practica4

February 16, 2021

1 Práctica 3: Clasificación con scikit-learn

1.1 Importar módulos

[1]:
```
%matplotlib inline

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

import sklearn
from sklearn import preprocessing, model_selection, neighbors, svm, tree,␣
 ↪ensemble
```

1.2 Seleccionar datasets

Los conjuntos de datos seleccionados se encuentran en el directorio `datasets`.

[2]:
```
accent_df = pd.read_csv('datasets/accent.csv', header=0)
avila_df = pd.read_csv('datasets/avila.csv', header=0)
cancer_df = pd.read_csv('datasets/cancer.csv', header=0, na_values='?')
digits_df = pd.read_csv('datasets/digits.csv', header=None)
fertility_df = pd.read_csv('datasets/fertility.csv', header=0)
glass_df = pd.read_csv('datasets/glass.csv', header=0)
iris_df = pd.read_csv('datasets/iris.csv', header=None)
column_df = pd.read_csv('datasets/column.csv', header=0)
phishing_df = pd.read_csv('datasets/phishing.csv', header=None)
wine_df = pd.read_csv('datasets/wine.csv', header=0)
```

1.2.1 Preprocesamiento

Aplicamos el mismo que en la práctica anterior, además de eliminar de Avila y Glass las clases con menos de 10 instancias para poder realizar 10-fold estratificado

```
[3]: accent_df = accent_df[accent_df.columns.to_list()[1:]+[accent_df.columns.
      ↪to_list()[0]]]
```

```
[4]: cancer_df = cancer_df.drop('id', axis=1)
```

```
[5]: cancer_df.bare_nuclei = cancer_df.bare_nuclei.fillna(np.mean(cancer_df.
      ↪bare_nuclei)).astype('int')
```

```
[6]: avila_df = avila_df[avila_df['class'] != 'B']
     glass_df = glass_df[glass_df['class'] != 6]
```

```
[7]: dfs = [accent_df, avila_df, cancer_df, digits_df, fertility_df, glass_df,␣
      ↪iris_df, column_df, phishing_df, wine_df]
     df_names = ['Accents', 'Avila', 'Cancer', 'Digits', 'Fertility', 'Glass',␣
      ↪'Iris', 'Vertebral Column', 'Phishing', 'Wine']
```

```
[8]: for df in dfs:
         df.iloc[:,-1] = df.iloc[:,-1].astype('category')
```

```
[9]: X = [df.iloc[:, :-1].values for df in dfs]
     y = [df.iloc[:, -1].values for df in dfs]
```

1.3 1. Seleccionar clasificadores

Usaremos los clasificadores siguientes: - `sklearn.neighbors.KNeighborsClassifier` - `sklearn.tree.DecisionTreeClassifier` - `sklearn.svm.SVC`

1.4 2. Comparar método base con *ensemble*

1.4.1 2.1 Entrenar y aplicar el método base

```
[23]: knn_scores = np.empty((len(dfs), 10))
      svc_scores = np.empty((len(dfs), 10))
      dtree_scores = np.empty((len(dfs), 10))
      from time import sleep
      print('[' + len(dfs)*'.'+']', end='\r', flush=True)
      for i in range(len(dfs)):
          print('['+'='*(i)+'>'+(len(dfs)-i-1)*'.'+']', end='\r', flush=True)

          knn_scores[i] = model_selection.cross_val_score(neighbors.
       ↪KNeighborsClassifier(), X[i], y[i], cv=10)
          svc_scores[i] = model_selection.cross_val_score(svm.SVC(), X[i], y[i],␣
       ↪cv=10)
          dtree_scores[i] = model_selection.cross_val_score(tree.
       ↪DecisionTreeClassifier() ,X[i], y[i], cv=10)
```

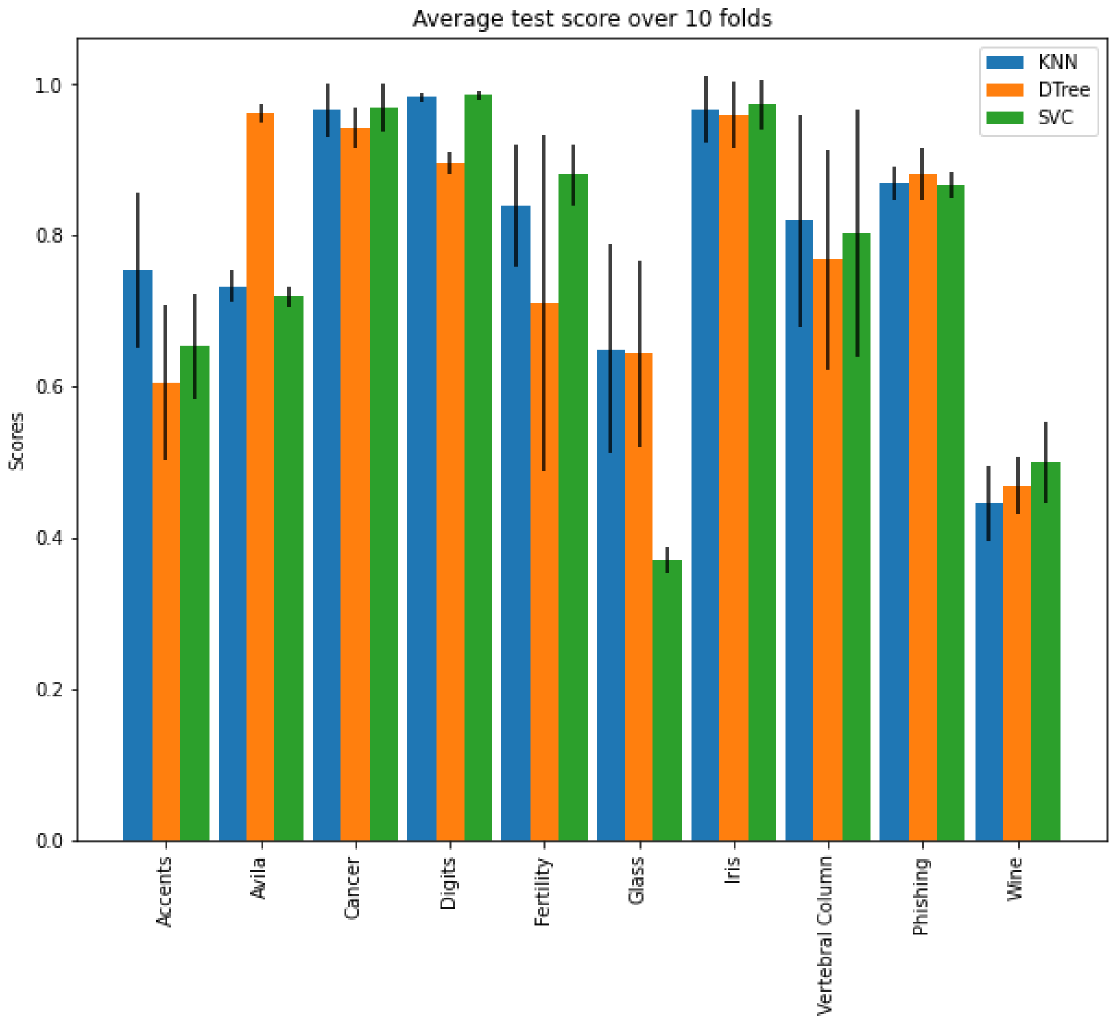
```
    print('['+'='*(i+1)+(len(dfs)-i-1)*'.'+']', end='\r', flush=True)
```

```
[==========]
```

[37]:
```
average_knn_scores = np.array([np.mean(x) for x in knn_scores])
knn_score_std = np.array([np.std(x) for x in knn_scores])

average_dtree_scores = np.array([np.mean(x) for x in dtree_scores])
dtree_score_std = np.array([np.std(x) for x in dtree_scores])

average_svc_scores = [np.mean(x) for x in svc_scores])
svc_score_std = np.array([np.std(x) for x in svc_scores])
```

```
  File "<ipython-input-37-c8faddf488e9>", line 7
    average_svc_scores = [np.mean(x) for x in svc_scores])
                                                         ^
SyntaxError: invalid syntax
```

[38]:
```
x = np.arange(len(dfs)*2, step=2)  # the label locations
width = 0.6  # the width of the bars

fig, ax = plt.subplots(figsize=(10,8))

ax.bar(x - width, average_knn_scores, width, label='KNN', yerr=knn_score_std)
ax.bar(x, average_dtree_scores, width, label='DTree', yerr=dtree_score_std)
ax.bar(x + width, average_svc_scores, width, label='SVC', yerr=svc_score_std)

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('Scores')
ax.set_title('Average test score over 10 folds')
ax.set_xticks(x)
ax.set_xticklabels(df_names, rotation='vertical')
ax.legend()

plt.show()
```



1.4.2 2.2 Aplicar Bagging a los clasificadores

Usamos un 70% de los patrones en cada estimador del *ensemble* para que sean distintos.

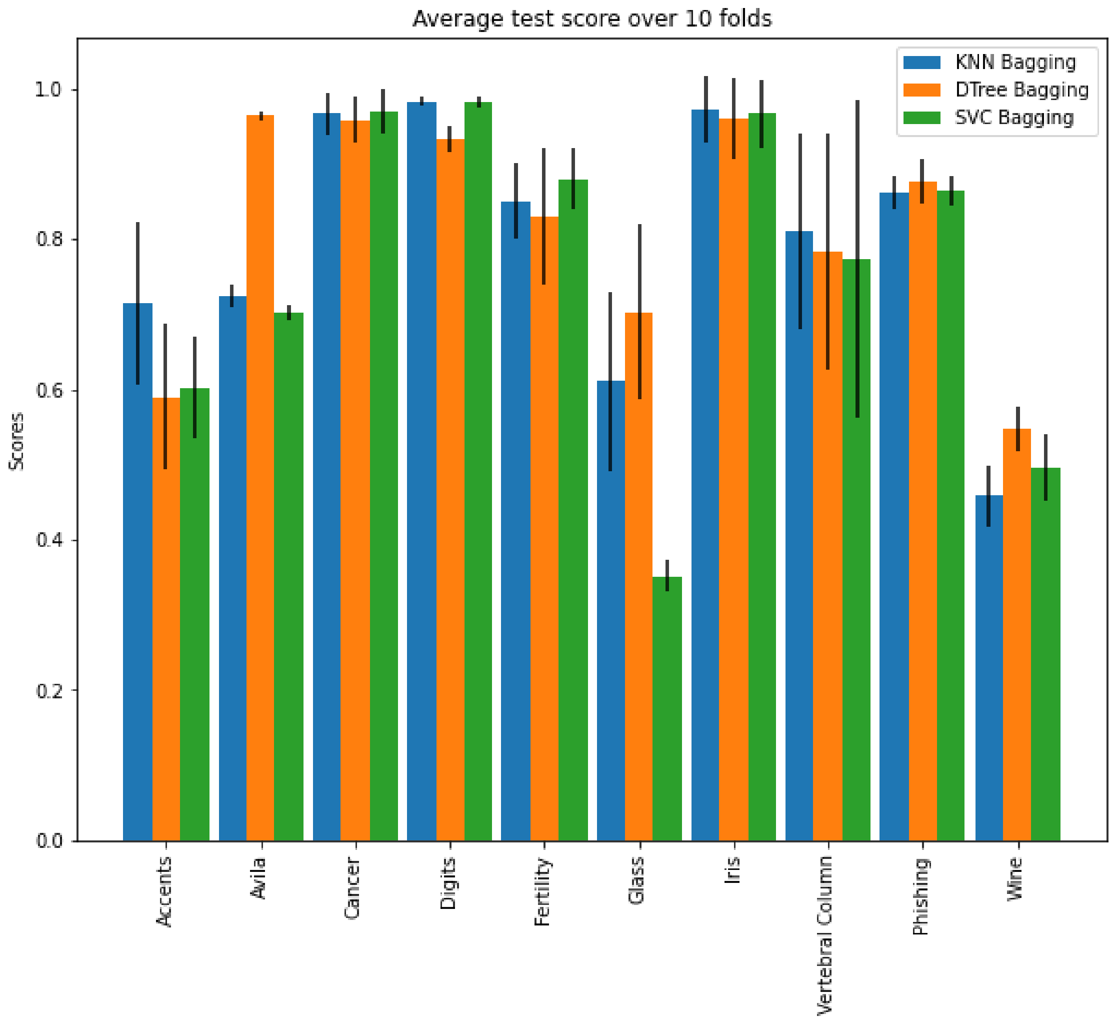
[33]:
```
knn_bagging = ensemble.BaggingClassifier(neighbors.KNeighborsClassifier(),␣
 ↪max_samples=.7, n_estimators=5, random_state=0)
dtree_bagging = ensemble.BaggingClassifier(tree.DecisionTreeClassifier(),␣
 ↪max_samples=.7, n_estimators=5, random_state=0)
svc_bagging = ensemble.BaggingClassifier(svm.SVC(), max_samples=.7,␣
 ↪n_estimators=5, random_state=0)
```

[34]:
```
knn_bagging_scores = np.empty((len(dfs), 10))
svc_bagging_scores = np.empty((len(dfs), 10))
dtree_bagging_scores = np.empty((len(dfs), 10))
```

```
for i in range(len(dfs)):
    print('['+'='*(i)+'>'+(len(dfs)-i-1)*'.'+']', end='\r', flush=True)
    knn_bagging_scores[i] = model_selection.cross_val_score(knn_bagging, X[i],␣
 ↪y[i], cv=10)
    svc_bagging_scores[i] = model_selection.cross_val_score(svc_bagging, X[i],␣
 ↪y[i], cv=10)
    dtree_bagging_scores[i] = model_selection.cross_val_score(dtree_bagging␣
 ↪,X[i], y[i], cv=10)
    print('['+'='*(i+1)+(len(dfs)-i-1)*'.'+']', end='\r', flush=True)
```

```
[==========]
```

[39]:
```
average_knn_b_scores = np.array([np.mean(x) for x in knn_bagging_scores])
knn_b_score_std = np.array([np.std(x) for x in knn_bagging_scores])

average_dtree_b_scores = np.array([np.mean(x) for x in dtree_bagging_scores])
dtree_b_score_std = np.array([np.std(x) for x in dtree_bagging_scores])

average_svc_b_scores = np.array([np.mean(x) for x in svc_bagging_scores])
svc_b_score_std = np.array([np.std(x) for x in svc_bagging_scores])

x = np.arange(len(dfs)*2, step=2)  # the label locations
width = 0.6  # the width of the bars

fig, ax = plt.subplots(figsize=(10,8))

ax.bar(x - width, average_knn_b_scores, width, label='KNN Bagging',␣
 ↪yerr=knn_b_score_std)
ax.bar(x, average_dtree_b_scores, width, label='DTree Bagging',␣
 ↪yerr=dtree_b_score_std)
ax.bar(x + width, average_svc_b_scores, width, label='SVC Bagging',␣
 ↪yerr=svc_b_score_std)

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('Scores')
ax.set_title('Average test score over 10 folds')
ax.set_xticks(x)
ax.set_xticklabels(df_names, rotation='vertical')
ax.legend()

plt.show()
```

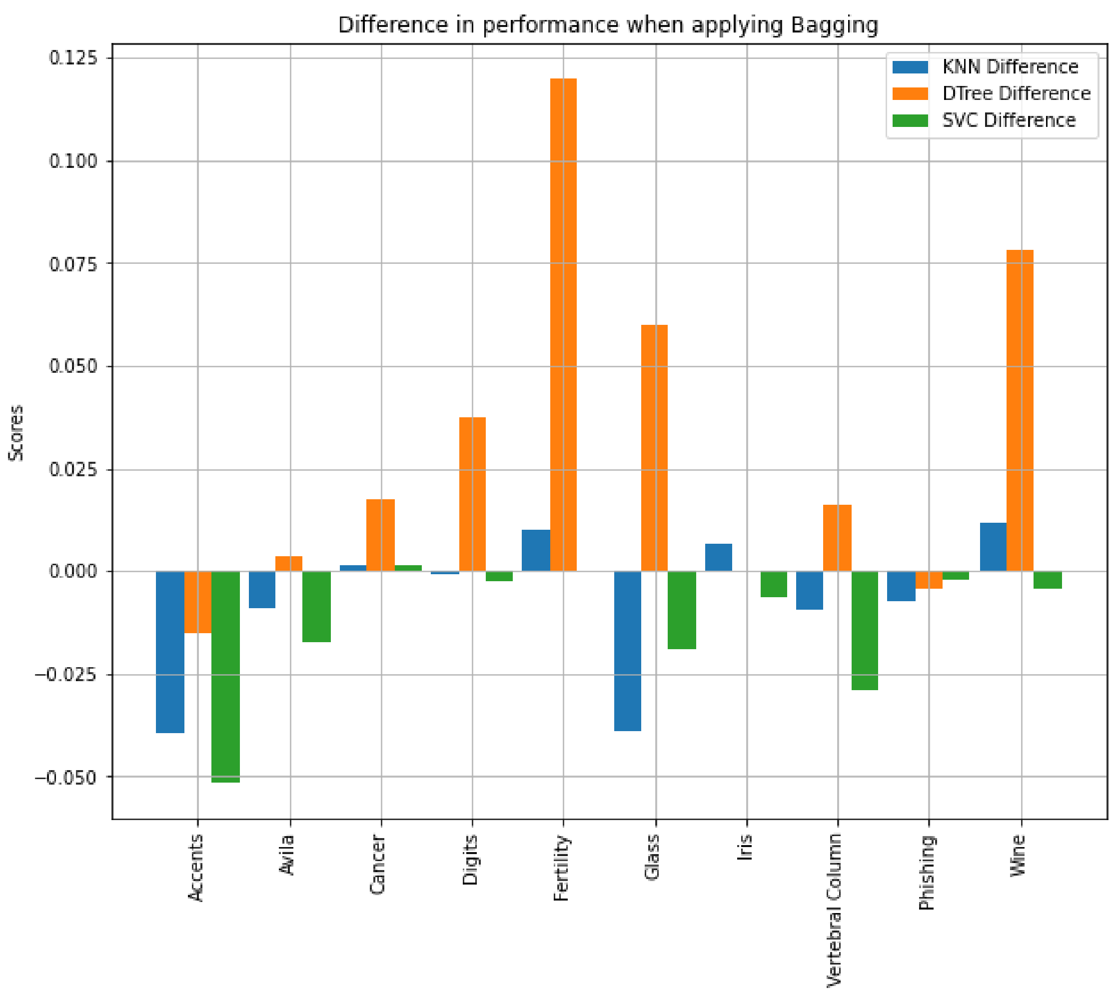


[48]:
```
knn_diff = average_knn_b_scores - average_knn_scores
svc_diff = average_svc_b_scores - average_svc_scores
dtree_diff = average_dtree_b_scores - average_dtree_scores
```

[50]:
```
print('Average change in accuracy for each method:')
print(f'\t KNN: {np.mean(knn_diff):.4f} (with std. {np.std(knn_diff):.4f})')
print(f'\t SVC: {np.mean(svc_diff):.4f} (with std. {np.std(svc_diff):.4f})')
print(f'\t DTree: {np.mean(dtree_diff):.4f} (with std. {np.std(dtree_diff):.
 ↪4f})')
```

```
Average change in accuracy for each method:
         KNN: -0.0075 (with std. 0.0174)
         SVC: -0.0131 (with std. 0.0159)
         DTree: 0.0313 (with std. 0.0407)
```

[53]:
```
x = np.arange(len(dfs)*2, step=2)  # the label locations
width = 0.6  # the width of the bars

fig, ax = plt.subplots(figsize=(10,8))

ax.bar(x - width, knn_diff, width, label='KNN Difference')
ax.bar(x, dtree_diff, width, label='DTree Difference')
ax.bar(x + width, svc_diff, width, label='SVC Difference')

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.grid()
ax.set_ylabel('Scores')
ax.set_title('Difference in performance when applying Bagging')
ax.set_xticks(x)
ax.set_xticklabels(df_names, rotation='vertical')
ax.legend()

plt.show()
```



1.4.3 2.3 Aplicar algoritmos de *boosting*

Usaremos AdaBoost y GradientTree, implementados en scikit.

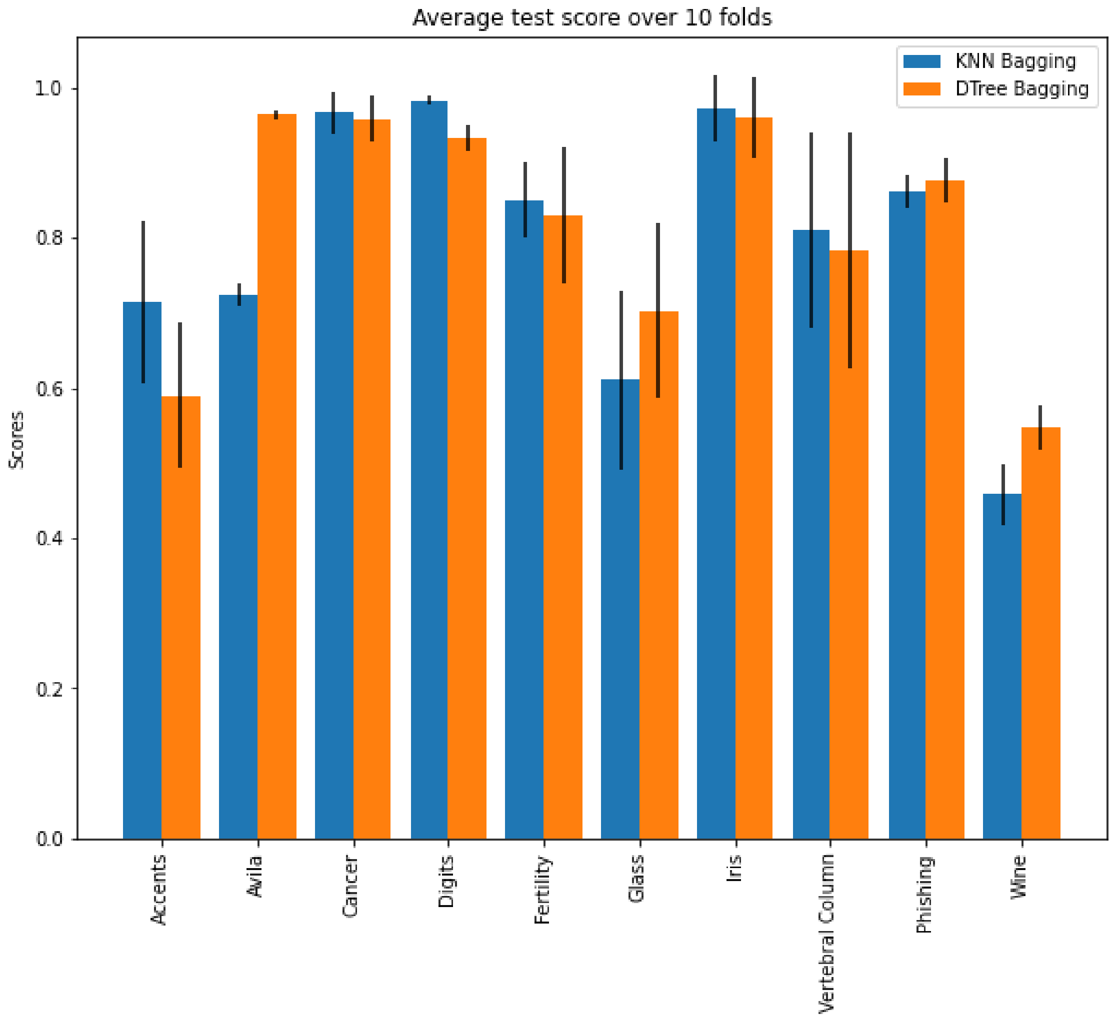
[54]:
```
ada = ensemble.AdaBoostClassifier(random_state=0)
gtree = ensemble.GradientBoostingClassifier(random_state=0)
```

[55]:
```
ada_scores = np.empty((len(dfs), 10))
gradient_scores = np.empty((len(dfs), 10))



for i in range(len(dfs)):
    print('['+'='*(i)+'>'+(len(dfs)-i-1)*'.'+']', end='\r', flush=True)
    ada_scores[i] = model_selection.cross_val_score(ada, X[i], y[i], cv=10)
    gradient_scores[i] = model_selection.cross_val_score(gtree, X[i], y[i],␣
 ↪cv=10)
    print('['+'='*(i+1)+(len(dfs)-i-1)*'.'+']', end='\r', flush=True)
```

```
[==========]
```

[60]:
```
average_ada_scores = np.array([np.mean(x) for x in ada_scores])
ada_score_std = np.array([np.std(x) for x in ada_scores])

average_gtree_scores = np.array([np.mean(x) for x in gradient_scores])
gtree_score_std = np.array([np.std(x) for x in gradient_scores])


x = np.arange(len(dfs))  # the label locations
width = 0.4  # the width of the bars

fig, ax = plt.subplots(figsize=(10,8))

ax.bar(x - width/2, average_knn_b_scores, width, label='KNN Bagging',␣
 ↪yerr=knn_b_score_std)
ax.bar(x + width/2, average_dtree_b_scores, width, label='DTree Bagging',␣
 ↪yerr=dtree_b_score_std)


# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('Scores')
ax.set_title('Average test score over 10 folds')
ax.set_xticks(x)
ax.set_xticklabels(df_names, rotation='vertical')
```

```
ax.legend()

plt.show()
```



1.5 3. Conclusiones

Podemos ver cómo el *ensemble* proporciona resultados positivos cuando el clasificador base es Decision Tree. Esto se debe a que KNN y SVM son métodos muy estables, en los que cada modelo del ensemble proporciona resultados muy similares.