In [1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from imblearn.over_sampling import RandomOverSampler
```

In [2]:
```python
cols = ["fLength", "fWidth", "fSize", "fConc", "fConc1", "fAsym", "fM3Long", "fM3Tr
df = pd.read_csv("magic04.data", names=cols)
df.head()
```

Out[2]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha	
0	28.7967	16.0021	2.6449	0.3918	0.1982	27.7004	22.0110	-8.2027	40.0920	81
1	31.6036	11.7235	2.5185	0.5303	0.3773	26.2722	23.8238	-9.9574	6.3609	205
2	162.0520	136.0310	4.0612	0.0374	0.0187	116.7410	-64.8580	-45.2160	76.9600	256
3	23.8172	9.5728	2.3385	0.6147	0.3922	27.2107	-6.4633	-7.1513	10.4490	116
4	75.1362	30.9205	3.1611	0.3168	0.1832	-5.5277	28.5525	21.8393	4.6480	356

In [3]:
```python
bool_mask = df['class'] == 'g'
print(type(bool_mask))
bool_mask
```

```
<class 'pandas.core.series.Series'>
```

Out[3]:
```
0         True
1         True
2         True
3         True
4         True
         ...
19015    False
19016    False
19017    False
19018    False
19019    False
Name: class, Length: 19020, dtype: bool
```

In [4]:
```python
print(type(bool_mask.shape))
bool_mask.shape
```

```
<class 'tuple'>
```

Out[4]:
```
(19020,)
```

In [5]:
```python
print(type(bool_mask.index))
bool_mask.index
```

```
<class 'pandas.core.indexes.range.RangeIndex'>
```

Out[5]:
```
RangeIndex(start=0, stop=19020, step=1)
```

In [6]:
```python
int_bool_mask = bool_mask.astype(int)
int_bool_mask
```

Out[6]:
```
0        1
1        1
2        1
3        1
4        1
        ..
19015    0
19016    0
19017    0
19018    0
19019    0
Name: class, Length: 19020, dtype: int32
```

In [7]:
```
bool_mask
```

Out[7]:
```
0         True
1         True
2         True
3         True
4         True
         ...
19015    False
19016    False
19017    False
19018    False
19019    False
Name: class, Length: 19020, dtype: bool
```

In [8]:
```
# df['class'] = 'z'
# df.head()
```

In [9]:
```
df['class'].unique()
```

Out[9]:
```
array(['g', 'h'], dtype=object)
```

In [10]:
```
type(df['class'].unique())
```

Out[10]:
```
numpy.ndarray
```

In [11]:
```
# df['class'] = int_bool_mask
# df.head()
```

In [12]:
```
df['class'] = (df['class'] == 'g').astype(int)
df.head()
```

Out[12]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha	
0	28.7967	16.0021	2.6449	0.3918	0.1982	27.7004	22.0110	-8.2027	40.0920	81
1	31.6036	11.7235	2.5185	0.5303	0.3773	26.2722	23.8238	-9.9574	6.3609	205
2	162.0520	136.0310	4.0612	0.0374	0.0187	116.7410	-64.8580	-45.2160	76.9600	256
3	23.8172	9.5728	2.3385	0.6147	0.3922	27.2107	-6.4633	-7.1513	10.4490	116
4	75.1362	30.9205	3.1611	0.3168	0.1832	-5.5277	28.5525	21.8393	4.6480	356

Hist

In [13]:

```
print(type(df[df["class"]==1]))
df[df["class"]==1]
```

```
<class 'pandas.core.frame.DataFrame'>
```

Out[13]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha
0	28.7967	16.0021	2.6449	0.3918	0.1982	27.7004	22.0110	-8.2027	40.0920
1	31.6036	11.7235	2.5185	0.5303	0.3773	26.2722	23.8238	-9.9574	6.3609
2	162.0520	136.0310	4.0612	0.0374	0.0187	116.7410	-64.8580	-45.2160	76.9600
3	23.8172	9.5728	2.3385	0.6147	0.3922	27.2107	-6.4633	-7.1513	10.4490
4	75.1362	30.9205	3.1611	0.3168	0.1832	-5.5277	28.5525	21.8393	4.6480
...	...	...	...	...	...	...	...	...	...
12327	12.8703	11.4444	2.3811	0.7360	0.3805	-15.0946	5.3032	11.6208	21.0120
12328	26.8595	20.5946	2.8754	0.3438	0.2152	-3.4556	-20.0014	-9.0535	3.9848
12329	22.0913	10.8949	2.2945	0.5381	0.2919	15.2776	18.2296	7.3975	21.0680
12330	56.2216	18.7019	2.9297	0.2516	0.1393	96.5758	-41.2969	11.3764	5.9110
12331	31.5125	19.2867	2.9578	0.2975	0.1515	38.1833	21.6729	-12.0726	17.5809

12332 rows × 11 columns

In [14]:

```
print(type(df[df["class"]==1]['fLength']))
df[df["class"]==1]['fLength']
```

```
<class 'pandas.core.series.Series'>
```

```
Out[14]: 0          28.7967
         1          31.6036
         2         162.0520
         3          23.8172
         4          75.1362
                     ...
         12327      12.8703
         12328      26.8595
         12329      22.0913
         12330      56.2216
         12331      31.5125
         Name: fLength, Length: 12332, dtype: float64
```

```
In [15]: print(type(df[df["class"]==0]['fLength']))
         df[df["class"]==0]['fLength']
```

```
<class 'pandas.core.series.Series'>
```

```
Out[15]: 12332      93.7035
         12333     102.0005
         12334     100.2775
         12335      91.6558
         12336      38.0195
                     ...
         19015      21.3846
         19016      28.9452
         19017      75.4455
         19018     120.5135
         19019     187.1814
         Name: fLength, Length: 6688, dtype: float64
```

```
In [16]: df[df["class"]==0]['fLength'].describe()
```

```
Out[16]: count    6688.000000
         mean       70.943504
         std        57.952729
         min         4.283500
         25%        26.145400
         50%        47.905400
         75%       104.026925
         max       334.177000
         Name: fLength, dtype: float64
```

```
In [17]: # plt.hist(df[df["class"]==1]['fLength'], color='blue', label='gamma', alpha=0.7, d
         # plt.hist(df[df["class"]==0]['fLength'], color='red', label='gamma', alpha=0.7, de
         # plt.ylabel("Probability")

         # # # plt.hist(df[df["class"]==0]['fLength'], color='red', label='gamma', alpha=0.7
         # # # plt.hist(df[df["class"]==0]['fLength'], color='red', label='gamma', alpha=0.7
         # # # plt.ylabel("Frequency")

         # plt.xlabel('fLength')
         # plt.title('fLength')
         # plt.legend()
         # plt.show()
```

```
In [18]: # for label in cols[:-1]:
```

```
#   plt.hist(df[df["class"]==1][label], color='blue', label='gamma', alpha=0.7, den
#   plt.hist(df[df["class"]==0][label], color='red', label='hadron', alpha=0.7, den
#   plt.title(label)
#   plt.ylabel("Probability")
#   plt.xlabel(label)
#   plt.legend()
#   plt.show()
```

Train, validation, test datasets

In [19]:
```
df_sample = df.sample(frac=1)
df_sample
```

Out[19]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha
4991	58.1344	23.1666	3.3556	0.2513	0.1351	36.3407	62.9897	-14.2864	4.9350
2558	73.9749	21.0084	3.0048	0.2779	0.1538	-116.7560	43.8813	18.8414	2.0060
2480	30.2588	13.9882	2.6010	0.3559	0.1892	21.9051	21.0869	9.6346	8.9360
4677	20.2473	12.0667	2.5472	0.5475	0.2738	2.9324	-14.1631	7.6082	27.1110
1144	28.3543	25.5873	2.7668	0.3234	0.1754	29.3307	17.5713	18.6666	33.5090
...	...	...	...	...	...	...	...	...	...
7332	22.4510	5.9922	2.2636	0.7956	0.5095	-20.2780	-16.9492	-6.6888	11.5290
9207	33.9295	12.1658	2.5296	0.3929	0.2378	44.5229	20.1583	-8.8548	11.4480
10312	24.9084	16.2600	2.7443	0.3820	0.2225	18.3663	4.8267	8.9724	0.7580
3647	22.6135	10.6883	2.1931	0.5385	0.2981	23.2508	18.9791	-10.3254	10.7152
382	27.5060	17.6938	2.7263	0.3380	0.1775	-28.9954	12.4763	-11.2782	3.3162

19020 rows × 11 columns

In [20]:
```
df_sample_numpy = df_sample.to_numpy()
df_sample_numpy
```

Out[20]:
```
array([[ 58.1344,  23.1666,   3.3556, ...,   4.935 , 252.649 ,   1.    ],
       [ 73.9749,  21.0084,   3.0048, ...,   2.006 , 303.874 ,   1.    ],
       [ 30.2588,  13.9882,   2.601 , ...,   8.936 , 126.812 ,   1.    ],
       ...,
       [ 24.9084,  16.26  ,   2.7443, ...,   0.758 , 148.265 ,   1.    ],
       [ 22.6135,  10.6883,   2.1931, ...,  10.7152, 174.583 ,   1.    ],
       [ 27.506 ,  17.6938,   2.7263, ...,   3.3162, 187.61  ,   1.    ]])
```

In [21]:
```
df_sample_numpy[0]
```

Out[21]:
```
array([ 5.81344e+01,  2.31666e+01,  3.35560e+00,  2.51300e-01,
        1.35100e-01,  3.63407e+01,  6.29897e+01, -1.42864e+01,
        4.93500e+00,  2.52649e+02,  1.00000e+00])
```

In [22]:
```python
df_sample_numpy.shape
```
Out[22]:
```
(19020, 11)
```
In [23]:
```python
df_sample_numpy[0] == 0
```
Out[23]:
```
array([False, False, False, False, False, False, False, False, False,
       False, False])
```
In [24]:
```python
df_sample_numpy[2] == 0
```
Out[24]:
```
array([False, False, False, False, False, False, False, False, False,
       False, False])
```
In [25]:
```python
len(df)
```
Out[25]:
```
19020
```
In [26]:
```python
0.6*len(df)
```
Out[26]:
```
11412.0
```
In [27]:
```python
[int(0.6*len(df)), int(0.8*len(df))]
```
Out[27]:
```
[11412, 15216]
```

train, valid, test

This line of code splits a DataFrame into three subsets: training, validation, and test sets. The df.sample(frac=1) method is used to shuffle the rows of the DataFrame randomly, and the np.split() method is used to split the shuffled DataFrame into the three subsets.

In [28]:
```python
train, valid, test = np.split(df.sample(frac=1), [int(0.6*len(df)), int(0.8*len(df)
```
In [29]:
```python
train
```

Out[29]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha
18580	25.8512	11.0935	2.5478	0.4674	0.2705	32.4601	16.6389	4.6739	81.6762
15355	276.2766	35.8288	3.5838	0.0604	0.0572	-457.9161	-169.1552	15.1931	68.1382
2464	45.3746	23.9865	3.1012	0.2131	0.1248	18.9356	29.9800	-15.0227	1.1294
6623	23.9993	10.9858	2.4141	0.5125	0.3064	12.0505	20.2358	5.8304	50.4126
5558	18.1377	10.5243	2.2041	0.5875	0.3219	22.4127	10.4913	4.1503	63.1860
...	...	...	...	...	...	...	...	...	...
1948	51.8528	27.1569	3.1116	0.2776	0.1396	-63.5061	37.7307	-11.6498	0.7280
14209	14.6656	7.9126	2.4422	0.7620	0.4984	-4.4123	-16.0882	-6.0178	34.0426
11837	35.3426	12.7244	2.5447	0.3652	0.1840	29.7077	-15.8117	5.1165	18.8214
16414	18.9805	14.7280	2.4997	0.5222	0.3465	-0.2513	10.4799	9.5463	72.4482
15333	12.2144	5.5700	2.0763	0.7769	0.4493	-5.1562	-11.0351	-5.4896	76.9712

11412 rows × 11 columns

In [30]:
```python
train['fLength']
```

Out[30]:
```
18580     25.8512
15355    276.2766
2464      45.3746
6623      23.9993
5558      18.1377
           ...   
1948      51.8528
14209     14.6656
11837     35.3426
16414     18.9805
15333     12.2144
Name: fLength, Length: 11412, dtype: float64
```

In [31]:
```python
# train['fLength'][10785]

# train['fLength'].loc[10785]

# train.loc[10785, 'fLength']
```

In [32]:
```python
train['fLength'].iloc[0]
```

Out[32]:
```
25.8512
```

In [33]:
```python
train.loc[train.index[0], 'fLength']
```

Out[33]:
```
25.8512
```

In [34]:
```python
train.loc[train.index[0:2], 'fLength']
```

Out[34]:
```
18580     25.8512
15355    276.2766
Name: fLength, dtype: float64
```

In [35]:
```python
train.iloc[0]['fLength']
```

Out[35]:
```
25.8512
```

In [36]:
```python
train.iloc[0:2]['fLength']
```

Out[36]:
```
18580     25.8512
15355    276.2766
Name: fLength, dtype: float64
```

In [37]:
```python
train.iloc[0, 0]
```

Out[37]:
```
25.8512
```

In [38]:
```python
train.iloc[0:2, 0]
```

Out[38]:
```
18580     25.8512
15355    276.2766
Name: fLength, dtype: float64
```

In [39]:
```python
train.iloc[0:2, 0:2]
```

Out[39]:

	fLength	fWidth
18580	25.8512	11.0935
15355	276.2766	35.8288

In [40]:
```python
print(type(train.index))
train.index
```

```
<class 'pandas.core.indexes.numeric.Int64Index'>
```

Out[40]:
```
Int64Index([18580, 15355,  2464,  6623,  5558,  9952,  3880, 16036,  7222,
             3393,
            ...
            18204,  8617,  9286,  6350,   940,  1948, 14209, 11837, 16414,
            15333],
           dtype='int64', length=11412)
```

🖤 StandardScaler, RandomOverSampler

In [41]:
```python
train
```

Out[41]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha
18580	25.8512	11.0935	2.5478	0.4674	0.2705	32.4601	16.6389	4.6739	81.6762
15355	276.2766	35.8288	3.5838	0.0604	0.0572	-457.9161	-169.1552	15.1931	68.1382
2464	45.3746	23.9865	3.1012	0.2131	0.1248	18.9356	29.9800	-15.0227	1.1294
6623	23.9993	10.9858	2.4141	0.5125	0.3064	12.0505	20.2358	5.8304	50.4126
5558	18.1377	10.5243	2.2041	0.5875	0.3219	22.4127	10.4913	4.1503	63.1860
...	...	...	...	...	...	...	...	...	...
1948	51.8528	27.1569	3.1116	0.2776	0.1396	-63.5061	37.7307	-11.6498	0.7280
14209	14.6656	7.9126	2.4422	0.7620	0.4984	-4.4123	-16.0882	-6.0178	34.0426
11837	35.3426	12.7244	2.5447	0.3652	0.1840	29.7077	-15.8117	5.1165	18.8214
16414	18.9805	14.7280	2.4997	0.5222	0.3465	-0.2513	10.4799	9.5463	72.4482
15333	12.2144	5.5700	2.0763	0.7769	0.4493	-5.1562	-11.0351	-5.4896	76.9712

11412 rows × 11 columns

In [42]:
```
valid
```

Out[42]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha
14987	22.8611	8.2654	2.1624	0.6170	0.3078	32.8702	28.8722	-9.4643	16.1564
5483	35.6953	28.3828	3.5252	0.2396	0.1290	-13.4253	-22.8975	8.6086	72.1710
11457	17.3357	10.9817	2.2833	0.5781	0.2995	-22.4642	-9.4314	3.6979	22.2335
5726	87.5724	30.8293	3.8825	0.1550	0.0783	38.2114	87.4380	17.8452	5.9170
739	36.9048	16.4389	2.7945	0.3323	0.1790	17.3720	34.0336	-9.2374	1.8977
...	...	...	...	...	...	...	...	...	...
13535	10.7015	10.2689	2.6054	0.5717	0.2778	-17.8989	-15.5452	0.8136	3.6583
9578	54.3344	14.5620	2.5838	0.4068	0.2699	-12.3226	-46.8887	-11.9187	16.1290
14762	65.7635	19.7758	2.6790	0.3707	0.2126	-86.8678	46.0977	-16.4593	47.0950
13621	39.5915	17.4182	2.5583	0.5685	0.3334	30.2382	19.5135	-14.2970	47.8241
17445	149.5450	35.5752	3.3561	0.1735	0.0887	-54.0293	107.0780	30.6711	51.0768

3804 rows × 11 columns

In [43]:
```
test
```

Out[43]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlph
18923	101.5260	75.7229	3.2306	0.2217	0.1126	-53.1276	-110.4310	61.4389	71.158
544	32.3920	14.8974	2.8663	0.3905	0.2211	34.5464	15.8798	6.6320	7.136
3695	43.4795	17.4512	2.6758	0.2827	0.1466	57.1446	-29.7525	15.0303	2.912
1121	26.3733	19.1659	2.8567	0.3644	0.2246	14.4958	14.4997	-15.1480	9.370
13274	34.2728	12.7234	2.2911	0.4450	0.2276	30.5691	-15.9443	9.0394	78.787
...	...	...	...	...	...	...	...	...	.
17854	246.1790	101.1780	3.4987	0.1431	0.0725	-326.1140	-149.5200	-84.2610	33.491
10418	36.1276	10.3417	2.4338	0.4972	0.2560	-33.3708	28.0494	-6.7114	0.584
6323	50.0677	17.6383	2.8052	0.2443	0.1245	-69.2489	-33.4756	-12.1053	21.887
9949	66.0024	12.6632	2.4616	0.3420	0.1744	39.6190	63.3203	6.2318	58.555
11365	60.6592	11.2519	2.8099	0.3005	0.1619	-16.8522	-52.1026	7.1181	1.307

3804 rows × 11 columns

The opposite of the columnar data format is the row-based or record-based data format.

In [44]:

```
test.values
```

Out[44]:

```
array([[101.526 ,  75.7229,   3.2306, ...,  71.158 , 232.424 ,   0.    ],
       [ 32.392 ,  14.8974,   2.8663, ...,   7.136 , 217.28  ,   1.    ],
       [ 43.4795,  17.4512,   2.6758, ...,   2.912 , 244.237 ,   1.    ],
       ...,
       [ 50.0677,  17.6383,   2.8052, ...,  21.887 , 233.149 ,   1.    ],
       [ 66.0024,  12.6632,   2.4616, ...,  58.555 , 186.794 ,   1.    ],
       [ 60.6592,  11.2519,   2.8099, ...,   1.307 , 209.682 ,   1.    ]])
```

In [45]:

```
test.to_numpy()
```

Out[45]:

```
array([[101.526 ,  75.7229,   3.2306, ...,  71.158 , 232.424 ,   0.    ],
       [ 32.392 ,  14.8974,   2.8663, ...,   7.136 , 217.28  ,   1.    ],
       [ 43.4795,  17.4512,   2.6758, ...,   2.912 , 244.237 ,   1.    ],
       ...,
       [ 50.0677,  17.6383,   2.8052, ...,  21.887 , 233.149 ,   1.    ],
       [ 66.0024,  12.6632,   2.4616, ...,  58.555 , 186.794 ,   1.    ],
       [ 60.6592,  11.2519,   2.8099, ...,   1.307 , 209.682 ,   1.    ]])
```

In [46]:

```
test.values == test.to_numpy()
```

Out[46]:

```
array([[ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True],
       ...,
       [ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True]])
```

In [47]:
```
np.array_equal(test.values, test.to_numpy())
```
Out[47]:
```
True
```

In [48]:
```
isinstance(test.columns, np.ndarray)
```
Out[48]:
```
False
```

In [49]:
```
type(test.columns)
```
Out[49]:
```
pandas.core.indexes.base.Index
```

In [50]:
```
test.columns
```
Out[50]:
```
Index(['fLength', 'fWidth', 'fSize', 'fConc', 'fConc1', 'fAsym', 'fM3Long',
       'fM3Trans', 'fAlpha', 'fDist', 'class'],
      dtype='object')
```

In [51]:
```
test[test.columns[:-1]]
```
Out[51]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlph
18923	101.5260	75.7229	3.2306	0.2217	0.1126	-53.1276	-110.4310	61.4389	71.158
544	32.3920	14.8974	2.8663	0.3905	0.2211	34.5464	15.8798	6.6320	7.136
3695	43.4795	17.4512	2.6758	0.2827	0.1466	57.1446	-29.7525	15.0303	2.912
1121	26.3733	19.1659	2.8567	0.3644	0.2246	14.4958	14.4997	-15.1480	9.370
13274	34.2728	12.7234	2.2911	0.4450	0.2276	30.5691	-15.9443	9.0394	78.787
...	...	...	...	...	...	...	...	...	.
17854	246.1790	101.1780	3.4987	0.1431	0.0725	-326.1140	-149.5200	-84.2610	33.491
10418	36.1276	10.3417	2.4338	0.4972	0.2560	-33.3708	28.0494	-6.7114	0.584
6323	50.0677	17.6383	2.8052	0.2443	0.1245	-69.2489	-33.4756	-12.1053	21.887
9949	66.0024	12.6632	2.4616	0.3420	0.1744	39.6190	63.3203	6.2318	58.555
11365	60.6592	11.2519	2.8099	0.3005	0.1619	-16.8522	-52.1026	7.1181	1.307

3804 rows × 10 columns

In [52]:
```
print(test[test.columns[:-1]].values.shape)
test[test.columns[:-1]].values
```
```
(3804, 10)
```
Out[52]:
```
array([[101.526 ,  75.7229,   3.2306, ...,  61.4389,  71.158 , 232.424 ],
       [ 32.392 ,  14.8974,   2.8663, ...,   6.632 ,   7.136 , 217.28  ],
       [ 43.4795,  17.4512,   2.6758, ...,  15.0303,   2.912 , 244.237 ],
       ...,
       [ 50.0677,  17.6383,   2.8052, ..., -12.1053,  21.887 , 233.149 ],
       [ 66.0024,  12.6632,   2.4616, ...,   6.2318,  58.555 , 186.794 ],
       [ 60.6592,  11.2519,   2.8099, ...,   7.1181,   1.307 , 209.682 ]])
```

In [53]:
```
print(test[test.columns[-1]].values.shape)
test[test.columns[-1]].values
```

```
(3804,)
```

Out[53]:
```
array([0, 1, 1, ..., 1, 1, 1])
```

In [54]:
```
train
```

Out[54]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha
18580	25.8512	11.0935	2.5478	0.4674	0.2705	32.4601	16.6389	4.6739	81.6762
15355	276.2766	35.8288	3.5838	0.0604	0.0572	-457.9161	-169.1552	15.1931	68.1382
2464	45.3746	23.9865	3.1012	0.2131	0.1248	18.9356	29.9800	-15.0227	1.1294
6623	23.9993	10.9858	2.4141	0.5125	0.3064	12.0505	20.2358	5.8304	50.4126
5558	18.1377	10.5243	2.2041	0.5875	0.3219	22.4127	10.4913	4.1503	63.1860
...	...	...	...	...	...	...	...	...	...
1948	51.8528	27.1569	3.1116	0.2776	0.1396	-63.5061	37.7307	-11.6498	0.7280
14209	14.6656	7.9126	2.4422	0.7620	0.4984	-4.4123	-16.0882	-6.0178	34.0426
11837	35.3426	12.7244	2.5447	0.3652	0.1840	29.7077	-15.8117	5.1165	18.8214
16414	18.9805	14.7280	2.4997	0.5222	0.3465	-0.2513	10.4799	9.5463	72.4482
15333	12.2144	5.5700	2.0763	0.7769	0.4493	-5.1562	-11.0351	-5.4896	76.9712

11412 rows × 11 columns

In [55]:
```
print(len(train[train['class']==1])) #gamma
print(len(train[train['class']==0])) #hadron
len(train[train['class']==1]) + len(train[train['class']==0])
```

```
7424
3988
```

Out[55]:
```
11412
```

In [56]:
```
def scale_dataset(dataframe):
    X = dataframe[dataframe.columns[:-1]].values
    y = dataframe[dataframe.columns[-1]].values

    scaler = StandardScaler()
    X = scaler.fit_transform(X)

    data = np.hstack((X, np.reshape(y, (-1, 1))))
    return data, X, y
```

In [57]:
```
scaled_train, X_train, y_train = scale_dataset(train)
```

In [58]:
```
X_train
```

Out[58]:
```
array([[-0.6445578 , -0.59734725, -0.58909923, ...,  0.20318868,
         2.06226144,  0.29942464],
       [ 5.26979743,  0.74089832,  1.59696482, ...,  0.70577104,
         1.54532928, -0.0901254 ],
       [-0.18346909,  0.10019837,  0.57863035, ..., -0.73786804,
        -1.01332072, -0.89683095],
       ...,
       [-0.42039718, -0.50911122, -0.59564055, ...,  0.22433505,
        -0.33777309,  0.29120355],
       [-0.80682472, -0.40071113, -0.69059507, ...,  0.43598036,
         1.70990142, -0.62810154],
       [-0.96662129, -0.8961833 , -1.58401159, ..., -0.28239919,
         1.88260671, -2.07067705]])
```

In [59]:
```
y_train
```

Out[59]:
```
array([0, 0, 1, ..., 1, 0, 0])
```

In [60]:
```
y_train.shape
```

Out[60]:
```
(11412,)
```

In [61]:
```
np.array_equal(y_train, train["class"].values)
```

Out[61]:
```
True
```

In [62]:
```
train
```

Out[62]:

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha
18580	25.8512	11.0935	2.5478	0.4674	0.2705	32.4601	16.6389	4.6739	81.6762
15355	276.2766	35.8288	3.5838	0.0604	0.0572	-457.9161	-169.1552	15.1931	68.1382
2464	45.3746	23.9865	3.1012	0.2131	0.1248	18.9356	29.9800	-15.0227	1.1294
6623	23.9993	10.9858	2.4141	0.5125	0.3064	12.0505	20.2358	5.8304	50.4126
5558	18.1377	10.5243	2.2041	0.5875	0.3219	22.4127	10.4913	4.1503	63.1860
...	...	...	...	...	...	...	...	...	...
1948	51.8528	27.1569	3.1116	0.2776	0.1396	-63.5061	37.7307	-11.6498	0.7280
14209	14.6656	7.9126	2.4422	0.7620	0.4984	-4.4123	-16.0882	-6.0178	34.0426
11837	35.3426	12.7244	2.5447	0.3652	0.1840	29.7077	-15.8117	5.1165	18.8214
16414	18.9805	14.7280	2.4997	0.5222	0.3465	-0.2513	10.4799	9.5463	72.4482
15333	12.2144	5.5700	2.0763	0.7769	0.4493	-5.1562	-11.0351	-5.4896	76.9712

11412 rows × 11 columns

In [63]:
```
scaled_train
```

Out[63]:
```
array([[-0.6445578 , -0.59734725, -0.58909923, ...,  2.06226144,
         0.29942464,  0.        ],
       [ 5.26979743,  0.74089832,  1.59696482, ...,  1.54532928,
        -0.0901254 ,  0.        ],
       [-0.18346909,  0.10019837,  0.57863035, ..., -1.01332072,
        -0.89683095,  1.        ],
       ...,
       [-0.42039718, -0.50911122, -0.59564055, ..., -0.33777309,
         0.29120355,  1.        ],
       [-0.80682472, -0.40071113, -0.69059507, ...,  1.70990142,
        -0.62810154,  0.        ],
       [-0.96662129, -0.8961833 , -1.58401159, ...,  1.88260671,
        -2.07067705,  0.        ]])
```

In [64]:
```python
scaled_train.shape
```

Out[64]:
```
(11412, 11)
```

In [65]:
```python
X_train
```

Out[65]:
```
array([[-0.6445578 , -0.59734725, -0.58909923, ...,  0.20318868,
         2.06226144,  0.29942464],
       [ 5.26979743,  0.74089832,  1.59696482, ...,  0.70577104,
         1.54532928, -0.0901254 ],
       [-0.18346909,  0.10019837,  0.57863035, ..., -0.73786804,
        -1.01332072, -0.89683095],
       ...,
       [-0.42039718, -0.50911122, -0.59564055, ...,  0.22433505,
        -0.33777309,  0.29120355],
       [-0.80682472, -0.40071113, -0.69059507, ...,  0.43598036,
         1.70990142, -0.62810154],
       [-0.96662129, -0.8961833 , -1.58401159, ..., -0.28239919,
         1.88260671, -2.07067705]])
```

In [66]:
```python
X_train.shape
```

Out[66]:
```
(11412, 10)
```

In [67]:
```python
def scale_dataset(dataframe, oversample=False):
    X = dataframe[dataframe.columns[:-1]].values
    y = dataframe[dataframe.columns[-1]].values

    scaler = StandardScaler()
    X = scaler.fit_transform(X)

    if oversample:
        ros = RandomOverSampler()
        X, y = ros.fit_resample(X, y)

    data = np.hstack((X, np.reshape(y, (-1, 1))))
    return data, X, y
```

In [68]:
```python
scaled_train, X_train, y_train = scale_dataset(train, oversample=True)
```

In [69]:
```python
scaled_train.shape
```

Out[69]: (14848, 11)

In [70]:
```
X_train.shape
```

Out[70]: (14848, 10)

In [71]:
```
y_train.shape
```

Out[71]: (14848,)

In [72]:
```
train[train['class'] == 1].shape
```

Out[72]: (7424, 11)

In [73]:
```
train[train['class'] == 0].shape
```

Out[73]: (3988, 11)

In [74]:
```
scaled_train[scaled_train == 1].shape
```

Out[74]: (7424,)

In [75]:
```
scaled_train[scaled_train == 0].shape
```

Out[75]: (7424,)

In [76]:
```
train, X_train, y_train = scale_dataset(train, oversample=True)
valid, X_valid, y_valid = scale_dataset(valid)
test, X_test, y_test = scale_dataset(test)
```

In [77]:
```
valid
```

Out[77]:
```
array([[-0.70899216, -0.73980473, -1.37904875, ..., -0.44840197,
        -0.82811585,  0.        ],
       [-0.40953065,  0.31345303,  1.51720476, ...,  1.72141256,
        -2.05838638,  1.        ],
       [-0.8379168 , -0.59759132, -1.12210932, ..., -0.21299585,
        -1.02549936,  1.        ],
       ...,
       [ 0.29205327, -0.13717128, -0.2811587 , ...,  0.75005385,
        -1.21221133,  0.        ],
       [-0.31862028, -0.26060475, -0.53767308, ...,  0.7782967 ,
        -0.02598149,  0.        ],
       [ 2.2469343 ,  0.69001517,  1.1578296 , ...,  0.9042952 ,
         1.30124873,  0.        ]])
```

In [78]:
```
X_valid
```

Out[78]:
```
array([[-0.70899216, -0.73980473, -1.37904875, ..., -0.46130433,
        -0.44840197, -0.82811585],
       [-0.40953065,  0.31345303,  1.51720476, ...,  0.39361088,
         1.72141256, -2.05838638],
       [-0.8379168 , -0.59759132, -1.12210932, ...,  0.16131656,
        -0.21299585, -1.02549936],
       ...,
       [ 0.29205327, -0.13717128, -0.2811587 , ..., -0.79219377,
         0.75005385, -1.21221133],
       [-0.31862028, -0.26060475, -0.53767308, ..., -0.68990896,
         0.7782967 , -0.02598149],
       [ 2.2469343 ,  0.69001517,  1.1578296 , ...,  1.43724897,
         0.9042952 ,  1.30124873]])
```

In [79]:
```
y_valid
```

Out[79]:
```
array([0, 1, 1, ..., 0, 0, 0])
```

kNN

In [80]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report
```

In [81]:
```
model = KNeighborsClassifier(n_neighbors=100)
model.fit(X_train, y_train)
```

Out[81]:
```
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=100)
```

In [82]:
```
y_pred = model.predict(X_test)
y_pred
```

Out[82]:
```
array([0, 1, 1, ..., 1, 0, 1])
```

In [83]:
```
y_test
```

Out[83]:
```
array([0, 1, 1, ..., 1, 1, 1])
```

In [84]:
```
y_test.shape
```

Out[84]:
```
(3804,)
```

In [85]:
```
y_test[y_test == 0].shape
```

Out[85]:
```
(1370,)
```

Precision (also called positive predictive value) is the fraction of relevant instances among the retrieved instances, while recall (also known as sensitivity) is the fraction of relevant instances that were retrieved. Both precision and recall are therefore based on relevance.

In [86]:
```
print(classification_report(y_test, y_pred))
```
```
              precision    recall  f1-score   support

           0       0.79      0.72      0.75      1370
           1       0.85      0.89      0.87      2434

    accuracy                           0.83      3804
   macro avg       0.82      0.81      0.81      3804
weighted avg       0.83      0.83      0.83      3804
```

Naive Bayes algorithm.

Conditional probability and Bayes' theorem are fundamental concepts in probability theory and statistics, and are central to the Naive Bayes algorithm.

Conditional probability refers to the probability of an event occurring given that another event has already occurred. In other words, it is the probability of an event A given that event B has occurred, and is denoted as P(A|B). The formula for conditional probability is:

P(A|B) = P(A and B) / P(B)

where P(A and B) is the probability of both events A and B occurring together, and P(B) is the probability of event B occurring.

Bayes' theorem is a mathematical formula that allows us to calculate the conditional probability of an event A given that another event B has occurred, based on the prior probability of A and B. The formula for Bayes' theorem is:

P(A|B) = P(B|A) * P(A) / P(B)

where P(A|B) is the conditional probability of A given B, P(B|A) is the conditional probability of B given A, P(A) is the prior probability of A (i.e., the probability of A occurring before we have any information about B), and P(B) is the prior probability of B (i.e., the probability of B occurring before we have any information about A).

In [87]:
```
from sklearn.naive_bayes import GaussianNB
```

In [88]:
```
nb_model = GaussianNB()
nb_model.fit(X_train, y_train)
```

Out[88]:
```
▾ GaussianNB
GaussianNB()
```

In [89]:
```
y_pred = nb_model.predict(X_test)
y_pred
```

Out[89]: array([0, 1, 1, ..., 1, 1, 1])

In [90]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.65      0.40      0.50      1370
           1       0.72      0.88      0.79      2434

    accuracy                           0.71      3804
   macro avg       0.69      0.64      0.65      3804
weighted avg       0.70      0.71      0.69      3804
```

Logistic Regression

Logistic Regression is a popular statistical algorithm used for binary classification problems, i.e., problems where the task is to predict one of two possible outcomes.

The main idea behind Logistic Regression is to model the probability of the positive outcome (i.e., the outcome we are interested in predicting) as a function of the input variables or features. Specifically, the algorithm models the log odds of the positive outcome as a linear function of the input variables, and then applies a sigmoid or logistic function to convert the log odds into probabilities.

The resulting logistic regression model can be used to make predictions on new data by calculating the probability of the positive outcome for each input sample, and then using a decision threshold to make a binary prediction.

Logistic Regression has several advantages, including being easy to implement and interpret, and being relatively robust to noise in the data. It can also handle both numerical and categorical features, making it a versatile algorithm. However, it assumes a linear relationship between the input variables and the log odds, which may not hold in all cases. Additionally, it is primarily designed for binary classification problems, and may not work as well for multi-class problems.

💚 Logistic regression is a type of supervised learning algorithm used for classification tasks. It is a statistical method used to analyze a dataset in which there are one or more independent variables that determine an outcome. The outcome is measured with a dichotomous variable (in which there are only two possible outcomes).

The logistic regression model is based on the logistic function, which is an S-shaped curve that can take any real-valued number and map it into a value between 0 and 1, making it useful for modeling probabilities.

In [95]:
```
from sklearn.linear_model import LogisticRegression
```

In [93]:
```
lg_model = LogisticRegression()
```

```
lg_model.fit(X_train, y_train)
```

Out[93]:

```
▾ LogisticRegression
LogisticRegression()
```

In [94]:

```
y_pred = lg_model.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.70      0.72      0.71      1370
           1       0.84      0.83      0.83      2434

    accuracy                           0.79      3804
   macro avg       0.77      0.77      0.77      3804
weighted avg       0.79      0.79      0.79      3804
```

Support Vector Machines

Support Vector Machines (SVM) is a machine learning algorithm that can be used for classification and regression tasks. The algorithm finds a line or surface that separates different types of data points by the largest margin possible, meaning the line or surface is as far away as possible from the closest data points of each type. SVM can handle complex decision boundaries and works well with high-dimensional data. It has advantages such as being able to work with different types of data and having a strong theoretical foundation, but it also requires tuning of some parameters and can be computationally expensive for large datasets. Overall, SVM is a powerful algorithm that can be used for many different types of problems in machine learning.

★ Sensitive to outliners

In [141…

```
from sklearn.svm import SVC
```

In [99]:

```
svm_model = SVC()
svm_model = svm_model.fit(X_train, y_train)
```

In [100…

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

In [101…

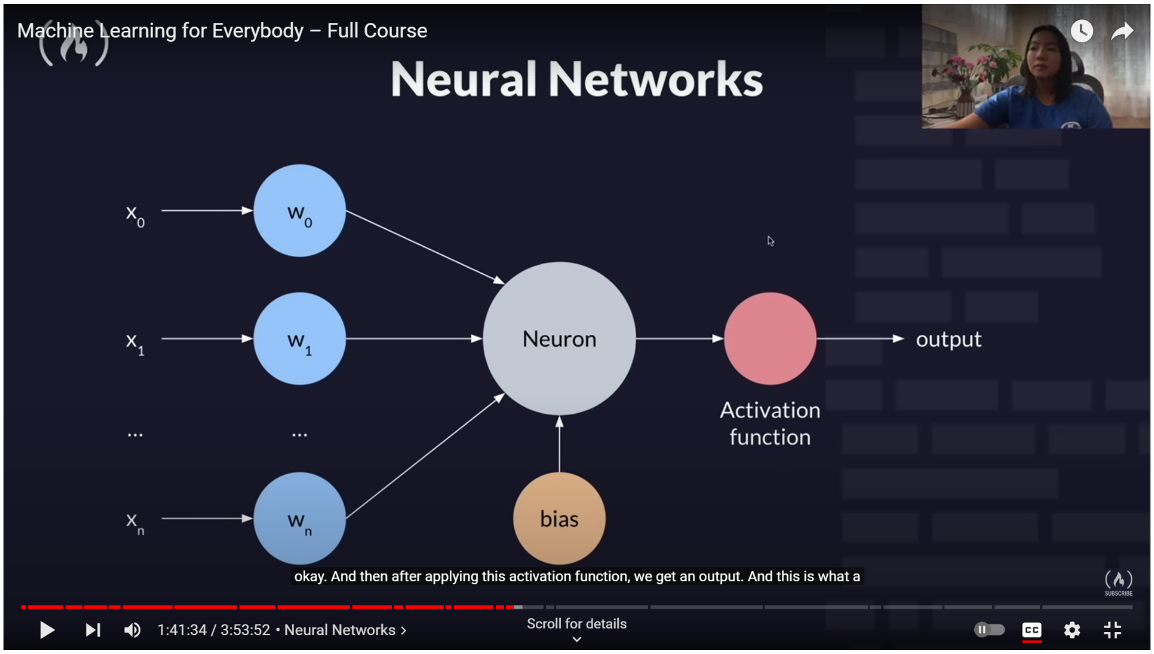
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.81      0.81      1370
           1       0.89      0.90      0.89      2434

    accuracy                           0.87      3804
   macro avg       0.85      0.85      0.85      3804
weighted avg       0.86      0.87      0.87      3804
```

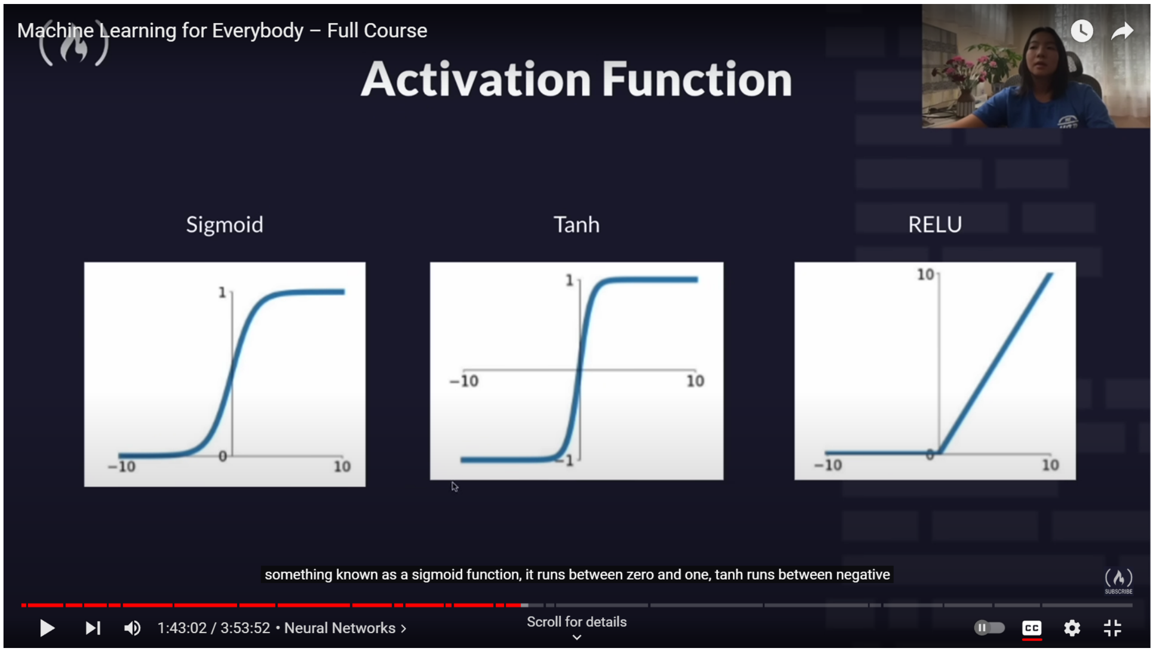
Neural Networks



The basic idea behind neural networks is to simulate the behavior of the human brain. The network consists of layers of artificial neurons, each of which receives input from the previous layer, processes the input using an activation function, and passes the output to the next layer. The input to the first layer is the raw data, and the output of the last layer is the final prediction.

During the training phase, the weights of the connections between neurons are adjusted to minimize the difference between the predicted output and the actual output. This is typically done using an optimization algorithm such as backpropagation, which computes the gradient of the error with respect to the weights and updates them accordingly.

There are several types of neural networks, such as feedforward neural networks, recurrent neural networks, and convolutional neural networks, each of which is designed for a specific type of problem. For example, feedforward neural networks are used for tasks such as classification and regression, while recurrent neural networks are used for tasks such as language modeling and speech recognition.



In [104…

```
import tensorflow as tf
```

In [122…

```
def plot_history(history):
  fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 4))
  ax1.plot(history.history['loss'], label='loss')
  ax1.plot(history.history['val_loss'], label='val_loss')
  ax1.set_xlabel('Epoch')
  ax1.set_ylabel('Binary crossentropy')
  ax1.legend()
  ax1.grid(True)

  ax2.plot(history.history['accuracy'], label='accuracy')
  ax2.plot(history.history['val_accuracy'], label='val_accuracy')
  ax2.set_xlabel('Epoch')
  ax2.set_ylabel('Accuracy')
  ax2.legend()
  ax2.grid(True)

  plt.show()
```

In [142…

```
%%time

def train_model(X_train, y_train, num_nodnum_nodes, dropout_prob, lr, batch_size, e
    nn_model = tf.keras.Sequential([
        tf.keras.layers.Dense(num_nodes, activation='relu', input_shape=(10,)),
        tf.keras.layers.Dropout(dropout_prob),
        tf.keras.layers.Dense(num_nodes, activation='relu'),
        tf.keras.layers.Dropout(dropout_prob),
        tf.keras.layers.Dense(1, activation='sigmoid')
    ])
    nn_model.compile(optimizer=tf.keras.optimizers.Adam(lr), loss='binary_crossentr
#     history = nn_model.fit(X_train, y_train, epochs=epochs, batch_size=batch_size
    history = nn_model.fit(X_train, y_train, epochs=epochs, batch_size=batch_size,

    return nn_model, history
```

```
CPU times: total: 0 ns
Wall time: 0 ns
```

In [145…

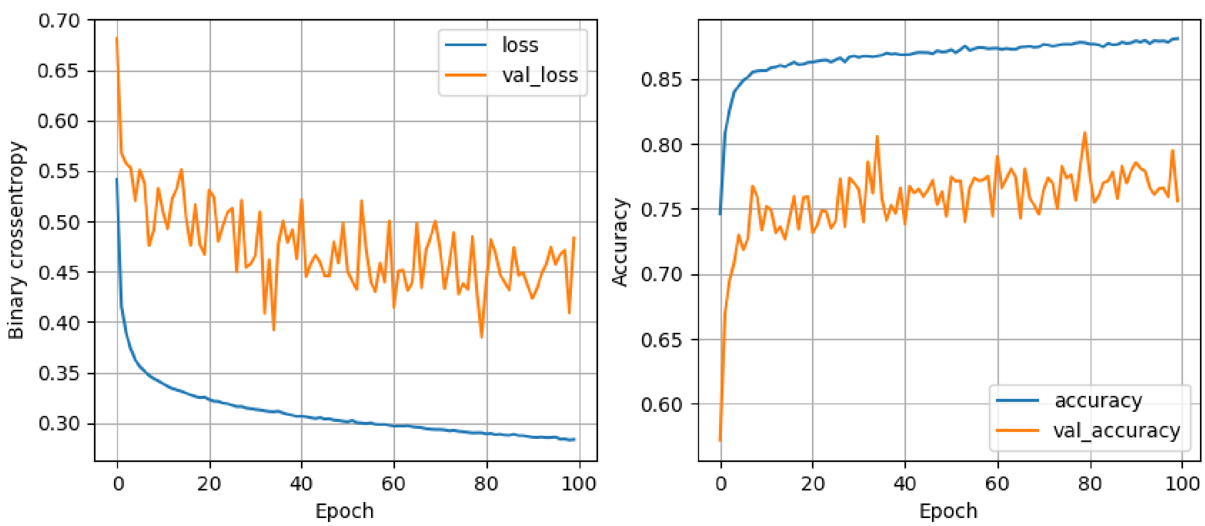
```
%%time

least_val_loss = float('inf')
least_loss_model = None
epochs=100

# for num_nodes in [16, 32, 64]:
#   for dropout_prob in[0, 0.2]:
#     for lr in [0.01, 0.005, 0.001]:
#       for batch_size in [32, 64, 128]:

for num_nodes in [32]:
  for dropout_prob in[0]:
    for lr in [0.001]:
      for batch_size in [128]:
        print(f"{num_nodes} nodes, dropout {dropout_prob}, lr {lr}, batch size {bat
        model, history = train_model(X_train, y_train, num_nodes, dropout_prob, lr,
        plot_history(history)
        val_loss = model.evaluate(X_valid, y_valid)[0]
        if val_loss < least_val_loss:
            least_val_loss = val_loss
            least_loss_model = model
```

```
32 nodes, dropout 0, lr 0.001, batch size 128
```




```
119/119 [==============================] - 0s 678us/step - loss: 0.2997 - accuracy:
0.8736
CPU times: total: 3.52 s
Wall time: 11.6 s
```

In [146…

```
y_pred = least_loss_model.predict(X_test)
y_pred = (y_pred > 0.5).astype(int).reshape(-1,)
```

```
119/119 [==============================] - 0s 602us/step
```

In [147…

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.77      0.82      1370
           1       0.88      0.94      0.91      2434

    accuracy                           0.88      3804
   macro avg       0.88      0.85      0.86      3804
weighted avg       0.88      0.88      0.87      3804
```

In [ ]: