

Importing Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.linear_model import Lasso
from sklearn import metrics
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
```

```
data = pd.read_csv('train_data.csv')
data.head()
```

Income	Employment status	Education level	Marital status	Dwelling	Age	Employment length	Has a mobile phone	Has a work phone	Has a phone
000.0	Working	Secondary / secondary special	Married	With parents	-16271	-3111	1.0	0.0	
000.0	Commercial associate	Higher education	Single / not married	House / apartment	-10130	-1651	1.0	0.0	
000.0	Commercial associate	Secondary / secondary special	Married	House / apartment	-12821	-5657	1.0	0.0	
000.0	Commercial associate	Higher education	Single / not married	House / apartment	-20929	-2046	1.0	0.0	
000.0	Working	Secondary / secondary special	Separated	House / apartment	-16207	-515	1.0	0.0	

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23893 entries, 0 to 23892
Data columns (total 20 columns):
#   Column                Non-Null Count  Dtype
---  -
0   ID                    23893 non-null  int64
1   Gender                23893 non-null  object
2   Has a car              23893 non-null  object
3   Has a property         23893 non-null  object
4   Children count        23893 non-null  int64
5   Income                23893 non-null  float64
6   Employment status     23893 non-null  object
7   Education level       23893 non-null  object
8   Marital status        23893 non-null  object
9   Dwelling              23893 non-null  object
10  Age                   23893 non-null  int64
11  Employment length     23893 non-null  object
12  Has a mobile phone    23892 non-null  float64
13  Has a work phone     23892 non-null  float64
14  Has a phone          23892 non-null  float64
15  Has an email         23892 non-null  float64
16  Job title            16467 non-null  object
17  Family member count  23892 non-null  float64
18  Account age          23892 non-null  float64
19  Is high risk         23892 non-null  float64
dtypes: float64(8), int64(3), object(9)
memory usage: 3.6+ MB
```

```
data.describe()
```

	Children count	Income	Age	Has a mobile phone	Has a work phone	Has a phone	Has an email
↓	23893.000000	2.389300e+04	23893.000000	23892.0	23892.000000	23892.000000	23892.000000
↓	0.431298	1.866992e+05	-15979.815050	1.0	0.224217	0.294366	0.000000
↓	0.740487	1.002271e+05	4206.166773	0.0	0.417075	0.455767	0.200000
↓	0.000000	2.700000e+04	-25152.000000	1.0	0.000000	0.000000	0.000000
↓	0.000000	1.215000e+05	-19453.000000	1.0	0.000000	0.000000	0.000000
↓	0.000000	1.575000e+05	-15563.000000	1.0	0.000000	0.000000	0.000000
↓	1.000000	2.250000e+05	-12461.000000	1.0	0.000000	1.000000	0.000000
↓	19.000000	1.575000e+06	-7705.000000	1.0	1.000000	1.000000	1.000000

Data Preprocesssing

```
print(data.isnull().sum())
```

```
ID          0
Gender       0
Has a car    0
Has a property  0
Children count  0
Income       0
Employment status  0
Education level  0
Marital status  0
Dwelling     0
Age          0
Employment length  0
Has a mobile phone  1
Has a work phone  1
Has a phone    1
Has an email   1
Job title      7426
Family member count  1
Account age    1
Is high risk   1
dtype: int64
```

```
data['Is high risk'].value_counts()
```

```
0.0    23487
1.0     405
Name: Is high risk, dtype: int64
```

```
data['Employment status'].value_counts()
```

```
Working          12353
Commercial associate  5553
Pensioner        4042
State servant     1940
Student           4
Name: Employment status, dtype: int64
```

```
data['Education level'].value_counts()
```

```
Secondary / secondary special  16249
Higher education              6462
Incomplete higher             921
Lower secondary               238
Academic degree               22
Name: Education level, dtype: int64
```

```
data['Dwelling'].value_counts()
```

```
House / apartment    21342
With parents         1158
Municipal apartment   741
Rented apartment     369
Office apartment     180
Co-op apartment      102
Name: Dwelling, dtype: int64
```

```
data['Marital status'].value_counts()

Married      16416
Single / not married  3172
Civil marriage  1891
Separated     1388
Widow         1025
Name: Marital status, dtype: int64

data.dropna(subset=['Has a mobile phone'],inplace = True)

print(data.isnull().sum())

ID      0
Gender  0
Has a car      0
Has a property 0
Children count 0
Income      0
Employment status 0
Education level 0
Marital status 0
Dwelling     0
Age         0
Employment length 0
Has a mobile phone 0
Has a work phone 0
Has a phone    0
Has an email   0
Job title     7425
Family member count 0
Account age   0
Is high risk  0
dtype: int64

data.replace({'Marital status':{'Married':1,'Single / not married':2,'Civil marriage':3,'Separated':4,'Widow':5}},inplace=True)

data.replace({'Employment status':{'Working':1,'Commercial associate':2,'Pensioner':3,'State servant':4,'Student':5}},inplace=True)

data.replace({'Education level':{'Secondary / secondary special':1,'Higher education':2,'Incomplete higher':3,'Lower secondary':4,'

data.replace({'Dwelling':{'House / apartment':1,'With parents':2,'Municipal apartment':3,'Rented apartment':4,'Office apartment':5,

data['Gender'].value_counts()

F      16025
M      7867
Name: Gender, dtype: int64

data.replace({'Gender':{'M':1,'F':2}},inplace=True)

data.replace({'Has a car':{'Y':1,'N':0}},inplace=True)

data.replace({'Has a property':{'Y':1,'N':0}},inplace=True)

data.head()
```

Income	Employment status	Education level	Marital status	Dwelling	Age	Employment length	Has a mobile phone	Has a work phone	Ha ph
35000.0	1	1	1	2	-16271	-3111	1.0	0.0	
35000.0	2	2	2	1	-10130	-1651	1.0	0.0	
30000.0	2	1	1	1	-12821	-5657	1.0	0.0	
30000.0	2	2	2	1	-20929	-2046	1.0	0.0	
70000.0	1	1	4	1	-16207	-515	1.0	0.0	

```
x=data.drop(['Is high risk','Job title'],axis=1)
```

```
print(x)
```

	ID	Gender	Has a car	Has a property	Children count	Income \
0	5037048	1	1	1	0	135000.0
1	5044630	2	1	0	1	135000.0
2	5079079	2	0	1	2	180000.0
3	5112872	2	1	1	0	360000.0
4	5105858	2	0	0	0	270000.0
...
23887	5009286	2	0	0	0	130500.0
23888	5068395	2	0	1	0	202500.0
23889	5117420	2	1	0	0	112500.0
23890	5116955	2	0	1	1	112500.0
23891	5068037	2	0	0	0	135000.0

	Employment status	Education level	Marital status	Dwelling	Age \
0	1	1	1	2	-16271
1	2	2	2	1	-10130
2	2	1	1	1	-12821
3	2	2	2	1	-20929
4	1	1	4	1	-16207
...
23887	1	1	3	1	-15140
23888	3	2	2	1	-21344
23889	1	1	1	1	-16215
23890	2	1	1	1	-17243
23891	2	1	1	1	-17614

	Employment length	Has a mobile phone	Has a work phone	Has a phone \
0	-3111	1.0	0.0	0.0
1	-1651	1.0	0.0	0.0
2	-5657	1.0	0.0	0.0
3	-2046	1.0	0.0	0.0
4	-515	1.0	0.0	1.0
...
23887	-4816	1.0	0.0	1.0
23888	365243	1.0	0.0	1.0
23889	-3567	1.0	0.0	0.0
23890	-2378	1.0	1.0	0.0
23891	-4219	1.0	0.0	0.0

	Has an email	Family member count	Account age
0	0.0	2.0	-17.0
1	0.0	2.0	-1.0
2	0.0	4.0	-38.0
3	1.0	1.0	-11.0
4	0.0	1.0	-41.0
...
23887	0.0	2.0	-48.0
23888	1.0	1.0	-44.0
23889	0.0	2.0	-6.0
23890	0.0	3.0	-55.0
23891	0.0	2.0	-37.0

```
[23892 rows x 18 columns]
```

```
y=data['Is high risk']
```

```
print(y)
```

0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
23887	0.0
23888	0.0
23889	0.0
23890	0.0
23891	0.0

Name: Is high risk, Length: 23892, dtype: float64

Machine Learning Model(Logistics Regression)

Train_Test split

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.1,random_state=2)
```

```
[x_train.shape,x_train.shape, y_train.shape, y_test.shape]
```

```
[(21502, 18), (21502, 18), (21502,), (2390,)]
```

```
leg=LogisticRegression()
```

```
leg.fit(x_train,y_train)
```

```
▼ LogisticRegression
LogisticRegression()
```

MODEL EVALUATION

Accuracy Score

```
x_tr_d=leg.predict(x_train)
```

```
trdaac=accuracy_score(y_train, x_tr_d)
print("Accuracy on Training data is :",trdaac)
```

```
Accuracy on Training data is : 0.9829783275974328
```

```
x_test_d=leg.predict(x_test)
testdacc=accuracy_score(y_test, x_test_d)
print("Accuracy on Test data is;",testdacc)
```

```
Accuracy on Test data is; 0.9836820083682009
```

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Prediction for Credit Card Approval

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Prediction for Credit Card Approval

```
input_data=[5037048, 1, 1, 1, 0, 135000.0, 1, 1, 1, 2, -16271,-3111, 1.0, 0.0, 0.0, 0.0, 2.0, -17.0]
inpasnum=np.array(input_data)
inres=inpasnum.reshape(1,-1)
```

```
pred=leg.predict(inres)
pred
if(pred[0]==0):
    print("High risk for approving Credit Card")
else:
    print("Credit Card Approved")
```

```
High risk for approving Credit Card
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but LogisticRegression
warnings.warn(
```

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