assignment-5

September 15, 2024

1 TASK 1

[1]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
```

1.1 Importing dataset

[2]:
```
from ucimlrepo import fetch_ucirepo
# fetch dataset
nursery = fetch_ucirepo(id=76)
# data (as pandas dataframes)
X = nursery.data.features
y = nursery.data.targets
```

[3]:
```
# Converting 'spec_prior' and 'very_recom' to 'recommend' class to make a 3␣
 ↪class problem
y = y.replace({'spec_prior': 'recommend', 'very_recom' : 'recommend'})
```

[4]:
```
# Label Encoding for both X and y
label_encoder = LabelEncoder()
y_label = label_encoder.fit_transform(y)
X_label = pd.DataFrame()
for i in X.columns:
    X_label[i] = label_encoder.fit_transform(X[i])
```

```
c:\Users\sakth\AppData\Local\Programs\Python\Python312\Lib\site-
packages\sklearn\preprocessing\_label.py:114: DataConversionWarning: A column-
vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

1.2 1. Decision Tree (categorical features)

Here I have used label encoding for both x and y. In other models, I have used one hot encoding for X and label encoding for y.

[5]:
```
# Decision Tree model
def decision_tree(X_train, y_train, X_val, y_val, X_test, y_test):
    param_grid_lr = {'max_depth': [1, 3, 5, 10]}
    best_model = None
    best_accuracy = 0
    for i in param_grid_lr['max_depth']:
        mdl_dtc = DecisionTreeClassifier(max_depth=i, random_state=int(100*i))
        mdl_dtc.fit(X_train, y_train)
        y_pred = mdl_dtc.predict(X_val)
        accuracy = accuracy_score(y_val, y_pred)
        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_model = mdl_dtc

    # Print the best model and its best accuracy
    y_pred = best_model.predict(X_test)
    test_accuracy = 100 * accuracy_score(y_test, y_pred)
    return test_accuracy
```

[6]:
```
# Train/Val/Test Split (60/20/20) for label encoded form
X_train_full, X_test, y_train_full, y_test = train_test_split(X_label, y_label,␣
 ↪test_size=0.2, stratify=y, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train_full, y_train_full,␣
 ↪test_size=0.25, stratify=y_train_full, random_state=42)

# Performance of test data
accuracy_dst_1 = decision_tree(X_train, y_train, X_val, y_val, X_test, y_test)
print(accuracy_dst_1)
```

```
96.6820987654321
```

[7]:
```
# Preprocess data (one-hot encoding)
encoder = OneHotEncoder()
X_encoded = encoder.fit_transform(X)
```

1.3 2. Decision Tree(categorical features in one-hot encoded form)

[8]:
```
# Decision Tree (one-hot encoded form) model
def decision_tree_one_hot_encoded_form(X_train, y_train, X_val, y_val, X_test,␣
 ↪y_test):
    param_grid_lr = {'max_depth': [1, 5, 10, 20, 30]}
    best_model = None
```

```
    best_accuracy = 0
    for i in param_grid_lr['max_depth']:
        mdl_dtc = DecisionTreeClassifier(max_depth=i, random_state=int(100*i))
        mdl_dtc.fit(X_train, y_train)
        y_val_pred = mdl_dtc.predict(X_val)
        accuracy = accuracy_score(y_val, y_val_pred)
        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_model = mdl_dtc
    # Print the best model and its test accuracy
    y_pred = best_model.predict(X_test)
    test_accuracy = 100 * accuracy_score(y_test, y_pred)
    return test_accuracy
```

[9]:
```
# Train/Val/Test Split (60/20/20) for (X is in one-hot) encoded form
X_train_full, X_test, y_train_full, y_test = train_test_split(X_encoded,␣
 ↪y_label, test_size=0.2, stratify=y, random_state=40)
X_train, X_val, y_train, y_val = train_test_split(X_train_full, y_train_full,␣
 ↪test_size=0.25, stratify=y_train_full, random_state=40)

# Performance of test data
accuracy_dst_2 = decision_tree_one_hot_encoded_form(X_train, y_train, X_val,␣
 ↪y_val, X_test, y_test)
print(accuracy_dst_2)
```

```
99.26697530864197
```

1.4 3. Logistic Regression with L1 regularizer

[10]:
```
# Logistic regression model with L1 regularization
def logistic_regression_with_L1(X_train, y_train, X_val, y_val, X_test, y_test):
    param_grid_lr = {'C': [0.01, 0.1, 1, 10, 100]}
    best_model = None
    best_accuracy = 0
    for i in param_grid_lr['C']:
        mdl_lr = LogisticRegression(penalty='l2', solver='liblinear', C=i)
        mdl_lr.fit(X_train, y_train)
        y_pred = mdl_lr.predict(X_val)
        accuracy = accuracy_score(y_val, y_pred)
        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_model = mdl_lr

    # Print the best model and its test accuracy
    y_pred = best_model.predict(X_test)
    test_accuracy = 100 * accuracy_score(y_test, y_pred)
    return test_accuracy
```

[11]:
```
# Train/Val/Test Split (60/20/20) for (X is in one-hot) encoded form
X_train_full, X_test, y_train_full, y_test = train_test_split(X_encoded,␣
 ↪y_label, test_size=0.2, stratify=y, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train_full, y_train_full,␣
 ↪test_size=0.25, stratify=y_train_full, random_state=42)

# Performance of test data
accuracy_lr = logistic_regression_with_L1(X_train, y_train, X_val, y_val,␣
 ↪X_test, y_test)
print(accuracy_lr)
```

```
91.62808641975309
```

1.5 4. k-Nearest Neighbors

[12]:
```
# k-Nearest Neighbors model
def k_nearest_neighbors(X_train, y_train, X_val, y_val, X_test, y_test):
    param_grid_lr = {'k': [3, 5, 7, 9, 11]}
    best_model = None
    best_accuracy = 0
    for i in param_grid_lr['k']:
        mdl_knn = KNeighborsClassifier(n_neighbors=i)
        mdl_knn.fit(X_train, y_train)
        y_pred = mdl_knn.predict(X_val)
        accuracy = accuracy_score(y_val, y_pred)
        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_model = mdl_knn

    # Print the best model and its test accuracy
    y_pred = best_model.predict(X_test)
    test_accuracy = 100 * accuracy_score(y_test, y_pred)
    return test_accuracy
```

[13]:
```
# Train/Val/Test Split (60/20/20) for (X is in one-hot) encoded form
X_train_full, X_test, y_train_full, y_test = train_test_split(X_encoded,␣
 ↪y_label, test_size=0.2, stratify=y, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train_full, y_train_full,␣
 ↪test_size=0.25, stratify=y_train_full, random_state=42)

# Performance of test data
accuracy_knn = k_nearest_neighbors(X_train, y_train, X_val, y_val, X_test,␣
 ↪y_test)
print(accuracy_knn)
```

```
95.25462962962963
```

1.6 Performance of all 4 models calculated

[14]:
```
print("Accuracy of Decision Tree model: ",accuracy_dst_1)
print("Accuracy of Decision Tree model with one-hot encoding: ",accuracy_dst_2)
print("Accuracy of Logistic Regression with L1 regularization model:␣
 ↪",accuracy_lr)
print("Accuracy of k-Nearest Neighbors model: ",accuracy_knn)
```

```
Accuracy of Decision Tree model:  96.6820987654321
Accuracy of Decision Tree model with one-hot encoding:  99.26697530864197
Accuracy of Logistic Regression with L1 regularization model:  91.62808641975309
Accuracy of k-Nearest Neighbors model:  95.25462962962963
```

To compute varaince and mean, I have repeated the task 5 times for each model and stored all the accuracies in a dictionary

[15]:
```
# Creating a dictionary to store each values of accuracy for each model
accuracy = {'accuracy_dst_1': [], 'accuracy_dst_2': [], 'accuracy_lr_l1': [],␣
 ↪'accuracy_knn': []}
for i in range(5):
    # Data split in label encoded form
    X_train_full, X_test, y_train_full, y_test = train_test_split(X_label,␣
 ↪y_label, test_size=0.2, stratify=y, random_state=i)
    X_train, X_val, y_train, y_val = train_test_split(X_train_full,␣
 ↪y_train_full, test_size=0.25, stratify=y_train_full, random_state=i)

    accuracy['accuracy_dst_1'].append(decision_tree(X_train, y_train, X_val,␣
 ↪y_val, X_test, y_test))

    # Data split in one-hot encoded form
    X_train_full, X_test, y_train_full, y_test = train_test_split(X_encoded,␣
 ↪y_label, test_size=0.2, stratify=y, random_state=i)
    X_train, X_val, y_train, y_val = train_test_split(X_train_full,␣
 ↪y_train_full, test_size=0.25, stratify=y_train_full, random_state=i)

    accuracy['accuracy_dst_2'].
 ↪append(decision_tree_one_hot_encoded_form(X_train, y_train, X_val, y_val,␣
 ↪X_test, y_test))
    accuracy['accuracy_lr_l1'].append(logistic_regression_with_L1(X_train,␣
 ↪y_train, X_val, y_val, X_test, y_test))
    accuracy['accuracy_knn'].append(k_nearest_neighbors(X_train, y_train,␣
 ↪X_val, y_val, X_test, y_test))

print(accuracy)
```

```
{'accuracy_dst_1': [96.72067901234568, 96.10339506172839, 96.52777777777779,
97.14506172839506, 96.83641975308642], 'accuracy_dst_2': [99.8070987654321,
99.5756172839506, 99.5756172839506, 99.30555555555556, 99.69135802469135],
```

```
'accuracy_lr_l1': [92.2067901234568, 91.66666666666666, 91.7824074074074,
91.43518518518519, 91.55092592592592], 'accuracy_knn': [96.06481481481481,
96.02623456790124, 95.5246913580247, 95.9104938271605, 95.2932098765432]}
```

Next, finding the mean and variance of these individual model accuracies

[16]:
```
mean_accuracy = {k: np.mean(v) for k, v in accuracy.items()}
print(mean_accuracy)

variance_accuracy = {k: np.var(v) for k, v in accuracy.items()}
print(variance_accuracy)
```

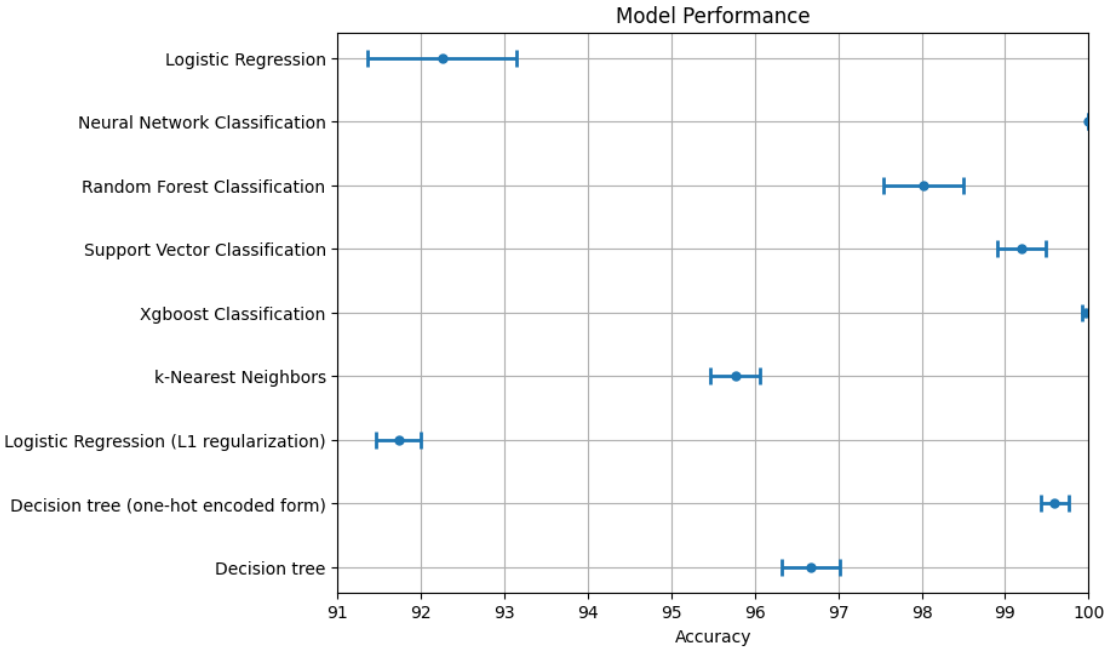
```
{'accuracy_dst_1': np.float64(96.66666666666666), 'accuracy_dst_2':
np.float64(99.59104938271604), 'accuracy_lr_l1': np.float64(91.72839506172839),
'accuracy_knn': np.float64(95.76388888888889)}
{'accuracy_dst_1': np.float64(0.11943206066148507), 'accuracy_dst_2':
np.float64(0.027744436823654968), 'accuracy_lr_l1':
np.float64(0.07061137783874538), 'accuracy_knn':
np.float64(0.09192577351013673)}
```

[17]:
```
# Adding accuracies of other models to the dictionary

mean_accuracy['accuracy_xgb'] = 99.969
mean_accuracy['accuracy_svc'] = 99.198
mean_accuracy['accuracy_rfc'] = 98.025
mean_accuracy['accuracy_nn'] = 100
mean_accuracy['accuracy_lr'] = 92.253

variance_accuracy['accuracy_xgb'] = 0.00216225
variance_accuracy['accuracy_svc'] = 0.085849
variance_accuracy['accuracy_rfc'] = 0.22896225
variance_accuracy['accuracy_nn'] = 0.0
variance_accuracy['accuracy_lr'] = 0.801025
```

1.7 Visualisation of all 9 methods

[18]:
```
# Define the model names, means, and variances (standard deviations)
models = ['Decision tree','Decision tree (one-hot encoded form)','Logistic␣
 ↪Regression (L1 regularization)','k-Nearest Neighbors','Xgboost␣
 ↪Classification', 'Support Vector Classification','Random Forest␣
 ↪Classification', 'Neural Network Classification','Logistic Regression']

mean_accuracies = list(mean_accuracy.values())
variances = list(variance_accuracy.values())

# Step 2: Calculate standard deviation (std = sqrt(variance))
std_devs = np.sqrt(variances)
```

```
# Step 3: Create the plot
plt.figure(figsize=(8, 6))
plt.errorbar(mean_accuracies, models, xerr=std_devs, fmt='o', capsize=5,␣
 ↪capthick=2, markersize=5, elinewidth=2)

# Step 4: Add labels and title
plt.xlabel('Accuracy')
plt.title('Model Performance')
plt.xlim(91, 100)  # Adjust the x-axis limits as needed

# Step 5: Show the plot
plt.grid(True)
plt.show()
```



2 TASK 2

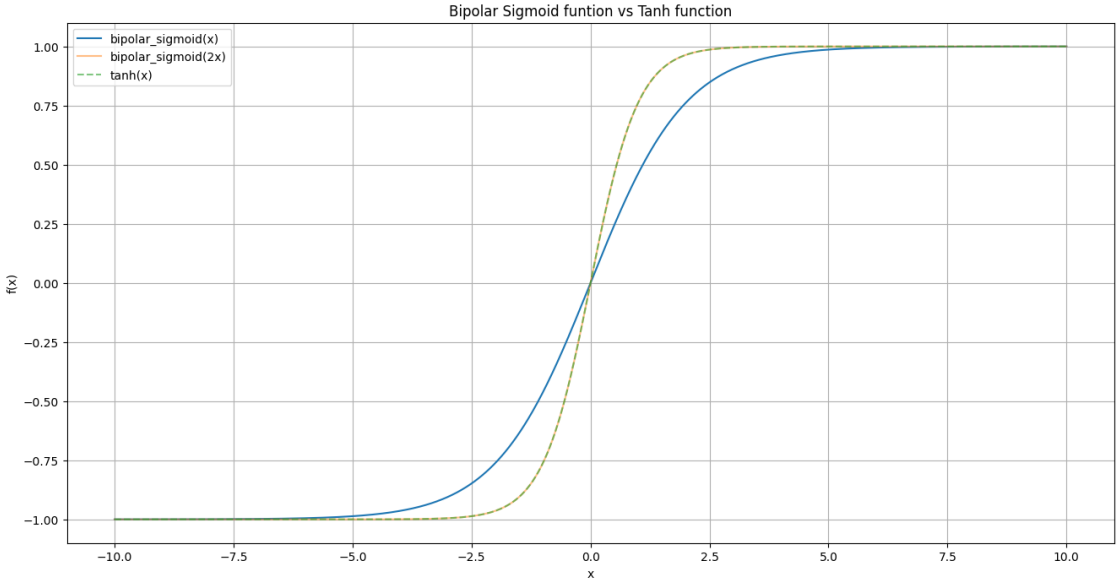
2.1 PART 1

[19]:
```
import numpy as np
import matplotlib.pyplot as plt

# Define sigmoid function
def sigmoid(x):
    return 1 / (1 + np.exp(-x))
```

```
# Define bipolar_sigmoid function as a function of sigmoid function
def bipolar_sigmoid(x):
    return 2 * sigmoid(x) - 1
```

2.2 PART 2

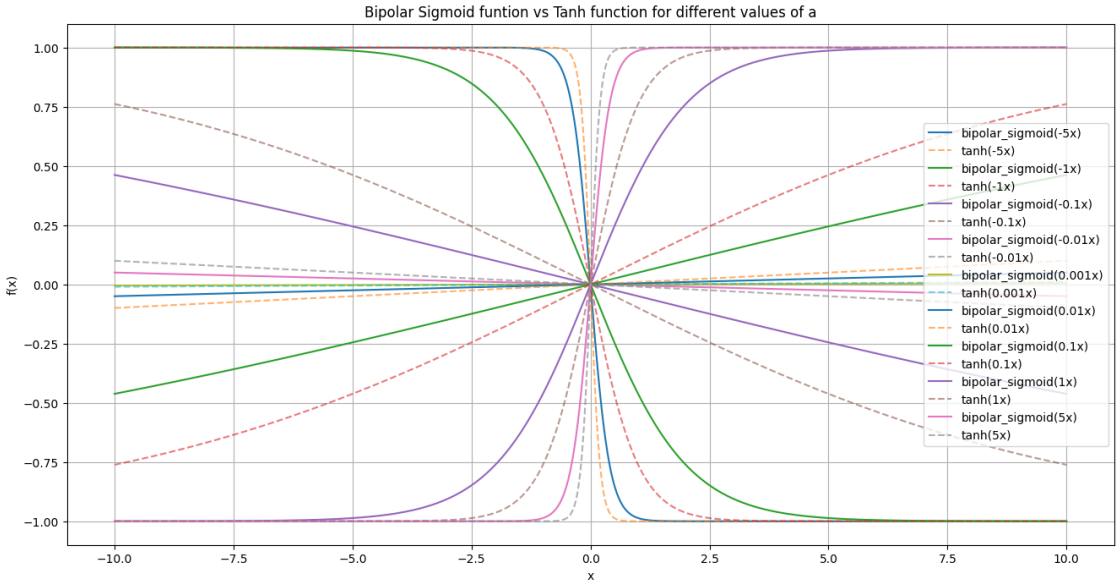
[20]:
```
# Defining tanh function
def tanh_fn(x):
    return np.tanh(x)

# Create x values
x = np.linspace(-10, 10, 1000)

# Plotting tanh and bipolar_sigmoid
plt.figure(figsize=(16, 8))
plt.plot(x, bipolar_sigmoid(x), label=f'bipolar_sigmoid(x)')
plt.plot(x, bipolar_sigmoid(2*x), label=f'bipolar_sigmoid(2x)', alpha = 0.5)
plt.plot(x, tanh_fn(x), '--', label=f'tanh(x)', alpha=0.6)

plt.title('Bipolar Sigmoid funtion vs Tanh function')
plt.xlabel('x')
plt.ylabel('f(x)')
plt.legend()
plt.grid(True)
plt.show()
```



From the graph above, we can see that tanh(x) is equivalent to bipolar_sigmoid(2*x)

2.3 PART 3

[21]:
```
# Define parameter 'a' values
a_values = [-5, -1, -0.1, -0.01, 0.001, 0.01, 0.1, 1, 5]

# Plot bipolar_sigmoid(ax) and tanh(ax) for different values of a
plt.figure(figsize=(16, 8))

for a in a_values:
    plt.plot(x, bipolar_sigmoid(a * x), label=f'bipolar_sigmoid({a}x)')
    plt.plot(x, tanh_fn(a * x), '--', label=f'tanh({a}x)', alpha=0.6)

plt.title('Bipolar Sigmoid funtion vs Tanh function for different values of a')
plt.xlabel('x')
plt.ylabel('f(x)')
plt.legend()
plt.grid(True)
plt.show()
```



2.4 PART 4

[22]:
```
def linear_range(a,x):

    y = bipolar_sigmoid(a * x)

    # Define the threshold for linearity
    threshold = 0.05
```

```
    # Finding derivative of y
    dy_dx = np.gradient(y, x)

    # Find the index where x is closest to 0 as the function is clearly linear␣
 ↪near x = 0
    x0_idx = np.abs(x).argmin()

    # Use the derivative at x = 0 as the reference
    dy_dx_ref = dy_dx[x0_idx]

    # Check for linearity based on deviations from the derivative at x = 0
    linear_idx = np.where(np.abs(dy_dx - dy_dx_ref) < threshold)[0]
    return linear_idx

x = np.linspace(-100, 100, 100000)

for a in a_values:
    linear_idx = linear_range(a, x)

    if len(linear_idx) > 0:
        print(f"Linear range for a = {a}: {x[linear_idx[0]]} to␣
 ↪{x[linear_idx[-1]]}")
```

```
Linear range for a = -5: -0.05500055000550219 to 0.05500055000548798
Linear range for a = -1: -0.6530065300653121 to 0.6530065300652979
Linear range for a = -0.1: -100.0 to 100.0
Linear range for a = -0.01: -100.0 to 100.0
Linear range for a = 0.001: -100.0 to 100.0
Linear range for a = 0.01: -100.0 to 100.0
Linear range for a = 0.1: -100.0 to 100.0
Linear range for a = 1: -0.6530065300653121 to 0.6530065300652979
Linear range for a = 5: -0.05500055000550219 to 0.05500055000548798
```

Clearly, we can see that for small ‘a’ values, the linearity range is high. Here I have considered x values to range from -100 to 100 so that it avoids arithmetic overflow.