cmps320_hw6_SammanBhetwal

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1 Problem 1

In this problem, you will use support vector approaches to predict whether a given car gets high or low gas mileage based on Auto data set: https://rdrr.io/cran/ISLR/man/Auto.html.

1.1 (a) What is the fundamental idea behind Support Vector Machines?

Support Vector Machines aim to find the optimal hyperplane that separates data points into distinct classes, maximizing the margin between them, represented as the widest possible gap or "street" between parallel boundary lines.

[3]:
```
import numpy as np
import pandas as pd
from sklearn import datasets
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.svm import LinearSVC
from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score

# To plot pretty figures
%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

[4]:
```
data = pd.read_csv("Auto.csv")
```

[5]:
```
data
```

[5]:
```
    mpg  cylinders  displacement horsepower  weight  acceleration  year  \
0  18.0          8         307.0        130    3504          12.0    70
1  15.0          8         350.0        165    3693          11.5    70
2  18.0          8         318.0        150    3436          11.0    70
```

```
3    16.0          8         304.0        150    3433          12.0    70
4    17.0          8         302.0        140    3449          10.5    70
..    …       …          …        …      …            …    …
392  27.0          4         140.0         86    2790          15.6    82
393  44.0          4          97.0         52    2130          24.6    82
394  32.0          4         135.0         84    2295          11.6    82
395  28.0          4         120.0         79    2625          18.6    82
396  31.0          4         119.0         82    2720          19.4    82

     origin                       name
0         1  chevrolet chevelle malibu
1         1          buick skylark 320
2         1         plymouth satellite
3         1              amc rebel sst
4         1                ford torino
..      …                        …
392       1            ford mustang gl
393       2                  vw pickup
394       1              dodge rampage
395       1                ford ranger
396       1                 chevy s-10

[397 rows x 9 columns]
```

[6]:
```
data.describe()
```

[6]:
```
              mpg   cylinders  displacement       weight  acceleration  \
count  397.000000  397.000000    397.000000   397.000000    397.000000
mean    23.515869    5.458438    193.532746  2970.261965     15.555668
std      7.825804    1.701577    104.379583   847.904119      2.749995
min      9.000000    3.000000     68.000000  1613.000000      8.000000
25%     17.500000    4.000000    104.000000  2223.000000     13.800000
50%     23.000000    4.000000    146.000000  2800.000000     15.500000
75%     29.000000    8.000000    262.000000  3609.000000     17.100000
max     46.600000    8.000000    455.000000  5140.000000     24.800000

             year      origin
count  397.000000  397.000000
mean    75.994962    1.574307
std      3.690005    0.802549
min     70.000000    1.000000
25%     73.000000    1.000000
50%     76.000000    1.000000
75%     79.000000    2.000000
max     82.000000    3.000000
```

[7]:
```python
# trying to find any null values
data.isnull().any()
```

[7]:
```
mpg             False
cylinders       False
displacement    False
horsepower      False
weight          False
acceleration    False
year            False
origin          False
name            False
dtype: bool
```

[8]:
```python
data[data['horsepower'] == '?']
```

[8]:
```
      mpg  cylinders  displacement horsepower  weight  acceleration  year  \
32   25.0          4          98.0          ?    2046          19.0    71
126  21.0          6         200.0          ?    2875          17.0    74
330  40.9          4          85.0          ?    1835          17.3    80
336  23.6          4         140.0          ?    2905          14.3    80
354  34.5          4         100.0          ?    2320          15.8    81

     origin                  name
32        1            ford pinto
126       1         ford maverick
330       2  renault lecar deluxe
336       1    ford mustang cobra
354       2           renault 18i
```

[9]:
```python
# Deleting the ? from the horsepower column
data = data[data['horsepower'] != '?']
data.loc[:, 'horsepower'] = data['horsepower'].astype(int)
```

[10]:
```python
# Checking if deleted succesfully
data[data['horsepower'] == '?']
```

[10]:
```
Empty DataFrame
Columns: [mpg, cylinders, displacement, horsepower, weight, acceleration, year,
origin, name]
Index: []
```

[11]:
```python
data.shape
```

[11]:
```
(392, 9)
```

1.2 (b) Create a binary variable that takes on a 1 for cars with gas mileage above the median, and a 0 for cars with gas mileage below the median.

[12]:
```
# Finding the median
mileage_median = data["mpg"].median()
mileage_median
```

[12]:
```
22.75
```

[13]:
```
data.loc[:, "mileage_rate"] = (data["mpg"] >= mileage_median).astype(np.intc)
data.iloc[-5:]
```

[13]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	\
392	27.0	4	140.0	86	2790	15.6	82	
393	44.0	4	97.0	52	2130	24.6	82	
394	32.0	4	135.0	84	2295	11.6	82	
395	28.0	4	120.0	79	2625	18.6	82	
396	31.0	4	119.0	82	2720	19.4	82	

	origin	name	mileage_rate
392	1	ford mustang gl	1
393	2	vw pickup	1
394	1	dodge rampage	1
395	1	ford ranger	1
396	1	chevy s-10	1

1.3 (c) Fit a linear support vector classifier to the data with various values of cost to predict whether a car gets high or low gas mileage. Comment on your results

[14]:
```
X = data.iloc[:,:-2]
y = data["mileage_rate"]
X.head()
```

[14]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	\
0	18.0	8	307.0	130	3504	12.0	70	
1	15.0	8	350.0	165	3693	11.5	70	
2	18.0	8	318.0	150	3436	11.0	70	
3	16.0	8	304.0	150	3433	12.0	70	
4	17.0	8	302.0	140	3449	10.5	70	

	origin
0	1
1	1
2	1
3	1
4	1

[15]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.
↪8,random_state = 0)
```

[23]:
```python
from sklearn import svm

# Define cost values and initialize data_list
cost_values = [0.0001, 1000]
data_list = {}

# Loop through cost values
for cost_value in cost_values:
    # Standardize features
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)

    # Create and train the SVM model
    svm_model = svm.LinearSVC(C=cost_value, loss="hinge", random_state=42,␣
↪max_iter=5000)
    svm_model.fit(X_train_scaled, y_train)

    # Make predictions
    predictions = svm_model.predict(X_test_scaled)

    # Store predictions and print results
    data_list[cost_value] = predictions
    print(f"C={cost_value}: {predictions}")
    print("Accuracy:", accuracy_score(y_test, predictions))
```

```
C=0.0001: [1 1 0 1 1 0 1 1 0 1 1 0 1 0 0 1 1 0 1 1 0 0 1 1 1 0 1 1 0 0 0 1 1 1 0
1 1
 0 0 0 0 1 1 0 1 0 1 0 0 0 1 0 0 1 1 1 0 0 1 1 0 1 1 0 1 0 0 1 1 1 1 1 0 0
 0 0 1 0 1]
Accuracy: 0.8987341772151899
C=1000: [1 0 0 1 1 0 1 1 0 0 1 0 1 0 0 1 0 0 1 1 0 0 0 1 1 0 1 1 0 0 0 1 0 1 0 1
1
 0 0 0 0 1 1 0 1 0 1 0 0 0 1 0 0 0 1 1 0 0 1 0 0 1 1 0 1 0 0 1 1 1 1 1 0 0
 1 0 1 0 1]
Accuracy: 1.0
```

[24]:
```python
data_list = pd.DataFrame(data_list)
data_list
```

[24]:

	0.0001	1000.0000
0	1	1
1	1	0
2	0	0
3	1	1

```
4           1          1
..         …         …
74          0          1
75          0          0
76          1          1
77          0          0
78          1          1

[79 rows x 2 columns]
```

[25]:

```
print("When C=0.0001:")
print("Low milage prediction: ",len(data_list[data_list[0.0001]==0]))
print("High mileage prediction: ",len(data_list[data_list[0.0001]==1]))
print("")
print("When C=1000.0:")
print("Low mileage prediction: ",len(data_list[data_list[1000.0]==0]))
print("High mileage prediction: ",len(data_list[data_list[1000.0]==1]))
```

```
When C=0.0001:
Low milage prediction:  36
High mileage prediction:  43

When C=1000.0:
Low mileage prediction:  42
High mileage prediction:  37
```

The C parameter in SVM balances misclassification errors and margin size. A high C value (e.g., 1000) reduces misclassification by narrowing the margin, improving accuracy but reducing flexibility. A low C (e.g., 0.0001) widens the margin, tolerating misclassifications to better handle outliers.

1.4 (d) Now repeat (c), this time using SVMs with radial and polynomial basis kernels with different values of gamma and degree, and cost. Comment on your results.

[26]:

```
from sklearn.svm import SVC
gamma = [0.1, 5]
degree = [3, 10]
```

[28]:

```
# Define hyperparameters
hyperparameters = [
    {"gamma": 0.1, "C": 0.001},
    {"gamma": 0.1, "C": 1000},
    {"gamma": 5, "C": 0.001},
    {"gamma": 5, "C": 1000},
]

# Initialize SVM classifiers
```

```python
svm_clfs = []

# Loop through hyperparameters
for params in hyperparameters:
    gamma = params["gamma"]
    C = params["C"]

    # Scale features
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)

    # Train SVM with RBF kernel
    svm_clf = SVC(kernel="rbf", gamma=gamma, C=C)
    svm_clf.fit(X_train_scaled, y_train)

    # Predict and evaluate
    y_pred = svm_clf.predict(X_test_scaled)
    svm_clfs.append(svm_clf)

    print(f"Radial SVM for gamma = {gamma}, C = {C}", y_pred)
    print("Accuracy:", accuracy_score(y_test, y_pred))
```

```
Radial SVM for gamma = 0.1, C = 0.001 [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1]
Accuracy: 0.46835443037974683
Radial SVM for gamma = 0.1, C = 1000 [1 1 0 1 1 0 1 1 0 0 1 0 1 0 0 1 0 0 1 1 0
0 0 1 1 0 1 1 0 0 0 1 0 1 0 1 1
 0 0 0 0 1 1 0 1 0 1 0 0 0 1 0 0 0 1 1 0 0 1 0 0 1 1 0 1 0 0 1 1 1 1 1 0 0
 0 0 1 0 1]
Accuracy: 0.9746835443037974
Radial SVM for gamma = 5, C = 0.001 [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1]
Accuracy: 0.46835443037974683
Radial SVM for gamma = 5, C = 1000 [1 1 0 1 1 0 1 1 0 1 1 0 1 0 0 1 0 0 1 1 1 0
0 1 1 0 1 1 0 0 1 1 1 1 0 1 1
 0 0 0 0 1 1 0 1 0 1 0 0 0 1 0 0 0 1 1 0 0 1 0 0 1 1 0 1 0 0 1 1 1 1 1 0 0
 0 0 1 0 1]
Accuracy: 0.9240506329113924
```

The radial SVM with gamma=0.1 and C=0.001 predicted predominantly high mileage, achieving only 46.8% accuracy, suggesting overfitting. Increasing C to 1000 improved the prediction balance and boosted accuracy to 97.5%, highlighting the role of regularization.

```
[29]: # Polynomial kernel SVMs
hyperparameters = [
    {"degree": 3, "C": 0.0001},
    {"degree": 10, "C": 1000},
]

for params in hyperparameters:
    degree = params["degree"]
    C = params["C"]

    # Build and train pipeline
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)

    svm_clf = SVC(kernel="poly", degree=degree, coef0=1, C=C)
    svm_clf.fit(X_train_scaled, y_train.values.ravel())

    # Make predictions
    y_pred = svm_clf.predict(X_test_scaled)

    print(f"Polynomial SVM for degree = {degree}, C = {C}", y_pred)
    print("Accuracy:", accuracy_score(y_test, y_pred))
```

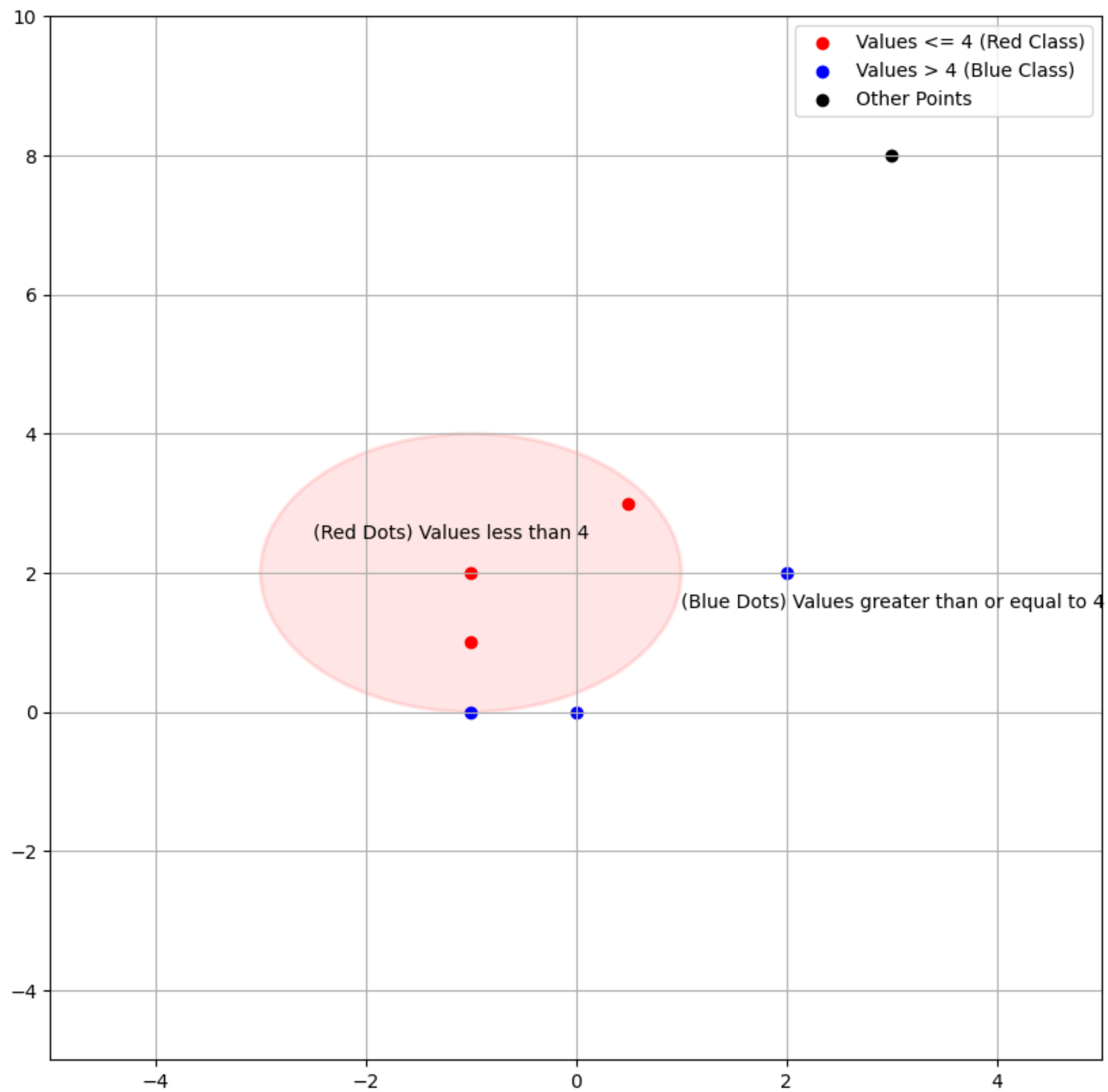
```
Polynomial SVM for degree = 3, C = 0.0001 [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1]
Accuracy: 0.46835443037974683
Polynomial SVM for degree = 10, C = 1000 [1 1 0 1 1 0 1 1 0 0 1 0 1 0 1 1 0 0 1
1 0 0 0 0 1 0 1 1 0 0 0 1 1 1 0 1 1
 0 0 0 0 1 1 0 1 0 1 0 0 0 1 0 0 0 1 1 0 0 1 0 0 1 1 0 1 0 0 1 1 1 1 1 0 0
 0 0 0 0 1]
Accuracy: 0.9240506329113924
```

A high gamma value (5) paired with a low C (0.001) caused similar overfitting, while increasing regularization (C=1000) improved accuracy to 92.4%. For polynomial kernels, degree 3 with low C and degree 10 with high C initially produced poor predictions, but accuracy reached 92.4% with higher degrees and proper regularization. These findings emphasize the critical interplay between regularization and kernel parameters for building accurate, generalizable SVM models.

2 Problem 2

```
[30]: # Define the circle and points
circle_center = (-1, 2)
circle_radius = 2
red_points = [(-1, 2), (-1, 1), (0.5, 3)]
```

```
blue_points = [(0, 0), (2, 2), (-1, 0)]
black_point = [(3, 8)]

# Create the plot
fig, ax = plt.subplots(figsize=(10, 10))

# Add circle representing the decision boundary
circle = plt.Circle(circle_center, radius=circle_radius, facecolor='r', alpha=0.
↪1, edgecolor='r', linewidth=2.0)
ax.add_artist(circle)

# Scatter points
red_x, red_y = zip(*red_points)
blue_x, blue_y = zip(*blue_points)
black_x, black_y = zip(*black_point)

ax.scatter(red_x, red_y, c='r', label="Values <= 4 (Red Class)")
ax.scatter(blue_x, blue_y, c='b', label="Values > 4 (Blue Class)")
ax.scatter(black_x, black_y, c='k', label="Other Points")

# Add text annotations
ax.text(-2.5, 2.5, "(Red Dots) Values less than 4", color='black', size=10)
ax.text(1, 1.5, "(Blue Dots) Values greater than or equal to 4", color='black',␣
↪size=10)

# Set axis limits and grid
ax.set_xlim(-5, 5)
ax.set_ylim(-5, 10)
ax.grid(True)

# Add legend
ax.legend()

# Show the plot
plt.show()
```



Points (-1,0), (2,2), (-1,-1) falls under (1 + x_1)^2 + (2 − x_2)^2 > 4

Points (-1, 1), (0,0) and (0.5, 3) falls under (1 + x_1)^2 + (2 − x_2)^2 4

Observations:

(0,0) : Blue Class

(-1,1) : Red Class

(2,2) : Red Class

(3,8) : Blue Class

[ ]: