Outline

- Python Programming Setup
- Python Platforms for DL
- Introduction to Numpy
- Plotting with Matplotlib
- Preparing Data for Machine Learning
- Lab Assignment

Part 1: Python Programming Setup

Setting up Python Environment (Anaconda 3)

What is Anaconda?

Anaconda is a distribution of the Python and R for scientific computing

- Comes with >250 packages automatically installed
- >7500 additional open-source packages available
- Equipped with Jupyter Notebook
- Conda environment manager for easy maintenance of packages

Setting up Python Environment (Anaconda 3)

Installing Anaconda 3

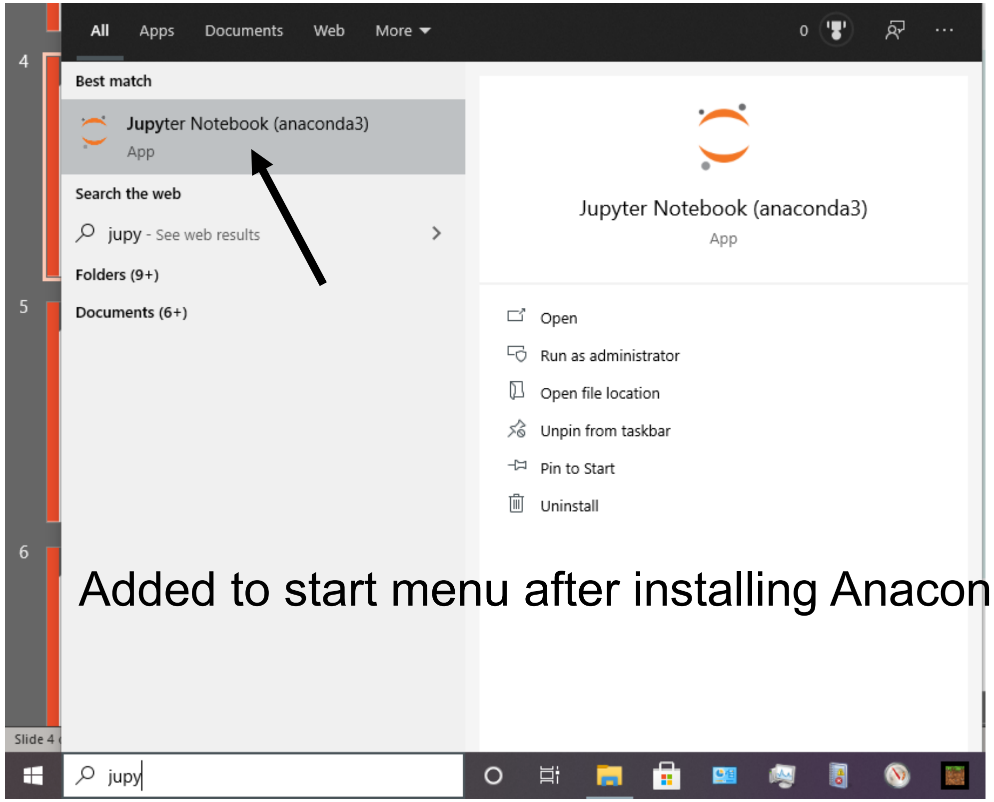
https://www.anaconda.com/products/individual

Anaconda Installers

Windows	MacOS	Linux
Python 3.8	Python 3.8	Python 3.8
64-Bit Graphical Installer (457 MB)	64-Bit Graphical Installer (435 MB)	64-Bit (x86) Installer (529 MB)
32-Bit Graphical Installer (403 MB)	64-Bit Command Line Installer (428 MB)	64-Bit (Power8 and Power9) Installer (279 MB)

Starting up Jupyter Notebook (Anaconda3)

Windows



Added to start menu after installing Anaconda 3

Mac/Linux

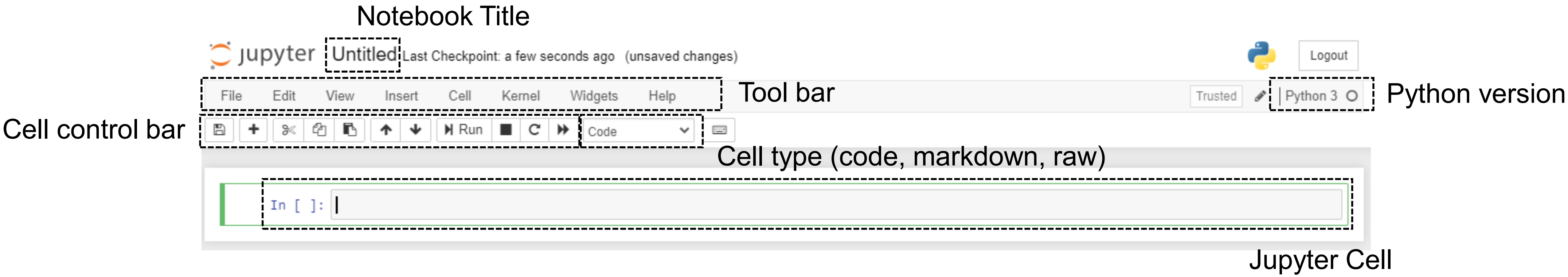
Start terminal

Type "jupyter notebook"

Starting up Jupyter Notebook (Anaconda3)

Create a new notebook

Starting up Jupyter Notebook (Anaconda3)



For more information, visit https://www.dataquest.io/blog/jupyter-notebook-tutorial/

Part 2: Python Platforms for DL

Google Colaboratory

A free Jupyter notebook environment that runs in the cloud

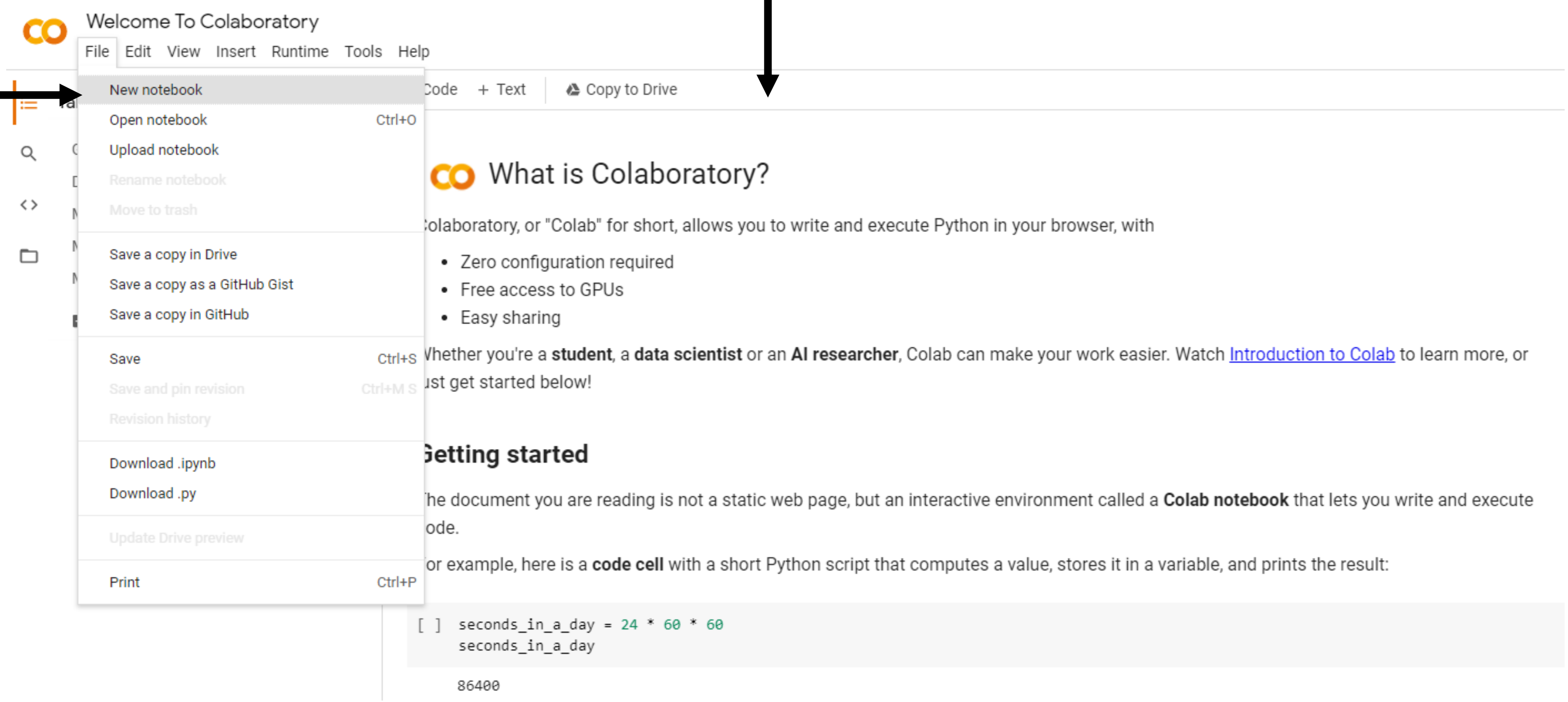
- Saves in Google drive
- Github commit style code sharing with others
- Maximum runtime of 12hrs (Free version)
- Support GPU or TPU for hardware acceleration
- Pre-equipped with latest scientific packages (Numpy, Scipy, etc)

Google Colaboratory: Getting started

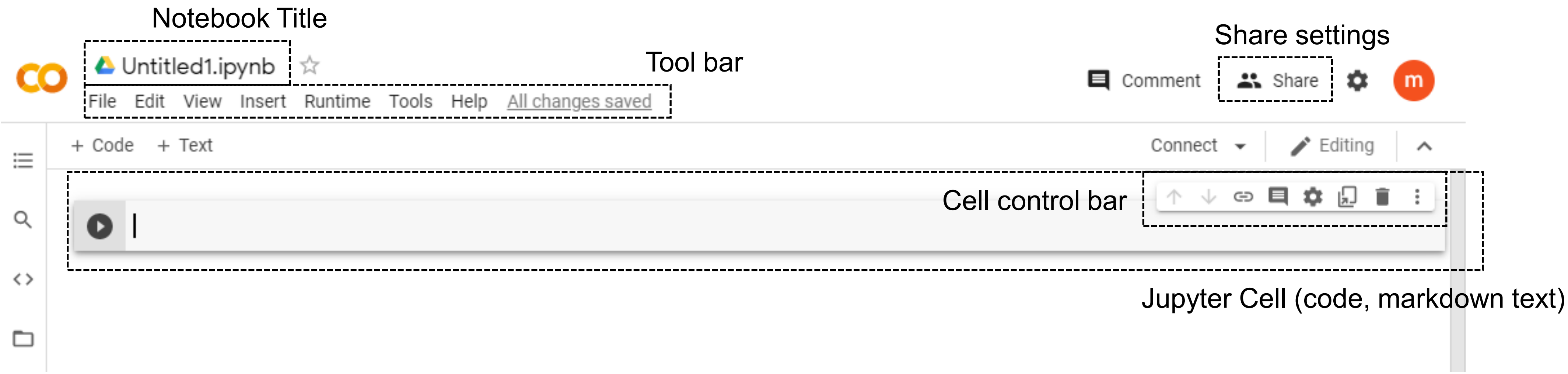
Tutorial to Colab

https://colab.research.google.com/notebooks/intro.ipynb

Create new Notebook



Google Colaboratory: Getting started



Google Cloud

Suite of cloud computing services offered by Google

- Offers AI Platform for deploying DL models
- Support Jupyter Notebook instances
- Provide instances with DL libraries
- Fully customizable hardware spec with state-of-the-art components
- Monthly charge for the service

Setup tutorial by “Towards data science” → https://towardsdatascience.com/get-deep-learning-on-google-cloud-platform-the-easy-way-53f74bab5ee9

Deep Learning Frameworks

PyTorch

Developed by Facebook

- Lots of modules that are easy to combine
- Easy to edit network
- Lots of pre-trained models
- Seamless integration into Python/Numpy framework

TensorFlow

Developed by Google

- Provides Tensorboard for visualization
- Uses its own session during training
- Great community support
- Tensorflow Lite can run models on mobile devices

mxnet

Developed by Apache

- Supported by Amazon Web Service
- Supports many languages
- Fast and flexible for running DL algorithms
- Features advanced GPU support
- Popular among industrial projects

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Framework for this class

Part 3: Introduction to Numpy

What is Numpy?

Fundamental package for scientific computing in Python

- Provides multi-dimensional array object
- Provides assortment of mathematical routines for arrays
- Fast array operations through pre-compiled C
- Support vectorization of operations
- Seamlessly integrated with DL frameworks such as PyTorch, TensorFlow

Constructing Numpy arrays

From python lists

```
# Defining a numpy array

# 1D array
arr = np.array([1,2,3,4,5])

# 2D array
arr_2d = np.array([[1,2,3,4,5],
                   [6,7,8,9,10],
                   [11,12,13,14,15]])

# 3D array
arr_3d = np.array([[[1,2,3,4,5],
                   [6,7,8,9,10],
                   [11,12,13,14,15]],
                    [[16,17,18,19,20],
                   [21,22,23,24,25],
                   [26,27,28,29,30]]])
```

From Numpy commands

```
# Define number of each dimension

n1 = 3
n2 = 4
n3 = 5

# Zeros array
zeros_1d = np.zeros(n1)
zeros_2d = np.zeros((n1,n2))
zeros_3d = np.zeros((n1,n2,n3))

# Ones array
ones_1d = np.ones(n1)
ones_2d = np.ones((n1,n2))
ones_3d = np.ones((n1,n2,n3))

# Creating array using np.arange
arr_arange = np.arange(0, 10, 1)      # (start, stop, stepsize)

# Creating an array using np.linspace
arr_linspace = np.linspace(0, 9, 10) # (start, stop, # of bins)
```

Random arrays

```
# Random array

np.random.seed(10)                   # Fixes the seed number so that random samplings always give same results

rand_arr = np.random.randn(n1, n2) # Random array sampled from standard normal distribution
```

Basic Matrix Operations in Numpy

Elementwise Addition – np.add()

Elementwise Subtraction – np.subtract()

Elementwise Multiplication – np.multiply()

Elementwise Division – np.divide()

Elementwise Power – np.power()

Dot Product – np.dot()

Transpose – .T operative or np.transpose()

Useful Numpy functions

Combining arrays

Concatenating arrays– np.concetenate()
Stacking arrays – np.stack() (Can add dimensions), np.hstack() (horizontal stack), np.vstack() (vertical stack)

Finding characteristic values of an array

Minimum, Maximum, Mean, Sum of array elements – np.min(), np.max(), np.mean(), np.sum()

Indexing an array

Indices of minimum and maximum element – np.argmin(), np.argmax()
Sorting the indices from low to high values – np.argsort()
Finding the indices that satisfy conditions – np.where()

Part 4: Plotting with Matplotlib

Basic plotting

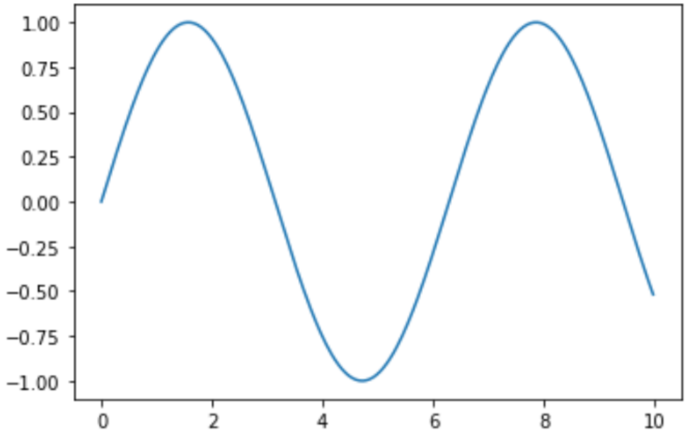
Import Matplotlib

```
#%matplotlib inline   # If using local notebook runtime, allows you to display the plot inside the jupyter notebook
#%matplotlib notebook # Alternatively, you can use this line instead for interactive plots

import matplotlib.pyplot as plt
```

Code

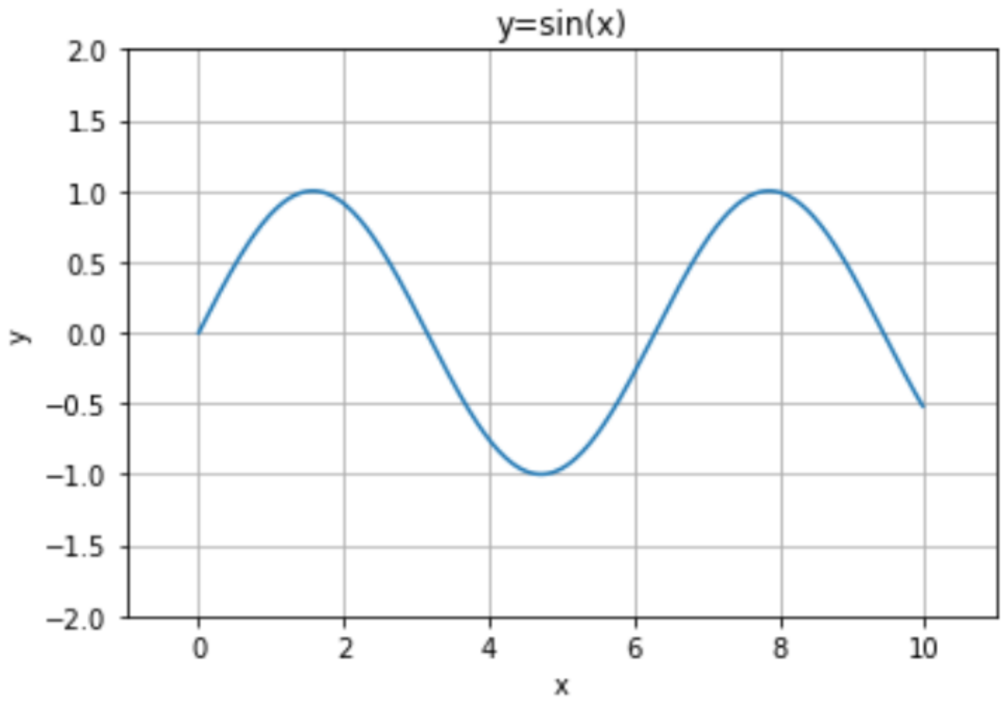
```
x = np.arange(0, 10, 1/32) # x axis data
y = np.sin(x)              # y axis data
plt.plot(x, y)             # plot the data
```

Output



Labeling your plots

Output



Code

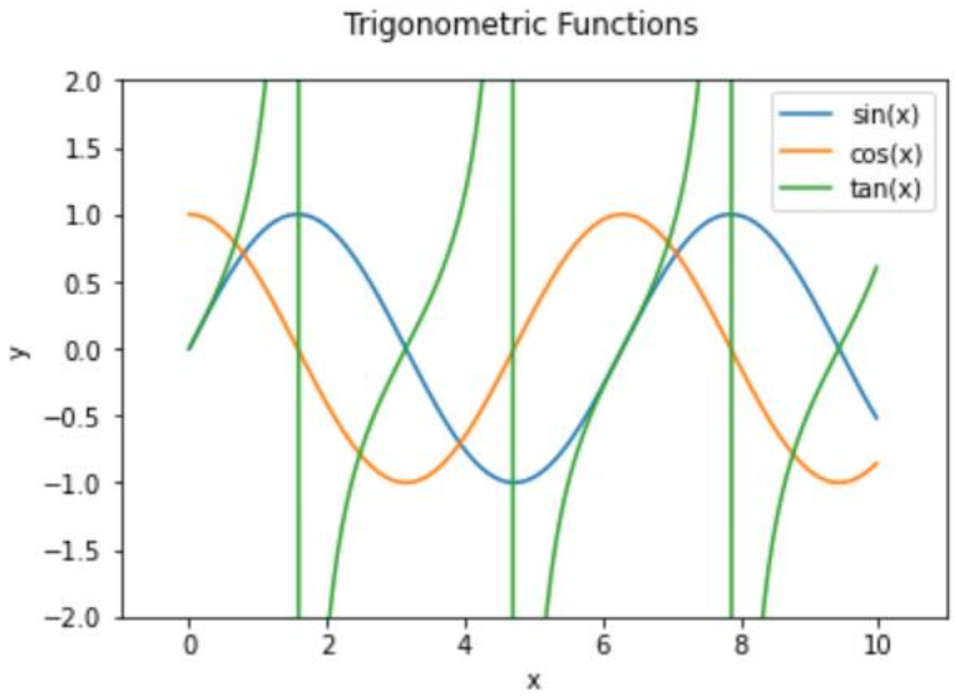
```
plt.plot(x, y)
plt.title('y=sin(x)')  # set the title
plt.xlabel('x')        # set the x axis label
plt.ylabel('y')        # set the y axis label
plt.xlim(-1, 11)       # set the x axis range
plt.ylim(-2, 2)        # set the y axis range
plt.grid()             # enable the grid
```

Multiple plots

Code

```python
# Multiple Plots
# On same figure
x = np.arange(0, 10, 1/32) # x axis data
y1 = np.sin(x)             # y axis data 1
y2 = np.cos(x)             # y axis data 2
y3 = np.tan(x)             # y axis data 3
plt.figure(1)              # create figure 1
plt.plot(x, y1, label='sin(x)')
plt.plot(x, y2, label='cos(x)')
plt.plot(x, y3, label='tan(x)')
plt.xlabel('x')
plt.ylabel('y')
plt.xlim(-1, 11)
plt.ylim(-2, 2)
plt.suptitle('Trigonometric Functions')
plt.legend()
plt.show()
```

Output

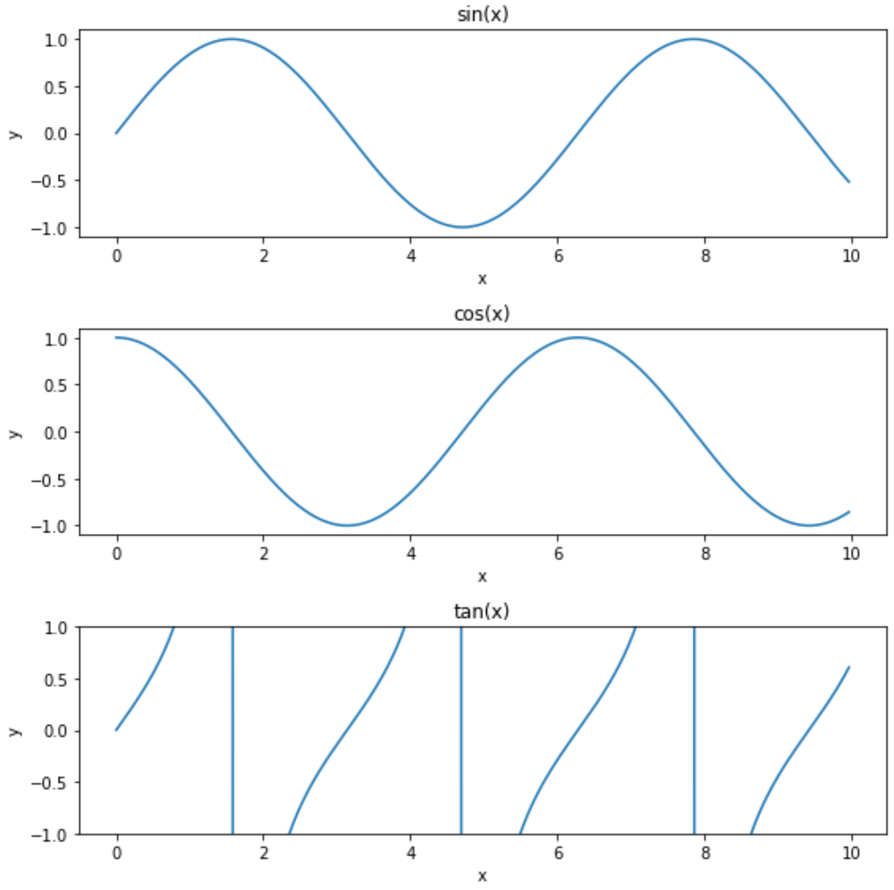


Creating subplots

Code

```
# Multiple Subplots
x = np.arange(0, 10, 1/32) # x axis data
y1 = np.sin(x)            # y axis data for subplot 1
y2 = np.cos(x)            # y axis data for subplot 2
y3 = np.tan(x)            # y axis data for subplot 3

fig = plt.figure(2,figsize=(8,8)) # create figure 2

plt.subplot(311)          # (number of rows, number of columns, current plot)
plt.plot(x, y1)
plt.title('sin(x)')
plt.xlabel('x')
plt.ylabel('y')

plt.subplot(312)
plt.plot(x, y2)
plt.title('cos(x)')
plt.xlabel('x')
plt.ylabel('y')

plt.subplot(313)
plt.plot(x, y3)
plt.title('tan(x)')
plt.xlabel('x')
plt.ylabel('y')
plt.ylim(-1, 1)

fig.tight_layout()
```

Output



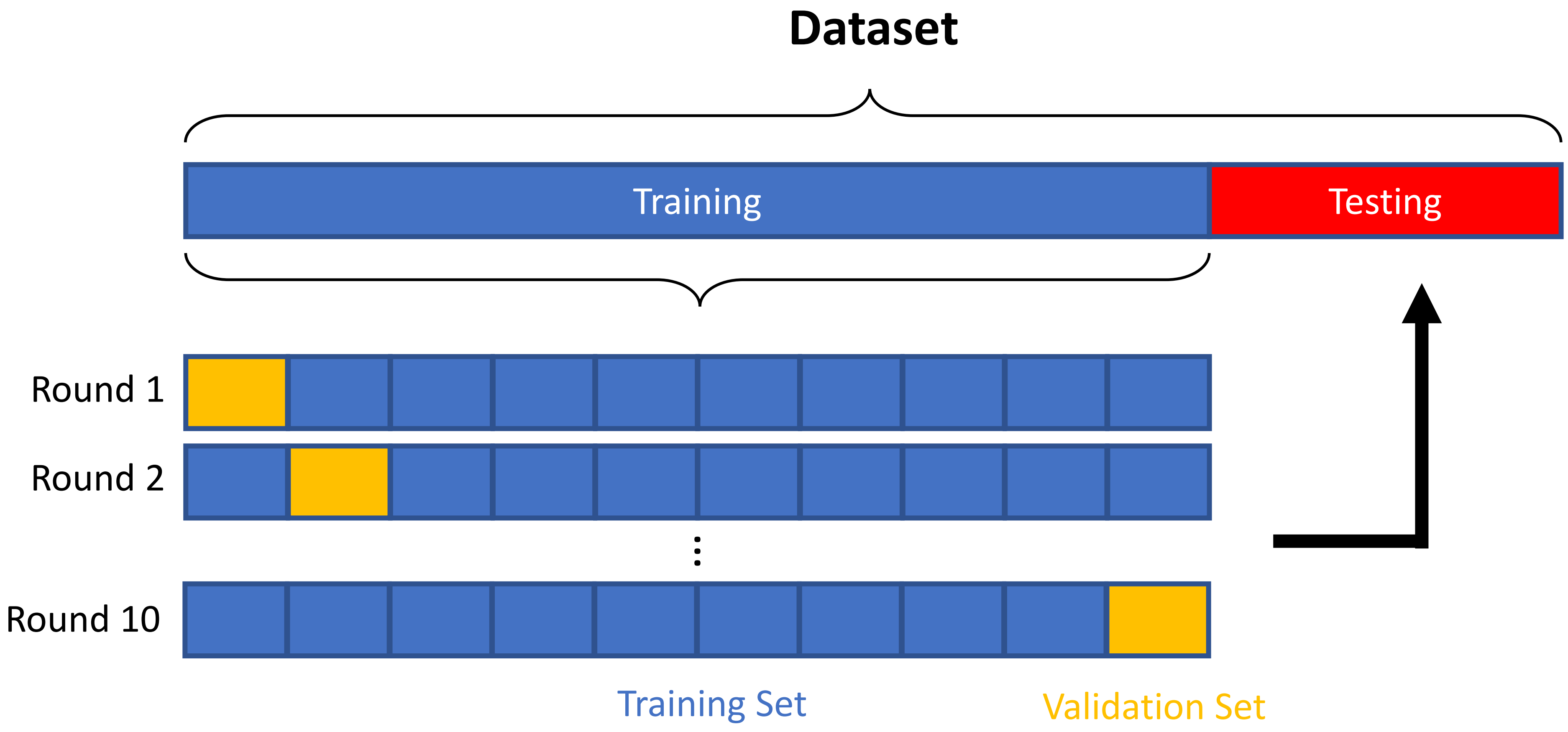
Part 5: Working with data

Loading dataset

```
import pandas as pd
import sklearn

# Import necessary modules
from sklearn.linear_model import LogisticRegressionCV

diabetes = pd.read_csv('diabetes.csv') # Read the dataset with pandas
diabetes.head() # Display the head of the data
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

Dividing dataset into Train, Validation, Test



Cross Validation

Logistic Regression using Scikit-Learn

Scaling the dataset

```
# Scaling the data

X1 = diabetes.values[:, :-1]                                           # Extract features
Y1 = diabetes.values[:, -1]                                            # Extract labels

# Scale the data z = (x - u) / s

X1_mean = np.mean(X1, axis = 0)                                        # Compute means
X1_std = np.std(X1, axis = 0)                                          # Compute stds
X1_mean_repeated = np.tile(X1_mean, (len(X1), 1))                      # Create repeated array of mean to match X1 dimension
X1_std_repeated = np.tile(X1_std, (len(X1), 1))                        # Create repeated array of std to match X1 dimension
X1_scaled = np.divide(np.subtract(X1, X1_mean_repeated), X1_std_repeated) # Compute z for the array
```

```
# Divide the data into training and testing

test_ratio = 0.3                          # Set the test data ratio
train_size = int(len(X1)*(1-test_ratio))  # Set training data size based on test ratio

X_train = X1_scaled[:train_size]
X_test = X1_scaled[train_size:]
Y_train = Y1[:train_size]
Y_test = Y1[train_size:]
```

Define Training and Testing sets

```
# Use cross validation to train
model = LogisticRegressionCV(cv=10).fit(X_train, Y_train)
result = model.score(X_test, Y_test)

print("Accuracy: %.2f%%" % (result*100))
```

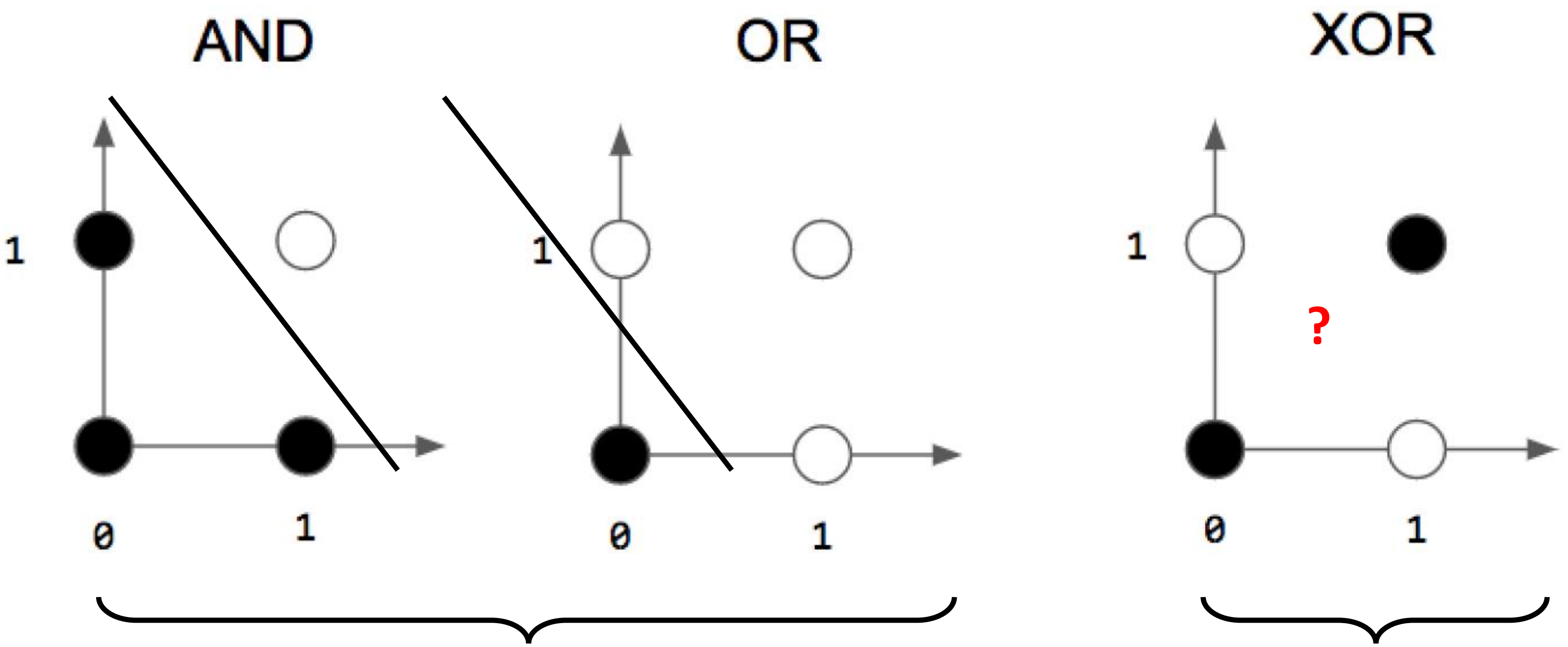
```
Accuracy: 78.79%
```

Perform Logistic Validation with CV

Lab Assignment:

Implement Neural Network for XOR gate with Numpy

XOR Problem



Linearly separable

NOT Linearly separable

Loading dataset into Numpy array

Using Pandas

```
# XOR table

# Using Pandas
import pandas as pd

XOR_table = pd.read_csv('XOR_table.csv')
XOR_table
```

	x1	x2	y
0	0	0	0
1	0	1	1
2	1	0	1
3	1	1	0

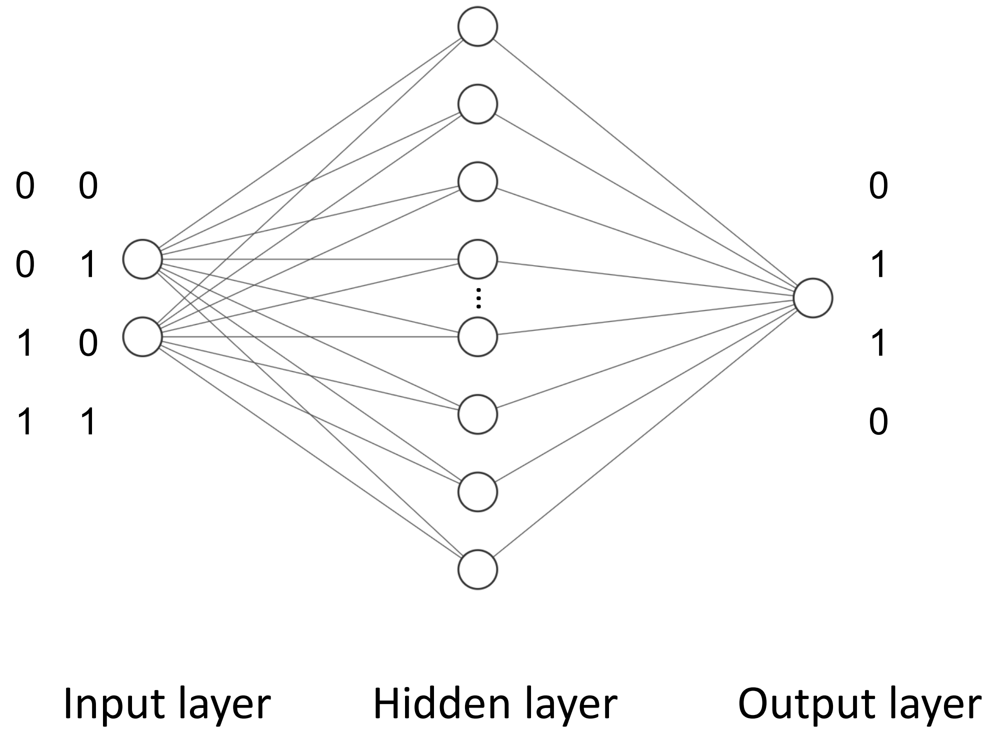
Converting data into Numpy array

```
XOR_table = XOR_table.values
X = XOR_table[:, :2]
targets = XOR_table[:, -1].reshape(-1,1)

print(X)       # Input data
print(targets) # Output targets
```

```
[[0 0]
 [0 1]
 [1 0]
 [1 1]]
[[0]
 [1]
 [1]
 [0]]
```

Solving XOR with a neural network

```
# Define dimensions on input, hidden and output layers
input_dim, hidden_dim, output_dim =

# Define learning rate
learning_rate=

# Define a hidden layer
W1=
# Define an output layer
W2=
# Define sigmoid activation function

for i in range(10000):

  # Forward pass: compute predicted y

  # Compute and print loss

  # Backprop to compute gradients of w1 and w2 with respect to L2-norm loss

  # Update weights

  # Save loss to an array
```



Solving XOR with a neural network (Forward Pass)

Feed Forward Eqns

$z = \sigma(W_1 x + b_1)$

$y = \sigma(W_2 \sigma(W_1 x + b_1) + b_2)$

$y = \sigma(W_2 z + b_2)$

Activation (sigmoid)

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

L2-Loss Function

$J = \sum_{i=1}^{N} (y - t)^2$

$y = predicted\ output$

$t = Target\ output$

Solving XOR with a neural network (Backward Pass)

Derivative of Activation

$$\frac{d(\sigma(x))}{dx} = \frac{1}{1+e^{-x}} * \left(1 - \frac{1}{1+e^{-x}}\right)$$

$$= \sigma(x)\big(1-\sigma(x)\big)$$

Gradient of J w.r.t. W_2

$$\frac{\partial J}{\partial W_2} = \frac{\partial J}{\partial y}\frac{\partial y}{\partial W_2}$$

$$\frac{\partial J}{\partial y} = 2(y-t)$$

$$\frac{\partial y}{\partial W_2} = \sigma(W_2 z + b_2)(1-\sigma(W_2 z + b_2))z$$

$$\frac{\partial J}{\partial W_2} = 2(y-t)y(1-y)z$$

Gradient of J w.r.t. W_1

$$\frac{\partial J}{\partial W_1} = \frac{\partial J}{\partial y}\frac{\partial y}{\partial z}\frac{\partial z}{\partial W_1}$$

$$\frac{\partial J}{\partial y} = 2(y-t)$$

$$\frac{\partial y}{\partial z} = \sigma(W_2 z + b_2)(1-\sigma(W_2 z + b_2))W_2$$

$$\frac{\partial z}{\partial W_1} = \sigma(W_1 x + b_1)(1-\sigma(W_1 z + b_1))x$$

$$\frac{\partial J}{\partial W_1} = 2(y-t)y(1-y)W_2 z(1-z)x$$

Update rule for W_2

$$W_2 = W_2 - \alpha\frac{\partial J}{\partial W_2}$$

$$W_2 = W_2 - \alpha 2(y-t)y(1-y)z$$

Update rule for W_1

$$W_1 = W_1 - \alpha\frac{\partial J}{\partial W_1}$$

$$W_1 = W_1 - \alpha 2(y-t)y(1-y)W_2 z(1-z)x$$