Bank Marketing Data from Kaggle: Implementing and Experimenting with Artificial Neural Network

About the Problem:

Objective is to find the best strategies to improve for the next marketing campaign. How can the financial institution have a greater effectiveness for future marketing campaigns? In order to answer this, we have to analyze the last marketing campaign the bank performed and identify the patterns that will help us find conclusions in order to develop future strategies.

Importing Libraries

In [1]:
```
import os
import sys
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
%matplotlib inline


import warnings
warnings.filterwarnings('ignore')
```

Reading the 'bank' Dataset

In [2]:
```
df_Bank=pd.read_csv('bank-full.csv',sep=';')
df_Bank.head(3)
```

Out[2]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duratio
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	26
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	15
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	7

In [3]:
```
df_Bank.shape
```

Out[3]:
```
(45211, 17)
```

Exploratory Data Analysis:

In [4]:
```
#Check for Missing Value

df_Bank.isnull().sum()
```

Out[4]:
```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

In [5]:
```
df_Bank.describe()
```

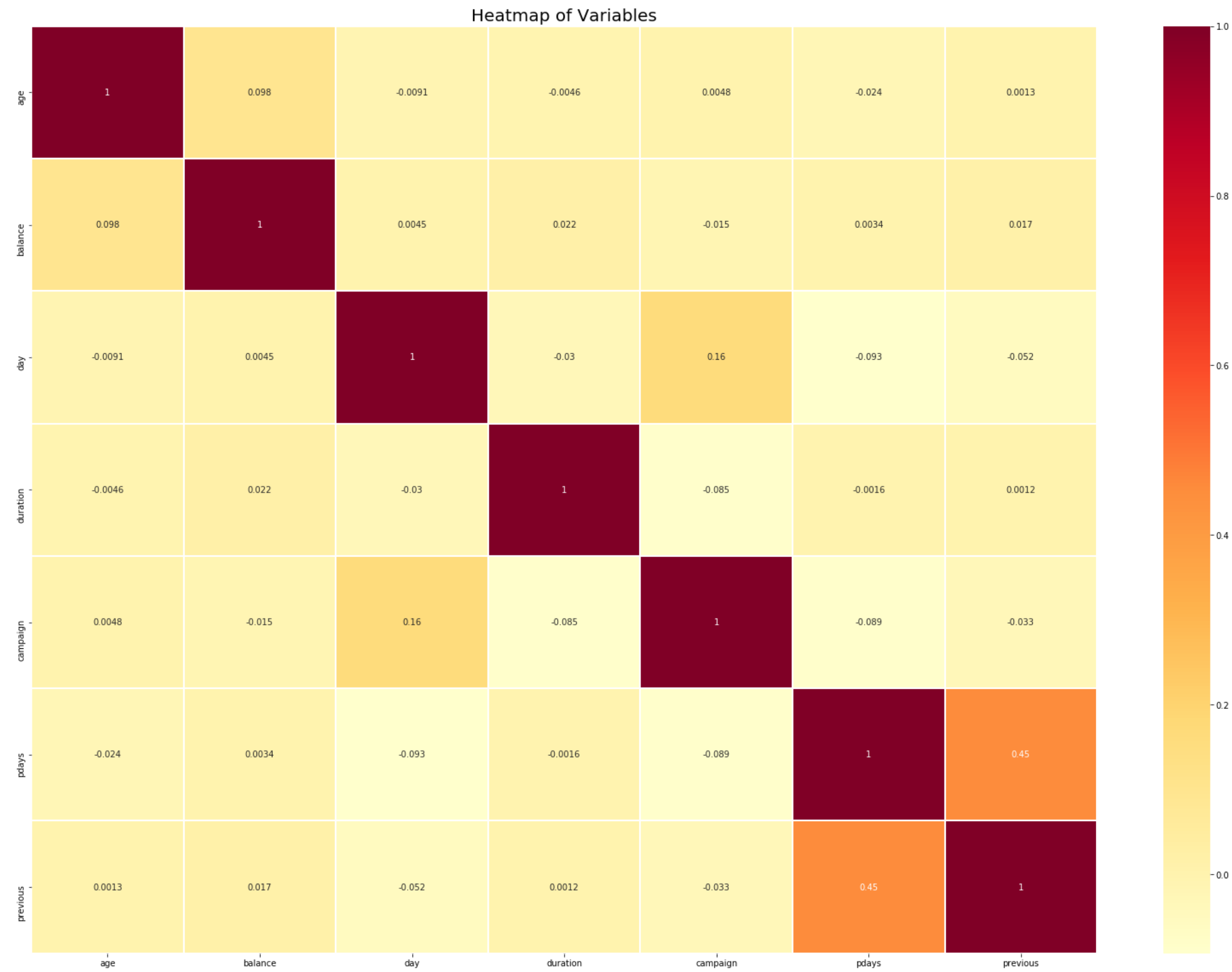
Out[5]:

	age	balance	day	duration	campaign	pdays	previo
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.0000
mean	40.936210	1362.272058	15.806419	258.163080	2.763841	40.197828	0.5803
std	10.618762	3044.765829	8.322476	257.527812	3.098021	100.128746	2.3034
min	18.000000	-8019.000000	1.000000	0.000000	1.000000	-1.000000	0.0000
25%	33.000000	72.000000	8.000000	103.000000	1.000000	-1.000000	0.0000
50%	39.000000	448.000000	16.000000	180.000000	2.000000	-1.000000	0.0000
75%	48.000000	1428.000000	21.000000	319.000000	3.000000	-1.000000	0.0000
max	95.000000	102127.000000	31.000000	4918.000000	63.000000	871.000000	275.0000

Correlation plot to pick out the best features for the model

In [6]:
```python
#Correlation:

fig = plt.figure(figsize=(28,20))

axis = sns.heatmap(df_Bank.corr(), cmap= 'YlOrRd', linewidth=1, linecolor='white', an
axis.set_title('Heatmap of Variables', fontsize=20)
```

Out[6]:
```
Text(0.5,1,'Heatmap of Variables')
```



For the feature selection we are implementing the elimination using correlation backed up by the business intuition-

In [7]:
```
corr_matrix = df_Bank.corr().abs()

#the matrix is symmetric so we need to extract upper triangle matrix without diagonal

sol = (corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(np.bool))
                 .stack()
                 .sort_values(ascending=False))
sol = sol.to_frame()
sol.columns=['corr']
sol[sol['corr'] >  0.88]
```

Out[7]:

	corr

In [8]:
```
df_Bank.columns
```

Out[8]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'y'],
      dtype='object')
```

In [9]:
```
cat=["job", "marital", "education","contact","month", "poutcome"]
```

Data Preparation:

Label Encoding for the above categorical features-

In [10]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

for i in cat:
    print("Encoding",i)
    df_Bank[i] = le.fit_transform(df_Bank[i])
```

```
Encoding job
Encoding marital
Encoding education
Encoding contact
Encoding month
Encoding poutcome
```

In [11]:
```
cleanup_nums = {"default":     {"yes": 1, "no": 0},
                "housing": {"yes": 1, "no": 0}, "loan":{"yes": 1, "no": 0}, "y":{"yes
```

In [12]:
```
df_Bank.replace(cleanup_nums, inplace=True)
```

In [13]:
```
df_Bank.columns
```

Out[13]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'y'],
      dtype='object')
```

Encoded data looks like this:

In [14]:
```
df_Bank.head()
```

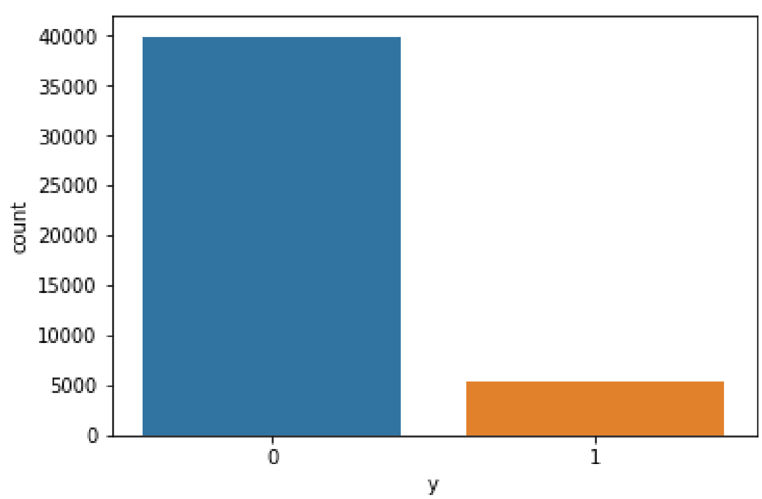
Out[14]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campa
0	58	4	1	2	0	2143	1	0	2	5	8	261	
1	44	9	2	1	0	29	1	0	2	5	8	151	
2	33	2	1	1	0	2	1	1	2	5	8	76	
3	47	1	1	3	0	1506	1	0	2	5	8	92	
4	33	11	2	3	0	1	0	0	2	5	8	198	

Lets have a overlook at the count of classes to check the Ratio of Classes:

In [15]:
```
sns.countplot(df_Bank['y'])
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x24f948989b0>



Its a clear case of "Class Imbalance Problem"-

Here the 'Class 0' which shows that "Client is not Subscribing a term deposit" accounts for more than 90% of the data and ' Class 1' accounts for merely 10%. But my objecive here is to identify the instances of 'Class 1'. I can reach an accuracy of around 90% by simply predicting 'Class 0' every time, but this provides a useless classifier for my intended use case.

time, but this provides a useless classifier for my intended use case. Due to this reason, I will 'undersample' the instances of majority class (i.e 'Class 0'). This way I will simply create a balanced data-set.

Undersampling data

In [16]:
```
yes = len(df_Bank[df_Bank["y"]==1])
yes
```

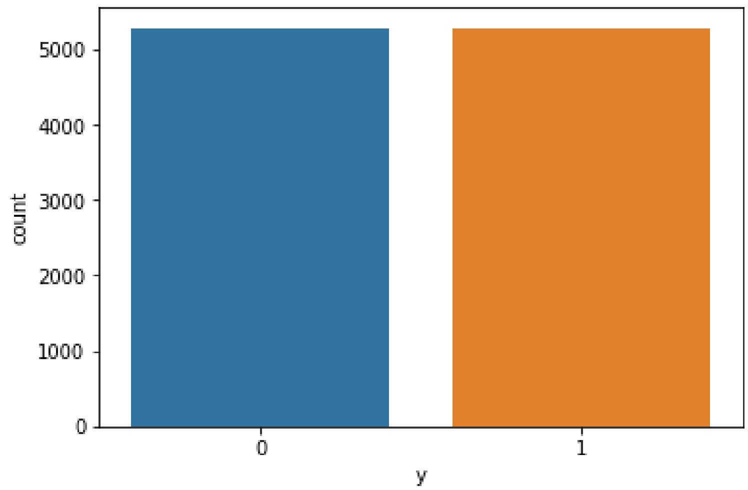
Out[16]:
```
5289
```

In [17]:
```
# Index of normal classes
no=df_Bank[df_Bank["y"]==0].index

# Random sample non-fraud indexes
no_ind=np.random.choice(no,yes,replace=False)

# Index of fraud classes
yes_ind=df_Bank[df_Bank.y==1].index

# Concat fraud indexes and sample normal indexes
final_ind=np.concatenate([no_ind,yes_ind])

# Final balanced dataframe from undersampling
balanced_df=df_Bank.loc[final_ind]

balanced_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10578 entries, 33007 to 45208
Data columns (total 17 columns):
age          10578 non-null int64
job          10578 non-null int64
marital      10578 non-null int64
education    10578 non-null int64
default      10578 non-null int64
balance      10578 non-null int64
housing      10578 non-null int64
loan         10578 non-null int64
contact      10578 non-null int64
day          10578 non-null int64
month        10578 non-null int64
duration     10578 non-null int64
campaign     10578 non-null int64
pdays        10578 non-null int64
previous     10578 non-null int64
poutcome     10578 non-null int64
y            10578 non-null int64
dtypes: int64(17)
memory usage: 1.5 MB
```

In [18]:
```
sns.countplot(balanced_df['y'])
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x24f94ccddd8>



Shape of new balanced data-set after Undersampling:

In [19]:
```
balanced_df.shape
```

Out[19]: (10578, 17)

Train Test Split: Splitting the data into Train and Test sets and scaling the data

In [20]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

x = balanced_df.drop(columns=['y'],axis=1)
y = balanced_df['y']

xTrain_org, xTest_org, yTrain, yTest = train_test_split(x,y, test_size = 0.3, random_

scaler = StandardScaler()

xTrain = scaler.fit_transform(xTrain_org)
xTest = scaler.transform(xTest_org)
```

In [21]:
```
print('Shape of xTrain Set', xTrain.shape)
print('Shape of yTrain Set', yTrain.shape)

print('')

print('Shape of xTest Set', xTest.shape)
print('Shape of yTest Set', yTest.shape)
```

```
Shape of xTrain Set (7404, 16)
Shape of yTrain Set (7404,)

Shape of xTest Set (3174, 16)
Shape of yTest Set (3174,)
```

Importing libraries for Neural Network and Grid Search

In [22]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.wrappers.scikit_learn import KerasClassifier

from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

1) Creating a basic Neural Network model with just Input and Output Layer

In [23]:
```
### Number of neurons in input layer = Number of features + 1(for bias)

model = Sequential()
model.add(Dense(17, input_dim = 16, activation = 'relu'))
model.add(Dense(1, activation = 'sigmoid'))
model.compile(loss = 'binary_crossentropy', optimizer = 'Adam', metrics = ['accuracy'

model.fit(xTrain,yTrain)
```

```
Epoch 1/1
7404/7404 [==============================] - 0s 47us/step - loss: 0.6175 - acc: 0.6
507
```

Out[23]: `<tensorflow.python.keras.callbacks.History at 0x24f9a72acf8>`

In [24]:
```
model.evaluate(xTrain,yTrain)
```

```
7404/7404 [==============================] - 0s 12us/step
```

Out[24]: `[0.5313108413687015, 0.748784440874989]`

In [25]:
```
model.evaluate(xTest,yTest)
```

```
3174/3174 [==============================] - 0s 10us/step
```

Out[25]: `[0.536472662973494, 0.7309388784244516]`

Confusion Metrics:

In [26]:
```
y_test_pred = model.predict(xTest)

y_pred = np.where(y_test_pred>= 0.5, 1, 0)

print('Classification Report:')
print(classification_report(yTest,y_pred))
print('Confusion Matrix:')
print(confusion_matrix(yTest,y_pred))
```

```
Classification Report:
             precision    recall  f1-score   support

          0       0.73      0.72      0.72      1568
          1       0.73      0.74      0.74      1606

avg / total       0.73      0.73      0.73      3174

Confusion Matrix:
[[1124  444]
 [ 410 1196]]
```

---Experimenting with different Parameters (showing various Learning Curves also for better understanding)---

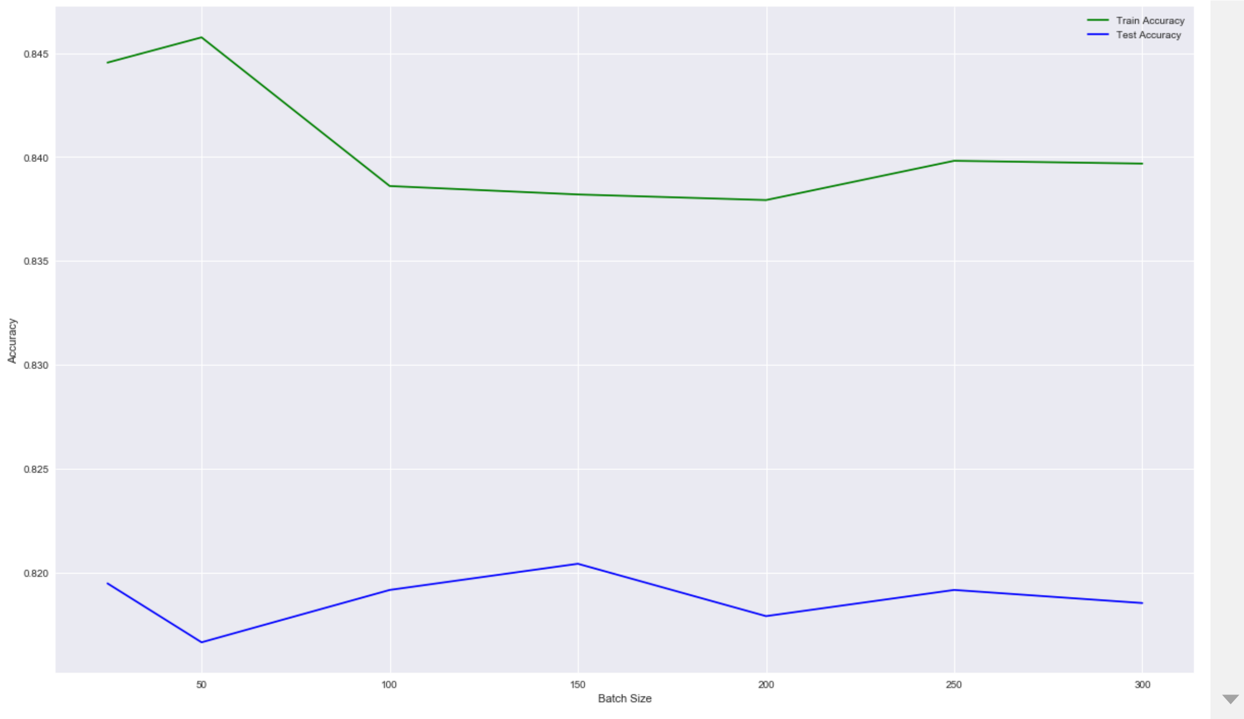
2a) Batch Size: Variation of Accuracy by Batch Size

In [27]:

```
sns.set(rc={'figure.figsize':(20,12)})

batch_size = [25,50,100,150,200,250,300]

train_accuracy_array = []
test_accuracy_array = []

for i in batch_size:
    model = Sequential()
    model.add(Dense(17, input_dim = 16, activation = 'relu'))
    model.add(Dense(1, activation = 'sigmoid'))
    model.compile(loss = 'binary_crossentropy', optimizer = 'Adam', metrics = ['accur

    model.fit(xTrain, yTrain, epochs=150, batch_size = i, verbose=0)

    train_accuracy_array.append(model.evaluate(xTrain, yTrain)[1])
    test_accuracy_array.append(model.evaluate(xTest, yTest)[1])


x_axis = [25,50,100,150,200,250,300]
plt.plot(x_axis, train_accuracy_array, c = 'g', label = 'Train Accuracy')
plt.plot(x_axis, test_accuracy_array, c = 'b', label = 'Test Accuracy')
plt.legend()
plt.xlabel('Batch Size')
plt.ylabel('Accuracy')
```

```
7404/7404 [==============================] - 0s 13us/step
3174/3174 [==============================] - 0s 12us/step
7404/7404 [==============================] - 0s 16us/step
3174/3174 [==============================] - 0s 9us/step
7404/7404 [==============================] - 0s 16us/step
3174/3174 [==============================] - 0s 11us/step
7404/7404 [==============================] - 0s 18us/step
3174/3174 [==============================] - 0s 10us/step
7404/7404 [==============================] - 0s 20us/step
3174/3174 [==============================] - 0s 10us/step
7404/7404 [==============================] - 0s 22us/step
3174/3174 [==============================] - 0s 10us/step
7404/7404 [==============================] - 0s 25us/step
3174/3174 [==============================] - 0s 10us/step
```

Out[27]: Text(0,0.5,'Accuracy')

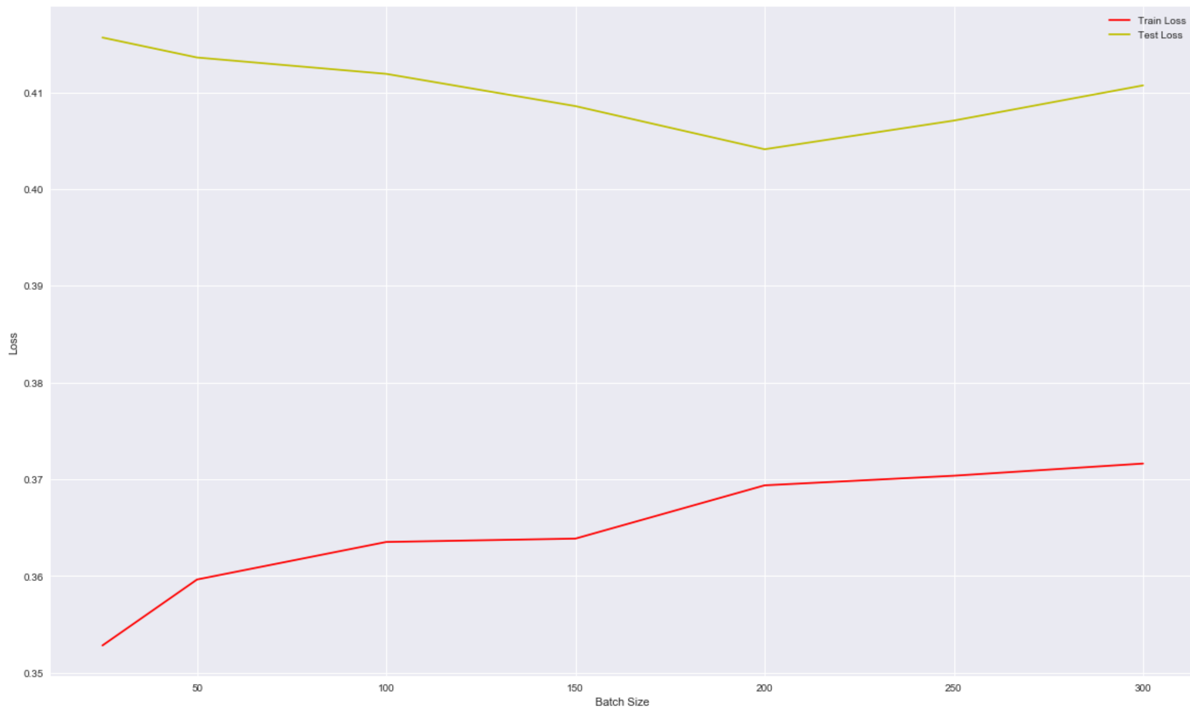


2b) Variation of Loss by Batch Size:

In [28]:
```python
sns.set(rc={'figure.figsize':(20,12)})

batch_size = [25,50,100,150,200,250,300]

train_loss_array =[]
test_loss_array =[]

for i in batch_size:
    model = Sequential()
    model.add(Dense(17, input_dim = 16, activation = 'relu'))
    model.add(Dense(1, activation = 'sigmoid'))
    model.compile(loss = 'binary_crossentropy', optimizer = 'Adam', metrics = ['accur
    model.fit(xTrain,yTrain,epochs=150,batch_size=i,verbose=0)

    train_loss_array.append(model.evaluate(xTrain, yTrain)[0])
    test_loss_array.append(model.evaluate(xTest, yTest)[0])

x_axis = [25,50,100,150,200,250,300]
plt.plot(x_axis, train_loss_array, c = 'r', label = 'Train Loss')
plt.plot(x_axis, test_loss_array, c = 'y', label = 'Test Loss')
plt.legend()
plt.xlabel('Batch Size')
plt.ylabel('Loss')
```

```
7404/7404 [==============================] - 0s 25us/step
3174/3174 [==============================] - 0s 10us/step
7404/7404 [==============================] - 0s 27us/step
3174/3174 [==============================] - 0s 9us/step
7404/7404 [==============================] - 0s 29us/step
3174/3174 [==============================] - 0s 11us/step
7404/7404 [==============================] - 0s 31us/step
3174/3174 [==============================] - 0s 9us/step
7404/7404 [==============================] - 0s 31us/step
3174/3174 [==============================] - 0s 10us/step
7404/7404 [==============================] - 0s 34us/step
3174/3174 [==============================] - 0s 11us/step
7404/7404 [==============================] - 0s 37us/step
3174/3174 [==============================] - 0s 12us/step
```

Out[28]: Text(0,0.5,'Loss')



Above experiment shows that for the "batch_size = 150" both Loss is less and Accuracy are optimal

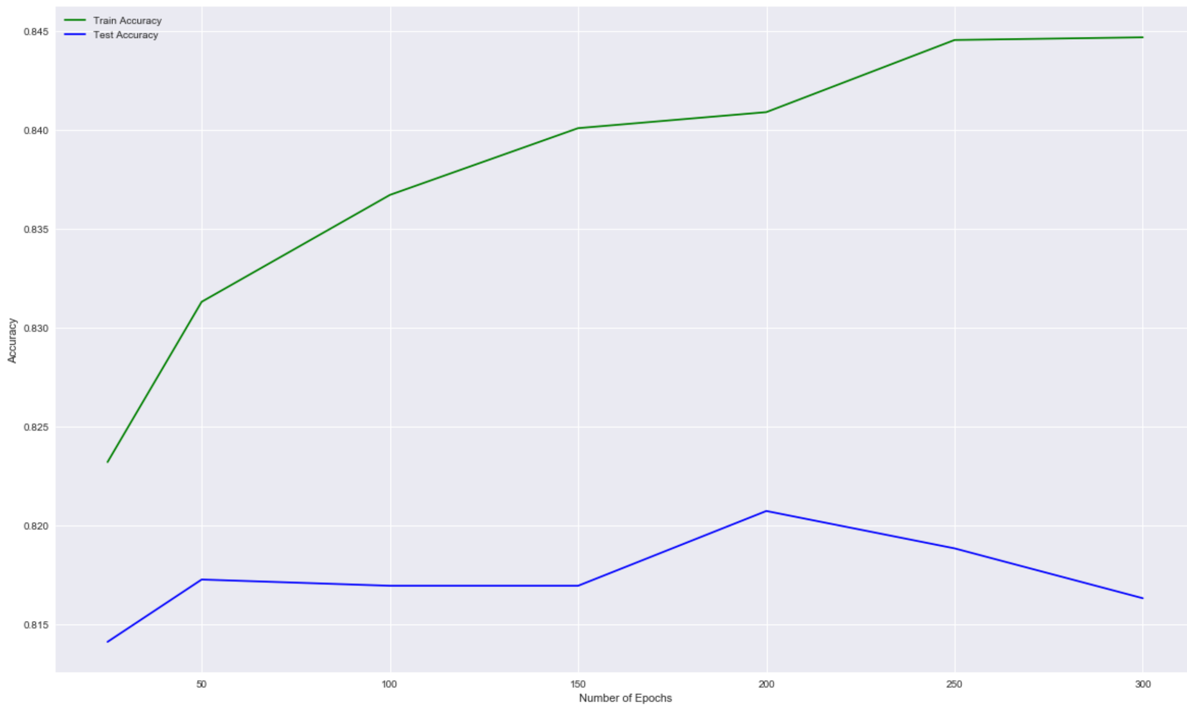
3a) Epochs: Variation of Accuracy by Epochs

In [39]:

```python
sns.set(rc={'figure.figsize':(20,12)})

epochs = [25,50,100,150,200,250,300]

train_accuracy_array = []
test_accuracy_array = []

for i in epochs:
    model = Sequential()
    model.add(Dense(17, input_dim = 16, activation = 'relu'))
    model.add(Dense(1, activation = 'sigmoid'))
    model.compile(loss = 'binary_crossentropy', optimizer = 'Adam', metrics = ['accur
    model.fit(xTrain,yTrain,epochs=i,batch_size=150,verbose=0)

    train_accuracy_array.append(model.evaluate(xTrain, yTrain)[1])
    test_accuracy_array.append(model.evaluate(xTest, yTest)[1])


x_axis = [25,50,100,150,200,250,300]
plt.plot(x_axis, train_accuracy_array, c = 'g', label = 'Train Accuracy')
plt.plot(x_axis, test_accuracy_array, c = 'b', label = 'Test Accuracy')
plt.legend()
plt.xlabel('Number of Epochs')
plt.ylabel('Accuracy')
```

```
7404/7404 [==============================] - 1s 110us/step
3174/3174 [==============================] - 0s 21us/step
7404/7404 [==============================] - 1s 102us/step
3174/3174 [==============================] - 0s 17us/step
7404/7404 [==============================] - 1s 114us/step
3174/3174 [==============================] - 0s 20us/step
7404/7404 [==============================] - 1s 126us/step
3174/3174 [==============================] - 0s 18us/step
7404/7404 [==============================] - 1s 114us/step
3174/3174 [==============================] - 0s 18us/step
7404/7404 [==============================] - 1s 122us/step
3174/3174 [==============================] - 0s 19us/step
7404/7404 [==============================] - 1s 122us/step
3174/3174 [==============================] - 0s 18us/step
```

Out[39]: Text(0,0.5,'Accuracy')



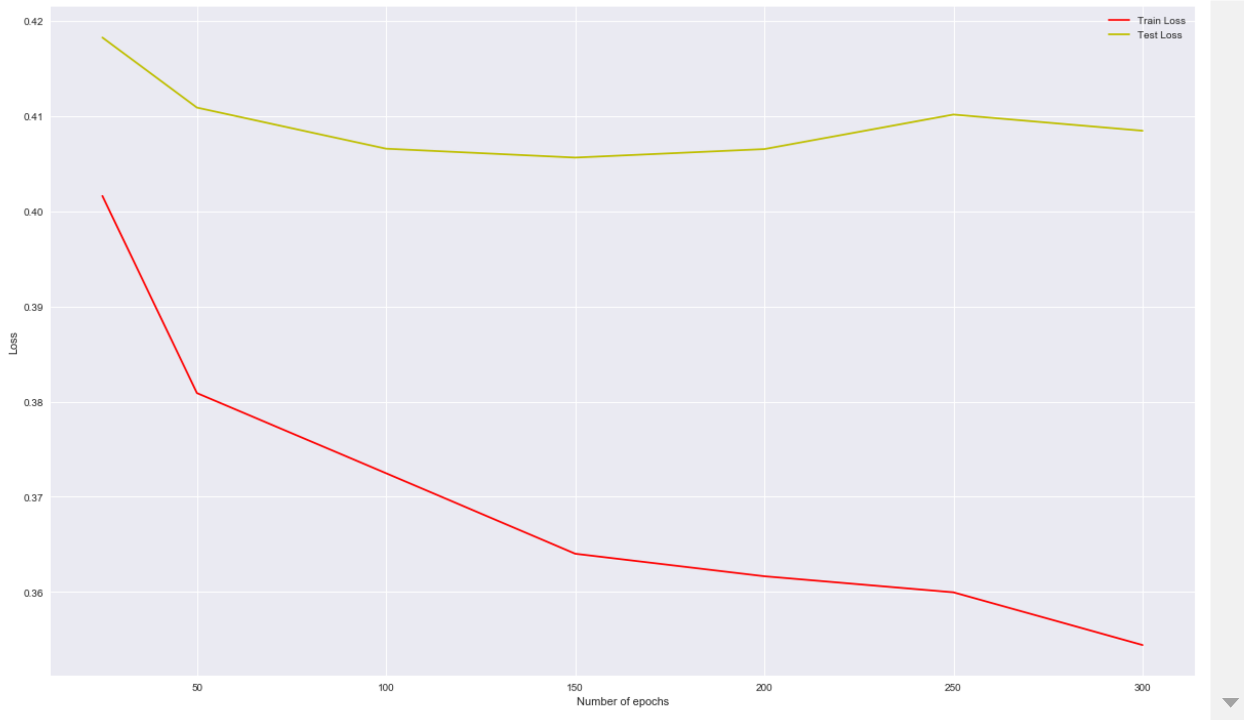
3b) Variation of Loss by Epochs

In [40]:

```python
sns.set(rc={'figure.figsize':(20,12)})

epochs = [25,50,100,150,200,250,300]

train_loss_array =[]
test_loss_array =[]

for i in batch_size:
    model = Sequential()
    model.add(Dense(17, input_dim = 16, activation = 'relu'))
    model.add(Dense(1, activation = 'sigmoid'))
    model.compile(loss = 'binary_crossentropy', optimizer = 'Adam', metrics = ['accur
    model.fit(xTrain,yTrain,epochs=i,batch_size=150,verbose=0)

    train_loss_array.append(model.evaluate(xTrain, yTrain)[0])
    test_loss_array.append(model.evaluate(xTest, yTest)[0])

x_axis = [25,50,100,150,200,250,300]
plt.plot(x_axis, train_loss_array, c = 'r', label = 'Train Loss')
plt.plot(x_axis, test_loss_array, c = 'y', label = 'Test Loss')
plt.legend()
plt.xlabel('Number of epochs')
plt.ylabel('Loss')
```

```
7404/7404 [==============================] - 1s 124us/step
3174/3174 [==============================] - 0s 19us/step
7404/7404 [==============================] - 1s 129us/step
3174/3174 [==============================] - 0s 18us/step
7404/7404 [==============================] - 1s 135us/step
3174/3174 [==============================] - 0s 19us/step
7404/7404 [==============================] - 1s 132us/step
3174/3174 [==============================] - 0s 22us/step
7404/7404 [==============================] - 1s 130us/step
3174/3174 [==============================] - 0s 19us/step
7404/7404 [==============================] - 1s 131us/step
3174/3174 [==============================] - 0s 19us/step
7404/7404 [==============================] - 1s 178us/step
3174/3174 [==============================] - 0s 29us/step
```

Out[40]: Text(0,0.5,'Loss')



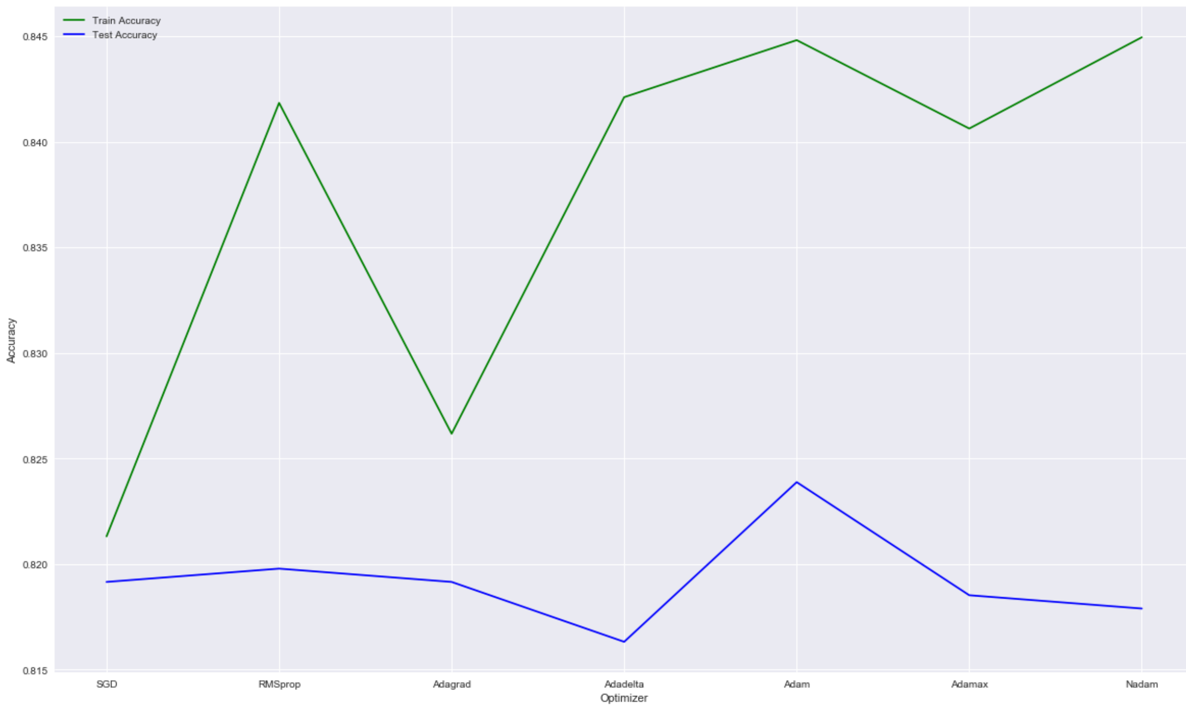
Above experiment shows that from epoch 150 to 200 Test Accuracy shows the incremental trend at "epoch = 200" it has highest value, similarly with 200 epochs value of loss is also low. So I will choose 200 Epochs for my experiment.

4a) Optimizer: Variation of Accuracy by Optimizer

In [41]:
```
sns.set(rc={'figure.figsize':(20,12)})

optimizer =['SGD', 'RMSprop', 'Adagrad', 'Adadelta', 'Adam', 'Adamax', 'Nadam']

train_accuracy_array = []
test_accuracy_array = []

for i in optimizer:
    model = Sequential()
    model.add(Dense(17, input_dim = 16, activation = 'relu'))
    model.add(Dense(1, activation = 'sigmoid'))
    model.compile(loss = 'binary_crossentropy', optimizer = i, metrics = ['accuracy']
    model.fit(xTrain,yTrain,epochs=200,batch_size=150,verbose=0)

    train_accuracy_array.append(model.evaluate(xTrain, yTrain)[1])
    test_accuracy_array.append(model.evaluate(xTest, yTest)[1])


x_axis = ['SGD', 'RMSprop', 'Adagrad', 'Adadelta', 'Adam', 'Adamax', 'Nadam']
plt.plot(x_axis, train_accuracy_array, c = 'g', label = 'Train Accuracy')
plt.plot(x_axis, test_accuracy_array, c = 'b', label = 'Test Accuracy')
plt.legend()
plt.xlabel('Optimizer')
plt.ylabel('Accuracy')
```

```
7404/7404 [==============================] - 1s 133us/step
3174/3174 [==============================] - 0s 21us/step
7404/7404 [==============================] - 1s 134us/step
3174/3174 [==============================] - 0s 21us/step
7404/7404 [==============================] - 1s 145us/step
3174/3174 [==============================] - 0s 22us/step
7404/7404 [==============================] - 1s 139us/step
3174/3174 [==============================] - 0s 20us/step
7404/7404 [==============================] - 1s 166us/step
3174/3174 [==============================] - 0s 28us/step
7404/7404 [==============================] - 1s 146us/step
3174/3174 [==============================] - 0s 21us/step
7404/7404 [==============================] - 1s 152us/step
3174/3174 [==============================] - 0s 21us/step
```

Out[41]: Text(0,0.5,'Accuracy')



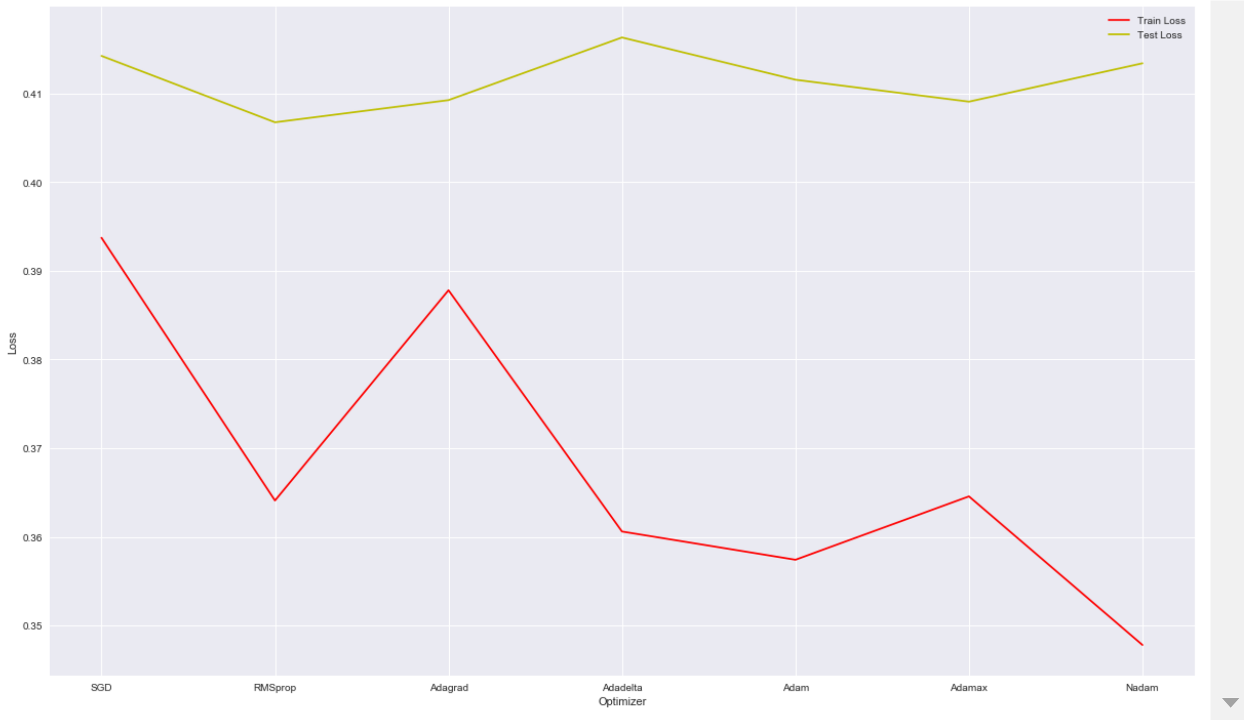
4b) Variation of Loss by Optimizer

In [42]:

```
sns.set(rc={'figure.figsize':(20,12)})

optimizer =['SGD', 'RMSprop', 'Adagrad', 'Adadelta', 'Adam', 'Adamax', 'Nadam']

train_loss_array =[]
test_loss_array =[]

for i in optimizer:
    model = Sequential()
    model.add(Dense(17, input_dim = 16, activation = 'relu'))
    model.add(Dense(1, activation = 'sigmoid'))
    model.compile(loss = 'binary_crossentropy', optimizer = i, metrics = ['accuracy']
    model.fit(xTrain,yTrain,epochs=200,batch_size=150,verbose=0)

    train_loss_array.append(model.evaluate(xTrain, yTrain)[0])
    test_loss_array.append(model.evaluate(xTest, yTest)[0])

x_axis = ['SGD', 'RMSprop', 'Adagrad', 'Adadelta', 'Adam', 'Adamax', 'Nadam']
plt.plot(x_axis, train_loss_array, c = 'r', label = 'Train Loss')
plt.plot(x_axis, test_loss_array, c = 'y', label = 'Test Loss')
plt.legend()
plt.xlabel('Optimizer')
plt.ylabel('Loss')
```

```
7404/7404 [==============================] - 1s 148us/step
3174/3174 [==============================] - 0s 22us/step
7404/7404 [==============================] - 1s 151us/step
3174/3174 [==============================] - 0s 21us/step
7404/7404 [==============================] - 1s 150us/step
3174/3174 [==============================] - 0s 25us/step
7404/7404 [==============================] - 1s 158us/step
3174/3174 [==============================] - 0s 21us/step
7404/7404 [==============================] - 1s 156us/step
3174/3174 [==============================] - 0s 20us/step
7404/7404 [==============================] - 1s 193us/step
3174/3174 [==============================] - 0s 38us/step
7404/7404 [==============================] - 1s 164us/step
3174/3174 [==============================] - 0s 22us/step
```

Out[42]: Text(0,0.5,'Loss')



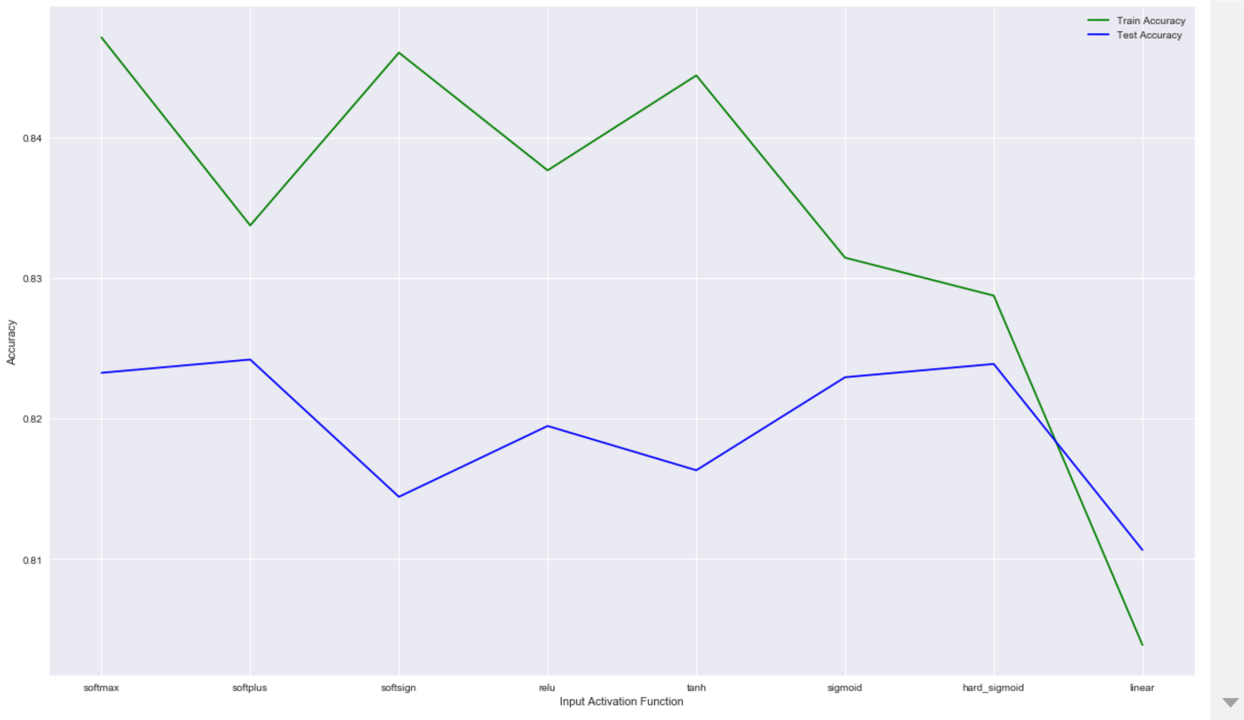
Above experiment for Optimizer shows that for "Adam", Train and Test accuracy is high and loss is also low

5a) Input Activation Function: Variation of Accuracy by input activation function:

In [43]:
```
sns.set(rc={'figure.figsize':(20,12)})

activations = ['softmax', 'softplus', 'softsign', 'relu', 'tanh', 'sigmoid', 'hard_si

train_accuracy_array = []
test_accuracy_array = []

for i in activations:
    model = Sequential()
    model.add(Dense(17, input_dim = 16, activation = i))
    model.add(Dense(1, activation = 'sigmoid'))
    model.compile(loss = 'binary_crossentropy', optimizer = 'Adam', metrics = ['accur
    model.fit(xTrain,yTrain,epochs=200,batch_size=150,verbose=0)
                                                                                # ba

    train_accuracy_array.append(model.evaluate(xTrain, yTrain)[1])
    test_accuracy_array.append(model.evaluate(xTest, yTest)[1])


x_axis = ['softmax', 'softplus', 'softsign', 'relu', 'tanh', 'sigmoid', 'hard_sigmoid
plt.plot(x_axis, train_accuracy_array, c = 'g', label = 'Train Accuracy')
plt.plot(x_axis, test_accuracy_array, c = 'b', label = 'Test Accuracy')
plt.legend()
plt.xlabel('Input Activation Function')
plt.ylabel('Accuracy')
```

```
7404/7404 [==============================] - 1s 153us/step
3174/3174 [==============================] - 0s 23us/step
7404/7404 [==============================] - 1s 156us/step
3174/3174 [==============================] - 0s 20us/step
7404/7404 [==============================] - 1s 165us/step
3174/3174 [==============================] - 0s 23us/step
7404/7404 [==============================] - 1s 169us/step
3174/3174 [==============================] - 0s 24us/step
7404/7404 [==============================] - 1s 170us/step
3174/3174 [==============================] - 0s 23us/step
7404/7404 [==============================] - 1s 174us/step
3174/3174 [==============================] - 0s 22us/step
7404/7404 [==============================] - 1s 188us/step
3174/3174 [==============================] - 0s 26us/step
7404/7404 [==============================] - 1s 183us/step
3174/3174 [==============================] - 0s 24us/step
```

Out[43]:
```
Text(0,0.5,'Accuracy')
```



5b) Variation of Loss by input activation function:

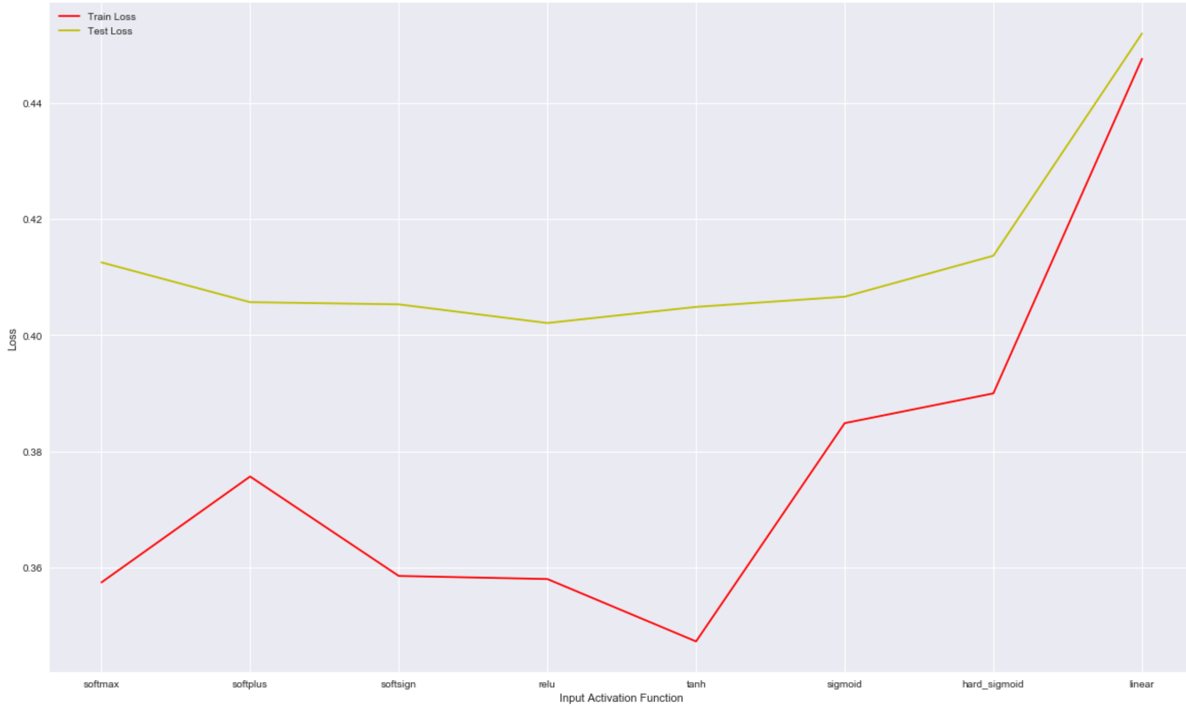
In [44]:

```
sns.set(rc={'figure.figsize':(20,12)})

activations = ['softmax', 'softplus', 'softsign', 'relu', 'tanh', 'sigmoid', 'hard_si

train_loss_array =[]
test_loss_array =[]

for i in activations:
    model = Sequential()
    model.add(Dense(17, input_dim = 16, activation = i))
    model.add(Dense(1, activation = 'sigmoid'))
    model.compile(loss = 'binary_crossentropy', optimizer = 'Adam', metrics = ['accur
    model.fit(xTrain,yTrain,epochs=200,batch_size=150,verbose=0)
                                                                                  # ba

    train_loss_array.append(model.evaluate(xTrain, yTrain)[0])
    test_loss_array.append(model.evaluate(xTest, yTest)[0])

x_axis = ['softmax', 'softplus', 'softsign', 'relu', 'tanh', 'sigmoid', 'hard_sigmoid
plt.plot(x_axis, train_loss_array, c = 'r', label = 'Train Loss')
plt.plot(x_axis, test_loss_array, c = 'y', label = 'Test Loss')
plt.legend()
plt.xlabel('Input Activation Function')
plt.ylabel('Loss')
```

```
7404/7404 [==============================] - 1s 177us/step
3174/3174 [==============================] - 0s 23us/step
7404/7404 [==============================] - 1s 202us/step
3174/3174 [==============================] - 0s 28us/step
7404/7404 [==============================] - 1s 184us/step
3174/3174 [==============================] - 0s 25us/step
7404/7404 [==============================] - 1s 197us/step
3174/3174 [==============================] - 0s 33us/step
7404/7404 [==============================] - 1s 194us/step
3174/3174 [==============================] - 0s 24us/step
7404/7404 [==============================] - 1s 193us/step
3174/3174 [==============================] - 0s 24us/step
7404/7404 [==============================] - 1s 196us/step
3174/3174 [==============================] - 0s 25us/step
7404/7404 [==============================] - 1s 198us/step
3174/3174 [==============================] - 0s 25us/step
```

Out[44]:

```
Text(0,0.5,'Loss')
```



So its clear from the above experiment that for "softplus" input activation function Accuracy is high and Loss is low

Summary of above Experiments:

From all of the above experiments we got the following best parameters-

1. batch_size = 150

2. Epochs = 200

3. Optimizer = Adam

4. Activation Function = softplus

Apply above parameters on the basic Neural Network (with only i/p and o/p layer):

In [45]:
```
model = Sequential()
model.add(Dense(17, input_dim = 16, activation = 'softplus'))
model.add(Dense(1, activation = 'sigmoid'))
model.compile(loss = 'binary_crossentropy', optimizer = 'Adam', metrics = ['accuracy'

model.fit(xTrain,yTrain,epochs=200,batch_size=150,verbose=0)
```

Out[45]:
```
<tensorflow.python.keras.callbacks.History at 0x24fe8768b70>
```

In [46]:
```
model.evaluate(xTrain, yTrain)
```

```
7404/7404 [==============================] - 1s 190us/step
```

Out[46]:
```
[0.377869840693242, 0.8326580227226389]
```

In [47]:
```
model.evaluate(xTest, yTest)
```

```
3174/3174 [==============================] - 0s 31us/step
```

Out[47]:
```
[0.40501939909557316, 0.8204158790170132]
```

In [64]:
```
y_test_pred = model.predict(xTest)
y_pred = np.where(y_test_pred>= 0.5, 1, 0)

print('Classification Report:')
print(classification_report(yTest,y_pred))
print('Confusion Matrix:')
print(confusion_matrix(yTest,y_pred))
```

```
Classification Report:
             precision    recall  f1-score   support

          0       0.82      0.82      0.82      1568
          1       0.82      0.83      0.83      1606

avg / total       0.82      0.82      0.82      3174

Confusion Matrix:
[[1280  288]
 [ 274 1332]]
```

Observation: These values of Train and Test Accuracies (and loss) are clearly better than the previous NN model that we trained and test at the very beginning (where loss was around 0.52 and accuracy was around 0.71)

Based upon our observation of various learning curves, these experiments helped us to find the good parameters.

Additional Experiments:

6) Adding a Hidden Layer to see if Accuracy is improved:

In [61]:
```
model = Sequential()
model.add(Dense(17, input_dim = 16, activation = 'softplus'))
model.add(Dense(9, activation = 'relu'))
model.add(Dense(1, activation = 'sigmoid'))
model.compile(loss = 'binary_crossentropy', optimizer = 'Adam', metrics = ['accuracy'

model.fit(xTrain,yTrain,epochs=200,batch_size=150,verbose=0)
```

Out[61]: <tensorflow.python.keras.callbacks.History at 0x24fec2e3d68>

In [62]:
```
model.evaluate(xTrain, yTrain)
```

```
7404/7404 [==============================] - ETA:  - 2s 220us/step
```

Out[62]: [0.3562574301343683, 0.8423824959803374]

In [63]:
```
model.evaluate(xTest, yTest)
```

```
3174/3174 [==============================] - 0s 28us/step
```

Out[63]: [0.40938626616611073, 0.8229363579080026]

In [65]:
```
y_test_pred = model.predict(xTest)
y_pred = np.where(y_test_pred>= 0.5, 1, 0)

print('Classification Report:')
print(classification_report(yTest,y_pred))
print('Confusion Matrix:')
print(confusion_matrix(yTest,y_pred))
```

```
Classification Report:
             precision    recall  f1-score   support

          0       0.82      0.82      0.82      1568
          1       0.82      0.83      0.83      1606

avg / total       0.82      0.82      0.82      3174

Confusion Matrix:
[[1280  288]
 [ 274 1332]]
```

Result:

A Term deposit is a deposit that a bank or a financial instituion offers with a fixed rate (often better than just opening deposit account) in which your money will be returned back at a specific maturity time.

Solution for next Marketing Campaign-

Banks should more focused on campaigns and customers with higher education, moreover, there should be some additional campaigning activities for the other cohort of users. A Questionaire or feedback forms

can also be implemented in practice to understand the customer's views. Seasonality also plays a critical role here. Previous credit history of cleints can also be another deciding factor.

In [ ]: