project1-feature_selection

October 7, 2024

Feature Selection Assistance Found At:

https://scikit-learn.org/stable/auto_examples/feature_selection/plot_rfe_with_cross_validation.html#sphx-glr-auto-examples-feature-selection-plot-rfe-with-cross-validation-py

https://scikit-learn.org/stable/auto_examples/feature_selection/plot_select_from_model_diabetes.html#sphx-glr-auto-examples-feature-selection-plot-select-from-model-diabetes-py

https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA.html#sklearn.decomposition.PCA

[53]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import copy
import scipy as sp
import scipy.stats as stats
import statsmodels.formula.api as smf
import statsmodels.api as sm
from sklearn.metrics import accuracy_score
from sklearn.metrics import balanced_accuracy_score
from sklearn.metrics import f1_score
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import RocCurveDisplay
from sklearn.preprocessing import LabelBinarizer
from sklearn.multiclass import OneVsRestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.base import clone
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
```

```python
ob = pd.read_excel("data/Obesity_Dataset.xlsx")
classifier_names = ['DecisionTreeClassifier', 'SVC', 'RandomForestClassifier',␣
↪'GradientBoostingClassifier', 'KNeighborsClassifier']
classifiers = [DecisionTreeClassifier, SVC, RandomForestClassifier,␣
↪GradientBoostingClassifier, KNeighborsClassifier]
models_dict = {}
RANDOMSTATE = 42

param_grids = {
    'DecisionTreeClassifier': {'max_depth': [i for i in range(1,15)],
                               'ccp_alpha': [0, .1, .2, .5, 1],
                               'class_weight': [None, 'balanced'],
                               'criterion': ['gini', 'entropy', 'log_loss'],
                               'random_state': [RANDOMSTATE]},

    'SVC': {'C': [i for i in range(90,101)],
            'gamma': ['auto', 'scale', .01],
            'kernel': ['rbf', 'linear', 'sigmoid'],
            'random_state': [RANDOMSTATE]},

    'RandomForestClassifier': {'n_estimators': [i*10 for i in range(5,13)],
                               'max_depth': [i for i in range(1,15)],
                               #'ccp_alpha': [0, .1, 1],
                               'criterion': ['gini', 'entropy', 'log_loss'],
                               'max_features': ['sqrt', 'log2', None],
                               'random_state': [RANDOMSTATE]},

    'GradientBoostingClassifier': {'n_estimators': [i*10 for i in range(1,15)],
                                   'max_depth': [i for i in range(1,10)],
                                   #'ccp_alpha': [0, .1, 1],
                                   'learning_rate': [.001, .01, .1, .4],
                                   'random_state': [RANDOMSTATE]},

    'KNeighborsClassifier': {'n_neighbors': [i for i in range(1,20)],
                             'algorithm': ['ball_tree', 'kd_tree', 'brute',␣
↪'auto'],
                             'weights': ['distance', 'uniform'],
                             'p': [1, 2]}
}

def ParamTournament(x_tr, x_te, y_tr, y_te, params_list,␣
↪scoring_param='accuracy', clf=DecisionTreeClassifier):
    top = 0, {}
    for params in params_list:
        m = clf(**params).fit(x_tr, y_tr)
```

```
        y_hat = m.predict(x_te)

        if scoring_param == 'accuracy':
            test_score = accuracy_score(y_true=y_te, y_pred=y_hat)

        elif scoring_param == 'balanced_accuracy':
            test_score = balanced_accuracy_score(y_true=y_te, y_pred=y_hat)

        elif scoring_param == 'f1_weighted':
            test_score = f1_score(y_true=y_te, y_pred=y_hat, average='weighted')

        top = (test_score, params) if test_score > top[0] else (top[0], top[1])

    return top[1]


def pipe_scores(clf, p_grid, x_tr, x_te, y_tr, y_te, scoring_param='accuracy'):
    '''pipeline for a given format of classifier'''

    models = GridSearchCV(estimator=clf(), param_grid=p_grid,␣
 ↪scoring=scoring_param, n_jobs=-1, cv=4)

    models.fit(x_tr, y_tr)

    pl = pd.DataFrame(models.cv_results_).sort_values('rank_test_score').
 ↪head(10)['params']
    params = ParamTournament(x_tr, x_te, y_tr, y_te, pl, scoring_param, clf)

    idx = models.cv_results_['params'].index(params)
    cv_score = models.cv_results_['mean_test_score'][idx]

    m0 = clf(**params).fit(x_tr, y_tr)

    y_hat = m0.predict(x_te)

    if scoring_param == 'accuracy':
        test_score = accuracy_score(y_true=y_te, y_pred=y_hat)
        train_score = accuracy_score(y_true=y_tr, y_pred=m0.predict(x_tr))

    elif scoring_param == 'balanced_accuracy':
        test_score = balanced_accuracy_score(y_true=y_te, y_pred=y_hat)
        train_score = balanced_accuracy_score(y_true=y_tr, y_pred=m0.
 ↪predict(x_tr))

    elif scoring_param == 'f1_weighted':
        test_score = f1_score(y_true=y_te, y_pred=y_hat, average='weighted')
```

```
        train_score = f1_score(y_true=y_tr, y_pred=m0.predict(x_tr),␣
↪average='weighted')

    return [cv_score, train_score, test_score]



def pipeline(clf, p_grid, x_tr, x_te, y_tr, y_te, scoring_param='accuracy',␣
↪m_d=models_dict):
    '''pipeline for a given format of classifier'''

    models = GridSearchCV(estimator=clf(), param_grid=p_grid,␣
↪scoring=scoring_param, n_jobs=-1, cv=4)

    models.fit(x_tr, y_tr)

    pl = pd.DataFrame(models.cv_results_).sort_values('rank_test_score').
↪head(10)['params']
    params = ParamTournament(x_tr, x_te, y_tr, y_te, pl, scoring_param, clf)

    idx = models.cv_results_['params'].index(params)
    cv_score = models.cv_results_['mean_test_score'][idx]

    m0 = clf(**params).fit(x_tr, y_tr)
    m_d[f'{clf.__name__}'] = { 'params': m0.get_params(), 'classifier': clf }

    y_hat = m0.predict(x_te)
    cm = confusion_matrix(y_true=y_te, y_pred=y_hat)

    if scoring_param == 'accuracy':
        test_score = m0.score(y_true=y_te, y_pred=y_hat)
        train_score = m0.score(y_true=y_tr, y_pred=m0.predict(x_tr))

    elif scoring_param == 'balanced_accuracy':
        test_score = balanced_accuracy_score(y_true=y_te, y_pred=y_hat)
        train_score = balanced_accuracy_score(y_true=y_tr, y_pred=m0.
↪predict(x_tr))

    elif scoring_param == 'f1_weighted':
        test_score = f1_score(y_true=y_te, y_pred=y_hat, average='weighted')
        train_score = f1_score(y_true=y_tr, y_pred=m0.predict(x_tr),␣
↪average='weighted')

    #plt.figure(figsize=(8, 6))
    #sns.heatmap(cm, annot=True, fmt="d", cmap="rocket_r")
```

```python
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.title("Confusion Matrix")

    print(m0.get_params())
    print(f"{clf.__name__} Mean Cross-Validation score: ", cv_score)
    print(f"{clf.__name__} Training Score: ", train_score)
    print(f"{clf.__name__} Testing Score: ", test_score)

    #return models.cv_results_


ob.info()
ob.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1610 entries, 0 to 1609
Data columns (total 15 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   Sex                               1610 non-null   int64
 1   Age                               1610 non-null   int64
 2   Height                            1610 non-null   int64
 3   Overweight_Obese_Family           1610 non-null   int64
 4   Consumption_of_Fast_Food          1610 non-null   int64
 5   Frequency_of_Consuming_Vegetables 1610 non-null   int64
 6   Number_of_Main_Meals_Daily        1610 non-null   int64
 7   Food_Intake_Between_Meals         1610 non-null   int64
 8   Smoking                           1610 non-null   int64
 9   Liquid_Intake_Daily               1610 non-null   int64
 10  Calculation_of_Calorie_Intake     1610 non-null   int64
 11  Physical_Excercise                1610 non-null   int64
 12  Schedule_Dedicated_to_Technology  1610 non-null   int64
 13  Type_of_Transportation_Used       1610 non-null   int64
 14  Class                             1610 non-null   int64
dtypes: int64(15)
memory usage: 188.8 KB
```

[53]:

```
   Sex  Age  Height  Overweight_Obese_Family  Consumption_of_Fast_Food  \
0    2   18     155                        2                         2
1    2   18     158                        2                         2
2    2   18     159                        2                         2
3    2   18     162                        2                         2
4    2   18     165                        2                         1

   Frequency_of_Consuming_Vegetables  Number_of_Main_Meals_Daily  \
0                                  3                           1
```

```
1                                  3                            1
2                                  2                            1
3                                  2                            2
4                                  2                            1

   Food_Intake_Between_Meals  Smoking  Liquid_Intake_Daily  \
0                          3        2                    1
1                          1        2                    1
2                          3        2                    3
3                          2        2                    2
4                          3        2                    1

   Calculation_of_Calorie_Intake  Physical_Excercise  \
0                              2                   3
1                              2                   1
2                              2                   2
3                              2                   1
4                              2                   3

   Schedule_Dedicated_to_Technology  Type_of_Transportation_Used  Class
0                                 3                            4      2
1                                 3                            3      2
2                                 3                            4      2
3                                 3                            4      2
4                                 3                            2      2
```

[54]:

```
y=ob['Class']
X=ob.drop(labels='Class', axis=1)

x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
 ↪random_state=RANDOMSTATE)
```

[3]:

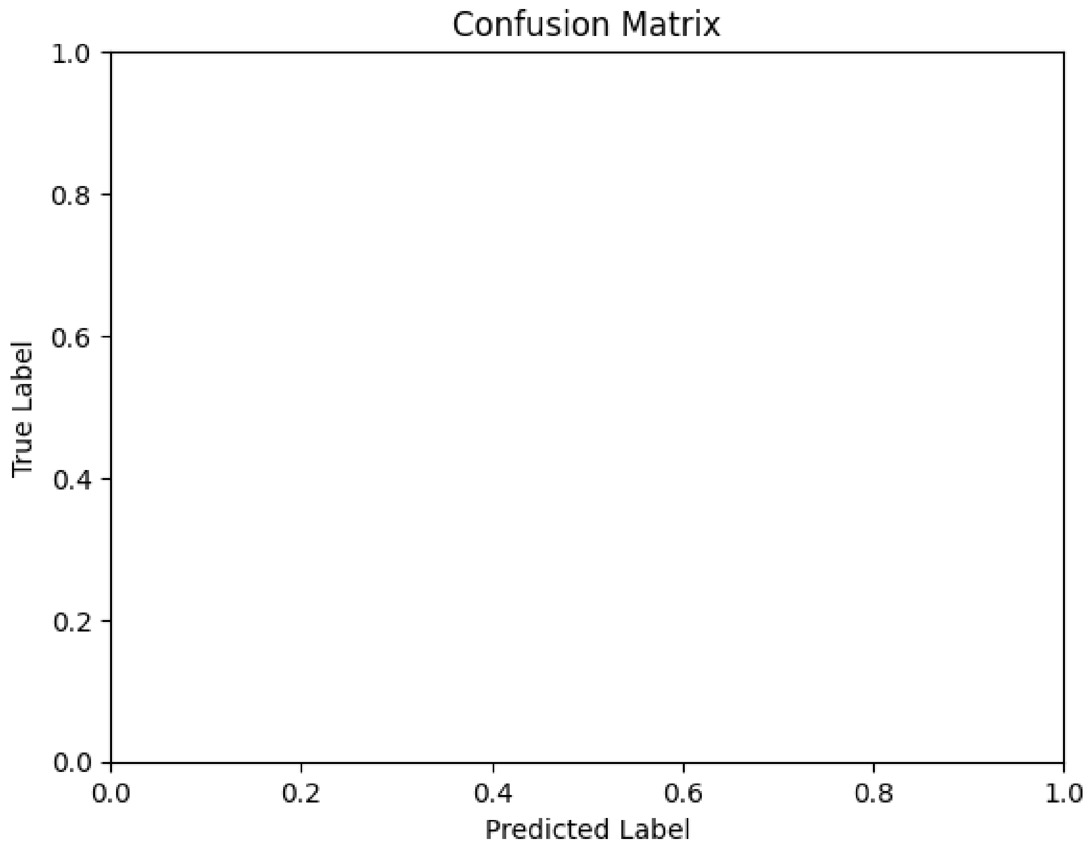
```
# reconfigure x_train, x_test to exclude Consumption_of_Fast_Food,␣
 ↪Schedule_Dedicated_to_Technology,
# Liquid_Intake_Daily, Food_Intake_Between_Meals, and Height

x_train = x_train.drop(['Consumption_of_Fast_Food',
                        'Schedule_Dedicated_to_Technology',
                        'Liquid_Intake_Daily',
                        'Food_Intake_Between_Meals',
                        #'Smoking',
                        #'Type_of_Transportation_Used',
                        #'Overweight_Obese_Family',
                        'Height'], axis=1)

x_test = x_test.drop(['Consumption_of_Fast_Food',
                      'Schedule_Dedicated_to_Technology',
```

```
                        'Liquid_Intake_Daily',
                        'Food_Intake_Between_Meals',
                        #'Smoking',
                        #'Type_of_Transportation_Used',
                        #'Overweight_Obese_Family',
                        'Height'], axis=1)
```

[17]:
```
for i in range(5):
    print(pipeline(classifiers[i], param_grids[classifier_names[i]], x_train,␣
 ↪x_test, y_train, y_test, scoring_param='balanced_accuracy'))
```

```
{'ccp_alpha': 0, 'class_weight': None, 'criterion': 'gini', 'max_depth': 14,
'max_features': None, 'max_leaf_nodes': None, 'min_impurity_decrease': 0.0,
'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0,
'random_state': 42, 'splitter': 'best'}
DecisionTreeClassifier Mean Cross-Validation score:  0.7826021524863419
DecisionTreeClassifier Training Score:  0.9653572079740024
DecisionTreeClassifier Testing Score:  0.8974844654052947
None
{'C': 98, 'break_ties': False, 'cache_size': 200, 'class_weight': None, 'coef0':
0.0, 'decision_function_shape': 'ovr', 'degree': 3, 'gamma': 'auto', 'kernel':
'rbf', 'max_iter': -1, 'probability': False, 'random_state': 42, 'shrinking':
True, 'tol': 0.001, 'verbose': False}
SVC Mean Cross-Validation score:  0.8006182411202096
SVC Training Score:  0.9687761396382397
SVC Testing Score:  0.9059488428122267
None
{'bootstrap': True, 'ccp_alpha': 0.0, 'class_weight': None, 'criterion': 'gini',
'max_depth': 14, 'max_features': None, 'max_leaf_nodes': None, 'max_samples':
None, 'min_impurity_decrease': 0.0, 'min_samples_leaf': 1, 'min_samples_split':
2, 'min_weight_fraction_leaf': 0.0, 'n_estimators': 120, 'n_jobs': None,
'oob_score': False, 'random_state': 42, 'verbose': 0, 'warm_start': False}
RandomForestClassifier Mean Cross-Validation score:  0.8019139067427205
RandomForestClassifier Training Score:  0.9711811939314186
RandomForestClassifier Testing Score:  0.8996251232535208
None
{'ccp_alpha': 0.0, 'criterion': 'friedman_mse', 'init': None, 'learning_rate':
0.4, 'loss': 'log_loss', 'max_depth': 9, 'max_features': None, 'max_leaf_nodes':
None, 'min_impurity_decrease': 0.0, 'min_samples_leaf': 1, 'min_samples_split':
2, 'min_weight_fraction_leaf': 0.0, 'n_estimators': 100, 'n_iter_no_change':
None, 'random_state': 42, 'subsample': 1.0, 'tol': 0.0001,
'validation_fraction': 0.1, 'verbose': 0, 'warm_start': False}
GradientBoostingClassifier Mean Cross-Validation score:  0.8156220841862721
GradientBoostingClassifier Training Score:  0.9694931634075397
GradientBoostingClassifier Testing Score:  0.9138771836803036
None
{'algorithm': 'brute', 'leaf_size': 30, 'metric': 'minkowski', 'metric_params':
```

```
None, 'n_jobs': None, 'n_neighbors': 8, 'p': 1, 'weights': 'distance'}
KNeighborsClassifier Mean Cross-Validation score:  0.7818246279970837
KNeighborsClassifier Training Score:  0.9690429583911013
KNeighborsClassifier Testing Score:  0.8892096193559189
None
```



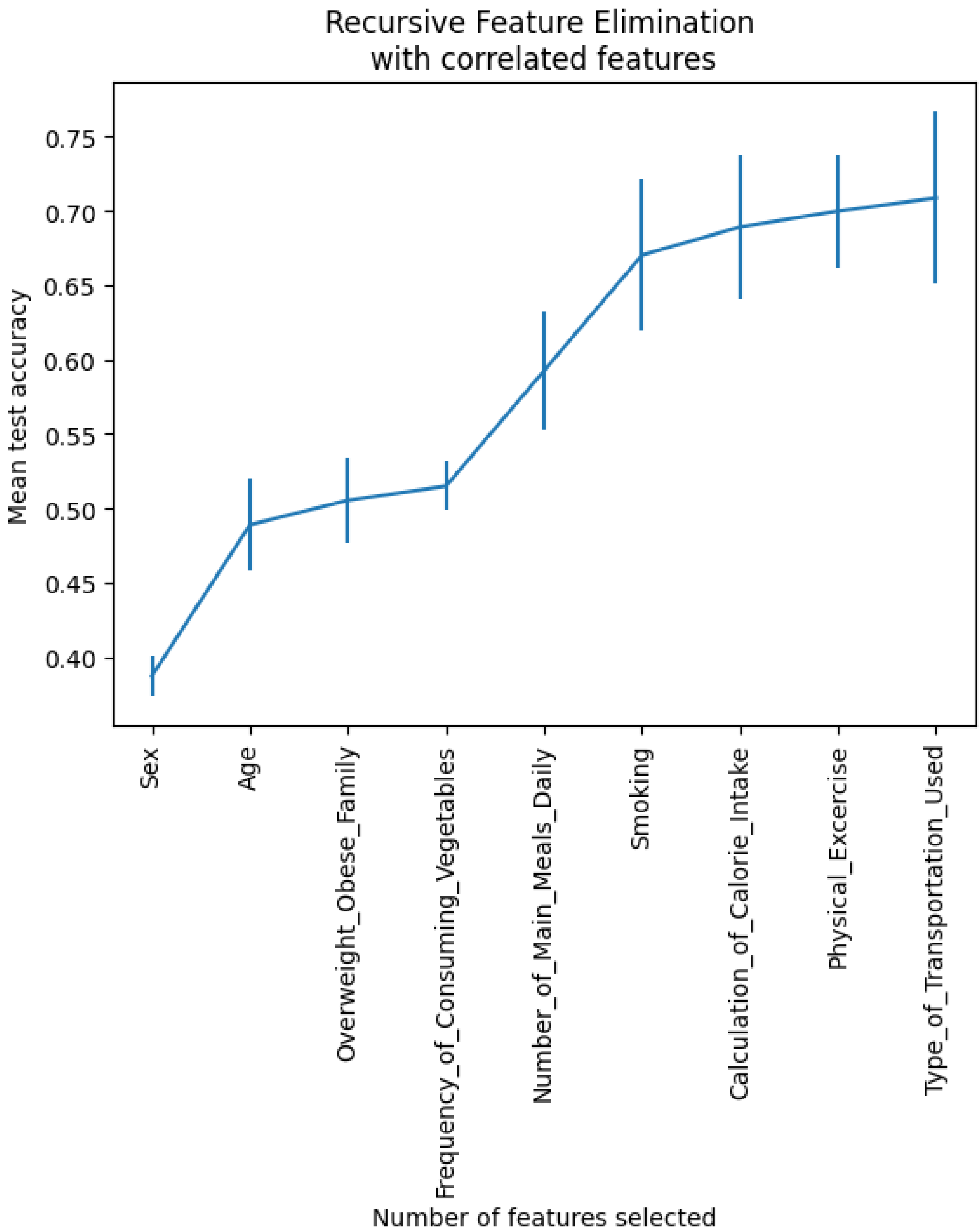
[46]:

```
from sklearn.feature_selection import RFECV
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import StratifiedKFold

min_features_to_select = 1
clf = GradientBoostingClassifier()
cv = StratifiedKFold(4)

rfecv = RFECV(
    estimator=clf,
    step=1,
    cv=cv,
    scoring="balanced_accuracy",
    min_features_to_select=min_features_to_select,
```

```
    n_jobs=2,
)
rfecv.fit(x_train, y_train)

print(f"Optimal number of features: {rfecv.n_features_}")
```

```
Optimal number of features: 9
```

[5]:
```
import matplotlib.pyplot as plt
import pandas as pd

cv_results = pd.DataFrame(rfecv.cv_results_)
plt.figure()
plt.xlabel("Number of features selected")
plt.ylabel("Mean test accuracy")
plt.errorbar(
    x=rfecv.feature_names_in_,
    y=cv_results["mean_test_score"],
    yerr=cv_results["std_test_score"],
)
plt.xticks(rotation=90)
plt.title("Recursive Feature Elimination \nwith correlated features")
plt.show()
```



[47]:
```
list(zip(rfecv.ranking_, rfecv.feature_names_in_))
```

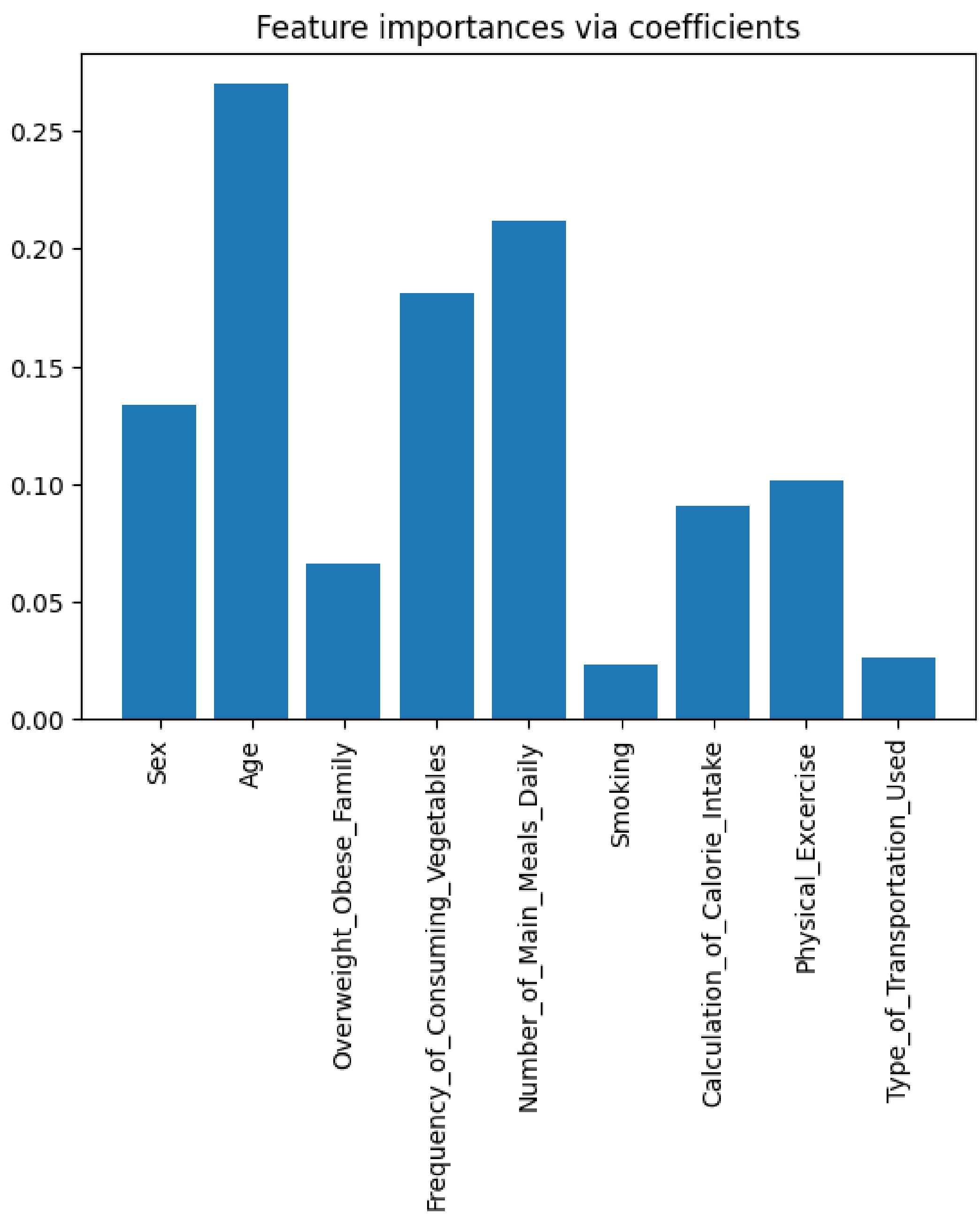
[47]:
```
[(1, 'Sex'),
 (1, 'Age'),
 (1, 'Overweight_Obese_Family'),
 (1, 'Frequency_of_Consuming_Vegetables'),
```

```
 (1, 'Number_of_Main_Meals_Daily'),
 (1, 'Smoking'),
 (1, 'Calculation_of_Calorie_Intake'),
 (1, 'Physical_Excercise'),
 (1, 'Type_of_Transportation_Used')]
```

[48]:
```python
np.logspace(-6, 6, num=5)
```

[48]:
```
array([1.e-06, 1.e-03, 1.e+00, 1.e+03, 1.e+06])
```

[49]:
```python
from sklearn.linear_model import RidgeCV

ridge = RidgeCV(alphas=np.logspace(-6, 6, num=4)).fit(x_train, y_train)
importance = np.abs(ridge.coef_)
feature_names = np.array(x_train.columns)
plt.bar(height=importance, x=feature_names)
plt.xticks(rotation=90)
plt.title("Feature importances via coefficients")
plt.show()
```



[50]:
```
importances = pd.Series(importance, index=x_train.columns)
importances
```

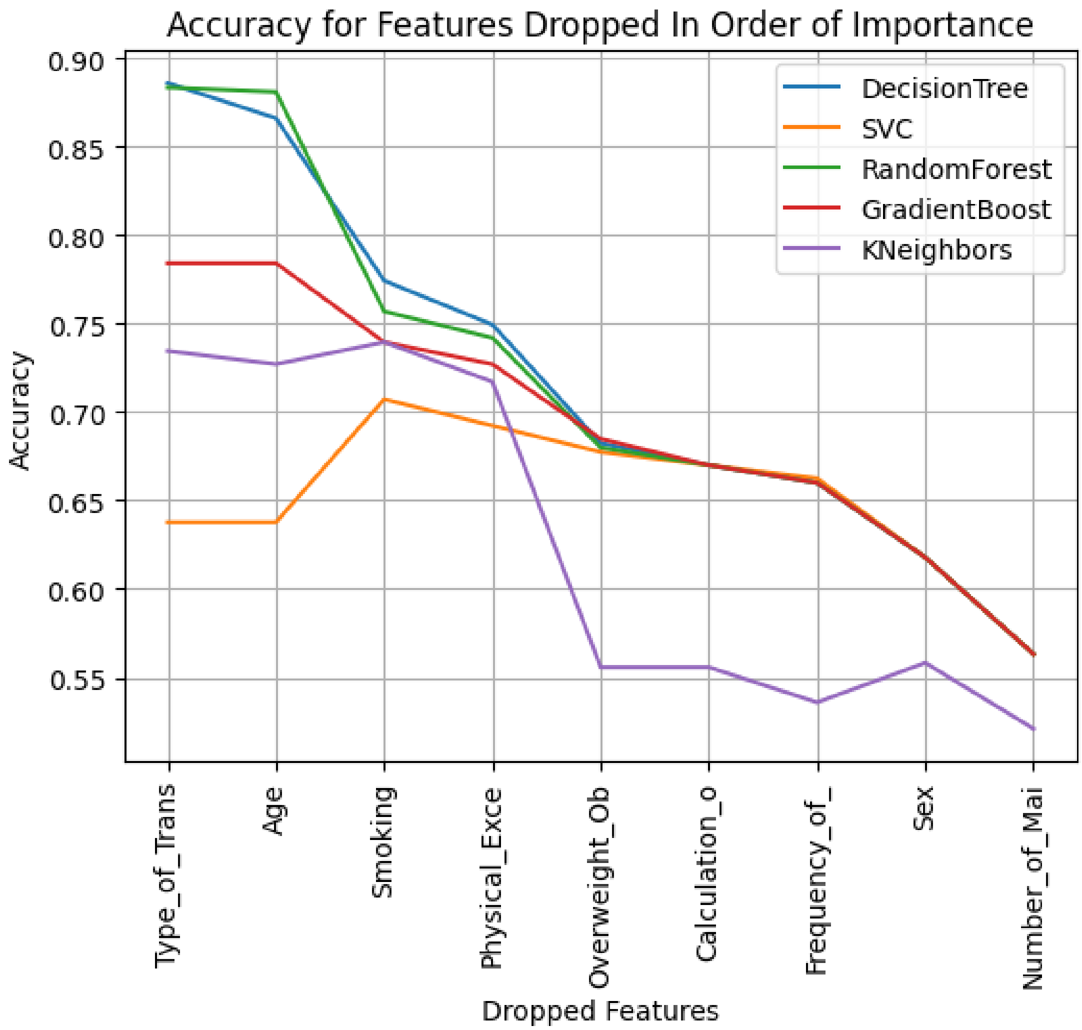
[50]:
```
Sex                                  0.133842
Age                                  0.269654
Overweight_Obese_Family              0.066424
Frequency_of_Consuming_Vegetables    0.180819
Number_of_Main_Meals_Daily           0.211558
```

```
Smoking                                  0.023430
Calculation_of_Calorie_Intake            0.090481
Physical_Excercise                       0.101175
Type_of_Transportation_Used              0.026161
dtype: float64
```

[21]:

```
to_reduce = list(importances.sort_values(ascending=True).index)

dt_d_redux, svm_d_redux, rf_d_redux, gb_d_redux, knn_d_redux = [], [], [], [],␣
↪[]

for i in range(len(to_reduce)):
    x_tr = x_train.drop(labels=to_reduce[:i], axis=1)
    x_te = x_test.drop(labels=to_reduce[:i], axis=1)

    dt_d_redux.append(DecisionTreeClassifier(random_state=RANDOMSTATE).
↪fit(x_tr, y_train).score(x_te, y_test))
    svm_d_redux.append(SVC(random_state=RANDOMSTATE).fit(x_tr, y_train).
↪score(x_te, y_test))
    rf_d_redux.append(RandomForestClassifier(random_state=RANDOMSTATE).
↪fit(x_tr, y_train).score(x_te, y_test))
    gb_d_redux.append(GradientBoostingClassifier(random_state=RANDOMSTATE).
↪fit(x_tr, y_train).score(x_te, y_test))
    knn_d_redux.append(KNeighborsClassifier().fit(x_tr, y_train).score(x_te,␣
↪y_test))

drops = np.argmax(np.array([dt_d_redux, svm_d_redux, rf_d_redux, gb_d_redux,␣
↪knn_d_redux]), axis=1)
print("Number of drops for best score: ", drops)
x = [x[:13] for x in to_reduce]

fig, ax = plt.subplots()
ax.set_xlabel("Dropped Features")
ax.set_ylabel("Accuracy")
ax.set_title("Accuracy for Features Dropped In Order of Importance")
ax.plot(x, dt_d_redux, label="DecisionTree")
ax.plot(x, svm_d_redux, label="SVC")
ax.plot(x, rf_d_redux, label="RandomForest")
ax.plot(x, gb_d_redux, label="GradientBoost")
ax.plot(x, knn_d_redux, label="KNeighbors")
plt.xticks(rotation=90)
plt.grid(True)
ax.legend()
plt.show()
```

```
Number of drops for best score:  [0 2 0 0 2]
```



[55]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

# Feature Scaling
X=ob.drop(labels='Class', axis=1)
X_scaled = pd.DataFrame(StandardScaler().fit_transform(X), columns=X.columns)
y=ob['Class']

x_train, x_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.
↪25, random_state=RANDOMSTATE)

x_train = x_train.drop(['Consumption_of_Fast_Food',
                        'Schedule_Dedicated_to_Technology',
                        'Liquid_Intake_Daily',
                        'Food_Intake_Between_Meals',
```

```
                        #'Smoking',
                        #'Type_of_Transportation_Used',
                        #'Overweight_Obese_Family',
                        'Height'], axis=1)

x_test = x_test.drop(['Consumption_of_Fast_Food',
                      'Schedule_Dedicated_to_Technology',
                      'Liquid_Intake_Daily',
                      'Food_Intake_Between_Meals',
                      #'Smoking',
                      #'Type_of_Transportation_Used',
                      #'Overweight_Obese_Family',
                      'Height'], axis=1)


pca = PCA(n_components=2)

pca.fit(x_train)
PCA(n_components=2)

print("explained_variance_ratio_", pca.explained_variance_ratio_)

print("singular_values_", pca.singular_values_)

pca = PCA(n_components=2, svd_solver='full')
print('\n')
pca.fit(x_train)
PCA(n_components=2, svd_solver='full')

print("explained_variance_ratio_", pca.explained_variance_ratio_)

print("singular_values_", pca.singular_values_)

print('\n')
pca.fit(X)
PCA(n_components=2, svd_solver='arpack')

print("explained_variance_ratio_", pca.explained_variance_ratio_)

print("singular_values_", pca.singular_values_)
```

```
explained_variance_ratio_ [0.28989713 0.14523317]
singular_values_ [55.71588552 39.43574006]


explained_variance_ratio_ [0.28989713 0.14523317]
singular_values_ [55.71588552 39.43574006]
```

```
explained_variance_ratio_ [0.59606793 0.36523595]
singular_values_ [402.11110512 314.76391991]
```

[56]:
```python
pca.components_
```

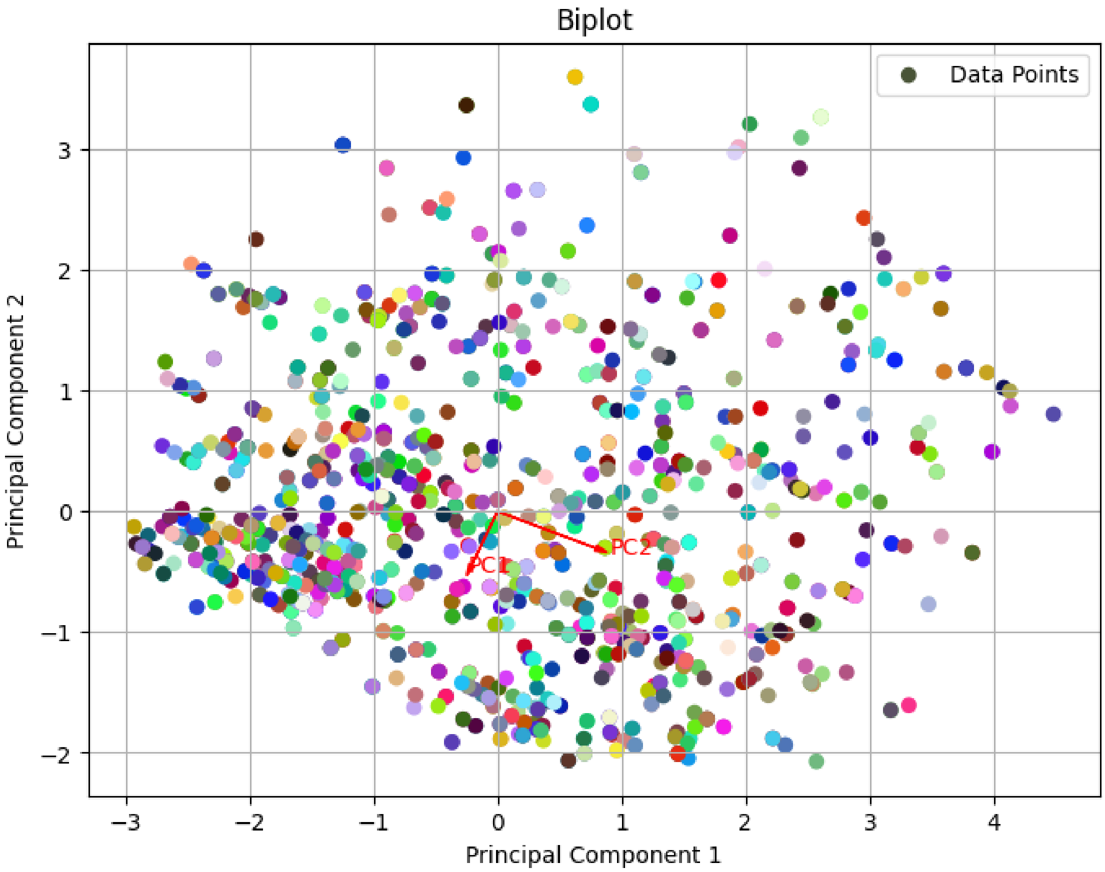
[56]:
```
array([[-0.01516593,  0.96326697,  0.23993692, -0.00697357, -0.01199328,
        -0.02967464,  0.01959419,  0.00460343, -0.00470924,  0.00165211,
        -0.00771695,  0.0462079 , -0.01709292, -0.10162208],
       [-0.03981006, -0.23717445,  0.96962453, -0.00541111,  0.0029475 ,
         0.00293978, -0.01263858, -0.00190415, -0.00686607, -0.0035864 ,
         0.00159411, -0.00472074,  0.00710364,  0.0405764 ]])
```

[57]:
```python
pca = PCA(n_components=2, svd_solver='arpack')

pca.fit(x_train)

for i in range(len(pca.components_[0])):
    print(f"{np.abs(pca.components_[0][i]):.3f} for first component {x_train.
 ↪columns[i]} loadings")
    print(f"{np.abs(pca.components_[1][i]):.3f} for second component {x_train.
 ↪columns[i]} loadings\n")
```

```
0.129 for first component Sex loadings
0.389 for second component Sex loadings

0.494 for first component Age loadings
0.268 for second component Age loadings

0.246 for first component Overweight_Obese_Family loadings
0.438 for second component Overweight_Obese_Family loadings

0.400 for first component Frequency_of_Consuming_Vegetables loadings
0.092 for second component Frequency_of_Consuming_Vegetables loadings

0.371 for first component Number_of_Main_Meals_Daily loadings
0.120 for second component Number_of_Main_Meals_Daily loadings

0.186 for first component Smoking loadings
0.592 for second component Smoking loadings

0.265 for first component Calculation_of_Calorie_Intake loadings
0.188 for second component Calculation_of_Calorie_Intake loadings

0.330 for first component Physical_Excercise loadings
0.019 for second component Physical_Excercise loadings
```

```
0.409 for first component Type_of_Transportation_Used loadings
0.419 for second component Type_of_Transportation_Used loadings
```

[58]:
```python
loadings = pca.components_.T * np.sqrt(pca.explained_variance_)

x_transformed = pca.fit_transform(x_train)
colors = np.random.rand(len(x_transformed), 3)

plt.figure(figsize=(8, 6))

plt.scatter(x_transformed[:, 0], x_transformed[:, 1], color=colors, label='Data␣
↪Points')

for i, feature in enumerate(['PC1', 'PC2']):
    plt.arrow(0, 0, loadings[i, 0], loadings[i, 1],
              color='red', head_width=0.05, head_length=0.1)
    plt.text(loadings[i, 0] * 1.15, loadings[i, 1] * 1.15, feature, color='red')

plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('Biplot')
plt.grid()
plt.legend()
plt.show()
```


Biplot
Data Points
PC1
PC2
Principal Component 1
Principal Component 2
−3 −2 −1 0 1 2 3 4
−2 −1 0 1 2 3

[ ]: