Module 6 - CKCS 113 Intro to Machine Learning

TensorFlow by Google, Here we preping ourself with data for TensorsFlow.

Median Example

To find the median value in a list with an **odd** amount of numbers, one would find the number that is in the middle with an equal amount of numbers on either side of the median. To find the median, first arrange the numbers in order, usually from lowest to highest.

For example, in a data set of {3, 13, 2, 34, 11, 26, 47}, the sorted order becomes {2, 3, 11, 13, 26, 34, 47}.

The median is the number in the middle {2, 3, 11, **13**, 26, 34, 47}, which in this instance is 13 since there are three numbers on either side.

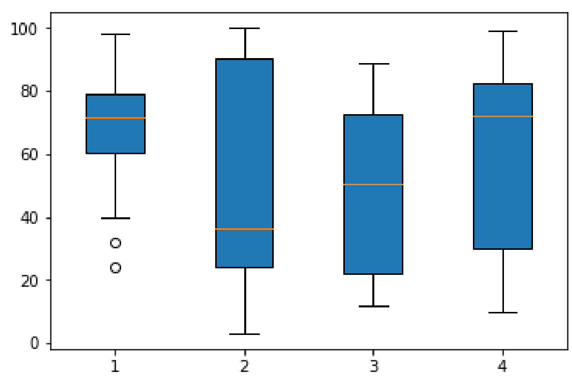
To find the median value in a list with an **even** amount of numbers, one must determine the middle pair, add them, and divide by two. Again, arrange the numbers in order from lowest to highest.

For example, in a data set of {3, 13, 2, 34, 11, 17, 27, 47}, the sorted order becomes {2, 3, 11, 13, 17, 27, 34, 47}. The median is the average of the two numbers in the middle {2, 3, 11, **13, 17**, 26 34, 47}, which in this case is fifteen {(13 + 17) ÷ 2 = 15}.

In [1]:
```
import matplotlib.pyplot as plt

value1 = [82,76,24,40,67,62,75,78,71,32,98,89,78,67,72,82,87,66,56,52]
value2=[62,5,91,25,36,32,96,95,3,90,95,32,27,55,100,15,71,11,37,21]
value3=[23,89,12,78,72,89,25,69,68,86,19,49,15,16,16,75,65,31,25,52]
value4=[59,73,70,16,81,61,88,98,10,87,29,72,16,23,72,88,78,99,75,30]

box_plot_data=[value1,value2,value3,value4]
plt.boxplot(box_plot_data, patch_artist=True)
plt.show()
```



In [2]:
```
import statistics

print(statistics.median(value1))
```

```
71.5
```

Class Inheritance

Inheritance allows us to define a class that inherits all the methods and properties from another class.

Parent class is the class being inherited from, also called base class.

Child class is the class that inherits from another class, also called derived class.

Create a Parent Class

Any class can be a parent class, so the syntax is the same as creating any other class:

Create a Parent Class

Any class can be a parent class, so the syntax is the same as creating any other class:

In [3]:
```
class Employee():
    """A class representing an Employee."""
    def __init__(self,n):
        print("Name of the Employee is:",n)
```

Create a Child Class

To create a class that inherits the functionality from another class, send the parent class as a parameter when creating the child class:

In [4]:
```
class Manager(Employee):
    """A class representing a Manager."""
    def __init__(self):
        print('This is printed from the Manager Class')
```

In [5]:
```
s = Manager()
```

```
This is printed from the Manager Class
```

In [6]:
```
class Manager(Employee):
    def __init__(self):
        super().__init__("John")
        print('This is printed from the Manager Class')
```

In [7]:
```
s = Manager()
```

```
Name of the Employee is: John
This is printed from the Manager Class
```

Manual Neural Network

Manually building out a neural network that mimics the TensorFlow API. This will greatly help your understand when working with the real TensorFlow!

Operation

```python
In [8]: class Operation():
    """
    An Operation is a node in a "Graph". TensorFlow will also use this concept of a Graph.

    This Operation class will be inherited by other classes that actually compute the specific
    operation, such as adding or matrix multiplication.
    """

    def __init__(self, input_nodes = []):
        """
        Intialize an Operation
        """
        self.input_nodes = input_nodes # The list of input nodes
        self.output_nodes = [] # List of nodes consuming this node's output

        # For every node in the input, we append this operation (self) to the list of
        # the consumers of the input nodes
        for node in input_nodes:
            node.output_nodes.append(self)

        # There will be a global default graph (TensorFlow works this way)
        # We will then append this particular operation
        # Append this operation to the list of operations in the currently active default graph
        _default_graph.operations.append(self)

    def compute(self):
        """
        This is a placeholder function. The inheritting classes will override by the actual specific operation

        """
        pass
```

Example Operations

Addition

```python
In [9]: class add(Operation):

    def __init__(self, x, y):

        super().__init__([x, y])

    def compute(self, x_var, y_var):

        self.inputs = [x_var, y_var]
        return x_var + y_var
```

these methods are over riding from super class.

Here no super class added; so all new things/variables applied here.
we can add super().__init__({ x...y.. })

Multiplication

```python
In [10]: class multiply(Operation):

    def __init__(self, a, b):

        super().__init__([a, b])

    def compute(self, a_var, b_var):

        self.inputs = [a_var, b_var]
        return a_var * b_var
```

Matrix Multiplication

In [11]:
```python
class matmul(Operation):

    def __init__(self, a, b):

        super().__init__([a, b])

    def compute(self, a_mat, b_mat):

        self.inputs = [a_mat, b_mat]
        return a_mat.dot(b_mat)
```

To multiply matrix.....use .dot() function

Placeholders

In [12]:
```python
class Placeholder():
    """
    A placeholder is a node that needs to be provided a value for computing the output in the Graph.
    """

    def __init__(self):
        self.output_nodes = []
        _default_graph.placeholders.append(self)
```

== We expect values from USER. PLACEHOLDER needs a VALUE.

Variables

In [13]:
```python
class Variable():
    """
    This variable is a changeable parameter of the Graph.
    """
    def __init__(self, initial_value = None):
        self.value = initial_value
        self.output_nodes = []
        _default_graph.variables.append(self)
```

Graph

In [14]:
```python
class Graph():
    def __init__(self):
        self.operations = []
        self.placeholders = []
        self.variables = []

    def set_as_default(self):
        """
        Sets this Graph instance as the Global Default Graph
        """
        global _default_graph
        _default_graph = self
```

3 Lists:

A Basic Graph

y = mx + c (Linear Regression)

$$z = Ax + b$$

A,b = variables / object
x = place holder

With A=10 and b=1

$$z = 10x + 1$$

Just need a placeholder for x and then once x is filled in we can solve it!

In [15]:
```python
g = Graph()
```

class
variable

In [16]:
```python
g.set_as_default()
```

In [17]:
```python
A = Variable(10)
```

object class
as defined above

In [18]:
```
b = Variable(1)
```
object

In [19]:
```
# Will be filled out later
x = Placeholder()
```
by user input

y = mx + c (Linear Regression)

In [20]:
```
y = multiply(A,x)
```
z = A x + b

A,b = variables
x = place holder

In [21]:
```
z = add(y,b)
```

Creating Session

In [22]:
```
import numpy as np
```

Traversing Operation Nodes

In [23]:
```
def traverse_postorder(operation):
    """
    PostOrder Traversal of Nodes. Basically makes sure computations are done in
    the correct order (mx first , then mx + c). Feel free to copy and paste this code.
    It is not super important for understanding the basic fundamentals of deep learning.
    """

    nodes_postorder = []
    def recurse(node):
        if isinstance(node, Operation):
            for input_node in node.input_nodes:
                recurse(input_node)
        nodes_postorder.append(node)

    recurse(operation)
    return nodes_postorder
```

In [24]:
```
class Session:

    def run(self, operation, feed_dict = {}):
        """
          operation: The operation to compute
          feed_dict: Dictionary mapping placeholders to input values (the data)
        """

        # Puts nodes in correct order
        nodes_postorder = traverse_postorder(operation)

        for node in nodes_postorder:

            if type(node) == Placeholder:

                node.output = feed_dict[node]

            elif type(node) == Variable:

                node.output = node.value

            else: # Operation

                node.inputs = [input_node.output for input_node in node.input_nodes]


                node.output = node.compute(*node.inputs)

            # Convert lists to numpy arrays
            if type(node.output) == list:
                node.output = np.array(node.output)

        # Return the requested node value
        return operation.output
```

Let's explore how a session will work

In [25]:
```
sess = Session()
```

In [26]:
```
result = sess.run(operation=z,feed_dict={x:10})
```

In [27]:
```
result
```

Out[27]: 101

In [28]:
```
10*10 + 1
```

Out[28]: 101

Lets try this with a Matrix multiplications, which is more common in tensorflow

A = matrix, not number list, so Here we go for Matrix multiplication, matrix addition.

In [29]:
```
g = Graph()

g.set_as_default()
#Here variables are matrix
A = Variable([[10,20],[30,40]])
b = Variable([1,1])
#x is a placeholder which is waiting a value
x = Placeholder()

y = matmul(A,x)
```
1....multiplication of matrix
```
z = add(y,b)
```
2....addition of matrix

In [30]:
```
sess = Session()
```

In [31]:
```python
result = sess.run(operation=z,feed_dict={x:10})
```

In [32]:
```python
result
```

Out[32]:
```
array([[101, 201],
       [301, 401]])
```

Activation Function

In [33]:
```python
import matplotlib.pyplot as plt
%matplotlib inline
```

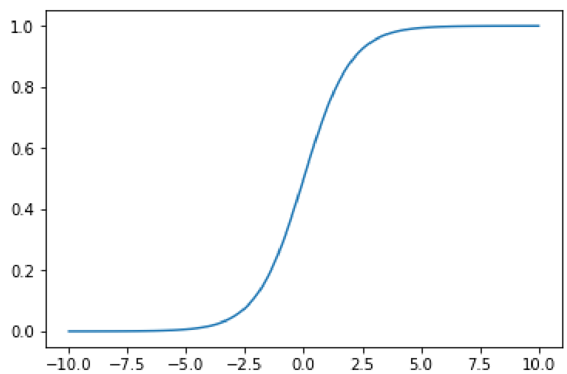
In [34]:
```python
def sigmoid(z):
    return 1/(1+np.exp(-z))
```

In [35]:
```python
sample_z = np.linspace(-10,10,100)
sample_a = sigmoid(sample_z)
```

pandas's linspace functn...generates data -10 to 10...in 100 data points
we use generated data into sigmoid functn.

In [36]:
```python
plt.plot(sample_z,sample_a)
```

Out[36]:
```
[&lt;matplotlib.lines.Line2D at 0x25c4fcc7860&gt;]
```



Sigmoid as an Operation

In [37]:
```python
class Sigmoid(Operation):


    def __init__(self, z):

        # a is the input node
        super().__init__([z])

    def compute(self, z_val):

        return 1/(1+np.exp(-z_val))
```

sigmoid equaltion

$$\frac{1}{1+\frac{1}{x}}$$

2 center

Classification Example

In [38]:
```python
from sklearn.datasets import make_blobs
```

In [39]:
```python
data = make_blobs(n_samples = 50,n_features=2,centers=2,random_state=75)
```

data generation to stabilize

sample size=50

array of array , each subset will have 2 items/variables

```
In [40]: data

Out[40]: (array([[  7.3402781 ,   9.36149154],
                [  9.13332743,   8.74906102],
                [  1.99243535,  -8.85885722],
                [  7.38443759,   7.72520389],
                [  7.97613887,   8.80878209],
                [  7.76974352,   9.50899462],
                [  8.3186688 ,  10.1026025 ],
                [  8.79588546,   7.28046702],
                [  9.81270381,   9.46968531],
                [  1.57961049,  -8.17089971],
                [  0.06441546,  -9.04982817],
                [  7.2075117 ,   7.04533624],
                [  9.10704928,   9.0272212 ],
                [  1.82921897,  -9.86956281],
                [  7.85036314,   7.986659  ],
                [  3.04605603,  -7.50486114],
                [  1.85582689,  -6.74473432],
                [  2.88603902,  -8.85261704],
                [ -1.20046211,  -9.55928542],
                [  2.00890845,  -9.78471782],
                [  7.68945113,   9.01706723],
                [  6.42356167,   8.33356412],
                [  8.15467319,   7.87489634],
                [  1.92000795,  -7.50953708],
                [  1.90073973,  -7.24386675],
                [  7.7605855 ,   7.05124418],
                [  6.90561582,   9.23493842],
                [  0.65582768,  -9.5920878 ],
                [  1.41804346,  -8.10517372],
                [  9.65371965,   9.35409538],
                [  1.23053506,  -7.98873571],
                [  1.96322881,  -9.50169117],
                [  6.11644251,   9.26709393],
                [  7.70630321,  10.78862346],
                [  0.79580385,  -9.00301023],
                [  3.13114921,  -8.6849493 ],
                [  1.3970852 ,  -7.25918415],
                [  7.27808709,   7.15201886],
                [  1.06965742,  -8.1648251 ],
                [  6.37298915,   9.77705761],
                [  7.24898455,   8.85834104],
                [  2.09335725,  -7.66278316],
                [  1.05865542,  -8.43841416],
                [  6.43807502,   7.85483418],
                [  6.94948313,   8.75248232],
                [ -0.07326715, -11.69999644],
                [  0.61463602,  -9.51908883],
                [  1.31977821,  -7.2710667 ],
                [  2.72532584,  -7.51956557],
                [  8.20949206,  11.90419283]]),
 array([1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1,
        1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1,
        1, 0, 0, 0, 0, 1]))
```

GENERATED random data from above equations

Typples

Class

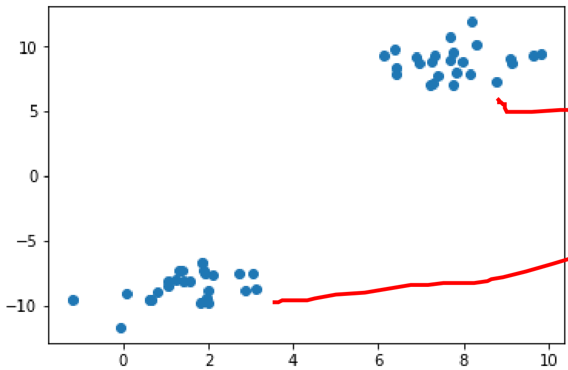
Here a tuple of features and labels is generated.

On Scatter plot:

......show our data on graph...

```
In [41]: features = data[0]
         plt.scatter(features[:,0],features[:,1])
```

```
Out[41]: <matplotlib.collections.PathCollection at 0x25c5083f240>
```

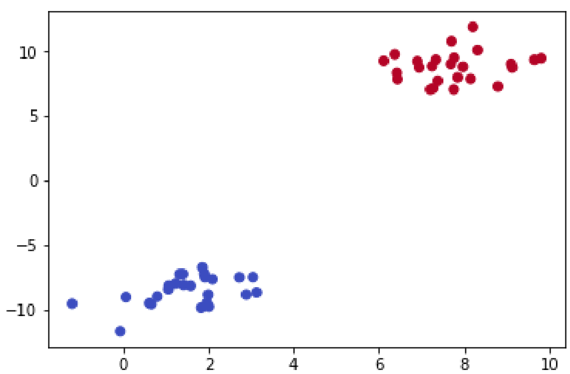


coloring..our .datapoints...0..........1

To give different color to each feature c = labels and cmap='coolwarm'

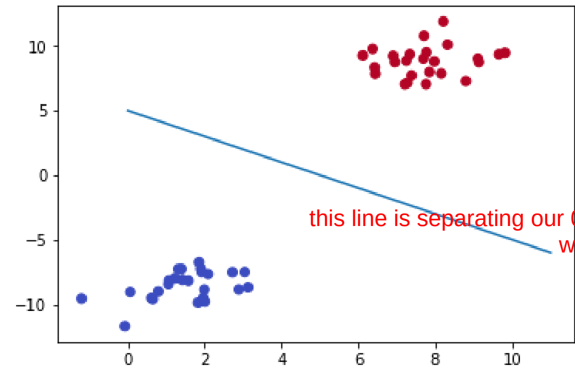
```
In [42]: labels = data[1]
         plt.scatter(features[:,0],features[:,1],c=labels,cmap='coolwarm')
```

```
Out[42]: <matplotlib.collections.PathCollection at 0x25c508a20b8>
```



Lets try to DRAW A LINE THAT SEPERATES CLASSES

In [43]:
```python
x = np.linspace(0,11,10)
y = -x + 5
plt.scatter(features[:,0],features[:,1],c=labels,cmap='coolwarm')
plt.plot(x,y)
```
Out[43]: [<matplotlib.lines.Line2D at 0x25c50868198>]



this line is separating our 0...vs...1 data points for us..
we have functions, libs..which finds this line automatically for us..

Defining the Perceptron

$$y = mx + b$$

$$y = -x + 5$$

$$f1 = mf2 + b, m = 1$$

$$f1 = -f2 + 5$$

$$f1 + f2 - 5 = 0$$

Convert to a Matrix Representation of Features

$$w^T x + b = 0$$

$$\left(1, 1\right) f - 5 = 0$$

Then if the result is > 0 its label 1, if it is less than 0, it is label=0

Example Point

Let's say we have the point f1=2 , f2=2 otherwise stated as (8,10). Then we have:

$$\left(1, 1\right)\begin{pmatrix} 8 \\ 10 \end{pmatrix} + 5 =$$

In [44]:
```python
np.array([1, 1]).dot(np.array([[8],[10]])) - 5
```
Out[44]: array([13])

Or if we have (4,-10)

array

x=4, y= -10 ...go to graph and look those point

In [45]:
```python
np.array([1,1]).dot(np.array([[4],[-10]])) - 5
```
Out[45]: array([-11])

multiply

Using an Example Session Graph

In [46]:
```python
g = Graph()
```

In [47]:
```
g.set_as_default()
```

x is a feature array

In [48]:
```
x = Placeholder()
```

In [49]:
```
w = Variable([1,1])
```

In [50]:
```
b = Variable(-5)
```

In [51]:
```
z = add(matmul(w,x),b)
```

In [52]:
```
a = Sigmoid(z)
```

Activation function

In [53]:
```
sess = Session()
```

In [54]:
```
sess.run(operation=a,feed_dict={x:[8,10]})
```

Out[54]:
```
0.999997739675702
```

In [55]:
```
sess.run(operation=a,feed_dict={x:[0,-10]})
```

Out[55]:
```
3.059022269256247e-07
```

[http://playground.tensorflow.org/ (http://playground.tensorflow.org/)](http://playground.tensorflow.org/)