Case study 6

Artificial Neural Networks

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Quantifying The World

Introduction

The goal of this project is to maximize accuracy and minimize loss using a dense neural network. The dataset contains 7 million records (big dataset), with 29 features. The features are just numbered from f0 to f26, label. "# label" is the target variable in the dataset.

Data Analysis

The dataset contains 7 million records (big dataset), with 29 features. The features are numbered from *f0* to *f26*, label. "*# label*" is the target variable in the dataset.
There are no missing values. This dataset doesn't require imputation for the features.

The correlation matrix below shows the collinearity among the variables. Data shows there is high collinearity for a few of the attributes.

This study considered all the features with lower than 99% correlation for this analysis. There are features with up to 83% of correlation. Since none of the features showed 99% or above collinearity, all features are considered for modeling, and none are dropped.

Correlation Analysis

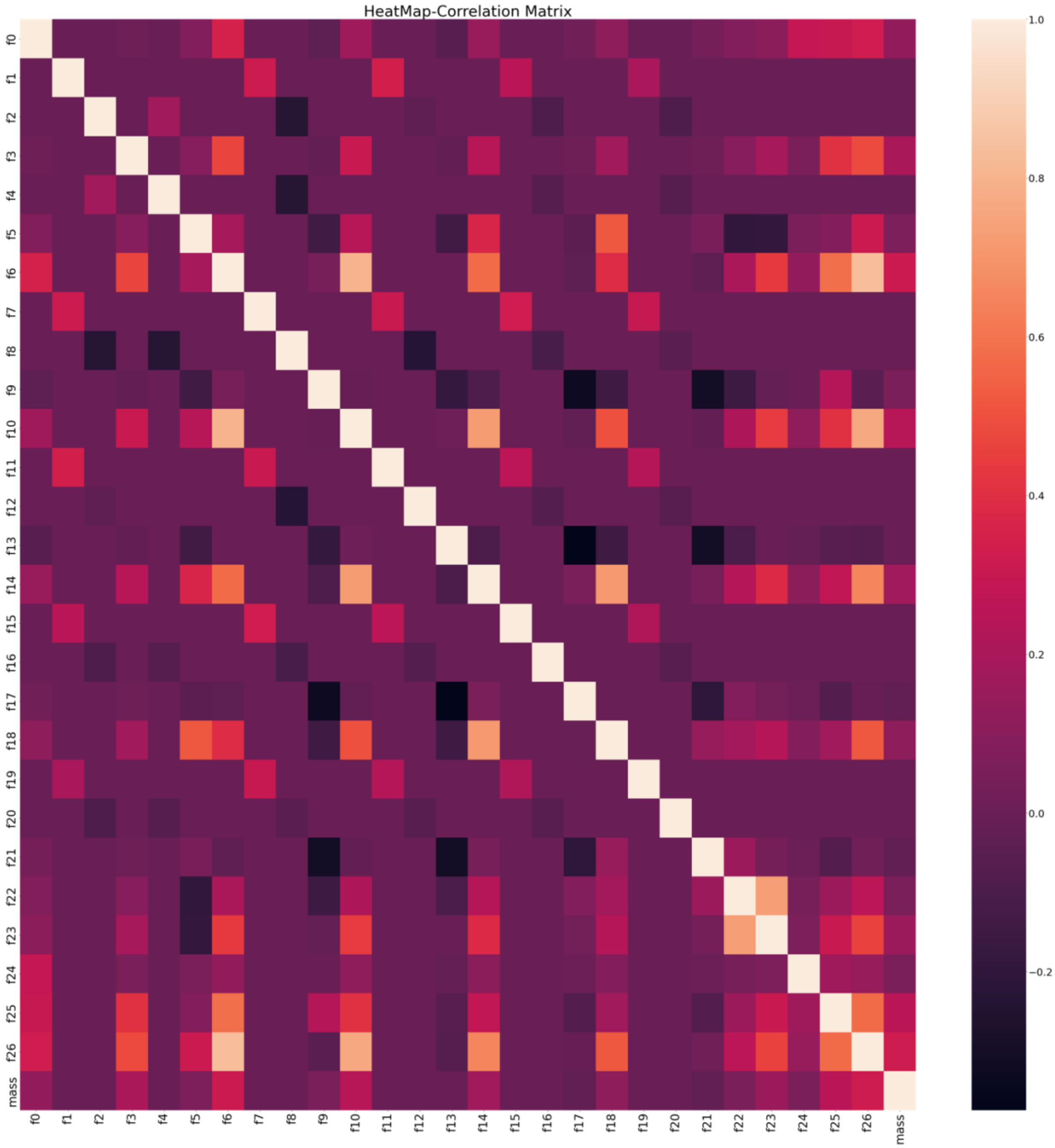


Figure 1: Collinearity heatmap of Attributes

Target

Target is a binary variable called *'# label'*, which has value either *0* or *1.*

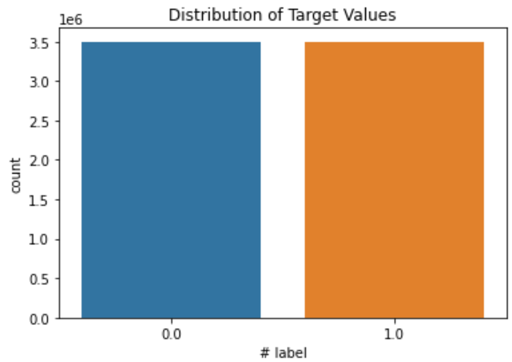


Figure 2: Target variable distribution plot

2. Methods

`f9, f13, f17, f21` are categorical variables, which are converted using one-hot encoding.

All the features are normalized using the `Standard Scaler` technique. After normalization, the data was split into train and test datasets by a factor of 80/20.

The training data was further split into training and validation set by 80/20. The validation set is used to validate the model performance during training.

The test data is unseen data and is used to calculate the final accuracy of the best model and ROC curve, and confusion matrix.

ANN

Artificial neural networks (ANNs) are models inspired by humans (or biological) neural networks.

An ANN is a collection of neurons (nodes) loosely based on the biological brain interconnected in a dense layer. Each neural is a linear regression created from each feature. The neurons send a signal once it crosses a certain threshold. Usually, they are aggregated into several layers (sequential or dense). The final layer depends on the type of classification required. For binary classification, sigmoid functions are used. The last layer uses a sigmoid function for this study, as the target is a binary classification.

Layers of Neural Network

In this study, the authors created two sets of neural networks, one with 3 layers and another with 4 layers.

First neural network with the following layers:

Layer	Activation Function	Number of Neurons	Input to Layer
1	gelu	512	Features
2	gelu	256	Layer1
3	gelu	128	Layer2
4	sigmoid	2	Layer3

Table 1: Layers of first Neural Network

Second neural network with the following layers:

Layer	Activation Function	Number of Neurons	Input to Layer
1	gelu	1024	Features
2	gelu	512	Layer1
3	gelu	256	Layer2
4	gelu	128	Layer3
5	sigmoid	2	Layer4

Table 2: Layers of second Neural Network

The hyper-parameters (tunable parameters) are:

Third neural network with the following layers:

Layer	Activation Function	Number of Neurons	Input to Layer
1	swish	512	Features
2	swish	256	Layer1
3	swish	128	Layer2
4	sigmoid	2	Layer3

Table 3:Layers of third Neural Network

Parameters:

batchsize: Constant that multiplies the regularization term; the higher the value, the stronger the regularization. Also used to compute the learning rate when *learning_rate* is set to '*optimal.*'

Optimizer: Adam(lr=1e-2).

loss: Sparse Categorical Cross-Entropy *safety:* Early Stopping (using *val_loss*)

patience: 3

min_delta: 2e-4

The models are compiled to run for 50 epochs. Each epoch runs the entire dataset once. With 50 epochs, the model runs each record in the dataset 50 times or unless early stopping condition is met (when loss stops reducing further). If the accuracy or val_loss doesn't improve, then the model doesn't run the entire 50 epochs and stops early. The model is configured to stop if `3` (hyper-param `patience`) consecutive epochs did not improve val_loss. This prevents running neural networks when the metrics don't improve.

3. Results

Model	Batch Size	Dense Neurons	Validation Accuracy
gelu/4 Layers	2048	1094 → 512 → 128	87.99%
gelu/3 Layers	2048	512 → 256	88.20%
gelu/3 Layers	1024	512 → 256	88.07%
swish/3 Layers	2048	512 → 256	88.12%
gelu/3 Layers	100	512 → 256	87.63%

Table 4: Results of various models

All the models are giving similar results. The *gelu* model with `3` layers and batch size of *2048* gives the highest accuracy of *88.20%*.
When batch size decreases, training time increases (when all others are kept same):

Batch Size	Training Time (in seconds)
2048	16
1024	31
100	250

Table 5: Training Times by Batch Size

The detailed results from the best of the models (`gelu/3layers/2048 batch`) are listed below:

	precision	recall	f1-score	support
0 (target)	0.9	0.85	0.88	699445
1 (target)	0.86	0.91	0.88	700555
accuracy			0.88	1400000
macro avg	0.88	0.88	0.88	1400000
weighted avg	0.88	0.88	0.88	1400000

Table 6: Confusion Matrix

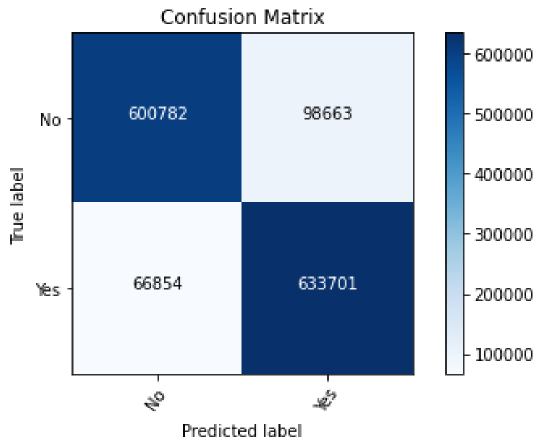


Figure 3: Confusion Matrix

4. Conclusion

All neural network models produced similar results. In terms of accuracy, there is no significant difference in the model output. Changing the activation function between `gelu` or `swish` doesn't change the final accuracy significantly. Similarly, the addition of the 4th layer doesn't produce higher accuracy results. The change in batch size between `1024` and `2048` also doesn't produce a significantly different output.

Due to early stopping criteria, the model stops much earlier than running all 50 epochs as it stops improving further. Overall model accuracy is around 88.20%.

The neural network model was able to accurately predict the existence of new particles with 88% accuracy, we can advise our clients to use neural network model to detect a new particle.

Appendix – Code

NB Viewer Link:
https://nbviewer.org/github/ravisiv/CaseStudy6_NN/blob/main/Case%20Study%206.ipynb

CaseStudy6_NN (/github/ravisiv/CaseStudy6_NN/tree/main)
/ Case Study 6.ipynb (/github/ravisiv/CaseStudy6_NN/tree/main/Case Study 6.ipynb)

In [1]:

```
import os
import
pandas as pd
import re
import
datetime as
dt import
numpy as np
from IPython.display
import display import
warnings import seaborn
as sns
from sklearn.preprocessing import
StandardScaler from sklearn import metrics
as mt
from sklearn.metrics import
classification_report from sklearn.metrics
import f1_score import
matplotlib.pyplot as plt
from sklearn.linear_model import
SGDClassifier
from sklearn.metrics import precision_recall_curve,
plot_precision_reca from sklearn.preprocessing import
label_binarize, StandardScaler from sklearn import metrics as mt
from sklearn.model_selection import cross_validate,
cross_val_predict, warnings.filterwarnings('ignore')
```

In [2]:

```
# load data
#df = pd.read_csv('all_train.csv') # read in the csv file
df = pd.read_csv('/Users/ravis/Downloads/data/all_train.csv')
```

In [3]:

```
df.mass
```

Out[3]:

```
0        1000.000000 1
750.000000
2        750.000000
3        1250.000000
4        750.000000        ...
```

```
6999995      750.000000
6999996      1250.000000
6999997      1500.000000
6999998      1500.000000
6999999      499.999969
Name: mass, Length: 7000000, dtype: float64
```

In [4]:

```
df . info  ()
```

```
<class 'pandas.core.frame.DataFrame'> RangeIndex:
7000000 entries, 0 to 6999999
Data columns (total 29 columns):
 #   Column   Dtype
---  ------   -----
0     # label  float64
1     f0      float64
2     f1      float64
3     f2      float64
4     f3      float64
5     f4      float64
6     f5      float64
7     f6      float64
8     f7      float64
9     f8      float64
10    f9      float64
11    f10     float64
12    f11     float64
13    f12     float64
14    f13     float64
15    f14     float64
16    f15     float64
17    f16     float64
18    f17     float64
19    f18     float64
20    f19     float64
21    f20     float64
22    f21     float64
23    f22     float64
24    f23     float64
25    f24     float64
26    f25     float64
27    f26     float64  28  mass     float64 dtypes: float64(29) memory usage: 1.5 GB In [5]:
```

```
df . describe   ()
```

Out[5]:

	# label	f0	f1	f2	f3	f4
count	7.000000e+06	7.000000e+06	7.000000e+06	7.000000e+06	7.000000e+06	7.000000e+06
mean	5.001256e-01	1.612528e-02	4.770022e-04	2.686578e-05	1.056081e-02	-1.050026e-04
std	5.000000e-01	1.004417e+00	9.974864e-01	1.000080e+00	9.956003e-01	9.998670e-01
min	0.000000e+00	-1.960549e+00	-2.365355e+00	-1.732165e+00	-9.980274e+00	-1.732137e+00
25%	0.000000e+00	-7.288206e-01	-7.332548e-01	-8.656704e-01	-6.092291e-01	-8.658025e-01
50%	1.000000e+00	-3.930319e-02	8.523957e-04	3.199154e-04	1.963316e-02	-5.070131e-04
75%	1.000000e+00	6.900799e-01	7.347832e-01	8.659464e-01	6.798818e-01	8.657646e-01
max	1.000000e+00	4.378282e+00	2.365287e+00	1.732370e+00	4.148023e+00	1.731978e+00

8 rows × 29 columns

Missing value analysis

In [6]:

```
# Validate null values in the csv file
df.isnull().sum().sum()
```

Out[6]: 0

In [7]:

```
df['# label'].value_counts()
```

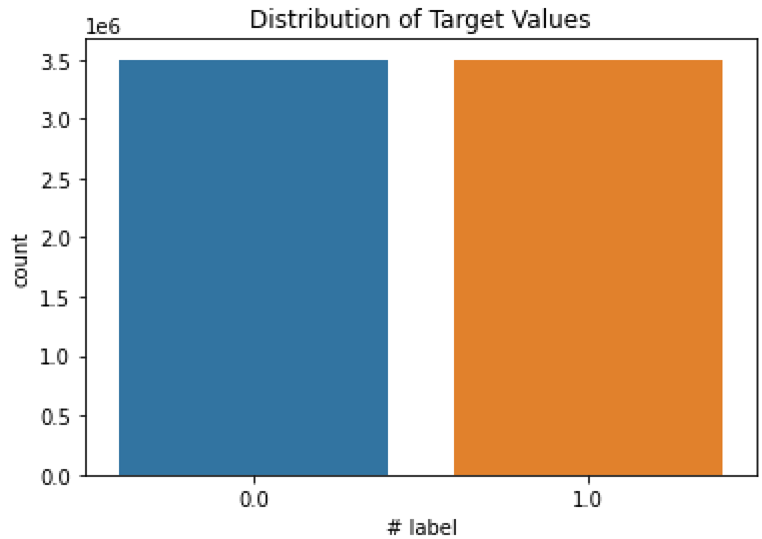
Out[7]:

Target

1.0 3500879
0.0 3499121
Name: # label, dtype: int64

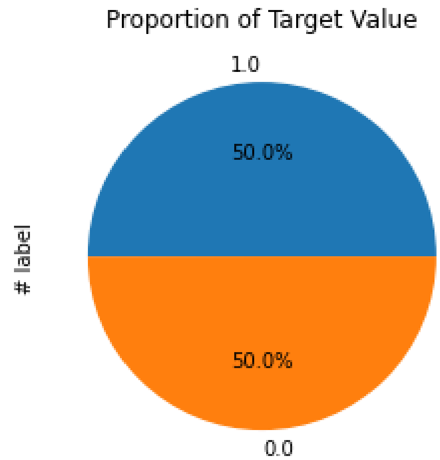
In [8]:

```
sns . countplot   ( x  =  "# label"     ,    data    =  df )
plt  . title    ( "Distribution of Target Values"              )
plt  . show()
```



In [9]:

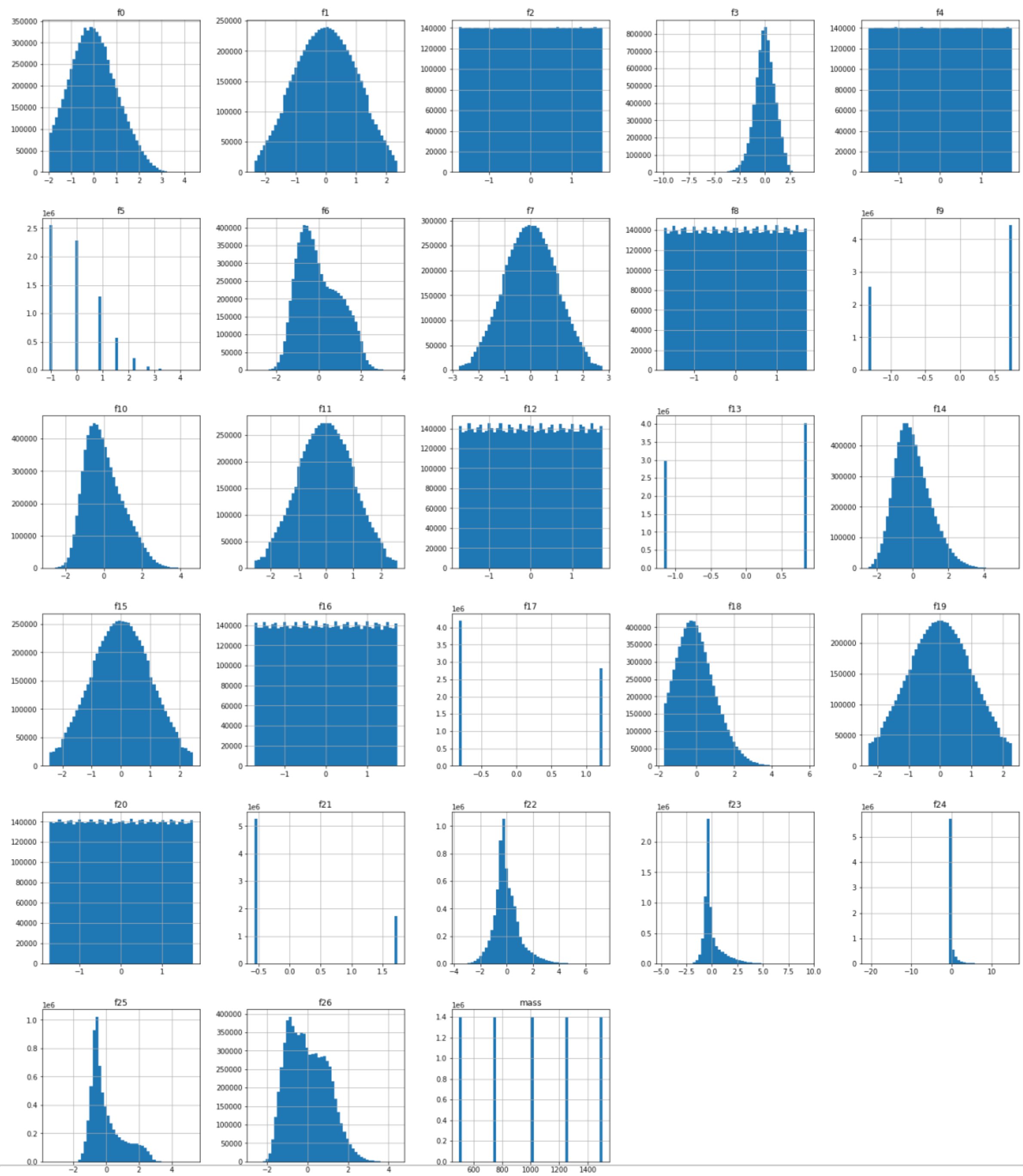
```
# Pie chart
df [ '# label'      ] . value_counts    () . plot  . pie ( autopct    =  "%.1f%%")
plt  . title    ( "Proportion of Target Value"          )
plt  . show()
```



Independent Variable analysis p y

In [10]:

```
#Visualizing the hist of data to check normality of independent v
df_X  =  df . drop ([  '# label'      ] , axis  =1)
df_X . hist  ( bins  =50, figsize     =( 25, 30))
plt  . show()
```



In [11]:

```
print(df['f9'].value_counts()) print(df['f13'].value_counts())
print(df['f17'].value_counts())  print(df['f21'].value_counts())
```

```
 0.754261    4438579 -1.325801    2561421
Name: f9, dtype: int64
 0.860649    4027351 -1.161915    2972649
Name: f13, dtype: int64
-0.815440    4187343
 1.226331    2812657 Name: f17, dtype: int64
-0.573682    5265796
 1.743123    1734204 Name: f21, dtype: int64
```

```
df . drop ([  '# label'      ] , axis  =1) . describe   ()
```

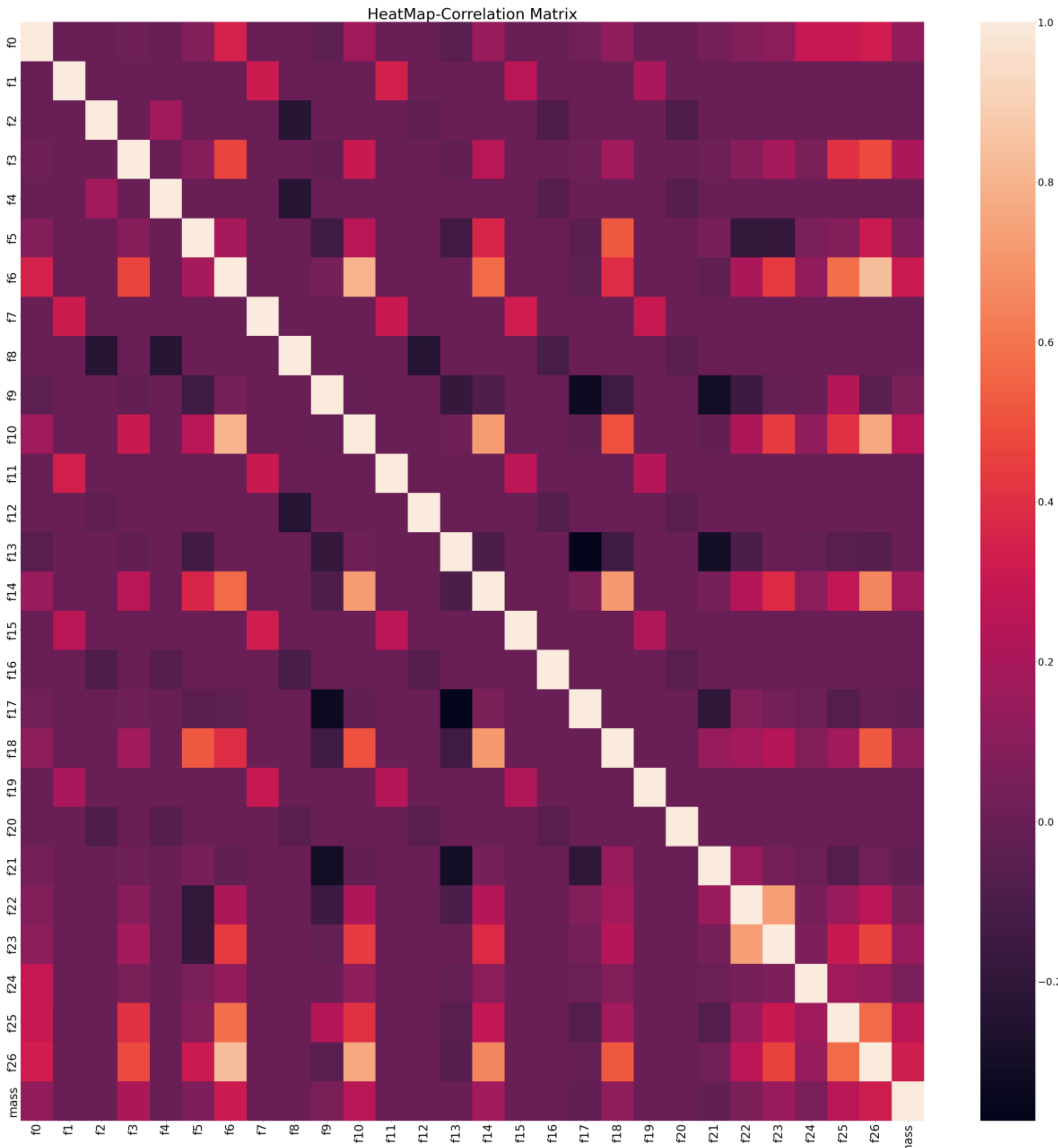
In [12]:
Out[12]:

	f0	f1	f2	f3	f4	f5
count	7.000000e+06	7.000000e+06	7.000000e+06	7.000000e+06	7.000000e+06	7.000000e+0
mean	1.612528e-02	4.770022e-04	2.686578e-05	1.056081e-02	-1.050026e-04	2.765919e-0
std	1.004417e+00	9.974864e-01	1.000080e+00	9.956003e-01	9.998670e-01	1.000957e+0
min	-1.960549e+00	-2.365355e+00	-1.732165e+00	-9.980274e+00	-1.732137e+00	-1.054221e+0
25%	-7.288206e-01	-7.332548e-01	-8.656704e-01	-6.092291e-01	-8.658025e-01	-1.054221e+0
50%	-3.930319e-02	8.523957e-04	3.199154e-04	1.963316e-02	-5.070131e-04	-5.983562e-03
75%	6.900799e-01	7.347832e-01	8.659464e-01	6.798818e-01	8.657646e-01	8.504885e-0
max	4.378282e+00	2.365287e+00	1.732370e+00	4.148023e+00	1.731978e+00	4.482618e+0

8 rows × 28 columns

In [13]:

```
#heatmap - correlation matrix
plt . figure ( figsize =( 60, 60)) #code reference (5-1)
plt . xticks ( rotation =90, fontsize = 35)
plt . yticks ( rotation =180, fontsize = 35)
ax =sns . heatmap( df_X . corr () , annot =False, cbar =True, annot_kws ={ "size" : 2
cbar = ax . collections [ 0] . colorbar
cbar . ax . tick_params ( labelsize =30)
plt . title ( 'HeatMap-Correlation Matrix' , fontsize = 45)
plt . show()
```



Check for Multicolliniarity

In [14]:
```
#https://www.projectpro.io/recipes/drop-out-highly-correlated-features-
# to drop features with colliniarity more than 95%
pd.set_option('display.max_rows', 100)

corr_df = pd.DataFrame(df_X.corr().abs()) corr_df.head(100)
```

Out[14]:

	f0	f1	f2	f3	f4	f5	f6	f7	f
f0	1.000000	0.000556	0.000321	0.012037	0.000464	0.078401	0.349973	0.000026	0.00092
f1	0.000556	1.000000	0.000200	0.000706	0.000131	0.000511	0.000454	0.315357	0.00058
f2	0.000321	0.000200	1.000000	0.000074	0.174967	0.000162	0.000436	0.000024	0.23231
f3	0.012037	0.000706	0.000074	1.000000	0.000385	0.092129	0.468157	0.000091	0.00018
f4	0.000464	0.000131	0.174967	0.000385	1.000000	0.000496	0.000307	0.000435	0.23300
f5	0.078401	0.000511	0.000162	0.092129	0.000496	1.000000	0.191900	0.000740	0.00067
f6	0.349973	0.000454	0.000436	0.468157	0.000307	0.191900	1.000000	0.000491	0.00069
f7	0.000026	0.315357	0.000024	0.000091	0.000435	0.000740	0.000491	1.000000	0.00088
f8	0.000924	0.000580	0.232319	0.000188	0.233003	0.000671	0.000699	0.000887	1.00000
f9	0.039924	0.000141	0.000426	0.021872	0.000084	0.143509	0.038961	0.000328	0.00054
f10	0.171641	0.000726	0.000291	0.306169	0.000229	0.243807	0.799686	0.000724	0.00048
f11	0.000564	0.336327	0.000268	0.000073	0.000174	0.000271	0.000290	0.306276	0.00046
f12	0.000268	0.000218	0.036190	0.000460	0.001119	0.000454	0.000685	0.000132	0.23824
f13	0.057995	0.000088	0.000378	0.024117	0.000092	0.137170	0.000264	0.000083	0.00012
f14	0.147686	0.000375	0.000017	0.244698	0.000189	0.363165	0.575503	0.000471	0.00040
f15	0.000105	0.256024	0.000185	0.001113	0.000011	0.000005	0.000920	0.324219	0.00046
f16	0.000684	0.000249	0.091000	0.000181	0.065579	0.000300	0.000205	0.000238	0.10618
f17	0.027194	0.000136	0.000912	0.008179	0.000023	0.042581	0.038356	0.000435	0.00047
f18	0.119041	0.000079	0.000026	0.174068	0.000338	0.517752	0.390014	0.000251	0.00023
f19	0.000152	0.195312	0.000399	0.000328	0.000400	0.000337	0.000226	0.299012	0.00012
f20	0.000617	0.000254	0.092043	0.000047	0.068271	0.000305	0.000303	0.000276	0.05167
f21	0.034794	0.000191	0.000312	0.010787	0.000485	0.044609	0.034123	0.000131	0.00004
f22	0.080169	0.000100	0.000171	0.096627	0.000136	0.195117	0.209496	0.000023	0.00009
f23	0.109947	0.000384	0.000075	0.190014	0.000061	0.188721	0.433089	0.000133	0.00035

f24	0.289670	0.000178	0.000499	0.056976	0.000009	0.050882	0.126159	0.000182	0.00065
f25	0.296976	0.000563	0.000186	0.406295	0.000346	0.082941	0.581645	0.000020	0.00037
f26	0.327533	0.000782	0.000315	0.482503	0.000414	0.308311	0.835995	0.000621	0.00029
mass	0.126717	0.000050	0.000169	0.203470	0.000002	0.064497	0.310024	0.000069	0.00075

28 rows × 28 columns

In [15]:

```
# Multi Colliniarity analysis on Independent variables
upper_tri = corr_df.where(np.triu(np.ones(corr_df.shape),k=1).astype(np
print(upper_tri)
```

f0 f1 f2 f3 f4 f5 f6 \ f0 NaN 0.000556 0.000321 0.012037
0.000464 0.078401 0.349973 f1 NaN NaN 0.000200 0.000706 0.000131 0.000511
0.000454 f2 NaN NaN NaN 0.000074 0.174967 0.000162 0.000436 f3 NaN NaN
NaN NaN 0.000385 0.092129 0.468157 f4 NaN NaN NaN NaN NaN
0.000496 0.000307 f5 NaN NaN NaN NaN NaN NaN 0.191900 f6 NaN
NaN NaN NaN NaN NaN NaN f7 NaN NaN NaN NaN NaN
NaN NaN f8 NaN NaN NaN NaN NaN NaN NaN f9 NaN NaN
NaN NaN NaN NaN NaN f10 NaN NaN NaN NaN NaN NaN
NaN f11 NaN NaN NaN NaN NaN NaN NaN f12 NaN NaN NaN
NaN NaN NaN NaN f13 NaN NaN NaN NaN NaN NaN NaN f14
NaN NaN NaN NaN NaN NaN NaN f15 NaN NaN NaN NaN
NaN NaN NaN f16 NaN NaN NaN NaN NaN NaN NaN f17 NaN
NaN NaN NaN NaN NaN NaN f18 NaN NaN NaN NaN NaN
NaN NaN f19 NaN NaN NaN NaN NaN NaN NaN f20 NaN NaN
NaN NaN NaN NaN NaN f21 NaN NaN NaN NaN NaN NaN
NaN f22 NaN NaN NaN NaN NaN NaN NaN f23 NaN NaN NaN
NaN NaN NaN NaN f24 NaN NaN NaN NaN NaN NaN NaN f25
NaN NaN NaN NaN NaN NaN NaN f26 NaN NaN NaN NaN
NaN NaN NaN mass NaN NaN NaN NaN NaN NaN NaN

f7 f8 f9 ... f18 f19 f20 f0 0.000026 0.000924 0.039924 ...
0.119041 0.000152 0.000617 f1 0.315357 0.000580 0.000141 ... 0.000079 0.195312
0.000254 f2 0.000024 0.232319 0.000426 ... 0.000026 0.000399 0.092043 f3
0.000091 0.000188 0.021872 ... 0.174068 0.000328 0.000047 f4 0.000435 0.233003
0.000084 ... 0.000338 0.000400 0.068271 f5 0.000740 0.000671 0.143509 ...
0.517752 0.000337 0.000305 f6 0.000491 0.000699 0.038961 ... 0.390014 0.000226
0.000303 f7 NaN 0.000887 0.000328 ... 0.000251 0.299012 0.000276 f8 NaN
NaN 0.000548 ... 0.000235 0.000124 0.051674 f9 NaN NaN NaN ... 0.146027
0.000023 0.000175 f10 NaN NaN NaN ... 0.497812 0.000294 0.000334 f11
NaN NaN NaN ... 0.000089 0.239606 0.000590 f12 NaN NaN NaN ...
0.000126 0.000859 0.054172 f13 NaN NaN NaN ... 0.148374 0.000217
0.000031 f14 NaN NaN NaN ... 0.714613 0.000295 0.000070 f15 NaN
NaN NaN ... 0.000265 0.221685 0.000307 f16 NaN NaN NaN ... 0.000242
0.000065 0.055865 f17 NaN NaN NaN ... 0.005241 0.000265 0.000239 f18
NaN NaN NaN ... NaN 0.000117 0.000113 f19 NaN NaN NaN ...
NaN NaN 0.000138 f20 NaN NaN NaN ... NaN NaN NaN f21
NaN NaN NaN ... NaN NaN NaN f22 NaN NaN NaN ... NaN
NaN NaN f23 NaN NaN NaN ... NaN NaN NaN f24 NaN NaN
NaN ... NaN NaN NaN f25 NaN NaN NaN ... NaN NaN NaN
f26 NaN NaN NaN ... NaN NaN NaN mass NaN NaN NaN ...
NaN NaN NaN

f21 f22 f23 f24 f25 f26 m f0 0.034794 0.080169 0.109947 0.289670
0.296976 0.327533 0.126 f1 0.000191 0.000100 0.000384 0.000178 0.000563 0.000782
0.000 f2 0.000312 0.000171 0.000075 0.000499 0.000186 0.000315 0.000 f3 0.010787
0.096627 0.190014 0.056976 0.406295 0.482503 0.203 f4 0.000485 0.000136 0.000061
0.000009 0.000346 0.000414 0.000 f5 0.044609 0.195117 0.188721 0.050882 0.082941
0.308311 0.064 f6 0.034123 0.209496 0.433089 0.126159 0.581645 0.835995 0.310 f7
0.000131 0.000023 0.000133 0.000182 0.000020 0.000621 0.000 f8 0.000047 0.000099
0.000354 0.000657 0.000375 0.000296 0.000 f9 0.307213 0.155551 0.015394 0.000711
0.235398 0.049122 0.055 f10 0.024445 0.211504 0.441256 0.123966 0.407570 0.760416
0.245 f11 0.000412 0.000509 0.000661 0.000559 0.001009 0.000406 0.000 f12 0.000263
0.000215 0.000447 0.000077 0.000146 0.000387 0.000 f13 0.306429 0.103286 0.000119
0.018679 0.055174 0.066454 0.000 f14 0.039548 0.234758 0.380652 0.104323 0.279477
0.656016 0.174 f15 0.000801 0.000806 0.001035 0.000278 0.000507 0.000914 0.000 f16
0.000275 0.000115 0.000236 0.000256 0.000441 0.000048 0.000 f17 0.205639 0.076665
0.033371 0.001520 0.076047 0.009786 0.028 f18 0.144685 0.184386 0.235264 0.082366
0.176284 0.521591 0.117 f19 0.000133 0.000185 0.000421 0.000060 0.000246 0.000005
0.000 f20 0.000442 0.000109 0.000493 0.000050 0.000220 0.000070 0.000 f21 NaN
0.153676 0.037039 0.003852 0.077928 0.021282 0.028 f22 NaN NaN 0.727996
0.039866 0.155997 0.261498 0.057 f23 NaN NaN NaN 0.064041 0.302942
0.461259 0.155 f24 NaN NaN NaN NaN 0.169888 0.141599 0.051 f25 NaN
NaN NaN NaN NaN 0.572478 0.253 f26 NaN NaN NaN NaN NaN
NaN 0.323 mass NaN NaN NaN NaN NaN NaN

[28 rows x 28 columns]

In [16]:

```
to_drop = [column for column in upper_tri.columns if any(upper_tri[colu
print((to_drop))
```

[]

In [17]:

```
df = pd.get_dummies(df, columns=['f9', 'f13', 'f17', 'f21'], prefix=['f
```

In [18]:

```
X = df.drop(['# label'],axis=1) ind_columns =
df.drop('# label',axis=1).columns y = df['# label']
```

We did normalize the attributes using StandardScaler() to scale them between 0 and 1 before running models.

In [19]:

```
# Normalize the data
scaler   = StandardScaler   ()
X_scaled   = scaler  . fit_transform    ( X)
```

In [20]:

```
from sklearn.model_selection import train_test_split
#Direct train/test split
X_train  ,  X_test  ,  Y_train  ,  Y_test   = train_test_split      (
     X_scaled  ,  y,  test_size   =0.20 ,  random_state  =1234
)
```

Neural Network Model

In [21]:

```
import tensorflow as tf
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.optimizers import Adam
```

In [22]:

```
my_model =  tf  . keras  . Model()
```

Metal device set to: Apple M1 Pro

2022-03-25 16:26:02.223468: I tensorflow/core/common_runtime/pluggable_
2022-03-25 16:26:02.223589: I tensorflow/core/common_runtime/pluggable_

Model 1 gelu - Four layers

In [23]:

```
layer_zero = tf.keras.Input(shape=(32,)) layer1 = tf.keras.layers.Dense(1094,
activation='gelu')(layer_zero) layer2 = tf.keras.layers.Dense(512,
activation='gelu')(layer1) layer3 = tf.keras.layers.Dense(128,
activation='gelu')(layer2) layer4 = tf.keras.layers.Dense(2,
activation='sigmoid')(layer2)
 my_model = tf.keras.Model(inputs=layer_zero, outputs=layer4)
```

In [24]:

```
my_model.compile(optimizer=Adam(lr=1e-2), loss=tf.keras.losses.SparseCa safety
= EarlyStopping(monitor='val_loss', patience=3, min_delta=2e-4)

x_train, x_val, y_train, y_val = train_test_split(X_train, Y_train, tes
```

In [25]:

```
nn_history = my_model.fit(x_train, y_train,
validation_data=(x_val, y_val),
callbacks=[safety],            epochs=50,
batch_size=100)
```

Epoch 1/50

2022-03-25 16:26:04.870768: W tensorflow/core/platform/profile_utils/cp

```
2022-03-25 16:26:05.102127: I tensorflow/core/grappler/optimizers/custo

2188/2188 [==============================] - ETA: 0s - loss: 0.2856 - a

2022-03-25 16:26:34.969380: I tensorflow/core/grappler/optimizers/custo

2188/2188 [==============================] - 33s 15ms/step - loss: 0.28 Epoch 2/50
2188/2188 [==============================] - 33s 15ms/step - loss: 0.27 Epoch 3/50
2188/2188 [==============================] - 31s 14ms/step - loss: 0.26 Epoch 4/50
2188/2188 [==============================] - 30s 14ms/step - loss: 0.26 Epoch 5/50
2188/2188 [==============================] - 30s 14ms/step - loss: 0.26 Epoch 6/50
2188/2188 [==============================] - 31s 14ms/step - loss: 0.26 Epoch 7/50
2188/2188 [==============================] - 31s 14ms/step - loss: 0.26 Epoch 8/50
```

In [26]:

```
2188/2188 [==============================] - 31s 14ms/step -                loss    : 0.26
```

```
my_model. summary()
```

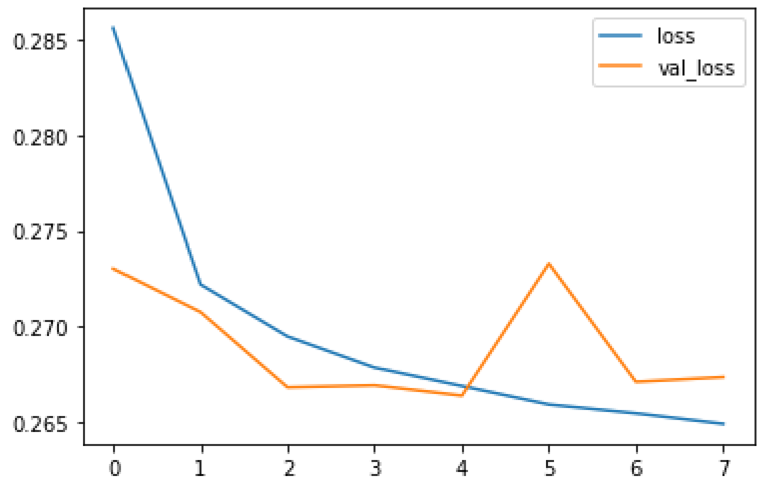
```
Model: "model_1"
_________________________________________________________________
 Layer (type)            Output Shape           Param #
=================================================================
input_1 (InputLayer)       [(None, 32)]           0
dense (Dense)            (None, 1094)           36102
dense_1 (Dense)            (None, 512)            560640
dense_3 (Dense)            (None, 2)            1026
================================================================= Total
params: 597,768
Trainable params: 597,768
Non-trainable params: 0
_________________________________________________________________
```

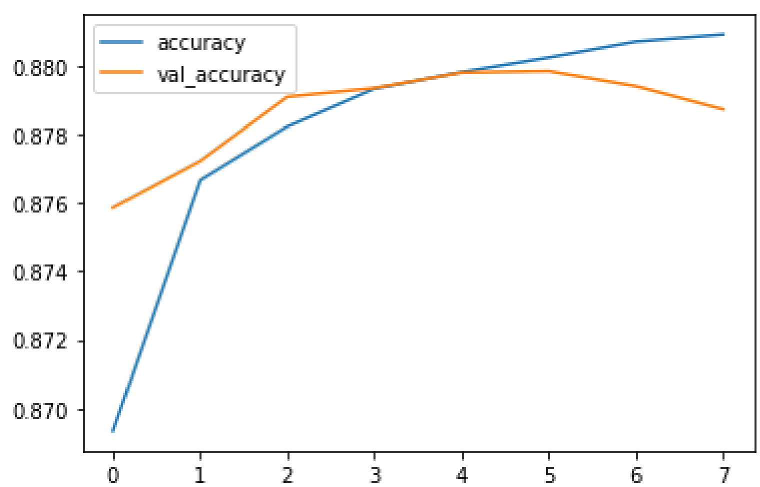
In [27]:

```
history_df = pd.DataFrame(nn_history.history) history_df[['loss',
'val_loss']].plot()

history_df = pd.DataFrame(nn_history.history) history_df[['accuracy',
'val_accuracy']].plot()
```

Out[27]: <AxesSubplot:>


loss
val_loss
0.285
0.280
0.275
0.270
0.265
0
1
2
3
4
5
6
7


accuracy
val_accuracy
0.880
0.878
0.876
0.874
0.872
0.870
0
1
2
3
4
5
6
7

Model 1 gelu - 3 layers

In [53]:

```
layer_zero = tf.keras.Input(shape=(32,)) layer1 = tf.keras.layers.Dense(512,
activation='gelu')(layer_zero) layer2 = tf.keras.layers.Dense(256,
activation='gelu')(layer1) #layer3 =
tf.keras.layers.Dense(128,
activation='gelu')(layer2) layer4 = tf.keras.layers.Dense(2,
activation='sigmoid')(layer2)
my_model = tf.keras.Model(inputs=layer_zero, outputs=layer4)
```

In [54]:

```
my_model.compile(optimizer=Adam(lr=1e-2), loss=tf.keras.losses.SparseCa safety
= EarlyStopping(monitor='val_loss', patience=3, min_delta=2e-4)
x_train, x_val, y_train, y_val = train_test_split(X_train, Y_train, tes
```

In [55]:

```
nn_history = my_model.fit(x_train, y_train,
validation_data=(x_val, y_val),
callbacks=[safety],              epochs=50,
batch_size=100)
```

```
Epoch 1/50

2022-03-26 10:27:51.674809: I tensorflow/core/grappler/optimizers/custo

44800/44800 [==============================] - ETA: 0s - loss: 0.2929 -

2022-03-26 10:31:34.644074: I tensorflow/core/grappler/optimizers/custo

44800/44800 [==============================] - 255s 6ms/step - loss: 0 Epoch 2/50
44800/44800 [==============================] - 249s 6ms/step - loss: 0 Epoch 3/50
44800/44800 [==============================] - 251s 6ms/step - loss: 0 Epoch 4/50
44800/44800 [==============================] - 253s 6ms/step - loss: 0 Epoch 5/50
44800/44800 [==============================] - 245s 5ms/step - loss: 0 Epoch 6/50
44800/44800 [==============================] - 244s 5ms/step - loss: 0
```

In [56]:

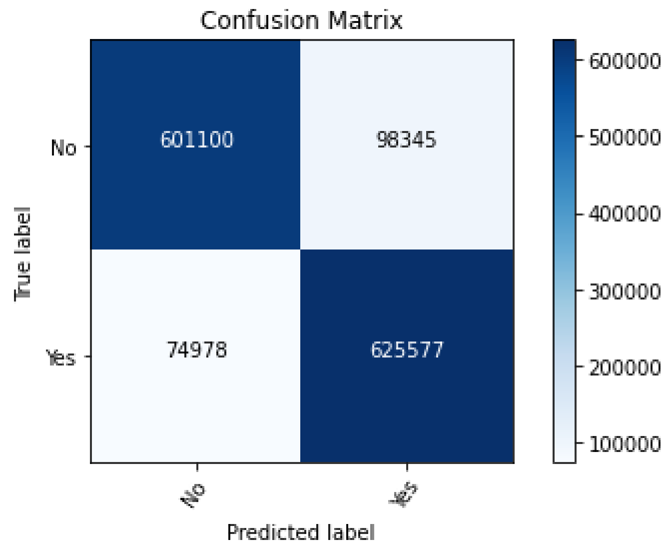
```
y_pred=my_model.predict(X_test)

cm = confusion_matrix(Y_test, np.argmax(y_pred, axis=1))

cm_plot_label =['No', 'Yes'] plot_confusion_matrix(cm, cm_plot_label, title
='Confusion Matrix')
```

```
2022-03-26 10:52:50.264679: I tensorflow/core/grappler/optimizers/custo

[[601100  98345]
 [ 74978 625577]]
```



In [57]:

```
my_model. summary()
```

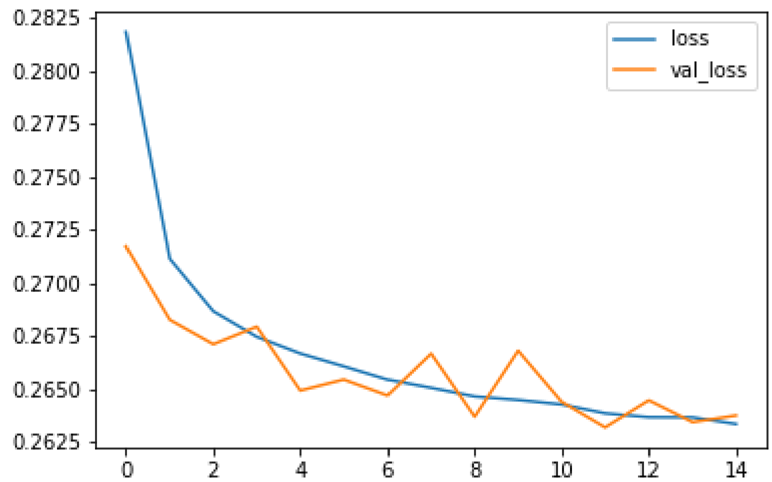
```
Model: "model_5"
_________________________________________________________________
 Layer (type)            Output Shape            Param #
=================================================================
input_5 (InputLayer)      [(None, 32)]            0
dense_13 (Dense)          (None, 512)             16896
dense_14 (Dense)          (None, 256)             131328
dense_15 (Dense)          (None, 2)              514
=================================================================
Total params: 148,738
Trainable params: 148,738
Non-trainable params: 0
_________________________________________________________________
```

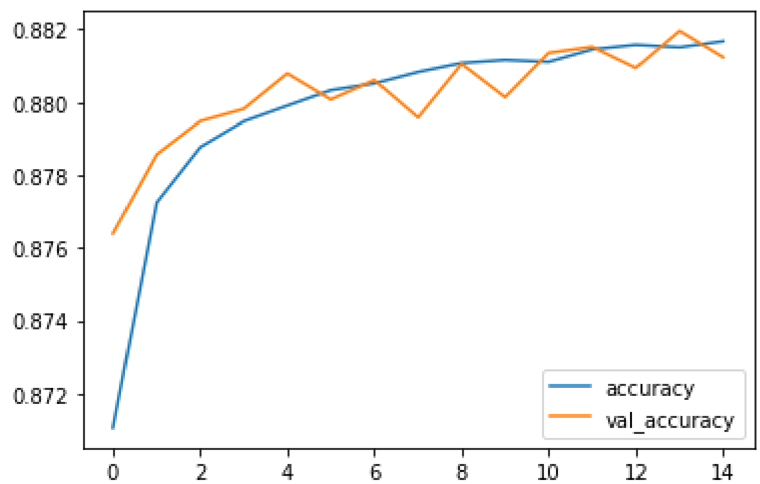
In [32]:

```
history_df = pd.DataFrame(nn_history.history) history_df[['loss',
'val_loss']].plot()

history_df = pd.DataFrame(nn_history.history) history_df[['accuracy',
'val_accuracy']].plot()
```

Out[32]: <AxesSubplot:>





Batch size 1024

In [33]:

```
nn_history = my_model.fit(x_train, y_train,
validation_data=(x_val, y_val),
callbacks=[safety],              epochs=50,
batch_size=1024)
```

Epoch 1/50

2022-03-25 16:35:50.010830: I tensorflow/core/grappler/optimizers/custo

```
4375/4375 [==============================] - 29s 7ms/step - loss: 0.267 Epoch 2/50
4375/4375 [==============================] - 31s 7ms/step - loss: 0.266 Epoch 3/50
4375/4375 [==============================] - 29s 7ms/step - loss: 0.266 Epoch 4/50
4375/4375 [==============================] - 29s 7ms/step - loss: 0.266 Epoch 5/50
4375/4375 [==============================] - 29s 7ms/step - loss: 0.266 Epoch 6/50
4375/4375 [==============================] - 27s 6ms/step - loss: 0.266 Epoch 7/50
```

In [34]:

```
4375/4375 [==============================] - 28s 6ms/step -                    loss    : 0.265
```

```
my_model. summary()
```

```
Model: "model_2"
_________________________________________________________________
Layer (type)             Output Shape           Param #
=================================================================
input_2 (InputLayer)     [(None, 32)]           0
dense_4 (Dense)          (None, 512)            16896
dense_5 (Dense)          (None, 256)            131328
dense_6 (Dense)          (None, 2)              514
=================================================================
Total params: 148,738
Trainable params: 148,738
Non-trainable params: 0
_________________________________________________________________
```

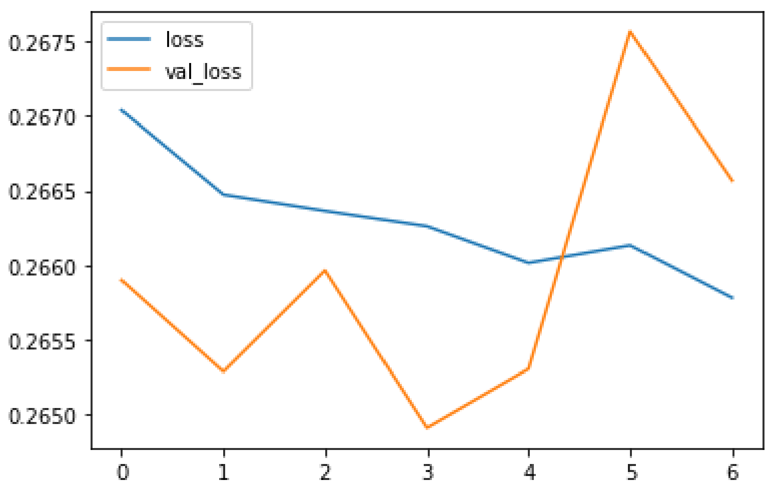
In [ ]:

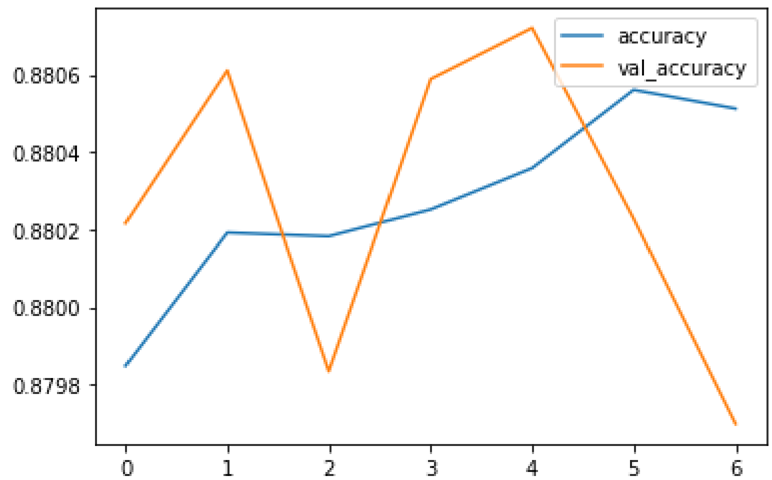
In [35]:

```
history_df = pd.DataFrame(nn_history.history) history_df[['loss',
'val_loss']].plot()

history_df = pd.DataFrame(nn_history.history) history_df[['accuracy',
'val_accuracy']].plot()
```

Out[35]: <AxesSubplot:>





Model 2 Swish - 3 layers

In [36]:

```
layer_zero = tf.keras.Input(shape=(32,)) layer1 = tf.keras.layers.Dense(512,
activation='swish')(layer_zero) layer2 = tf.keras.layers.Dense(256,
activation='swish')(layer1) #layer3 =
tf.keras.layers.Dense(128,
activation='gelu')(layer2) layer4 = tf.keras.layers.Dense(2,
activation='sigmoid')(layer2)
my_model = tf.keras.Model(inputs=layer_zero, outputs=layer4)
```

In [37]:

```
my_model.compile(optimizer=Adam(lr=1e-2), loss=tf.keras.losses.SparseCa safety
= EarlyStopping(monitor='val_loss', patience=3, min_delta=2e-4)
x_train, x_val, y_train, y_val = train_test_split(X_train, Y_train, tes
```

In [38]:

```
nn_history = my_model.fit(x_train, y_train,
validation_data=(x_val, y_val),
callbacks=[safety],               epochs=50,
batch_size=2048)
```

```
Epoch 1/50

2022-03-25 16:39:18.261506: I tensorflow/core/grappler/optimizers/custo

2188/2188 [==============================] - ETA: 0s - loss: 0.2841 - a

2022-03-25 16:39:33.405411: I tensorflow/core/grappler/optimizers/custo

2188/2188 [==============================] - 17s 8ms/step - loss: 0.284 Epoch 2/50
2188/2188 [==============================] - 16s 7ms/step - loss: 0.271 Epoch 3/50
2188/2188 [==============================] - 16s 7ms/step - loss: 0.269 Epoch 4/50
2188/2188 [==============================] - 16s 7ms/step - loss: 0.268 Epoch 5/50
2188/2188 [==============================] - 16s 8ms/step - loss: 0.267 Epoch 6/50
2188/2188 [==============================] - 16s 7ms/step - loss: 0.266 Epoch 7/50
```

```
2188/2188 [==============================] - 17s 8ms/step - loss: 0.265 Epoch 8/50
2188/2188 [==============================] - 16s 7ms/step - loss: 0.264 Epoch 9/50
2188/2188 [==============================] - 16s 7ms/step - loss: 0.265 Epoch 10/50
2188/2188 [==============================] - 16s 7ms/step - loss: 0.264 Epoch 11/50
2188/2188 [==============================] - 16s 7ms/step - loss: 0.264
```

In [39]:

```
my_model. summary()
```

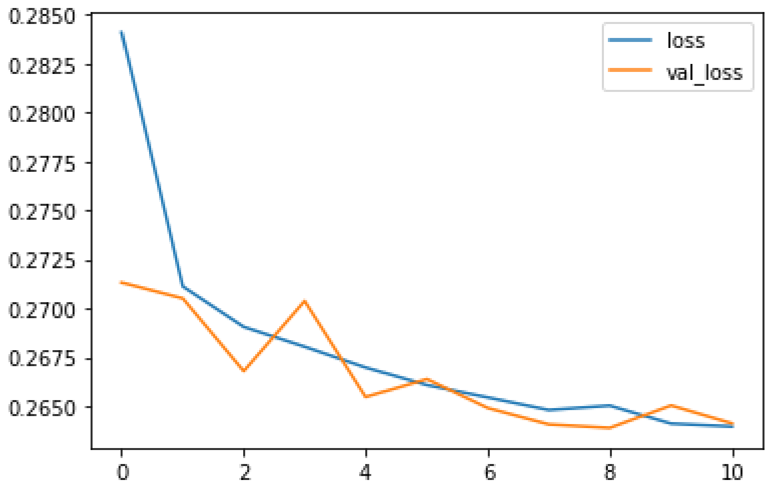
```
Model: "model_3"
_________________________________________________________________
 Layer (type)            Output Shape            Param #
=================================================================
input_3 (InputLayer)       [(None, 32)]           0
dense_7 (Dense)          (None, 512)           16896
dense_8 (Dense)          (None, 256)           131328
dense_9 (Dense)          (None, 2)            514
=================================================================
Total params: 148,738
Trainable params: 148,738
Non-trainable params: 0
_________________________________________________________________
```

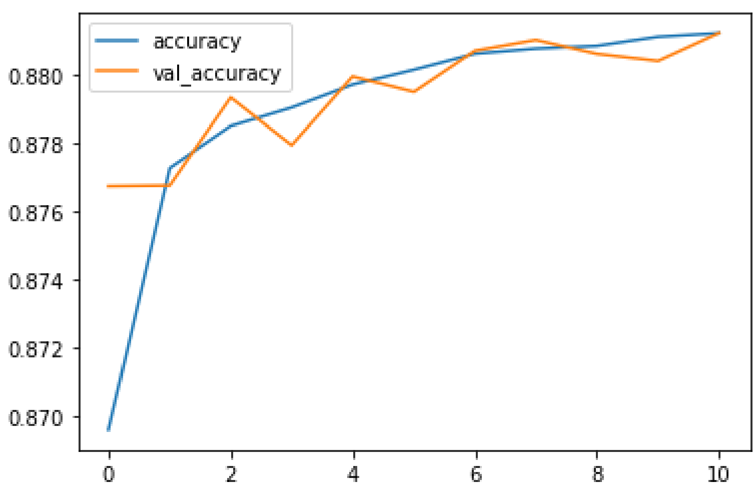
In [40]:

```
history_df = pd.DataFrame(nn_history.history) history_df[['loss',
'val_loss']].plot()

history_df = pd.DataFrame(nn_history.history) history_df[['accuracy',
'val_accuracy']].plot()
```

Out[40]: <AxesSubplot:>





In [41]:

```
my_model. summary()
```

```
Model: "model_3"
_________________________________________________________________
 Layer (type)              Output Shape              Param #
=================================================================
input_3 (InputLayer)       [(None, 32)]              0
dense_7 (Dense)            (None, 512)               16896
dense_8 (Dense)            (None, 256)               131328
dense_9 (Dense)            (None, 2)                 514
=================================================================
```

Total params: 148,738
Trainable params: 148,738
Non-trainable params: 0
____

Model Evaluation

In [42]:

```
y_pred =my_model. predict  ( X_test  )
```

2022-03-25 16:42:18.676823: I tensorflow/core/grappler/optimizers/custo

In [43]:

```
y_pred
```

Out[43]:

```
array([[0.48715827, 0.46217152],
       [0.08716998, 0.96522045],
       [0.5221664 , 0.43013135],       ...,
       [0.23122704, 0.9607484 ],
       [0.17528357, 0.8504923 ],
       [0.24064562, 0.7891484 ]], dtype=float32)
```

In [44]:

```
from sklearn.metrics import classification_report
print(classification_report(Y_test, np.argmax(y_pred, axis=1)))
```

```
            precision    recall  f1-score   support
        0.0       0.90      0.85      0.88    699445
        1.0       0.86      0.91      0.88    700555
   accuracy                           0.88   1400000    macro avg       0.88
0.88      0.88   1400000 weighted avg       0.88      0.88      0.88
1400000
```

In [47]:

```
from sklearn.metrics import
confusion_matrix import itertools

def plot_confusion_matrix(cm, classes,
                          title='Confusion matrix',                          cmap=plt.cm.Blues):

    print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
plt.title(title)     plt.colorbar()
    tick_marks = np.arange(len(classes))     plt.xticks(tick_marks, classes,
rotation=55)     plt.yticks(tick_marks, classes)
    #fmt =
'.2f''d'     thresh =
cm.max() / 2.
```

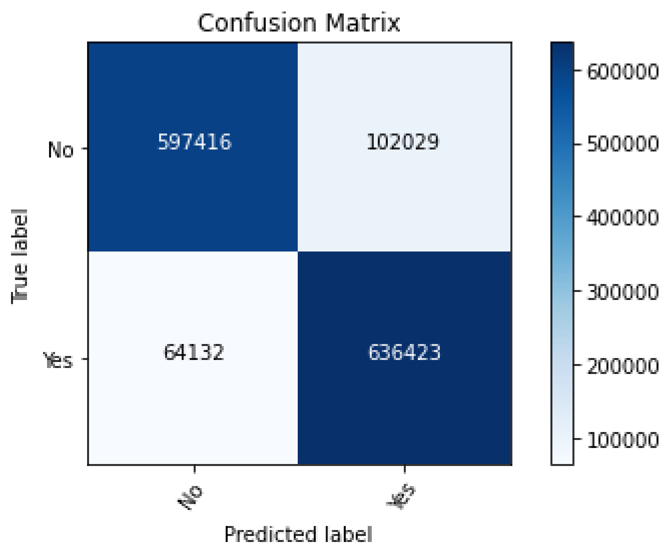
```
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1]
plt.text(j, i, format(cm[i, j]),              horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")

    plt.ylabel('True label')    plt.xlabel('Predicted label')
plt.tight_layout()

cm = confusion_matrix(Y_test, np.argmax(y_pred, axis=1))

cm_plot_label =['No', 'Yes']
plot_confusion_matrix(cm, cm_plot_label, title ='Confusion Matrix')
```

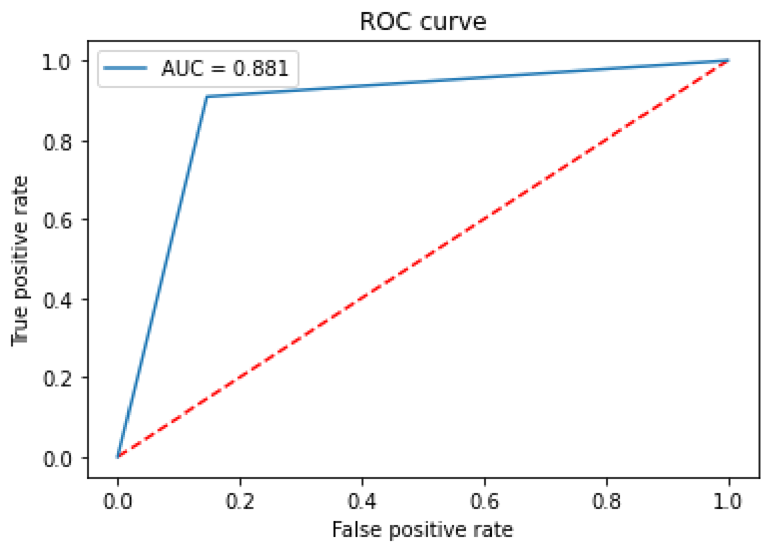
```
[[597416 102029]
 [ 64132 636423]]
```



In [46]:

```
from sklearn.metrics import roc_auc_score , auc
from sklearn.metrics import roc_curve
roc_log = roc_auc_score ( Y_test , np. argmax( y_pred , axis =1))
false_positive_rate , true_positive_rate , threshold = roc_curve ( Y_test ,
area_under_curve = auc( false_positive_rate , true_positive_rate )

plt . plot ([ 0, 1] , [ 0, 1] , 'r--' )
plt . plot ( false_positive_rate , true_positive_rate , label ='AUC = {:.3f}.
plt . xlabel ( 'False positive rate' )
plt . ylabel ( 'True positive rate' )
plt . title ( 'ROC curve' )
plt . legend ( loc ='best' )
plt . show()
plt . close ()
```



In [ ]:

In [ ]:

In [ ]: