```python
# Chaitnaya Mangla AI - DS B1
# Credit Risk Assesssment ML Project
# Use Classification to predict if a loan applicant is at low Risk or high Risk for defaulting
```

[222] ✓ 0.0s Python

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[223] ✓ 0.0s Python

```python
# Creating a synthetic dataset
np.random.seed(42)
n_samples = 1000

data = pd.DataFrame({'Income' : np.random.normal(50000, 15000, n_samples).astype(int),
                     'Credit_Score' : np.random.randint(300,850,n_samples),
                      'Loan_Amount' : np.random.normal(20000, 5000, n_samples).astype(int),
                       'Employment_Status' : np.random.choice(['Employed','Unemployed','Self-Employed'], n_samples),
                        'Existing_Debts': np.random.normal(5000, 2000, n_samples).astype(int)
                        })
```

[224] ✓ 0.0s Python

```python
# Here we are loading this dataset in the tabular form
data
```

[225] ✓ 0.0s

	Income	Credit_Score	Loan_Amount	Employment_Status	Existing_Debts
0	57450	727	26109	Unemployed	3601
1	47926	604	28747	Unemployed	7324
2	59715	616	14927	Employed	5093
3	72845	308	23914	Unemployed	6393
4	46487	372	15172	Unemployed	5640
...	...	...	...	...	...
995	45783	826	21660	Self-Employed	1126
996	76965	325	24405	Self-Employed	4184
997	59612	705	18098	Employed	1332
998	41432	531	10409	Employed	3993
999	58588	832	19249	Unemployed	3270

1000 rows × 5 columns

```python
# Generate target variable: 0 = Low Risk, 1 = High Risk
# Simplified rule: high debt-to-income ratio and low credit score -> high risk
data['Debt_to_Income'] = data['Existing_Debts'] / data['Income']
data['Risk'] = ((data['Debt_to_Income'] > 0.2) & (data['Credit_Score'] < 600)).astype(int)
```

[258] ✓ 0.0s

```python
data=pd.get_dummies (data,columns=['Employment_Status'], drop_first=True)
```

[259] ✓ 0.0s

```python
X = data.drop(['Risk'], axis=1)
y = data['Risk']
```

[260] ✓ 0.0s

```python
X # Importing the dataset without the risk column
```

[261] ✓ 0.0s Pyth

...

	Income	Credit_Score	Loan_Amount	Existing_Debts	Debt_to_Income	Employment_Status_Self-Employed	Employment_Status_Unemployed
0	57450	727	26109	3601	0.062681	False	True
1	47926	604	28747	7324	0.152819	False	True
2	59715	616	14927	5093	0.085288	False	False
3	72845	308	23914	6393	0.087762	False	True
4	46487	372	15172	5640	0.121324	False	True
...	...	...	...	...	...	...	...
995	45783	826	21660	1126	0.024594	True	False
996	76965	325	24405	4184	0.054362	True	False
997	59612	705	18098	1332	0.022344	False	False
998	41432	531	10409	3993	0.096375	False	False
999	58588	832	19249	3270	0.055813	False	True

1000 rows × 7 columns

```
y  # The coulmn with risk 0: Low Risk 1: High Risk
```

[262] ✓ 0.0s

```
0      0
1      0
2      0
3      0
4      0
      ..
995    0
996    0
997    0
998    0
999    0
Name: Risk, Length: 1000, dtype: int64
```

```
# Train test and split the model
```

```python
# Train test and split the model
from sklearn.model_selection import train_test_split
X_train,X_test, y_train, y_test = train_test_split(X,y,test_size = 0.25, random_state = 42, stratify = y)
```

[263] ✓ 0.0s Python

```python
X_train # data on which model is trained
```

[264] ✓ 0.0s Python

	Income	Credit_Score	Loan_Amount	Existing_Debts	Debt_to_Income	Employment_Status_Self-Employed	Employment_Status_Unemployed
139	31537	516	15632	4163	0.132004	False	False
921	34602	759	22746	4295	0.124126	False	True
741	30806	707	18560	3023	0.098130	True	False
271	28462	519	25627	3193	0.112185	False	True
524	38551	386	8454	5346	0.138673	False	True
...	...	...	...	...	...	...	...
963	60635	521	23995	1728	0.028498	False	True
302	61209	673	12977	4141	0.067653	False	False
504	40240	724	24317	-160	-0.003976	False	True
569	44727	650	29673	9703	0.216938	False	False
370	50367	660	21694	7439	0.147696	False	False

750 rows × 7 columns

```python
X_test # data on which model is tested
```

[265] ✓ 0.0s Python

	Income	Credit_Score	Loan_Amount	Existing_Debts	Debt_to_Income	Employment_Status_Self-Employed	Employment_Status_Unemployed
103	37965	660	19193	6483	0.170763	False	False
284	81995	501	27843	5968	0.072785	False	False
245	44982	405	21675	1719	0.038215	True	False
800	64074	643	20957	6111	0.095374	True	False
532	49008	576	17886	5738	0.117083	True	False
...	...	...	...	...	...	...	...
329	59425	429	14330	1312	0.022078	False	True
587	37252	521	19232	5847	0.156958	False	False
942	59753	382	24762	5788	0.096865	True	False
849	42035	519	19216	3735	0.088855	True	False
411	33130	635	20206	1282	0.038696	False	True

250 rows × 7 columns

```
y_train # data on which model is trained
```

[266] ✓ 0.0s

```
139    0
921    0
741    0
271    0
524    0
      ..
963    0
302    0
504    0
569    0
370    0
Name: Risk, Length: 750, dtype: int64
```

```
y_test # data on which model is tested
```

[267] ✓ 0.0s

```
103    0
284    0
245    0
800    0
532    0
      ..
329    0
587    0
942    0
849    0
411    0
Name: Risk, Length: 250, dtype: int64
```

```python
# Scaling the numnerical features
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[268] ✓ 0.0s

```python
X_train_scaled # The model is trained
```

[269] ✓ 0.0s

```
array([[-1.26442551, -0.43077518, -0.88052201, ...,  0.30133601,
        -0.72843136, -0.69020139],
       [-1.05705629,  1.12203988,  0.57359094, ...,  0.19850818,
        -0.72843136,  1.4488525 ],
       [-1.3138829 ,  0.78975024, -0.28203414, ..., -0.14080344,
         1.37281295, -0.69020139],
       ...,
       [-0.67560518,  0.89838339,  0.89470585, ..., -1.47356601,
        -0.72843136,  1.4488525 ],
       [-0.37202746,  0.42550967,  1.98948079, ...,  1.40996122,
        -0.72843136, -0.69020139],
       [ 0.00955897,  0.48941152,  0.35856046, ...,  0.50616182,
        -0.72843136, -0.69020139]], shape=(750, 7))
```

```
X_test_scaled # The model is tested
[270] ✓ 0.0s

array([[-0.82952523,  0.48941152, -0.15264793, ...,  0.80724335,
        -0.72843136, -0.69020139],
       [ 2.14941988, -0.52662796,  1.61542587, ..., -0.47162782,
        -0.72843136, -0.69020139],
       [-0.35477489, -1.14008576,  0.35467683, ..., -0.9228545 ,
         1.37281295, -0.69020139],
       ...,
       [ 0.64458915, -1.28706003,  0.98566456, ..., -0.15731255,
         1.37281295, -0.69020139],
       [-0.55416056, -0.41160462, -0.14794669, ..., -0.26187636,
         1.37281295, -0.69020139],
       [-1.15664764,  0.32965689,  0.05441089, ..., -0.91657929,
        -0.72843136,  1.4488525 ]], shape=(250, 7))
```

```python
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier(n_estimators = 100,random_state = 42)
model.fit(X_train, y_train)
```

[271] ✓ 0.1s

RandomForestClassifier

▼ Parameters

	n_estimators	100
	criterion	'gini'
	max_depth	None
	min_samples_split	2
	min_samples_leaf	1
	min_weight_fraction_leaf	0.0
	max_features	'sqrt'
	max_leaf_nodes	None
	min_impurity_decrease	0.0
	bootstrap	True
	oob_score	False
	n_jobs	None
	random_state	42
	verbose	0
	warm_start	False
	class_weight	None
	ccp_alpha	0.0
	max_samples	None
	monotonic_cst	None

```python
# Evaluating the model
y_pred = model.predict(X_test)
y_prob = model.predict_proba(X_test) [:,1]
```

[272] ✓ 0.0s

```python
print(y_pred) # Predictions of the whole data
```

[273] ✓ 0.0s

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

[274]

```python
print(y_prob) # Probabilities of the whole dataset
```

✓ 0.0s

```
[0.   0.   0.02 0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
 0.   0.   0.   0.   0.   0.   0.   0.   0.02 0.   0.   0.84 0.   0.
 0.58 0.   0.   0.   0.6  0.   0.   0.03 0.   0.   0.   0.   0.   0.
 0.   0.01 0.   0.   0.   0.81 0.01 0.7  0.15 0.62 0.   0.   0.   0.
 0.   0.26 0.01 0.   0.02 0.01 0.01 0.54 0.02 0.01 0.14 0.   0.   0.02
 0.01 0.   0.01 0.05 0.   0.01 0.01 0.   0.   0.   0.   0.   0.   0.
 0.   0.01 0.   0.14 0.   0.   0.   0.   0.07 0.   0.   0.   0.   0.
 0.   0.   0.   0.   0.   0.05 0.03 0.   0.   0.   0.   0.1  0.29 0.03
 0.   0.05 0.   0.   0.   0.   0.01 0.   0.   0.   0.   0.   0.   0.
 0.11 0.   0.01 0.   0.   0.   0.01 0.   0.   0.   0.   0.   0.   0.
 0.   0.   0.   0.   0.   0.   0.   0.   0.91 0.   0.   0.   0.   0.
 0.   0.   0.01 0.   0.   0.   0.06 0.   0.   0.01 0.03 0.   0.   0.
 0.02 0.   0.01 0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.16
 0.   0.   0.15 0.01 0.   0.   0.   0.   0.   0.01 0.   0.   0.   0.
 0.82 0.02 0.16 0.   0.   0.01 0.01 0.   0.   0.   0.02 0.   0.   0.01
 0.   0.   0.   0.01 0.   0.   0.   0.   0.   0.   0.   0.01 0.01 0.
 0.   0.   0.   0.   0.01 0.81 0.   0.   0.   0.   0.   0.   0.7  0.
 0.   0.   0.   0.   0.   0.   0.11 0.   0.   0.   0.   0.  ]
```

[275]

```python
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score
```

✓ 0.0s

```
print("Confusion Matrix\n", confusion_matrix(y_test, y_pred))
# Confusion matrix used to visulaize the actual and the predicted values
```

[276] ✓ 0.0s

```
Confusion Matrix
 [[239   0]
 [  0  11]]
```

```
print("ROC-AUC_Score\n" , roc_auc_score(y_test, y_prob))
# It tells teh ability to differentiate between the positive and negative values
```

[277] ✓ 0.0s

```
ROC-AUC_Score
 1.0
```

```
print("ClassificationReport\n", classification_report(y_test,y_pred))
# It tells the values of the the all the types
```

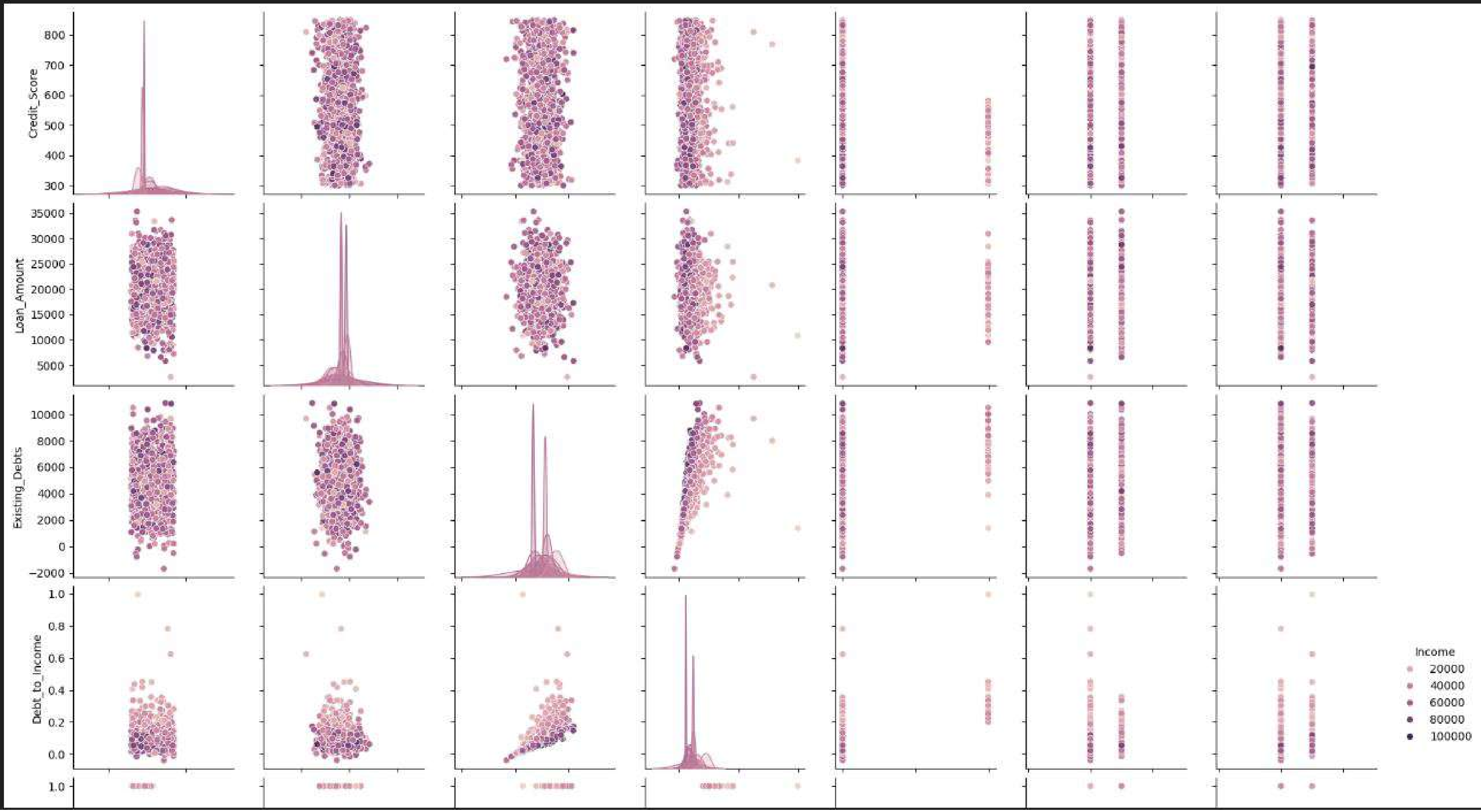
[278] ✓ 0.0s

```
ClassificationReport
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       239
           1       1.00      1.00      1.00        11

    accuracy                           1.00       250
   macro avg       1.00      1.00      1.00       250
weighted avg       1.00      1.00      1.00       250
```

```python
sns.pairplot(data, hue='Income')
```

[279] ✓ 12.8s Python

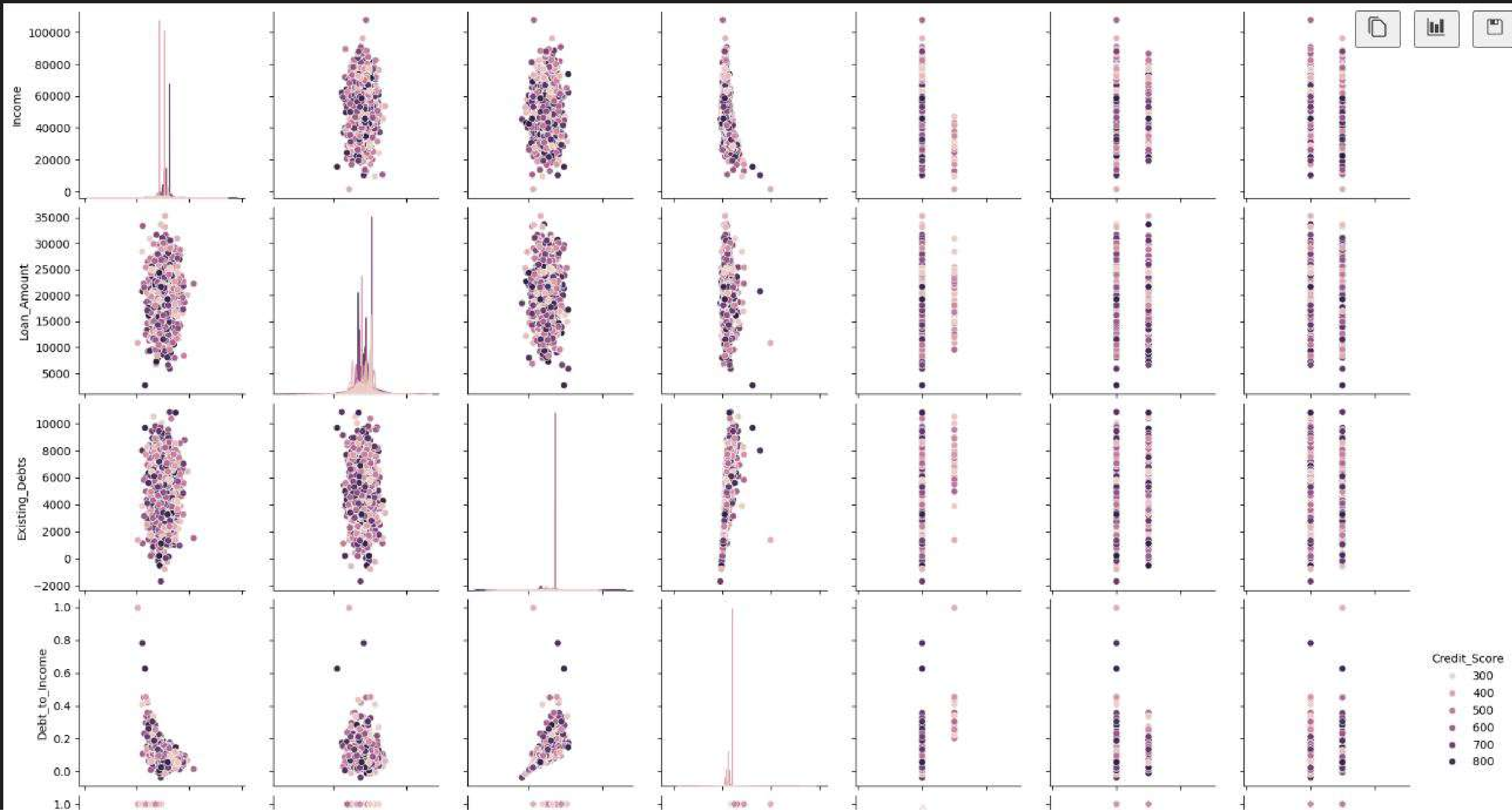
```
<seaborn.axisgrid.PairGrid at 0x29b5e9f7e10>
```



```python
sns.pairplot(data, hue='Credit_Score')
```

[280] ✓ 26.5s Python

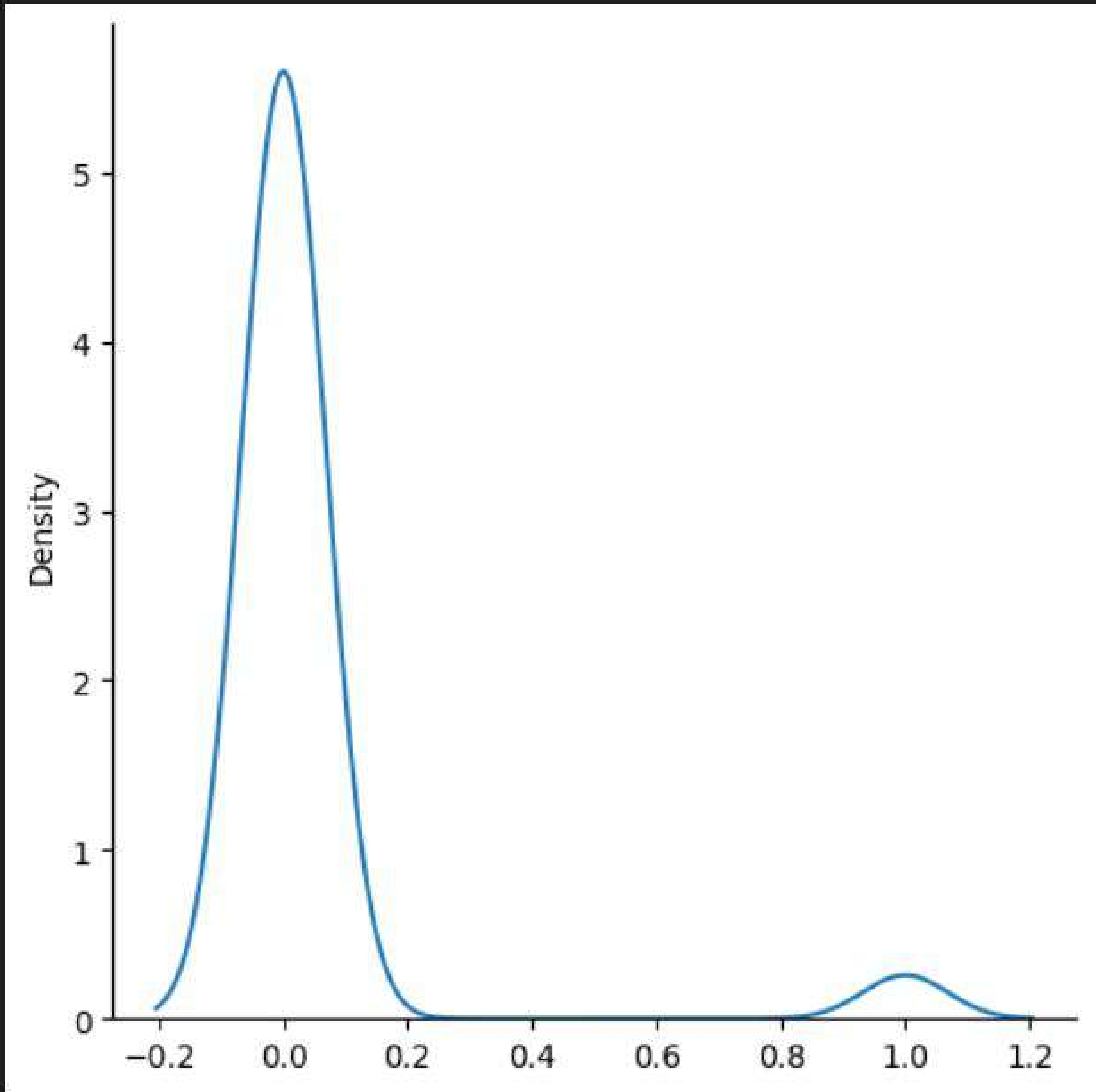
```
<seaborn.axisgrid.PairGrid at 0x29b5e9f68b0>
```



```
sns.displot(y_pred, kind='kde')
# Line Graph id there is probability distribution
```

[281] ✓ 0.1s

```
<seaborn.axisgrid.FacetGrid at 0x29b1f5c9450>
```



```python
# Prediction of Applicant 1
new_applicant = pd.DataFrame({
    'Income': [55000],
    'Credit_Score': [650],
    'Loan_Amount': [25000],
    'Existing_Debts': [4000],
    'Debt_to_Income': [4000/55000],
    'Employment_Status_Self-Employed': [0],
    'Employment_Status_Unemployed': [0]
})

new_applicant_scaled =scaler.transform(new_applicant)
prediction = model.predict(new_applicant_scaled)
probability = model.predict_proba(new_applicant_scaled)[:,1]

print("Example of Applicant Prediction:")
print("Predicted outcome", "High risk" if prediction[0] == 1 else "Low Risk")
print("New Applicantt Predicted Risk", round(probability[0], 3))
```

[282] ✓ 0.0s

```
Example of Applicant Prediction:
Predicted outcome Low Risk
New Applicantt Predicted Risk 0.15
```

```python
# Prediction of Applicant 2
new_applicant = pd.DataFrame({
    'Income': [25000],
    'Credit_Score': [200],
    'Loan_Amount': [20000],
    'Existing_Debts': [4000],
    'Debt_to_Income': [4000/25000],
    'Employment_Status_Self-Employed': [0],
    'Employment_Status_Unemployed': [0]
})

new_applicant_scaled =scaler.transform(new_applicant)
prediction = model.predict(new_applicant_scaled)
probability = model.predict_proba(new_applicant_scaled)[:,1]

print("Example of Applicant Prediction:")
print("Predicted outcome", "High risk" if prediction[0] == 1 else "Low Risk")
print("New Applicantt Predicted Risk", round(probability[0], 3))
```

[283] ✓ 0.0s

```
Example of Applicant Prediction:
Predicted outcome High risk
New Applicantt Predicted Risk 0.85
```