Due data: 9/25/2019, end of the day.

For question 1-3, please submit a PDF file via Canvas.

For question 4 (programming question), please submit an .ipynb file via Canvas.

Please answer the following questions:

- 1. [6 points] Prove Bayes' Theorem. Briefly explain why it is useful for machine learning problems, i.e., by converting posterior probability to likelihood and prior probability.
- 2. [10 points] In Lecture 3-1, we gave the normal equation (i.e., closed-form solution) for linear regression using MSE as the cost function. **Prove that the closed-form solution for Ridge Regression** is $\mathbf{w} = (\lambda I + X^T \cdot X)^{-1} \cdot X^T \cdot \mathbf{y}$, where I is the identity matrix, $X = (x^{(1)}, x^{(2)}, \dots, x^{(m)})^T$ is the input data matrix, $x^{(i)} = (1, x_1, x_2, \dots, x_n)$ is the ith data sample, and $y = (y^{(1)}, y^{(2)}, \dots, y^m)$. Assume the hypothesis function $h_w(x) = w_0 + w_1x_1 + w_2x_2 + \dots + w_nx_n$, and $y^{(j)}$ is the measurement of $h_w(x)$ for the jth training sample. The cost function of the Ridge Regression is $E(\mathbf{w}) = MSE(\mathbf{w}) + \frac{\lambda}{2}\sum_{i=1}^m w_i^2$. [Hint: please refer to the proof of the normal equation of linear regression].
- 3. [10 points] Recall the multi-class Softmax Regression model on page 16 of Lecture 3-3. Assume we have K different classes. The posterior probability is $\hat{p}_k = \delta(s_k(x))_k = \frac{\exp(s_k(x))}{\sum_{j=1}^K s_j(x)}$ for k = 1, 2, ..., K, where $s_k(x) = \theta_k^T \cdot x$, and input x is an n-dimension vector.
 - 1) To learn this Softmax Regression model, how many parameters we need to estimate? What are these parameters?
 - 2) Consider the cross-entropy cost function $J(\theta)$ (see page 16 of Lecture 3-3) of m training samples $\{(x_i, y_i)\}_{i=1,2,...,m}$. Derive the gradient of $J(\theta)$ regarding to θ_k as shown in page 17 of Lecture 3-3

Programming Problem:

- 4. [44 points] In this problem, we write a program to find the coefficients for a linear regression model for the dataset provided (data2.txt). Assume a linear model: $y = w_0 + w_1*x$. You need to
 - 1) Plot the data (i.e., x-axis for 1st column, y-axis for 2nd column),

and use Python to implement the following methods to find the coefficients:

- 2) Normal equation, and
- 3) Gradient Descent using **batch** AND **stochastic** modes respectively:
 - a) Determine an appropriate termination condition (e.g., when cost function is less than a threshold, and/or after a given number of iterations).
 - b) Print the cost function vs. iterations for each mode; compare and discuss the accuracy of batch and stochastic modes.
 - c) Did you see overfitting? If yes, choose one regularization method to control the overfitting. Plot the cost function vs. iteration for each mode again. Discuss how overfitting is controlled if any.
 - d) Choose a best learning rate. For example, you can plot cost function vs. learning rate to determine the best learning rate.