Gregory Ditzler

ECE523: Engineering Applications of Machine Learning and Data Analytics Due 02/10/2017 @ 11:59PM (D2L)

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are partially correc		n for answers that	given for answers that are wrong or illegible. for credit.
	Theory:		
	Practice:		
	Total:		

Part A: Theory (15pts)

(5pts) Linear Regression and Regularization

In class we derived and discussed linear regression in detail. Find the result of minimize the loss of sum of the squared errors; however, add in a penalty for an L_2 penalty on the weights. More formally,

$$\arg\min_{\mathbf{w}} \left\{ \sum_{i} (\mathbf{w}^{\mathsf{T}} \mathbf{x}_{i} - y_{i})^{2} + \lambda \|\mathbf{w}\|_{2}^{2} \right\}$$
 (1)

How does this change the solution to the original linear regression solution? What is the impact of adding in this penalty?

(5pts) Density Estimation

In k-nearest neighbors (KNN), the classification is achieved by majority vote in the vicinity of data. Suppose there are two classes of data each of n/2 points overlapped to some extent in a 2-dimensional space. Describe what happens to the training error (using all available data) when the neighbor size k varies from n to 1.

(5pts) Feature Selection & Preprocessing

A friend asks you for some help with a feature selection project. Your friend goes out and collects data, \mathcal{D} , for their project. Using \mathcal{D} , your friend tries many subsets $\mathcal{F} \subset \mathcal{X}$ by adapting \mathcal{F} based on the error of a classifier. They return \mathcal{F} that corresponds to the smallest classification error.

This is the procedure they carry out to validate the impact of the feature selection routine. This procedure is repeated

- Make a new data set \mathcal{D}' with \mathcal{F} features using the feature selection routine.
- Repeat 50 times
 - Split \mathcal{D}' into randomized training & testing sets (80/20% splits)
 - Train a classifier and record its error
- Report the error averaged over 50 trials

Critique and respond to how your friend performed their analysis.

Part B: Practice (25pts)

You are free to use functions already implemented in Matlab, Python or R with the exception of problem 1. I recommend using Python's Scikit-learn (http://scikit-learn.org/stable/) as is implements most of the methods we will be discussing in this course... as well as problems in this homework!

(10pts) Logistic Regression on Synthetic and Real-World Data

Write your own implementation of logistic regression and implement your model on either real-world (see Github data sets), or synthetic data. If you simply use Scikit-learn's (R's, Matlab's, or another builtin procedure) implementation of the logistic regression classifier then you'll receive a maximum of 6 out of 15 points. A full 10/10 will be awarded to those that actually implement logistic regression using the optimization of cross-entropy using stochastic gradient descent.

(5pts) Dimensionality Reduction + 2 Bonus

Choose 10 data sets of your choice from the ECE523. Implement a comparison between either two classifiers of your choice, or a classifier with does and does not using a preprocessing step (i.e., feature selection, PCA, etc.), and report the accuracies of the two models in table for (e.g., a 10×2 table of classifier accuracies). For two bonus points use a hypothesis testing procedure from homework #1 to determine if there is statistical significance (i.e., do both approaches perform equally well).

(10pts) Density Estimation in Practice

The ECE523 Github page has code for generating data from a checkerboard data set. Generate checkerboard data from two classes and use any density estimate technique we discussed to classify new data using

$$\widehat{P}(Y|X) = \frac{\widehat{P}(X|Y)\widehat{P}(Y)}{\widehat{P}(X)}$$

where $\widehat{P}(Y|X)$ is your estimate of the posterior given you estimates of $\widehat{P}(X|Y)$ using a density estimator and $\widehat{P}(Y)$ using a maximum likelihood estimator.