CMPT 210: Probability and Computing

Lecture 10

Sharan Vaswani

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Recap

Conditional probability: $Pr[E|F] = \frac{Pr[E \cap F]}{Pr[F]}$.

Multiplication Rule: For events E_1, E_2, \ldots, E_n ,

$$\Pr[E_1 \cap E_2 \dots \cap E_n] = \Pr[E_1] \; \Pr[E_2 | E_1] \; \Pr[E_3 | E_1 \cap E_2] \; \dots \\ \Pr[E_n | E_1 \cap E_2 \cap \dots \cap E_{n-1}].$$

Conditional probability for complement events: For events E, F, $Pr[E^c|F] = 1 - Pr[E|F]$.

Bayes Rule: For events E and F if $\Pr[E] \neq 0$ and $\Pr[F] \neq 0$, then, $\Pr[F|E] = \frac{\Pr[E|F] \Pr[F]}{\Pr[E]}$.

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$$E = (E \cap F) \cup (E \cap F^c)$$

$$\implies \Pr[E] = \Pr[(E \cap F) \cup (E \cap F^c)] = \Pr[E \cap F] + \Pr[E \cap F^c]$$
(By union-rule for disjoint events)
$$\Pr[E] = \Pr[E|F] \Pr[F] + \Pr[E|F^c] \Pr[F^c]$$
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Combining Bayes rule and Law of total probability

$$\Pr[F|E] = \frac{\Pr[F \cap E]}{\Pr[E]} = \frac{\Pr[E|F] \Pr[F]}{\Pr[E]}$$
 (By definition of conditional probability)
$$\Pr[F|E] = \frac{\Pr[E|F] \Pr[F]}{\Pr[E|F] \Pr[F] + \Pr[E|F^c] \Pr[F^c]}$$
 (By law of total probability)

Q: In answering a question on a multiple-choice test, a student either knows the answer or she guesses. Let p be the probability that she knows the answer and 1-p the probability that she guesses. Assume that a student who guesses at the answer will be correct with probability $\frac{1}{m}$, where m is the number of multiple-choice alternatives. What is the conditional probability that a student knew the answer to a question given that she answered it correctly?

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Let C be the event that the student answers the question correctly. Let K be the event that the student knows the answer. We wish to compute $\Pr[K|C]$.

We know that
$$\Pr[K] = p$$
 and $\Pr[C|K^c] = 1/m$, $\Pr[C|K] = 1$. Hence, $\Pr[C] = \Pr[C|K] \Pr[K] + \Pr[C|K^c] \Pr[K^c] = (1)(p) + \frac{1}{m}(1-p)$.
$$\Pr[K|C] = \frac{\Pr[C|K] \Pr[K]}{\Pr[C]} = \frac{mp}{1+(m-1)p}$$
.

Q: An insurance company believes that people can be divided into two classes — those that are accident prone and those that are not. Their statistics show that an accident-prone person will have an accident at some time within a fixed 1-year period with probability 0.4, whereas this probability decreases to 0.2 for a non-accident-prone person. If we assume that 30% of the population is accident prone, what is the probability that a new policy holder will have an accident within a year of purchasing a policy?

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Let A= event that a new policy holder will have an accident within a year of purchasing a policy. Let B= event that the new policy holder is accident prone. We know that $\Pr[B]=0.3$, $\Pr[A|B]=0.4$, $\Pr[A|B^c]=0.2$. By the law of total probability, $\Pr[A]=\Pr[A|B]\Pr[B]+\Pr[A|B^c]\Pr[B^c]=(0.4)(0.3)+(0.2)(0.7)=0.26$.

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Q: Suppose that a new policy holder has an accident within a year of purchasing their policy. What is the probability that they are accident prone?

Compute
$$Pr[B|A] = \frac{Pr[A|B] \ Pr[B]}{Pr[A]} = \frac{0.12}{0.26} = 0.4615$$
.

Q: Alice is taking a probability class and at the end of each week she can be either up-to-date or she may have fallen behind. If she is up-to-date in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.8 (or 0.2, respectively). If she is behind in a given week, the probability that she will be up-to-date (or behind) in the next week is 0.6 (or 0.4, respectively). Alice is (by default) up-to-date when she starts the class. What is the probability that she is up-to-date after three weeks?

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Let U_i and B_i be the events that Alice is up-to-date or behind respectively after i weeks. Since Alice starts the class up-to-date, $\Pr[U_1]=0.8$ and $\Pr[B_1]=0.2$. We also know that $\Pr[U_2|U_1]=0.8$, $\Pr[U_3|U_2]=0.8$ and $\Pr[B_2|U_1]=0.2$, $\Pr[B_3|U_2]=0.2$. Similarly, $\Pr[U_2|B_1]=0.6$, $\Pr[U_3|B_2]=0.6$ and $\Pr[B_2|B_1]=0.4$, $\Pr[B_3|B_2]=0.4$.

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We wish to compute $Pr[U_3]$. By the law of total probability,

$$\Pr[U_3] = \Pr[U_3|U_2] \Pr[U_2] + \Pr[U_3|B_2] \Pr[B_2]$$
 and $\Pr[U_2] = \Pr[U_2|U_1] \Pr[U_1] + \Pr[U_2|B_1] \Pr[B_1]$.

Hence,
$$Pr[U_2] = (0.8)(0.8) + (0.6)(0.2) = 0.76$$
, and $Pr[U_3] = (0.8)(0.76) + (0.6)(0.24) = 0.752$.

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Let us consider a simplified case – there are two departments, EE and CS, and men and women apply to the program of their choice. Let us define the following events: A is the event that the candidate is admitted to the program of their choice, F_E is the event that the candidate is a woman applying to EE, F_C is the event that the candidate is a woman applying to CS. Similarly, we can define M_E and M_C . Assumption: Candidates are either men or women, and that no candidate is allowed to be part of both EE and CS.

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Lawsuit claim: Male candidate is more likely to be admitted to the university than a female i.e. $Pr[A|M_E \cup M_C] > Pr[A|F_E \cup F_C]$.

University response: In any given department, a male applicant is less likely to be admitted than a female i.e. $\Pr[A|F_E] > \Pr[A|M_E]$ and $\Pr[A|F_C] > \Pr[A|M_C]$.

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Simpson's Paradox: Both the above statements can be simultaneously true.

| CS | 2 men admitted out of 5 candidates | 40% |
|---------|---|----------------|
| | 50 women admitted out of 100 candidates | 50% |
| EE | 70 men admitted out of 100 candidates | 70% |
| | 4 women admitted out of 5 candidates | 80% |
| Overall | 72 men admitted, 105 candidates | $\approx 69\%$ |
| | 54 women admitted, 105 candidates | $\approx 51\%$ |

In the above example, $\Pr[A|F_E] = 0.8 > 0.7 = \Pr[A|M_E]$ and $\Pr[A|F_C] = 0.5 > 0.4 = \Pr[A|M_C]$. $\Pr[A|F_E \cup F_C] \approx 0.51$. Similarly, $\Pr[A|M_E \cup M_C] \approx 0.69$.

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In general, Simpson's Paradox occurs when multiple small groups of data all exhibit a similar trend, but that trend reverses when those groups are aggregated.



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Hence,
$$\Pr[E \cap F] = \Pr[E|F] \Pr[F] = \Pr[E] \Pr[F] = \frac{1}{6} \frac{1}{6} = \frac{1}{36}$$
.

Independent Events: Events E and F are said to be independent, if knowledge that F has occurred does not change the probability that E occurs. Formally,

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$$\Pr[E \cap F] = \Pr[E] \Pr[F] = \frac{1}{2} \frac{1}{2} = \frac{1}{4}.$$

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Q: I randomly choose a number from $\{1, 2, ..., 10\}$. E is the event that the number I picked is a prime. F is the event that the number I picked is odd. Are E and F independent?

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 $\Pr[E] = \frac{2}{5}$, $\Pr[F] = \frac{1}{2}$, $\Pr[E \cap F] = \frac{3}{10}$. $\Pr[E \cap F] \neq \Pr[E]$ $\Pr[F]$. Another way: $\Pr[E|F] = \frac{3}{5}$ and $\Pr[E] = \frac{2}{5}$, and hence $\Pr[E|F] \neq \Pr[E]$. Conditioning on F tell us that prime number cannot be 2, so it changes the probability of E.

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 $\Pr[M] = \Pr[E_1 \cap E_2]$. Since the two components are independent, E_1 and E_2 are independent, meaning that $\Pr[E_1 \cap E_2] = \Pr[E_1] \Pr[E_2] = p^2$.

Probability that the machine does not break $= \Pr[M^c] = 1 - \Pr[M] = 1 - p^2$.

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For this machine, let M' be the event that it breaks. In this case, $\Pr[M'] = \Pr[E_1 \cup E_2]$.

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Correct way:

$$\Pr[E_1 \cup E_2] = \Pr[E_1] + \Pr[E_2] - \Pr[E_1 \cap E_2]$$
 (By the inclusion-exclusion rule)
= $\Pr[E_1] + \Pr[E_2] - \Pr[E_1] \Pr[E_2] = 2p - p^2$ (Since E_1 and E_2 are independent.)



Matrix Multiplication

Given two $n \times n$ matrices – A and B, if C = AB, then,

$$C_{i,j} = \sum_{k=1}^{n} A_{i,k} B_{k,j}$$

Hence, in the worst case, computing $C_{i,j}$ is an O(n) operation. There are n^2 entries to fill in C and hence, in the absence of additional structure, matrix multiplication takes $O(n^3)$ time.

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There are non-trivial algorithms for doing matrix multiplication more efficiently:

- (Strassen, 1969) Requires $O(n^{2.81})$ operations.
- (Coppersmith-Winograd, 1987) Requires $O(n^{2.376})$ operations.
- (Alman-Williams, 2020) Requires $O(n^{2.373})$ operations.
- Belief is that it can be done in time $O(n^{2+\epsilon})$ for $\epsilon > 0$.

As an example, let us focus on A, B being binary 2×2 matrices.

Example:
$$A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$
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Frievald's Algorithm: Randomized algorithm to verify matrix multiplication with high probability in $O(n^2)$ time.

Q: For $n \times n$ matrices A, B and D, is D = AB?

Algorithm:

1. Generate a random n-bit vector x, by making each bit x_i either 0 or 1 independently with probability $\frac{1}{2}$. E.g, for n=2, toss a fair coin independently twice with the scheme – H is 0 and T is 1). If we get HT, then set $x=[0\,;\,1]$.

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Computational complexity: Step 1 can be done in O(n) time. Step 2 requires 3 matrix vector multiplications and can be done in $O(n^2)$ time. Step 3 requires comparing two n-dimensional vectors and can be done in O(n) time. Hence, the total computational complexity is $O(n^2)$.

Let us run the algorithm on an example. Suppose we have generated x = [1; 0]

$$A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \quad ; \quad B = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \quad ; \quad D = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$$
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Hence the algorithm will correctly output "no" since $D \neq AB$.

Q: Suppose we have generated x = [0; 0]. What is y and z?

In this case, y = z and the algorithm will incorrectly output "yes" even though $D \neq AB$.

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$$A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \quad ; \quad B = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \quad ; \quad C = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}$$
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Hence the algorithm will correctly output "yes" since C = AB.

Q: Suppose we have generated x = [0; 1]. What is y and z?

In this case again, y=z and the algorithm will correctly output "yes".

Let us analyze the algorithm for general matrix multiplication.

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Claim: For any input matrices A, B, D if $D \neq AB$, then the (Basic) Frievald's algorithm will output "no" with probability $\geq \frac{1}{2}$.

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Claim: For any input matrices A, B, D if $D \neq AB$, then the (Basic) Frievald's algorithm will output "no" with probability $\geq \frac{1}{2}$.

Table 1: Probabilities for Basic Frievalds Algorithm

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$$\implies$$
 $\Pr[\mathsf{Algorithm\ outputs\ "yes"}] \leq \Pr[r_i = 0]$ (Probabilities are in $[0,1]$)

To complete the proof, on the next slide, we will prove that $\Pr[r_i = 0] \leq \frac{1}{2}$.

$$r_i = \sum_{k=1}^{n} E_{i,k} x_k = E_{i,j} x_j + \sum_{k \neq j} E_{i,k} x_k = E_{i,j} x_j + \omega \qquad (\omega := \sum_{k \neq j} E_{i,k} x_k)$$

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$$\Pr[r_i = 0] = \Pr[r_i = 0 | \omega = 0] \Pr[\omega = 0] + \Pr[r_i = 0 | \omega \neq 0] \Pr[\omega \neq 0]$$
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$$\Pr[r_i = 0 | \omega = 0] = \Pr[x_j = 0] = \frac{1}{2} \qquad (\text{Since } E_{i,j} \neq 0 \text{ and } \Pr[x_j = 1] = \frac{1}{2})$$

$$\Pr[r_i = 0 | \omega \neq 0] = \Pr[(x_j = 1) \cap E_{i,j} = -\omega] = \Pr[(x_j = 1)] \Pr[E_{i,j} = -\omega | x_j = 1]$$

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 \implies Pr[Algorithm outputs "yes"] \leq Pr[$r_i = 0$] $\leq \frac{1}{2}$.

Hence, if $D \neq AB$, the Algorithm outputs "yes" with probability $\leq \frac{1}{2} \implies$ the Algorithm outputs "no" with probability $\geq \frac{1}{2}$.

In the worst case, the algorithm can be incorrect half the time! We promised the algorithm would return the correct answer with "high" probability close to 1.

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A common trick in randomized algorithms is to have *m* independent trials of an algorithm and aggregate the answer in some way, reducing the probability of error, thus *amplifying the* probability of success.

