Given historical data on loans given out with information on whether or not the borrower defaulted (charge-off), can we build a model that can predict wether or nor a borrower will pay back their loan? This way in the future when we get a new potential customer we can assess whether or not they are likely to pay back the loan. Keep in mind classification metrics when evaluating the performance of your model! source: https://www.kaggle.com/harlfoxem/housesalesprediction

```
In [1]:
import pandas as pd
In [2]:
df=pd.read_csv((r'C:\Users\chumj\Downloads\Data.csv'))
In [3]:
df.tail(3)
Out[3]:
        Unnamed:
                 loan_amnt term int_rate installment annual_inc
                                                              dti open_acc pub_rec revol_bal ... sub_grade_F1 sub_gra
 395216
          396027
                    5000.0
                                   9.99
                                           161.32
                                                     56500.0 17.56
                                                                      15.0
                                                                                    32704.0 ...
 395217
          396028
                   21000.0
                             60
                                  15.31
                                           503.02
                                                    64000.0 15.88
                                                                       9.0
                                                                               0.0
                                                                                    15704.0 ...
                                                                                                         0
 395218
          396029
                    2000.0
                             36
                                  13.61
                                            67.98
                                                     42996.0
                                                            8.32
                                                                       3.0
                                                                               0.0
                                                                                     4292.0 ...
3 rows × 80 columns
In [4]:
from sklearn.model_selection import train_test_split
In [5]:
X=df.drop('repaid loans',axis=1).values
y=df['repaid loans'].values
In [6]:
len(df)
Out[6]:
395219
In [7]:
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=101)
In [8]:
# Data normalizing
from sklearn.preprocessing import MinMaxScaler
In [9]:
scaler=MinMaxScaler()
In [10]:
X_train=scaler.fit_transform(X_train)
```

```
In [11]:
X test=scaler.transform(X test)
In [42]:
#Creating the model
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation, Dropout
import warnings
warnings .filterwarnings('ignore')
In [13]:
X train.shape
Out[13]:
(276653, 79)
In [14]:
model=Sequential()
In [15]:
model.add(Dense(79,activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(40,activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(20,activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(units=1,activation='sigmoid'))
model.compile(loss='binary crossentropy',optimizer='adam')
WARNING:tensorflow:From C:\Users\chumj\Anaconda3\Ben\lib\site-
packages\tensorflow\python\ops\init_ops.py:1251: calling VarianceScaling.__init__ (from
tensorflow.python.ops.init ops) with dtype is deprecated and will be removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
In [16]:
\verb|model.fit(x=X_train,y=y_train,epochs=40,batch_size=300,validation_data=(X_test,y_test),verbose=1)|
WARNING:tensorflow:From C:\Users\chumj\Anaconda3\Ben\lib\site-
packages\tensorflow\python\ops\nn impl.py:180: add dispatch support.<locals>.wrapper (from
tensorflow.python.ops.array ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
Train on 276653 samples, validate on 118566 samples
Epoch 1/40
276653/276653 [============== ] - 8s 28us/sample - loss: 0.3155 - val loss: 0.2657
Epoch 2/40
Epoch 3/40
276653/276653 [============] - 7s 25us/sample - loss: 0.2631 - val loss: 0.2621
Epoch 4/40
276653/276653 [============] - 7s 25us/sample - loss: 0.2615 - val_loss: 0.2618
Epoch 5/40
276653/276653 [============= ] - 7s 25us/sample - loss: 0.2609 - val loss: 0.2617
Epoch 6/40
276653/276653 [============] - 7s 25us/sample - loss: 0.2600 - val loss: 0.2617
Epoch 7/40
276653/276653 [============] - 7s 25us/sample - loss: 0.2596 - val loss: 0.2617
```

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Epoch 8/40	[=====]		7 ~	25		1	0 2502]]	0 0610
Epoch 9/40	[]	_	15	ZJus/sampie	_	1055:	0.2392	- vai_1055:	0.2010
-	[=====]	_	7s	25us/sample	_	loss:	0.2591	- val loss:	0.2619
Epoch 10/40	-							_	
	[======]	-	7s	25us/sample	-	loss:	0.2585	- val_loss:	0.2613
Epoch 11/40									
	[=====]	-	7s	25us/sample	-	loss:	0.2581	- val_loss:	0.2616
Epoch 12/40	[=====]	_	7.0	25uc/cample	_	1000	0 2591	- 772] 1000	0 2617
Epoch 13/40	[]		15	2Jus/sampie		1055.	0.2301	- vai_1055.	0.2017
-	[=====]	_	7s	25us/sample	_	loss:	0.2576	- val loss:	0.2616
Epoch 14/40	-							_	
	[=====]	-	7s	25us/sample	-	loss:	0.2574	- val_loss:	0.2611
Epoch 15/40			_	0.5 / 3		_			0.054.5
276653/276653 Epoch 16/40	[=====]	-	7/s	25us/sample	-	loss:	0.2574	- val_loss:	0.2615
-	[=====]	_	7.s	25us/sample	_	loss:	0.2570	- val loss:	0.2614
Epoch 17/40	ı			Loud, campio		1000.	0.2070	.u1_1000.	0.2021
276653/276653	[=====]	-	7s	25us/sample	_	loss:	0.2568	- val_loss:	0.2617
Epoch 18/40									
	[======]	-	7s	25us/sample	-	loss:	0.2566	- val_loss:	0.2613
Epoch 19/40	[=====]	_	7 <	26us/sample	_	1088.	0 2564	- val loss:	0 2615
Epoch 20/40	L J		75	2005/ Sampic		1000.	0.2301	vai_1035.	0.2015
_	[======]	_	7s	25us/sample	_	loss:	0.2561	- val loss:	0.2616
Epoch 21/40									
	[======]	-	7s	25us/sample	-	loss:	0.2560	- val_loss:	0.2621
Epoch 22/40	[=====]	_	7 0	2511c/cample	_	1000	0 2560	- 7721 1088.	0 2615
Epoch 23/40	i j		75	23db/ bampic		1055.	0.2300	vai_1033.	0.2013
276653/276653	[=====]	-	7s	25us/sample	-	loss:	0.2558	- val_loss:	0.2617
Epoch 24/40									
276653/276653 Epoch 25/40	[=====]	-	7s	25us/sample	-	loss:	0.2556	- val_loss:	0.2620
-	[=====]	_	7s	25us/sample	_	loss:	0.2554	- val loss:	0.2617
Epoch 26/40	-							_	
	[=====]	-	7s	25us/sample	-	loss:	0.2550	- val_loss:	0.2616
Epoch 27/40	[]		7 ~	25		1	0 2540		0 0616
Epoch 28/40	[=====]	_	75	25us/sample	_	TOSS:	0.2349	- val_1088:	0.2010
-	[======]	_	7s	25us/sample	_	loss:	0.2551	- val loss:	0.2616
Epoch 29/40								_	
	[=====]	-	7s	25us/sample	-	loss:	0.2546	- val_loss:	0.2616
Epoch 30/40	[=====]	_	۵ ۵	27us/sample	_	1000	0 25//	- 221 1000	0 2616
Epoch 31/40	[]		0.5	2703/30111916		1033.	0.2344	vai_1033.	0.2010
276653/276653	[======]	-	8s	29us/sample	-	loss:	0.2542	- val_loss:	0.2628
Epoch 32/40									
276653/276653 Epoch 33/40	[=====]	-	7s	26us/sample	-	loss:	0.2540	- val_loss:	0.2627
-	[======]	_	7.s	25us/sample	_	loss:	0.2538	- val loss:	0.2623
Epoch 34/40	ı			zoao, campio		1000.	0.2000	.u1000.	0.2020
276653/276653	[=====]	-	7s	25us/sample	-	loss:	0.2541	- val_loss:	0.2620
Epoch 35/40	_		_	05 / 5		,	0.0505		0.0505
276653/276653 Epoch 36/40	[======]	-	/s	∠5us/sample	-	loss:	0.2535	- val_loss:	0.2632
-	[======]	_	7s	25us/sample	_	loss:	0.2538	- val loss:	0.2619
Epoch 37/40				,					
	[=====]	-	7s	25us/sample	-	loss:	0.2537	- val_loss:	0.2619
Epoch 38/40			7	05 / 3		,	0.0504		0.000
276653/276653 Epoch 39/40	[=====]	-	/s	∠5us/sample	-	loss:	U.2534	- val_loss:	U.2622
	[=====]	_	7s	25us/sample	_	loss:	0.2532	- val loss:	0.2628
Epoch 40/40								_	
276653/276653	[======]	-	7s	25us/sample	-	loss:	0.2531	- val_loss:	0.2624

Out[16]:

<tensorflow.python.keras.callbacks.History at 0x2878650bcc8>

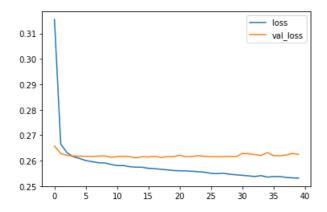
In [17]:

In [18]:

```
loss.plot()
```

Out[18]:

<matplotlib.axes._subplots.AxesSubplot at 0x2879a77f888>



In [24]:

```
predictions3=model.predict_classes(X_test)
```

In [25]:

```
# Implementing callbacks
#from tensorflow.keras.callbacks import EarlyStopping
```

In [26]:

```
#early=EarlyStopping(monitor='val_loss',mode='min',verbose=1,patience=26)
```

In [27]:

```
\# model.fit (x=X\_train,y=y\_train,epochs=400,validation\_data=(X\_test,y\_test),verbose=1,callbacks=[early])
```

In [23]:

 $\textbf{from sklearn.metrics import} \ \texttt{classification_report,} \\ \texttt{confusion_matrix,} \\ \texttt{accuracy_score}$

In [28]:

```
print(classification_report(y_test,predictions3))
print(confusion_matrix(y_test,predictions3))
print(accuracy_score(y_test,predictions3))
```

support	ecall f1-score supp		precision	
23363 95203	0.60 0.93	0.43	1.00 0.88	0 1
118566 118566	0.89	0.71	0.94	accuracy
118566	0.87	0.89	0.90	weighted avg

```
[[ 9958 13405]
[ 0 95203]]
0.886940606919353
```

In [37]:

```
#Given a customer below we you offer loan to the person or not import random
```

```
random_ind=random.randint(0,len(df))
In [38]:
new_person=df.drop('repaid_loans',axis=1).iloc[random_ind]
In [39]:
new_person
Out[39]:
Unnamed: 0 348599.00 loan_amnt 22400.00
                 36.00
term
int_rate
                   12.49
installment
                  749.26
sub_grade_G1
sub_grade_G2
                 0.00
sub_grade_G3
                    0.00
sub_grade_G4
                   0.00
sub_grade_G5 0.00
Name: 347877, Length: 79, dtype: float64
In [40]:
model.predict_classes(new_person.values.reshape(1,79))
Out[40]:
array([[1]])
In [41]:
#check if this person end up paying the loan
df.iloc[random_ind]['repaid_loans']
Out[41]:
1.0
In [ ]:
```