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Aug 09 26

## COGS 118A Spring 2016 - Assignment #2

Due: April 19, 2017, 11:59pm

Grade: \_\_\_\_ out of 100 points

### Instructions:

Please answer the questions below and insert your answers to create a pdf file (you can have the hand-written version and scan it to create a pdf file); submit your file to TED (ted.ucsd.edu) by 11:59pm, 04/19/2016. You may search information online but you have to use your own words to answer the questions.

**Late policy:** 5% of the total points will be deducted for the first late day, then every 10% of the total points will be deducted for every extra day past due.

## 1 (10 points) Probability & Events

Given three events  $A, B, C$  with  $P(A) = 1/2$ ,  $P(B) = 1/3$ ,  $P(C) = 1/5$ , and  $P(A, B, C) = 1/30$ , can we determine whether  $A, B, C$  are all independent? Why?

$A, B, C$  are independent iff  $A \perp\!\!\!\perp B, B \perp\!\!\!\perp C, \text{ and } C \perp\!\!\!\perp A$ . However,  $A \perp\!\!\!\perp B$  iff  $\Pr(A, B) = \Pr(A) \cdot \Pr(B)$  iff  $\Pr(A|B) = \Pr(A)$  iff  $\Pr(B|A) = \Pr(B)$ .

From the provided information, it is not enough to determine if  $A \perp\!\!\!\perp B$ .  
Henceforth, it is inconclusive to determine whether  $A, B, C$  are all independent.

## 2 (20 points) Conditional Probability

Below describes some standard definition about a test:

- True positive rate (correctly identified):  $P(\text{test}+ | \text{sick}+)$  Sick people correctly diagnosed as sick
- False positive rate (incorrectly identified):  $P(\text{test}+ | \text{sick}-)$  Healthy people incorrectly identified as sick
- True negative rate (correctly rejected):  $P(\text{test}- | \text{sick}-)$  Healthy people correctly identified as healthy
- False negative rate (incorrectly rejected):  $P(\text{test}- | \text{sick}+)$  Sick people incorrectly identified as healthy

A mammogram tests for breast cancer. The true positive rate of a particular mammogram is 97% ( $P(\text{test}+ | \text{cancer}+)$ ). The true negative rate is also pretty good, at 93% ( $P(\text{test}- | \text{cancer}-)$ ). If the frequency of breast cancer in the population is  $P(\text{cancer}+) = 0.05\%$ , and people are randomly selected to receive mammograms.

$$\Pr(\text{test}+ | \text{cancer}-) = 1 - \Pr(\text{test}- | \text{cancer}-) = 0.07$$

$$\Pr(\text{test}- | \text{cancer}+) = 1 - \Pr(\text{test}+ | \text{cancer}+) = 0.03$$

## 2.1

What is the probability of having breast cancer, given they got positive test results,  $P(\text{cancer}+|\text{test}+)$ ?

*Hint:* you can simply use the conditional probability equation to derive this.

$$\begin{aligned}\Pr(\text{cancer}+|\text{test}+) &= \frac{\Pr(\text{test}+|\text{cancer}+)\cdot\Pr(\text{cancer}+)}{\Pr(\text{test}+|\text{cancer}+)\cdot\Pr(\text{cancer}+)+\Pr(\text{test}+|\text{cancer}-)\cdot\Pr(\text{cancer}-)} \\ &= \frac{(0.97)(0.05)}{(0.97)(0.05)+(0.03)(0.95)} = \frac{0.0485}{0.115} = 0.422\end{aligned}$$

## 2.2

What is the probability of not having breast cancer, given they got negative test results,  $P(\text{cancer}-|\text{test}-)$ ?

$$\begin{aligned}\Pr(\text{cancer}-|\text{test}-) &= \frac{\Pr(\text{test}-|\text{cancer}-)\cdot\Pr(\text{cancer}-)}{\Pr(\text{test}-|\text{cancer}-)\cdot\Pr(\text{cancer}-)+\Pr(\text{test}-|\text{cancer}+)\cdot\Pr(\text{cancer}+)} \\ &= \frac{(0.93)(0.95)}{(0.93)(0.95)+(0.03)(0.05)} = \frac{0.8835}{0.885} = 0.998\end{aligned}$$

## 2.3

Compute precision, recall, and  $F - \text{value} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$ .

$$\text{Precision} = \Pr(\text{cancer}+|\text{test}+) = 0.422$$

$$\text{Recall} = \Pr(\text{test}+|\text{cancer}+) = 0.97$$

$$\Rightarrow F\text{-value} = \frac{2 \cdot \text{Precision} \cdot \text{recall}}{\text{Precision} + \text{recall}} = \frac{2 \cdot (0.422)(0.97)}{0.422 + 0.97} = \frac{0.819}{1.392} = 0.588$$

## 3 (25 points) Communication Channel

In a communication channel shown in Figure below signal 3 is sent more frequently than 1, with  $P(X=3) = 3 \times P(X=1)$ ;  $P(X=2) = 2 \times P(X=1)$ .

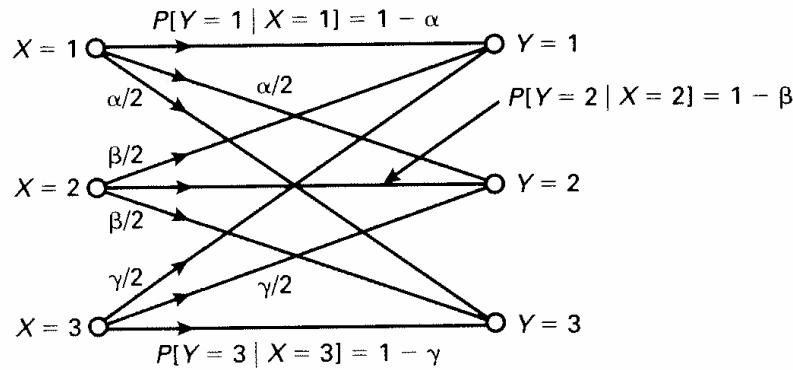
*Hint:* Use the conditional probability equation discussed in the class. Consider  $\alpha$ ,  $\beta$ , and  $\gamma$  as fixed value, and carry  $\alpha$ ,  $\beta$ , and  $\gamma$  in your answers, if needed.

$$\begin{aligned}3.1 \quad \Pr(X=1) &= \frac{1}{6} \quad \Pr(X=3) = \frac{3}{6} \quad \text{Let } \Pr(X=1) = \delta \\ \Pr(X=2) &= \frac{2}{6} \quad \Rightarrow \delta = \frac{1}{6}\end{aligned}$$

When  $Y=1$  is observed; what is the conditional probability that  $X=1$  was sent?

$$\Pr(X=1|Y=1) = \frac{\Pr(Y=1|X=1) \cdot \Pr(X=1)}{\Pr(Y=1)} = \frac{\Pr(Y=1|X=1) \cdot \Pr(X=1)}{\sum_{k=1}^3 \Pr(Y=1|X=k) \cdot \Pr(X=k)}$$

$$P_Y(x=1|y=1) = \frac{(1-\alpha)\delta}{(1-\alpha)\delta + \beta\delta + \frac{3}{2}\alpha\delta} = \frac{(1-\alpha)}{(1-\alpha) + \beta + \frac{3}{2}\alpha}$$



### 3.2

What is  $P(X=1, Y=1)$ ,  $P(X=2, Y=1)$ ,  $P(X=3, Y=1)$ ?

$$\begin{aligned} P_Y(x=1, y=1) &= P_Y(x=1) = \frac{\delta}{\delta + \frac{\alpha}{2} + \frac{\beta}{6}} \\ P_Y(x=2, y=1) &= 0 \end{aligned}$$

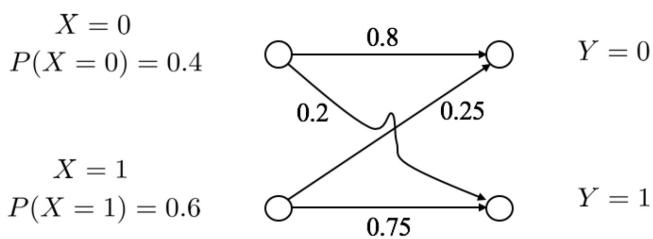
### 3.3

What is  $P(X=1|Y=1)$ ,  $P(X=2|Y=1)$ ,  $P(X=3|Y=1)$ ?

$$\begin{aligned} P_Y(x=1|y=1) &= 1 \\ P_Y(x=2|y=1) &= \frac{P_Y(x=2, y=1)}{P_Y(y=1)} = \frac{0}{\frac{\delta}{\delta + \frac{\alpha}{2} + \frac{\beta}{6}}} = 0 \\ P_Y(x=3|y=1) &= \frac{P_Y(x=3, y=1)}{P_Y(y=1)} = \frac{0}{\frac{\delta}{\delta + \frac{\alpha}{2} + \frac{\beta}{6}}} = 0 \end{aligned}$$

## 4 (15 points) Binary Communication System

For the binary communication system shown in Figure below compute  $P(Y=0)$  and  $P(Y=1)$ .



$$\begin{aligned} P_Y(y=0) &= P_Y(y=0|x=0) \cdot P_Y(x=0) + P_Y(y=0|x=1) \cdot P_Y(x=1) \\ &= (0.8)(0.4) + (0.25)(0.6) \\ &= 0.32 + 0.15 = 0.47 \end{aligned}$$

$$\begin{aligned} P_Y(y=1) &= P_Y(y=1|x=1) \cdot P_Y(x=1) + P_Y(y=1|x=0) \cdot P_Y(x=0) \\ &= (0.75)(0.6) + (0.2)(0.4) \\ &= 0.45 + 0.08 = 0.53 \end{aligned}$$

## 5 (15 points) Maximum Likelihood Estimation

By setting the derivatives of the log likelihood function equal to zero

$$\ln p(\mathbf{x}|\mu, \sigma^2) = -\frac{1}{2\sigma^2} \sum_{n=1}^N (x_n - \mu)^2 - \frac{N}{2} \ln \sigma^2 - \frac{N}{2} \ln(2\pi)$$

with respect to  $\mu$  and  $\sigma$ ,

$$\mu_{ML} = \arg \min_{\mu} - \sum_{n=1}^N \ln p(x_n; \mu, \sigma) = \underset{\mu}{\operatorname{argmax}} \sum_{n=1}^N \ln p(x_n; \mu, \sigma) = \sum_{n=1}^N (x_n - \mu)^2$$

$$\sigma_{ML} = \arg \min_{\sigma} - \sum_{n=1}^N \ln p(x_n; \mu_{ML}, \sigma) = \underset{\sigma}{\operatorname{argmax}} \sum_{n=1}^N \ln p(x_n; \mu_{ML}, \sigma) = \frac{1}{2\sigma^2} \sum_{n=1}^N (x_n - \mu_{ML})^2 - \frac{N}{2} \ln \sigma^2$$

verify the following results using the maximum likelihood estimation concept:

$$\mu_{ML} = \frac{1}{N} \sum_{n=1}^N x_n$$

$$\sigma_{ML} = \left[ \frac{1}{N} \sum_{n=1}^N (x_n - \mu_{ML})^2 \right]^{\frac{1}{2}}$$

$$\frac{d\mu_{ML}}{d\mu} = -2 \sum_{n=1}^N (x_n - \mu) \Rightarrow \frac{d\mu_{ML}}{d\mu} = 0 \text{ when } -2 \sum_{n=1}^N (x_n - \mu) = 0 \Leftrightarrow \sum_{n=1}^N (x_n - \mu) = 0 \Leftrightarrow \left( \sum_{n=1}^N x_n \right) - N\mu = 0 \Leftrightarrow \mu = \frac{1}{N} \sum_{n=1}^N x_n$$

$$\therefore \mu_{ML} = \frac{1}{N} \sum_{n=1}^N x_n$$

$$\frac{d\sigma_{ML}}{d\sigma} = \frac{\sum_{n=1}^N (x_n - \mu_{ML})^2}{\sigma^3} - \frac{N}{\sigma} \Rightarrow \frac{d\sigma_{ML}}{d\sigma} = 0 \text{ when } \frac{\sum_{n=1}^N (x_n - \mu_{ML})^2}{\sigma^3} - \frac{N}{\sigma} = 0 \Leftrightarrow \sum_{n=1}^N (x_n - \mu_{ML})^2 - \sigma^2 N = 0 \Leftrightarrow \sum_{n=1}^N (x_n - \mu_{ML})^2 = N\sigma^2 \Leftrightarrow \sigma = \left[ \frac{1}{N} \sum_{n=1}^N (x_n - \mu_{ML})^2 \right]^{\frac{1}{2}}$$

## 6 (15 points) Least Squares Estimation

Please download the file **data.mat** from the course website, and load it into your environment (Python or MATLAB). Now do the following procedures, paste your source code and show the result in your report:

**Python:**

- (0) Import Python packages and load data

```
import scipy.io as sio
import matplotlib.pyplot as plt
import numpy as np
```

```
data = sio.loadmat('data.mat')
x = data['x'].reshape([-1, 1])
y = data['y'].reshape([-1, 1])
```

- (1) Plot the data using plot function.

```
plt.plot(x, y)
plt.grid()
```

- (2) Create the matrix

```
X = np.hstack((np.ones((len(x),1)),np.power(x,1)))
```

- (3) Compute the least squares line over the given data by:

```
X_t = X.transpose((1,0))
sol = np.dot(np.linalg.inv(np.dot(X_t,X)),np.dot(X_t,y))
```

- (4) Overlay the computed least square line over the given data:

```
plt.hold(True)
plt.plot(x,sol[0]+sol[1]*x)
```

- (5) Assign a title to this figure:

```
plt.title('Least square line fitting')
plt.xlabel('x')
plt.ylabel('y')
```

- (6) Copy and paste the figure in your report.

## MATLAB:

- (1) Plot the data using plot function.

```
>> plot(x,y); grid;
```

- (2) Create the matrix

```
>> A = [x.^0 x.^1];
```

- (3) Compute the least squares line over the given data by:

```
>> sol = inv(A'*A)*A'*y;
```

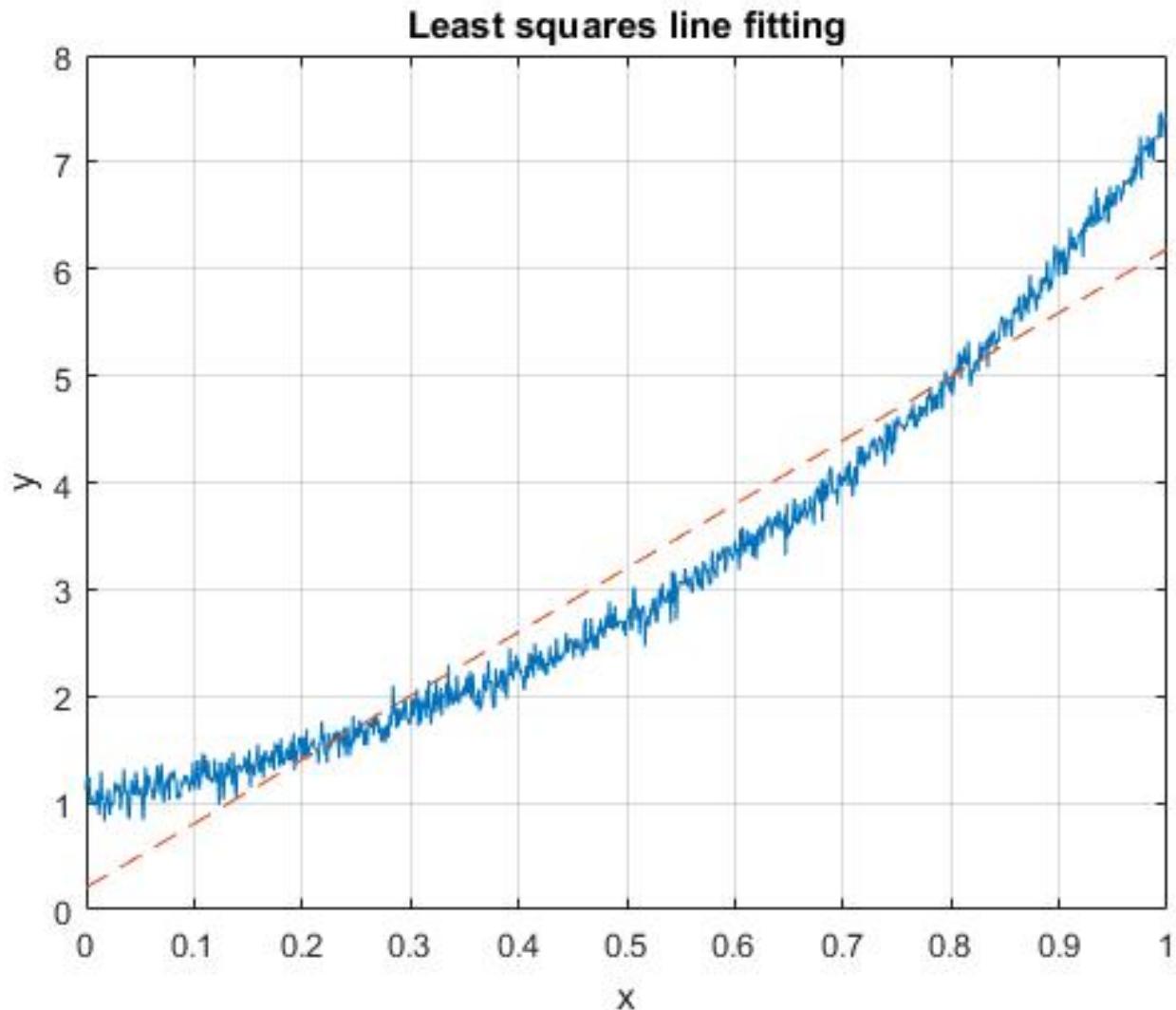
- (4) Overlay the computed least square line over the given data:

```
>> hold on; plot(x, sol(1)+sol(2)*x, '--');
```

- (5) Assign a title to this figure:

```
>> title('Least squares line fitting'); xlabel('x'); ylabel('y');
```

- (6) Copy and paste the figure in your report.



## 7 (5 points) Bonus Question

Starting with the equation for a Gaussian distribution,  $p(x; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$

$$\text{let } C = \frac{1}{\sigma\sqrt{2\pi}}$$

### 7.1

Show that the mean of  $p(x; 0, \sigma)$  is indeed at zero using the equation: mean =  $E[X] = \int_{-\infty}^{+\infty} xp(x)dx$ .

*Hint:* change variables to  $y = x^2/2$ ,  $dy = xdx$ .

$$E[X] = \int_{-\infty}^{+\infty} x p_r(x) dx = C \int_{-\infty}^{+\infty} x \exp\left\{-\frac{x^2}{2\sigma^2}\right\} dx = \\ \text{let } y = \frac{x^2}{2\sigma^2} \Rightarrow \sigma^2 dy = x dx \Rightarrow C \int_{-\infty}^{+\infty} x \exp\left\{-\frac{x^2}{2\sigma^2}\right\} dx = \sigma C \int_{-\infty}^{+\infty} e^{-y} dy = 0$$

$$\therefore E[X] = \int_{-\infty}^{+\infty} x p_r(x) dx = 0 \quad \square$$

### 7.2

Show that the most likely variable (with the highest probability density) is also  $\mu$  for  $p(x; \mu, \sigma)$ .

*Hint 1:* The derivative of a function is zero at the peak.

*Hint 2:* The peak of the log of the normal distribution  $\log p(x; \mu, \sigma)$  and that of the original normal distribution  $p(x; \mu, \sigma)$  are at the same  $x$  value.

By MLE, the most likely variable is when  $X^* = \arg \max_x \ln(p_r(x; \mu, \sigma)) = \arg \max_x \ln(p_r(x; \mu, \sigma))$

$$X^* = \arg \max_x \left[ \ln \left( p_r(x; \mu, \sigma) \right) \right] = \arg \max_x \left[ \ln \left( C \exp \left\{ -\frac{(x-\mu)^2}{2\sigma^2} \right\} \right) \right] = \arg \max_x \left[ \ln(C) - \frac{(x-\mu)^2}{2\sigma^2} \right] = \arg \min_x \left[ \frac{(x-\mu)^2}{2\sigma^2} \right]$$

$$\text{Let } f(x) = \frac{(x-\mu)^2}{2\sigma^2} \Rightarrow X^* = \arg \min_x f(x).$$

$$\frac{df(x)}{dx} = \frac{x-\mu}{\sigma^2} \Rightarrow \frac{df(x)}{dx} = 0 \text{ when } \frac{x-\mu}{\sigma^2} = 0 \Leftrightarrow x = \mu.$$

$$\therefore \text{by MLE, } X^* = \mu$$

$\therefore$  The most likely variable is also  $\mu$  for  $p_r(x; \mu, \sigma)$