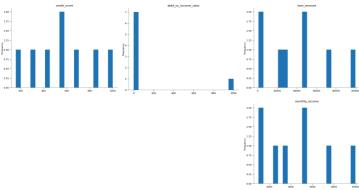
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from \ sklearn.preprocessing \ import \ StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM
# Simulating borrower profiles and financial indicators
np.random.seed(42)
n_samples = 1000
sequence_length = 5 # Length of sequence for each borrower profile
# Simulating borrower profiles and financial indicators
borrower_data = pd.DataFrame({
    'credit_score': np.random.randint(300, 850, n_samples),
    'debt_to_income_ratio': np.random.uniform(0, 1, n_samples),
    'loan_amount': np.random.randint(1000, 100000, n_samples),
    'monthly_income': np.random.randint(1000, 10000, n_samples),
    'open_credit_lines': np.random.randint(0, 20, n_samples),
    \verb|'loan_default': np.random.choice([0, 1], size=n\_samples, p=[0.8, 0.2])|\\
})
borrower_data.describe()
```

	credit_score	debt_to_income_ratio	loan_amount	monthly_income	open_credit_
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.00
mean	563.991000	0.507523	48800.058000	5465.066000	9.88
std	160.508436	0.291419	29061.771183	2545.531549	5.6
min	300.000000	0.003218	1138.000000	1002.000000	0.00
25%	423.750000	0.244882	22577.500000	3420.250000	5.00
50%	553.000000	0.519428	49446.000000	5369.500000	10.00
75%	701.250000	0.758245	74901.000000	7594.500000	15.00
max	849.000000	0.999414	99876.000000	9996.000000	19.00

Distributions



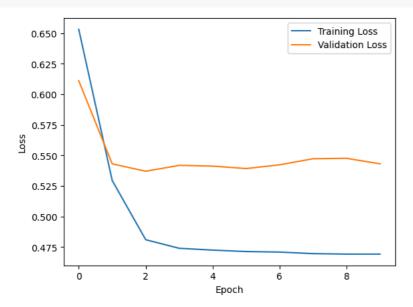
2-d distributions



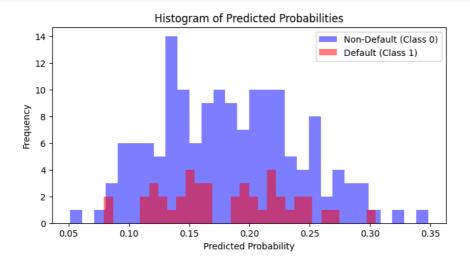
```
# Reshape data into sequences
X sequence = []
y sequence = []
for i in range(len(borrower_data) - sequence_length):
      X_sequence.append(borrower_data.iloc[i:i+sequence_length, :-1].values)
       y_sequence.append(borrower_data.iloc[i+sequence_length, -1])
X_sequence = np.array(X_sequence)
y_sequence = np.array(y_sequence)
print("X_sequence shape:", X_sequence.shape)
print("y_sequence shape:", y_sequence.shape)
print("\nSample X_sequence:")
print(X_sequence[:1]) # Prints first sequence
print("\nSample y_sequence:")
print(y_sequence[:1]) # Prints first target label
        X_sequence shape: (995, 5, 5)
        y_sequence shape: (995,)
        Sample X sequence:
        [[[4.02000000e+02 9.00018642e-01 9.59470000e+04 7.68700000e+03
             7.00000000e+001
            [7.35000000e+02 8.73890078e-01 6.46900000e+03 6.56500000e+03
             1.40000000e+01]
            [5.70000000e+02 5.97413102e-01 2.98540000e+04 8.24100000e+03
             1.30000000e+01]
           [4.06000000e+02 6.00516860e-01 7.25600000e+03 8.65100000e+03
             1.90000000e+01]
           [3.71000000e+02 6.65036675e-01 7.72560000e+04 6.57500000e+03
            6.00000000e+00]]]
        Sample y_sequence:
        [0]
# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X_sequence, y_sequence, test_size=0.2, random_state=42)
# Normalize features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train.reshape(-1, X_train.shape[-1])).reshape(X_train.shape)
X_{\text{test\_scaled}} = \text{scaler.transform}(X_{\text{test.reshape}}(-1, X_{\text{test.shape}}[-1])).\text{reshape}(X_{\text{test.shape}})
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("y_train shape:", y_train.shape)
print("y_test shape:", y_test.shape)
        X_train shape: (796, 5, 5)
        X_test shape: (199, 5, 5)
        y train shape: (796,)
        y_test shape: (199,)
# Build RNN model
model = Sequential([
      LSTM(units=64, input_shape=(X_train.shape[1], X_train.shape[2])),
      Dense(units=1, activation='sigmoid')
])
# Compile, train and evaluate
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
history = model.fit(X_train_scaled, y_train, epochs=10, batch_size=32, validation_data=(X_test_scaled, y_test))
loss, accuracy = model.evaluate(X_test_scaled, y_test)
print("Accuracy:", accuracy)
# Calculate profit and loss
 profit = np.sum((y\_pred\_binary == 1) * profit\_per\_approved\_loan) - np.sum((y\_pred\_binary == 0) * loss\_per\_rejected\_loan * (1 - y\_pred)) 
loss\_incorrect\_approvals = np.sum((y\_pred\_binary != y\_test) \& (y\_pred\_binary == 1)) * loss\_per\_rejected\_loan | loss\_incorrect\_approvals = np.sum((y\_pred\_binary != y\_test) & (y\_pred\_binary == 1)) * loss\_per\_rejected\_loan | loss\_incorrect\_approvals = np.sum((y\_pred\_binary != y\_test) & (y\_pred\_binary == 1)) * loss\_per\_rejected\_loan | loss\_incorrect\_approvals = np.sum((y\_pred\_binary != y\_test) & (y\_pred\_binary != y\_test)
loss_incorrect_rejections = np.sum((y_pred_binary != y_test) & (y_pred_binary == 0)) * profit_per_approved_loan
total_loss = loss_incorrect_approvals + loss_incorrect_rejections
print("Profit:", profit)
print("Loss:", total_loss)
        Epoch 1/10
        25/25 [===
                                           =========] - 5s 52ms/step - loss: 0.6471 - accuracy: 0.6972 - val_loss: 0.6014 - val_accuracy: 0.7789
        Epoch 2/10
        Enoch 3/10
        25/25 [====
                                         :===========] - 0s 6ms/step - loss: 0.4803 - accuracy: 0.8141 - val_loss: 0.5352 - val_accuracy: 0.7789
        Epoch 4/10
        Epoch 5/10
                                         =========] - 0s 6ms/step - loss: 0.4740 - accuracy: 0.8141 - val_loss: 0.5464 - val_accuracy: 0.7789
```

```
Epoch 6/10
                     ========] - 0s 7ms/step - loss: 0.4720 - accuracy: 0.8141 - val_loss: 0.5405 - val_accuracy: 0.7789
25/25 [====
Epoch 7/10
25/25 [===
                                 ==] - 0s 6ms/step - loss: 0.4710 - accuracy: 0.8141 - val_loss: 0.5442 - val_accuracy: 0.7789
Epoch 8/10
25/25 [====
                        ========] - 0s 7ms/step - loss: 0.4695 - accuracy: 0.8141 - val_loss: 0.5405 - val_accuracy: 0.7789
Epoch 9/10
25/25 [====
                     =========] - 0s 7ms/step - loss: 0.4690 - accuracy: 0.8141 - val_loss: 0.5488 - val_accuracy: 0.7789
Epoch 10/10
25/25 [============] - 0s 7ms/step - loss: 0.4687 - accuracy: 0.8141 - val_loss: 0.5423 - val_accuracy: 0.7789
7/7 [=========== ] - 0s 4ms/step - loss: 0.5423 - accuracy: 0.7789
Accuracy: 0.7788944840431213
Profit: -81345.73024511337
Loss: 8756000
```

```
# Plot training and validation loss
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



```
# Generate histograms for predicted probabilities
plt.figure(figsize=(8, 4))  # Adjust the figsize here to change the size of the plot
plt.hist(y_pred[y_test == 0], bins=30, alpha=0.5, label='Non-Default (Class 0)', color='blue')
plt.hist(y_pred[y_test == 1], bins=30, alpha=0.5, label='Default (Class 1)', color='red')
plt.title('Histogram of Predicted Probabilities')
plt.xlabel('Predicted Probability')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```



```
{\tt from \ sklearn.metrics \ import \ confusion\_matrix}
import seaborn as sns
# Make predictions on the test set
y_pred_probs = model.predict(X_test_scaled)
y_pred_binary = (y_pred_probs > 0.5).astype(int)
\hbox{\tt\# Calculate confusion matrix}
conf_matrix = confusion_matrix(y_test, y_pred_binary)
\hbox{\it\# Print confusion matrix}
print("Confusion Matrix:")
print(conf_matrix)
# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
7/7 [======] - 0s 5ms/step
Confusion Matrix:
[[155 0]
[ 44 0]]
```

