

# LendingClubLoanData

February 11, 2023

```
[1]: # import required library
import pandas as pd
import numpy as np
pd.set_option('display.max_rows',None)
pd.set_option('display.max_columns',None)
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

```
[2]: #loading data
df_loan=pd.read_csv("loan_data.csv")
df_loan.head()
```

```
[2]: credit.policy      purpose  int.rate  installment  log.annual.inc  \
0          1  debt_consolidation    0.1189         829.10      11.350407
1          1      credit_card    0.1071         228.22      11.082143
2          1  debt_consolidation    0.1357         366.86      10.373491
3          1  debt_consolidation    0.1008         162.34      11.350407
4          1      credit_card    0.1426         102.92      11.299732

      dti  fico  days.with.cr.line  revol.bal  revol.util  inq.last.6mths  \
0  19.48  737      5639.958333      28854         52.1           0
1  14.29  707      2760.000000      33623         76.7           0
2  11.63  682      4710.000000       3511         25.6           1
3   8.10  712      2699.958333      33667         73.2           1
4  14.97  667      4066.000000       4740         39.5           0

delinq.2yrs  pub.rec  not.fully.paid
0           0         0              0
1           0         0              0
2           0         0              0
3           0         0              0
4           1         0              0
```

```
[3]: #shape of data
df_loan.shape
```

[3]: (9578, 14)

```
[4]: #info of data
df_loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 14 columns):
 #   Column                Non-Null Count  Dtype
---  -
 0   credit.policy         9578 non-null   int64
 1   purpose               9578 non-null   object
 2   int.rate              9578 non-null   float64
 3   installment           9578 non-null   float64
 4   log.annual.inc        9578 non-null   float64
 5   dti                   9578 non-null   float64
 6   fico                  9578 non-null   int64
 7   days.with.cr.line     9578 non-null   float64
 8   revol.bal             9578 non-null   int64
 9   revol.util            9578 non-null   float64
10   inq.last.6mths        9578 non-null   int64
11   delinq.2yrs           9578 non-null   int64
12   pub.rec               9578 non-null   int64
13   not.fully.paid        9578 non-null   int64
dtypes: float64(6), int64(7), object(1)
memory usage: 1.0+ MB
```

```
[5]: #description of data
df_loan.describe()
```

```
[5]:
```

	credit.policy	int.rate	installment	log.annual.inc	dti \
count	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000
mean	0.804970	0.122640	319.089413	10.932117	12.606679
std	0.396245	0.026847	207.071301	0.614813	6.883970
min	0.000000	0.060000	15.670000	7.547502	0.000000
25%	1.000000	0.103900	163.770000	10.558414	7.212500
50%	1.000000	0.122100	268.950000	10.928884	12.665000
75%	1.000000	0.140700	432.762500	11.291293	17.950000
max	1.000000	0.216400	940.140000	14.528354	29.960000

	fico	days.with.cr.line	revol.bal	revol.util \
count	9578.000000	9578.000000	9.578000e+03	9578.000000
mean	710.846314	4560.767197	1.691396e+04	46.799236
std	37.970537	2496.930377	3.375619e+04	29.014417
min	612.000000	178.958333	0.000000e+00	0.000000
25%	682.000000	2820.000000	3.187000e+03	22.600000
50%	707.000000	4139.958333	8.596000e+03	46.300000

75%	737.000000	5730.000000	1.824950e+04	70.900000
max	827.000000	17639.958330	1.207359e+06	119.000000

	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid
count	9578.000000	9578.000000	9578.000000	9578.000000
mean	1.577469	0.163708	0.062122	0.160054
std	2.200245	0.546215	0.262126	0.366676
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	1.000000	0.000000	0.000000	0.000000
75%	2.000000	0.000000	0.000000	0.000000
max	33.000000	13.000000	5.000000	1.000000

```
[6]: #value count on purpose column
df_loan['purpose'].value_counts()
```

```
[6]: debt_consolidation    3957
all_other                2331
credit_card              1262
home_improvement         629
small_business            619
major_purchase           437
educational              343
Name: purpose, dtype: int64
```

```
[7]: #groupby purpose on revolving balance to get the amount due in various cate
df_loan.groupby('purpose')['revol.bal'].sum()
```

```
[7]: purpose
all_other                30030366
credit_card              29253186
debt_consolidation       67849534
educational              3714312
home_improvement        10899788
major_purchase           3181995
small_business           17072765
Name: revol.bal, dtype: int64
```

```
[8]: #purpose is categorical column
#applying label encoder to convert categorical to numerocal values.
from sklearn.preprocessing import LabelEncoder
LB = LabelEncoder()
df_loan['purpose']=LB.fit_transform(df_loan['purpose'])
```

```
[9]: df_loan.head()
```

```
[9]: credit.policy  purpose  int.rate  installment  log.annual.inc  dti  fico  \
0          1          2    0.1189      829.10      11.350407  19.48  737
1          1          1    0.1071      228.22      11.082143  14.29  707
2          1          2    0.1357      366.86      10.373491  11.63  682
3          1          2    0.1008      162.34      11.350407   8.10  712
4          1          1    0.1426      102.92      11.299732  14.97  667

      days.with.cr.line  revol.bal  revol.util  inq.last.6mths  delinq.2yrs  \
0          5639.958333      28854      52.1              0              0
1          2760.000000      33623      76.7              0              0
2          4710.000000      3511       25.6              1              0
3          2699.958333      33667      73.2              1              0
4          4066.000000      4740       39.5              0              1

      pub.rec  not.fully.paid
0          0          0
1          0          0
2          0          0
3          0          0
4          0          0
```

```
[10]: df_loan.tail()
```

```
[10]: credit.policy  purpose  int.rate  installment  log.annual.inc  dti  \
9573          0          0    0.1461      344.76      12.180755  10.39
9574          0          0    0.1253      257.70      11.141862   0.21
9575          0          2    0.1071       97.81      10.596635  13.09
9576          0          4    0.1600      351.58      10.819778  19.18
9577          0          2    0.1392      853.43      11.264464  16.28

      fico  days.with.cr.line  revol.bal  revol.util  inq.last.6mths  \
9573   672      10474.000000      215372      82.1              2
9574   722       4380.000000       184        1.1              5
9575   687       3450.041667      10036      82.9              8
9576   692       1800.000000         0        3.2              5
9577   732       4740.000000      37879      57.0              6

      delinq.2yrs  pub.rec  not.fully.paid
9573          0          0          1
9574          0          0          1
9575          0          0          1
9576          0          0          1
9577          0          0          1
```

```
[11]: #value counts to credit policy
df_loan['credit.policy'].value_counts()
```

```
[11]: 1    7710
      0    1868
      Name: credit.policy, dtype: int64
```

```
[12]: #APPLYING ONE HOT ENCODING ON CREDIT POLICY
df_loan=pd.get_dummies(df_loan, columns=['credit.policy'])
df_loan.head()
```

```
[12]:  purpose  int.rate  installment  log.annual.inc  dti  fico  \
0         2    0.1189         829.10      11.350407  19.48   737
1         1    0.1071         228.22      11.082143  14.29   707
2         2    0.1357         366.86      10.373491  11.63   682
3         2    0.1008         162.34      11.350407   8.10   712
4         1    0.1426         102.92      11.299732  14.97   667

      days.with.cr.line  revol.bal  revol.util  inq.last.6mths  delinq.2yrs  \
0      5639.958333      28854         52.1              0          0
1      2760.000000      33623         76.7              0          0
2      4710.000000       3511         25.6              1          0
3      2699.958333      33667         73.2              1          0
4      4066.000000       4740         39.5              0          1

      pub.rec  not.fully.paid  credit.policy_0  credit.policy_1
0          0              0              0              1
1          0              0              0              1
2          0              0              0              1
3          0              0              0              1
4          0              0              0              1
```

```
[13]: #creating dependent and independent features
x=df_loan.drop('not.fully.paid', axis=1)
y=df_loan['not.fully.paid']
```

```
[14]: np.random.seed(12345)
```

```
[15]: #train test split
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test=train_test_split(x, y,
                                                    stratify=y,
                                                    test_size=0.2,
                                                    random_state=12345)
```

```
[16]: #shape of train test data
print(f'training data shape {x_train.shape} {y_train.shape}')
print(f'testing data shape {x_test.shape} {y_test.shape}')
```

```
training data shape (7662, 14) (7662,)
```

testing data shape (1916, 14) (1916,)

```
[17]: x_train.head()
```

```
[17]:
```

	purpose	int.rate	installment	log.annual.inc	dti	fico	\
1279	2	0.1412	167.76	10.385914	23.85	682	
262	0	0.0933	319.54	10.505068	19.46	727	
7922	1	0.1438	359.95	11.245046	9.98	642	
1959	3	0.0963	176.52	10.650887	15.63	727	
4095	0	0.0859	221.28	11.350407	3.92	762	

	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	\
1279	3569.958333	2379	68.0		1	0
262	4470.041667	827	6.6		2	0
7922	4679.958333	15918	101.4		6	0
1959	4200.041667	21002	36.7		1	0
4095	1896.000000	17390	86.1		1	0

	pub.rec	credit.policy_0	credit.policy_1
1279	1	0	1
262	0	0	1
7922	0	1	0
1959	0	0	1
4095	0	0	1

```
[18]: #applying scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
```

```
[19]: x_train.columns
```

```
[19]: Index(['purpose', 'int.rate', 'installment', 'log.annual.inc', 'dti', 'fico',
        'days.with.cr.line', 'revol.bal', 'revol.util', 'inq.last.6mths',
        'delinq.2yrs', 'pub.rec', 'credit.policy_0', 'credit.policy_1'],
        dtype='object')
```

```
[20]: columns_for_scaling=['purpose','int.rate', 'installment', 'log.annual.inc',
        ↪ 'dti', 'fico',
        'days.with.cr.line', 'revol.bal', 'revol.util', 'inq.last.6mths',
        'delinq.2yrs', 'pub.rec']
```

```
[21]: x_train_sc=pd.DataFrame(data=sc.fit_transform(x_train.drop(['credit.
        ↪ policy_0','credit.policy_1'],axis=1)), columns=columns_for_scaling)
x_train_sc.head()
```

```
[21]:
```

	purpose	int.rate	installment	log.annual.inc	dti	fico	\
0	0.045953	0.697111	-0.732563	-0.879480	1.630647	-0.758297	

```

1 -1.151643 -1.097370    0.000840    -0.687085  0.992340  0.432807
2 -0.552845  0.794514    0.196102    0.507739 -0.386055 -1.817057
3  0.644751 -0.984980   -0.690234   -0.451634  0.435457  0.432807
4 -1.151643 -1.374596   -0.473953    0.677862 -1.267180  1.359221

```

```

      days.with.cr.line  revol.bal  revol.util  inq.last.6mths  delinq.2yrs  \
0      -0.396417  -0.488924    0.722720    -0.267287    -0.306244
1      -0.035727  -0.542009   -1.391680     0.189642    -0.306244
2       0.048393  -0.025831    1.872899     2.017358    -0.306244
3      -0.143924  0.148064   -0.355142    -0.267287    -0.306244
4      -1.067223  0.024517    1.346020    -0.267287    -0.306244

```

```

      pub.rec
0  3.471782
1 -0.243413
2 -0.243413
3 -0.243413
4 -0.243413

```

```
[22]: appending_columns= x_train[['credit.policy_0','credit.policy_1']].reset_index()
      appending_columns.drop('index', axis=1).head()
```

```
[22]:   credit.policy_0  credit.policy_1
0              0              1
1              0              1
2              1              0
3              0              1
4              0              1

```

```
[23]: x_train_sc=pd.concat([x_train_sc, appending_columns], axis=1)
      x_train_sc.head()
```

```
[23]:   purpose  int.rate  installment  log.annual.inc      dti      fico  \
0  0.045953  0.697111   -0.732563   -0.879480  1.630647 -0.758297
1 -1.151643 -1.097370    0.000840   -0.687085  0.992340  0.432807
2 -0.552845  0.794514    0.196102    0.507739 -0.386055 -1.817057
3  0.644751 -0.984980   -0.690234   -0.451634  0.435457  0.432807
4 -1.151643 -1.374596   -0.473953    0.677862 -1.267180  1.359221

```

```

      days.with.cr.line  revol.bal  revol.util  inq.last.6mths  delinq.2yrs  \
0      -0.396417  -0.488924    0.722720    -0.267287    -0.306244
1      -0.035727  -0.542009   -1.391680     0.189642    -0.306244
2       0.048393  -0.025831    1.872899     2.017358    -0.306244
3      -0.143924  0.148064   -0.355142    -0.267287    -0.306244
4      -1.067223  0.024517    1.346020    -0.267287    -0.306244

```

```

      pub.rec  index  credit.policy_0  credit.policy_1

```

```

0  3.471782  1279          0          1
1 -0.243413   262          0          1
2 -0.243413  7922          1          0
3 -0.243413  1959          0          1
4 -0.243413  4095          0          1

```

```
[24]: x_test.columns
```

```
[24]: Index(['purpose', 'int.rate', 'installment', 'log.annual.inc', 'dti', 'fico',
        'days.with.cr.line', 'revol.bal', 'revol.util', 'inq.last.6mths',
        'delinq.2yrs', 'pub.rec', 'credit.policy_0', 'credit.policy_1'],
        dtype='object')
```

```
[25]: x_test.shape
```

```
[25]: (1916, 14)
```

```
[26]: x_test.head()
```

```
[26]:
```

	purpose	int.rate	installment	log.annual.inc	dti	fico	\
8806	2	0.1791	86.66	11.107210	2.45	647	
8676	5	0.0976	128.62	10.752484	7.29	707	
7411	6	0.0788	112.61	10.712059	11.79	717	
2791	1	0.1189	238.79	10.692036	6.98	712	
2501	0	0.0932	111.82	11.373663	13.50	727	

	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	\
8806	720.000000	1601	50.0	3	0	
8676	990.000000	0	19.3	0	0	
7411	2820.041667	1773	20.9	3	1	
2791	5040.000000	9144	25.5	0	0	
2501	5011.000000	18695	53.7	3	0	

	pub.rec	credit.policy_0	credit.policy_1
8806	0	1	0
8676	0	1	0
7411	0	0	1
2791	0	0	1
2501	0	0	1

```
[27]: x_test_sc = sc.transform(x_test.drop(['credit.policy_0', 'credit.policy_1'],
    ↪axis=1))
x_test_sc = pd.DataFrame(x_test_sc, columns=columns_for_scaling)
x_test_sc.shape
```

```
[27]: (1916, 12)
```



```
[28]: appending_columns=x_test[['credit.policy_0', 'credit.policy_1']].reset_index()
      appending_columns.drop('index', axis=1).head()
```

```
[28]:   credit.policy_0  credit.policy_1
0             1             0
1             1             0
2             0             1
3             0             1
4             0             1
```

```
[29]: x_test_sc=pd.concat([x_test_sc, appending_columns], axis=1)
      x_test_sc.head()
```

```
[29]:   purpose  int.rate  installment  log.annual.inc      dti      fico \
0  0.045953  2.116960   -1.124439      0.285179 -1.480919 -1.684712
1  1.842347 -0.936278   -0.921687     -0.287588 -0.777182 -0.096573
2  2.441145 -1.640584   -0.999048     -0.352861 -0.122880  0.168117
3 -0.552845 -0.138316   -0.389345     -0.385192 -0.822256  0.035772
4 -1.151643 -1.101116   -1.002865      0.715414  0.125754  0.432807

      days.with.cr.line  revol.bal  revol.util  inq.last.6mths  delinq.2yrs \
0      -1.538481   -0.515535    0.102863      0.646571   -0.306244
1      -1.430284   -0.570296   -0.954337     -0.724216   -0.306244
2      -0.696931   -0.509652   -0.899239      0.646571    1.583000
3       0.192672   -0.257532   -0.740831     -0.724216   -0.306244
4       0.181051    0.069154    0.230278      0.646571   -0.306244

      pub.rec  index  credit.policy_0  credit.policy_1
0 -0.243413   8806             1             0
1 -0.243413   8676             1             0
2 -0.243413   7411             0             1
3 -0.243413   2791             0             1
4 -0.243413   2501             0             1
```

```
[30]: x_train_sc.drop('index', axis=1, inplace=True)
```

```
[31]: x_test_sc.drop('index', axis=1, inplace=True)
```

```
[32]: print(x_train_sc.shape, x_train.shape)
      print(x_test_sc.shape, x_test.shape)
```

```
(7662, 14) (7662, 14)
(1916, 14) (1916, 14)
```

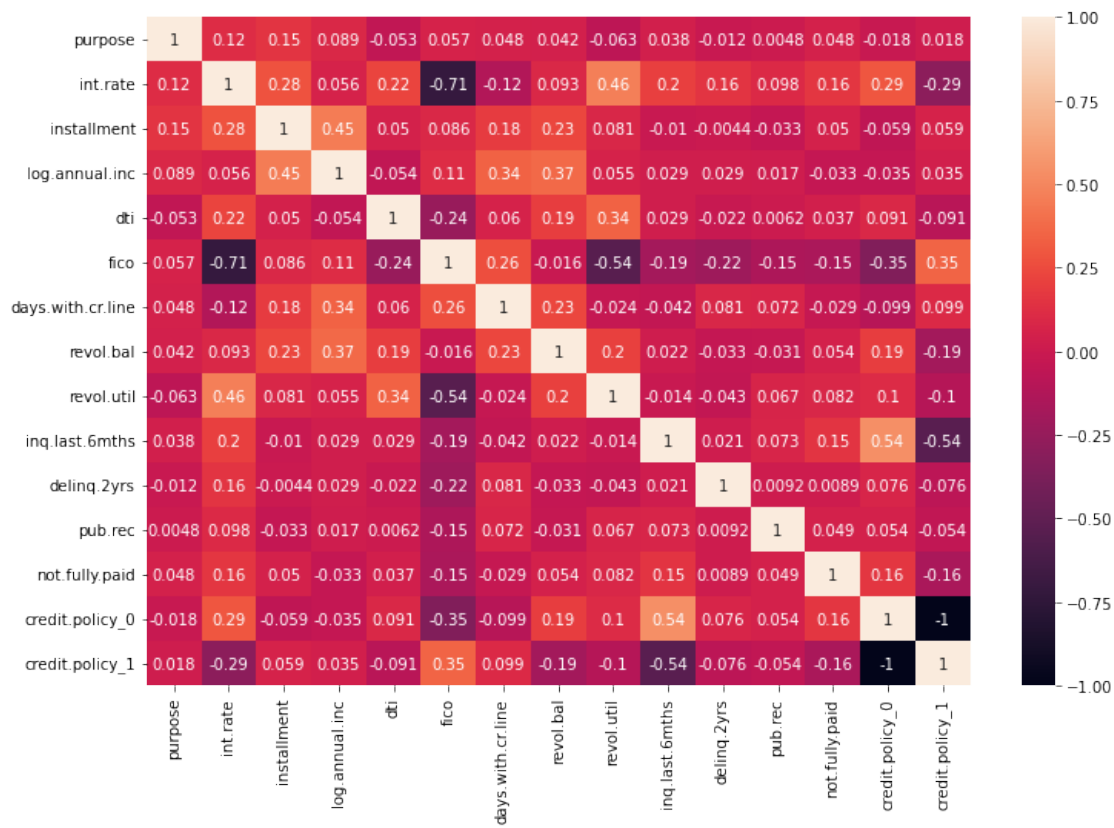
```
[33]: y_train.head()
```

```
[33]: 1279    0
      262    1
      7922   1
      1959   0
      4095   0
      Name: not.fully.paid, dtype: int64
```

```
[34]: y_test.head()
```

```
[34]: 8806    0
      8676    0
      7411    0
      2791    0
      2501    0
      Name: not.fully.paid, dtype: int64
```

```
[35]: #correlation matrix
plt.figure(figsize=(12,8))
sns.heatmap(df_loan.corr(), annot=True)
plt.show()
```



```
[36]: #checking vif score for correlation among variables
vif_data = pd.DataFrame()
vif_data['features'] = x_train.columns
from statsmodels.stats.outliers_influence import variance_inflation_factor as vif
vif_data['score'] = [vif(x_train_sc.values, i)
                    for i in range(len(x_train_sc.columns))]

vif_data
```

```
[36]:
```

	features	score
0	purpose	1.069554
1	int.rate	2.852813
2	installment	1.600678
3	log.annual.inc	1.561518
4	dti	1.214252
5	fico	3.378618
6	days.with.cr.line	1.315642
7	revol.bal	1.459020
8	revol.util	1.767070
9	inq.last.6mths	1.470540
10	delinq.2yrs	1.142994
11	pub.rec	1.051614
12	credit.policy_0	1.564075
13	credit.policy_1	1.136516

```
[37]: #there is no multicollinearity
```

```
[38]: #building model
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input
```

```
[39]: model=Sequential()
```

```
[40]: model.add(Input(shape=(x_train_sc.shape[1],)))
```

```
[41]: #first hidden layer
model.add(Dense(units=128,
                activation="relu"))
```

```
[42]: #second hidden layer
model.add(Dense(units=64,
                activation='relu'))
#third hidden layer
model.add(Dense(units=32,
                activation='relu'))
```

```
#output layer
model.add(Dense(units=1,
                  activation='sigmoid'))
```

```
[43]: model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 128)	1920
dense_1 (Dense)	(None, 64)	8256
dense_2 (Dense)	(None, 32)	2080
dense_3 (Dense)	(None, 1)	33

```
=====
Total params: 12,289
Trainable params: 12,289
Non-trainable params: 0
=====
```

```
[44]: #compilation
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

```
[45]: #fitting data
result = model.fit(x_train_sc,
                   y_train,
                   validation_data=(x_test_sc, y_test),
                   epochs=100)
```

```
Epoch 1/100
240/240 [=====] - 1s 3ms/step - loss: 0.4338 -
accuracy: 0.8354 - val_loss: 0.4175 - val_accuracy: 0.8403
Epoch 2/100
240/240 [=====] - 0s 2ms/step - loss: 0.4137 -
accuracy: 0.8403 - val_loss: 0.4166 - val_accuracy: 0.8387
Epoch 3/100
240/240 [=====] - 0s 2ms/step - loss: 0.4080 -
accuracy: 0.8423 - val_loss: 0.4181 - val_accuracy: 0.8361
```

Epoch 4/100  
240/240 [=====] - 0s 2ms/step - loss: 0.4060 -  
accuracy: 0.8429 - val\_loss: 0.4191 - val\_accuracy: 0.8387

Epoch 5/100  
240/240 [=====] - 0s 2ms/step - loss: 0.4024 -  
accuracy: 0.8426 - val\_loss: 0.4198 - val\_accuracy: 0.8382

Epoch 6/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3982 -  
accuracy: 0.8433 - val\_loss: 0.4190 - val\_accuracy: 0.8377

Epoch 7/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3962 -  
accuracy: 0.8440 - val\_loss: 0.4192 - val\_accuracy: 0.8340

Epoch 8/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3930 -  
accuracy: 0.8446 - val\_loss: 0.4183 - val\_accuracy: 0.8398

Epoch 9/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3910 -  
accuracy: 0.8447 - val\_loss: 0.4236 - val\_accuracy: 0.8377

Epoch 10/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3873 -  
accuracy: 0.8470 - val\_loss: 0.4341 - val\_accuracy: 0.8392

Epoch 11/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3834 -  
accuracy: 0.8480 - val\_loss: 0.4297 - val\_accuracy: 0.8377

Epoch 12/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3792 -  
accuracy: 0.8493 - val\_loss: 0.4328 - val\_accuracy: 0.8351

Epoch 13/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3761 -  
accuracy: 0.8530 - val\_loss: 0.4350 - val\_accuracy: 0.8351

Epoch 14/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3697 -  
accuracy: 0.8533 - val\_loss: 0.4510 - val\_accuracy: 0.8241

Epoch 15/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3682 -  
accuracy: 0.8537 - val\_loss: 0.4371 - val\_accuracy: 0.8335

Epoch 16/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3603 -  
accuracy: 0.8587 - val\_loss: 0.4507 - val\_accuracy: 0.8272

Epoch 17/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3590 -  
accuracy: 0.8570 - val\_loss: 0.4493 - val\_accuracy: 0.8335

Epoch 18/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3492 -  
accuracy: 0.8645 - val\_loss: 0.4548 - val\_accuracy: 0.8314

Epoch 19/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3450 -  
accuracy: 0.8645 - val\_loss: 0.4752 - val\_accuracy: 0.7985

Epoch 20/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3395 -  
accuracy: 0.8671 - val\_loss: 0.4643 - val\_accuracy: 0.8184  
Epoch 21/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3358 -  
accuracy: 0.8717 - val\_loss: 0.4867 - val\_accuracy: 0.8299  
Epoch 22/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3269 -  
accuracy: 0.8733 - val\_loss: 0.4751 - val\_accuracy: 0.8262  
Epoch 23/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3209 -  
accuracy: 0.8750 - val\_loss: 0.4903 - val\_accuracy: 0.8220  
Epoch 24/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3150 -  
accuracy: 0.8810 - val\_loss: 0.5064 - val\_accuracy: 0.8100  
Epoch 25/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3110 -  
accuracy: 0.8794 - val\_loss: 0.4996 - val\_accuracy: 0.8147  
Epoch 26/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3031 -  
accuracy: 0.8845 - val\_loss: 0.5166 - val\_accuracy: 0.8168  
Epoch 27/100  
240/240 [=====] - 0s 2ms/step - loss: 0.3015 -  
accuracy: 0.8824 - val\_loss: 0.5120 - val\_accuracy: 0.8105  
Epoch 28/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2929 -  
accuracy: 0.8891 - val\_loss: 0.5032 - val\_accuracy: 0.8199  
Epoch 29/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2859 -  
accuracy: 0.8900 - val\_loss: 0.5255 - val\_accuracy: 0.8225  
Epoch 30/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2805 -  
accuracy: 0.8927 - val\_loss: 0.5355 - val\_accuracy: 0.8163  
Epoch 31/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2757 -  
accuracy: 0.8948 - val\_loss: 0.5565 - val\_accuracy: 0.8173  
Epoch 32/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2716 -  
accuracy: 0.8960 - val\_loss: 0.5515 - val\_accuracy: 0.8168  
Epoch 33/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2611 -  
accuracy: 0.9016 - val\_loss: 0.5834 - val\_accuracy: 0.8194  
Epoch 34/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2588 -  
accuracy: 0.9015 - val\_loss: 0.5880 - val\_accuracy: 0.8058  
Epoch 35/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2573 -  
accuracy: 0.9016 - val\_loss: 0.5699 - val\_accuracy: 0.8194

Epoch 36/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2503 -  
accuracy: 0.9038 - val\_loss: 0.5823 - val\_accuracy: 0.8090  
Epoch 37/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2439 -  
accuracy: 0.9071 - val\_loss: 0.6260 - val\_accuracy: 0.7865  
Epoch 38/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2416 -  
accuracy: 0.9103 - val\_loss: 0.6248 - val\_accuracy: 0.8126  
Epoch 39/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2343 -  
accuracy: 0.9118 - val\_loss: 0.6630 - val\_accuracy: 0.7970  
Epoch 40/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2279 -  
accuracy: 0.9171 - val\_loss: 0.6332 - val\_accuracy: 0.8095  
Epoch 41/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2284 -  
accuracy: 0.9165 - val\_loss: 0.6389 - val\_accuracy: 0.8022  
Epoch 42/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2197 -  
accuracy: 0.9169 - val\_loss: 0.6498 - val\_accuracy: 0.8011  
Epoch 43/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2115 -  
accuracy: 0.9221 - val\_loss: 0.6792 - val\_accuracy: 0.8079  
Epoch 44/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2084 -  
accuracy: 0.9203 - val\_loss: 0.7099 - val\_accuracy: 0.8085  
Epoch 45/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2066 -  
accuracy: 0.9242 - val\_loss: 0.7295 - val\_accuracy: 0.8178  
Epoch 46/100  
240/240 [=====] - 0s 2ms/step - loss: 0.2044 -  
accuracy: 0.9244 - val\_loss: 0.7026 - val\_accuracy: 0.7954  
Epoch 47/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1965 -  
accuracy: 0.9244 - val\_loss: 0.7290 - val\_accuracy: 0.7933  
Epoch 48/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1972 -  
accuracy: 0.9239 - val\_loss: 0.7230 - val\_accuracy: 0.7928  
Epoch 49/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1927 -  
accuracy: 0.9287 - val\_loss: 0.7480 - val\_accuracy: 0.8053  
Epoch 50/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1825 -  
accuracy: 0.9317 - val\_loss: 0.8061 - val\_accuracy: 0.8011  
Epoch 51/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1812 -  
accuracy: 0.9315 - val\_loss: 0.7618 - val\_accuracy: 0.8048

Epoch 52/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1761 -  
accuracy: 0.9353 - val\_loss: 0.7982 - val\_accuracy: 0.7891  
Epoch 53/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1777 -  
accuracy: 0.9329 - val\_loss: 0.8046 - val\_accuracy: 0.7469  
Epoch 54/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1707 -  
accuracy: 0.9342 - val\_loss: 0.8339 - val\_accuracy: 0.7891  
Epoch 55/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1702 -  
accuracy: 0.9370 - val\_loss: 0.8499 - val\_accuracy: 0.7975  
Epoch 56/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1642 -  
accuracy: 0.9366 - val\_loss: 0.8470 - val\_accuracy: 0.8001  
Epoch 57/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1620 -  
accuracy: 0.9379 - val\_loss: 0.8580 - val\_accuracy: 0.7944  
Epoch 58/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1560 -  
accuracy: 0.9428 - val\_loss: 0.8610 - val\_accuracy: 0.8085  
Epoch 59/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1508 -  
accuracy: 0.9427 - val\_loss: 0.8885 - val\_accuracy: 0.7996  
Epoch 60/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1531 -  
accuracy: 0.9437 - val\_loss: 0.9064 - val\_accuracy: 0.7938  
Epoch 61/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1464 -  
accuracy: 0.9441 - val\_loss: 0.9695 - val\_accuracy: 0.7803  
Epoch 62/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1572 -  
accuracy: 0.9410 - val\_loss: 0.9323 - val\_accuracy: 0.7970  
Epoch 63/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1479 -  
accuracy: 0.9423 - val\_loss: 0.9498 - val\_accuracy: 0.7975  
Epoch 64/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1365 -  
accuracy: 0.9504 - val\_loss: 0.9447 - val\_accuracy: 0.7891  
Epoch 65/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1332 -  
accuracy: 0.9509 - val\_loss: 0.9749 - val\_accuracy: 0.8085  
Epoch 66/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1361 -  
accuracy: 0.9473 - val\_loss: 1.0072 - val\_accuracy: 0.7897  
Epoch 67/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1322 -  
accuracy: 0.9509 - val\_loss: 0.9980 - val\_accuracy: 0.8001



Epoch 68/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1252 -  
accuracy: 0.9528 - val\_loss: 1.0841 - val\_accuracy: 0.7771  
Epoch 69/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1291 -  
accuracy: 0.9504 - val\_loss: 1.0276 - val\_accuracy: 0.7850  
Epoch 70/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1249 -  
accuracy: 0.9528 - val\_loss: 1.0384 - val\_accuracy: 0.7996  
Epoch 71/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1160 -  
accuracy: 0.9568 - val\_loss: 1.0892 - val\_accuracy: 0.7902  
Epoch 72/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1230 -  
accuracy: 0.9571 - val\_loss: 1.0959 - val\_accuracy: 0.7923  
Epoch 73/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1359 -  
accuracy: 0.9492 - val\_loss: 1.0810 - val\_accuracy: 0.7918  
Epoch 74/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1158 -  
accuracy: 0.9578 - val\_loss: 1.1351 - val\_accuracy: 0.7944  
Epoch 75/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1098 -  
accuracy: 0.9598 - val\_loss: 1.1556 - val\_accuracy: 0.7777  
Epoch 76/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1212 -  
accuracy: 0.9545 - val\_loss: 1.1484 - val\_accuracy: 0.7912  
Epoch 77/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1054 -  
accuracy: 0.9616 - val\_loss: 1.2054 - val\_accuracy: 0.7891  
Epoch 78/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1098 -  
accuracy: 0.9598 - val\_loss: 1.1755 - val\_accuracy: 0.7923  
Epoch 79/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1100 -  
accuracy: 0.9598 - val\_loss: 1.1954 - val\_accuracy: 0.7766  
Epoch 80/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0988 -  
accuracy: 0.9648 - val\_loss: 1.2216 - val\_accuracy: 0.7865  
Epoch 81/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1075 -  
accuracy: 0.9601 - val\_loss: 1.2687 - val\_accuracy: 0.8027  
Epoch 82/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1052 -  
accuracy: 0.9601 - val\_loss: 1.2950 - val\_accuracy: 0.7505  
Epoch 83/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0959 -  
accuracy: 0.9646 - val\_loss: 1.2649 - val\_accuracy: 0.7996

Epoch 84/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0869 -  
accuracy: 0.9704 - val\_loss: 1.2908 - val\_accuracy: 0.7797  
Epoch 85/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0862 -  
accuracy: 0.9699 - val\_loss: 1.2717 - val\_accuracy: 0.7745  
Epoch 86/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0888 -  
accuracy: 0.9676 - val\_loss: 1.3066 - val\_accuracy: 0.7902  
Epoch 87/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1066 -  
accuracy: 0.9572 - val\_loss: 1.3012 - val\_accuracy: 0.7876  
Epoch 88/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0975 -  
accuracy: 0.9666 - val\_loss: 1.3595 - val\_accuracy: 0.7970  
Epoch 89/100  
240/240 [=====] - 0s 2ms/step - loss: 0.1064 -  
accuracy: 0.9582 - val\_loss: 1.3252 - val\_accuracy: 0.7860  
Epoch 90/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0886 -  
accuracy: 0.9653 - val\_loss: 1.2910 - val\_accuracy: 0.7938  
Epoch 91/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0759 -  
accuracy: 0.9722 - val\_loss: 1.3367 - val\_accuracy: 0.7876  
Epoch 92/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0780 -  
accuracy: 0.9697 - val\_loss: 1.3501 - val\_accuracy: 0.7818  
Epoch 93/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0771 -  
accuracy: 0.9704 - val\_loss: 1.3407 - val\_accuracy: 0.7756  
Epoch 94/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0759 -  
accuracy: 0.9726 - val\_loss: 1.4218 - val\_accuracy: 0.7897  
Epoch 95/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0871 -  
accuracy: 0.9680 - val\_loss: 1.4595 - val\_accuracy: 0.7959  
Epoch 96/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0872 -  
accuracy: 0.9684 - val\_loss: 1.4751 - val\_accuracy: 0.7876  
Epoch 97/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0752 -  
accuracy: 0.9736 - val\_loss: 1.5155 - val\_accuracy: 0.8006  
Epoch 98/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0714 -  
accuracy: 0.9749 - val\_loss: 1.5118 - val\_accuracy: 0.7970  
Epoch 99/100  
240/240 [=====] - 0s 2ms/step - loss: 0.0610 -  
accuracy: 0.9781 - val\_loss: 1.5168 - val\_accuracy: 0.7818

```
Epoch 100/100
240/240 [=====] - 0s 2ms/step - loss: 0.0922 -
accuracy: 0.9679 - val_loss: 1.5578 - val_accuracy: 0.7839
```

```
[46]: #prediction
y_train_pred = model.predict(x_train_sc)
y_test_pred = model.predict(x_test_sc)
```

```
[47]: #accuracy
from sklearn.metrics import confusion_matrix, accuracy_score
```

```
[48]: #confusion matrix on training data
confusion_matrix(y_train_pred >=0.5,
                  y_train)
```

```
[48]: array([[6356, 169],
            [ 80, 1057]])
```

```
[49]: #confusion matrix on test data
confusion_matrix(y_test_pred >= 0.5,
                  y_test)
```

```
[49]: array([[1448, 253],
            [161, 54]])
```

```
[50]: # accuracy score on training data
accuracy_score(y_train_pred >=0.5, y_train)
```

```
[50]: 0.9675019577133908
```

```
[51]: #accuracy score on test data
accuracy_score(y_test_pred >=0.5, y_test)
```

```
[51]: 0.7839248434237995
```

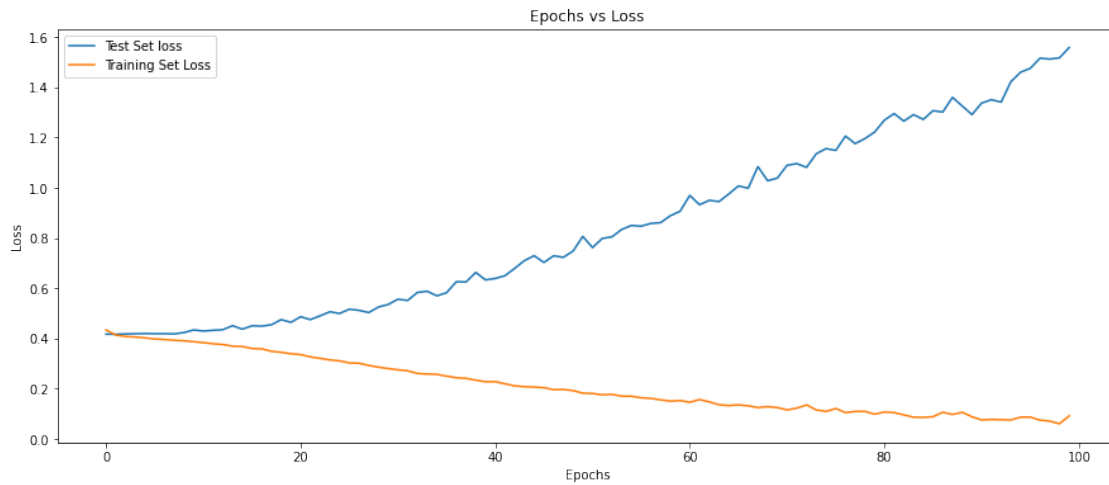
```
[52]: history = pd.DataFrame(result.history)
history.head()
```

```
[52]:
```

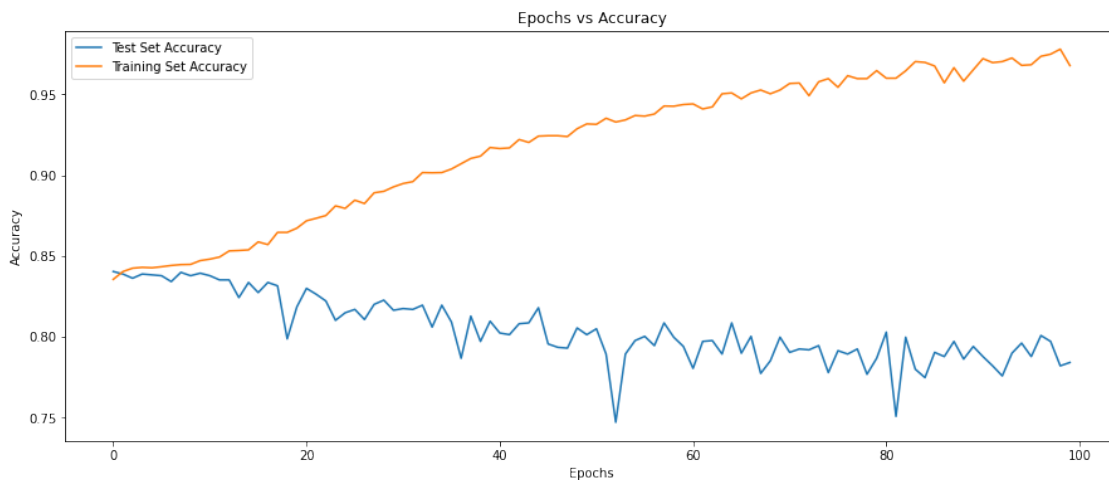
	loss	accuracy	val_loss	val_accuracy
0	0.433824	0.835422	0.417523	0.840292
1	0.413673	0.840251	0.416624	0.838727
2	0.408014	0.842339	0.418101	0.836117
3	0.405994	0.842861	0.419053	0.838727
4	0.402447	0.842600	0.419753	0.838205

```
[53]: plt.figure(figsize= (15,6))
plt.plot(history.val_loss, label='Test Set loss')
```

```
plt.plot(history.loss, label='Training Set Loss')
plt.title('Epochs vs Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



```
[54]: plt.figure(figsize= (15,6))
plt.plot(history.val_accuracy, label='Test Set Accuracy')
plt.plot(history.accuracy, label='Training Set Accuracy')
plt.title('Epochs vs Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



```

[55]: # model is overfitting
      # lets apply regularization
      model_1 = Sequential()

[56]: model_1.add(Input((x_train_sc.shape[1],)))

[57]: model_1.add(Dense(units=128, activation='relu', kernel_regularizer = tf.keras.
      ↳regularizers.L1()))

[58]: from tensorflow.keras.layers import Dropout

[59]: model_1.add(Dropout(0.2))

[60]: model_1.add(Dense(units=128, activation='relu'))
      model_1.add(Dropout(0.2))

      model_1.add(Dense(units=32, activation='relu'))

      model_1.add(Dense(units=1, activation='sigmoid'))

[61]: model_1.summary()

```

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
dense_4 (Dense)	(None, 128)	1920
dropout (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 128)	16512
dropout_1 (Dropout)	(None, 128)	0
dense_6 (Dense)	(None, 32)	4128
dense_7 (Dense)	(None, 1)	33

=====  
 Total params: 22,593  
 Trainable params: 22,593  
 Non-trainable params: 0  
 =====

```
[75]: model_1.compile(optimizer='adam',  
                    loss= 'binary_crossentropy',  
                    metrics=['accuracy'])
```

```
[77]: result_1 = model_1.fit(x_train_sc,  
                             y_train,  
                             epochs=100,  
                             validation_data = (x_test_sc , y_test)  
                             )
```

```
Epoch 1/100  
240/240 [=====] - 1s 3ms/step - loss: 0.4470 -  
accuracy: 0.8400 - val_loss: 0.4425 - val_accuracy: 0.8398  
Epoch 2/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4426 -  
accuracy: 0.8400 - val_loss: 0.4405 - val_accuracy: 0.8398  
Epoch 3/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4400 -  
accuracy: 0.8400 - val_loss: 0.4369 - val_accuracy: 0.8398  
Epoch 4/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4376 -  
accuracy: 0.8400 - val_loss: 0.4418 - val_accuracy: 0.8398  
Epoch 5/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4364 -  
accuracy: 0.8400 - val_loss: 0.4350 - val_accuracy: 0.8398  
Epoch 6/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4376 -  
accuracy: 0.8400 - val_loss: 0.4361 - val_accuracy: 0.8398  
Epoch 7/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4353 -  
accuracy: 0.8400 - val_loss: 0.4357 - val_accuracy: 0.8398  
Epoch 8/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4334 -  
accuracy: 0.8400 - val_loss: 0.4364 - val_accuracy: 0.8398  
Epoch 9/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4349 -  
accuracy: 0.8400 - val_loss: 0.4332 - val_accuracy: 0.8398  
Epoch 10/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4323 -  
accuracy: 0.8400 - val_loss: 0.4343 - val_accuracy: 0.8398  
Epoch 11/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4326 -  
accuracy: 0.8400 - val_loss: 0.4350 - val_accuracy: 0.8398  
Epoch 12/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4328 -  
accuracy: 0.8400 - val_loss: 0.4351 - val_accuracy: 0.8398  
Epoch 13/100
```

240/240 [=====] - 1s 2ms/step - loss: 0.4311 -  
 accuracy: 0.8400 - val\_loss: 0.4314 - val\_accuracy: 0.8398  
 Epoch 14/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4314 -  
 accuracy: 0.8400 - val\_loss: 0.4343 - val\_accuracy: 0.8398  
 Epoch 15/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4311 -  
 accuracy: 0.8400 - val\_loss: 0.4320 - val\_accuracy: 0.8398  
 Epoch 16/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4318 -  
 accuracy: 0.8400 - val\_loss: 0.4310 - val\_accuracy: 0.8398  
 Epoch 17/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4300 -  
 accuracy: 0.8400 - val\_loss: 0.4326 - val\_accuracy: 0.8398  
 Epoch 18/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4314 -  
 accuracy: 0.8400 - val\_loss: 0.4283 - val\_accuracy: 0.8398  
 Epoch 19/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4288 -  
 accuracy: 0.8400 - val\_loss: 0.4304 - val\_accuracy: 0.8398  
 Epoch 20/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4308 -  
 accuracy: 0.8400 - val\_loss: 0.4311 - val\_accuracy: 0.8398  
 Epoch 21/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4300 -  
 accuracy: 0.8400 - val\_loss: 0.4297 - val\_accuracy: 0.8398  
 Epoch 22/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4293 -  
 accuracy: 0.8400 - val\_loss: 0.4325 - val\_accuracy: 0.8398  
 Epoch 23/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4291 -  
 accuracy: 0.8400 - val\_loss: 0.4247 - val\_accuracy: 0.8398  
 Epoch 24/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4285 -  
 accuracy: 0.8400 - val\_loss: 0.4317 - val\_accuracy: 0.8398  
 Epoch 25/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4284 -  
 accuracy: 0.8400 - val\_loss: 0.4300 - val\_accuracy: 0.8398  
 Epoch 26/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4290 -  
 accuracy: 0.8400 - val\_loss: 0.4304 - val\_accuracy: 0.8398  
 Epoch 27/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4288 -  
 accuracy: 0.8400 - val\_loss: 0.4329 - val\_accuracy: 0.8398  
 Epoch 28/100  
 240/240 [=====] - 1s 2ms/step - loss: 0.4281 -  
 accuracy: 0.8400 - val\_loss: 0.4295 - val\_accuracy: 0.8398  
 Epoch 29/100

240/240 [=====] - 1s 2ms/step - loss: 0.4297 -  
accuracy: 0.8400 - val\_loss: 0.4296 - val\_accuracy: 0.8398  
Epoch 30/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4280 -  
accuracy: 0.8400 - val\_loss: 0.4313 - val\_accuracy: 0.8398  
Epoch 31/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4264 -  
accuracy: 0.8400 - val\_loss: 0.4291 - val\_accuracy: 0.8398  
Epoch 32/100  
240/240 [=====] - 1s 3ms/step - loss: 0.4284 -  
accuracy: 0.8400 - val\_loss: 0.4276 - val\_accuracy: 0.8398  
Epoch 33/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4266 -  
accuracy: 0.8400 - val\_loss: 0.4325 - val\_accuracy: 0.8398  
Epoch 34/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4288 -  
accuracy: 0.8400 - val\_loss: 0.4281 - val\_accuracy: 0.8398  
Epoch 35/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4279 -  
accuracy: 0.8400 - val\_loss: 0.4298 - val\_accuracy: 0.8398  
Epoch 36/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4273 -  
accuracy: 0.8400 - val\_loss: 0.4278 - val\_accuracy: 0.8398  
Epoch 37/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4281 -  
accuracy: 0.8400 - val\_loss: 0.4289 - val\_accuracy: 0.8398  
Epoch 38/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4282 -  
accuracy: 0.8400 - val\_loss: 0.4261 - val\_accuracy: 0.8398  
Epoch 39/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4280 -  
accuracy: 0.8400 - val\_loss: 0.4291 - val\_accuracy: 0.8398  
Epoch 40/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4264 -  
accuracy: 0.8400 - val\_loss: 0.4297 - val\_accuracy: 0.8398  
Epoch 41/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4273 -  
accuracy: 0.8400 - val\_loss: 0.4262 - val\_accuracy: 0.8398  
Epoch 42/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4275 -  
accuracy: 0.8400 - val\_loss: 0.4275 - val\_accuracy: 0.8398  
Epoch 43/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4277 -  
accuracy: 0.8400 - val\_loss: 0.4293 - val\_accuracy: 0.8398  
Epoch 44/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4260 -  
accuracy: 0.8400 - val\_loss: 0.4376 - val\_accuracy: 0.8398  
Epoch 45/100



240/240 [=====] - 1s 2ms/step - loss: 0.4298 -  
accuracy: 0.8400 - val\_loss: 0.4302 - val\_accuracy: 0.8398  
Epoch 46/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4262 -  
accuracy: 0.8400 - val\_loss: 0.4289 - val\_accuracy: 0.8398  
Epoch 47/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4263 -  
accuracy: 0.8400 - val\_loss: 0.4290 - val\_accuracy: 0.8398  
Epoch 48/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4270 -  
accuracy: 0.8400 - val\_loss: 0.4297 - val\_accuracy: 0.8398  
Epoch 49/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4284 -  
accuracy: 0.8400 - val\_loss: 0.4283 - val\_accuracy: 0.8398  
Epoch 50/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4303 -  
accuracy: 0.8400 - val\_loss: 0.4266 - val\_accuracy: 0.8398  
Epoch 51/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4279 -  
accuracy: 0.8400 - val\_loss: 0.4265 - val\_accuracy: 0.8398  
Epoch 52/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4285 -  
accuracy: 0.8400 - val\_loss: 0.4293 - val\_accuracy: 0.8398  
Epoch 53/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4272 -  
accuracy: 0.8400 - val\_loss: 0.4290 - val\_accuracy: 0.8398  
Epoch 54/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4290 -  
accuracy: 0.8400 - val\_loss: 0.4297 - val\_accuracy: 0.8398  
Epoch 55/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4282 -  
accuracy: 0.8400 - val\_loss: 0.4293 - val\_accuracy: 0.8398  
Epoch 56/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4277 -  
accuracy: 0.8400 - val\_loss: 0.4290 - val\_accuracy: 0.8398  
Epoch 57/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4276 -  
accuracy: 0.8400 - val\_loss: 0.4297 - val\_accuracy: 0.8398  
Epoch 58/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4260 -  
accuracy: 0.8400 - val\_loss: 0.4254 - val\_accuracy: 0.8398  
Epoch 59/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4264 -  
accuracy: 0.8400 - val\_loss: 0.4296 - val\_accuracy: 0.8398  
Epoch 60/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4289 -  
accuracy: 0.8400 - val\_loss: 0.4263 - val\_accuracy: 0.8398  
Epoch 61/100

240/240 [=====] - 1s 2ms/step - loss: 0.4279 -  
accuracy: 0.8400 - val\_loss: 0.4263 - val\_accuracy: 0.8398  
Epoch 62/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4285 -  
accuracy: 0.8400 - val\_loss: 0.4292 - val\_accuracy: 0.8398  
Epoch 63/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4267 -  
accuracy: 0.8400 - val\_loss: 0.4338 - val\_accuracy: 0.8398  
Epoch 64/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4259 -  
accuracy: 0.8400 - val\_loss: 0.4269 - val\_accuracy: 0.8398  
Epoch 65/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4280 -  
accuracy: 0.8400 - val\_loss: 0.4278 - val\_accuracy: 0.8398  
Epoch 66/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4267 -  
accuracy: 0.8400 - val\_loss: 0.4298 - val\_accuracy: 0.8398  
Epoch 67/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4274 -  
accuracy: 0.8400 - val\_loss: 0.4261 - val\_accuracy: 0.8398  
Epoch 68/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4280 -  
accuracy: 0.8400 - val\_loss: 0.4291 - val\_accuracy: 0.8398  
Epoch 69/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4268 -  
accuracy: 0.8400 - val\_loss: 0.4248 - val\_accuracy: 0.8398  
Epoch 70/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4279 -  
accuracy: 0.8400 - val\_loss: 0.4288 - val\_accuracy: 0.8398  
Epoch 71/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4276 -  
accuracy: 0.8400 - val\_loss: 0.4258 - val\_accuracy: 0.8398  
Epoch 72/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4267 -  
accuracy: 0.8400 - val\_loss: 0.4267 - val\_accuracy: 0.8398  
Epoch 73/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4278 -  
accuracy: 0.8400 - val\_loss: 0.4291 - val\_accuracy: 0.8398  
Epoch 74/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4259 -  
accuracy: 0.8400 - val\_loss: 0.4288 - val\_accuracy: 0.8398  
Epoch 75/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4275 -  
accuracy: 0.8400 - val\_loss: 0.4294 - val\_accuracy: 0.8398  
Epoch 76/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4284 -  
accuracy: 0.8400 - val\_loss: 0.4304 - val\_accuracy: 0.8398  
Epoch 77/100

240/240 [=====] - 1s 2ms/step - loss: 0.4269 -  
accuracy: 0.8400 - val\_loss: 0.4278 - val\_accuracy: 0.8398  
Epoch 78/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4270 -  
accuracy: 0.8400 - val\_loss: 0.4286 - val\_accuracy: 0.8398  
Epoch 79/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4264 -  
accuracy: 0.8400 - val\_loss: 0.4279 - val\_accuracy: 0.8398  
Epoch 80/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4281 -  
accuracy: 0.8400 - val\_loss: 0.4286 - val\_accuracy: 0.8398  
Epoch 81/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4274 -  
accuracy: 0.8400 - val\_loss: 0.4291 - val\_accuracy: 0.8398  
Epoch 82/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4280 -  
accuracy: 0.8400 - val\_loss: 0.4329 - val\_accuracy: 0.8398  
Epoch 83/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4266 -  
accuracy: 0.8400 - val\_loss: 0.4272 - val\_accuracy: 0.8398  
Epoch 84/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4266 -  
accuracy: 0.8400 - val\_loss: 0.4290 - val\_accuracy: 0.8398  
Epoch 85/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4279 -  
accuracy: 0.8400 - val\_loss: 0.4269 - val\_accuracy: 0.8398  
Epoch 86/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4275 -  
accuracy: 0.8400 - val\_loss: 0.4292 - val\_accuracy: 0.8398  
Epoch 87/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4285 -  
accuracy: 0.8400 - val\_loss: 0.4264 - val\_accuracy: 0.8398  
Epoch 88/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4274 -  
accuracy: 0.8400 - val\_loss: 0.4264 - val\_accuracy: 0.8398  
Epoch 89/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4269 -  
accuracy: 0.8400 - val\_loss: 0.4264 - val\_accuracy: 0.8398  
Epoch 90/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4252 -  
accuracy: 0.8400 - val\_loss: 0.4252 - val\_accuracy: 0.8398  
Epoch 91/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4286 -  
accuracy: 0.8400 - val\_loss: 0.4272 - val\_accuracy: 0.8398  
Epoch 92/100  
240/240 [=====] - 1s 2ms/step - loss: 0.4287 -  
accuracy: 0.8400 - val\_loss: 0.4304 - val\_accuracy: 0.8398  
Epoch 93/100

```

240/240 [=====] - 1s 2ms/step - loss: 0.4271 -
accuracy: 0.8400 - val_loss: 0.4277 - val_accuracy: 0.8398
Epoch 94/100
240/240 [=====] - 1s 2ms/step - loss: 0.4272 -
accuracy: 0.8400 - val_loss: 0.4283 - val_accuracy: 0.8398
Epoch 95/100
240/240 [=====] - 1s 2ms/step - loss: 0.4270 -
accuracy: 0.8400 - val_loss: 0.4260 - val_accuracy: 0.8398
Epoch 96/100
240/240 [=====] - 1s 2ms/step - loss: 0.4264 -
accuracy: 0.8400 - val_loss: 0.4315 - val_accuracy: 0.8398
Epoch 97/100
240/240 [=====] - 1s 2ms/step - loss: 0.4258 -
accuracy: 0.8400 - val_loss: 0.4275 - val_accuracy: 0.8398
Epoch 98/100
240/240 [=====] - 1s 2ms/step - loss: 0.4287 -
accuracy: 0.8400 - val_loss: 0.4288 - val_accuracy: 0.8398
Epoch 99/100
240/240 [=====] - 1s 2ms/step - loss: 0.4263 -
accuracy: 0.8400 - val_loss: 0.4290 - val_accuracy: 0.8398
Epoch 100/100
240/240 [=====] - 1s 2ms/step - loss: 0.4262 -
accuracy: 0.8400 - val_loss: 0.4270 - val_accuracy: 0.8398

```

```

[78]: # predictions
y_pred_tr = model_1.predict(x_train_sc)
y_pred_ts = model_1.predict(x_test_sc)

```

```

[79]: # confusion matrix on training data
confusion_matrix(y_pred_tr >=0.5, y_train)

```

```

[79]: array([[6436, 1226],
           [  0,    0]])

```

```

[80]: # confusion matrix on test data
confusion_matrix(y_pred_ts >= 0.5, y_test)

```

```

[80]: array([[1609,  307],
           [  0,    0]])

```

```

[81]: # accuracy score on training data
accuracy_score(y_pred_tr >=0.5, y_train)

```

```

[81]: 0.839989558861916

```

```

[82]: # accuracy score on test data
accuracy_score(y_pred_ts >=0.5, y_test)

```

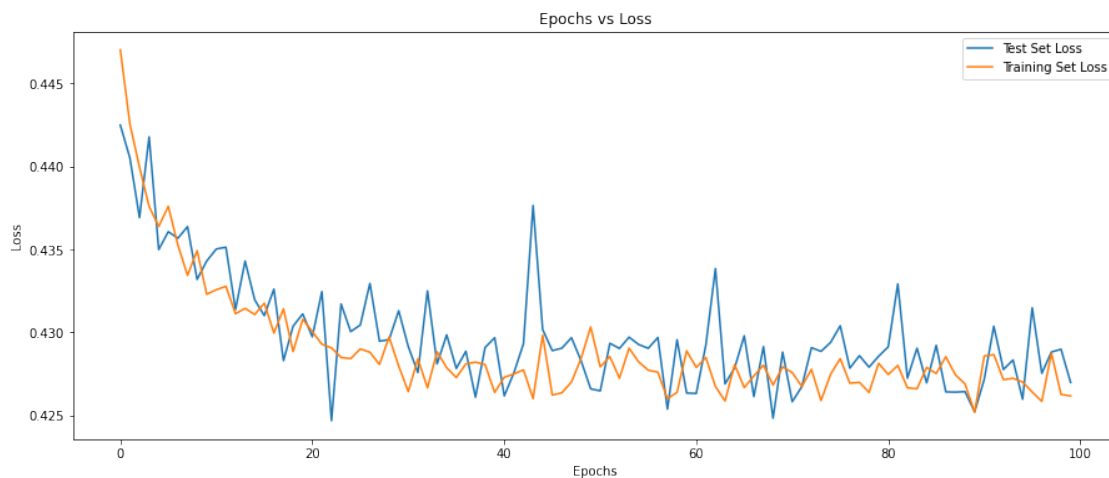
[82]: 0.8397703549060542

```
[87]: # history
history_1 = pd.DataFrame(result_1.history)
history_1.head()
```

```
[87]:
```

	loss	accuracy	val_loss	val_accuracy
0	0.447038	0.83999	0.442501	0.83977
1	0.442559	0.83999	0.440511	0.83977
2	0.439956	0.83999	0.436915	0.83977
3	0.437589	0.83999	0.441788	0.83977
4	0.436383	0.83999	0.434987	0.83977

```
[88]: # plotting loss vs epochs
plt.figure(figsize = (15,6))
plt.plot(history_1.val_loss, label = 'Test Set Loss')
plt.plot(history_1.loss, label = 'Training Set Loss')
plt.title('Epochs vs Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



```
[89]: # plot Epochs vs Accuracy
plt.figure(figsize = (15, 6))
plt.plot(history_1.val_accuracy, label = 'Test Set Accuracy' )
plt.plot(history_1.accuracy, label = 'Training Set Accuracy')
plt.title('Epochs vs Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
```

```
plt.show()
```

