ЛАБОРАТОРНА РОБОТА № 4

ДОСЛІДЖЕННЯ МЕТОДІВ АНСАМБЛЕВОГО НАВЧАННЯ ТА СТВОРЕННЯ РЕКОМЕНДАЦІЙНИХ СИСТЕМ

Мета: *використовуючи спеціалізовані бібліотеки та мову програмування Python дослідити методи ансамблів у машинному навчанні та створити рекомендаційні системи..*

GitHub: https://github.com/ingaliptn/AI

Хід роботи:

Завдання 2.1. Створення класифікаторів на основі випадкових та гранично випадкових лісів

```
import argparse
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report
from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier
from utilities import visualize_classifier
from sklearn.model_selection import cross_val_score, train_test_split

# Парсер аргументів
def build_arg_parser():
    parser = argparse.ArgumentParser(description='Classify data using Ensemble Learning techniques')
    parser.add_argument("--classifier-type", dest="classifier_type", required=True, choices=['rf', 'erf'],
                        help="Type of classifier to use; can be either 'rf' or 'erf'")
    return parser


if __name__ == '__main__':
    args = build_arg_parser().parse_args()
    classifier_type = args.classifier_type
    input_file = 'data_random_forests.txt'
    data = np.loadtxt(input_file, delimiter=',')
    X, Y = data[:, :-1], data[:, -1]
    print(X)
    class_0 = np.array(X[Y == 0])
    class_1 = np.array(X[Y == 1])
    class_2 = np.array(X[Y == 2])
    plt.figure()
    plt.scatter(class_0[:, 0], class_0[:, 1], s=75, facecolors='red', edgecolors='black', linewidth=1, marker='s')
    plt.scatter(class_1[:, 0], class_1[:, 1], s=75, facecolors='green', edgecolors='black', linewidth=1, marker='o')
```

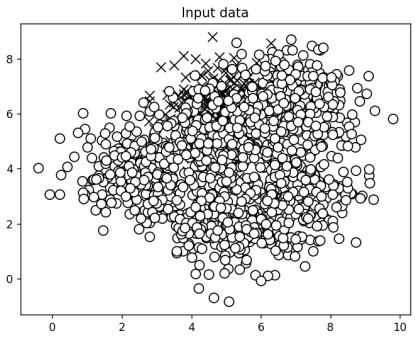
```
    plt.scatter(class_2[:, 0], class_2[:, 1], s=75, facecolors='blue',
edgecolors='black', linewidth=1, marker='^')


plt.title('Input data')
plt.show()
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.25, random_state=5)
params = {'n_estimators': 100, 'max_depth': 4, 'random_state': 0}

if classifier_type == 'rf':
    classifier = RandomForestClassifier(**params)
else:
    classifier = ExtraTreesClassifier(**params)

classifier.fit(X_train, Y_train)
visualize_classifier(classifier, X_train, Y_train, 'Training dataset')

class_names = ['Class-0', 'Class-1', 'Class-2']
print("\n" + "#" * 40)
print("\nClassifier performance on training dataset\n")
Y_train_pred = classifier.predict(X_train)
print(classification_report(Y_train, Y_train_pred, target_names=class_names))
print("#" * 40 + "\n")

print("#" * 40)
print("\nClassifier performance on test dataset\n")
Y_test_pred = classifier.predict(X_test)
print(classification_report(Y_test, Y_test_pred, target_names=class_names))
print("#" * 40 + "\n")
```

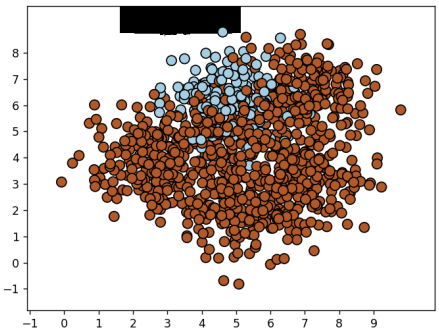
Завдання 2.2. Обробка дисбалансу класів

```
import sys
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.metrics import classification_report
from utilities import visualize_classifier

if __name__ == '__main__':
    input_file = 'data_imbalance.txt'
    data = np.loadtxt(input_file, delimiter=',')
    X, Y = data[:, :-1], data[:, -1]
    # Поділ вхідних даних на два класи на підставі міток
    class_0 = np.array(X[Y == 0])
    class_1 = np.array(X[Y == 1])
    # Візуалізація вхідних даних
    plt.figure()
    plt.scatter(class_0[:, 0], class_0[:, 1], s=75, facecolors='black',
edgecolors='black', linewidth=1, marker='x')
```

```
    plt.scatter(class_1[:, 0], class_1[:, 1], s=75, facecolors='white',
edgecolors='black', linewidth=1, marker='o')
    plt.title('Input data')
    X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.25,
random_state=5)
    params = {'n_estimators': 100, 'max_depth': 4, 'random_state': 0}

    if len(sys.argv) > 1:
        if sys.argv[1] == 'balance':
            params['class_weight'] = 'balanced'
        else:
            raise TypeError("Invalid input argument; should be 'balance' or nothing")

    classifier = ExtraTreesClassifier(**params)
    classifier.fit(X_train, Y_train)
    visualize_classifier(classifier, X_train, Y_train)

    Y_test_pred = classifier.predict(X_test)
    class_names = ['Class-0', 'Class-1']
    print("\n" + "#"*40)
    print("Classifier performance on training dataset")
    print(classification_report(Y_test, Y_test_pred, target_names=class_names))
    print("#"*40)
    print("Classifier performance on test dataset")
    print(classification_report(Y_test, Y_test_pred, target_names=class_names))
    print("#"*40 + "\n")
    plt.show()
```

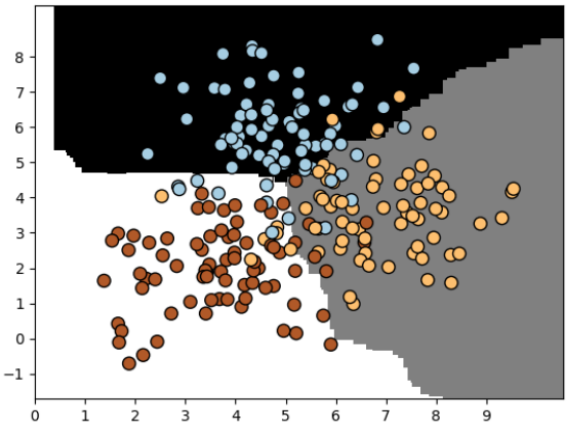
```
              precision    recall  f1-score   support

     Class-0       0.00      0.00      0.00        69
     Class-1       0.82      1.00      0.90       306

    accuracy                           0.82       375
   macro avg       0.41      0.50      0.45       375
weighted avg       0.67      0.82      0.73       375
```





Завдання 2.3. Знаходження оптимальних навчальних параметрів за допомогою сіткового пошуку

```
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.metrics import classification_report
from utilities import visualize_classifier

input_file = 'data_random_forests.txt'
data = np.loadtxt(input_file, delimiter=',')
X, Y = data[:, :-1], data[:, -1]

class_0 = np.array(X[Y == 0])
class_1 = np.array(X[Y == 1])
class_2 = np.array(X[Y == 2])

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.25, random_state=5)

parameter_grid = [{'n_estimators': [100], 'max_depth': [2, 4, 7, 12, 16]},
                  {'max_depth': [4], 'n_estimators': [25, 50, 100, 250]}]

metrics = ['precision_weighted', 'recall_weighted']

for metric in metrics:
    print("#### Searching optimal parameters for", metric)
    classifier = GridSearchCV(ExtraTreesClassifier(random_state=0), parameter_grid, cv=5,
scoring=metric)
    classifier.fit(X_train, Y_train)
    print("\nScores across the parameter grid:")

    for params, avg_score in classifier.cv_results_.items():
        print(params, '-->', avg_score)
    print("\nHighest scoring parameter set:", classifier.best_params_)

    Y_test_pred = classifier.predict(X_test)
    class_names = ['Class-0', 'Class-1', 'Class-2']
    print("#"*40)
    print("Classifier performance on training dataset")
    print(classification_report(Y_test, Y_test_pred, target_names=class_names))
    print("#"*40 + "\n")

    visualize_classifier(classifier, X_test, Y_test)
```



```
#### Searching optimal parameters for precision_weighted

Scores across the parameter grid:
mean_fit_time --> [0.09180737 0.08260851 0.08705239 0.11181955 0.12884998 0.0275557
 0.04735537 0.0958828  0.22818317]
std_fit_time --> [0.01598732 0.00162326 0.00189239 0.00797985 0.01401099 0.00561894
 0.01106165 0.01231471 0.00891607]
mean_score_time --> [0.00881486 0.00839248 0.00860729 0.0099936  0.01039705 0.00421009
 0.00579996 0.00919642 0.01918497]
std_score_time --> [0.00098309 0.00080052 0.00049601 0.00109821 0.00049354 0.00074881
 0.00043982 0.00147684 0.00222508]
param_max_depth --> [2 4 7 12 16 4 4 4 4]
param_n_estimators --> [100 100 100 100 100 25 50 100 250]
params --> [{'max_depth': 2, 'n_estimators': 100}, {'max_depth': 4, 'n_estimators': 100}, {'max_dept
split0_test_score --> [0.87460317 0.85323424 0.85381333 0.81554507 0.80037449 0.87558579
 0.84512618 0.85323424 0.86067019]
split1_test_score --> [0.87694315 0.86737731 0.87662655 0.87651671 0.85190389 0.85594956
 0.85035187 0.86737731 0.87887866]
split2_test_score --> [0.81956872 0.82834119 0.82611079 0.81030267 0.77569734 0.834651
 0.83784535 0.82834119 0.82834119]
split3_test_score --> [0.82078374 0.80260075 0.80192593 0.80351421 0.7942149  0.7931046
 0.80260075 0.80260075 0.80192593]
split4_test_score --> [0.8568842  0.85412387 0.86062409 0.85389639 0.86023157 0.86857693
 0.86332922 0.85412387 0.85412387]
mean_test_score --> [0.8497566  0.84113547 0.84382014 0.83195501 0.81648444 0.84557357
 0.83985067 0.84113547 0.84478797]
std_test_score --> [0.02513165 0.02303185 0.02656029 0.02833428 0.03342873 0.02969796
 0.02040062 0.02303185 0.0268672 ]
rank_test_score --> [1 5 4 8 9 2 7 5 3]
```

```
#### Searching optimal parameters for recall_weighted

Scores across the parameter grid:
mean_fit_time --> [0.10659809 0.11259551 0.11132517 0.14639978 0.15358634 0.02581511
 0.04799857 0.10060058 0.22042842]
std_fit_time --> [0.0094338  0.01538916 0.00737717 0.02073206 0.01189806 0.00222163
 0.00090358 0.00546274 0.01468245]
mean_score_time --> [0.0098022  0.00960431 0.01019492 0.01219978 0.0115983  0.00358062
 0.00619597 0.00919991 0.01839719]
std_score_time --> [0.00075193 0.0011976  0.00194128 0.00160016 0.00101969 0.00048033
 0.00040006 0.00039969 0.00102426]
param_max_depth --> [2 4 7 12 16 4 4 4 4]
param_n_estimators --> [100 100 100 100 100 25 50 100 250]
params --> [{'max_depth': 2, 'n_estimators': 100}, {'max_depth': 4, 'n_estimators': 100}, {'max_depth': 7,
split0_test_score --> [0.87407407 0.85185185 0.85185185 0.81481481 0.8        0.87407407
 0.84444444 0.85185185 0.85925926]
split1_test_score --> [0.86666667 0.85925926 0.87407407 0.87407407 0.85185185 0.85185185
 0.84444444 0.85925926 0.87407407]
split2_test_score --> [0.80740741 0.82222222 0.82222222 0.80740741 0.77037037 0.82962963
 0.82962963 0.82222222 0.82222222]
split3_test_score --> [0.81481481 0.8        0.8        0.8        0.79259259 0.79259259
 0.8        0.8        0.8        ]
split4_test_score --> [0.85185185 0.85185185 0.85925926 0.85185185 0.85925926 0.86666667
 0.85925926 0.85185185 0.85185185]
mean_test_score --> [0.84296296 0.83703704 0.84148148 0.82962963 0.81481481 0.84296296
 0.83555556 0.83703704 0.84148148]
std_test_score --> [0.02707506 0.02246778 0.02674884 0.02849687 0.03474382 0.02940657
 0.02009579 0.02246778 0.02674884]
rank_test_score --> [1 5 3 8 9 1 7 5 3]
```

Завдання 2.4. Обчислення відносної важливості ознак

```
Mean absolute error = 7.42

Predicted traffic: 26
```

Завдання 2.5. Прогнозування інтенсивності дорожнього руху за допомогою класифікатора на основі гранично випадкових лісів

```python
import numpy as np
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import train_test_split
from sklearn.ensemble import ExtraTreesRegressor
from sklearn import preprocessing

input_file = 'traffic_data.txt'
data = []
with open(input_file, 'r') as f:
```

```
    for line in f.readlines():
        items = line[:-1].split(',')
        data.append(items)

data = np.array(data)

label_encoder = []
X_encoded = np.empty(data.shape)
for i, item in enumerate(data[0]):
    if item.isdigit():
        X_encoded[:, i] = data[:, i]
    else:
        label_encoder.append(preprocessing.LabelEncoder())
        X_encoded[:, i] = label_encoder[-1].fit_transform(data[:, i])

X = X_encoded[:, :-1].astype(int)
Y = X_encoded[:, -1].astype(int)

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.25, random_state=5)
params = {'n_estimators': 100, 'max_depth': 4, 'random_state': 0}
regressor = ExtraTreesRegressor(**params)
regressor.fit(X_train, Y_train)

Y_pred = regressor.predict(X_test)
print("Mean absolute error =", round(mean_absolute_error(Y_test, Y_pred), 2))

test_datapoint = ['Saturday', '10:20', 'Atlanta', 'no']
test_datapoint_encoded = [-1] * len(test_datapoint)
count = 0

for i, item in enumerate(test_datapoint):
    if item.isdigit():
        test_datapoint_encoded[i] = int(test_datapoint[i])
    else:
        test_datapoint_encoded[i] =
int(label_encoder[count].transform([test_datapoint[i]]))
        count = count + 1

test_datapoint_encoded = np.array(test_datapoint_encoded)

print("Predicted traffic:", int(regressor.predict([test_datapoint_encoded])[0]))
```

Завдання 2.6. Створення навчального конвеєра (конвеєра машинного навчання)

```
from sklearn.datasets import _samples_generator
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.pipeline import Pipeline
from sklearn.ensemble import ExtraTreesClassifier

X, Y = _samples_generator.make_classification(n_samples=150, n_features=25, n_classes=3,
                                              n_informative=6, n_redundant=0,
random_state=7)
```

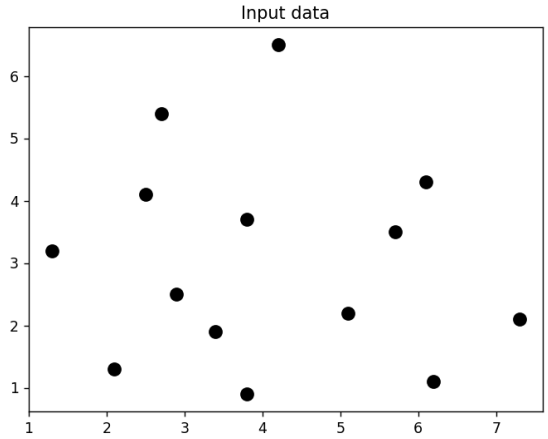
```
k_best_selector = SelectKBest(f_regression, k=10)

classifier = ExtraTreesClassifier(n_estimators=60, max_depth=4)

processor_pipeline = Pipeline([('selector', k_best_selector), ('erf', classifier)])

processor_pipeline.set_params(selector__k=7, erf__n_estimators=30)
processor_pipeline.fit(X, Y)

print("Predicted output:", processor_pipeline.predict(X))
print("Score:", processor_pipeline.score(X, Y))

status = processor_pipeline.named_steps['selector'].get_support()
selected = [i for i, x in enumerate(status) if x]
print("Selected features:", selected)
```

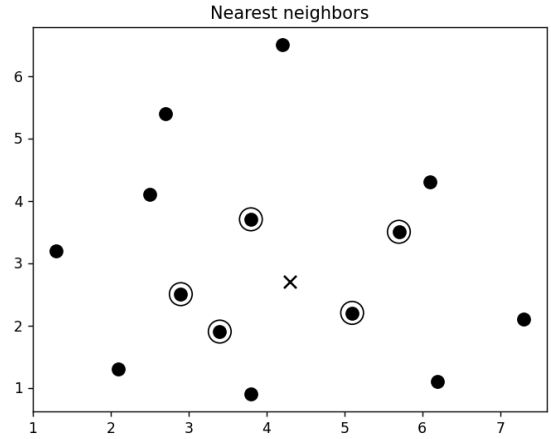
```
Predicted output: [1 2 2 0 2 0 2 1 0 1 1 2 2 0 2 2 1 0 0 1 0 2 1 1 2 2 0 0 1 2 1 2 1 0 2 2 1
 1 2 2 2 0 1 2 2 1 1 2 1 0 1 2 2 2 2 0 2 2 0 2 2 0 1 0 2 2 1 1 1 2 0 1 0 2
 0 0 1 2 2 0 0 1 2 2 2 0 0 0 2 2 2 1 2 0 2 2 2 2 0 0 1 1 1 1 2 2 0 2 0 1 1
 0 2 1 1 0 1 1 1 1 0 0 0 1 2 1 0 0 2 1 2 0 0 1 0 1 1 0 1 1 1 1 2 2 1 1 2 0
 2 2]
Score: 0.8933333333333333
Selected features: [4, 7, 8, 12, 14, 17, 22]
```

Завдання 2.7. Пошук найближчих сусідів

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.neighbors import NearestNeighbors

X = np.array([[2.1, 1.3], [1.3, 3.2], [2.9, 2.5], [2.7, 5.4], [3.8, 0.9],
        [7.3, 2.1], [4.2, 6.5], [3.8, 3.7], [2.5, 4.1], [3.4, 1.9],
        [5.7, 3.5], [6.1, 4.3], [5.1, 2.2], [6.2, 1.1]])
k = 5

test_datapoint = [4.3, 2.7]

plt.figure()
plt.title('Input data')
plt.scatter(X[:,0], X[:,1], marker='o', s=75, color='black')

knn_model = NearestNeighbors(n_neighbors=k, algorithm='ball_tree').fit(X)
distances, indices = knn_model.kneighbors([test_datapoint])

print("\nK Nearest Neighbors:")
for rank, index in enumerate(indices[0][:k], start=1):
    print(str(rank) + " ==>", X[index])

plt.figure()
plt.title('Nearest neighbors')
plt.scatter(X[:, 0], X[:, 1], marker='o', s=75, color='k')
```

```
plt.scatter(X[indices][0][:][:, 0], X[indices][0][:][:, 1],
        marker='o', s=250, color='k', facecolors='none')
plt.scatter(test_datapoint[0], test_datapoint[1],
        marker='x', s=75, color='k')

plt.show()
```

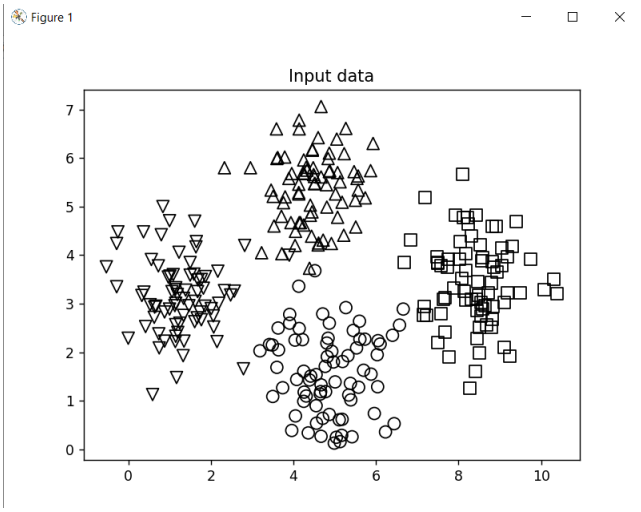


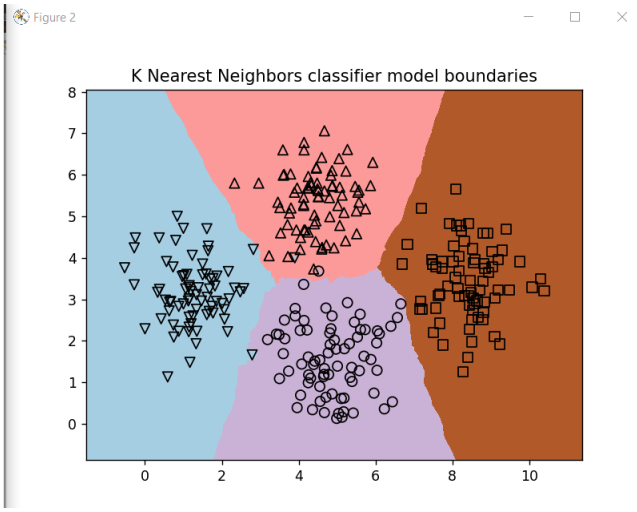


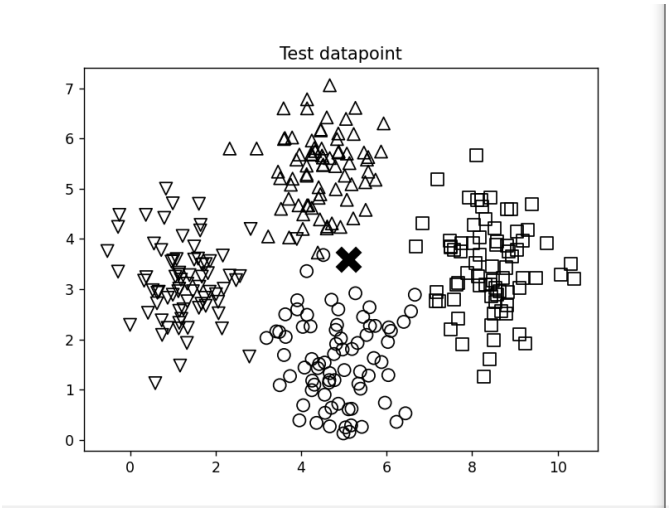
Завдання 2.8. Створити класифікатор методом *k* найближчих сусідів

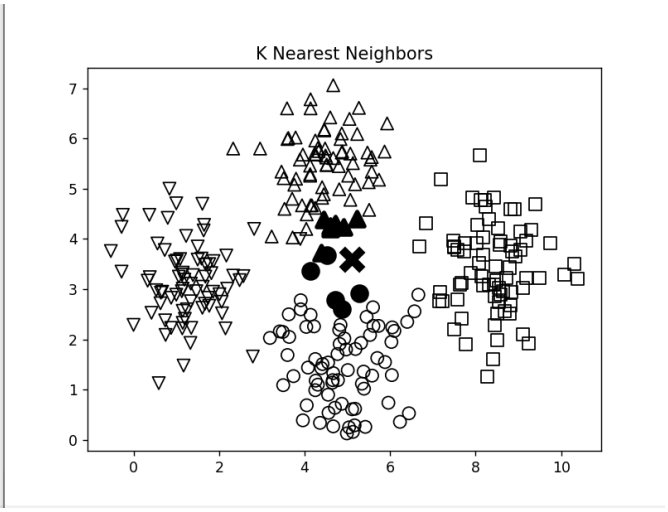
```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.cm as cm
from sklearn import neighbors

input_file = 'data.txt'
data = np.loadtxt(input_file, delimiter=',')
X, y = data[:, :-1], data[:, -1].astype(int)

plt.figure()
plt.title('Input data')
marker_shapes = 'v^os'
mapper = [marker_shapes[i] for i in y]
for i in range(X.shape[0]):
    plt.scatter(X[i, 0], X[i, 1], marker=mapper[i],
            s=75, edgecolors='black', facecolors='none')

num_neighbors = 12
step_size = 0.01

classifier = neighbors.KNeighborsClassifier(num_neighbors, weights='distance')
classifier.fit(X, y)

x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
x_values, y_values = np.meshgrid(np.arange(x_min, x_max, step_size),
        np.arange(y_min, y_max, step_size))
```

```
output = classifier.predict(np.c_[x_values.ravel(), y_values.ravel()])

output = output.reshape(x_values.shape)
plt.figure()
plt.pcolormesh(x_values, y_values, output, cmap=cm.Paired)

for i in range(X.shape[0]):
    plt.scatter(X[i, 0], X[i, 1], marker=mapper[i],
            s=50, edgecolors='black', facecolors='none')

plt.xlim(x_values.min(), x_values.max())
plt.ylim(y_values.min(), y_values.max())
plt.title('K Nearest Neighbors classifier model boundaries')

test_datapoint = [5.1, 3.6]
plt.figure()
plt.title('Test datapoint')
for i in range(X.shape[0]):
    plt.scatter(X[i, 0], X[i, 1], marker=mapper[i],
            s=75, edgecolors='black', facecolors='none')

plt.scatter(test_datapoint[0], test_datapoint[1], marker='x',
        linewidth=6, s=200, facecolors='black')

_, indices = classifier.kneighbors([test_datapoint])
indices = indices.astype(int)[0]

plt.figure()
plt.title('K Nearest Neighbors')

for i in indices:
    plt.scatter(X[i, 0], X[i, 1], marker=mapper[y[i]],
            linewidth=3, s=100, facecolors='black')

plt.scatter(test_datapoint[0], test_datapoint[1], marker='x',
        linewidth=6, s=200, facecolors='black')

for i in range(X.shape[0]):
    plt.scatter(X[i, 0], X[i, 1], marker=mapper[i],
            s=75, edgecolors='black', facecolors='none')

print("Predicted output:", classifier.predict([test_datapoint])[0])

plt.show()
```









Завдання 2.9. Обчислення оцінок подібності

```
import argparse
import json
import numpy as np


def build_arg_parser():
    parser = argparse.ArgumentParser(description='Compute similarity score')
    parser.add_argument('--user1', dest='user1', required=True,
                        help='First user')
    parser.add_argument('--user2', dest='user2', required=True,
                        help='Second user')
    parser.add_argument("--score-type", dest="score_type", required=True,
                        choices=['Euclidean', 'Pearson'], help='Similarity metric to be
used')
    return parser

def euclidean_score(dataset, user1, user2):
    if user1 not in dataset:
```

```
        raise TypeError('Cannot find ' + user1 + ' in the dataset')

    if user2 not in dataset:
        raise TypeError('Cannot find ' + user2 + ' in the dataset')

    common_movies = {}
    for item in dataset[user1]:
        if item in dataset[user2]:
            common_movies[item] = 1

    if len(common_movies) == 0:
        return 0

    squared_diff = []

    for item in dataset[user1]:
        if item in dataset[user2]:
            squared_diff.append(np.square(dataset[user1][item] - dataset[user2][item]))

    return 1 / (1 + np.sqrt(np.sum(squared_diff)))


def pearson_score(dataset, user1, user2):
    if user1 not in dataset:
        raise TypeError('Cannot find ' + user1 + ' in the dataset')

    if user2 not in dataset:
        raise TypeError('Cannot find ' + user2 + ' in the dataset')

    common_movies = {}
    for item in dataset[user1]:
        if item in dataset[user2]:
            common_movies[item] = 1

    num_ratings = len(common_movies)

    if num_ratings == 0:
        return 0

    user1_sum = np.sum([dataset[user1][item] for item in common_movies])
    user2_sum = np.sum([dataset[user2][item] for item in common_movies])

    user1_squared_sum = np.sum([np.square(dataset[user1][item]) for item in
common_movies])
    user2_squared_sum = np.sum([np.square(dataset[user2][item]) for item in
common_movies])

    sum_of_products = np.sum([dataset[user1][item] * dataset[user2][item] for item in
common_movies])

    Sxy = sum_of_products - (user1_sum * user2_sum / num_ratings)
    Sxx = user1_squared_sum - np.square(user1_sum) / num_ratings
    Syy = user2_squared_sum - np.square(user2_sum) / num_ratings
```

```
    if Sxx * Syy == 0:
        return 0

    return Sxy / np.sqrt(Sxx * Syy)


if __name__ == '__main__':
    args = build_arg_parser().parse_args()
    user1 = args.user1
    user2 = args.user2
    score_type = args.score_type

    ratings_file = 'ratings.json'

    with open(ratings_file, 'r') as f:
        data = json.loads(f.read())

    if score_type == 'Euclidean':
        print("\nEuclidean score:")
        print(euclidean_score(data, user1, user2))
    else:
        print("\nPearson score:")
        print(pearson_score(data, user1, user2))
```

```
PS D:\Labs\AI\AILab4> python3 LR_4_task_9.py --user1 "David Smith" --user2 "Bill Duffy" --score-type Euclidean

Euclidean score:
0.585786437626905
PS D:\Labs\AI\AILab4> python3 LR_4_task_9.py --user1 "David Smith" --user2 "Bill Duffy" --score-type Pearson

Pearson score:
0.9909924304103233
PS D:\Labs\AI\AILab4> python3 LR_4_task_9.py --user1 "David Smith" --user2 "Brenda Peterson" --score-type Euclidean

Euclidean score:
0.1424339656566283
PS D:\Labs\AI\AILab4> python3 LR_4_task_9.py --user1 "David Smith" --user2 "Brenda Peterson" --score-type Pearson

Pearson score:
-0.7236759610155113
PS D:\Labs\AI\AILab4> python3 LR_4_task_9.py --user1 "David Smith" --user2 "Samuel Miller" --score-type Euclidean

Euclidean score:
0.30383243470068705
PS D:\Labs\AI\AILab4> python3 LR_4_task_9.py --user1 "David Smith" --user2 "Samuel Miller" --score-type Pearson

Pearson score:
0.7587869106393281
```

Висновки:. *В ході виконання лабораторної, я,використовуючи спеціалізовані бібліотеки та мову програмування Python дослідив методи ансамблів у машинному навчанні та створив рекомендаційні системи..*