# STAT 154: Homework 1

#### Release date: Thursday, January 24

#### Due by: 6 PM, Wednesday, February 6

#### Submission instructions

It is a good idea to revisit your notes, slides and reading; and synthesize their main points BEFORE doing the homework.

A .Rnw file corresponding to the homework is also uploaded for you. You may use that to write-up your solutions. Alternately, you can typeset your solutions in latex or submit neatly handwritten/scanned solutions. However for the parts that ask you to implement/run some R code, your answer should look something like this (code followed by result):

```
myfun<- function(){
  show('this is a dummy function')
}
myfun()</pre>
```

Note that this is automatically generated if you use the R sweave environment. You need to submit the following:

- 1. A pdf of your write-up to "HW1 write-up".
- 2. A Rmd or Rnw file, that has all your code, to "HW1 code".

Ensure a proper submission to gradescope, otherwise it will not be graded. Make use of the first lab to clear all your doubts regarding the submission/gradescope.

<sup>## [1] &</sup>quot;this is a dummy function"

## The honor code

(a) Please state the names of people who you worked with for this homework. You can also provide your comments about the homework here.

(b) Please type/write the following sentences yourself and sign at the end. We want to make it *extra* clear that nobody cheats even unintentionally.

I hereby state that all of my solutions were entirely in my words and were written by me. I have not looked at another students solutions and I have fairly credited all external sources in this write up. This homework revisits several concepts from matrix algebra, besides doing some EDA with R, and, some concepts from the lectures.

## 1 A few basics (10\*9 = 90 points)

Define the following quantities:

- (a) Linear space spanned by a given set of vectors  $S = {\mathbf{a}_1, \dots, \mathbf{a}_k}$
- (b) Column space of a matrix
- (c) Rank of a matrix.

Answer the following:

- (d) When is a square matrix called a singular matrix?
- (e) When is a square matrix called an orthogonal matrix?
- (f) When is a matrix said to have full column rank?

Recall that a symmetric matrix  $\mathbf{A} \in \mathbb{R}^{d \times d}$  is *positive semi-definite* (PSD) if  $\mathbf{x}^{\top} \mathbf{A} \mathbf{x} \ge 0$  for any  $\mathbf{x} \in \mathbb{R}^d$ . Now answer the following:

- (g) Show that the matrix  $\mathbf{A} = \mathbf{a}\mathbf{a}^{\top}$ , where  $\mathbf{a} \in \mathbb{R}^d$  is nonzero, is PSD.
- (h) What is the rank of  $\mathbf{A} = \mathbf{a}\mathbf{a}^{\top}$ ?
- (i) For any matrix  $\mathbf{C} \in \mathbb{R}^{d \times d}$ , is the matrix  $\mathbf{C}\mathbf{C}^{\top}$  a PSD matrix?

### 2 Eigendecomposition with R (10\*6 = 60 points)

Consider the following matrices

$$\mathbf{X} = \begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix} \quad \text{and} \quad \mathbf{Y} = \begin{bmatrix} -1/3 & 2/3 \\ 2/3 & -1/3 \end{bmatrix}$$

- (a) Create these matrices in R and show them.
- (b) Which of the two matrices are invertible and why? Find the inverse if it exists. How does one compute the inverse in R?
- (c) Compute the eigenvalues and eigenvectors of the matrix **X**. We expect you to be able to do this by hand but you may still use R for this part.
- (d) Use the results of previous part to directly compute the eigenvalues and eigenvectors of the matrix **Y**.

- (e) What are the eigenvalues and eigenvectors of  $\mathbf{X}^2$ ? You may use direct computations or R to answer this question.
- (f) Prove that if  $(\lambda, v)$  denotes an eigenvalue-eigenvector pair for the matrix **X**, then the pair  $(\lambda^2, v)$  is a valid eigenvalue-eigenvector pair for the matrix **X**<sup>2</sup>.

## 3 Understanding orthogonal projection (10\*12+40 = 160 points)

In this problem, we will understand orthogonal projection in quite some detail. The length of the problem should not bother you as several parts are relatively easy.

- (a) For any vector  $\mathbf{x} = [x_1, x_2, x_3]^\top \in \mathbb{R}^3$ , what is its projection on the vector  $[1, 0, 0]^\top$ ?
- (b) What is the orthogonal projection of  $\mathbf{x} = [x_1, x_2, x_3]^\top \in \mathbb{R}^3$  on the subspace spanned by the vectors  $[1, 0, 0]^\top$  and  $[0, 1, 0]^\top$ ?
- (c) Write the projection matrices in the previous two cases.
- (d) Create the previous projection matrices in R and compute the projections of two random vectors whose entries are drawn independently from the uniform distribution on [0, 1]. Do not forget to set the seed.
- (e) Let's make the problem more general. Write the expression for the orthogonal projection of a vector  $\mathbf{x} \in \mathbb{R}^d$  along any given vector  $\mathbf{a} \in \mathbb{R}^d$ . What is the projection matrix in this case?
- (f) Create a function in R that takes in input two vectors  $\mathbf{x}, \mathbf{a}$  and computes the projection from previous part. Call the function with  $\mathbf{x} = [3, 2, -1]^{\top}$  and  $\mathbf{a} = [1, 0, 1]^{\top}$ .
- (g) Given two orthogonal vectors  $\mathbf{a}_1$  and  $\mathbf{a}_2$  in  $\mathbb{R}^d$ , what is the orthogonal projection of a generic vector  $\mathbf{x}$  on to the subspace spanned by these two vectors?
- (h) Now let's make the problem a bit more challenging. Suppose that the two vectors  $\mathbf{a}_1$  and  $\mathbf{a}_2$  are not orthogonal. How will you compute the orthogonal projection of  $\mathbf{x}$  in this case? It may be useful to revise Gram Schmidt Orthogonalization.
- (i) Implement your method in the previous part in R for  $\mathbf{x} = [3, 2, -1]^{\top}$  and  $\mathbf{a}_1 = [1, 0, 1]^{\top}$  and  $\mathbf{a}_2 = [1, -1, 0]^{\top}$ .
- (j) Can you generalize the answer from previous part to the case to compute the orthogonal projection along a k-dimensional subspace spanned by the vectors  $\mathbf{a}_1, \ldots, \mathbf{a}_k$  which need not be orthogonal?
- (k) Challenging (40 points): Define the matrix

$$\mathbf{A} = [\mathbf{a}_1, \dots, \mathbf{a}_k] \in \mathbb{R}^{d \times k}$$

such that the columns are independent. Then the orthogonal projection of any vector  $\mathbf{x} \in \mathbb{R}^d$  onto the k-dimensional subspace spanned by the vectors  $\mathbf{a}_1, \ldots, \mathbf{a}_k$  is given by

$$\mathbf{A}(\mathbf{A}^{\top}\mathbf{A})^{-1}\mathbf{A}^{\top}\mathbf{x}.$$
 (1)

*Hint:* Consider the least squares problem

$$\min_{y} \|\mathbf{A}\mathbf{y} - \mathbf{x}\|_2^2$$

- (l) Compute the projection for  $\mathbf{x} = [3, 2, -1]^{\top}$  on the space spanned by the vectors  $\mathbf{a}_1 = [1, 0, 1]^{\top}$  and  $\mathbf{a}_2 = [1, -1, 0]^{\top}$  using the expression in previous part using R. Compare it with your answer from part (i).
- (m) How does the expression in the equation (1) simplify if the vectors  $\mathbf{a}_1, \ldots, \mathbf{a}_k$  are orthogonal?

#### 4 Exploring a dataset with R $(10^{*}8 + 2^{*}20 = 120 \text{ points})$

ISL (with applications in R): Chapter 2, Problem 10 (Boston dataset) After parts (a)-(h), please answer the following parts that try to emphasize a few aspects of the PQRS framework:

- (i) What do you think defines the population for this dataset?
- (j) Can you define a prediction problem that you may use this dataset for? Describe it in the framing of the three-circle representation discussed in the class.

#### 5 True or false (10\*7 = 70 points)

Examine whether the following statements are true or false and provide one line justification.

- (a) Cross validation is a powerful tool to select hyper-parameters in several machine learning tasks.
- (b) Cross validation error is always a good proxy for the prediction error.
- (c) Vanilla cross validation is a good idea for time-series data.
- (d) For a machine learning problem, exploratory data analysis by itself is generally sufficient to determine the complete relevance of the dataset for the problem.
- (e) Data collection process usually has no-to-little influence on the outcome of a prediction problem.
- (f) For a model to make meaningful predictions on the future data, we need some similarity between the representative data that was used to build the model and the future data.
- (g) Prediction is often the end goal of a machine learning task.