Kartikeya Agarwal 2019UCO1692 COE-3 Machine Learning

DECISION TREE

Importing Libraries

In [ ]:

```
import pandas as pd
import numpy as np
```

Reading Dataset

In [ ]:

```
df = pd.read_csv("Train.csv")
```

In [ ]:

```
df.tail()
```

Out[ ]:

	pclass	survived	name	sex	age	sibsp	parch	ticket	fare	cabin	embarked
1004	1.0	1.0	Blank, Mr. Henry	male	40.0	0.0	0.0	112277	31.0000	A31	C
1005	3.0	0.0	Laitinen, Miss. Kristina Sofia	female	37.0	0.0	0.0	4135	9.5875	NaN	S
1006	1.0	1.0	Newell, Miss. Marjorie	female	23.0	1.0	0.0	35273	113.2750	D36	C
1007	3.0	1.0	Nicola-Yarred, Master. Elias	male	12.0	1.0	0.0	2651	11.2417	NaN	C
1008	3.0	0.0	Corn, Mr. Harry	male	30.0	0.0	0.0	SOTON/OQ 392090	8.0500	NaN	S

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1009 entries, 0 to 1008
Data columns (total 14 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   pclass     1009 non-null   float64
 1   survived   1009 non-null   float64
 2   name       1009 non-null   object 
 3   sex        1009 non-null   object 
 4   age        812 non-null    float64
 5   sibsp      1009 non-null   float64
 6   parch      1009 non-null   float64
 7   ticket     1009 non-null   object 
 8   fare       1008 non-null   float64
 9   cabin      229 non-null    object 
 10  embarked   1008 non-null   object 
 11  boat       374 non-null    object 
 12  body       98 non-null     float64
```

```
 13  home.dest  582 non-null    object
dtypes: float64(7), object(7)
memory usage: 110.5+ KB
```

Dropping Redundant Columns

In [ ]:
```python
columns_to_drop = ["cabin","embarked","home.dest","name","body","boat", "ticket"]
```

In [ ]:
```python
data_clean = df.drop(columns_to_drop,axis=1)
```

In [ ]:
```python
data_clean.head()
```

Out[ ]:

	pclass	survived	sex	age	sibsp	parch	fare
0	3.0	0.0	female	NaN	0.0	0.0	7.750
1	2.0	0.0	male	39.0	0.0	0.0	26.000
2	2.0	1.0	female	40.0	0.0	0.0	13.000
3	3.0	1.0	female	31.0	1.0	1.0	20.525
4	3.0	1.0	female	NaN	2.0	0.0	23.250

Encoding Class Labels to Numeric Labels

In [ ]:
```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
data_clean['sex'] = le.fit_transform(data_clean['sex'])
```

In [ ]:
```python
data_clean.head()
```

Out[ ]:

	pclass	survived	sex	age	sibsp	parch	fare
0	3.0	0.0	0	NaN	0.0	0.0	7.750
1	2.0	0.0	1	39.0	0.0	0.0	26.000
2	2.0	1.0	0	40.0	0.0	0.0	13.000
3	3.0	1.0	0	31.0	1.0	1.0	20.525
4	3.0	1.0	0	NaN	2.0	0.0	23.250

In [ ]:
```python
data_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1009 entries, 0 to 1008
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   pclass    1009 non-null   float64
 1   survived  1009 non-null   float64
 2   sex       1009 non-null   int32  
 3   age       812 non-null    float64
```

```
 4   sibsp     1009 non-null   float64
 5   parch     1009 non-null   float64
 6   fare      1008 non-null   float64
dtypes: float64(6), int32(1)
memory usage: 51.4 KB
```

In [ ]:

```
data_clean = data_clean.fillna(data_clean['age'].mean())
data_clean = data_clean.fillna(data_clean['fare'].mode())
```

In [ ]:

```
data_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1009 entries, 0 to 1008
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   pclass    1009 non-null   float64
 1   survived  1009 non-null   float64
 2   sex       1009 non-null   int32  
 3   age       1009 non-null   float64
 4   sibsp     1009 non-null   float64
 5   parch     1009 non-null   float64
 6   fare      1009 non-null   float64
dtypes: float64(6), int32(1)
memory usage: 51.4 KB
```

Dividing Data into X and Y

In [ ]:

```
input_cols = ['pclass', 'sex', 'age', 'sibsp', 'parch', 'fare']
output_cols = ['survived']
```

In [ ]:

```
X = data_clean[input_cols]
Y = data_clean[output_cols]
```

In [ ]:

```
X.shape,Y.shape
```

Out[ ]:

```
((1009, 6), (1009, 1))
```

Defining Entropy and Information Gain

In [ ]:

```
def entropy(col):
    count = np.unique(col,return_counts=True)
    N = float(col.shape[0])
    ent = 0.0
    for ix in count[1]:
        p = ix/N
        ent+=(-1.0 * p*np.log2(p))
    return ent

def divide_data(x_data,fkey,fval):
    x_right = pd.DataFrame([],columns=x_data.columns)
    x_left = pd.DataFrame([],columns=x_data.columns)
    for ix in range(x_data.shape[0]):
        val = x_data[fkey].loc[ix]
```

```
        if val>fval:
            x_right = x_right.append(x_data.loc[ix])
        else:
            x_left = x_left.append(x_data.loc[ix])
    return x_left,x_right

def info_gain(x_data,fkey,fval):
    left,right = divide_data(x_data,fkey,fval)

    l = float(left.shape[0])/x_data.shape[0]
    r = float(right.shape[0])/x_data.shape[0]

    if(left.shape[0] == 0 or right.shape[0] == 0):
        return -100000
    i_gain = entropy(x_data.survived) - (l*entropy(left.survived) + r*entropy(right.
    return i_gain
```

In [ ]:

```
for fx in X.columns:
    print(fx)
    print(info_gain(data_clean,fx,data_clean[fx].mean()))
```

```
pclass
0.055456910002982474
sex
0.19274737190850932
age
0.001955929827451075
sibsp
0.006492394392888956
parch
0.01975608012294816
fare
0.04242793401428169
```

Implementing Decision Tree Class

In [ ]:

```
class DecisionTree:
    def __init__(self,depth = 0,max_depth = 5):
        self.left = None
        self.right = None
        self.fkey = None
        self.fval = None
        self.max_depth = max_depth
        self.depth = depth
        self.target = None

    def train(self,X_train):
        features = ['pclass', 'sex', 'age', 'sibsp', 'parch', 'fare']
        info_gains = []
        for ix in features:
            i_gain = info_gain(X_train,ix,X_train[ix].mean())
            info_gains.append(i_gain)
        self.fkey = features[np.argmax(info_gains)]
        self.fval = X_train[self.fkey].mean()

        print("Making Decision Tree, Current Node is: ",self.fkey)

        data_left,data_right = divide_data(X_train,self.fkey,self.fval)
        data_left = data_left.reset_index(drop=True)
        data_right = data_right.reset_index(drop=True)
```

```
        if data_left.shape[0] == 0 or data_right.shape[0] == 0:
            if(X_train.survived.mean()>0.5):
                self.target = "Survived"
            else:
                self.target = "Dead"
            return
        if self.depth >= self.max_depth:
            if(X_train.survived.mean()>0.5):
                self.target = "Survived"
            else:
                self.target = "Dead"
            return

        self.left = DecisionTree(depth=self.depth+1,max_depth=self.max_depth)
        self.left.train(data_left)

        self.right = DecisionTree(depth=self.depth+1,max_depth=self.max_depth)
        self.right.train(data_right)

        if(X_train.survived.mean()>0.5):
            self.target = "Survived"
        else:
            self.target = "Dead"
        return

    def predict(self,test):
        if test[self.fkey] > self.fval:
            if self.right is None:
                return self.target
            return self.right.predict(test)
        else:
            if self.left is None:
                return self.target
            return self.left.predict(test)
```

Creating test and train split

In [ ]:

```
split = int(0.7*data_clean.shape[0])
train_data = data_clean[:split]
test_data = data_clean[split:]
test_data = test_data.reset_index(drop=True)
```

In [ ]:

```
print(train_data.shape)
```

```
(706, 7)
```

Training Decsion Tree

In [ ]:

```
dt = DecisionTree(max_depth=5)
dt.train(train_data)
```

```
Making Decision Tree, Current Node is:  sex
Making Decision Tree, Current Node is:  pclass
Making Decision Tree, Current Node is:  parch
Making Decision Tree, Current Node is:  fare
Making Decision Tree, Current Node is:  fare
Making Decision Tree, Current Node is:  fare
Making Decision Tree, Current Node is:  fare
```

```
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  fare
Making Decision Tree, Current Node is:  pclass
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  sibsp
Making Decision Tree, Current Node is:  fare
Making Decision Tree, Current Node is:  fare
Making Decision Tree, Current Node is:  parch
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  parch
Making Decision Tree, Current Node is:  fare
Making Decision Tree, Current Node is:  parch
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  fare
Making Decision Tree, Current Node is:  fare
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  fare
Making Decision Tree, Current Node is:  parch
Making Decision Tree, Current Node is:  sibsp
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  pclass
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  pclass
Making Decision Tree, Current Node is:  fare
Making Decision Tree, Current Node is:  parch
Making Decision Tree, Current Node is:  sibsp
Making Decision Tree, Current Node is:  pclass
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  pclass
Making Decision Tree, Current Node is:  pclass
Making Decision Tree, Current Node is:  fare
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  sibsp
Making Decision Tree, Current Node is:  pclass
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  pclass
Making Decision Tree, Current Node is:  sibsp
Making Decision Tree, Current Node is:  pclass
Making Decision Tree, Current Node is:  pclass
Making Decision Tree, Current Node is:  fare
Making Decision Tree, Current Node is:  parch
Making Decision Tree, Current Node is:  fare
Making Decision Tree, Current Node is:  pclass
Making Decision Tree, Current Node is:  age
Making Decision Tree, Current Node is:  age
```

Predicting test data

In [ ]:

```
y_pred = []
for ix in range(test_data.shape[0]):
    y_pred.append(dt.predict(test_data.loc[ix]))
```

In [ ]:

```
y_actual = test_data[output_cols]
```

In [ ]:

```
le = LabelEncoder()
y_pred = le.fit_transform(y_pred)
```

In [ ]:

```
y_pred = np.array(y_pred).reshape((-1,1))
print(y_pred.shape)
acc = np.sum((y_pred==y_actual))/y_pred.shape[0]
```

```
(303, 1)
```

In [ ]:

```
print(acc)
```

```
survived    0.752475
dtype: float64
```

ENSEMBLE METHODS

Importing Dataset

In [ ]:

```
import pandas as pd
import numpy as np
```

In [ ]:

```
data = pd.read_csv("train.csv")
```

In [ ]:

```
data.head()
```

Out[ ]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Em
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	

Data Description

In [ ]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
```

```
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

Data Cleaning and Preprocessing

In [ ]:

```python
columns_to_drop = ["PassengerId", "Name", "Ticket", "Cabin", "Embarked"]
data_clean = data.drop(columns_to_drop, axis=1)
data_clean.head()
```

Out[ ]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
0	0	3	male	22.0	1	0	7.2500
1	1	1	female	38.0	1	0	71.2833
2	1	3	female	26.0	0	0	7.9250
3	1	1	female	35.0	1	0	53.1000
4	0	3	male	35.0	0	0	8.0500

Label Encoding

In [ ]:

```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
data_clean["Sex"] = le.fit_transform(data_clean["Sex"])
```

In [ ]:

```python
data_clean.head()
```

Out[ ]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
0	0	3	1	22.0	1	0	7.2500
1	1	1	0	38.0	1	0	71.2833
2	1	3	0	26.0	0	0	7.9250
3	1	1	0	35.0	1	0	53.1000
4	0	3	1	35.0	0	0	8.0500

In [ ]:

```python
data_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
```

```
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Survived  891 non-null    int64  
 1   Pclass    891 non-null    int64  
 2   Sex       891 non-null    int32  
 3   Age       714 non-null    float64
 4   SibSp     891 non-null    int64  
 5   Parch     891 non-null    int64  
 6   Fare      891 non-null    float64
dtypes: float64(2), int32(1), int64(4)
memory usage: 45.4 KB
```

In [ ]:

```
data_clean.describe()
```

Out[ ]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	0.647587	29.699118	0.523008	0.381594	32.204208
std	0.486592	0.836071	0.477990	14.526497	1.102743	0.806057	49.693429
min	0.000000	1.000000	0.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	0.000000	20.125000	0.000000	0.000000	7.910400
50%	0.000000	3.000000	1.000000	28.000000	0.000000	0.000000	14.454200
75%	1.000000	3.000000	1.000000	38.000000	1.000000	0.000000	31.000000
max	1.000000	3.000000	1.000000	80.000000	8.000000	6.000000	512.329200

In [ ]:

```
data_clean = data_clean.fillna(data_clean["Age"].mean()) #Imputer can also be used
```

In [ ]:

```
data_clean.describe()
```

Out[ ]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	0.647587	29.699118	0.523008	0.381594	32.204208
std	0.486592	0.836071	0.477990	13.002015	1.102743	0.806057	49.693429
min	0.000000	1.000000	0.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	0.000000	22.000000	0.000000	0.000000	7.910400
50%	0.000000	3.000000	1.000000	29.699118	0.000000	0.000000	14.454200
75%	1.000000	3.000000	1.000000	35.000000	1.000000	0.000000	31.000000
max	1.000000	3.000000	1.000000	80.000000	8.000000	6.000000	512.329200

In [ ]:

```
input_cols = ["Pclass", "Sex", "Age", "SibSp", "Parch", "Fare"]
output_cols = ["Survived"]
```

In [ ]:
```
X = data_clean[input_cols]
Y = data_clean[output_cols]
```

In [ ]:
```
X.shape,Y.shape
```

Out[ ]:
```
((891, 6), (891, 1))
```

Creating Test-Train Split

In [ ]:
```
split = int(0.7*data_clean.shape[0])
train_data = data_clean[:split]
test_data = data_clean[split:]
test_data = test_data.reset_index(drop=True)
```

In [ ]:
```
X_train = train_data[input_cols]
Y_train = np.array(train_data[output_cols]).reshape((-1,))
X_test = test_data[input_cols]
Y_test = np.array(test_data[output_cols]).reshape((-1,))
```

Random Forest Classfier

- Ensemble Learning

In [ ]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [ ]:
```
rf  = RandomForestClassifier(n_estimators=10, criterion='entropy', max_depth=8)
rf.fit(X_train,Y_train)
```

Out[ ]:
```
RandomForestClassifier(criterion='entropy', max_depth=8, n_estimators=10)
```

Train Accuracy

In [ ]:
```
rf.score(X_train,Y_train)
```

Out[ ]:
```
0.8940609951845907
```

Test Accuracy

In [ ]:
```
rf.score(X_test,Y_test)
```

Out[ ]:
```
0.8432835820895522
```

Cross Validation

In [ ]:

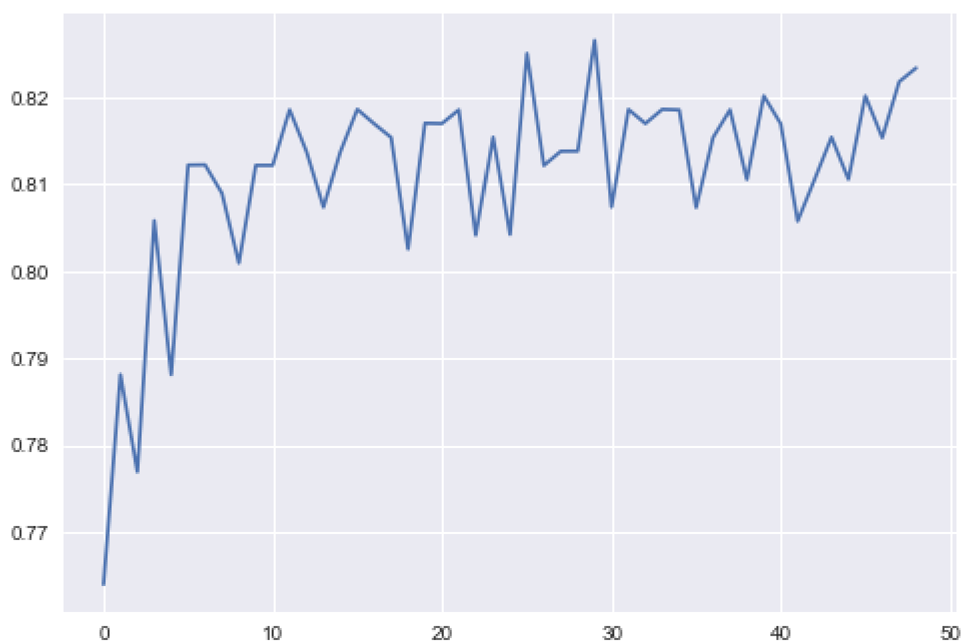
```
from sklearn.model_selection import cross_val_score
```

In [ ]:

```
acc_list = []
for i in range(1,50):
    acc = cross_val_score(RandomForestClassifier(n_estimators=i,max_depth=5,criterion='
    acc_list.append(acc)
```

In [ ]:

```
import matplotlib.pyplot as plt
plt.style.use('seaborn')
plt.plot(acc_list)
plt.show()
```



In [ ]:

```
print(np.argmax(acc_list))
```

29

In [ ]:

```
rf_test = RandomForestClassifier(n_estimators=29,max_depth=5,criterion='entropy')
```

In [ ]:

```
rf_test.fit(X_train,Y_train)
rf_test.score(X_train,Y_train)
```

Out[ ]: 0.8619582664526485

In [ ]:

```
rf_test.score(X_test,Y_test)
```

Out[ ]: 0.8246268656716418

```
In [ ]:
```

BAYESIAN CLASSIFIER

In [ ]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [ ]:

```
df = pd.read_csv('mushrooms.csv')
df.head(n=10)
```

Out[ ]:

	type	cap_shape	cap_surface	cap_color	bruises	odor	gill_attachment	gill_spacing	gill_size	gill_co
0	p	x	s	n	t	p	f	c	n	
1	e	x	s	y	t	a	f	c	b	
2	e	b	s	w	t	l	f	c	b	
3	p	x	y	w	t	p	f	c	n	
4	e	x	s	g	f	n	f	w	b	
5	e	x	y	y	t	a	f	c	b	
6	e	b	s	w	t	a	f	c	b	
7	e	b	y	w	t	l	f	c	b	
8	p	x	y	w	t	p	f	c	n	
9	e	b	s	y	t	a	f	c	b	

10 rows × 23 columns

In [ ]:

```
df.shape
```

Out[ ]:

```
(8124, 23)
```

In [ ]:

```
df.describe()
```

Out[ ]:

	type	cap_shape	cap_surface	cap_color	bruises	odor	gill_attachment	gill_spacing	gill_size
count	8124	8124	8124	8124	8124	8124	8124	8124	8124
unique	2	6	4	10	2	9	2	2	2
top	e	x	y	n	f	n	f	c	b
freq	4208	3656	3244	2284	4748	3528	7914	6812	5612

4 rows × 23 columns

In [ ]:

```
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
```

In [ ]:

```
le = LabelEncoder()
```

In [ ]:

```
ds = df.apply(le.fit_transform) # Applies transform on each collumn
```

In [ ]:

```
ds
```

Out[ ]:

	type	cap_shape	cap_surface	cap_color	bruises	odor	gill_attachment	gill_spacing	gill_size	gi
0	1	5	2	4	1	6	1	0	1	
1	0	5	2	9	1	0	1	0	0	
2	0	0	2	8	1	3	1	0	0	
3	1	5	3	8	1	6	1	0	1	
4	0	5	2	3	0	5	1	1	0	
...	...	...	...	...	...	...	...	...	...	
8119	0	3	2	4	0	5	0	0	0	
8120	0	5	2	4	0	5	0	0	0	
8121	0	2	2	4	0	5	0	0	0	
8122	1	3	3	4	0	8	1	0	1	
8123	0	5	2	4	0	5	0	0	0	

8124 rows × 23 columns

In [ ]:

```
data = ds.values
print(data.shape)
```

```
(8124, 23)
```

In [ ]:

```
print(data[:5,:])
data_y = data[:,0]
data_x = data[:,1:]
```

```
[[1 5 2 4 1 6 1 0 1 4 0 3 2 2 7 7 0 2 1 4 2 3 5]
 [0 5 2 9 1 0 1 0 0 4 0 2 2 2 7 7 0 2 1 4 3 2 1]
 [0 0 2 8 1 3 1 0 0 5 0 2 2 2 7 7 0 2 1 4 3 2 3]
 [1 5 3 8 1 6 1 0 1 5 0 3 2 2 7 7 0 2 1 4 2 3 5]
 [0 5 2 3 0 5 1 1 0 4 1 3 2 2 7 7 0 2 1 0 3 0 1]]
```

In [ ]:

```
x_train,x_test,y_train,y_test = train_test_split(data_x,data_y, test_size = 0.2)
```

In [ ]:

```
x_train.shape,y_train.shape
```

Out[ ]:

```
((6499, 22), (6499,))
```

In [ ]:
```
x_test.shape,y_test.shape
```
Out[ ]:
```
((1625, 22), (1625,))
```
In [ ]:
```
np.unique(y_train)
```
Out[ ]:
```
array([0, 1])
```
In [ ]:
```
a = np.array([0,0,0,1,1,0])
np.sum(a==1)
```
Out[ ]:
```
2
```
In [ ]:
```
def prior_prob(y_train,label):
    total_ex = y_train.shape[0]
    class_ex = np.sum(y_train==label)
    return (class_ex/float(total_ex))
```
In [ ]:
```
y = np.array([0,0,5,5,1,1,1,1,0,0])
```
In [ ]:
```
prior_prob(y,5)
```
Out[ ]:
```
0.2
```
In [ ]:
```
def cond_prob(x_train,y_train,feature_col,feature_val,label):
    x_filtered = x_train[y_train==label]
    numerator = np.sum(x_filtered[:,feature_col] == feature_val)
    denom = np.sum(y_train == label)
    return numerator/float(denom)
```
In [ ]:
```
def predict(x_train,y_train,xtest):
    classes = np.unique(y_train)
    n_features = x_train.shape[1]
    post_probs = []
    for label in classes:
        likelihood = 1.0
        for f in range(n_features):
            cond = cond_prob(x_train,y_train,f,xtest[f],label)
            likelihood *= cond
        prior = prior_prob(y_train,label)
        post = prior*likelihood
        post_probs.append(post)
    pred = np.argmax(post_probs)
    return pred
```
In [ ]:
```
output = predict(x_train,y_train,x_test[1])
print(output)
```
```
1
```

In [ ]:

```
print(y_test[1])
```

```
1
```

In [ ]:

```
def score(x_train,y_train,x_test,y_test):
    pred = []

    for i in range(x_test.shape[0]):
        pred_label = predict(x_train,y_train,x_test[i])
        pred.append(pred_label)
    pred = np.array(pred)
    accuracy = np.sum(pred==y_test)/y_test.shape[0]
    return accuracy
```

In [ ]:

```
print(score(x_train,y_train,x_test,y_test))
```

```
0.9987692307692307
```

In [ ]:

```

```

MULTI-LAYER PERCEPTRON

Layered Neural Network

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

In [ ]:
```
input_size = 2
layers = [4,3]
output_size = 2
```

In [ ]:
```
def softmax(a):
    ea = np.exp(a)
    ans = ea/np.sum(ea,axis=1,keepdims=True) # To preserves the dimensions
    return ans
```

In [ ]:
```
a = np.array([[20,30],[20,20]])
a_ = softmax(a)
print(a_)
```

```
[[4.53978687e-05 9.99954602e-01]
 [5.00000000e-01 5.00000000e-01]]
```

In [ ]:
```
class NeuralNetwork:
    def __init__(self, input_size, layers, output_size):
        np.random.seed(0)

        model = {}

        model['W1'] = np.random.randn(input_size, layers[0])
        model['b1'] = np.zeros((1,layers[0]))
        model['W2'] = np.random.randn(layers[0], layers[1])
        model['b2'] = np.zeros((1,layers[1]))
        model['W3'] = np.random.randn(layers[1], output_size)
        model['b3'] = np.zeros((1,output_size))

        self.model = model
        self.activation_outputs = None

    def forward(self,x):
        W1,W2,W3 = self.model['W1'],self.model['W2'],self.model['W3']
        b1,b2,b3 = self.model['b1'],self.model['b2'],self.model['b3']

        z1 = np.dot(x,W1) + b1
        a1 = np.tanh(z1)

        z2 = np.dot(a1,W2) + b2
        a2 = np.tanh(z2)

        z3 = np.dot(a2,W3) + b3
        y_ = softmax(z3)

        self.activation_outputs = (a1,a2,y_)
        return y_
```

```
    def backward(self,x,y,learning_rate=0.001):
        W1,W2,W3 = self.model['W1'],self.model['W2'],self.model['W3']
        b1,b2,b3 = self.model['b1'],self.model['b2'],self.model['b3']

        a1,a2,y_ = self.activation_outputs

        m = x.shape[0]

        delta3 = y_-y
        dw3 = np.dot(a2.T,delta3)
        db3 = np.sum(delta3,axis=0)

        delta2 = (1-np.square(a2))*np.dot(delta3,W3.T)
        dw2 = np.dot(a1.T,delta2)
        db2 = np.sum(delta2,axis=0)

        delta1 = (1-np.square(a1))*np.dot(delta2,W2.T)
        dw1 = np.dot(x.T,delta1)
        db1 = np.sum(delta1,axis=0)

        self.model["W1"] -= learning_rate*dw1
        self.model["b1"] -= learning_rate*db1

        self.model["W2"] -= learning_rate*dw2
        self.model["b2"] -= learning_rate*db2

        self.model["W3"] -= learning_rate*dw3
        self.model["b3"] -= learning_rate*db3

    def predict(self,x):
        y_out = self.forward(x)
        return np.argmax(y_out,axis=1)
    def summary(self):
        W1,W2,W3 = self.model['W1'],self.model['W2'],self.model['W3']
        a1,a2,y_ = self.activation_outputs

        print("W1 ",W1.shape)
        print("A1 ",a1.shape)

        print("W2 ",W2.shape)
        print("A2 ",a2.shape)

        print("W3 ",W3.shape)
        print("Y_ ",y_.shape)
```

In [ ]:

```
def loss(y_oht, p):
    l = -np.mean(y_oht*np.log(p))
    return l

def one_hot(y,depth):
    m = y.shape[0]
    y_oht = np.zeros((m,depth))
    y_oht[np.arange(m),y] = 1

    return y_oht
```

In [ ]:

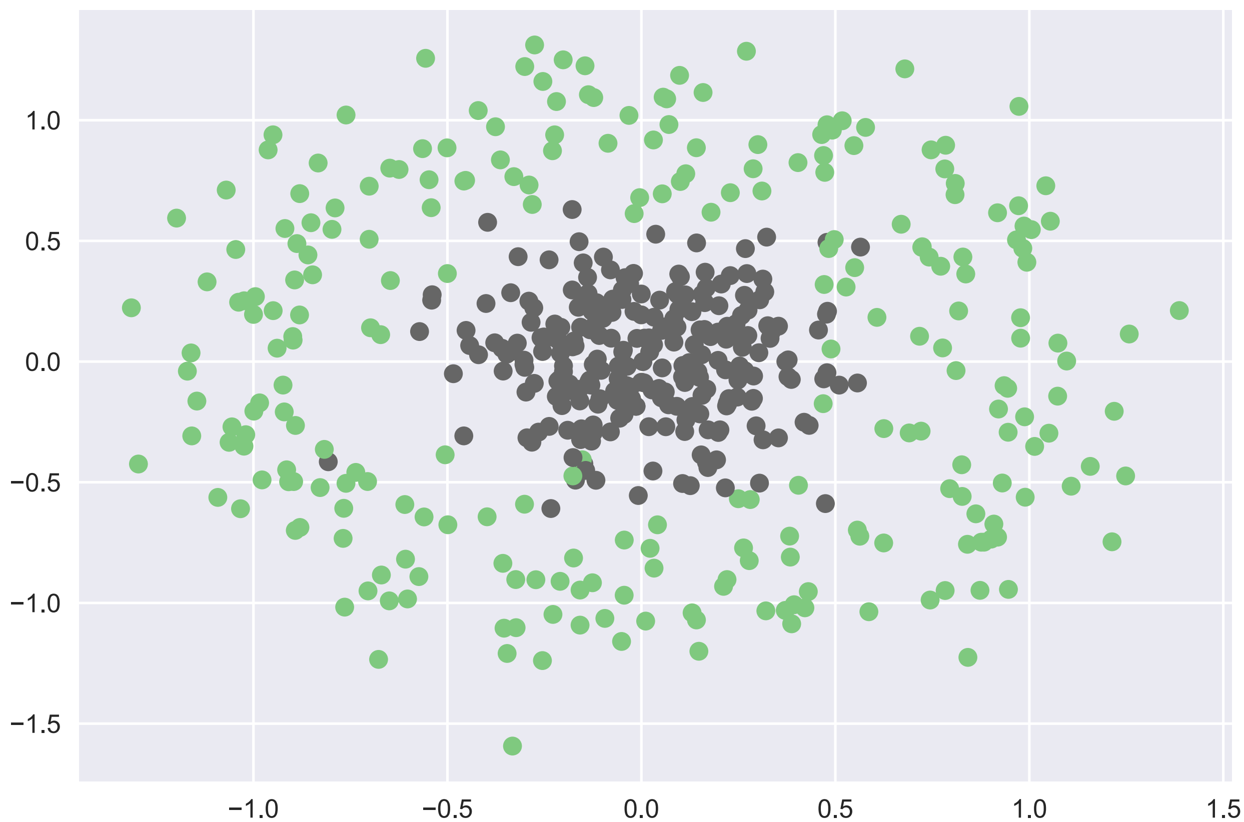
```
from sklearn.datasets import make_circles
import matplotlib.pyplot as plt
```

In [ ]:

```
x,y = make_circles(n_samples=500, shuffle=True, noise=0.2, random_state=1, factor=0.2)
```

In [ ]:

```
plt.style.use('seaborn')
plt.scatter(x[:,0],x[:,1],c=y,cmap=plt.cm.Accent)
plt.show()
```



In [ ]:

```
model = NeuralNetwork(input_size=2,layers=[10,5],output_size=2)
```

In [ ]:

```
model.forward(x)
```

Out[ ]:

```
array([[0.52335135, 0.47664865],
       [0.53144257, 0.46855743],
       [0.57726974, 0.42273026],
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```

```
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```

In [ ]:

```
model.summary()
```

```
W1  (2, 10)
```

```
A1  (500, 10)
W2  (10, 5)
A2  (500, 5)
W3  (5, 2)
Y_  (500, 2)
```

In [ ]:

```
# y_oht = one_hot(y,2)
# print(y_oht)
```

In [ ]:

```
def train(X,Y,model,epochs,learning_rate,logs=True):
    training_loss = []

    classes = 2
    Y_OHT = one_hot(Y,classes)

    for ix in range(epochs):

        Y_ = model.forward(X)
        l = loss(Y_OHT,Y_)
        training_loss.append(l)
        model.backward(X,Y_OHT,learning_rate)

        if(logs):
            print("Epoch %d Loss %.4f"%(ix,l))


    return training_loss
```

In [ ]:

```
losses = train(x,y,model,500,0.001)
```

```
Epoch 0 Loss 0.3571
Epoch 1 Loss 0.3554
Epoch 2 Loss 0.2593
Epoch 3 Loss 0.2407
Epoch 4 Loss 0.2258
Epoch 5 Loss 0.2132
Epoch 6 Loss 0.2020
Epoch 7 Loss 0.1919
Epoch 8 Loss 0.1827
Epoch 9 Loss 0.1742
Epoch 10 Loss 0.1664
Epoch 11 Loss 0.1593
Epoch 12 Loss 0.1527
Epoch 13 Loss 0.1467
Epoch 14 Loss 0.1411
Epoch 15 Loss 0.1360
Epoch 16 Loss 0.1313
Epoch 17 Loss 0.1270
Epoch 18 Loss 0.1230
Epoch 19 Loss 0.1193
Epoch 20 Loss 0.1159
Epoch 21 Loss 0.1127
Epoch 22 Loss 0.1098
Epoch 23 Loss 0.1070
Epoch 24 Loss 0.1045
Epoch 25 Loss 0.1021
Epoch 26 Loss 0.0999
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Epoch 27 Loss 0.0978
Epoch 28 Loss 0.0958
Epoch 29 Loss 0.0940
Epoch 30 Loss 0.0922
Epoch 31 Loss 0.0906
Epoch 32 Loss 0.0891
Epoch 33 Loss 0.0876
Epoch 34 Loss 0.0862
Epoch 35 Loss 0.0849
Epoch 36 Loss 0.0837
Epoch 37 Loss 0.0825
Epoch 38 Loss 0.0814
Epoch 39 Loss 0.0803
Epoch 40 Loss 0.0793
Epoch 41 Loss 0.0783
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```
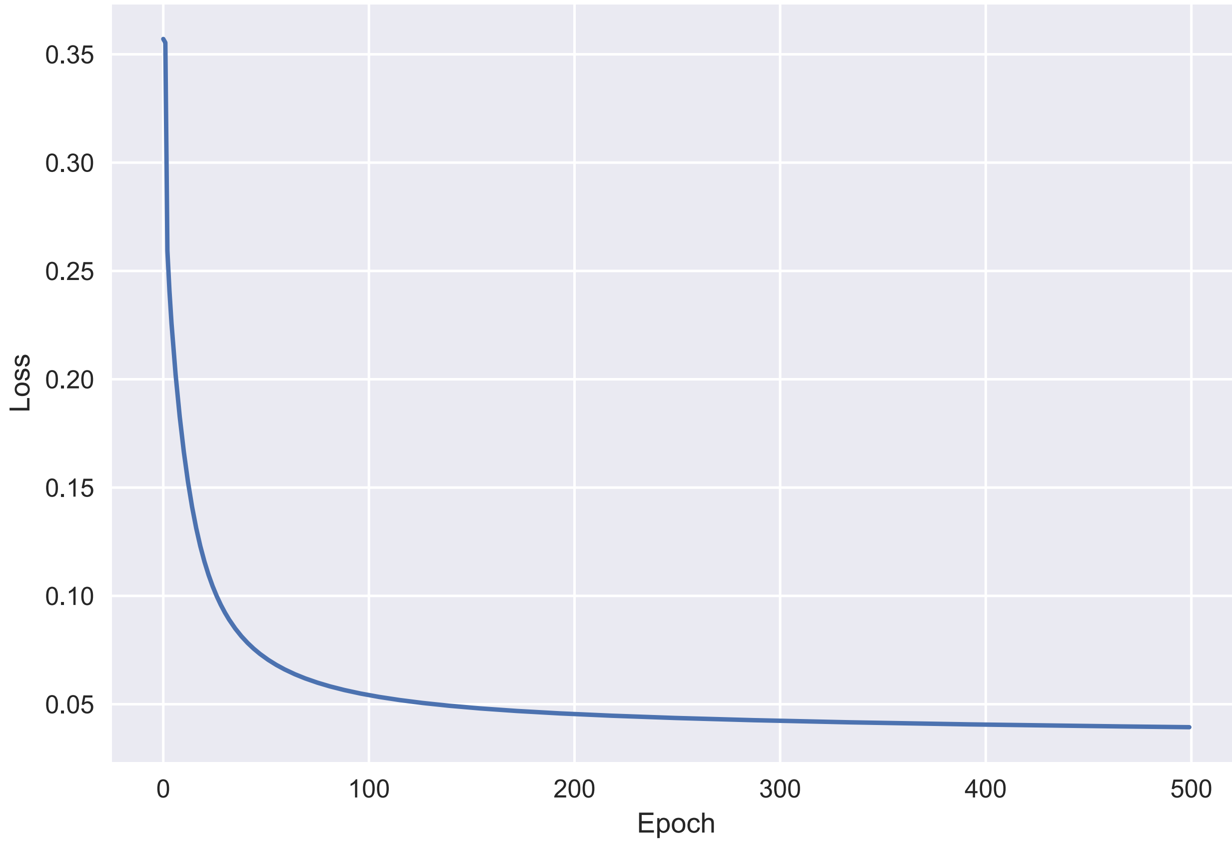

In [ ]:

```
plt.plot(losses)
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.show()
```

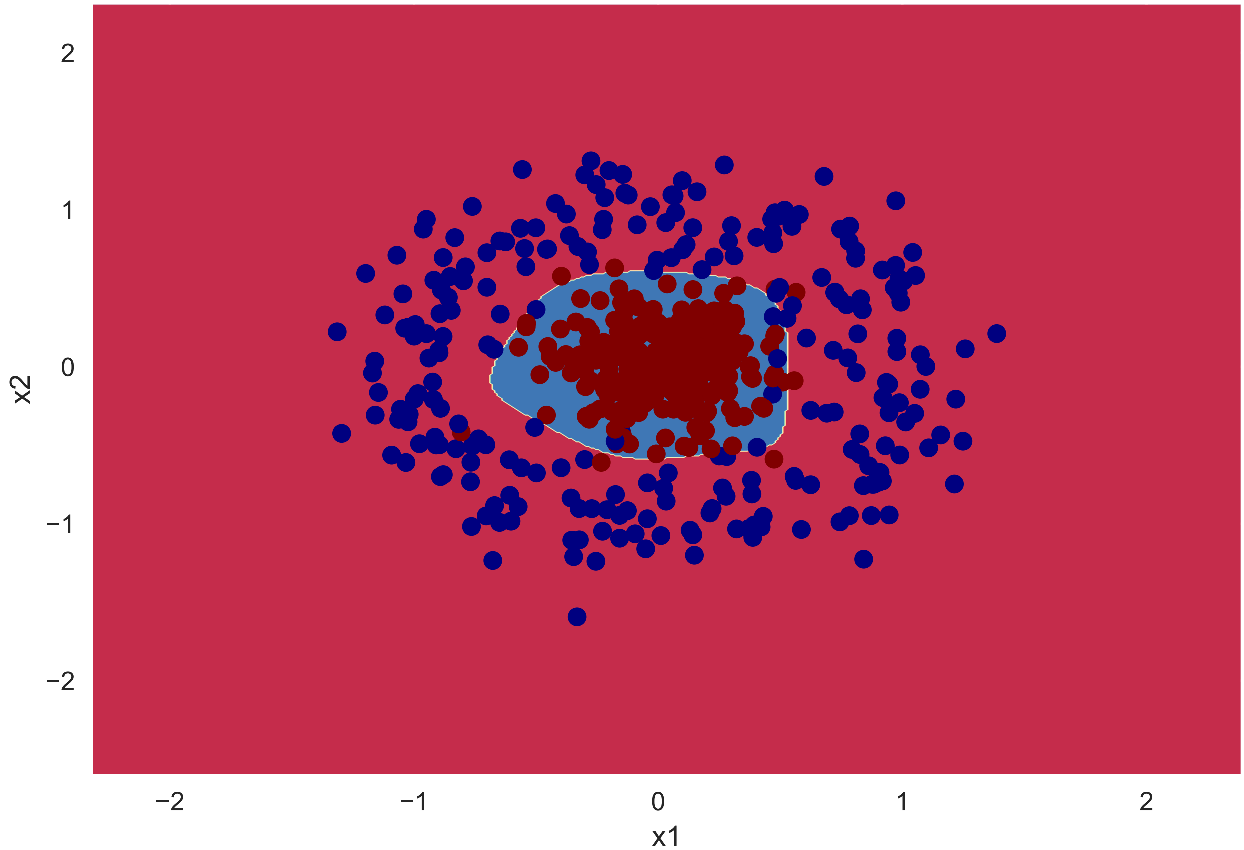


In [ ]:

```
## Find Accuracy
from visualize import plot_decision_boundary
```

In [ ]:

```
plot_decision_boundary(lambda X:model.predict(X),x,y)
```



In [ ]:

```
outputs = model.predict(x)
```

In [ ]:

```
training_accuracy = np.sum(outputs==y)/y.shape[0]
print("Training Accuracy %.4f"%(training_accuracy*100))
```

```
Training Accuracy 97.0000
```

Other Data Sets

In [ ]:

```
model  = NeuralNetwork(input_size=2,layers=[10,5],output_size=2)
```

XOR Data Set

In [ ]:

```
X = np.array([[0,0],
              [0,1],
              [1,0],
              [1,1]
             ])

Y = np.array([0,1,1,0])
```

In [ ]:

```
losses = train(X,Y,model,300,0.1)
```

```
Epoch 0 Loss 0.3427
```

```
Epoch 1 Loss 0.2543
Epoch 2 Loss 0.2126
Epoch 3 Loss 0.1926
Epoch 4 Loss 0.1778
Epoch 5 Loss 0.1639
Epoch 6 Loss 0.1493
Epoch 7 Loss 0.1346
Epoch 8 Loss 0.1207
Epoch 9 Loss 0.1089
Epoch 10 Loss 0.1008
Epoch 11 Loss 0.1004
Epoch 12 Loss 0.1244
Epoch 13 Loss 0.1949
Epoch 14 Loss 0.3900
Epoch 15 Loss 0.1355
Epoch 16 Loss 0.0958
Epoch 17 Loss 0.0762
Epoch 18 Loss 0.0636
Epoch 19 Loss 0.0552
Epoch 20 Loss 0.0492
Epoch 21 Loss 0.0447
Epoch 22 Loss 0.0412
Epoch 23 Loss 0.0384
Epoch 24 Loss 0.0361
Epoch 25 Loss 0.0341
Epoch 26 Loss 0.0323
Epoch 27 Loss 0.0307
Epoch 28 Loss 0.0293
Epoch 29 Loss 0.0281
Epoch 30 Loss 0.0269
Epoch 31 Loss 0.0258
Epoch 32 Loss 0.0248
Epoch 33 Loss 0.0239
Epoch 34 Loss 0.0231
Epoch 35 Loss 0.0223
Epoch 36 Loss 0.0215
Epoch 37 Loss 0.0208
Epoch 38 Loss 0.0202
Epoch 39 Loss 0.0196
Epoch 40 Loss 0.0190
Epoch 41 Loss 0.0184
Epoch 42 Loss 0.0179
Epoch 43 Loss 0.0174
Epoch 44 Loss 0.0170
Epoch 45 Loss 0.0165
Epoch 46 Loss 0.0161
Epoch 47 Loss 0.0157
Epoch 48 Loss 0.0153
Epoch 49 Loss 0.0149
Epoch 50 Loss 0.0146
Epoch 51 Loss 0.0143
Epoch 52 Loss 0.0139
Epoch 53 Loss 0.0136
Epoch 54 Loss 0.0133
Epoch 55 Loss 0.0131
Epoch 56 Loss 0.0128
Epoch 57 Loss 0.0125
Epoch 58 Loss 0.0123
Epoch 59 Loss 0.0120
Epoch 60 Loss 0.0118
Epoch 61 Loss 0.0116
```

```
Epoch 62 Loss 0.0114
Epoch 63 Loss 0.0112
Epoch 64 Loss 0.0110
Epoch 65 Loss 0.0108
Epoch 66 Loss 0.0106
Epoch 67 Loss 0.0104
Epoch 68 Loss 0.0102
Epoch 69 Loss 0.0100
Epoch 70 Loss 0.0099
Epoch 71 Loss 0.0097
Epoch 72 Loss 0.0096
Epoch 73 Loss 0.0094
Epoch 74 Loss 0.0093
Epoch 75 Loss 0.0091
Epoch 76 Loss 0.0090
Epoch 77 Loss 0.0089
Epoch 78 Loss 0.0087
Epoch 79 Loss 0.0086
Epoch 80 Loss 0.0085
Epoch 81 Loss 0.0084
Epoch 82 Loss 0.0082
Epoch 83 Loss 0.0081
Epoch 84 Loss 0.0080
Epoch 85 Loss 0.0079
Epoch 86 Loss 0.0078
Epoch 87 Loss 0.0077
Epoch 88 Loss 0.0076
Epoch 89 Loss 0.0075
Epoch 90 Loss 0.0074
Epoch 91 Loss 0.0073
Epoch 92 Loss 0.0072
Epoch 93 Loss 0.0071
Epoch 94 Loss 0.0070
Epoch 95 Loss 0.0070
Epoch 96 Loss 0.0069
Epoch 97 Loss 0.0068
Epoch 98 Loss 0.0067
Epoch 99 Loss 0.0066
Epoch 100 Loss 0.0066
Epoch 101 Loss 0.0065
Epoch 102 Loss 0.0064
Epoch 103 Loss 0.0064
Epoch 104 Loss 0.0063
Epoch 105 Loss 0.0062
Epoch 106 Loss 0.0061
Epoch 107 Loss 0.0061
Epoch 108 Loss 0.0060
Epoch 109 Loss 0.0060
Epoch 110 Loss 0.0059
Epoch 111 Loss 0.0058
Epoch 112 Loss 0.0058
Epoch 113 Loss 0.0057
Epoch 114 Loss 0.0057
Epoch 115 Loss 0.0056
Epoch 116 Loss 0.0055
Epoch 117 Loss 0.0055
Epoch 118 Loss 0.0054
Epoch 119 Loss 0.0054
Epoch 120 Loss 0.0053
Epoch 121 Loss 0.0053
Epoch 122 Loss 0.0052
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```
Epoch 123 Loss 0.0052
Epoch 124 Loss 0.0051
Epoch 125 Loss 0.0051
Epoch 126 Loss 0.0050
Epoch 127 Loss 0.0050
Epoch 128 Loss 0.0050
Epoch 129 Loss 0.0049
Epoch 130 Loss 0.0049
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Epoch 132 Loss 0.0048
Epoch 133 Loss 0.0047
Epoch 134 Loss 0.0047
Epoch 135 Loss 0.0047
Epoch 136 Loss 0.0046
Epoch 137 Loss 0.0046
Epoch 138 Loss 0.0046
Epoch 139 Loss 0.0045
Epoch 140 Loss 0.0045
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Epoch 145 Loss 0.0043
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Epoch 182 Loss 0.0033
Epoch 183 Loss 0.0033
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Epoch 184 Loss 0.0033
Epoch 185 Loss 0.0033
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Epoch 244 Loss 0.0024
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```
Epoch 245 Loss 0.0024
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Epoch 295 Loss 0.0019
Epoch 296 Loss 0.0019
Epoch 297 Loss 0.0019
Epoch 298 Loss 0.0019
Epoch 299 Loss 0.0019
```
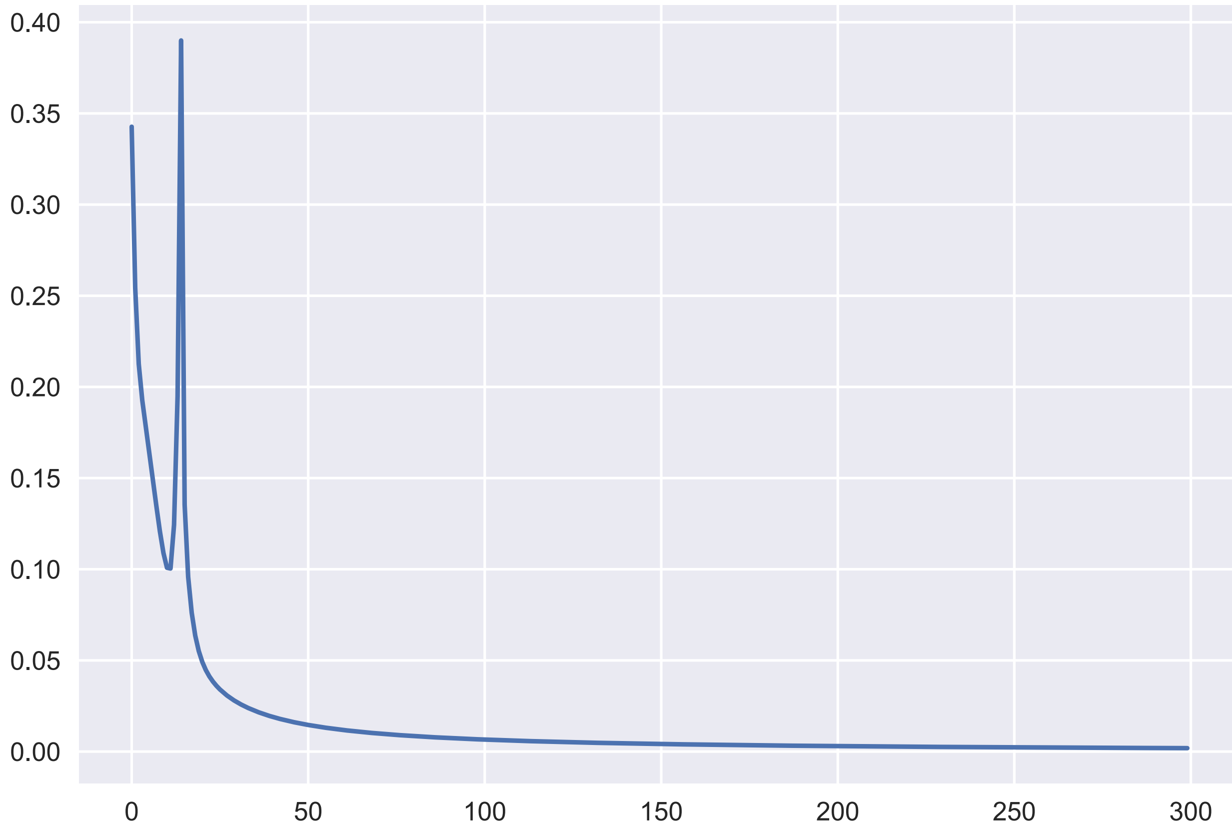
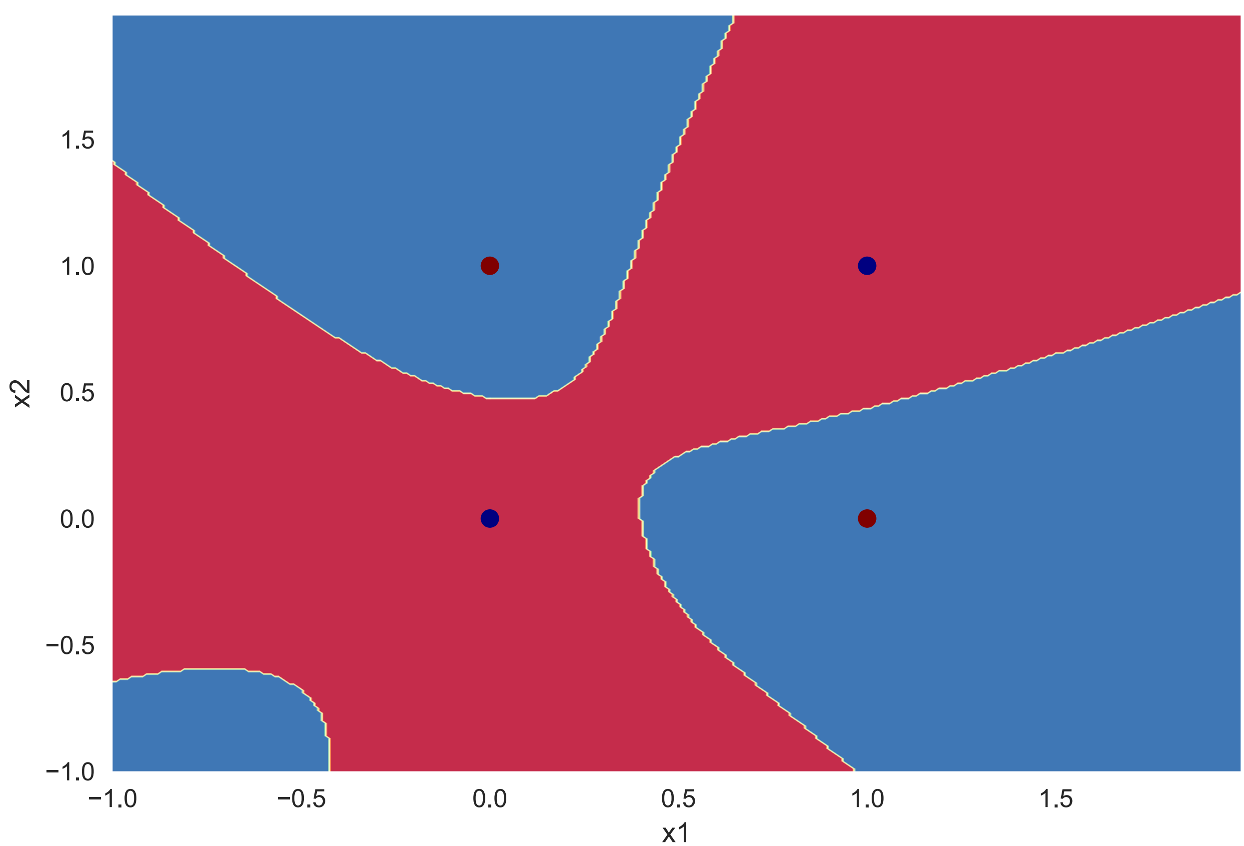

In [ ]:

```
plt.plot(losses)
plt.show()
```



In [ ]:
```
plot_decision_boundary(lambda x:model.predict(x),X,Y)
```



In [ ]:
```
from sklearn.datasets import make_moons,make_circles,make_classification
```

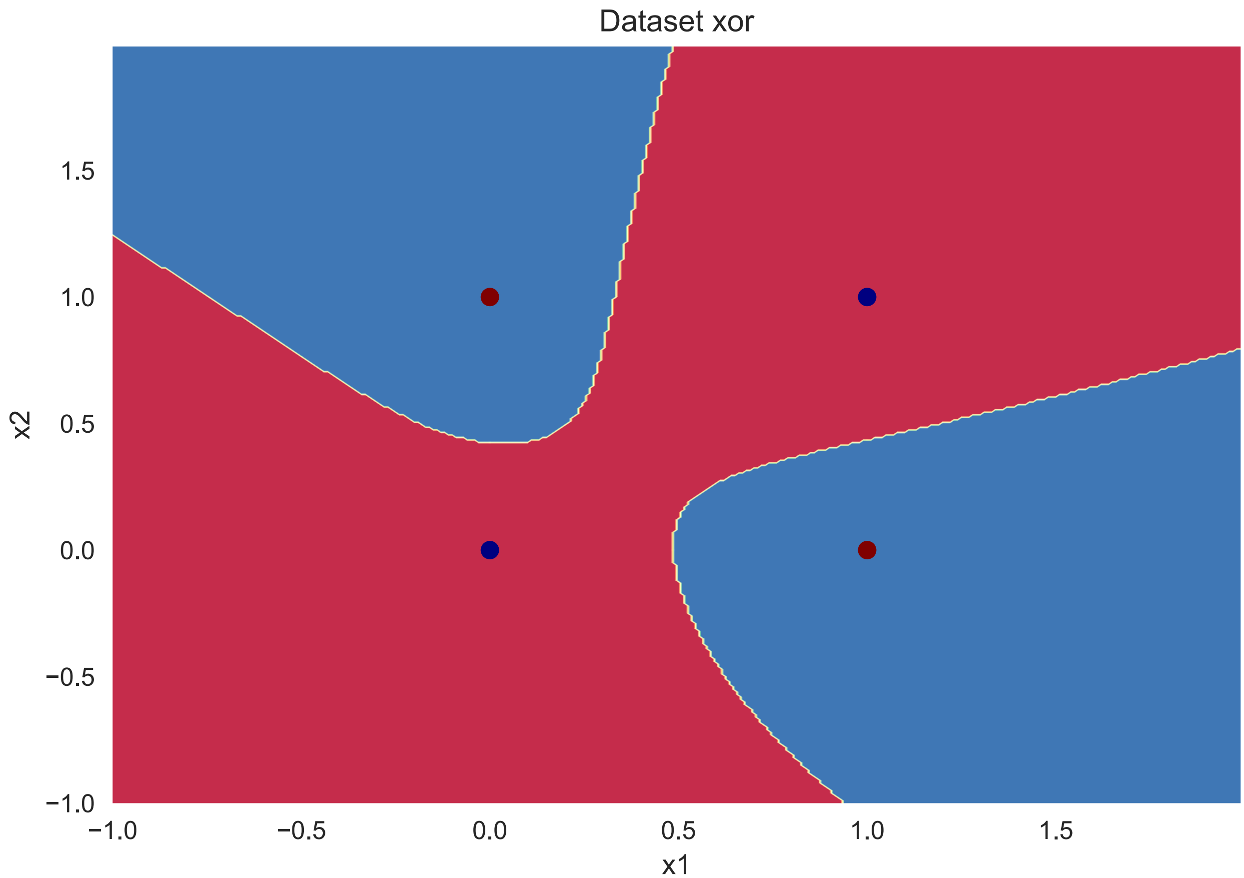
In [ ]:

```python
def load_dataset(dataset):
    if dataset=='moons':
        X,Y = make_moons(n_samples=500,noise=0.2,random_state=1) #Perceptron
    elif dataset=='circles':
        X,Y = make_circles(n_samples=500, shuffle=True, noise=0.2, random_state=1, fact
    elif dataset=='classification':
        X,Y = make_classification(n_samples=500,n_classes=2,n_features=2,n_informative=
    else:
        #Create XOR Dataset
        X = np.array([[0,0],
                    [0,1],
                    [1,0],
                    [1,1]])
        Y = np.array([0,1,1,0])

    return X,Y
```

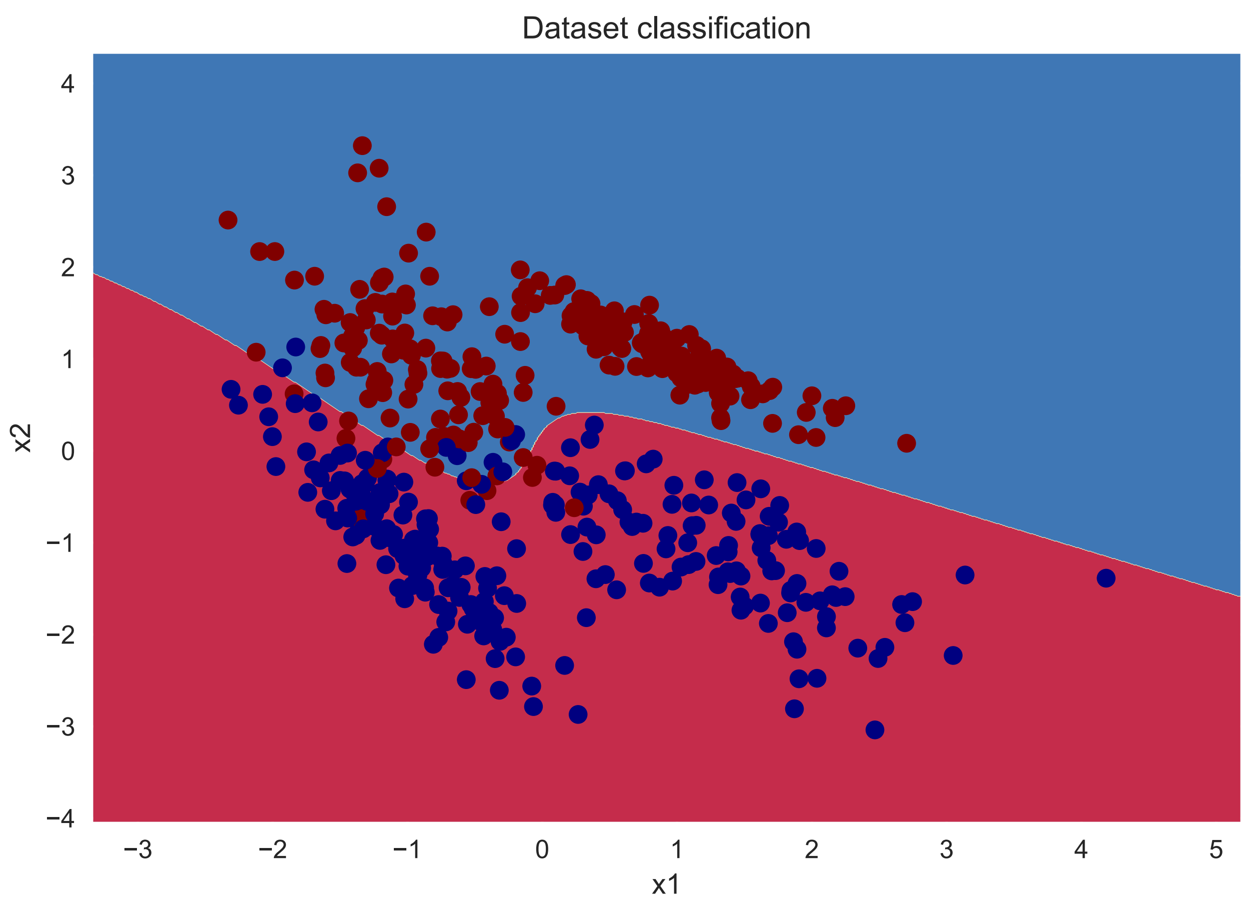
In [ ]:

```python
datasets = ["xor","classification","moons","circles"]

for d in datasets:
    model = NeuralNetwork(input_size=2,layers=[4,3],output_size=2)
    X,Y  = load_dataset(d)
    train(X,Y,model,1000,0.001,logs=False)
    outputs = model.predict(X)

    training_accuracy = np.sum(outputs==Y)/Y.shape[0]
    print("Training Acc %.4f"%training_accuracy)

    plt.title("Dataset "+d)
    plot_decision_boundary(lambda x:model.predict(x),X,Y)
    plt.show()
```

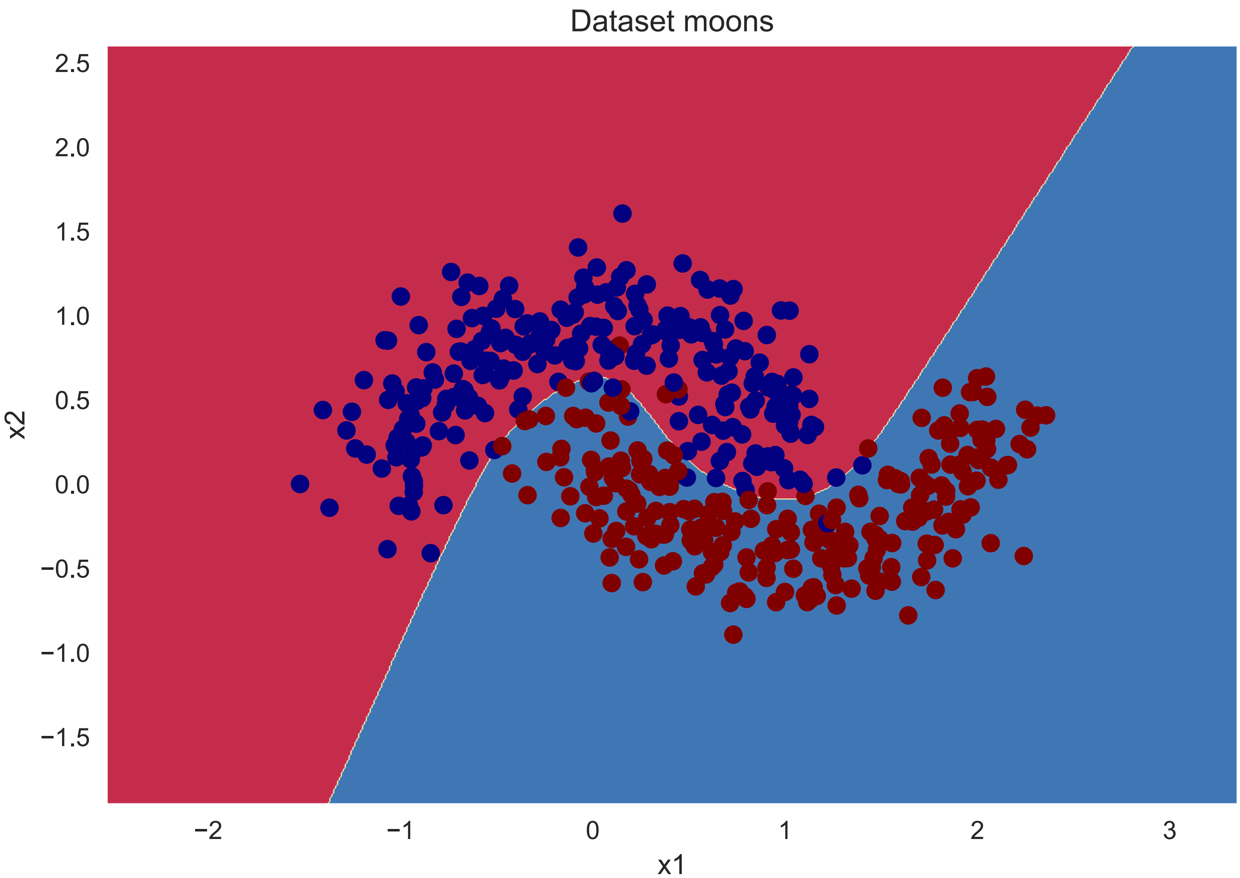
```
Training Acc 1.0000
```



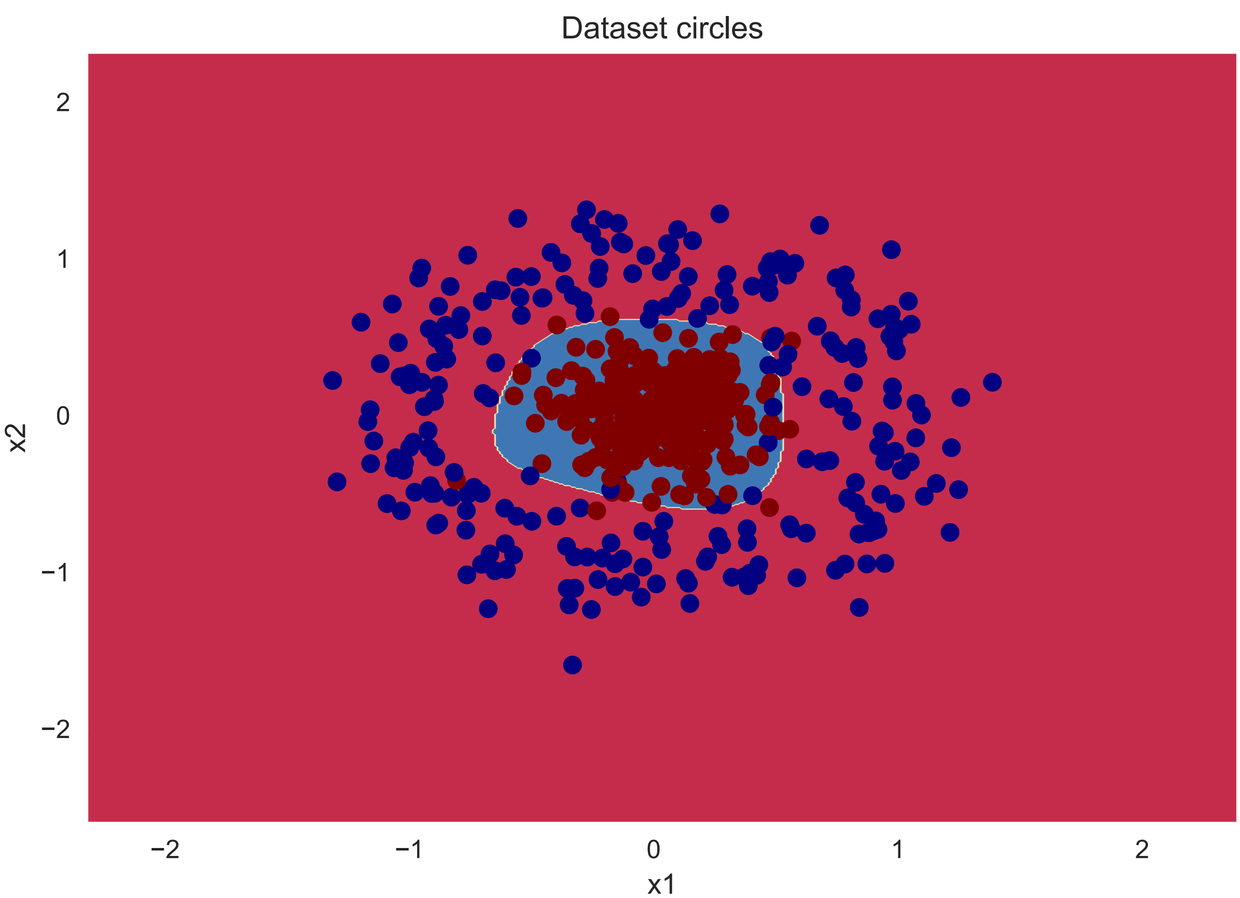

```
Training Acc 0.9600
```




```
Training Acc 0.9740
```




```
Training Acc 0.9640
```




```
In [ ]:
```