MACHINE LEARNING ASSIGNMENT -1

Santhoshi Veera Haritha (vytlasa)

Djeinaba Ba (badb)

Victoria Wangia-Anderson (wangiava)

1)Designing the features for and target function for Tic Tac Toe algorithm

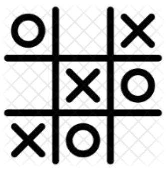
Machine Learning is all about linear combination of the inputs and output connected to each other by different weights. Below are the board features that I consider for designing the Tic Tac Toe algorithm:

X – Computer (First Player), O – Human. Here I am going to train the computer to win the game.

X wins → +100

X loses → -100

Draw → 0



(Row meant either consecutive row, column or diagonal)

- x1 = Instances where there are 2 X's in a row with one blank cell.
- x2 = Instances where there are 2 O's in a row with one blank cell.
- x3 = Instances where there is an X in a row with the rest 2 blank cells.
- x4 = Instances where there is an O in a row with the rest 2 blank cells.
- x5 = Instances of 3 X's in a row (End of the game with X as winner).
- x6 = Instances of 3 O's in a row (End of the game with X as loser)

Learning System

1) **Task** *Playing Tic Tac Toe*
2) **Performance** *% of games won against Humans*
3) **Experience** *Games played against itself*
4) **Ideal Target Function** *V: Board → R*
5) **Target Function Representation** *V': Board → ∑ w*x*

(w- Weights of the target function, x- Features of the board state)

6) Here is the Squared Error E between the training values(V) and values predicted by the hypothesis(V`):

$$E \equiv \sum_{\langle b, V_{train}(b)\rangle \in \text{ training examples}} (V_{train}(b) - \hat{V}(b))^2$$

7) To find weights (W0 to W6) of a linear function that minimizes E, we employ LMS (Least Mean Squares) Update rule:

$$w_i \leftarrow w_i + \eta \; (V_{train}(b) - \hat{V}(b)) \; x_i$$

8) V: Board ← V': Board (Successor)
9) V(finalBoardState) ←100 (Win) | 0 (Draw) | -100 (Loss)

Implementation

1) Finding the Best Move. This function evaluates all the available moves using **minimax()** and then returns the best move.

```
bestMove = null
for each move in board:
    if current move is better than bestMove
        bestMove = current move
  return bestMove
```

2) Minimax. To check whether or not the current move is better than the best move we take the help of **minimax()** function which will consider all the possible ways the game can go and returns the best value for that move, assuming the opponent also plays optimally

```
function minimax(board, depth, isMaximizingPlayer):

  if current board state is a terminal state :
    return value of the board

  if isMaximizingPlayer :
    bestVal = -INFINITY
    for each move in board :
      value = minimax(board, depth+1, false)
      bestVal = max( bestVal, value)
    return bestVal

  else :
    bestVal = +INFINITY
    for each move in board :
      value = minimax(board, depth+1, true)
      bestVal = min( bestVal, value)
    return bestVal
```

3) Check for Game Over. To check whether the game is over and to make sure there are no moves left we use **isMovesLeft** function. It is a simple straightforward function which checks whether a move is available or not and returns true or false respectively.

```
function isMovesLeft(board):
  for each cell in board:
    if current cell is empty:
      return true
  return false
```

2. Let's consider Tic Tac Toe problem.

Features: represents no. of instances.

x_1 - 3 X's in a row.

x_2 - 3 O's in a row

x_3 - 2 X's with one blank cell in a row

x_4 - 2 X's, 1 O in a row

Target function $V(X) = w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_4$

Training data:

x_1	x_2	x_3	x_4	O/P
1	0	0	0	+100
0	1	0	0	−100
0	0	2	0	+100
0	0	2	2	0

+100 → X wins ; −100 → X looses ; 0 → Draw

d = +100 is the most frequent O/P.

Given I/p:

X	O	X
X	X	O
O		O

x_1	x_2	x_3	x_4	O/P.
0	0	0	3	(d = +100)

For the given input, there is no instance in training data & hence we output d (most frequent O/P). Here training data is less in size (4 instances) & we're having a random output & not the accurate one. If our training data is high in number, we'll have most of the instances in training data itself & there's a scope for accurate output. Hence performance of the algorithm is not to the mark in this "straw man". Baseline for this problem indicates minimal performance of the above learning algorithm. Performance ∝ Training data size (Proportional)

In [127]:
```
import pandas as pd
import numpy as np
import sklearn
import seaborn as sns
from sklearn import datasets
from sklearn.model_selection import train_test_split,cross_val_score
from sklearn.linear_model import LogisticRegression
from mlxtend.plotting import plot_decision_regions
from sklearn.metrics import accuracy_score
```

In [128]:
```
#Loading dataset into iris. Data into X and target Label into Y
iris = sklearn.datasets.load_iris()
X = iris.data
y = (iris.target != 0) * 1
print ("X" + str(X.shape) + "  y" + str(y.shape))
```

```
X(150, 4)  y(150,)
```

In [129]:
```
#Convert Numpy Array to Pandas Dataframe
columns = ['SepalLength','SepalWidth','PetalLength','PetalWidth']
iris_df = pd.DataFrame(data = X, columns = columns)
target = ['Name']
iris_target = pd.DataFrame(data = y, columns = target)
iris_df = iris_df.join(iris_target)
iris_df.Name[iris_df.Name==0] = "Setosa"
iris_df.Name[iris_df.Name==1] = "Non Setosa"
iris_df.head()
```

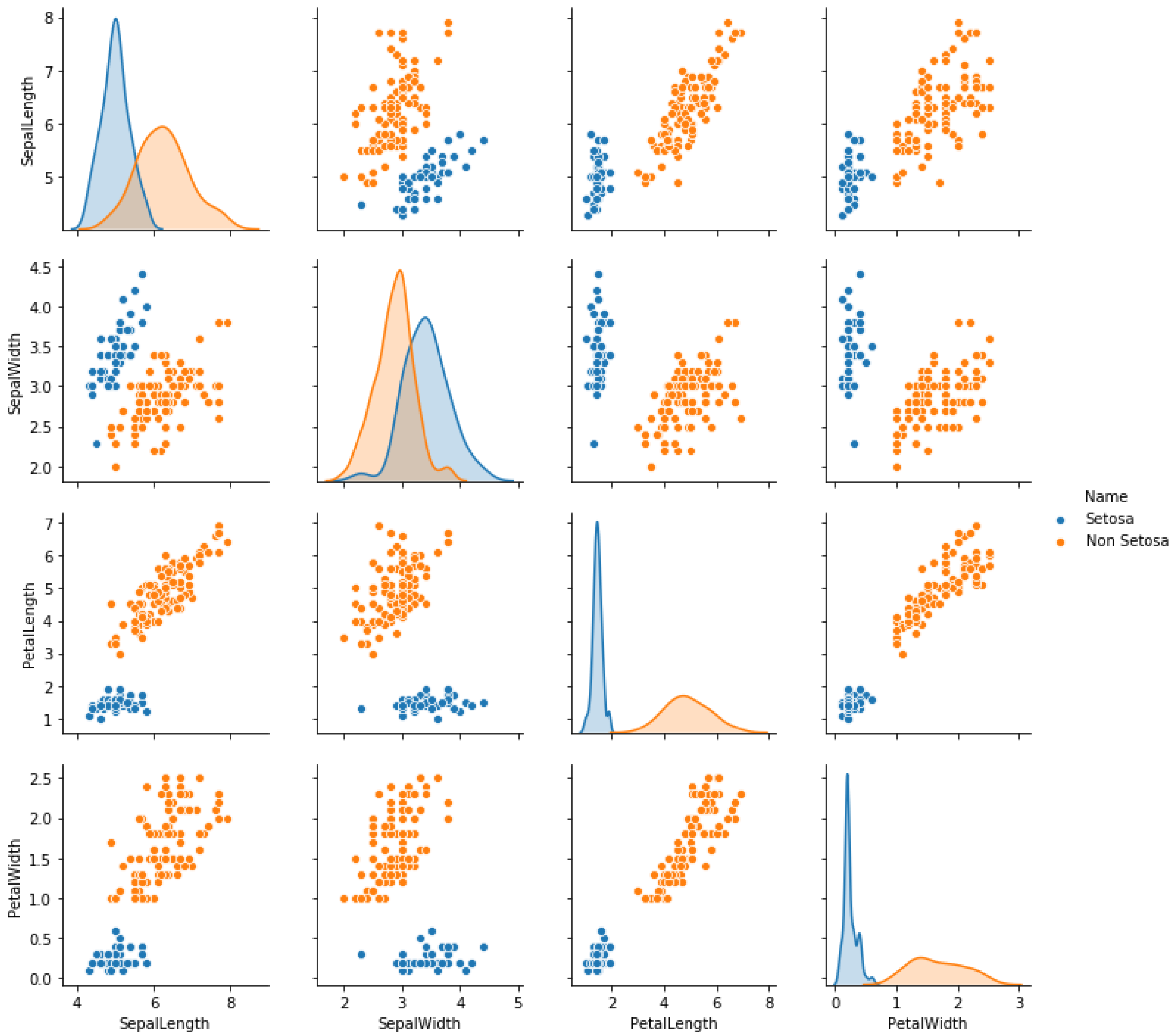
```
C:\Users\bnama\Anaconda3\lib\site-packages\ipykernel_launcher.py:7: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
  import sys
```

Out[129]:

	SepalLength	SepalWidth	PetalLength	PetalWidth	Name
0	5.1	3.5	1.4	0.2	Setosa
1	4.9	3.0	1.4	0.2	Setosa
2	4.7	3.2	1.3	0.2	Setosa
3	4.6	3.1	1.5	0.2	Setosa
4	5.0	3.6	1.4	0.2	Setosa

In [130]:
```
#Visualise the classes
sns.pairplot(iris_df, hue="Name")
```

Out[130]: <seaborn.axisgrid.PairGrid at 0x176271d6748>



From the above plots. it can be observed that the two classes Setosa and Non Setosa are seperable in perfect manner and our goal is to build a Linear Regression model with 100% accuracy

In [131]:
```
#Splitting data into train and test with 50% size
X_train, X_test, Y_train, Y_test = train_test_split(X, y, test_size=0.5, rando
m_state=42)
```

In [132]:
```
class regression_algo:

    #Initilisation
    def __init__(self, lr=0.01, iter=100000, fit_intercept=True):
        self.lr = lr
        self.iter = iter
        self.fit_intercept = fit_intercept

    #Intercept
    def __add_intercept(self, X):
        intercept = np.ones((X.shape[0], 1))
        return np.concatenate((intercept, X), axis=1)

    #Sigmoid function
    def __sigmoid(self, z):
        return 1 / (1 + np.exp(-z))

    #Loss Function
    def __loss(self, h, y):
        return (-y * np.log(h) - (1 - y) * np.log(1 - h)).mean()

    #Fitting data into the model
    def fit_data(self, X, y):
        if self.fit_intercept:
            X = self.__add_intercept(X)
        # weights initialization
        self.theta = np.zeros(X.shape[1])
        for i in range(self.iter):
            z = np.dot(X, self.theta)
            h = self.__sigmoid(z)
            gradient = np.dot(X.T, (h - y)) / y.size
            self.theta -= self.lr * gradient
            if(i % 10000 == 0):
                z = np.dot(X, self.theta)
                h = self.__sigmoid(z)
                print(f'loss: {self.__loss(h, y)} \t')

    #Predict Probability
    def predict_probability(self, X):
        if self.fit_intercept:
            X = self.__add_intercept(X)
        return self.__sigmoid(np.dot(X, self.theta))

    #Predict function to test the model on test data
    def predict(self, X, threshold=0.5):
        return self.predict_probability(X) >= threshold
```

In [133]:
```
#Apply model on training data with 0.1 as learning rate.
model = regression_algo(lr=0.1, iter=300000)
model.fit_data(X_train, Y_train)
```

```
loss: 0.5051179800715164
loss: 0.0010339075551264259
loss: 0.0005557167413380687
loss: 0.00038544032730126977
loss: 0.0002969248805658176
loss: 0.00024233467885127391
loss: 0.0002051631836324902
loss: 0.00017815416096801233
loss: 0.00015760575962341816
loss: 0.00014142686995736735
loss: 0.0001283449060344772
loss: 0.00011753998976981666
loss: 0.00010845954643489935
loss: 0.00010071727654203103
loss: 9.40348105048839e-05
loss: 8.820636565633182e-05
loss: 8.307646432107917e-05
loss: 7.8525400981526e-05
loss: 7.445948240842348e-05
loss: 7.080430429083386e-05
loss: 6.750001496482024e-05
loss: 6.449791224998314e-05
loss: 6.175795460660116e-05
loss: 5.924691188422046e-05
loss: 5.6936971493183586e-05
loss: 5.4804674110717224e-05
loss: 5.283009133475039e-05
loss: 5.099618336162017e-05
loss: 4.928829225762682e-05
loss: 4.769373851388175e-05
```

Loss is being reduced gradually and hence our objective function of minimisation is achieved using Gradient Descent.

In [134]:
```
#Apply model on test data and check for accuracy
pred = model.predict(X_test)
(pred == Y_test).mean()
```

Out[134]:
```
1.0
```

In [135]:
```
#Implementing sklearn pre-defined model
regression_model = LogisticRegression(random_state=42, solver="lbfgs", multi_c
lass="auto")
regression_model.fit(X_train, Y_train)
```

Out[135]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=42, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [136]:
```
#Test accuracy of the results obtained from pre defined model with the newly b
uilt model
accuracy = cross_val_score(regression_model, X, y, cv=10,scoring='accuracy')
print (accuracy.mean())
```

```
1.0
```