part_2_orange

January 23, 2025

0.0.1 Introduction

In this part of the analysis, we build upon the clustering results obtained in the first step, where we identified groups using the best-performing clustering method for this dataset. We then compared two algorithms, Random Forest and Gradient Boosting, to develop an effective classification algorithm capable of assigning individuals to the identified groups based on their responses. Random Forest was chosen for its robustness, interpretability, and ability to handle diverse data types, while Gradient Boosting was selected for its strong predictive performance and capacity to capture non-linear relationships. Finally, we optimized the number of questions used in the classification process by analyzing feature importance and iteratively reducing the feature set to achieve the best trade-off between performance and simplicity. This step ensures that the resulting algorithm remains both efficient and accurate, providing a practical solution for future use with minimal inputs.

0.1 IMPORT

[12]:
```
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score
import pandas as pd
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
```

0.2 Data Loading

[13]:
```
file_path = "fic_epita_kantar_codes.csv"
data_codes = pd.read_csv(file_path, sep=';')
```

Select relevant columns

[14]:
```
columns_of_interest = [
    "A9_1_slice", "A9_2_slice", "A9_3_slice", "A9_4_slice", "A9_5_slice",
    "A9_6_slice", "A9_7_slice", "A9_8_slice", "A9_9_slice", "A9_10_slice",
    "A9_11_slice", "A9_12_slice", "A9_13_slice", "A9_14_slice", "A9_15_slice",
    "A9_16_slice", "A10_1_slice", "A10_2_slice", "A10_3_slice", "A10_4_slice",
```

```
    "A10_5_slice", "A10_6_slice", "A10_7_slice", "A10_8_slice",
    "A11_1_slice", "A11_2_slice", "A11_3_slice", "A11_4_slice", "A11_5_slice",
    "A11_6_slice", "A11_7_slice", "A11_8_slice", "A11_9_slice", "A11_10_slice",
    "A11_11_slice", "A11_12_slice", "A11_13_slice"
]
subset_data = data_codes[columns_of_interest]
```

0.3 Adding the cluster column using the best algo with the best number of cluster found in part 1

[ ]:
```
# Scale the data
scaler = StandardScaler()
scaled_data = scaler.fit_transform(subset_data.fillna(0))  # Replace missing␣
 ↪values

# Perform KMeans clustering
kmeans = KMeans(n_clusters=3, random_state=42)
kmeans_labels = kmeans.fit_predict(scaled_data)

# Add cluster labels to the data
subset_data['cluster'] = kmeans_labels
```

```
/tmp/ipykernel_131606/3220641698.py:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  subset_data['cluster'] = kmeans_labels
```

0.4 Training Random Forest

[16]:
```
# Define features (golden questions) and target (clusters)
X = subset_data.drop(columns=['cluster'])
y = subset_data['cluster']

# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Train and Evaluate model
rf = RandomForestClassifier(random_state=42)
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Classification Report:
               precision    recall  f1-score   support
```

```
           0       0.93      0.97      0.95       262
           1       0.98      0.90      0.94       184
           2       0.95      0.96      0.96       554

    accuracy                           0.95      1000
   macro avg       0.96      0.94      0.95      1000
weighted avg       0.95      0.95      0.95      1000
```

0.5 Training Gradient Boosting

[17]:
```python
# Define features (questions) and target (clusters)
X2 = subset_data.drop(columns=['cluster'])
y2 = subset_data['cluster']

# Split into training and test sets
X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2, test_size=0.2,␣
 ↪random_state=42)

# Train and Evaluate model
gb = GradientBoostingClassifier(random_state=42)
gb.fit(X_train2, y_train2)
y_pred2 = gb.predict(X_test2)
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.93      0.97      0.95       262
           1       0.98      0.90      0.94       184
           2       0.95      0.96      0.96       554

    accuracy                           0.95      1000
   macro avg       0.96      0.94      0.95      1000
weighted avg       0.95      0.95      0.95      1000
```

0.6 Getting the importance of each question

For random forest

[18]:
```python
feature_importance = rf.feature_importances_
importance_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': feature_importance
}).sort_values(by='Importance', ascending=False)
```

```
print("Feature Importance (Top Questions) for Random Forest:\n", importance_df)
```

```
Feature Importance (Top Questions) for Random Forest:
          Feature  Importance
33   A11_10_slice    0.083317
30    A11_7_slice    0.071852
28    A11_5_slice    0.071477
26    A11_3_slice    0.056607
31    A11_8_slice    0.052130
7      A9_8_slice    0.043957
13    A9_14_slice    0.040699
36   A11_13_slice    0.039214
20    A10_5_slice    0.038229
3      A9_4_slice    0.035639
34   A11_11_slice    0.035226
2      A9_3_slice    0.029591
1      A9_2_slice    0.029545
0      A9_1_slice    0.026178
24    A11_1_slice    0.023914
25    A11_2_slice    0.022092
9     A9_10_slice    0.021260
32    A11_9_slice    0.020025
35   A11_12_slice    0.019942
27    A11_4_slice    0.019370
16    A10_1_slice    0.018899
6      A9_7_slice    0.018642
10    A9_11_slice    0.017545
15    A9_16_slice    0.016899
12    A9_13_slice    0.016795
11    A9_12_slice    0.016338
14    A9_15_slice    0.016270
22    A10_7_slice    0.014869
23    A10_8_slice    0.013685
8      A9_9_slice    0.011098
29    A11_6_slice    0.009880
19    A10_4_slice    0.009809
17    A10_2_slice    0.008753
5      A9_6_slice    0.008104
21    A10_6_slice    0.007870
18    A10_3_slice    0.007530
4      A9_5_slice    0.006751
```

For Gradient Boosting

[19]:
```
feature_importance2 = gb.feature_importances_
importance_df2 = pd.DataFrame({
    'Feature': X2.columns,
    'Importance': feature_importance2
```

```
}).sort_values(by='Importance', ascending=False)

print("Feature Importance (Top Questions) for Gradiant Boosting:\n",␣
↪importance_df2)
```

```
Feature Importance (Top Questions) for Gradiant Boosting:
          Feature  Importance
28    A11_5_slice    0.140620
30    A11_7_slice    0.112928
33   A11_10_slice    0.098550
7      A9_8_slice    0.064707
26    A11_3_slice    0.060625
31    A11_8_slice    0.055011
13    A9_14_slice    0.048094
3      A9_4_slice    0.043571
34   A11_11_slice    0.042199
36   A11_13_slice    0.037003
20    A10_5_slice    0.036868
0      A9_1_slice    0.031365
2      A9_3_slice    0.030072
1      A9_2_slice    0.028438
16    A10_1_slice    0.023673
35   A11_12_slice    0.017286
27    A11_4_slice    0.015426
9     A9_10_slice    0.014880
24    A11_1_slice    0.014104
6      A9_7_slice    0.013802
10    A9_11_slice    0.012057
25    A11_2_slice    0.011214
12    A9_13_slice    0.008521
32    A11_9_slice    0.007891
15    A9_16_slice    0.006086
22    A10_7_slice    0.005294
14    A9_15_slice    0.005157
23    A10_8_slice    0.002945
19    A10_4_slice    0.002839
17    A10_2_slice    0.002215
11    A9_12_slice    0.001998
8      A9_9_slice    0.001505
29    A11_6_slice    0.001439
5      A9_6_slice    0.000662
21    A10_6_slice    0.000586
18    A10_3_slice    0.000263
4      A9_5_slice    0.000106
```

0.7 Finding performance when lowering question amount

For random forest

[20]:

```python
results = []
for i in range(1, len(importance_df) + 1):
    top_features = importance_df['Feature'].head(i)
    X_train_reduced = X_train[top_features]
    X_test_reduced = X_test[top_features]

    rf_reduced = RandomForestClassifier(random_state=42)
    rf_reduced.fit(X_train_reduced, y_train)
    y_pred_reduced = rf_reduced.predict(X_test_reduced)

    acc = accuracy_score(y_test, y_pred_reduced)
    results.append({'Num_Features': i, 'Accuracy': acc})

results_df = pd.DataFrame(results)
print(results_df)
```

```
    Num_Features  Accuracy
0              1     0.730
1              2     0.749
2              3     0.795
3              4     0.800
4              5     0.806
5              6     0.830
6              7     0.836
7              8     0.836
8              9     0.841
9             10     0.875
10            11     0.881
11            12     0.882
12            13     0.889
13            14     0.893
14            15     0.903
15            16     0.901
16            17     0.906
17            18     0.902
18            19     0.906
19            20     0.919
20            21     0.925
21            22     0.929
22            23     0.937
23            24     0.939
24            25     0.942
25            26     0.942
26            27     0.944
27            28     0.940
28            29     0.947
29            30     0.950
30            31     0.948
```

```
31              32     0.948
32              33     0.956
33              34     0.955
34              35     0.957
35              36     0.951
36              37     0.948
```

For Gradient Boosting

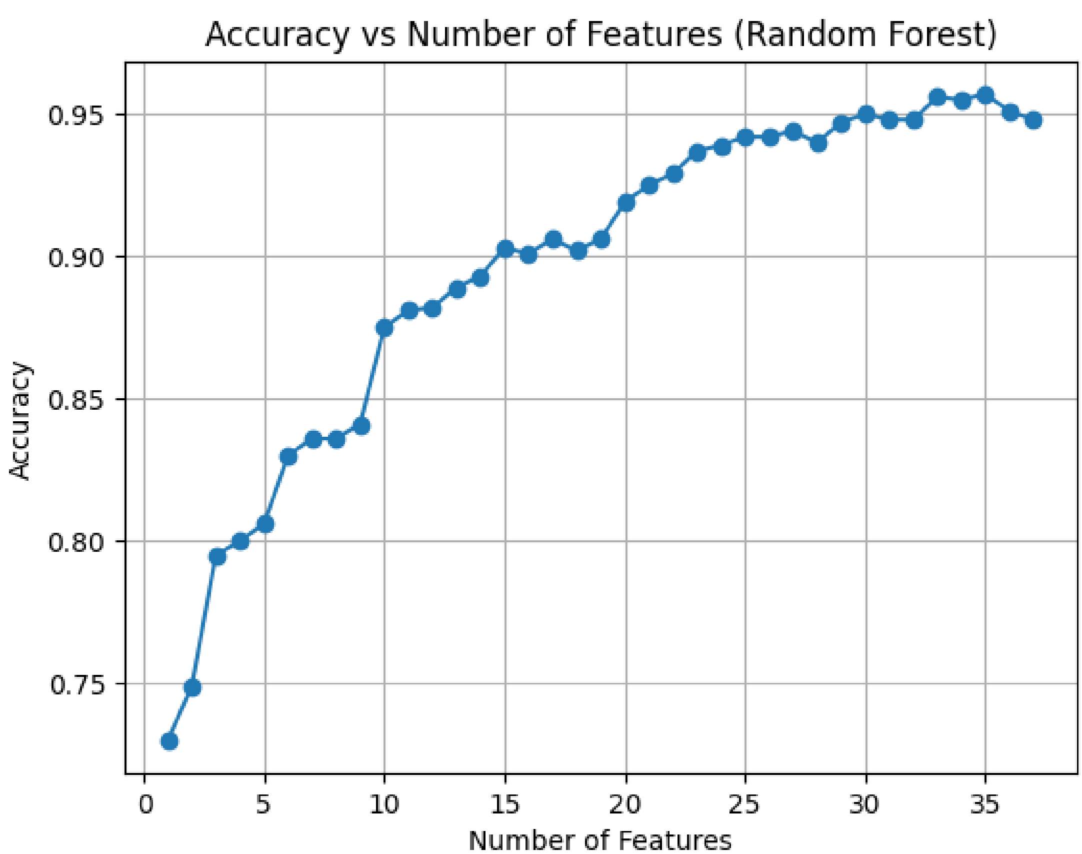
[21]:
```
results2 = []
for i in range(1, len(importance_df2) + 1):
    top_features2 = importance_df2['Feature'].head(i)
    X_train_reduced2 = X_train2[top_features2]
    X_test_reduced2 = X_test2[top_features2]

    gb_reduced = GradientBoostingClassifier(random_state=42)
    gb_reduced.fit(X_train_reduced2, y_train2)
    y_pred_reduced2 = gb_reduced.predict(X_test_reduced2)

    acc = accuracy_score(y_test2, y_pred_reduced2)
    results2.append({'Num_Features': i, 'Accuracy': acc})

results_df2 = pd.DataFrame(results2)
print(results_df2)
```

```
    Num_Features  Accuracy
0              1     0.752
1              2     0.750
2              3     0.796
3              4     0.825
4              5     0.838
5              6     0.851
6              7     0.859
7              8     0.865
8              9     0.888
9             10     0.896
10            11     0.899
11            12     0.906
12            13     0.910
13            14     0.914
14            15     0.918
15            16     0.918
16            17     0.923
17            18     0.921
18            19     0.920
19            20     0.929
20            21     0.929
21            22     0.937
22            23     0.947
```

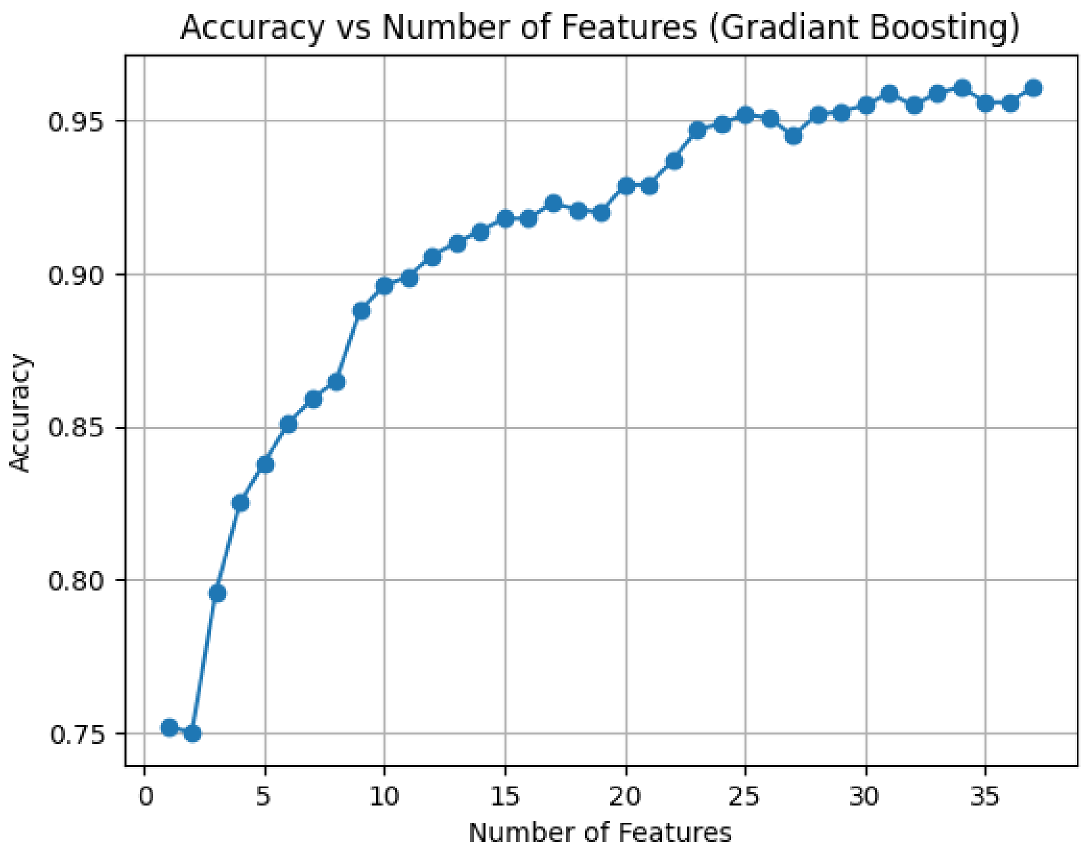
```
23              24      0.949
24              25      0.952
25              26      0.951
26              27      0.945
27              28      0.952
28              29      0.953
29              30      0.955
30              31      0.959
31              32      0.955
32              33      0.959
33              34      0.961
34              35      0.956
35              36      0.956
36              37      0.961
```

[22]:

```python
plt.plot(results_df['Num_Features'], results_df['Accuracy'], marker='o')
plt.xlabel("Number of Features")
plt.ylabel("Accuracy")
plt.title("Accuracy vs Number of Features (Random Forest)")
plt.grid()
plt.show()
```



[23]:
```
plt.plot(results_df2['Num_Features'], results_df2['Accuracy'], marker='o')
plt.xlabel("Number of Features")
plt.ylabel("Accuracy")
plt.title("Accuracy vs Number of Features (Gradiant Boosting)")
plt.grid()
plt.show()
```



0.7.1 Conclusion

Both Random Forest and Gradient Boosting are similarly effective, with Gradient Boosting being slightly better in terms of accuracy. Therefore, the optimal choice is Gradient Boosting.

Using 23 features results in an accuracy nearing 95%, striking the best balance between performance and complexity. Beyond that, the improvements in accuracy become minimal, and the model starts to slow down, making it the optimal choice for maximizing classification performance while maintaining efficiency.