```
import warnings
warnings.filterwarnings("ignore")
```

```
import pandas as pd
```

Since the error " Unmatched "" when when decoding 'string' " occurs,the below line has been done to check the mistakes

- The JSONDecodeError is caused by an unterminated string in the JSON file. This could be due to a missing closing quotation mark or an invalid escape sequence.

```
!cat /content/drive/MyDrive/SlashMark/loan_approval/loan_approval_dataset.json | grep -o "\"$"
```

```
import json

with open('/content/drive/MyDrive/SlashMark/loan_approval/loan_approval_dataset.json', 'r') as f:
    data = json.load(f)
```

```
df = pd.read_json('/content/drive/MyDrive/SlashMark/loan_approval/loan_approval_dataset.json')
```

Start coding or generate with AI.

```
df.head()
```

	Id	Income	Age	Experience	Married/Single	House_Ownership	Car_Ownership	
0	1	1303834	23	3	single	rented	no	Mech
1	2	7574516	40	10	single	rented	no	Soft
2	3	3991815	66	4	married	rented	no	
3	4	6256451	41	2	single	rented	yes	Soft
4	5	5768871	47	11	single	rented	no	

Data Cleaning,Preprocessing and Visualisation

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 252000 entries, 0 to 251999
Data columns (total 13 columns):
 #   Column             Non-Null Count   Dtype 
---  ------             --------------   ----- 
 0   Id                 252000 non-null  int64 
 1   Income             252000 non-null  int64 
 2   Age                252000 non-null  int64 
 3   Experience         252000 non-null  int64 
 4   Married/Single     252000 non-null  object
 5   House_Ownership    252000 non-null  object
 6   Car_Ownership      252000 non-null  object
 7   Profession         252000 non-null  object
 8   CITY               252000 non-null  object
 9   STATE              252000 non-null  object
 10  CURRENT_JOB_YRS    252000 non-null  int64 
 11  CURRENT_HOUSE_YRS  252000 non-null  int64 
 12  Risk_Flag          252000 non-null  int64 
dtypes: int64(7), object(6)
memory usage: 26.9+ MB
```

```
df.isna().sum()
```

```
Id                   0
Income               0
Age                  0
Experience           0
Married/Single       0
House_Ownership      0
Car_Ownership        0
Profession           0
CITY                 0
STATE                0
CURRENT_JOB_YRS      0
CURRENT_HOUSE_YRS    0
Risk_Flag            0
dtype: int64
```

```
df.duplicated().sum()
```

```
0
```

```
df.describe(include='all').T
```

	count	unique	top	freq	mean	
Id	252000.0	NaN	NaN	NaN	126000.5	72746
Income	252000.0	NaN	NaN	NaN	4997116.665325	2878311
Age	252000.0	NaN	NaN	NaN	49.954071	17
Experience	252000.0	NaN	NaN	NaN	10.084437	
Married/Single	252000	2	single	226272	NaN	
House_Ownership	252000	3	rented	231898	NaN	
Car_Ownership	252000	2	no	176000	NaN	
Profession	252000	51	Physician	5957	NaN	
CITY	252000	317	Vijayanagaram	1259	NaN	
STATE	252000	29	Uttar_Pradesh	28400	NaN	
CURRENT_JOB_YRS	252000.0	NaN	NaN	NaN	6.333877	3
CURRENT_HOUSE_YRS	252000.0	NaN	NaN	NaN	11.997794	1
Risk_Flag	252000.0	NaN	NaN	NaN	0.123	C

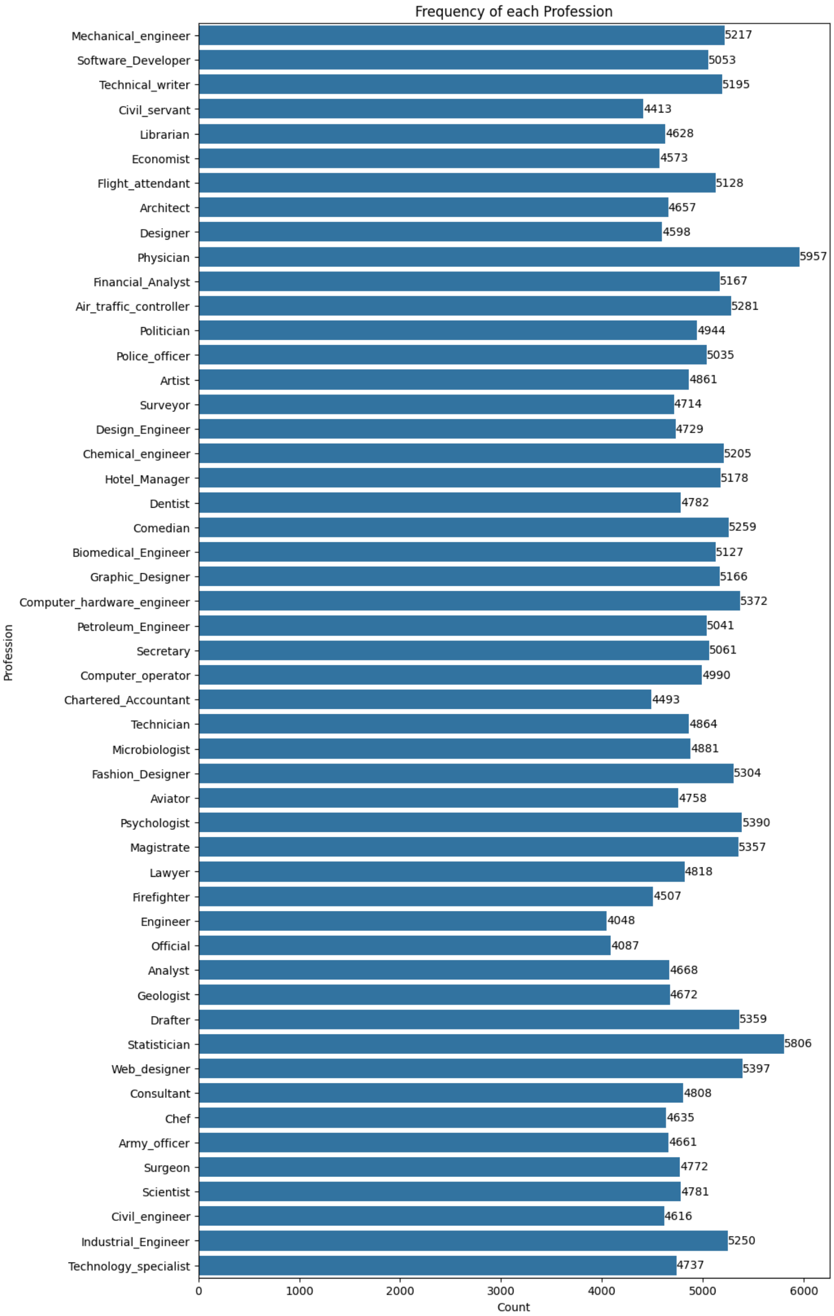
```
df.describe().T
```

	count	mean	std	min	25%	
Id	252000.0	1.260005e+05	7.274628e+04	1.0	63000.75	1260
Income	252000.0	4.997117e+06	2.878311e+06	10310.0	2503015.00	50006
Age	252000.0	4.995407e+01	1.706385e+01	21.0	35.00	
Experience	252000.0	1.008444e+01	6.002590e+00	0.0	5.00	
CURRENT_JOB_YRS	252000.0	6.333877e+00	3.647053e+00	0.0	3.00	
CURRENT_HOUSE_YRS	252000.0	1.199779e+01	1.399037e+00	10.0	11.00	
Risk_Flag	252000.0	1.230000e-01	3.284379e-01	0.0	0.00	

```
df.columns
```

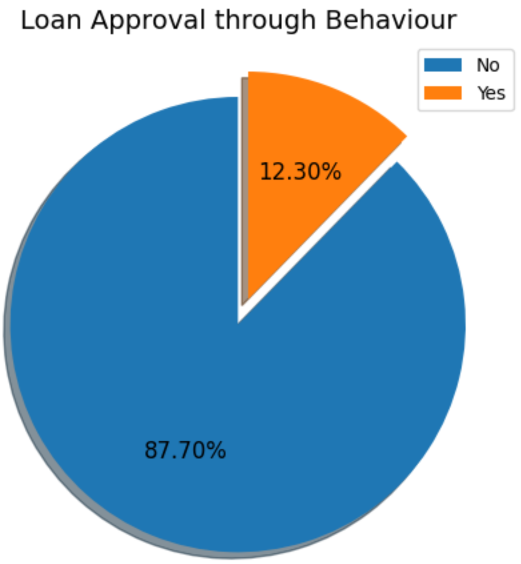
```
Index(['Id', 'Income', 'Age', 'Experience', 'Married/Single',
       'House_Ownership', 'Car_Ownership', 'Profession', 'CITY', 'STATE',
       'CURRENT_JOB_YRS', 'CURRENT_HOUSE_YRS', 'Risk_Flag'],
      dtype='object')
```

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


plt.figure(figsize=(10, 20))


ax = sns.countplot(y=df['Profession'])


plt.title("Frequency of each Profession")
plt.ylabel("Profession")
plt.xlabel("Count")

for container in ax.containers:
    ax.bar_label(container)

plt.show()
```


Frequency of each Profession
Mechanical_engineer
Software_Developer
Technical_writer
Civil_servant
Librarian
Economist
Flight_attendant
Architect
Designer
Physician
Financial_Analyst
Air_traffic_controller
Politician
Police_officer
Artist
Surveyor
Design_Engineer
Chemical_engineer
Hotel_Manager
Dentist
Comedian
Biomedical_Engineer
Graphic_Designer
Computer_hardware_engineer
Petroleum_Engineer
Secretary
Computer_operator
Chartered_Accountant
Technician
Microbiologist
Fashion_Designer
Aviator
Psychologist
Magistrate
Lawyer
Firefighter
Engineer
Official
Analyst
Geologist
Drafter
Statistician
Web_designer
Consultant
Chef
Army_officer
Surgeon
Scientist
Civil_engineer
Industrial_Engineer
Technology_specialist
5217
5053
5195
4413
4628
4573
5128
4657
4598
5957
5167
5281
4944
5035
4861
4714
4729
5205
5178
4782
5259
5127
5166
5372
5041
5061
4990
4493
4864
4881
5304
4758
5390
5357
4818
4507
4048
4087
4668
4672
5359
5806
5397
4808
4635
4661
4772
4781
4616
5250
4737
Profession
0
1000
2000
3000
4000
5000
6000
Count

```
loany=df['Risk_Flag'].replace({0:'No' ,1:'Yes'}).value_counts()
```

```
plt.pie(loany.values, labels=loany.index,

        startangle=90, autopct="%1.2f%%",
        labeldistance=None, textprops={'fontsize': 12}, shadow=True, explode=[0, 0.12])
plt.legend()
plt.title('Loan Approval through Behaviour', fontsize=14)

plt.tight_layout()
plt.show()
```

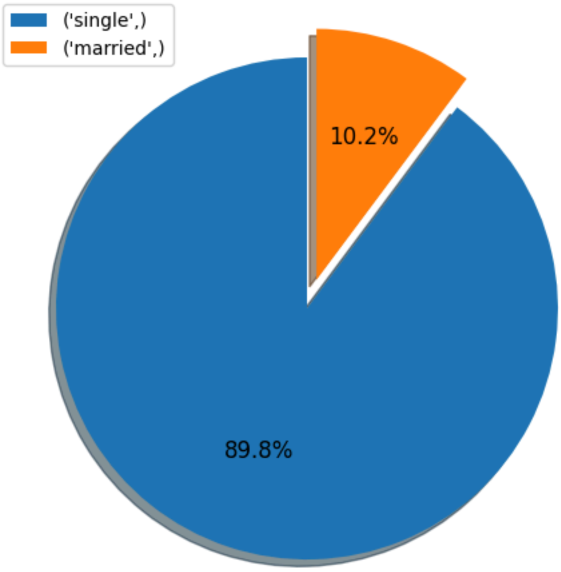



```
df_count =df[['Married/Single']].value_counts()
df_count
```

```
Married/Single
single            226272
married            25728
Name: count, dtype: int64
```

```
plt.figure(figsize=(5, 5))
plt.pie(df_count, labels=df_count.index, autopct='%1.1f%%', startangle=90,
        labeldistance=None, textprops={'fontsize': 12}, shadow=True, explode=[0, 0.12])
plt.tight_layout()
plt.legend()

plt.title('percentage of "single/married" ')
```

```
Text(0.5, 1.0, 'percentage of "single/married" ')
```




```
df_Age =df[['Age']].value_counts()
df_Age
```

```
48      4967
33      4921
41      4827
45      4806
54      4785
68      4772
35      4643
50      4624
69      4617
76      4585
55      4563
25      4543
72      4533
79      4505
60      4504
59      4498
53      4490
47      4483
30      4468
78      4455
22      4430
34      4414
57      4394
58      4368
56      4344
24      4326
23      4322
62      4311
31      4257
70      4251
61      4235
40      4233
43      4206
21      4205
49      4203
26      4156
37      4153
71      4150
42      4134
64      4132
29      4109
67      3995
65      3969
74      3954
63      3942
77      3916
28      3901
32      3834
75      3829
39      3800
38      3793
```

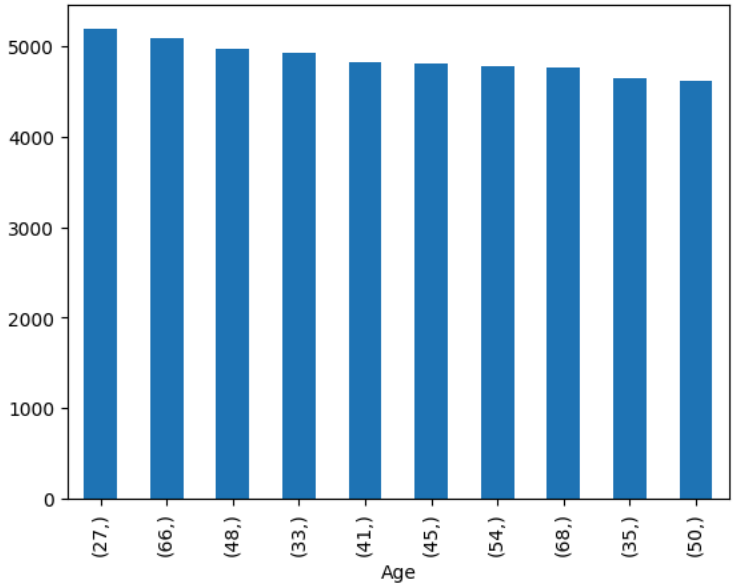
```
36      3444
51      3397
52      3197
Name: count, dtype: int64
```

```
df_age1=df_Age.head(10).sort_values( ascending=False)
df_age1
```

```
Age
27      5197
66      5092
48      4967
33      4921
41      4827
45      4806
54      4785
68      4772
35      4643
50      4624
Name: count, dtype: int64
```

```
df_age1.plot(kind ='bar')
```

```
<Axes: xlabel='Age'>
```

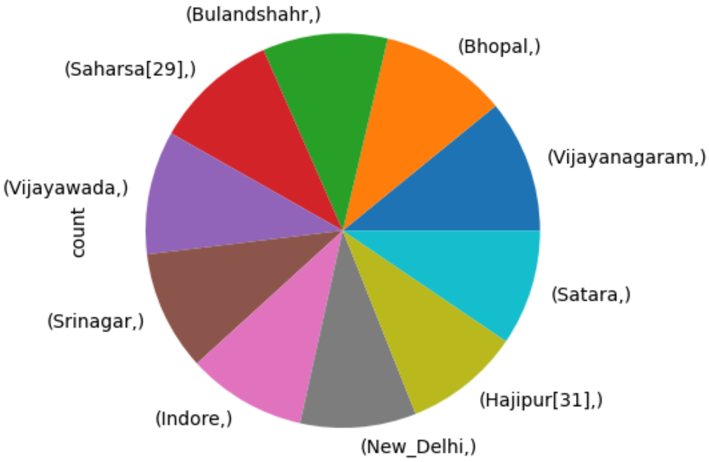



```
df_CITY =df[['CITY']].value_counts().head(10)
df_CITY
```

```
CITY
Vijayanagaram    1259
Bhopal           1208
Bulandshahr      1185
Saharsa[29]      1180
Vijayawada       1172
Srinagar         1136
Indore           1130
New_Delhi        1098
Hajipur[31]      1098
Satara           1096
Name: count, dtype: int64
```

```
df_CITY.plot(kind ='pie')
```

<Axes: ylabel='count'>

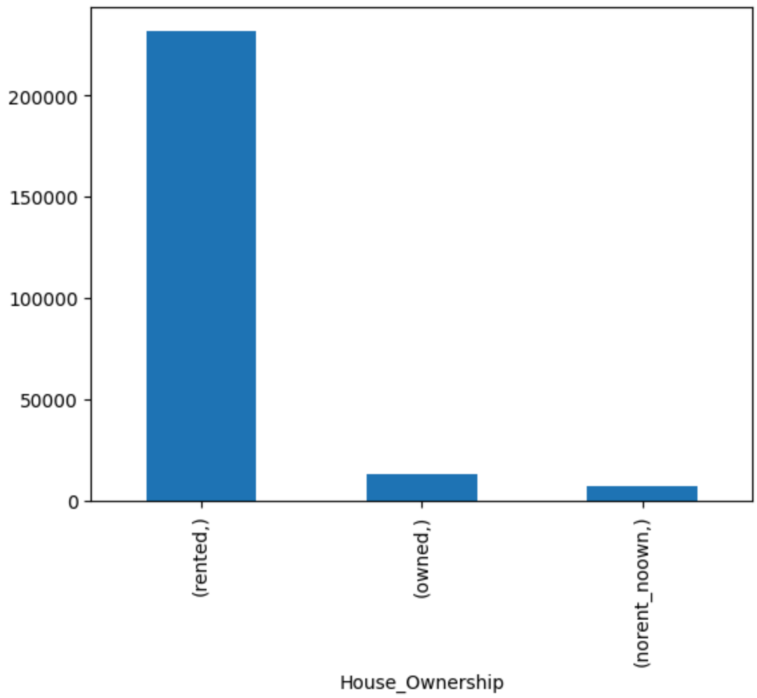



```
df_owner_ship =df[['House_Ownership']].value_counts().head(10)
df_owner_ship
```

```
House_Ownership
rented           231898
owned             12918
norent_noown       7184
Name: count, dtype: int64
```

```
df_owner_ship.plot(kind ='bar')
```

<Axes: xlabel='House_Ownership'>

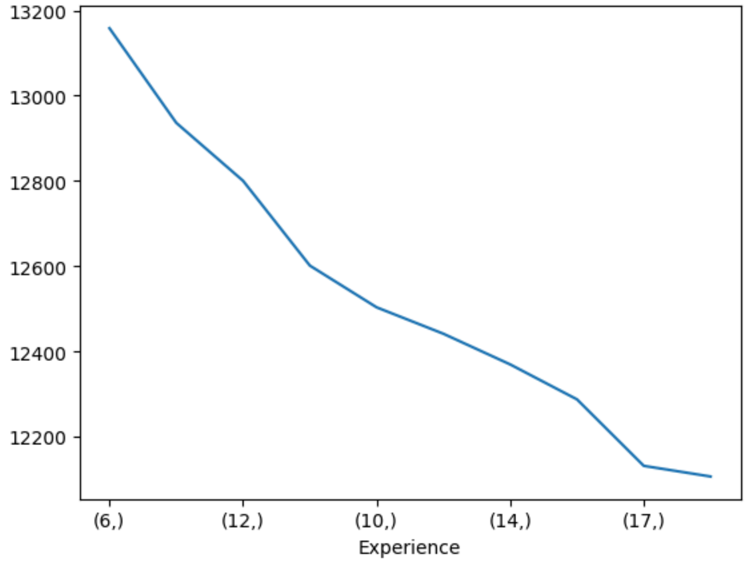



```
df_experience =df[['Experience']].value_counts().head(10)
df_experience
```

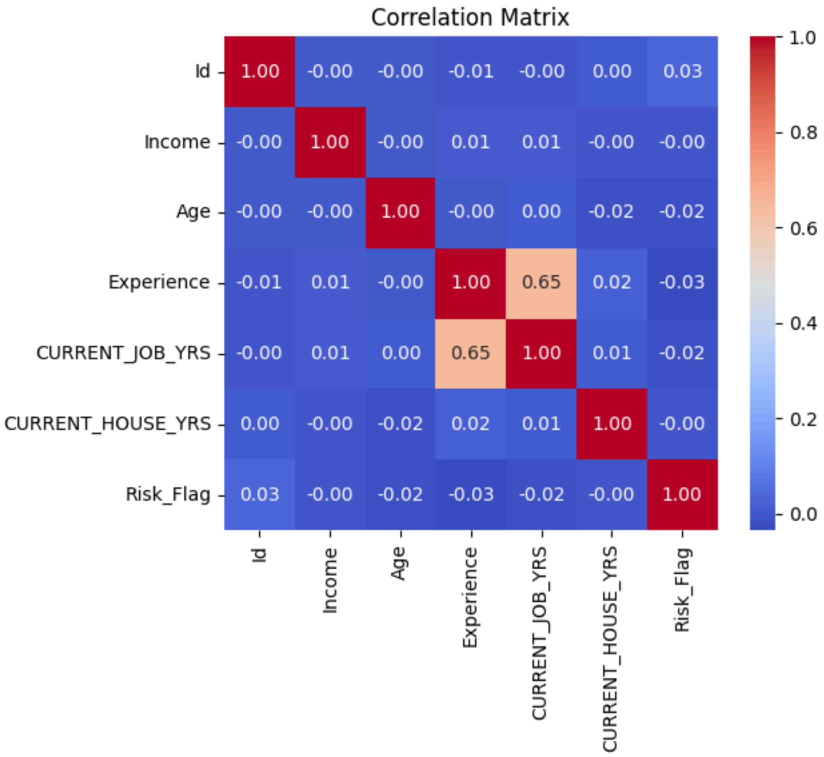
```
Experience
6             13158
9             12936
12            12800
18            12601
10            12503
5             12441
14            12369
19            12287
17            12131
16            12106
Name: count, dtype: int64
```

```
df_experience.plot(kind ='line')
```

```
<Axes: xlabel='Experience'>
```



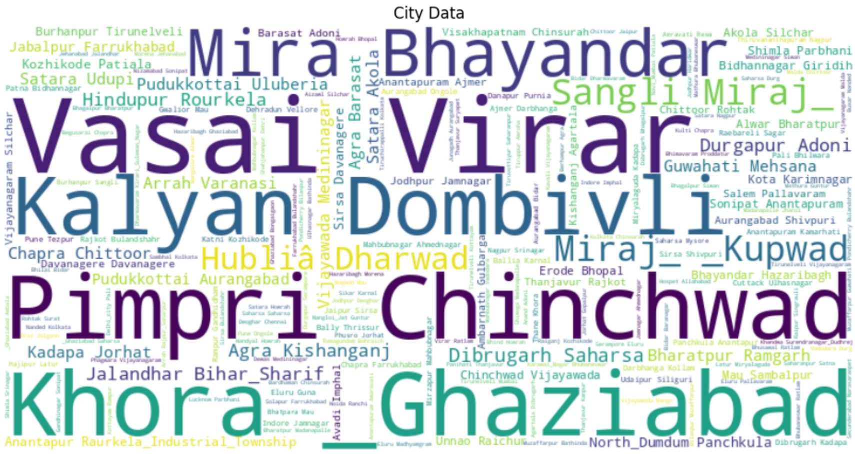

```
correlation_matrix = df.corr(numeric_only=True)

# Plot heatmap
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', square=True)
plt.title('Correlation Matrix')
plt.show()
```




```
#Top Highly correlated features with the target variable
correlation_matrix['Risk_Flag'].sort_values(ascending=False)
```

```
Risk_Flag            1.000000
Id                   0.032153
Income              -0.003091
CURRENT_HOUSE_YRS   -0.004375
CURRENT_JOB_YRS     -0.016942
Age                 -0.021809
Experience          -0.034523
Name: Risk_Flag, dtype: float64
```

```
from wordcloud import WordCloud

reviews_text = ' '.join(df['CITY'].dropna())
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(reviews_text)
plt.figure(figsize=(12, 6))
plt.imshow(wordcloud, interpolation='bilinear')
plt.title('City Data')
plt.axis('off')
plt.show()
```



Start coding or generate with AI.

Insights

1.singles are seeking loans mostly and the rate of risk is also low.

2.people with rented rooms and no cars are applying for loans more compared to others.

3.people with house or car are less risky.

4.all profession people are applying for loans at nearly same rate.

5.people from uttarpradesh and maharashtra are applying more for loans.

```
from sklearn.preprocessing import StandardScaler

df["Income"]=StandardScaler().fit_transform(df[["Income"]])
```

```
df["Married/Single"]=df["Married/Single"].replace({'single':0,'married':1}).astype(int)
df["Car_Ownership"]=df["Car_Ownership"].replace({'no':0,'yes':1}).astype(int)
```

```
from sklearn.preprocessing import LabelEncoder

df["House_Ownership"]= LabelEncoder().fit_transform(df[["House_Ownership"]])
df["Profession"]= LabelEncoder().fit_transform(df[["Profession"]])
df["STATE"]= LabelEncoder().fit_transform(df[["STATE"]])
df["CITY"]= LabelEncoder().fit_transform(df[["CITY"]])
```

Start coding or generate with AI.

Start coding or generate with AI.

Feature Engineering and model development

WIth the help of heatmap of correlation matrix,these are the factors affecting the target column: age,exp,martial status,car,house,current job

```
# Separate features and target variable
X = df.drop(columns=['Id', 'Risk_Flag'])
y = df['Risk_Flag']
```

```
# Split the data
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Standardize the features for models that require scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.svm import SVC
from sklearn.metrics import classification_report, roc_auc_score, roc_curve, confusion_matrix, ConfusionMatrixDisplay
```

```
# Initialize models
models = {
    "Logistic Regression": LogisticRegression(),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(n_estimators=100),
    "XGBoost": XGBClassifier(use_label_encoder=False, eval_metric='logloss')
}
```

```
# Train and evaluate models
for name, model in models.items():
    if name in ["Logistic Regression", "SVM"]:
        model.fit(X_train_scaled, y_train)
        y_pred = model.predict(X_test_scaled)
        y_proba = model.predict_proba(X_test_scaled)[:, 1]
    else:
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)
        y_proba = model.predict_proba(X_test)[:, 1]

    print(f"Model: {name}")
    print(classification_report(y_test, y_pred))
    print(f"AUC-ROC: {roc_auc_score(y_test, y_proba)}")
    print("-" * 40)
```

```
Model: Logistic Regression
              precision    recall  f1-score   support

           0       0.88      1.00      0.93     44147
           1       0.00      0.00      0.00      6253

    accuracy                           0.88     50400
   macro avg       0.44      0.50      0.47     50400
weighted avg       0.77      0.88      0.82     50400

AUC-ROC: 0.55135175453744
----------------------------------------
Model: Decision Tree
              precision    recall  f1-score   support

           0       0.94      0.92      0.93     44147
           1       0.52      0.57      0.54      6253

    accuracy                           0.88     50400
   macro avg       0.73      0.75      0.74     50400
weighted avg       0.89      0.88      0.88     50400

AUC-ROC: 0.8505028330053463
----------------------------------------
Model: Random Forest
              precision    recall  f1-score   support

           0       0.94      0.95      0.94     44147
           1       0.61      0.54      0.57      6253

    accuracy                           0.90     50400
   macro avg       0.77      0.74      0.76     50400
weighted avg       0.89      0.90      0.90     50400

AUC-ROC: 0.9375357540116536
----------------------------------------
```