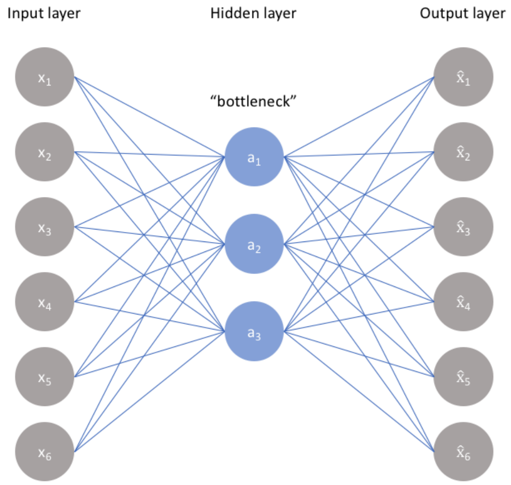
Introduction to Deep Learning (I2DL)

Exercise 8: Autoencoder

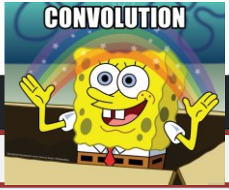
Today's Outline

- Exercise 07: Example Solutions
- Exercise 08
  - Batch Normalization & Dropout
  - Transfer Learning
  - Autoencoder



Exercise 7: Solutions

Leaderboard: Ex7



#	User	Score
1	u0787	64.30
2	u0120	59.87
3	u0807	56.85
4	u0146	56.59
5	u0746	55.47
6	u0638	55.40
7	u0766	54.34
8	u0676	54.19
9	u0853	54.16
10	u1490	54.13

Leaderboard of previous semester

Solution 1: 59,87%

Manual Transforms:

- Crop
- Gaussian filter
- Rotation
- Flip
- etc

```
self.model = nn.Sequential(
    nn.Linear(self.hparams["input_size"], self.hparams["nn_hidden_Layer1"]),
    nn.ReLU(),
    nn.Linear(self.hparams["nn_hidden_Layer1"], self.hparams["num_classes"]),
    nn.ReLU()
    )
```

```
my_transform = transforms.Compose([
                                   transforms.ToTensor(),
                                   transforms.Normalize(mean, std)])
```

```
def configure_optimizers(self):

    optim = None
    ########################################################################
    # TODO: Define your optimizer.                                         #
    ########################################################################

    optim = torch.optim.Adam(self.model.parameters(), self.hparams["learning_rate"], weight_decay=self.hparams['weight_decay'])
    StepLR = torch.optim.lr_scheduler.MultiStepLR(optim, milestones=[30],gamma=0.5)

    ########################################################################
    #                           END OF YOUR CODE                           #
    ########################################################################
    return optim
```

```
split = {
    'train': 0.9,
    'val': 0.05,
    'test': 0.05
}
split_values = [v for k,v in split.items()]
assert sum(split_values) == 1.0
```

```
hparams["loading_method"] = 'Memory'
hparams['num_workers'] = 1
hparams['input_size'] = 3 * 32 * 32
hparams['batch_size'] = 1000
hparams['learning_rate'] = 5e-5
hparams['weight_decay'] = 1e-3
hparams['nn_hidden_Layer1'] = 1500
hparams['num_classes'] = 10
```

Solution 2: 56,85%

```python
self.model = nn.Sequential(
    nn.Linear(self.hparams["input_size"], self.hparams["hidden_size"]),
    nn.ReLU(),
    nn.Linear(self.hparams["hidden_size"], self.hparams["num_classes"]),
        )
```

```python
my_transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize(mean, std), transforms.RandomCrop(32, padding=4),
transforms.RandomHorizontalFlip()])
```

```python
def configure_optimizers(self):

    optim = None
    ########################################################################
    # TODO: Define your optimizer.                                         #
    ########################################################################
    optim = torch.optim.SGD(self.model.parameters(), self.hparams["learning_rate"], momentum=0.9)
```

```python
# Note: you can change the splits if you want :)
split = {
    'train': 0.6,
    'val': 0.2,
    'test': 0.2
}
split_values = [v for k,v in split.items()]
assert sum(split_values) == 1.0
```

```python
hparams = {
    "batch_size": 16,
    "learning_rate": 1e-3,
    "input_size": 3 * 32 * 32,
    "hidden_size": 512,
    "num_classes": 10,
    "num_workers": 2,     # used
}
```

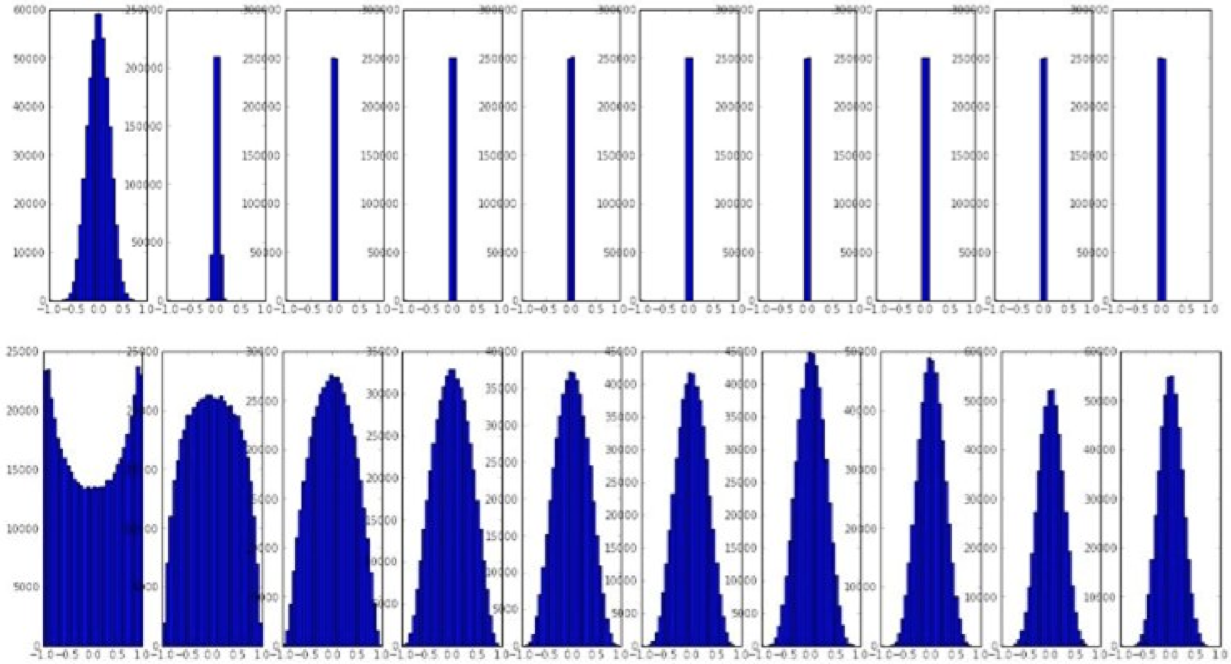
Summary

- Network: Linear + ReLU (Depth: 2-4)
- Initialization of Network Weights
- Optimizer: SGD or Adam, LR Scheduler
- Data Augmentation

Improve your training!

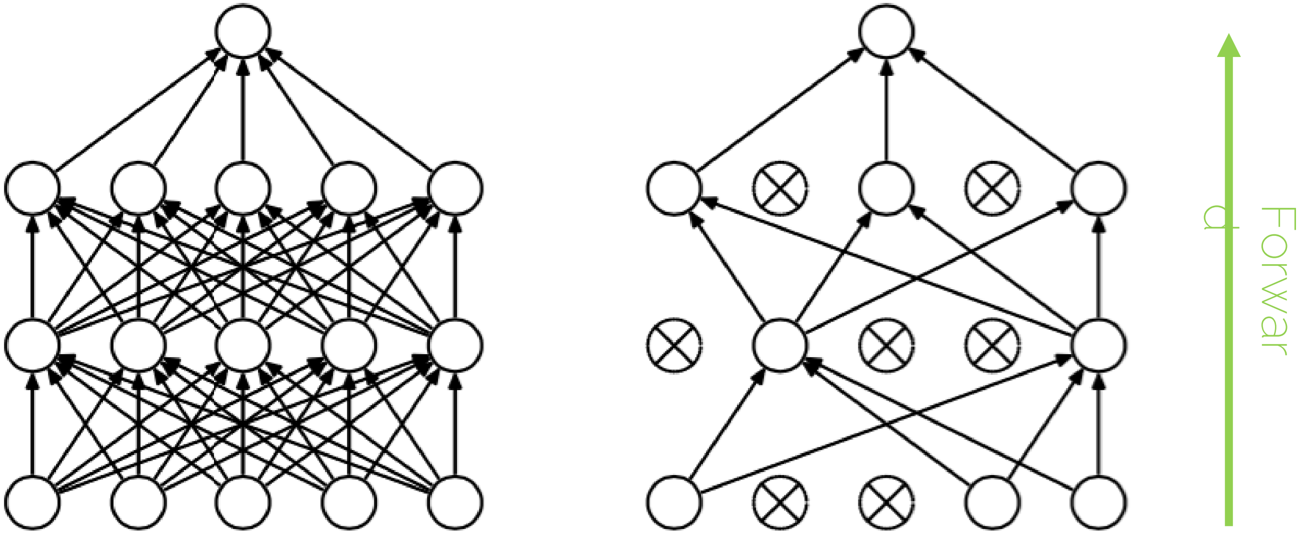
Batch Normalization

- All we want is that our activations do not die out



Dropout

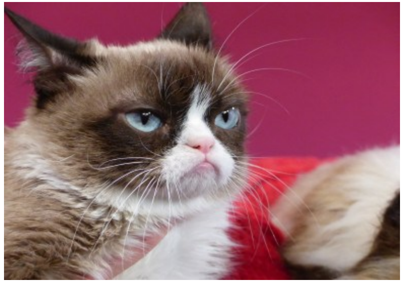
- Using half the network = half capacity

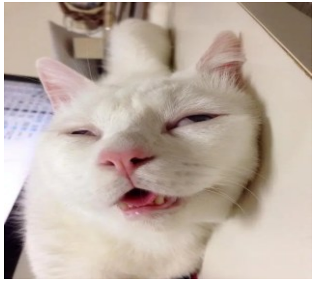


(a) Standard Neural Net (b) After applying dropout.

Transfer Learning

Transfer Learning: Example Scenario



- Need to build a Cat classifier
- Only have a few images ~10 000

Transfer Learning

- Problem Statement:
  - Training a Deep Neural Network needs a lot of data
  - Collecting much data is expensive or just not possible

- Idea:
  - Some problems/ tasks are closely related
  - Can we transfer knowledge from one task to another?
  - Can we re-use (at least parts of) a pre-trained network for the new task?

Transfer Learning

Distribution

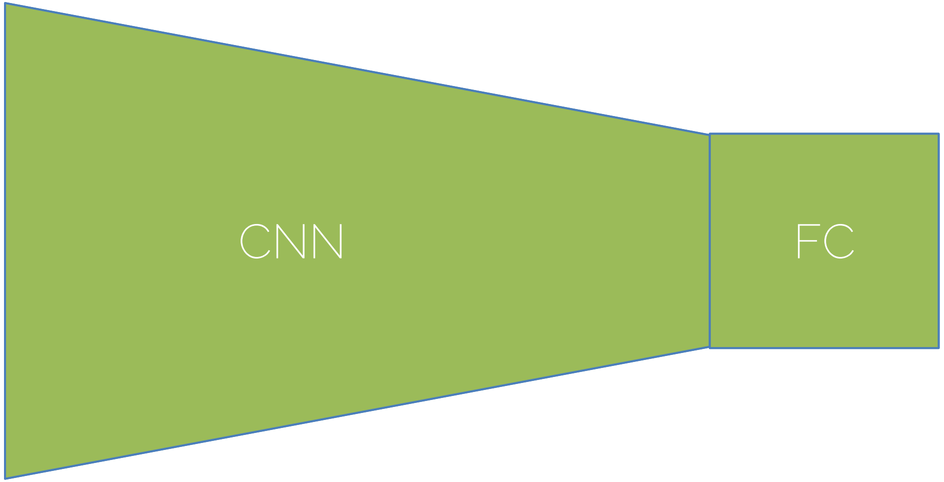
Distribution

Large dataset

Small dataset

Use what has been learned for another setting

Transfer Learning



2 classes

Feature Extractor

Classifier

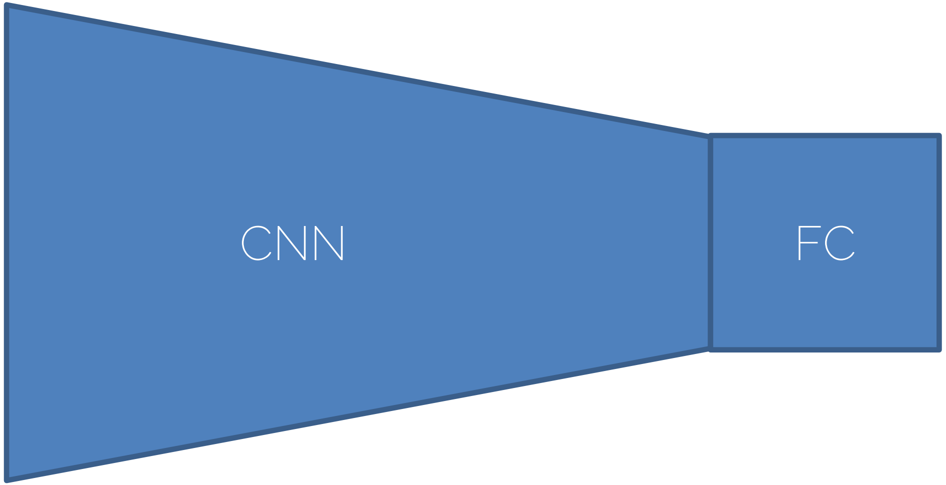
Trainable Parameters

Coloring Legend:

Untrained

Trained

Transfer Learning

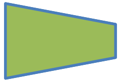


1000 classes

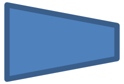
Feature Extractor

Classifier

Coloring Legend:

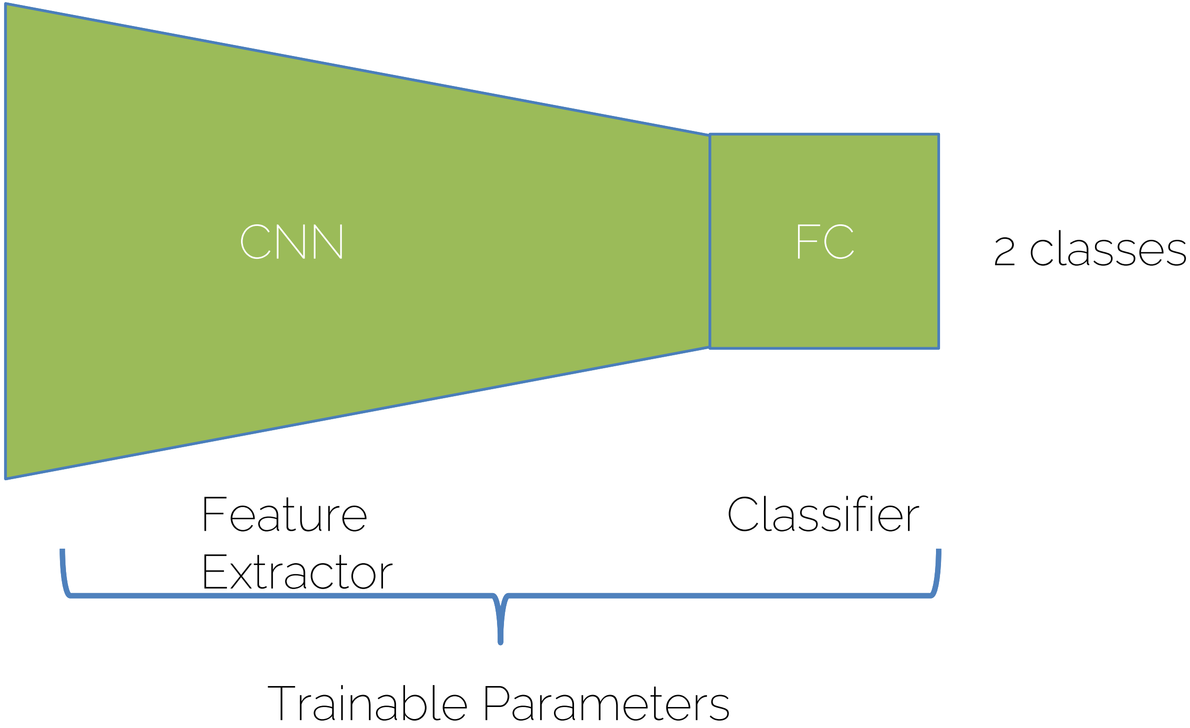


Untrained



Trained

Transfer Learning

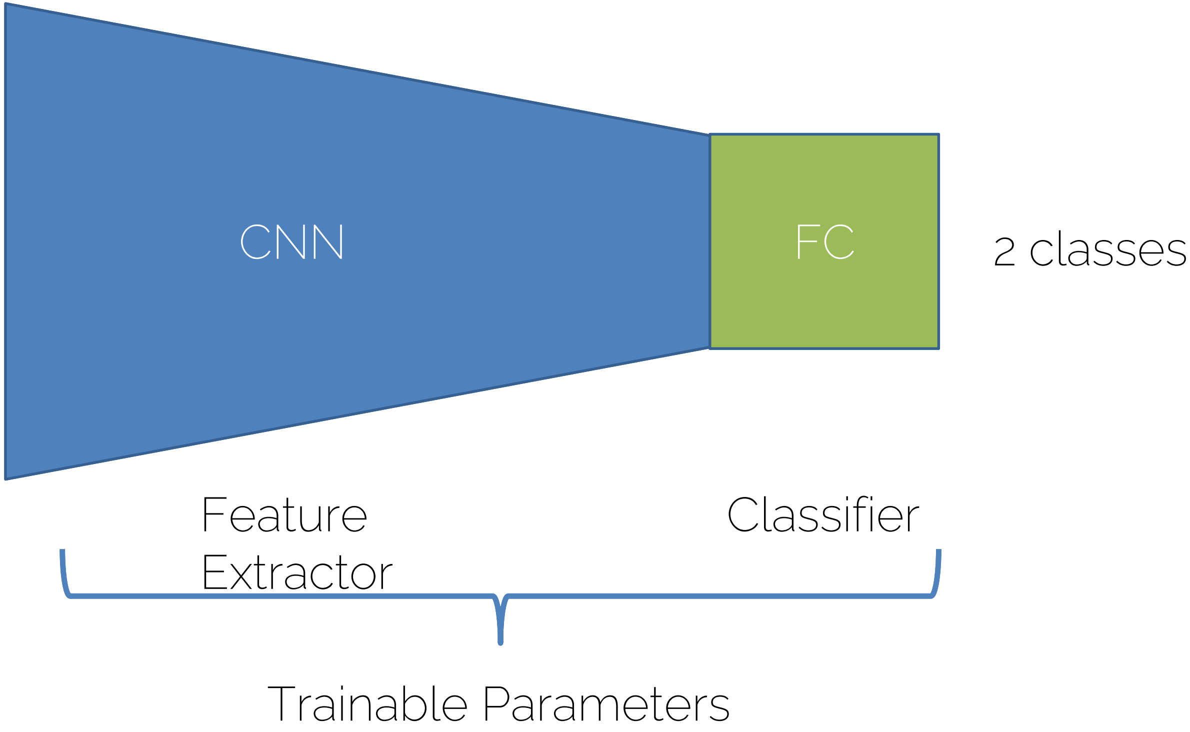


Coloring Legend:

Untrained

Trained

Transfer Learning

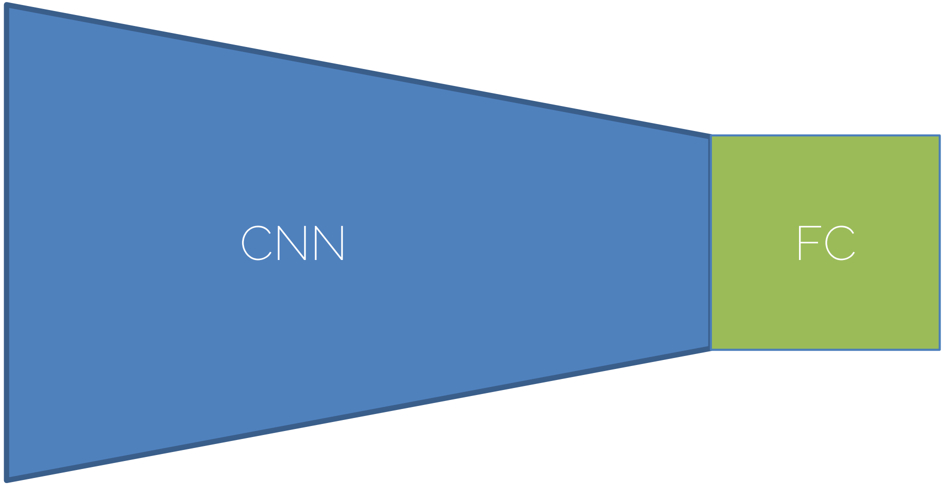


Coloring Legend:

Untrained

Trained

Transfer Learning



2 classes

Feature Extractor

Classifier

Maybe freeze weights/ slower learning rate/ nothing special

Newly initialized head

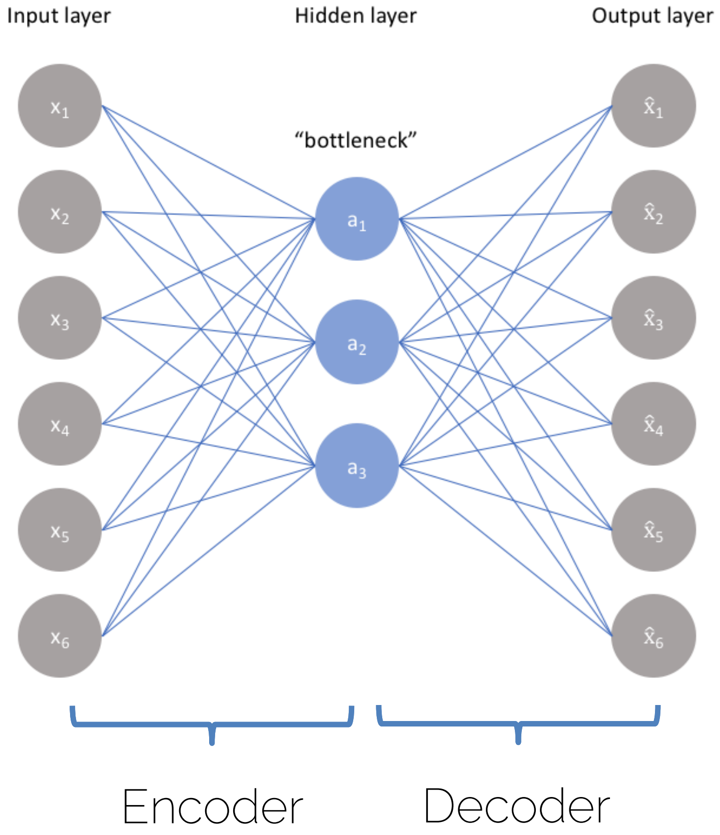
Coloring Legend:

- Untrained
- Trained

Application: Autoencoder

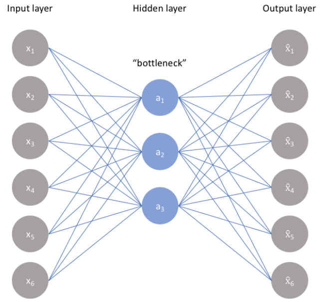
Autoencoder

- Task
  - Reconstruct the input given a lower dimensional bottleneck
  - Loss: L1/L2 per pixel
- Actually need no labels!
- Without non-linearities: similar to PCA

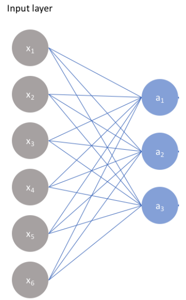


Transfer Using an Autoencoder

- Step 1:
  - Train an Autoencoder on a large (maybe unlabelled) dataset very similar to your target dataset



- Step 2:
  - Take pre-trained Autoencoder and use it as the first part of a classification architecture for your target dataset

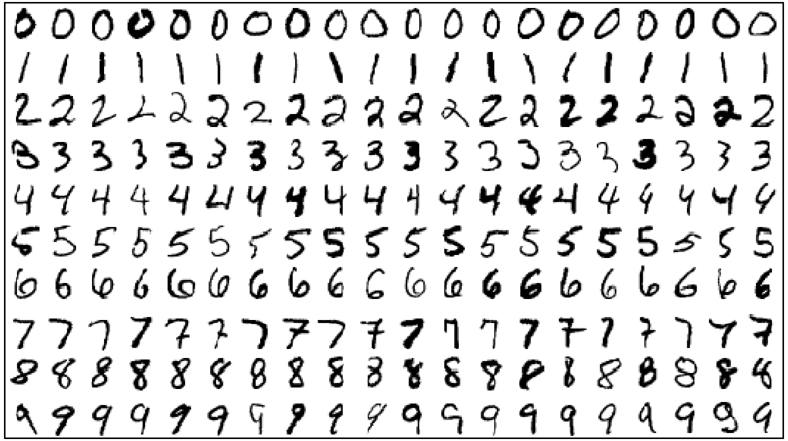


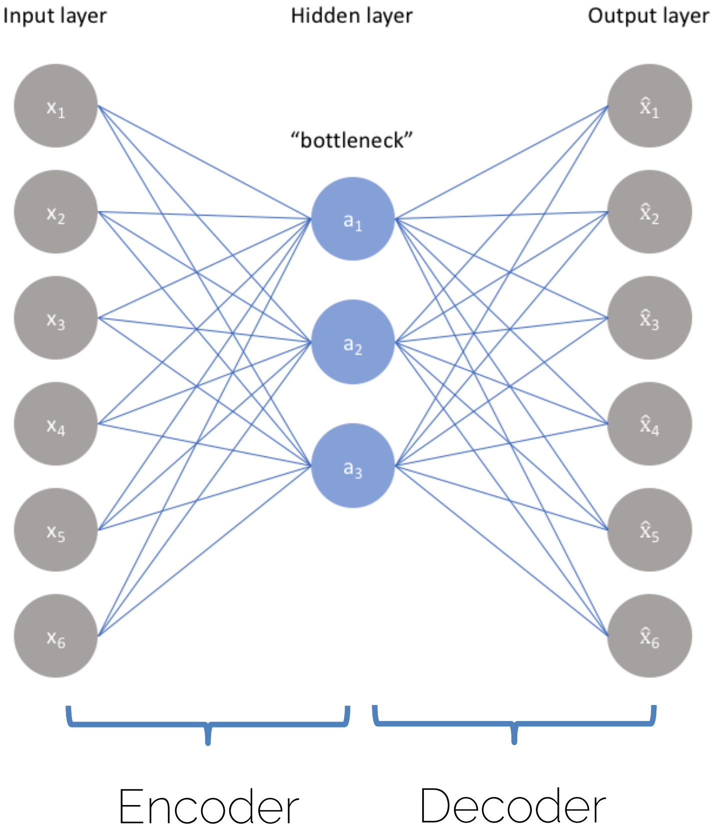
Exercise 8

Autoencoder

- Exercise Task:
  - 60 000 Images
  - Only 300 with labels

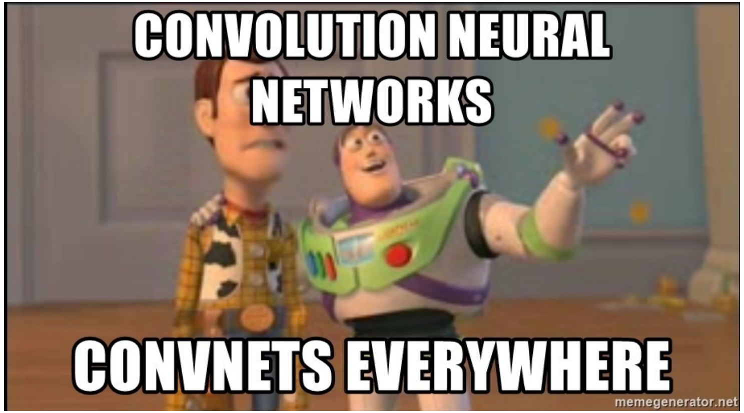
MNIST database





We get there…

No convolutions yet,
but be prepared…



Next week will be the week.

But that means for now, we stick (one last time) with our linear layers.

Good Luck

&

See you next time!