Programming

March 27, 2024

0.1 Programming: Question 3 - 50 points

In this problem, we will use university application data for the purpose of admission classification. Find `data_train` and `data_test` on canvas.

[1]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from IPython.display import display, Markdown
from sklearn.metrics import accuracy_score
from sklearn.svm import SVC
```

- **(a)** Data Pre-processing: Create a binary label based on the column "Chance of Admit". Convert any values bigger than the median to 1 and 0 otherwise. Split the data into training and validation sets. You can use a 80-20 split.

[2]:
```
df = pd.read_csv('data_train-2.csv')
admit_threshold = df['Chance of Admit '].median()
df['Admit'] = df['Chance of Admit '].apply(lambda x: 1 if x > admit_threshold␣
 ↪else 0)
display(Markdown(f"**Admission Threshold:** {admit_threshold}"))
```

Admission Threshold: 0.72

[3]:
```
markdown_table = df.head().to_markdown(index=False)
display(Markdown(f"**Original DataFrame:**\n\n{markdown_table}"))
```

Original DataFrame:

Unnamed: 0	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit	Admit
0	109	331	116	5	5	5	9.38	1	0.93	1
1	346	316	98	1	1.5	2	7.43	0	0.49	0
2	99	332	119	4	5	4.5	9.24	1	0.9	1
3	210	301	104	3	3.5	4	8.12	1	0.68	0
4	242	317	103	2	2.5	2	8.15	0	0.65	0

[4]:
```
X = df.drop(['Serial No.', 'Chance of Admit ', 'Admit'], axis=1)
y = df['Admit']
```

```
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

shapes_md = f"""
**Dataset Shapes:**
- X_train: {X_train.shape}
- y_train: {y_train.shape}
- X_val: {X_val.shape}
- y_val: {y_val.shape}
"""
display(Markdown(shapes_md))
```

Dataset Shapes: - X_train: (256, 8) - y_train: (256,) - X_val: (64, 8) - y_val: (64,)

[5]:
```
train_dist_md = f"**Training Set Distribution:**\n\n{y_train.
↪value_counts(normalize=True).to_markdown()}"
display(Markdown(train_dist_md))
```

Training Set Distribution:

Admit	proportion
0	0.519531
1	0.480469

[6]:
```
val_dist_md = f"**Validation Set Distribution:**\n\n{y_val.
↪value_counts(normalize=True).to_markdown()}"
display(Markdown(val_dist_md))
```

Validation Set Distribution:

Admit	proportion
1	0.5625
0	0.4375

- **(b)** Model Initialization: Initialize 4 different SVM models with the following kernels:
  1. Linear kernel
  2. RBF kernel
  3. Polynomial (degree 3) kernel

[7]:
```
svc_linear = SVC(kernel='linear', C=1, random_state=42)
svc_rbf = SVC(kernel='rbf', C=1, random_state=42)
svc_poly = SVC(kernel='poly', C=1, degree=3, random_state=42)

models = [svc_linear, svc_rbf, svc_poly]
model_names = ['Linear SVM', 'RBF SVM', 'Polynomial SVM']
```

```
markdown_str = "**Initialized Models:**\n"
for model, name in zip(models, model_names):
    model_str = f"**{name}**\n```python\n{model}\n```"
    markdown_str += model_str + "\n\n"

display(Markdown(markdown_str))
```

Initialized Models: Linear SVM

```
SVC(C=1, kernel='linear', random_state=42)
```

RBF SVM

```
SVC(C=1, random_state=42)
```

Polynomial SVM

```
SVC(C=1, kernel='poly', random_state=42)
```

- **(c)** Feature Selection and Model Training: Train each SVM Model above with the following feature combinations to predict admission.
  1. CGPA and SOP
  2. CGPA and GRE Score
  3. SOP and LOR
  4. LOR and GRE Score

[8]:
```
feature_sets = [
    ['CGPA', 'SOP'],
    ['CGPA', 'GRE Score'],
    ['SOP', 'LOR '],
    ['LOR ', 'GRE Score']
]

for features in feature_sets:
    display(Markdown(f"**Feature Set:** {features}"))
    for model, name in zip(models, model_names):
        model.fit(X_train[features], y_train)
        y_train_pred = model.predict(X_train[features])
        y_val_pred = model.predict(X_val[features])
        train_acc = accuracy_score(y_train, y_train_pred)
        val_acc = accuracy_score(y_val, y_val_pred)
        markdown_result = f"""
**{name}**
- Training Accuracy: {train_acc:.3f}
- Validation Accuracy: {val_acc:.3f}
"""
        display(Markdown(markdown_result))
```

Feature Set: ['CGPA', 'SOP']

Linear SVM
- Training Accuracy: 0.867 - Validation Accuracy: 0.812

RBF SVM
- Training Accuracy: 0.875 - Validation Accuracy: 0.828

Polynomial SVM
- Training Accuracy: 0.867 - Validation Accuracy: 0.812

Feature Set: ['CGPA', 'GRE Score']

Linear SVM
- Training Accuracy: 0.852 - Validation Accuracy: 0.812

RBF SVM
- Training Accuracy: 0.828 - Validation Accuracy: 0.766

Polynomial SVM
- Training Accuracy: 0.828 - Validation Accuracy: 0.766

Feature Set: ['SOP', 'LOR']

Linear SVM
- Training Accuracy: 0.812 - Validation Accuracy: 0.719

RBF SVM
- Training Accuracy: 0.812 - Validation Accuracy: 0.750

Polynomial SVM
- Training Accuracy: 0.816 - Validation Accuracy: 0.766

Feature Set: ['LOR', 'GRE Score']

Linear SVM
- Training Accuracy: 0.859 - Validation Accuracy: 0.812

RBF SVM
- Training Accuracy: 0.828 - Validation Accuracy: 0.766

Polynomial SVM
- Training Accuracy: 0.828 - Validation Accuracy: 0.766

[9]:
```python
results = []
for features in feature_sets:
    for model, name in zip(models, model_names):
        model.fit(X_train[features], y_train)

        y_train_pred = model.predict(X_train[features])
        y_val_pred = model.predict(X_val[features])

        train_acc = accuracy_score(y_train, y_train_pred)
        val_acc = accuracy_score(y_val, y_val_pred)

        results.append([name, ", ".join(features), train_acc, val_acc])
```

```
results_df = pd.DataFrame(
    results, columns=['Model', 'Features', 'Train Accuracy', 'Validation␣
↪Accuracy'])
display(Markdown("**Summary of Results**"))
display(Markdown(results_df.to_markdown(index=False)))
```

Summary of Results

Model	Features	Train Accuracy	Validation Accuracy
Linear SVM	CGPA, SOP	0.867188	0.8125
RBF SVM	CGPA, SOP	0.875	0.828125
Polynomial SVM	CGPA, SOP	0.867188	0.8125
Linear SVM	CGPA, GRE Score	0.851562	0.8125
RBF SVM	CGPA, GRE Score	0.828125	0.765625
Polynomial SVM	CGPA, GRE Score	0.828125	0.765625
Linear SVM	SOP, LOR	0.8125	0.71875
RBF SVM	SOP, LOR	0.8125	0.75
Polynomial SVM	SOP, LOR	0.816406	0.765625
Linear SVM	LOR , GRE Score	0.859375	0.8125
RBF SVM	LOR , GRE Score	0.828125	0.765625
Polynomial SVM	LOR , GRE Score	0.828125	0.765625

- **(d)** Support Vectors: What are the support vectors for each model and feature combination? How many support vectors does each class have in each case?

[10]:
```
for features in feature_sets:
    display(Markdown(f"**Feature Set:** {features}"))

    for model, name in zip(models, model_names):
        model.fit(X_train[features], y_train)

        support_vectors = X_train[features].iloc[model.support_]
        n_support_per_class = model.n_support_
        sample_support_vectors = support_vectors.head(5)

        markdown_table = f"**{name}**\n" + \
                         f"- Number of Support Vectors for Class 0:␣
↪{n_support_per_class[0]}\n" + \
                         f"- Number of Support Vectors for Class 1:␣
↪{n_support_per_class[1]}\n\n" + \
                         "**Sample Support Vectors:**\n\n" + \
                         sample_support_vectors.to_markdown(index=False)
        markdown_stats = "\n**Support Vectors Statistics:**\n\n" + \
                         support_vectors.describe().to_markdown()

        display(Markdown(markdown_table))
```

```
        display(Markdown(markdown_stats))
```

Feature Set: ['CGPA', 'SOP']

Linear SVM - Number of Support Vectors for Class 0: 46 - Number of Support Vectors for Class 1: 45

Sample Support Vectors:

CGPA	SOP
8.2	3.5
8.6	3.5
8.5	3
8.69	4
8.73	3

Support Vectors Statistics:

	CGPA	SOP
count	91	91
mean	8.57143	3.41209
std	0.214929	0.626247
min	8.1	2
25%	8.45	3
50%	8.56	3.5
75%	8.69	4
max	9.11	5

RBF SVM - Number of Support Vectors for Class 0: 58 - Number of Support Vectors for Class 1: 57

Sample Support Vectors:

CGPA	SOP
8.2	3.5
8.6	3.5
8.5	3
8.17	3.5
8.69	4

Support Vectors Statistics:

	CGPA	SOP
count	115	115

	CGPA	SOP
mean	8.56861	3.46957
std	0.293798	0.639651
min	7.66	2
25%	8.4	3
50%	8.56	3.5
75%	8.755	4
max	9.4	5

Polynomial SVM - Number of Support Vectors for Class 0: 42 - Number of Support Vectors for Class 1: 41

Sample Support Vectors:

CGPA	SOP
8.6	3.5
8.5	3
8.69	4
8.73	3
8.64	5

Support Vectors Statistics:

	CGPA	SOP
count	83	83
mean	8.56711	3.41566
std	0.193923	0.628681
min	8.14	2
25%	8.45	3
50%	8.56	3.5
75%	8.675	4
max	9.04	5

Feature Set: ['CGPA', 'GRE Score']

Linear SVM - Number of Support Vectors for Class 0: 43 - Number of Support Vectors for Class 1: 43

Sample Support Vectors:

CGPA	GRE Score
8.6	308
8.5	318
8.69	313

CGPA	GRE Score
8.73	316
8.64	304

Support Vectors Statistics:

	CGPA	GRE Score
count	86	86
mean	8.56465	316.221
std	0.213386	5.74231
min	8.1	303
25%	8.4325	312
50%	8.56	316
75%	8.6775	320
max	9.04	329

RBF SVM - Number of Support Vectors for Class 0: 108 - Number of Support Vectors for Class 1: 108

Sample Support Vectors:

CGPA	GRE Score
8.2	304
8.2	311
8.6	308
8.5	318
8.17	300

Support Vectors Statistics:

	CGPA	GRE Score
count	216	216
mean	8.58639	316.792
std	0.536218	9.42279
min	6.8	300
25%	8.2175	310
50%	8.56	316
75%	9.02	324
max	9.87	335

Polynomial SVM - Number of Support Vectors for Class 0: 63 - Number of Support Vectors for Class 1: 63

Sample Support Vectors:

CGPA	GRE Score
8.2	311
8.5	318
8.12	309
8.01	312
8.69	313

Support Vectors Statistics:

	CGPA	GRE Score
count	126	126
mean	8.54833	316.77
std	0.411627	5.3204
min	7.3	303
25%	8.285	312.25
50%	8.56	316
75%	8.7975	321
max	9.45	329

Feature Set: ['SOP', 'LOR']

Linear SVM - Number of Support Vectors for Class 0: 58 - Number of Support Vectors for Class 1: 58

Sample Support Vectors:

SOP	LOR
3.5	3
3.5	2.5
4	4.5
3	3.5
5	4

Support Vectors Statistics:

	SOP	LOR
count	116	116
mean	3.46983	3.5
std	0.61251	0.543739
min	2	2.5
25%	3	3
50%	3.5	3.5
75%	4	4

	SOP	LOR
max	5	5

RBF SVM - Number of Support Vectors for Class 0: 59 - Number of Support Vectors for Class 1: 59

Sample Support Vectors:

SOP	LOR
3.5	3
3.5	2.5
4	4.5
3	3.5
5	4

Support Vectors Statistics:

	SOP	LOR
count	118	118
mean	3.50424	3.42797
std	0.755311	0.677083
min	1	1
25%	3	3
50%	3.5	3.5
75%	4	4
max	5	5

Polynomial SVM - Number of Support Vectors for Class 0: 58 - Number of Support Vectors for Class 1: 57

Sample Support Vectors:

SOP	LOR
3.5	3
3.5	2.5
4	4.5
3	3
3	3.5

Support Vectors Statistics:

	SOP	LOR
count	115	115
mean	3.48696	3.47391
std	0.594053	0.529165
min	2	2.5
25%	3	3
50%	3.5	3.5
75%	4	4
max	5	5

Feature Set: [‘LOR’, ‘GRE Score’]

Linear SVM - Number of Support Vectors for Class 0: 43 - Number of Support Vectors for Class 1: 43

Sample Support Vectors:

LOR	GRE Score
3	318
4.5	313
3	320
3.5	316
4	318

Support Vectors Statistics:

	LOR	GRE Score
count	86	86
mean	3.44767	316.593
std	0.632591	5.93569
min	1.5	303
25%	3	312.25
50%	3.5	316
75%	4	320
max	5	329

RBF SVM - Number of Support Vectors for Class 0: 109 - Number of Support Vectors for Class 1: 109

Sample Support Vectors:

LOR	GRE Score
3	304
2	311

LOR	GRE Score
3	308
3	318
2.5	300

Support Vectors Statistics:

	LOR	GRE Score
count	218	218
mean	3.48624	316.798
std	0.891482	9.54618
min	1.5	299
25%	3	310
50%	3.5	316
75%	4	324
max	5	336

Polynomial SVM - Number of Support Vectors for Class 0: 63 - Number of Support Vectors for Class 1: 63

Sample Support Vectors:

LOR	GRE Score
2	311
3	318
3	309
1.5	312
4.5	313

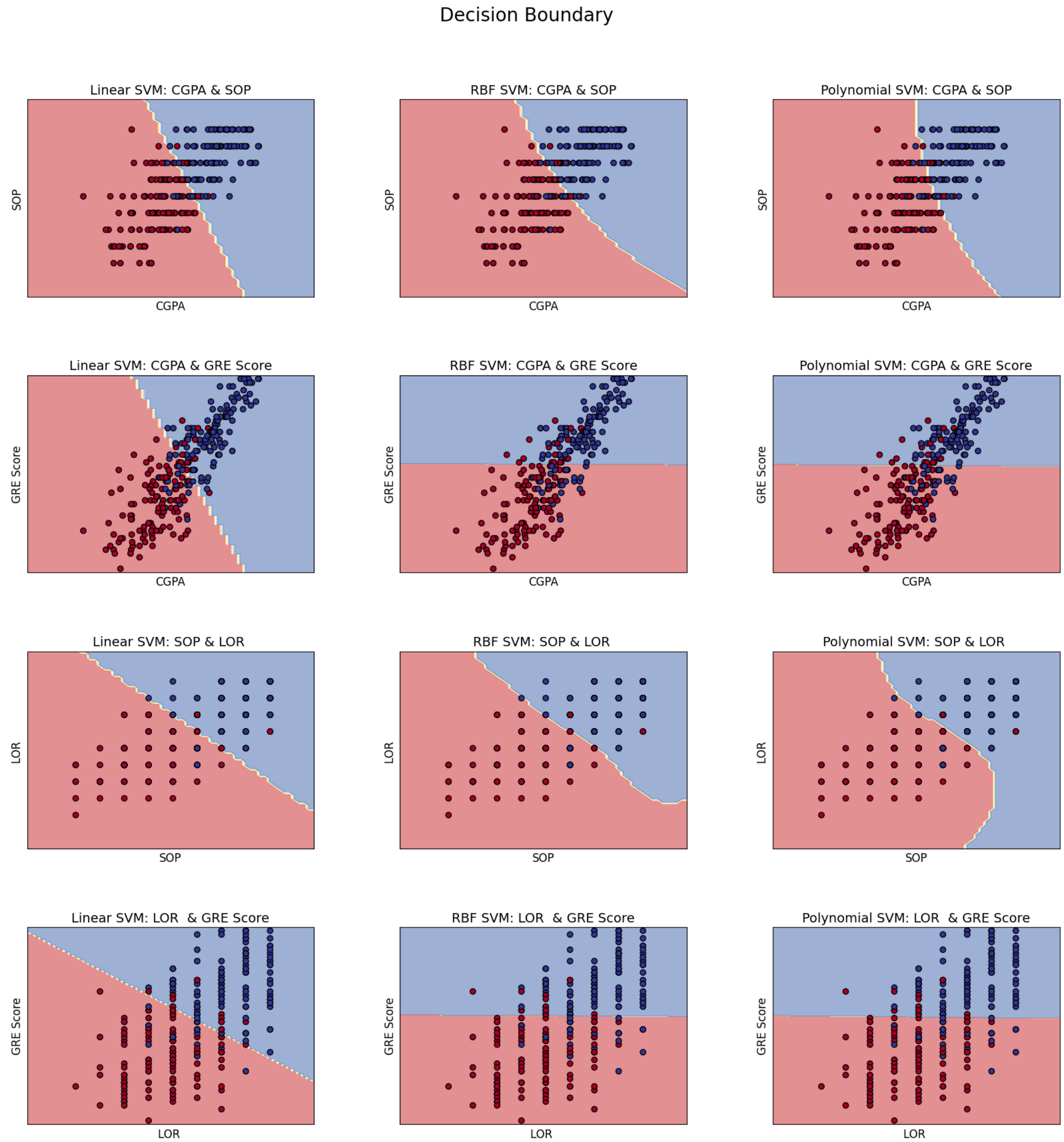
Support Vectors Statistics:

	LOR	GRE Score
count	126	126
mean	3.46825	316.77
std	0.854976	5.3204
min	1.5	303
25%	3	312.25
50%	3.5	316
75%	4	321
max	5	329

- **(e)** Result Visualization: For each kernel - input combination, visualize the predictions on the training set. Color code the points by their labels.

[12]:

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

fig, axs = plt.subplots(len(feature_sets), len(models), figsize=(20, 20))
fig.subplots_adjust(hspace=0.4, wspace=0.3)

for i, features in enumerate(feature_sets):
    for j, model in enumerate(models):
        ax = axs[i, j]

        X_plot = X_train[features]
        y_plot = y_train

        model.fit(X_plot, y_plot)

        x_min, x_max = X_plot.iloc[:, 0].min() - 1, X_plot.iloc[:, 0].max() + 1
        y_min, y_max = X_plot.iloc[:, 1].min() - 1, X_plot.iloc[:, 1].max() + 1
        xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                             np.arange(y_min, y_max, 0.1))

        predict_data = pd.DataFrame(
            np.c_[xx.ravel(), yy.ravel()], columns=features)
        Z = model.predict(predict_data).reshape(xx.shape)

        ax.contourf(xx, yy, Z, alpha=0.5, cmap=plt.cm.RdYlBu)
        ax.scatter(X_plot.iloc[:, 0], X_plot.iloc[:, 1],
                   c=y_plot, cmap=plt.cm.RdYlBu, edgecolor='k')

        ax.set_title(
            f"{model_names[j]}: {features[0]} & {features[1]}", fontsize=14)
        ax.set_xlabel(features[0], fontsize=12)
        ax.set_ylabel(features[1], fontsize=12)

        ax.grid(False)
        ax.set_xticks(())
        ax.set_yticks(())

plt.suptitle('Decision Boundary', fontsize=20, y=0.95)
plt.show()
```



- **(f)** Result Analysis: Just by looking at the figures you generated, answer this question: Which features + kernel combinations give you the best result? Validate your model on the validation set and find the best performing combination with respect to accuracy.

[14]:
```
best_model_idx = results_df['Validation Accuracy'].argmax()
best_model_row = results_df.iloc[best_model_idx]

best_model_md = f"""
**Best Model Configuration:**

- Model: {best_model_row['Model']}
```

```
- Features: {best_model_row['Features']}
- Training Accuracy: {best_model_row['Train Accuracy']:.3f}
- Validation Accuracy: {best_model_row['Validation Accuracy']:.3f}
"""
display(Markdown(best_model_md))
```

Best Model Configuration:

- Model: RBF SVM
- Features: CGPA, SOP
- Training Accuracy: 0.875
- Validation Accuracy: 0.828

[15]:
```
feature_performances = results_df.groupby(
    'Features')['Validation Accuracy'].mean().sort_values(ascending=False)
feature_importances_md = "**Feature Importance Analysis:**\n\n" + \
    "|Feature Set|Validation Accuracy|\n|---|---|\n"
for index, value in feature_performances.items():
    feature_importances_md += f"|{index}|{value:.3f}|\n"

display(Markdown(feature_importances_md))
```

Feature Importance Analysis:

Feature Set	Validation Accuracy
CGPA, SOP	0.818
CGPA, GRE Score	0.781
LOR , GRE Score	0.781
SOP, LOR	0.745

[16]:
```
kernel_performances = results_df.groupby(
    'Model')['Validation Accuracy'].mean().sort_values(ascending=False)

kernel_comparison_md = "**Kernel Comparison:**\n\n" + \
    "|Kernel|Validation Accuracy|\n|---|---|\n"
for index, value in kernel_performances.items():
    kernel_comparison_md += f"|{index}|{value:.3f}|\n"

display(Markdown(kernel_comparison_md))
```

Kernel Comparison:

Kernel	Validation Accuracy
Linear SVM	0.789
Polynomial SVM	0.777
RBF SVM	0.777

- **(g)** Inference: Use the best model you found in the previous step to predict the label of the test data. Save the prediction in a csv file "FirstName_LastName_preds.csv"

[17]:
```
test_df = pd.read_csv('data_test-2.csv')
X_test = test_df.drop(['Serial No.'], axis=1)
best_model = svc_linear
best_features = ['CGPA', 'GRE Score']
best_model.fit(X_train[best_features], y_train)
test_pred = best_model.predict(X_test[best_features])
output = pd.DataFrame({'pred_svm': test_pred})
output.to_csv('FirstName_LastName_preds.csv', index=False)
```

[20]:
```
test_predictions_md = output.to_markdown(index=False)
display(Markdown(test_predictions_md))
```

pred_svm
0
0
1
1
0
0
1
1
1
1
1
1
0
1
0
1
0
1
1
1
1
1
0
1
1
0
1
1
0
1
0

pred_svm
0
1
0
0
0
1
1
1
0
0
1
1
1
0
1
0
1
1
0
1
1
1
1
1
0
0
0
0
0
0
0
0
0
1
1
1
0
0
0
0
1
0
1
1
0
1

pred_svm
0
0
1

[21]:
```
test_pred_distribution = output['pred_svm'].value_counts().to_frame('count')
display(Markdown("**Test Prediction Distribution:**\n"))
test_pred_distribution_md = test_pred_distribution.to_markdown()
display(Markdown(test_pred_distribution_md))
```

Test Prediction Distribution:

pred_svm	count
1	43
0	37