# COMP3670: Introduction to Machine Learning

#### Errata: All corrections are in red.

**Note:** For the purposes of this assignment, if X is a random variable we let  $p_X$  denote the probability density function (pdf) of X,  $F_X$  to denote it's cumulative distribution function, and P to denote probabilities. These can all be related as follows:

$$P(X \le x) = F_X(x) = \int_{-\infty}^x p_X(z)dz$$

$$P(a \le X \le b) = F_X(b) - F_X(a) = \int_a^b p_X(z)dz$$

Often, we will simply write  $p_X$  as p, where it's clear what random variable the distribution refers to. You should show your derivations, but **you may use a computer algebra system (CAS)** to assist with integration or differentiation. We are not assessing your ability to integrate/differentiate here.<sup>1</sup>.

## Question 1 Continuous Bayesian Inference

5+5+2+4+4+6+6+5=37 credits

Let X be a random variable representing the outcome of a biased coin with possible outcomes  $\mathcal{X} = \{0,1\}, x \in \mathcal{X}$ . The bias of the coin is itself controlled by a random variable  $\Theta$ , with outcomes  $\theta \in \theta$ , where

$$\boldsymbol{\theta} = \{ \theta \in \mathbb{R} : 0 \le \theta \le 1 \}$$

The two random variables are related by the following conditional probability distribution function of X given  $\Theta$ .

$$p(X = 1 \mid \Theta = \theta) = \theta$$
$$p(X = 0 \mid \Theta = \theta) = 1 - \theta$$

We can use  $p(X = 1 \mid \theta)$  as a shorthand for  $p(X = 1 \mid \Theta = \theta)$ .

We wish to learn what  $\theta$  is, based on experiments by flipping the coin.

We flip the coin a number of times.<sup>3</sup> After each coin flip, we update the probability distribution for  $\theta$  to reflect our new belief of the distribution on  $\theta$ , based on evidence.

Suppose we flip the coin n times, and obtain the sequence of coin flips  $^4 x_{1:n}$ .

- a) Compute the new PDF for  $\theta$  after having observed n consecutive **ones** (that is,  $x_{1:n}$  is a sequence where  $\forall i.x_i = 1$ ), for an arbitrary prior pdf  $p(\theta)$ . Simplify your answer as much as possible.
- b) Compute the new PDF for  $\theta$  after having observed n consecutive **zeros**, (that is,  $x_{1:n}$  is a sequence where  $\forall i.x_i = 0$ ) for an arbitrary prior pdf  $p(\theta)$ . Simplify your answer as much as possible.
- c) Compute  $p(\theta|x_{1:n}=1^n)$  for the uniform prior  $p(\theta)=1$ .
- d) Compute the expected value  $\mu_n$  of  $\theta$  after observing n consecutive ones, with a uniform prior  $p(\theta) = 1$ . Provide intuition explaining the behaviour of  $\mu_n$  as  $n \to \infty$ .

For example, asserting that  $\int_0^1 x^2 \left(x^3 + 2x\right) dx = 2/3$  with no working out is adequate, as you could just plug the integral into Wolfram Alpha using the command Integrate [x^2(x^3 + 2x), {x,0,1}]

<sup>&</sup>lt;sup>2</sup>For example, a value of  $\theta = 1$  represents a coin with 1 on both sides. A value of  $\theta = 0$  represents a coin with 0 on both sides, and  $\theta = 1/2$  represents a fair, unbaised coin.

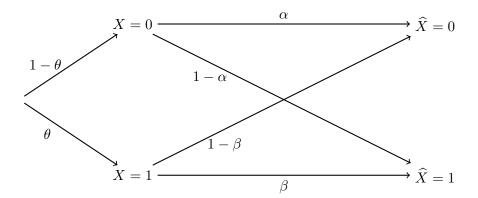
<sup>&</sup>lt;sup>3</sup>The coin flips are independent and identically distributed (i.i.d).

<sup>&</sup>lt;sup>4</sup>We write  $x_{1:n}$  as shorthand for the sequence  $x_1x_2...x_n$ .

- e) Compute the variance  $\sigma_n^2$  of the distribution of  $\theta$  after observing n consecutive ones, with a uniform prior  $p(\theta) = 1$ . Provide intuition explaining the behaviour of  $\sigma_n^2$  as  $n \to \infty$ .
- f) Compute the maximum a posteriori estimation  $\theta_{MAP_n}$  of the distribution on  $\theta$  after observing n consecutive ones, with a uniform prior  $p(\theta) = 1$ . Provide intuition explaining how  $\theta_{MAP_n}$  varies with n.
- g) Given we have observed n consecutive coin flips of ones in a row, what do you think would be a better choice for the best guess of the true value of  $\theta$ ?  $\mu_n$  or  $\theta_{MAP}$ ? Justify your answer.
- h) Plot the probability distributions  $p(\theta|x_{1:n}=1)$  over the interval  $0 \le \theta \le 1$  for  $n \in \{0,1,2,3,4\}$  to compare them. Assume  $p(\theta)=1$ .

## Question 2 Bayesian Inference on Imperfect Information (4+5+8+4+4=25 credits)

We have a Bayesian agent running on a computer, trying to learn information about what the parameter  $\theta$  could be in the coin flip problem, based on observations through a noisy camera. The noisy camera takes a photo of each coin flip and reports back if the result was a 0 or a 1. Unfortunately, the camera is not perfect, and sometimes reports the wrong value.<sup>5</sup> The probability that the camera makes mistakes is controlled by two parameters  $\alpha$  and  $\beta$ , that control the likelihood of correctly reporting a zero, and a one, respectively. Letting X denote the true outcome of the coin, and  $\widehat{X}$  denoting what the camera reported back, we can draw the relationship between X and  $\widehat{X}$  as shown.



So, we have

$$p(\hat{X} = 0 \mid X = 0) = \alpha$$

$$p(\hat{X} = 0 \mid X = 1) = 1 - \beta$$

$$p(\hat{X} = 1 \mid X = 1) = \beta$$

$$p(\hat{X} = 1 \mid X = 0) = 1 - \alpha$$

We would now like to investigate what posterior distributions are obtained, as a function of the parameters  $\alpha$  and  $\beta$ .

- a) (5 credits) Briefly comment about how the camera behaves for  $\alpha = \beta = 1$ , for  $\alpha = \beta = 1/2$ , and for  $\alpha = \beta = 0$ . For each of these cases, how would you expect this would change how the agent updates it's prior to a posterior on  $\theta$ , given an observation of  $\hat{X}$ ? (No equations required.)
- b) (10 credits) Compute  $p(\widehat{X} = x | \theta)$  for all  $x \in \{0, 1\}$ .
- c) (15 credits) The coin is flipped, and the camera reports seeing a one. (i.e. that  $\hat{X}=1$ .) Given an arbitrary prior  $p(\theta)$ , compute the posterior  $p(\theta|\hat{X}=1)$ . What does  $p(\theta|\hat{X}=1)$  simplify to when  $\alpha=\beta=1$ ? When  $\alpha=\beta=1/2$ ? When  $\alpha=\beta=0$ ? Explain your observations.

<sup>&</sup>lt;sup>5</sup>The errors made by the camera are i.i.d, in that past camera outputs do not affect future camera outputs.

- d) Evaluate  $p(\theta|\hat{X}=1)$  for the uniform prior  $p(\theta)=1$ . Simplify it under the assumption that  $\beta:=\alpha$ .
- e) (10 credits) Let  $\beta = \alpha$ . Plot  $p(\theta|\hat{X} = 1)$  as a function of  $\theta$ , for all  $\alpha \in \{0, \frac{1}{4}, \frac{2}{4}, \frac{3}{4}, 1\}$  on the same graph to compare them. Comment on how the shape of the distribution changes with  $\alpha$ . Explain your observations. (Assume  $p(\theta) = 1$ .)

#### Question 3

#### Relating Random Variables

(10+7+5+16=38 credits)

A casino offers a new game. Let  $X \sim f_X$  be a random variable on (0,1] with pdf  $p_X$ . Let Y be a random variable on  $[1,\infty)$  such that Y=1/X. A random number c is sampled from Y, and the player guesses a number  $m \in [1,\infty)$ . If the player's guess m was lower than c, then the player wins m-1 dollars from the casino (which means higher guesses pay out more money). But if the player guessed too high,  $(m \ge c)$ , they go bust, and have to pay the casino 1 dollar.

a) Show that the probability density function  $p_Y$  for Y is given by



- b) Hence, or otherwise, compute the expected profit for the player under this game. Your answer will be in terms of m and  $p_X$ , and should be as simplified as possible.
- c) Suppose the casino chooses a uniform distribution over (0,1] for X, that is,

$$p_X(x) = \begin{cases} 1 & 0 < x \le 1 \\ 0 & \text{otherwise} \end{cases}$$

What strategy should the player use to maximise their expected profit?

d) Find a pdf  $p_X : (0,1] \to \mathbb{R}$  such that for any B > 0, there exists a corresponding player guess m such that the expected profit for the player is at least B. (That is, prove that the expected profit for  $p_X$ , as a function of m, is unbounded.)

Make sure that your choice for  $p_X$  is a valid pdf, i.e. it should satisfy

$$\int_0^1 p_X(x)dx = 1 \text{ and } p_X(x) \ge 0$$

You should also briefly mention how you came up with your choice for  $p_X$ .

**Hint:** We want X to be extremely biased towards small values, so that Y is likely to be large, and the player can choose higher values of m without going bust.