temp

October 12, 2024



```
[19]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import os
# base_path = "/kaggle/input/playground-series-s4e10"
df_train = pd.read_csv(os.path.join('train.csv'))
df_test = pd.read_csv(os.path.join('test.csv'))
df_sample = pd.read_csv(os.path.join('sample_submission.csv'))
TARGET = 'loan_status'
```

```
Preprocessing

[20]: for column in df_train.columns:
    nan_count = df_train[column].isna().sum()
    print(f"Column '{column}' has {nan_count} NaN values.")

Column 'id' has 0 NaN values.

Column 'person_age' has 0 NaN values.

Column 'person_income' has 0 NaN values.

Column 'person_home_ownership' has 0 NaN values.

Column 'person_emp_length' has 0 NaN values.

Column 'loan_intent' has 0 NaN values.

Column 'loan_grade' has 0 NaN values.

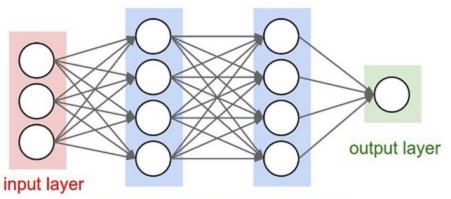
Column 'loan_amnt' has 0 NaN values.
```

```
Column 'loan_percent_income' has 0 NaN values.
     Column 'cb_person_default_on_file' has 0 NaN values.
     Column 'cb_person_cred_hist_length' has 0 NaN values.
     Column 'loan status' has O NaN values.
[21]: from sklearn.preprocessing import LabelEncoder
      label_encoder = LabelEncoder()
      for col in df train.select dtypes(include=['object']).columns:
          df_train[col] = label_encoder.fit_transform(df_train[col])
      for col in df_test.select_dtypes(include=['object']).columns:
          df_test[col] = label_encoder.fit_transform(df_test[col])
      print(df_train.head())
           person_age
                         person_income person_home_ownership
                                                                 person_emp_length
     0
                     37
                                  35000
                                                                                0.0
         1
                     22
                                                              2
                                                                                6.0
     1
                                  56000
     2
         2
                     29
                                  28800
                                                              2
                                                                                8.0
     3
                     30
                                  70000
                                                              3
                                                                               14.0
         3
                                  60000
     4
         4
                     22
                                                              3
                                                                                2.0
                                  loan_amnt
                                              loan_int_rate
                                                             loan_percent_income
        loan_intent
                      loan_grade
     0
                                                                              0.17
                   1
                               1
                                        6000
                                                       11.49
                               2
     1
                   3
                                        4000
                                                       13.35
                                                                              0.07
                   4
                               0
     2
                                        6000
                                                       8.90
                                                                              0.21
     3
                   5
                                       12000
                                                                              0.17
                               1
                                                       11.11
                   3
                                                                              0.10
                               0
                                        6000
                                                        6.92
        cb_person_default_on_file
                                     cb_person_cred_hist_length
                                                                  loan_status
     0
                                  0
                                                               2
                                                                             0
     1
     2
                                  0
                                                              10
                                                                             0
     3
                                  0
                                                               5
                                                                             0
                                  0
                                                               3
                                                                             0
[22]: print(df_train.describe())
                             person_age
                                          person_income
                                                         person_home_ownership
            58645.000000
                           58645.000000
                                           5.864500e+04
                                                                   58645.000000
     count
             29322.000000
                              27.550857
                                           6.404617e+04
     mean
                                                                       1.673578
             16929.497605
                               6.033216
                                           3.793111e+04
                                                                       1.452534
     std
     min
                 0.000000
                              20.000000
                                           4.200000e+03
                                                                       0.000000
     25%
             14661.000000
                              23.000000
                                           4.200000e+04
                                                                       0.000000
     50%
             29322.000000
                              26.000000
                                           5.800000e+04
                                                                       3.000000
     75%
             43983.000000
                              30.000000
                                           7.560000e+04
                                                                       3.000000
```

Column 'loan_int_rate' has 0 NaN values.

	max	58644.000000	123.000000	1.90	0000e+06	3.00	0000
		person_emp_leng	th loan_int	tent	loan_grade	loan_amnt	\
	count	58645.00000			58645.000000	58645.000000	
	mean	4.7010	15 2.519	9430	1.066638	9217.556518	
	std	3.95978	34 1.722	2896	1.046181	5563.807384	
	min	0.0000	0.000	0000	0.000000	500.000000	
	25%	2.0000	00 1.000	0000	0.000000	5000.000000	
	50%	4.0000	3.000	0000	1.000000	8000.000000	
	75%	7.0000	00 4.000	0000	2.000000	12000.000000	
	max	123.0000	5.000	0000	6.000000	35000.000000	
		loan_int_rate	loan_percent	_incom	e cb_person_	_default_on_fil	e \
	count	58645.000000	58645	.00000	0	58645.00000	0
	mean	10.677874	0	. 15923	8	0.14838	4
	std	3.034697	0	.09169	2	0.35548	4
	min	5.420000	0	.00000	0	0.00000	0
	25%	7.880000	0	.09000	0	0.00000	0
	50%	10.750000	0	. 14000	0	0.00000	0
	75%	12.990000	0	.21000	0	0.00000	0
	max	23.220000	0	. 83000	0	1.00000	0
	cb_person_cred_hist_length loan_status						
	count	58	3645.000000	58645	.000000		
	mean		5.813556	0	.142382		
	std		4.029196	0	.349445		
	min		2.000000	0	.000000		
	25%		3.000000	0	.000000		
	50%		4.000000	0	.000000		
	75%		8.000000		.000000		
	max		30.000000	1	.000000		
[40]:	<pre>[40]: X_train = df_train.drop(['id','loan_status'], axis=1).values # print(X_train[0,:])</pre>						
	y_tra	in = df_train['lo	oan_status'].	values	5		
	X_tes	t = df_test.value	es				
	[3.700	e+01 3.500e+04 3	.000e+00 0.00	00e+00	1.000e+00 1.	000e+00 6.000e	+03

1.149e+01 1.700e-01 0.000e+00 1.400e+01]



hidden layer 1 hidden layer 2

```
[41]: from tensorflow.keras.models import Sequential
      from tensorflow.keras.layers import Dense
      # from sklearn.metrics import roc_auc_score
      # from sklearn.preprocessing import LabelEncoder
      from sklearn.preprocessing import StandardScaler
      scaler = StandardScaler()
      X_scaled = scaler.fit_transform(df_train.drop(['id','loan_status'], axis=1))
      # Create the model
      model = Sequential()
      model.add(Dense(4, input_dim=X_scaled.shape[1], activation='relu')) # Firstu
       ⇔hidden layer
      model.add(Dense(4, activation='relu')) # Second hidden layer
      model.add(Dense(1, activation='sigmoid')) # Output layer
      # Compile the model
      model.compile(loss='binary crossentropy', optimizer='sgd')
      # Fit the model
      model.fit(X_scaled, y_train, epochs=100, batch_size=10, verbose=1)
```

Epoch 1/100

c:\Users\Big_Guppy\AppData\Local\Programs\Python\Python312\Lib\sitepackages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an
`input_shape'/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
 super().__init__(activity_regularizer=activity_regularizer, **kwargs)

5865/5865 18s 3ms/step -

loss: 0.3834 Epoch 2/100

5865/5865 15s 3ms/step -

loss: 0.2877 Epoch 3/100

	5865/5865 loss: 0.2568	12s	2ms/step -
	Epoch 4/100		
	5865/5865	19s	2ms/step -
	loss: 0.2385	105	2.m2, 200p
	Epoch 5/100		
	5865/5865	24s	2ms/step -
	loss: 0.2310		-
	Epoch 6/100		
į	5865/5865	20s	2ms/step -
	loss: 0.2287		
	Epoch 7/100		
į	5865/5865	22s	3ms/step -
	loss: 0.2331		
1	Epoch 8/100		
į	5865/5865	28s	4ms/step -
	loss: 0.2254		
	Epoch 9/100		
	5865/5865	32s	2ms/step -
	loss: 0.2257		
	Epoch 10/100		_ ,
	5865/5865	25s	3ms/step -
	loss: 0.2250		
	Epoch 11/100	00	2 / .
	5865/5865	20s	3ms/step -
	loss: 0.2251		
	Epoch 12/100	17-	2/
	5865/5865 loss: 0.2177	178	3ms/step -
	Epoch 13/100		
	5865/5865	150	3ms/step -
	loss: 0.2138	105	oms/scep
	Epoch 14/100		
	5865/5865	14s	2ms/step -
	loss: 0.2164		2.m2, 200p
	Epoch 15/100		
	5865/5865	27s	3ms/step -
	loss: 0.2189		•
]	Epoch 16/100		
	5865/5865	17s	3ms/step -
	loss: 0.2163		•
	Epoch 17/100		
	5865/5865	22s	3ms/step -
	loss: 0.2170		-
]	Epoch 18/100		
į	5865/5865	18s	3ms/step -
	loss: 0.2098		

Epoch 19/100

	58 65/5865 loss: 0.2149	19s	3ms/step -
	Epoch 20/100		
	5865/5865	17s	3ms/step -
	loss: 0.2143	1.5	Cimb, Boop
	Epoch 21/100		
	5865/5865	17s	3ms/step -
	loss: 0.2110		
1	Epoch 22/100		
	5865/5865	18s	3ms/step -
	loss: 0.2086		_
]	Epoch 23/100		
į	5865/5865	17s	2ms/step -
-	loss: 0.2117		
]	Epoch 24/100		
į	5865/5865	13s	2ms/step -
-	loss: 0.2108		
	Epoch 25/100		
	5865/5865	22s	2ms/step -
-	loss: 0.2073		
	Epoch 26/100		
	5865/5865	16s	3ms/step -
	loss: 0.2088		
	Epoch 27/100		
	5865/5865	12s	2ms/step -
	loss: 0.2133		
	Epoch 28/100		- 1
	5865/5865	12s	2ms/step -
	loss: 0.2111		
	Epoch 29/100 5865/5865	10-	0
	•	138	2ms/step -
	loss: 0.2097		
	Epoch 30/100	150	2mg/gton -
	5865/5865 loss: 0.2120	158	3ms/step -
	Epoch 31/100		
	5865/5865	12e	2ms/step -
	loss: 0.2110	125	zms/scep
	Epoch 32/100		
	5865/5865	29s	3ms/step -
	loss: 0.2086		Cimb, Book
	Epoch 33/100		
	5865/5865	28s	5ms/step -
	loss: 0.2124		r
	Epoch 34/100		
	5865/5865	44s	5ms/step -
	loss: 0.2064		•
]	Epoch 35/100		

5865/5865	32s	5ms/step	_
loss: 0.2102			
Epoch 36/100			
5865/5865	36s	4ms/step	-
loss: 0.2127			
Epoch 37/100			
5865/5865	44s	5ms/step	-
loss: 0.2111			
Epoch 38/100			
5865/5865	46s	6ms/step	-
loss: 0.2094			
Epoch 39/100			
5865/5865	16s	3ms/step	-
loss: 0.2092			
Epoch 40/100			
5865/5865	20s	3ms/step	-
loss: 0.2133			
Epoch 41/100			
5865/5865	18s	3ms/step	-
loss: 0.2066			
Epoch 42/100			
5865/5865	17s	3ms/step	-
loss: 0.2134			
Epoch 43/100			
5865/5865	16s	3ms/step	-
loss: 0.2119			
Epoch 44/100			
5865/5865	25s	3ms/step	-
loss: 0.2134			
Epoch 45/100			
5865/5865	24s	4ms/step	-
loss: 0.2067			
Epoch 46/100			
5865/5865	17s	3ms/step	-
loss: 0.2081			
Epoch 47/100			
5865/5865	21s	4ms/step	-
loss: 0.2103			
Epoch 48/100			
5865/5865	22s	4ms/step	-
loss: 0.2084			
Epoch 49/100			
5865/5865	38s	3ms/step	-
loss: 0.2094			
Epoch 50/100			
5865/5865	30s	5ms/step	-
loss: 0.2078			
Epoch 51/100			

5865/5865 loss: 0 2081	27s	5ms/step	-
=	46s	5ms/sten	_
	100	ошь, в сер	
•	35s	4ms/step	_
_	46s	5ms/step	_
_	38s	4ms/step	_
=	25s	4ms/step	_
Epoch 57/100			
5865/5865	24s	4ms/step	_
loss: 0.2042			
Epoch 58/100			
5865/5865	46s	5ms/step	_
loss: 0.2059		•	
Epoch 59/100			
5865/5865	40s	4ms/step	_
loss: 0.2089		_	
Epoch 60/100			
5865/5865	37s	4ms/step	_
loss: 0.2082			
Epoch 61/100			
5865/5865	54s	6ms/step	-
loss: 0.2100			
Epoch 62/100			
5865/5865	31s	4ms/step	-
loss: 0.2061			
Epoch 63/100			
5865/5865	45s	5ms/step	-
loss: 0.2060			
Epoch 64/100			
5865/5865	24s	4ms/step	-
loss: 0.2118			
Epoch 65/100			
5865/5865	40s	7ms/step	-
loss: 0.2086			
Epoch 66/100			
5865/5865	52s	8ms/step	-
loss: 0.2117			
	loss: 0.2081 Epoch 52/100 5865/5865 loss: 0.2089 Epoch 53/100 5865/5865 loss: 0.2049 Epoch 54/100 5865/5865 loss: 0.2076 Epoch 55/100 5865/5865 loss: 0.2092 Epoch 56/100 5865/5865 loss: 0.2055 Epoch 57/100 5865/5865 loss: 0.2042 Epoch 58/100 5865/5865 loss: 0.2042 Epoch 58/100 5865/5865 loss: 0.2089 Epoch 59/100 5865/5865 loss: 0.2089 Epoch 60/100 5865/5865 loss: 0.2082 Epoch 61/100 5865/5865 loss: 0.2061 Epoch 62/100 5865/5865 loss: 0.2060 Epoch 64/100 5865/5865 loss: 0.2118 Epoch 65/100 5865/5865 loss: 0.2086 Epoch 66/100 5865/5865	Loss: 0.2081 Epoch 52/100 5865/5865 46s Loss: 0.2089 Epoch 53/100 5865/5865 35s Loss: 0.2049 Epoch 54/100 5865/5865 46s Loss: 0.2076 Epoch 55/100 5865/5865 38s Loss: 0.2092 Epoch 56/100 5865/5865 25s Loss: 0.2055 Epoch 57/100 5865/5865 24s Loss: 0.2042 Epoch 58/100 5865/5865 46s Loss: 0.2059 Epoch 59/100 5865/5865 40s Loss: 0.2089 Epoch 60/100 5865/5865 37s Loss: 0.2082 Epoch 61/100 5865/5865 31s Loss: 0.2100 Epoch 62/100 5865/5865 31s Loss: 0.2061 Epoch 63/100 5865/5865 45s Loss: 0.2060 Epoch 64/100 5865/5865 45s Loss: 0.2060 Epoch 64/100 5865/5865 40s Loss: 0.2086 Epoch 65/100 5865/5865 40s Loss: 0.2086 Epoch 66/100 5865/5865 52s Loss: 0.2086 Epoch 66/100 Loss: 0.2086 Loss: 0.2	loss: 0.2081 Epoch 52/100 5865/5865 loss: 0.2089 Epoch 53/100 5865/5865 loss: 0.2049 Epoch 54/100 5865/5865 loss: 0.2076 Epoch 55/100 5865/5865 loss: 0.2092 Epoch 56/100 5865/5865 loss: 0.2092 Epoch 57/100 5865/5865 loss: 0.2042 Epoch 58/100 5865/5865 loss: 0.2059 Epoch 59/100 5865/5865 loss: 0.2089 Epoch 60/100 5865/5865 loss: 0.2082 Epoch 61/100 5865/5865 loss: 0.2082 Epoch 61/100 5865/5865 loss: 0.2082 Epoch 62/100 5865/5865 loss: 0.2100 Epoch 62/100 5865/5865 loss: 0.2061 Epoch 63/100 5865/5865 loss: 0.2060 Epoch 64/100 5865/5865 loss: 0.2086 Epoch 65/100 5865/5865 loss: 0.2086 Epoch 66/100

Epoch 67/100

5865/5865 loss: 0.2146	61s	5ms/step -
Epoch 68/100		
5865/5865	23s	4ms/step -
loss: 0.2100		
Epoch 69/100		
5865/5865	23s	4ms/step -
loss: 0.2070		
Epoch 70/100		
5865/5865	40s	4ms/step -
loss: 0.2049		
Epoch 71/100		
5865/5865	22s	4ms/step -
loss: 0.2079		
Epoch 72/100	00	
5865/5865	23s	4ms/step -
loss: 0.2085		
Epoch 73/100	00-	1
5865/5865 loss: 0.2086	22S	4ms/step -
Epoch 74/100		
5865/5865	40e	3ms/step -
loss: 0.2058	105	ошь, в сер
Epoch 75/100		
5865/5865	22s	4ms/step -
loss: 0.2094		, 2 ° ° ° P
Epoch 76/100		
5865/5865	22s	4ms/step -
loss: 0.2060		•
Epoch 77/100		
5865/5865	40s	3ms/step -
loss: 0.2112		
Epoch 78/100		
5865/5865	20s	3ms/step -
loss: 0.2063		
Epoch 79/100		
5865/5865	19s	3ms/step -
loss: 0.2072		
Epoch 80/100		- 1
5865/5865	21s	3ms/step -
loss: 0.2099		
Epoch 81/100	10	O /
5865/5865	198	3ms/step -
loss: 0.2059		
Epoch 82/100 5865/5865	10~	2mg/a+~~
loss: 0.2097	198	3ms/step -
1088: 0.2091		

Epoch 83/100

5865/5865	31s 5ms/step -
loss: 0.2091 Epoch 84/100	
5865/5865	38s 4ms/step -
loss: 0.2108	Jos 4ms/step
Epoch 85/100	
5865/5865	24s 4ms/step -
loss: 0.2082	
Epoch 86/100	
5865/5865	27s 4ms/step -
loss: 0.2072	•
Epoch 87/100	
5865/5865	39s 4ms/step -
loss: 0.2084	
Epoch 88/100	
5865/5865	18s 3ms/step -
loss: 0.2123	
Epoch 89/100	
5865/5865	16s 2ms/step -
loss: 0.2051	
Epoch 90/100	
5865/5865	18s 3ms/step -
loss: 0.2058	
Epoch 91/100	
5865/5865	19s 3ms/step -
loss: 0.2075	
Epoch 92/100	
5865/5865	20s 3ms/step -
loss: 0.2075	
Epoch 93/100	45 0 / .
5865/5865	17s 3ms/step -
loss: 0.2067	
Epoch 94/100	47 0 / 1
5865/5865	17s 3ms/step -
loss: 0.2107	
Epoch 95/100 5865/5865	17s 3ms/step -
loss: 0.2105	178 Sms/step -
Epoch 96/100	
5865/5865	22s 3ms/step -
loss: 0.2093	zzs oms/scep
Epoch 97/100	
5865/5865	17s 3ms/step -
loss: 0.2030	2.5 cm5/50cp
Epoch 98/100	
5865/5865	17s 3ms/step -
loss: 0.2064	3 , 2.3p
Epoch 99/100	
1	

```
5865/5865
                           23s 3ms/step -
     loss: 0.2066
     Epoch 100/100
     5865/5865
                           20s 3ms/step -
     loss: 0.2093
[41]: <keras.src.callbacks.history.History at 0x1500617b110>
[30]: print(df_test['id'])
     0
              58645
     1
              58646
     2
              58647
     3
              58648
     4
              58649
     39093
             97738
     39094
            97739
     39095 97740
            97741
     39096
     39097
              97742
     Name: id, Length: 39098, dtype: int64
[42]: # Assuming 'id' is the first column in the NumPy array
      X_test_ids = df_test['id'] # Get the 'id' values (first column)
      X_test_scaled = scaler.transform(df_test.drop('id', axis=1)) # Scale the test_
      ⇔set features
      # Make predictions
      y_test_pred_probs = model.predict(X_test_scaled).flatten()
      # Prepare the submission DataFrame
      submission_df = pd.DataFrame({
          'id': X_test_ids,
          'loan_status': y_test_pred_probs
      })
      # Save to CSV
      submission_df.to_csv('submission.csv', index=False)
     1222/1222
                           4s 3ms/step
```