Bayesian Machine Learning: Assignment #1

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Problem 1

(a) Using Integration by parts,

$$\mathrm{E}[X] = \int_{-\infty}^{\infty} xf(x)\,\mathrm{d}x = \int_{-\infty}^{\theta} x\cdot 0\,\mathrm{d}x + \int_{\theta}^{\infty} xe^{\theta-x}\,\mathrm{d}x = 1+\theta$$

$$\mathrm{Var}[X] = \mathrm{E}[X^2]-\mathrm{E}[X]^2 = \int_{\theta}^{\infty} x^2e^{\theta-x}\,\mathrm{d}x - (1+\theta)^2 = \theta^2+2(1+\theta)-(1+\theta)^2 = 1$$

(b) To show unbiasedness, compare θ with the exepectation. Note X_i's are i.i.d., and $\mathrm{E}[X_i]=1+\theta$ in (a):

$$\begin{aligned}
\mathrm{E}[\hat{\theta}_n] &= \mathrm{E}[\frac{1}{n}\sum_{i=1}^{n}(X_i-1)] \\
&= \frac{1}{n}\sum_{i=1}^{n}\mathrm{E}[X_i-1] \\
&= \frac{1}{n}\sum_{i=1}^{n}(\mathrm{E}[X_i]-1) \\
&= \frac{1}{n}\sum_{i=1}^{n}((1+\theta)-1) \\
&= \frac{1}{n}\sum_{i=1}^{n}\theta \\
&= \frac{1}{n}(n\theta) \\
&= \theta
\end{aligned}$$

(c) Let $Y_i = X_i - 1$. Then, $\mathrm{E}[Y_i]=\theta$ and $\mathrm{Var}[Y_i]=1$. Now, according to (b) and Central Limit Theorem,

$$\frac{\hat{\theta}_n-\theta}{1/\sqrt{n}} \xrightarrow{d} \mathcal{N}(0,1)$$

holds. Then, $100(1-\alpha)\%$ confidence interval of θ is $[\hat{\theta}_n - \frac{\Phi^{-1}(1-\frac{\alpha}{2})}{\sqrt{n}}, \hat{\theta}_n - \frac{\Phi^{-1}(\frac{\alpha}{2})}{\sqrt{n}}]$ where Φ is Cumulative Density Function (CDF) of unit normal distribution.

(d) According to given fact and that unit normal distribution is an even function, $\Phi^{-1}(0.025)=-1.96$ and $\Phi^{-1}(0.975)=1.96$. Thus, 95% confidence interval of θ is $[11.33-\frac{1.96}{\sqrt{3}}, 11.33+\frac{1.96}{\sqrt{3}}] = [10.20, 12.46]$. It is weird that the observed data 10.0 is contradictory for any θ in the obtained confidence interval according to the PDF of X.

Problem 2

1. The proof is straightforward:

$$\begin{aligned}
\mu(B) &= \mu(B\cap(A\cup A^c)) \\
&= \mu((B\cap A)\cup(B\cap A^c)) && \because \text{distributive law} \\
&= \mu(B\cap A)+\mu(B\cap A^c) && \because \text{countable additivity of } \mu \\
&= \mu(A)+\mu(B\cap A^c) && \because A\subset B \implies B\cap A = A \\
&\geq \mu(A) && \because \mu(B\cap A^c)\geq 0 : \text{nonnegativity of } \mu
\end{aligned}$$

2. Use induction. (Base case) We first show it holds for $n = 1$:

$$\begin{aligned}
\mu(\bigcup_{i=1}^{1} A_i) &= \mu(A_1) \\
&= \sum_{i=1}^{1} \mu(A_i) \\
&\leq \sum_{i=1}^{1} \mu(A_i)
\end{aligned}$$

(Inductive case) Assume it holds for $n = k$. Want to show it holds for $n = k+1$:

$$\begin{aligned}
\mu(\bigcup_{i=1}^{k+1} A_i) &= \mu(\bigcup_{i=1}^{k} A_i \cup A_{k+1}) \\
&= \mu(\bigcup_{i=1}^{k} A_i \uplus (A_{k+1} - \bigcup_{i=1}^{k} A_i)) && \because \text{simple Venn Diagram argument} \\
&= \mu(\bigcup_{i=1}^{k} A_i) + \mu(A_{k+1} - \bigcup_{i=1}^{k} A_i) && \because \text{countable additivity of } \mu \\
&\leq \mu(\bigcup_{i=1}^{k} A_i) + \mu(A_{k+1}) && \because (A_{k+1} - \bigcup_{i=1}^{k} A_i) \subseteq A_{k+1} \text{ and 1.} \\
&\leq \sum_{i=1}^{k} \mu(A_i) + \mu(A_{k+1}) && \because \text{inductive hypothesis} \\
&= \sum_{i=1}^{k+1} \mu(A_i)
\end{aligned}$$

□

Problem 3

Give an appropriate positive constant c such that $f(n) \leq c \cdot g(n)$ for all $n > 1$.

1. $f(n) = n^2 + n + 1$, $g(n) = 2n^3$
2. $f(n) = n\sqrt{n} + n^2$, $g(n) = n^2$
3. $f(n) = n^2 - n + 1$, $g(n) = n^2/2$

Solution
We solve each solution algebraically to determine a possible constant c.

Part One

$$\begin{aligned}
n^2 + n + 1 &= \\
&\leq n^2 + n^2 + n^2 \\
&= 3n^2 \\
&\leq c \cdot 2n^3
\end{aligned}$$

Thus a valid c could be when $c = 2$.

Part Two

$$
\begin{aligned}
n^2 + n\sqrt{n} = & \\
&= n^2 + n^{3/2} \\
&\leq n^2 + n^{4/2} \\
&= n^2 + n^2 \\
&= 2n^2 \\
&\leq c \cdot n^2
\end{aligned}
$$

Thus a valid c is $c = 2$.

Part Three

$$
\begin{aligned}
n^2 - n + 1 = & \\
&\leq n^2 \\
&\leq c \cdot n^2/2
\end{aligned}
$$

Thus a valid c is $c = 2$.

Problem 4

Let $\Sigma = \{0, 1\}$. Construct a DFA A that recognizes the language that consists of all binary numbers that can be divided by 5.

Let the state q_k indicate the remainder of k divided by 5. For example, the remainder of 2 would correlate to state q_2 because $7 \mod 5 = 2$.

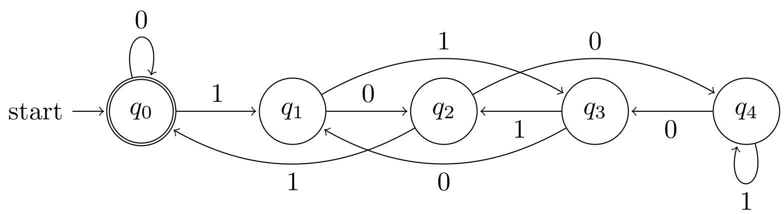

Figure 1: DFA, A, this is really beautiful, ya know?

Justification

Take a given binary number, x. Since there are only two inputs to our state machine, x can either become $x0$ or $x1$. When a 0 comes into the state machine, it is the same as taking the binary number and multiplying it by two. When a 1 comes into the machine, it is the same as multipying by two and adding one.

Using this knowledge, we can construct a transition table that tell us where to go:

	$x \mod 5 = 0$	$x \mod 5 = 1$	$x \mod 5 = 2$	$x \mod 5 = 3$	$x \mod 5 = 4$
$x0$	0	2	4	1	3
$x1$	1	3	0	2	4

Therefore on state q_0 or ($x \mod 5 = 0$), a transition line should go to state q_0 for the input 0 and a line should go to state q_1 for input 1. Continuing this gives us the Figure 1.

Problem 5

Write part of **Quick-Sort**($list, start, end$)

```
function QUICK-SORT(list, start, end)
    if start ≥ end then
        return
    end if
    mid ← PARTITION(list, start, end)
    QUICK-SORT(list, start, mid − 1)
    QUICK-SORT(list, mid + 1, end)
end function
```

Algorithm 1: Start of QuickSort

Problem 6

Suppose we would like to fit a straight line through the origin, i.e., $Y_i = \beta_1 x_i + e_i$ with $i = 1, \ldots, n$, $\mathrm{E}[e_i] = 0$, and $\mathrm{Var}[e_i] = \sigma_e^2$ and $\mathrm{Cov}[e_i, e_j] = 0, \forall i \neq j$.

Part A

Find the least squares esimator for $\hat{\beta}_1$ for the slope β_1.

Solution

To find the least squares estimator, we should minimize our Residual Sum of Squares, RSS:

$$\begin{aligned} RSS &= \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 \\ &= \sum_{i=1}^{n} \left(Y_i - \hat{\beta}_1 x_i\right)^2 \end{aligned}$$

By taking the partial derivative in respect to $\hat{\beta}_1$, we get:

$$\frac{\partial}{\partial \hat{\beta}_1}(RSS) = -2\sum_{i=1}^{n} x_i(Y_i - \hat{\beta}_1 x_i) = 0$$

This gives us:

$$\begin{aligned} \sum_{i=1}^{n} x_i(Y_i - \hat{\beta}_1 x_i) &= \sum_{i=1}^{n} x_i Y_i - \sum_{i=1}^{n} \hat{\beta}_1 x_i^2 \\ &= \sum_{i=1}^{n} x_i Y_i - \hat{\beta}_1 \sum_{i=1}^{n} x_i^2 \end{aligned}$$

Solving for $\hat{\beta}_1$ gives the final estimator for β_1:

$$\hat{\beta}_1 = \frac{\sum x_i Y_i}{\sum x_i^2}$$

Problem 6 continued on next page...

Part B

Calculate the bias and the variance for the estimated slope $\hat{\beta_1}$.

Solution

For the bias, we need to calculate the expected value $\mathrm{E}[\hat{\beta_1}]$:

$$
\begin{aligned}
\mathrm{E}[\hat{\beta_1}] &= \mathrm{E}\left[\frac{\sum x_i Y_i}{\sum x_i^2}\right] \\
&= \frac{\sum x_i \mathrm{E}[Y_i]}{\sum x_i^2} \\
&= \frac{\sum x_i(\beta_1 x_i)}{\sum x_i^2} \\
&= \frac{\sum x_i^2 \beta_1}{\sum x_i^2} \\
&= \beta_1 \frac{\sum x_i^2 \beta_1}{\sum x_i^2} \\
&= \beta_1
\end{aligned}
$$

Thus since our estimator's expected value is β_1, we can conclude that the bias of our estimator is 0.

For the variance:

$$
\begin{aligned}
\mathrm{Var}[\hat{\beta_1}] &= \mathrm{Var}\left[\frac{\sum x_i Y_i}{\sum x_i^2}\right] \\
&= \frac{\sum x_i^2}{\sum x_i^2 \sum x_i^2} \mathrm{Var}[Y_i] \\
&= \frac{\sum x_i^2}{\sum x_i^2 \sum x_i^2} \mathrm{Var}[Y_i] \\
&= \frac{1}{\sum x_i^2} \mathrm{Var}[Y_i] \\
&= \frac{1}{\sum x_i^2} \sigma^2 \\
&= \frac{\sigma^2}{\sum x_i^2}
\end{aligned}
$$

Problem 7

Prove a polynomial of degree k, $a_k n^k + a_{k-1} n^{k-1} + \ldots + a_1 n^1 + a_0 n^0$ is a member of $\Theta(n^k)$ where $a_k \ldots a_0$ are nonnegative constants.

Proof. To prove that $a_k n^k + a_{k-1} n^{k-1} + \ldots + a_1 n^1 + a_0 n^0$, we must show the following:

$$\exists c_1 \exists c_2 \forall n \geq n_0,\ c_1 \cdot g(n) \leq f(n) \leq c_2 \cdot g(n)$$

For the first inequality, it is easy to see that it holds because no matter what the constants are, $n^k \leq a_k n^k + a_{k-1} n^{k-1} + \ldots + a_1 n^1 + a_0 n^0$ even if $c_1 = 1$ and $n_0 = 1$. This is because $n^k \leq c_1 \cdot a_k n^k$ for any nonnegative constant, c_1 and a_k.

Taking the second inequality, we prove it in the following way. By summation, $\sum_{i=0}^{k} a_i$ will give us a new constant, A. By taking this value of A, we can then do the following:

$$\begin{aligned}
a_k n^k + a_{k-1} n^{k-1} + \ldots + a_1 n^1 + a_0 n^0 = & \\
& \leq (a_k + a_{k-1} \ldots a_1 + a_0) \cdot n^k \\
& = A \cdot n^k \\
& \leq c_2 \cdot n^k
\end{aligned}$$

where $n_0 = 1$ and $c_2 = A$. c_2 is just a constant. Thus the proof is complete. □

Problem 18

Evaluate $\sum_{k=1}^{5} k^2$ and $\sum_{k=1}^{5}(k-1)^2$.

Problem 19

Find the derivative of $f(x) = x^4 + 3x^2 - 2$

Problem 6

Evaluate the integrals $\int_0^1 (1 - x^2)\,\mathrm{d}x$ and $\int_1^\infty \frac{1}{x^2}\,\mathrm{d}x$.

Problem 20

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