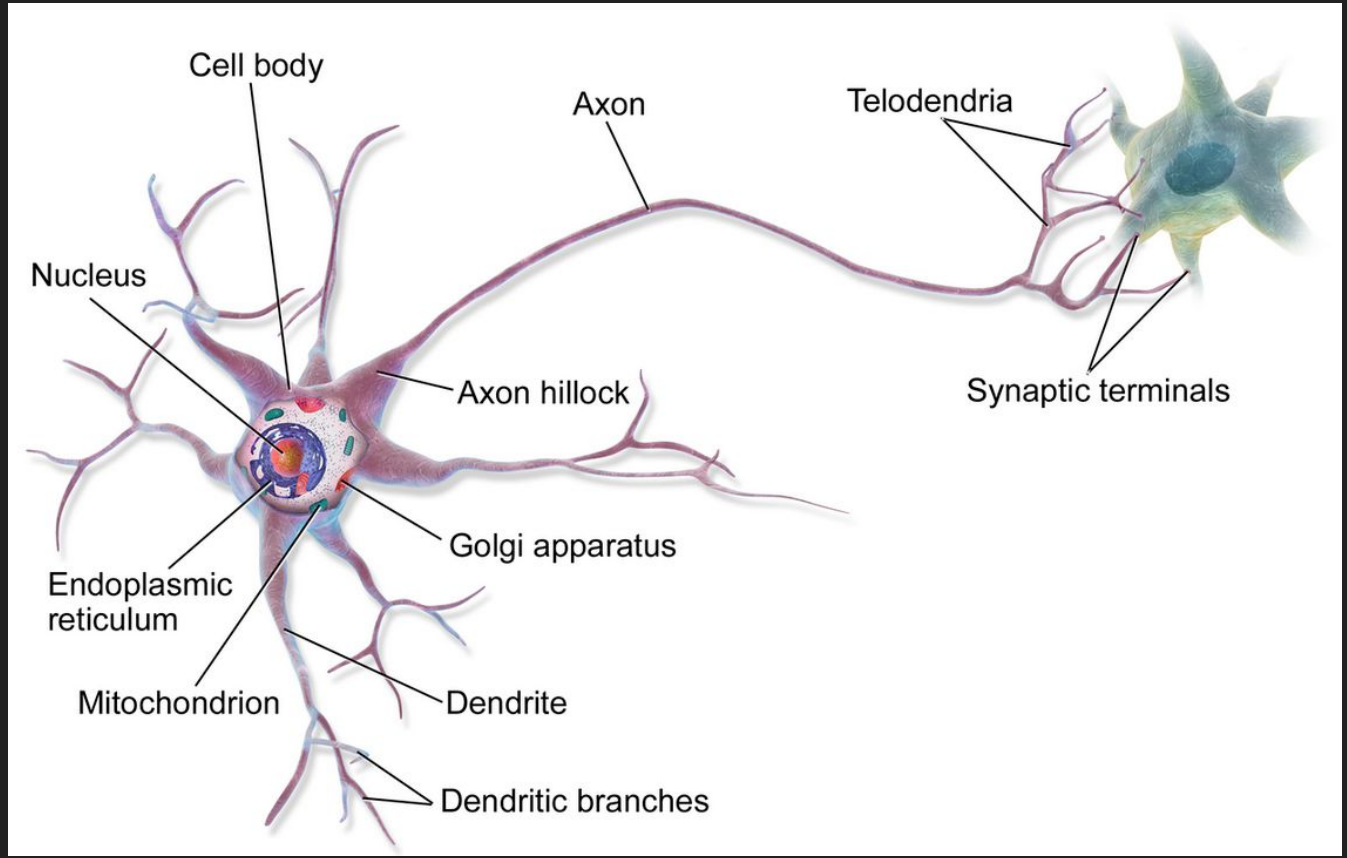
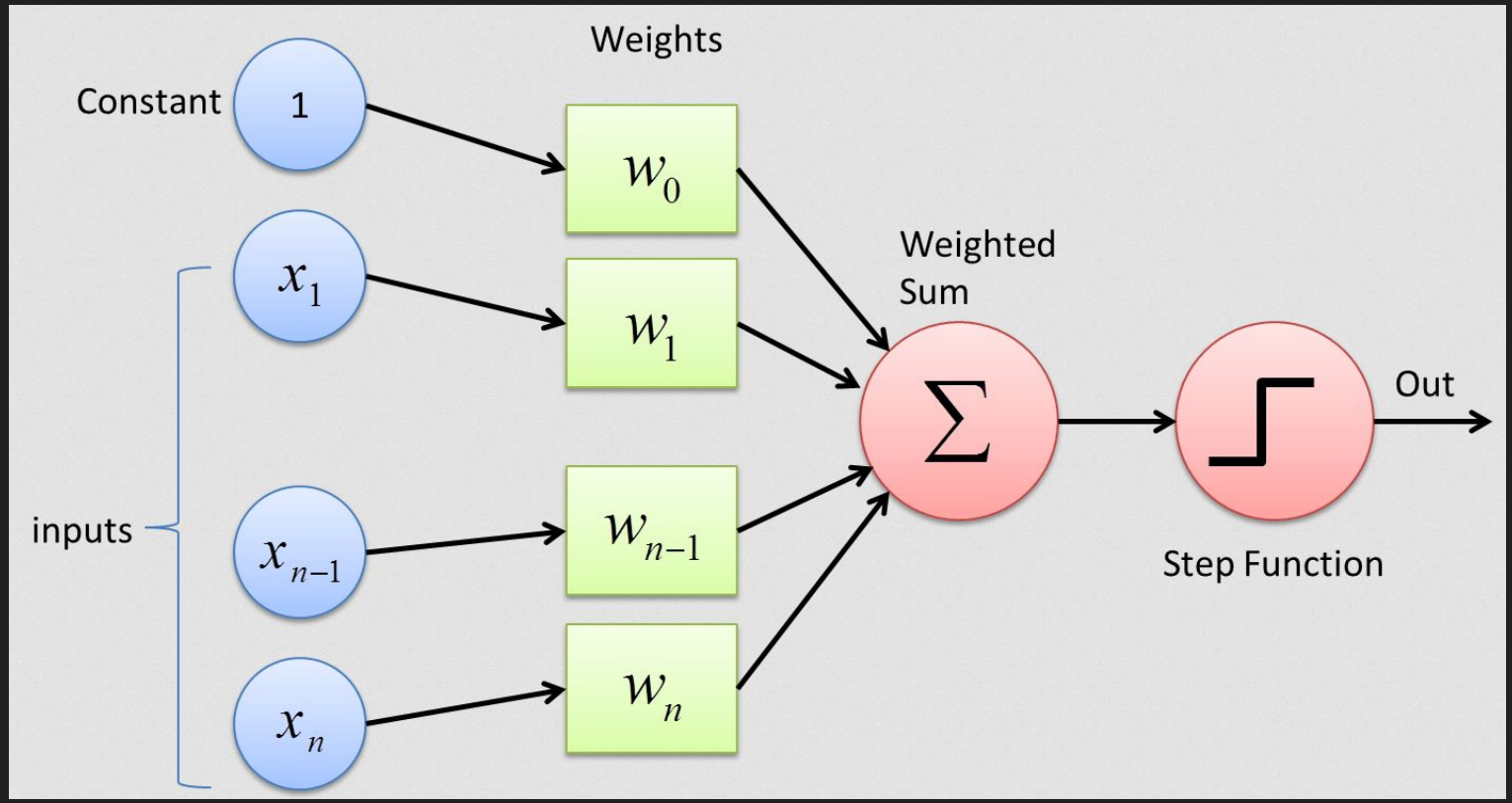
L04

Perceptron
Simple NN

Biological Neuron

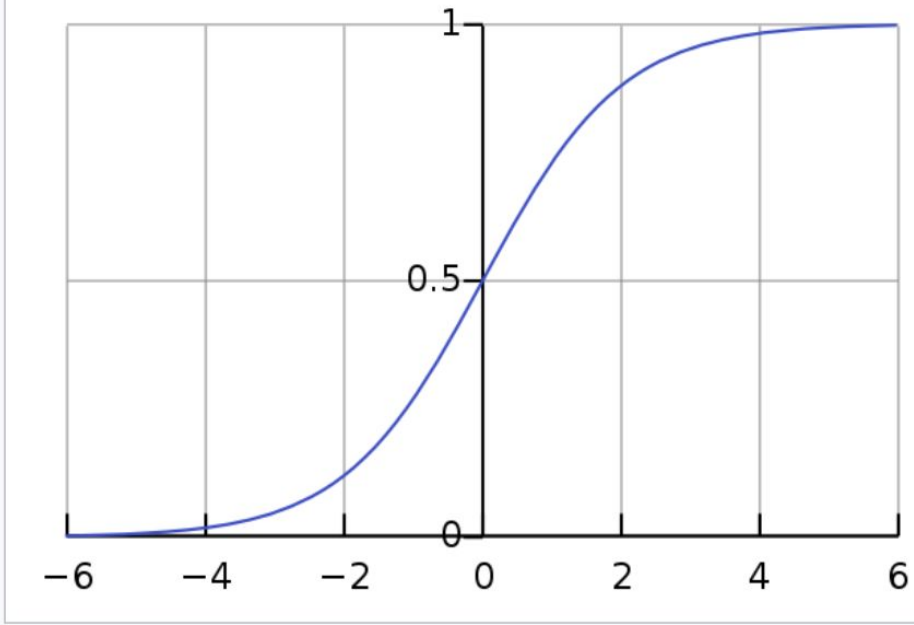


Perceptron. Model of Neuron



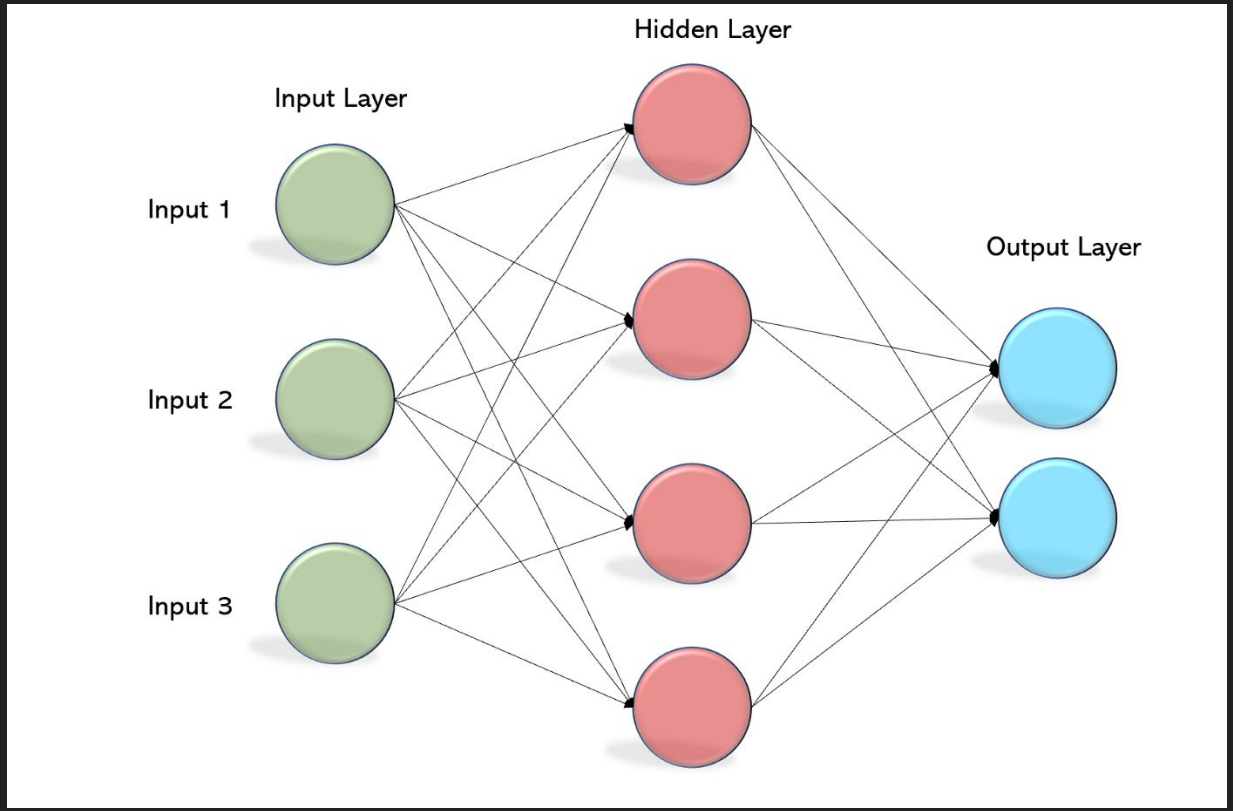
Sigmoid Activation Function

$$f(x) = \frac{1}{1 + e^{-x}}$$

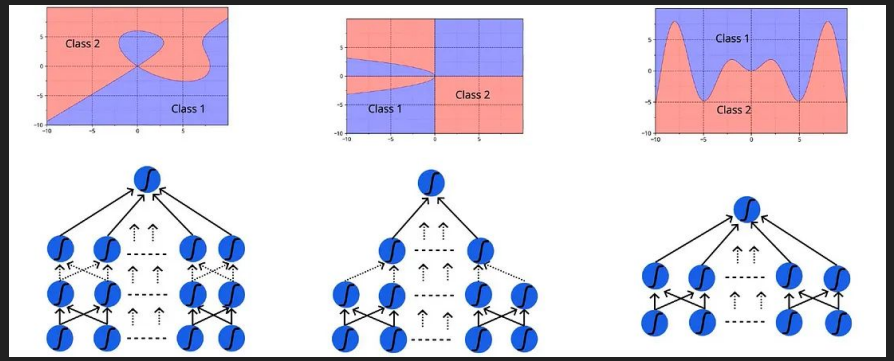


Standard logistic function where
$L = 1, k = 1, x_0 = 0$

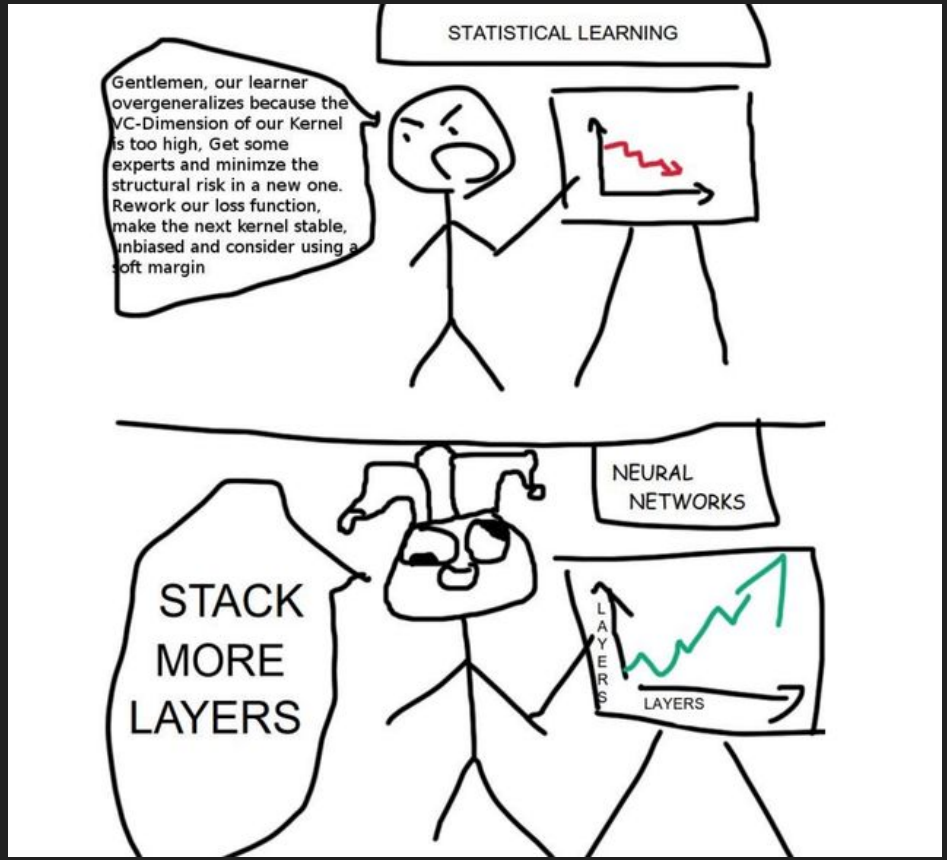
Multilayer Perceptron



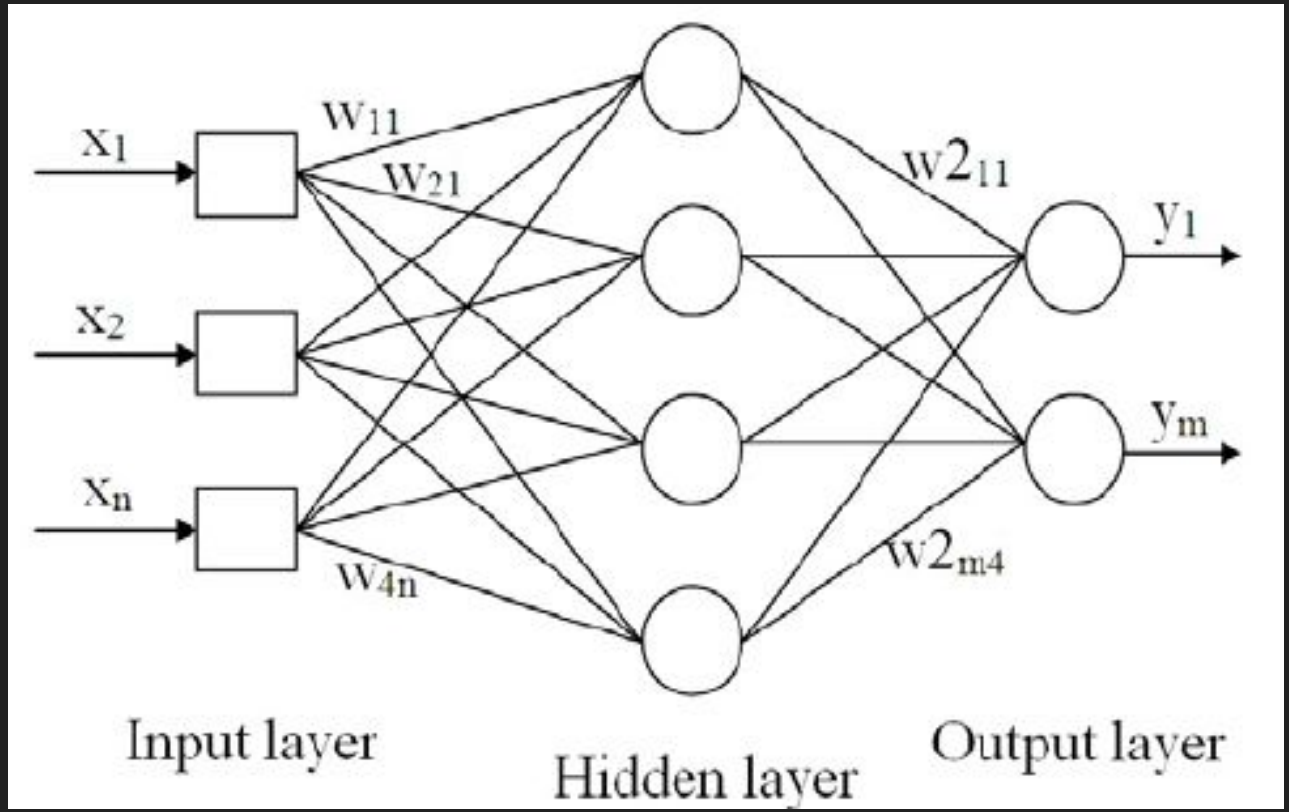
Universal approximation theorem



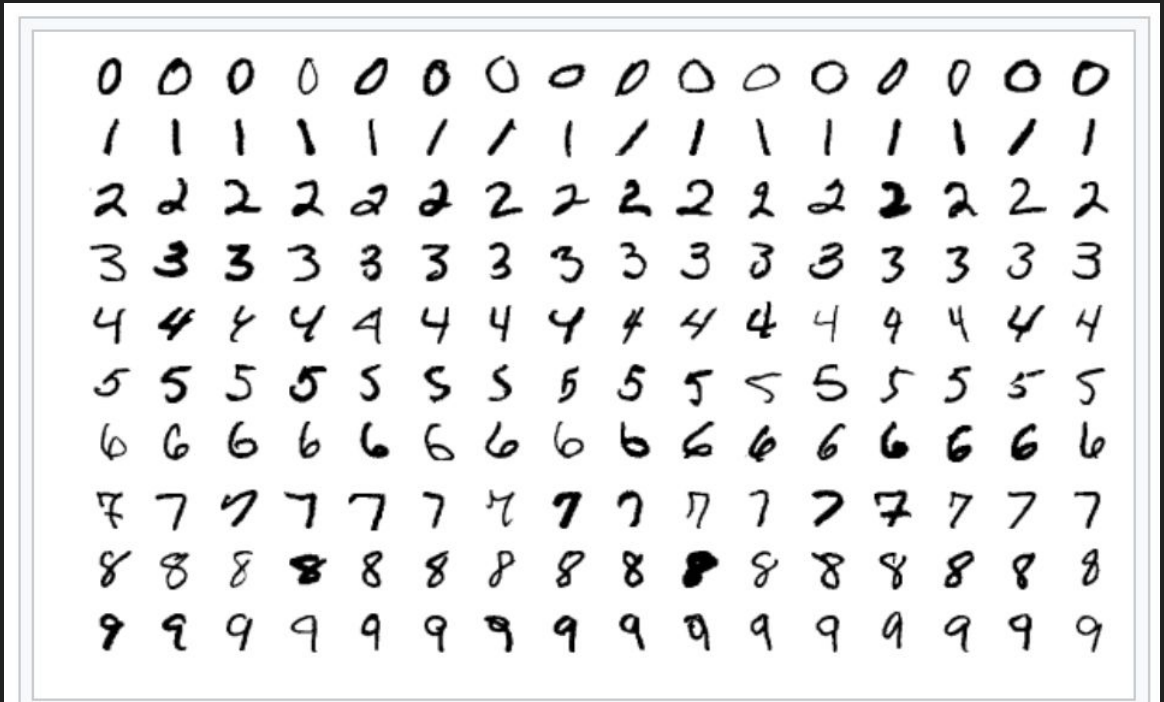
Ref: [read]



Matrices in MLP

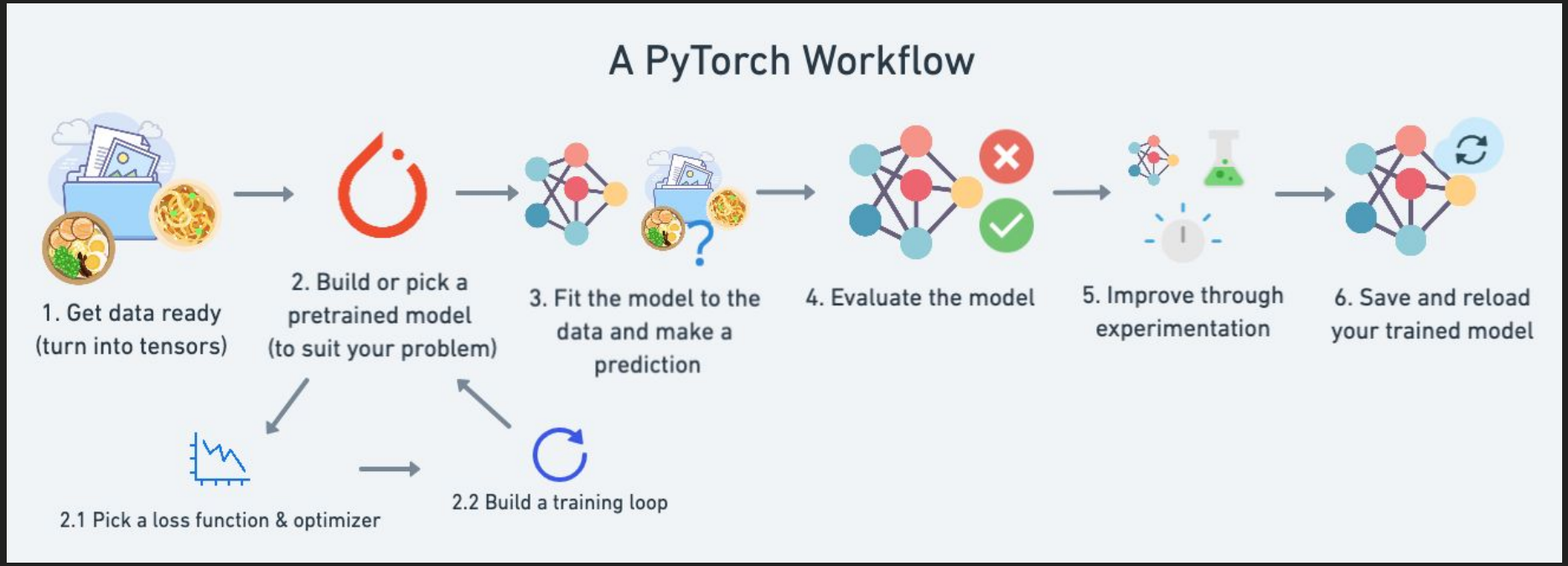


MLP Demo with Numpy on MNIST Dataset

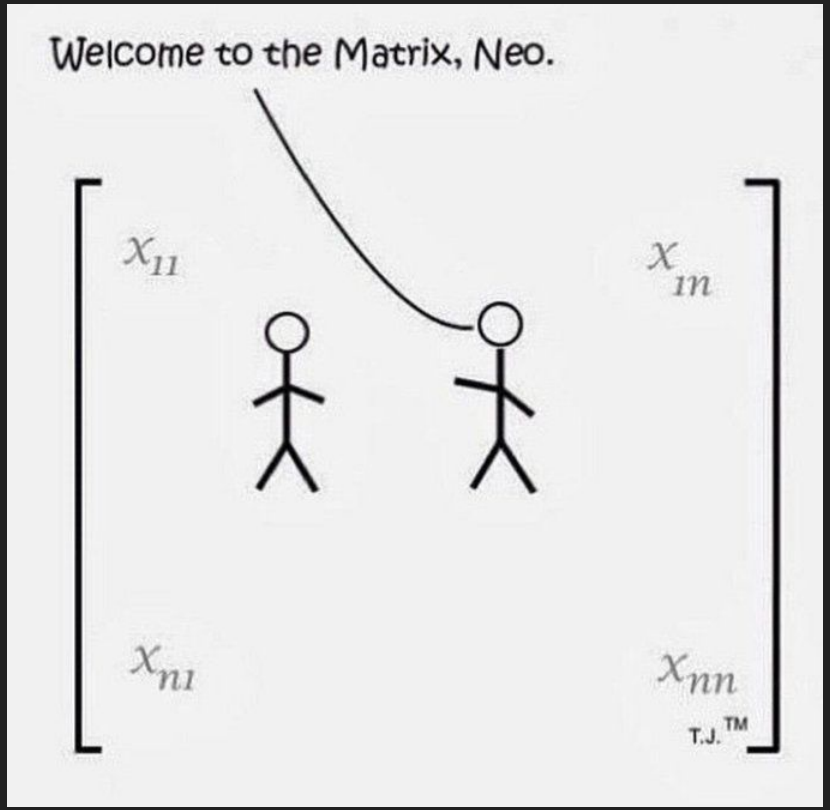


Sample images from MNIST test dataset

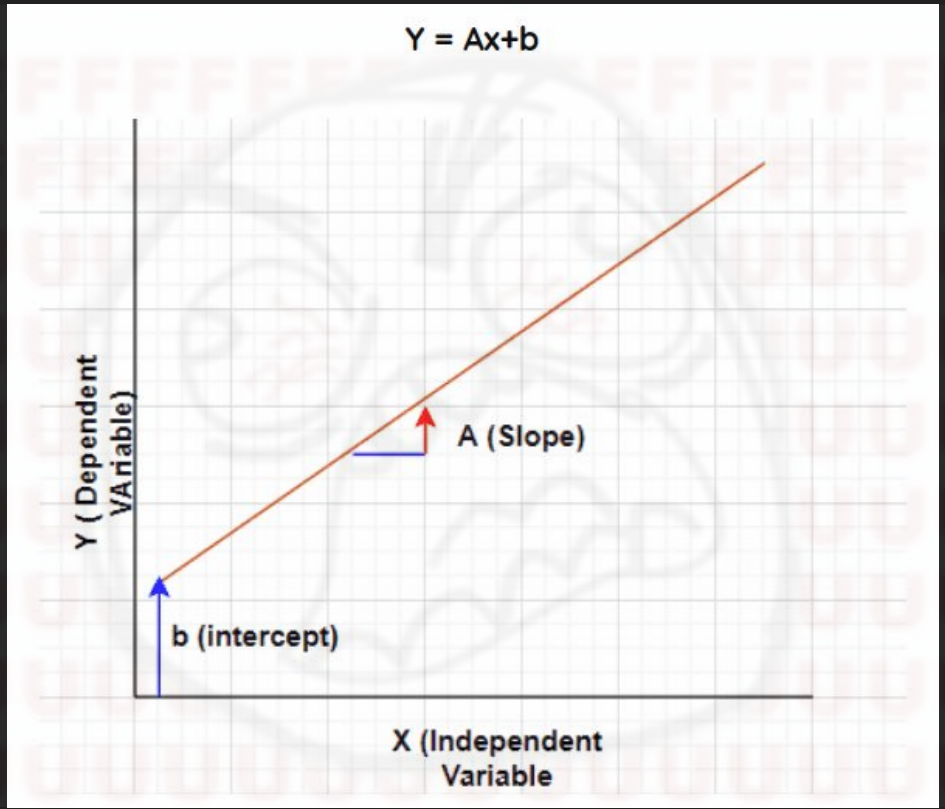
Pytorch. Beginning.



Demo. Pytorch Matrix Operations



Demo. Pytorch Linear Regression



Pytorch Model

```python
# Create a linear regression model in PyTorch
class LinearRegressionModel(nn.Module):
    def __init__(self):
        super().__init__()

        # Initialize model parameters
        self.weights = nn.Parameter(torch.randn(1,
            requires_grad=True,
            dtype=torch.float
        ))

        self.bias = nn.Parameter(torch.randn(1,
            requires_grad=True,
            dtype=torch.float
        ))

    # forward() defines the computation in the model
    def forward(self, x: torch.Tensor) -> torch.Tensor:
        return self.weights * x + self.bias
```

Subclass `nn.Module`
(this contains all the building blocks for neural networks)

Initialise model parameters to be used in various computations (these could be different layers from `torch.nn`, single parameters, hard-coded values or functions)

`requires_grad=True` means PyTorch will track the gradients of this specific parameter for use with `torch.autograd` and gradient descent (for many `torch.nn` modules, `requires_grad=True` is set by default)

Any subclass of `nn.Module` needs to override `forward()`
(this defines the forward computation of the model)

PyTorch training loop

```python
# Pass the data through the model for a number of epochs (e.g. 100)
for epoch in range(epochs):

    # Put model in training mode (this is the default state of a model)
    model.train()

    # 1. Forward pass on train data using the forward() method inside
    y_pred = model(X_train)

    # 2. Calculate the loss (how different are the model's predictions to the true values)
    loss = loss_fn(y_pred, y_true)

    # 3. Zero the gradients of the optimizer (they accumulate by default)
    optimizer.zero_grad()

    # 4. Perform backpropagation on the loss
    loss.backward()

    # 5. Progress/step the optimizer (gradient descent)
    optimizer.step()
```

Note: all of this can be turned into a function

Pass the data through the model for a number of epochs (e.g. 100 for 100 passes of the data)

Pass the data through the model, this will perform the `forward()` method located within the model object

Calculate the loss value (how wrong the model's predictions are)

Zero the optimizer gradients (they accumulate every epoch, zero them to start fresh each forward pass)

Perform backpropagation on the loss function (compute the gradient of every parameter with `requires_grad=True`)

Step the optimizer to update the model's parameters with respect to the gradients calculated by `loss.backward()`

PyTorch testing loop

```python
# Setup empty lists to keep track of model progress
epoch_count = []
train_loss_values = []
test_loss_values = []

# Pass the data through the model for a number of epochs (e.g. 100) pochs):
for epoch in range(epochs):

    ### Training loop code here ###

    ### Testing starts ###

    # Put the model in evaluation mode
    model.eval()

    # Turn on inference mode context manager
    with torch.inference_mode():
        # 1. Forward pass on test data
        test_pred = model(X_test)

        # 2. Caculate loss on test data
        test_loss = loss_fn(test_pred, y_test)

    # Print out what's happening every 10 epochs
    if epoch % 10 == 0:
        epoch_count.append(epoch)
        train_loss_values.append(loss)
        test_loss_values.append(test_loss)
        print(f"Epoch: {epoch} | MAE Train Loss: {loss} | MAE Test Loss: {test_loss} ")
```

Note: all of this can be turned into a function

Create empty lists for storing useful values (helpful for tracking model progress)

Tell the model we want to evaluate rather than train (this turns off functionality used for training but not evaluation)

Turn on `torch.inference_mode()` context manager to disable functionality such as gradient tracking for inference (gradient tracking not needed for inference)

Pass the test data through the model (this will call the model's implemented `forward()` method)

Calculate the test loss value (how wrong the model's predictions are on the test dataset, lower is better)

Display information outputs for how the model is doing during training/testing every ~10 epochs (note: what gets printed out here can be adjusted for specific problems)

HW (numpy example)

- Report on learning rate, number of epochs, and number of neurons on hidden layer influence on the final performance

Optional:

- Introduce more layers to the NN
- Make report on influence of number and width of layers on the final performance

HW (torch example)

- Plot loss curve
- Print model weights and compare with original ones
- Plot results (predicted line along with data set data)
- Make forward pass for a simple MLP on a paper
  - In step-by-step form
  - In matrix form

Questions (optional):

- How predicted line will chance if `self.bias = nn.Parameter(0)`?
- What will be the value of `self.bias` if `self.weights = nn.Parameter(0)`?