# svm

February 21, 2025

[1]:
```
!pip install ucimlrepo
```

```
Requirement already satisfied: ucimlrepo in
/home/kip/projects/MathsRequiredForAI/EnvMaths/lib/python3.12/site-packages
(0.0.7)
Requirement already satisfied: pandas>=1.0.0 in
/home/kip/projects/MathsRequiredForAI/EnvMaths/lib/python3.12/site-packages
(from ucimlrepo) (2.2.3)
Requirement already satisfied: certifi>=2020.12.5 in
/home/kip/projects/MathsRequiredForAI/EnvMaths/lib/python3.12/site-packages
(from ucimlrepo) (2024.8.30)
Requirement already satisfied: numpy>=1.26.0 in
/home/kip/projects/MathsRequiredForAI/EnvMaths/lib/python3.12/site-packages
(from pandas>=1.0.0->ucimlrepo) (2.0.2)
Requirement already satisfied: python-dateutil>=2.8.2 in
/home/kip/projects/MathsRequiredForAI/EnvMaths/lib/python3.12/site-packages
(from pandas>=1.0.0->ucimlrepo) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in
/home/kip/projects/MathsRequiredForAI/EnvMaths/lib/python3.12/site-packages
(from pandas>=1.0.0->ucimlrepo) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in
/home/kip/projects/MathsRequiredForAI/EnvMaths/lib/python3.12/site-packages
(from pandas>=1.0.0->ucimlrepo) (2024.2)
Requirement already satisfied: six>=1.5 in
/home/kip/projects/MathsRequiredForAI/EnvMaths/lib/python3.12/site-packages
(from python-dateutil>=2.8.2->pandas>=1.0.0->ucimlrepo) (1.16.0)
```

[2]:
```
from ucimlrepo import fetch_ucirepo
import pandas as pd
import numpy as np
import cvxpy as cp
from matplotlib import pyplot as plt
```

[3]:
```
# !! DO NOT MODIFY THIS CELL !!

# Download and preprocess the dataset.
# fetch dataset
heart_disease = fetch_ucirepo(id=45)
```

```python
X = heart_disease.data.features
# Convert categorical features into one-hot encode
categorical_features = ['cp','thal','slope','restecg']
X = pd.get_dummies(X, columns=categorical_features)

y = heart_disease.data.targets
print(f"Number of samples in all full dataset is: {len(X)}.")

# Check if our train set has missing value
na_in_features = X.isna().any(axis=1).sum()
na_in_trainY = y.isna().sum()
print(f"Number of rows with missing values in features: {na_in_features}")

# Drop the rows with missing values.
indices_with_nan = X.index[X.isna().any(axis=1)]
X = X.drop(indices_with_nan)
y = y.drop(indices_with_nan)

# Divide train/test
np.random.seed(6464)
msk = np.random.rand(len(X)) < 0.75
X_train = X[msk]
X_test = X[~msk]
y_train = y[msk]
y_test = y[~msk]

# Convert problem to binary problem
X_train = np.array(X_train,dtype='float')
X_test = np.array(X_test,dtype='float')
y_train = np.array([-1 if i==0 else 1 for i in y_train.values],dtype='float')
y_test = np.array([-1 if i==0 else 1 for i in y_test.values],dtype='float')

print(f"Shapes: X_train: {X_train.shape}, y_train: {y_train.shape}, X_test:␣
 ↪{X_test.shape}, y_test: {y_test.shape}")
```

```
Number of samples in all full dataset is: 303.
Number of rows with missing values in features: 4
Shapes: X_train: (216, 22), y_train: (216,), X_test: (83, 22), y_test: (83,)
```

[4]:
```python
# Normalize X_train and X_test using the statistics of X_train.
# 1. Compute the mean and standard deviation for each feature in X_train
# 2. Subtract the mean from each feature and divide by the standard deviation
#    for both X_train and X_test.

mean = np.mean(X_train,axis=0)
std = np.std(X_train,axis=0)
X_train_normalized = (X_train-mean)/std
```

```
X_test_normalized = (X_test-mean)/std

print(f"Shapes: X_train: {X_train_normalized.shape}, y_train: {y_train.shape},␣
↪X_test: {X_test_normalized.shape}, y_test: {y_test.shape}")
```

```
Shapes: X_train: (216, 22), y_train: (216,), X_test: (83, 22), y_test: (83,)
```

[5]:
```
# Print the mean and standard deviation of the first and last feature.

print(f"Mean of the first feature: {np.mean(X_train_normalized[:, 0])}")
print(f"Standard deviation of the first feature: {np.std(X_train_normalized[:,␣
↪0])}")
print(f"Mean of the last feature: {np.mean(X_train_normalized[:, -1])}")
print(f"Standard deviation of the last feature: {np.std(X_train_normalized[:,␣
↪-1])}")
```

```
Mean of the first feature: 4.11193712824132e-17
Standard deviation of the first feature: 0.9999999999999999
Mean of the last feature: -5.756711979537848e-17
Standard deviation of the last feature: 1.0
```

### 0.0.1 Explanation of Normalization Using Training Data Statistics

The mean and standard deviation for normalization are estimated from the training data to prevent **data leakage** and ensure that the model generalizes well to unseen data. Using separate statistics for `X_test` could lead to inconsistent feature scaling, making model predictions unreliable.

### 0.0.2 TRAIN SVM

[6]:
```
# Train SVM

# Complete the `trainSVM` function to find the optimal w and b that minimize
# the primal SVM objective given in the write-up.
# The function takes three inputs:
# - trainX: the normalized train features with shape (#train_samples, #features)
# - trainY: train labels with shape (#train_samples,)
# - C: C parameter of the minimization problem
# The function should return a three-tuple with:
# - w: the weight vector with shape (#features,)
# - b: the bias. A scalar with shape (1,)
# - xi: the slack variables with shape (#train_samples,)

# You can use cvxpy that we imported as cp
# You may find cp.Variable, cp.Minimize, cp.Problem useful
# For the problem solver, prefer the default, cp.CLARABEL

def trainSVM(trainX, trainY, C):
    w = cp.Variable(trainX.shape[1])
```

```
    b = cp.Variable()
    xi = cp.Variable(trainX.shape[0])

    objective = cp.Minimize(0.5*cp.norm(w,2)**2 + C*cp.sum(xi))
    constraints = [cp.multiply(trainY,(trainX@w+b)) >= 1-xi, xi >= 0]
    prob = cp.Problem(objective, constraints)
    prob.solve()
    return w.value, b.value, xi
```

[7]:
```
# Solve SVM with C = 1 and print the first three weights, b and the first
# three slack variables as instructed in the write-up

Y = y_train
C = 1
w, b, xi = trainSVM(X_train_normalized, Y, C)
print(f"First three weights: {w[:3]}")
print(f"b: {b}")
print(f"First three slack variables: {xi.value[:3]}")
```

```
First three weights: [-0.01280084  0.51706872  0.27813637]
b: 0.08109278708401382
First three slack variables: [-1.70119328e-10 -1.64395885e-10 -1.69587409e-10]
```

[8]:
```
# Solve SVM with C = 0 and print the first three weights, b and the first
# three slack variables as instructed in the write-up

C = 0
w, b, xi = trainSVM(X_train_normalized, Y, C)
print(f"First three weights: {w[:3]}")
print(f"b: {b}")
print(f"Actual first three slack variables: {xi.value[:3]}")
```

```
First three weights: [ 3.09523259e-06 -8.18802636e-06 -9.46615246e-06]
b: -10.447621082517728
Actual first three slack variables: [429.58840105 434.02071004 414.34670026]
```

#### 0.0.3 Difference Between the Slack Variables When C = 1 and C = 0

When we solve the SVM with different values of C, the slack variables ( ) change. The slack variables represent the degree to which each data point violates the margin.

For C = 1: - The first three slack variables are: [-1.70119246e-10 -1.64395808e-10 -1.69587327e-10]

For C = 0: - The first three slack variables are: [429.58840105 434.02071004 414.34670026]

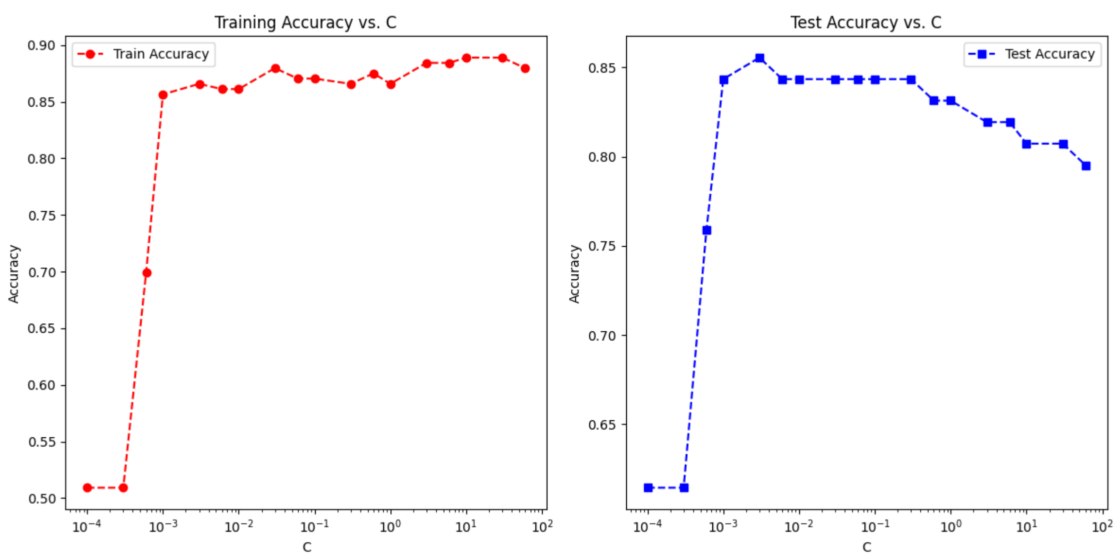
The slack variables $x_i$ will be larger when C = 0 compared to C = 1. This is because with a smaller C, the model has less penalty for misclassification because it encourages large margins, allowing more slack (larger $x_i$) for violations of the margin. As C increases it penalizes the misclassifications. It encourages the correct classification over a wider margin, enventually with a large c it will approach SVM hard margin

[9]:
```python
# Eval SVM

# Write a function to evaluate the SVM model given its `w` and `b` parameters
# on evaluation data `X_eval` and true labels `y_eval`.
#  1. Estimate the labels of `X_eval`.
#  2. Return the ratio of accurately estimated labels by comparing with␣
↪`y_eval`.


def evalSVM(X_eval, y_eval, w, b):
    y_pred = np.sign(X_eval@w + b)
    return np.mean(y_pred == y_eval)

print(f"Accuracy on the test set: {evalSVM(X_test_normalized, y_test, w, b):.
↪2f}")
```

```
Accuracy on the test set: 0.61
```

[18]:
```python
# Define the range of C values
C_values = [a * 10**q for a in [1, 3, 6] for q in [-4, -3, -2, -1, 0, 1]]
C_values = sorted(C_values)

train_accuracies = []
test_accuracies = []

# Calculate the optimal w, b and accuracies for each C value
for C in C_values:
    w, b, _ = trainSVM(X_train_normalized, y_train, C)
    train_acc = evalSVM(X_train_normalized, y_train, w, b)
    test_acc = evalSVM(X_test_normalized, y_test, w, b)
    train_accuracies.append(train_acc)
    test_accuracies.append(test_acc)

# Plot the training accuracy vs. the value of C
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(C_values, train_accuracies, label='Train Accuracy', color='red',␣
↪linestyle='dashed', marker='o')
plt.xscale('log')
plt.xlabel('C')
plt.ylabel('Accuracy')
plt.title('Training Accuracy vs. C')
plt.legend()

# Plot the test accuracy vs. the value of C
plt.subplot(1, 2, 2)
```

```
plt.plot(C_values, test_accuracies, label='Test Accuracy', color='blue', linestyle='dashed', marker='s')
plt.xscale('log')
plt.xlabel('C')
plt.ylabel('Accuracy')
plt.title('Test Accuracy vs. C')
plt.legend()

plt.tight_layout()
plt.show()

# Report the values of C that maximize the training and test accuracies
max_train_acc_index = np.argmax(train_accuracies)
max_train_acc_C = C_values[max_train_acc_index]
max_train_acc = train_accuracies[max_train_acc_index]

max_test_acc_index = np.argmax(test_accuracies)
max_test_acc_C = C_values[max_test_acc_index]
max_test_acc = test_accuracies[max_test_acc_index]

print(f"The value of C that maximizes training accuracy is: {max_train_acc_C}")
print(f"The corresponding training accuracy is: {max_train_acc}")

print(f"The value of C that maximizes test accuracy is: {max_test_acc_C}")
print(f"The corresponding test accuracy is: {max_test_acc}")
```




```
The value of C that maximizes training accuracy is: 10
The corresponding training accuracy is: 0.8888888888888888
The value of C that maximizes test accuracy is: 0.003
```

```
The corresponding test accuracy is: 0.8554216867469879
```