FR. CONCEICAO RODRIGUES COLLEGE OF ENGINEERING

Department of Computer Engineering

Course, Subject & Experiment Details

Assignment No:	1
Title:	Case Study – Credit Card Approval Prediction
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Evaluation:

Sr. No.	Rubric	Grade
1	On time submission/completion (2)	
2	Preparedness (2)	
3	Skill (4)	
4	Output (2)	

Signature of the Teacher

CREDIT CARD APPROVAL PREDICTION

Introduction

The financial industry has been leveraging machine learning algorithms to automate decision-making processes, and credit card approval prediction is one such process. Financial institutions face the challenge of assessing an applicant's creditworthiness before approving a credit card. The traditional approach involves evaluating factors such as the applicant's credit history, income, and debt-to-income ratio. However, with the proliferation of machine learning algorithms, financial institutions can leverage credit card approval prediction models to make more informed decisions.

Problem Statement

The goal of this project is to build a credit card approval prediction model that accurately predicts whether an applicant will be approved or denied a credit card. The model will be based on a range of features such as the applicant's age, gender, income, employment status, credit score, and credit history. The primary aim is to create a model that can help financial institutions make more informed decisions about approving or denying credit card applications.

Credit card approval prediction models have become crucial in the financial industry as they can help mitigate the risks associated with lending credit cards. The model should be trained on a historical dataset of credit card applications and should use machine learning algorithms to identify patterns and correlations between the features and the target variable. The model should be able to accurately predict whether an applicant will be approved or denied a credit card.

The project will involve several challenges, such as preprocessing the dataset to remove any duplicates, missing values, or outliers. Additionally, categorical variables will need to be converted into numeric values using techniques such as one-hot encoding. Furthermore, the dataset will need to be transformed to create new features that are more informative for the credit card approval prediction model.

The project's success will depend on selecting the most appropriate machine learning algorithm for the model. Several algorithms will be evaluated based on their performance metrics such as accuracy, precision, recall, and F1-score. The best-performing model will be selected for deployment.

The credit card approval prediction model aims to help financial institutions make more informed decisions about approving or denying credit card applications. The model should accurately predict whether an applicant will be approved or denied a credit card based on a range of factors such as age, gender, income, employment status, credit score, and credit history. By leveraging machine learning algorithms, the financial industry can automate decision-making processes, reduce risk, and improve the customer experience.

application_record.csv			
Feature name	**Explanation**	**Type**	**Remarks**
`ID`	Client number	Interval	
`CODE_GENDER`	Gender	Nominal	
`FLAG_OWN_CAR`	Is there a car	Nominal	
`FLAG_OWN_REALTY`	Is there a property	Nominal	
`CNT_CHILDREN`	Number of children	Ratio	
`AMT_INCOME_TOTAL`	Annual income	Ratio	
`NAME_INCOME_TYPE`	Income category	Nominal	
`NAME_EDUCATION_TYPE`	Education level	Ordinal	
`NAME_FAMILY_STATUS`	Marital status	Nominal	
`NAME_HOUSING_TYPE`	Way of living	Nominal	
`DAYS_BIRTH`	Birthday	Ratio	Count backwards from current day (0), -1 means yesterday
`DAYS_EMPLOYED`	Start date of employment	Interval	Count backwards from current day (0).
`FLAG_MOBIL`	Is there a mobile phone	Nominal	
`FLAG_WORK_PHONE`	Is there a work phone	Nominal	
`FLAG_PHONE`	Is there a phone	Nominal	
`FLAG_EMAIL`	Is there an email	Nominal	
`OCCUPATION_TYPE`	Occupation	Nominal	
`CNT_FAM_MEMBERS`	Family size	Ratio	

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	ID	CODE_GENDEI	FLAG_OWN_CAF	FLAG_OWN_REALT	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE	NAME_EDUCATION_TYPE	NAME_FAMILY_STATUS	NAME_HOUSING_TYPE	DAYS_BIRTH	DAYS_EMPLOYED	FLAG_MOBIL	FLAG_WORK_PHONE	FLAG_PHONE	FLAG_EMAIL	OCCUPATION_TYPE	CNT_FAM_M
2	5008804	M	Y	Y	0	427500	Working	Higher education	Civil marriage	Rented apartment	-12005	-4542	1	1	0	0		2
3	5008805	M	Y	Y	0	427500	Working	Higher education	Civil marriage	Rented apartment	-12005	-4542	1	1	0	0		2
4	5008806	M	Y	Y	0	112500	Working	Secondary / secondary spe	Married	House / apartment	-21474	-1134	1	0	0	0	Security staff	2
5	5008808	F	N	Y	0	270000	Commercial associate	Secondary / secondary spe	Single / not married	House / apartment	-19110	-3051	1	0	1	1	Sales staff	1
6	5008809	F	N	Y	0	270000	Commercial associate	Secondary / secondary spe	Single / not married	House / apartment	-19110	-3051	1	0	1	1	Sales staff	1
7	5008810	F	N	Y	0	270000	Commercial associate	Secondary / secondary spe	Single / not married	House / apartment	-19110	-3051	1	0	1	1	Sales staff	1
8	5008811	F	N	Y	0	270000	Commercial associate	Secondary / secondary spe	Single / not married	House / apartment	-19110	-3051	1	0	1	1	Sales staff	1
9	5008812	F	N	Y	0	283500	Pensioner	Higher education	Separated	House / apartment	-22464	365243	1	0	0	0		1
10	5008813	F	N	Y	0	283500	Pensioner	Higher education	Separated	House / apartment	-22464	365243	1	0	0	0		1
11	5008814	F	N	Y	0	283500	Pensioner	Higher education	Separated	House / apartment	-22464	365243	1	0	0	0		1
12	5008815	M	Y	Y	0	270000	Working	Higher education	Married	House / apartment	-16872	-769	1	1	1	1	Accountants	2
13	5112956	M	Y	Y	0	270000	Working	Higher education	Married	House / apartment	-16872	-769	1	1	1	1	Accountants	2
14	6153651	M	Y	Y	0	270000	Working	Higher education	Married	House / apartment	-16872	-769	1	1	1	1	Accountants	2
15	5008819	M	Y	Y	0	135000	Commercial associate	Secondary / secondary spe	Married	House / apartment	-17778	-1194	1	0	0	0	Laborers	2
16	5008820	M	Y	Y	0	135000	Commercial associate	Secondary / secondary spe	Married	House / apartment	-17778	-1194	1	0	0	0	Laborers	2
17	5008821	M	Y	Y	0	135000	Commercial associate	Secondary / secondary spe	Married	House / apartment	-17778	-1194	1	0	0	0	Laborers	2
18	5008822	M	Y	Y	0	135000	Commercial associate	Secondary / secondary spe	Married	House / apartment	-17778	-1194	1	0	0	0	Laborers	2
19	5008823	M	Y	Y	0	135000	Commercial associate	Secondary / secondary spe	Married	House / apartment	-17778	-1194	1	0	0	0	Laborers	2
20	5008824	M	Y	Y	0	135000	Commercial associate	Secondary / secondary spe	Married	House / apartment	-17778	-1194	1	0	0	0	Laborers	2
21	5008825	F	Y	N	0	130500	Working	Incomplete higher	Married	House / apartment	-10669	-1103	1	0	0	0	Accountants	2
22	5008826	F	Y	N	0	130500	Working	Incomplete higher	Married	House / apartment	-10669	-1103	1	0	0	0	Accountants	2
23	5008830	F	N	Y	0	157500	Working	Secondary / secondary spe	Married	House / apartment	-10031	-1469	1	0	1	0	Laborers	2
24	5008831	F	N	Y	0	157500	Working	Secondary / secondary spe	Married	House / apartment	-10031	-1469	1	0	1	0	Laborers	2
25	5008832	F	N	Y	0	157500	Working	Secondary / secondary spe	Married	House / apartment	-10031	-1469	1	0	1	0	Laborers	2
26	5008834	F	N	Y	1	112500	Working	Secondary / secondary spe	Single / not married	House / apartment	-10968	-1620	1	0	0	0		2
27	5008835	F	N	Y	1	112500	Working	Secondary / secondary spe	Single / not married	House / apartment	-10968	-1620	1	0	0	0		2
28	6153712	F	N	Y	1	112500	Working	Secondary / secondary spe	Single / not married	House / apartment	-10968	-1620	1	0	0	0		2
29	5008836	M	Y	Y	3	270000	Working	Secondary / secondary spe	Married	House / apartment	-12689	-1163	1	0	0	0	Laborers	5
30	5008837	M	Y	Y	3	270000	Working	Secondary / secondary spe	Married	House / apartment	-12689	-1163	1	0	0	0	Laborers	5
31	5008838	M	N	Y	1	405000	Commercial associate	Higher education	Married	House / apartment	-11842	-2016	1	0	0	0	Managers	3
32	5008839	M	N	Y	1	405000	Commercial associate	Higher education	Married	House / apartment	-11842	-2016	1	0	0	0	Managers	3
33	5008840	M	N	Y	1	405000	Commercial associate	Higher education	Married	House / apartment	-11842	-2016	1	0	0	0	Managers	3
34	5008841	M	N	Y	1	405000	Commercial associate	Higher education	Married	House / apartment	-11842	-2016	1	0	0	0	Managers	3
35	5008842	M	N	Y	1	405000	Commercial associate	Higher education	Married	House / apartment	-11842	-2016	1	0	0	0	Managers	3
36	5008843	M	N	Y	1	405000	Commercial associate	Higher education	Married	House / apartment	-11842	-2016	1	0	0	0	Managers	3
37	5008844	M	Y	Y	0	112500	Commercial associate	Secondary / secondary spe	Married	House / apartment	-20502	-4450	1	0	1	0	Drivers	2

credit_record.csv			
Feature name	**Explanation**	**Type**	**Remarks**
`ID`	Client number	Interval	
`MONTHS_BALANCE`	Record month	Ratio	The month of the extracted data is the starting point, backwards, 0 is the current month, -1 is the previous month, and so on
`STATUS`	Status	Ordinal	0: 1-29 days past due 1: 30-59 days past due 2: 60-89 days overdue 3: 90-119 days overdue 4: 120-149 days overdue 5: Overdue or bad debts, write-offs for more than 150 days C: paid off that month X: No loan for the month

	A	B	C
1	ID	MONTHS_BALANCE	STATUS
2	5001711	0	X
3	5001711	-1	0
4	5001711	-2	0
5	5001711	-3	0
6	5001712	0	C
7	5001712	-1	C
8	5001712	-2	C
9	5001712	-3	C
10	5001712	-4	C
11	5001712	-5	C
12	5001712	-6	C
13	5001712	-7	C
14	5001712	-8	C
15	5001712	-9	0