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.

In [1]:
```
#Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from math import sqrt
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn import preprocessing
from sklearn.feature_selection import VarianceThreshold
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
import seaborn as sns
import pydotplus
from IPython.display import Image
from sklearn import tree
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import scale
```

In [2]:
```
housing_df = pd.read_csv("train.csv")
```

In [3]:
```
print(housing_df.shape)
housing_df.head(5)
```

```
(1460, 81)
```

Out[3]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolAr
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...	

5 rows × 81 columns

2. Drop the "Id" column and any features that are missing more than 40% of their values.

In [4]:
```
housing_df.drop('Id',axis=1,inplace=True)
housing_df.head(5)
```

Out[4]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	...

0	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	Inside	...
1	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	FR2	...
2	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	Inside	...
3	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	Corner	...
4	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	FR2	...

5 rows × 80 columns

In [5]:
```
housing_df_null = housing_df.isnull().sum() / len(housing_df) #Calculate % of null value
housing_df_null
```

Out[5]:
```
MSSubClass       0.000000
MSZoning         0.000000
LotFrontage      0.177397
LotArea          0.000000
Street           0.000000
                   ...
MoSold           0.000000
YrSold           0.000000
SaleType         0.000000
SaleCondition    0.000000
SalePrice        0.000000
Length: 80, dtype: float64
```

In [6]:
```
missing_features = housing_df_null[housing_df_null > 0.40].index #Identify columns with
missing_features
```

Out[6]:
```
Index(['Alley', 'FireplaceQu', 'PoolQC', 'Fence', 'MiscFeature'], dtype='object')
```

In [7]:
```
#Drop the columns with over 40% missing values

housing_df.drop(missing_features, axis=1, inplace=True)
```

In [8]:
```
housing_df.head(5)
```

Out[8]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope
0	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	Inside	Gtl
1	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	FR2	Gtl
2	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	Inside	Gtl
3	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	Corner	Gtl
4	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	FR2	Gtl

5 rows × 75 columns

In [9]:
```
housing_df.shape #Display the number of rows and columns in the dataframe
```

Out[9]:
```
(1460, 75)
```

3. For numerical columns, fill in any missing data with the median value.

In [10]:
```
#Identify numeric columns in the dataframe
housing_df.select_dtypes(include=np.number).columns
```

```
Index(['MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual', 'OverallCond',
```

Out[10]:
```
         'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2',
         'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
         'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
         'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces',
         'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
         'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal',
         'MoSold', 'YrSold', 'SalePrice'],
        dtype='object')
```

In [11]:
```
#Look for the number of missing values in the numeric fields of the dataframe
housing_df.select_dtypes([np.number]).isnull().sum()
```

Out[11]:
```
MSSubClass         0
LotFrontage      259
LotArea            0
OverallQual        0
OverallCond        0
YearBuilt          0
YearRemodAdd       0
MasVnrArea         8
BsmtFinSF1         0
BsmtFinSF2         0
BsmtUnfSF          0
TotalBsmtSF        0
1stFlrSF           0
2ndFlrSF           0
LowQualFinSF       0
GrLivArea          0
BsmtFullBath       0
BsmtHalfBath       0
FullBath           0
HalfBath           0
BedroomAbvGr       0
KitchenAbvGr       0
TotRmsAbvGrd       0
Fireplaces         0
GarageYrBlt       81
GarageCars         0
GarageArea         0
WoodDeckSF         0
OpenPorchSF        0
EnclosedPorch      0
3SsnPorch          0
ScreenPorch        0
PoolArea           0
MiscVal            0
MoSold             0
YrSold             0
SalePrice          0
dtype: int64
```

In [12]:
```
#Median before the update
housing_df.select_dtypes([np.number]).median()
```

Out[12]:
```
MSSubClass          50.0
LotFrontage         69.0
LotArea           9478.5
OverallQual          6.0
OverallCond          5.0
YearBuilt         1973.0
YearRemodAdd      1994.0
MasVnrArea           0.0
BsmtFinSF1         383.5
BsmtFinSF2           0.0
BsmtUnfSF          477.5
TotalBsmtSF        991.5
```

```
1stFlrSF            1087.0
2ndFlrSF               0.0
LowQualFinSF           0.0
GrLivArea           1464.0
BsmtFullBath           0.0
BsmtHalfBath           0.0
FullBath               2.0
HalfBath               0.0
BedroomAbvGr           3.0
KitchenAbvGr           1.0
TotRmsAbvGrd           6.0
Fireplaces             1.0
GarageYrBlt         1980.0
GarageCars             2.0
GarageArea           480.0
WoodDeckSF             0.0
OpenPorchSF           25.0
EnclosedPorch          0.0
3SsnPorch              0.0
ScreenPorch            0.0
PoolArea               0.0
MiscVal                0.0
MoSold                 6.0
YrSold              2008.0
SalePrice         163000.0
dtype: float64
```

In [13]:

```
#Filling the missing/null values in the dataframe with the median
housing_df.fillna(housing_df.select_dtypes([np.number]).median().iloc[0],inplace=True)
```

In [14]:

```
#Look for the number of missing values in the numeric fields of the dataframe after upda
housing_df.select_dtypes([np.number]).isnull().sum()
```

Out[14]:

```
MSSubClass       0
LotFrontage      0
LotArea          0
OverallQual      0
OverallCond      0
YearBuilt        0
YearRemodAdd     0
MasVnrArea       0
BsmtFinSF1       0
BsmtFinSF2       0
BsmtUnfSF        0
TotalBsmtSF      0
1stFlrSF         0
2ndFlrSF         0
LowQualFinSF     0
GrLivArea        0
BsmtFullBath     0
BsmtHalfBath     0
FullBath         0
HalfBath         0
BedroomAbvGr     0
KitchenAbvGr     0
TotRmsAbvGrd     0
Fireplaces       0
GarageYrBlt      0
GarageCars       0
GarageArea       0
WoodDeckSF       0
OpenPorchSF      0
EnclosedPorch    0
3SsnPorch        0
ScreenPorch      0
```

```
PoolArea         0
MiscVal          0
MoSold           0
YrSold           0
SalePrice        0
dtype: int64
```

In [15]:
```
#Median after the update
housing_df.select_dtypes([np.number]).median()
```

Out[15]:
```
MSSubClass            50.0
LotFrontage           63.0
LotArea             9478.5
OverallQual            6.0
OverallCond            5.0
YearBuilt           1973.0
YearRemodAdd        1994.0
MasVnrArea             0.0
BsmtFinSF1           383.5
BsmtFinSF2             0.0
BsmtUnfSF            477.5
TotalBsmtSF          991.5
1stFlrSF            1087.0
2ndFlrSF               0.0
LowQualFinSF           0.0
GrLivArea           1464.0
BsmtFullBath           0.0
BsmtHalfBath           0.0
FullBath               2.0
HalfBath               0.0
BedroomAbvGr           3.0
KitchenAbvGr           1.0
TotRmsAbvGrd           6.0
Fireplaces             1.0
GarageYrBlt         1977.0
GarageCars             2.0
GarageArea           480.0
WoodDeckSF             0.0
OpenPorchSF           25.0
EnclosedPorch          0.0
3SsnPorch              0.0
ScreenPorch            0.0
PoolArea               0.0
MiscVal                0.0
MoSold                 6.0
YrSold              2008.0
SalePrice         163000.0
dtype: float64
```

4. For categorical columns, fill in any missing data with the most common value (mode).

In [16]:
```
#Identify categorical columns and their most common values
housing_df.select_dtypes([object]).mode()
```

Out[16]:

	MSZoning	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Condit
0	RL	Pave	Reg	Lvl	AllPub	Inside	Gtl	NAmes	Norm	N

1 rows × 38 columns

In [17]:
```
#Replace missing values in categorical columns with their most common values
housing_df.fillna(housing_df.select_dtypes([object]).mode().iloc[0],inplace=True)
```

```
housing_df.head(5)
```

Out[17]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope
0	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	Inside	Gtl
1	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	FR2	Gtl
2	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	Inside	Gtl
3	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	Corner	Gtl
4	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	FR2	Gtl

5 rows × 75 columns

In [18]:

```
housing_df.select_dtypes([object]).isnull().sum()
```

Out[18]:

```
MSZoning         0
Street           0
LotShape         0
LandContour      0
Utilities        0
LotConfig        0
LandSlope        0
Neighborhood     0
Condition1       0
Condition2       0
BldgType         0
HouseStyle       0
RoofStyle        0
RoofMatl         0
Exterior1st      0
Exterior2nd      0
MasVnrType       0
ExterQual        0
ExterCond        0
Foundation       0
BsmtQual         0
BsmtCond         0
BsmtExposure     0
BsmtFinType1     0
BsmtFinType2     0
Heating          0
HeatingQC        0
CentralAir       0
Electrical       0
KitchenQual      0
Functional       0
GarageType       0
GarageFinish     0
GarageQual       0
GarageCond       0
PavedDrive       0
SaleType         0
SaleCondition    0
dtype: int64
```

5. Convert the categorical columns to dummy variables.

In [19]:

```
housing_dummy_df = pd.get_dummies(housing_df, columns = housing_df.select_dtypes([object
housing_dummy_df.head(5)
```

Out[19]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFin

0	60	65.0	8450	7	5	2003	2003	196.0
1	20	80.0	9600	6	8	1976	1976	0.0
2	60	68.0	11250	7	5	2001	2002	162.0
3	70	60.0	9550	7	5	1915	1970	0.0
4	60	84.0	14260	8	5	2000	2000	350.0

5 rows × 282 columns

6. Split the data into a training and test set, where the SalePrice column is the target.

In [20]:
```
x = housing_dummy_df.loc[:,housing_dummy_df.columns != 'SalePrice']
#get the target
y = housing_dummy_df['SalePrice']

#split the data into training and test sets (80% Training/20% Test)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_state=
```

In [21]:
```
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

Out[21]:
```
((1168, 281), (292, 281), (1168,), (292,))
```

7. Run a linear regression and report the R2-value and RMSE on the test set.

In [22]:
```
lr_model = LinearRegression()
# Train the model
lr_model.fit(x_train,y_train)
```

Out[22]:
```
▾ LinearRegression
LinearRegression()
```

In [23]:
```
# Use model to make predictions on test set
predictions = lr_model.predict(x_test)
```

In [24]:
```
print("Root Mean Squared Error (RMSE):", sqrt(mean_squared_error(y_test, predictions)))
print("Coefficient of Determination (R2):", r2_score(y_test, predictions))
```

```
Root Mean Squared Error (RMSE): 30342.908937203494
Coefficient of Determination (R2): 0.8709058563473847
```

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).

In [25]:
```
# Load the data
# Standardize the feature matrix
standard_scalar = StandardScaler()
features = standard_scalar.fit_transform(x_train)
# Create a PCA that will retain 90% of variance
pca = PCA(n_components=0.9, whiten=True)
# Conduct PCA
features_pca = pca.fit_transform(scale(features))
```

9. How many features are in the PCA-transformed matrix?

In [26]:
```
print("Original number of features:", features.shape[1])
print("Reduced number of features:", features_pca.shape[1])
```

```
Original number of features: 281
Reduced number of features: 139
```

10. Transform but DO NOT fit the test features with the same PCA.

In [27]:
```
test_features = standard_scalar.transform(x_test)
test_features
```

Out[27]:
```
array([[ 0.07765223,  0.56347098,  0.19172366, ..., -0.12153092,
         0.46955369, -0.30599503],
       [ 0.4342622 , -0.27716525, -0.21701974, ..., -0.12153092,
         0.46955369, -0.30599503],
       [-0.8733077 , -0.69748336, -0.07327578, ..., -0.12153092,
         0.46955369, -0.30599503],
       ...,
       [-0.63556772, -0.27716525,  0.02609901, ..., -0.12153092,
         0.46955369, -0.30599503],
       [-0.63556772,  0.77363004,  0.0083716 , ..., -0.12153092,
        -2.12968191, -0.30599503],
       [ 0.07765223,  0.77363004,  0.02609901, ..., -0.12153092,
        -2.12968191,  3.26802693]])
```

In [28]:
```
test_features_pca = pca.transform(test_features) #Transfor with the same PCA.
test_features_pca.shape
```

Out[28]:
```
(292, 139)
```

11. Repeat step 7 with your PCA transformed data.

In [29]:
```
lr_model_pca = LinearRegression()
# Train the model
lr_model_pca.fit(features_pca,y_train)
```

Out[29]:
```
▾ LinearRegression
LinearRegression()
```

In [30]:
```
# Use model to make predictions on test set
pca_predictions = lr_model_pca.predict(test_features_pca)
```

In [31]:
```
print("Root Mean Squared Error (RMSE):", sqrt(mean_squared_error(y_test, pca_predictions
print("Coefficient of Determination (R2):", r2_score(y_test, pca_predictions))
```

```
Root Mean Squared Error (RMSE): 32908.91879995908
Coefficient of Determination (R2): 0.8481484106916732
```

12. Take your original training features (from step 6) and apply a min-max scaler to them.

In [32]:
```
#Create scaler
minmax_scale = preprocessing.MinMaxScaler(feature_range=(0, 1))
```

In [33]:
```
# Scale feature
scaled_feature = minmax_scale.fit_transform(x_train)
```

```
scaled_feature
```

Out[33]:
```
array([[0.41176471, 0.15753425, 0.03494823, ..., 0.        , 1.        ,
        0.        ],
       [1.        , 0.13356164, 0.04440394, ..., 0.        , 1.        ,
        0.        ],
       [0.        , 0.15068493, 0.03490149, ..., 0.        , 0.        ,
        1.        ],
       ...,
       [0.29411765, 0.13356164, 0.02609082, ..., 0.        , 1.        ,
        0.        ],
       [0.82352941, 0.        , 0.00177616, ..., 0.        , 1.        ,
        0.        ],
       [0.05882353, 0.3390411 , 0.07805744, ..., 0.        , 1.        ,
        0.        ]])
```

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).

In [34]:
```
# Create thresholder
thresholder = VarianceThreshold(threshold=.1)
```

In [35]:
```
# Create high variance feature matrix
features_high_variance = thresholder.fit_transform(scaled_feature)
```

In [36]:
```
# View high variance feature matrix
features_high_variance[0:3]
```

Out[36]:
```
array([[0.88333333, 0.5       , 1.        , 0.        , 0.        ,
        1.        , 0.        , 1.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 1.        , 0.        ,
        0.        , 1.        , 0.        , 0.        , 0.        ,
        1.        , 0.        , 0.        , 0.        , 1.        ,
        0.        , 1.        , 1.        , 1.        , 0.        ,
        0.        , 1.        , 0.        , 1.        , 1.        ,
        0.        , 0.        , 1.        , 0.        , 1.        ,
        0.        , 0.        , 1.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 1.        , 1.        ],
       [0.83333333, 0.5       , 1.        , 0.        , 0.        ,
        1.        , 0.        , 1.        , 0.        , 1.        ,
        0.        , 0.        , 1.        , 1.        , 0.        ,
        0.        , 1.        , 0.        , 0.        , 0.        ,
        1.        , 0.        , 0.        , 0.        , 1.        ,
        0.        , 1.        , 1.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        1.        , 0.        , 1.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 1.        , 1.        ],
       [0.91666667, 0.        , 1.        , 0.        , 1.        ,
        0.        , 0.        , 1.        , 0.        , 1.        ,
        1.        , 1.        , 0.        , 1.        , 0.        ,
        0.        , 0.        , 1.        , 0.        , 0.        ,
        0.        , 1.        , 0.        , 0.        , 1.        ,
        1.        , 0.        , 1.        , 0.        , 1.        ,
        1.        , 0.        , 1.        , 0.        , 0.        ,
        1.        , 0.        , 1.        , 1.        , 0.        ,
        0.        , 1.        , 0.        , 1.        , 0.        ,
        1.        , 0.        , 0.        , 0.        , 0.        ]])
```

14. Transform but DO NOT fit the test features with the same steps applied in steps 11 and 12.

In [37]:
```
# Scale feature
scaled_test_feature = minmax_scale.transform(x_test)
scaled_test_feature
```

Out[37]:
```
array([[0.23529412, 0.20205479, 0.05204609, ..., 0.        , 1.        ,
         0.        ],
        [0.32352941, 0.13356164, 0.0331861 , ..., 0.        , 1.        ,
         0.        ],
        [0.        , 0.09931507, 0.03981864, ..., 0.        , 1.        ,
         0.        ],
        ...,
        [0.05882353, 0.13356164, 0.04440394, ..., 0.        , 1.        ,
         0.        ],
        [0.05882353, 0.21917808, 0.04358597, ..., 0.        , 0.        ,
         0.        ],
        [0.23529412, 0.21917808, 0.04440394, ..., 0.        , 0.        ,
         1.        ]])
```

In [38]:
```
# Create high variance feature matrix
test_features_high_variance = thresholder.transform(scaled_test_feature)
# View high variance feature matrix
test_features_high_variance[0:3]
```

Out[38]:
```
array([[0.85      , 0.5       , 1.        , 0.        , 0.        ,
         1.        , 0.        , 1.        , 0.        , 1.        ,
         1.        , 0.        , 1.        , 1.        , 0.        ,
         0.        , 0.        , 1.        , 0.        , 0.        ,
         0.        , 1.        , 0.        , 1.        , 0.        ,
         1.        , 0.        , 1.        , 0.        , 1.        ,
         1.        , 0.        , 0.        , 1.        , 0.        ,
         1.        , 0.        , 1.        , 1.        , 0.        ,
         0.        , 1.        , 0.        , 1.        , 0.        ,
         0.        , 1.        , 0.        , 1.        , 1.        ],
        [0.78333333, 0.5       , 1.        , 0.        , 0.        ,
         1.        , 0.        , 1.        , 0.        , 1.        ,
         1.        , 0.        , 0.        , 1.        , 0.        ,
         0.        , 0.        , 0.        , 1.        , 0.        ,
         0.        , 0.        , 1.        , 0.        , 1.        ,
         0.        , 1.        , 1.        , 0.        , 1.        ,
         0.        , 1.        , 0.        , 1.        , 0.        ,
         0.        , 0.        , 1.        , 1.        , 0.        ,
         0.        , 1.        , 0.        , 0.        , 1.        ,
         0.        , 0.        , 1.        , 1.        , 1.        ],
        [0.28333333, 1.        , 1.        , 0.        , 1.        ,
         0.        , 0.        , 1.        , 0.        , 1.        ,
         1.        , 1.        , 0.        , 1.        , 0.        ,
         0.        , 1.        , 0.        , 0.        , 0.        ,
         1.        , 0.        , 0.        , 1.        , 0.        ,
         0.        , 1.        , 0.        , 1.        , 0.        ,
         0.        , 1.        , 0.        , 1.        , 0.        ,
         0.        , 0.        , 1.        , 0.        , 0.        ,
         1.        , 0.        , 1.        , 0.        , 1.        ,
         0.        , 0.        , 1.        , 1.        , 1.        ]])
```

15. Repeat step 7 with the high variance data.

In [39]:
```
#lr_model = LinearRegression()
# Train the model
lr_model.fit(features_high_variance,y_train)
# Use model to make predictions on test set
high_variance_predictions = lr_model.predict(test_features_high_variance)

print("Root Mean Squared Error (RMSE):", sqrt(mean_squared_error(y_test, high_variance_p
print("Coefficient of Determination (R2):", r2_score(y_test, high_variance_predictions))
```

```
Root Mean Squared Error (RMSE): 55034.32256655691
Coefficient of Determination (R2): 0.5753223910429259
```

16. Summarize your findings.

Findings: In linear regression, the R2 value is between 0 and 1 and is a measure of how well the regression predictions approximate real values (goodness of fit of a model). Among the models run above, I see Linear Regression Model gives a better result for R2 compared to the other 2 model trainings.

Linear Regression Model

Root Mean Squared Error (RMSE): 30342.908937203494

Coefficient of Determination (R2): 0.8709058563473847

PCA Transformed Model

Root Mean Squared Error (RMSE): 32908.91879995908

Coefficient of Determination (R2): 0.8481484106916732

Min-Max Transformed Model

Root Mean Squared Error (RMSE): 55034.32256655691

Coefficient of Determination (R2): 0.5753223910429259

Part 2: Categorical Feature Selection

1. Import the data as a data frame and ensure it is loaded correctly.

In [40]:

```
mushroom_df = pd.read_csv("mushrooms.csv")
print(mushroom_df.shape)
mushroom_df.head(5)
```

```
(8124, 23)
```

Out[40]:

	class	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	gill-spacing	gill-size	gill-color	...	stalk-surface-below-ring	stalk-color-above-ring	stalk-color-below-ring	v ty
0	p	x	s	n	t	p	f	c	n	k	...	s	w	w	
1	e	x	s	y	t	a	f	c	b	k	...	s	w	w	
2	e	b	s	w	t	l	f	c	b	n	...	s	w	w	
3	p	x	y	w	t	p	f	c	n	n	...	s	w	w	
4	e	x	s	g	f	n	f	w	b	k	...	s	w	w	

5 rows × 23 columns

2. Convert the categorical features (all of them) to dummy variables.

In [41]:

```
mushroom_dummy_df = pd.get_dummies(mushroom_df, columns = mushroom_df.select_dtypes([obj
mushroom_dummy_df.head(5)
```

Out[41]:

	class_e	class_p	cap-shape_b	cap-shape_c	cap-shape_f	cap-shape_k	cap-shape_s	cap-shape_x	cap-surface_f	cap-surface_g	...	population_s
0	0	1	0	0	0	0	0	1	0	0	...	1
1	1	0	0	0	0	0	0	1	0	0	...	0
2	1	0	1	0	0	0	0	0	0	0	...	0
3	0	1	0	0	0	0	0	1	0	0	...	1
4	1	0	0	0	0	0	0	1	0	0	...	0

5 rows × 119 columns

3. Split the data into a training and test set.

In [42]:

```
x = mushroom_dummy_df.drop(['class_e','class_p'], axis = 1)
y = mushroom_dummy_df['class_e']

#split the data into training and test sets (80% Training/20% Test)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_state=
```

4. Fit a decision tree classifier on the training set.

In [43]:

```
# Create decision tree classifier object
decisiontree = tree.DecisionTreeClassifier(random_state=1)
dt_model = decisiontree.fit(x_train, y_train)
y_pred = dt_model.predict(x_test)
y_pred
```

Out[43]:

```
array([1, 0, 0, ..., 0, 1, 1], dtype=uint8)
```

5. Report the accuracy and create a confusion matrix for the model prediction on the test set.

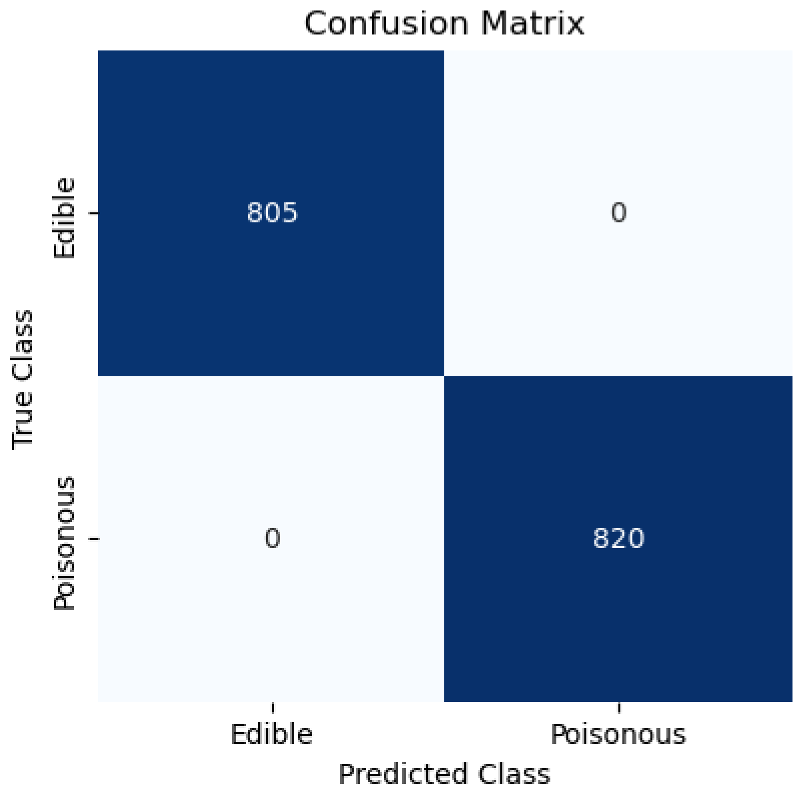
In [44]:

```
score = round(accuracy_score(y_test, y_pred)*100,2)
print("Test Accuracy: {}%".format(score))
```

```
Test Accuracy: 100.0%
```

In [45]:

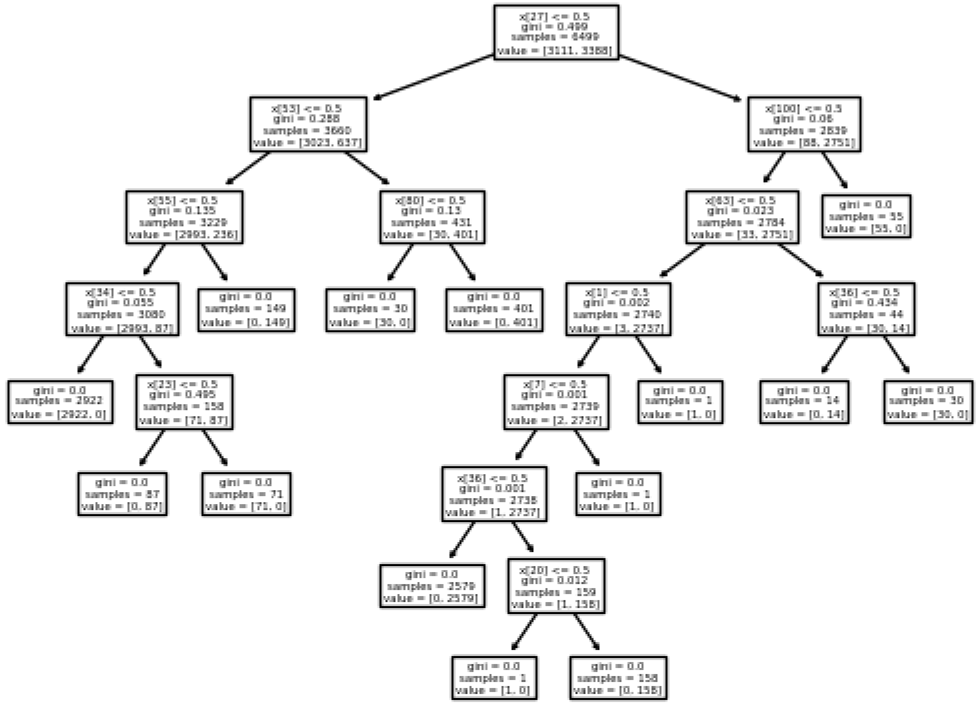
```
# Create confusion matrix
matrix = confusion_matrix(y_test, y_pred)

x_axis_labels = ["Edible", "Poisonous"]
y_axis_labels = ["Edible", "Poisonous"]

#HeatMap
f, ax = plt.subplots(figsize =(4,4))
sns.heatmap(matrix, annot=True, cbar=None, cmap="Blues",fmt = ".0f", xticklabels=x_axis_
plt.title("Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



6. Create a visualization of the decision tree.

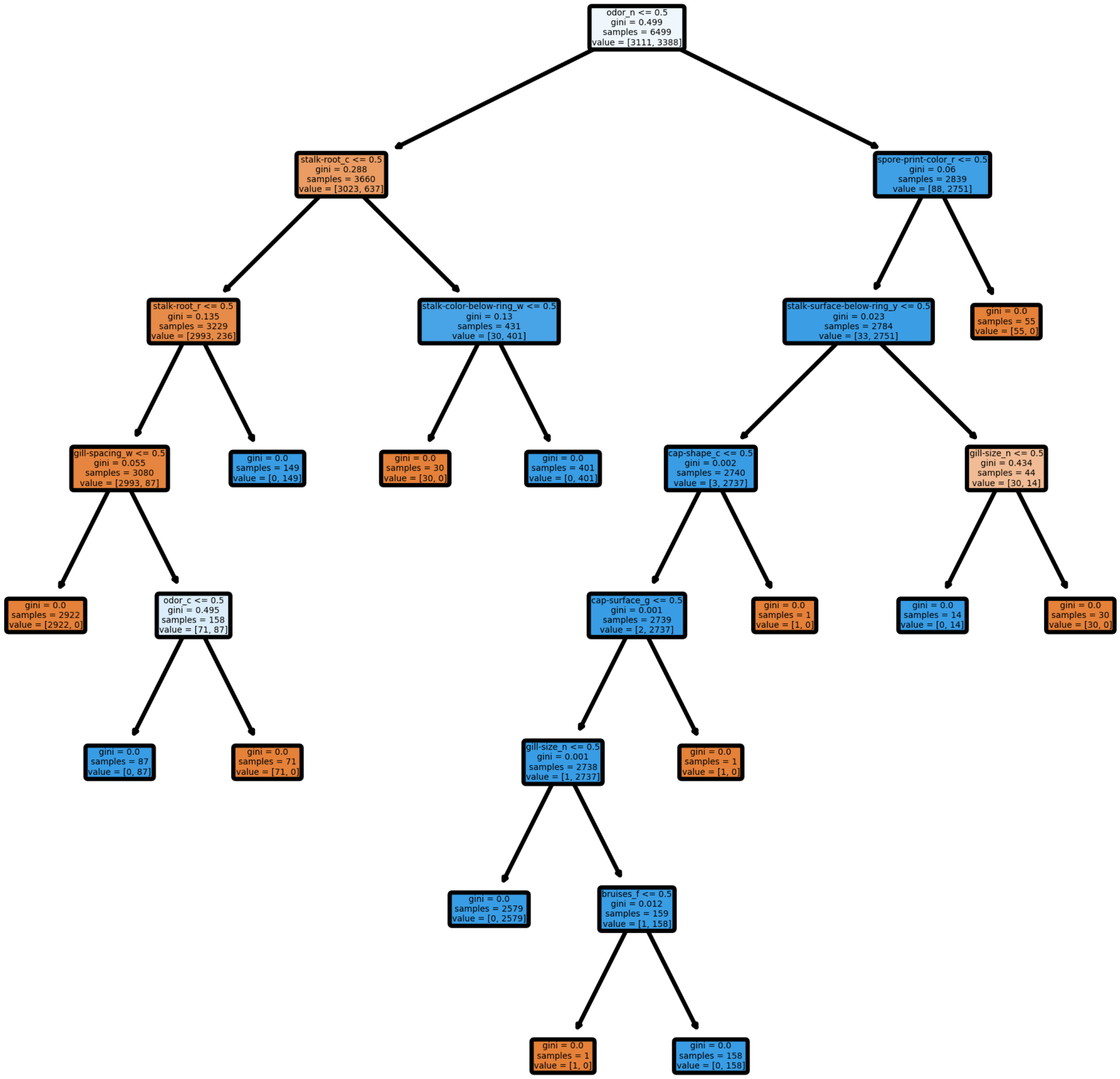
In [46]:
```
tree.plot_tree(decisiontree)
```

Out[46]:
```
[Text(0.5625, 0.9375, 'x[27] <= 0.5\ngini = 0.499\nsamples = 6499\nvalue = [3111, 338
8]'),
 Text(0.3125, 0.8125, 'x[53] <= 0.5\ngini = 0.288\nsamples = 3660\nvalue = [3023, 63
7]'),
 Text(0.1875, 0.6875, 'x[55] <= 0.5\ngini = 0.135\nsamples = 3229\nvalue = [2993, 23
6]'),
 Text(0.125, 0.5625, 'x[34] <= 0.5\ngini = 0.055\nsamples = 3080\nvalue = [2993, 87]'),
 Text(0.0625, 0.4375, 'gini = 0.0\nsamples = 2922\nvalue = [2922, 0]'),
 Text(0.1875, 0.4375, 'x[23] <= 0.5\ngini = 0.495\nsamples = 158\nvalue = [71, 87]'),
 Text(0.125, 0.3125, 'gini = 0.0\nsamples = 87\nvalue = [0, 87]'),
 Text(0.25, 0.3125, 'gini = 0.0\nsamples = 71\nvalue = [71, 0]'),
 Text(0.25, 0.5625, 'gini = 0.0\nsamples = 149\nvalue = [0, 149]'),
 Text(0.4375, 0.6875, 'x[80] <= 0.5\ngini = 0.13\nsamples = 431\nvalue = [30, 401]'),
 Text(0.375, 0.5625, 'gini = 0.0\nsamples = 30\nvalue = [30, 0]'),
 Text(0.5, 0.5625, 'gini = 0.0\nsamples = 401\nvalue = [0, 401]'),
 Text(0.8125, 0.8125, 'x[100] <= 0.5\ngini = 0.06\nsamples = 2839\nvalue = [88, 2751]'),
 Text(0.75, 0.6875, 'x[63] <= 0.5\ngini = 0.023\nsamples = 2784\nvalue = [33, 2751]'),
 Text(0.625, 0.5625, 'x[1] <= 0.5\ngini = 0.002\nsamples = 2740\nvalue = [3, 2737]'),
 Text(0.5625, 0.4375, 'x[7] <= 0.5\ngini = 0.001\nsamples = 2739\nvalue = [2, 2737]'),
 Text(0.5, 0.3125, 'x[36] <= 0.5\ngini = 0.001\nsamples = 2738\nvalue = [1, 2737]'),
 Text(0.4375, 0.1875, 'gini = 0.0\nsamples = 2579\nvalue = [0, 2579]'),
 Text(0.5625, 0.1875, 'x[20] <= 0.5\ngini = 0.012\nsamples = 159\nvalue = [1, 158]'),
 Text(0.5, 0.0625, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(0.625, 0.0625, 'gini = 0.0\nsamples = 158\nvalue = [0, 158]'),
 Text(0.625, 0.3125, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(0.6875, 0.4375, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(0.875, 0.5625, 'x[36] <= 0.5\ngini = 0.434\nsamples = 44\nvalue = [30, 14]'),
 Text(0.8125, 0.4375, 'gini = 0.0\nsamples = 14\nvalue = [0, 14]'),
 Text(0.9375, 0.4375, 'gini = 0.0\nsamples = 30\nvalue = [30, 0]'),
 Text(0.875, 0.6875, 'gini = 0.0\nsamples = 55\nvalue = [55, 0]')]
```



In [47]:

```
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (5,5), dpi=500)
tree.plot_tree(decisiontree, feature_names=x.columns,filled=True, rounded=True);
fig.savefig('imagename.png')
```



7. Use a χ2-statistic selector to pick the five best features for this data (see section 10.4 of the Machine Learning with Python Cookbook).

In [48]:
```
# Convert to categorical data by converting data to integers
features = x_train.astype(int)

# Select five features with highest chi-squared statistics
chi2_selector = SelectKBest(chi2, k=5)
features_kbest = chi2_selector.fit_transform(features, y_train)
features_kbest
```

Out[48]:
```
array([[0, 1, 0, 0, 0],
       [0, 1, 0, 0, 0],
       [0, 0, 1, 1, 1],
       ...,
       [1, 0, 0, 1, 1],
       [0, 0, 0, 0, 0],
       [1, 0, 0, 0, 0]])
```

In [49]:
```
# Show results
```

```
print("Original number of features:", features.shape[1])
print("Reduced number of features:", features_kbest.shape[1])
```

```
Original number of features: 117
Reduced number of features: 5
```

8. Which five features were selected in step 7? Hint: Use the get_support function.

In [50]:
```
# Get columns to keep and create new dataframe with those only
cols = chi2_selector.get_support(indices = True)
features_df = features.iloc[:,cols]
print(features_df.shape)
features_df.head(5)
```

```
(6499, 5)
```

Out[50]:

	odor_f	odor_n	gill-color_b	stalk-surface-above-ring_k	stalk-surface-below-ring_k
1610	0	1	0	0	0
1939	0	1	0	0	0
5573	0	0	1	1	1
7076	0	0	1	1	0
2000	0	1	0	0	0

9. Repeat steps 4 and 5 with the five best features selected in step 7.

In [51]:
```
x_best_5_train, x_best_5_test, y_best_5_train, y_best_5_test = train_test_split(features
```

In [52]:
```
decisiontree = tree.DecisionTreeClassifier(random_state=1)
dt_model = decisiontree.fit(x_best_5_train, y_best_5_train)
y_best_5_pred = dt_model.predict(x_best_5_test)
y_best_5_pred
```

Out[52]:
```
array([0, 1, 1, ..., 1, 1, 1], dtype=uint8)
```

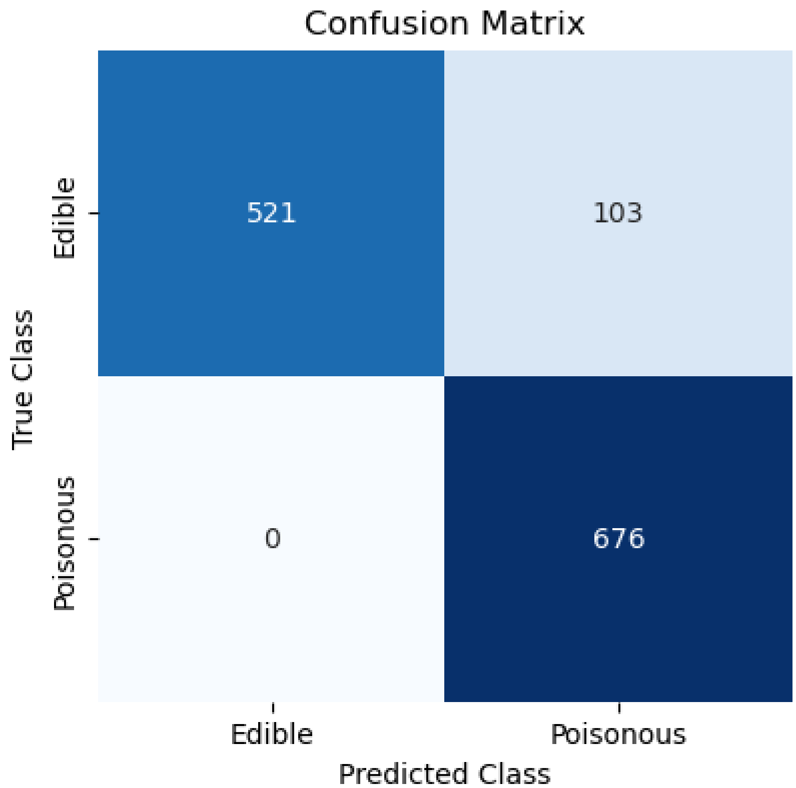
In [53]:
```
score = round(accuracy_score(y_best_5_test, y_best_5_pred)*100,2)
print("Test Accuracy: {}%".format(score))
```

```
Test Accuracy: 92.08%
```

In [54]:
```
# Create confusion matrix
best_matrix = confusion_matrix(y_best_5_test, y_best_5_pred)
best_matrix
```

Out[54]:
```
array([[521, 103],
       [  0, 676]], dtype=int64)
```

In [55]:
```
x_axis_labels = ["Edible", "Poisonous"]
y_axis_labels = ["Edible", "Poisonous"]

#HeatMap
f, ax = plt.subplots(figsize =(4,4))
sns.heatmap(best_matrix, annot=True, cbar=None, cmap="Blues",fmt = ".0f", xticklabels=x_
plt.title("Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



10. Summarize your findings.

Findings: With all the features in the first Decision Tree Classifier there was 100% accuracy, and after reducing to 5 best features using X2 it went down to 92.08%. This revised accuracy is still high with only 5 features instead of 117. We get a relatively good accuracy percentage with 95% reduction in features.