C550-T301-Data_mining_2241_week7_Samanta_rajib

October 15, 2023

0.1 Class : C550-T301 Data Mining (2241-1)

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0.2.1 Assignment : Week 7

Part 1: PCA and Variance Threshold in a Linear Regression

1. Import the housing data as a data frame and ensure that the data is loaded properly.
2. Drop the "Id" column and any features that are missing more than 40% of their values.
3. For numerical columns, fill in any missing data with the median value.
4. For categorical columns, fill in any missing data with the most common value (mode).
5. Convert the categorical columns to dummy variables.
6. Split the data into a training and test set, where the SalePrice column is the target.
7. Run a linear regression and report the R2-value and RMSE on the test set.
8. Fit and transform the training features with a PCA so that 90% of the variance is retained (see section 9.1 in the Machine Learning with Python Cookbook).
9. How many features are in the PCA-transformed matrix?
10. Transform but DO NOT fit the test features with the same PCA.
11. Repeat step 7 with your PCA transformed data.
12. Take your original training features (from step 6) and apply a min-max scaler to them.
13. Find the min-max scaled features in your training set that have a variance above 0.1 (see Section 10.1 in the Machine Learning with Python Cookbook).
14. Transform but DO NOT fit the test features with the same steps applied in steps 11 and 12.
15. Repeat step 7 with the high variance data.
16. Summarize your findings.

[73]:
```python
# Import Libraries
import pandas as pd
import os
#pip install textblob
from textblob import TextBlob
# pip install vaderSentiment
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
import re
from sklearn.model_selection import train_test_split
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.decomposition import PCA
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.feature_selection import VarianceThreshold
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.tree import DecisionTreeClassifier
```

[74]:
```
# Read the labeled training dataset  file ('labeledTrainData.tsv') from local:
directory = '/Users/rajibsamanta/Documents/Rajib/College/Sem6_fall_2023/Week7'
# Set the working directory
os.chdir(directory)
print(os.getcwd())
# 1. Import the movie review data as a data frame and ensure that the data is␣
 ↪loaded properly.

file_name = "train.csv"

# Load the dataset into a pandas DataFrame
df = pd.read_csv(file_name)

# Display few records.
df.head()
```

```
/Users/rajibsamanta/Documents/Rajib/College/Sem6_fall_2023/Week7
```

[74]:
```
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave   NaN      Reg
1   2          20       RL         80.0     9600   Pave   NaN      Reg
2   3          60       RL         68.0    11250   Pave   NaN      IR1
3   4          70       RL         60.0     9550   Pave   NaN      IR1
4   5          60       RL         84.0    14260   Pave   NaN      IR1

  LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
0         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
1         Lvl    AllPub  …        0    NaN   NaN         NaN       0      5
2         Lvl    AllPub  …        0    NaN   NaN         NaN       0      9
3         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
4         Lvl    AllPub  …        0    NaN   NaN         NaN       0     12

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500
2   2008        WD         Normal     223500
```

```
3   2006         WD        Abnorml      140000
4   2008         WD         Normal      250000

[5 rows x 81 columns]
```

[75]:
```
# 2. Drop the "Id" column and any features that are missing more than 40% of␣
↪their values.
# Drop the "Id" column
df.drop(columns=['Id'], inplace=True)

# Calculate the threshold for dropping columns
threshold = 0.4 * len(df)
df = df.dropna(thresh=threshold, axis=1)

# Check the resulting dataset
df.head()
```

[75]:
```
   MSSubClass MSZoning  LotFrontage  LotArea Street LotShape LandContour  \
0          60       RL         65.0     8450   Pave      Reg         Lvl
1          20       RL         80.0     9600   Pave      Reg         Lvl
2          60       RL         68.0    11250   Pave      IR1         Lvl
3          70       RL         60.0     9550   Pave      IR1         Lvl
4          60       RL         84.0    14260   Pave      IR1         Lvl

  Utilities LotConfig LandSlope  … EnclosedPorch 3SsnPorch ScreenPorch  \
0    AllPub    Inside       Gtl  …             0         0           0
1    AllPub       FR2       Gtl  …             0         0           0
2    AllPub    Inside       Gtl  …             0         0           0
3    AllPub    Corner       Gtl  …           272         0           0
4    AllPub       FR2       Gtl  …             0         0           0

  PoolArea MiscVal  MoSold  YrSold  SaleType  SaleCondition SalePrice
0        0       0       2    2008        WD         Normal    208500
1        0       0       5    2007        WD         Normal    181500
2        0       0       9    2008        WD         Normal    223500
3        0       0       2    2006        WD        Abnorml    140000
4        0       0      12    2008        WD         Normal    250000

[5 rows x 76 columns]
```

[76]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 76 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   MSSubClass     1460 non-null   int64
```

1	MSZoning	1460 non-null	object
2	LotFrontage	1201 non-null	float64
3	LotArea	1460 non-null	int64
4	Street	1460 non-null	object
5	LotShape	1460 non-null	object
6	LandContour	1460 non-null	object
7	Utilities	1460 non-null	object
8	LotConfig	1460 non-null	object
9	LandSlope	1460 non-null	object
10	Neighborhood	1460 non-null	object
11	Condition1	1460 non-null	object
12	Condition2	1460 non-null	object
13	BldgType	1460 non-null	object
14	HouseStyle	1460 non-null	object
15	OverallQual	1460 non-null	int64
16	OverallCond	1460 non-null	int64
17	YearBuilt	1460 non-null	int64
18	YearRemodAdd	1460 non-null	int64
19	RoofStyle	1460 non-null	object
20	RoofMatl	1460 non-null	object
21	Exterior1st	1460 non-null	object
22	Exterior2nd	1460 non-null	object
23	MasVnrType	1452 non-null	object
24	MasVnrArea	1452 non-null	float64
25	ExterQual	1460 non-null	object
26	ExterCond	1460 non-null	object
27	Foundation	1460 non-null	object
28	BsmtQual	1423 non-null	object
29	BsmtCond	1423 non-null	object
30	BsmtExposure	1422 non-null	object
31	BsmtFinType1	1423 non-null	object
32	BsmtFinSF1	1460 non-null	int64
33	BsmtFinType2	1422 non-null	object
34	BsmtFinSF2	1460 non-null	int64
35	BsmtUnfSF	1460 non-null	int64
36	TotalBsmtSF	1460 non-null	int64
37	Heating	1460 non-null	object
38	HeatingQC	1460 non-null	object
39	CentralAir	1460 non-null	object
40	Electrical	1459 non-null	object
41	1stFlrSF	1460 non-null	int64
42	2ndFlrSF	1460 non-null	int64
43	LowQualFinSF	1460 non-null	int64
44	GrLivArea	1460 non-null	int64
45	BsmtFullBath	1460 non-null	int64
46	BsmtHalfBath	1460 non-null	int64
47	FullBath	1460 non-null	int64
48	HalfBath	1460 non-null	int64

```
 49   BedroomAbvGr   1460 non-null   int64
 50   KitchenAbvGr   1460 non-null   int64
 51   KitchenQual    1460 non-null   object
 52   TotRmsAbvGrd   1460 non-null   int64
 53   Functional     1460 non-null   object
 54   Fireplaces     1460 non-null   int64
 55   FireplaceQu    770 non-null    object
 56   GarageType     1379 non-null   object
 57   GarageYrBlt    1379 non-null   float64
 58   GarageFinish   1379 non-null   object
 59   GarageCars     1460 non-null   int64
 60   GarageArea     1460 non-null   int64
 61   GarageQual     1379 non-null   object
 62   GarageCond     1379 non-null   object
 63   PavedDrive     1460 non-null   object
 64   WoodDeckSF     1460 non-null   int64
 65   OpenPorchSF    1460 non-null   int64
 66   EnclosedPorch  1460 non-null   int64
 67   3SsnPorch      1460 non-null   int64
 68   ScreenPorch    1460 non-null   int64
 69   PoolArea       1460 non-null   int64
 70   MiscVal        1460 non-null   int64
 71   MoSold         1460 non-null   int64
 72   YrSold         1460 non-null   int64
 73   SaleType       1460 non-null   object
 74   SaleCondition  1460 non-null   object
 75   SalePrice      1460 non-null   int64
dtypes: float64(3), int64(34), object(39)
memory usage: 867.0+ KB
```

[77]:
```
# 3. For numerical columns, fill in any missing data with the median value.
# Identify numerical columns with missing values
# Find numerical columns with missing values
numerical_columns_with_missing = df.select_dtypes(include=['number']).
↪columns[df.select_dtypes(include=['number']).isnull().any()]

# Print the numerical columns with missing values
print(numerical_columns_with_missing)
# Fill missing values with the median for numerical columns
for column in numerical_columns_with_missing:
    median = df[column].median()
    df[column].fillna(median, inplace=True)

# Check the resulting dataset
df.head()
```

```
Index(['LotFrontage', 'MasVnrArea', 'GarageYrBlt'], dtype='object')
```

[77]:
```
   MSSubClass MSZoning  LotFrontage  LotArea Street LotShape LandContour  \
0          60       RL         65.0     8450   Pave      Reg         Lvl
1          20       RL         80.0     9600   Pave      Reg         Lvl
2          60       RL         68.0    11250   Pave      IR1         Lvl
3          70       RL         60.0     9550   Pave      IR1         Lvl
4          60       RL         84.0    14260   Pave      IR1         Lvl

  Utilities LotConfig LandSlope  … EnclosedPorch 3SsnPorch ScreenPorch  \
0    AllPub    Inside       Gtl  …             0         0           0
1    AllPub       FR2       Gtl  …             0         0           0
2    AllPub    Inside       Gtl  …             0         0           0
3    AllPub    Corner       Gtl  …           272         0           0
4    AllPub       FR2       Gtl  …             0         0           0

  PoolArea MiscVal  MoSold  YrSold  SaleType  SaleCondition SalePrice
0        0       0       2    2008        WD         Normal    208500
1        0       0       5    2007        WD         Normal    181500
2        0       0       9    2008        WD         Normal    223500
3        0       0       2    2006        WD        Abnorml    140000
4        0       0      12    2008        WD         Normal    250000

[5 rows x 76 columns]
```

[78]:
```python
# 4. For categorical columns, fill in any missing data with the most common␣
↪value (mode).
# Identify categorical columns with missing values
#categorical_columns_with_missing = df.select_dtypes(exclude=['number']).
↪columns[df.isnull().any()]
categorical_columns_with_missing = df.select_dtypes(exclude=['number']).
↪columns[df.select_dtypes(exclude=['number']).isnull().any()]

# Fill missing values with the mode for categorical columns
for column in categorical_columns_with_missing:
    mode = df[column].mode().iloc[0]  # Calculate the mode (most common value)␣
↪of the column
    df[column].fillna(mode, inplace=True)

# Check the resulting dataset
df.head()
```

[78]:
```
   MSSubClass MSZoning  LotFrontage  LotArea Street LotShape LandContour  \
0          60       RL         65.0     8450   Pave      Reg         Lvl
1          20       RL         80.0     9600   Pave      Reg         Lvl
2          60       RL         68.0    11250   Pave      IR1         Lvl
3          70       RL         60.0     9550   Pave      IR1         Lvl
4          60       RL         84.0    14260   Pave      IR1         Lvl
```

```
  Utilities LotConfig LandSlope  … EnclosedPorch 3SsnPorch ScreenPorch  \
0    AllPub    Inside       Gtl  …             0         0           0
1    AllPub       FR2       Gtl  …             0         0           0
2    AllPub    Inside       Gtl  …             0         0           0
3    AllPub    Corner       Gtl  …           272         0           0
4    AllPub       FR2       Gtl  …             0         0           0

  PoolArea MiscVal  MoSold  YrSold  SaleType  SaleCondition SalePrice
0        0       0       2    2008        WD         Normal    208500
1        0       0       5    2007        WD         Normal    181500
2        0       0       9    2008        WD         Normal    223500
3        0       0       2    2006        WD        Abnorml    140000
4        0       0      12    2008        WD         Normal    250000

[5 rows x 76 columns]
```

[79]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 76 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   MSSubClass     1460 non-null   int64
 1   MSZoning       1460 non-null   object
 2   LotFrontage    1460 non-null   float64
 3   LotArea        1460 non-null   int64
 4   Street         1460 non-null   object
 5   LotShape       1460 non-null   object
 6   LandContour    1460 non-null   object
 7   Utilities      1460 non-null   object
 8   LotConfig      1460 non-null   object
 9   LandSlope      1460 non-null   object
 10  Neighborhood   1460 non-null   object
 11  Condition1     1460 non-null   object
 12  Condition2     1460 non-null   object
 13  BldgType       1460 non-null   object
 14  HouseStyle     1460 non-null   object
 15  OverallQual    1460 non-null   int64
 16  OverallCond    1460 non-null   int64
 17  YearBuilt      1460 non-null   int64
 18  YearRemodAdd   1460 non-null   int64
 19  RoofStyle      1460 non-null   object
 20  RoofMatl       1460 non-null   object
 21  Exterior1st    1460 non-null   object
 22  Exterior2nd    1460 non-null   object
 23  MasVnrType     1460 non-null   object
 24  MasVnrArea     1460 non-null   float64
```

```
25  ExterQual      1460 non-null   object
26  ExterCond      1460 non-null   object
27  Foundation     1460 non-null   object
28  BsmtQual       1460 non-null   object
29  BsmtCond       1460 non-null   object
30  BsmtExposure   1460 non-null   object
31  BsmtFinType1   1460 non-null   object
32  BsmtFinSF1     1460 non-null   int64
33  BsmtFinType2   1460 non-null   object
34  BsmtFinSF2     1460 non-null   int64
35  BsmtUnfSF      1460 non-null   int64
36  TotalBsmtSF    1460 non-null   int64
37  Heating        1460 non-null   object
38  HeatingQC      1460 non-null   object
39  CentralAir     1460 non-null   object
40  Electrical     1460 non-null   object
41  1stFlrSF       1460 non-null   int64
42  2ndFlrSF       1460 non-null   int64
43  LowQualFinSF   1460 non-null   int64
44  GrLivArea      1460 non-null   int64
45  BsmtFullBath   1460 non-null   int64
46  BsmtHalfBath   1460 non-null   int64
47  FullBath       1460 non-null   int64
48  HalfBath       1460 non-null   int64
49  BedroomAbvGr   1460 non-null   int64
50  KitchenAbvGr   1460 non-null   int64
51  KitchenQual    1460 non-null   object
52  TotRmsAbvGrd   1460 non-null   int64
53  Functional     1460 non-null   object
54  Fireplaces     1460 non-null   int64
55  FireplaceQu    1460 non-null   object
56  GarageType     1460 non-null   object
57  GarageYrBlt    1460 non-null   float64
58  GarageFinish   1460 non-null   object
59  GarageCars     1460 non-null   int64
60  GarageArea     1460 non-null   int64
61  GarageQual     1460 non-null   object
62  GarageCond     1460 non-null   object
63  PavedDrive     1460 non-null   object
64  WoodDeckSF     1460 non-null   int64
65  OpenPorchSF    1460 non-null   int64
66  EnclosedPorch  1460 non-null   int64
67  3SsnPorch      1460 non-null   int64
68  ScreenPorch    1460 non-null   int64
69  PoolArea       1460 non-null   int64
70  MiscVal        1460 non-null   int64
71  MoSold         1460 non-null   int64
72  YrSold         1460 non-null   int64
```

```
 73  SaleType       1460 non-null   object
 74  SaleCondition  1460 non-null   object
 75  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(34), object(39)
memory usage: 867.0+ KB
```

It shows all 1460 etries for all columns have values.

[80]:
```python
# 5. Convert the categorical columns to dummy variables.
# Identify categorical columns
categorical_columns = df.select_dtypes(exclude=['number']).columns

# Convert categorical columns to dummy variables
df = pd.get_dummies(df, columns=categorical_columns, drop_first=True)

# Check the resulting dataset
df.head()
```

[80]:
```
   MSSubClass  LotFrontage  LotArea  OverallQual  OverallCond  YearBuilt  \
0          60         65.0     8450            7            5       2003
1          20         80.0     9600            6            8       1976
2          60         68.0    11250            7            5       2001
3          70         60.0     9550            7            5       1915
4          60         84.0    14260            8            5       2000

   YearRemodAdd  MasVnrArea  BsmtFinSF1  BsmtFinSF2  …  SaleType_ConLI  \
0          2003       196.0         706           0  …               0
1          1976         0.0         978           0  …               0
2          2002       162.0         486           0  …               0
3          1970         0.0         216           0  …               0
4          2000       350.0         655           0  …               0

   SaleType_ConLw  SaleType_New  SaleType_Oth  SaleType_WD  \
0               0             0             0            1
1               0             0             0            1
2               0             0             0            1
3               0             0             0            1
4               0             0             0            1

   SaleCondition_AdjLand  SaleCondition_Alloca  SaleCondition_Family  \
0                      0                     0                     0
1                      0                     0                     0
2                      0                     0                     0
3                      0                     0                     0
4                      0                     0                     0

   SaleCondition_Normal  SaleCondition_Partial
0                     1                      0
```

```
1                     1                     0
2                     1                     0
3                     0                     0
4                     1                     0

[5 rows x 237 columns]
```

[81]:
```python
# 6. Split the data into a training and test set, where the SalePrice column is␣
↪the target.
# Define features (X) and target (y)
X = df.drop(columns=['SalePrice'])  # Features (all columns except 'SalePrice')
y = df['SalePrice']  # Target variable

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Check the shapes of the resulting sets
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("y_train shape:", y_train.shape)
print("y_test shape:", y_test.shape)
```

```
X_train shape: (1168, 236)
X_test shape: (292, 236)
y_train shape: (1168,)
y_test shape: (292,)
```

[82]:
```python
# 7. Run a linear regression and report the R2-value and RMSE on the test set.
# Initialize and train a linear regression model
lr = LinearRegression()
lr.fit(X_train, y_train)

# Make predictions on the test set
y_pred = lr.predict(X_test)

# Calculate R-squared (R2) and RMSE
r2 = r2_score(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

# Report the results
print("R-squared (R2) on the test set:", r2)
print("Root Mean Squared Error (RMSE) on the test set:", rmse)
```

```
R-squared (R2) on the test set: 0.6443655136574274
Root Mean Squared Error (RMSE) on the test set: 52228.65612643088
```

$0 < R2 < 1$: The model explains a portion of the variation in the target variable. A higher R2 value indicates a better fit, with values closer to 1 indicating a stronger relationship between the features and the target. Here it is 0.64 means that the model has medium positive relationship.

[83]:
```
# 8. Fit and transform the training features with a PCA so that 90% of the␣
↪variance is retained
# 9. How many features are in the PCA-transformed matrix?
# Standardize the features (mean=0, std=1)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Fit PCA to retain 90% of the variance
pca = PCA(n_components=0.90)
X_pca = pca.fit_transform(X_scaled)

# Check the number of retained principal components
print("Number of retained principal components:", X_pca.shape[1])
```

```
Number of retained principal components: 133
```

Number of retained principal components: 133

[84]:
```
# 10. Transform but DO NOT fit the test features with the same PCA.
# Use the same PCA transformation on the test features (without refitting)
X_test_scaled = scaler.transform(X_test)  # Standardize the test features
X_test_pca = pca.transform(X_test_scaled)  # Apply the same PCA transformation

# Check the shape of the PCA-transformed test features
print("Shape of PCA-transformed test features:", X_test_pca.shape)
```

```
Shape of PCA-transformed test features: (292, 133)
```

[85]:
```
# 11. Repeat step 7 with your PCA transformed data
# Initialize and train a linear regression model on the PCA-transformed␣
↪training data
lr = LinearRegression()
lr.fit(X_test_pca, y_test)

# Make predictions on the PCA-transformed test data
y_pred_pca = lr.predict(X_test_pca)

# Calculate R-squared (R2) and RMSE
r2_pca = r2_score(y_test, y_pred_pca)
rmse_pca = np.sqrt(mean_squared_error(y_test, y_pred_pca))

# Report the results
print("R-squared (R2) on the PCA-transformed test set:", r2_pca)
print("Root Mean Squared Error (RMSE) on the PCA-transformed test set:",␣
↪rmse_pca)
```

```
R-squared (R2) on the PCA-transformed test set: 0.949684899472069
Root Mean Squared Error (RMSE) on the PCA-transformed test set:
```

```
19645.183485950038
```

0 < R2 < 1: A higher R2 value indicates a better fit, with values closer to 1 indicating a stronger relationship between the features and the target. Here it is 0.9496 means that the model has strong positive relationship.

[86]:
```
# 12. Take your original training features (from step 6) and apply a min-max␣
↪scaler to them.
# Define features (X) and target (y)
X = df.drop(columns=['SalePrice'])  # Original training features (all columns␣
↪except 'SalePrice')
y = df['SalePrice']  # Target variable

# Initialize the Min-Max scaler
scaler = MinMaxScaler()

# Fit and transform the features using the Min-Max scaler
X_scaled = scaler.fit_transform(X)

# Check the resulting scaled features
print("Scaled features using Min-Max scaler:")
print(X_scaled)
```

```
Scaled features using Min-Max scaler:
[[0.23529412 0.15068493 0.0334198  … 0.         1.         0.        ]
 [0.         0.20205479 0.03879502 … 0.         1.         0.        ]
 [0.23529412 0.1609589  0.04650728 … 0.         1.         0.        ]
 …
 [0.29411765 0.15410959 0.03618687 … 0.         1.         0.        ]
 [0.         0.1609589  0.03934189 … 0.         1.         0.        ]
 [0.         0.18493151 0.04037019 … 0.         1.         0.        ]]
```

[87]:
```
# 13. Find the min-max scaled features in your training set that have a␣
↪variance above 0.1
# Initialize the VarianceThreshold selector with a threshold of 0.1
selector = VarianceThreshold(threshold=0.1)

# Fit the selector on the scaled features
selector.fit(X_scaled)

# Get the indices of the selected features
selected_feature_indices = selector.get_support(indices=True)

# Get the names of the selected features
selected_features = X.columns[selected_feature_indices]

# Check the names of the selected features
print("Selected features with variance above 0.1:")
```

```
print(selected_features)
```

```
Selected features with variance above 0.1:
Index(['YearRemodAdd', 'YrSold', 'MSZoning_RL', 'MSZoning_RM', 'LotShape_Reg',
       'LotConfig_Inside', 'Neighborhood_NAmes', 'Condition1_Norm',
       'HouseStyle_1Story', 'HouseStyle_2Story', 'RoofStyle_Gable',
       'RoofStyle_Hip', 'Exterior1st_HdBoard', 'Exterior1st_MetalSd',
       'Exterior1st_VinylSd', 'Exterior1st_Wd Sdng', 'Exterior2nd_HdBoard',
       'Exterior2nd_MetalSd', 'Exterior2nd_VinylSd', 'Exterior2nd_Wd Sdng',
       'MasVnrType_BrkFace', 'MasVnrType_None', 'ExterQual_Gd', 'ExterQual_TA',
       'ExterCond_TA', 'Foundation_CBlock', 'Foundation_PConc', 'BsmtQual_Gd',
       'BsmtQual_TA', 'BsmtExposure_No', 'BsmtFinType1_GLQ',
       'BsmtFinType1_Unf', 'BsmtFinType2_Unf', 'HeatingQC_Gd', 'HeatingQC_TA',
       'KitchenQual_Gd', 'KitchenQual_TA', 'FireplaceQu_Gd', 'FireplaceQu_TA',
       'GarageType_Attchd', 'GarageType_Detchd', 'GarageFinish_RFn',
       'GarageFinish_Unf', 'SaleType_WD', 'SaleCondition_Normal'],
      dtype='object')
```

[88]:
```
# 14. Transform but DO NOT fit the test features with the same steps applied in␣
 ↪steps 11 and 12.
# Initialize the Min-Max scaler
scaler = MinMaxScaler()

# Fit and transform the training features using the Min-Max scaler
X_train_scaled = scaler.fit_transform(X_train)

# Initialize the VarianceThreshold selector with a threshold of 0.1
selector = VarianceThreshold(threshold=0.1)

# Fit the selector on the scaled training features
selector.fit(X_train_scaled)

# Transform the test features using the same Min-Max scaling and variance␣
 ↪threshold
X_test_scaled = scaler.transform(X_test)
X_test_filtered = selector.transform(X_test_scaled)

# Check the shape of the transformed test features
print("Shape of test features after Min-Max scaling and variance threshold␣
 ↪filtering:", X_test_filtered.shape)
```

```
Shape of test features after Min-Max scaling and variance threshold filtering:
(292, 44)
```

[89]:
```
# 15. Repeat step 7 with the high variance data.
# Define features (X) and target (y)
X = df.drop(columns=['SalePrice'])  # Features (all columns except 'SalePrice')
y = df['SalePrice']  # Target variable
```

```
# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=50)

# Check the shapes of the resulting sets
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("y_train shape:", y_train.shape)
print("y_test shape:", y_test.shape)

# Initialize the Min-Max scaler
scaler = MinMaxScaler()

# Fit and transform the training features using the Min-Max scaler
X_train_scaled = scaler.fit_transform(X_train)

# Initialize the VarianceThreshold selector with a threshold of 0.1
selector = VarianceThreshold(threshold=0.1)

# Fit the selector on the scaled training features
selector.fit(X_train_scaled)

# Transform the training and test features using the same Min-Max scaling and␣
 ↪variance threshold
X_train_filtered = selector.transform(X_train_scaled)
X_test_scaled = scaler.transform(X_test)
X_test_filtered = selector.transform(X_test_scaled)

# Initialize and train a linear regression model on the training data
lr = LinearRegression()
lr.fit(X_train_filtered, y_train)

# Make predictions on the test data with the high variance data
y_pred_filtered = lr.predict(X_test_filtered)

# Calculate R-squared (R2) and RMSE
r2_filtered = r2_score(y_test, y_pred_filtered)
rmse_filtered = np.sqrt(mean_squared_error(y_test, y_pred_filtered))

# Report the results
print("R-squared (R2) on the test set with high variance data:", r2_filtered)
print("Root Mean Squared Error (RMSE) on the test set with high variance data:
 ↪", rmse_filtered)
```

```
X_train shape: (1168, 236)
X_test shape: (292, 236)
```

```
y_train shape: (1168,)
y_test shape: (292,)
R-squared (R2) on the test set with high variance data: 0.6223372171333519
Root Mean Squared Error (RMSE) on the test set with high variance data:
49573.384043468955
```

Using the PCA the R-squared (R2) value is 0.95 which is closed to 1 , means model has strong relationship and its close to actual whereas with attribute's feature linear regression model's R-squared (R2) is around 0.6 means meduim accurecy.

0.2.2 Part 2: Categorical Feature Selection

1. Import the data as a data frame and ensure it is loaded correctly.
2. Convert the categorical features (all of them) to dummy variables.
3. Split the data into a training and test set.
4. Fit a decision tree classifier on the training set.
5. Report the accuracy and create a confusion matrix for the model prediction on the test set.
6. Create a visualization of the decision tree.
7. Use a 2-statistic selector to pick the five best features for this data (see section 10.4 of the Machine Learning with Python Cookbook).
8. Which five features were selected in step 7? Hint: Use the get_support function.
9. Repeat steps 4 and 5 with the five best features selected in step 7.
10. Summarize your findings.

[90]:
```python
# 1. Import the data as a data frame and ensure it is loaded correctly.

file_name = "mushrooms.csv"

# Load the dataset into a pandas DataFrame
dataset = pd.read_csv(file_name)

# Display few records.
dataset.head()
```

[90]:
```
  class cap-shape cap-surface cap-color bruises odor gill-attachment  \
0     p         x           s         n       t    p               f
1     e         x           s         y       t    a               f
2     e         b           s         w       t    l               f
3     p         x           y         w       t    p               f
4     e         x           s         g       f    n               f

  gill-spacing gill-size gill-color … stalk-surface-below-ring  \
0            c         n          k …                        s
1            c         b          k …                        s
2            c         b          n …                        s
3            c         n          n …                        s
4            w         b          k …                        s
```

```
  stalk-color-above-ring stalk-color-below-ring veil-type veil-color  \
0                      w                      w         p          w
1                      w                      w         p          w
2                      w                      w         p          w
3                      w                      w         p          w
4                      w                      w         p          w

  ring-number ring-type spore-print-color population habitat
0           o         p                 k          s       u
1           o         p                 n          n       g
2           o         p                 n          n       m
3           o         p                 k          s       u
4           o         e                 n          a       g

[5 rows x 23 columns]
```

[91]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8124 entries, 0 to 8123
Data columns (total 23 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   class                     8124 non-null   object
 1   cap-shape                 8124 non-null   object
 2   cap-surface               8124 non-null   object
 3   cap-color                 8124 non-null   object
 4   bruises                   8124 non-null   object
 5   odor                      8124 non-null   object
 6   gill-attachment           8124 non-null   object
 7   gill-spacing              8124 non-null   object
 8   gill-size                 8124 non-null   object
 9   gill-color                8124 non-null   object
 10  stalk-shape               8124 non-null   object
 11  stalk-root                8124 non-null   object
 12  stalk-surface-above-ring  8124 non-null   object
 13  stalk-surface-below-ring  8124 non-null   object
 14  stalk-color-above-ring    8124 non-null   object
 15  stalk-color-below-ring    8124 non-null   object
 16  veil-type                 8124 non-null   object
 17  veil-color                8124 non-null   object
 18  ring-number               8124 non-null   object
 19  ring-type                 8124 non-null   object
 20  spore-print-color         8124 non-null   object
 21  population                8124 non-null   object
 22  habitat                   8124 non-null   object
dtypes: object(23)
memory usage: 1.4+ MB
```

[92]:
```
# 2. Convert the categorical features (all of them) to dummy variables.

# Convert categorical features to dummy variables
dataset_dummies = pd.get_dummies(dataset)

# Save the dataset with dummy variables to a new CSV file
dataset_dummies.to_csv('mushrooms_with_dummies.csv', index=False)
dataset_dummies.head()
```

[92]:
```
   class_e  class_p  cap-shape_b  cap-shape_c  cap-shape_f  cap-shape_k  \
0        0        1            0            0            0            0
1        1        0            0            0            0            0
2        1        0            1            0            0            0
3        0        1            0            0            0            0
4        1        0            0            0            0            0

   cap-shape_s  cap-shape_x  cap-surface_f  cap-surface_g  …  population_s  \
0            0            1              0              0  …             1
1            0            1              0              0  …             0
2            0            0              0              0  …             0
3            0            1              0              0  …             1
4            0            1              0              0  …             0

   population_v  population_y  habitat_d  habitat_g  habitat_l  habitat_m  \
0             0             0          0          0          0          0
1             0             0          0          1          0          0
2             0             0          0          0          0          1
3             0             0          0          0          0          0
4             0             0          0          1          0          0

   habitat_p  habitat_u  habitat_w
0          0          1          0
1          0          0          0
2          0          0          0
3          0          1          0
4          0          0          0

[5 rows x 119 columns]
```

[93]:
```
dataset_dummies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8124 entries, 0 to 8123
Columns: 119 entries, class_e to habitat_w
dtypes: uint8(119)
memory usage: 944.2 KB
```

[94]:
```
print(dataset.columns)
```

```
Index(['class', 'cap-shape', 'cap-surface', 'cap-color', 'bruises', 'odor',
       'gill-attachment', 'gill-spacing', 'gill-size', 'gill-color',
       'stalk-shape', 'stalk-root', 'stalk-surface-above-ring',
       'stalk-surface-below-ring', 'stalk-color-above-ring',
       'stalk-color-below-ring', 'veil-type', 'veil-color', 'ring-number',
       'ring-type', 'spore-print-color', 'population', 'habitat'],
      dtype='object')
```

[95]:

```
# 3. Split the data into a training and test set.
# 4. Fit a decision tree classifier on the training set.
# Encode categorical features into dummy variables
dataset = pd.get_dummies(dataset, columns=dataset.
 ↪select_dtypes(include=['object']).columns)

# Split the data into features (X) and the target (y)
X = dataset.drop(columns=['class_e'])  # Features (all columns except 'class')
y = dataset['class_e']  # Target variable

# Split the data into a training set and a test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Create a Decision Tree Classifier
clf = DecisionTreeClassifier(random_state=42)

# Fit the classifier on the training set
clf.fit(X_train, y_train)
```

[95]:

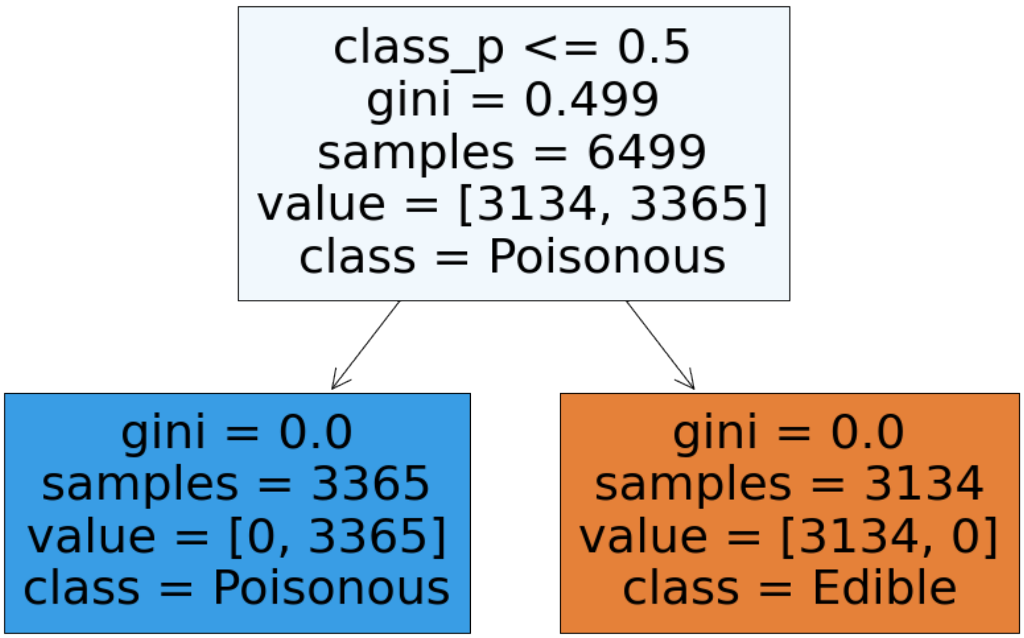
```
DecisionTreeClassifier(random_state=42)
```

[96]:

```
# 5. Report the accuracy and create a confusion matrix for the model prediction␣
 ↪on the test set.
# Make predictions on the test set
y_pred = clf.predict(X_test)

# Calculate the accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

# Create a confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
```

```
Accuracy: 1.0
Confusion Matrix:
[[782   0]
 [  0 843]]
```

[97]:
```
# 6. Create a visualization of the decision tree.
# Create a figure and set its size
plt.figure(figsize=(15, 10))

# Use the plot_tree function to visualize the decision tree
plot_tree(clf, feature_names=X.columns, class_names=["Edible", "Poisonous"],␣
↪filled=True)

# Display the tree plot
plt.show()
```



[98]:
```
# 7. Use a 2-statistic selector to pick the five best features for this data
# 8. Which five features were selected in step 7?
# Initialize the SelectKBest feature selector with chi2 scoring
selector = SelectKBest(score_func=chi2, k=5)  # Select the top 5 features

# Fit the selector on the features and target
X_new = selector.fit_transform(X, y)

# Get the indices of the selected features
selected_feature_indices = selector.get_support(indices=True)

# Get the names of the selected features
```

```
selected_features = X.columns[selected_feature_indices]

# Print the names of the selected features
print("Selected Features:")
print(selected_features)
```

```
Selected Features:
Index(['class_p', 'odor_f', 'odor_n', 'stalk-surface-above-ring_k',
       'stalk-surface-below-ring_k'],
      dtype='object')
```

Selected Features : 'class_p', 'odor_f', 'odor_n', 'stalk-surface-above-ring_k','stalk-surface-below-ring_k'

[99]:
```
# 9. Repeat steps 4 and 5 with the five best features selected in step 7.

# Use only the selected features for X
X_selected = X[selected_features]

# Split the data into a training set and a test set using the selected features
X_train_selected, X_test_selected, y_train, y_test =␣
 ↪train_test_split(X_selected, y, test_size=0.2, random_state=42)

# Create a Decision Tree Classifier
clf_selected = DecisionTreeClassifier(random_state=42)

# Fit the classifier on the training set using the selected features
clf_selected.fit(X_train_selected, y_train)
```

[99]:
```
DecisionTreeClassifier(random_state=42)
```

[100]:
```
# 9.2 : Report the accuracy and create a confusion matrix for the model␣
 ↪prediction on the test set.
# Make predictions on the test set using the model with selected features
y_pred_selected = clf_selected.predict(X_test_selected)

# Calculate the accuracy
accuracy_selected = accuracy_score(y_test, y_pred_selected)
print("Accuracy (Selected Features):", accuracy_selected)

# Create a confusion matrix
conf_matrix_selected = confusion_matrix(y_test, y_pred_selected)
print("Confusion Matrix (Selected Features):")
print(conf_matrix_selected)
```

```
Accuracy (Selected Features): 1.0
Confusion Matrix (Selected Features):
[[782   0]
 [  0 843]]
```

Predicted Negative Positive Actual Negative TN FP Positive FN TP 1. True Positives (TP): These are correct positive predictions, indicating that the model correctly identified cases of the positive class & the value is 843 2. True Negatives (TN): These are correct negative predictions, indicating that the model correctly identified cases of the negative class & the value is 782 3. False Positives (FP): These are incorrect positive predictions, meaning the model predicted the positive class when it was actually the negative class. This is also known as a Type I error. The value is 0, which means good model. 4. False Negatives (FN): These are incorrect negative predictions, meaning the model predicted the negative class when it was actually the positive class. This is also known as a Type II error.The value is 0, which means good model. * The confusion matrix is a valuable tool for understanding the performance of a classification model and can be used to calculate various evaluation metrics such as accuracy, precision, recall, and F1-score. These metrics help assess the model's overall performance and the balance between true and false predictions.This model shows strong prediction results.

[ ]:
```

```