Stanford
SCHOOL OF EARTH, ENERGY & ENVIRONMENTAL SCIENCES

Subsurface Imaging using GANs

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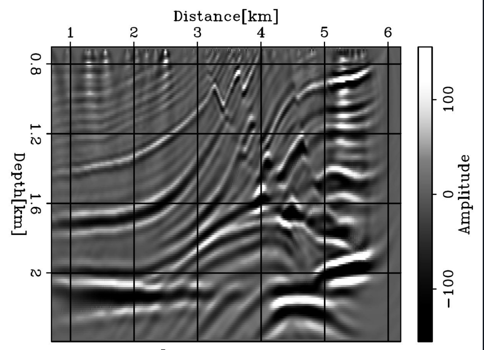
1. Background

Background:
Seismic imaging is a way to map the subsurface using observed seismic waves mainly for resource exploration

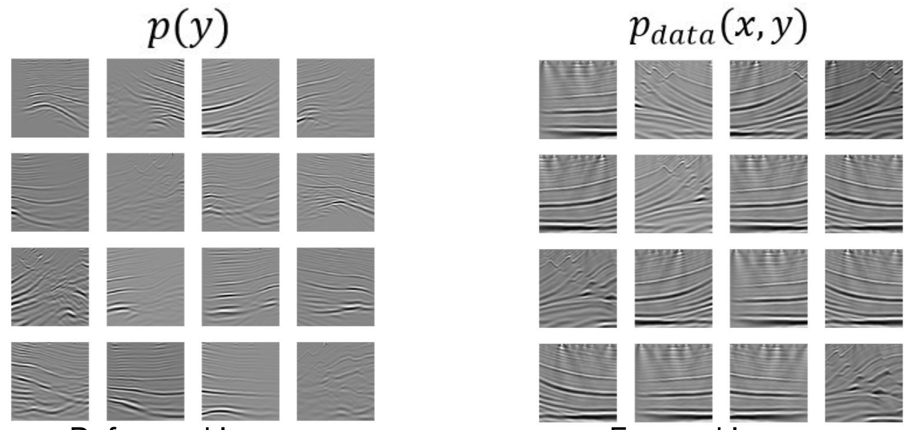


Problem Statement:
Seismic imaging - computationally expensive, iterative, human controlled process. ML might substantially simplify the process

Why Deep Generative Models?
- Physics based solutions start from scratch, are deterministic, expensive and non-unique
- In real data it is hard to know the true solution
- In industry data is not always labeled

What are we learning?
- $p_{model}(x,y) = p_{model}(x|y)p_{model}(y)$
- We want to learn $p_{model}(x|y)$ from:

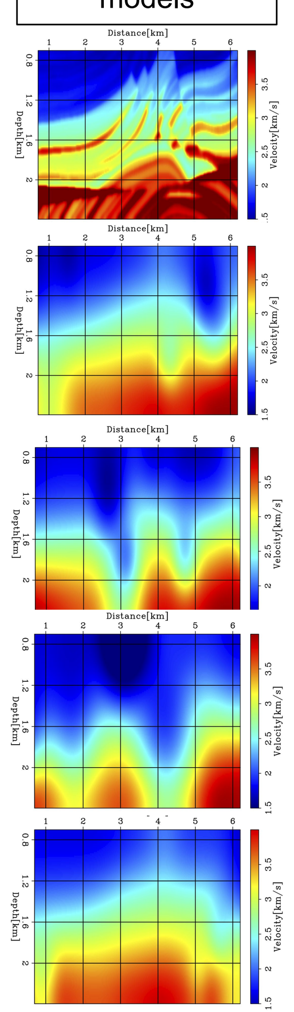
$p(y)$ $p_{data}(x,y)$



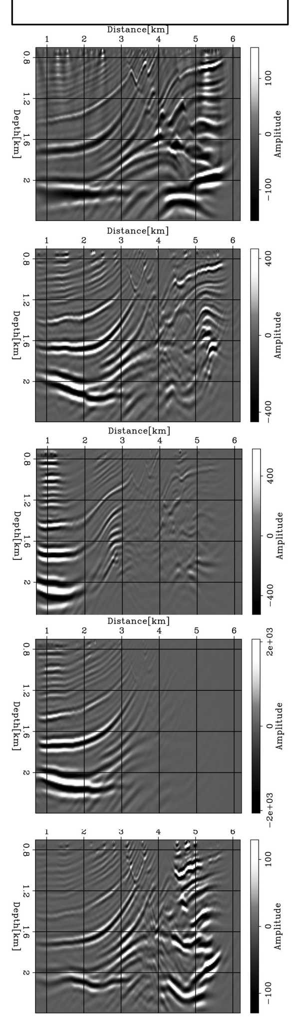
Defocused Images Focused Images

2. Data Generation

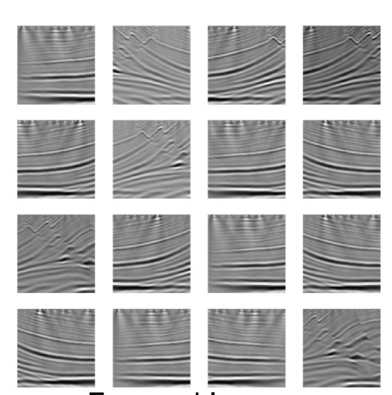
Step 1: random velocity models



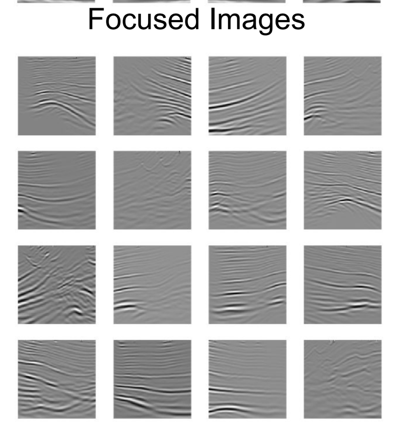
Step 2: seismic migration



Step 3: patching / data augmentation / standardize



Focused Images

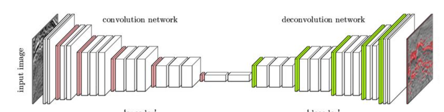


Defocused Images

Summary:
- Velocity models - 100
- Migrations - 100
- **Total images - 1800**

3. Deterministic Approach (baseline)

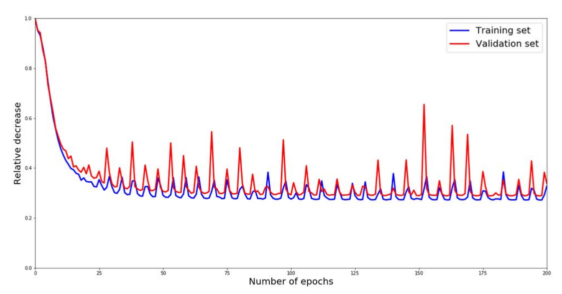
Model



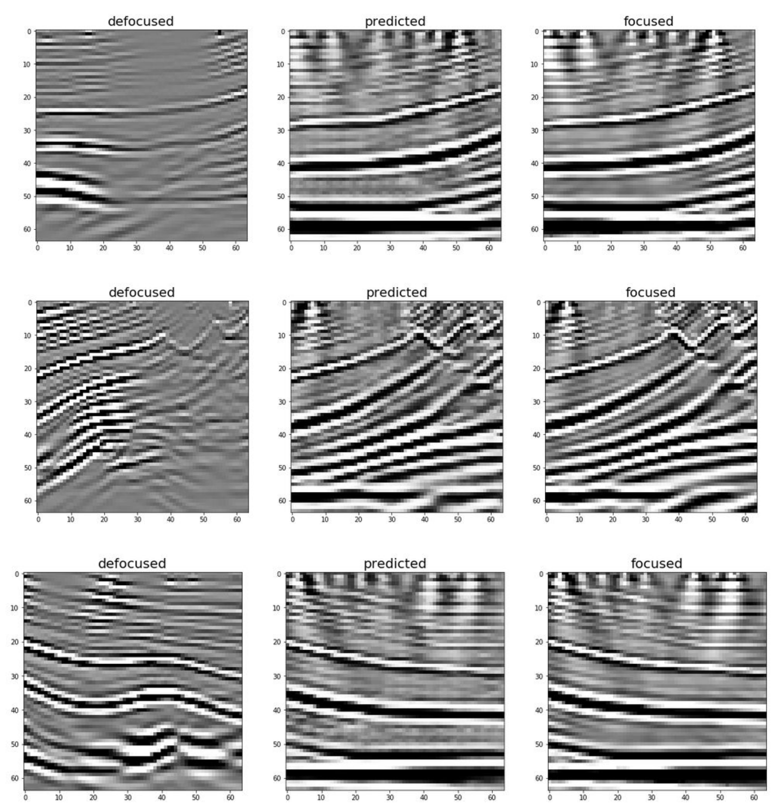
UNet (Convolution - Deconvolution):

Architecture:
- 7 encoding + 7 decoding
- No dropout
- L2 weight regularization

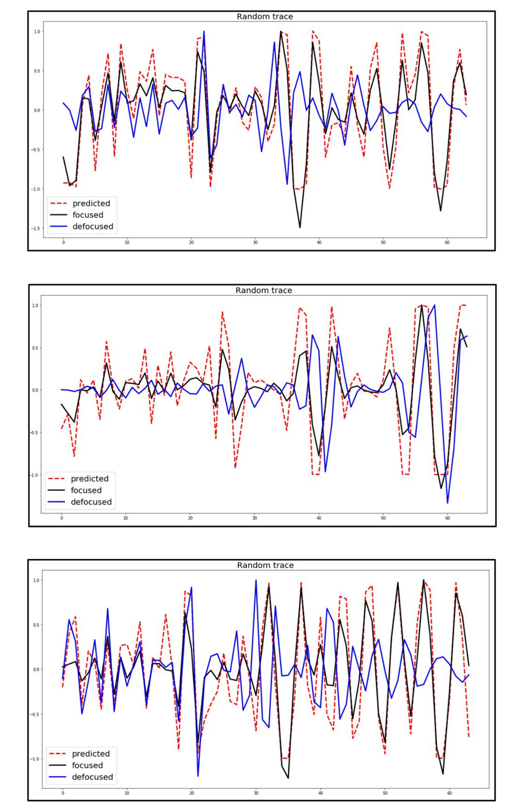
Optimization:
- Adam
- Learning rate = 0.001
- Batch size = 5



Results



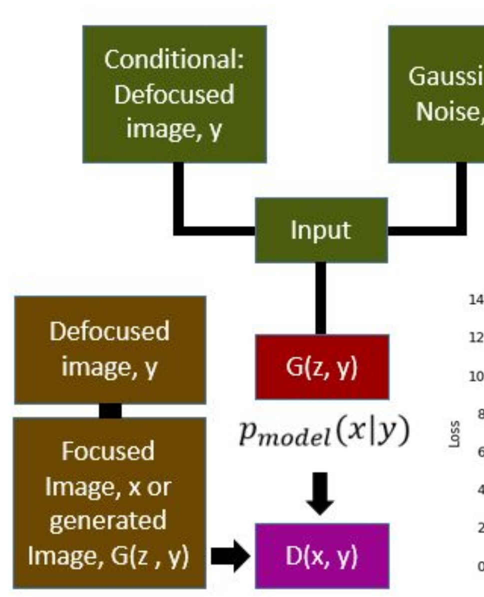
Evaluation

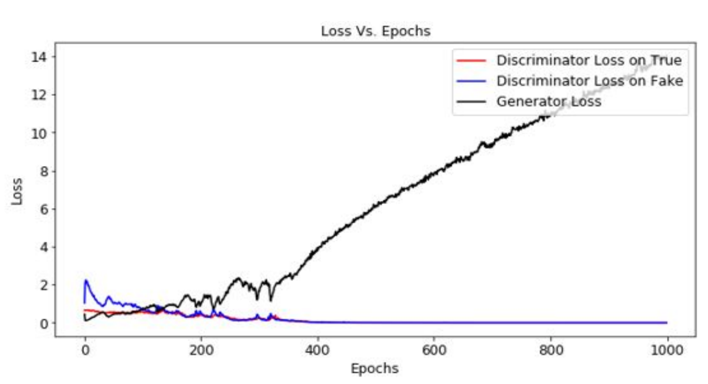


4. Experiment 1: cGAN

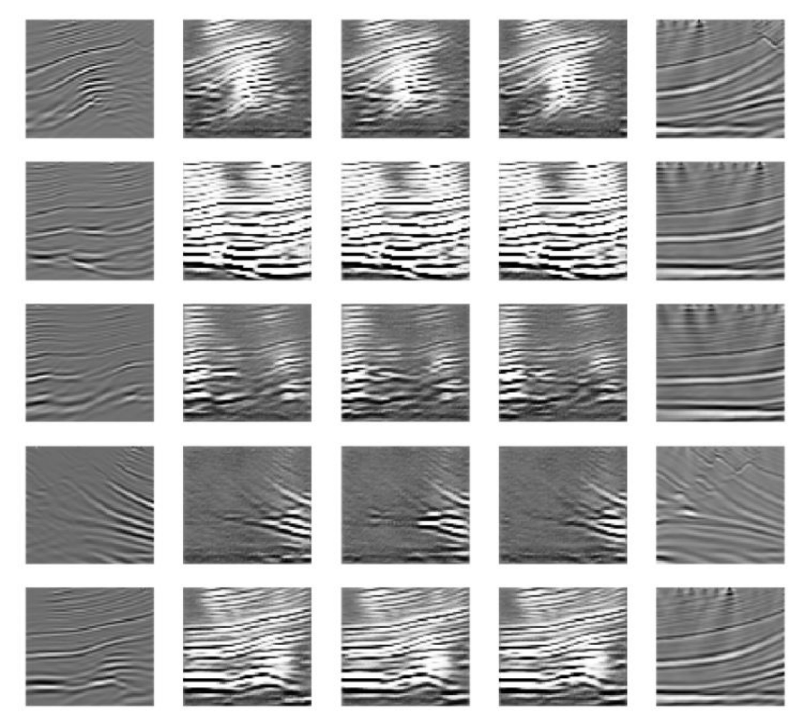
Model

- $$\min_{\theta}\max_{\phi} V(G,D) = \mathbb{E}_{(x,y)\sim p_{data}(x,y)}[\log(D(x,y))] + \mathbb{E}_{y\sim p_{\theta}(y)}[\mathbb{E}_{z\sim p_z(z)}[\log(1-D_{\phi}(G_{\theta}(z,y))]]$$





Results

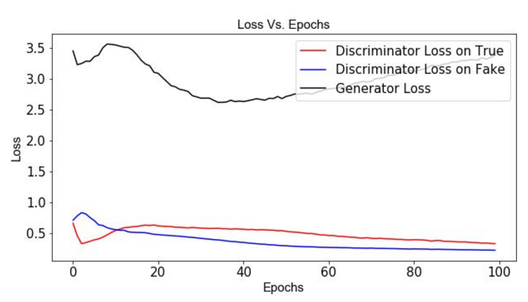


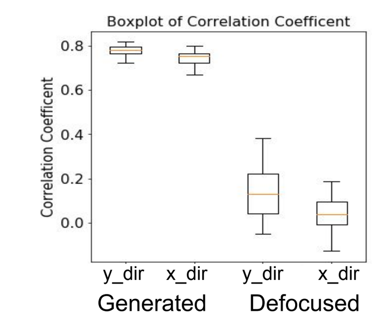
Defocused Generated Focused

5. Experiment 2: pix2pix

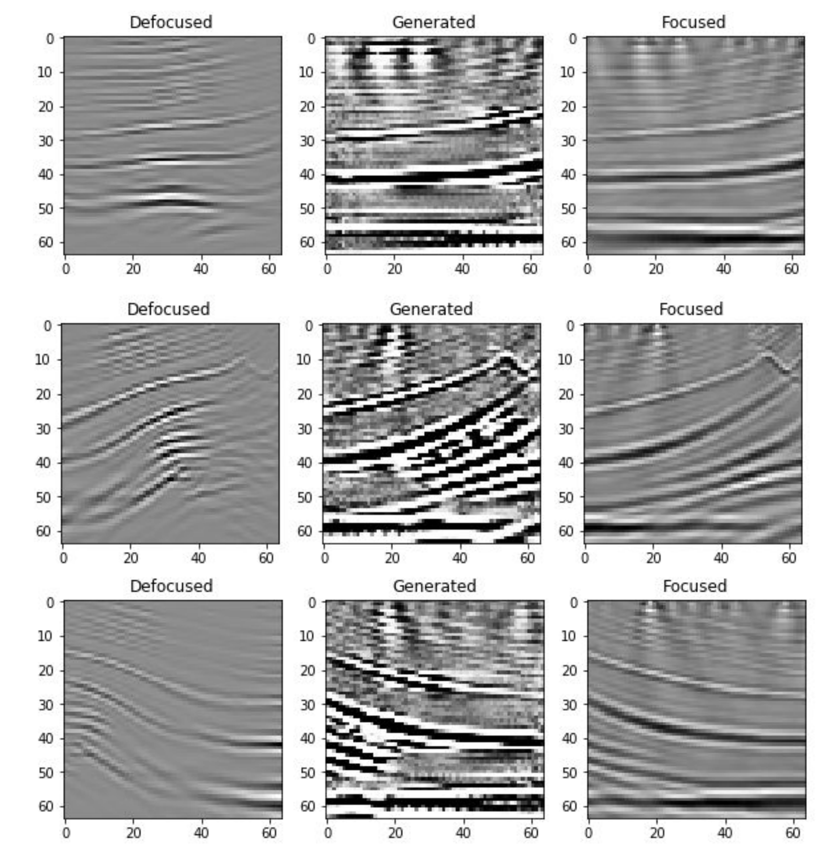
Model

- $$\min_{\theta}\max_{\phi} V(G,D) = L_{cGAN}(G,D) + \lambda L_{L2}(G)$$
- Involves paired setting (supervised component)

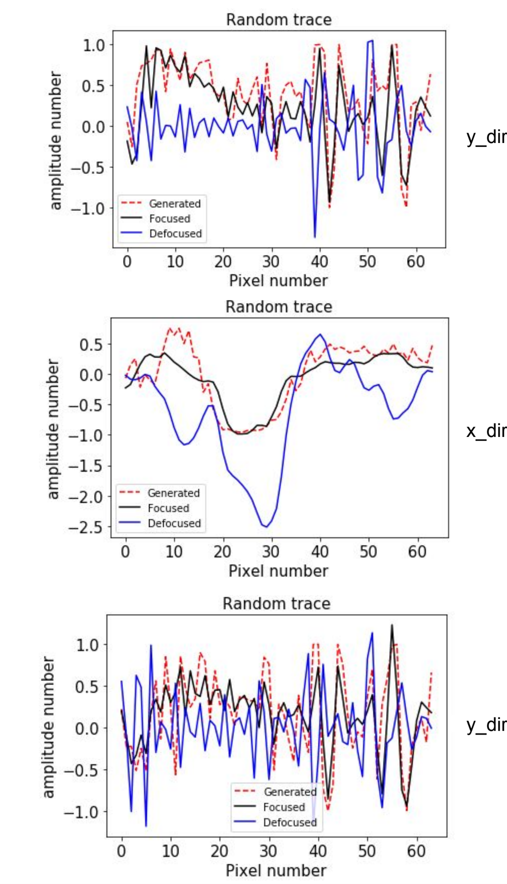




Results

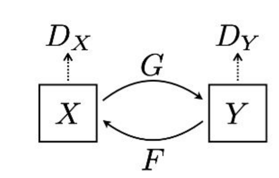


Evaluation



6. Experiment 3: cycleGAN

Model



$$\mathcal{L}(G,F,D_X,D_Y) = \mathcal{L}_{\text{GAN}}(G,D_Y,X,Y) + \mathcal{L}_{\text{GAN}}(F,D_X,Y,X) + \lambda\mathcal{L}_{\text{cyc}}(G,F),$$

$$\arg\min_{G,F}\max_{D_x,D_Y} \mathcal{L}(G,F,D_X,D_Y).$$

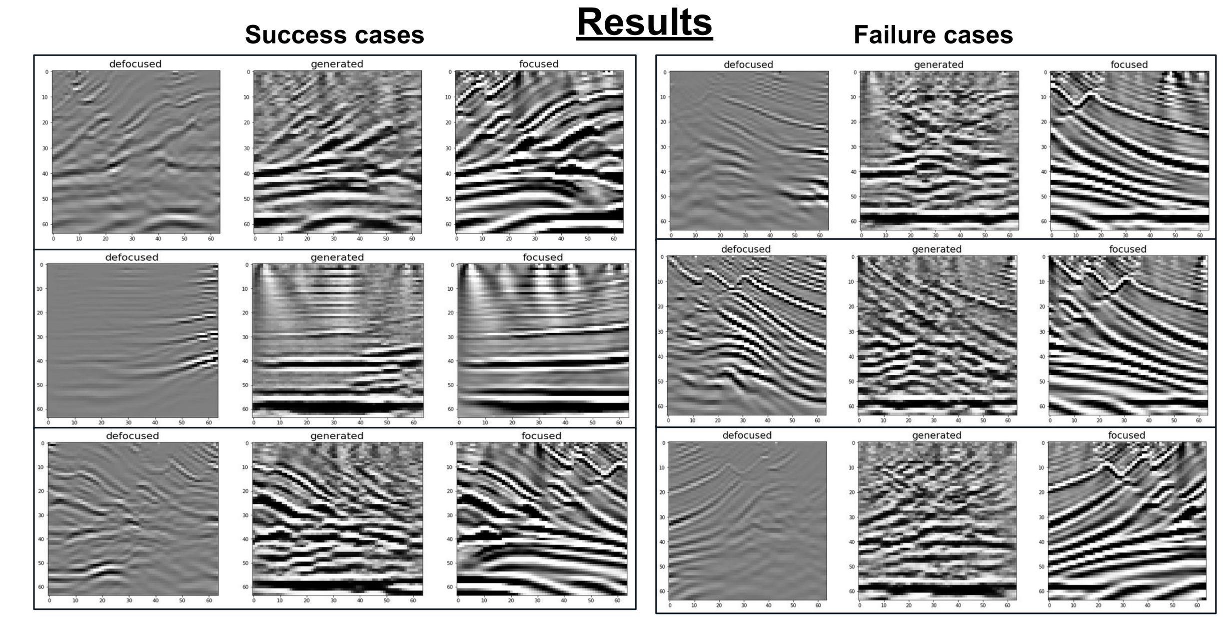
Generator G, F: same model as in the baseline

Discriminator DX, DF:
- encoder with 4 layers
- LeakyReLU with neg. slope = 0.2
- Last layer - ReLU
- Dilated convolutions -> capture geometric change

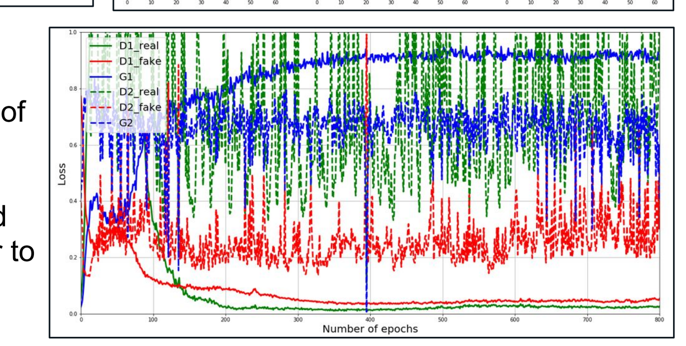
Optimization:
- RMSprop (lr = 1e-4, momentum=0.1)
- Weight on DX, DY = 1e-3, G = 1, cycle = 10

Results

Success cases Failure cases



Observations:
- Equalize the convergence of both GANs by choosing separate learning rate
- Mild defocusing - corrected
- Strong defocusing - harder to correct



7. Conclusions

- Learning the functional mapping for subsurface imaging has deep learning potential
- A GAN framework with a ground truth guided objective produces results that capture structure and amplitude of the data (focused images) distribution
- CycleGAN, a completely unsupervised framework, is able to learn the defocused - focused transformation without explicit pairs of examples
- (Hopefully) learning the distribution has greater generalization capability

8. Future work

- Implement semi-supervised pix2pix
- Implement WGAN
- Stabilize convergence of cycleGAN
- Try other objective functions for cycle-consistency (e.g. SSIM instead of L1)
- Test results in another geological setting (generalization capacity)

9. References

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