

Math 7243 Machine Learning - Homework 3

For programming questions, you can only use **numpy** library, and Matplotlib for plotting. You should not use scikit-learn or statmodel libraries.

Question 1. Softmax regression Recall the setup of logistic regression: We assume that the posterior probability is of the form

$$p(Y = 1|\vec{x}) = \frac{1}{1 + e^{-\beta^T \vec{x}}}$$

This assumes that $Y|X$ is a Bernoulli random variable. We now turn to the case where $Y|X$ is a multinomial random variable over K outcomes. This is called softmax regression, because the posterior probability is of the form

$$p(Y = k|\vec{x}) = \frac{e^{\beta_k^T \vec{x}}}{\sum_{j=1}^K e^{\beta_j^T \vec{x}}}$$

which is called the softmax function. Assume we have observed data $D = \{\vec{x}^{(i)}, y^{(i)}\}_{i=1}^N$. Our goal is to learn the weight β_1, \dots, β_K .

- (1) Find the negative log likelihood of the data $l(\beta_1, \dots, \beta_K) = -\log L(\beta_1, \dots, \beta_K) = -\log P(Y|X)$
- (2) We want to minimize the negative log likelihood. To combat overfitting, we put a regularizer on the objective function. Find the **gradient** w.r.t. β_k of the regularized objective

$$l(\beta_1, \dots, \beta_K) + \lambda \sum_{k=1}^K \|\beta_k\|^2$$

- (3) State the gradient updates for both batch gradient descent and stochastic gradient descent.

Question 2. Logistics Regression Consider the categorical learning problem consisting of a data set with two labels:

Label 1:

| | | | | | |
|-------|-------|------|------|------|------|
| X_1 | 3.81 | 0.23 | 3.05 | 0.68 | 2.67 |
| X_2 | -0.55 | 3.37 | 3.53 | 1.84 | 2.74 |

Label 2:

| | | | | | |
|-------|-------|-------|-------|-------|-------|
| X_1 | -2.04 | -0.72 | -2.46 | -3.51 | -2.05 |
| X_2 | -1.25 | -3.35 | -1.31 | 0.13 | -2.82 |

- (1) Use **gradient descent** to find the logistic regression model

$$p(Y = 1|\vec{x}) = \frac{1}{1 + e^{-\beta^T \vec{x}}}$$

and the boundary. (Plot the boundary, only use numpy and Matplotlib.)

- (2) Try **quadratic** Logistics Regression method for this question and obtain an quadratic boundary. (bonus)
(Hint: this means to use new features: $X_1, X_2, X_1^2, X_1X_2, X_2^2$.)

Question 3. - Linear Discriminant Analysis: Consider the same categorical learning problem consisting of a data set with two labels:

Label 1:

| | | | | | | |
|-------|-------|------|------|------|------|--|
| X_1 | 3.81 | 0.23 | 3.05 | 0.68 | 2.67 | |
| X_2 | -0.55 | 3.37 | 3.53 | 1.84 | 2.74 | |

Label 2:

| | | | | | | |
|-------|-------|-------|-------|-------|-------|--|
| X_1 | -2.04 | -0.72 | -2.46 | -3.51 | -2.05 | |
| X_2 | -1.25 | -3.35 | -1.31 | 0.13 | -2.82 | |

- For each label above, the data follow a multivariate normal distribution $\text{Normal}(\mu_i, \Sigma)$ where the covariance Σ is the same for both label 1 and for label 2. Fit a pair of Gaussian discriminant functions to the labels by computing the covariances, means, and proportions of datapoints as discussed in the Linear Discriminant Analysis section. You may use a computer, but you should **not** use an LDA solver. You should report the values for μ_i and Σ . (Hint, since we use LDA, you need to compute Σ using all data.)
- Give the **formula for the line** forming the discretion boundary. Plot the points and boundary.
- Use the **QDA** method for this question and obtain an quadratic boundary. (Hint, you need to calculate Σ_1 and Σ_2 separately.)
- Try quadratic LDA method for this question and obtain an quadratic boundary. (bonus)