

Natacha Zanon Dametto

PhD in Astrophysics | Data Scientist | Problem-Solving | Fast-Learner | Polyglot | Communication Skills

Greater Bergamo Region

Introduction.

Study Case.

Dataset

quotations requested by Esprinet customers.

Objectives

- to analyse the dataset and extract meaningful insights;
- Communicate and share results;
- Develop a model for predicting the acceptance or rejection of a quotation.

Introduction.

Structured Plan

- 1. Data Acquisition.
- 2. Data Understanding.
- 3. Data Processing.
- 4. Modeling
- 5. Model Evaluation

Data Acquisition.

```
In [45]: import numpy as np import pandas as pd from ydata_profiling import ProfileReport from cleaning_data import load_clean_data import seaborn as sns from sklearn.model_selection import train_test_split from sklearn.preprocessing import StandardScaler from sklearn.linear_model import LogisticRegression from sklearn.dummy import DummyClassifier from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, roc_auc_score, roc_curve, roc_a from sklearn.pipeline import make_pipeline from sklearn.preprocessing import LabelEncoder from plots import generate_histogram_plot, plot_channelid_distribution from model import evaluate_classifier

%matplotlib inline
```

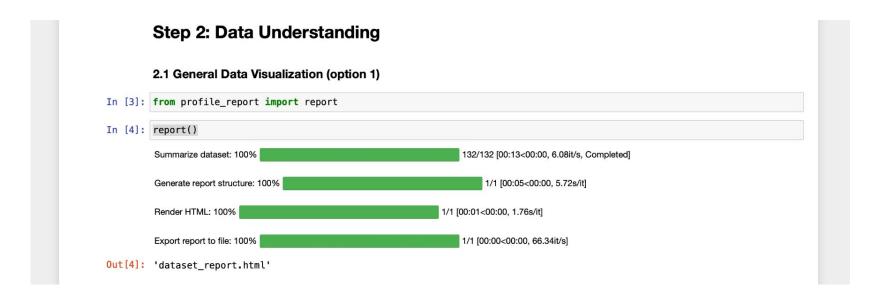
In [2]: df = pd.read csv("case study anonymized.csv", sep="|", encoding="latin")

Data Acquisition.

```
In [45]: import numpy as np
import pandas as pd
from ydata_profiling import ProfileReport
from cleaning_data import load_clean_data
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.dummy import DummyClassifier
| from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, roc_auc_score, roc_curve, roc_a
from sklearn.pripeline import make_pipeline
from sklearn.preprocessing import LabelEncoder
from plots import generate_histogram_plot, plot_channelid_distribution
from model import evaluate_classifier
%matplotlib inline
```

In [2]: df = pd.read csv("case study anonymized.csv", sep="|", encoding="latin")

Data Understanding.



Data Understanding.

▼ Step 2: Data Understanding

- Check the first few rows of data using df.head().
- Use df.info() to get an overview of data types and missing values.
- Check basic statistics with df.describe() to understand numeric variables
- Explore the dataset to understand its structure and contents.
- Get the unique values of a variable.

```
unique_categories = df['CHANNELID'].unique()
```

▶ Use a simple, fast and efficient tool to overview the dataset

Before start analysing our data, it is important to understand what it is the dataset we are working with.

- Dataset statistics
- Variable types

Data Processing.

Step 3: Data Preprocessing

```
In [13]: dataset = load_clean_data()
```

3.1. Handling missing data

```
In [14]: missing_values = dataset.isnull().sum()

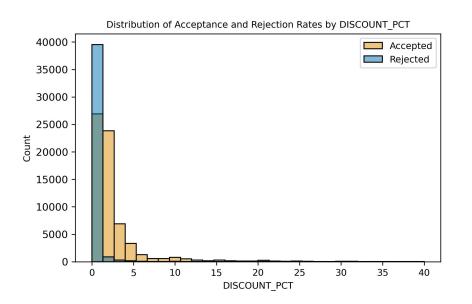
# Calculate the percentage of missing values
percentage_missing = (missing_values / len(df)) * 100

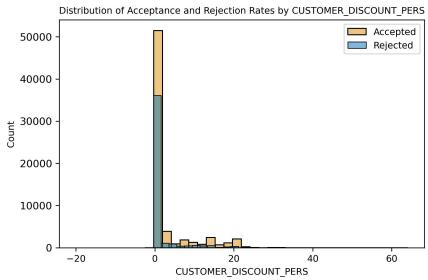
# Create a summary of missing values
missing_data_summary = pd.DataFrame({
    'Missing Values': missing_values,
    'Percentage Missing': percentage_missing
})

# Print the summary
print(missing_data_summary)
```

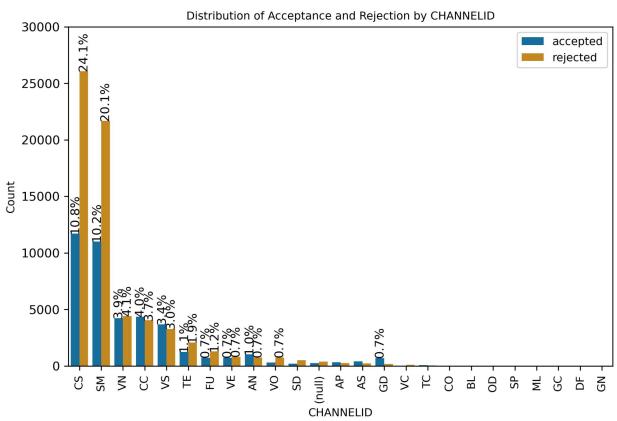
	Missing Values	Percentage Missing
Unnamed	0	0.000000
DEALKEY	0	0.000000
DEALDETKEY	0	0.000000
CUSTOMERID	0	0.000000
CHANNELID	0	0.000000
CHANNELDSC	650	0.601774
HAS_REAL_ORDER	0	0.000000
DEALVALUE	0	0.000000
DEALQTY	0	0.000000
ORDER_PRICE	0	0.000000
ORIGINAL_PRICE	0	0.000000

Insights.

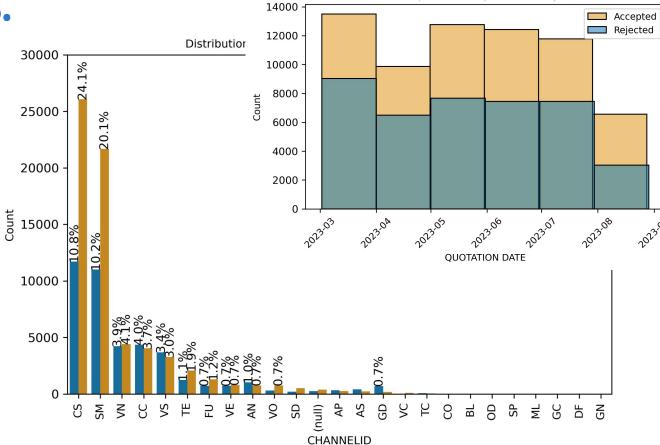




Insights.



Insights.



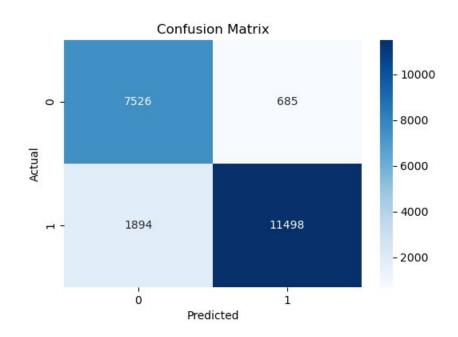
Distribution of Acceptance and Rejection Rates by QUOTATION DATE

Model.

```
def evaluate_classifier(dataset, classifier, save=True):
   Evaluate a logistic regression model on the given dataset.
   Parameters:
   - dataset: The dataset containing features and the target variable.
   - classifier: The classifier to evaluate (LogisticRegression or DummyClassifier).
   - save: Whether to save the plots as image files.
   Returns:
   - A dictionary with evaluation metrics including accuracy, classification report, confusion matrix, AUC score,
     and plots for confusion matrix, ROC curve, precision-recall curve, and feature importance (for Logistic Regre
   # Split data into features (X) and target (y)
   exclude_columns = ['HAS_REAL_ORDER', 'Unnamed', 'DEALKEY', 'DEALDETKEY', 'CHANNELDSC', 'CATEGORYDSC', 'ARTDSC',
   X = dataset.drop(columns=exclude columns)
   v = dataset['HAS REAL ORDER']
   # Split data into training and testing sets (e.g., 80% train, 20% test)
   X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
   # Initialize the label encoder
   label encoder = LabelEncoder()
   # Fit the label encoder on your target variable and transform it
   v train encoded = label encoder.fit transform(v train)
   v test encoded = label encoder.transform(v test)
   if classifier == 'LogisticRegression':
       # Create a pipeline with data scaling and logistic regression
       pipe = make_pipeline(StandardScaler(), LogisticRegression(max_iter=1000))
   elif classifier == 'DummvClassifier':
       # Create a DummyClassifier
       pipe = DummyClassifier(strategy='most frequent') # You can change the strategy here
       raise ValueError("Invalid classifier. Supported classifiers are 'LogisticRegression' and 'DummyClassifier'.
   # Fit the model on the training data
   pipe.fit(X train. v train encoded)
   # Make predictions on the testing data
   y pred = pipe.predict(X test)
   # Calculate evaluation metrics
   accuracy = accuracy_score(y_test_encoded, y_pred)
   report = classification_report(y_test_encoded, y_pred)
   confusion = confusion matrix(y test encoded, y pred)
   auc score = roc auc score(y test encoded, y pred)
```

Model.

```
def evaluate_classifier(dataset, classifier, save=True):
   Evaluate a logistic regression model on the given dataset.
   Parameters:
   - dataset: The dataset containing features and the target variable.
   - classifier: The classifier to evaluate (LogisticRegression or DummyClassifier).
   - save: Whether to save the plots as image files.
   Returns:
   - A dictionary with evaluation metrics including accuracy, classification report, confusion matrix, AUC score,
     and plots for confusion matrix, ROC curve, precision-recall curve, and feature importance (for Logistic Regre
   # Split data into features (X) and target (y)
   exclude_columns = ['HAS_REAL_ORDER', 'Unnamed', 'DEALKEY', 'DEALDETKEY', 'CHANNELDSC', 'CATEGORYDSC', 'ARTDSC',
   X = dataset.drop(columns=exclude columns)
   v = dataset['HAS REAL ORDER']
   # Split data into training and testing sets (e.g., 80% train, 20% test)
   X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
   # Initialize the label encoder
   label encoder = LabelEncoder()
   # Fit the label encoder on your target variable and transform it
   v train encoded = label encoder.fit transform(v train)
   v test encoded = label encoder.transform(v test)
   if classifier == 'LogisticRegression':
       # Create a pipeline with data scaling and logistic regression
       pipe = make_pipeline(StandardScaler(), Log sticRegression(max_iter=1000))
   elif classifier == 'DummyClassifier':
       # Create a DummvClassifier
       pipe = DummyClassifier(strategy='most freq ent') # You can change the strategy here
   euse:
       raise ValueError("Invalid classifier. Supported classifiers are 'LogisticRegression' and 'DummyClassifier'.
   # Fit the model on the training data
   pipe.fit(X train. v train encoded)
   # Make predictions on the testing data
   y pred = pipe.predict(X test)
   # Calculate evaluation metrics
   accuracy = accuracy_score(y_test_encoded, y_pred)
   report = classification_report(y_test_encoded, y_pred)
   confusion = confusion matrix(y test encoded, y pred)
   auc score = roc auc score(y test encoded, y pred)
```



Logistic Regression

```
Metrics for LogisticRegression:
Accuracy: 0.88
Classification Report:
                                     precision
                                                 recall f1-score
                                                                     support
           0
                   0.80
                             0.92
                                       0.85
                                                 8211
           1
                   0.94
                             0.86
                                       0.90
                                                13392
                                       0.88
                                                21603
    accuracy
                             0.89
                                       0.88
                                                21603
   macro avg
                   0.87
weighted avg
                   0.89
                             0.88
                                       0.88
                                                21603
```

Confusion Matrix: [[7526 685]

[1894 11498]] AUC Score: 0.89

Metrics for DummyClassifier:

Accuracy: 0.50
Classification Report:

		5		31	
	0	0.38	0.49	0.42	8211
	1	0.62	0.50	0.55	13392
accurac	у			0.50	21603
macro av	g	0.50	0.50	0.49	21603
weighted av	g	0.52	0.50	0.50	21603

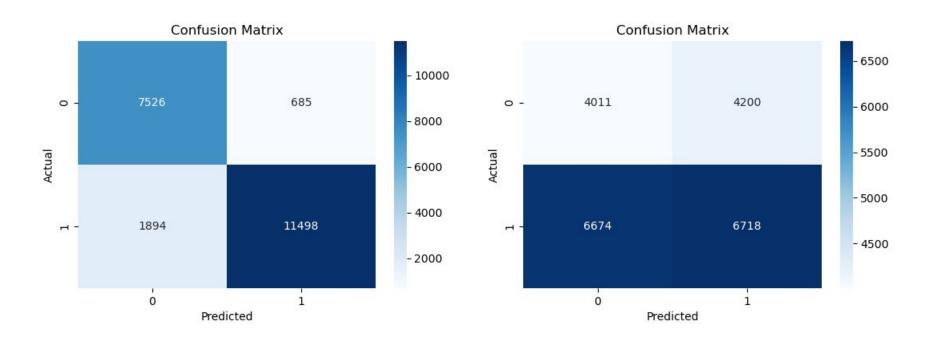
precision

recall f1-score

support

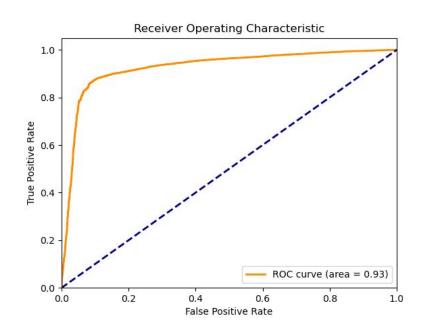
Confusion Matrix: [[4011 4200]

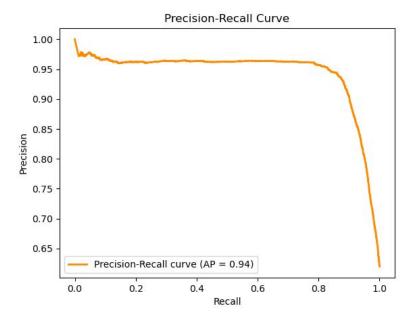
[6674 6718]] AUC Score: 0.50

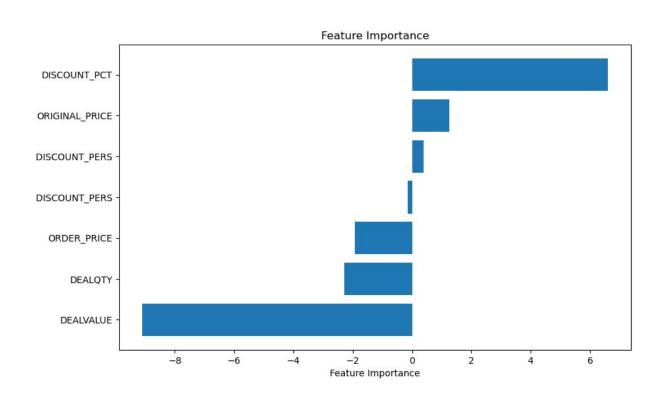


Logistic Regression

Dummy CLassifier







Thank you for your attention.