shroomies

December 16, 2022

[1]:

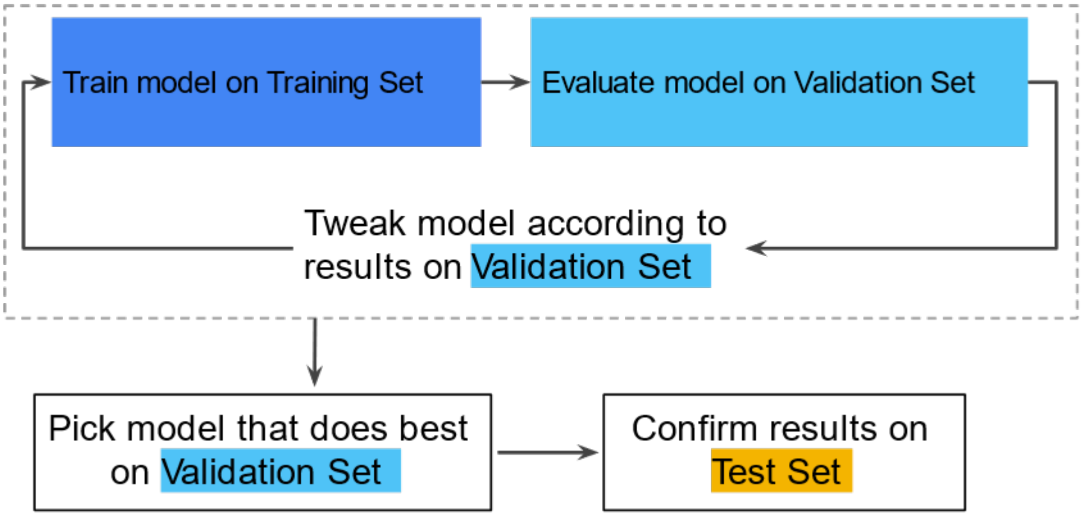
```
# Used libraries
import numpy as np
import pandas as pd
import seaborn as sns
import missingno as msn
import matplotlib.pyplot as plt
import os
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn import tree


# Jupyter configs
%matplotlib inline
pd.set_option('display.max_columns', None)
import warnings
warnings.filterwarnings('ignore')
```

1 The Seen/Unseen split (aka the Test split)

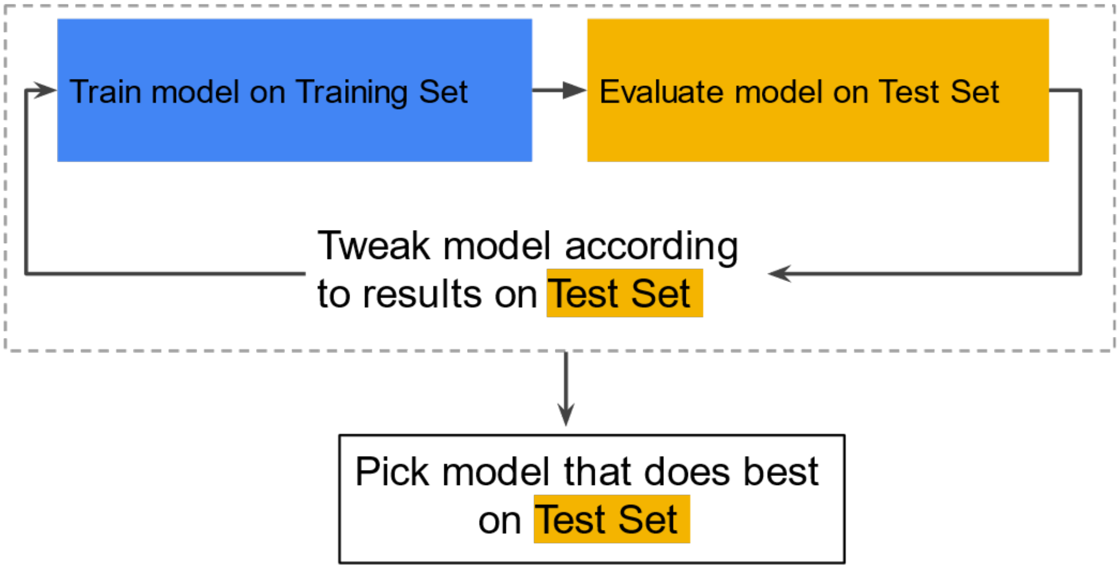
[2]:

```
df = pd.read_csv('mushrooms.csv')
df_train, df_test = train_test_split(df, test_size=0.2, random_state=42)
print('Train size:', df_train.shape)
print('Test size:', df_test.shape)
```

```
Train size: (6499, 23)
Test size: (1625, 23)
```


Train model on Training Set
Evaluate model on Validation Set
Tweak model according to results on Validation Set
Pick model that does best on Validation Set
Confirm results on Test Set

2


Train model on Training Set
Evaluate model on Test Set
Tweak model according to results on Test Set
Pick model that does best on Test Set

[3]:
```
df_test.to_csv('test_split.csv', index=False)
df_train.to_csv('train_split.csv', index=False)
```

3 A first good glance at the data

[4]:
```
df_train.head()
```

[4]:
```
     class cap-shape cap-surface cap-color bruises odor gill-attachment  \
7873     p         k           s         e       f    s               f
6515     p         x           s         n       f    f               f
6141     p         f           y         e       f    y               f
```

```
2764     e         f           f         n       t    n               f
438      e         b           y         y       t    l               f

     gill-spacing gill-size gill-color stalk-shape stalk-root  \
7873            c         n          b           t          ?
6515            c         n          b           t          ?
6141            c         n          b           t          ?
2764            c         b          u           t          b
438             c         b          k           e          c

     stalk-surface-above-ring stalk-surface-below-ring stalk-color-above-ring  \
7873                        s                        k                      p
6515                        k                        s                      w
6141                        s                        s                      p
2764                        s                        s                      g
438                         s                        s                      w

     stalk-color-below-ring veil-type veil-color ring-number ring-type  \
7873                      w         p          w           o         e
6515                      w         p          w           o         e
6141                      w         p          w           o         e
2764                      p         p          w           o         p
438                       w         p          w           o         p

     spore-print-color population habitat
7873                 w          v       d
6515                 w          v       p
6141                 w          v       l
2764                 n          v       d
438                  n          n       m
```

[5]:

```
df_train.tail()
```

[5]:

```
     class cap-shape cap-surface cap-color bruises odor gill-attachment  \
5226     p         x           y         n       f    f               f
5390     e         k           y         e       t    n               f
860      e         f           y         n       t    l               f
7603     p         k           s         e       f    f               f
7270     e         k           f         g       f    n               f

     gill-spacing gill-size gill-color stalk-shape stalk-root  \
5226            c         n          b           t          ?
5390            c         b          w           e          ?
860             c         b          w           e          r
7603            c         n          b           t          ?
7270            w         b          g           e          ?
```

```
     stalk-surface-above-ring stalk-surface-below-ring stalk-color-above-ring  \
5226                        k                        s                      p   
5390                        s                        s                      w   
860                         s                        y                      w   
7603                        s                        s                      p   
7270                        s                        k                      w   

     stalk-color-below-ring veil-type veil-color ring-number ring-type  \
5226                      w         p          w           o         e   
5390                      e         p          w           t         e   
860                       w         p          w           o         p   
7603                      p         p          w           o         e   
7270                      w         p          w           t         p   

     spore-print-color population habitat  
5226                 w          v       p  
5390                 w          c       w  
860                  n          y       p  
7603                 w          v       p  
7270                 w          n       g  
```

[6]:

```
df_train.sample(5)
```

[6]:

```
     class cap-shape cap-surface cap-color bruises odor gill-attachment  \
2045     e         x           y         y       t    a               f   
1258     e         f           s         w       f    n               f   
5134     e         k           s         n       t    n               f   
727      e         x           f         w       f    n               f   
5131     p         b           f         y       f    n               f   

     gill-spacing gill-size gill-color stalk-shape stalk-root  \
2045            c         b          p           e          r   
1258            w         b          h           t          e   
5134            c         b          w           e          ?   
727             w         b          h           t          e   
5131            c         n          w           e          ?   

     stalk-surface-above-ring stalk-surface-below-ring stalk-color-above-ring  \
2045                        s                        y                      w   
1258                        f                        s                      w   
5134                        s                        s                      e   
727                         f                        s                      w   
5131                        k                        y                      w   

     stalk-color-below-ring veil-type veil-color ring-number ring-type  \
2045                      w         p          w           o         p   
1258                      w         p          w           o         e   
```

```
5134                      w         p          w           t         e
727                       w         p          w           o         e
5131                      y         p          w           o         e

     spore-print-color population habitat
2045                 n          s       p
1258                 n          a       g
5134                 w          c       w
727                  n          s       g
5131                 w          v       d
```

4

5

6 Exploratory Data Analyis (EDA)

7

7.1 Examining the Data

[7]:

```
print('DataSet size:', df_train.shape)
print()
print(df_train.dtypes)
```

```
DataSet size: (6499, 23)

class                       object
cap-shape                   object
cap-surface                 object
cap-color                   object
bruises                     object
odor                        object
gill-attachment             object
gill-spacing                object
gill-size                   object
gill-color                  object
stalk-shape                 object
stalk-root                  object
stalk-surface-above-ring    object
stalk-surface-below-ring    object
stalk-color-above-ring      object
stalk-color-below-ring      object
veil-type                   object
veil-color                  object
ring-number                 object
ring-type                   object
```

```
spore-print-color           object
population                  object
habitat                     object
dtype: object
```

Data Types From A Machine Learning Perspective

[8]:

```
for column in df_train.columns:
    print(column, '==>', df_train[column].unique())
```

```
class ==> ['p' 'e']
cap-shape ==> ['k' 'x' 'f' 'b' 's' 'c']
cap-surface ==> ['s' 'y' 'f' 'g']
cap-color ==> ['e' 'n' 'y' 'g' 'w' 'b' 'p' 'r' 'c' 'u']
bruises ==> ['f' 't']
odor ==> ['s' 'f' 'y' 'n' 'l' 'p' 'a' 'c' 'm']
gill-attachment ==> ['f' 'a']
gill-spacing ==> ['c' 'w']
gill-size ==> ['n' 'b']
gill-color ==> ['b' 'u' 'k' 'w' 'e' 'p' 'n' 'y' 'o' 'g' 'h' 'r']
stalk-shape ==> ['t' 'e']
stalk-root ==> ['?' 'b' 'c' 'e' 'r']
stalk-surface-above-ring ==> ['s' 'k' 'f' 'y']
stalk-surface-below-ring ==> ['k' 's' 'f' 'y']
stalk-color-above-ring ==> ['p' 'w' 'g' 'o' 'n' 'e' 'b' 'c' 'y']
stalk-color-below-ring ==> ['w' 'p' 'g' 'n' 'o' 'b' 'e' 'c' 'y']
veil-type ==> ['p']
veil-color ==> ['w' 'n' 'o' 'y']
ring-number ==> ['o' 't' 'n']
ring-type ==> ['e' 'p' 'l' 'n' 'f']
spore-print-color ==> ['w' 'n' 'h' 'k' 'b' 'y' 'u' 'r' 'o']
population ==> ['v' 'n' 'y' 'c' 's' 'a']
habitat ==> ['d' 'p' 'l' 'm' 'w' 'u' 'g']
```

[9]:

```
df_train.describe()
```

[9]:

```
       class cap-shape cap-surface cap-color bruises  odor gill-attachment  \
count   6499      6499        6499      6499    6499  6499            6499
unique     2         6           4        10       2     9               2
top        e         x           y         n       f     n               f
freq    3365      2956        2602      1823    3802  2833            6331

       gill-spacing gill-size gill-color stalk-shape stalk-root  \
count          6499      6499       6499        6499       6499
unique            2         2         12           2          5
top               c         b          b           t          b
freq           5451      4496       1398        3702       3007
```

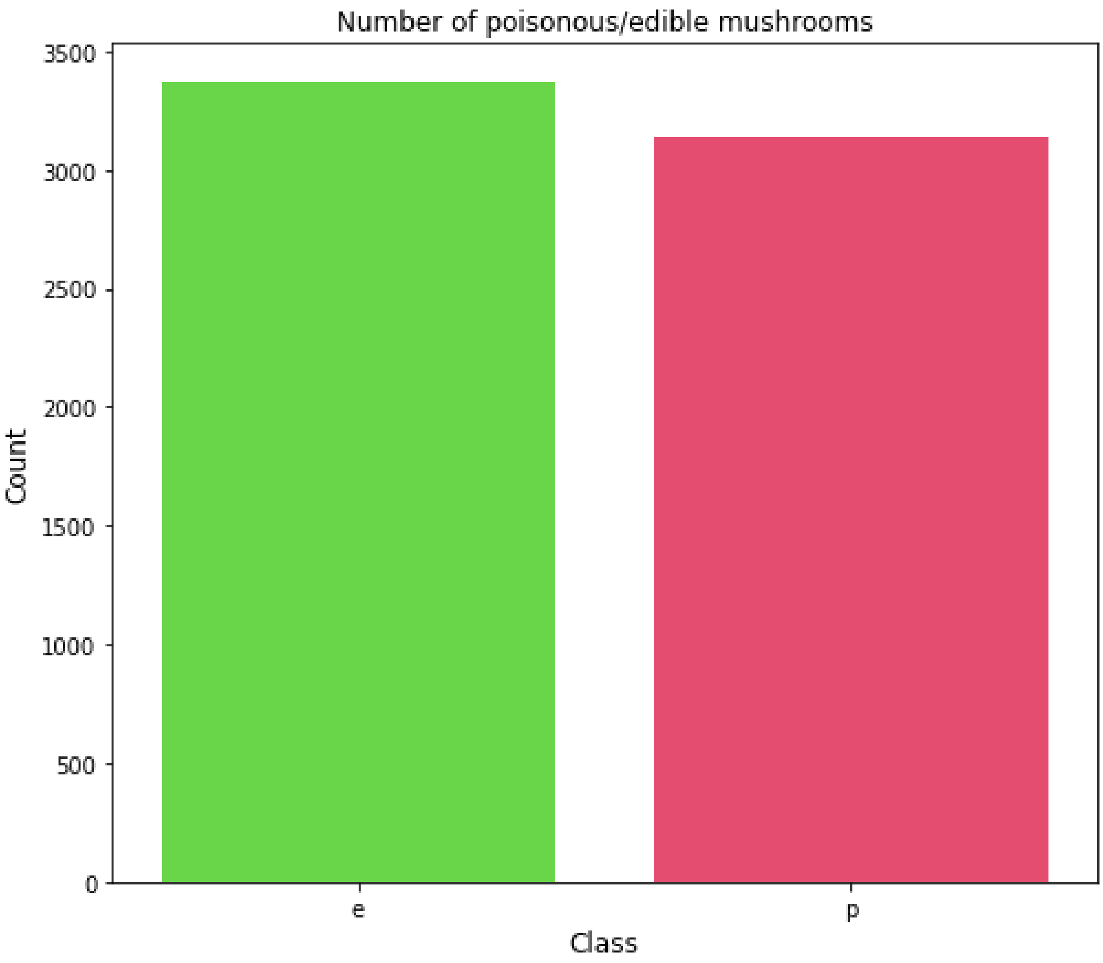
```
       stalk-surface-above-ring stalk-surface-below-ring  \
count                      6499                     6499
unique                        4                        4
top                           s                        s
freq                       4119                     3944

       stalk-color-above-ring stalk-color-below-ring veil-type veil-color  \
count                    6499                   6499      6499       6499
unique                      9                      9         1          4
top                         w                      w         p          w
freq                     3573                   3502      6499       6340

       ring-number ring-type spore-print-color population habitat
count         6499      6499              6499       6499    6499
unique           3         5                 9          6       7
top              o         p                 w          v       d
freq          5976      3154              1936       3218    2513
```

7.2 Taking a look at the target feature/labe/classes

… their distribution/balance to be more specific

[10]:

```
count = df_train['class'].value_counts()
plt.figure(figsize=(8,7))
sns.barplot(x=count.index, y=count.values, alpha=0.8, palette="prism")
plt.ylabel('Count', fontsize=12)
plt.xlabel('Class', fontsize=12)
plt.title('Number of poisonous/edible mushrooms')
#plt.savefig("mushrooms1.png", format='png', dpi=900)
plt.show()
```



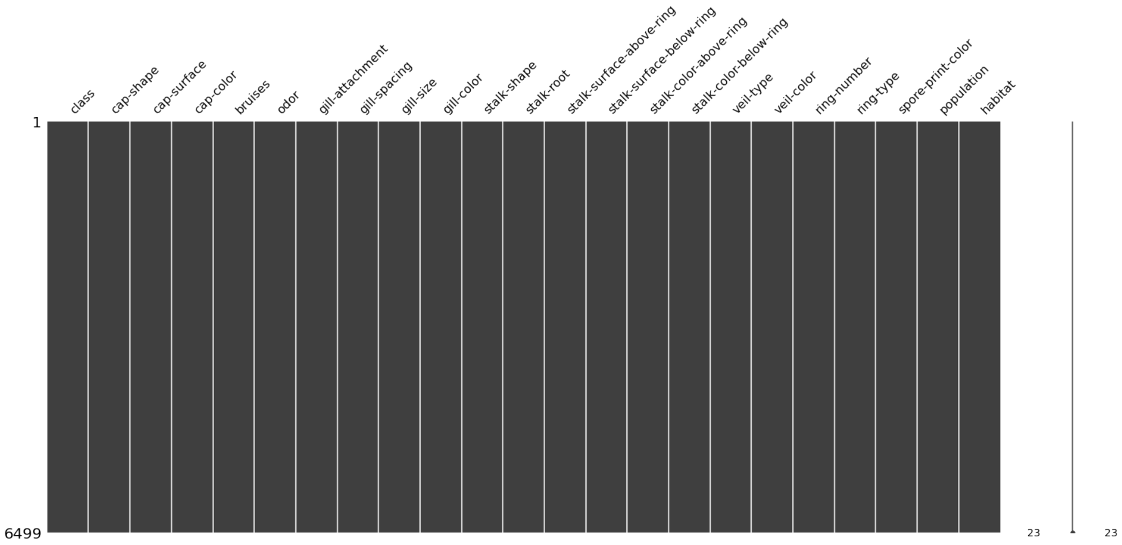
7.3 Missing Values

NaN isn't the only missing value

[11]:
```
print('DataSet size:', df_train.shape)
print()
print(df_train.info())
```

```
DataSet size: (6499, 23)

<class 'pandas.core.frame.DataFrame'>
Int64Index: 6499 entries, 7873 to 7270
Data columns (total 23 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   class                     6499 non-null   object
 1   cap-shape                 6499 non-null   object
 2   cap-surface               6499 non-null   object
 3   cap-color                 6499 non-null   object
 4   bruises                   6499 non-null   object
 5   odor                      6499 non-null   object
 6   gill-attachment           6499 non-null   object
 7   gill-spacing              6499 non-null   object
 8   gill-size                 6499 non-null   object
 9   gill-color                6499 non-null   object
 10  stalk-shape               6499 non-null   object
 11  stalk-root                6499 non-null   object
 12  stalk-surface-above-ring  6499 non-null   object
 13  stalk-surface-below-ring  6499 non-null   object
 14  stalk-color-above-ring    6499 non-null   object
 15  stalk-color-below-ring    6499 non-null   object
 16  veil-type                 6499 non-null   object
 17  veil-color                6499 non-null   object
 18  ring-number               6499 non-null   object
 19  ring-type                 6499 non-null   object
 20  spore-print-color         6499 non-null   object
 21  population                6499 non-null   object
 22  habitat                   6499 non-null   object
dtypes: object(23)
memory usage: 1.2+ MB
None
```

[12]:
```
msn.matrix(df_train);
```



[13]:
```
print(df_train['stalk-root'].unique())
```

```
['?' 'b' 'c' 'e' 'r']
```

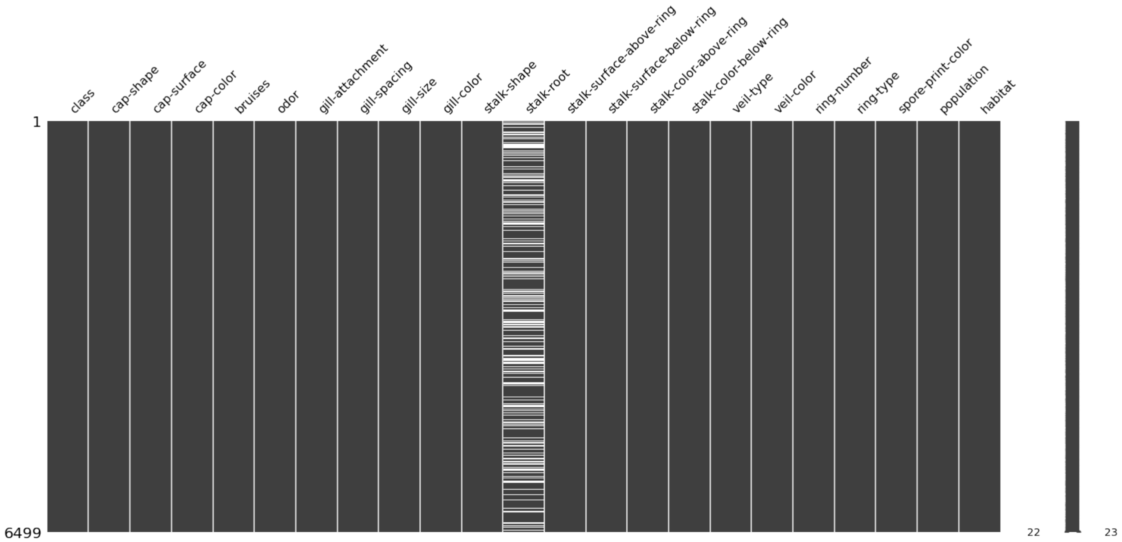
[14]:

```
def replaceMissing(x):
    if(x=='?'):
        return np.NaN
    else:
        return x


#df_train['stalk-root'] = df_train['stalk-root'].map(lambda x : np.NaN if x=='?
 ↪' else x)
df_train['stalk-root'] = df_train['stalk-root'].map(replaceMissing)
print(df_train['stalk-root'].unique())
```

```
[nan 'b' 'c' 'e' 'r']
```

[15]:

```
msn.matrix(df_train);
```



[16]:

```
print(("%.2f" % (df_train['stalk-root'].isna().sum()/df_train.shape[0]*100)),␣
 ↪'%')
```

```
30.88 %
```

But what about the data we can't see? What do we do if we have missing values there?

7.4 Plotting the data for visualisation

For visualisation purposes ONLY, we encode for the data TEMPORARY using a very simple encoding scheme (ordinal encoding). The data must transformed in a format that allows us to visualise it.

Take the following example/metaphor: We have some text on a piece of paper. The text is written in reverse. We know how to read the text when it is not reversed, and we also know if we use a mirror, and we reflect the text, we can see it in the correct orientation. So: “Text seems to be reversed” “Mirrors can be used to reverse text” Thus “Mirrors can reverse our reverse text to uncover the message”

The plot is a representation of the data (what we see) The mirror is the transformation you apply to it

Here’s another example of a such transformation.

[17]:
```
# Change the dtypes of the data-frame to 'category'. Panda recognises this␣
 ↪data-type, and it improves compatibility within the data.
df_eval = df_train.astype('category')

# We run a default Label encoding over the categorical features (which for this␣
 ↪data, it's all the features)
labelencoder=LabelEncoder()
for column in df_eval.columns:
    df_eval[column] = labelencoder.fit_transform(df_eval[column])
df_eval.head()
```

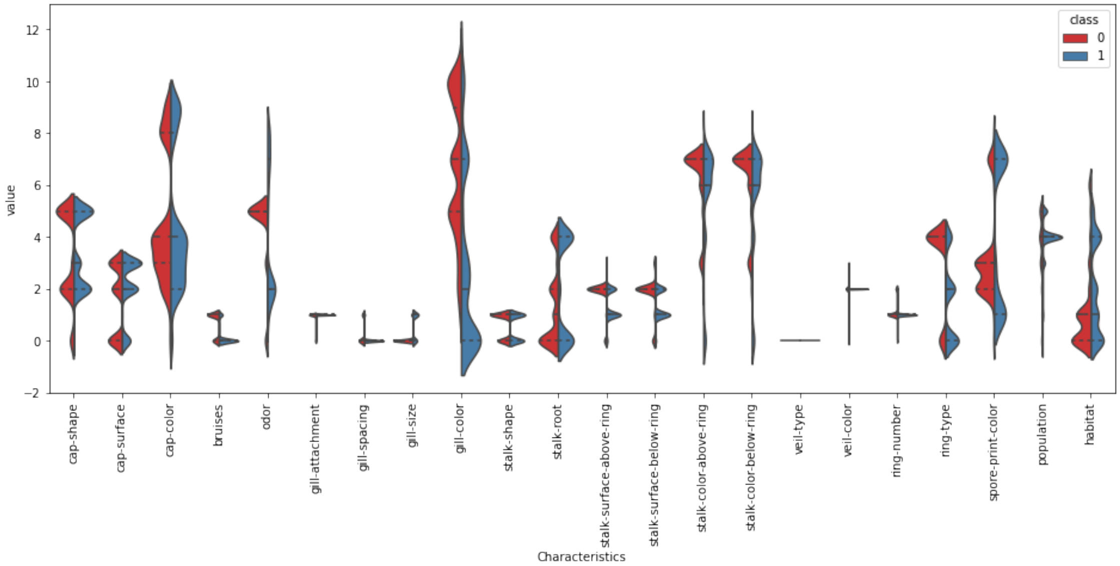
[17]:
```
      class  cap-shape  cap-surface  cap-color  bruises  odor  \
7873      1          3            2          2        0     7
6515      1          5            2          4        0     2
6141      1          2            3          2        0     8
2764      0          2            0          4        1     5
438       0          0            3          9        1     3

      gill-attachment  gill-spacing  gill-size  gill-color  stalk-shape  \
7873                1             0          1           0            1
6515                1             0          1           0            1
6141                1             0          1           0            1
2764                1             0          0           9            1
438                 1             0          0           4            0

      stalk-root  stalk-surface-above-ring  stalk-surface-below-ring  \
7873           4                         2                         1
6515           4                         1                         2
6141           4                         2                         2
2764           0                         2                         2
438            1                         2                         2

      stalk-color-above-ring  stalk-color-below-ring  veil-type  veil-color  \
7873                       6                       7          0           2
6515                       7                       7          0           2
6141                       6                       7          0           2
2764                       3                       6          0           2
438                        7                       7          0           2
```

```
      ring-number  ring-type  spore-print-color  population  habitat
7873            1          0                  7           4        0
6515            1          0                  7           4        4
6141            1          0                  7           4        2
2764            1          4                  3           4        0
438             1          4                  3           2        3
```

7.4.1 Violin Plot

A Violin Plot show the same information as a Box Plot, plus the entire distribution of the data.

```
[18]: df_div = pd.melt(df_eval, "class", var_name="Characteristics")
fig, ax = plt.subplots(figsize=(16,6))
p = sns.violinplot(ax = ax, x="Characteristics", y="value", hue="class", split␣
 ↪= True, data=df_div, inner = 'quartile', palette = 'Set1')
df_features = df_eval.drop(["class"],axis = 1)
p.set_xticklabels(rotation = 90, labels = list(df_features.columns));
plt.savefig("IMG/violinplot.jpg", format='jpg', dpi=900, bbox_inches='tight')
#plt.savefig("IMG/violinplot.png", format='png', dpi=900, bbox_inches='tight')
```



The violin plot above represents the distribution of the classification characteristics. It allows us to see the distribution of properties per class:

For example, it is possible to see that "gill-color" property of the mushroom breaks to two parts, one below 3 and one above 3, that may contribute to the classification.

Also, is this deduction correlating to the real-life phenomena? What do we know about mushrooms? Are there any facts about mushrooms that can help us identify if it's edible or not, without the need of a ML model?

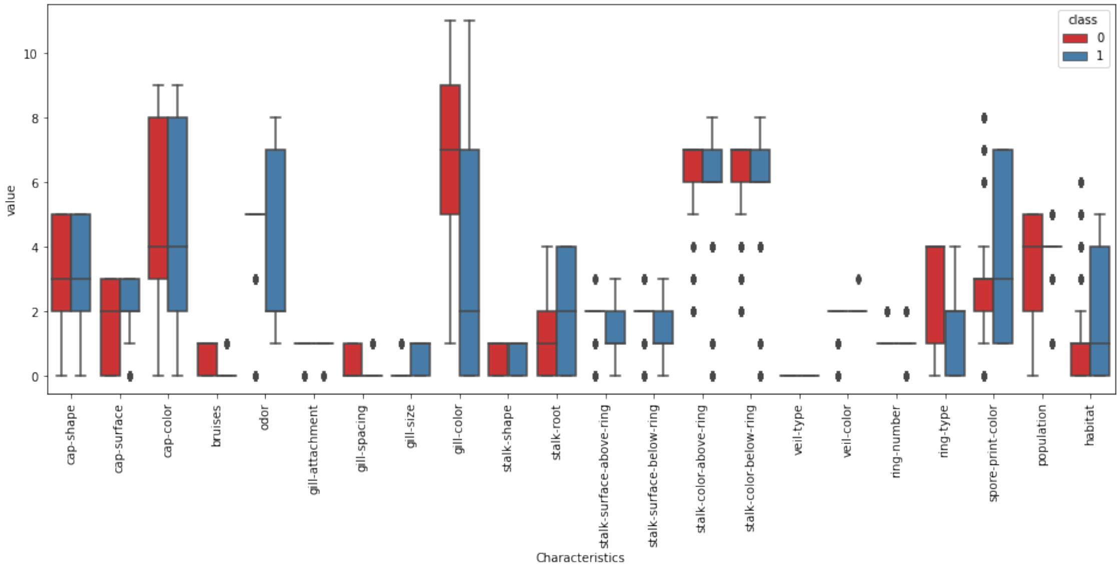
```
[19]: # Let's look at another property, like 'odor'. Does this have any tangent to␣
       ↪any real-life phenomena?
      pd.DataFrame(data=[df_train['odor'].unique(),df_eval['odor'].unique()])
```

```
[19]:    0  1  2  3  4  5  6  7  8
      0  s  f  y  n  l  p  a  c  m
      1  7  2  8  5  3  6  0  1  4
```

8

8.0.1 Box Plot

```
[20]: fig, ax = plt.subplots(figsize=(16,6))
      p = sns.boxplot(ax = ax, x="Characteristics", y="value", hue="class",␣
       ↪data=df_div, palette = 'Set1')
      p.set_xticklabels(rotation = 90, labels = list(df_features.columns));
      plt.savefig("IMG/boxplot.jpg", format='jpg', dpi=900, bbox_inches='tight')
      #plt.savefig("IMG/boxplot.png", format='png', dpi=900, bbox_inches='tight')
```



On the Box Plot above it is easier to spot outliers, looking at points that are furthest away from the mean.

9

9.0.1 Correlation matrix

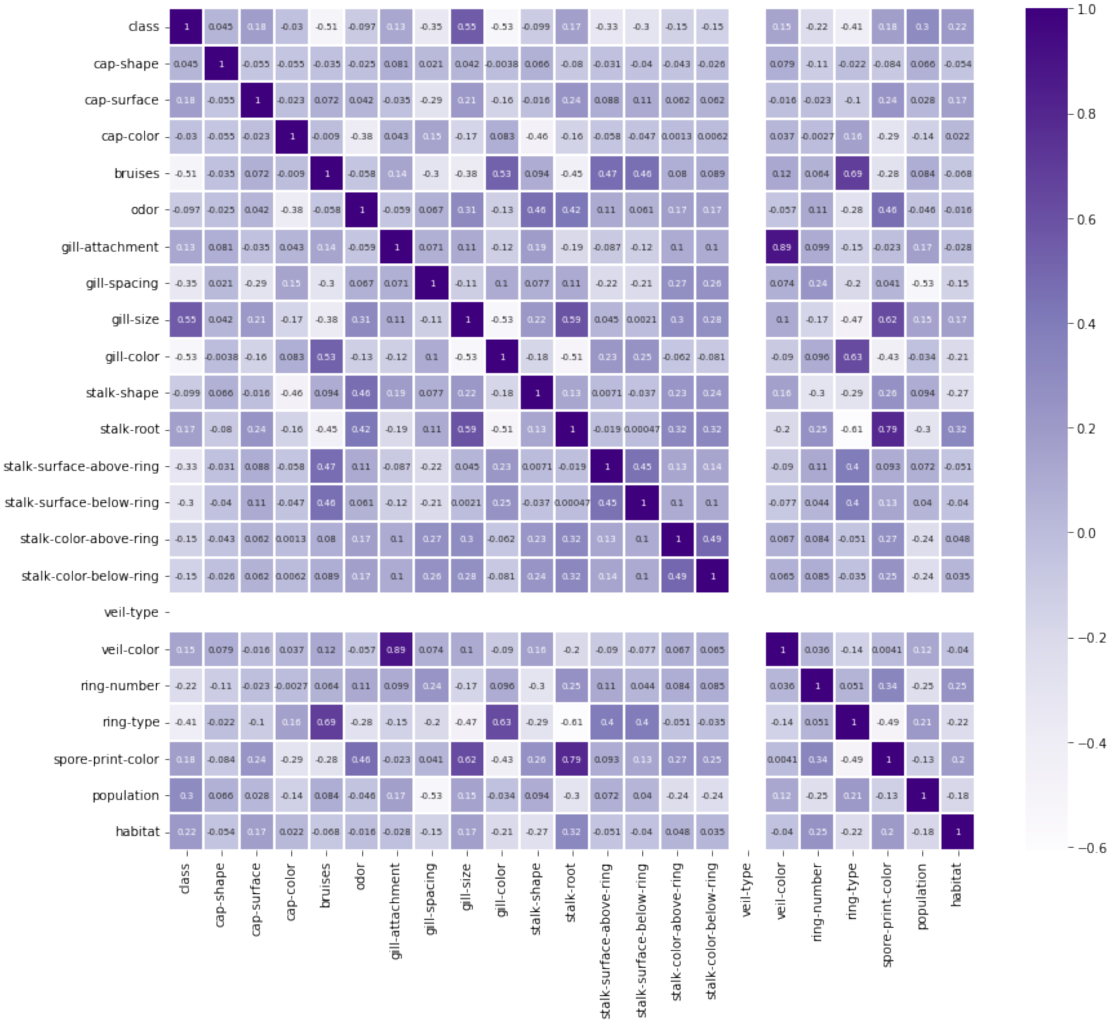
Correlation measures the strength of a relationship between two variables. The correlation coefficient expresses the degree of change in one variable as a function of the change in the other variable.

In other words, if two properties are strongly correlated, when one changes, we expect the other to change in the same manner.

The correlation between two variables can be positive or negative based on the value of the correlation coefficient.

It might be the case that out of these training features, some features are highly correlated. That may introduce redundancy (or noise) in your feature space, so it can indicate which features to drop and still achieve a good result.

```
[21]: plt.figure(figsize=(14,12))
      sns.heatmap(df_eval.corr(),linewidths=.1,cmap="Purples", annot=True,␣
       ↪annot_kws={"size": 7})
      plt.yticks(rotation=0);
      plt.savefig("IMG/corr.jpg", format='jpg', dpi=900, bbox_inches='tight')
      #plt.savefig("IMG/corr.png", format='png', dpi=900, bbox_inches='tight')
```



We are seeing some really strong corellations between properties and some significant ones between features and the target label.

[22]:
```
# For example, 'gill-attachment' and 'veil-color' are strongly correlated.
print(df_train['veil-color'].unique())
print(df_train['gill-attachment'].unique())
df_train[['veil-color','gill-attachment']].sample(25)
```

```
['w' 'n' 'o' 'y']
['f' 'a']
```

[22]:
```
     veil-color gill-attachment
1052          w               f
1458          w               f
5892          w               f
7810          w               f
3894          w               f
6195          w               f
6526          w               f
3481          w               f
300           w               f
4242          w               f
4948          w               f
3462          w               f
1722          w               f
2197          w               f
4746          w               f
3971          w               f
2967          w               f
4829          w               f
1958          w               f
3744          w               f
3690          w               f
539           w               f
6335          w               f
5648          w               f
275           w               f
```

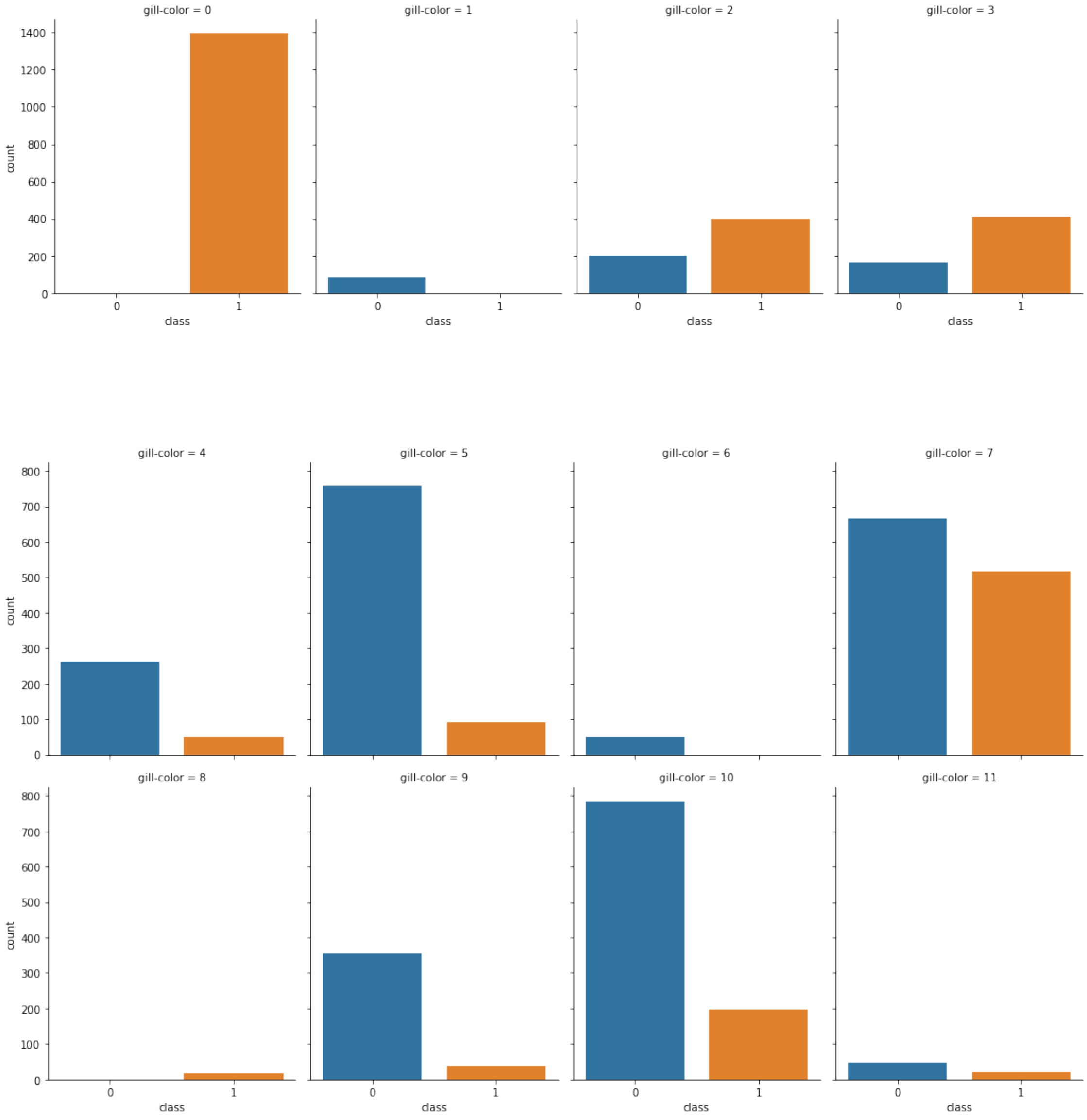
10

11

What about correlation between a feature and the target label? Let's take a closer look at 'gil-color'.

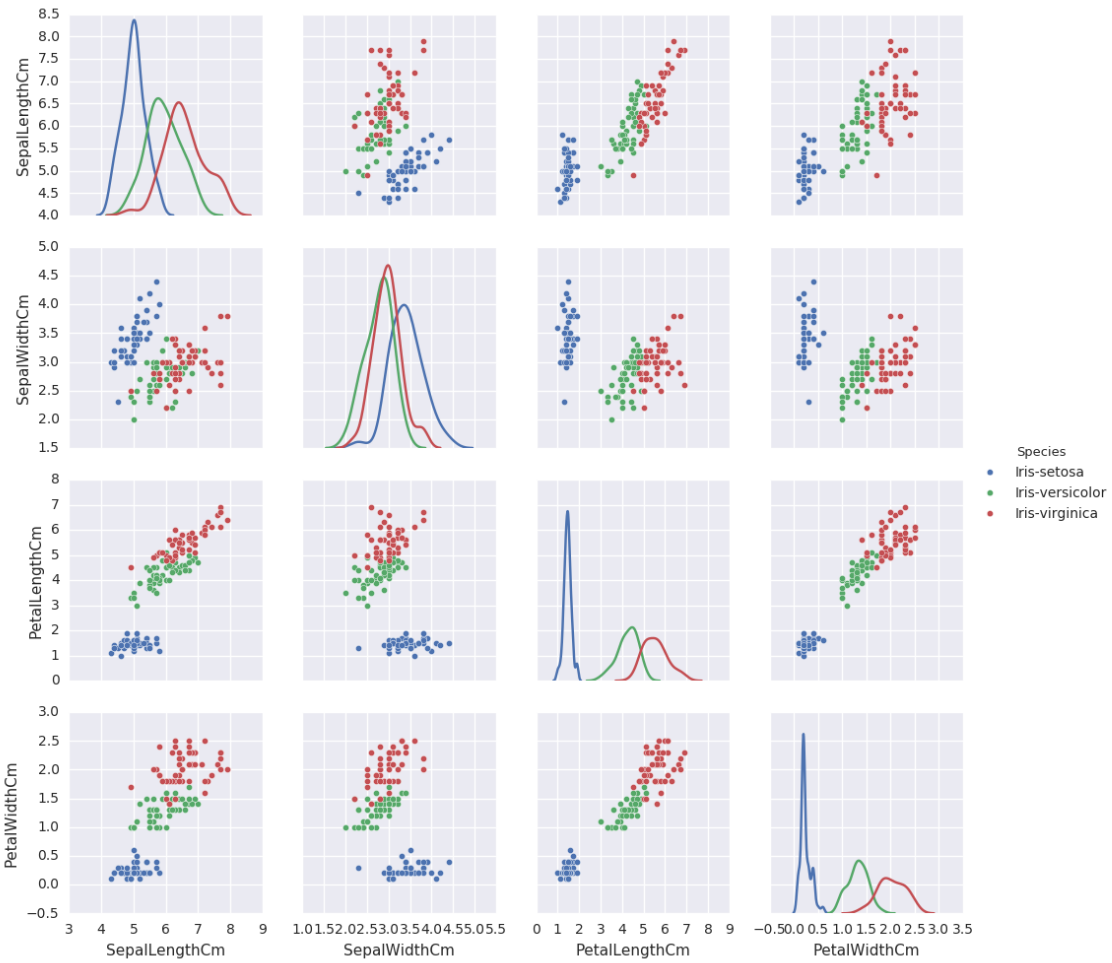
[23]:
```
new_var = df_eval[['class', 'gill-color']]
new_var = new_var[new_var['gill-color']<=3.5]
sns.factorplot('class', col='gill-color', data=new_var, kind='count', size=4.5,␣
 ↪aspect=.8, col_wrap=4);
```

```
new_var=df_eval[['class', 'gill-color']]
new_var=new_var[new_var['gill-color']>3.5]
sns.factorplot('class', col='gill-color', data=new_var, kind='count', size=4.5, aspect=.8, col_wrap=4);
```



Sometimes, through visualisation, we can extract meaningful information before we even raech the training stage.

Here is a similar example in the benchmark Iris data-set, where some class separation is more proeminent.



12 Data Pre-Processing

Carrying out necessary transformations

```
[24]: df_train = df_train.astype('category')
      df_train.dtypes
```

```
[24]: class                       category
      cap-shape                   category
      cap-surface                 category
      cap-color                   category
      bruises                     category
      odor                        category
      gill-attachment             category
      gill-spacing                category
      gill-size                   category
      gill-color                  category
      stalk-shape                 category
      stalk-root                  category
```

```
stalk-surface-above-ring    category
stalk-surface-below-ring    category
stalk-color-above-ring      category
stalk-color-below-ring      category
veil-type                   category
veil-color                  category
ring-number                 category
ring-type                   category
spore-print-color           category
population                  category
habitat                     category
dtype: object
```

13

13.1 Data Cleaning

Getting rid of what we don't need: Missing Values, Reduntant Values, Outliers

For missing values, let's look back at the Missingno Matrix. For redundant values, let's look back at the Correlation Matrix. For outliers, let's look back at the Box Plot

[25]:
```
df_train_clean = df_train.drop(['stalk-root', 'gill-attachment', 'veil-type'],␣
 ↪axis=1)
df_train_clean.to_csv('df_train_clean.csv', index=False)
```

14

14.1 Data encoding

[26]:
```
df_train_clean.sample(5)
```

[26]:
```
     class cap-shape cap-surface cap-color bruises odor gill-spacing  \
2316     e         x           y         e       t    n            c
5511     p         x           y         e       f    y            c
4718     p         x           f         y       f    f            c
2721     e         x           y         e       t    n            c
3450     e         f           y         e       t    n            c

     gill-size gill-color stalk-shape stalk-surface-above-ring  \
2316         b          p           t                        s
5511         n          b           t                        k
4718         b          g           e                        k
2721         b          n           t                        s
3450         b          u           t                        s

     stalk-surface-below-ring stalk-color-above-ring stalk-color-below-ring  \
2316                        s                       w                      w
5511                        k                       w                      p
4718                        k                       b                      b
2721                        s                       g                      p
3450                        s                       w                      w

     veil-color ring-number ring-type spore-print-color population habitat
2316          w           o         p                 k          v       d
5511          w           o         e                 w          v       l
4718          w           o         l                 h          y       g
2721          w           o         p                 n          y       d
3450          w           o         p                 k          y       d
```

14.2 One-Hot encoding

with trimming

[27]:

```
df_train_oh_encoded = pd.get_dummies(df_train_clean)
```

[28]:

```
df_train_oh_encoded
```

[28]:

```
      class_e  class_p  cap-shape_b  cap-shape_c  cap-shape_f  cap-shape_k  \
7873        0        1            0            0            0            1
6515        0        1            0            0            0            0
6141        0        1            0            0            1            0
2764        1        0            0            0            1            0
438         1        0            1            0            0            0
…       …      …          …          …          …          …
5226        0        1            0            0            0            0
5390        1        0            0            0            0            1
860         1        0            0            0            1            0
7603        0        1            0            0            0            1
7270        1        0            0            0            0            1

      cap-shape_s  cap-shape_x  cap-surface_f  cap-surface_g  cap-surface_s  \
7873            0            0              0              0              1
6515            0            1              0              0              1
6141            0            0              0              0              0
2764            0            0              1              0              0
438             0            0              0              0              0
…           …          …            …            …            …
5226            0            1              0              0              0
5390            0            0              0              0              0
860             0            0              0              0              0
7603            0            0              0              0              1
7270            0            0              1              0              0

      cap-surface_y  cap-color_b  cap-color_c  cap-color_e  cap-color_g  \
7873              0            0            0            1            0
6515              0            0            0            0            0
6141              1            0            0            1            0
2764              0            0            0            0            0
438               1            0            0            0            0
…             …          …          …          …          …
5226              1            0            0            0            0
5390              1            0            0            1            0
860               1            0            0            0            0
7603              0            0            0            1            0
7270              0            0            0            0            1

      cap-color_n  cap-color_p  cap-color_r  cap-color_u  cap-color_w  \
7873            0            0            0            0            0
6515            1            0            0            0            0
6141            0            0            0            0            0
2764            1            0            0            0            0
438             0            0            0            0            0
…           …          …          …          …          …
5226            1            0            0            0            0
5390            0            0            0            0            0
860             1            0            0            0            0
7603            0            0            0            0            0
7270            0            0            0            0            0

      cap-color_y  bruises_f  bruises_t  odor_a  odor_c  odor_f  odor_l  \
7873            0          1          0       0       0       0       0
6515            0          1          0       0       0       1       0
6141            0          1          0       0       0       0       0
2764            0          0          1       0       0       0       0
438             1          0          1       0       0       0       1
…           …        …        …     …     …     …     …
5226            0          1          0       0       0       1       0
5390            0          0          1       0       0       0       0
860             0          0          1       0       0       0       1
7603            0          1          0       0       0       1       0
7270            0          1          0       0       0       0       0

      odor_m  odor_n  odor_p  odor_s  odor_y  gill-spacing_c  gill-spacing_w  \
7873       0       0       0       1       0               1               0
6515       0       0       0       0       0               1               0
6141       0       0       0       0       1               1               0
2764       0       1       0       0       0               1               0
438        0       0       0       0       0               1               0
…      …     …     …     …     …             …             …
5226       0       0       0       0       0               1               0
5390       0       1       0       0       0               1               0
```

```
860        0       0       0       0       0               1               0
7603       0       0       0       0       0               1               0
7270       0       1       0       0       0               0               1

      gill-size_b  gill-size_n  gill-color_b  gill-color_e  gill-color_g  \
7873            0            1             1             0             0
6515            0            1             1             0             0
6141            0            1             1             0             0
2764            1            0             0             0             0
438             1            0             0             0             0
…           …          …           …           …           …
5226            0            1             1             0             0
5390            1            0             0             0             0
860             1            0             0             0             0
7603            0            1             1             0             0
7270            1            0             0             0             1

      gill-color_h  gill-color_k  gill-color_n  gill-color_o  gill-color_p  \
7873             0             0             0             0             0
6515             0             0             0             0             0
6141             0             0             0             0             0
2764             0             0             0             0             0
438              0             1             0             0             0
…            …           …           …           …           …
5226             0             0             0             0             0
5390             0             0             0             0             0
860              0             0             0             0             0
7603             0             0             0             0             0
7270             0             0             0             0             0

      gill-color_r  gill-color_u  gill-color_w  gill-color_y  stalk-shape_e  \
7873             0             0             0             0              0
6515             0             0             0             0              0
6141             0             0             0             0              0
2764             0             1             0             0              0
438              0             0             0             0              1
…            …           …           …           …            …
5226             0             0             0             0              0
5390             0             0             1             0              1
860              0             0             1             0              1
7603             0             0             0             0              0
7270             0             0             0             0              1

      stalk-shape_t  stalk-surface-above-ring_f  stalk-surface-above-ring_k  \
7873              1                           0                           0
6515              1                           0                           1
6141              1                           0                           0
```

```
2764              1                           0                           0
438               0                           0                           0
…             …                         …                         …
5226              1                           0                           1
5390              0                           0                           0
860               0                           0                           0
7603              1                           0                           0
7270              0                           0                           0

      stalk-surface-above-ring_s  stalk-surface-above-ring_y  \
7873                           1                           0
6515                           0                           0
6141                           1                           0
2764                           1                           0
438                            1                           0
…                          …                         …
5226                           0                           0
5390                           1                           0
860                            1                           0
7603                           1                           0
7270                           1                           0

      stalk-surface-below-ring_f  stalk-surface-below-ring_k  \
7873                           0                           1
6515                           0                           0
6141                           0                           0
2764                           0                           0
438                            0                           0
…                          …                         …
5226                           0                           0
5390                           0                           0
860                            0                           0
7603                           0                           0
7270                           0                           1

      stalk-surface-below-ring_s  stalk-surface-below-ring_y  \
7873                           0                           0
6515                           1                           0
6141                           1                           0
2764                           1                           0
438                            1                           0
…                          …                         …
5226                           1                           0
5390                           1                           0
860                            0                           1
7603                           1                           0
7270                           0                           0
```

```
      stalk-color-above-ring_b  stalk-color-above-ring_c  \
7873                         0                         0
6515                         0                         0
6141                         0                         0
2764                         0                         0
438                          0                         0
…                          …                         …
5226                         0                         0
5390                         0                         0
860                          0                         0
7603                         0                         0
7270                         0                         0

      stalk-color-above-ring_e  stalk-color-above-ring_g  \
7873                         0                         0
6515                         0                         0
6141                         0                         0
2764                         0                         1
438                          0                         0
…                          …                         …
5226                         0                         0
5390                         0                         0
860                          0                         0
7603                         0                         0
7270                         0                         0

      stalk-color-above-ring_n  stalk-color-above-ring_o  \
7873                         0                         0
6515                         0                         0
6141                         0                         0
2764                         0                         0
438                          0                         0
…                          …                         …
5226                         0                         0
5390                         0                         0
860                          0                         0
7603                         0                         0
7270                         0                         0

      stalk-color-above-ring_p  stalk-color-above-ring_w  \
7873                         1                         0
6515                         0                         1
6141                         1                         0
2764                         0                         0
438                          0                         1
…                          …                         …
```

```
5226                         1                         0
5390                         0                         1
860                          0                         1
7603                         1                         0
7270                         0                         1

      stalk-color-above-ring_y  stalk-color-below-ring_b  \
7873                         0                         0
6515                         0                         0
6141                         0                         0
2764                         0                         0
438                          0                         0
…                        …                       …
5226                         0                         0
5390                         0                         0
860                          0                         0
7603                         0                         0
7270                         0                         0

      stalk-color-below-ring_c  stalk-color-below-ring_e  \
7873                         0                         0
6515                         0                         0
6141                         0                         0
2764                         0                         0
438                          0                         0
…                        …                       …
5226                         0                         0
5390                         0                         1
860                          0                         0
7603                         0                         0
7270                         0                         0

      stalk-color-below-ring_g  stalk-color-below-ring_n  \
7873                         0                         0
6515                         0                         0
6141                         0                         0
2764                         0                         0
438                          0                         0
…                        …                       …
5226                         0                         0
5390                         0                         0
860                          0                         0
7603                         0                         0
7270                         0                         0

      stalk-color-below-ring_o  stalk-color-below-ring_p  \
7873                         0                         0
```

```
6515                         0                         0
6141                         0                         0
2764                         0                         1
438                          0                         0
…                        …                       …
5226                         0                         0
5390                         0                         0
860                          0                         0
7603                         0                         1
7270                         0                         0

      stalk-color-below-ring_w  stalk-color-below-ring_y  veil-color_n  \
7873                         1                         0             0
6515                         1                         0             0
6141                         1                         0             0
2764                         0                         0             0
438                          1                         0             0
…                        …                       …           …
5226                         1                         0             0
5390                         0                         0             0
860                          1                         0             0
7603                         0                         0             0
7270                         1                         0             0

      veil-color_o  veil-color_w  veil-color_y  ring-number_n  ring-number_o  \
7873             0             1             0              0              1
6515             0             1             0              0              1
6141             0             1             0              0              1
2764             0             1             0              0              1
438              0             1             0              0              1
…            …           …           …            …            …
5226             0             1             0              0              1
5390             0             1             0              0              0
860              0             1             0              0              1
7603             0             1             0              0              1
7270             0             1             0              0              0

      ring-number_t  ring-type_e  ring-type_f  ring-type_l  ring-type_n  \
7873              0            1            0            0            0
6515              0            1            0            0            0
6141              0            1            0            0            0
2764              0            0            0            0            0
438               0            0            0            0            0
…             …          …          …          …          …
5226              0            1            0            0            0
5390              1            1            0            0            0
860               0            0            0            0            0
```

```
7603              0            1            0            0            0
7270              1            0            0            0            0

      ring-type_p  spore-print-color_b  spore-print-color_h  \
7873            0                    0                    0
6515            0                    0                    0
6141            0                    0                    0
2764            1                    0                    0
438             1                    0                    0
…           …                  …                  …
5226            0                    0                    0
5390            0                    0                    0
860             1                    0                    0
7603            0                    0                    0
7270            1                    0                    0

      spore-print-color_k  spore-print-color_n  spore-print-color_o  \
7873                    0                    0                    0
6515                    0                    0                    0
6141                    0                    0                    0
2764                    0                    1                    0
438                     0                    1                    0
…                   …                  …                  …
5226                    0                    0                    0
5390                    0                    0                    0
860                     0                    1                    0
7603                    0                    0                    0
7270                    0                    0                    0

      spore-print-color_r  spore-print-color_u  spore-print-color_w  \
7873                    0                    0                    1
6515                    0                    0                    1
6141                    0                    0                    1
2764                    0                    0                    0
438                     0                    0                    0
…                   …                  …                  …
5226                    0                    0                    1
5390                    0                    0                    1
860                     0                    0                    0
7603                    0                    0                    1
7270                    0                    0                    1

      spore-print-color_y  population_a  population_c  population_n  \
7873                    0             0             0             0
6515                    0             0             0             0
6141                    0             0             0             0
2764                    0             0             0             0
```

```
438                     0             0             0             1
…                   …           …           …           …
5226                    0             0             0             0
5390                    0             0             1             0
860                     0             0             0             0
7603                    0             0             0             0
7270                    0             0             0             1

      population_s  population_v  population_y  habitat_d  habitat_g  \
7873             0             1             0          1          0
6515             0             1             0          0          0
6141             0             1             0          0          0
2764             0             1             0          1          0
438              0             0             0          0          0
…            …           …           …        …        …
5226             0             1             0          0          0
5390             0             0             0          0          0
860              0             0             1          0          0
7603             0             1             0          0          0
7270             0             0             0          0          1

      habitat_l  habitat_m  habitat_p  habitat_u  habitat_w
7873          0          0          0          0          0
6515          0          0          1          0          0
6141          1          0          0          0          0
2764          0          0          0          0          0
438           0          1          0          0          0
…         …        …        …        …        …
5226          0          0          1          0          0
5390          0          0          0          0          1
860           0          0          1          0          0
7603          0          0          1          0          0
7270          0          0          0          0          0

[6499 rows x 111 columns]
```

[29]:

```
df_train_oh_encoded['class'] = df_train_oh_encoded['class_e']
df_train_oh_encoded.drop(['class_e', 'class_p', 'cap-shape_x', 'cap-surface_y',␣
 ↪'cap-color_y', 'bruises_t', 'odor_y', 'gill-spacing_w', 'gill-size_n',␣
 ↪'gill-color_y', 'stalk-shape_t', 'stalk-surface-above-ring_y',␣
 ↪'stalk-surface-below-ring_y', 'stalk-color-above-ring_y',␣
 ↪'stalk-color-below-ring_y', 'veil-color_y', 'ring-number_t', 'ring-type_p',␣
 ↪'spore-print-color_y', 'population_v', 'habitat_w'], axis=1, inplace=True)
```

[30]:

```
print(df_train_oh_encoded.shape)
df_train_oh_encoded.to_csv('df_train_oh_encoded.csv', index=False)
```

```
(6499, 91)
```

15

15.1 Ordinal encoding

```
[31]: df_train_or_encoded = df_train_clean.copy()

      labelencoder=LabelEncoder()
      for column in df_train_clean.columns:
          df_train_or_encoded[column] = labelencoder.
       ↪fit_transform(df_train_or_encoded[column])
      df_train_or_encoded.to_csv('df_train_or_encoded.csv', index=False)
      df_train_or_encoded.sample(5)
```

```
[31]:       class  cap-shape  cap-surface  cap-color  bruises  odor  gill-spacing  \
      1678      0          2            2          4        0     5             1
      988       0          5            2          3        0     5             1
      4550      1          5            3          9        0     2             0
      1798      1          2            3          8        1     6             0
      7381      1          2            3          4        0     7             0

            gill-size  gill-color  stalk-shape  stalk-surface-above-ring  \
      1678          0           5            1                         2
      988           0           4            1                         2
      4550          0           7            0                         1
      1798          1           4            0                         2
      7381          1           0            1                         1

            stalk-surface-below-ring  stalk-color-above-ring  \
      1678                         2                       7
      988                          0                       7
      4550                         1                       6
      1798                         2                       7
      7381                         2                       6

            stalk-color-below-ring  veil-color  ring-number  ring-type  \
      1678                       7           2            1          0
      988                        7           2            1          0
      4550                       4           2            1          2
      1798                       7           2            1          4
      7381                       6           2            1          0

            spore-print-color  population  habitat
      1678                  2           0        1
      988                   2           0        1
      4550                  1           5        4
      1798                  2           4        5
      7381                  7           4        2
```

16

17

18 Model Training

18.1 with Decision Trees Classifier

19

19.1 Train-Validation Split

[32]:
```
# For each ML algorithm, we need to specify which part of the dataset contains␣
 ↪the features ...
X = df_train_or_encoded.drop(['class'], axis=1)
# ... and which is the target
Y = df_train_or_encoded['class']

# Split dataset again, one big portion for training the model, the other to␣
 ↪validate the model
X_train, X_validation, y_train, y_validation = train_test_split(X, Y,␣
 ↪test_size=0.2, random_state=42)

print('X_train:', X_train.shape)
print('y_train:', y_train.shape)
print('X_validation:', X_validation.shape)
print('y_validation:', y_validation.shape)
```

```
X_train: (5199, 19)
y_train: (5199,)
X_validation: (1300, 19)
y_validation: (1300,)
```

19.2 Training the model

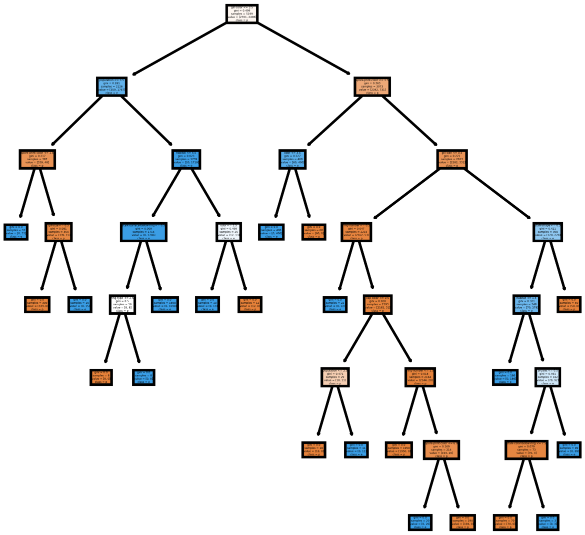
[33]:
```
clf = DecisionTreeClassifier()
clf.fit(X_train, y_train)
```

[33]:
```
DecisionTreeClassifier()
```

19.2.1 Visualising the produced decision tree

[34]:
```
fn = X_train.columns
cn = df_train['class'].unique()

# Setting dpi = 900 to make image clearer than default
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=900)
```

```
tree.plot_tree(clf,
               feature_names = fn,
               class_names=cn,
               filled = True);
```



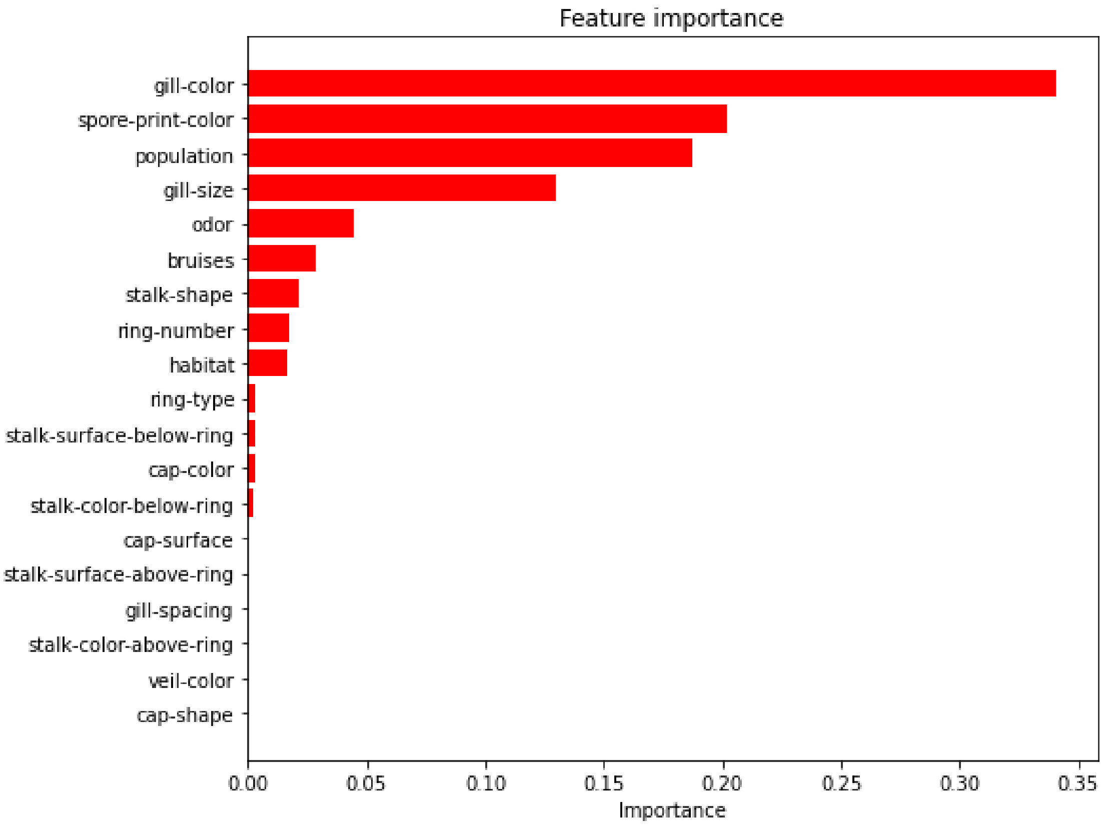
19.2.2 Feature importance

Drawing a graph showing the feature importance for the trained model. Looking both at the graph below and the three above, what relation can you see?

If you look back at the EDA stage, which assumption that we made about the data are reflected here?

[35]:

```
features_list = X.columns.values
feature_importance = clf.feature_importances_
sorted_idx = np.argsort(feature_importance)

plt.figure(figsize=(8,7))
plt.barh(range(len(sorted_idx)), feature_importance[sorted_idx],␣
 ↪align='center', color ="red")
plt.yticks(range(len(sorted_idx)), features_list[sorted_idx])
plt.xlabel('Importance')
plt.title('Feature importance')
plt.draw()
#plt.savefig("IMG/featureimp.png", format='png', dpi=900, bbox_inches='tight')
plt.show()
```



20

21 Validation

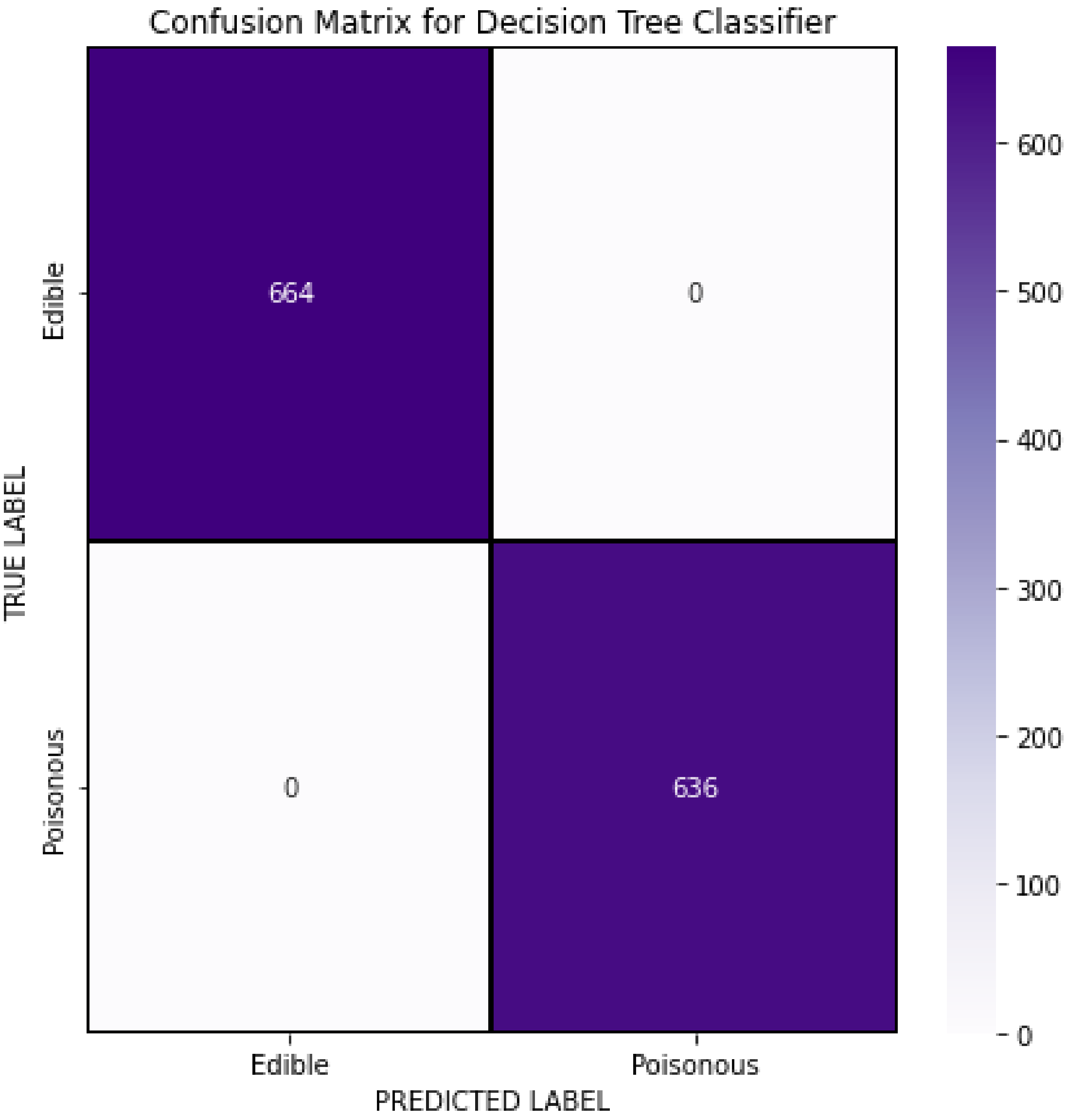
Accuracy scores and Confusion Matrix

[36]:

```
y_pred_validation = clf.predict(X_validation)
print("Decision Tree Classifier report: \n\n",␣
 ↪classification_report(y_validation, y_pred_validation))
print("Test Accuracy: {}%".format(round(clf.score(X_validation,␣
 ↪y_validation)*100, 2)))

# Confusion matrix
cm = confusion_matrix(y_validation, y_pred_validation)

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

f, ax = plt.subplots(figsize =(7,7))
```

```
sns.heatmap(cm, annot = True, linewidths=0.2, linecolor="black", fmt = ".0f",␣
 ↪ax=ax, cmap="Purples", xticklabels=x_axis_labels, yticklabels=y_axis_labels)
plt.xlabel("PREDICTED LABEL")
plt.ylabel("TRUE LABEL")
plt.title('Confusion Matrix for Decision Tree Classifier')
#plt.savefig("IMG/dtcm_validation.png", format='png', dpi=900,␣
 ↪bbox_inches='tight')
plt.show()
```

```
Decision Tree Classifier report:

               precision    recall  f1-score   support

           0       1.00      1.00      1.00       664
           1       1.00      1.00      1.00       636

    accuracy                           1.00      1300
   macro avg       1.00      1.00      1.00      1300
weighted avg       1.00      1.00      1.00      1300

Test Accuracy: 100.0%
```



22

23

24

25 Testing

With unseen data - Now we see how the model actually performs

26

26.1 Preparing the test data

First, to be able to fit the data into the model, we need to apply the EXACT SAME Pre-Processing steps as we did on the training data.

Think of it like this, you are carving a hole into a wall to mount a bar, and the bar must fit perfectly to not be too loose. The tool you use to cut the hole, is a CIRCLE bit of 35MM. Now, given that you have drilled then hole correctly, with the right bit, the you can fit a CIRCULAR bar in the hole with a diameter of 35MM.

Your model is the wall, your training data is the circle bit, training the model is cutting the hole with the bit, the test data is the bar and testing the model is to try and fit the bar in the cut hole. If your test data is not the same shape as your training data, it simply won't fit the algorithm. If your data is not encoded in the same way, then the algorithm will not be able to recognise the links it made out in the training data.

Finally, think as the test results as the error margin in how you've cut the hole, does the bar sit too loose, too tight or not at all?

[37]:

```
# No visualisation of any sorts this time. Remember, you cannot see this data,␣
 ↪it's like it wasn't produced yet.
df_test = df_test.astype('category')
df_test_clean = df_test.drop(['stalk-root', 'gill-attachment', 'veil-type'],␣
 ↪axis=1)
df_test_or_encoded = df_test_clean.copy()

labelencoder=LabelEncoder()
for column in df_test_clean.columns:
    df_test_or_encoded[column] = labelencoder.
 ↪fit_transform(df_test_or_encoded[column])
```

26.2 Predicting on test data

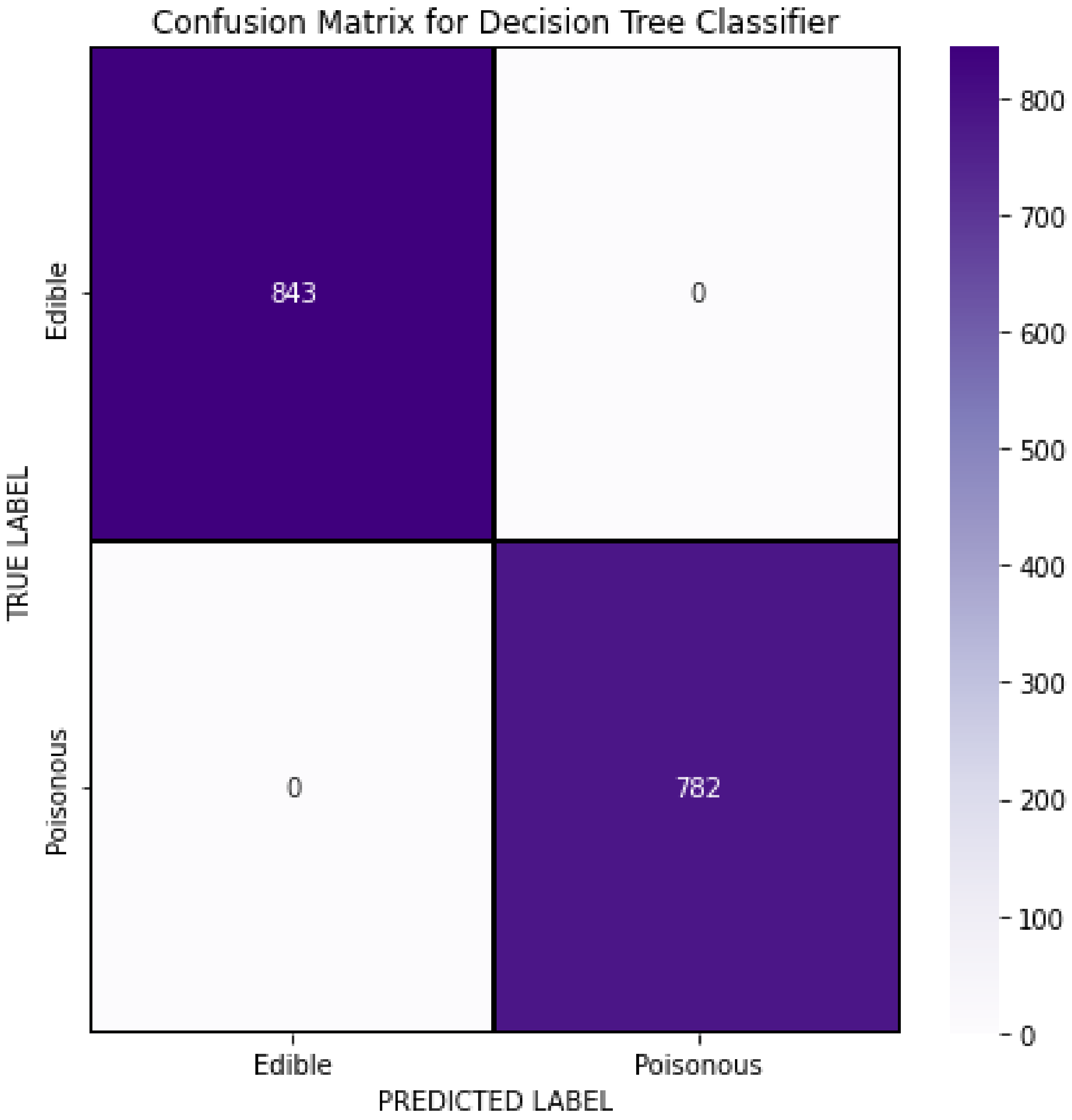
We predict on the test data using the SAME MODEL we trained earlier.

[38]:

```
# features
X_test = df_test_or_encoded.drop(['class'], axis=1)
# target
Y_test = df_test_or_encoded['class']

y_pred_validation = clf.predict(X_test)
print("Decision Tree Classifier report: \n\n", classification_report(Y_test,␣
 ↪y_pred_validation))
print("Test Accuracy: {}%".format(round(clf.score(X_test, Y_test)*100, 2)))

# Confusion matrix
cm = confusion_matrix(Y_test, y_pred_validation)
```

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

f, ax = plt.subplots(figsize =(7,7))
sns.heatmap(cm, annot = True, linewidths=0.2, linecolor="black", fmt = ".0f",␣
 ↪ax=ax, cmap="Purples", xticklabels=x_axis_labels, yticklabels=y_axis_labels)
plt.xlabel("PREDICTED LABEL")
plt.ylabel("TRUE LABEL")
plt.title('Confusion Matrix for Decision Tree Classifier')
#plt.savefig("IMG/dtcm_test.png", format='png', dpi=900, bbox_inches='tight')
plt.show()
```

```
Decision Tree Classifier report:

              precision    recall  f1-score   support

           0       1.00      1.00      1.00       843
           1       1.00      1.00      1.00       782

    accuracy                           1.00      1625
   macro avg       1.00      1.00      1.00      1625
weighted avg       1.00      1.00      1.00      1625

Test Accuracy: 100.0%
```


Confusion Matrix for Decision Tree Classifier
TRUE LABEL
Edible
Poisonous
843
0
0
782
Edible
Poisonous
PREDICTED LABEL
800
700
600
500
400
300
200
100
0

27

28

29

30

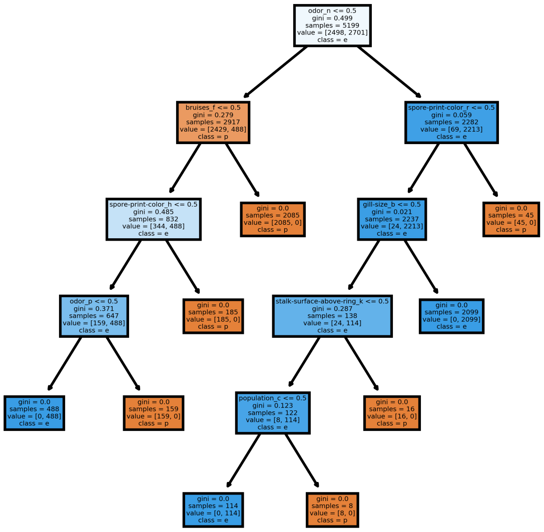
31

32 Appendix

I didn't forget about the one-hot encoded train set

[39]:

```
# SPLITTING
X = df_train_oh_encoded.drop(['class'], axis=1)
Y = df_train_oh_encoded['class']
X_train, X_validation, y_train, y_validation = train_test_split(X, Y,␣
 ↪test_size=0.2, random_state=42)

# TRAINING
clf_oh = DecisionTreeClassifier() # New model this time btw
clf_oh.fit(X_train, y_train)

# Some visualisation
fn = X_train.columns
cn = df_train['class'].unique()
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=900)
tree.plot_tree(clf_oh,
           feature_names = fn,
           class_names=cn,
           filled = True);
```

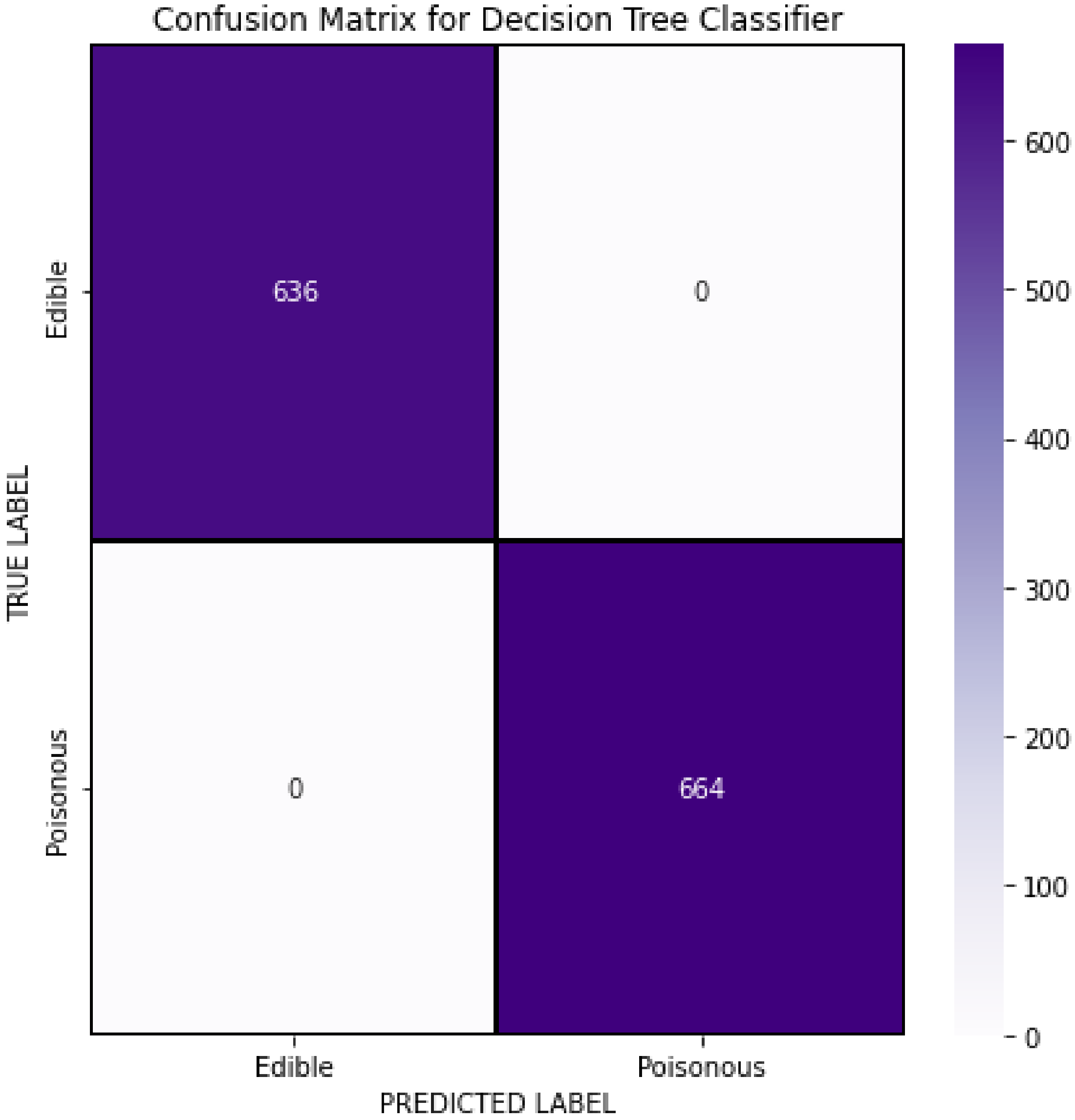


[40]:

```
# VALIDATION
y_pred_validation = clf_oh.predict(X_validation)
print("Decision Tree Classifier report: \n\n",␣
 ↪classification_report(y_validation, y_pred_validation))
print("Test Accuracy: {}%".format(round(clf_oh.score(X_validation,␣
 ↪y_validation)*100, 2)))

cm = confusion_matrix(y_validation, y_pred_validation)

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

f, ax = plt.subplots(figsize =(7,7))
sns.heatmap(cm, annot = True, linewidths=0.2, linecolor="black", fmt = ".0f",␣
 ↪ax=ax, cmap="Purples", xticklabels=x_axis_labels, yticklabels=y_axis_labels)
plt.xlabel("PREDICTED LABEL")
plt.ylabel("TRUE LABEL")
plt.title('Confusion Matrix for Decision Tree Classifier')
plt.show()
```

```
Decision Tree Classifier report:

              precision    recall  f1-score   support

           0       1.00      1.00      1.00       636
           1       1.00      1.00      1.00       664
```

```
    accuracy                           1.00      1300
   macro avg       1.00      1.00      1.00      1300
weighted avg       1.00      1.00      1.00      1300

Test Accuracy: 100.0%
```



```
[ ]:
```