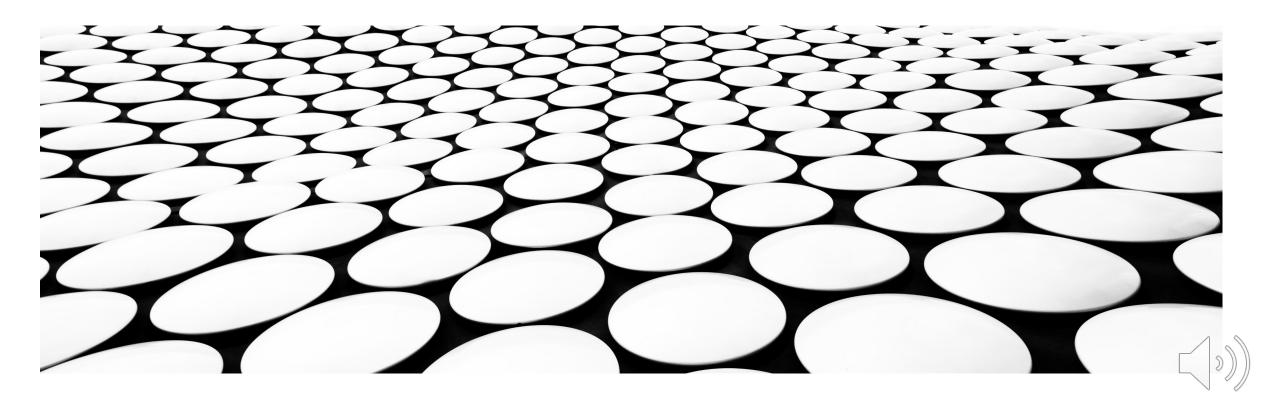
GITHUB REPOSITORY:

https://github.com/nicovy/bank-personal-Loan

BANK PERSONAL LOAN

NICOLAS VEAS



CONTEXT

- Predicting if a customer will buy a personal loan or not has high importance to the banks, especially when it comes to marketing campaigns. If we know whether a customer will buy a loan or not, we can make better target marketing campaigns to increase the success ratio.
- In this project, I'll use a classification model to predict customers have a higher probability of purchasing a loan.
- The data used is from kaggle from the following link:

https://www.kaggle.com/datasets/mahnazarjmand/bank-personal-loan?resource=download

OBJECTIVE

- Build a model that will help identify potential customers with a higher probability of purchasing a loan.
- Predict whether a customer will buy a personal loan or not.



DATA INFORMATION

Contains the following Variables

ID: Customer ID

Age: Customer's age in completed year

Experience: #years of professional experience

Income: Annual income of the customer (in thousand dollars)

ZIP Code: Home Address ZIP code.

Family: the Family size of the customer

CCAvg: Average spending on credit cards per month (in thousand dollars)

• Education: Education Level. 1: Undergrad; 2: Graduate; 3: Advanced/Professional

Mortgage: Value of house mortgage if any. (in thousand dollars)

Personal Loan: Did this customer accept the personal loan offered in the last campaign?

Securities Account: Does the customer have securities account with the bank?

CD Account: Does the customer have a certificate of deposit (CD) account with the bank?

Online: Do customers use internet banking facilities?

CreditCard: Does the customer use a credit card issued by any other Bank (excluding All life Bank)?

5000 Observations
14 Variables
5 Numerical Variables
8 Categorical Variables
No missing values
No duplicated Values



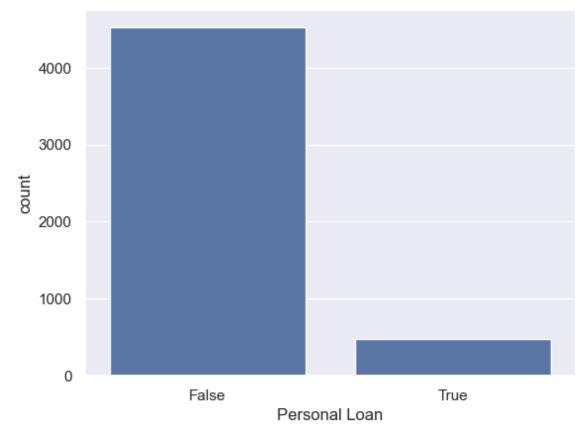
EXPLORATORY DATA ANALYSIS

- Data from 245 cities and 39 counties, Most of the customers are from Los Angeles County, around 21%
- All data is from California
- Customers age between 23 and 67 years old
- Most customers don't have a Mortgage
- Most customers are single
- Over 2000 customers are Undergraduate
- Only 480 customers out of 5000 had Personal Loan (around 10%)
- Most customers have online usage
- 4478 customers don't have a Securities account, ~10% have it
- 4478 customers don't have CD accounts, ~10% have it
- 3530 customers don't have Credit Cards in another bank, ~30% have it

	Age	Experience	Income	Family	CCAvg	Education	Mortgage	Personal_Loan	Securities_Account	CD_Account	Online	CreditCard	city	county	state
0	25	1	49000	4	1600.0	Undergrad	0	False	True	False	False	False	Pasadena	Los Angeles County	CA
1	45	19	34000	3	1500.0	Undergrad	0	False	True	False	False	False	Los Angeles	Los Angeles County	CA
2	39	15	11000	1	1000.0	Undergrad	0	False	False	False	False	False	Berkeley	Alameda County	CA
3	35	9	100000	1	2700.0	Graduate	0	False	False	False	False	False	San Francisco	San Francisco County	CA
4	35	8	45000	4	1000.0	Graduate	0	False	False	False	False	True	Northridge	Los Angeles County	CA
4995	29	3	40000	1	1900.0	Advanced/Professional	0	False	False	False	True	False	Irvine	Orange County	CA
4996	30	4	15000	4	400.0	Undergrad	85000	False	False	False	True	False	La Jolla	San Diego County	CA
4997	63	39	24000	2	300.0	Advanced/Professional	0	False	False	False	False	False	Ojai	Ventura County	CA
4998	65	40	49000	3	500.0	Graduate	0	False	False	False	True	False	Los Angeles	Los Angeles County	CA
4999	28	4	83000	3	800.0	Undergrad	0	False	False	False	True	True	Irvine	Orange County	CA



EXPLORATORY DATA ANALYSIS TARGET VARIABLE VARIABLE - PERSONAL_LOAN



^{* 90.4%} of customers didn't accept personal loan on the previous campaign



^{* 9.6%} accepted personal loan on the previous campaign

EXPLORATORY DATA ANALYSIS CORRELATION HEATMAP

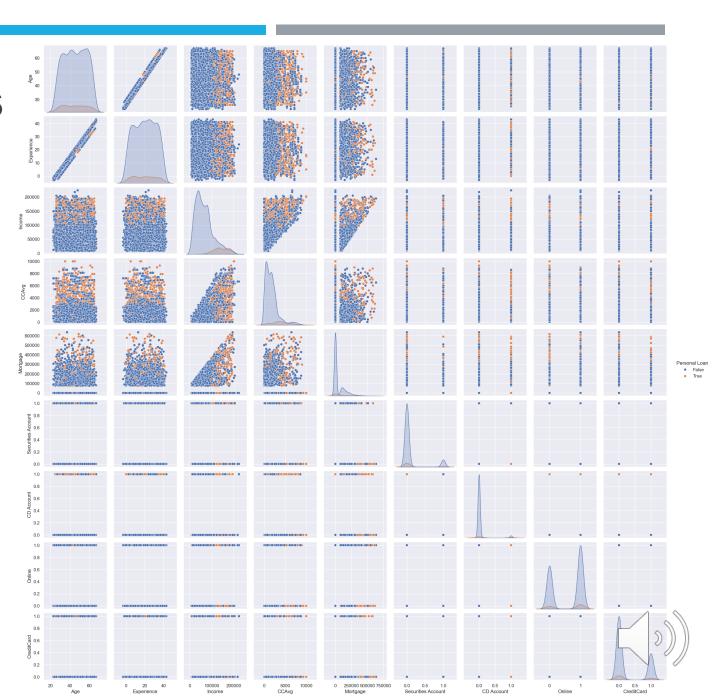
- Personal loan is most correlated with Income
- Age and experience are highly correlated (.99), as we can expect.

313										
Age	1	0.99	-0.055	-0.052	-0.013	-0.0077	-0.00044	0.008	0.014	0.0077
Experience	0.99	1	-0.047	-0.05	-0.011	-0.0074	-0.0012	0.01	0.014	0.009
Income	-0.055	-0.047	1	0.65	0.21	0.5	-0.0026	0.17	0.014	-0.0024
CCAvg	-0.052	-0.05	0.65	1	0.11	0.37	0.015	0.14	-0.0036	-0.0067
Mortgage	-0.013	-0.011	0.21	0.11	1	0.14	-0.0054	0.089	-0.006	-0.0072
Personal Loan	-0.0077	-0.0074	0.5	0.37	0.14	1	0.022	0.32	0.0063	0.0028
Securities Account	-0.00044	-0.0012	-0.0026	0.015	-0.0054	0.022	1	0.32	0.013	-0.015
CD Account	0.008	0.01	0.17	0.14	0.089	0.32	0.32	1	0.18	0.28
Online	0.014	0.014	0.014	-0.0036	-0.006	0.0063	0.013	0.18	1	0.0042
CreditCard	0.0077	0.009	-0.0024	-0.0067	-0.0072	0.0028	-0.015	0.28	0.0042	1
	Age	Experience	Income	CCAvg	Mortgage	Personal Loan	curities Account	CD Account	Online	CreditCard

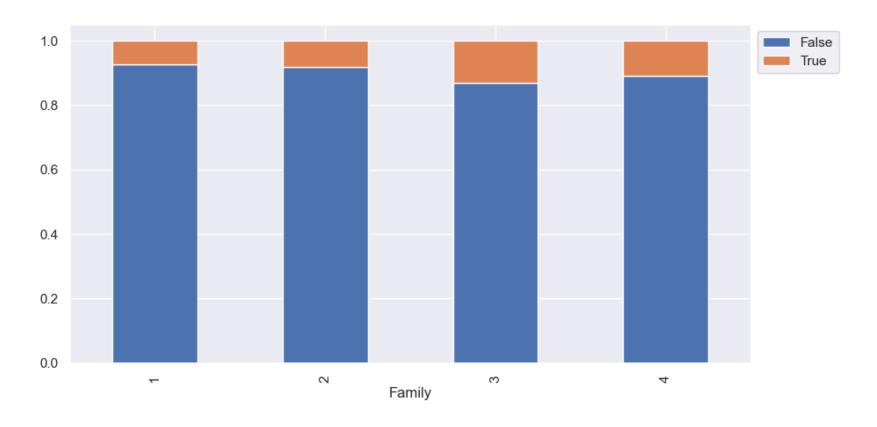


EXPLORATORY DATA ANALYSIS SCATTER PLOT

- We can see the linear correlation between Experience and Age
- People with high incomes get more loans than the rest.
- People with high credit card usage also trends to gem more loans.



EXPLORATORY DATA ANALYSIS CATEGORICALS

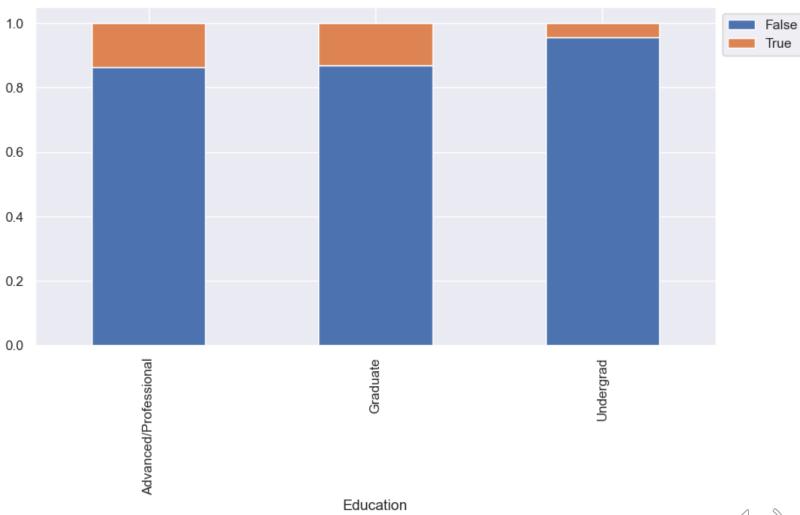


Personal loans are given more to families of 3 and 4 children.



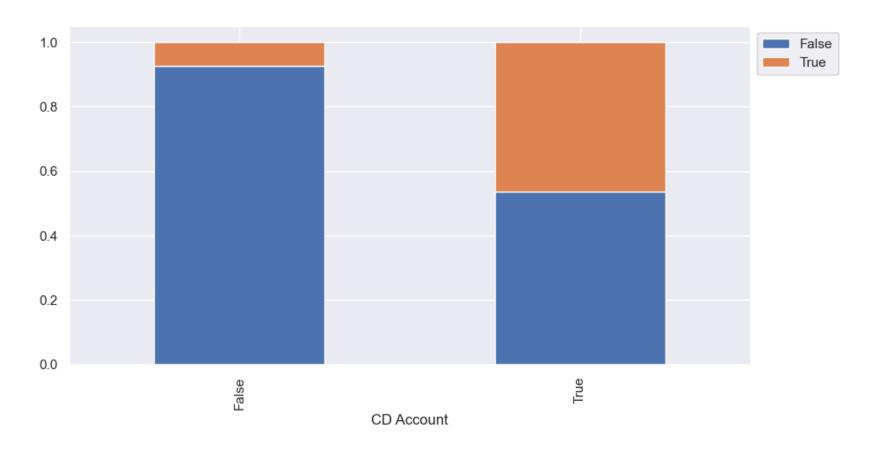
EXPLORATORY DATA ANALYSIS
CATEGORICALS

 Personal loans were given more to customer graduated and andvanced/professional





EXPLORATORY DATA ANALYSIS CATEGORICALS







MODEL BUILDING DATA PREPARATION

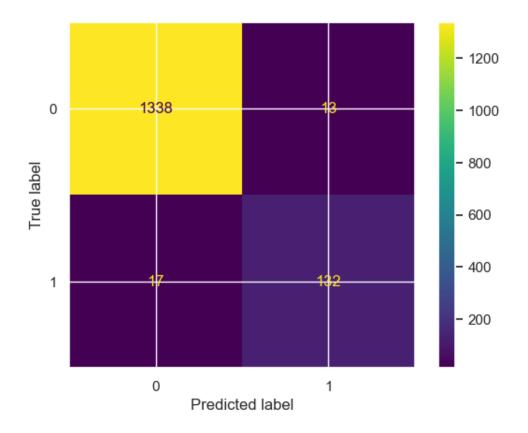
We want to optimize **recall,** as we like to get as less false positives as possible. the marketing campaings should aim to the most of potential loan buyers as possible.

- Zipcode and ID Removed
- Personal loan is our Target variable
- Data Divided into 70% for training and 30% for testing
- Converted categorical into dummy variables for modeling purposes

	Age	Experience	Income	CCAvg	Mortgage	Personal Loan	Securities Account	CD Account	Online	CreditCard	Family_2	Family_3	Family_4	Education_Graduate	Education_Undergrad
0	25	1	49000	1600.0	0.0	False	True	False	False	False	0	0	1	0	1
1	45	19	34000	1500.0	0.0	False	True	False	False	False	0	1	0	0	1
2	39	15	11000	1000.0	0.0	False	False	False	False	False	0	0	0	0	1
3	35	9	100000	2700.0	0.0	False	False	False	False	False	0	0	0	1	1.8
4	35	8	45000	1000.0	0.0	False	False	False	False	True	0	0	1	1	

MODEL BUILDING LOGISTIC REGRESSION

- Used Skleanr
- Best threshold for the model:
 - 0.081
- The model is not overfitted
- We get a recall of 92.62%

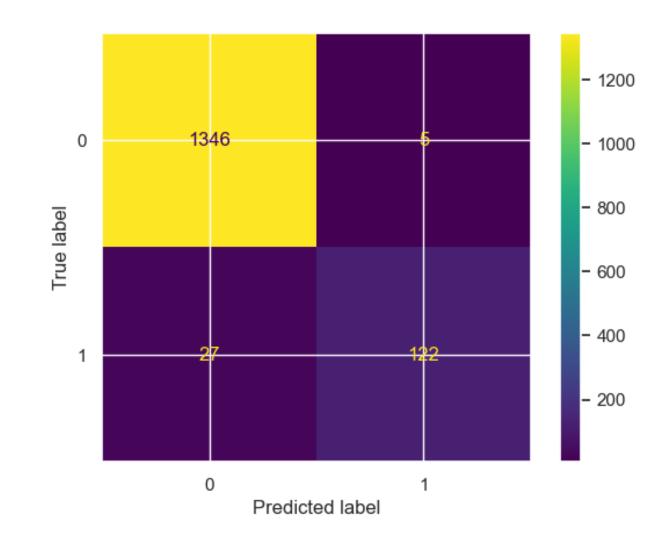


The 5 most important features for this model are 'Experience', 'Income', 'Securities_Account', 'CD_Account', 'Online'



MODEL BUILDING DECISION TREE

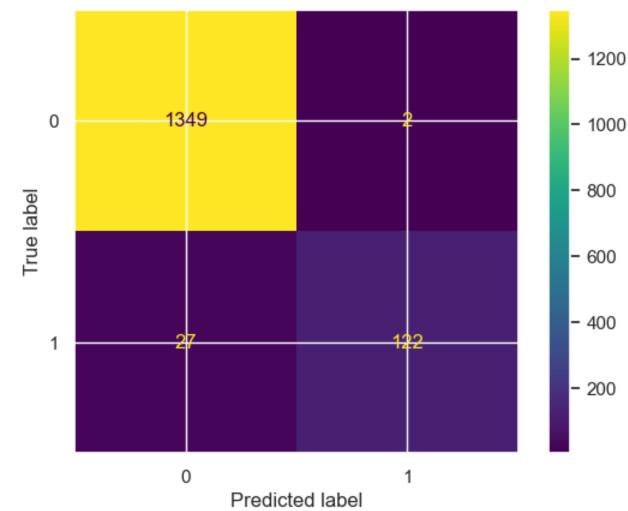
- Used GridSearchCV
 - Cpp_alpha 0.001
 - Criterion entropy
 - Max_depth 11
 - Min_samples_leaf 4
 - Min samples_split 2
- Recall on training set: 0.925
- Recall on test set: 0.82
- It suggest the model is overfitted





MODEL BUILDING RANDOM FORES

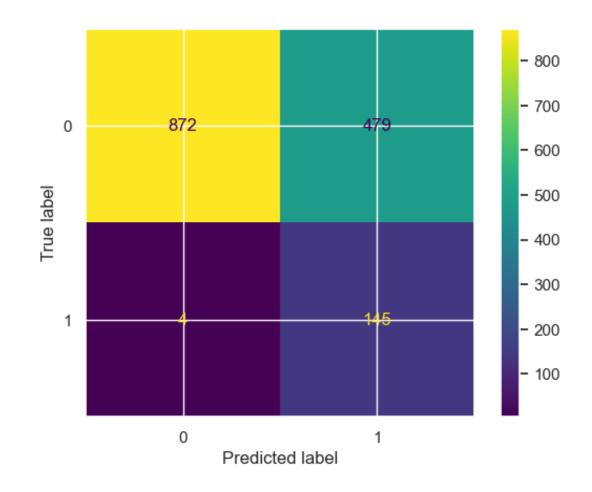
- Used GridSearchCV
 - max_depth=20,
 - max_features="sqrt",
 - min_samples_leaf=1,
 - n_estimators=20
- Recall on training set: 0.99
- Recall on test set: 0.82
- It suggest the model is overfitted





MODEL BUILDING ADA BOOST

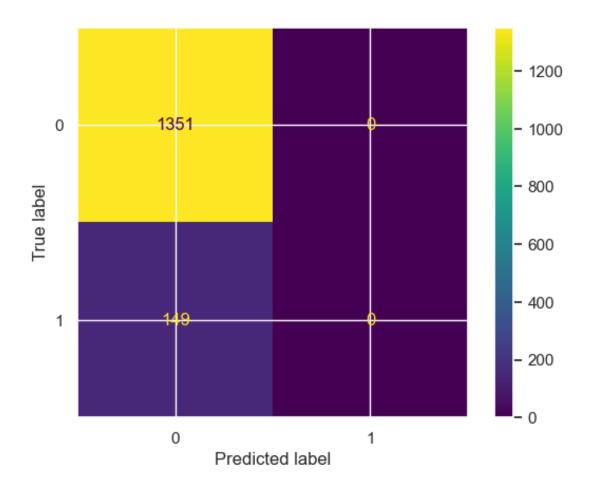
- Used GridSearchCV
 - learning_rate=2
 - n_estimators=10
- Recall on training set: 0.98
- Recall on test set: 0.9732





MODEL BUILDING VECTOR MACHINE

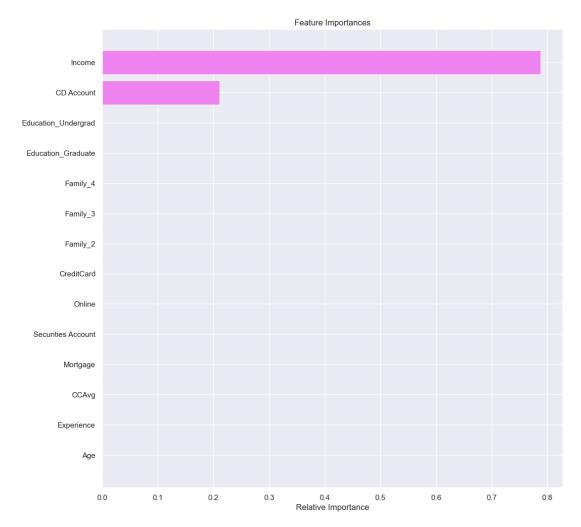
- Used GridSearchCV
 - C=0.03125,
 - gamma=0.03125,
 - kernel="rbf"
- Recall on training set: 0
- Recall on test set: 0





RESUMEN

- Recall Logistic Regression optimized: 0.9261744966442953
- Recall Decision Tree optimized: 0.8187919463087249
- Recall Random Forest optimized: 0.8187919463087249
- Recall AdaBoost optimized: 0.9731543624161074
- Recall SVM optimized: 0.0





CONCLUSIONS

- We chose the AdaBoost model as our best model for this project.
- Customers with high income >\$100,000 are more likely to get a personal loan
- Customers with credit card usage over \$2,000 are more likely to get a personal loan
- Customers with mortgages under \$200,000 are more likely to get a personal loan

