# Deep Learning on Computational Accelerators

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## 1 Introduction

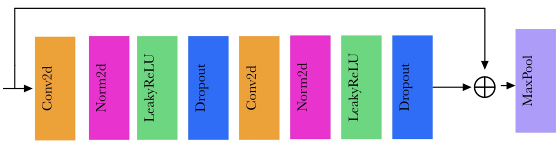
In this project we experiment with the task of MRI compressed sensing, where we design and train a neural network which performs reconstruction of subsampled images. Given an MR image in frequency domain $\tilde{x}$ and a binary mask $\mathcal{M}$, our models $m_\Theta$ goal is to reconstruct $m_\Theta(\mathcal{M}(\tilde{x}) = x$ as much as possible.

## 2 Solution & Architecture

$m_\Theta$ is constructed by an Encoder - Decoder, where each consists of several blocks of convolutional layers followed by max-pooling, and are separated by a bottleneck layer.

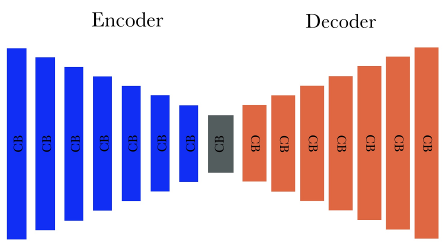
Denote: CB as Convolutional Block.

**CB is constructed by:**




Where the kernel size of Conv2d is 3 with padding no bias, and the negative slope of LeakyRelU is 0.2.

**Encoder and Decoder are constructed by 7 CB layers, each:**




### 2.1 Why Convolution?

In this task we deal with MRI images, we want our model to be able to capture the complex features whom matter the most for the reconstruction task. In order to achieve that we designed the encoder to fatten up the feature space and create a complex connections, allowing the model to train and find the wanted complex features. For that we turned to convolutional layers, as they are known for:

- Invariance and equivariance
- Great for feature extraction

### 2.2 Deeper is better?

Yes, in theory it will not bring worse results, and could potentially help finding complex features. An issue with a deep model is Vanishing Gradients, but we were prepared for it by using Residual Blocks and Instance Normalization which helped solve it.

### 2.3 LeakyReLU

We chose LeakyReLU for the following reasons:

- Avoid zero gradients
- Easy hyperparamters settings

### 2.4 Loss Function - MSE

We chose MSE for the following reasons:

- Low loss interpreters good reconstruction - intuitively.
- Penalization over large errors
- Convex and smooth - Promises a global minima

### 2.5 Optimizer - Adam

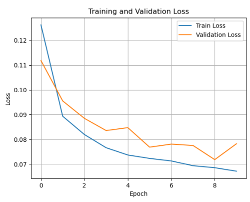
We chose Adam for it's adaptive learning rate:

- Momentum
- Bias correction
- Efficient and easy with hyperparamters settings

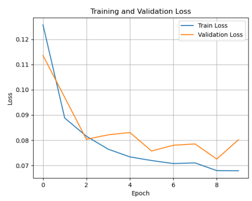
# 3 Results

We trained the model for both learned and unlearned mask for drop rates $\{0.2, 0.4, 0.6\}$

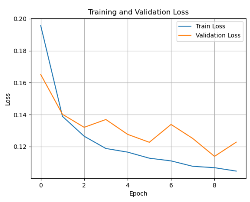
### 3.1 Training & Validation graphs



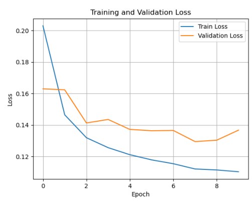

(a) learned 0.2



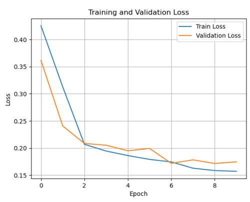

(b) unlearned 0.2



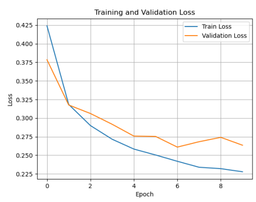

(a) learned 0.4




(b) unlearned 0.4




(a) learned 0.6




(b) unlearned 0.6

### 3.2 Conclusions

Underfitting:
None of the models got caught underfitting!

Overfitting:
The models with drop rate 0.4 and 0.6 caught a slight overfitting. We believe the reason behind it is due to the drop rate being *just enough* to deceive the model to learn how to reconstruct from specific *latent space*, which led to reconstructing from specific features, resulting bad reconstruction for the whole task.

Drop rate 0.2 avoided overfitting!

### 3.3 Test Results

| | Drop Rate | Train | Test |
|---|---|---|---|
| | | Mean \| STD | Mean \| STD |
| unlearned mask | 0.2 | 30.10 \| 1.22 | 28.56 \| 1.69 |
| learned mask | 0.2 | 30.14 \| 1.21 | 28.71 \| 1.71 |
| unlearned mask | 0.4 | 27.99 \| 1.21 | 26.32 \| 1.77 |
| leaned mask | 0.4 | 28.22 \| 1.20 | 26.68 \| 1.64 |
| unlearned mask | 0.6 | 24.82 \| 1.20 | 23.22 \| 1.50 |
| learned mask | 0.6 | 26.45 \| 1.21 | 25.13 \| 1.60 |

### 3.4 Why those results?

First most, looking at the Train vs Test results which are not far from one another, we acknowledge the conclusions from the Training vs Validation, avoided overfitting and underfitting (for most cases).

Secondly, for all drop rates, we see that the *learned mask* models outperformed their respective *unlearned mask* models. Which was expected (by us) since it expends the hypothesis class offering better models, which are not too strong avoiding overfitting.

Lastly, the models preformed better in the order of, $0.2 \to 0.4 \to 0.6$. which was also quite expected (by us). Since using high drop rates halts the model from actual training, yet a small drop rate helps avoid overfitting, therefore 0.2 was exactly the drop rate the model needed.

### 3.5 Visualization

We've taken an original picture, which represents the perfect reconstruction, and attached the reconstructions that each model was able to produce.

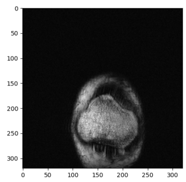
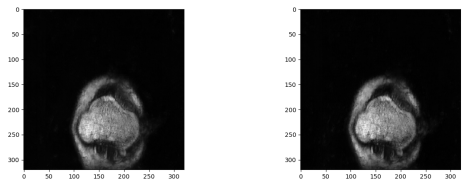
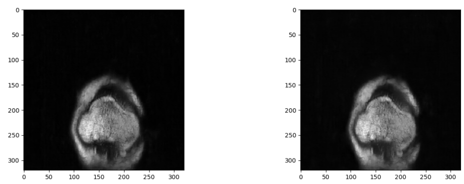


Figure 1: Original Image



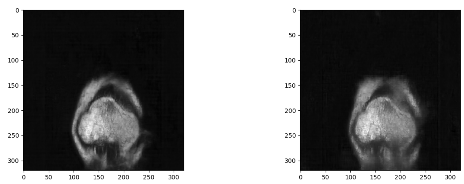
(a) learned mask (b) unlearned mask

Figure 2: Drop rate 0.2



(a) learned mask (b) unlearned mask

Figure 3: Drop rate 0.4



(a) learned mask (b) unlearned mask

Figure 4: Drop rate 0.6

### 3.6 What do we see?

Visually, we see our conclusions stated at the Training Vs Testing results!

Where *learned mask* models preformed better than *unlearned mask* and the order of best results by Drop rate 0.2 $\rightarrow$ 0.4 $\rightarrow$ 0.6, is reflected by the quality of the pictures, and how much of the small details they were able to capture.

The *unlearned mask* models are very fuzzy, while the *learned mask* models are sharp and detailed. The amount of detailed reconstructed is better by the order of the drop rate mentioned.

### 3.7 What did it reconstruct well?

Since the *unlearned mask* models are fuzzy we are not interested in visual comparisons of detail. We will go on to compare the *learned mask* models and look for the details that each captures and missed.

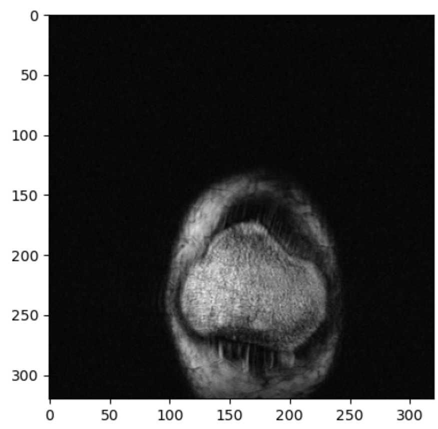



Figure 5: Original

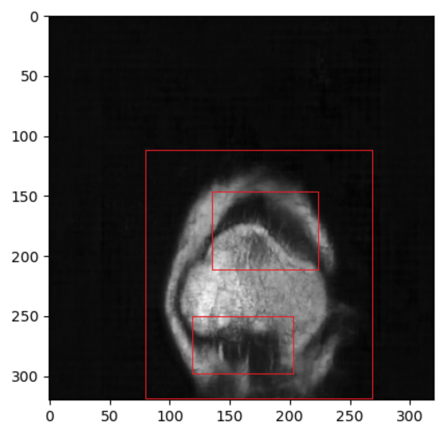



Figure 6: Learned mask | Drop rate 0.6

Starting with the worse one, *learned mask with drop rate 0.6*, is **overall** fuzzy and missed all the small details (**marked red**).

It only captured the overall shape of the picture. Conclusion: Bad reconstruction, expected by the results of training and testing.

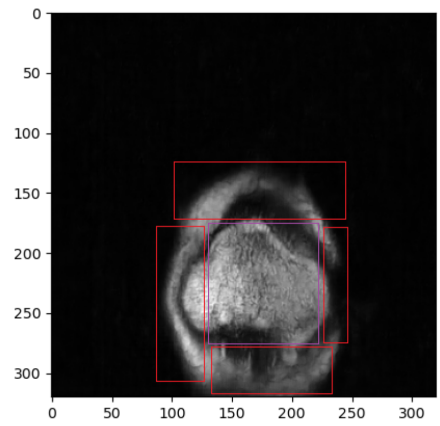



Figure 7: Learned mask | Drop rate 0.4

*Learned mask with 0.4 drop rate* is also fuzzy, less, perhaps capture some details, it does not satisfy us with reconstruction, yet it does reflect our conclusions from it's training and testing results.

**Marked red** where we were unsatisfied with missed details. **Marked purple for adequate detail.**

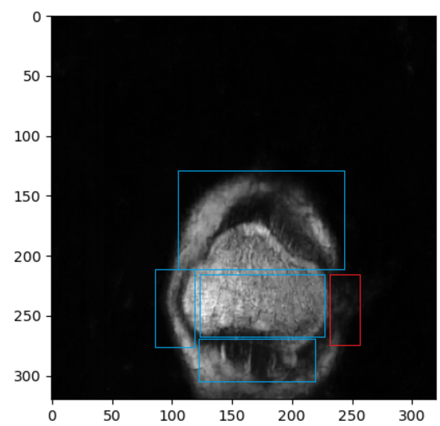



Figure 8: Learned mask | Drop rate 0.2

Best for last, *Learned mask with 0.2 drop rate*, the reconstructed image is **overall** not fuzzy and well understood.

**Marked blue** are details we are quite satisfied with, the model was able to capture and reconstruct complex patterns.

**Marked red** is one spot we are unsatisfied with. We discuss on how we would deal with it in the next section.

# 4 How did our choices effect the results?

## 4.1 Model

As stated in the **Why convolution** and **Deeper is Better** sections, we designed our model to be able to capture complex patterns and feature extraction, which is did quite well.

We believe the reason for the models of *learned mask* being better than *unlearned mask* is because they represent a stronger hypothesis class which can adapt and capture complex patterns (Classic Machine Learning).

## 4.2 optimization

Our optimization algorithm did it's job well, our training vs testing graphs and results prove so. Therefore, we are satisfied with our choices.

However, we do believe that choosing a different Loss function could potentially solve some of the missed patterns. MSE has some flaws when it come to images, especially in reconstruction tasks, It finds solutions which mathematically are close to the desired solution, but does not look like it. Therefore, we believe that a different loss function could improve the model (SSIM perhaps).

# 5 $\infty$ resources and a year What if?

If we had unlimited hardware resources and a whole year to work on the project, we would research the following:

- Find a different Loss function - for better results which do not have the flaws of MSE in image reconstructions.
- Replace CNN layers by different components - Reducing the amount of parameters of the model, perhaps using Transformers.
- Learn more about Fourier Transforms which could help in finding a better model for the given task.
- Join a research lab on the subject of image reconstruction (there's obviously a lot to learn).