Final Project

June 4, 2022

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.formula.api as sm
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_val_score,train_test_split
from sklearn.metrics import␣
↪mean_squared_error,r2_score,roc_curve,auc,precision_recall_curve, auc,␣
↪make_scorer, recall_score, accuracy_score, precision_score
from sklearn.model_selection import KFold
from sklearn.tree import DecisionTreeRegressor,DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV, ParameterGrid
from sklearn.ensemble import␣
↪BaggingRegressor,BaggingClassifier,RandomForestRegressor,RandomForestClassifier,StackingCla
from sklearn.linear_model import LinearRegression,LogisticRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.linear_model import Ridge, RidgeCV, Lasso, LassoCV
import itertools as it
from sklearn.model_selection import StratifiedKFold, KFold

from sklearn.tree import export_graphviz
import xgboost as xgb
from six import StringIO
from IPython.display import Image
import pydotplus
import time as time
```

0.1 Data Cleaning

[2]:
```
data = pd.read_csv('mushrooms.csv')
```

[3]:
```
data.rename(columns = {'class':'classes'}, inplace=True)
```

[4]:
```
data.columns.to_list()
```

[4]:
```
['classes',
 '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']
```

[5]:
```
data.columns = data.columns.str.strip().str.lower().str.replace('-', '_')
```

[6]:
```
data.isna().sum()
```

[6]:
```
classes                     0
cap_shape                   0
cap_surface                 0
cap_color                   0
bruises                     0
odor                        0
gill_attachment             0
gill_spacing                0
gill_size                   0
gill_color                  0
stalk_shape                 0
stalk_root                  0
stalk_surface_above_ring    0
stalk_surface_below_ring    0
stalk_color_above_ring      0
stalk_color_below_ring      0
veil_type                   0
veil_color                  0
ring_number                 0
```

```
ring_type                 0
spore_print_color         0
population                0
habitat                   0
dtype: int64
```

[7]:
```
data.head()
```

[7]:
```
  classes 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]
```

[8]:
```
classes = {
    'e':'edible',
    'p':'poisonous'
}

cap_shapes = {
    'b':'bell',
    'c':'conical',
    'x':'convex',
```

```
    'f':'flat',
    'k':'knobbed',
    's':'sunken'
}

cap_surfaces = {
    'f':'fibrous',
    'g':'grooves',
    'y':'scaly',
    's':'smooth'
}

cap_colors = {
    'n':'brown',
    'b':'buff',
    'c':'cinnamon',
    'g':'gray',
    'r':'green',
    'p':'pink',
    'u':'purple',
    'e':'red',
    'w':'white',
    'y':'yellow'
}

bruise_class = {
    't':'bruises',
    'f':'no_bruises'
}

odors = {
    'a':'almond',
    'l':'anise',
    'c':'creosote',
    'y':'fishy',
    'f':'foul',
    'm':'musty',
    'n':'none',
    'p':'pungent',
    's':'spicy'
}

gill_attachments = {
    'a':'attached',
    'd':'descending',
    'f':'free',
    'n':'notched'
```

```
}

gill_spacings = {
    'c':'close',
    'w':'crowded',
    'd':'distant'
}

gill_sizes = {
    'b':'broad',
    'n':'narrow'
}

gill_colors = {
    'k':'black',
    'n':'brown',
    'b':'buff',
    'h':'chocolate',
    'g':'gray',
    'r':'green',
    'o':'orange',
    'p':'pink',
    'u':'purple',
    'e':'red',
    'w':'white',
    'y':'yellow'
}

stalk_shapes = {
    'e':'enlarging',
    't':'tapering'
}

stalk_roots = {
    'b':'bulbous',
    'c':'club',
    'u':'cup',
    'e':'equal',
    'z':'rhizomorphs',
    'r':'rooted',
    '?':'NA'
}

stalk_surface_above_rings = {
    'f':'fibrous',
    'y':'scaly',
    'k':'silky',
```

```
    's':'smooth'
}

stalk_surface_below_rings = {
    'f':'fibrous',
    'y':'scaly',
    'k':'silky',
    's':'smooth'
}

stalk_color_above_rings = {
    'n':'brown',
    'b':'buff',
    'c':'cinnamon',
    'g':'gray',
    'o':'orange',
    'p':'pink',
    'e':'red',
    'w':'white',
    'y':'yellow'
}

stalk_color_below_rings = {
    'n':'brown',
    'b':'buff',
    'c':'cinnamon',
    'g':'gray',
    'o':'orange',
    'p':'pink',
    'e':'red',
    'w':'white',
    'y':'yellow'
}

veil_types = {
    'p':'partial',
    'u':'universal'
}

veil_colors = {
    'n':'brown',
    'o':'orange',
    'w':'white',
    'y':'yellow'
}

ring_numbers = {
```

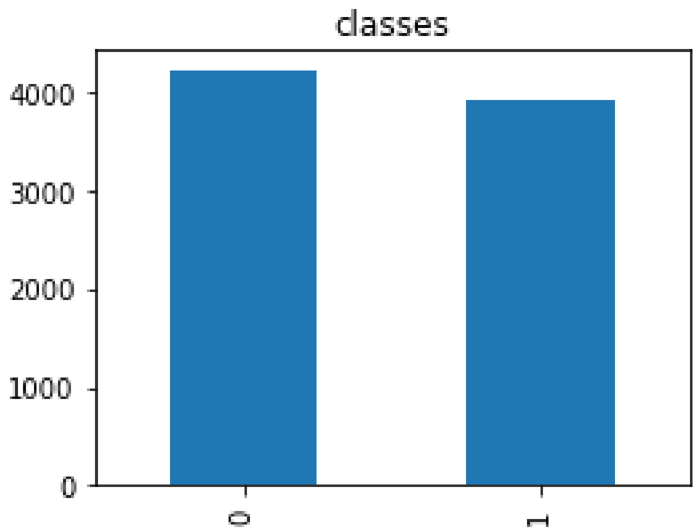
```
    'n':'none',
    'o':'one',
    't':'two'
}

ring_types = {
    'c':'cobwebby',
    'e':'evanescent',
    'f':'flaring',
    'l':'large',
    'n':'none',
    'p':'pendant',
    's':'sheathing',
    'z':'zone'
}

spore_print_colors = {
    'k':'black',
    'n':'brown',
    'b':'buff',
    'h':'chocolate',
    'r':'green',
    'o':'orange',
    'u':'purple',
    'w':'white',
    'y':'yellow'
}

populations = {
    'a':'abundant',
    'c':'clustered',
    'n':'numerous',
    's':'scattered',
    'v':'several',
    'y':'solitary'
}

habitats = {
    'g':'grasses',
    'l':'leaves',
    'm':'meadows',
    'p':'paths',
    'u':'urban',
    'w':'waste',
    'd':'woods'
}
```

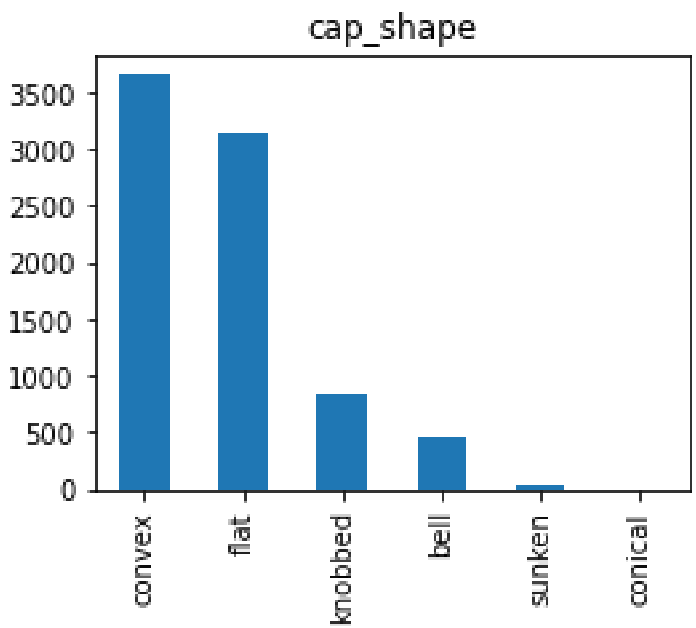
[9]:
```
data.replace({'classes': classes,
              'cap_shape': cap_shapes,
              'cap_surface': cap_surfaces,
              'cap_color': cap_colors,
              'bruises': bruise_class,
              'odor': odors,
              'gill_attachment': gill_attachments,
              'gill_spacing': gill_spacings,
              'gill_size': gill_sizes,
              'gill_color': gill_colors,
              'stalk_shape': stalk_shapes,
              'stalk_root': stalk_roots,
              'stalk_surface_above_ring': stalk_surface_above_rings,
              'stalk_surface_below_ring': stalk_surface_below_rings,
              'stalk_color_above_ring': stalk_color_above_rings,
              'stalk_color_below_ring': stalk_color_below_rings,
              'veil_type': veil_types,
              'veil_color': veil_colors,
              'ring_number': ring_numbers,
              'ring_type': ring_types,
              'spore_print_color': spore_print_colors,
              'population': populations,
              'habitat': habitats},
             inplace=True)
```

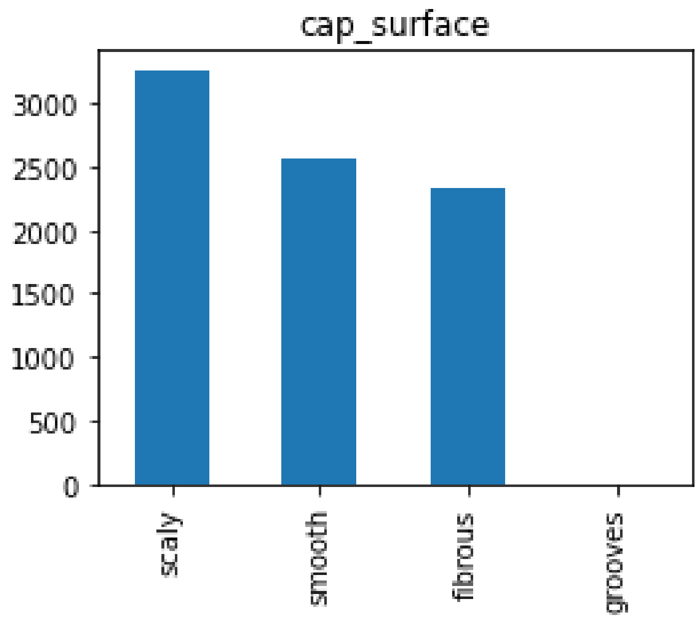
0.2 Data Visualization

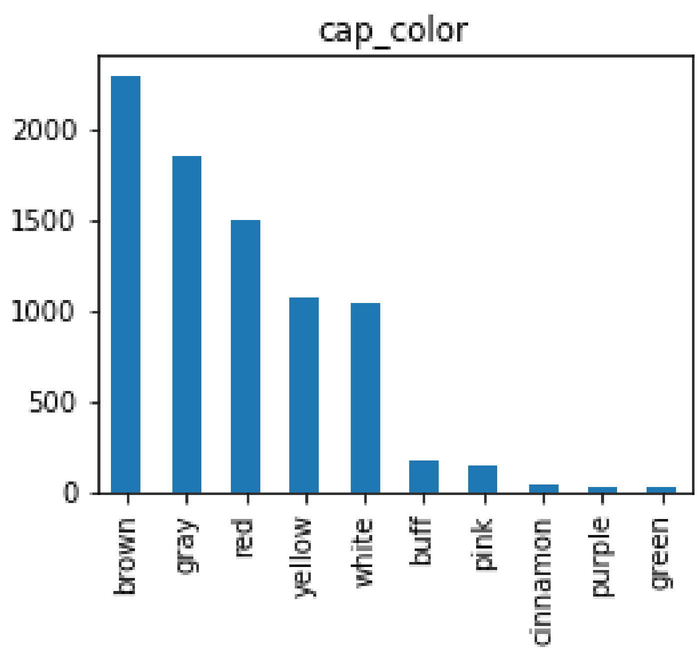
[10]:
```
data['classes'] = np.where(data['classes'] == 'poisonous', 1, 0)
```

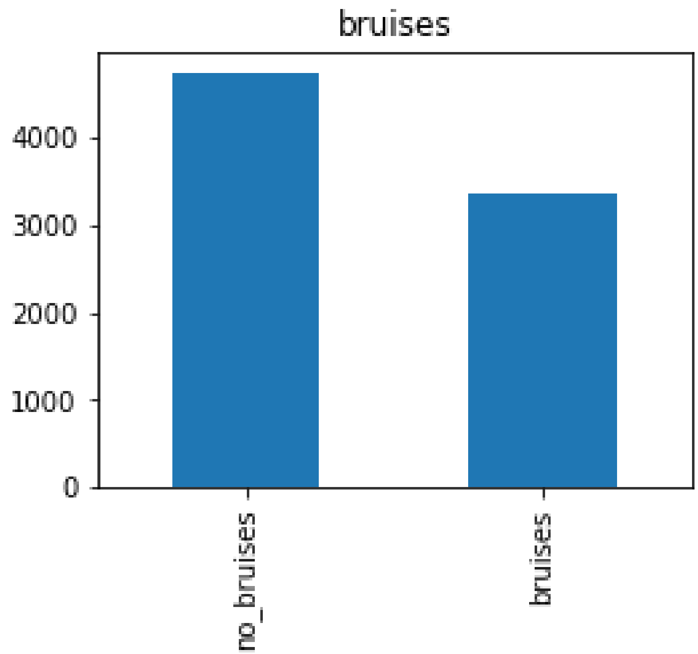
[11]:
```
for col in data.columns:
    plt.figure(figsize = (4,3))
    data[col].value_counts().plot(kind='bar')
    plt.title(col)
    plt.show()
```

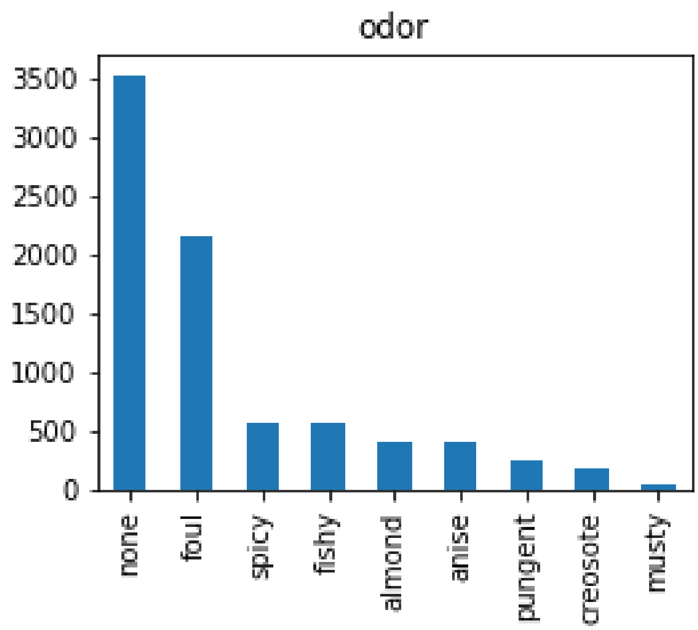

classes
4000
3000
2000
1000
0
0
1

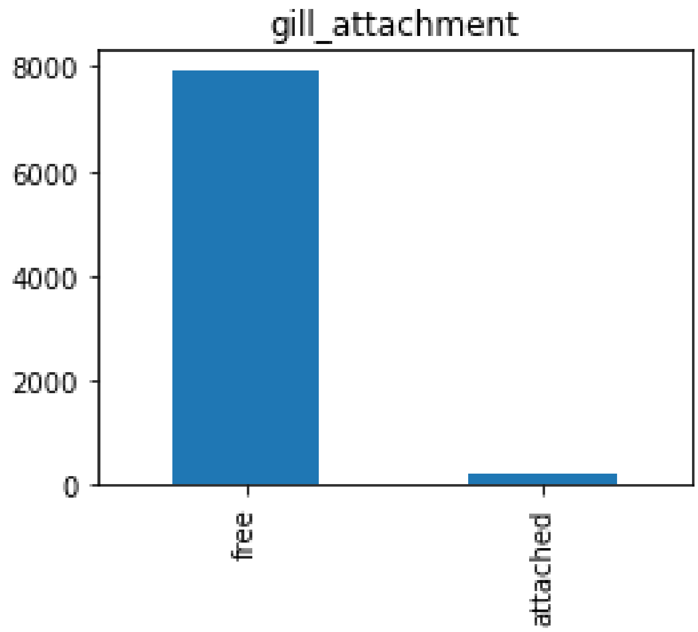

cap_shape
3500
3000
2500
2000
1500
1000
500
0
convex
flat
knobbed
bell
sunken
conical

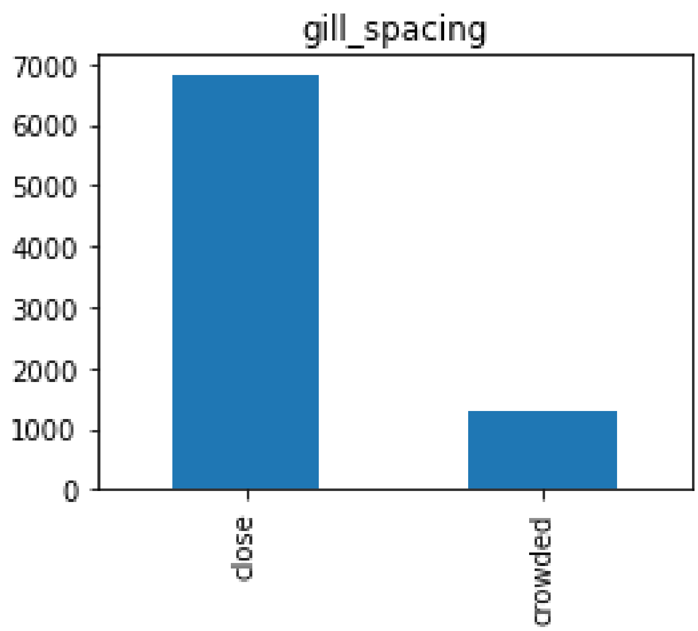

cap_surface
3000
2500
2000
1500
1000
500
0
scaly
smooth
fibrous
grooves

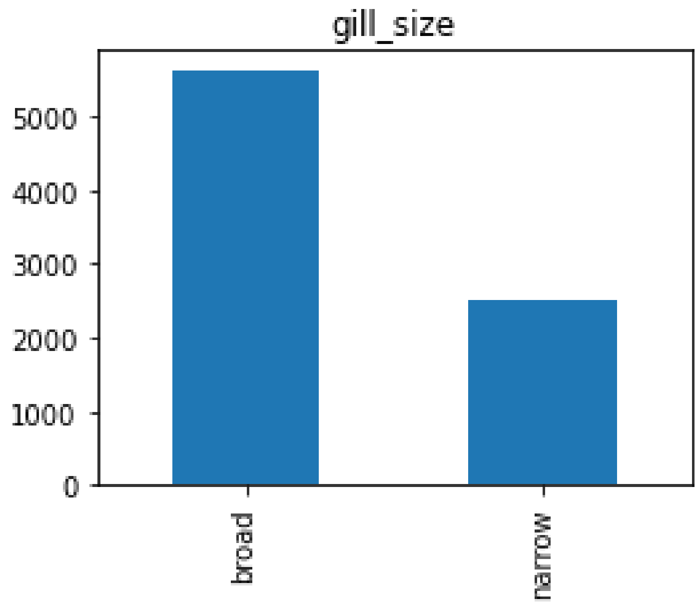

cap_color
2000
1500
1000
500
0
brown
gray
red
yellow
white
buff
pink
cinnamon
purple
green

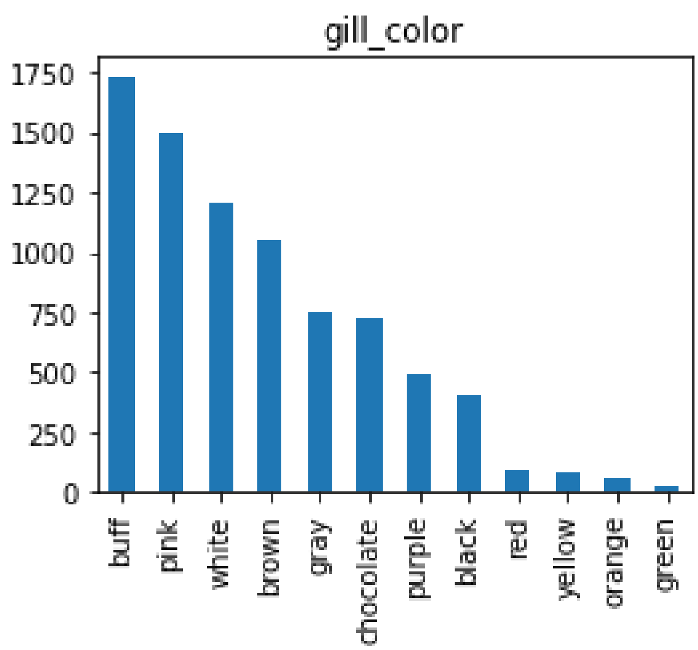

bruises
4000
3000
2000
1000
0
no_bruises
bruises

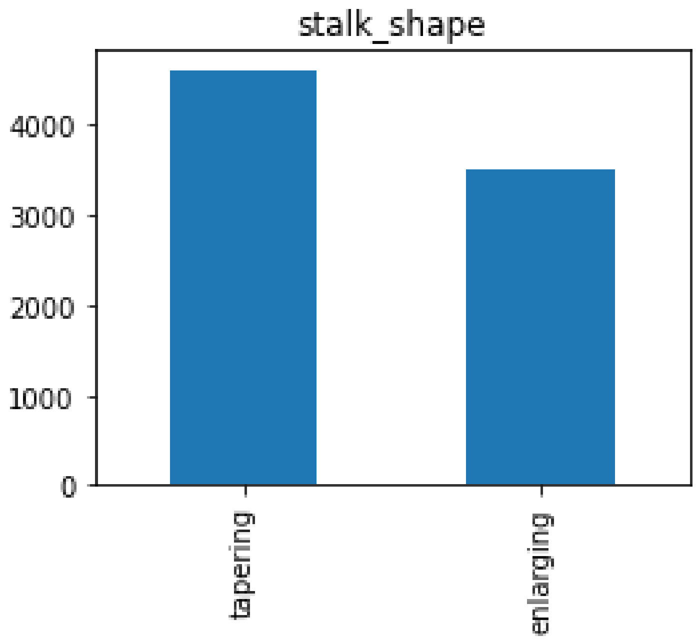

odor
3500
3000
2500
2000
1500
1000
500
0
none
foul
spicy
fishy
almond
anise
pungent
creosote
musty

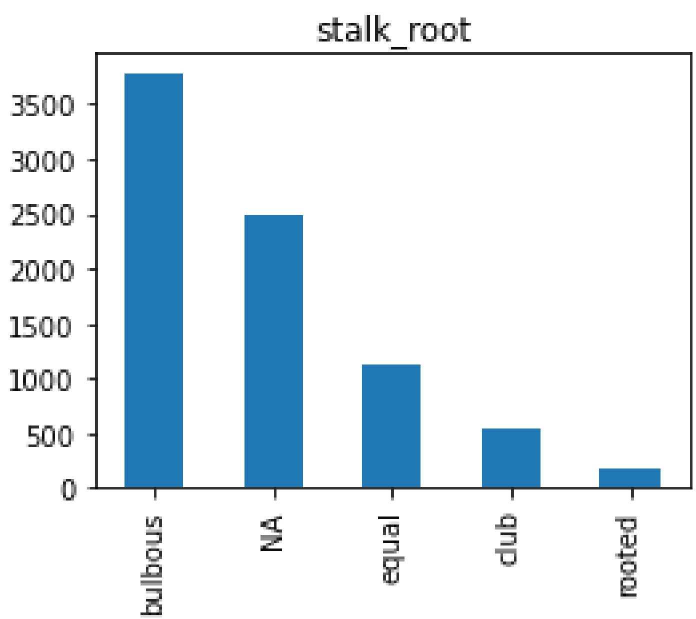

gill_attachment
8000
6000
4000
2000
0
free
attached

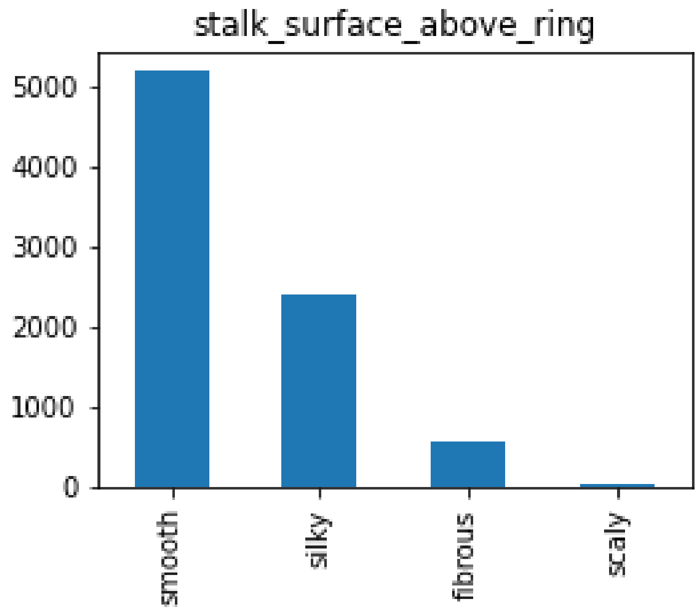

gill_spacing
7000
6000
5000
4000
3000
2000
1000
0
close
crowded


gill_size
5000
4000
3000
2000
1000
0
broad
narrow

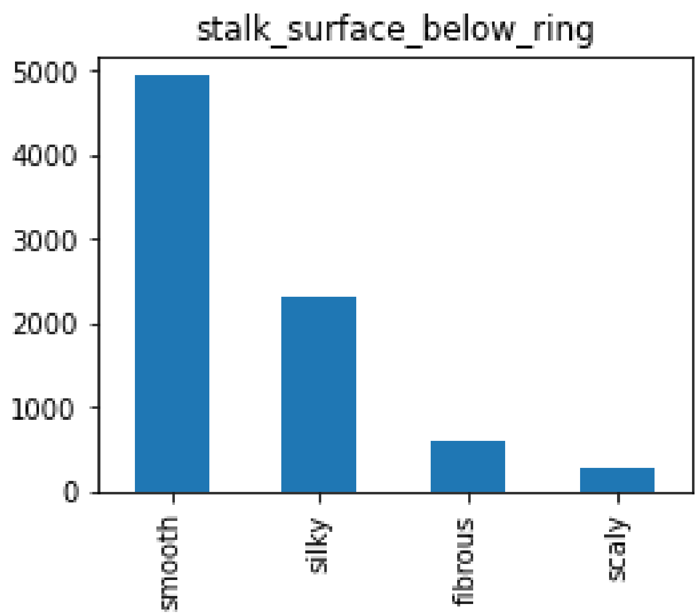

gill_color
1750
1500
1250
1000
750
500
250
0
buff
pink
white
brown
gray
chocolate
purple
black
red
yellow
orange
green


stalk_shape
4000
3000
2000
1000
0
tapering
enlarging

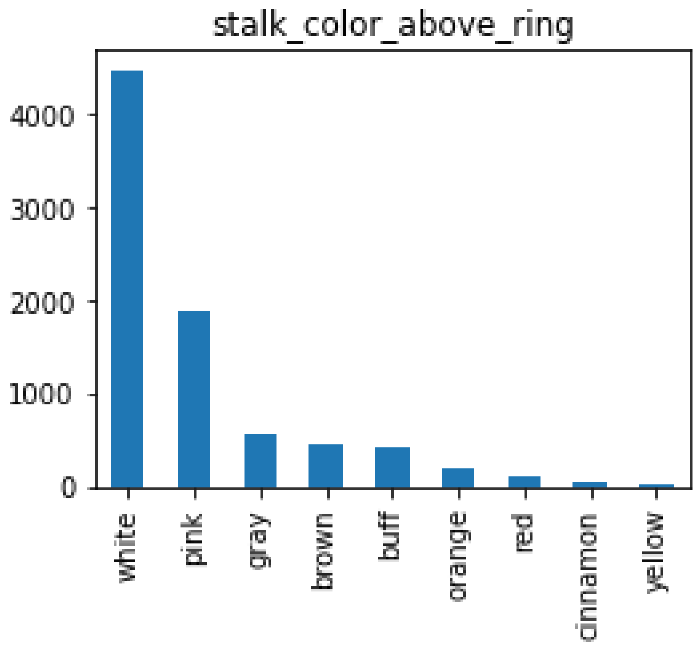

stalk_root
3500
3000
2500
2000
1500
1000
500
0
bulbous
NA
equal
club
rooted

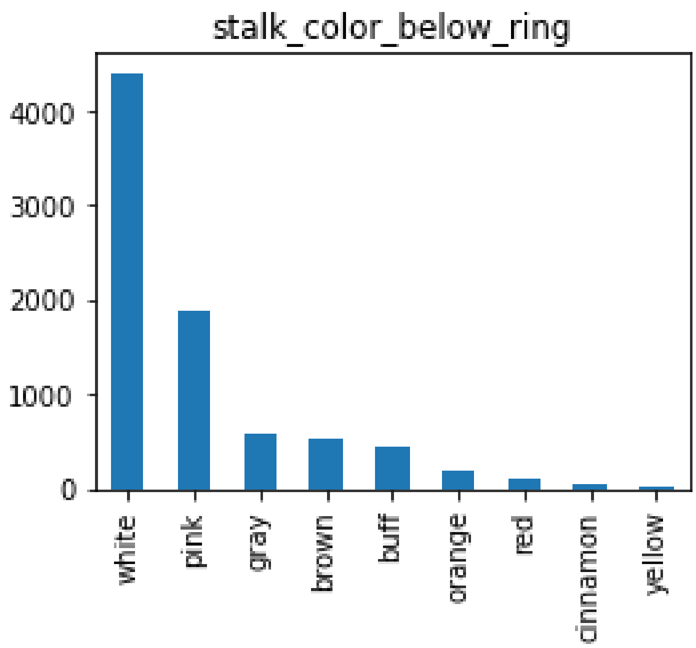


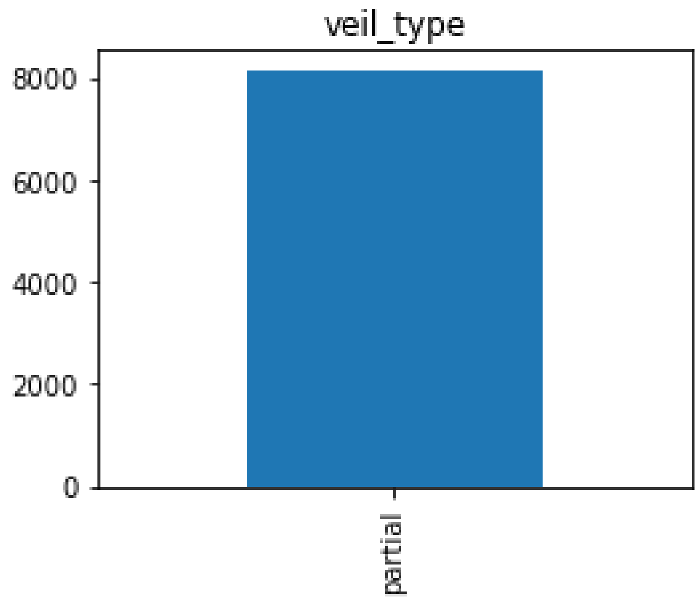
stalk_surface_above_ring
5000
4000
3000
2000
1000
0
smooth
silky
fibrous
scaly

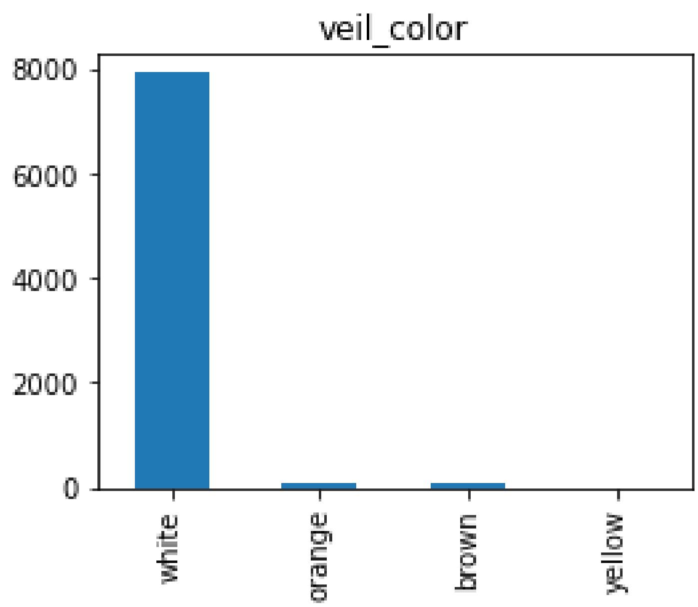


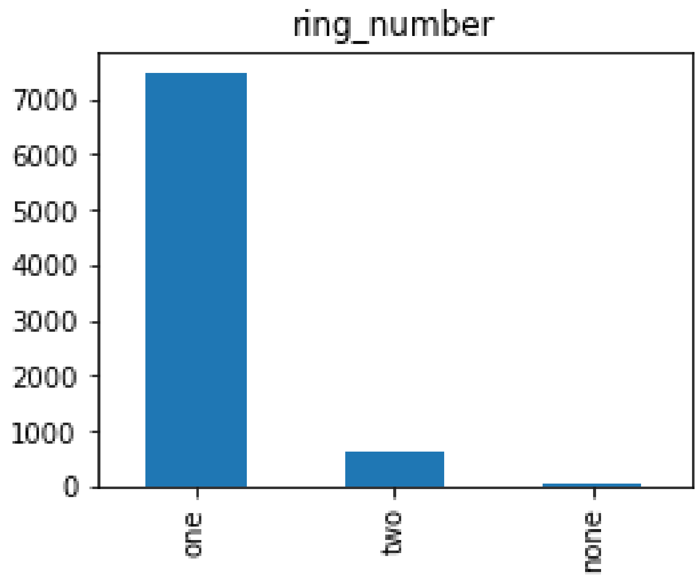
stalk_surface_below_ring
5000
4000
3000
2000
1000
0
smooth
silky
fibrous
scaly

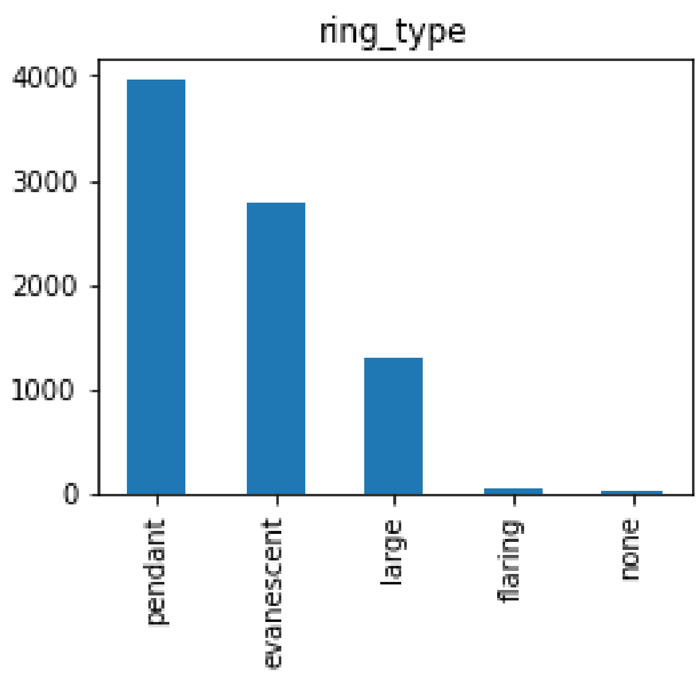

stalk_color_above_ring
4000
3000
2000
1000
0
white
pink
gray
brown
buff
orange
red
cinnamon
yellow

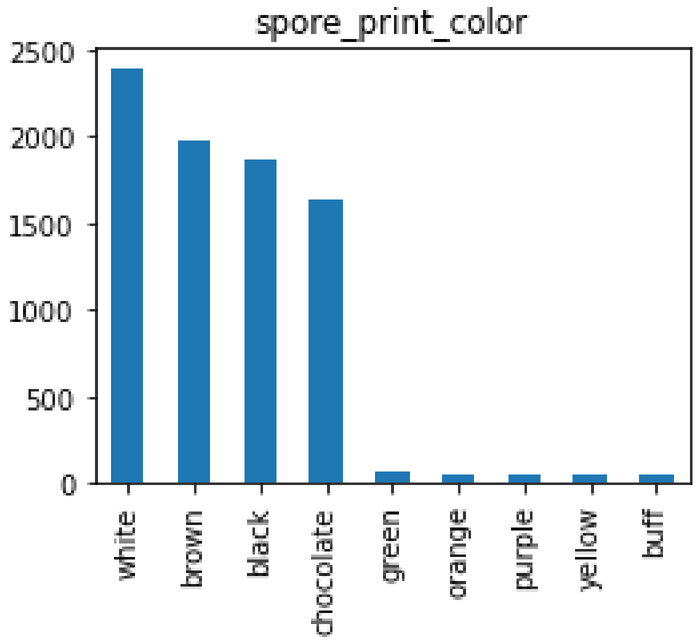

stalk_color_below_ring
4000
3000
2000
1000
0
white
pink
gray
brown
buff
orange
red
cinnamon
yellow

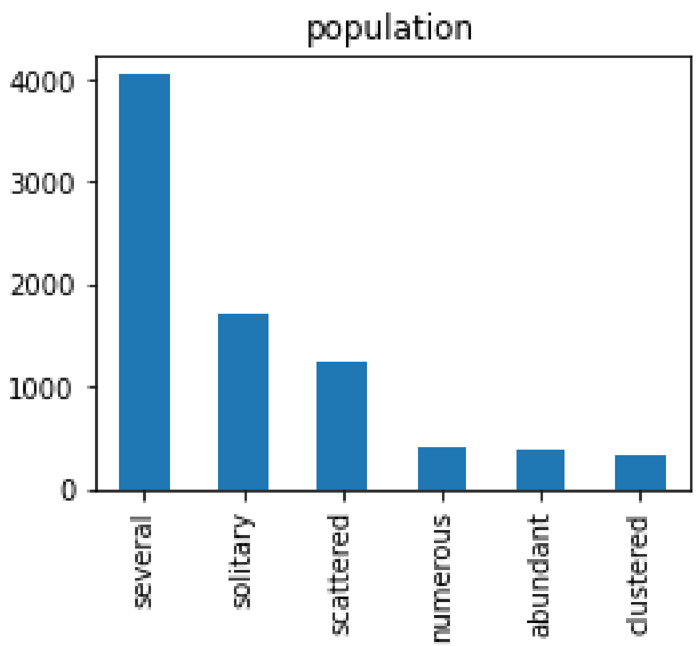

veil_type
8000
6000
4000
2000
0
partial

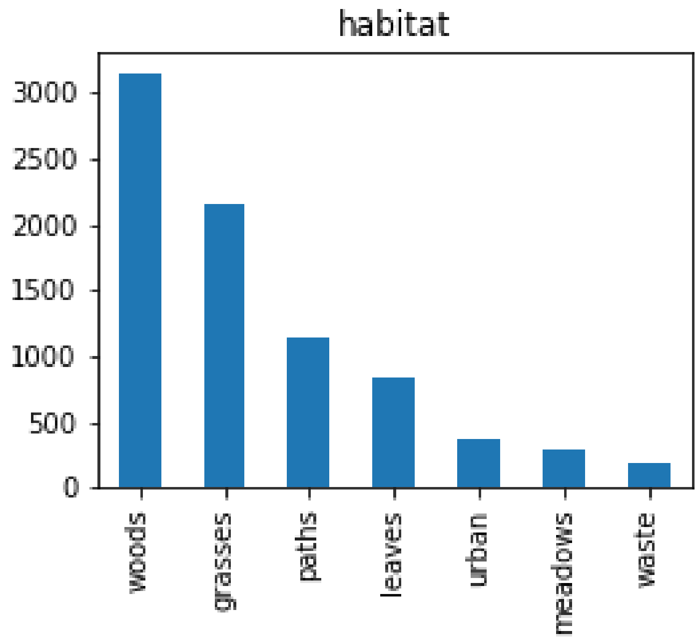

veil_color
8000
6000
4000
2000
0
white
orange
brown
yellow


ring_number
7000
6000
5000
4000
3000
2000
1000
0
one
two
none


ring_type
4000
3000
2000
1000
0
pendant
evanescent
large
flaring
none

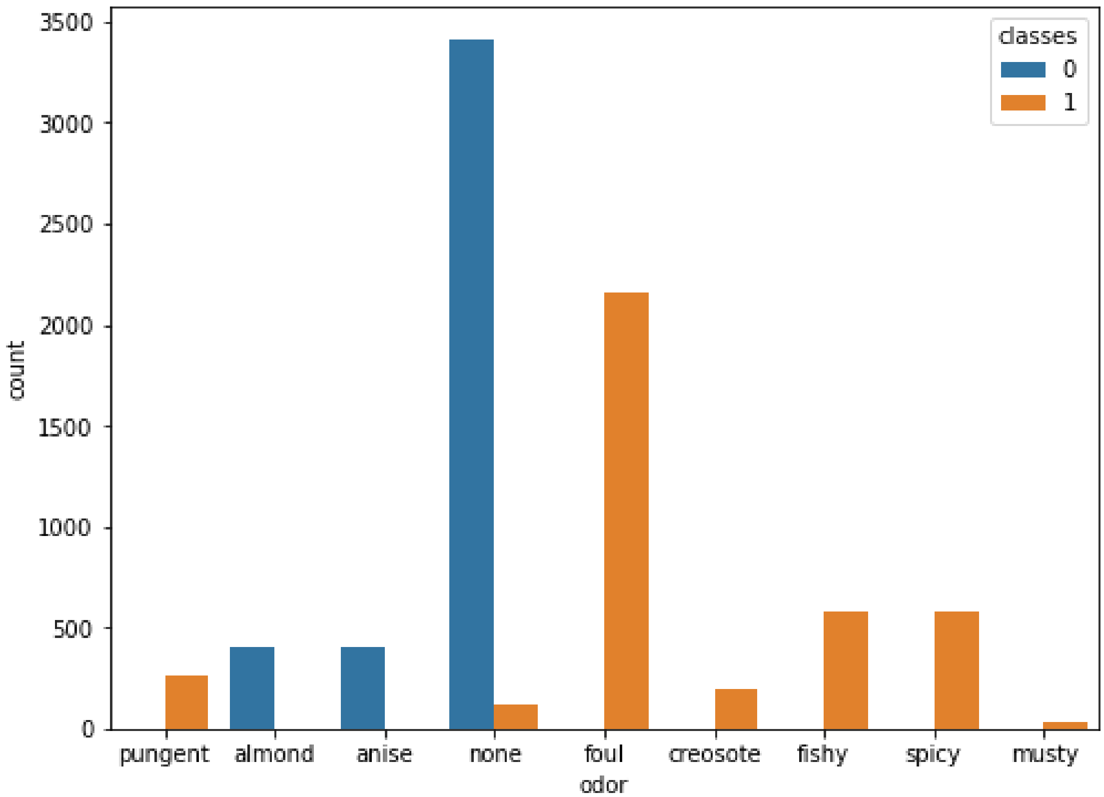

spore_print_color
2500
2000
1500
1000
500
0
white
brown
black
chocolate
green
orange
purple
yellow
buff


population
4000
3000
2000
1000
0
several
solitary
scattered
numerous
abundant
clustered



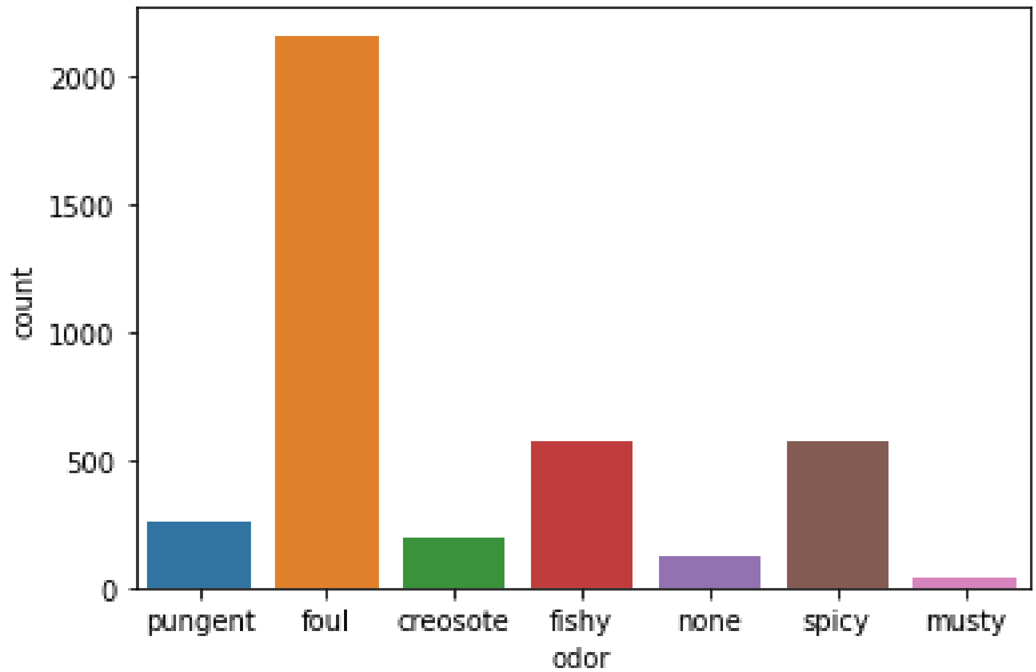
[12]:
```
plt.figure(figsize = (8,6))
sns.countplot(data = data, x = 'odor', hue = 'classes')
```

[12]: <AxesSubplot:xlabel='odor', ylabel='count'>



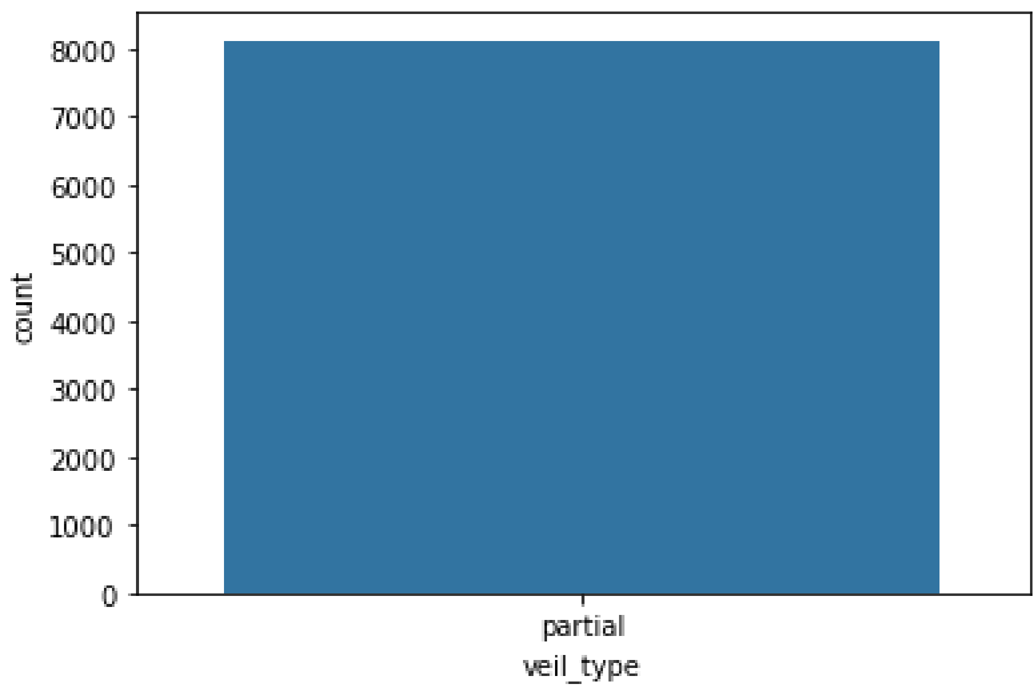
[13]:
```
sns.countplot(data = data[data['classes'] == 1], x = 'odor')
```

[13]: <AxesSubplot:xlabel='odor', ylabel='count'>




```
[14]: sns.countplot(data = data, x = 'veil_type')
```

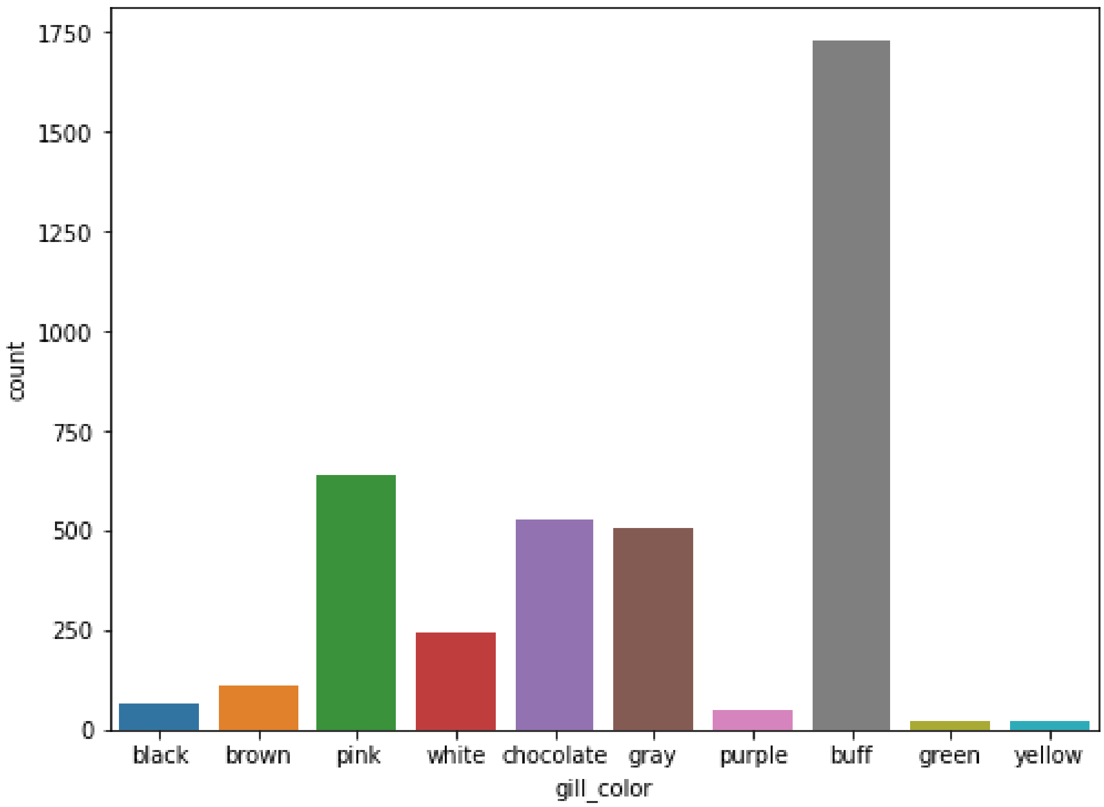
```
[14]: <AxesSubplot:xlabel='veil_type', ylabel='count'>
```



[15]:
```
poison_df = data[data['classes'] == 1]
edible_df = data[data['classes'] == 0]
```

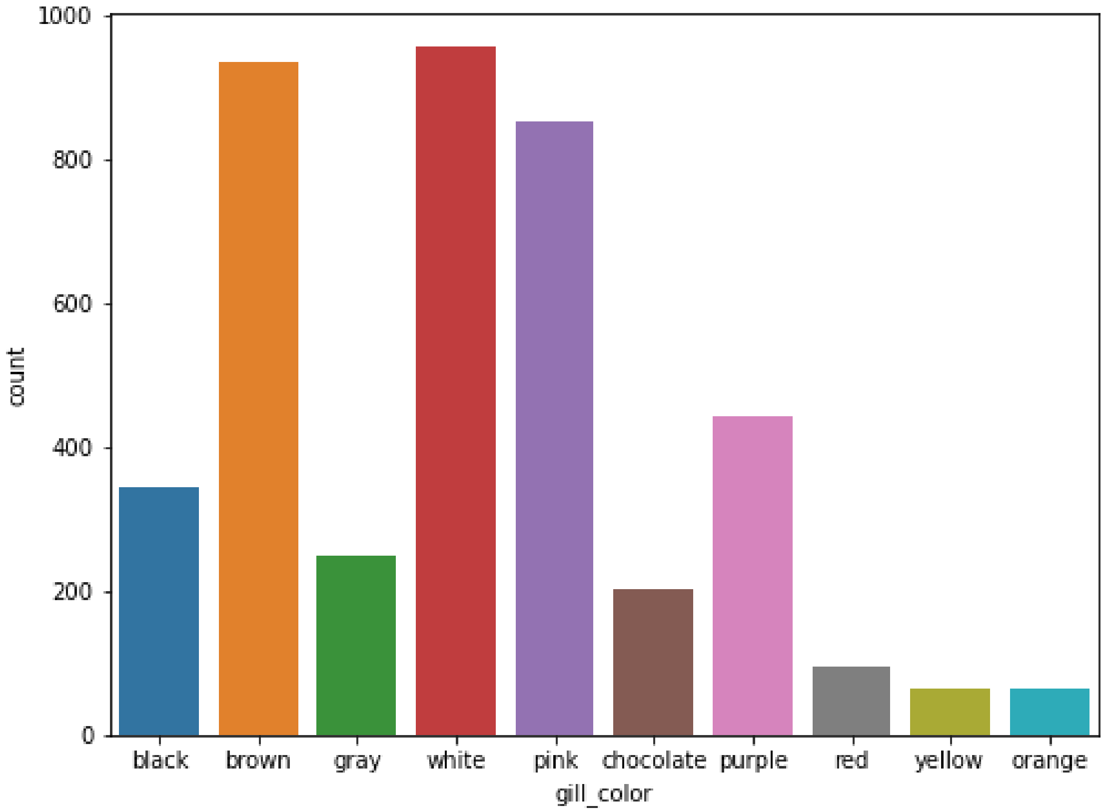
[16]:
```
plt.figure(figsize = (8,6))
sns.countplot(data=poison_df, x='gill_color')
```

[16]: <AxesSubplot:xlabel='gill_color', ylabel='count'>



[17]:
```
plt.figure(figsize = (8,6))
sns.countplot(data=edible_df, x='gill_color')
```

[17]: <AxesSubplot:xlabel='gill_color', ylabel='count'>



0.3 Confusion Matrix Functions

[18]:
```
#Function to compute confusion matrix and prediction accuracy on test/train␣
↪data -- Decision Tree
def confusion_matrix_data(data,actual_values,model,cutoff=0.5):
#Predict the values using the Logit model
    pred_values = model.predict_proba(data)[:,1]
# Specify the bins
    bins=np.array([0,cutoff,1])
#Confusion matrix
    cm = np.histogram2d(actual_values, pred_values, bins=bins)[0]
    cm_df = pd.DataFrame(cm)
    cm_df.columns = ['Predicted 0','Predicted 1']
    cm_df = cm_df.rename(index={0: 'Actual 0',1:'Actual 1'})
# Calculate the accuracy
    accuracy = 100*(cm[0,0]+cm[1,1])/cm.sum()
    fpr = 100*(cm[0,1])/(cm[0,1]+cm[0,0])
    fnr = 100*(cm[1,0])/(cm[1,0]+cm[1,1])
    recall = 100*(cm[1,1])/(cm[1,0]+cm[1,1])
    print("Accuracy = ", accuracy)
    print("Recall = ", recall)
```

```
    print("FPR = ", fpr)
    print("FNR = ", fnr)
    print("Confusion matrix = \n", cm_df)
    return (" ")
```

[19]:
```
#Function to compute confusion matrix and prediction accuracy on test/train␣
 ↪data -- Decision Tree
def confusion_matrix_data_logit(data,actual_values,model,cutoff=0.5):
#Predict the values using the Logit model
    pred_values = model.predict(data)
# Specify the bins
    bins=np.array([0,cutoff,1])
#Confusion matrix
    cm = np.histogram2d(actual_values, pred_values, bins=bins)[0]
    cm_df = pd.DataFrame(cm)
    cm_df.columns = ['Predicted 0','Predicted 1']
    cm_df = cm_df.rename(index={0: 'Actual 0',1:'Actual 1'})
# Calculate the accuracy
    accuracy = 100*(cm[0,0]+cm[1,1])/cm.sum()
    fnr = 100*(cm[1,0])/(cm[1,0]+cm[1,1])
    print("Accuracy = ", accuracy)
    print("FNR = ", fnr)
    print("Confusion matrix = \n", cm_df)
    return (" ")
```

[20]:
```
from sklearn.model_selection import train_test_split
train, test = train_test_split(data, test_size=0.33, random_state=1)
```

[21]:
```
print(train.shape)
print(test.shape)
```

```
(5443, 23)
(2681, 23)
```

0.4 Linear model – LOGISTIC REGRESSION

[22]:
```
train.columns.to_list()
```

[22]:
```
['classes',
 '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']
```

[23]:
```
train_m1 = train[['classes',
 'cap_shape',
 'cap_surface',
 'cap_color',
 'bruises',
 '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_color',
 'ring_number',
 'ring_type',
 'spore_print_color',
 'population',
 'habitat']]

test_m1 = test[['classes',
 'cap_shape',
 'cap_surface',
 'cap_color',
 'bruises',
 '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_color',
 'ring_number',
 'ring_type',
 'spore_print_color',
 'population',
 'habitat']]
```

[24]:
```
X=data.drop(['classes', 'odor', 'veil_type'],axis=1) #Predictors
y=data['classes'] #Response
```

[25]:
```
from sklearn.preprocessing import LabelEncoder
Encoder_X = LabelEncoder()
for col in X.columns:
    X[col] = Encoder_X.fit_transform(X[col])
Encoder_y=LabelEncoder()
y = Encoder_y.fit_transform(y)
```

[26]:
```
X=pd.get_dummies(X,columns=X.columns,drop_first=True)
```

[27]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
```

[28]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

[29]:
```
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression()

classifier.fit(X_train,y_train)
```

[29]:
```
LogisticRegression()
```

[30]:
```
from sklearn.metrics import confusion_matrix,classification_report
from sklearn.model_selection import cross_val_predict, cross_val_score
from sklearn.metrics import␣
↪confusion_matrix,classification_report,accuracy_score
```

[31]:
```
def print_score(classifier,X_train,y_train,X_test,y_test,train=True):
    if train == True:
```

```
        print("Training results:\n")
        print('Accuracy Score: {0:.4f}\n'.
↪format(accuracy_score(y_train,classifier.predict(X_train))))
        print('Classification Report:\n{}\n'.
↪format(classification_report(y_train,classifier.predict(X_train))))
        print('Confusion Matrix:\n{}\n'.
↪format(confusion_matrix(y_train,classifier.predict(X_train))))
        res = cross_val_score(classifier, X_train, y_train, cv=10, n_jobs=-1,␣
↪scoring='accuracy')
        print('Average Accuracy:\t{0:.4f}\n'.format(res.mean()))
        print('Standard Deviation:\t{0:.4f}'.format(res.std()))
    elif train == False:
        print("Test results:\n")
        print('Accuracy Score: {0:.4f}\n'.
↪format(accuracy_score(y_test,classifier.predict(X_test))))
        print('Classification Report:\n{}\n'.
↪format(classification_report(y_test,classifier.predict(X_test))))
        print('Confusion Matrix:\n{}\n'.
↪format(confusion_matrix(y_test,classifier.predict(X_test))))
```

[32]:
```
print_score(classifier,X_train,y_train,X_test,y_test,train=True)
```

```
Training results:

Accuracy Score: 1.0000

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2951
           1       1.00      1.00      1.00      2735

    accuracy                           1.00      5686
   macro avg       1.00      1.00      1.00      5686
weighted avg       1.00      1.00      1.00      5686


Confusion Matrix:
[[2951    0]
 [   0 2735]]

Average Accuracy:       0.9998

Standard Deviation:     0.0005
```

0.5 Non-linear model – DECISION TREE

[33]:
```python
train_m2 = pd.get_dummies(train)
test_m2 = pd.get_dummies(test)
```

[34]:
```python
X2 = train_m2.drop(columns = 'classes')
X2test = test_m2.drop(columns = 'classes')
y2 = train_m2['classes']
y2test = test_m2['classes']
```

[35]:
```python
model2 = DecisionTreeClassifier(random_state=1, max_depth=3)
model2.fit(X2, y2)
```

[35]:
```
DecisionTreeClassifier(max_depth=3, random_state=1)
```

[36]:
```python
confusion_matrix_data(X2, train_m2.classes, model2, cutoff=0.5)
```

```
Accuracy =  98.40161675546574
Recall =  99.88461538461539
FPR =  2.9546253957087583
FNR =  0.11538461538461539
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0       2759.0         84.0
Actual 1          3.0       2597.0
```

[36]:
```
' '
```

[37]:
```python
X2.columns[pd.Series(model2.feature_importances_ > 0)]
```

[37]:
```
Index(['odor_none', 'stalk_root_club', 'stalk_surface_below_ring_scaly',
       'stalk_surface_below_ring_smooth', 'spore_print_color_green'],
      dtype='object')
```

[38]:
```python
model2.feature_importances_
```

[38]:
```
array([0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.6656145 , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.1827068 , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.09808967, 0.        , 0.01753364, 0.        ,
```

```
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.03605539,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        ])
```

0.6 Data Cleaning for further models

[39]:
```
train.columns.to_list()
```

[39]:
```
['classes',
 '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']
```

[40]:
```
train.gill_spacing.value_counts()
```

[40]:
```
close      4544
crowded     899
Name: gill_spacing, dtype: int64
```

[41]:
```
train.gill_size.value_counts()
```

[41]:
```
broad     3771
narrow    1672
Name: gill_size, dtype: int64
```

[42]:
```
train.stalk_root.value_counts()
```

[42]:
```
bulbous    2555
NA         1653
equal       750
club        362
rooted      123
Name: stalk_root, dtype: int64
```

[43]:
```
train.stalk_surface_above_ring.value_counts()
```

[43]:
```
smooth     3477
silky      1584
fibrous     366
scaly        16
Name: stalk_surface_above_ring, dtype: int64
```

[44]:
```
train.population.value_counts()
```

[44]:
```
several      2724
solitary     1143
scattered     822
numerous      278
abundant      257
clustered     219
Name: population, dtype: int64
```

0.7 RANDOM FOREST

[45]:
```
train_m3 = pd.get_dummies(train[['classes','cap_shape', 'cap_surface',␣
↪'cap_color', 'habitat', 'stalk_shape']])
test_m3 = pd.get_dummies(test[['classes','cap_shape', 'cap_surface',␣
↪'cap_color', 'habitat', 'stalk_shape']])
```

[46]:
```
X = train_m3.drop(columns = 'classes')
Xtest = test_m3.drop(columns = 'classes')
y = train_m3['classes']
ytest = test_m3['classes']
```

[47]:
```
params = {'n_estimators': [500],
          'max_features': range(1,6),
         }

param_list = list(it.product(*(params[Name] for Name in list(params.keys()))))
```

```
recall = [0]*len(param_list)

i=0
for pr in param_list:
    model = RandomForestClassifier(random_state=1,
                                   oob_score=True,
                                   verbose=False,
                                   n_estimators = pr[0],
                                   max_features=pr[1],
                                   n_jobs=-1).fit(X,y)
    oob_pred = model.oob_decision_function_[:,1]
    bins=np.array([0,0.5,1])
    cm = np.histogram2d(y, oob_pred, bins=bins)[0]
    recall[i] = 100*(cm[1,1])/(cm[1,0]+cm[1,1])
    i=i+1

end_time = time.time()

print("max recall = ", np.max(recall))
print("params= ", param_list[np.argmax(recall)])
```

```
max recall =  90.5
params=  (500, 1)
```

[48]:
```
model3 = RandomForestClassifier(random_state=1, n_jobs=-1, max_features=1,␣
 ↪n_estimators=100).fit(X, y)
```

[49]:
```
confusion_matrix_data(X, y, model3, cutoff=0.5)
```

```
Accuracy =  93.7167003490722
Recall =  90.84615384615384
FPR =  3.658107632782272
FNR =  9.153846153846153
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0       2739.0        104.0
Actual 1        238.0       2362.0
```

[49]: ' '

[50]:
```
confusion_matrix_data(Xtest, ytest, model3, cutoff=0.5)
```

```
Accuracy =  92.83849309958971
Recall =  91.48936170212765
FPR =  5.86080586080586
FNR =  8.51063829787234
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0       1285.0         80.0
```

```
Actual 1        112.0       1204.0
```

[50]: ' '

0.8 Tuned Decision Tree – Rule of Five

[51]:
```python
param_grid = {
    'max_depth': range(1,5),
    'max_leaf_nodes': range(1,30),
    'max_features': range(1,5),
}

skf = StratifiedKFold(n_splits=5)

grid_search = GridSearchCV(DecisionTreeClassifier(random_state=1),
                           param_grid,
                           scoring=['precision','recall','accuracy'],
                           refit="recall",
                           cv=skf,
                           n_jobs=-1,
                           verbose = True).fit(X,y)

print('Best params for recall')
print(grid_search.best_params_)
```

```
Fitting 5 folds for each of 464 candidates, totalling 2320 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:    0.7s
[Parallel(n_jobs=-1)]: Done 762 tasks      | elapsed:    2.2s

Best params for recall
{'max_depth': 4, 'max_features': 4, 'max_leaf_nodes': 5}

[Parallel(n_jobs=-1)]: Done 2320 out of 2320 | elapsed:    4.8s finished
```

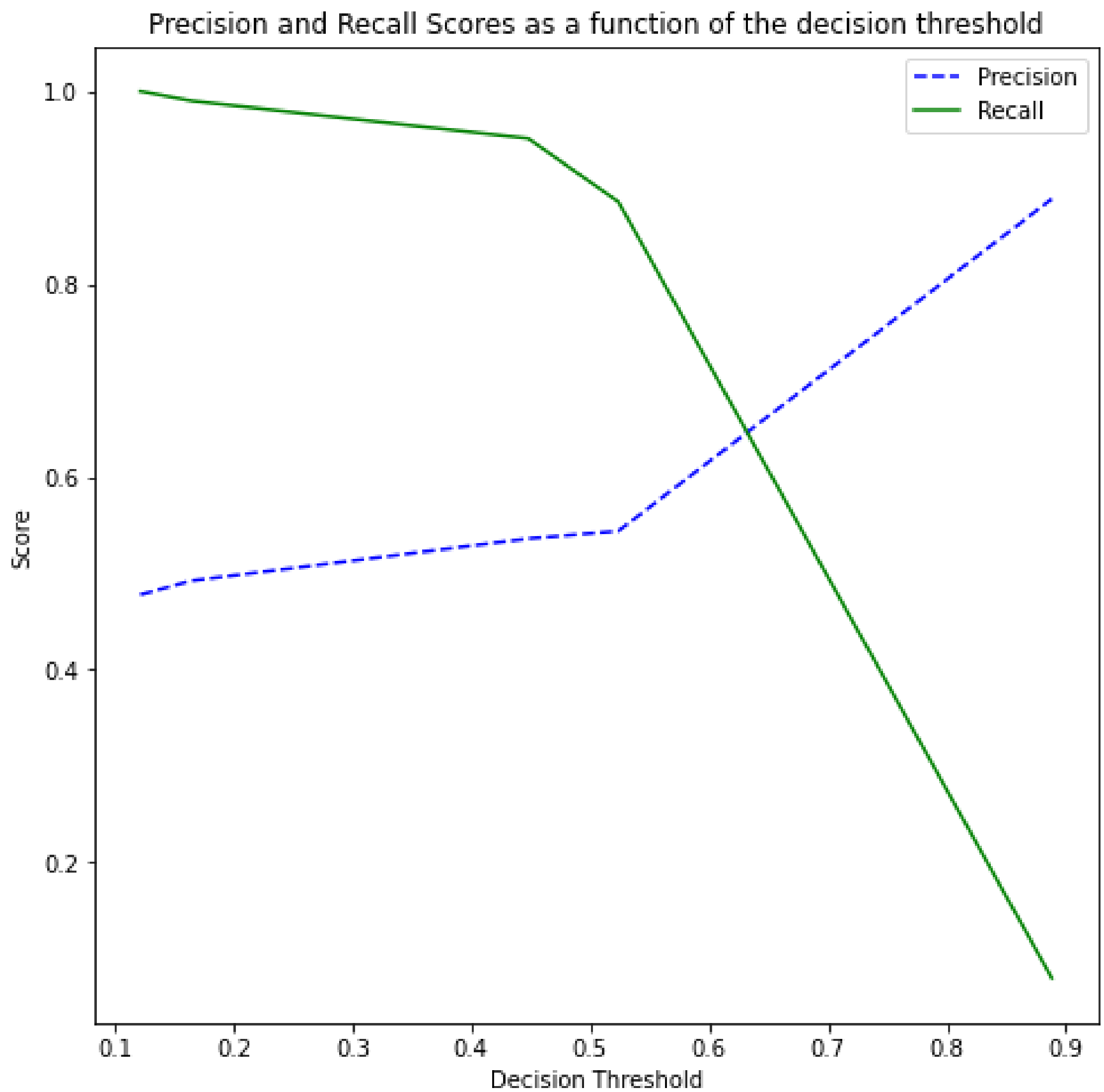
[52]:
```python
model4 = DecisionTreeClassifier(random_state=1, max_depth = 4, max_features =␣
 ↪4, max_leaf_nodes=5)

model4.fit(X,y)
print(confusion_matrix_data(X,y,model4))
print(confusion_matrix_data(Xtest,ytest,model4,cutoff=0.4))
```

```
Accuracy =  59.02994672055851
Recall =  88.53846153846153
FPR =  67.95638410130144
FNR =  11.461538461538462
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0        911.0       1932.0
```

```
Actual 1        298.0       2302.0

Accuracy =  59.716523685192094
Recall =  95.82066869300913
FPR =  75.0915750915751
FNR =  4.179331306990881
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0        340.0       1025.0
Actual 1         55.0       1261.0
```

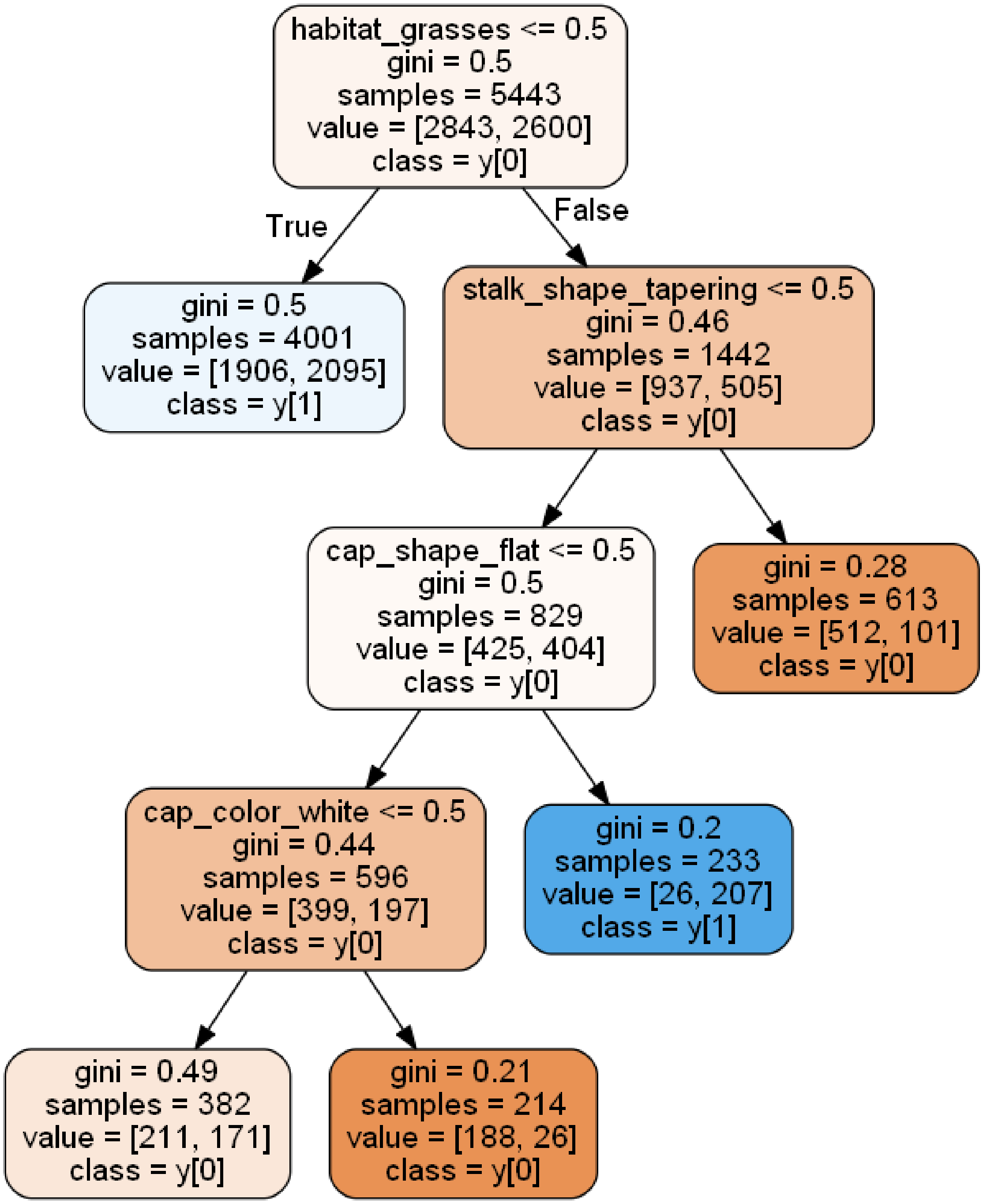
[53]:
```python
ypred = model4.predict_proba(X)[:, 1]
p, r, thresholds = precision_recall_curve(y, ypred)
```

[54]:
```python
def plot_precision_recall_vs_threshold(precisions, recalls, thresholds):
    plt.figure(figsize=(8, 8))
    plt.title("Precision and Recall Scores as a function of the decision␣
 ↪threshold")
    plt.plot(thresholds, precisions[:-1], "b--", label="Precision")
    plt.plot(thresholds, recalls[:-1], "g-", label="Recall")
    plt.ylabel("Score")
    plt.xlabel("Decision Threshold")
    plt.legend(loc='best')

plot_precision_recall_vs_threshold(p, r, thresholds)
```



[55]:
```python
#Visualizing the regression tree
dot_data = StringIO()
export_graphviz(model4, out_file=dot_data,
                filled=True, rounded=True, class_names=True,
                feature_names =X.columns,precision=2)
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png('car_price_tree.png')
Image(graph.create_png())
```

[55]:



0.8.1 Finding most accurate prediction subset

[56]:
```
#The following function finds indices of the leaf nodes, given the decision␣
↪tree model.
#The indices of nodes in a decision tree starts at the top from 0.
```

```
#The child nodes obtained from the first split have indices 1 (left) and 2␣
↪(right),
#the child nodes obtained from the second split have indices 3 (left) and 4␣
↪(right), and so on.
def leaf_nodes_indices(model):
    children_left = model.tree_.children_left
    children_right = model.tree_.children_right
    leaf_nodes = []
    for i in range(model.tree_.node_count):
        if children_left[i] == children_right[i]:
            leaf_nodes.append(i)
    return leaf_nodes

#The following function finds the *mean squared error* of nodes with indices␣
↪*node_indices*
def mse(model,node_indices):
    return model.tree_.impurity[node_indices]

#The following function gives the decision rules for a node with index as␣
↪*node_index*
def decision_rules(model,node_index):
    child_node = node_index
    node_list=[]
    children_left = model.tree_.children_left
    children_right = model.tree_.children_right
    features=model.tree_.feature
    fnames = X.columns
    threshold = model.tree_.threshold
    p=1
    while p>0:
        if node_index%2>0:
            p= np.where(children_left==node_index)[0][0]
        else:
            p= np.where(children_right==node_index)[0][0]
        node_list.append(p)
        node_index=p
    node_list.reverse()
    node_list.append(child_node)
    cc=1
    for n in node_list[0:(len(node_list)-1)]:
        cnode = node_list[cc]
        if cnode%2==0:
            ineq_sign = ">"
        else:
            ineq_sign = "<="
        print("Split "+ str(cc)+":
↪"+fnames[features][n]+ineq_sign+str(threshold[n]))
```

```
        cc=cc+1
    node_list=[]
    return ""
```

[57]:
```
nodes = leaf_nodes_indices(model4)
m = nodes[0]
for i in nodes:
    if mse(model4, i)< m:
        m=i
print("leaf=",m, "mse=", mse(model4, m))
```

```
leaf= 8 mse= 0.2134684251899729
```

[59]:
```
print(decision_rules(model4, 8))
```

```
Split 1:habitat_grasses>0.5
Split 2:stalk_shape_tapering<=0.5
Split 3:cap_shape_flat<=0.5
Split 4:cap_color_white>0.5
```

[60]:
```
test_filtered = test_m3[(test_m3.habitat_grasses<=0.5) &
                     (test_m3.stalk_shape_tapering<=0.5) &
                     (test_m3.cap_color_brown<=0.5) &
                     (test_m3.cap_surface_smooth>0.5) &
                     (test_m3.cap_color_pink<=0.5) &
                     (test_m3.habitat_waste<=0.5) &
                     (test_m3.cap_color_white>0.5) &
                     (test_m3.habitat_meadows>0.5)]
```

[61]:
```
Xtest_filt = test_filtered.drop(columns = 'classes')
ytest_filt = test_filtered['classes']
```

[62]:
```
print(confusion_matrix_data(Xtest_filt,ytest_filt,model4))
```

```
Accuracy =  8.695652173913043
Recall =  100.0
FPR =  100.0
FNR =  0.0
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0          0.0         21.0
Actual 1          0.0          2.0
```

0.9 Tuned Decision Tree (more predictors) - Max Depth 3

[63]:
```
train_m4 = pd.get_dummies(train.drop(columns = ['odor','veil_type']))
test_m4 = pd.get_dummies(test.drop(columns = ['odor','veil_type']))
```

[64]:
```
X = train_m4.drop(columns = 'classes')
Xtest = test_m4.drop(columns = 'classes')
y = train_m4['classes']
ytest = test_m4['classes']
```

[65]:
```
param_grid = {
    'max_leaf_nodes': range(10,40),
    'max_features': range(1,108),
    'max_depth': range(1,9)
}

skf = StratifiedKFold(n_splits=5)

grid_search = GridSearchCV(DecisionTreeClassifier(random_state=1),
                           param_grid,
                           scoring=['precision','recall','accuracy'],
                           refit="recall",
                           cv=skf,
                           n_jobs=-1,
                           verbose = True).fit(X,y)

print('Best params for recall')
print(grid_search.best_params_)
```

```
Fitting 5 folds for each of 25680 candidates, totalling 128400 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  28 tasks      | elapsed:    0.0s
[Parallel(n_jobs=-1)]: Done 1000 tasks      | elapsed:    2.3s
[Parallel(n_jobs=-1)]: Done 3000 tasks      | elapsed:    6.7s
[Parallel(n_jobs=-1)]: Done 5800 tasks      | elapsed:   13.3s
[Parallel(n_jobs=-1)]: Done 9400 tasks      | elapsed:   22.3s
[Parallel(n_jobs=-1)]: Done 13800 tasks      | elapsed:   34.3s
[Parallel(n_jobs=-1)]: Done 19000 tasks      | elapsed:   48.3s
[Parallel(n_jobs=-1)]: Done 25000 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 31800 tasks      | elapsed:  1.4min
[Parallel(n_jobs=-1)]: Done 39400 tasks      | elapsed:  1.8min
[Parallel(n_jobs=-1)]: Done 47800 tasks      | elapsed:  2.3min
[Parallel(n_jobs=-1)]: Done 57000 tasks      | elapsed:  2.7min
[Parallel(n_jobs=-1)]: Done 67000 tasks      | elapsed:  3.3min
[Parallel(n_jobs=-1)]: Done 77800 tasks      | elapsed:  4.0min
[Parallel(n_jobs=-1)]: Done 89400 tasks      | elapsed:  4.7min
[Parallel(n_jobs=-1)]: Done 101800 tasks      | elapsed:  5.4min
[Parallel(n_jobs=-1)]: Done 115000 tasks      | elapsed:  6.2min
```

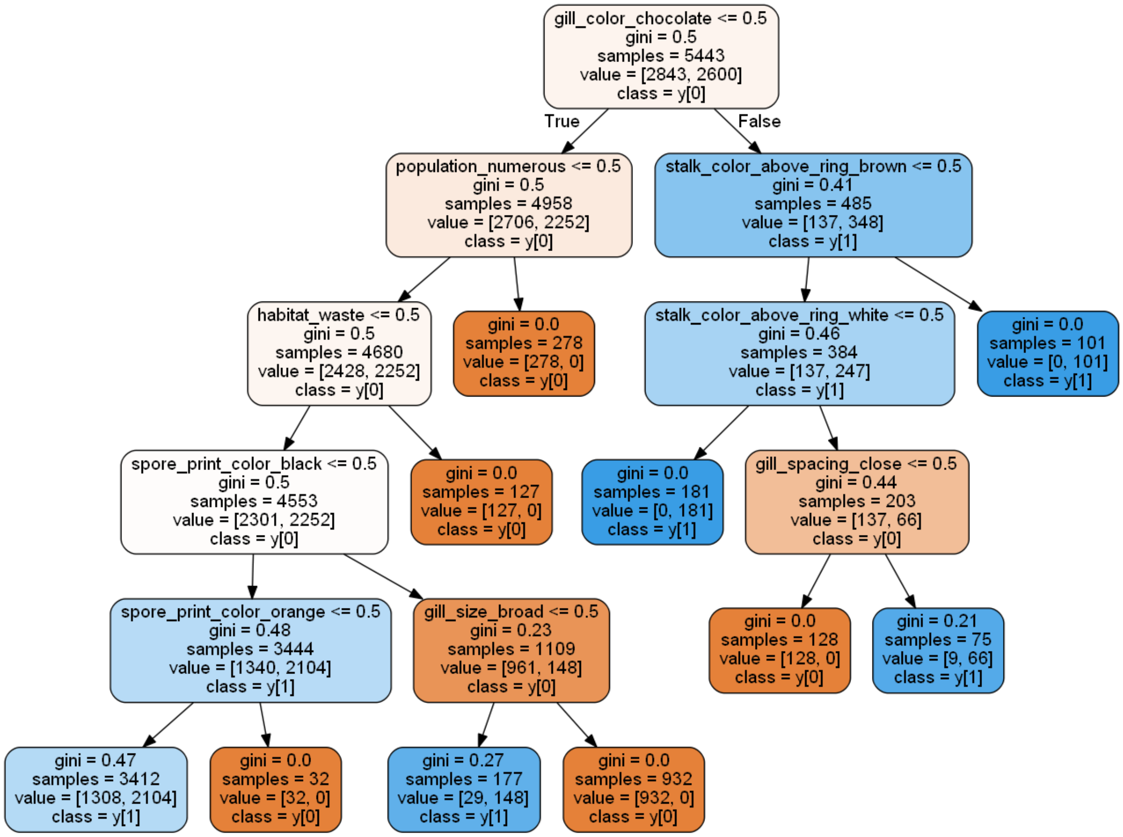
```
[Parallel(n_jobs=-1)]: Done 128400 out of 128400 | elapsed:  7.1min finished

Best params for recall
{'max_depth': 5, 'max_features': 2, 'max_leaf_nodes': 10}
```

[66]:
```
model5 = DecisionTreeClassifier(random_state=1, max_features = 2,␣
↪max_leaf_nodes=10, max_depth = 5)

model5.fit(X,y)
print(confusion_matrix_data(X,y,model5))
print(confusion_matrix_data(Xtest,ytest,model5))
```

```
Accuracy =  75.27099026272276
Recall =  100.0
FPR =  47.34435455504749
FNR =  0.0
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0       1497.0       1346.0
Actual 1          0.0       2600.0

Accuracy =  75.60611712047744
Recall =  100.0
FPR =  47.91208791208791
FNR =  0.0
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0        711.0        654.0
Actual 1          0.0       1316.0
```

[67]:
```
#Visualizing the regression tree
dot_data = StringIO()
export_graphviz(model5, out_file=dot_data,
                filled=True, rounded=True, class_names = True,
                feature_names =X.columns,precision=2)
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
#graph.write_png('car_price_tree.png')
Image(graph.create_png())
```

[67]:



[68]:
```
X.columns[pd.Series(model5.feature_importances_ > 0)]
```

[68]:
```
Index(['gill_spacing_close', 'gill_size_broad', 'gill_color_chocolate',
       'stalk_color_above_ring_brown', 'stalk_color_above_ring_white',
       'spore_print_color_black', 'spore_print_color_orange',
       'population_numerous', 'habitat_waste'],
      dtype='object')
```

[69]:
```
train_m5 = pd.get_dummies(train[['classes', 'gill_spacing', 'gill_size',␣
↪'gill_color', 'stalk_color_above_ring',
                              'spore_print_color', 'population', 'habitat']])
test_m5 = pd.get_dummies(test[['classes', 'gill_spacing', 'gill_size',␣
↪'gill_color', 'stalk_color_above_ring',
                              'spore_print_color', 'population', 'habitat']])
```

[70]:
```
X = train_m5.drop(columns = 'classes')
Xtest = test_m5.drop(columns = 'classes')
y = train_m5['classes']
ytest = test_m5['classes']
```

[71]:
```
param_grid = {
    'max_leaf_nodes': range(10,40),
    'max_features': range(1,48),
    'max_depth': range(1,9)
}

skf = StratifiedKFold(n_splits=5)

grid_search = GridSearchCV(DecisionTreeClassifier(random_state=1),
                           param_grid,
                           scoring=['precision','recall','accuracy'],
                           refit="recall",
                           cv=skf,
                           n_jobs=-1,
                           verbose = True).fit(X,y)

print('Best params for recall')
print(grid_search.best_params_)
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  28 tasks      | elapsed:    0.0s

Fitting 5 folds for each of 11280 candidates, totalling 56400 fits

[Parallel(n_jobs=-1)]: Done 1000 tasks      | elapsed:    2.1s
[Parallel(n_jobs=-1)]: Done 3000 tasks      | elapsed:    6.3s
[Parallel(n_jobs=-1)]: Done 5800 tasks      | elapsed:   12.2s
[Parallel(n_jobs=-1)]: Done 9400 tasks      | elapsed:   19.7s
[Parallel(n_jobs=-1)]: Done 13800 tasks      | elapsed:   29.1s
[Parallel(n_jobs=-1)]: Done 19000 tasks      | elapsed:   41.4s
[Parallel(n_jobs=-1)]: Done 25000 tasks      | elapsed:   55.0s
[Parallel(n_jobs=-1)]: Done 31800 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 39400 tasks      | elapsed:  1.5min
[Parallel(n_jobs=-1)]: Done 47800 tasks      | elapsed:  1.8min
[Parallel(n_jobs=-1)]: Done 56400 out of 56400 | elapsed:  2.2min finished

Best params for recall
{'max_depth': 6, 'max_features': 25, 'max_leaf_nodes': 15}
```

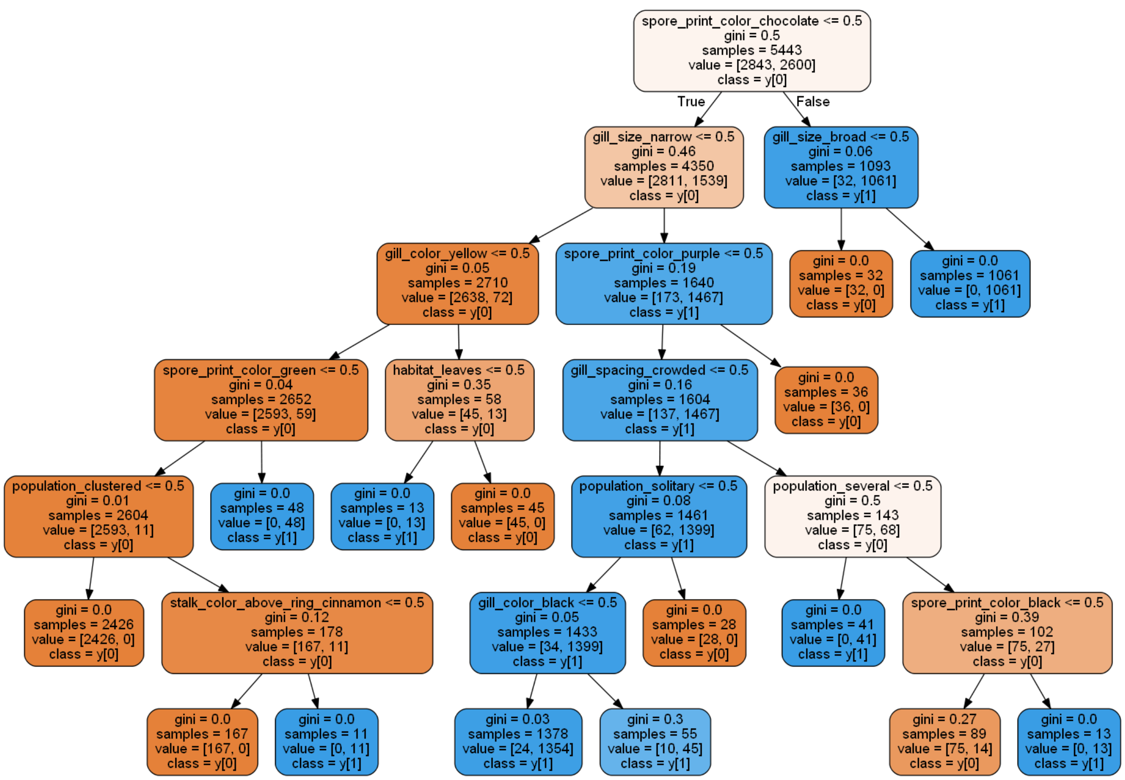
[72]:
```
model6 = DecisionTreeClassifier(random_state=1, max_features = 25,␣
 ↪max_leaf_nodes=15, max_depth = 6)

model6.fit(X,y)
print(confusion_matrix_data(X,y,model6))
print(confusion_matrix_data(Xtest,ytest,model6))
```

```
Accuracy =  99.11813338232592
Recall =  99.46153846153847
FPR =  1.1959198030249736
FNR =  0.5384615384615384
```

```
Confusion matrix =
             Predicted 0  Predicted 1
Actual 0         2809.0         34.0
Actual 1           14.0       2586.0

Accuracy =  99.10481163744872
Recall =  99.24012158054711
FPR =  1.0256410256410255
FNR =  0.7598784194528876
Confusion matrix =
             Predicted 0  Predicted 1
Actual 0         1351.0         14.0
Actual 1           10.0       1306.0
```

[73]:
```python
#Visualizing the decision tree
dot_data = StringIO()
export_graphviz(model6, out_file=dot_data,
                filled=True, rounded=True, class_names = True,
                feature_names =X.columns,precision=2)
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
#graph.write_png('car_price_tree.png')
Image(graph.create_png())
```

[73]:



0.10 ENSEMBLE MODEL

0.10.1 Decision Tree

[74]:
```
m1 = model6
```

0.10.2 Random Forest

[75]:
```
params = {'n_estimators': [500],
          'max_features': range(1,48),
         }

param_list=list(it.product(*(params[Name] for Name in list(params.keys()))))
recall = [0]*len(param_list)

i=0
for pr in param_list:
    model =␣
 ↪RandomForestClassifier(random_state=1,oob_score=True,verbose=False,n_estimators␣
 ↪= pr[0],
                                  max_features=pr[1], n_jobs=-1).fit(X,y)
    oob_pred = model.oob_decision_function_[:,1]
    bins=np.array([0,0.5,1])
    cm = np.histogram2d(y, oob_pred, bins=bins)[0]
    recall[i] = 100*(cm[1,1])/(cm[1,0]+cm[1,1])
    i=i+1

print("max recall = ", np.max(recall))
print("params= ", param_list[np.argmax(recall)])
```

```
max recall =  99.3076923076923
params=  (500, 1)
```

[76]:
```
m2 =␣
 ↪RandomForestClassifier(random_state=1,n_jobs=-1,max_features=1,n_estimators=500).
 ↪fit(X, y)
```

0.10.3 XGBoost

[77]:
```
param_grid = {'n_estimators':[25,100,500],
              'max_depth': [6,7,8],
              'learning_rate': [0.01,0.1,0.2],
              'gamma': [0.1,0.25,0.5],
              'reg_lambda':[0,0.01,0.001],
              'scale_pos_weight':[1.25,1.5,1.75]
             }

cv = StratifiedKFold(n_splits=5,shuffle=True,random_state=1)
```

```
optimal_params = GridSearchCV(estimator=xgb.XGBClassifier(objective = 'binary:
 ↪logistic',random_state=1,
                                                                              ␣
 ↪use_label_encoder=False),
                             param_grid = param_grid,
                             scoring = 'accuracy',
                             verbose = 1,
                             n_jobs=-1,
                             cv = cv).fit(X,y)

print(optimal_params.best_params_,optimal_params.best_score_)
```

```
Fitting 5 folds for each of 729 candidates, totalling 3645 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:    1.4s
[Parallel(n_jobs=-1)]: Done 176 tasks      | elapsed:   42.8s
[Parallel(n_jobs=-1)]: Done 426 tasks      | elapsed:  2.2min
[Parallel(n_jobs=-1)]: Done 776 tasks      | elapsed:  3.8min
[Parallel(n_jobs=-1)]: Done 1226 tasks      | elapsed:  6.2min
[Parallel(n_jobs=-1)]: Done 1776 tasks      | elapsed:  9.0min
[Parallel(n_jobs=-1)]: Done 2426 tasks      | elapsed: 12.5min
[Parallel(n_jobs=-1)]: Done 3176 tasks      | elapsed: 16.1min

{'gamma': 0.1, 'learning_rate': 0.2, 'max_depth': 6, 'n_estimators': 25,
'reg_lambda': 0, 'scale_pos_weight': 1.25} 0.9932027494193271

[Parallel(n_jobs=-1)]: Done 3645 out of 3645 | elapsed: 18.7min finished
```

[78]:
```
m3 = xgb.XGBClassifier(objective = 'binary:logistic',random_state=1,gamma=0.
 ↪1,learning_rate = 0.2,max_depth=6,
                              n_estimators = 25,reg_lambda =␣
 ↪0,scale_pos_weight=1.25,use_label_encoder=False).fit(X,y)
```

0.10.4 Stacking Classifier

[79]:
```
ensemble_model = StackingClassifier(estimators=[('dt',m1),('rf',m2),('xgb',m3)],
                                               ␣
 ↪final_estimator=LogisticRegression(random_state=1,max_iter=10000),n_jobs=-1,
                                    cv =␣
 ↪StratifiedKFold(n_splits=5,shuffle=True,random_state=1))
ensemble_model.fit(X,y)
```

[79]:
```
StackingClassifier(cv=StratifiedKFold(n_splits=5, random_state=1, shuffle=True),
                   estimators=[('dt',
                                DecisionTreeClassifier(max_depth=6,
                                                       max_features=25,
                                                       max_leaf_nodes=15,
                                                       random_state=1)),
```

```
                        ('rf',
                         RandomForestClassifier(max_features=1,
                                                n_estimators=500,
                                                n_jobs=-1,
                                                random_state=1)),
                        ('xgb',
                         XGBClassifier(base_score=0.5, booster='gbtree',
                                       callbacks=None,
                                       colsample_by…
                                       interaction_constraints='',
                                       learning_rate=0.2, max_bin=256,
                                       max_cat_to_onehot=4,
                                       max_delta_step=0, max_depth=6,
                                       max_leaves=0, min_child_weight=1,
                                       missing=nan,
                                       monotone_constraints='()',
                                       n_estimators=25, n_jobs=0,
                                       num_parallel_tree=1,
                                       predictor='auto', random_state=1,
                                       reg_alpha=0, reg_lambda=0, …))],
            final_estimator=LogisticRegression(max_iter=10000,
                                               random_state=1),
            n_jobs=-1)
```

[80]:

```
print(confusion_matrix_data(X,y,ensemble_model))
print(confusion_matrix_data(Xtest,ytest,ensemble_model))
```

```
Accuracy =  99.33860003674444
Recall =  99.61538461538461
FPR =  0.914526908195568
FNR =  0.38461538461538464
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0       2817.0         26.0
Actual 1         10.0       2590.0

Accuracy =  99.55240581872435
Recall =  99.84802431610942
FPR =  0.7326007326007326
FNR =  0.1519756838905775
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0       1355.0         10.0
Actual 1          2.0       1314.0
```