```
import random
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt


from sklearn.svm import SVC
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import classification_report
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.feature_selection import VarianceThreshold
from sklearn.metrics import classification_report, accuracy_score
from sklearn.feature_selection import SequentialFeatureSelector
from sklearn.feature_selection import RFE
from sklearn.model_selection import GridSearchCV, StratifiedKFold, cross_val_predict
from sklearn.preprocessing import StandardScaler


data = np.loadtxt("P1_4.txt")


x = data[:,1:]
y = data[:,0]


print("----- Imbalanced sample -----")
x = data[:,1:]
y = data[:,0]

kf = StratifiedKFold(n_splits=5, shuffle = True)
clf = SVC(kernel = 'linear')

cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]
    clf.fit(x_train, y_train)

    x_test = x[test_index, :]
    y_test = y[test_index]
    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- Imbalanced sample -----
              precision    recall  f1-score   support

         1.0       0.87      0.87      0.87       299
         2.0       0.96      0.96      0.96       895

    accuracy                           0.94      1194
   macro avg       0.92      0.92      0.92      1194
weighted avg       0.94      0.94      0.94      1194
```

```
print("----- Subsamplig -----")

clf = SVC(kernel = 'linear')
kf = StratifiedKFold(n_splits=5, shuffle = True)

cv_y_test = []
cv_y_pred = []
```

```
for train_index, test_index in kf.split(x, y):

    # Training phase
    x_train = x[train_index, :]
    y_train = y[train_index]

    x1 = x_train[y_train==1, :]
    y1 = y_train[y_train==1]
    n1 = len(y1)

    x2 = x_train[y_train==2, :]
    y2 = y_train[y_train==2]
    n2 = len(y2)

    ind = random.sample([i for i in range(n2)], n1)

    x_sub = np.concatenate((x1, x2[ind,:]), axis=0)
    y_sub = np.concatenate((y1, y2[ind]), axis=0)

    clf.fit(x_sub, y_sub)

    # Test phase
    x_test = x[test_index, :]
    y_test = y[test_index]
    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- Subsamplig -----
              precision    recall  f1-score   support

         1.0       0.73      0.89      0.80       299
         2.0       0.96      0.89      0.93       895

    accuracy                           0.89      1194
   macro avg       0.85      0.89      0.87      1194
weighted avg       0.90      0.89      0.90      1194
```

```
print("----- Upsampling -----")
clf = SVC(kernel='linear')
kf = StratifiedKFold(n_splits=5, shuffle=True)

cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]

    x1 = x_train[y_train==1, :]
    y1 = y_train[y_train==1]
    n1 = len(y1)

    x2 = x_train[y_train==2, :]
    y2 = y_train[y_train==2]
    n2 = len(y2)

    ind = random.choices([i for i in range(n1)], k=n2)

    x_sub = np.concatenate((x1[ind,:], x2), axis=0)
    y_sub = np.concatenate((y1[ind], y2), axis=0)

    clf.fit(x_sub, y_sub)

    x_test = x[test_index, :]
    y_test = y[test_index]
    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)
```

```
print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- Upsampling -----
              precision    recall  f1-score   support

         1.0       0.84      0.85      0.84       299
         2.0       0.95      0.94      0.95       895

    accuracy                           0.92      1194
   macro avg       0.89      0.90      0.90      1194
weighted avg       0.92      0.92      0.92      1194
```

```
print("----- Weighted loss function -----")
clf = SVC(kernel='linear', class_weight='balanced')
kf = StratifiedKFold(n_splits=5, shuffle=True)

cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]
    clf.fit(x_train, y_train)

    x_test = x[test_index, :]
    y_test = y[test_index]
    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- Weighted loss function -----
              precision    recall  f1-score   support

         1.0       0.83      0.88      0.85       299
         2.0       0.96      0.94      0.95       895

    accuracy                           0.92      1194
   macro avg       0.89      0.91      0.90      1194
weighted avg       0.92      0.92      0.92      1194
```

```
print('----- Linear-SVM -----')
kf = StratifiedKFold(n_splits=5, shuffle = True)

cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]

    x_test = x[test_index, :]
    y_test = y[test_index]

    clf = SVC(kernel = 'linear')
    clf.fit(x_train, y_train)

    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- Linear-SVM -----
              precision    recall  f1-score   support

         1.0       0.91      0.86      0.88       299
```

```
         2.0       0.95      0.97      0.96       895

    accuracy                           0.94      1194
   macro avg       0.93      0.91      0.92      1194
weighted avg       0.94      0.94      0.94      1194
```

```
print('----- RBF-SVM -----')
kf = StratifiedKFold(n_splits=5, shuffle = True)

cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]

    x_test = x[test_index, :]
    y_test = y[test_index]

    clf = SVC(kernel = 'rbf')
    clf.fit(x_train, y_train)

    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- RBF-SVM -----
              precision    recall  f1-score   support

         1.0       0.98      0.84      0.90       299
         2.0       0.95      0.99      0.97       895

    accuracy                           0.95      1194
   macro avg       0.96      0.91      0.94      1194
weighted avg       0.95      0.95      0.95      1194
```

```
print('----- KNN -----')
kf = StratifiedKFold(n_splits=5, shuffle = True)

cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]

    x_test = x[test_index, :]
    y_test = y[test_index]

    clf = KNeighborsClassifier(n_neighbors=3)
    clf.fit(x_train, y_train)

    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- KNN -----
              precision    recall  f1-score   support

         1.0       0.89      0.81      0.85       299
         2.0       0.94      0.97      0.95       895

    accuracy                           0.93      1194
   macro avg       0.91      0.89      0.90      1194
weighted avg       0.93      0.93      0.93      1194
```

```
print('----- Decision tree -----')
kf = StratifiedKFold(n_splits=5, shuffle = True)

cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]

    x_test = x[test_index, :]
    y_test = y[test_index]

    clf = DecisionTreeClassifier()
    clf.fit(x_train, y_train)

    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- Decision tree -----
              precision    recall  f1-score   support

         1.0       0.72      0.71      0.71       299
         2.0       0.90      0.91      0.90       895

    accuracy                           0.86      1194
   macro avg       0.81      0.81      0.81      1194
weighted avg       0.86      0.86      0.86      1194
```

```
print('----- Linear Discriminant Analysis -----')

kf = StratifiedKFold(n_splits=5, shuffle = True)

cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]

    x_test = x[test_index, :]
    y_test = y[test_index]

    clf = LinearDiscriminantAnalysis()
    clf.fit(x_train, y_train)

    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- Linear Discriminant Analysis -----
              precision    recall  f1-score   support

         1.0       0.89      0.87      0.88       299
         2.0       0.96      0.97      0.96       895

    accuracy                           0.94      1194
   macro avg       0.92      0.92      0.92      1194
weighted avg       0.94      0.94      0.94      1194
```

```
print('----- Naive Bayes -----')

kf = StratifiedKFold(n_splits=5, shuffle = True)
```

```
cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]
    x_test = x[test_index, :]
    y_test = y[test_index]

    clf = GaussianNB()
    clf.fit(x_train, y_train)

    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- Naive Bayes -----
              precision    recall  f1-score   support

         1.0       0.84      0.88      0.86       299
         2.0       0.96      0.94      0.95       895

    accuracy                           0.93      1194
   macro avg       0.90      0.91      0.90      1194
weighted avg       0.93      0.93      0.93      1194
```

```
print('----- Gradient Boosting -----')

kf = StratifiedKFold(n_splits=5, shuffle = True)

cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]
    x_test = x[test_index, :]
    y_test = y[test_index]

    clf = GradientBoostingClassifier()
    clf.fit(x_train, y_train)

    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- Gradient Boosting -----
              precision    recall  f1-score   support

         1.0       0.90      0.78      0.83       299
         2.0       0.93      0.97      0.95       895

    accuracy                           0.92      1194
   macro avg       0.91      0.87      0.89      1194
weighted avg       0.92      0.92      0.92      1194
```

```
print('----- Random Forest -----')

kf = StratifiedKFold(n_splits=5, shuffle = True)

cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
```

```
    y_train = y[train_index]
    x_test = x[test_index, :]
    y_test = y[test_index]

    clf = RandomForestClassifier(n_estimators=100)
    clf.fit(x_train, y_train)

    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- Random Forest -----
              precision    recall  f1-score   support

         1.0       0.94      0.78      0.85       299
         2.0       0.93      0.98      0.96       895

    accuracy                           0.93      1194
   macro avg       0.94      0.88      0.90      1194
weighted avg       0.93      0.93      0.93      1194
```

```
print('----- Logistic Regression -----')

kf = StratifiedKFold(n_splits=5, shuffle = True)

cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]
    x_test = x[test_index, :]
    y_test = y[test_index]


    clf = LogisticRegression(max_iter=1000)
    clf.fit(x_train, y_train)

    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- Logistic Regression -----
              precision    recall  f1-score   support

         1.0       0.92      0.88      0.90       299
         2.0       0.96      0.97      0.97       895

    accuracy                           0.95      1194
   macro avg       0.94      0.93      0.93      1194
weighted avg       0.95      0.95      0.95      1194
```

```
n_features = x.shape[1]


constant_filter = VarianceThreshold(threshold=0)
x_filtered = constant_filter.fit_transform(x)

print(f"Número de características originales: {x.shape[1]}")
print(f"Número de características restantes: {x_filtered.shape[1]}")
```

```
Número de características originales: 154
Número de características restantes: 153
```

```
print("----- Feature selection using 50% of predictors -----")

fselection = SelectKBest(f_classif, k=int(x_filtered.shape[1] / 2))
```

```
fselection.fit(x_filtered, y)

clf = SVC(kernel='linear')
x_transformed = fselection.transform(x_filtered)
clf.fit(x_transformed, y)

cv_y_test = []
cv_y_pred = []

kf = StratifiedKFold(n_splits=5, shuffle=True)

for train_index, test_index in kf.split(x_filtered, y):
    x_train = x_filtered[train_index, :]
    y_train = y[train_index]

    x_test = x_filtered[test_index, :]
    y_test = y[test_index]

    clf_cv = SVC(kernel='linear')
    fselection_cv = SelectKBest(f_classif, k=int(x_filtered.shape[1] / 2))
    fselection_cv.fit(x_train, y_train)
    x_train = fselection_cv.transform(x_train)

    clf_cv.fit(x_train, y_train)

    x_test = fselection_cv.transform(x_test)
    y_pred = clf_cv.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

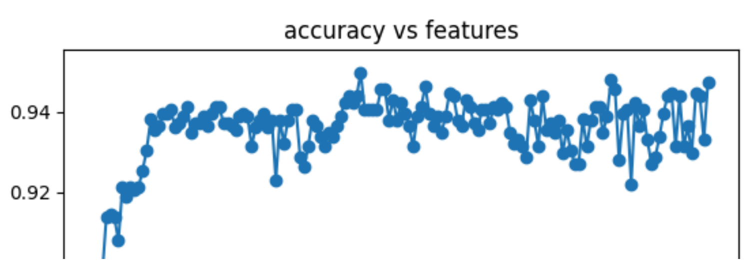
```
----- Feature selection using 50% of predictors -----
              precision    recall  f1-score   support

         1.0       0.87      0.87      0.87       299
         2.0       0.96      0.96      0.96       895

    accuracy                           0.93      1194
   macro avg       0.91      0.91      0.91      1194
weighted avg       0.93      0.93      0.93      1194
```

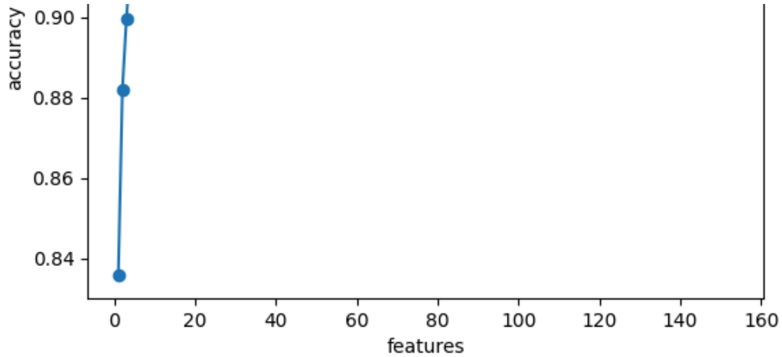
```
print("----- Optimal selection of number of features -----")

n_feats = np.arange(1, x_filtered.shape[1] + 1)
acc_nfeat = []

kf = StratifiedKFold(n_splits=5, shuffle=True)

for n_feat in n_feats:
    acc_cv = []
    for train_index, test_index in kf.split(x_filtered, y):
        x_train, x_test = x_filtered[train_index], x_filtered[test_index]
        y_train, y_test = y[train_index], y[test_index]

        fselection = SelectKBest(f_classif, k=n_feat)
        fselection.fit(x_train, y_train)

        x_train_sel = fselection.transform(x_train)
        x_test_sel = fselection.transform(x_test)

        clf = SVC(kernel='linear')
        clf.fit(x_train_sel, y_train)
        y_pred = clf.predict(x_test_sel)

        acc_cv.append(accuracy_score(y_test, y_pred))

    acc_nfeat.append(np.mean(acc_cv))
    print(f"features: {n_feat}, accuracy: {np.mean(acc_cv):.4f}")


opt_features = n_feats[np.argmax(acc_nfeat)]
print("Optimal number of features: ", opt_features)
```

```
plt.plot(n_feats, acc_nfeat, marker='o')
plt.xlabel('features')
plt.ylabel('accuracy')
plt.title('accuracy vs features')
plt.show()
```

```
----- Optimal selection of number of features -----
features: 1, accuracy: 0.8359
features: 2, accuracy: 0.8819
features: 3, accuracy: 0.8995
features: 4, accuracy: 0.9137
features: 5, accuracy: 0.9146
features: 6, accuracy: 0.9138
features: 7, accuracy: 0.9079
features: 8, accuracy: 0.9213
features: 9, accuracy: 0.9187
features: 10, accuracy: 0.9213
features: 11, accuracy: 0.9204
features: 12, accuracy: 0.9213
features: 13, accuracy: 0.9255
features: 14, accuracy: 0.9305
features: 15, accuracy: 0.9380
features: 16, accuracy: 0.9355
features: 17, accuracy: 0.9364
features: 18, accuracy: 0.9397
features: 19, accuracy: 0.9397
features: 20, accuracy: 0.9405
features: 21, accuracy: 0.9363
features: 22, accuracy: 0.9372
features: 23, accuracy: 0.9388
features: 24, accuracy: 0.9414
features: 25, accuracy: 0.9347
features: 26, accuracy: 0.9372
features: 27, accuracy: 0.9372
features: 28, accuracy: 0.9389
features: 29, accuracy: 0.9364
features: 30, accuracy: 0.9397
features: 31, accuracy: 0.9414
features: 32, accuracy: 0.9414
features: 33, accuracy: 0.9372
features: 34, accuracy: 0.9372
features: 35, accuracy: 0.9364
features: 36, accuracy: 0.9355
features: 37, accuracy: 0.9388
features: 38, accuracy: 0.9397
features: 39, accuracy: 0.9389
features: 40, accuracy: 0.9313
features: 41, accuracy: 0.9363
features: 42, accuracy: 0.9380
features: 43, accuracy: 0.9397
features: 44, accuracy: 0.9363
features: 45, accuracy: 0.9380
features: 46, accuracy: 0.9230
features: 47, accuracy: 0.9380
features: 48, accuracy: 0.9321
features: 49, accuracy: 0.9380
features: 50, accuracy: 0.9405
features: 51, accuracy: 0.9405
features: 52, accuracy: 0.9288
features: 53, accuracy: 0.9263
features: 54, accuracy: 0.9313
features: 55, accuracy: 0.9380
features: 56, accuracy: 0.9364
features: 57, accuracy: 0.9338
features: 58, accuracy: 0.9313
features: 59, accuracy: 0.9346
features: 60, accuracy: 0.9338
features: 61, accuracy: 0.9363
features: 62, accuracy: 0.9389
features: 63, accuracy: 0.9422
features: 64, accuracy: 0.9439
features: 65, accuracy: 0.9422
features: 66, accuracy: 0.9439
features: 67, accuracy: 0.9498
features: 68, accuracy: 0.9405
features: 69, accuracy: 0.9406
features: 70, accuracy: 0.9405
features: 71, accuracy: 0.9405
features: 72, accuracy: 0.9456
features: 73, accuracy: 0.9456
features: 74, accuracy: 0.9380
features: 75, accuracy: 0.9430
features: 76, accuracy: 0.9380
features: 77, accuracy: 0.9422
features: 78, accuracy: 0.9397
features: 79, accuracy: 0.9363
features: 80, accuracy: 0.9313
features: 81, accuracy: 0.9389
features: 82, accuracy: 0.9414
```

```
features: 83, accuracy: 0.9464
features: 84, accuracy: 0.9397
features: 85, accuracy: 0.9364
features: 86, accuracy: 0.9389
features: 87, accuracy: 0.9347
features: 88, accuracy: 0.9388
features: 89, accuracy: 0.9447
features: 90, accuracy: 0.9439
features: 91, accuracy: 0.9380
features: 92, accuracy: 0.9364
features: 93, accuracy: 0.9431
features: 94, accuracy: 0.9414
features: 95, accuracy: 0.9372
features: 96, accuracy: 0.9355
features: 97, accuracy: 0.9405
features: 98, accuracy: 0.9406
features: 99, accuracy: 0.9372
features: 100, accuracy: 0.9414
features: 101, accuracy: 0.9405
features: 102, accuracy: 0.9422
features: 103, accuracy: 0.9414
features: 104, accuracy: 0.9347
features: 105, accuracy: 0.9322
features: 106, accuracy: 0.9330
features: 107, accuracy: 0.9313
features: 108, accuracy: 0.9288
features: 109, accuracy: 0.9430
features: 110, accuracy: 0.9380
features: 111, accuracy: 0.9313
features: 112, accuracy: 0.9439
features: 113, accuracy: 0.9355
features: 114, accuracy: 0.9372
features: 115, accuracy: 0.9347
features: 116, accuracy: 0.9380
features: 117, accuracy: 0.9297
features: 118, accuracy: 0.9355
features: 119, accuracy: 0.9305
features: 120, accuracy: 0.9271
features: 121, accuracy: 0.9272
features: 122, accuracy: 0.9380
features: 123, accuracy: 0.9313
features: 124, accuracy: 0.9380
features: 125, accuracy: 0.9414
features: 126, accuracy: 0.9414
features: 127, accuracy: 0.9347
features: 128, accuracy: 0.9389
features: 129, accuracy: 0.9481
features: 130, accuracy: 0.9456
features: 131, accuracy: 0.9279
features: 132, accuracy: 0.9397
features: 133, accuracy: 0.9405
features: 134, accuracy: 0.9221
features: 135, accuracy: 0.9422
features: 136, accuracy: 0.9364
features: 137, accuracy: 0.9405
features: 138, accuracy: 0.9330
features: 139, accuracy: 0.9271
features: 140, accuracy: 0.9288
features: 141, accuracy: 0.9338
features: 142, accuracy: 0.9397
features: 143, accuracy: 0.9439
features: 144, accuracy: 0.9447
features: 145, accuracy: 0.9313
features: 146, accuracy: 0.9439
features: 147, accuracy: 0.9313
features: 148, accuracy: 0.9363
features: 149, accuracy: 0.9297
features: 150, accuracy: 0.9447
features: 151, accuracy: 0.9439
features: 152, accuracy: 0.9330
features: 153, accuracy: 0.9473
Optimal number of features:  67
```



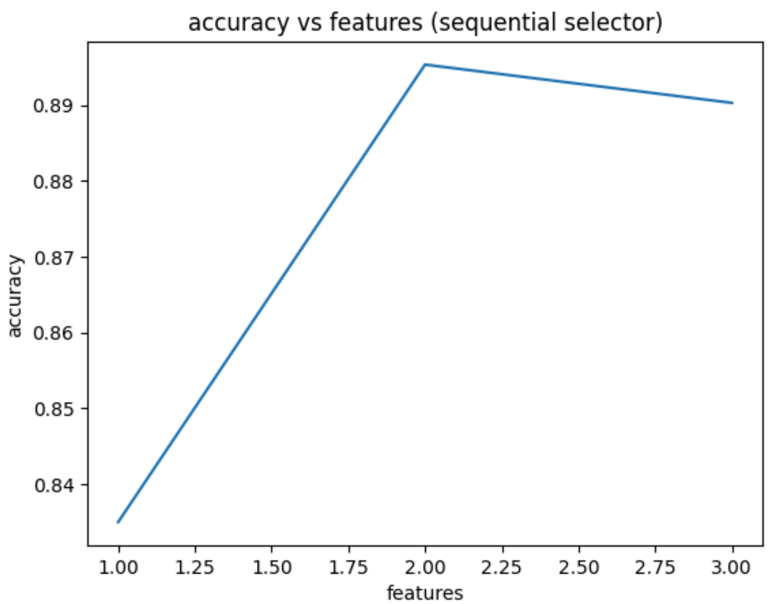

accuracy
0.90
0.88
0.86
0.84
0
20
40
60
80
100
120
140
160
features

```
# Fit model with optimal number of features

fselection = SelectKBest(f_classif, k = opt_features)
fselection.fit(x, y)

selected_indices = fselection.get_support(indices=True)
print(f"features: {selected_indices}")

x_transformed = fselection.transform(x)
clf = SVC(kernel='linear')
clf.fit(x_transformed, y)

cv_y_test = []
cv_y_pred = []

kf = StratifiedKFold(n_splits=5, shuffle=True)

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]

    fselection_cv = SelectKBest(f_classif, k=opt_features)
    fselection_cv.fit(x_train, y_train)
    x_train = fselection_cv.transform(x_train)

    clf_cv = SVC(kernel='linear')
    clf_cv.fit(x_train, y_train)

    x_test = fselection_cv.transform(x[test_index, :])
    y_test = y[test_index]
    y_pred = clf_cv.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:112: UserWarning: Features [0]
  warnings.warn("Features %s are constant." % constant_features_idx, UserWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:113: RuntimeWarning: invalid va
  f = msb / msw
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:112: UserWarning: Features [0]
  warnings.warn("Features %s are constant." % constant_features_idx, UserWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:113: RuntimeWarning: invalid va
  f = msb / msw
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:112: UserWarning: Features [0]
  warnings.warn("Features %s are constant." % constant_features_idx, UserWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:113: RuntimeWarning: invalid va
  f = msb / msw
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:112: UserWarning: Features [0]
  warnings.warn("Features %s are constant." % constant_features_idx, UserWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:113: RuntimeWarning: invalid va
  f = msb / msw
features: [  1   2   3  11  12  13  16  17  18  19  20  21  23  24  25  26  27  28
  29  30  31  34  35  36  54  62  63  64  66  67  68  69  73  74  75  76
  80  81  82  83  84  88  89  90  91  92  93  94 102 119 120 121 125 126
 127 128 135 136 137 138 139 140 141 142 143 152 153]
              precision    recall  f1-score   support

         1.0       0.91      0.89      0.90       299
         2.0       0.96      0.97      0.97       895

    accuracy                           0.95      1194
   macro avg       0.93      0.93      0.93      1194
weighted avg       0.95      0.95      0.95      1194

/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:112: UserWarning: Features [0]
  warnings.warn("Features %s are constant." % constant_features_idx, UserWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:113: RuntimeWarning: invalid va
  f = msb / msw
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:112: UserWarning: Features [0]
  warnings.warn("Features %s are constant." % constant_features_idx, UserWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:113: RuntimeWarning: invalid va
  f = msb / msw
```

```
n_feats = np.arange(1, min(x.shape[1], 3) + 1)
acc_nfeat = []

for n_feat in n_feats:
    print(f"---- n features = {n_feat}")

    acc_cv = []

    kf = StratifiedKFold(n_splits=5, shuffle=True)

    for train_index, test_index in kf.split(x, y):

        x_train = x[train_index, :]
        y_train = y[train_index]

        clf_cv = SVC(kernel='linear')

        fselection_cv = SequentialFeatureSelector(clf_cv, n_features_to_select=n_feat, direction='forward')
        fselection_cv.fit(x_train, y_train)
        x_train = fselection_cv.transform(x_train)

        clf_cv.fit(x_train, y_train)

        x_test = fselection_cv.transform(x[test_index, :])
        y_test = y[test_index]
        y_pred = clf_cv.predict(x_test)

        acc_i = accuracy_score(y_test, y_pred)
        acc_cv.append(acc_i)

    acc = np.average(acc_cv)
    acc_nfeat.append(acc)
    print(f'accuracy: {acc:.4f}')

opt_index = np.argmax(acc_nfeat)
opt_features = n_feats[opt_index]
print(f"optimal number of features: {opt_features}")

plt.plot(n_feats, acc_nfeat)
plt.xlabel("features")
plt.ylabel("accuracy")
plt.title("accuracy vs features (sequential selector)")
plt.show()
```

```
---- n features = 1
accuracy: 0.8350
---- n features = 2
accuracy: 0.8953
---- n features = 3
accuracy: 0.8903
optimal number of features: 2
```



```
print("---- Fit model (sequential)-----")

clf = SVC(kernel='linear')
fselection = SequentialFeatureSelector(clf, n_features_to_select=opt_features, direction='forward')
fselection.fit(x, y)

selected_indices = fselection.get_support(indices=True)
print(f"features: {selected_indices}")

x_transformed = fselection.transform(x)
clf.fit(x_transformed, y)

cv_y_test = []
cv_y_pred = []

kf = StratifiedKFold(n_splits=5, shuffle=True)

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]

    fselection_cv = SequentialFeatureSelector(clf, n_features_to_select=opt_features, direction='forward')
    fselection_cv.fit(x_train, y_train)
    x_train = fselection_cv.transform(x_train)

    clf_cv = SVC(kernel='linear')
    clf_cv.fit(x_train, y_train)

    x_test = fselection_cv.transform(x[test_index, :])
    y_test = y[test_index]
    y_pred = clf_cv.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
---- Fit model (sequential)-----
features: [19 28]
              precision    recall  f1-score   support

         1.0       0.82      0.75      0.78       299
         2.0       0.92      0.95      0.93       895

    accuracy                           0.90      1194
   macro avg       0.87      0.85      0.86      1194
weighted avg       0.89      0.90      0.89      1194
```

```
rfe = RFE(estimator=clf, n_features_to_select=int(n_features / 2))
rfe.fit(x, y)

selected_indices = rfe.get_support(indices=True)
print(f"features: {selected_indices}")

x_transformed = rfe.transform(x)

cv_y_test = []
cv_y_pred = []

kf = StratifiedKFold(n_splits=5, shuffle=True)

for train_index, test_index in kf.split(x_transformed, y):
    x_train = x_transformed[train_index, :]
    y_train = y[train_index]

    x_test = x_transformed[test_index, :]
    y_test = y[test_index]

    clf_cv = SVC(kernel='linear')
    clf_cv.fit(x_train, y_train)

    y_pred = clf_cv.predict(x_test)
```

```
        cv_y_test.append(y_test)
        cv_y_pred.append(y_pred)

    print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))


    print("----- Optimal selection of number of features -----")

    n_feats = np.arange(1, min(x.shape[1], 3) + 1)
    acc_nfeat = []

    for n_feat in n_feats:
        print(f"---- n features = {n_feat}")
        acc_cv = []
        for train_index, test_index in kf.split(x, y):
            x_train = x[train_index, :]
            y_train = y[train_index]

            rfe = RFE(estimator=clf, n_features_to_select=n_feat)
            rfe.fit(x_train, y_train)

            x_train_sel = rfe.transform(x_train)
            x_test_sel = rfe.transform(x[test_index, :])

            clf.fit(x_train_sel, y_train)
            y_pred = clf.predict(x_test_sel)

            acc_i = accuracy_score(y[test_index], y_pred)
            acc_cv.append(acc_i)

        acc_nfeat.append(np.mean(acc_cv))
        print(f"features: {n_feat}, accuracy: {np.mean(acc_cv):.4f}")

    opt_features = n_feats[np.argmax(acc_nfeat)]
    print(f"Optimal number of features: {opt_features}")

    plt.plot(n_feats, acc_nfeat, marker='o')
    plt.xlabel('features')
    plt.ylabel('accuracy')
    plt.title('accuracy vs features')
    plt.show()


    rfe = RFE(estimator=clf, n_features_to_select=opt_features)
    rfe.fit(x, y)

    selected_indices = rfe.get_support(indices=True)
    print(f"features: {selected_indices}")

    x_transformed = rfe.transform(x)
    clf.fit(x_transformed, y)
```

```
features: [20 28]
▾       SVC
SVC(kernel='linear')
```

```
opt_features = 10

fselection = SelectKBest(f_classif, k=opt_features)
fselection.fit(x, y)

selected_indices = fselection.get_support(indices=True)
print(f"features: {selected_indices}")

x_transformed = fselection.transform(x)

clf = SVC(kernel='linear')
clf.fit(x_transformed, y)

print("Modelo para producción.")
```

Contesta las siguientes preguntas:

a. ¿Qué pasa si no se considera el problema de tener datos desbalanceados para este caso? ¿Por qué?

R = El modelo puede tender a favorecer a la clase que es mayoría. El clasificador se inclinaría a predecir siempre la clase que es mayoría ignorando a la clase minoritaria.

Podría tener un muy alto accuracy, dando un falso ¨buen¨ rendimiento.

El modelo puede sobreajustarse a la clase mayoritaria porque tiene más datos para aprender de esa clase.

b. De todos los clasificadores, ¿cuál o cuales consideras que son adecuados para los datos? ¿Qué propiedades tienen dichos modelos que los hacen apropiados para los datos? Argumenta tu respuesta.

R = SVM y Random Forest parecen ser los más adecuados, ya que ofrecen propiedas necesarias para poder ajustarse a datos complejos y ambos pueden manejar clases desbalanceadas.

b. ¿Es posibles reducir la dimensionalidad del problema sin perder rendimiento en el modelo? ¿Por qué?

R = Sí es posible. En muchos casos los modelos no necesitan todas las caracteristicas para tener un buen rendimiento, reducir la dimensionalidad ayuda a eliminar ruido y se vuelve más eficiente.

c. ¿Qué método de selección de características consideras el más adecuado para este caso? ¿Por qué?

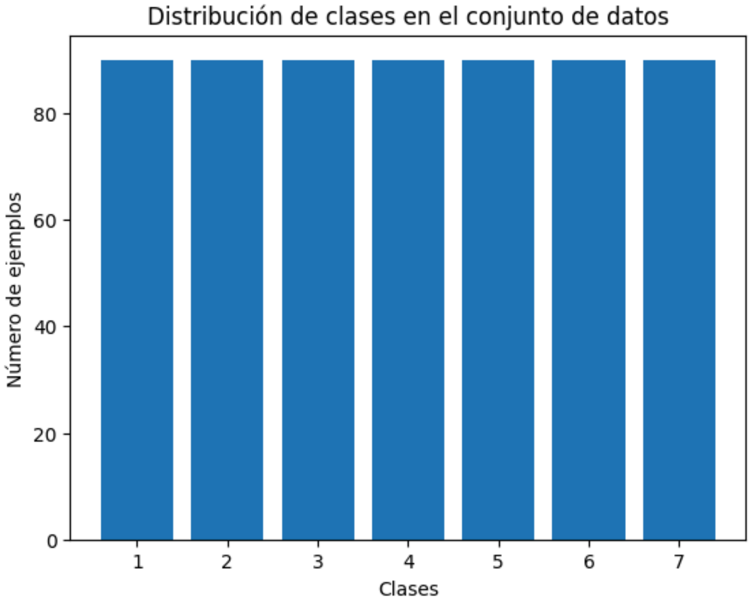
El método filter es el más adecuado por su simplicidad, eficiencia, independencia y la capacidad para identificar las características más relevantes.

d. Si quisieras mejorar el rendimiento de tus modelos, ¿qué más se podría hacer?

R = Es fundamental balancear datos y seleccionar características, optimizar hiperparámetros y probar modelos más avanzados.

```
data = np.loadtxt('M_3.txt')


x = data[:,1:]
y = data[:,0]


unique, counts = np.unique(y, return_counts=True)
class_distribution = dict(zip(unique, counts))

print("Distribución de clases:", class_distribution)

plt.bar(unique, counts)
plt.xlabel('Clases')
plt.ylabel('Número de ejemplos')
plt.title('Distribución de clases en el conjunto de datos')
plt.show()

total = sum(counts)
class_ratios = [count / total for count in counts]

for i, ratio in enumerate(class_ratios):
    print(f"Proporción de la clase {unique[i]}: {ratio:.2%}")

if min(class_ratios) / max(class_ratios) < 0.5:
    print("Es necesario balancear los datos.")
else:
    print("No es necesario balancear los datos.")
```

```
Distribución de clases: {1.0: 90, 2.0: 90, 3.0: 90, 4.0: 90, 5.0: 90, 6.0: 90, 7.0: 90}
```




```
Proporción de la clase 1.0: 14.29%
Proporción de la clase 2.0: 14.29%
Proporción de la clase 3.0: 14.29%
Proporción de la clase 4.0: 14.29%
Proporción de la clase 5.0: 14.29%
Proporción de la clase 6.0: 14.29%
Proporción de la clase 7.0: 14.29%
No es necesario balancear los datos.
```

```
print('----- Linear-SVM -----')
kf = StratifiedKFold(n_splits=5, shuffle = True)

cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]

    x_test = x[test_index, :]
    y_test = y[test_index]

    clf = SVC(kernel = 'linear')
    clf.fit(x_train, y_train)

    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- Linear-SVM -----
              precision    recall  f1-score   support

         1.0       0.86      0.86      0.86       299
         2.0       0.95      0.95      0.95       895

    accuracy                           0.93      1194
   macro avg       0.91      0.91      0.91      1194
weighted avg       0.93      0.93      0.93      1194
```

```
print('----- RBF-SVM -----')
kf = StratifiedKFold(n_splits=5, shuffle = True)

cv_y_test = []
cv_y_pred = []
```

```
for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]

    x_test = x[test_index, :]
    y_test = y[test_index]

    clf = SVC(kernel = 'rbf')
    clf.fit(x_train, y_train)

    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- RBF-SVM -----
              precision    recall  f1-score   support

         1.0       0.97      0.84      0.90       299
         2.0       0.95      0.99      0.97       895

    accuracy                           0.95      1194
   macro avg       0.96      0.92      0.94      1194
weighted avg       0.95      0.95      0.95      1194
```

```
print('----- KNN -----')
kf = StratifiedKFold(n_splits=5, shuffle = True)

cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]

    x_test = x[test_index, :]
    y_test = y[test_index]

    clf = KNeighborsClassifier(n_neighbors=3)
    clf.fit(x_train, y_train)

    y_pred = clf.predict(x_test)

    cv_y_test.append(y_test)
    cv_y_pred.append(y_pred)

print(classification_report(np.concatenate(cv_y_test), np.concatenate(cv_y_pred)))
```

```
----- KNN -----
              precision    recall  f1-score   support

         1.0       0.89      0.80      0.84       299
         2.0       0.93      0.97      0.95       895

    accuracy                           0.93      1194
   macro avg       0.91      0.88      0.90      1194
weighted avg       0.92      0.93      0.92      1194
```

```
print('----- Decision tree -----')
kf = StratifiedKFold(n_splits=5, shuffle = True)

cv_y_test = []
cv_y_pred = []

for train_index, test_index in kf.split(x, y):

    x_train = x[train_index, :]
    y_train = y[train_index]

    x_test = x[test_index, :]
```