Section #3 Solutions

Based on the work of many CS109 staffs

1. **Email Predictions:** Let’s say that on average you get an email every 5 minutes. Assume that the time between email arrivals is exponentially distributed. What is the probability that you get no emails in the next 10 minutes?

   Let $X$ be the number of minutes until the next email. $X \sim \text{Exp}(\lambda = \frac{1}{5})$.

   $P(X > 10) = 1 - F_X(10) = 1 - (1 - e^{-\lambda t}) = e^{-2} \approx 0.1353$

   Alternatively, let $Y$ be the number of emails you get in the next 10 minutes. The average email rate is 2 emails per 10 minutes. $Y \sim \text{Poi}(\lambda = 2)$.

   $P(Y = 0) = \frac{2^0 e^{-2}}{0!} = e^{-2} \approx 0.1353$

2. **Are we due for an earthquake?** After the class in which we talked about the probability of earthquakes, a student asked: “Doesn’t the probability of an earthquake happening change based on the fact that we haven’t had one for a while?” Let’s explore! Recall the USGS rate of earthquakes of magnitude 8+ in California is $\lambda = 0.002$ earthquakes per year.

   a. What is the probability of no 8+ earthquakes in four years after the 1906 earthquake (recall that earthquakes are exponentially distributed)?

   b. What is the probability of no 8+ earthquakes in the 117 years between 1906 and four years from now?

   c. What is the probability of no 8+ earthquakes in the 117 years between 1906 and four years from now given that there have been no earthquakes in the last 113 years?

   d. Did you notice anything interesting? Would this work for any value of $\lambda$?

   a. Let $X$ be the time until an earthquake. $X \sim \text{Exp}(\lambda = 0.002)$.

   $P(X \geq 4) = 1 - P(X < 4) = 1 - F_X(4) = 1 - [1 - e^{-0.002 \cdot 4}] = e^{-0.008} \approx 0.992$
b. 

\[
P(X \geq 117) = 1 - P(X < 117) \\
= 1 - F_X(117) \\
= 1 - [1 - e^{-0.002 \cdot 117}] \\
= e^{-0.234} \approx 0.791
\]

c. 

\[
P(X > 117|X > 113) = \frac{P(X > 117, X > 113)}{P(X > 113)} \\
= \frac{P(X > 117)}{P(X > 113)} \cdot \frac{1 - F_X(117)}{1 - F_X(113)} \\
= \frac{e^{-0.002 \cdot 117}}{e^{-0.002 \cdot 113}} = e^{-0.008} \approx 0.992
\]

d. The exponential is an example of a “memoryless distribution.” We can follow a similar procedure to part (c) to prove that \( P(X > s + t|X > t) = P(X > s) \) as long as \( X \sim \text{Exp}(\lambda) \).

\[
P(X > s + t|X > t) = \frac{P(X > s + t, X > t)}{P(X > t)} \\
= \frac{P(X > s + t)}{P(X > t)} \\
= \frac{1 - F_X(s + t)}{1 - F_X(t)} \\
= \frac{e^{-\lambda(s+t)}}{e^{-\lambda t}} \\
= e^{-\lambda s} \\
= 1 - F_X(s) \\
= P(X > s)
\]

3. Continuous Random Variable: Let \( X \) be a continuous random variable with the following probability density function:

\[
f_X(x) = \begin{cases} 
  c(e^{x-1} + e^{-x}) & \text{if } 0 \leq x \leq 1 \\
  0 & \text{otherwise}
\end{cases}
\]

a. Find the value of \( c \) that makes \( f_X \) a valid probability distribution.

b. What is \( P(X > 0.75) \)?
a. We need \( \int_{-\infty}^{\infty} f_X(x) \, dx = 1. \)

\[
\int_{-\infty}^{\infty} f_X(x) \, dx = \int_{0}^{1} c(e^{x-1} + e^{-x}) \, dx \\
1 = c \left[ e^{x-1} - e^{-x} \right]_{x=0}^{1} \\
1 = c(e^{1-1} - e^{-1} - (e^{0-1} - e^{-0})) \\
c = \frac{1}{1 - e^{-1} - (e^{-1} - 1)} = \frac{1}{2 - \frac{2}{e}}
\]

b.

\[
P(X > 0.75) = \int_{0.75}^{1} c(e^{x-1} + e^{-x}) \, dx \\
= c \left[ e^{x-1} - e^{-x} \right]_{x=0.75}^{1} \\
= c\left( e^{1-1} - e^{-1} - (e^{0.75-1} - e^{-0.75}) \right) \\
= c\left( 1 - e^{-1} - e^{-0.25} + e^{-0.75} \right) = \frac{1 - e^{-1} - e^{-0.25} + e^{-0.75}}{2 - \frac{2}{e}}
\]

4. Air Quality: Throughout the United States, the Environmental Protection Agency monitors levels of PM2.5, a type of dangerous air pollution. These PM2.5 measurements can be approximately modeled by a normal distribution.

a. Let us model PM2.5 measurements with a normal distribution that has a mean of 8. If three-quarters of all measurements fall below 11.4, what is the standard deviation? Round to the nearest integer.

b. PM2.5 values above 12 can pose some health risks, especially to sensitive populations. Using the standard deviation found above, what is the probability that a randomly selected PM2.5 measurement is over 12?

c. What is the probability that a randomly selected PM2.5 measurement is between 7 and 8?

a. \( \Phi(\frac{x-\mu}{\sigma}) = \Phi(\frac{11.4-8}{\sigma}) = 0.75 \implies \frac{3.4}{\sigma} \approx .68 \implies \sigma \approx 5. \)

b. \( P(q > 12) = 1 - P(q < 12) = 1 - \Phi(\frac{12-8}{5}) = 1 - \Phi(.8) = 1 - .7881 = .2119. \)

c. \( P(7 < h < 8) = P(h < 8) - P(h < 7) = \Phi(\frac{8-8}{5}) - \Phi(\frac{7-8}{5}) \)
\( = \Phi(\frac{8-8}{5}) - \Phi(\frac{-1}{5}) = \Phi(\frac{8-8}{5}) - (1 - \Phi(\frac{1}{5})) \)
\( = \Phi(0) - (1 - \Phi(0.2)) = .5 - (1 - .5793) = .0793 \)
5. **Elections:** We would like to see how we could predict an election between two candidates in France (A and B), given data from 10 polls. For each of the 10 polls, we report below their sample size, how many people said they would vote for candidate A, and how many people said they would vote for candidate B. Not all polls are created equal, so for each poll we also report a value "weight" which represents how accurate we believe the poll was. The data for this problem can be found on the class website in polls.csv:

<table>
<thead>
<tr>
<th>Poll</th>
<th>N samples</th>
<th>A votes</th>
<th>B votes</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>862</td>
<td>548</td>
<td>314</td>
<td>0.93</td>
</tr>
<tr>
<td>2</td>
<td>813</td>
<td>542</td>
<td>271</td>
<td>0.85</td>
</tr>
<tr>
<td>3</td>
<td>984</td>
<td>682</td>
<td>302</td>
<td>0.82</td>
</tr>
<tr>
<td>4</td>
<td>443</td>
<td>236</td>
<td>207</td>
<td>0.87</td>
</tr>
<tr>
<td>5</td>
<td>863</td>
<td>497</td>
<td>366</td>
<td>0.89</td>
</tr>
<tr>
<td>6</td>
<td>648</td>
<td>331</td>
<td>317</td>
<td>0.81</td>
</tr>
<tr>
<td>7</td>
<td>891</td>
<td>552</td>
<td>339</td>
<td>0.98</td>
</tr>
<tr>
<td>8</td>
<td>661</td>
<td>479</td>
<td>182</td>
<td>0.79</td>
</tr>
<tr>
<td>9</td>
<td>765</td>
<td>609</td>
<td>156</td>
<td>0.63</td>
</tr>
<tr>
<td>10</td>
<td>523</td>
<td>405</td>
<td>118</td>
<td>0.68</td>
</tr>
<tr>
<td><strong>Totals:</strong></td>
<td><strong>7453</strong></td>
<td><strong>4881</strong></td>
<td><strong>2572</strong></td>
<td></td>
</tr>
</tbody>
</table>

a. First, assume that each sample in each poll is an independent experiment of whether or not a random person in France would vote for candidate A (disregard weights).

- Calculate the probability that a random person in France votes for candidate A.
- Assume each person votes for candidate A with the probability you’ve calculated and otherwise votes for candidate B. If the population of France is 64,888,792, what is the probability that candidate A gets more than half of the votes?

b. Nate Silver at fivethirtyeight pioneered an approach called the "Poll of Polls" to predict elections. For each candidate A or B, we have a random variable $S_A$ or $S_B$ which represents their strength on election night (like ELO scores). The probability that A wins is $P(S_A > S_B)$.

- Identify the parameters for the random variables $S_A$ and $S_B$. Both $S_A$ and $S_B$ are defined to be normal with the following parameters:

\[
S_A \sim \mathcal{N}\left(\mu = \sum_i p_{Ai} \cdot \text{weight}_i, \sigma^2\right) \quad S_B \sim \mathcal{N}\left(\mu = \sum_i p_{Bi} \cdot \text{weight}_i, \sigma^2\right)
\]

where $p_{Ai}$ is the ratio of A votes to N samples in poll $i$, $p_{Bi}$ is the ratio of B votes to N samples in poll $i$, weight$_i$ is the weight of poll $i$, $m_i$ is the N samples in poll $i$ and:

\[
\sigma = \frac{K}{\sqrt{\sum_i m_i}} \quad \text{s.t.} \quad K = 350; \quad \text{thus} \quad \sigma = 4.054.
\]

- We will calculate $P(S_A > S_B)$ by simulating 100,000 fake elections. In each fake election, we draw a random sample for the strength of A from $S_A$ and a random
sample for the strength of B from \( S_B \). If \( S_A \) is greater than \( S_B \), candidate A wins. What do we expect to see if we simulate so many times? What do we actually see?

c. Which model, the one from (a) or the model from (b) seems more appropriate? Why might that be the case? On election night candidate A wins. Was your prediction from part (b) "correct"?

\begin{itemize}
  \item[a.] \( P(\text{random person votes for A}) = \frac{\text{votes for A}}{\text{total votes}} = \frac{4881}{7453} = 0.655 \)

     Now, let \( X \) be the number of votes for candidate A. We assume that \( X \sim \text{Bin}(64888792, 0.655) \).

     \begin{itemize}
       \item \( \mu = np = 42502158.76 \), \( \text{Variance} = np(1 - p) = 14663244.77 \) \( \text{Std Dev} = 3829.26 \)
       \item \( \text{Votes to win} = \frac{64888792}{2} = 32444396 \)
       \item \( P(\text{A gets enough votes}) = P(X > 32444396) \approx P(Y > 32444396.5) = 1.00 \)
     \end{itemize}

  \item[b.] \( S_A \sim \text{N}(5.324, 16.436) \)

     \( S_B \sim \text{N}(2.926, 16.436) \)

     \( P(S_A > S_B) \approx 0.66 \)

     We can figure this out through simulation by drawing from \( S_A \) and \( S_B \) 100,000 times and seeing how often the \( S_A \) value is greater than the \( S_B \) value. Later in the quarter, when we learn the convolution of independent normals, you will be able to figure this out mathematically.

  \item[c.] Algorithm (a) makes very few assumptions, and simplicity can be useful, but it does assume that each voter is independent - which we definitely know isn’t the case in real elections. Algorithm (b) allows us to model bias (using the weights we incorporated), and doesn’t think of each voter as necessarily independent.