Q6 - SVM Programming

In this question, you will employ SVM to solve a classification problem for the provided data file "hw3q6.csv". Each row in the data file indicates a sample. The first 12 columns are features and the last column "Class" indicates the label, with 1 and 0 indicating the positive and negative samples, respectively.

Import Libraries

```
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.svm import SVC

import matplotlib.pyplot as plt
import numpy as np
import sys
import os

%matplotlib inline
```

(a) Load data. Report the size of positive and negative samples in dataset

```
def data_and_headers(filename):
    data = None
    with open(filename) as fp:
        data = [x.strip().split(',') for x in fp.readlines()]
    headers = data[0]
    headers = np.asarray(headers)
    class_field = len(headers) - 1
    data_x = [[float(x[i]) for i in range(class_field)] for x in data[1:]]
    data_x = np.asarray(data_x)
    data_y = [[int(x[i]) for i in range(class_field, class_field + 1)] for x in data[1:]]
    data_y = np.asarray(data_y)
    return headers, data_x, data_y
```

```python
headers, features_x, labels_y = data_and_headers('Data' + os.sep +
'hw3q6.csv')
```

```python
print('Data')
print('Number of features - ' + str(features_x.shape[1]))
print('Total Number of observations - ' + str(features_x.shape[0]))
print('Number of Positive Samples - ' + str(labels_y[labels_y==1].shape[0]))
print('Number of Negative Samples - ' + str(labels_y[labels_y==0].shape[0]))
print()
```

```
Data
Number of features - 12
Total Number of observations - 200
Number of Positive Samples - 90
Number of Negative Samples - 110
```

(b) Use stratified random sampling to divide the dataset into training data (75%) and testing data (25%). Report the number of positive and negative samples in both training and testing data.

```python
train_x, test_x, train_y, test_y = train_test_split(features_x,
                                                    labels_y,
                                                    test_size=0.25,
                                                    random_state=10,
                                                    shuffle=True,
                                                    stratify=labels_y)
```

```python
print('Training Data')
print('Number of features - ' + str(train_x.shape[1]))
print('Total Number of observations - ' + str(train_x.shape[0]))
print('Number of Positive Samples - ' + str(train_y[train_y==1].shape[0]))
print('Number of Negative Samples - ' + str(train_y[train_y==0].shape[0]))
print()
print('Testing Data')
print('Number of features - ' + str(test_x.shape[1]))
print('Total Number of observations - ' + str(test_x.shape[0]))
print('Number of Positive Samples - ' + str(test_y[test_y==1].shape[0]))
print('Number of Negative Samples - ' + str(test_y[test_y==0].shape[0]))
print()
```

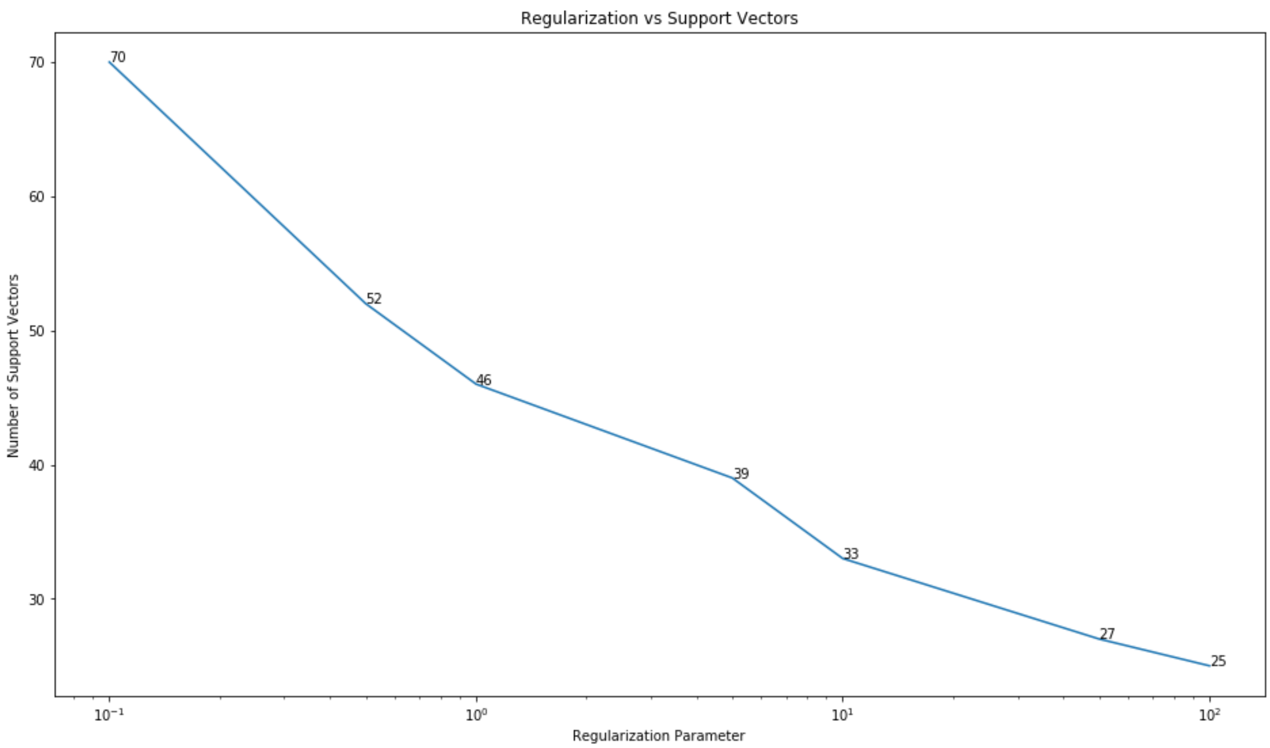
```
Training Data
Number of features - 12
Total Number of observations - 150
Number of Positive Samples - 67
Number of Negative Samples - 83

Testing Data
Number of features - 12
Total Number of observations - 50
Number of Positive Samples - 23
Number of Negative Samples - 27
```

(c) Take SVM with linear kernel as classifier (third-party packages are allowed to use) and set the regularization parameter C as: [0.1, 0.5, 1, 5, 10, 50, 100], respectively. For each value of C, train a SVM classifier with the training data and get the number of support vectors (SVs). Generate a plot with C as the horizontal axis and number of SVs as the vertical axis. Give a brief analysis for the plot.

```python
C = [0.1, 0.5, 1, 5, 10, 50, 100]
models = [SVC(C[i],'linear',random_state=10).fit(train_x,train_y.flatten())
for i in range(len(C))]
```

```python
fig, ax = plt.subplots(figsize=(16,9))
ax.set_title('Regularization vs Support Vectors')
ax.set_ylabel('Number of Support Vectors')
ax.set_xlabel('Regularization Parameter')
ax.set_xscale('log')
plty = [x.support_.shape[0] for x in models]
#ax.bar(C, plty, color='orange')
ax.plot(C, plty)
for i, txt in enumerate(C):
    ax.annotate(plty[i], (C[i], plty[i]))
plt.show()
```



(d) Compare 4 different kernel functions, including linear, polynomial, radial basic function (Gaussian kernel), and sigmoid kernel. Make a table to record the accuracy, precision, recall and f-measure of the classification results for the 4 kernel functions. Try to tune the parameters via grid search and report your best results with the optimal parameters. Based on the results, which kernel function will you choose?

Linear Kernel

```
param_grid = [
    {'C':[0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 5, 10, 50, 100],
     'kernel':['linear']}
]

lsvc = SVC(random_state=10)
linear_clf = GridSearchCV(lsvc, param_grid,
                  ['f1', 'accuracy', 'recall', 'precision'],
                  cv=5, refit='accuracy', verbose=1, n_jobs=4)
linear_clf.fit(train_x, train_y.flatten())
y_pred = linear_clf.predict(test_x)
```

```
Fitting 5 folds for each of 11 candidates, totalling 55 fits
[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  55 out of  55 | elapsed:    0.3s finished
```

```
print('Best Parameters - ')
print(linear_clf.best_params_)
print()
print('Linear Kernel Classification Results on Test Set with Optimal Parameters')
print('Accuracy - \t{:.4f}'.format(accuracy_score(test_y.flatten(), y_pred)))
print('F1 Score - \t{:.4f}'.format(f1_score(test_y.flatten(), y_pred)))
print('Precision - \t{:.4f}'.format(precision_score(test_y.flatten(), y_pred)))
print('Recall - \t{:.4f}'.format(recall_score(test_y.flatten(), y_pred)))
```

```
Best Parameters -
{'C': 10, 'kernel': 'linear'}

Linear Kernel Classification Results on Test Set with Optimal Parameters
Accuracy -  0.9600
F1 Score -  0.9565
Precision -     0.9565
Recall -    0.9565
```

Radial Basis Function

```python
param_grid = [
    {'C':[0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 5, 10, 50, 100],
     'kernel':['rbf'],
     'gamma': [0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0]}
]

rsvc = SVC(random_state=10)
radial_clf = GridSearchCV(rsvc, param_grid,
                   ['f1', 'accuracy', 'recall', 'precision'],
                   cv=5, refit='accuracy', verbose=1, n_jobs=4)
radial_clf.fit(train_x, train_y.flatten())
y_pred = radial_clf.predict(test_x)
```

```
Fitting 5 folds for each of 110 candidates, totalling 550 fits
[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done 550 out of 550 | elapsed:    1.4s finished
```

```python
print('Best Parameters - ')
print(radial_clf.best_params_)
print()
print('Radial Basis Function Kernel Classification Results on Test Set with Optimal Parameters')
print('Accuracy - \t{:.4f}'.format(accuracy_score(test_y.flatten(), y_pred)))
print('F1 Score - \t{:.4f}'.format(f1_score(test_y.flatten(), y_pred)))
print('Precision - \t{:.4f}'.format(precision_score(test_y.flatten(), y_pred)))
print('Recall - \t{:.4f}'.format(recall_score(test_y.flatten(), y_pred)))
```

```
Best Parameters - 
{'C': 1, 'gamma': 0.2, 'kernel': 'rbf'}

Radial Basis Function Kernel Classification Results on Test Set with Optimal Parameters
Accuracy -  0.9800
F1 Score -  0.9778
Precision -     1.0000
Recall -    0.9565
```

Polynomial Kernel

```
param_grid = [
    {'C':[0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 5, 10, 50, 100],
     'kernel':['poly'],
     'degree':[2,3,4,5,6],
     'gamma': [0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0],
     'coef0': [0.1,0.5,1.0,1.5,2.0,5.0,10.0,20.0]}
]

psvc = SVC(random_state=10)
poly_clf = GridSearchCV(psvc, param_grid,
                   ['f1', 'accuracy', 'recall', 'precision'],
                   cv=5, refit='accuracy', verbose=1, n_jobs=4)
poly_clf.fit(train_x, train_y.flatten())
y_pred = poly_clf.predict(test_x)
```

```
Fitting 5 folds for each of 4400 candidates, totalling 22000 fits
[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done 756 tasks      | elapsed:    2.2s
[Parallel(n_jobs=4)]: Done 4056 tasks      | elapsed:    9.3s
[Parallel(n_jobs=4)]: Done 9556 tasks      | elapsed:   20.5s
[Parallel(n_jobs=4)]: Done 17256 tasks      | elapsed:   34.6s
[Parallel(n_jobs=4)]: Done 22000 out of 22000 | elapsed:   43.7s finished
```

```
print('Best Parameters - ')
print(poly_clf.best_params_)
print()
print('Polynomial Kernel Classification Results on Test Set with Optimal Parameters')
print('Accuracy - \t{:.4f}'.format(accuracy_score(test_y.flatten(), y_pred)))
print('F1 Score - \t{:.4f}'.format(f1_score(test_y.flatten(), y_pred)))
print('Precision - \t{:.4f}'.format(precision_score(test_y.flatten(), y_pred)))
print('Recall - \t{:.4f}'.format(recall_score(test_y.flatten(), y_pred)))
```

```
Best Parameters -
{'C': 0.001, 'coef0': 5.0, 'degree': 4, 'gamma': 0.8, 'kernel': 'poly'}

Polynomial Kernel Classification Results on Test Set with Optimal Parameters
Accuracy -  0.9600
F1 Score -  0.9565
Precision -     0.9565
Recall -    0.9565
```

Sigmoid Kernel

```
param_grid = [
    {'C':[0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 5, 10, 50, 100],
     'kernel':['sigmoid'],
     'gamma': [0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0],
     'coef0': [0.1,0.5,1.0,1.5,2.0,5.0,10.0,20.0]}
]

ssvc = SVC(random_state=10)
sig_clf = GridSearchCV(ssvc, param_grid,
                   ['f1', 'accuracy', 'recall', 'precision'],
                   cv=5, refit='accuracy', verbose=1, n_jobs=4)
sig_clf.fit(train_x, train_y.flatten())
y_pred = sig_clf.predict(test_x)
```

```
Fitting 5 folds for each of 880 candidates, totalling 4400 fits
[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done 416 tasks      | elapsed:    4.6s
[Parallel(n_jobs=4)]: Done 2216 tasks      | elapsed:   15.1s
[Parallel(n_jobs=4)]: Done 4400 out of 4400 | elapsed:   20.9s finished
```

```python
print('Best Parameters - ')
print(sig_clf.best_params_)
print()
print('Sigmoid Kernel Classification Results on Test Set with Optimal Parameters')
print('Accuracy - \t{:.4f}'.format(accuracy_score(test_y.flatten(), y_pred)))
print('F1 Score - \t{:.4f}'.format(f1_score(test_y.flatten(), y_pred)))
print('Precision - \t{:.4f}'.format(precision_score(test_y.flatten(), y_pred)))
print('Recall - \t{:.4f}'.format(recall_score(test_y.flatten(), y_pred)))
```

```
Best Parameters - 
{'C': 0.05, 'coef0': 0.1, 'gamma': 0.3, 'kernel': 'sigmoid'}

Sigmoid Kernel Classification Results on Test Set with Optimal Parameters
Accuracy -  0.9000
F1 Score -  0.9020
Precision -     0.8214
Recall -    1.0000
```

Results

Kernel with Tuned Hyperparameter	Accuracy	F1-score	Precision	Recall
Linear **{'C': 10}**	0.9600	0.9565	0.9565	0.9565
RBF **{'C': 1, 'gamma': 0.2}**	0.9800	0.9778	1.0000	0.9565
Polynomial **{'C': 0.001, 'coef0': 5.0, 'degree': 4, 'gamma': 0.8}**	0.9600	0.9565	0.9565	0.9565
Sigmoid **{'C': 0.05, 'coef0': 0.1, 'gamma': 0.3}**	0.9000	0.9020	0.8214	1.0000

Based on the above results, we will choose the RBF kernel, with C=1 and gamma=0.2 as the kernel function. This is because it is giving the best score across 3 categories - accuracy, f1 and precision.