Introduction

Machine learning algorithms, such as artificial neural networks, allow computers to learn from experience and make predictions on multidimensional data. Generally, neural networks learn to map inputs to outputs with a specified loss function that match specific predictive modelling problems, i.e. classification or regression. Generative adversarial network (GANs) consists of two trained models, a generator and a discriminator (Goodfellow et al., 2014). With GANs, the loss function is automatically computed, which makes them more generic and useful for a range of image classification problems.

GANs are particularly good at translating the style of an image, such as to colorize grayscale images or to translate real photographs to artistic images. This opens for faster and more generic workflows related to seismic processing and seismic interpretation (Picetti et al., 2018, Ferreira et al., 2019, Mosser et al., 2018, Bugge et al., 2019). Some recent publications on GANs for seismic image translations include generalized seismic forward and inverse modelling (Mosser et al., 2018), translation from sketches to synthetic seismic images (Ferreira et al., 2019), low-quality migrated image to high-quality migrated image (Picetti et al., 2018) and migrated image to deconvolved reflectivity image (Picetti et al., 2018).

In this study, we use a tensorflow implementation of a conditional GAN (Isola et al., 2017) in order to perform image to image translations on seismic images. Conditional GANs (cGANs) learn a conditional generative model to map from an observed image x and random noise vector z, to an output image y, G : {x, z} → y. In such image to image translation tasks, the cGAN trains a generator to produce output images, while the discriminator is an adversarial network trained to evaluate if the output image produced by the generator is a “real” reference image or a “fake” generated image. Here, the generator is a U-Net-based network, and the discriminator is a convolutional “PatchGAN” classifier (Isola et al., 2017). The U-Net architecture is a fully convolutional neural network proposed by Ronneberger et al. (2015). Because of a large number of feature channels in the up sampling, the U-Net can propagate information to higher resolution layers and yields a u-shaped architecture (Figure 1).

We demonstrate a variety of seismic image-to-image translation tasks: (1) relative inversion (Kolbjørnsen and Evensen, 2019), (2) noise and multiple removal, (3) fault detection and (4) multiple removal from gather data (illustrated with Table 1). Whereas Isola et al. (2017), propose image to image translation for 3-channel 8-bit images, we train and apply the cGAN on 32-bits segy-data. With our examples, we have trained on pairs of input and output data (e.g. seismic data with and without multiples), and applied the trained network on new seismic images from the same dataset as used in training operation. The examples show that a trained cGAN can successfully imitate seismic operations related to processing and interpretation, such as filter operations or attribute generation. Further, we show that a cGAN trained on synthetic gather data can successfully remove multiples from real gathers even when the multiples interfere with primary signals.

Figure 1. In this study, we use a generative adversarial network, where the generator is a U-Net-based network. The U-Net architecture is illustrated with the figure (Ronneberger et al. 2015).
As Table 1 illustrates, cGANs are good at imitating results and can potentially replacing seismic workflows. Therefore, the use of GANs can significantly reduce the man-hours required to process large seismic volumes (gather data or final stack seismic volumes). In our experience, this approach is somewhat limited to individual datasets, and requires training data from the dataset of interest. In the next section, we eliminate the need for dataset dependent training data by training a cGAN model on synthetic data. This allows us to train generic model that is applicable to real datasets.

Table 1. Segy to segy translation for seismic images

<table>
<thead>
<tr>
<th>Operation</th>
<th>Seismic data</th>
<th>Target (ground truth)</th>
<th>cGAN results</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) Relative inversion</td>
<td>The SW Barents Sea</td>
<td><img src="image1" alt="Image" /></td>
<td><img src="image2" alt="Image" /></td>
</tr>
<tr>
<td>Bubble pulse removal</td>
<td>The Arctic Sea (scientific data)</td>
<td><img src="image3" alt="Image" /></td>
<td><img src="image4" alt="Image" /></td>
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<tr>
<td>Fault identification</td>
<td>The SW Barents Sea</td>
<td><img src="image5" alt="Image" /></td>
<td><img src="image6" alt="Image" /></td>
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<tr>
<td>Multiple removal</td>
<td>Gather data from the North Sea</td>
<td><img src="image7" alt="Image" /></td>
<td><img src="image8" alt="Image" /></td>
</tr>
</tbody>
</table>

**cGANs trained on synthetic datasets**

Training on synthetic data opens for more generic models, where the trained network is “dataset independent” and applicable to different real seismic volumes. Recently, Wu et al. (2019) showed how to train on synthetic fault cubes in order to obtain a generic fault model that can identify faults in unseen, real seismic volumes. Here we generate synthetic seismic pre-stack data (gathers), with and without dipping multiples. The purpose of this is to compute generic training data, and train a model that can separate multiples from primary signals in unseen datasets where we do not have the ground truth. The goal is to separate multiples from primary signals even when they interfere. In general, interference between multiples and primary signals are often challenging to address with conventional radon processing. Therefore, it is difficult to obtain perfect real training data without multiples. However, this is possible with synthetic data because elements of wave propagation physics can be included.
We generate 500 pairs of gathers for our training data. These pairs, generated with a ricker wavelet, contain varying degrees of random noise, varying AVO-effects for both the primaries and multiples, and varying number of multiples. Figure 2 show two different pairs of synthetic gathers used in the training. The computation of 500 synthetic gather takes about 1.5 hour, while training the network for 200 epochs takes ~3 hours. All computations have been done on a single workstation with a dedicated GPU (NVIDIA Tesla V100 SXM2 32 GB).

![Figure 2](image)

*Figure 2. Two pairs of synthetic gathers (with and without multiples) generated with different AVO-effects, different levels of random noise and different multiple frequency.*

The trained network is applied on real pre-stack data from the Barents Sea. The notion of applying the network takes only milliseconds per gather, or ~5-6 minutes for one inline consisting of 3713 gathers. Figure 3 shows a real gather with multiples (a), the gather after application of the trained cGAN (b) and the difference between input and results (c). The difference (Figure 3c) illustrates how the network remove dipping multiples without changing the primary signals. For comparison, Figure 4 show the same real gather before and after conventional radon processing. Figure 3 and 4 illustrate that a conditional generative adversarial network trained on synthetic training data performs well when applied on real data and remove dipping multiples even when they interfere with primary signals. Additionally, is seems efficient in removal of noise and aliasing. These results further indicate that the proposed process is significantly faster and potentially better than conventional radon processing, particularly on the near offset.

![Figure 3](image)

*Figure 3. The figures show (a) a real gather from a Barents Sea dataset with multiples, (b) the results after application of the trained cGAN, and (c) the difference between input and results. These results demonstrate that a network trained only on synthetic pre-stack data can remove multiples from real data. For a comparison to conventional radon processing, see Figure 4.*
Figure 4. The figures show (a) a real gather from a Barents Sea dataset with dipping multiples, (b) the same gather after conventional radon processing (c) the difference between a and b.

Conclusions
In this paper, we have demonstrated that conditional generative adversarial networks are particularly good at imitating and potentially replacing a range of seismic workflows related to both seismic processing and seismic interpretation. Furthermore, our case study on pre-stack data has shown that that a model trained on synthetic data only can be applied to real data. With a synthetically trained cGAN, we demonstrate that it is possible to successfully remove multiples, noise and aliasing on real gathers from the Barents Sea. Not only is the cGAN approach significantly faster than conventional radon processing, it also indicates a potential to be better, particularly on the near offset.

References
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