```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import learning_curve
df = pd.read_csv("E:/ml/train.csv")

df.head()
```

```
  Customer ID               Name Gender  Age  Income (USD) Income
Stability  \
0     C-36995   Frederica Shealy      F   56       1933.05
Low
1     C-33999  America Calderone      M   32       4952.91
Low
2      C-3770      Rosetta Verne      F   65        988.19
High
3     C-26480         Zoe Chitty      F   65           NaN
High
4     C-23459       Afton Venema      F   31       2614.77
Low

  Profession     Type of Employment    Location  Loan Amount Request
(USD)  \
0    Working            Sales staff  Semi-Urban
72809.58
1    Working                    NaN  Semi-Urban
46837.47
2  Pensioner                    NaN  Semi-Urban
45593.04
3  Pensioner                    NaN       Rural
80057.92
4    Working  High skill tech staff  Semi-Urban
113858.89

   ...  Credit Score No. of Defaults Has Active Credit Card  Property
ID  \
0  ...        809.44               0                    NaN
746
1  ...        780.40               0            Unpossessed
608
2  ...        833.15               0            Unpossessed
546
3  ...        832.70               1            Unpossessed
890
4  ...        745.55               1                 Active
715
```

```
   Property Age  Property Type Property Location  Co-Applicant  \
0       1933.05              4             Rural             1
1       4952.91              2             Rural             1
2        988.19              2             Urban             0
3           NaN              2        Semi-Urban             1
4       2614.77              4        Semi-Urban             1

   Property Price  Loan Sanction Amount (USD)
0       119933.46                    54607.18
1        54791.00                    37469.98
2        72440.58                    36474.43
3       121441.51                    56040.54
4       208567.91                    74008.28

[5 rows x 24 columns]
```

```python
df.drop(['Customer ID', 'Name', 'Property ID'],axis =1 ,inplace=True)

print(df.shape)

df = df.dropna(subset=['Loan Sanction Amount (USD)'])

print (df.shape)
```

```
(30000, 21)
(29660, 21)
```

```python
missing_counts = df.isnull().sum()

print(missing_counts)
```

```
Gender                            52
Age                                0
Income (USD)                    4493
Income Stability                1658
Profession                         0
Type of Employment              7188
Location                           0
Loan Amount Request (USD)          0
Current Loan Expenses (USD)      167
Expense Type 1                     0
Expense Type 2                     0
Dependents                      2446
Credit Score                    1670
No. of Defaults                    0
Has Active Credit Card          1546
Property Age                    4760
Property Type                      0
Property Location                347
Co-Applicant                       0
```

```
Property Price                       0
Loan Sanction Amount (USD)           0
dtype: int64
```

```python
num_cols = df.select_dtypes(include=['int64', 'float64']).columns
cat_cols = df.select_dtypes(include=['object']).columns

for col in num_cols:
    df[col] = df[col].fillna(df[col].median())

encoders = {}

for col in cat_cols:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col].astype(str))
    encoders[col] = le
print("Missing values after handling [VERIFICATION]")
print(df.isnull().sum().sum())
```

```
Missing values after handling [VERIFICATION]
0
```

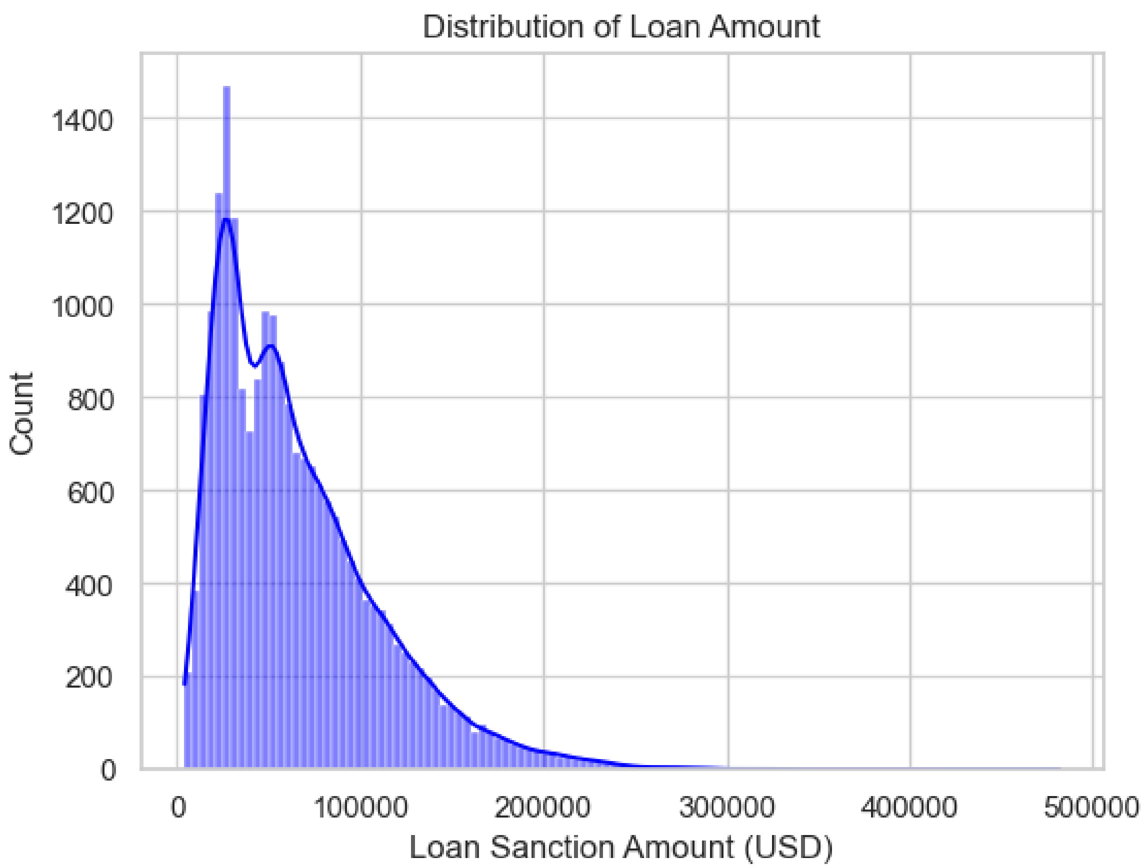
```python
le = LabelEncoder()

for col in cat_cols:
    df[col] = le.fit_transform(df[col])

#Dropping loan amount 0
df = df[df['Loan Sanction Amount (USD)'] > 0]


print(df.describe())
```

```
             Gender           Age  Income (USD)  Income Stability  \
count  21457.000000  21457.000000  2.145700e+04      21457.000000
mean       0.504591     40.389430  2.608860e+03          0.966957
std        0.503428     16.212181  1.222496e+04          0.407881
min        0.000000     18.000000  3.787600e+02          0.000000
25%        0.000000     25.000000  1.769020e+03          1.000000
50%        1.000000     40.000000  2.223300e+03          1.000000
75%        1.000000     56.000000  2.869780e+03          1.000000
max        2.000000     65.000000  1.777460e+06          2.000000

         Profession  Type of Employment      Location  \
count  21457.000000        21457.000000  21457.000000
mean       4.711516           10.483991      0.940159
std        2.626624            5.922649      0.525947
min        0.000000            0.000000      0.000000
25%        1.000000            6.000000      1.000000
50%        7.000000           10.000000      1.000000
75%        7.000000           18.000000      1.000000
```

```
max        7.000000           18.000000      2.000000

       Loan Amount Request (USD)  Current Loan Expenses (USD)  Expense
Type 1  \
count                21457.000000                 21457.000000
21457.000000
mean                 91495.926906                   405.901925
0.354803
std                  60796.889284                   249.574325
0.478465
min                   6108.050000                  -999.000000
0.000000
25%                  42053.750000                   251.630000
0.000000
50%                  77334.440000                   378.320000
0.000000
75%                 123930.540000                   527.810000
1.000000
max                 602384.150000                  3840.880000
1.000000

       ...    Dependents  Credit Score  No. of Defaults  \
count  ...  21457.000000  21457.000000     21457.000000
mean   ...      2.227758    756.849588         0.193690
std    ...      0.893101     60.774241         0.395198
min    ...      1.000000    620.080000         0.000000
25%    ...      2.000000    708.550000         0.000000
50%    ...      2.000000    749.060000         0.000000
75%    ...      3.000000    805.920000         0.000000
max    ...     10.000000    896.260000         1.000000

       Has Active Credit Card  Property Age  Property Type  Property
Location  \
count            21457.000000  2.145700e+04   21457.000000
21457.000000
mean                 1.089481  2.604765e+03       2.458825
1.000233
std                  0.912621  1.222387e+04       1.119531
0.835372
min                  0.000000  3.787600e+02       1.000000
0.000000
25%                  0.000000  1.787940e+03       1.000000
0.000000
50%                  1.000000  2.223965e+03       2.000000
1.000000
75%                  2.000000  2.849640e+03       3.000000
2.000000
max                  3.000000  1.777460e+06       4.000000
3.000000
```

```
       Co-Applicant  Property Price  Loan Sanction Amount (USD)
count  21457.000000    2.145700e+04                21457.000000
mean      -5.247891    1.355782e+05                65881.397768
std       78.484035    9.573963e+04                44858.650085
min     -999.000000   -9.990000e+02                 4023.180000
25%        1.000000    6.245823e+04                30310.860000
50%        1.000000    1.133293e+05                55191.660000
75%        1.000000    1.852552e+05                89126.820000
max        1.000000    1.028083e+06               481907.320000

[8 rows x 21 columns]
```

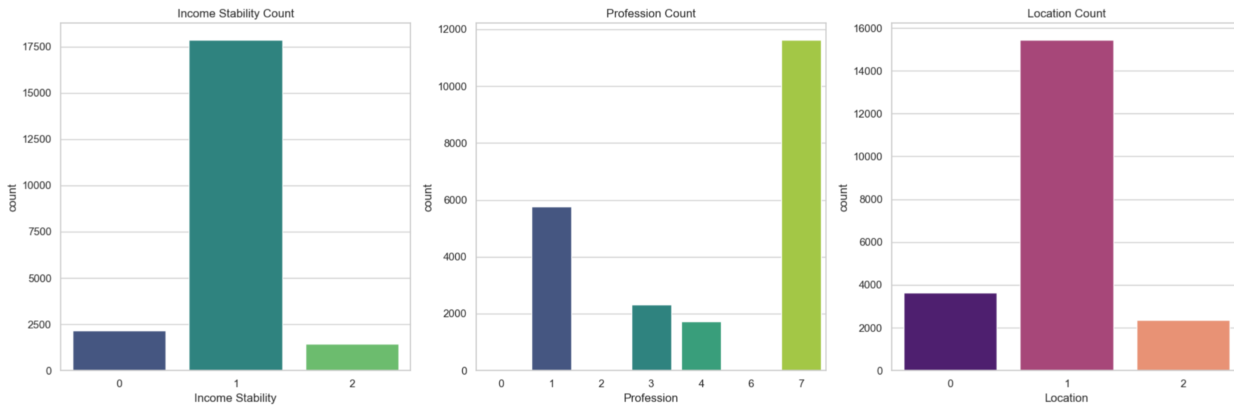
```
sns.histplot(df['Loan Sanction Amount (USD)'], kde=True, color='blue')
plt.title('Distribution of Loan Amount')
plt.show()
```



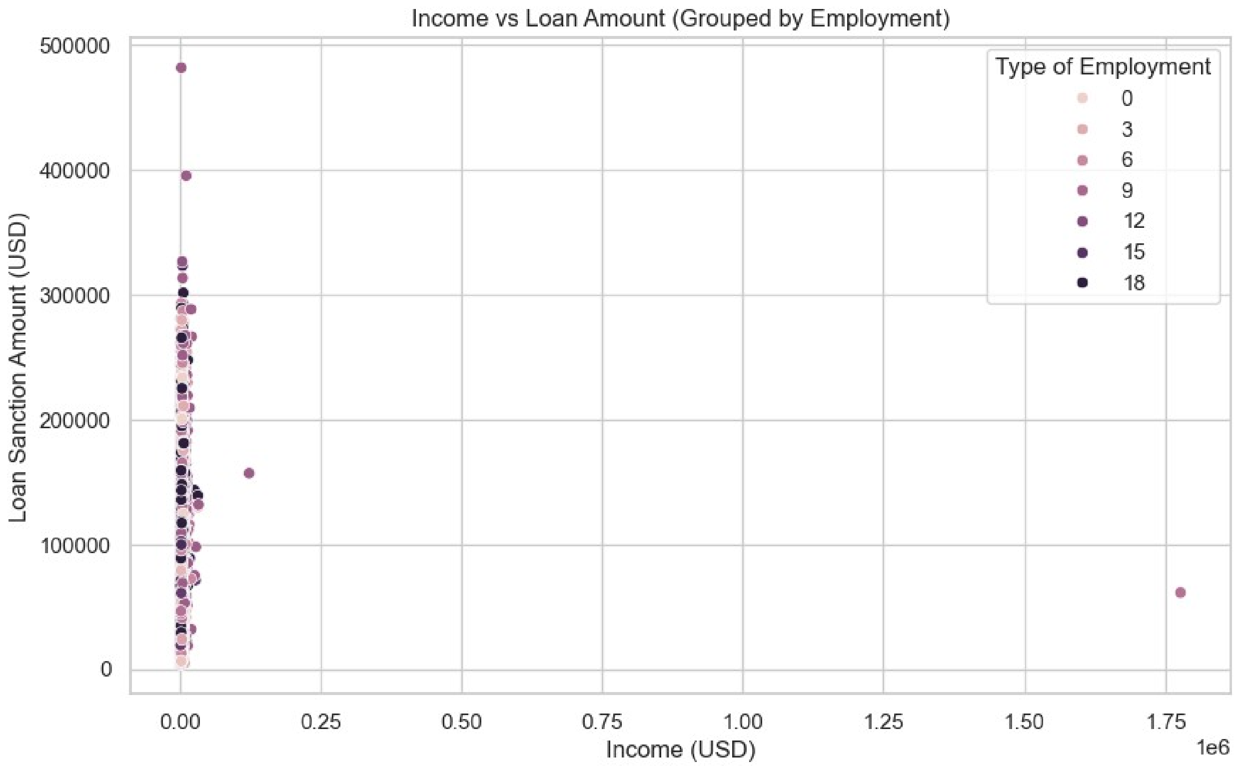

```
fig, axes = plt.subplots(1, 3, figsize=(18, 6))

sns.countplot(x='Income Stability', data=df, ax=axes[0],
palette='viridis')
axes[0].set_title('Income Stability Count')

sns.countplot(x='Profession', data=df, ax=axes[1], palette='viridis')
```

```python
axes[1].set_title('Profession Count')


sns.countplot(x='Location', data=df, ax=axes[2], palette='magma')
axes[2].set_title('Location Count')

plt.tight_layout()
plt.show()

print("--- Income Stability Mapping ---")
for index, label in enumerate(encoders['Income Stability'].classes_):
    print(f"Number {index} means: {label}")

print("\n--- Profession Mapping ---")
for index, label in enumerate(encoders['Profession'].classes_):
    print(f"Number {index} means: {label}")

print("\n--- Location Mapping ---")
for index, label in enumerate(encoders['Location'].classes_):
    print(f"Number {index} means: {label}")
```

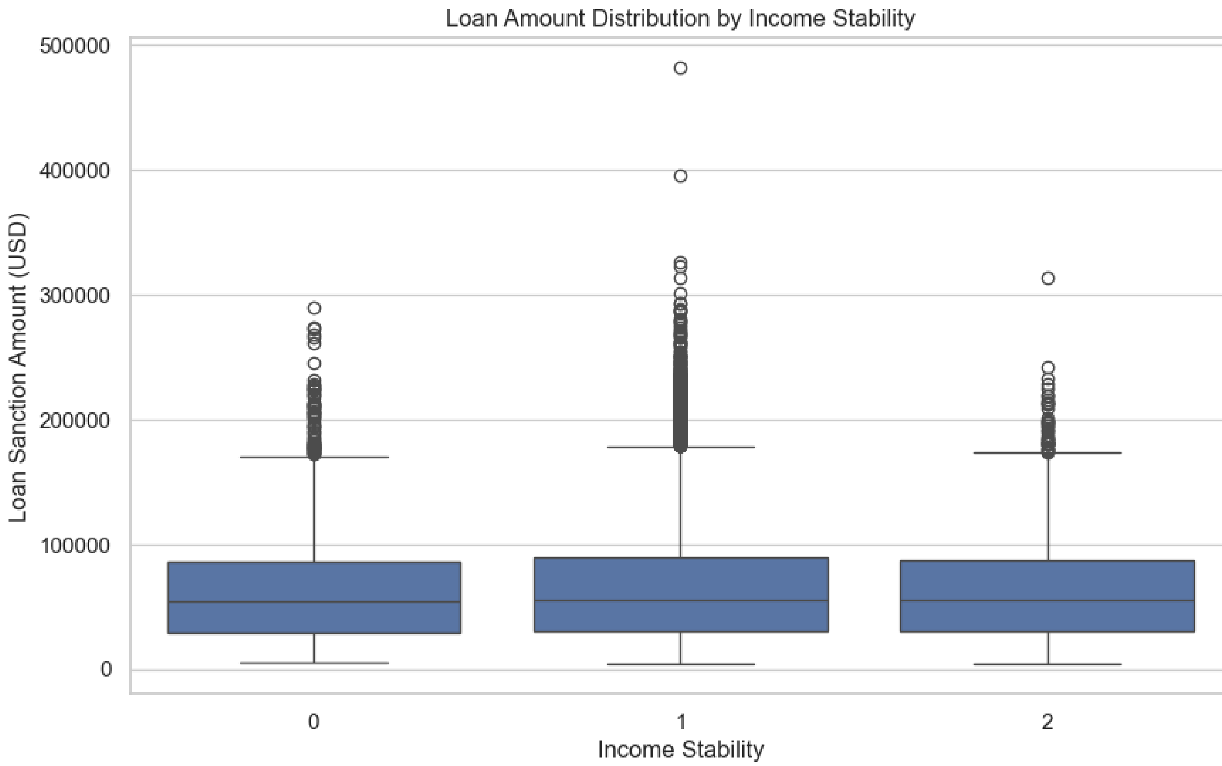
```
C:\Users\KESHA\AppData\Local\Temp\ipykernel_27448\1852018604.py:3:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x='Income Stability', data=df, ax=axes[0],
palette='viridis')
C:\Users\KESHA\AppData\Local\Temp\ipykernel_27448\1852018604.py:6:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x='Profession', data=df, ax=axes[1],
palette='viridis')
C:\Users\KESHA\AppData\Local\Temp\ipykernel_27448\1852018604.py:10:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x='Location', data=df, ax=axes[2], palette='magma')
```



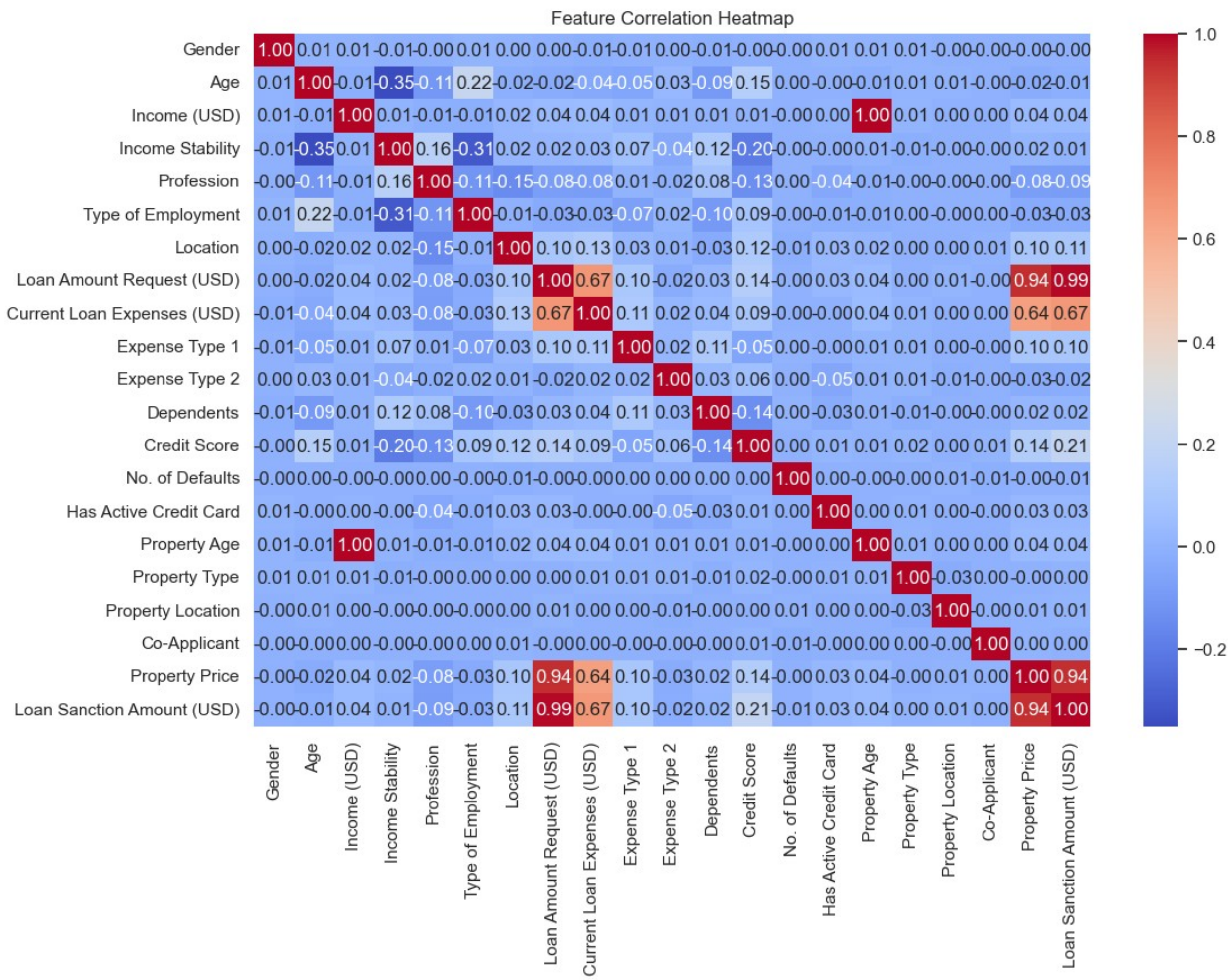

```
--- Income Stability Mapping ---
Number 0 means: High
Number 1 means: Low
Number 2 means: nan

--- Profession Mapping ---
Number 0 means: Businessman
Number 1 means: Commercial associate
Number 2 means: Maternity leave
Number 3 means: Pensioner
Number 4 means: State servant
Number 5 means: Student
Number 6 means: Unemployed
Number 7 means: Working

--- Location Mapping ---
Number 0 means: Rural
Number 1 means: Semi-Urban
Number 2 means: Urban

plt.figure(figsize=(10, 6))
sns.scatterplot(x='Income (USD)', y='Loan Sanction Amount (USD)',
hue='Type of Employment', data=df)# use legend='full' if want to see
the full thing
plt.title('Income vs Loan Amount (Grouped by Employment)')
plt.show()

for index, label in enumerate(encoders['Type of
Employment'].classes_):
    print(f"Number {index} means: {label}")

plt.figure(figsize=(10, 6))
sns.boxplot(x='Income Stability', y='Loan Sanction Amount (USD)',
data=df)
plt.title('Loan Amount Distribution by Income Stability')
plt.show()
```




```
Number 0 means: Accountants
Number 1 means: Cleaning staff
Number 2 means: Cooking staff
Number 3 means: Core staff
Number 4 means: Drivers
Number 5 means: HR staff
Number 6 means: High skill tech staff
Number 7 means: IT staff
Number 8 means: Laborers
Number 9 means: Low-skill Laborers
Number 10 means: Managers
Number 11 means: Medicine staff
Number 12 means: Private service staff
Number 13 means: Realty agents
Number 14 means: Sales staff
Number 15 means: Secretaries
Number 16 means: Security staff
Number 17 means: Waiters/barmen staff
Number 18 means: nan
```




```
plt.figure(figsize=(12, 8))
correlation_matrix = df.select_dtypes(include=[np.number]).corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt='.2f')
plt.title('Feature Correlation Heatmap')
plt.show()
```




```
from sklearn.model_selection import train_test_split

X = df.drop('Loan Sanction Amount (USD)', axis=1)
y = df['Loan Sanction Amount (USD)']


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

X_final = pd.DataFrame(X_scaled, columns=X.columns)
X = X_final


X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)


print(f"Training shapes: {X_train.shape}, {y_train.shape}")
print(f"Testing shapes: {X_test.shape}, {y_test.shape}")
```

```
Training shapes: (17165, 20), (17165,)
Testing shapes: (4292, 20), (4292,)
```

```python
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score

model = LinearRegression()
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print(f"Mean Absolute Error: {mae:.2f}")
print(f"RMSE: {rmse:.2f}")
print(f"R2 Score: {r2:.2f}")
```

```
Mean Absolute Error: 3736.34
RMSE: 5576.15
R2 Score: 0.99
```

```python
from sklearn.linear_model import Ridge, Lasso, ElasticNet
from sklearn.metrics import r2_score, mean_absolute_error

ridge = Ridge(alpha=0.1)
ridge.fit(X_train, y_train)
y_pred_ridge = ridge.predict(X_test)

lasso = Lasso(alpha=0.1)
lasso.fit(X_train, y_train)
y_pred_lasso = lasso.predict(X_test)

enet = ElasticNet(alpha=0.1, l1_ratio=0.5) # l1_ratio=0.5 means 50%
Lasso, 50% Ridge
enet.fit(X_train, y_train)
y_pred_enet = enet.predict(X_test)

results = {
    "Model": ["Ridge", "Lasso", "Elastic Net"],
    "MAE": [
        mean_absolute_error(y_test, y_pred_ridge),
        mean_absolute_error(y_test, y_pred_lasso),
        mean_absolute_error(y_test, y_pred_enet)
    ],
    "R2 Score": [
        r2_score(y_test, y_pred_ridge),
        r2_score(y_test, y_pred_lasso),
```

```python
        r2_score(y_test, y_pred_enet)
    ]
}

print(pd.DataFrame(results))
```

```
         Model          MAE  R2 Score
0        Ridge  3736.315081  0.985198
1        Lasso  3735.974004  0.985205
2  Elastic Net  4460.673938  0.978412
```

```python
from sklearn.model_selection import GridSearchCV

param_grid = {'alpha': [0.001, 0.01, 0.1, 1, 10, 100]}

ridge_cv = GridSearchCV(Ridge(), param_grid, cv=5, scoring='r2')
ridge_cv.fit(X_train, y_train)

lasso_cv = GridSearchCV(Lasso(), param_grid, cv=5, scoring='r2')
lasso_cv.fit(X_train, y_train)

print(f"Best Ridge Alpha: {ridge_cv.best_params_}")
print(f"Best Lasso Alpha: {lasso_cv.best_params_}")

enet_params = {
    'alpha': [0.1, 1, 10],
    'l1_ratio': [0.2, 0.5, 0.8]
}

enet_cv = GridSearchCV(ElasticNet(), enet_params, cv=5, scoring='r2')
enet_cv.fit(X_train, y_train)

print(f"Best Elastic Net Params: {enet_cv.best_params_}")
```

```
e:\anaconda\Lib\site-packages\sklearn\linear_model\
_coordinate_descent.py:695: ConvergenceWarning: Objective did not
converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation.
Duality gap: 5.587e+10, tolerance: 2.756e+09
  model = cd_fast.enet_coordinate_descent(
e:\anaconda\Lib\site-packages\sklearn\linear_model\
_coordinate_descent.py:695: ConvergenceWarning: Objective did not
converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation.
Duality gap: 7.446e+10, tolerance: 2.713e+09
  model = cd_fast.enet_coordinate_descent(
e:\anaconda\Lib\site-packages\sklearn\linear_model\
_coordinate_descent.py:695: ConvergenceWarning: Objective did not
converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation.
Duality gap: 1.434e+11, tolerance: 2.742e+09
```

```
  model = cd_fast.enet_coordinate_descent(
e:\anaconda\Lib\site-packages\sklearn\linear_model\
_coordinate_descent.py:695: ConvergenceWarning: Objective did not
converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation.
Duality gap: 2.560e+10, tolerance: 2.743e+09
  model = cd_fast.enet_coordinate_descent(
e:\anaconda\Lib\site-packages\sklearn\linear_model\
_coordinate_descent.py:695: ConvergenceWarning: Objective did not
converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation.
Duality gap: 4.647e+10, tolerance: 2.707e+09
  model = cd_fast.enet_coordinate_descent(
e:\anaconda\Lib\site-packages\sklearn\linear_model\
_coordinate_descent.py:695: ConvergenceWarning: Objective did not
converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation.
Duality gap: 3.918e+09, tolerance: 2.713e+09
  model = cd_fast.enet_coordinate_descent(
e:\anaconda\Lib\site-packages\sklearn\linear_model\
_coordinate_descent.py:695: ConvergenceWarning: Objective did not
converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation.
Duality gap: 2.897e+10, tolerance: 2.742e+09
  model = cd_fast.enet_coordinate_descent(
```

```
Best Ridge Alpha: {'alpha': 1}
Best Lasso Alpha: {'alpha': 10}
Best Elastic Net Params: {'alpha': 0.1, 'l1_ratio': 0.8}
```

```
best_ridge = ridge_cv.best_estimator_
best_lasso = lasso_cv.best_estimator_
best_enet = enet_cv.best_estimator_

models = [best_ridge, best_lasso, best_enet]
model_names = ["Tuned Ridge", "Tuned Lasso", "Tuned Elastic Net"]

for name, model in zip(model_names, models):
    score = model.score(X_test, y_test)
    print(f"{name} R2 Score: {score:.4f}")
```

```
Tuned Ridge R2 Score: 0.9852
Tuned Lasso R2 Score: 0.9856
Tuned Elastic Net R2 Score: 0.9834
```

```
from sklearn.model_selection import cross_validate
from sklearn.metrics import make_scorer, mean_absolute_error,
mean_squared_error, r2_score
import numpy as np
```

```
models = {
    "Linear Regression": LinearRegression(),
    "Ridge Regression": ridge_cv.best_estimator_,
    "Lasso Regression": lasso_cv.best_estimator_,
    "Elastic Net Regression": enet_cv.best_estimator_
}

scoring = {
    "mae": make_scorer(mean_absolute_error, greater_is_better=False),
    "mse": make_scorer(mean_squared_error, greater_is_better=False),
    "r2": make_scorer(r2_score)
}

cv_results = []

for name, model in models.items():
    scores = cross_validate(model, X_train, y_train, cv=5,
scoring=scoring)
    cv_results.append([
        name,
        -scores["test_mae"].mean(),
        -scores["test_mse"].mean(),
        np.sqrt(-scores["test_mse"].mean()),
        scores["test_r2"].mean()
    ])

table2 = pd.DataFrame(
    cv_results,
    columns=["Model", "MAE", "MSE", "RMSE", "R²"]
)

table2
```

	Model	MAE	MSE	RMSE	R²
0	Linear Regression	3609.000583	2.764272e+07	5257.634035	0.986109
1	Ridge Regression	3608.588185	2.764016e+07	5257.391122	0.986110
2	Lasso Regression	3605.700848	2.762616e+07	5256.059731	0.986117
3	Elastic Net Regression	3825.689632	3.179339e+07	5638.563133	0.984025

```
models = {
    "Linear Regression": model,
    "Tuned Ridge": best_ridge,
    "Tuned Lasso": best_lasso,
    "Tuned Elastic Net": best_enet
}
```

```python
eval_metrics = []

for name, model_obj in models.items():
    preds = model_obj.predict(X_test)

    mae = mean_absolute_error(y_test, preds)
    mse = mean_squared_error(y_test, preds)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_test, preds)

    eval_metrics.append({
        "Model": name,
        "MAE": round(mae, 2),
        "MSE": round(mse,2),
        "RMSE": round(rmse, 2),
        "R2 Score": round(r2, 4)
    })

results_df = pd.DataFrame(eval_metrics)
print(results_df.sort_values(by="R2 Score", ascending=False))
```

```
               Model      MAE          MSE     RMSE  R2 Score
2        Tuned Lasso  3719.83  30323919.93  5506.72    0.9856
1        Tuned Ridge  3736.13  31082233.67  5575.14    0.9852
0  Linear Regression  3960.60  34931250.26  5910.27    0.9834
3  Tuned Elastic Net  3960.60  34931250.26  5910.27    0.9834
```

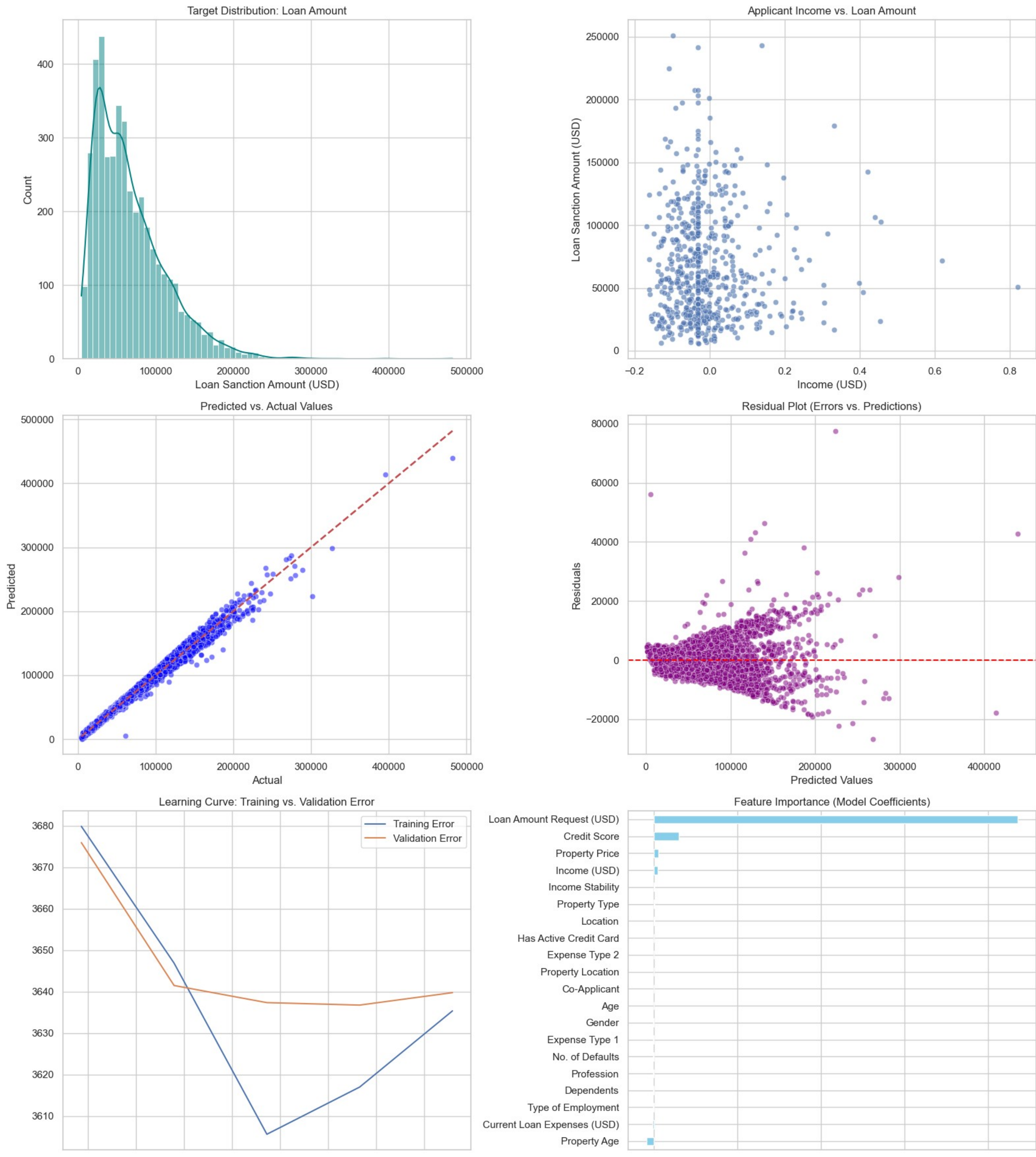
```python
coef_table = pd.DataFrame({
    "Feature": X_train.columns,
    "Linear": models["Linear Regression"].coef_,
    "Ridge": models[ "Tuned Ridge"].coef_,
    "Lasso": models["Tuned Lasso"].coef_,
    "Elastic Net": models["Tuned Elastic Net"].coef_
})

coef_table
```

```
                        Feature      Linear       Ridge
Lasso  \
0                        Gender   17.580328  -13.749662      -
3.332303
1                           Age    2.577235   -8.053297      -
0.000000
2                  Income (USD)   14.711576  467.419995      -
0.000000
3              Income Stability  113.774970   96.178853
83.734410
4                    Profession  -62.116131  -49.089305     -
34.995102
```

```
5              Type of Employment    -95.298883    -77.458892    -
67.525299
6                        Location     64.721397     72.108777
59.081410
7     Loan Amount Request (USD)  37114.264323  43555.327303
43567.138220
8   Current Loan Expenses (USD)    724.552055   -105.200195    -
87.614799
9                  Expense Type 1      1.649791    -40.258424    -
35.701416
10                 Expense Type 2     11.295738     31.770559
19.856662
11                     Dependents    -58.948498    -62.172947    -
51.819072
12                   Credit Score   3030.738136   2989.115500
2980.104096
13                 No. of Defaults    -54.441014    -42.373181    -
32.993159
14         Has Active Credit Card     81.524001     46.118142
36.565360
15                   Property Age      0.559413   -858.754419     -
0.000000
16                  Property Type     96.813176     92.930411
82.030963
17              Property Location     27.391578      1.153002
0.000000
18                   Co-Applicant    -14.548111     -6.096593     -
0.000000
19                 Property Price   5968.459789    545.564251
502.370322

     Elastic Net
0      17.580328
1       2.577235
2      14.711576
3     113.774970
4     -62.116131
5     -95.298883
6      64.721397
7   37114.264323
8     724.552055
9       1.649791
10     11.295738
11    -58.948498
12   3030.738136
13    -54.441014
14     81.524001
15      0.559413
16     96.813176
```

17	27.391578
18	-14.548111
19	5968.459789

```
y_pred = best_ridge.predict(X_test)
residuals = y_test - y_pred

sns.set_theme(style="whitegrid")
fig, axes = plt.subplots(3, 2, figsize=(16, 18))

sns.histplot(y_test, kde=True, ax=axes[0, 0], color='teal')
axes[0, 0].set_title('Target Distribution: Loan Amount')

sns.scatterplot(x=X_test['Income (USD)'], y=y_test, ax=axes[0, 1],
alpha=0.6)
axes[0, 1].set_title('Applicant Income vs. Loan Amount')

sns.scatterplot(x=y_test, y=y_pred, ax=axes[1, 0], color='blue',
alpha=0.5)
axes[1, 0].plot([y_test.min(), y_test.max()], [y_test.min(),
y_test.max()], 'r--', lw=2)
axes[1, 0].set_title('Predicted vs. Actual Values')
axes[1, 0].set_xlabel('Actual')
axes[1, 0].set_ylabel('Predicted')

sns.scatterplot(x=y_pred, y=residuals, ax=axes[1, 1], color='purple',
alpha=0.5)
axes[1, 1].axhline(0, color='red', linestyle='--')
axes[1, 1].set_title('Residual Plot (Errors vs. Predictions)')
axes[1, 1].set_xlabel('Predicted Values')
axes[1, 1].set_ylabel('Residuals')


train_sizes, train_scores, val_scores = learning_curve(best_ridge, X,
y, cv=5, scoring='neg_mean_absolute_error')
train_mae = -train_scores.mean(axis=1)
val_mae = -val_scores.mean(axis=1)

axes[2, 0].plot(train_sizes, train_mae, label='Training Error')
axes[2, 0].plot(train_sizes, val_mae, label='Validation Error')
axes[2, 0].set_title('Learning Curve: Training vs. Validation Error')
axes[2, 0].legend()

coefs = pd.Series(best_ridge.coef_, index=X.columns).sort_values()
coefs.plot(kind='barh', ax=axes[2, 1], color='skyblue')
axes[2, 1].set_title('Feature Importance (Model Coefficients)')
plt.savefig('regression_analysis_results.png', dpi=600,format="png",
bbox_inches='tight')
plt.tight_layout()
plt.show()
```


Target Distribution: Loan Amount
Count
Loan Sanction Amount (USD)
0
100
200
300
400
100000
200000
300000
400000
500000
Applicant Income vs. Loan Amount
Loan Sanction Amount (USD)
Income (USD)
250000
200000
150000
100000
50000
−0.2
0.0
0.2
0.4
0.6
0.8
Predicted vs. Actual Values
Predicted
Actual
Residual Plot (Errors vs. Predictions)
Residuals
Predicted Values
80000
60000
40000
20000
−20000
Learning Curve: Training vs. Validation Error
Training Error
Validation Error
3680
3670
3660
3650
3640
3630
3620
3610
2000
4000
6000
8000
10000
12000
14000
16000
Feature Importance (Model Coefficients)
Loan Amount Request (USD)
Credit Score
Property Price
Income (USD)
Income Stability
Property Type
Location
Has Active Credit Card
Expense Type 2
Property Location
Co-Applicant
Age
Gender
Expense Type 1
No. of Defaults
Profession
Dependents
Type of Employment
Current Loan Expenses (USD)
Property Age
10000
20000
30000
40000