UBC CPSC 340 2018W1
MIDTERM EXAM

Oct 18th, 2018

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TIME: 80 minutes

- Do not open the exam until you are directed to do so.
- Once you open the exam, make sure that it contains this cover page plus 9 pages of exam questions.
- One letter-size sheet (both sides) of notes is allowed. No other material or accessories may be used.
- You may use either pen or pencil, but exams written in pencil may not be eligible for regrading.
- Please be prepared to present, upon request, a student card for identification.
- If you need more space, use the blank page at the end of the exam, and clearly indicate that your work continues there.
- Most questions require a short answer. Work efficiently and avoid writing lengthy answers.
- Unless otherwise stated, n refers to the number of training examples and d is the number of features.
- If anything is unclear or seems ambiguous, **state your assumptions**.

Question:	1	2	3	4	5	6	7	8	Total
Points:	8	6	6	6	6	6	6	6	50
Score:									

Question 1. **(8 points)**

Answer the questions below using 1-2 short sentences.

2 pts (a) What are two differences between KNN and k-means? (No more than two, please.)

2 pts (b) Is it possible to have a machine learning model that makes predictions in $O(1)$ time? If yes, give an example; if no, explain why not.

2 pts (c) You're working on a machine learning problem and decide you need more data. You collect twice as much training data but end up with the same validation error for your parametric model. Are you likely experiencing underfitting or overfitting? Briefly justify your answer.

2 pts (d) What is an advantage and a disadvantage of using more folds with cross-validation?

Question 2. **(6 points)**

Answer the questions below using 1-2 short sentences.

2 pts (a) Assume you have a classifier that takes $O(nd)$ time to train and $O(td)$ time to predict on t examples, like naive Bayes. If you are testing p possible values of a hyper-parameter, what is the cost of choosing the best value of the hyper-parameter using k-fold cross-validation? Express the result in terms of n, d, t, k, and p (if these affect the runtime).

2 pts (b) Consider the "consistent nearest neighbour" classifier: it runs our usual KNN classifier but instead of viewing k as a hyper-parameter it always sets $k = \lceil \log(n) \rceil$ (the logarithm of n rounded up to the nearest integer). Would call this a parametric classifier or a non-parametric classifier? Briefly justify your answer.

2 pts (c) Consider the "condensed nearest neighbour" classifier: at training time it chooses the c "best" training examples (where c is a hyper-parameter), and at test time uses the usual KNN prediction but based only on these c training examples. Would call this a parametric classifier or a non-parametric classifier? Briefly justify your answer.

Question 3. **(6 points)**

Answer the questions below using 1-2 short sentences.

2 pts (a) Does it make sense to do k-means clustering with $k > n$? Briefly justify your answer.

2 pts (b) Does it make sense to do k-means clustering with $k > d$? Briefly justify your answer.

2 pts (c) In k-means we can often obtain a much better clustering by using a large number of random initializations of the initial means. In DBSCAN (density-based clustering), we could randomize the order of the training examples that we test for new clusters. Is it generally a good idea to run DBSCAN with a large number of different random orderings? Briefly justify your answer.

Question 4. **(6 points)**

Answer the questions below using 1-2 short sentences.

2 pts (a) Name one advantage and one disadvantage of using gradient descent instead of the normal equations to fit a least squares linear regression model.

2 pts (b) When we do regression with a polynomial basis, how does the degree of the polynomial p affect the two parts of the fundamental trade-off?

2 pts (c) Construct a matrix X where the least squares solution would not be unique.

Question 5. **(6 points)**

Loss functions.

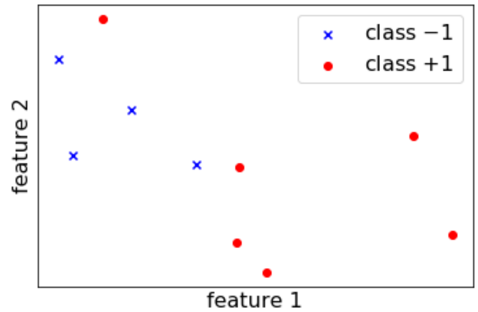
2 pts (a) Describe a situation where using a linear regression model with the squared error could give very misleading results.

2 pts (b) Consider the loss function $f(r) = \sum_{i=1}^{n} \max\{r_i, -2r_i\}$. Write down a version of this loss function that is smoothed with the log-sum-exp.

2 pts (c) The Huber loss has a hyperparameter, δ, which controls where you switch from a parabola to a constant slope. What could go wrong if δ is set to an extremely large (far from zero) value?

Question 6. **(6 points)**

Consider the binary classification training data set shown below. The two classes are denoted with o's and $\times$'s.



3 pts (a) What is the minimum depth of decision tree needed to get zero training error on this data set? Briefly explain your reasoning. Feel free to draw on the plot if it helps.

3 pts (b) What is the maximum value of k such that KNN gets zero training error on this data set? Assume ties are broken by voting for class +1 (the circles). Briefly explain your reasoning. Feel free to draw on the plot if it helps.

Question 7. **(6 points)**

Consider the following one-dimensional data set:

$$X = \begin{bmatrix} -3 \\ 4 \\ -1 \\ 3 \end{bmatrix}, \quad y = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix}.$$

2 pts (a) Write down the Z matrix for using a polynomial basis with $p = 2$ (quadratic) on this data set. Use the same standard format/notation that we used in the lectures and assignments.

2 pts (b) Let's say the weights come out to be $v = \begin{bmatrix} -1 \\ 3 \\ 0 \end{bmatrix}$. What is the model's prediction for $\tilde{x} = 2$?

2 pts (c) If we instead used $p = 1$ on this dataset, would we expect the weights to be $\begin{bmatrix} -1 \\ 3 \end{bmatrix}$ (i.e. the first two elements of our previous v), or something different? Briefly justify your answer.

Question 8. **(6 points)**

3 pts (a) Consider the following objective, which considers a weighted worst-case error with a penalty on the absolute value of the weights,

$$f(w) = \max_{i \in \{1,2,\ldots,n\}} \{v_i |w^T x_i - y_i|\} + \lambda \sum_{j=1}^{d} |w_j|,$$

where λ is a non-negative scalar. Re-write this objective function in matrix and norm notation. You can use V as a diagonal matrix with the elements v_i along the diagonal.

3 pts (b) Consider the L2-regularized *tilted* least squares objective,

$$f(w) = \frac{1}{2} \sum_{i=1}^{n} (w^T x_i - y_i)^2 + \frac{\lambda}{2} \sum_{j=1}^{d} w_j^2 + \sum_{j=1}^{d} v_j w_j,$$

where the λ is a non-negative scalar and the v_j are real-valued "tilting" variables. Write down a linear system whose solution minimizes this (convex and quadratic) objective function. You can use v as a vector containing the v_j values.

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