CA3_template

March 21, 2024

1 Truls de Lange - CA3

1.1 Some circumstance:

I have 4 subjects this semester and am really trying to make a good effort in all of them. A backside to this, is that all subjects are bound to have overlapping assignments with corresponding deadlines right before easter. Thus, I had one midway exam, two major compulsory assignments and two weekly copulsory assignments to get done just the past two weeks - four of which within the first 4 days of this week. If this weren't the case, I would have put much more effort into this assignment to get a score as good as possible. I couldn't do that this time, which I hope you understand. The methods I used here may also not be that thorough or tidy - I'm sorry, but I couldn't really pay that much attention to it. I just had to beat the Kaggle score and get it done.

1.1.1 Imports

[3]:
```
# Whenever I needed to import a library at any point in the notebook, I entered␣
↪it here at the top
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.svm import SVC
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.feature_selection import SequentialFeatureSelector
from sklearn.ensemble import RandomForestClassifier
```

1.1.2 Reading data

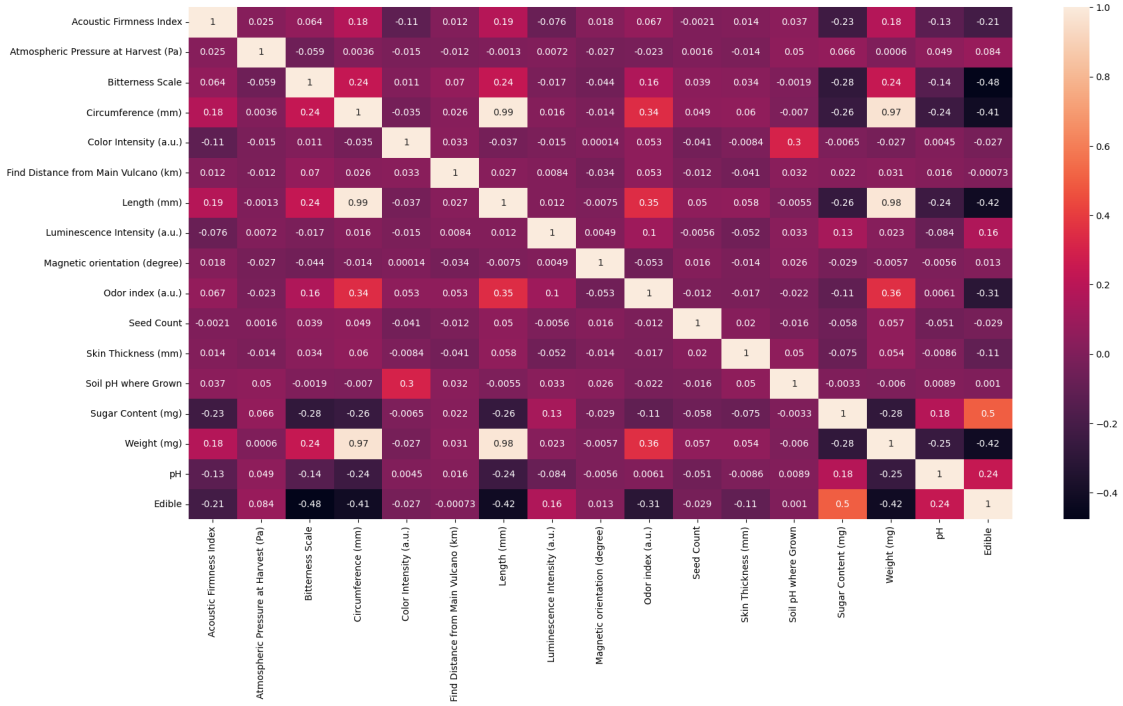
[4]:
```
# I read the data in as a pandas dataframe, so that it can be managed with␣
↪pandas features
data = pd.read_csv("train.csv")
df = pd.DataFrame(data)
df = df.drop(columns='Unnamed: 0')
df.columns
```

[4]:
```
Index(['Acoustic Firmness Index', 'Atmospheric Pressure at Harvest (Pa)',
       'Bitterness Scale', 'Circumference (mm)', 'Color Intensity (a.u.)',
       'Find Distance from Main Vulcano (km)', 'Length (mm)',
       'Luminescence Intensity (a.u.)', 'Magnetic orientation (degree)',
       'Odor index (a.u.)', 'Seed Count', 'Skin Thickness (mm)',
       'Soil pH where Grown', 'Sugar Content (mg)', 'Weight (mg)', 'pH',
       'Edible'],
      dtype='object')
```

1.1.3 Data exploration and visualisation

[5]:
```
# Plotting a heatmap of the linear correlation coefficient between all features␣
  ↪in the dataset, to check for linear correlation
plt.figure(figsize=(20, 10))
sns.heatmap(df.corr(), annot=True)
plt.plot()

print(len(df))
```

1248

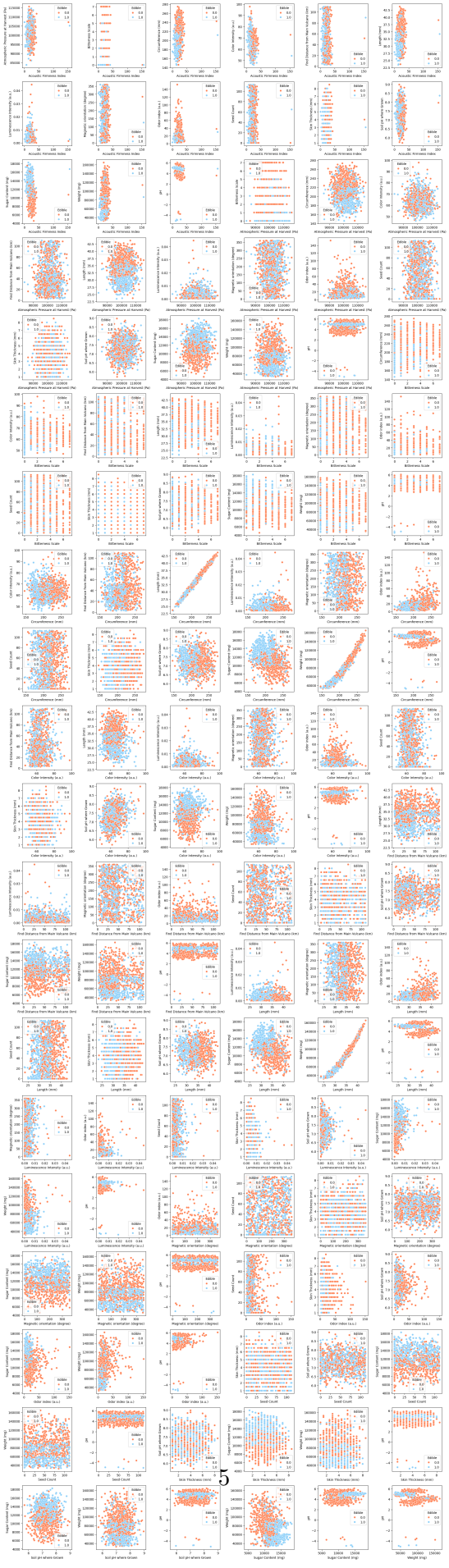


[6]:
```
"""Since there was little linear correlation between any two features, I plot␣
  ↪scatter plots of all pairs to check for any other
kind of correlation"""
```

```
features = list(df)
target = 'Edible'

features.remove('Edible')
features1 = features.copy()
features2 = features.copy()

fig, ax = plt.subplots(20, 6, figsize=(20, 70))

row = 0
col = 0

for feat1 in features1:
    for feat2 in features2:
        if feat2 == feat1:
            continue
        sns.scatterplot(x=feat1, y=feat2, hue=target, data=df, palette={0:␣
 ↪'coral', 1: 'lightskyblue'}, ax=ax[row][col])
        if col == 5:
            col = 0
            row += 1
            print(f'Row {row} complete')
        else:
            col += 1
    features2.remove(feat1)

plt.tight_layout()
plt.show()

"""

categories = [train_df.]
"""
```

```
Row 1 complete
Row 2 complete
Row 3 complete
Row 4 complete
Row 5 complete
Row 6 complete
Row 7 complete
Row 8 complete
Row 9 complete
Row 10 complete
Row 11 complete
Row 12 complete
Row 13 complete
```

```
Row 14 complete
Row 15 complete
Row 16 complete
Row 17 complete
Row 18 complete
Row 19 complete
Row 20 complete
```



[6]:
```
'\n\ncategories = [train_df.]\n'
```

Comments on the initial visualisation:

After pairing features and visualising them in scatter plots with target label `Edible`as hue parameter, it seems as if the pH feture, first and foremost, is going to be of great significance to the classification. This is because almost all the plots with pH as one of the features display more or less clearly separable data points. Secondly come the size features (circumference, length, weight…), which also seem to create tidy plots.

One can also see some outliers, above all in the pH-values. This is something I didn't take into account in my calculations, because I thought it would harm the accuracy of the eventual model to get rid of these. This is a decision I grew uncertain of later on, as they may have made both the standardisation, the swapping of NaN-values with mean-values and the final predictions less accurate.

1.1.4 Data cleaning

[20]:
```
# Z-score (I more or less copy-pasted this code section from the lecture codes,␣
 ↪because I'm not used to this kind of numpy notation:)
z_scores = (df - df.mean()) / df.std()
outliers = np.abs(z_scores) > 3
np.sum(outliers, axis=0)
# A z-score of 3 although matches with what is visible in the scatter plots (8␣
 ↪outliers in pH, 18 in luminescence ...). I stick to the z-score of 3.
```

[20]:
```
Acoustic Firmness Index                 2
Atmospheric Pressure at Harvest (Pa)    3
Bitterness Scale                        0
Circumference (mm)                      0
Color Intensity (a.u.)                 12
Find Distance from Main Vulcano (km)    0
Length (mm)                             0
Luminescence Intensity (a.u.)          18
Magnetic orientation (degree)           0
Odor index (a.u.)                      28
Seed Count                              0
Skin Thickness (mm)                     1
Soil pH where Grown                     2
Sugar Content (mg)                      1
Weight (mg)                             1
pH                                      8
Edible                                  0
dtype: int64
```

[30]:
```
df_clean = df.mask(outliers)
```

[38]:
```
# X / y split:
y = pd.DataFrame(df['Edible'])
X = df.drop(y, axis=1)
y = y['Edible'].tolist()
```

[39]:
```
print(X[X.isnull().any(axis=1)].shape)
X[X.isnull().any(axis=1)]
```

```
(37, 16)
```

[39]:

	Acoustic Firmness Index	Atmospheric Pressure at Harvest (Pa)	\
9	18.6	98441.0	
25	25.3	102300.0	
135	24.4	98459.0	
161	21.8	97338.0	
190	21.0	109623.0	
203	31.4	110062.0	
237	16.6	106015.0	
280	27.3	101351.0	
330	6.2	100398.0	
354	18.0	95815.0	
411	11.8	103065.0	
422	23.0	98213.0	
434	NaN	103487.0	
440	NaN	100351.0	
450	25.0	99958.0	
474	20.6	97311.0	
557	24.7	103056.0	
568	13.6	96623.0	
585	7.6	98346.0	
761	12.7	97565.0	
788	17.3	95421.0	
810	23.0	102198.0	
827	15.8	109257.0	
859	NaN	98582.0	
896	14.0	98721.0	
915	19.9	102155.0	
970	31.3	104463.0	
986	12.8	103134.0	
1009	23.7	101788.0	
1033	20.3	90924.0	
1063	27.0	101195.0	
1105	17.7	103471.0	
1124	15.8	102290.0	
1132	21.9	101497.0	
1146	18.4	98481.0	
1162	20.4	106357.0	
1212	22.6	102717.0	

	Bitterness Scale	Circumference (mm)	Color Intensity (a.u.)	\
9	NaN	193.742185	56.51	
25	4.0	190.527909	60.61	
135	0.0	217.066116	56.70	
161	2.0	196.793798	64.13	
190	0.0	217.672365	58.28	
203	6.0	247.568906	70.78	
237	4.0	223.744843	62.78	
280	2.0	245.449299	62.16	
330	0.0	218.614502	62.09	
354	0.0	210.940636	62.55	
411	4.0	226.188200	81.36	
422	NaN	191.714105	60.34	
434	4.0	188.322992	55.76	
440	0.0	162.971214	60.46	
450	2.0	NaN	66.92	
474	0.0	213.961499	56.04	
557	4.0	248.559479	73.22	
568	1.0	147.912611	72.40	
585	1.0	171.635520	88.89	
761	3.0	215.217767	76.75	
788	3.0	244.434093	64.32	
810	0.0	217.929700	56.76	
827	3.0	222.373678	83.53	
859	0.0	214.689279	55.94	
896	5.0	211.831280	63.53	
915	2.0	218.172347	60.58	
970	1.0	253.669400	71.81	
986	1.0	220.724250	65.83	
1009	1.0	NaN	58.63	
1033	0.0	213.938035	69.95	
1063	3.0	224.896956	56.85	
1105	NaN	170.113774	63.58	
1124	NaN	210.795330	60.26	
1132	2.0	216.742020	59.52	
1146	2.0	217.577700	55.32	
1162	1.0	230.559923	64.53	
1212	1.0	240.215622	65.03	

	Find Distance from Main Vulcano (km)	Length (mm)	\
9	45.007483	30.460301	
25	24.900029	30.716374	
135	24.815873	34.428125	
161	NaN	30.856497	
190	69.797327	34.187210	
203	40.967272	38.856970	

237	26.472882	NaN
280	79.354862	38.491853
330	4.736373	34.457676
354	51.437889	32.705569
411	83.659900	35.234751
422	24.955445	30.435190
434	99.135826	29.436697
440	34.438603	26.033394
450	38.414601	36.108872
474	15.133414	33.573348
557	82.960324	39.769754
568	103.505177	23.451799
585	66.064369	27.057183
761	51.297853	34.043937
788	61.459410	39.709118
810	48.953358	34.487692
827	46.763876	NaN
859	44.564549	34.286630
896	NaN	33.858635
915	42.191753	34.049559
970	3.829190	40.290785
986	17.935211	34.957661
1009	82.015093	35.250488
1033	24.477174	NaN
1063	15.991895	NaN
1105	46.105552	27.819630
1124	3.311543	33.701773
1132	54.215669	34.588742
1146	82.012560	33.170715
1162	91.175719	36.107012
1212	51.436561	38.476410

	Luminescence Intensity (a.u.)	Magnetic orientation (degree) \
9	0.007231	260.540489
25	NaN	100.715689
135	0.000225	160.302385
161	0.010620	72.248874
190	0.004681	51.740222
203	0.002345	333.611746
237	0.010376	263.399529
280	0.000640	117.491764
330	0.004980	81.390160
354	0.006073	212.767272
411	0.001196	68.335102
422	0.000451	319.324289
434	0.004168	164.072470
440	0.000720	70.502503

450	0.006247	285.433610
474	0.008167	22.250269
557	0.002554	208.514280
568	0.004546	169.575803
585	0.006756	NaN
761	0.007350	144.872814
788	0.027688	NaN
810	0.000163	130.976220
827	0.004054	97.865194
859	0.010160	203.174763
896	0.002089	57.695418
915	0.000136	306.533553
970	0.000218	256.752783
986	0.002530	53.787698
1009	0.001554	208.565966
1033	0.002593	331.099150
1063	0.000237	123.826226
1105	0.000531	115.569281
1124	0.001257	100.680008
1132	0.002604	217.827823
1146	0.000267	45.654897
1162	0.001020	NaN
1212	0.008272	286.196730

	Odor index (a.u.)	Seed Count	Skin Thickness (mm)	Soil pH where Grown	\
9	6.283100	9.934014	4.5	6.88	
25	10.094517	96.583640	4.0	7.55	
135	NaN	110.052118	5.5	7.07	
161	4.148618	51.922424	4.0	6.78	
190	8.679276	94.442947	NaN	7.43	
203	22.240862	6.767937	7.5	7.74	
237	43.789815	6.082008	2.0	7.87	
280	11.453696	0.000000	4.0	7.73	
330	26.009272	92.676919	3.5	7.04	
354	8.246290	29.564740	2.0	NaN	
411	63.382994	5.852810	2.5	7.65	
422	4.782352	0.000000	2.0	8.08	
434	6.831412	10.503935	1.5	6.77	
440	5.732340	91.311354	4.5	7.18	
450	13.529207	93.910669	5.0	7.68	
474	8.781531	61.811010	2.5	7.77	
557	11.130196	9.454643	5.0	7.81	
568	11.798712	22.511723	3.5	NaN	
585	15.040867	106.452684	5.0	7.75	
761	16.544032	85.969285	2.0	7.93	
788	58.732013	64.148965	3.0	7.18	
810	10.306349	84.718283	1.5	6.69	

827	33.092417	36.835411	6.5	8.63
859	2.739507	15.321905	5.5	6.96
896	15.061711	78.268009	3.0	7.80
915	6.631049	81.932015	1.0	7.27
970	19.309590	NaN	6.0	7.66
986	15.824135	0.000000	5.5	6.86
1009	24.820283	0.000000	1.5	7.61
1033	6.815152	24.157196	5.0	7.80
1063	12.424632	14.998318	3.0	6.02
1105	4.434950	27.037439	3.0	7.28
1124	6.083661	83.167741	4.0	7.18
1132	NaN	66.932591	4.0	6.81
1146	18.547906	96.998290	5.5	6.71
1162	6.653647	35.543018	6.0	8.16
1212	24.850870	108.791301	2.5	NaN

	Sugar Content (mg)	Weight (mg)	pH
9	11982.0	49288.1826	4.880000
25	12719.0	54448.7826	3.400888
135	9821.0	79927.1826	4.940000
161	16100.0	58319.1826	4.790000
190	16826.0	86009.1826	5.040000
203	8096.0	NaN	3.849393
237	14125.0	84148.7826	3.392290
280	8754.0	NaN	4.090321
330	NaN	84379.1826	4.970000
354	11727.0	71459.1826	4.960000
411	13239.0	88069.1826	NaN
422	13907.0	54842.1826	4.860000
434	13439.0	49526.1826	4.970000
440	13151.0	40103.1826	4.970000
450	10178.0	95596.3026	3.588140
474	11146.0	75254.1826	NaN
557	10206.0	124487.0226	NaN
568	12718.0	34697.1826	5.230000
585	12779.0	35430.1826	5.290000
761	14550.0	69563.1826	NaN
788	11907.0	123846.2226	4.339953
810	NaN	82257.1826	4.960000
827	11010.0	89549.7426	4.583286
859	13255.0	75659.1826	4.890000
896	14377.0	74937.1826	5.080000
915	11736.0	NaN	5.130000
970	8524.0	130367.0226	4.103869
986	12180.0	NaN	4.031517
1009	12617.0	81403.1826	5.770722
1033	15056.0	77434.1826	4.880000

```
1063              10505.0   84472.7826  3.633814
1105              12480.0   42718.1826  4.910000
1124              13055.0   76409.1826  4.890000
1132              13420.0   81501.1826  5.060000
1146                  NaN   72933.5826  4.267374
1162               9658.0   91667.9826  3.991340
1212               6439.0  106196.1426  4.263931
```

1.1.5 Data preprocessing and visualisation

[40]:
```
"""As shown above, there are very many rows with NaN-values scattered over many␣
 ↪different columns. I thus see removing rows
and/or columns with NaN-values as inconvenient, considering the fairly small␣
 ↪size of the dataset. I chose the mean-strategy instead,
which I thought would be a good substitute - although I see now, that I maybe␣
 ↪should have taken care of the outliers first then, to get a cleaner mean."""
# Feature imputing:
imputer = SimpleImputer(missing_values=np.nan, strategy='mean') # Don't want to␣
 ↪remove any rows, because the train set is very small
imputer.fit(X)
X = imputer.transform(X)
X = pd.DataFrame(X, columns=['Acoustic Firmness Index', 'Atmospheric Pressure␣
 ↪at Harvest (Pa)',
       'Bitterness Scale', 'Circumference (mm)', 'Color Intensity (a.u.)',
       'Find Distance from Main Vulcano (km)', 'Length (mm)',
       'Luminescence Intensity (a.u.)', 'Magnetic orientation (degree)',
       'Odor index (a.u.)', 'Seed Count', 'Skin Thickness (mm)',
       'Soil pH where Grown', 'Sugar Content (mg)', 'Weight (mg)', 'pH'])

# Mean and std computation:
mean = X.mean()
std = X.std()

# Train / test split:
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
 ↪random_state=42) # I chose a .25 share test set, because I thought it seemed␣
 ↪like a good share
```

Random Forest:

As many of the features seemed to show some kinds of non-linear correlation, I thought of the random forest and SVM classifiers, which can make non-linear decision boundaries. First out, I tried various hyperparameters for the random forest:

[43]:
```
"""I decided to try random forest, because it's effective and deals well with␣
 ↪non-linear decision boundaries. As seen in the initial
visualisation, the two classes are namely separated non-linearly. I also␣
 ↪experimented with kNN before this, and Kernel SVM afterwards, but
```

```
since it was strictly threatened with rejection for submissions that didn't␣
 ↪contain only the MOST NECESSARY, I deleted the lot of it. Still think it was
an important part of the process though."""
import csv

with open('random_forest.csv', 'w', newline='') as f:
    csv.writer(f).writerow(['Estimators', 'Jobs', 'Depth', 'Accuracy Train',␣
 ↪'Accuracy Test'])

# I created a loop that takes ages, but computes a thorough list over␣
 ↪parameters and performance on the test set and stores it in a .csv-file
    for estimators in range(700, 1401, 100):
        print(f'{estimators} estimators:')
        for jobs in range(3, 7):
            print(f'{jobs} jobs:')
            for depth in range(2, 12, 2):
                print('Depth: ', depth)
                rf = RandomForestClassifier(n_estimators=estimators,␣
 ↪random_state=42, n_jobs=jobs, max_depth=depth, criterion='gini')
                rf.fit(X_train, y_train)

                y_pred_t = rf.predict(X_train)
                accuracy_train = accuracy_score(y_pred_t, y_train)

                y_pred = rf.predict(X_test)
                accuracy_test = accuracy_score(y_pred, y_test)

                csv.writer(f).writerow([estimators, jobs, depth,␣
 ↪accuracy_train, accuracy_test])
```

```
700 estimators:
3 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
4 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
5 jobs:
Depth:  2
Depth:  4
Depth:  6
```

```
Depth:  8
Depth:  10
6 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
800 estimators:
3 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
4 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
5 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
6 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
900 estimators:
3 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
4 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
5 jobs:
Depth:  2
```

```
Depth:  4
Depth:  6
Depth:  8
Depth:  10
6 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
1000 estimators:
3 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
4 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
5 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
6 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
1100 estimators:
3 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
4 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
```

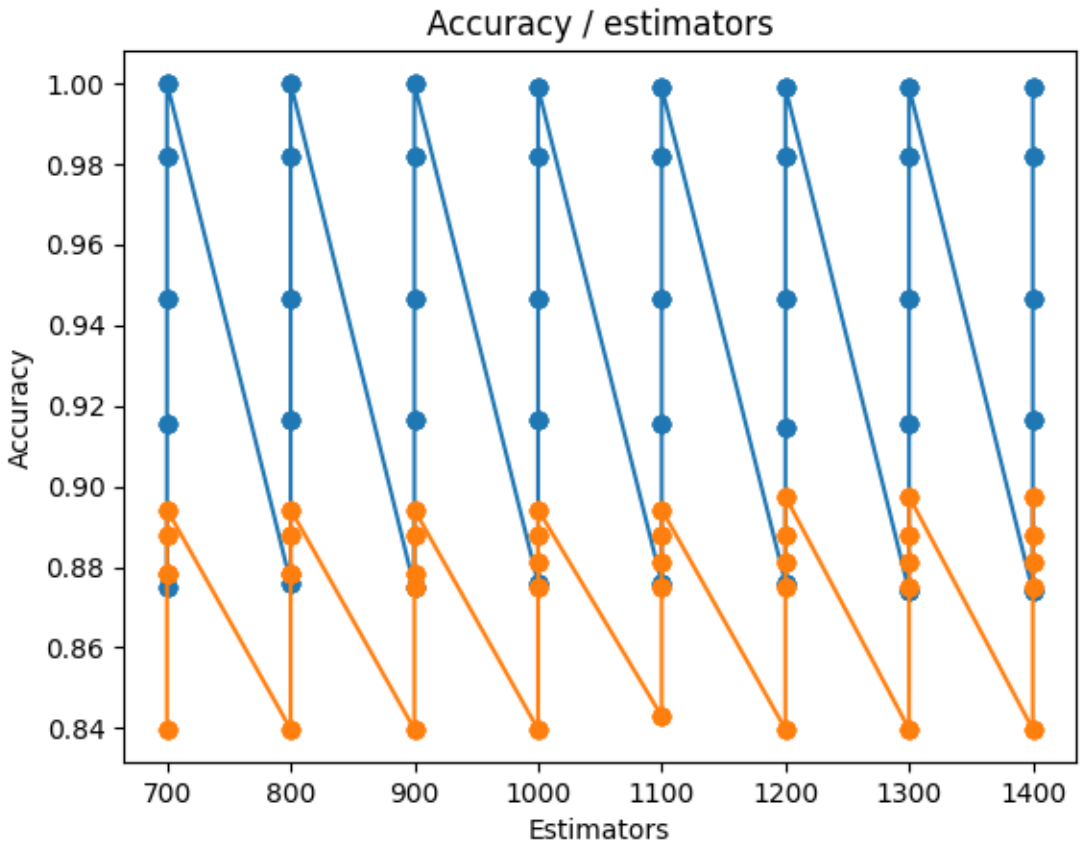
```
5 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
6 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
1200 estimators:
3 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
4 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
5 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
6 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
1300 estimators:
3 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
4 jobs:
Depth:  2
Depth:  4
Depth:  6
```

```
Depth:  8
Depth:  10
5 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
6 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
1400 estimators:
3 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
4 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
5 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
6 jobs:
Depth:  2
Depth:  4
Depth:  6
Depth:  8
Depth:  10
```

After looking through the resulting .csv-file, i found that 1200-1400 estimators, 3 jobs and a max depth of 10 were the best parameters.

[63]:
```
plot_data = pd.read_csv('random_forest.csv', header=0)
plot_df = pd.DataFrame(plot_data)


plt.plot(plot_df['Estimators'], plot_df['Accuracy Train'], marker='o')
```

```
plt.plot(plot_df['Estimators'], plot_df['Accuracy Test'], marker='o')
plt.xlabel('Estimators')
plt.ylabel('Accuracy')
plt.title('Accuracy / estimators')
plt.show()
```



[232]:
```
# Testing feature selection on the best performing RandomForest:

sfs = SequentialFeatureSelector(knn, n_features_to_select=5,␣
 ↪direction="forward", n_jobs=4)
sfs = sfs.fit(X_train, y_train)

rf2 = RandomForestClassifier(n_estimators=1800, random_state=42, n_jobs=4,␣
 ↪max_depth=15, criterion='gini')

X_train_sfs = sfs.transform(X_train)
X_test_sfs = sfs.transform(X_test)
# X_eval_sfs = sfs.transform(X_eval)
```

```
rf2.fit(X_train_sfs, y_train)
y_pred = rf.predict(X_test)
accuracy = accuracy_score(y_pred, y_test)
accuracy

# It didn't work out well
```

[232]: 0.8974358974358975

1.1.6 Kaggle submission

[20]:
```
"""The .csv-list over random forest performances indicated that 1200-1400␣
 ↪estimators, 3 jobs and max depth 10 would do.
I then made this code to create .csv-lists of predictions for different random␣
 ↪forests with nearby hyperparameters. Surprisingly,
the first one I uploaded - 1200 estimators, 3 jobs, 10 max depth - still holds␣
 ↪the record amongst my submissions with .91452, although I did upload
several models with the parameters tweaked a bit to check for wiggle room."""

rf_final = RandomForestClassifier(n_estimators=1200, random_state=42,␣
 ↪n_jobs=10, max_depth=200)

rf_final.fit(X_train, y_train)
y_pred = rf_final.predict(X_eval)

rf_df = pd.DataFrame(y_pred, columns=['Edible'])
rf_df.to_csv(f'RandomForest_1200_3_10.csv', index_label='index')
```