Classification Models on Our Dataset from the Previous Project

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Using the dataset from our previous project, we will first perform data preprocessing before moving on to apply the following classification models and measure their accuracy: Naïve Bayes, Decision Tree (DT), K-Nearest Neighbor (KNN), Support Vector Machines (SVM), and Logistic Regression (Logit).

The dataset we used in the last project (linear regression project) was a housing dataset that contained data consisting of house prices and factors that influenced house prices such as average area income, area population, and more.

Data Preprocessing - Rahul

Before applying the models, we need to preprocess the data and modify it so it will fit the classification models, since the housing data has mainly continuous data. We will need to perform standard preprocessing steps and then move on to converting from continuous to categorical.

Reading the Data

First we need to read the data and load it into a pandas dataframe so we can preprocess and then apply models.

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

housing_df = pd.read_csv('./data/Housing.csv')
housing_df.head()
```

Out[1]:

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	
0	79545.458574	5.682861	7.009188	4.09	23086.800503	1.059034e+06	208 Michael 674\r\nLau
1	79248.642455	6.002900	6.730821	3.09	40173.072174	1.505891e+06	188 Johnson \ 079\r\nLake k
2	61287.067179	5.865890	8.512727	5.13	36882.159400	1.058988e+06	912 Stravenue\r\nD
3	63345.240046	7.188236	5.586729	3.26	34310.242831	1.260617e+06	USS Barnett\
4	59982.197226	5.040555	7.839388	4.23	26354.109472	6.309435e+05	USNS Raymo

Dropping Columns & Missing Values

In the last project using this dataset, we determined that house addresses would not have a significant influence on house prices and could be dropped, so we will be doing this again.

We will also check and deal with missing values. Just like last time, there are no missing values.

In [2]:

```
# Drop column
housing_df = housing_df.drop('Address', axis=1)

# Check for missing values
missing_values = housing_df.isna().sum()
print(missing_values)
```

```
Avg. Area Income                0
Avg. Area House Age             0
Avg. Area Number of Rooms       0
Avg. Area Number of Bedrooms    0
Area Population                 0
Price                           0
dtype: int64
```

Z-Score Normalization & Outliers

We will normalize the dataset and remove any outliers, turning values into z scores.

In [3]:

```
# Normalize
normal_df = (housing_df - housing_df.mean())/housing_df.std()
```

```
# Remove Outliers
normal_df = normal_df.loc[((normal_df > -3).sum(axis=1)==6) & ((normal_df <= 3).sum

print('Entries before outliers = %d' % (housing_df.shape[0]))
print('Entries after outliers = %d' % (normal_df.shape[0]))
print('Entries removed = %d' % (housing_df.shape[0] - normal_df.shape[0]))
```

```
Entries before outliers = 5000
Entries after outliers = 4943
Entries removed = 57
```

Discretization

In this step, we will use bins and labels to turn continuous data into categorical data so we can use it to fit the classification models. This will group continuous data into bins and assign that bin an appropriate label.

In [4]:
```
# Define bin edges
bins = [-3, -1.5, 0, 1.5, 3]

# Define labels for each bin
labels = ['Low Price', 'Medium Price', 'High Price', 'Very High Price']

# Discretize the Price column into categories
normal_df['Price Category'] = pd.cut(normal_df['Price'], bins=bins, labels=labels)

# Display the first few rows
print(normal_df[['Price', 'Price Category']].head())
```

```
      Price Price Category
0 -0.490032   Medium Price
1  0.775431     High Price
2 -0.490162   Medium Price
3  0.080835     High Price
4 -1.702348      Low Price
```

Training and Testing Split

We will split the data just like in the regression project. The price category is what we want to predict, hence why it is the y value. All other attributes, except for the actual price value, will be included as X.

In [5]:
```
from sklearn.model_selection import train_test_split

X = normal_df[['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Room
y = normal_df['Price Category']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

X_train.head()
```

Out[5]:

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population
4291	-0.501987	1.385214	0.273562	0.209596	-0.254448
4004	0.683442	0.616873	-0.229666	-0.706024	-0.387276
1178	1.167356	-0.181790	-0.271100	-1.564923	-1.040300
4722	0.684353	-1.625994	-0.680797	0.177185	-0.004475
4882	-0.596727	0.448013	-0.066086	-1.240810	-0.071830

Naïve Bayes Model - Rahul

Here, we will apply the Naïve Bayes model to the z-score normalized and discretized data and measure its accuracy.

In [6]:
```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score

naive_bayes = GaussianNB()
naive_bayes.fit(X_train, y_train)
naive_bayes_pred = naive_bayes.predict(X_test)

naive_bayes_acc = accuracy_score(y_test, naive_bayes_pred)

print('Naïve Bayes Accuracy: = %f%%' % (naive_bayes_acc * 100))
```

```
Naïve Bayes Accuracy: = 78.968655%
```

Decision Tree (DT) Classification Model - Rahul

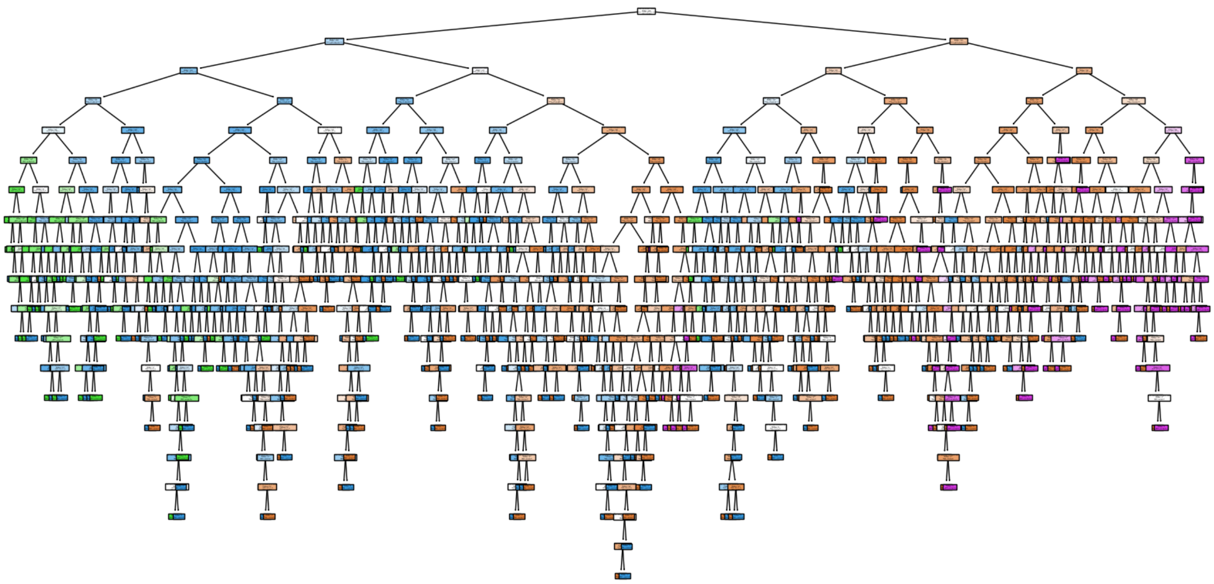
We will use a Decision Tree model to predict the price category of the houses. Given that our data has been discretized into bins for categorical classification, we will opt for a decision tree classifier rather than a decision tree regressor, aligning with the nature of our task where we're predicting discrete categories rather than continuous values.

In [7]:
```
from sklearn.tree import DecisionTreeClassifier, plot_tree

dec_tree = DecisionTreeClassifier(criterion='entropy')
dec_tree = dec_tree.fit(X_train, y_train)

dec_tree_pred = dec_tree.predict(X_test)
dec_tree_acc = accuracy_score(y_test, dec_tree_pred)

print('Decision Tree Accuracy: = %f%%' % (dec_tree_acc * 100))
```

```
Decision Tree Accuracy: = 73.407482%
```

Since we are using a decision tree, we can also display it, although the tree is quite large since we did not set a max tree length. Setting a max tree length results in a smaller tree, however, a smaller tree can also be less accurate.

In [8]:
```
plt.figure(figsize=(20,10))
plot_tree(dec_tree, filled=True, feature_names=X_train.columns, class_names=labels)
plt.show()
```

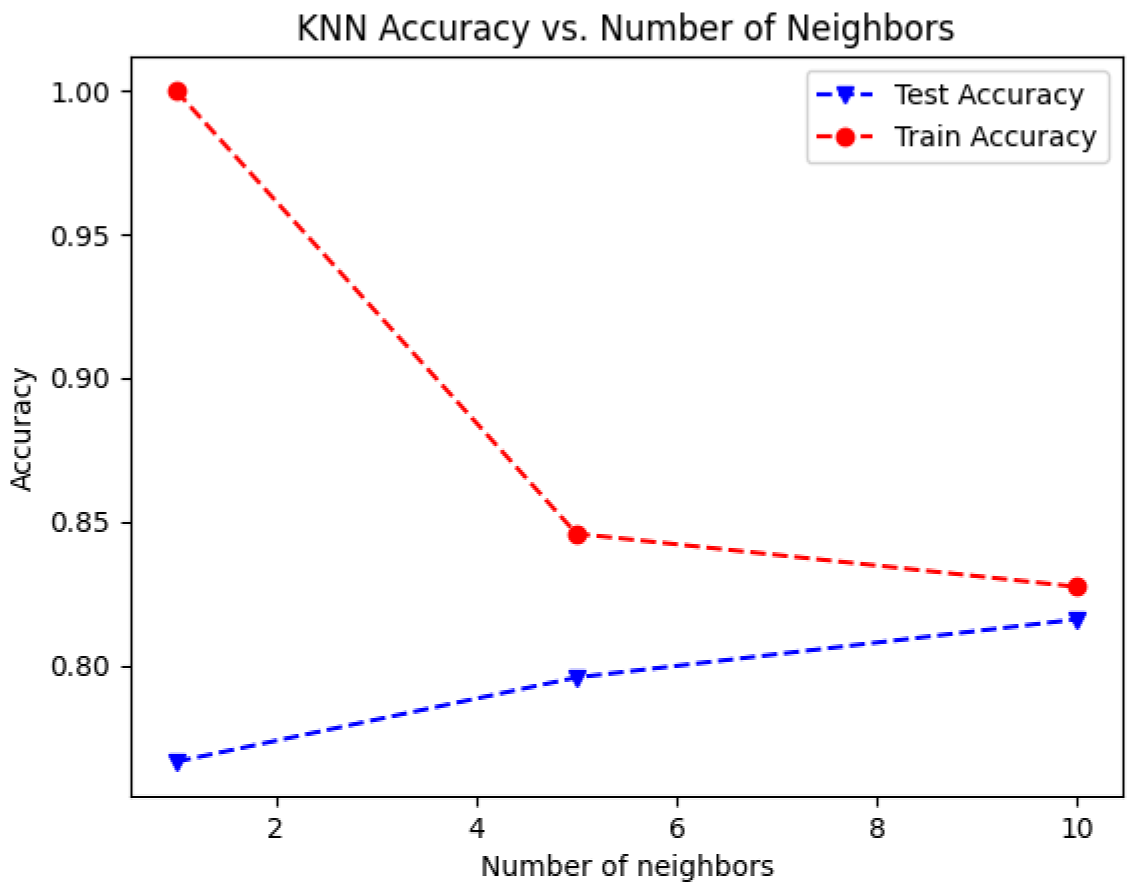


K-Nearest Neighbor (KNN) - Maddie

We use the K-Nearest Neighbor to calculate the distance between the input data point and all the training examples, subsequently relying on the majority vote of its nearest neighbors for classification. This method is intuitive, as it assigns the class label of the most prevalent category among the k nearest neighbors, making it particularly effective for locally structured datasets.

In [9]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt

numNeighbors = [1, 5, 10]
testAcc = []
trainAcc = []

for k in numNeighbors:
    clf = KNeighborsClassifier(n_neighbors=k, metric='minkowski', p=2)
    clf.fit(X_train, y_train)
    knn_pred = clf.predict(X_test)
    knn_pred_train = clf.predict(X_train)
    testAcc.append(accuracy_score(y_test, knn_pred))
    trainAcc.append(accuracy_score(y_train, knn_pred_train))

plt.plot(numNeighbors, testAcc, 'bv--', numNeighbors, trainAcc, 'ro--')
```

```
plt.legend(['Test Accuracy', 'Train Accuracy'])
plt.xlabel('Number of neighbors')
plt.ylabel('Accuracy')
plt.title('KNN Accuracy vs. Number of Neighbors')
plt.show()

knn_acc = accuracy_score(y_test, knn_pred)
print('K-Nearest Neightbor (KNN): = %f%%' % (knn_acc * 100))
```



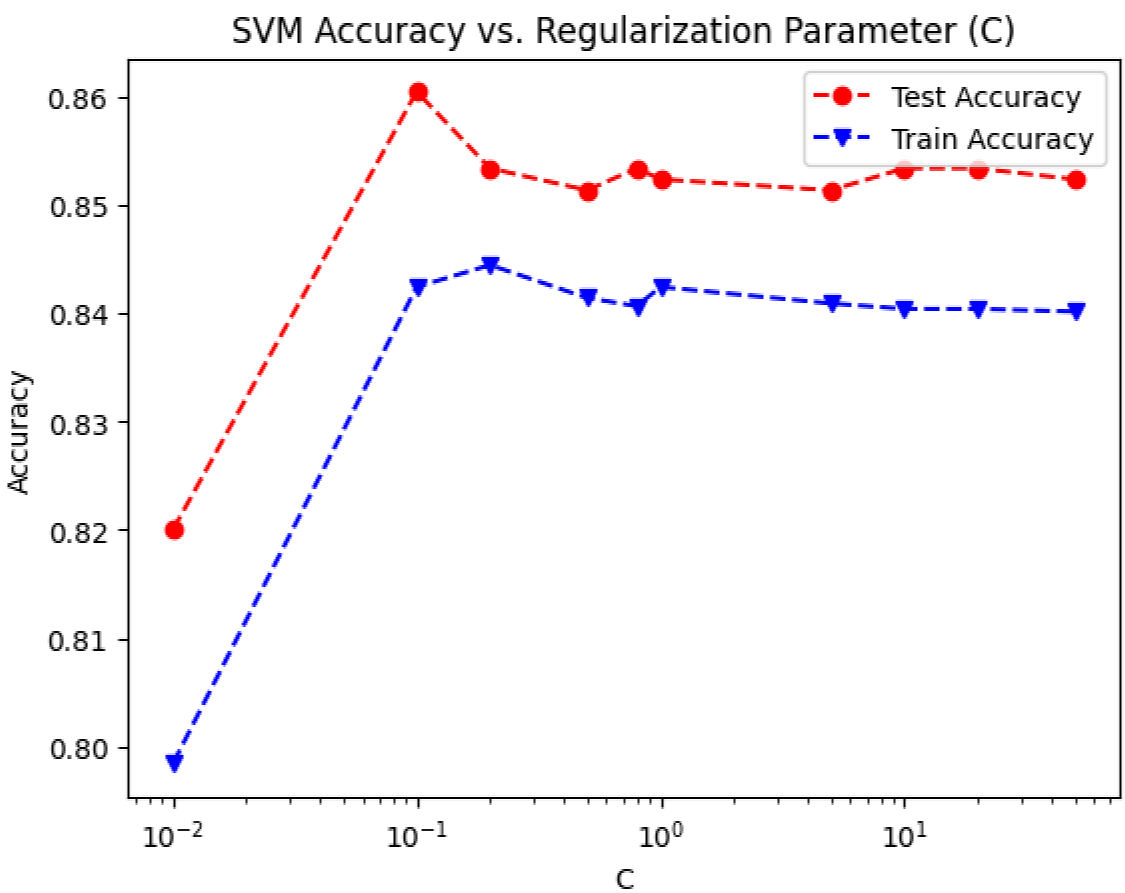

```
K-Nearest Neightbor (KNN): = 81.597573%
```

Support Vector Machines (SVM) - Maddie

We use SVM in high-dimensional spaces because of its capability to effectively tackle non-linear classification tasks via kernel functions. This method provides robust theoretical underpinnings and exhibits memory efficiency by leveraging support vectors, which are a subset of training data points that determine the decision boundary. By employing kernel functions, SVMs can map input data into higher-dimensional spaces where non-linear relationships between features can be more easily captured, thus enhancing their ability to discern complex patterns in the data. This combination of theoretical soundness, memory efficiency, and flexibility in handling non-linearities makes SVMs a compelling choice for various classification tasks, particularly those involving intricate feature interactions.

In [10]:
```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
```

```
import matplotlib.pyplot as plt

C = [0.01, 0.1, 0.2, 0.5, 0.8, 1, 5, 10, 20, 50]

SVMLtestAcc = []
SVMLtrainAcc = []

for param in C:
    clf = SVC(C=param, kernel='linear')
    clf.fit(X_train, y_train)
    svml_pred = clf.predict(X_test)
    svml_pred_train = clf.predict(X_train)
    SVMLtestAcc.append(accuracy_score(y_test, svml_pred))
    SVMLtrainAcc.append(accuracy_score(y_train, svml_pred_train))

plt.plot(C, SVMLtestAcc, 'ro--', C, SVMLtrainAcc, 'bv--')
plt.legend(['Test Accuracy', 'Train Accuracy'])
plt.xlabel('C')
plt.xscale('log')
plt.ylabel('Accuracy')
plt.title('SVM Accuracy vs. Regularization Parameter (C)')
plt.show()

svm_acc = accuracy_score(y_test, svml_pred)
print('Support Vector Machines (SVM): = %f%%' % (svm_acc * 100))
```



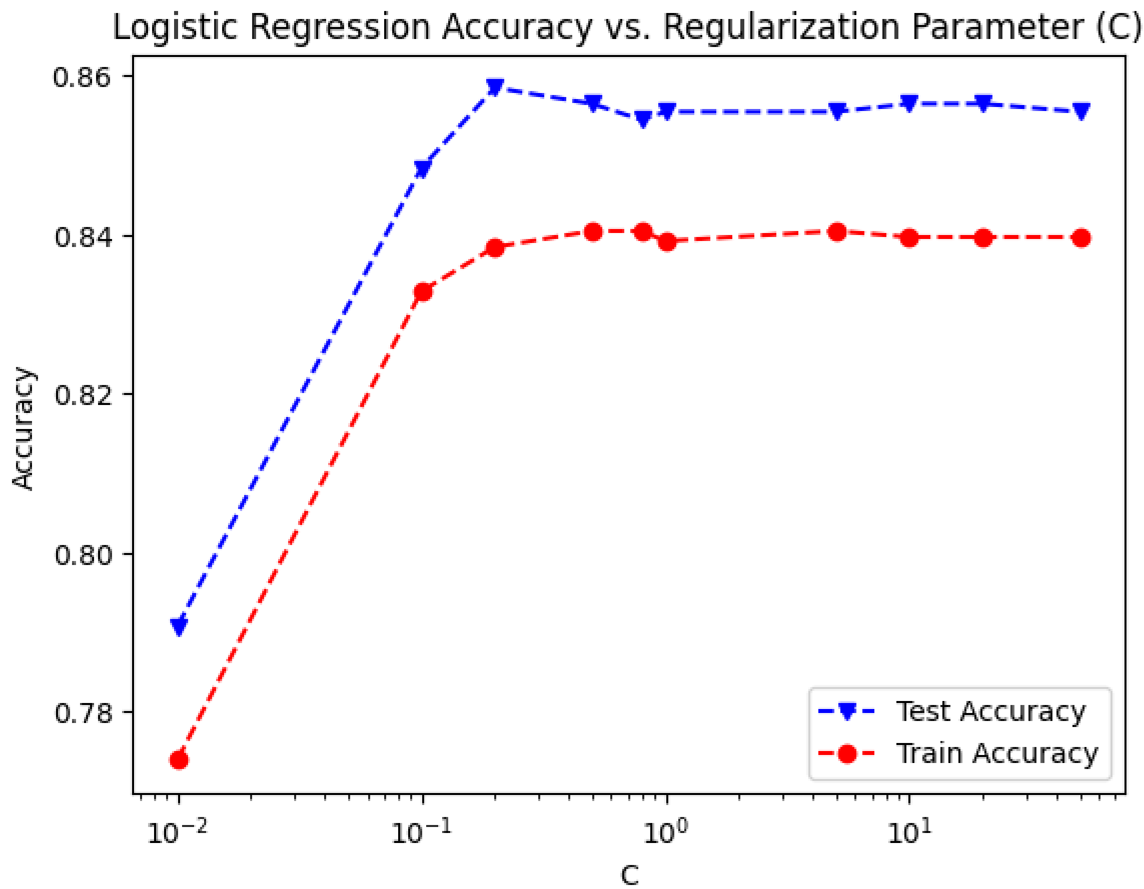

```
Support Vector Machines (SVM): = 85.237614%
```

Logistic Regression (Logit) - Maddie

We use Logistic Regression because it's well-suited for binary classification endeavors, offering utility when there is an approximate linear relationship between features and the target variable as desired. It becomes particularly advantageous when there is a need for probabilistic outputs, allowing for the assessment of the likelihood of an instance belonging to a certain class.

In [11]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt

C = [0.01, 0.1, 0.2, 0.5, 0.8, 1, 5, 10, 20, 50]

LRtestAcc = []
LRtrainAcc = []

for param in C:
    clf = LogisticRegression(C=param)
    clf.fit(X_train, y_train)
    log_reg_pred = clf.predict(X_test)
    log_reg_pred_train = clf.predict(X_train)
    LRtestAcc.append(accuracy_score(y_test, log_reg_pred))
    LRtrainAcc.append(accuracy_score(y_train, log_reg_pred_train))

plt.plot(C, LRtestAcc, 'bv--', C, LRtrainAcc, 'ro--')
plt.legend(['Test Accuracy', 'Train Accuracy'])
plt.xlabel('C')
plt.xscale('log')
plt.ylabel('Accuracy')
plt.title('Logistic Regression Accuracy vs. Regularization Parameter (C)')
plt.show()

log_reg_acc = accuracy_score(y_test, log_reg_pred)
print('Logistic Regression (Logit): = %f%%' % (log_reg_acc * 100))
```




```
Logistic Regression (Logit): = 85.540950%
```

Conclusion - Rahul

Here are all the accuracies of the models applied to the housing dataset so they can be compared.

In [12]:
```
print('Naïve Bayes Accuracy: = %f%%' % (naive_bayes_acc * 100))
print('Decision Tree Accuracy: = %f%%' % (dec_tree_acc * 100))
print('K-Nearest Neightbor (KNN): = %f%%' % (knn_acc * 100))
print('Support Vector Machines (SVM): = %f%%' % (svm_acc * 100))
print('Logistic Regression (Logit): = %f%%' % (log_reg_acc * 100))
```

```
Naïve Bayes Accuracy: = 78.968655%
Decision Tree Accuracy: = 73.407482%
K-Nearest Neightbor (KNN): = 81.597573%
Support Vector Machines (SVM): = 85.237614%
Logistic Regression (Logit): = 85.540950%
```

We can see that logistic regression (logit) had the highest accuracy value. This is a little odd because logistic regression is designed for binary classification e.g. true or false classes.

In [13]:
```
label_counts = normal_df['Price Category'].value_counts()
print(label_counts)
```

```
Price Category
Medium Price       2149
High Price         2146
Low Price           324
Very High Price     324
Name: count, dtype: int64
```

Upon further investigation, it appears that the dataset contains a disproportionate number of entries categorized as medium and high prices compared to those labeled as low and very high prices. This skewed distribution likely contributed to the higher accuracy observed with logistic regression, as it might have facilitated a de facto binary classification scenario due to most entries being either high price or medium price. To enhance accuracy for other models, adjusting the distribution of bins to achieve a more balanced representation across price categories could be beneficial, ensuring a fairer assessment of model performance across all classes.