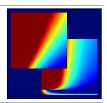**CS/CNS/EE 156a Learning Systems**
Caltech - Fall 2024
https://caltech.instructure.com/courses/7624
(Learning From Data campus version)

Homework # 8

Due Monday, November 25, 2024, at 2:00 PM PST

Definitions and notation follow the lectures. All questions have multiple-choice answers ([a], [b], [c], ...). Collaboration is allowed but without discussing selected or excluded choices. *Your solutions must be based on your own work. See the initial* "**Course Description and Policies**" *handout for important details about collaboration, open book, and chatGPT policies.*

Note about the homework

- Answer each question by deriving the answer (carries 6 points) then selecting from the multiple-choice answers (carries 4 points). You can select 1 or 2 of the multiple-choice answers for each question, but you will get 4 or 2 points, respectively, for a correct answer. See the initial "**Course Description and Policies**" handout for important details.

- The problems range from easy to difficult, and from practical to theoretical. Some problems require running a full experiment to arrive at the answer.

- The answer may not be obvious or numerically close to one of the choices, but one (and only one) choice will be correct if you follow the instructions precisely in each problem. You are encouraged to explore the problem further by experimenting with variations on these instructions, for the learning benefit.

- You are encouraged to take part in the Piazza discussion forum. Please make sure you don't discuss specific answers, or specific excluded answers, before the homework is due.

● **Primal versus Dual Problem**

1. Recall that N is the size of the data set and d is the dimensionality of the input space. The original formulation of the hard-margin SVM problem (minimize $\frac{1}{2}\mathbf{w}^{\mathrm{T}}\mathbf{w}$ subject to the inequality constraints), without going through the Lagrangian dual problem, is

   [**a**] a quadratic programming problem with N variables

   [**b**] a quadratic programming problem with $N + 1$ variables

   [**c**] a quadratic programming problem with d variables

   [**d**] a quadratic programming problem with $d + 1$ variables

   [**e**] not a quadratic programming problem

Notice: The following problems deal with a real-life data set. In addition, the computational packages you use may employ different heuristics and require different tweaks. This is a typical situation that a Machine Learning practitioner faces. There are uncertainties, and the answers may or may not match our expectations. Although this situation is not as 'sanitized' as other homework problems, it is important to go through it as part of the learning experience.

SVM with Soft Margins

In the rest of the problems of this homework set, we apply soft-margin SVM to handwritten digits from the processed US Postal Service Zip Code data set. Download the data (extracted features of intensity and symmetry) for training and testing:

http://www.amlbook.com/data/zip/features.train

http://www.amlbook.com/data/zip/features.test

(the format of each row is: **digit intensity symmetry**). We will train two types of binary classifiers; one-versus-one (one digit is class $+1$ and another digit is class -1, with the rest of the digits disregarded), and one-versus-all (one digit is class $+1$ and the rest of the digits are class -1).

The data set has thousands of points, and some quadratic programming packages cannot handle this size. You may need stronger SVM packages such as **fitcsvm** in MatLab or the free **libsvm** (http://www.csie.ntu.edu.tw/~cjlin/libsvm/).

Implement SVM with soft margin on the above zip-code data set by solving

$$\min_{\boldsymbol{\alpha}} \quad \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N}\alpha_n\alpha_m y_n y_m K(\mathbf{x}_n,\mathbf{x}_m) - \sum_{n=1}^{N}\alpha_n$$

$$\text{s.t.} \quad \sum_{n=1}^{N} y_n\alpha_n = 0$$

$$0 \le \alpha_n \le C \quad n = 1,\cdots,N$$

When evaluating E_{in} and E_{out} of the resulting classifier, use binary classification error. E_{out} is estimated using the test set.

Practical remarks:

(i) For the purpose of this homework, do not scale the data when you use libsvm or other packages, otherwise you may inadvertently change the (effective) kernel and get different results.

(ii) In some packages, you need to specify double precision.

(iii) In 10-fold cross validation, if the data size is not a multiple of 10, the sizes of the 10 subsets may be off by 1 data point.

(iv) Some packages have software parameters whose values affect the outcome. ML practitioners have to deal with this kind of added uncertainty.

● **Polynomial Kernels**

Consider the polynomial kernel $K(\mathbf{x}_n,\mathbf{x}_m) = (1 + \mathbf{x}_n^{\text{T}}\mathbf{x}_m)^Q$, where Q is the degree of the polynomial.

2. With $C = 0.01$ and $Q = 2$, which of the following classifiers has the **highest** E_{in}?

   [a] 0 versus all
   [b] 2 versus all
   [c] 4 versus all
   [d] 6 versus all
   [e] 8 versus all

3. With $C = 0.01$ and $Q = 2$, which of the following classifiers has the **lowest** E_{in}?

   [a] 1 versus all
   [b] 3 versus all

[c] 5 versus all

[d] 7 versus all

[e] 9 versus all

4. Comparing the two selected classifiers from Problems 2 and 3, which of the following values is the closest to the difference between the number of support vectors of these two classifiers?

[a] 600

[b] 1200

[c] 1800

[d] 2400

[e] 3000

5. Consider the 1 versus 5 classifier with $Q = 2$ and $C \in \{0.001, 0.01, 0.1, 1\}$. Which of the following statements is correct? Going up or down means strictly so.

[a] The number of support vectors goes down when C goes up.

[b] The number of support vectors goes up when C goes up.

[c] E_{out} goes down when C goes up.

[d] Maximum C achieves the lowest E_{in}.

[e] None of the above

6. In the 1 versus 5 classifier, comparing $Q = 2$ with $Q = 5$, which of the following statements is correct?

[a] When $C = 0.0001$, E_{in} is higher at $Q = 5$.

[b] When $C = 0.001$, the number of support vectors is lower at $Q = 5$.

[c] When $C = 0.01$, E_{in} is higher at $Q = 5$.

[d] When $C = 1$, E_{out} is lower at $Q = 5$.

[e] None of the above

● **Cross Validation**

In the next two problems, we will experiment with 10-fold cross validation for the polynomial kernel. Because E_{cv} is a random variable that depends on the random partition of the data, we will try 100 runs with different partitions and base our answer on how many runs lead to a particular choice.

7. Consider the 1 versus 5 classifier with $Q = 2$. We use E_{cv} to select $C \in \{0.0001, 0.001, 0.01, 0.1, 1\}$. If there is a tie in E_{cv}, select the smaller C. Within the 100 random runs, which of the following statements is correct?

[a] $C = 0.0001$ is selected most often.

[b] $C = 0.001$ is selected most often.

[c] $C = 0.01$ is selected most often.

[d] $C = 0.1$ is selected most often.

[e] $C = 1$ is selected most often.

8. Again, consider the 1 versus 5 classifier with $Q = 2$. For the overall winning selection in the previous problem, the average value of E_{cv} over the 100 runs is closest to

[a] 0.001

[b] 0.003

[c] 0.005

[d] 0.007

[e] 0.009

● **RBF Kernel**

Consider the radial basis function (RBF) kernel $K(\mathbf{x}_n, \mathbf{x}_m) = \exp\left(-||\mathbf{x}_n - \mathbf{x}_m||^2\right)$ in the soft-margin SVM approach. Focus on the 1 versus 5 classifier.

9. Which of the following values of C results in the lowest E_{in}?

[a] $C = 0.01$

[b] $C = 1$

[c] $C = 100$

[d] $C = 10^4$

[e] $C = 10^6$

10. Which of the following values of C results in the lowest E_{out}?

[a] $C = 0.01$

[b] $C = 1$

[c] $C = 100$

[d] $C = 10^4$

[e] $C = 10^6$