CA3

March 19, 2024

0.0.1 Imports

```
[1022]: import pandas as pd
        import matplotlib.pyplot as plt
        import numpy as np
        import seaborn as sns
        from sklearn.model_selection import train_test_split
        from sklearn.preprocessing import StandardScaler
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.metrics import accuracy_score
```

0.0.2 Reading data

```
[1023]: df= pd.read_csv("train.csv",index_col=0 )
```

0.0.3 Data exploration and visualisation

```
[1024]: # # for comparing different features to each other from the dataset, with hue␣
         ↪as Edible
        # #I just made comments out of this so you dont have to read all the output

        # sns.pairplot(df, hue='Edible')
        # plt.show()
```

```
[1025]: #For looking at the distribution of the data of each feature in the dataset
        #I just made comments out of this so you dont have to read all the output

        # for column in df.columns:
        #     plt.figure(figsize=(10, 4))
        #     sns.histplot(df[column], kde=True)  # kde (Kernel Density Estimate) adds␣
         ↪a density curve
        #     plt.title(f'Distribution of {column}')
        #     plt.xlabel(column)
        #     plt.ylabel('Frequency')
        #     plt.show()
```

```
[1026]: #Looking for correlation between features in the dataset
        #I just made comments out of this so you dont have to read all the output
```

```
# corr_matrix = df.corr()
# # Apply formatting to round the values to two decimal places.
# # The .applymap() method applies a lambda function to each element of the␣
 ↪correlation matrix.
# # The lambda function converts each value 'x' in the matrix to a formatted␣
 ↪string with two decimal places.
# corr_matrix_rounded = corr_matrix.applymap(lambda x: f'{x:.2f}')

# # Plotting the heatmap, first setting the size of the heatmap
# plt.figure(figsize=(10, 8))
# # 'annot=corr_matrix_rounded' is used to display the rounded correlation␣
 ↪values as annotations on the heatmap.
# # 'fmt=' specifies that the annotation texts (rounded values) are strings,␣
 ↪not floats or integers.
# # 'cmap='coolwarm' sets the colormap to 'coolwarm'
# sns.heatmap(corr_matrix, annot=corr_matrix_rounded, fmt='', cmap='coolwarm')
# plt.title('Correlation Heatmap')
# plt.show()
```

[1027]:
```
# Looking at df to see how many rows and columns there is
#I just made comments out of this so you dont have to read all the output
#df
```

[1028]:
```
df.describe()
```

[1028]:
```
       Acoustic Firmness Index  Atmospheric Pressure at Harvest (Pa)  \
count              1245.000000                           1248.000000
mean                 21.570077                         101327.543269
std                   8.131888                           4772.582203
min                   0.600000                          83825.000000
25%                  17.300000                          98095.750000
50%                  21.300000                         101357.000000
75%                  25.300000                         104470.750000
max                 156.520701                         115636.000000

       Bitterness Scale  Circumference (mm)  Color Intensity (a.u.)  \
count       1244.000000         1246.000000             1248.000000
mean           1.808682          211.046062               63.300962
std            1.960279           24.652278                7.118135
min            0.000000          145.867667               46.060000
25%            0.000000          192.982222               58.577500
50%            1.000000          212.429730               62.390000
75%            3.000000          226.313333               67.202500
max            7.000000          274.719407               97.810000

       Find Distance from Main Vulcano (km)  Length (mm)  \
count                          1246.000000  1244.000000
mean                             44.188204    33.589646
std                              28.331532     3.874355
min                               2.550790    23.451799
25%                              21.203453    30.777936
50%                              38.880858    33.784401
75%                              60.680816    36.049083
max                             109.952511    43.691515

       Luminescence Intensity (a.u.)  Magnetic orientation (degree)  \
count                    1247.000000                    1245.000000
mean                        0.002850                     178.933737
std                         0.003607                     102.113321
min                         0.000004                       0.085357
25%                         0.000627                      90.582930
50%                         0.001757                     180.043851
75%                         0.003767                     266.481765
max                         0.044624                     359.443812

       Odor index (a.u.)   Seed Count  Skin Thickness (mm)  \
count        1246.000000  1247.000000          1247.000000
mean           16.602442    48.926812             3.839615
std            14.882420    35.871733             1.483029
min             1.722825     0.000000             1.000000
25%             7.615908    15.852008             3.000000
50%            12.258785    47.932723             4.000000
75%            20.302048    80.413165             5.000000
max           152.041780   112.968004             8.500000

       Soil pH where Grown  Sugar Content (mg)    Weight (mg)           pH  \
count          1245.000000         1245.000000    1244.000000  1244.000000
mean              7.278739        11835.978313   78446.779224     4.614780
std               0.529815         2417.733775   26637.766132     0.993407
min               5.710000         4566.000000   32352.182600    -5.120000
25%               6.910000        10353.000000   57087.682600     4.174979
50%               7.280000        11807.000000   77440.682600     4.910000
75%               7.660000        13534.000000   92664.102600     5.080000
max               8.980000        18246.000000  164679.342600     6.081918

            Edible
count  1248.000000
mean      0.494391
std       0.500169
min       0.000000
25%       0.000000
50%       0.000000
75%       1.000000
```

```
max       1.000000
```

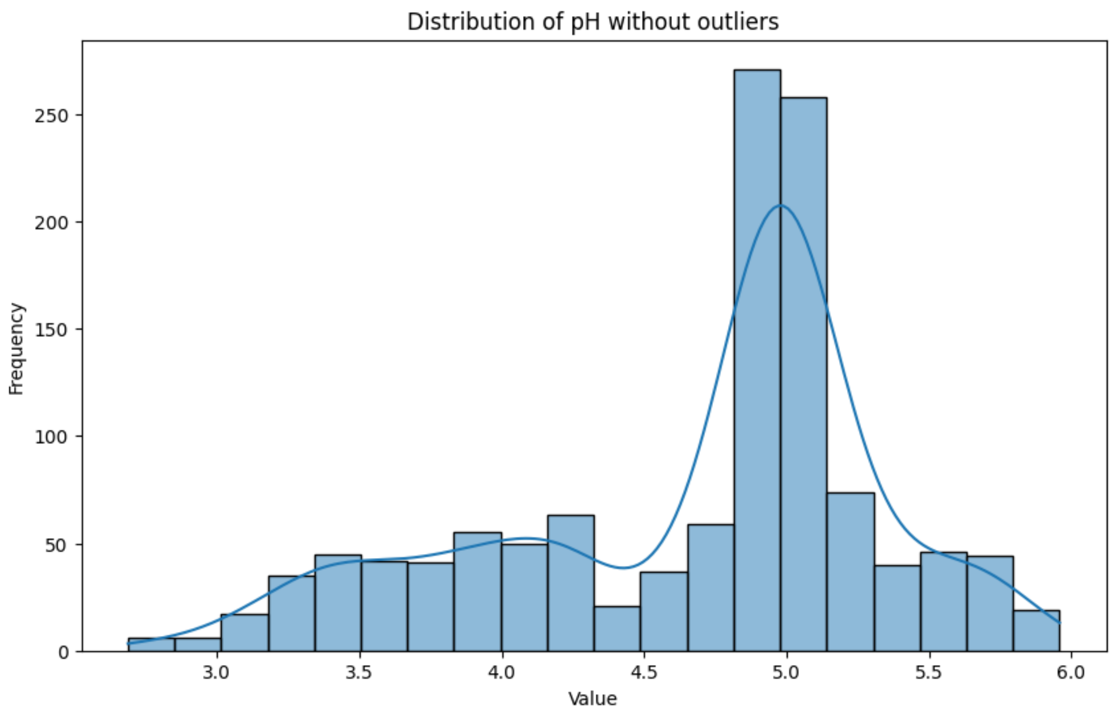
Comments on the data after visualization Some of the pH values didn't look right. There was some negative ph values, which doesn't make sense. It looked like there was some outliers on some of the features, which is also getting removed before training.

0.0.4 Data cleaning

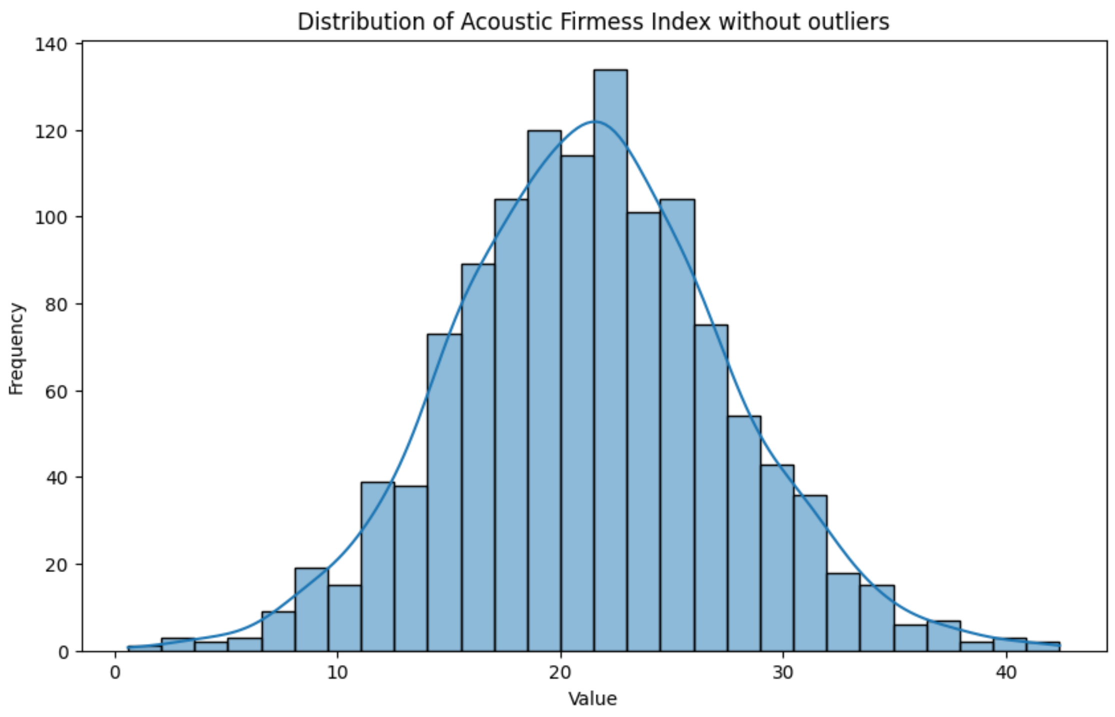
[1029]:
```
#replacing nan-values with median
# I do this instead of removing the rows, because it gave me better accuracy␣
↪when training models
df_cleaned= df.fillna(df.median())

# Dropping rows with negative pH values
df_cleaned = df_cleaned.drop(df_cleaned[df_cleaned['pH'] < 0].index)

#Dropping rows with feature values that clearly looks like outliers.
# I did this manually by just looking at the plots, but i could've also removed␣
↪data with z-score
df_cleaned= df_cleaned.drop(df_cleaned[df_cleaned["Acoustic Firmness Index"] >␣
↪50].index)
df_cleaned= df_cleaned.drop(df_cleaned[df_cleaned["Odor index (a.u.)"] > 85].
↪index)

#I've could've also dropped these rows under, but the accuracy got worse when␣
↪doing this
#df_cleaned= df_cleaned.drop(df_cleaned[df_cleaned["Luminescence Intensity (a.u.
↪)"] > 0.017].index)

# For checking how many rows i've removed
#I just made comments out of this so you dont have to read all the output
#df_cleaned
```

0.0.5 Data preprocessing and visualisation

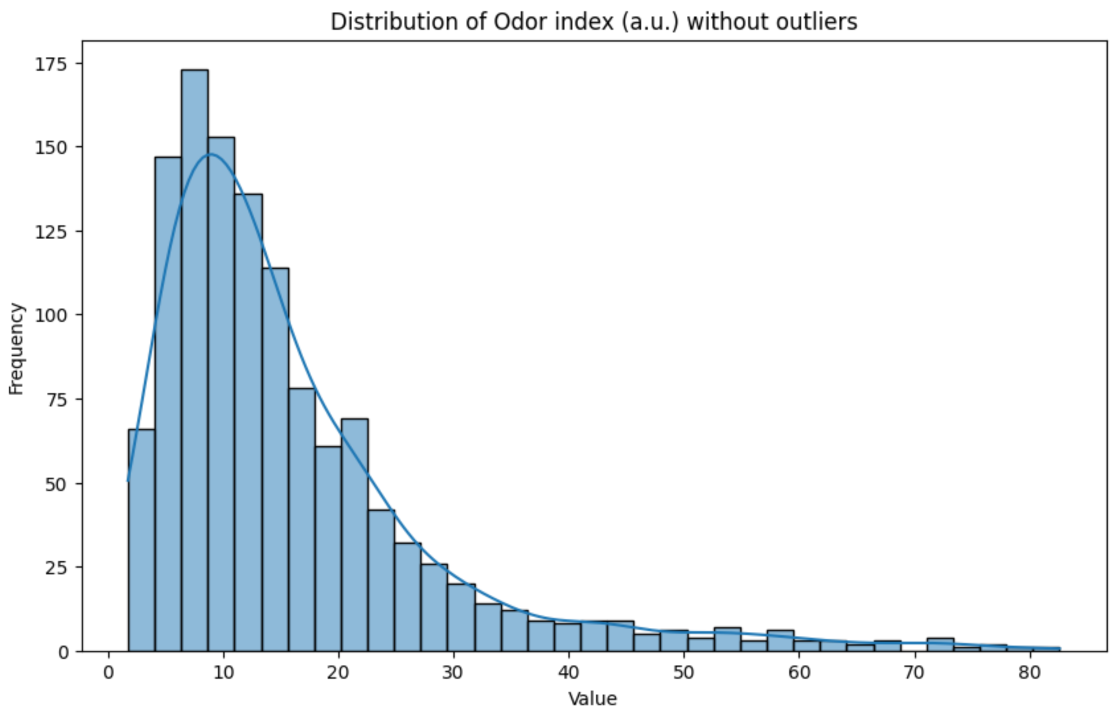
[1030]:
```
# Plotting the distribution of pH values after data-cleaning
plt.figure(figsize=(10, 6))
sns.histplot(df_cleaned["pH"], kde=True)
plt.title('Distribution of pH without outliers')
plt.xlabel('Value')
plt.ylabel('Frequency')
plt.show()
```



```
[1031]: # Plotting the distribution of Acoustic Firmess Index after data-cleaning
        plt.figure(figsize=(10, 6))
        sns.histplot(df_cleaned["Acoustic Firmness Index"], kde=True)
        plt.title('Distribution of Acoustic Firmess Index without outliers')
        plt.xlabel('Value')
        plt.ylabel('Frequency')
        plt.show()
```



[1032]:
```
# Plotting the distribution of Odor index (a.u.) after data-cleaning
plt.figure(figsize=(10, 6))
sns.histplot(df_cleaned["Odor index (a.u.)"], kde=True)
plt.title('Distribution of Odor index (a.u.) without outliers')
plt.xlabel('Value')
plt.ylabel('Frequency')
plt.show()
```



[1033]:

```
# Removing the target column from the DataFrame and uses the rest as features
X = df_cleaned.drop('Edible', axis=1)
# Selcts Edible as target columns
y = df_cleaned['Edible']

#Splitting up into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=42, stratify=y)

# Initialise standard scaler and compute mean and stddev from training data
sc = StandardScaler()
sc.fit(X_train)


# Transform (standardise) both X_train and X_test with mean and stddev from
# training data, to avoid leakage
X_train_sc = sc.transform(X_train)
X_test_sc = sc.transform(X_test)
```

0.0.6 Modelling

[1034]:
```
# No need to standardize the data for Random Forest

# Trying ot RandomForestClassifier
rfc = RandomForestClassifier(random_state=42)
rfc.fit(X_train, y_train)

# Making predictions with training data
y_pred_train = rfc.predict(X_train)
#computing accuracy from training data
accuracy_train = accuracy_score(y_train, y_pred_train)
print(f'Accuracy on training data: {accuracy_train:.2f}')

# Making predictions with test data
y_pred = rfc.predict(X_test)
#computing accuracy from test data
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy on test data: {accuracy:.2f}')
```

```
Accuracy on training data: 1.00
Accuracy on test data: 0.92
```

Here i tried different classifiers, but i took it out so you have less code to look at!

0.0.7 Final evaluation

Got best accuracy from randomforest, so i use this classifier

[1041]:
```
# Getting feature importance
feature_importances = rfc.feature_importances_

# Creating a DataFrame for feature importances
features_df = pd.DataFrame({'Feature': X.columns, 'Importance':␣
 ↪feature_importances})

# Sorting the features by importance
features_df = features_df.sort_values(by='Importance', ascending=False)
print("Feature importances:\n", features_df)
```

```
Feature importances:
                                   Feature  Importance
15                                     pH    0.234173
13                     Sugar Content (mg)    0.126118
2                       Bitterness Scale    0.117119
14                            Weight (mg)    0.080775
6                             Length (mm)    0.069948
7         Luminescence Intensity (a.u.)    0.068749
9                        Odor index (a.u.)    0.056343
```

```
3                        Circumference (mm)    0.047983
0                   Acoustic Firmness Index    0.038648
8              Magnetic orientation (degree)    0.026284
1    Atmospheric Pressure at Harvest (Pa)    0.025742
4                   Color Intensity (a.u.)    0.025164
5    Find Distance from Main Vulcano (km)    0.024629
12                    Soil pH where Grown    0.023813
10                             Seed Count    0.018422
11                    Skin Thickness (mm)    0.016090
```

In the next box i try all different combinations of features. I use the feautre combination that has the highest accuracy

[1042]:
```python
# Selecting subsets of features starting from the most important
best_average_accuracy = 0
best_features = []



for i in range(1, len(features_df.Feature) + 1):
    #Selecting the combination to use for the model
    selected_features = features_df.Feature.head(i)
    X_selected = X[selected_features]

    #storing accuracy
    accuracies = []

    # Iterate over a range of random states for train-test split
    for r in range(1,100, 10):
        # Splitting data with varying random states, to avoid overfitting
        #splitting with only the selected features
        X_train, X_test, y_train, y_test = train_test_split(X_selected, y,␣
↪test_size=0.2, random_state=r)

        # Initialize the model
        model = RandomForestClassifier(random_state=42)
        model.fit(X_train, y_train)

        # Evaluate the model on the test set
        predictions = model.predict(X_test)
        accuracy = accuracy_score(y_test, predictions)
        accuracies.append(accuracy)

    # Calculate the average accuracy across all splits for this set of features
    average_accuracy = np.mean(accuracies)

    # Update the best feature-lsit if the current average accuracy is better
    if average_accuracy > best_average_accuracy:
        best_average_accuracy = average_accuracy
        best_features = selected_features.tolist()

print(f"Best Average Accuracy: {best_average_accuracy:.4f}")
print(f"Best Features: {best_features}")
```

```
Best Average Accuracy: 0.9106
Best Features: ['pH', 'Sugar Content (mg)', 'Bitterness Scale', 'Weight (mg)',
'Length (mm)', 'Luminescence Intensity (a.u.)', 'Odor index (a.u.)',
'Circumference (mm)', 'Acoustic Firmness Index']
```

In the next box, i try to find the best paramters for the model. I started with looping over n_estimators, and selected the value with the best accuracy. Then i adjusted the code with best_n_estimators, and looped over different values of max_depth. I select the max_depth-value that gave me the highest accuraccy with the best_n_estimators. This goes on in the same pattern for the next parameter.

I've tried using different criterions and random_states for the model, and earlier i've found that criterion= "gini" and randomstate= 42 has worked well for me..

I could have tried to find more paramters to use in the model, but the ones i've used here has worked well enough.

[1051]:
```
# Here i set the best values for parameters i've already found.
best_n_estimators = 181
best_max_depth= 11

# Stores the best configuration in the loop
best_accuracy = 0
best_config = {}

#looping over different values for the next parameter to find, which here is␣
 ↪min_samples split
parameters_to_try= [n for n in range(2,30,3)]

for parameter in parameters_to_try:
    #Storing accuracies for different random states
    accuracies = []

    # Iterate over a range of random states for train-test split
    for r in range(1, 100, 10):

        # Splitting data with varying random states, to avoid overfitting
        #also only using the selected features
        X_train, X_test, y_train, y_test = train_test_split(X[best_features],␣
 ↪y, test_size=0.2, random_state=r)

        # Initialize and train the RandomForest model
        #Using the best paramters that i've found earlier with the same code
        #using different values for min_samples_split to find the new best one␣
↪in this case
        model = RandomForestClassifier(random_state=42, criterion="gini",␣
↪n_estimators=best_n_estimators, max_depth= best_max_depth,␣
↪min_samples_split= parameter)
        model.fit(X_train, y_train)

        # Evaluate the model on the validation set
        predictions = model.predict(X_test)
        accuracy = accuracy_score(y_test, predictions)
        accuracies.append(accuracy)

    # Calculate the average accuracy across all splits
    average_accuracy = np.mean(accuracies)

    # Update the best configuration for new parameter if necessary
    if average_accuracy > best_accuracy:
        best_accuracy = average_accuracy
        best_parameter= parameter
        best_config = {
            'n_estimators': best_n_estimators,
            'max_depth': best_max_depth,
            'random_state': 42,
            'criterion': "gini",
            'min_samples_split': best_parameter #store best new parameter
            #if im trying to find more paramters:
            #'min_samples_split': best_mms
            #'new_parameter': best_parameter
        }

# Print the best configuration and its accuracy
print("Best Configuration:")
print(best_config)
print(f"Best Validation Accuracy: {best_accuracy:.4f}")
```

```
Best Configuration:
{'n_estimators': 181, 'max_depth': 11, 'random_state': 42, 'criterion': 'gini',
'min_samples_split': 2}
Best Validation Accuracy: 0.9114
```

[1053]:
```
# Just checking what parameters i ended up with
best_config
```

[1053]:
```
{'n_estimators': 181,
 'max_depth': 11,
 'random_state': 42,
 'criterion': 'gini',
 'min_samples_split': 2}
```

[1054]:
```
# Create a new RandomForestClassifier with the best configuration
final_model= RandomForestClassifier(**best_config)

#Training model with the whole dataset, but only with the selected features
final_model.fit(X[best_features], y)

#loading up the test-set
x_val= pd.read_csv("test.csv",index_col=0 )
#Selecting only the best feautres
x_val_selected = x_val[best_features]

#predicting
predictions= final_model.predict(x_val_selected).astype(int)
```

[1055]:
```
# Create a DataFrame with predictions
predictions_df = pd.DataFrame(predictions, columns=['Edible'])
predictions_df.index.name = 'index'

# Save to a CSV file
predictions_df.to_csv('predictions.csv')
```