CSE 158, Fall 2018: Midterm

Name:	Student ID:

Instructions

The test will start at 5:10pm. Hand in your solution at or before 6:10pm. Answers should be written directly in the spaces provided.

Do not open or start the test before instructed to do so.

Note that the final page contains some algorithms and definitions. Total marks = 26

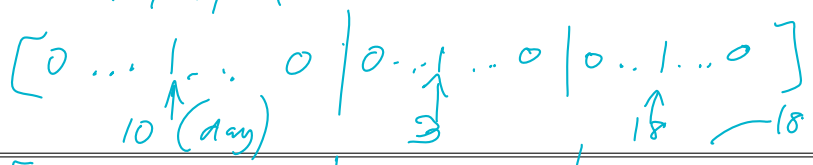
Section 1: Regression and Ranking (6 marks)

Suppose you wanted to predict *Air Quality* measurements (generally measured using an index of particulate matter called 'PM2.5') for a large city. Suppose you have a dataset containing thousands of hourly measurements to do so. Examples of previous measurements look like:

Observation	Date	Time	**PM2.5**	Temp (c)	Wind sp. (km/h)	wind direction	humidity
1	10/03/2004	18.00.00	150	24.4	4.1	NNW	76
2	10/03/2004	19.00.00	112	22.8	5.8	NW	84
3	10/03/2004	20.00.00	88	20.7	2.2	NW	87
4	10/03/2004	21.00.00	80	16.5	4.4	NNW	89
5	10/03/2004	22.00.00	51	15.5	2.1	W	90
6	10/03/2004	23.00.00	38	12.8	0.4	W	83
7	11/03/2004	00.00.00	31	11.8	0.6	SW	78
8	11/03/2004	01.00.00	31	10.9	1.3	S	69

1. Both the time and the date could be useful for this type of prediction. Suggest a scheme for representing the date and time, and write down the resulting features for the first two observations (2 marks).

A: 10/03/04 18.00 one-hot day/month/hour



1: [00 ... 1 | 0..1..0 | 0 ...10..0]

2: [0 ... 1 | 0..1..0 | 0 ...01..0]

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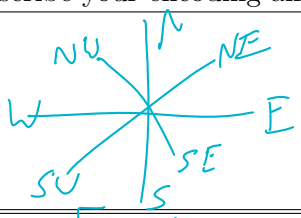
2. Similarly, suppose you wanted to incorporate the wind direction[1] and wind speed into your predictor. Describe your encoding and write down the features of the first two datapoints (2 marks).

A: N NE E SE S SW W NW



1: [4.1 | 0 0 0 0 0 0 0 1]

2: [5.8 | 0 0 0 0 0 0 0 1]

3. When predicting a future PM2.5 value, a useful predictor might be one (or several) *previous* PM2.5 values (i.e., the labels of previous observations become features for the current observation, so you might predict the 8^{th} observation using features derived from the previous 7 observations, etc.). This procedure is known as *autoregression*. Describe which previous observations you might use, or what other features you might extract from past observations, in order to make a system that was effective at forecasting future observations (2 marks).

A: y = pm2.5 X = [pm2.5 1 hour ago, 2 hour ago, 24 hour ago, same day 1 wk ago, year ago]

concatenate X with features from previous Qs

[1] NNW = North-North-West, etc.

Section 2: Classification and Diagnostics (9 marks)

Suppose you wish to build a classifier to detect malicious e-mails (e.g. spam, phishing, etc.). You collect 10,000 e-mails, and obtain ground-truth labels indicating which e-mails are malicious (i.e., malicious e-mails are labeled *True*). You then train three classifiers, whose performance is as follows:

Classifier 1:

False Positives	150
False Negatives	21
True Positives	35
True Negatives	9794

Classifier 2:

False Positives	3828
False Negatives	6
True Positives	50
True Negatives	6135

Classifier 2:

False Positives	843
False Negatives	40
True Positives	16
True Negatives	9101

4. How many of the 10,000 instances have a positive label (i.e., $y_i = True$) (1 mark)?

   A:

5. How many of the 10,000 instances have a positive prediction **for Classifier 1** (i.e., $f(X) = True$) (1 mark)?

   A:

6. Compute the following statistics **for Classifier 1**. You can leave your results as unsimplified expressions (4 marks):

   Accuracy: A:

   BER: A:

   Precision: A:

   Recall: A:

Which of the three classifiers would you select if your goal is to optimize the measures below? Assume that content where the prediction is positive is filtered/blocked (e.g. moved to a spam folder). **Briefly state your reasoning for each answer**. (1 mark each).

7. The classifier with the highest accuracy:

   A:

8. The classifier that lets the *fewest malicious e-mails* through the filter:

   A:

9. The classifier that filters the *fewest non-malicious e-mails*:

   A:

Section 3: Clustering / Communities (5 marks)

Suppose you collect a dataset of taxi rides in New York, containing pickup and dropoff locations, among other features. After generating a scatterplot of the data you obtain the following result:[2]

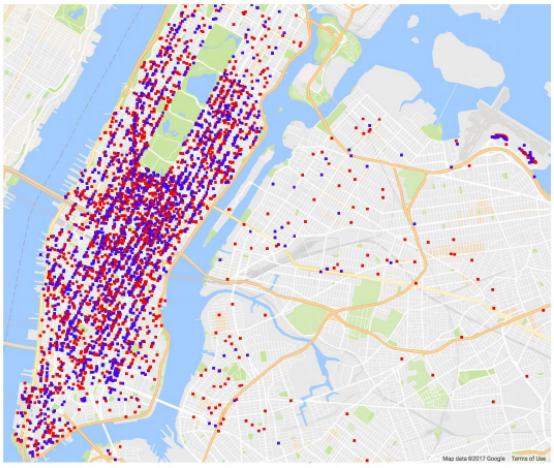


Fig. 1: Mapping of pick-up and drop-off locations

Suppose your goal is to predict the *total tip* that a given fare will receive.

You consider three alternative techniques to incorporate the geographical location into your model:

- (Grid:) Split the data into a grid (over latitude and longitude), and include a feature indicating which grid position each datapoint belongs to.
- (Nearest Neighbor:) For each new trip, identify the 'most similar' trip in the training data in terms of the distance between start and end locations. Predict the tip for the new trip to be the same as the tip for this previous trip (this is known as 'nearest neighbor' classification).
- (Clustering:) Run a clustering algorithm (e.g. k-means or hierarchical clustering) to obtain feature representations of each point.

10. Suggest one reason why clustering the data might be preferable to each of the 'grid' or 'nearest neighbor' models (2 marks):

Versus Grid:

Versus Nearest Neighbor:

11. (Design thinking) In addition to geographical features, suggest (at least three) additional features that may be useful in predicting tip amounts (3 marks):

A:

[2]Scatterplot taken from a previous CSE258 assignment on taxi tip prediction.

Section 4: Recommender Systems (6 marks)

Suppose you collect the following ratings of teen romance novels from *Goodreads*:

Item ID	Book	Read?					Rated?				
		Nathan	Thomas	Dhruv	Kevin	Prateek	Nathan	Thomas	Dhruv	Kevin	Prateek
1	*To All the Boys I've Loved Before*	1	1	0	1	1	5	3	?	1	4
2	*P.S. I Still Love You*	1	0	0	0	1	5	?	?	?	4
3	*Always and Forever, Lara Jean*	1	0	0	0	0	4	?	?	?	?
4	*It All Started with an Apple*	0	1	0	0	0	?	2	?	?	?
5	*The Kissing Booth*	1	0	1	1	1	1	?	1	2	4

You want to make a simple recommender that identifies the 'all time best' books, using a model of the form

$$\text{rating}(i) = \alpha + \beta_i.$$

Here α is a global term, and β_i is an item bias. You fit your model by setting α to the global mean of all ratings, and β_i to be the remainder. Finally, you make recommendations simply by identifying those items with the highest bias terms, i.e.,

$$\underset{i}{\text{argmax}}\, \beta_i.$$

12. Noting that the average rating is 3.0, what is the bias term β_i for Item #1 (1 mark)

    A:

13. What item would receive the highest ranking according to this global recommender (1 mark)?

    A:

Items 1, 2, and 3 are consecutive books from the same series. You notice that users only read each sequel if they liked the previous book, which biases ratings of sequels (items 2 and 3) to be particularly high. You propose modifying your model to take the form

$$\text{rating}(i) = \text{rating(previous book in sequence)} + \beta_i.$$

Non-sequels are still assigned ratings according to $\text{rating}(i) = \alpha + \beta_i$.

14. After fitting your model following the above formula, which item will now receive the highest ranking (1 mark)?

    A:

15. (Critical Thinking) Suppose you wanted to design a recommender system to estimate the compatibility between candidates and job openings. Describe what data you would collect from users, how you would model the problem, and any issues that make this problem different or unique compared to those we saw in class (3 marks).

A:

Precision:

$$\frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|}$$

Recall:

$$\frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{relevant documents}\}|}$$

Balanced Error Rate (BER):

$$\frac{1}{2}(\text{False Positive Rate} + \text{False Negative Rate})$$

F-score:

$$2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

Jaccard similarity:

$$\text{Sim}(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

Cosine similarity:

$$\text{Sim}(A, B) = \frac{A \cdot B}{\|A\|\|B\|}$$

Algorithm 1 Hierarchical clustering

Initially, every point is assigned to its own cluster
while there is more than one cluster **do**
  Compute the center of each cluster
  Combine the two clusters with the nearest centers

Algorithm 2 K-means

Initialize every cluster to contain a random set of points
while cluster assignments change between iterations **do**
  Assign each X_i to its nearest centroid
  Update each centroid to be the mean of points assigned to it

Write any additional answers/corrections/comments here: