CSE 255, Fall 2015: Midterm

Name:  

Student ID:  

Instructions

The test will start at 6:40pm. Hand in your solution at or before 7:40pm. 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 = 25
Section 1: Regression

Feature design

Suppose we collected the following data about businesses from Google Local:

<table>
<thead>
<tr>
<th>ID</th>
<th>Name</th>
<th>Rating</th>
<th>Price</th>
<th>Address</th>
<th>latitude/longitude</th>
<th>hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>T C’s Referee Sports Bar</td>
<td>5.0</td>
<td>$$</td>
<td>Sioux Falls, SD 57106</td>
<td>43.529, -96.792</td>
<td>m-f/11am-10pm, s-s/11am-1am</td>
</tr>
<tr>
<td>1</td>
<td>Old Chicago</td>
<td>3.0</td>
<td>$$</td>
<td>Beaverton, OR 97006</td>
<td>45.535, -122.862</td>
<td>m-f/11am-1am</td>
</tr>
<tr>
<td>2</td>
<td>Sabatinos Italian Kitchen</td>
<td>4.0</td>
<td>$$$</td>
<td>Arlington, MA 02474</td>
<td>42.406, -71.143</td>
<td>m-f/10am-10pm, s-s/10am-9pm</td>
</tr>
<tr>
<td>3</td>
<td>Oakville Grocery</td>
<td>4.5</td>
<td>$</td>
<td>Healdsburg, CA 95448</td>
<td>25.063, 121.524</td>
<td>mon-sun/9am-5pm</td>
</tr>
<tr>
<td>4</td>
<td>Hog Wild Pit BBQ</td>
<td>3.5</td>
<td>$$</td>
<td>Wichita, KS 67213</td>
<td>37.681, -97.389</td>
<td>mon-sun/11am-8pm</td>
</tr>
</tbody>
</table>

1. Suppose we wanted to train a personalized model that predicted the rating I would give to a business based on the population-level average and price, i.e.,

   \[
   \text{my rating} = \theta_0 + \theta_1[\text{average rating}] + \theta_2[\text{price}].
   \]

   Write down the complete feature matrix (in the space below) that you would use to solve the above equation (1 mark):

   \[
   \begin{bmatrix}
   y_0 \\
   y_1 \\
   y_2 \\
   y_3 \\
   y_4
   \end{bmatrix} = \begin{bmatrix}
   \theta_0 \\
   \theta_1 \\
   \theta_2
   \end{bmatrix} \cdot \begin{bmatrix}
   \text{average rating}_0 \\
   \text{average rating}_1 \\
   \text{average rating}_2 \\
   \text{average rating}_3 \\
   \text{average rating}_4
   \end{bmatrix} + \begin{bmatrix}
   \text{price}_0 \\
   \text{price}_1 \\
   \text{price}_2 \\
   \text{price}_3 \\
   \text{price}_4
   \end{bmatrix}
   \]

2. Write down the predictions that would be obtained for the five businesses if using the features above if the parameters were \( \theta = [0.1, 1.0, -0.2]^T \) (1 mark)

<table>
<thead>
<tr>
<th>ID</th>
<th>Name</th>
<th>Predicted Rating</th>
<th>Q4 answer</th>
<th>Q5 answer</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>T C’s Referee Sports Bar</td>
<td></td>
<td>Q4 answer</td>
<td>Q5 answer</td>
</tr>
<tr>
<td>1</td>
<td>Old Chicago</td>
<td></td>
<td>Q4 answer</td>
<td>Q5 answer</td>
</tr>
<tr>
<td>2</td>
<td>Sabatinos Italian Kitchen</td>
<td></td>
<td>Q4 answer</td>
<td>Q5 answer</td>
</tr>
<tr>
<td>3</td>
<td>Oakville Grocery</td>
<td></td>
<td>Q4 answer</td>
<td>Q5 answer</td>
</tr>
<tr>
<td>4</td>
<td>Hog Wild Pit BBQ</td>
<td></td>
<td>Q4 answer</td>
<td>Q5 answer</td>
</tr>
</tbody>
</table>

3. The opening hours might also influence my preferences. How would you construct useful features for the above businesses, if I have a preference toward businesses that are open late? Using your representation write down (in the table above) the features corresponding to each business (1 mark):

   A:

4. How would you incorporate opening-hour features if my preferences are toward businesses that are open outside of work hours (i.e., mon-fri/9am-5pm)? Write down the features corresponding to each business (1 mark):

   A:

5. Finally, suppose I want to model how people’s preferences change as a function of geography (based on 1,000 U.S. businesses including the five above), i.e.,

   \[
   \text{average rating} = x(\text{geographical features}) \cdot \theta
   \]

   How might you use the features available above (e.g. address or latitude/longitude) to model such geographical trends (1 mark)? (describe your solution, rather than writing down the actual features)
Diagnostics

6. Suppose we trained our model above by minimizing the regularized mean squared error, i.e.,

$$\arg\min_{\theta} \| y - X\theta \|^2_2 + \lambda \| \theta \|^2_2$$

Suppose that we split our data into training, validation, and test sets (and that we do so randomly, given plenty of data). Which of the plots below could correspond to the performance (i.e., MSE) on the training and validation sets? For each that could not, briefly explain why below (1 mark).

(hard) Suppose you are trying to predict star ratings using some regression model (e.g. $\alpha + \beta_u + \beta_i$). You figure that since the output of your model is a real number, while the labels themselves are integers (i.e., 1, 2, 3, 4, or 5), that you might simply round the output to the nearest integer to improve your predictor. You perform a quick check and find that when your model outputs the number $a$, the correct answer is $\lfloor a \rfloor$ with probability $\lceil a \rceil - a$, and $\lceil a \rceil$ with probability $a - \lfloor a \rfloor$ (e.g. if it outputs 4.2 then the correct answer is 4 80% of the time and 5 20% of the time; recall that $\lfloor \cdot \rfloor$ and $\lceil \cdot \rceil$ are the floor and ceiling function).

7. Based on the above description, would rounding be expected to increase or decrease the MSE, or have no effect? Explain your answer (2 marks).

A:

8. What effect would the above rounding procedure have if we were trying to optimize the mean absolute error (MAE) instead of the MSE (2 marks)? Explain.

A:
Section 2: Classification

The following is a list of Vin Diesel’s films:

<table>
<thead>
<tr>
<th>No.</th>
<th>Title</th>
<th>Year</th>
<th>IMDB rating</th>
<th>MPAA rating</th>
<th>length (minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>The Last Witch Hunter</td>
<td>2015</td>
<td>6.3</td>
<td>PG-13</td>
<td>106</td>
</tr>
<tr>
<td>2</td>
<td>Furious 7</td>
<td>2015</td>
<td>7.4</td>
<td>PG-13</td>
<td>137</td>
</tr>
<tr>
<td>3</td>
<td>Guardians of the Galaxy</td>
<td>2014</td>
<td>8.1</td>
<td>PG-13</td>
<td>121</td>
</tr>
<tr>
<td>4</td>
<td>Riddick</td>
<td>2013</td>
<td>6.4</td>
<td>R</td>
<td>119</td>
</tr>
<tr>
<td>5</td>
<td>Fast &amp; Furious 6</td>
<td>2013</td>
<td>7.2</td>
<td>PG-13</td>
<td>130</td>
</tr>
<tr>
<td>6</td>
<td>Fast Five</td>
<td>2011</td>
<td>7.3</td>
<td>PG-13</td>
<td>131</td>
</tr>
<tr>
<td>7</td>
<td>Fast &amp; Furious</td>
<td>2009</td>
<td>6.6</td>
<td>PG-13</td>
<td>107</td>
</tr>
<tr>
<td>8</td>
<td>The Fast and the Furious: Tokyo Drift</td>
<td>2006</td>
<td>6.0</td>
<td>PG-13</td>
<td>104</td>
</tr>
<tr>
<td>9</td>
<td>The Pacifier</td>
<td>2005</td>
<td>5.5</td>
<td>PG</td>
<td>95</td>
</tr>
<tr>
<td>10</td>
<td>The Chronicles of Riddick</td>
<td>2004</td>
<td>6.7</td>
<td>PG-13</td>
<td>119</td>
</tr>
<tr>
<td>11</td>
<td>xXx</td>
<td>2002</td>
<td>5.8</td>
<td>PG-13</td>
<td>124</td>
</tr>
<tr>
<td>12</td>
<td>The Fast and the Furious</td>
<td>2001</td>
<td>6.7</td>
<td>PG-13</td>
<td>106</td>
</tr>
<tr>
<td>13</td>
<td>Pitch Black</td>
<td>2000</td>
<td>7.1</td>
<td>R</td>
<td>109</td>
</tr>
<tr>
<td>14</td>
<td>The Iron Giant</td>
<td>1999</td>
<td>8.0</td>
<td>PG</td>
<td>86</td>
</tr>
<tr>
<td>15</td>
<td>Saving Private Ryan</td>
<td>1998</td>
<td>8.6</td>
<td>R</td>
<td>169</td>
</tr>
</tbody>
</table>

You hear a rumor that Vin Diesel has a new film coming out that is (A) Over two hours long (B) Rated PG-13 (C) Has the word “Furious” in the title. Let’s try to estimate the probability that it will (D) have an IMDB rating of 7.0 or above.

9. Based on the data above (and not making any other assumptions) write down the probability

\[ p(D|A \land B \land C) \]

(1 mark) A:

10. The above probability may be unreliable as it is based on very few observations that exhibit the required features. So, we’ll try to decide whether D is likely to be true or not following the Naïve Bayes assumption. Write down all of the terms involved and finally the probability ratio, and the conclusion you draw as a result (2 marks).

A:

11. Can you comment on the appropriateness of the naïve bayes assumption for this task (i.e., predicting IMDB ratings based on movie features) (1 mark)?

A:

Evaluation measures

Suppose we are performing a ranking task to try and identify pages that are relevant to some particular search query, and that we achieve this by building a logistic regressor that outputs a score indicating the probability that a page is relevant. Suppose the scores we obtain are the following:
12. Complete the table below by ranking pages in decreasing order of confidence. (Roughly) plot the precision against the recall to the right of the table (3 marks).

<table>
<thead>
<tr>
<th>page id</th>
<th>confidence</th>
<th>actually relevant?</th>
<th>precision@k</th>
<th>recall@k</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>0.95</td>
<td>yes</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Section 3: Communities & clustering

13. Suppose a social network is divided into the two communities shown below (filled vs. unfilled nodes). If we wanted an algorithm to find these communities automatically, which of ratio cuts versus normalized cuts would be more appropriate and why (1 mark)?

A:

14. What would be the result of running clique percolation on the graphs below (3 marks)? Circle the communities that would be found directly on the graphs.
15. Suppose you ran hierarchical clustering on the points below, resulting in the dendrogram shown in the center. How would you use the output of this algorithm (i.e., the clusters/dendrogram) to generate useful feature representations for the original points? Write your features for the 7 points below (1 mark).

A:

![Dendrogram Image]

Algorithm design

16. Suppose you wanted to design a system to estimate what tip a prospective fare would give for a taxi ride in San Diego. Describe below what data and features you would collect to estimate this value, and what techniques you would use to solve the task (3 marks).

A:

![Algorithm Design Image]

Here are a few more graphs in case you need to re-write your clique-percolation solutions:
Algorithm 1 Ratio cut

Choose communities \( c \in C \) that minimize \( \frac{1}{2} \sum_{c \in C} \frac{\text{edges in cut} \ (c, \bar{c})}{|c|} \)

Algorithm 2 Normalized cut

Choose communities \( c \in C \) that minimize \( \frac{1}{2} \sum_{c \in C} \frac{\text{cut}(c, \bar{c})}{\sum \text{degrees in } c} \)

Algorithm 3 Clique percolation with parameter \( k \)

Initially, all \( k \)-cliques in the graph are communities

while there are two communities that have a \((k-1)\)-clique in common do
    merge both communities into a single community

Algorithm 4 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

Naïve Bayes:

\[
p(label|features) \sim \frac{p(label) \prod_i p(feature_i|label)}{p(features)}
\]

Precision:

\[
\frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|}
\]

Recall:

\[
\frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{relevant documents}\}|}
\]

Write any additional answers/corrections/comments here: