```
import pandas as pd
```

```
data = pd.read_csv('/content/loan_approval_dataset.csv')
data
```

	Age	Income	Education_Level	Credit_Score	Loan_Amount	Loan_Purpose	Loan_Approval
0	56	24000	PhD	333	26892	Personal	0
1	46	90588	Master	316	26619	Home	1
2	32	113610	PhD	452	1281	Personal	1
3	60	117856	High School	677	28420	Personal	0
4	25	58304	PhD	641	16360	Car	0
...	...	...	...	...	...	...	...
495	37	108236	High School	455	44668	Education	1
496	41	117579	Bachelor	666	24177	Car	1
497	29	26469	PhD	550	25022	Medical	0
498	52	50105	High School	633	41761	Medical	0
499	50	62101	Bachelor	810	6542	Home	1

500 rows × 7 columns

1.** Eksplorasi Data**

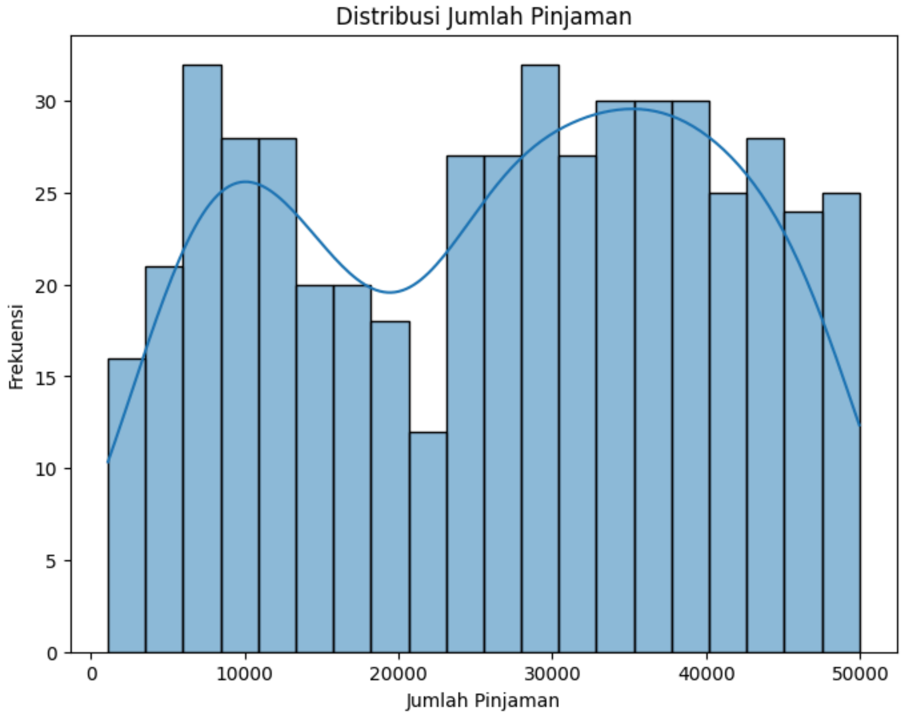
```
#check missing values
data.isna().sum()
```

	0
Age	0
Income	0
Education_Level	0
Credit_Score	0
Loan_Amount	0
Loan_Purpose	0
Loan_Approval	0

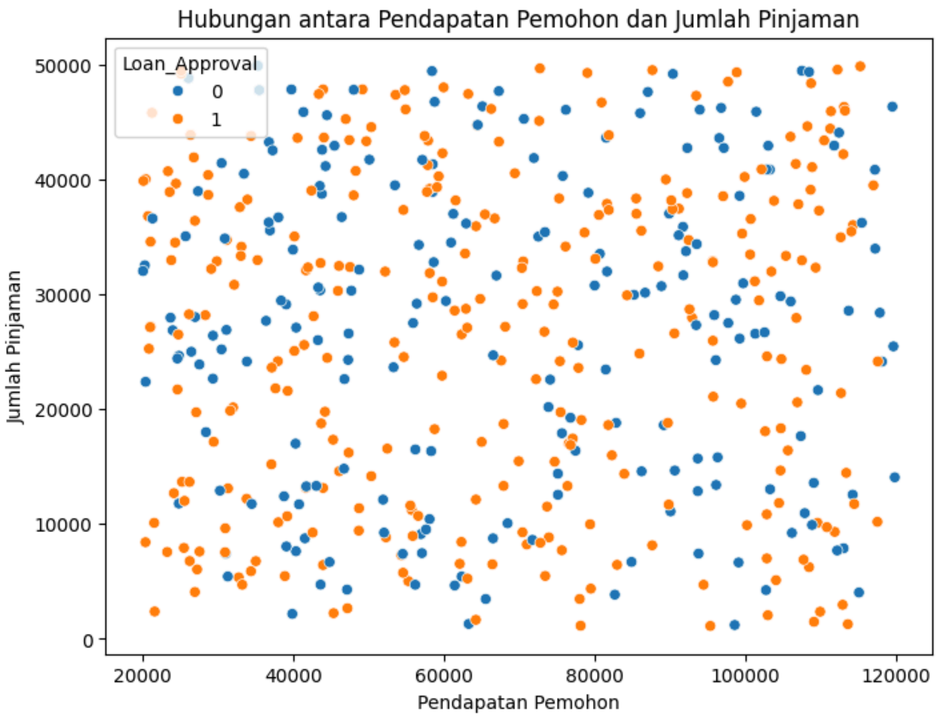
dtype: int64

Tidak ada missing values

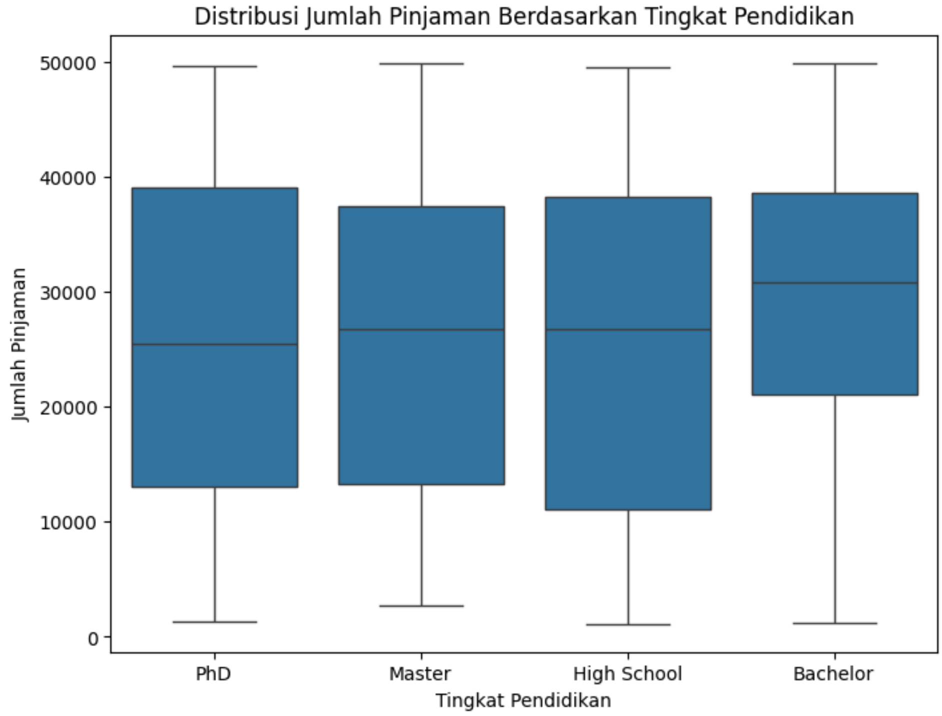
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 6))
sns.histplot(data['Loan_Amount'], bins=20, kde=True)  # Replace 'LoanAmount' with the correct column name
plt.title('Distribusi Jumlah Pinjaman')
plt.xlabel('Jumlah Pinjaman')
plt.ylabel('Frekuensi')
plt.show()
```




```
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Income', y='Loan_Amount', data=data, hue='Loan_Approval')  # Membuat scatter plot dengan warna berdasarkan status pi
plt.title('Hubungan antara Pendapatan Pemohon dan Jumlah Pinjaman')
plt.xlabel('Pendapatan Pemohon')
plt.ylabel('Jumlah Pinjaman')
plt.show()
```




```
plt.figure(figsize=(8, 6))
sns.boxplot(x='Education_Level', y='Loan_Amount', data=data)  # Membuat box plot berdasarkan tingkat pendidikan
plt.title('Distribusi Jumlah Pinjaman Berdasarkan Tingkat Pendidikan')
plt.xlabel('Tingkat Pendidikan')
plt.ylabel('Jumlah Pinjaman')
plt.show()
```



2. Pemrosesan Data

```
from sklearn.preprocessing import LabelEncoder

# Buat objek LabelEncoder
label_encoder = LabelEncoder()

# Lakukan Label Encoding pada kolom 'Education'
data['Education_Encoded'] = label_encoder.fit_transform(data['Education_Level'])
data
```

	Age	Income	Education_Level	Credit_Score	Loan_Amount	Loan_Purpose	Loan_Approval	Education_Encoded
0	56	24000	PhD	333	26892	Personal	0	3
1	46	90588	Master	316	26619	Home	1	2
2	32	113610	PhD	452	1281	Personal	1	3
3	60	117856	High School	677	28420	Personal	0	1
4	25	58304	PhD	641	16360	Car	0	3
...	...	...	...	...	...	...	...	...
495	37	108236	High School	455	44668	Education	1	1
496	41	117579	Bachelor	666	24177	Car	1	0
497	29	26469	PhD	550	25022	Medical	0	3
498	52	50105	High School	633	41761	Medical	0	1
499	50	62101	Bachelor	810	6542	Home	1	0

500 rows × 8 columns

```
from sklearn.preprocessing import StandardScaler

# Pilih kolom numerik yang akan diskalakan
numerical_cols = ['Income', 'Loan_Amount', 'Loan_Approval',  'Education_Encoded', 'Credit_Score']

# Buat objek StandardScaler
scaler = StandardScaler()

# Lakukan scaling pada kolom numerik
data[numerical_cols] = scaler.fit_transform(data[numerical_cols])
data
```

	Age	Income	Education_Level	Credit_Score	Loan_Amount	Loan_Purpose	Loan_Approval	Education_Encoded
0	56	-1.496205	PhD	-1.500286	0.026245	Personal	-1.214598	1.383498
1	46	0.809486	Master	-1.606833	0.006629	Home	0.823318	0.475691
2	32	1.606651	PhD	-0.754461	-1.813972	Personal	0.823318	1.383498
3	60	1.753674	High School	0.655712	0.136035	Personal	-1.214598	-0.432116
4	25	-0.308387	PhD	0.430084	-0.730507	Car	-1.214598	1.383498
...	...	...	...	...	...	...	...	...
495	37	1.420569	High School	-0.735659	1.303496	Education	0.823318	-0.432116
496	41	1.744082	Bachelor	0.586770	-0.168835	Car	0.823318	-1.339924
497	29	-1.410713	PhD	-0.140253	-0.108120	Medical	-1.214598	1.383498
498	52	-0.592287	High School	0.379945	1.094621	Medical	-1.214598	-0.432116
499	50	-0.176911	Bachelor	1.489281	-1.435956	Home	0.823318	-1.339924

500 rows × 8 columns

```
from sklearn.model_selection import train_test_split

# Define features (X) and target (y)
X = data[['Income', 'Loan_Amount',  'Education_Encoded', 'Credit_Score']]  # Features
y = data['Loan_Approval']  # Target variable

# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)  # random_state for reproducibility

# Print the shapes of the resulting sets
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: (400, 4)
X_test shape: (100, 4)
y_train shape: (400,)
y_test shape: (100,)
```

3. Pemilihan Training dan Model

Logistic Regression

Alasan Pemilihan:

- Sederhana dan mudah diinterpretasi: Logistic Regression adalah algoritma yang relatif sederhana dan mudah dipahami. Hasilnya dapat diinterpretasi dengan mudah, seperti melihat odds ratio untuk setiap fitur.
- Cocok untuk klasifikasi biner: Karena prediksi persetujuan pinjaman adalah masalah klasifikasi biner (ya/tidak), Logistic Regression sangat cocok.
- Efisien untuk dataset yang relatif kecil: Logistic Regression dapat bekerja dengan baik pada dataset dengan ukuran yang tidak terlalu besar.

Random Forest

Alasan Pemilihan:

- Performa yang tinggi: Random Forest dikenal memiliki performa yang tinggi dan akurasi yang baik dalam banyak kasus.
- Robust terhadap overfitting: Karena menggunakan ensemble dari decision tree, Random Forest cenderung lebih robust terhadap overfitting dibandingkan dengan decision tree tunggal.
- Mampu menangani fitur kategorikal dan numerik: Random Forest dapat menangani berbagai jenis fitur tanpa perlu preprocessing yang rumit.
- Dapat mengidentifikasi fitur penting: Random Forest dapat memberikan informasi tentang fitur-fitur yang paling penting dalam prediksi.

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix


# Logistic Regression
logreg_model = LogisticRegression(random_state=42)  # random_state untuk reproduksibilitas

# Random Forest
rf_model = RandomForestClassifier(random_state=42)


# Assuming 'Loan_Approval' is your target variable
```

```
# Assuming 'Loan_Approval' is your target variable
# Remove 'Loan_Approval' from numerical_cols
numerical_cols = ['Income', 'Loan_Amount', 'Education_Encoded', 'Credit_Score']

# Create a StandardScaler object
scaler = StandardScaler()

# Fit and transform the scaler on the selected numerical columns
data[numerical_cols] = scaler.fit_transform(data[numerical_cols])

# Define features (X) and target (y)
X = data[['Income', 'Loan_Amount', 'Education_Encoded', 'Credit_Score']]
y = data['Loan_Approval']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Convert the target variable to discrete classes if necessary
# (If 'Loan_Approval' is not already 0 or 1)
threshold = 0  # Adjust this threshold based on your data
y_train = (y_train > threshold).astype(int)
y_test = (y_test > threshold).astype(int)

# Initialize the models
logreg_model = LogisticRegression(random_state=42)
rf_model = RandomForestClassifier(random_state=42)

# Fit the models
logreg_model.fit(X_train, y_train)
rf_model.fit(X_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

```
# Logistic Regression
y_pred_logreg = logreg_model.predict(X_test)
accuracy_logreg = accuracy_score(y_test, y_pred_logreg)
print("Logistic Regression Accuracy:", accuracy_logreg)
print(classification_report(y_test, y_pred_logreg))
print(confusion_matrix(y_test, y_pred_logreg))

# Random Forest
y_pred_rf = rf_model.predict(X_test)
accuracy_rf = accuracy_score(y_test, y_pred_rf)
print("Random Forest Accuracy:", accuracy_rf)
print(classification_report(y_test, y_pred_rf))
print(confusion_matrix(y_test, y_pred_rf))
```

```
Logistic Regression Accuracy: 0.63
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        37
           1       0.63      1.00      0.77        63

    accuracy                           0.63       100
   macro avg       0.32      0.50      0.39       100
weighted avg       0.40      0.63      0.49       100

[[ 0 37]
 [ 0 63]]
Random Forest Accuracy: 0.52
              precision    recall  f1-score   support

           0       0.33      0.30      0.31        37
           1       0.61      0.65      0.63        63

    accuracy                           0.52       100
   macro avg       0.47      0.47      0.47       100
weighted avg       0.51      0.52      0.51       100

[[11 26]
 [22 41]]
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
print("Logistic Regression Accuracy:", accuracy_logreg)
print("Random Forest Accuracy:", accuracy_rf)
```

```
Logistic Regression Accuracy: 0.63
Random Forest Accuracy: 0.52
```

```
print("Logistic Regression Classification Report:\n", classification_report(y_test, y_pred_logreg))
print("Random Forest Classification Report:\n", classification_report(y_test, y_pred_rf))
```

```
Logistic Regression Classification Report:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00        37
           1       0.63      1.00      0.77        63

    accuracy                           0.63       100
   macro avg       0.32      0.50      0.39       100
weighted avg       0.40      0.63      0.49       100

Random Forest Classification Report:
               precision    recall  f1-score   support

           0       0.33      0.30      0.31        37
           1       0.61      0.65      0.63        63

    accuracy                           0.52       100
   macro avg       0.47      0.47      0.47       100
weighted avg       0.51      0.52      0.51       100

/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

4. Evaluasi Model

```
print("Logistic Regression Confusion Matrix:\n", confusion_matrix(y_test, y_pred_logreg))
print("Random Forest Confusion Matrix:\n", confusion_matrix(y_test, y_pred_rf))
```

```
Logistic Regression Confusion Matrix:
 [[ 0 37]
 [ 0 63]]
Random Forest Confusion Matrix:
 [[11 26]
 [22 41]]
```

Logistic Regression akurasinya 63% dengan sonfusion matrix [[0 37] [0 63]]

**5. Tuning Model dengan Grid Search atau Random Search *

```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression


param_grid = {
    'penalty': ['l1', 'l2'],  # Jenis regularisasi
    'C': [0.001, 0.01, 0.1, 1, 10, 100],  # Parameter regularisasi terbalik
    'solver': ['liblinear', 'saga'],  # Algoritma yang digunakan untuk optimasi
}


grid_search = GridSearchCV(
    estimator=LogisticRegression(random_state=42),  # Model dasar
    param_grid=param_grid,  # Parameter grid
    scoring='accuracy',  # Metrik evaluasi
    cv=5,  # Jumlah lipatan untuk cross-validation
    n_jobs=-1,  # Gunakan semua core CPU
)


grid_search.fit(X_train, y_train)
```

```
GridSearchCV
best_estimator_:
LogisticRegression
LogisticRegression
```

```
best_logreg_model = grid_search.best_estimator_
```

```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

y_pred_best_logreg = best_logreg_model.predict(X_test)
accuracy_best_logreg = accuracy_score(y_test, y_pred_best_logreg)
print("Best Logistic Regression Accuracy:", accuracy_best_logreg)
print(classification_report(y_test, y_pred_best_logreg))
print(confusion_matrix(y_test, y_pred_best_logreg))
```

```
Best Logistic Regression Accuracy: 0.63
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        37
           1       0.63      1.00      0.77        63

    accuracy                           0.63       100
   macro avg       0.32      0.50      0.39       100
weighted avg       0.40      0.63      0.49       100

[[ 0 37]
 [ 0 63]]
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
from sklearn.model_selection import GridSearchCV

# Tentukan parameter yang akan di-tuning dan nilainya
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 5, 10],
    'min_samples_split': [2, 5, 10],
}

# Buat objek GridSearchCV
grid_search = GridSearchCV(rf_model, param_grid, cv=5, scoring='accuracy')

# Latih model dengan GridSearchCV
grid_search.fit(X_train, y_train)

# Dapatkan model terbaik
best_rf_model = grid_search.best_estimator_

# Evaluasi model terbaik
y_pred_best_rf = best_rf_model.predict(X_test)
accuracy_best_rf = accuracy_score(y_test, y_pred_best_rf)
print("Best Random Forest Accuracy:", accuracy_best_rf)
```

```
Best Random Forest Accuracy: 0.57
```

```
print("Best Hyperparameters for Random Forest:", grid_search.best_params_)
```

```
Best Hyperparameters for Random Forest: {'max_depth': 5, 'min_samples_split': 2, 'n_estimators': 300}
```

```
**6. Perbandingan Performa Sebelum dan Sesudah Tuning **
```

*6. Perbandingan Performa Sebelum dan Sesudah Tuning *

```
# Evaluasi model sebelum tuning
model_before = logreg_model  # or rf_model, depending on which model you want to compare
y_pred_before = model_before.predict(X_test)
accuracy_before = accuracy_score(y_test, y_pred_before)
report_before = classification_report(y_test, y_pred_before)

# Evaluasi model sesudah tuning
model_after = best_logreg_model # or best_rf_model, depending on which model you want to compare
y_pred_after = model_after.predict(X_test)
accuracy_after = accuracy_score(y_test, y_pred_after)
report_after = classification_report(y_test, y_pred_after)

# Tampilkan perbandingan
print("Accuracy Before Tuning:", accuracy_before)
print("Accuracy After Tuning:", accuracy_after)
print("\nClassification Report Before Tuning:\n", report_before)
print("\nClassification Report After Tuning:\n", report_after)
```

```
Accuracy Before Tuning: 0.63
Accuracy After Tuning: 0.63

Classification Report Before Tuning:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        37
           1       0.63      1.00      0.77        63

    accuracy                           0.63       100
   macro avg       0.32      0.50      0.39       100
weighted avg       0.40      0.63      0.49       100
```