## CSE512 Fall 2018 - Machine Learning - Homework 4

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Q1.1 and 1.2 81.1 support vectors. maximize SVMs main objective is to minimize the morgin i.e maximize the minimum distance of the points from the clavifier plane Loocy error = 2 f(yi, xi: 0 b i)

yi expected = xi 0 + b where o is the value of weights leaving ith example. It bias leaving ith example. If y'x y'expected = 1 (correctly classified) elu (mis clanified) and value of f(x) = 0 if x = 1, elue . 1 Now considering 2 cares: is If a point is not a support vector. Then the morgine donot charge since the margine are solely defined by support vectors :. f(m) = 0 is it a point is a support vector. Then the margin will shift giving a new classifier plane. This may lead to the case where this point is misclauified. ... f(n) = 0 is correctly clarified =1 if mis claufied.

In the worst can, it is possible that all in the support vectors may be now clauffied the support vectors is m

LOOLV error = - 1 / (yi, xi; o-i, b-i)

whole data.

For worst case scenario +(x)=1 +x = Support

: mox Loowerror = In E (1)
= m

: LOOCH error & M

Ali The data is linearly seperable in higher dimension. Even in this case, since the points are linearly seperable, the moveyin is decided by support vector.

The the loss function of in 1:1 will there the loss function of in 1:1 will evaluate to 0 for mon-support vectors evaluate to 0 for mon-support vectors and may evaluate to 1 for a support and may evaluate to 1 for a support holds.

Nector. Hence above concept holds.

```
Q21) maximize £xj - 1 Z Z Yixiyjxj k (ai, xj)
                                                              s.t. = 7 | x | = 0
                                                                             0 < x ; << 4 j
    minimize - 2 2 Ji xi y j xj . k(xi, xj) - 2 xj
                                                                        s. + 2 yj xj = 0
                                                                            0 5 4 5 6 4 5
Quadprog in matlab:
        min 1 2 THX + fTx S.t. S.t. Aexx = bear
                         since we are using linear kennel,
                    H = (YYT) . * (XTX) .* > element wise

product
                    f = -1 \times \text{one} \left( \text{size}(4,1), 1 \right) = \begin{bmatrix} -1 \\ -1 \end{bmatrix} \times 1
                       A=[] } empty matrices
                     Aea = \[ \begin{array}{c} \quad \qua
                     bear = Zeros (size (4,1), D = [] nx1
                     16 = Zeros (Size (Y,1),1) = 0 nx1
                   ub = C x ones (size (4,1),1) = [ ]nx1
```

Q2.4)

For C = 0.1

Accuracy: 90.76%
Objective Function: 24.765
Number of Support Vectors: 339

Confusion Matrix:

152	2
32	181

Q2.5)

For C = 10

Accuracy: 97.82%
Objective Function: 112.146
Number of Support Vectors: 123

Confusion Matrix:

180	4
4	179

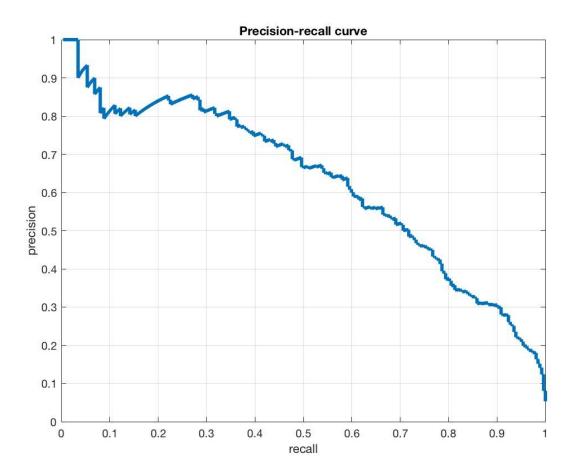
#### Q2.6)

Best accuracy achieved is 0.78369 based on Kaggle submission.

Used One Vs All approach to solve for multi-class. Used Linear Kernel and C value is 0.1.

Changing the C value had no impact on accuracy.

Q3.4.1) AP: 0.636



Q3.4.3) Objective Values:

Iteration	0	1	2	3	4	5	6	7	8	9	10
Obj Value	111.171	681.34	950.48	989.03	1009.90	1037.04	1046.28	1058.20	1062.92	1068.46	1072.97

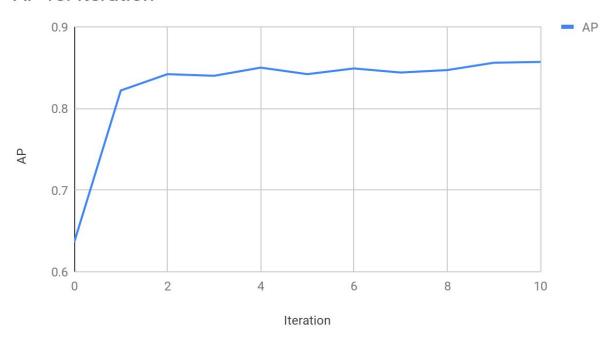
### AP Values:

Iteration	0	1	2	3	4	5	6	7	8	9	10
AP	0.636	0.822	0.842	0.840	0.850	0.842	0.849	0.844	0.847	0.856	0.857

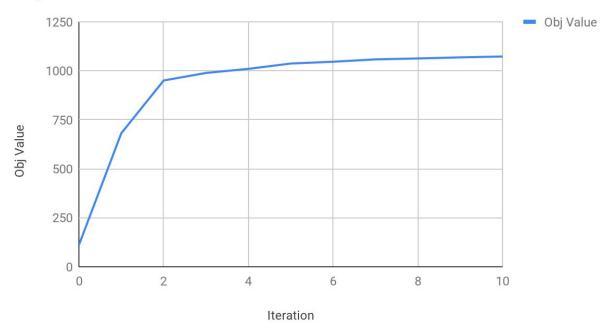
0th index is the values before starting hard negative mining.

C = 10

## AP vs. Iteration



# Obj Value vs. Iteration



Q3.4.4 AP: 0.813638