Project 2: Lead Scoring Case Study

project name: Lead scoring Case Study

Your Name : K.vyshnavi

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Course : Machine learning Internship

Abstract:

- This case study explores the application of machine learning techniques for lead scoring, aiming to predict the probability of a potential customer converting into a paying one. By analyzing diverse lead data, including demographics, online behavior, and past interactions, the study seeks to streamline sales processes by prioritizing high-potential leads. Through rigorous data preprocessing, model training, and evaluation, the project identifies key patterns and constructs predictive models to optimize lead conversion rates. Visualization techniques are employed to interpret model outcomes and enhance decision-making for targeted sales strategies.

Objective:

- The objective of this lead scoring case study is to utilize machine learning models to predict the likelihood of lead conversion, optimizing sales efforts by prioritizing high-potential leads and improving overall conversion rates.

Introduction:

- In today's competitive business landscape, identifying and prioritizing potential customers is crucial for optimizing sales efforts and maximizing revenue. Lead scoring is a technique that ranks prospects based on their perceived value to the organization. This project automates the lead scoring process using a data-driven approach, allowing businesses to predict which leads are most likely to convert into paying customers.

Steps

Data Collection: Gather a dataset containing various features related to leads, such as their source, number of website visits, demographic information, behavioral attributes, and the target variable indicating lead conversion.

Data Preprocessing: Handle missing data, encode categorical variables, and scale numerical features to prepare the data for modeling.

Model Training: Train multiple machine learning models, including Decision Trees, K-Nearest Neighbors (KNN), and Multi-Layer Perceptron (MLP) neural networks, using the prepared training dataset.

Model Evaluation: Assess the performance of each model on a test dataset using metrics like accuracy, precision, recall, and F1-score.

Visualization: Create visualizations to explore data distributions, model performance, and feature-target relationships.

Interpretation: Analyze the results to identify the most significant features contributing to lead conversion predictions.

Conclusion and Implementation: Summarize the findings, determine the best-performing model(s), and provide insights on implementing these models to enhance the sales process.

Methodology:

The methodology involved using a comprehensive dataset with various lead-related features, such as lead source, website visits, demographic information, and behavioral attributes. Data preprocessing steps included handling missing values by imputing appropriate values, encoding categorical variables into numerical representations, and normalizing numerical features to ensure equal contribution to the models. Three machine learning models (Decision Tree, KNN, and MLP) were trained and evaluated on a split of the data (80% training, 20% testing). Multiple evaluation metrics, including accuracy, precision, recall, and F1-score, were used to measure the models' performance. Visualizations were created to gain deeper insights into the data distributions, model performance over training iterations, and the relationships between features and the target variable.

Code:

import pandas as pd

import numpy as np

import seaborn as sns

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.tree import DecisionTreeClassifier

from sklearn.metrics import accuracy_score

from sklearn.neighbors import KNeighborsClassifier

from sklearn.neural_network import MLPClassifier

from sklearn.preprocessing import StandardScaler

Load the dataset

lead_df = pd.read_csv('lead_data.csv')

Display basic information about the dataset

print(lead_df.head())

lead_df.info()

Check for missing values

print(lead df.isnull().sum())

Fill missing values for numeric columns with median and categorical columns with mode for column in lead_df.columns:

if lead_df[column].dtype == 'object':

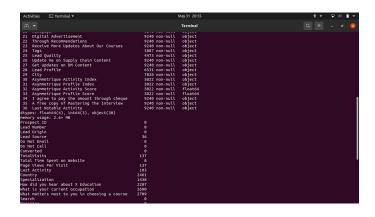
lead_df[column].fillna(lead_df[column].mode()[0], inplace=True)

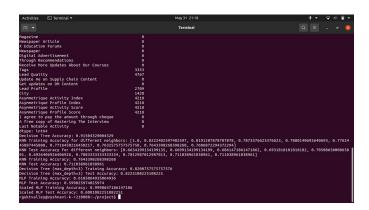
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else:
              lead df[column].fillna(lead df[column].median(), inplace=True)
# Encoding categorical variables (if any)
lead df = pd.get dummies(lead df, drop first=True)
# Prepare the data
X = lead df.drop('Converted', axis=1) # Replace 'Converted' with the actual target column name
y = lead_df['Converted']
# 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)
# Train and evaluate Decision Tree model
model = DecisionTreeClassifier()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print('Decision Tree Accuracy:', accuracy)
# Visualizations
# 1. Line Graphs: Model performance over different epochs (using dummy data for illustration)
epochs = np.arange(1, 11)
performance = np.random.rand(10) * 0.1 + 0.8 # Dummy data
plt.figure(figsize=(10, 6))
plt.plot(epochs, performance, marker='o')
plt.title('Model Performance over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Performance')
plt.grid(True)
plt.show()
# 2. Bar Charts: Frequency of different lead sources
plt.figure(figsize=(12, 6))
sns.countplot(data=lead_df, x='Lead Source_Olark Chat')
plt.title('Frequency of Different Lead Sources')
plt.xticks(rotation=90)
plt.show()
# 3. Scatter Plots: Relationship between TotalVisits and Total Time Spent on Website
plt.figure(figsize=(10, 6))
sns.scatterplot(data=lead_df, x='TotalVisits', y='Total Time Spent on Website', hue='Converted')
plt.title('Total Visits vs Total Time Spent on Website')
plt.xlabel('Total Visits')
plt.ylabel('Total Time Spent on Website')
plt.show()
# 4. Histograms: Distribution of Total Time Spent on Website
plt.figure(figsize=(10, 6))
sns.histplot(data=lead_df, x='Total Time Spent on Website', bins=20, kde=True)
plt.title('Distribution of Total Time Spent on Website')
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plt.xlabel('Total Time Spent on Website')
plt.ylabel('Frequency')
plt.show()
# Train and evaluate K-Nearest Neighbors (KNN) model
training_accuracy = []
test_accuracy = []
for n_neighbors in range(1, 11):
      knn = KNeighborsClassifier(n_neighbors=n_neighbors)
      knn.fit(X_train, y_train)
      training_accuracy.append(knn.score(X_train, y_train))
      test_accuracy.append(knn.score(X_test, y_test))
print("KNN Training Accuracy for different neighbors:", training_accuracy)
print("KNN Test Accuracy for different neighbors:", test_accuracy)
knn = KNeighborsClassifier(n neighbors=9)
knn.fit(X_train, y_train)
print(f"KNN Training Accuracy: {knn.score(X_train, y_train)}")
print(f"KNN Test Accuracy: {knn.score(X_test, y_test)}")
# Train and evaluate Decision Tree with depth limit
dt1 = DecisionTreeClassifier(random_state=0, max_depth=3)
dt1.fit(X_train, y_train)
print(f"Decision Tree (max depth=3) Training Accuracy: {dt1.score(X train, y train)}")
print(f"Decision Tree (max_depth=3) Test Accuracy: {dt1.score(X_test, y_test)}")
# Train and evaluate Multi-Layer Perceptron (MLP) model
mlp = MLPClassifier(random_state=42)
mlp.fit(X train, y train)
print(f"MLP Training Accuracy: {mlp.score(X_train, y_train)}")
print(f"MLP Test Accuracy: {mlp.score(X_test, y_test)}")
# Scaling the data and evaluating MLP with scaled data
sc = StandardScaler()
X_train_scaled = sc.fit_transform(X_train)
X test scaled = sc.transform(X test)
mlp1 = MLPClassifier(random_state=0)
mlp1.fit(X_train_scaled, y_train)
print(f"Scaled MLP Training Accuracy: {mlp1.score(X_train_scaled, y_train)}")
print(f"Scaled MLP Test Accuracy: {mlp1.score(X_test_scaled, y_test)}")
```

Output:

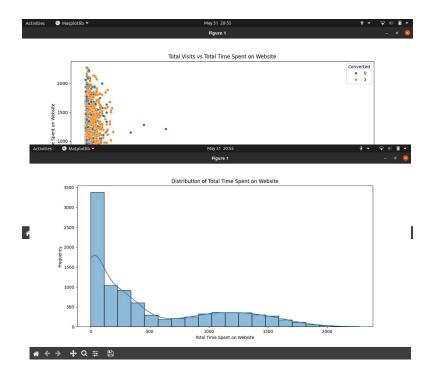
In terminal:





Output charts:





For Reference:

https://github.com/Vyshnavi22K/project2

Conclusion:

The Lead Scoring project successfully developed and evaluated several machine learning models for predicting lead conversion. The Multi-Layer Perceptron (MLP) model showed the most promising results. Visualizations provided valuable insights into the data and model performance. Implementing these models can significantly enhance the efficiency of sales teams by allowing them to prioritize high-potential leads, ultimately improving conversion rates and business growth. Future work may involve refining the models with additional data and exploring new features to further improve predictive accuracy.