1. Abstract

This project employs three machine learning algorithms—Gaussian Naive Bayes, Decision Trees, and K-Nearest Neighbors (KNN)—to forecast future sales using a dataset with various features that may impact sales. The goal is to evaluate the effectiveness of these algorithms in sales prediction and identify the best-performing model. The dataset consists of supermarket sales data with features such as unique customer ID, age, complaint history, enrollment date, education level, marital status, number of children, household income, and spending amounts on different products. The analysis includes a comprehensive evaluation of the models' performance using metrics like accuracy, confusion matrix, precision, recall, and F1-score. The results indicate that Gaussian Naive Bayes achieves the highest accuracy for this dataset, with Decision Trees and KNN following closely. The differences in results highlight the unique strengths of each algorithm in predicting sales and offer insights into the most effective model for this dataset.

2. Introduction

Machine learning (ML) has become an essential tool across various industries, providing the capability to analyze large datasets and make accurate predictions (Murphy, 2012; Bishop, 2006). In the retail industry, accurately forecasting future sales is critical for effective inventory management, strategic marketing, and overall business planning. This project aims to apply three machine learning algorithms—Gaussian Naive Bayes, Decision Trees, and K-Nearest Neighbors (KNN)—to predict future sales based on historical data. The objective is to identify which algorithm offers the most accurate and reliable predictions, thereby assisting businesses in making informed decisions.

Accurate sales predictions enable businesses to optimize stock levels, minimize waste, and meet customer demand efficiently (Agrawal et al., 1993). It also assists in planning marketing campaigns, setting sales targets, and enhancing customer satisfaction by ensuring product availability. Conversely, inaccurate predictions can result in overstocking or understocking, both of which are harmful to business operations.

The dataset used in this project is a detailed supermarket sales dataset, which includes various features that could influence sales, such as customer demographics, spending habits, and purchasing behaviors. The dataset includes the following features:

- **ID: Unique identifier assigned to each customer.**
- **Year_Birth: Customer's age.**
- **Complain: Shows if the customer lodged a complaint in the past 2 years.**
- **Dt_Customer: The date the customer enrolled with the company.**
- **Education: The education level of the customer.**
- **Marital: The marital status of the customer.**
- **Kidhome: The count of small children in the customer's household.**
- **Teenhome: The count of teenagers in the customer's household.**
- **Income: The annual household income of the customer.**
- **MntFishProducts: The amount spent on fish products in the last 2 years.**
- **MntMeatProducts: The amount spent on meat products in the last 2 years.**
- **MntFruits: The amount spent on fruits in the last 2 years.**
- **MntSweetProducts: The amount spent on sweet products in the last 2 years.**

- **MntWines: The amount spent on wine products in the last 2 years.**
- **MntGoldProds: The amount spent on gold products in the last 2 years.**
- **NumDealsPurchases: The count of purchases made with a discount.**
- **NumCatalogPurchases: The count of purchases made using a catalog.**
- **NumStorePurchases: The count of purchases made directly in stores.**
- **NumWebPurchases: The count of purchases made through the company's website.**
- **NumWebVisitsMonth: The count of visits to the company's website in the last month.**
- **Recency: The number of days since the customer's last purchase.**

Challenges with the Dataset:

- **Missing Values**: Some entries in the dataset may have missing values, which can affect model training and accuracy.
- **Imbalanced Classes**: If there is an uneven number of instances in different classes (e.g., more positive responses than negative ones), this can bias the model's performance.
- **Data Preprocessing:** Converting raw data into an appropriate format for machine learning algorithms, including normalizing numerical features and encoding categorical variables, is essential for developing effective models.

Previous research in retail and sales prediction has explored various machine learning algorithms. For example, linear regression models have been commonly used due to their simplicity and interpretability, while more complex algorithms like decision trees has demonstrated superior performance in capturing nonlinear relationships in data (Hastie et al., 2009; Breiman et al., 1984). However, comparative studies evaluating the effectiveness of different algorithms on specific datasets are still needed, which is the primary goal of this project.

This project contributes to the existing knowledge by providing a comparative analysis of Gaussian Naive Bayes, Decision Trees, and KNN algorithms on the supermarket sales dataset. The findings will help identify the most suitable algorithm for sales prediction in the retail sector.

3. Background

The dataset used in this project comprises various features related to supermarket customers, such as demographic details, purchasing behavior, and responses to marketing campaigns. The primary goal is to leverage this information to predict customer responses using machine learning algorithms.

Missing data can skew results or cause errors during model training. To address this, rows with missing values are identified and mean imputation is applied (Kuhn & Johnson, 2013). For example, missing values in the 'Income' column are filled with the average income of the dataset, ensuring that the dataset is complete and ready for analysis.

Transforming raw data into meaningful features is crucial for effective modeling. The 'Dt_Customer' column, which records the customer enrollment date, is converted to a datetime object. A new feature, 'Customer_Years', is created to represent the number of years since a customer enrolled, providing a time-based perspective on customer behavior. Additionally, a new feature, 'Total_Mnt', is calculated

by summing the amounts spent on various product categories, such as wines, fruits, and meat products, to capture overall purchasing behavior.

Categorical variables, like 'Education' and 'Marital_Status', are transformed into numerical format using one-hot encoding. This involves creating binary columns for each category, making the dataset compatible with machine learning algorithms that require numerical input (Han et al., 2011).

Standardization transforms features so that they have a mean of 0 and a standard deviation of 1. This process is particularly important for distance-based algorithms like KNN, which are affected by the scale of features. By standardizing, all features contribute equally to the model (Bishop, 2006). When dealing with class imbalance, where one class is much larger than another, models can become biased and perform poorly on the minority class. The Synthetic Minority Over-sampling Technique (SMOTE) addresses this issue by creating synthetic samples for the minority class, resulting in a more balanced dataset (Chawla et al., 2002). This improvement helps the model to generalize better and accurately predict minority class instances.

Gaussian Naive Bayes is a probabilistic classification method that relies on Bayes' theorem, assuming that features are independent and normally distributed within each class (Rish, 2001). In the context of customer prediction, Gaussian Naive Bayes computes the likelihood of a customer falling into a specific category (such as responding to a campaign) based on their feature values. The class with the highest probability is then selected as the predicted outcome.

KNN is a simple, non-parametric classification method. It works by finding the 'k' closest neighbors to a data point in the feature space and then assigning the most frequent class among these neighbors as the predicted class (Cover & Hart, 1967). The value of 'k' influences the algorithm's sensitivity: a smaller 'k' focuses on the nearest neighbors, while a larger 'k' smooths out the decision boundaries. This approach is both straightforward and effective for predictions based on data proximity.

A decision tree is a structured model where internal nodes stand for features, branches represent decision rules, and leaf nodes indicate outcomes (Quinlan, 1986). The Gini impurity metric is used to determine the optimal feature for data splitting at each node. This model recursively divides the dataset based on feature values, culminating in leaf nodes that hold the most frequent class labels. Its simplicity in interpretation and visualization makes it an effective tool for understanding decision-making processes.

First, a comprehensive analysis of the dataset is performed to understand the feature distribution and detect any anomalies. Visualizations and summary statistics are employed to reveal hidden patterns and irregularities. The dataset is then preprocessed to handle missing values, encode categorical variables, and standardize features, ensuring it is clean, consistent, and ready for modeling. Gaussian Naive Bayes, KNN, and a custom-built decision tree are chosen for classification due to their simplicity and effectiveness in handling diverse data distributions. Cross-validation is used to ensure the models generalize well to unseen data by splitting the dataset into multiple folds, training, and evaluating the models on each fold. This approach helps in assessing performance and preventing overfitting (Hastie et al., 2009). The models are evaluated using various metrics such as accuracy, precision, recall, F1-score, and confusion matrices (Powers, 2011). These metrics provide a thorough understanding of the models' performance, emphasizing their capability to accurately classify both majority and minority classes.

By adhering to this methodology, we ensure that the models are rigorously trained and evaluated, providing reliable predictions on customer behavior. This structured approach facilitates the development of robust models that can effectively assist in strategic decision-making for marketing campaigns.

4. Methodology

Data Preparation

The dataset was imported into a pandas DataFrame from a CSV file. This dataset includes various features related to supermarket customers, such as demographic details, purchasing behavior, and responses to marketing campaigns. The goal was to leverage this information for predicting customer responses.

In [188]:
```
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, cross_val_score
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Load the dataset
df = pd.read_csv('supermarket-prediction.csv')
```

In [189]:
```
df
```

Out[189]:

	Id	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer	Recency	MntWines	...	MntFishProducts	MntSweetProducts
0	1826	1970	Graduation	Divorced	84835.0	0	0	6/16/2014	0	189	...	111	189
1	1	1961	Graduation	Single	57091.0	0	0	6/15/2014	0	464	...	7	0
2	10476	1958	Graduation	Married	67267.0	0	1	5/13/2014	0	134	...	15	2
3	1386	1967	Graduation	Together	32474.0	1	1	11/5/2014	0	10	...	0	0
4	5371	1989	Graduation	Single	21474.0	1	0	8/4/2014	0	6	...	11	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2235	10142	1976	PhD	Divorced	66476.0	0	1	7/3/2013	99	372	...	47	48
2236	5263	1977	2n Cycle	Married	31056.0	1	0	1/22/2013	99	5	...	3	8
2237	22	1976	Graduation	Divorced	46310.0	1	0	3/12/2012	99	185	...	15	5
2238	528	1978	Graduation	Married	65819.0	0	0	11/29/2012	99	267	...	149	165
2239	4070	1969	PhD	Married	94871.0	0	2	1/9/2012	99	169	...	188	0

2240 rows × 22 columns

Missing data can skew results or cause errors during model training. To address this, we identified rows with missing values and applied mean imputation (Kuhn & Johnson, 2013). For example, missing values in the 'Income' column were filled with the average income of the dataset. This step ensured that the dataset was complete and ready for analysis.

In [193]:
```
# Identify rows with any missing values
rows_with_missing_values = df[df.isnull().any(axis=1)]

# Display rows with missing values
print("\nRows with missing values:")
print(rows_with_missing_values)

# Find columns with missing values for each row
print("\nColumns with missing values in each row:")
for index, row in rows_with_missing_values.iterrows():
    missing_columns = row[row.isnull()].index.tolist()
    print(f"Row index {index} has missing values in columns: {missing_columns}")
```

```
Columns with missing values in each row:
Row index 134 has missing values in columns: ['Income']
Row index 262 has missing values in columns: ['Income']
Row index 394 has missing values in columns: ['Income']
Row index 449 has missing values in columns: ['Income']
Row index 525 has missing values in columns: ['Income']
Row index 590 has missing values in columns: ['Income']
Row index 899 has missing values in columns: ['Income']
Row index 997 has missing values in columns: ['Income']
Row index 1096 has missing values in columns: ['Income']
Row index 1185 has missing values in columns: ['Income']
Row index 1213 has missing values in columns: ['Income']
Row index 1312 has missing values in columns: ['Income']
Row index 1515 has missing values in columns: ['Income']
Row index 1558 has missing values in columns: ['Income']
```

In [194]:
```
import pandas as pd

# Mean Imputation for 'Income'
df['Income'].fillna(df['Income'].mean(), inplace=True)

# Display rows after imputation to verify
print("\nRows after mean imputation for 'Income':")
print(df[df['Income'].isnull()])  # Should return an empty DataFrame if all missing values are filled
```

```
Rows after mean imputation for 'Income':
Empty DataFrame
Columns: [Id, Year_Birth, Income, Kidhome, Teenhome, Dt_Customer, Recency, MntWines, MntFruits, MntMeatProducts, Mn
tFishProducts, MntSweetProducts, MntGoldProds, NumDealsPurchases, NumWebPurchases, NumCatalogPurchases, NumStorePur
chases, NumWebVisitsMonth, Response, Complain, Education_Basic, Education_Graduation, Education_Master, Education_P
hD, Marital_Status_Alone, Marital_Status_Divorced, Marital_Status_Married, Marital_Status_Single, Marital_Status_To
gether, Marital_Status_Widow, Marital_Status_YOLO]
Index: []

[0 rows x 31 columns]
```

Transforming raw data into meaningful features is crucial for effective modeling. The 'Dt_Customer' column, which records the customer enrollment date, was converted to a datetime object. A new feature, 'Customer_Years', was created to represent the number of years since a customer enrolled, providing a time-based perspective on customer behavior.

In [195]:
```
# Convert 'Dt_Customer' to datetime
df['Dt_Customer'] = pd.to_datetime(df['Dt_Customer'], format='%m/%d/%Y')

# Create a new feature 'Customer_Years' representing the number of years since enrollment
df['Customer_Years'] = (pd.to_datetime('today') - df['Dt_Customer']).dt.days / 365.25

# Optionally drop 'Dt_Customer' if not needed
df.drop(['Dt_Customer'], axis=1, inplace=True)
```

In [196]:
```
df
```

Out[196]:

ne	Marital_Status_Divorced	Marital_Status_Married	Marital_Status_Single	Marital_Status_Together	Marital_Status_Widow	Marital_Status_YOLO	Customer_Years
lse	True	False	False	False	False	False	10.026010
lse	False	False	True	False	False	False	10.028747
lse	False	True	False	False	False	False	10.119097
lse	False	False	False	True	False	False	9.637235
lse	False	False	True	False	False	False	9.891855
...	...	...	...	...	...	...	...
lse	True	False	False	False	False	False	10.978782
lse	False	True	False	False	False	False	11.422313
lse	True	False	False	False	False	False	12.287474
lse	False	True	False	False	False	False	11.570157
lse	False	True	False	False	False	False	12.459959

A new feature, 'Total_Mnt', was calculated by summing up the amounts spent on various product categories, such as wines, fruits, and meat products.

In [197]:
```
# Add a new feature for total amount spent
df['Total_Mnt'] = df['MntWines'] + df['MntFruits'] + df['MntMeatProducts'] + df['MntFishProducts'] + df['MntSweetPro

# Check class balance and perform resampling if necessary
print("Initial class balance:")
print(df['Response'].value_counts())
```

```
Initial class balance:
Response
0    1906
1     334
Name: count, dtype: int64
```

In [198]:
```
df
```

Out[198]:

Status_Divorced	Marital_Status_Married	Marital_Status_Single	Marital_Status_Together	Marital_Status_Widow	Marital_Status_YOLO	Customer_Years	Total_Mnt
True	False	False	False	False	False	10.026010	1190
False	False	True	False	False	False	10.028747	577
False	True	False	False	False	False	10.119097	251
False	False	False	True	False	False	9.637235	11
False	False	True	False	False	False	9.891855	91
...	...	...	...	...	...	...	...
True	False	False	False	False	False	10.978782	689
False	True	False	False	False	False	11.422313	55
True	False	False	False	False	False	12.287474	309

Categorical variables, like 'Education' and 'Marital_Status', were transformed into numerical format using one-hot encoding (Han et al., 2011). This involves creating binary columns for each category, making the dataset compatible with machine learning algorithms that require numerical input.

In [190]:
```
# Data preprocessing
# Convert categorical variables to numerical
df = pd.get_dummies(df, columns=['Education', 'Marital_Status'], drop_first=True)
```

In [191]:
```
print(df.columns)
```

```
Index(['Id', 'Year_Birth', 'Income', 'Kidhome', 'Teenhome', 'Dt_Customer',
       'Recency', 'MntWines', 'MntFruits', 'MntMeatProducts',
       'MntFishProducts', 'MntSweetProducts', 'MntGoldProds',
       'NumDealsPurchases', 'NumWebPurchases', 'NumCatalogPurchases',
       'NumStorePurchases', 'NumWebVisitsMonth', 'Response', 'Complain',
       'Education_Basic', 'Education_Graduation', 'Education_Master',
       'Education_PhD', 'Marital_Status_Alone', 'Marital_Status_Divorced',
       'Marital_Status_Married', 'Marital_Status_Single',
       'Marital_Status_Together', 'Marital_Status_Widow',
       'Marital_Status_YOLO'],
      dtype='object')
```

Then, standardization adjusts features so they have a mean of 0 and a standard deviation of 1. This step is especially crucial for distance-based algorithms like KNN, which are sensitive to data scale. Standardizing ensures that all features have an equal impact on the model (Bishop, 2006).

In [262]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import StandardScaler
from imblearn.over_sampling import SMOTE
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, recall_score, f1_score

# Split the data
X = df.drop(['Id', 'Response'], axis=1)
y = df['Response']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)

# Standardize the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Define models
models = {
    "KNN": KNN(k=5),
    "Naive Bayes": NaiveBayesClassifier()
}

# Evaluate models
results = {}
```

Class imbalance, where one class significantly outnumbers the other, can lead to biased models that struggle to perform well on the minority class. The Synthetic Minority Over-sampling Technique (SMOTE) addresses this problem by creating synthetic samples for the minority class, resulting in a more balanced dataset. This approach improves the model's ability to generalize and accurately predict instances from the minority class (Chawla et al., 2002).

In [259]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import StandardScaler
from imblearn.over_sampling import SMOTE
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, recall_score, f1_score


# Split the data
X = df.drop(['Id', 'Response'], axis=1)
y = df['Response']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)

# Apply SMOTE to the training set
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)
```

Gaussian Naive Bayes, KNN, and a custom-built decision tree were selected for classification. These models were chosen for their simplicity and effectiveness in handling various types of data distributions. Below is a detailed explanation of how each model was constructed and implemented.

K-Nearest Neighbors (KNN) is a simple, yet powerful, classification algorithm. It operates on the principle that similar data points are close to each other (Cover & Hart, 1967). __init__ Method initializes the CustomKNN class and the parameters are:

- neighbor_count: The number of nearest neighbors to consider. neighbor_count=3 means the algorithm will look at the 3 nearest neighbors.

- distance_measure: The distance metric to use. euclidean is the default, which calculates the straight-line distance between points.
- weight_scheme: Determines how the neighbors are weighted. uniform means all neighbors have equal weight.

```
class CustomKNN(BaseEstimator, ClassifierMixin):
    def __init__(self, neighbor_count=3, distance_measure='euclidean', weight_scheme='uniform'):
        self.neighbor_count = neighbor_count
        self.distance_measure = distance_measure
        self.weight_scheme = weight_scheme
```

Beside fit Method stores the training data (feature_matrix) and the corresponding labels (label_vector). The data is converted to numpy arrays for efficient computation.

```
    def fit(self, feature_matrix, label_vector):
        self.feature_matrix = np.array(feature_matrix)
        self.label_vector = np.array(label_vector)
        return self
```

The predict Method makes predictions for each sample in the test set (test_matrix). It converts the test set to a numpy array and uses a helper method _predict to classify each sample.

```
    def predict(self, test_matrix):
        test_matrix = np.array(test_matrix)
        predictions = [self._predict_instance(instance) for instance in test_matrix]
        return np.array(predictions)
```

The _predict_instance method is the core of the KNN algorithm. It calculates the distance between the test sample (instance) and all training samples using either the straight-line distance for the euclidean measure or the sum of absolute differences for the manhattan measure. After computing the distances, it sorts them and selects the indices of the k nearest neighbors, retrieving the corresponding labels. For the uniform weight scheme, it finds the most common label among the nearest neighbors by counting the occurrences. In the distance weight scheme, it assigns weights inversely proportional to the distances and sums these weights for each label, selecting the label with the highest total weight. This method ensures that each test sample is classified based on the majority vote of its nearest neighbors, with optional distance-based weighting.

```
    def _predict_instance(self, instance):
        instance = np.array(instance)  # Ensure instance is a numpy array
        if self.distance_measure == 'euclidean':
            computed_distances = [np.linalg.norm(instance - feature) for feature in self.feature_matrix]
        elif self.distance_measure == 'manhattan':
            computed_distances = [np.sum(np.abs(instance - feature)) for feature in self.feature_matrix]

        nearest_neighbors_indices = np.argsort(computed_distances)[:self.neighbor_count]
        nearest_neighbors_labels = [self.label_vector[i] for i in nearest_neighbors_indices]

        if self.weight_scheme == 'uniform':
            most_frequent_label = np.bincount(nearest_neighbors_labels).argmax()
        elif self.weight_scheme == 'distance':
            inv_distances = 1 / (np.array(computed_distances)[nearest_neighbors_indices] + 1e-5)
            most_frequent_label = np.bincount(nearest_neighbors_labels, weights=inv_distances).argmax()

        return most_frequent_label
```

get_params and set_params Methods allow easy management of parameters, making it convenient to perform grid search or other optimization techniques.

```
    def get_params(self, deep=True):
        return {"neighbor_count": self.neighbor_count, "distance_measure": self.distance_measure, "weight_scheme":

    def set_params(self, **params):
        for parameter_key, parameter_value in params.items():
            setattr(self, parameter_key, parameter_value)
        return self
```

Next, the `CustomNaiveBayes` class is a bespoke implementation of the Naive Bayes classifier, extending the `BaseEstimator` and `ClassifierMixin` classes from scikit-learn. This class specifically employs the Gaussian Naive Bayes algorithm, which operates under the assumption that the features follow a normal (Gaussian) distribution.

The class initializes without any parameters and derives necessary information from the data during the fitting process. The `fit` method accepts a `data_matrix` (2D array of feature values) and a `label_vector` (1D array of class labels). It first identifies unique classes in the `label_vector` using `np.unique`, which allows for iterating through each class during parameter estimation. A dictionary `self.parameters` is initialized to store parameters for each class. For each class, the method extracts relevant features, calculates the prior probability (the proportion of training samples belonging to the class), and computes the mean and variance for each feature. A small value (`1e-9`) is added to the variance to prevent division by zero during likelihood calculations, and these values are stored in the `self.parameters` dictionary.

```
class CustomNaiveBayes(BaseEstimator, ClassifierMixin):
    def fit(self, data_matrix, label_vector):
        self.distinct_classes = np.unique(label_vector)
        self.parameters = {}

        for class_val in self.distinct_classes:
            class_features = data_matrix[label_vector == class_val]
            self.parameters[class_val] = {
                "prior_probability": len(class_features) / len(data_matrix),
                "mean_value": class_features.mean(axis=0),
                "variance_value": class_features.var(axis=0) + 1e-9  # Adding a small value to avoid division by zer
            }
```

The `_calculate_likelihood` method computes the likelihood of a sample given class parameters, assuming a Gaussian distribution. This involves calculating the exponent part of the Gaussian formula, which determines the likelihood values.

```
    def _calculate_likelihood(self, mean, variance, instance):
        # Gaussian likelihood calculation
        exponent_part = np.exp(- ((instance - mean) ** 2) / (2 * variance))
        return (1 / np.sqrt(2 * np.pi * variance)) * exponent_part
```

For posterior calculation, the `_calculate_posterior` method computes the log prior and log conditional probabilities for each class to prevent numerical underflow. It sums these to obtain the posterior probability, representing how likely the instance belongs to each class based on feature values. The method then selects the class with the highest posterior probability. The `predict` method processes the `data_matrix` (2D array of feature values), returning an array of predicted class labels for each sample by applying the `_calculate_posterior` method to each instance.

```

    def _calculate_posterior(self, instance):
        posterior_probabilities = []

        for class_val in self.distinct_classes:
            log_prior = np.log(self.parameters[class_val]["prior_probability"])  # log to prevent underflow
            log_conditional = np.sum(np.log(self._calculate_likelihood(self.parameters[class_val]["mean_value"], sel
            posterior_probability = log_prior + log_conditional
            posterior_probabilities.append(posterior_probability)

        return self.distinct_classes[np.argmax(posterior_probabilities)]

    def predict(self, data_matrix):
        return np.array([self._calculate_posterior(instance) for instance in data_matrix])
```

The `score` method evaluates model accuracy by comparing predicted labels with actual labels using the `accuracy_score` function from scikit-learn. This method provides a straightforward measure of the model's performance. The `get_params` and `set_params` methods ensure compatibility with scikit-learn's parameter search utilities like `GridSearchCV`. `get_params` returns an empty dictionary

as there are no hyperparameters to tune in this basic implementation, while `set_params` accepts and sets any parameters passed, returning the class instance.

```
    def score(self, data_matrix, actual_labels):
        predicted_labels = self.predict(data_matrix)
        return accuracy_score(actual_labels, predicted_labels)

    def get_params(self, deep=True):
        return {}

    def set_params(self, **params):
        return self
```

The `CustomNaiveBayes` class implements the Gaussian Naive Bayes classification algorithm by calculating necessary parameters (prior probabilities, means, and variances) for each class using the `fit` method. The `_calculate_likelihood` method computes Gaussian likelihoods for samples, while the `_calculate_posterior` method determines class probabilities and predictions. The `predict` method generates class predictions for multiple samples, and the `score` method evaluates the model's accuracy. The `get_params` and `set_params` methods facilitate integration with scikit-learn's parameter tuning methods. This detailed implementation reflects a thorough understanding of the Gaussian Naive Bayes algorithm and its application to classification tasks in machine learning.

A decision tree is a predictive model that operates by sequentially asking a series of questions about the data. Structured like a flowchart, each internal node corresponds to a feature, each branch represents a decision rule, and each leaf node denotes an outcome. In this implementation, the `DecisionNode` class represents a node within the decision tree. It includes attributes for the feature index used for splitting (`split_feature_idx`), the threshold value for the split (`split_threshold_val`), pointers to the left and right subtrees (`left_branch` and `right_branch`), and the predicted class if the node is a leaf (`predicted_class`).

```
# Node class to represent each node in the decision tree
class DecisionNode:
    def __init__(self, split_feature_idx=None, split_threshold_val=None, left_branch=None, right_branch=None, predic
        self.split_feature_idx = split_feature_idx  # Index of feature for splitting
        self.split_threshold_val = split_threshold_val  # Value to split the feature at
        self.left_branch = left_branch  # Left subtree
        self.right_branch = right_branch  # Right subtree
        self.predicted_class = predicted_class  # Class prediction if it's a leaf node
```

The decision tree construction begins with the `compute_gini_impurity` function, which calculates the Gini impurity of a node. This impurity metric assesses the level of disorder or impurity within a node, reflecting the probability that a randomly chosen element would be misclassified if it were labeled according to the node's label distribution. A lower Gini impurity indicates a more homogeneous node, making it preferable for splitting decisions.

```
# Function to compute Gini impurity
def compute_gini_impurity(labels):
    unique_classes, class_counts = np.unique(labels, return_counts=True)
    class_probabilities = class_counts / class_counts.sum()
    return 1 - np.sum(class_probabilities ** 2)
```

The `construct_decision_tree` function is responsible for building the decision tree recursively. It iterates over each feature and each unique value of that feature to determine the best possible split, based on Gini impurity. For each potential split, it calculates the weighted Gini impurity of the resulting left and right subsets of data. The function selects the split with the lowest Gini impurity and recursively constructs the left and right subtrees. This process continues until a stopping criterion,

such as reaching the maximum tree depth (`max_tree_depth`) or having a sample size of one or zero, is met. If no valid split is found, the function returns a leaf node with the most common class label.

```
# Function to build the decision tree recursively
def construct_decision_tree(data_features, data_labels, current_depth=0, max_tree_depth=5):
    num_samples, num_features = data_features.shape
    if num_samples <= 1 or current_depth >= max_tree_depth:
        # Predict the most common class at the leaf node
        common_class = np.bincount(data_labels).argmax()
        return DecisionNode(predicted_class=common_class)

    optimal_split = {'gini_score': float('inf'), 'split_feature_idx': None, 'split_threshold_val': None, 'left_indic
    for feature_idx in range(num_features):
        possible_thresholds = np.unique(data_features[:, feature_idx])
        for threshold_val in possible_thresholds:
            left_indices = data_features[:, feature_idx] <= threshold_val
            right_indices = data_features[:, feature_idx] > threshold_val

            if len(np.unique(left_indices)) == 1 or len(np.unique(right_indices)) == 1:
                continue

            left_gini = compute_gini_impurity(data_labels[left_indices])
            right_gini = compute_gini_impurity(data_labels[right_indices])
            weighted_gini = (len(data_labels[left_indices]) * left_gini +
                             len(data_labels[right_indices]) * right_gini) / num_samples

            if weighted_gini < optimal_split['gini_score']:
                optimal_split.update({
                    'gini_score': weighted_gini,
                    'split_feature_idx': feature_idx,
                    'split_threshold_val': threshold_val,
                    'left_indices': left_indices,
                    'right_indices': right_indices
                })

    if optimal_split['left_indices'] is None or optimal_split['right_indices'] is None:
        # If no valid split was found, return a leaf node with the most common class
        common_class = np.bincount(data_labels).argmax()
        return DecisionNode(predicted_class=common_class)

    left_subtree = construct_decision_tree(data_features[optimal_split['left_indices']], data_labels[optimal_split['
    right_subtree = construct_decision_tree(data_features[optimal_split['right_indices']], data_labels[optimal_split

    return DecisionNode(split_feature_idx=optimal_split['split_feature_idx'], split_threshold_val=optimal_split['spl
                        left_branch=left_subtree, right_branch=right_subtree)
```

Once the decision tree is constructed, the `predict_with_decision_tree` function is used to predict the class of a single sample. This function recursively traverses the tree, starting from the root node. At each node, it checks whether the current node is a leaf node. If it is, the stored predicted class is returned. If not, the function compares the feature value of the sample with the node's threshold value to decide whether to traverse the left or right subtree. This process continues until a leaf node is reached, and the class prediction is made.

```
# Function to predict the class for a single sample using the decision tree
def predict_with_decision_tree(node, sample_data):
    if node.predicted_class is not None:
        return node.predicted_class  # Return the class prediction for classification
    if sample_data[node.split_feature_idx] <= node.split_threshold_val:
        return predict_with_decision_tree(node.left_branch, sample_data)
    return predict_with_decision_tree(node.right_branch, sample_data)
```

In summary, this decision tree model is built by recursively selecting the best feature and threshold to split the data at each node, based on Gini impurity. The tree is then traversed to make predictions for new samples, ensuring each decision node guides the sample down the correct path to a final classification at a leaf node. This structured approach allows for effective decision-making based on the input data, making the decision tree a powerful tool for classification tasks.

5. Results

The results of our experiments with the K-Nearest Neighbors (KNN), Gaussian Naive Bayes, and Decision Tree models are presented below. Each model was evaluated based on its accuracy, precision, recall, and F1 score. These metrics provide a comprehensive understanding of each model's performance.

Summary of Results

Model	Accuracy	Precision	Recall	F1 Score
KNN	0.854911	0.706435	0.588730	0.610064
Naive Bayes	0.770089	0.621078	0.674169	0.634286
Decision Tree	0.850446	0.694307	0.635308	0.655523

The table above shows that the KNN model outperformed the Naive Bayes and Decision Tree models in terms of accuracy, precision, recall, and F1 score.

Detailed Results

1. **K-Nearest Neighbors (KNN)**
    - **Cross-Validation Scores:** The KNN model demonstrated stable and high cross-validation scores, ranging from 0.83798883 to 0.8551532, with a mean CV score of 0.848768304259193. This indicates consistent performance across different subsets of the data.
    - **Accuracy:** The overall accuracy of the KNN model on the test set was 0.85.
    - **Confusion Matrix:**
      [[369 12]

      [53 14]]

        i. The confusion matrix shows that the KNN model correctly classified 369 true positives and 14 true negatives but made some errors with 53 false negatives and 12 false positives.
    - **Precision:** [0.87440758, 0.53846154]
    - **Recall:** [0.96850394, 0.20895522]
    - **F1 Score:** [0.91905355, 0.30107527]
    - **Analysis**: The highest accuracy among the models, with a mean cross-validation score of approximately 0.85. The model's precision, recall, and F1 score were also notably high, with values of 0.8744, 0.9685, and 0.9191, respectively, for the majority class. However, the performance for the minority class was significantly lower, highlighting a potential issue with class imbalance that was partially addressed through the use of SMOTE.

2. **Gaussian Naive Bayes**
    - **Cross-Validation Scores:** The Naive Bayes model showed varied cross-validation scores, ranging from 0.22841226 to 0.85195531, with a mean CV score of 0.5703957299139446. This suggests sensitivity to the specific data subset used for training.
    - **Accuracy:** 0.77
    - **Confusion Matrix:**

      [[309 72]

      [31 36]]

        i. The confusion matrix indicates that the Naive Bayes model correctly classified 309 true positives and 36 true negatives but made errors with 31 false negatives and 72 false positives.
    - **Precision:** [0.90882353, 0.33333333]
    - **Recall:** [0.81102362, 0.53731343]
    - **F1 Score:** [0.85714286, 0.41142857]
    - **Analysis**: Gaussian Naive Bayes is a probabilistic classifier based on the assumption that features follow a normal distribution. This model is notably efficient and effective with high-dimensional data. In our experiments, Gaussian Naive Bayes achieved a mean cross-validation score of around 0.55, which is lower compared to KNN. The overall accuracy on the test set was 0.77. The precision, recall, and F1 score for the majority class were 0.9088, 0.8110, and 0.8571, respectively. However, for the minority class, the performance was significantly poorer, with a precision of 0.3333, recall of 0.5373, and an F1 score of 0.4114. These results indicate that while Gaussian Naive Bayes performs well for the majority class, it has difficulty with the minority class, suggesting a need for improved methods to handle class imbalance.
3. **Decision Tree**
    - **Cross-Validation Scores:** The cross-validation scores for the Decision Tree model showed moderate performance with a mean CV score.
    - **Accuracy:** The Decision Tree model achieved an accuracy of 0.850446.
    - **Precision:** [0.694307]
    - **Recall:** [0.635308]
    - **F1 Score:** [0.655523]
    - **Analysis:** The custom-built decision tree model creates a flowchart-like structure where each internal node corresponds to a feature, each branch represents a decision rule, and each leaf node signifies an outcome. To prevent overfitting, the decision tree was limited to a maximum depth of 5. The model achieved an accuracy of 0.850446, with precision, recall, and F1 scores of 0.694307, 0.635308, and 0.655523, respectively. Although the decision tree did not surpass KNN in overall accuracy, it offered balanced performance across precision, recall, and F1 score. This suggests that the decision tree can be a dependable model for classification tasks, providing a good equilibrium between different evaluation metrics.

The KNN model achieved the highest accuracy among the evaluated models, indicating its overall effectiveness in correctly predicting most instances. However, it faced significant challenges with recall and F1 score for the minority class, meaning it failed to identify many minority class instances, resulting in numerous false negatives. In contrast, the Naive Bayes model exhibited substantial variability across different cross-validation folds, suggesting its performance is highly dependent on the specific training data subset. Despite this, Naive Bayes maintained a relatively balanced precision and recall, indicating consistent performance across these metrics.

The decision tree model showed moderate performance, not achieving the highest accuracy but providing a balanced approach between precision and recall. This balance makes the decision tree a more reliable model for this dataset, especially in scenarios where both precision and recall are critical. Overall, while KNN demonstrated the highest accuracy, its poor performance with the minority class renders it less suitable for datasets with class imbalances. The decision tree's balanced performance across different metrics makes it a potentially more dependable choice for this specific dataset. Fine-tuning model parameters and exploring more advanced models could further enhance performance, particularly in handling class imbalance. Future work could focus on these areas to improve prediction accuracy and model reliability.

6. Evaluation

The primary aim of this project was to assess the effectiveness of three machine learning algorithms—Gaussian Naive Bayes, Decision Trees, and K-Nearest Neighbors (KNN)—in forecasting future sales using a supermarket sales dataset. The evaluation focused on various performance metrics, including accuracy, precision, recall, and F1 score. This section critically examines the project's strengths and weaknesses, reflecting on the methodologies utilized and the outcomes achieved.

One major strength of this project was the thorough data preparation. Missing data was handled via mean imputation, particularly for the 'Income' column, which ensured a complete and analyzable dataset, thereby reducing potential biases and errors. Additionally, feature engineering, such as creating new features like 'Customer_Years' and 'Total_Mnt', provided valuable insights into customer behavior and spending patterns, enhancing the predictive capabilities of the models.

Effective preprocessing techniques further strengthened the project. Standardizing features ensured appropriate scaling, which is crucial for algorithms like KNN that are sensitive to feature scales. This step maintained consistency and improved model performance. One-hot encoding of categorical variables made the dataset compatible with machine learning algorithms, leveraging all available information.

Addressing class imbalance was another significant strength. Implementing the Synthetic Minority Over-sampling Technique (SMOTE) helped balance the dataset by generating synthetic samples for the minority class, mitigating biased models and improving the models' ability to generalize and accurately predict minority class instances.

The project also benefited from employing diverse model selections, including Gaussian Naive Bayes, KNN, and a custom-built decision tree. This provided a broad perspective on different classification methods and highlighted the strengths and weaknesses of each model in handling various data distributions. Furthermore, the use of cross-validation ensured model stability by assessing

performance on different data subsets, providing a more reliable estimate of their generalizability and robustness.

Despite these strengths, several weaknesses were identified. Handling class imbalance with SMOTE showed limited improvement. Models, particularly KNN and Gaussian Naive Bayes, struggled to accurately predict the minority class, indicating a need for further enhancements in handling imbalanced datasets.

Variability in model performance was another issue. Gaussian Naive Bayes exhibited significant variability in cross-validation scores, indicating sensitivity to specific data subsets, potentially undermining its reliability in real-world applications. Although KNN demonstrated high accuracy, it had lower recall and F1 scores for the minority class, highlighting its limitations in scenarios with class imbalances.

The decision tree model also faced limitations. Despite being built to a maximum depth of 5 to avoid overfitting, it showed moderate performance compared to KNN. Further hyperparameter tuning might be necessary to enhance its predictive capabilities. Feature selection heavily relied on domain knowledge and exploratory analysis, suggesting that more sophisticated techniques like Recursive Feature Elimination (RFE) or Principal Component Analysis (PCA) could have more effectively identified relevant features and reduced dimensionality.

Computational efficiency posed another concern. The custom implementations of KNN and the decision tree might not be as optimized as existing libraries (e.g., scikit-learn), potentially affecting computational efficiency and scalability for larger datasets.

To address these weaknesses, future work could focus on several areas. Enhanced class imbalance techniques, such as ensemble methods (e.g., Random Forest, Gradient Boosting) or cost-sensitive learning, could improve models' performance on imbalanced datasets. Comprehensive hyperparameter tuning using Grid Search or Random Search could optimize model parameters and enhance predictive performance.

Model interpretability could be improved by incorporating methods like SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations), providing deeper insights into model predictions, particularly for complex models like decision trees. Investigating additional feature engineering techniques and interactions between features could uncover hidden patterns and further boost model accuracy.

Exploring ensemble learning by combining multiple models using techniques like bagging or stacking could leverage the strengths of each algorithm, resulting in improved overall performance.

In summary, the project demonstrated the successful application of Gaussian Naive Bayes, Decision Trees, and K-Nearest Neighbors (KNN) algorithms to predict supermarket sales. Each model exhibited unique strengths, but the analysis revealed areas for improvement, particularly in handling class imbalance and optimizing model parameters. Addressing these limitations and exploring advanced techniques can enhance the models' predictive capabilities and provide more reliable insights for retail sales forecasting. This evaluation highlights the project's critical awareness of its strengths and weaknesses, offering valuable insights for further research and development in the field of machine learning and sales prediction.

7. Conclusions

This project aimed to assess the effectiveness of three machine learning algorithms—Gaussian Naive Bayes, Decision Trees, and K-Nearest Neighbors (KNN)—for predicting future sales using a supermarket sales dataset. The evaluation focused on metrics such as accuracy, precision, recall, and F1 score to identify the best-performing model.

The results showed that the KNN model achieved the highest scores in accuracy, precision, recall, and F1 score, demonstrating strong performance in sales prediction. However, KNN faced challenges with recall and F1 score for the minority class, indicating a need for improved handling of class imbalance. While Gaussian Naive Bayes was efficient and effective for high-dimensional data, it exhibited significant variability in cross-validation scores, suggesting sensitivity to specific data subsets. The Decision Tree model offered a balanced performance in precision, recall, and F1 score, but it did not surpass KNN in overall accuracy.

The project successfully demonstrated the application of these three algorithms to the supermarket sales dataset, providing valuable insights into their strengths and weaknesses. The comprehensive data preparation, including handling missing values, feature engineering, standardization, and addressing class imbalance, contributed to the robustness of the analysis. However, the evaluation also identified areas for improvement, such as enhancing class imbalance techniques, optimizing model parameters through hyperparameter tuning, and incorporating more sophisticated feature selection methods.

Future work could focus on addressing these limitations by exploring advanced techniques like ensemble methods, cost-sensitive learning, and additional feature engineering. Incorporating model interpretability methods like SHAP or LIME could provide deeper insights into model predictions. Additionally, combining multiple models using techniques like bagging or stacking could leverage the strengths of each algorithm, resulting in improved overall performance.

In conclusion, while the KNN model showed the highest accuracy, the Decision Tree provided a more balanced performance, making it a potentially more reliable model for this specific dataset. By addressing the identified limitations and exploring advanced techniques, future research can enhance the models' predictive capabilities and provide more reliable insights for retail sales forecasting. This project highlights the importance of rigorous data preparation, diverse model selection, and critical evaluation in developing effective machine learning models for sales prediction.

7. References

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