svm_testing

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1 SVM Implementations

In [2]: import numpy as np

1.1 Machine Learning, University of Utah

1.1.1 Cade Parkison

```
import pandas as pd
        import cvxopt
1.1.2 Data Import and Preprocessing
In [3]: test_data = pd.read_csv('bank-note/test.csv', header=None)
        train_data = pd.read_csv('bank-note/train.csv', header=None)
In [4]: # first 7 columns are features, last column (Slump) is output
        columns = ['var', 'skew', 'curt', 'ent', 'label']
        features = columns[:-1]
        output = columns[-1]
        test_data.columns = columns
        train_data.columns = columns
In [5]: train_data.head()
Out [5]:
                         skew
                                  curt
                                            ent
                                                 label
                var
        0 3.848100 10.15390 -3.85610 -4.22280
                                                     0
        1 4.004700
                     0.45937 1.36210 1.61810
                                                     0
                                                     0
        2 -0.048008 -1.60370 8.47560 0.75558
        3 -1.266700
                      2.81830 -2.42600 -1.88620
                                                     1
        4 2.203400
                     5.99470 0.53009 0.84998
In [6]: train_X = train_data.iloc[:,:-1].values
```

test_X = test_data.iloc[:,:-1].values

In [7]: train_X.shape, test_X.shape

```
Out[7]: ((872, 4), (500, 4))
In [8]: train_y = train_data.iloc[:,-1].values
        test_y = test_data.iloc[:,-1].values
In [9]: train_y.shape, test_y.shape
Out[9]: ((872,), (500,))
In [10]: # Convert labels to {-1,1}
         train_y = np.array([1 if x else -1 for x in train_y])
         test_y = np.array([1 if x else -1 for x in test_y])
         # reshape to 2D array
         train_y = train_y.reshape(-1,1)
         test_y = test_y.reshape(-1,1)
In [11]: train_y.shape, test_y.shape
Out[11]: ((872, 1), (500, 1))
In [216]: class SVM(object):
              def __init__(self, no_of_inputs, epoch, C, rate_schedule):
                  self.epoch = epoch
                  self.C = C
                  self.rate_schedule = rate_schedule
                  self.weights = np.zeros(no_of_inputs + 1) # initialize weights to zero
              def predict(self, X):
                  # predicts the label of one training example input with current weights
                  return np.sign(np.dot(X, self.weights[:-1]) + self.weights[-1])
              def train(self, X, y):
                  N = y.shape[0]
                  #labels = np.expand_dims(labels, axis=1)
                  data = np.hstack((X,y))
                  for e in range(self.epoch):
                      #print("Epoch: "+ str(e))
                      #print("Weights: " + str(self.weights))
                      #print('')
                      rate = self.rate_schedule(e)
                      np.random.shuffle(data)
                      for i,row in enumerate(data):
```

```
x = row[:-1]
            y = row[-1]
            val = y*(np.dot(x, self.weights[:-1]) + self.weights[-1])
            if val <= 1:</pre>
                self.weights[:-1] = (1-rate)*self.weights[:-1] + rate*self.C*N*y
                self.weights[-1] = rate*self.C*N*y
            else:
                self.weights[:-1] = (1-rate)*self.weights[:-1]
    return self.weights
def evaluate(self, X, y):
    # calculates average prediction error on testing dataset
    errors = []
    for inputs, label in zip(X, y):
        prediction = self.predict(inputs)
        if np.sign(prediction) != label:
            errors.append(1)
        else:
            errors.append(0)
    return 100*(sum(errors) / float(X.shape[0]))
```

1.2 Evaluation

1.2.1 2.2

Part a:

$$\gamma_t = \frac{\gamma_0}{1 + \frac{\gamma_0}{d}t}$$

```
svm = SVM(4, 100, c, schedule_a)
                                    svm.train(train_X, train_y)
                                    print('C {}: weights = {}'.format(c,svm.weights))
                                    train_errors.append(svm.evaluate(train_X, train_y))
                                    test_errors.append(svm.evaluate(test_X, test_y))
                         print('Training Errors: {}'.format(train_errors))
                         print('Testing Errors: {}'.format(test_errors))
C 0.001145475372279496: weights = [-3.74999012e-01 -1.71782612e-01 -1.46115309e-01 -7.80712244]
     9.16380298e-05]
C 0.011454753722794959: weights = [-0.74050692 -0.37308407 -0.37429121 -0.19790761 -0.00091638]
C = 0.0572737686139748: weights = [-1.13026463 - 0.55535113 - 0.69693188 - 0.31042097 0.0045819]
C 0.1145475372279496: weights = [-1.44720154 -0.71534303 -0.80515422 -0.32493326 0.0091638]
C 0.3436426116838488: weights = [-2.00728194 -1.1476715 -1.04464131 -0.68690303 0.02749141]
C = 0.572737686139748: weights = [-2.62307216 -1.73517131 -1.29206735 -1.02332767 0.04581901]
C = 0.8018327605956472: weights = [-3.42848911 -2.24249739 -1.97210138 -0.83556891 -0.06414662]
Training Errors: [5.045871559633028, 4.128440366972478, 5.045871559633028, 4.013761467889909,
Testing Errors: [7.1999999999999, 4.8, 6.4, 4.8, 5.60000000000005, 6.8000000000001, 7.000
In [253]: schedule_b = lambda t:gamma_0 / (1 + t)
In [254]: train_errors = []
                         test_errors = []
                         for c in C_list:
                                    svm = SVM(4, 100, c, schedule_b)
                                    svm.train(train_X, train_y)
                                    print('C {}: weights = {}'.format(c,svm.weights))
                                    train_errors.append(svm.evaluate(train_X, train_y))
                                    test_errors.append(svm.evaluate(test_X, test_y))
                         print('Training Errors: {}'.format(train_errors))
                         print('Testing Errors: {}'.format(test_errors))
C 0.001145475372279496: weights = [-3.73505563e-01 -1.70655237e-01 -1.45437691e-01 -7.89171176e-01 -1.45437691e-01 -1.45437691e-01 -7.89171176e-01 -1.45437691e-01 -7.89171176e-01 -1.45437691e-01 -7.89171176e-01 -1.45437691e-01 -7.89171176e-01 -1.45437691e-01 -7.89171176e-01 -1.45437691e-01 -7.89171176e-01 -7.89176e-01 -7.89
     9.98854525e-06]
C 0.011454753722794959: weights = [-7.28630240e-01 -3.68194467e-01 -3.69761376e-01 -1.93643088]
C 0.0572737686139748: weights = [-1.10445012e+00 -5.89441091e-01 -6.33769389e-01 -2.47590179e-01 -6.33769389e-01 -6.30769389e-01 -6.307693899-01 -6.30769389-01 -6.30769389-01 -6.3076989-01 -6.3076989-01 -6.3076989-01 -6.3076989-01 -6.307698-01 -6.307698-01 -6.3076989-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.307698-01 -6.30768-01 -6.30768-01 -6.307688-01 -6.30768-01 -6.307688-01 -6.307688-01 -6.307688-01 -6.30768-01 -6.30768-01 -6.30768-01 -
     4.99427262e-04]
9.98854525e-04]
C 0.3436426116838488: weights = [-1.58527834 - 0.85788808 - 0.90598141 - 0.33869477 0.00299656]
C = 0.572737686139748: weights = [-1.72428192 - 0.96253544 - 1.05129922 - 0.35398384  0.00499427]
C 0.8018327605956472: weights = [-1.88370336 -1.07649151 -1.07785222 -0.39328958 0.00699198]
Training Errors: [5.045871559633028, 4.128440366972478, 4.013761467889909, 4.013761467889909,
Testing Errors: [7.1999999999999, 4.8, 4.6, 4.6, 4.8, 4.8, 5.2]
```

2 Dual SVM

Dual Form SVM:

$$\min_{\{0 \leq \alpha_i \leq C\}, \sum_i \alpha_i y_i = 0} \frac{1}{2} \sum_i \sum_j y_i y_j \alpha_i \alpha_j {x_i}^T x_j - \sum_i \alpha_i$$

Dual form with Kernel:

$$\min_{\alpha} \frac{1}{2} \sum_{i} \sum_{j} y_{i} y_{j} \alpha_{i} \alpha_{j} K(x_{i}, x_{j}) - \sum_{i} \alpha_{i}$$

$$s.t. \ 0 \le \alpha_{i} \le C$$

$$\sum_{i} \alpha_{i} y_{i} = 0$$

Converting to Matrix notation:

H is a matrix such that $H_{i,j} = y_i y_j K(x_i, x_j)$ We now convert the sums into vectors:

$$\min_{\alpha} \frac{1}{2} \alpha^T \mathbf{H} \mathbf{f} \mathbf{f} - \mathbf{1}^{\mathbf{T}} \mathbf{f} \mathbf{f}$$

$$s.t. 0 \le \alpha_i \le C$$
$$y^T \alpha = 0$$

CVXOPT QP Solver:

$$\min_{x} \frac{1}{2} x^{T} P x - q^{T} x$$

$$s.t. Gx \le h$$

$$and Ax = b$$

Converting to cvxopt format:

P = H matrix (mxm)

q = -1 vector (mx1)

G = (2mxm) matrix, first 3 rows are $0 \le alpha$ constraint, last 3 are alpha $\le C$ constraint

h = vector (2mx1), first 3 elements are 0, last three elements are C

A = y labels vector (mx1)

b = 0 scalar

```
In [261]: class DualSVM(object):
              def __init__(self, C, kernel=linear_kernel):
                  self.C = C
                  self.kernel = kernel
              def predict(self, inputs):
                  # predicts the label of one training example input with current weights
                  if self.kernel == linear_kernel:
                      return np.sign(np.dot(inputs, self.weights[:-1]) + self.weights[-1])
                  else:
                      result = 0
                      for a, sv_y, sv in zip(self.a, self.sv_y, self.sv):
                          result += a * sv_y * self.kernel(inputs, sv)
                      return np.sign(result).item()
              def train(self, X, y):
                  n_samples, n_features = X.shape
                  # Kernel Matrix
                  K = np.zeros((n_samples, n_samples))
                  for i in range(n_samples):
                      for j in range(n_samples):
                          K[i,j] = self.kernel(X[i], X[j])
                  P = cvxopt.matrix(np.outer(y,y)*K)
                  q = cvxopt.matrix(-1*np.ones(n_samples))
                  G = cvxopt.matrix(np.vstack((np.diag(-1*np.ones(n_samples)), np.identity(n_samples)),
                  h = cvxopt.matrix(np.hstack((np.zeros(n_samples),self.C*np.ones(n_samples)))
                  A = cvxopt.matrix(y, (1,n_samples), 'd')
                  b = cvxopt.matrix(0.0)
                  cvxopt.solvers.options['show_progress'] = False
                  cvxopt.solvers.options['abstol'] = 1e-10
                  cvxopt.solvers.options['reltol'] = 1e-10
                  cvxopt.solvers.options['feastol'] = 1e-10
                  # Quadratic Programming solution from cvxopt
                  sol = cvxopt.solvers.qp(P,q,G,h,A,b)
                  # Lagrange Multipliers
                  alphas = np.array(sol['x'])
                  # weights
                  w = ((y * alphas).T @ X).reshape(-1,1)
                  # non-zero alphas
                  S = (alphas > 1e-4).flatten()
```

```
self.S = S
                  self.n_supports = np.sum(S)
                  # intercept
                  b = y[S] - np.dot(X[S], w)
                  ind = np.arange(len(alphas))[S]
                  self.a = alphas[S]
                  self.sv = X[S]
                  self.sv_y = y[S]
                  self.b = 0
                  for n in range(len(self.a)):
                      self.b += float(self.sv_y[n])
                      self.b -= np.sum(self.a * self.sv_y * K[ind[n],S])
                  self.b /= len(self.a)
                  self.weights = np.zeros(n_features + 1)
                  self.weights[:-1] = w.flatten()
                  self.weights[-1] = b[0]
              def evaluate(self, X, y):
                  # calculates average prediction error on dataset, in percentage
                  errors = []
                  for inputs, label in zip(X, y):
                      prediction = self.predict(inputs)
                      if np.sign(prediction) != label:
                          errors.append(1)
                      else:
                          errors.append(0)
                  return 100*(sum(errors) / float(X.shape[0]))
In [158]: C_list = [100.0/873, 500.0/873, 700.0/873]
In [255]: # Training and Testing errors for each C value
          train_errors = []
          test_errors = []
          for c in C:
              svm = DualSVM(c,kernel=linear_kernel)
              svm.train(train_X,train_y)
              print('C {}: weights = {}'.format(c,svm.weights))
              train_errors.append(svm.evaluate(train_X,train_y))
              test_errors.append(svm.evaluate(test_X,test_y))
          print(train_errors, test_errors)
C \ 0.1145475372279496: weights = [-0.94303948 \ -0.65147876 \ -0.73370349 \ -0.04098535 \ 1.52256115]
C = 0.572737686139748: weights = [-1.56426251 -1.0137622 -1.18050792 -0.15618296 1.91748011]
```

```
C 0.8018327605956472: weights = [-2.04253733 -1.28008058 -1.5132451 -0.24830283 2.18696284] [1.4908256880733946, 0.8027522935779817, 0.8027522935779817] [1.40000000000000001, 0.8, 0.8]
```

Gaussian Kernel

```
In [244]: gamma list = [0.01, 0.1, 0.5, 1.0, 2.0, 5.0, 10.0, 100.0]
In [249]: # Training and Testing errors for each C value
          train_errors = []
          test_errors = []
          for c in C:
              svm = DualSVM(c,kernel=gaussian_kernel())
              svm.train(train_X,train_y)
              train_errors.append(svm.evaluate(train_X,train_y))
              test_errors.append(svm.evaluate(test_X,test_y))
          print(train_errors, test_errors)
[0.0, 0.0, 0.0] [0.2, 0.2, 0.2]
In [245]: for g in gamma_list:
              train_errors = []
              test_errors = []
              for c in C:
                  svm = DualSVM(c,kernel=gaussian_kernel(g))
                  svm.train(train_X,train_y)
                  train_errors.append(svm.evaluate(train_X,train_y))
                  test_errors.append(svm.evaluate(test_X,test_y))
              print('Gamma {}: {}, {}'.format(g,train_errors, test_errors))
Gamma 0.01: [0.0, 0.0, 0.0], [0.2, 0.2, 0.2]
Gamma 0.1: [0.0, 0.0, 0.0], [0.2, 0.2, 0.2]
Gamma 0.5: [0.0, 0.0, 0.0], [0.2, 0.2, 0.2]
Gamma 1: [0.0, 0.0, 0.0], [0.2, 0.2, 0.2]
Gamma 2: [0.0, 0.0, 0.0], [0.2, 0.2, 0.2]
Gamma 5: [0.8027522935779817, 0.0, 0.0], [0.6, 0.2, 0.2]
Gamma 10: [0.8027522935779817, 0.0, 0.0], [0.6, 0.2, 0.2]
Gamma 100: [0.34403669724770647, 0.0, 0.0], [0.4, 0.0, 0.0]
In [260]: for g in gamma_list:
              supports = []
              for c in C:
                  svm = DualSVM(c,kernel=gaussian_kernel(g))
                  svm.train(train_X,train_y)
                  supports.append(svm.n_supports)
```

```
#train_errors.append(sum.evaluate(train_X, train_y))
                  #test_errors.append(svm.evaluate(test_X, test_y))
              print('N Supports: {}'.format(supports))
N Supports: [872, 872, 872]
N Supports: [869, 868, 864]
N Supports: [825, 730, 689]
N Supports: [805, 555, 519]
N Supports: [693, 389, 359]
N Supports: [442, 208, 193]
N Supports: [316, 130, 114]
N Supports: [290, 116, 98]
In [262]: supports = []
          for g in gamma_list:
              svm = DualSVM(500/873,kernel=gaussian_kernel(g))
              svm.train(train_X,train_y)
              supports.append(svm.S)
In [264]: overlap_supports = []
          for i in range(7):
              overlap_supports.append(np.sum(np.logical_and(supports[i], supports[i+1])))
          print(overlap_supports)
[868, 730, 552, 379, 194, 122, 64]
```