cause is that their clients are not depositing as frequently as before. Knowing that term deposits allow banks to hold onto a deposit for a specific amount of time, so banks can invest in higher gain financial products to make a profit. In addition, banks also hold better chance to persuade term deposit clients into buying other products such as funds or insurance to further increase their revenues. As a result, the Portuguese bank would like to identify existing clients that have higher chance to subscribe for a term deposit and focus marketing efforts on such clients. Project Description Your client is a retail banking institution. Term deposits are a major source of income for a bank. A term deposit is a cash investment held at a financial institution. Your money is invested for an agreed rate of interest over a fixed amount of time, or term. The bank has various outreach plans to sell term deposits to their customers such as email marketing, advertisements, telephonic marketing and digital marketing. Telephonic marketing campaigns still remain one of the most effective way to reach out to people. However, they require huge investment as large call centers are hired to actually execute these campaigns. Hence, it is crucial to identify the customers most likely to convert beforehand so that they can be specifically targeted via call. You are provided with the client data such as : age of the client, their job type, their marital status, etc. Along with the client data, you are also provided with the information of the call such as the duration of the call, day and month of the call, etc. Given this information, your task is to predict if the client will subscribe to term deposit. About The Dataset The dataset is related with direct marketing campaigns (phone calls) of a Portuguese banking institution. The classification goal of this dataset is to predict if the client or the customer of polish banking institution will subscribe a term deposit product of the bank or not. You are provided with following 2 files: 1. train.csv: Use this dataset to train the model. This file contains all the client and call details as well as the target variable "subscribed". You have to train your model using this 2. test.csv: Use the trained model to predict whether a new set of clients will subscribe the term deposit. Dataset Attributes Here is the description of all the variables: • Var • education: Education level • default: Credit in default. • housing: Housing loan • loan: Personal loan • contact: Type of communication • month: Contact month • day_of_week: Day of week of contact • duration: Contact duration • campaign: number of contacts performed during this campaign to the client • pdays: number of days that passed by after the client was last contacted • previous: number of contacts performed before this campaign • poutcome: outcome of the previous marketing campaign Output variable (desired target): • Subscribed (target): has the client subscribed a term deposit? (YES/NO) Dataset Link- • https://github.com/dsrscientist/dataset5 • https://raw.githubusercontent.com/dsrscientist/dataset5/main/termdeposit_train.csv • https://raw.githubusercontent.com/dsrscientist/dataset5/main/termdeposit_test.csv # Step 1: Import Libraries In [59]: import pandas as pd import numpy as np import matplotlib.pyplot as plt import seaborn as sns from sklearn.model_selection import train_test_split from sklearn.preprocessing import StandardScaler, LabelEncoder from sklearn.ensemble import RandomForestClassifier from sklearn.metrics import confusion_matrix, classification_report, accuracy_score In [60]: # Step 2: Load the Data trainurl = "https://raw.githubusercontent.com/dsrscientist/dataset5/main/termdeposit_train.csv" testurl = "https://raw.githubusercontent.com/dsrscientist/dataset5/main/termdeposit_test.csv" train_df = pd.read_csv(trainurl) test_df = pd.read_csv(testurl) # Step 3: Exploratory Data Analysis (EDA) In [61]: # Display basic information about the dataset print(train_df.info()) # Display summary statistics print(train_df.describe()) # Check for missing values print(train_df.isnull().sum()) # Explore the distribution of the target variable sns.countplot(x='subscribed', data=train_data) plt.title('Distribution of Subscribed') plt.show() <class 'pandas.core.frame.DataFrame'> RangeIndex: 31647 entries, 0 to 31646 Data columns (total 18 columns): Column Non-Null Count Dtype 0 ID 31647 non-null int64 31647 non-null 1 age int64 object 2 job 31647 non-null 31647 non-null object 3 marital education 31647 non-null object 4 5 default 31647 non-null object 6 balance 31647 non-null int64 7 housing 31647 non-null object 8 loan 31647 non-null object 9 contact 31647 non-null object day 10 31647 non-null int64 11 month 31647 non-null object duration 31647 non-null int64 campaign 31647 non-null int64 14 pdays 31647 non-null int64 31647 non-null int64 15 previous 31647 non-null object 16 poutcome 17 subscribed 31647 non-null object dtypes: int64(8), object(10) memory usage: 4.3+ MB None duration \ ID balance age day 31647.000000 count 31647.000000 31647.000000 31647.000000 31647.000000 22563.972162 40.957247 1363.890258 15.835466 258.113534 mean 13075.936990 10.625134 3028.304293 8.337097 257.118973 std 18.000000 -8019.000000 1.000000 0.000000 min 2.000000 25% 11218.000000 33.000000 73.000000 8.000000 104.000000 50% 22519.000000 39.000000 450.000000 16.000000 180.000000 75% 33879.500000 48.000000 1431.000000 21.000000 318.500000 max 45211.000000 95.000000 102127.000000 31.000000 4918.000000 campaign pdays previous 31647.000000 31647.000000 31647.000000 count 39.576042 mean 2.765697 0.574272 std 3.113830 99.317592 2.422529 1.000000 -1.000000 0.000000 min 1.000000 -1.000000 0.000000 25% 50% 2.000000 -1.000000 0.000000 75% 3.000000 -1.000000 0.000000 63.000000 871.000000 275.000000 max ID 0 0 age 0 job marital education default balance housing loan contact day month 0 duration 0 campaign pdays 0 previous 0 poutcome 0 subscribed dtype: int64 Distribution of Subscribed 25000 20000 15000 10000 5000 no yes subscribed # Step 4: Data Preprocessing # Handle missing values if any train_df.fillna(method='ffill', inplace=True) # Encode categorical variables encoder = LabelEncoder() # Adjust the list of categorical columns based on the actual columns in the dataset categorical_cols = ['job', 'marital', 'education', 'default', 'housing', 'loan', 'contact', 'month', 'poutcome'] for col in categorical_cols: try: train_df[col] = label_encoder.fit_transform(train_data[col]) except KeyError: # Handle unseen labels by adding 'unknown' to the classes encoder.classes_ = np.append(encoder.classes_, 'unknown') train_df[col] = encoder.transform(train_df[col]) # Split the data into features and target variable X = train_df.drop(['ID', 'subscribed'], axis=1) y = train_df['subscribed'] # Split the data into training and validation sets X_{train} , X_{val} , y_{train} , y_{val} = $train_{\text{test}}$, $train_{\text{val}}$, tr# Standardize the features scaler = StandardScaler() X_train = scaler.fit_transform(X_train) $X_{val} = scaler.transform(X_{val})$ In [63]: # Step 5: Model Training # Initialize and train the RandomForestClassifier model = RandomForestClassifier(random_state=42) model.fit(X_train, y_train) Out[63]: RandomForestClassifier RandomForestClassifier(random_state=42) In [64]: # Step 6: Model Evaluation # Predict on the validation set y_pred = model.predict(X_val) # Evaluate the model print("Confusion Matrix:\n", confusion_matrix(y_val, y_pred)) print("\nClassification Report:\n", classification_report(y_val, y_pred)) print("Accuracy:", accuracy_score(y_val, y_pred)) Confusion Matrix: [[5418 181] [415 316]] Classification Report: precision recall f1-score support 0.93 0.97 0.95 5599 no 0.64 0.43 0.51 731 yes accuracy 0.91 6330 0.70 0.73 6330 macro avg 0.78 0.90 6330 weighted avg 0.90 0.91 Accuracy: 0.9058451816745655 # Handle the case where there is a new category in the test data if 'unknown' in label_encoder.classes_: # 'unknown' is already in classes, use its label test_df[col] = label_encoder.transform(['unknown'])[0] else: # Add 'unknown' to the classes and use its label label_encoder.classes_ = np.append(label_encoder.classes_, 'unknown') test_df[col] = label_encoder.transform(['unknown'])[0] C:\Users\nishi\AppData\Local\Temp\ipykernel_26400\1026747192.py:2: FutureWarning: elementwise comparison failed; returning scalar instead, but in the future will perform elementwise comparison if 'unknown' in label_encoder.classes_: feature_importances = model.feature_importances_ In [49]: features = X.columns sns.barplot(x=feature_importances, y=features) plt.title('Feature Importance') plt.show() Feature Importance age job marital education default balance housing loan contact day month duration campaign pdays previous poutcome 0.00 0.05 0.10 0.15 0.20 0.25 0.30 2. Student grades prediction Project Description The dataset contains grades scored by students throughout their university tenure in various courses and their CGPA calculated based on their grades Columns Description- total 43 columns -Seat No : The enrolled number of candidate that took the exams CGPA: The cumulative GPA based on the four year total grade progress of each candidate. CGPA is a Final Marks -- provided to student. · All other columns are course codes in the format AB-XXX where AB are alphabets representing candidates' departments and XXX are numbers where first X represents the year the canditate took exam Predict - CGPA of a student based on different grades in four years. Dataset Link- • https://github.com/dsrscientist/dataset4 • https://github.com/dsrscientist/dataset4/blob/main/Grades.csv # Import necessary libraries import pandas as pd from sklearn.model_selection import train_test_split from sklearn.linear_model import LinearRegression from sklearn.metrics import mean_squared_error import matplotlib.pyplot as plt from sklearn.preprocessing import LabelEncoder # Load the dataset link = "https://raw.githubusercontent.com/dsrscientist/dataset4/main/Grades.csv" data = pd.read_csv(url) # Display the first few rows of the dataset print(data.head()) # Select relevant columns for prediction # Assuming you want to use grades in four years as features feature = ['PH-121', 'HS-101', 'CY-105', 'HS-105/12', 'MT-111', 'CS-105', 'CS-106', 'EL-102', 'EE-119'] # Convert grades to numerical values using Label Encoding encoder = LabelEncoder() data[feature] = data[feature].apply(encoder.fit_transform) # X contains the features, and y contains the target variable (CGPA) X = data[feature] y = data['CGPA'] # Split the dataset 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) # Create a linear regression model model = LinearRegression() # Fit the model on the training data model.fit(X_train, y_train) # Make predictions on the test set y_pred = model.predict(X_test) # Calculate Mean Squared Error to evaluate the model mse = mean_squared_error(y_test, y_pred) print(f"Mean Squared Error: {mse}") # Visualize the predicted vs actual CGPA plt.scatter(y_test, y_pred) plt.xlabel("Actual CGPA") plt.vlabel("Predicted CGPA") plt.title("Actual vs Predicted CGPA") plt.show() Seat No. PH-121 HS-101 CY-105 HS-105/12 MT-111 CS-105 CS-106 EL-102 EE-119 \ 0 CS-97001 D+ C-D+ D C-С C-B-1 CS-97002 Α D D+ D B-С D Α D+ 2 CS-97003 Α В B-B+ Α B-B+ A-Α D+ 3 CS-97004 D C+ D D Α-D+ C-D 4 CS-97005 Α-A-B+ ... CS-312 CS-317 CS-403 CS-421 CS-406 CS-414 CS-419 CS-423 CS-412 CGPA A- 2.205 C -C -C-C-Α-Α C-. . . 1 ... D С С С B 2.008 D+ D Α-B-2 ... С A 3.608 В В Α Α Α Α A -3 ... С C+ D+ D+ C -В-В C+ C+ 1.906 A 3.448 4 ... [5 rows x 43 columns] Mean Squared Error: 0.05898541553879833 Actual vs Predicted CGPA 4.0 3.5 Predicted CGPA 3.0 2.5 2.0 1.5 2.0 2.5 1.5 3.0 3.5 4.0 Actual CGPA Glass Identification Project Description The dataset describes the chemical properties of glass and involves classifying samples of glass using their chemical properties as one of six classes. The dataset was credited to Vina Spiehler in 1987. The study of classification of types of glass was motivated by criminological investigation. At the scene of the crime, the glass left can be used as evidence...if it is correctly identified! The chemical compositions are measured as the weight percent in corresponding oxide. Attribute Information-1. Id number: 1 to 214 2. RI: refractive index 3. Na: Sodium (unit measurement: weight percent in corresponding oxide, as are attributes 4-10) 4. Mg: Magnesium 5. Al: Aluminum 6. Si: Silicon 7. K: Potassium 8. Ca: Calcium 9. Ba: Barium 10. Fe: Iron 11. Type of glass: (class attribute) • 1- building_windows_float_processed • 2- building_windows_non_float_processed • 3- vehicle_windows_float_processed • 4vehicle_windows_non_float_processed (none in this database) • 5- containers • 6- tableware • 7- headlamps There are 214 observations in the dataset. The dataset can be divided into window glass (classes 1-4) and non-window glass (classes 5-7). Predict: Type of glass Dataset Link- • https://raw.githubusercontent.com/dsrscientist/dataset3/main/glass.csv • https://github.com/dsrscientist/dataset3 # Importing necessary libraries In [87]: import pandas as pd from sklearn.model_selection import train_test_split from sklearn.ensemble import RandomForestClassifier from sklearn.metrics import accuracy_score, classification_report import matplotlib.pyplot as plt import seaborn as sns # Load the dataset link = "https://raw.githubusercontent.com/dsrscientist/dataset3/main/glass.csv" glassdf = pd.read_csv(url) # Display the first few rows of the dataset print(glassdf.head()) # Data Preprocessing glassdf.columns = glass_data.columns.str.strip() # Trim whitespace from column names # Assuming the correct column name is '1.1', replace 'Type of glass' with the correct name y = glassdf['1.1'] # Target variable # Split the data into features (X) and target variable (y) X = glassdf.drop(['1.1'], axis=1) # Features # Split the 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) # Initialize the Random Forest Classifier clf = RandomForestClassifier(random_state=42) # Train the classifier clf.fit(X_train, y_train) # Make predictions on the test set y_pred = clf.predict(X_test) # Evaluate the model accuracy = accuracy_score(y_test, y_pred) classification_report_result = classification_report(y_test, y_pred) # Display the results print(f"Accuracy: {accuracy}") print("Classification Report:\n", classification_report_result) # Plot a bar graph of the feature importances feature_significance = clf.feature_importances_ features = X.columns sns.barplot(x=feature_significance, y=features) plt.title(' Importances of Features') plt.show() 1 1.52101 13.64 4.49 1.10 71.78 0.06 8.75 0.00 0.00.1 1.1 1.51761 13.89 3.60 1.36 72.73 0.48 7.83 0.0 0.00 1 1.51618 13.53 3.55 1.54 72.99 0.39 7.78 0.0 0.00 1 4 1.51766 13.21 3.69 1.29 72.61 0.57 8.22 0.0 0.00 1 5 1.51742 13.27 3.62 1.24 73.08 0.55 8.07 0.0 0.00 1 4 6 1.51596 12.79 3.61 1.62 72.97 0.64 8.07 0.0 0.26 1 Accuracy: 0.9767441860465116 Classification Report: precision recall f1-score support 0.95 1 0.91 1.00 10 2 1.00 0.93 0.97 15 3 1.00 1.00 1.00 5 1.00 1.00 1.00 6 1.00 1.00 1.00 7 1.00 1.00 1.00 0.98 43 accuracy 0.99 macro avq 0.98 0.99 43 weighted avg 0.98 0.98 0.98 43 Importances of Features 1 1.52101 13.64 4.49 1.10 71.78 0.06 8.75 0.00 0.00.1 0.0 In []:

1. BANK MARKETING: Predicting Whether The Customer Will Subscribe To Term Deposit (FIXED DEPOSIT) or not.

Business Use Case There has been a revenue decline for a Portuguese bank and they would like to know what actions to take. After investigation, they found out that the root