Binary Classification Using Keras Deep Learning Library

Data source:

The data set is originally from the ISLR library, the current version was imported from Github. The college dataset has 777 observations and 18 variables.

Attributes:

[Private] Whether the college is public or private

[Apps] Number of applications received

[Accept] Number of applications accepted

[Enroll] Number of new students enrolled

[Top10perc] Percentage of new students from top 10% of High School class

[Top25perc] Percentage new students from top 25% of High School class

[F.Undergrad] Number of fulltime undergraduates

[P.Undergrad] Number of parttime undergraduates

[Outstate] Out-of-state tuition

[Room.Board] Room and board costs

[Books] Estimated book costs

[Personal] Estimated personal spending

[PhD] Percentage of faculty with Ph.D.’s

[Terminal] Percentage of faculty with terminal degree

[S.F.Ratio] Student/faculty ratio

[perc.alumni] Pct. alumni who donate

[Expend] Instructional expenditure per student

[Grad.Rate] Graduation rate

In [3]:
```
# Importing required classes and functions for Neural Network
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

from keras import backend as k
from keras.models import Sequential
from keras import models
from sklearn.model_selection import train_test_split
from keras.layers import Dense, Activation, Dropout
from sklearn.preprocessing import LabelEncoder, StandardScaler
```

```
Using TensorFlow backend.
```

In [4]:
```
# Importing required packages to load the dataset and to visualize
# the data preprocessing tasks
import numpy
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
sns.set_style("whitegrid")
plt.style.use('fivethirtyeight')
```

In [5]:
```
# Loading the dataset
df=pd.read_csv('college.csv', header=0)
```

In [6]:
```
# Checking the fisrt row
df.head(5)
```

Out[6]:

	School	Private	Apps	Accept	Enroll	Top10perc	Top25perc	F_Undergrad	P_Undergrad	Outstate	Roor
0	Abilene Christian University	Yes	1660	1232	721	23	52	2885	537	7440	
1	Adelphi University	Yes	2186	1924	512	16	29	2683	1227	12280	
2	Adrian College	Yes	1428	1097	336	22	50	1036	99	11250	
3	Agnes Scott College	Yes	417	349	137	60	89	510	63	12960	
4	Alaska Pacific University	Yes	193	146	55	16	44	249	869	7560	

In [7]:
```
# Checking the datatypes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 777 entries, 0 to 776
Data columns (total 19 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   School       777 non-null    object 
 1   Private      777 non-null    object 
 2   Apps         777 non-null    int64  
 3   Accept       777 non-null    int64  
 4   Enroll       777 non-null    int64  
 5   Top10perc    777 non-null    int64  
 6   Top25perc    777 non-null    int64  
 7   F_Undergrad  777 non-null    int64  
 8   P_Undergrad  777 non-null    int64  
 9   Outstate     777 non-null    int64  
 10  Room_Board   777 non-null    int64  
 11  Books        777 non-null    int64  
 12  Personal     777 non-null    int64  
 13  PhD          777 non-null    int64  
 14  Terminal     777 non-null    int64  
 15  S_F_Ratio    777 non-null    float64
 16  perc_alumni  777 non-null    int64  
 17  Expend       777 non-null    int64  
 18  Grad_Rate    777 non-null    int64  
dtypes: float64(1), int64(16), object(2)
memory usage: 115.5+ KB
```

In [8]:
```
# Checking for missing data
df.isnull().sum()
```

Out[8]:
```
School         0
Private        0
Apps           0
Accept         0
Enroll         0
Top10perc      0
Top25perc      0
F_Undergrad    0
P_Undergrad    0
Outstate       0
Room_Board     0
Books          0
Personal       0
PhD            0
Terminal       0
S_F_Ratio      0
perc_alumni    0
Expend         0
Grad_Rate      0
dtype: int64
```

In [9]:
```
X = df.iloc[:,0:17]
Y = df.iloc[:,0]
```

In [10]:
```
# Dropping unnecessary column
df=df.drop(['School'],axis=1)
df.head()
```

Out[10]:

	Private	Apps	Accept	Enroll	Top10perc	Top25perc	F_Undergrad	P_Undergrad	Outstate	Room_Board	E
0	Yes	1660	1232	721	23	52	2885	537	7440	3300	
1	Yes	2186	1924	512	16	29	2683	1227	12280	6450	
2	Yes	1428	1097	336	22	50	1036	99	11250	3750	
3	Yes	417	349	137	60	89	510	63	12960	5450	
4	Yes	193	146	55	16	44	249	869	7560	4120	

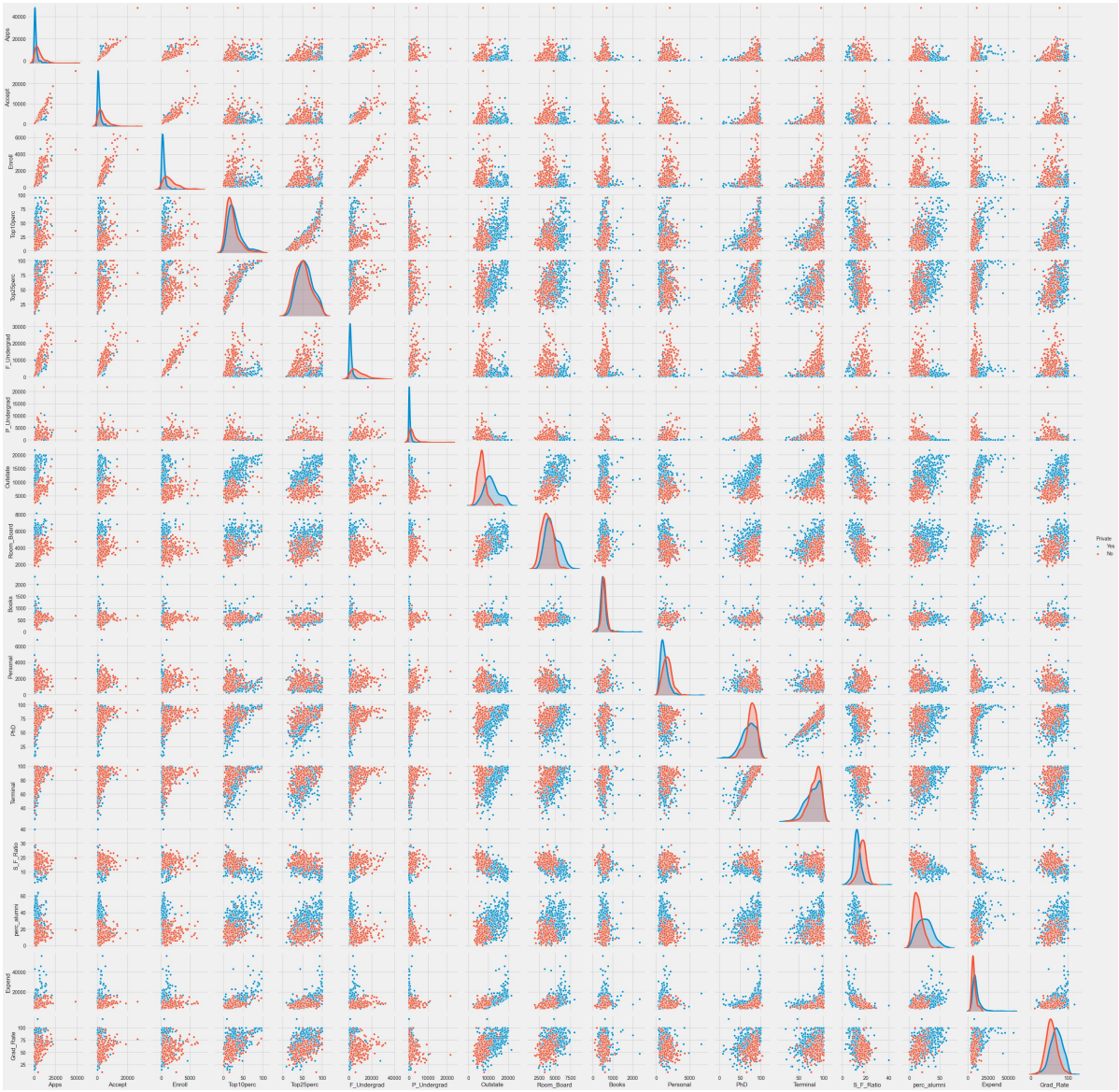
In [11]:
```
# Summary statistics
pd.set_option('display.float_format', '{:.4}'.format)
df.describe()
```

Out[11]:

	Apps	Accept	Enroll	Top10perc	Top25perc	F_Undergrad	P_Undergrad	Outstate	Room_
count	777.0	777.0	777.0	777.0	777.0	777.0	777.0	777.0	
mean	3.002e+03	2.019e+03	780.0	27.56	55.8	3.7e+03	855.3	1.044e+04	4.35
std	3.87e+03	2.451e+03	929.2	17.64	19.8	4.85e+03	1.522e+03	4.023e+03	1.09
min	81.0	72.0	35.0	1.0	9.0	139.0	1.0	2.34e+03	1.7
25%	776.0	604.0	242.0	15.0	41.0	992.0	95.0	7.32e+03	3.59
50%	1.558e+03	1.11e+03	434.0	23.0	54.0	1.707e+03	353.0	9.99e+03	4.
75%	3.624e+03	2.424e+03	902.0	35.0	69.0	4.005e+03	967.0	1.292e+04	5.0
max	4.809e+04	2.633e+04	6.392e+03	96.0	100.0	3.164e+04	2.184e+04	2.17e+04	8.12

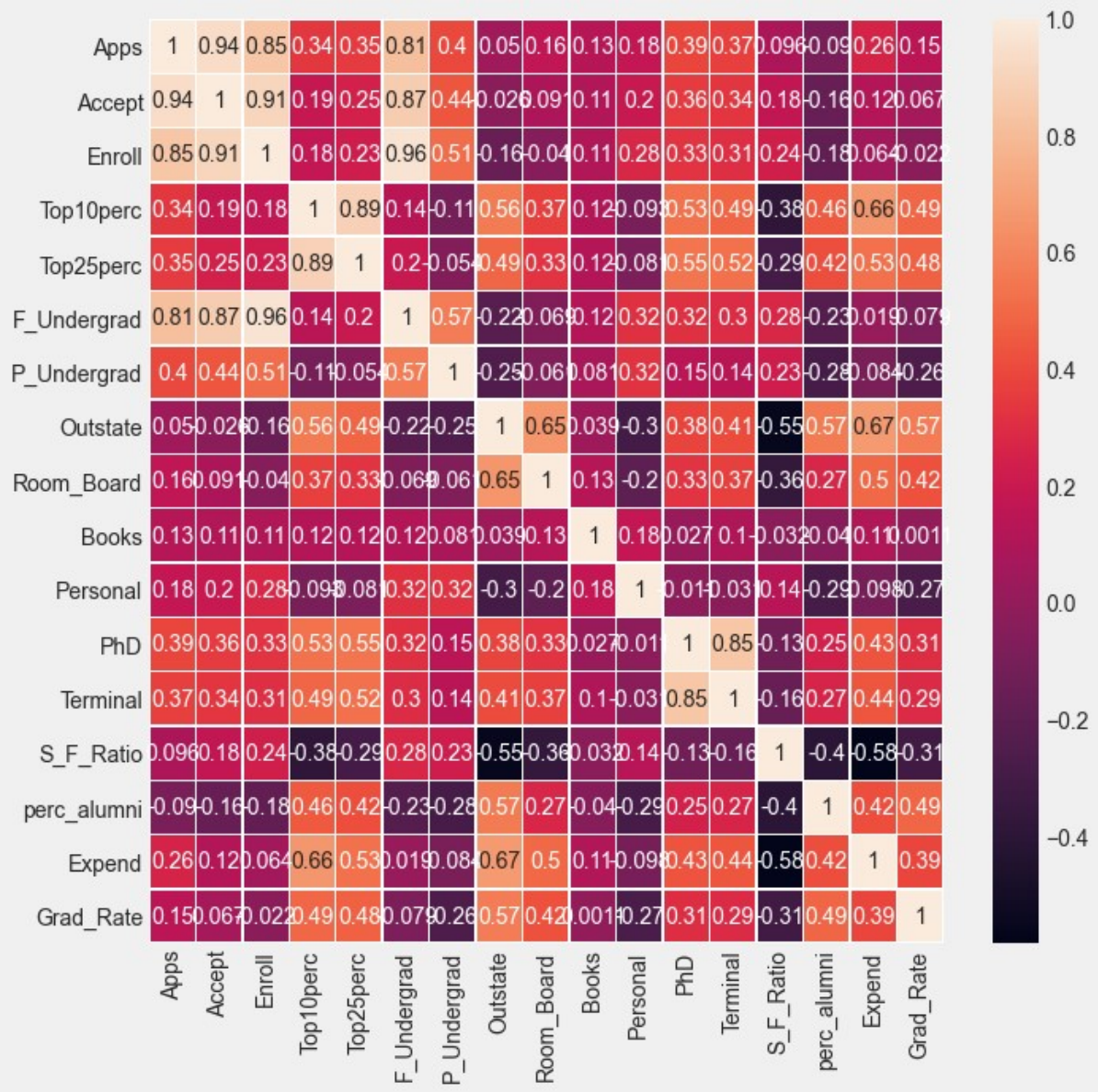
In [12]:
```
# Initial correlation check
sns.pairplot(df, hue='Private')
```

Out[12]: <seaborn.axisgrid.PairGrid at 0x12160d80f88>



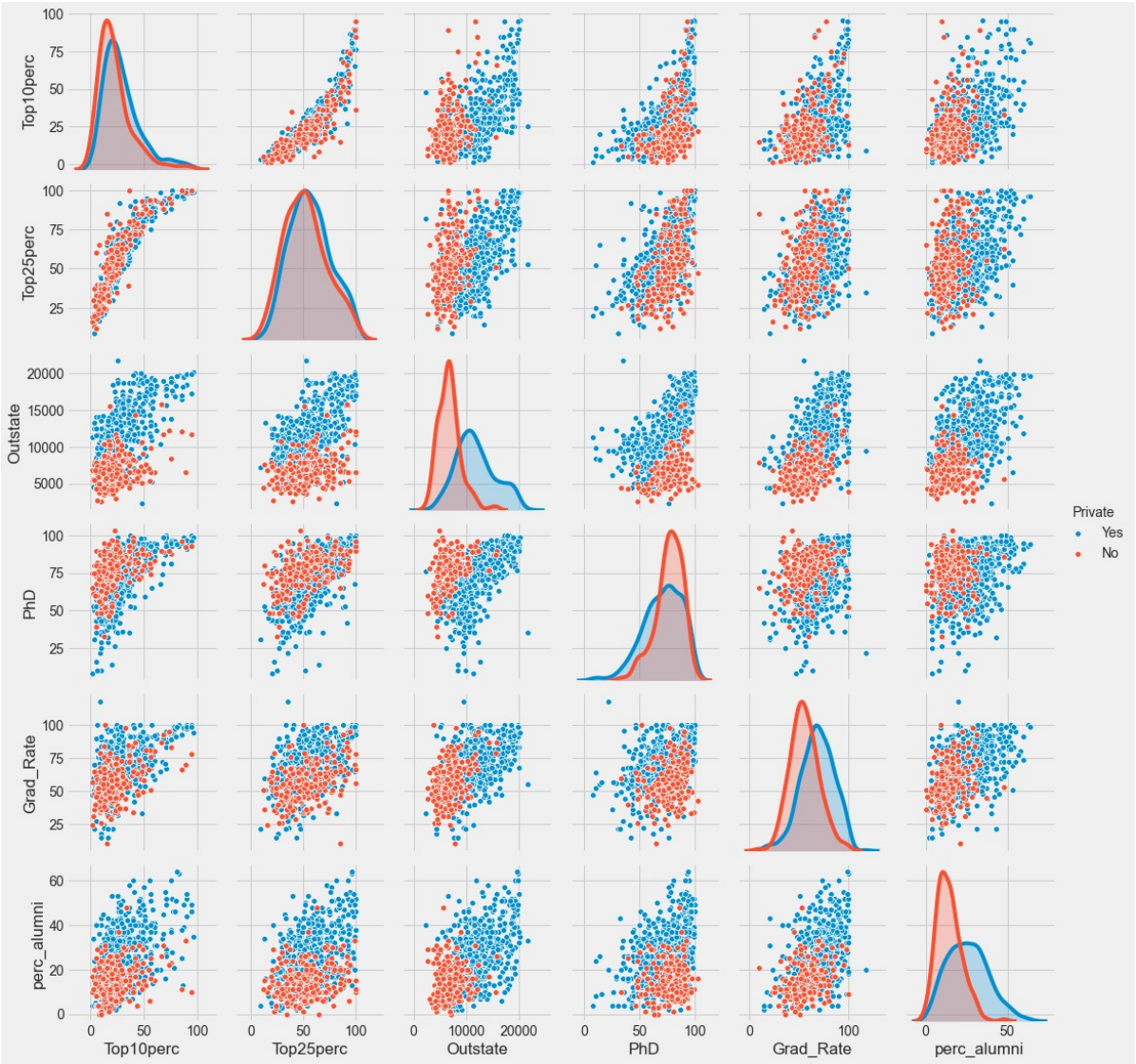
In [13]:
```
# A correlation plot with actual numerical values
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(df.corr(), annot=True, linewidth=.5, ax=ax)
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x12175045a08>



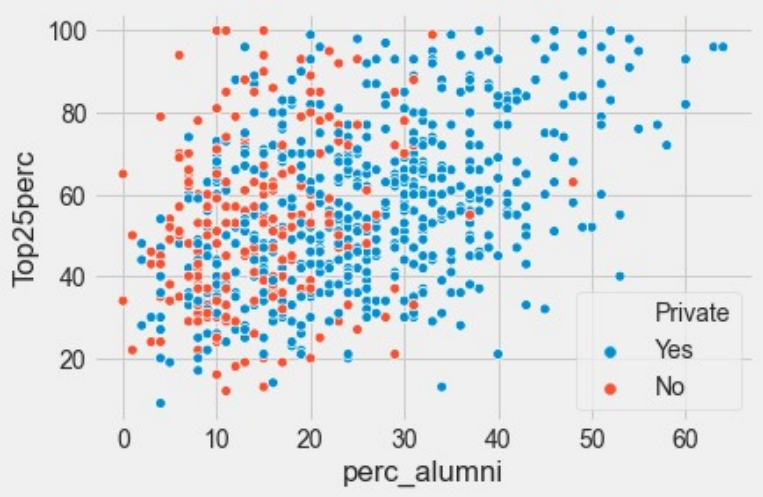
In [14]:
```
# Plotting a portio of the datasets
sns.pairplot(df,vars=['Top10perc','Top25perc','Outstate','PhD',
                      'Grad_Rate','perc_alumni'], hue='Private')
```

Out[14]: <seaborn.axisgrid.PairGrid at 0x1217723c388>



In [15]:
```
# Visualizing the correlation between % alumni who
# donate to the school and % new students from top 25% of H.S. class
sns.scatterplot(x="perc_alumni", y="Top25perc", data=df, hue="Private")
plt.figure(figsize=(12,12))
```

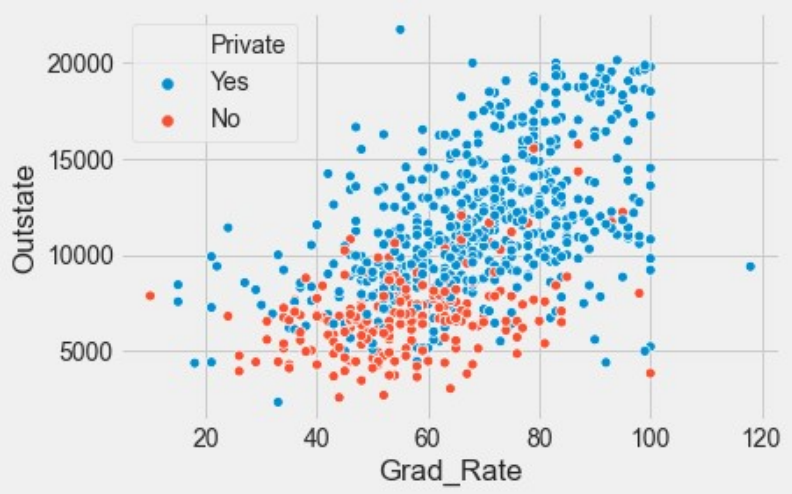
Out[15]:
```
<Figure size 864x864 with 0 Axes>
```




```
<Figure size 864x864 with 0 Axes>
```

In [16]:
```
# Correlation between out-of-state tuition and
# % if fuculty with Ph.D.s
sns.scatterplot(x=df["Grad_Rate"], y=df["Outstate"], data=df, hue="Private")
plt.figure(figsize=(12, 12))
```

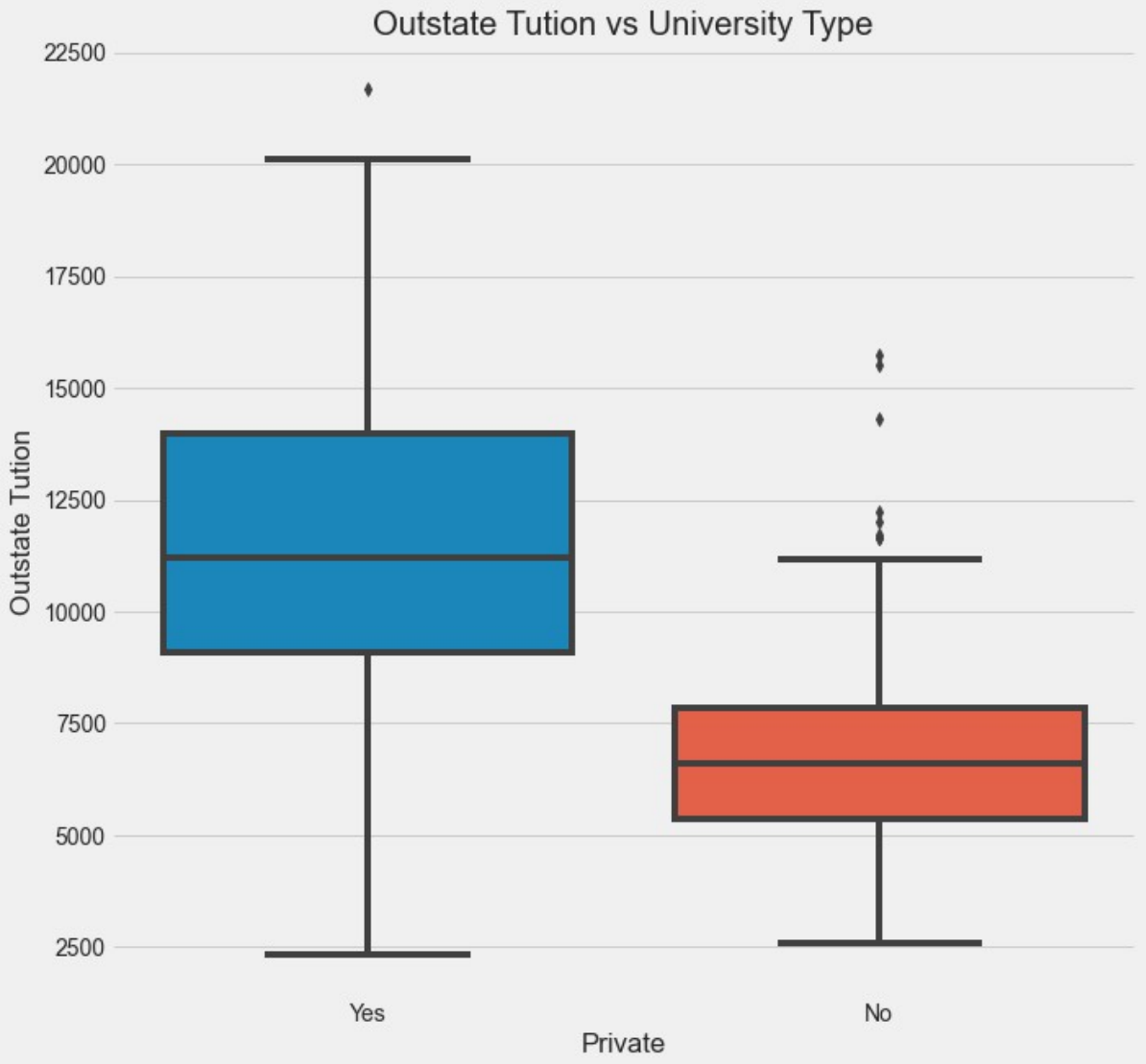
Out[16]:
```
<Figure size 864x864 with 0 Axes>
```




```
<Figure size 864x864 with 0 Axes>
```

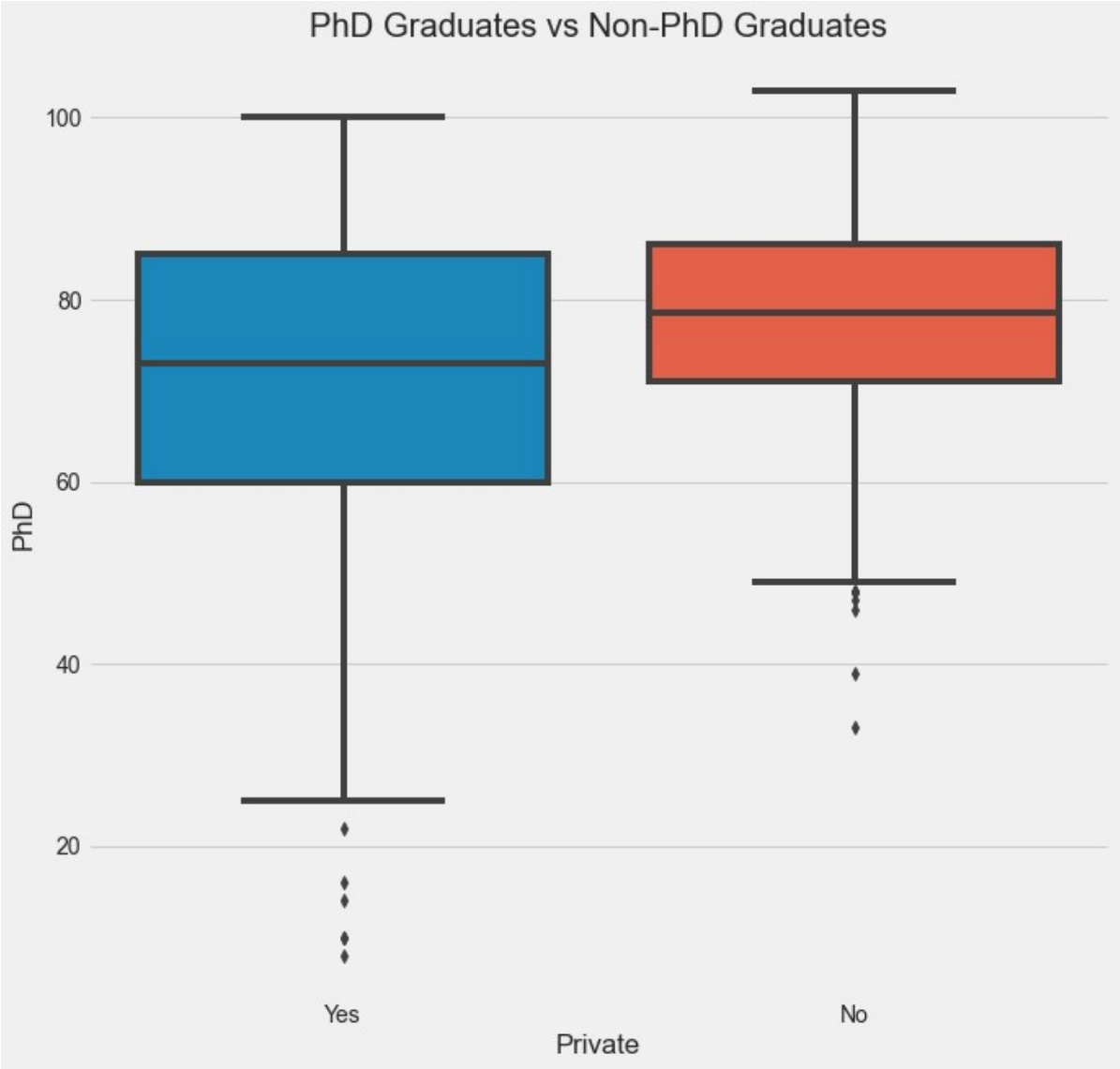
In [17]:
```
# Boxplot showing comparison of out-of-state tuition
import matplotlib.pyplot as plt
fig = plt.figure(figsize=(10, 10))
ax = fig.add_subplot(111)

sns.boxplot(y="Outstate", x="Private", data=df)
ax.set_xlabel('Private')
ax.set_ylabel('Outstate Tution')
ax.set_title('Outstate Tution vs University Type')
plt.show()
```



In [149]:
```
# Boxplot comparing % of faculty with Ph.D.s
fig = plt.figure(figsize=(10, 10))
ax = fig.add_subplot(111)

sns.boxplot(x="Private", y="PhD", data=df)
ax.set_xlabel('Private')
ax.set_ylabel('PhD')
ax.set_title('PhD Graduates vs Non-PhD Graduates')
plt.show()
```



In [287]:
```
# Transforming "Private" values which are strings into numerical values
df["Private"]=df["Private"].astype("category").cat.codes
```

In [288]:
```
df.head()
```

Out[288]:

	Private	Apps	Accept	Enroll	Top10perc	Top25perc	F_Undergrad	P_Undergrad	Outstate	Room_Board	E
0	1	1660	1232	721	23	52	2885	537	7440	3300	
1	1	2186	1924	512	16	29	2683	1227	12280	6450	
2	1	1428	1097	336	22	50	1036	99	11250	3750	
3	1	417	349	137	60	89	510	63	12960	5450	
4	1	193	146	55	16	44	249	869	7560	4120	

In [289]:
```
df.Private.value_counts()
```

Out[289]:
```
1    565
0    212
Name: Private, dtype: int64
```

In [306]:
```
# Train and test data split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.20)
```

In [307]:
```
# Creating the model and compile the Neural Network
def create_baseline():
    model=Sequential()
    model.add(Dense(60, input_dim=17, activation='relu'))
    model.add(Dense(1, activation='sigmoid'))
    return model
```

In [308]:
```
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

In [309]:
```
model.fit(X_train,Y_train, validation_data=(X_test,Y_test),epochs=100,batch_size=1
0)
```

```
Train on 621 samples, validate on 156 samples
Epoch 1/100
621/621 [==============================] - 0s 323us/step - loss: 196.5020 - accu
racy: 0.7601 - val_loss: 56.4815 - val_accuracy: 0.8974
Epoch 2/100
621/621 [==============================] - 0s 161us/step - loss: 32.3041 - accur
acy: 0.9002 - val_loss: 45.7249 - val_accuracy: 0.8397
Epoch 3/100
621/621 [==============================] - 0s 136us/step - loss: 19.5804 - accur
acy: 0.8921 - val_loss: 27.4339 - val_accuracy: 0.8718
Epoch 4/100
621/621 [==============================] - 0s 136us/step - loss: 13.6670 - accur
acy: 0.9163 - val_loss: 19.8695 - val_accuracy: 0.8654
Epoch 5/100
621/621 [==============================] - 0s 161us/step - loss: 11.4710 - accur
acy: 0.9050 - val_loss: 22.8717 - val_accuracy: 0.8718
Epoch 6/100
621/621 [==============================] - 0s 187us/step - loss: 12.4141 - accur
acy: 0.9130 - val_loss: 19.8704 - val_accuracy: 0.8141
Epoch 7/100
621/621 [==============================] - 0s 136us/step - loss: 10.3996 - accur
acy: 0.8986 - val_loss: 12.0437 - val_accuracy: 0.9103
Epoch 8/100
621/621 [==============================] - 0s 161us/step - loss: 12.3290 - accur
acy: 0.8841 - val_loss: 22.4011 - val_accuracy: 0.8782
Epoch 9/100
621/621 [==============================] - 0s 161us/step - loss: 7.0239 - accura
cy: 0.9291 - val_loss: 16.3788 - val_accuracy: 0.8910
Epoch 10/100
621/621 [==============================] - 0s 161us/step - loss: 16.4830 - accur
acy: 0.9018 - val_loss: 18.2500 - val_accuracy: 0.9231
Epoch 11/100
621/621 [==============================] - 0s 136us/step - loss: 10.5992 - accur
acy: 0.8953 - val_loss: 28.9811 - val_accuracy: 0.8782
Epoch 12/100
621/621 [==============================] - 0s 161us/step - loss: 17.3041 - accur
acy: 0.9114 - val_loss: 19.5432 - val_accuracy: 0.8974
Epoch 13/100
621/621 [==============================] - 0s 161us/step - loss: 6.6615 - accura
cy: 0.9420 - val_loss: 12.9065 - val_accuracy: 0.8654
Epoch 14/100
621/621 [==============================] - 0s 136us/step - loss: 8.9748 - accura
cy: 0.9130 - val_loss: 10.4192 - val_accuracy: 0.8590
Epoch 15/100
621/621 [==============================] - 0s 161us/step - loss: 6.8842 - accura
cy: 0.9002 - val_loss: 14.7038 - val_accuracy: 0.8462
Epoch 16/100
621/621 [==============================] - 0s 161us/step - loss: 13.1427 - accur
acy: 0.8921 - val_loss: 28.2521 - val_accuracy: 0.8974
Epoch 17/100
621/621 [==============================] - 0s 161us/step - loss: 12.1396 - accur
acy: 0.9147 - val_loss: 39.9789 - val_accuracy: 0.7051
Epoch 18/100
621/621 [==============================] - 0s 136us/step - loss: 18.2731 - accur
acy: 0.9018 - val_loss: 17.4080 - val_accuracy: 0.8974
Epoch 19/100
621/621 [==============================] - 0s 136us/step - loss: 7.9052 - accura
cy: 0.9308 - val_loss: 20.1578 - val_accuracy: 0.8974
Epoch 20/100
621/621 [==============================] - 0s 161us/step - loss: 11.6006 - accur
acy: 0.9227 - val_loss: 20.0414 - val_accuracy: 0.9038
Epoch 21/100
621/621 [==============================] - 0s 161us/step - loss: 6.4158 - accura
cy: 0.9340 - val_loss: 16.7210 - val_accuracy: 0.8462
```

Out[309]: <keras.callbacks.callbacks.History at 0x1e54099fd88>

In [312]:
```
# Compiling the NN to find out if adding more layers to
# the network improves the performance
from sklearn.model_selection import StratifiedKFold
seed=100
numpy.random.seed(seed)
kfold=StratifiedKFold(n_splits=10, shuffle=True, random_state=seed)
cveval_model = []
for train, test in kfold.split(X,Y):
    model=Sequential()
    model.add(Dense(120, input_dim=17, activation='relu'))
    model.add(Dense(1, activation='sigmoid'))
    model.compile(loss='binary_crossentropy',
                  optimizer='adam',
                  metrics=['accuracy'])
```

In [313]:
```
# Evaluating the model
eval_model=model.evaluate(X_train, Y_train)

print("%s: %.2f%%" % (model.metrics_names[1], eval_model[1]*100))
cveval_model.append(eval_model[1] * 100)
print("%.2f%% (+/- %.2f%%)" % (numpy.mean(cveval_model), numpy.std(cveval_model)))
```

```
621/621 [==============================] - 0s 50us/step
accuracy: 77.78%
77.78% (+/- 0.00%)
```

In [314]:
```
y_pred = model.predict(X_test)
y_pred = (y_pred>0.5)
```

In [315]:
```
# Looking at the confusion matrix below and the result from
# the evaluation we can confidently assume that the accuracy is
# around 78% which is good. In other words this means, if the
# prediction value is less than 0.5 then the prediction is
# class = 0 = "No" otherwise the prediction is
# class = 1 = "Yes".
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(Y_test, y_pred)
print(cm)
```

```
[[  4  35]
 [  0 117]]
```

Summary

The Baseline performed better in this case, we did get a marginal lift but more training, for example, by optimizing the algorithm and increasing the number of training epochs could produce better scores. Overall the results of the score for the NN model was good.

In [ ]: