COMP90051 Statistical Machine Learning

Workshop Week 7

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https://github.com/HanXudong/COMP90051_Workshops

Pytorch

- Pytorch is an open-source Python library designed for fast matrix computations on CPU/GPU. This includes both standard linear algebra and deep learning-specific operations. It is based on the neural network backend of the Torch library. A central feature of Pytorch is its use of Automatic on-the-fly differentiation (Autograd) to compute derivatives of (almost) all computations involving tensors, so we can make use of gradient-based updates to optimize some objective function. In this workshop we will introduce some fundamental operations in Pytorch and reimplement the Perceptron and logistic regression classifiers in Pytorch.

Perceptron training algorithm

$\textsc{Perceptron}(\mathbf{w}_0)$

$\mathbf{w}_1 \leftarrow \mathbf{w}_0$ $\quad \triangleright$ typically $\mathbf{w}_0 = \mathbf{0}$

for $t \leftarrow 1$ **to** T **do**

  $\textsc{Receive}(\mathbf{x}_t)$

  $\widehat{y}_t \leftarrow \operatorname{sgn}(\mathbf{w}_t \cdot \mathbf{x}_t)$

  $\textsc{Receive}(y_t)$

  if $(\widehat{y}_t \neq y_t)$ **then**

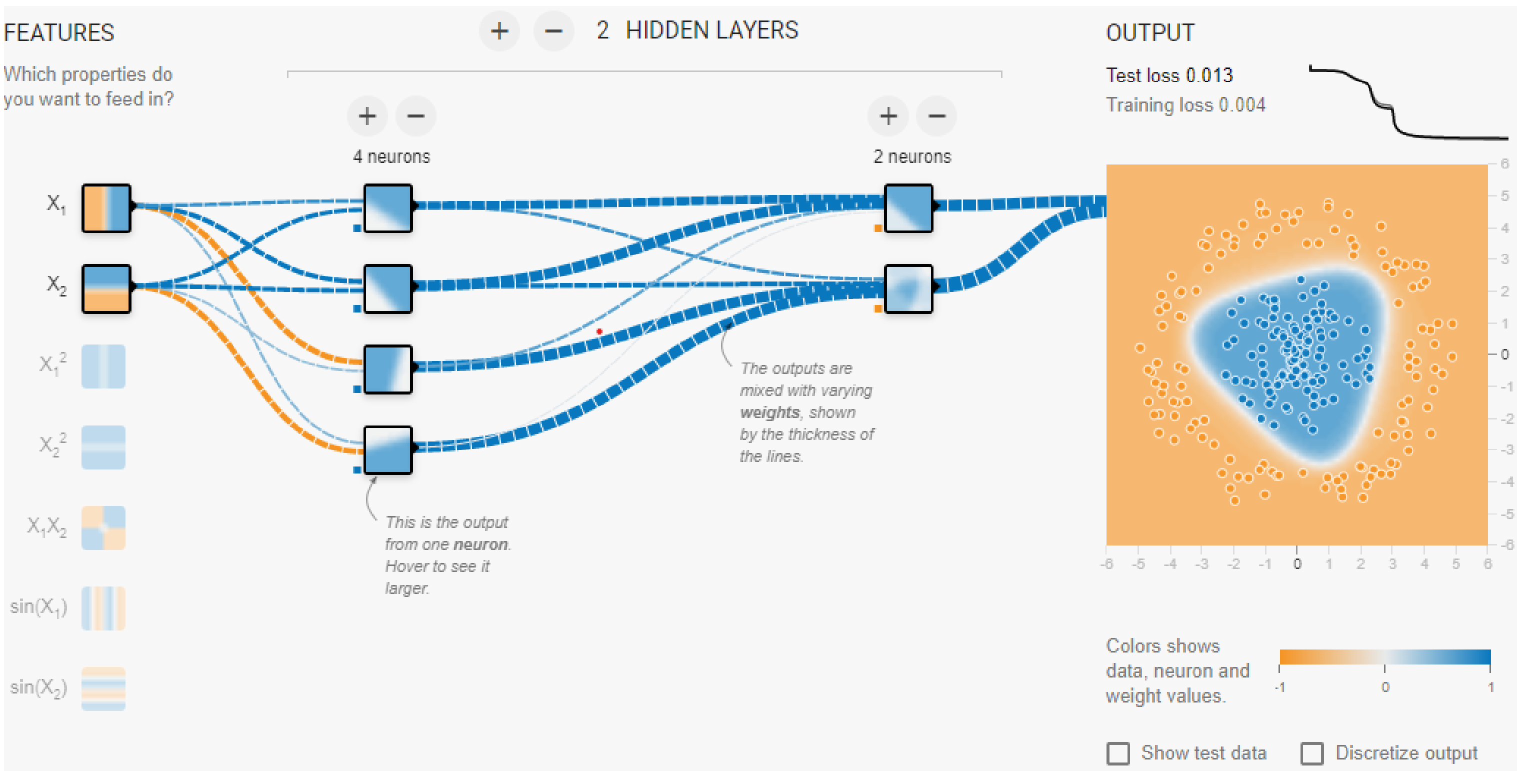
    $\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + y_t \mathbf{x}_t$ $\quad \triangleright$ more generally $\eta y_t \mathbf{x}_t, \eta > 0.$

  else $\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t$

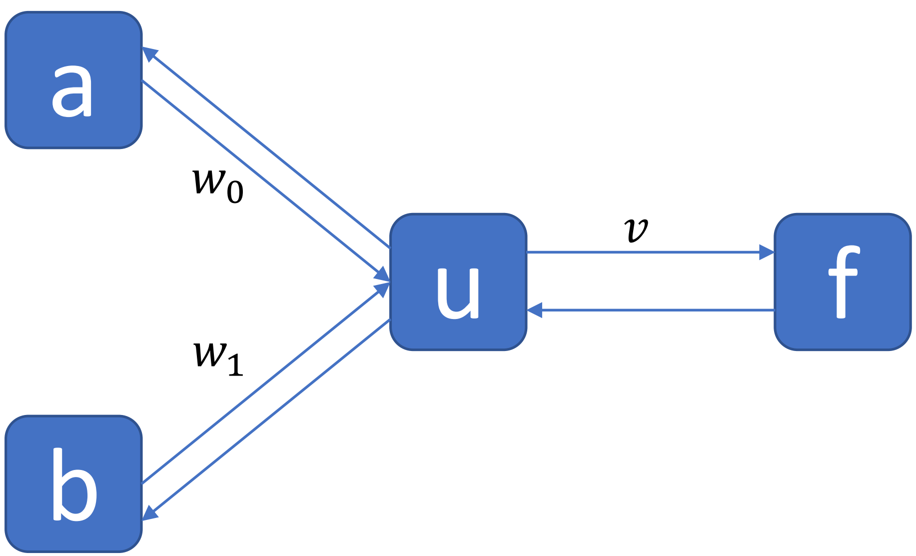
return $\mathbf{w}_{T+1}$

Computational Model

- https://playground.tensorflow.org

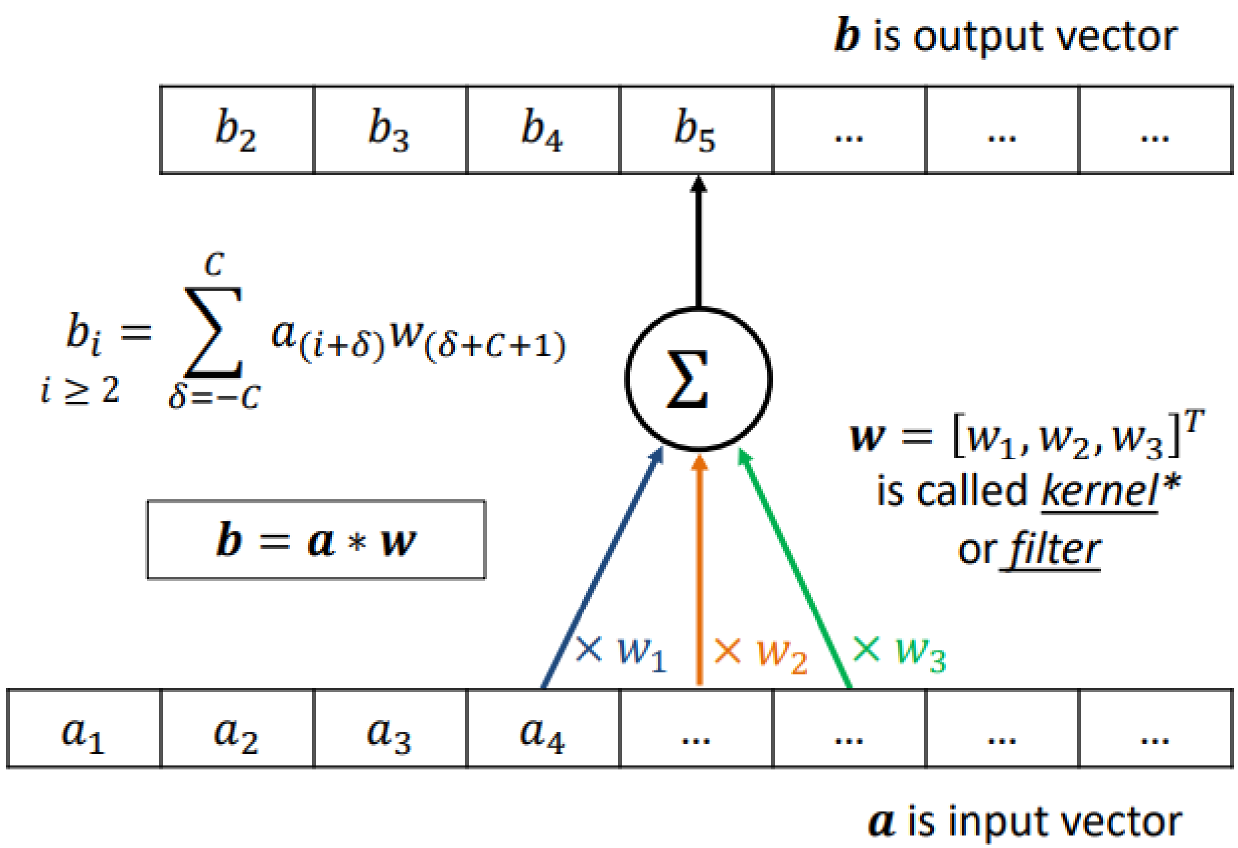


- MSE $\mathrm{L} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
- $\frac{\partial L}{\partial v} = \frac{\partial L}{\partial f}\frac{\partial f}{\partial v} = 2(\hat{y}_i - y_i) \times u = -50$
- $\frac{\partial L}{\partial w_0} = \frac{\partial L}{\partial f}\frac{\partial f}{\partial u}\frac{\partial u}{\partial w_0} = 2(\hat{y}_i - y_i) \times v \times a = -20$
- $\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial f}\frac{\partial f}{\partial u}\frac{\partial u}{\partial w_1} = 2(\hat{y}_i - y_i) \times v \times b = -30$



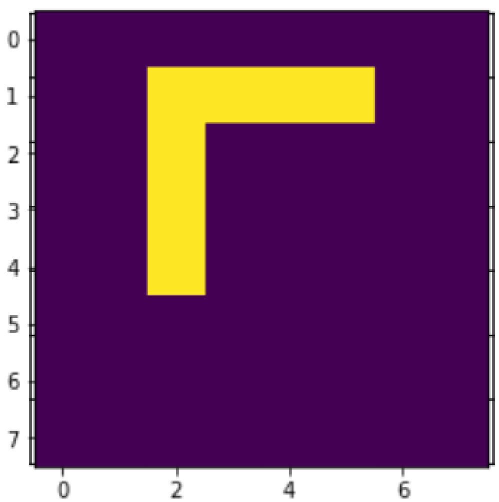
$$u = a \times w_0 + b \times w_1$$
$$f = u \times v$$

Model Design in PyTorch
Convolutional Neural Networks



Idea of filters

Filters are learned from training data!

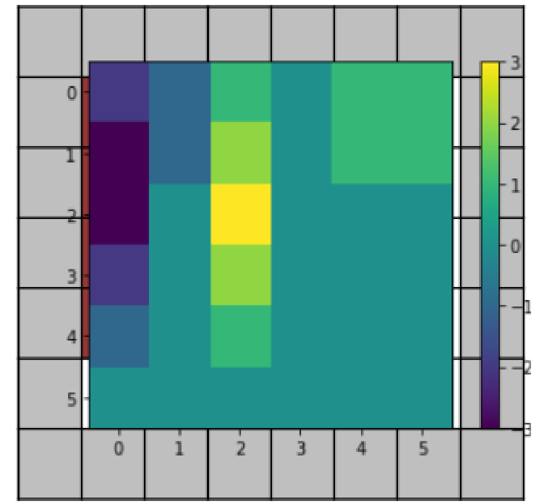


Filters/Kernels

-1	0	1
-1	0	1
-1	0	1

1	1	1
0	0	0
-1	-1	-1

Patterns/Features



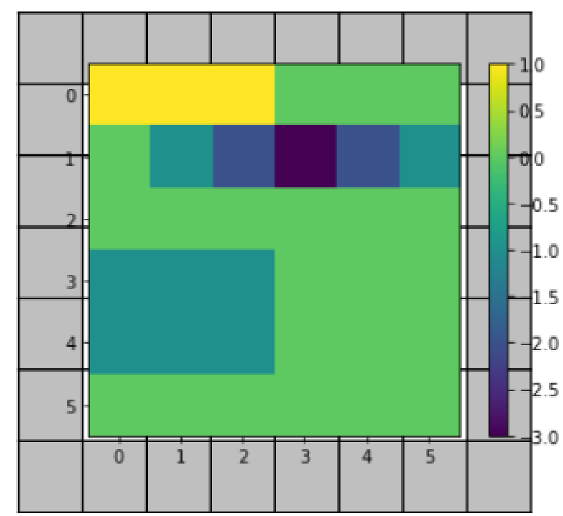
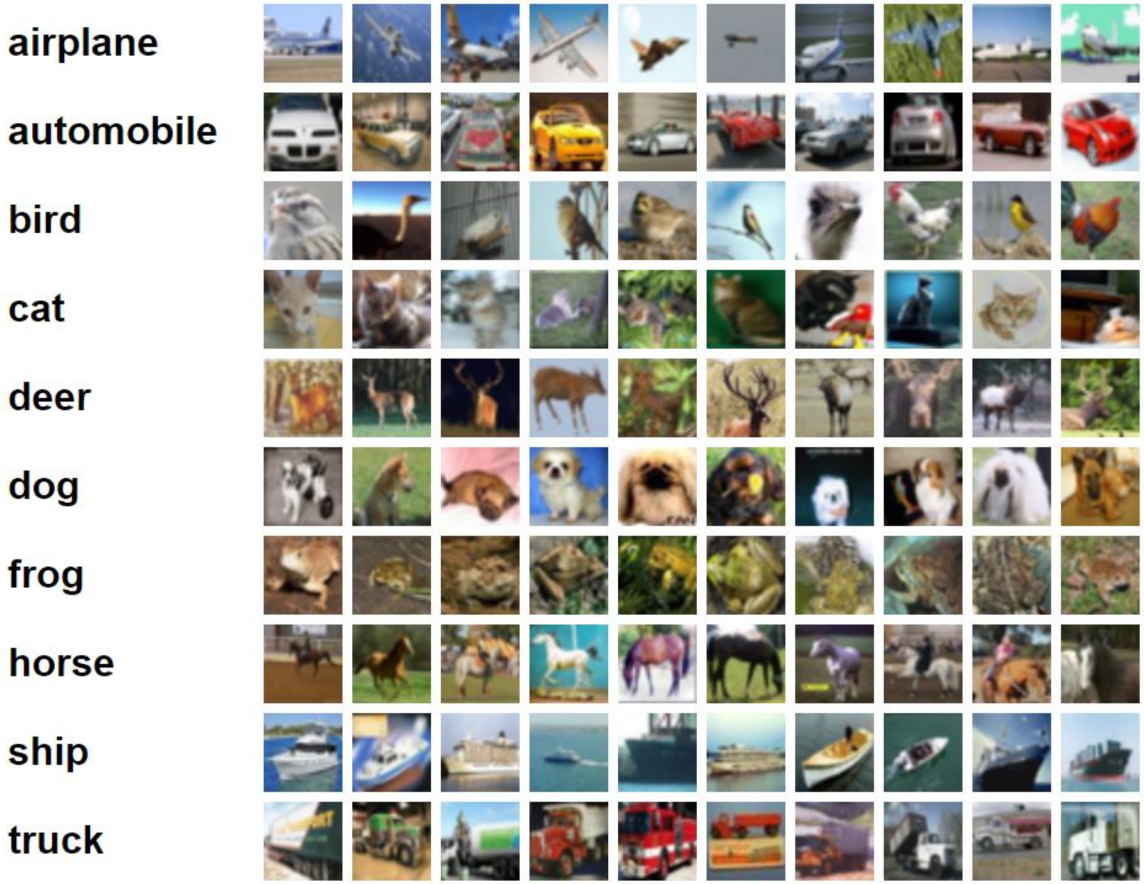


Image Classification on CIFAR-10

https://www.cs.toronto.edu/~kriz/cifar.html



Model design with torch.nn.Module

- Implement the constructor __init__(self, ...). Here we define all network parameters.
- Override the forward method forward(self, x). This accepts the input tensor x and returns our desired model output.
- Provided your operations are autograd-compliant, the backward pass is implemented automatically as PyTorch walks the computational graph backward.

```python
import torch.nn as nn
import torch.nn.functional as F

class LogisticRegressionModel(nn.Module):

    def __init__(self, n_features, n_classes):
        super(LogisticRegressionModel, self).__init__()

        # Register weight matrix and bias term as model parameters - automatically tracks operations for gradient compu
        self.W = torch.nn.Parameter(torch.nn.init.xavier_uniform_(torch.empty([n_features, n_classes])))  # Weights
        self.b = torch.nn.Parameter(torch.zeros([n_classes]))  # Biases

    def forward(self, x):
        """
        Forward pass for logistic regression.
        Input: Tensor x of shape [N,C,H,W]
        Output: Logits W @ x + b
        """
        batch_size = x.shape[0]

        x = x.view(batch_size, -1)  # Flatten image into vector, retaining batch dimension
        out = torch.matmul(x,self.W) + self.b  # Compute scores
        return out
```

```python
def train(model, train_loader, test_loader, optimizer, n_epochs=10):
    """
    Generic training loop for supervised multiclass learning
    """
    LOG_INTERVAL = 250
    running_loss, running_accuracy = list(), list()
    start_time = time.time()
    criterion = torch.nn.CrossEntropyLoss()

    for epoch in range(n_epochs):  # Loop over training dataset `n_epochs` times

        epoch_loss = 0.

        for i, data in enumerate(train_loader):  # Loop over elements in training set

            x, labels = data

            logits = model(x)

            predictions = torch.argmax(logits, dim=1)
            train_acc = torch.mean(torch.eq(predictions, labels).float()).item()

            loss = criterion(input=logits, target=labels)

            loss.backward()               # Backward pass (compute parameter gradients)
            optimizer.step()              # Update weight parameter using SGD
            optimizer.zero_grad()         # Reset gradients to zero for next iteration
```

Convolutional Networks

- Convolutional Layer #1 | 8 5×5 filters with a stride of 1, ReLU activation function.
- Max Pooling #1 | Kernel size 2 with a stride of 1.
- Convolutional Layer #2 | 16 5×5 filters with a stride of 1, ReLU activation function.
- Max Pooling #2 | Kernel size 2 with a stride of 1.
- Fully Connected Layer #1 | 400 input units (flattened convolutional output), 256 output units.
- Fully Connected Layer #2 | 256 input units, 10 output units - yields logits for classification.

```python
OUT_C1 = 8
OUT_C2 = 16
DENSE_UNITS = 256

class BasicConvNet(nn.Module):
    def __init__(self, out_c1, out_c2, dense_units, n_classes=10):
        super(BasicConvNet, self).__init__()
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=out_c1, kernel_size=5)
        self.pool = nn.MaxPool2d(kernel_size=2, stride=2)
        self.conv2 = nn.Conv2d(in_channels=out_c1, out_channels=out_c2, kernel_size=5)
        self.fc1 = nn.Linear(16 * 5 * 5, dense_units)
        self.logits = nn.Linear(dense_units, n_classes)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 16 * 5 * 5)
        x = F.relu(self.fc1(x))
        out = self.logits(x)
        return out


conv2D_model = BasicConvNet(OUT_C1, OUT_C2, DENSE_UNITS)
```

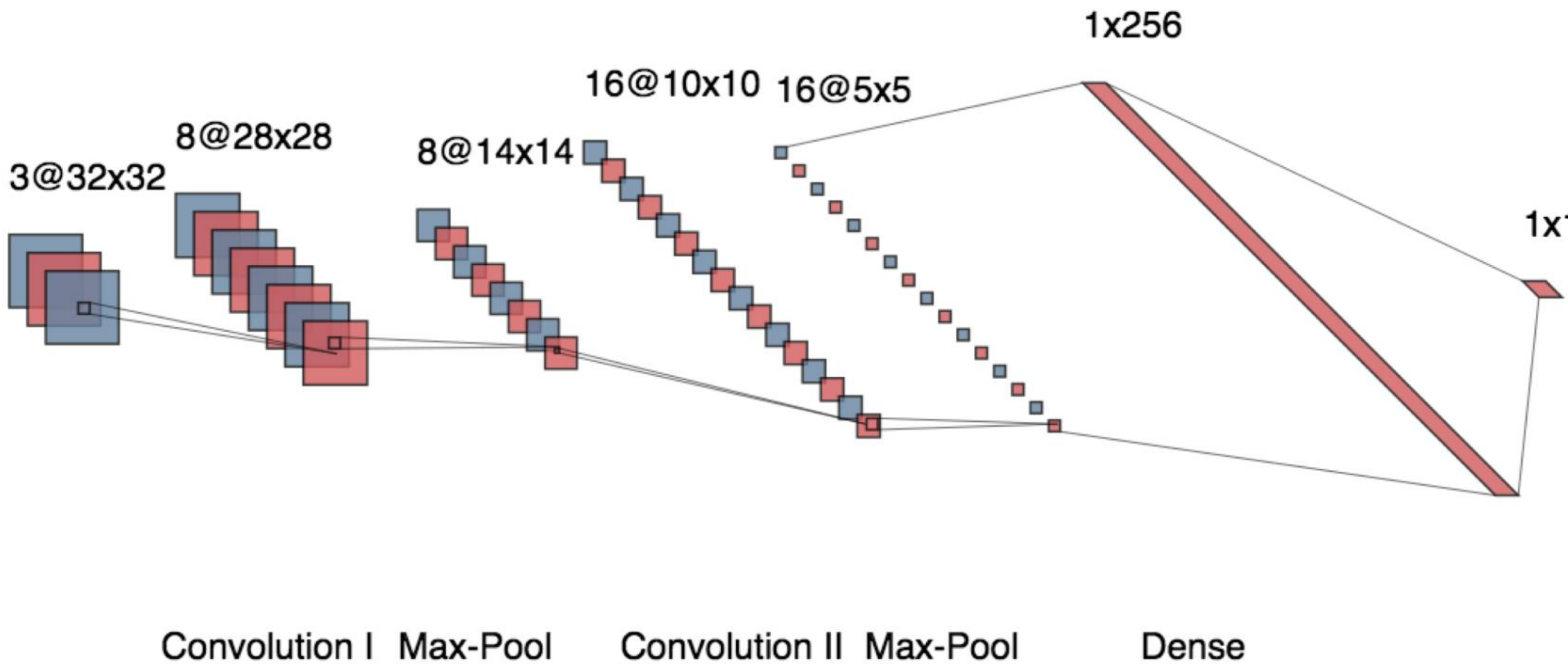
Downsampling Max-Pool

1	2	3	4
1	3	2	5
3	2	1	5
2	4	5	3

kernel_size=2, stride=2

3	5
4	5

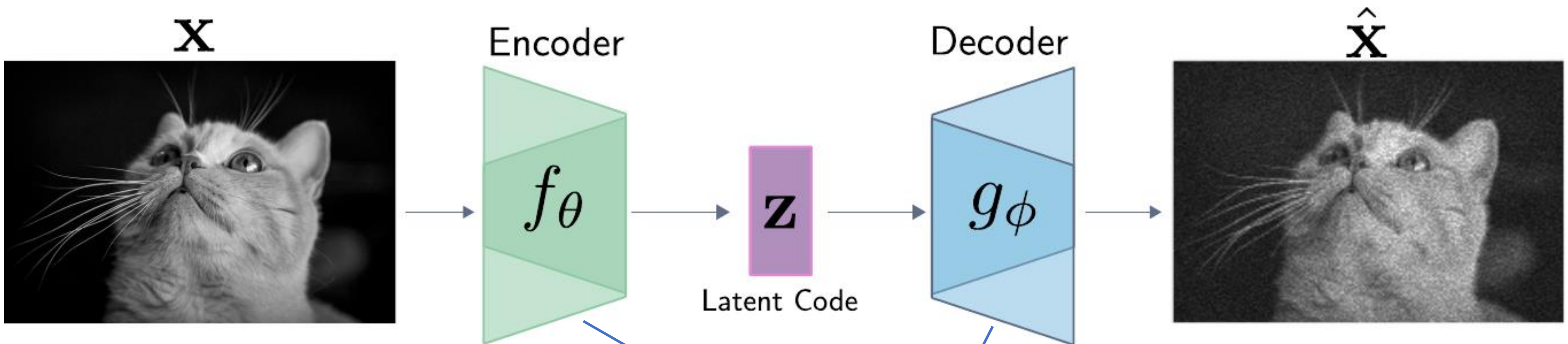
Calculate the number of parameters



Convolution I: $3 \times 8 \times 5 \times 5 + 8$

Dense I: $16 \times 5 \times 5 \times 256 + 256$

Autoencoders



$$\min_{f,g} \sum_k \|\mathbf{x}_k - g \circ f(\mathbf{x}_k)\|^2$$