k,j \in B} \log \left( F(M_i(k), M_i(j)) \right) \]

The term \( w_i \) refers to a scaling factor dependant on the layer \( i \):

\[ w_4 = 0.03125, \quad w_8 = 0.0625 \]

\[ w_{16} = 0.125, \quad w_{32} = 0.25 \]

\[ w_{64} = 0.53125 \]

The combination of losses that was observed to be the most beneficial was
\[ L = 3L_{split} + 10L_{cGAN} + 100L_{VGG} + 25L_m + 100L_{sub} \]

**Results**

Significant variety in the output data was achieved giving an impression of dynamic patterns generation as if produced by a classic generative adversarial network. At the each iteration, 1 out of 1024 paths was chosen giving the appearance of random behaviour. As a consequence even if the same target group is selected a PGAN generates different images at each run.

In the following examples, the images were generated for each target category. Different paths were used for each image, resulting in the different patterns.
Conclusion
Stochastic generative models can be beneficial for a wide range of applications where generative transformations have unlimited solutions. In such instances the suggested approach can help in covering a subset without making the model’s structure significantly bigger and/or complicated. In particular it can be useful for chatbot applications. Answers to the same question could be formulated in a different way giving the appearance of more human speech.

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