

# CSE 5523 Homework 3: Parameter Estimation

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## Problem 1

Consider the following data set on lung diseases. Your goal is to build a Naïve Bayes classifier that predicts whether a person has Bronchitis or Tuberculosis, given his/her symptoms.

Disease	X-ray Shadow	Dyspnea	Lung Inflammation
Bronchitis	Yes	Yes	Yes
Bronchitis	Yes	Yes	Yes
Bronchitis	No	No	Yes
Tuberculosis	Yes	Yes	No
Tuberculosis	Yes	No	No
Tuberculosis	No	No	Yes

1. (1 point) List the distributions that would be learned if you use a maximum likelihood estimate (MLE) to estimate the parameters of a Naïve Bayes model from this data (e.g.  $P(\text{Dyspnea}|\text{Bronchitis}) = ?$ ). Include all of the parameters. Show your work.
2. (1 point) Based on your learned model, diagnose a patient with the following symptoms (show your work):

X-ray Shadow	Dyspnea	Lung Inflammation
Yes	No	Yes

## Problem 2

Assume you are given a dataset of  $n$  real numbers  $D = \{X^1, X^2, \dots, X^n\}$ ,  $X^i \in \mathcal{R}$ . Derive the maximum likelihood mean,  $\mu$  and variance,  $\sigma$  parameters of a 1-dimensional Gaussian distribution.

1. (1 point) Write down the log-likelihood of  $D$  as a function of  $\mu$  and  $\sigma$ ,  $\mathcal{L}(\mu, \sigma)$ .
2. (1 point) Compute the partial derivative of  $\mathcal{L}(\mu, \sigma)$  with respect to  $\mu$ , equate to zero and solve for  $\mu$ .
3. (1 point) Compute the partial derivative of  $\mathcal{L}(\mu, \sigma)$  with respect to  $\sigma$ , equate to zero and solve for  $\sigma$ .

### Problem 3

Consider a training sample of inputs  $X^1, X^2, \dots, X^n$  and outputs  $Y^1, Y^2, \dots, Y^n$ , where inputs are real-valued vectors  $X^i \in \mathcal{R}^V$  and outputs are binary  $Y^i \in [0, 1]$ .

Recall (from the slides presented in class) that the conditional log likelihood can be written as follows:

$$\begin{aligned}
 \mathcal{L}(W) &= \sum_l Y^l \log P(Y = 1|X^l, W) + (1 - Y^l) \log P(Y = 0|X^l, W) \\
 &= \sum_l Y^l \log \frac{P(Y = 1|X^l, W)}{P(Y = 0|X^l, W)} + \log P(Y = 0|X^l, W) \\
 &= \sum_l Y^l \left( w_0 + \sum_{i=1}^V w_i X_i^l \right) - \log \left( 1 + \exp(w_0 + \sum_{i=1}^V w_i X_i^l) \right)
 \end{aligned}$$

1. (2 points) Show that the partial derivative of  $\mathcal{L}(W)$  with respect to  $w_i$  is as follows:

$$\frac{\partial \mathcal{L}(W)}{\partial w_i} = \sum_l X_i^l (Y^l - P(Y = 1|X^l, W))$$

2. (2 points) Now, assume a zero-mean Gaussian prior over the weights:

$$P(w_i) = \mathcal{N}(0, \sigma)$$

Write down the expression for the posterior distribution over  $w_i$ , and derive the gradient (e.g. that can be used for estimating MAP parameters in gradient decent).