# CMPT 210: Probability and Computing 

Lecture 9

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## Recap

For events $E$ and $F$, we wish to compute $\operatorname{Pr}[E \mid F]$, the probability of event $E$ conditioned on $F$.
Approach 1: With conditioning, $F$ can be interpreted as the new sample space such that for $\omega \notin F, \operatorname{Pr}[\omega \mid F]=0$.
Approach 2: $\operatorname{Pr}[E \mid F]=\frac{\operatorname{Pr}[E \cap F]}{\operatorname{Pr}[F]}$.
Multiplication Rule: For events $E_{1}, E_{2}, \ldots, E_{n}$,

$$
\operatorname{Pr}\left[E_{1} \cap E_{2} \ldots \cap E_{n}\right]=\operatorname{Pr}\left[E_{1}\right] \operatorname{Pr}\left[E_{2} \mid E_{1}\right] \operatorname{Pr}\left[E_{3} \mid E_{1} \cap E_{2}\right] \ldots \operatorname{Pr}\left[E_{n} \mid E_{1} \cap E_{2} \cap \ldots E_{n-1}\right] .
$$

## Tree Diagrams:

- Helpful in calculating probabilities in a sequential process (E.g. In the Monty Hall problem, the process is choose car location, choose door, reveal door).
- In a tree diagram, edge-weights correspond to conditional probabilities and leaf nodes correspond to outcomes.
- The probability of an outcome can be calculated by multiplying the relevant probabilities along a path.


## Conditional Probability - Examples

Let us play a game with three strange dice shown in the figure. Each player selects one die and rolls it once. The player with the lower value pays the other player $\$ 100$. We can pick a die first, after which the other player can pick one of the other two.


A


B


C

Q: Suppose we choose die B because it has a 9, and the other player selects die A. What is the probability that we will win?

## Conditional Probability - Examples

die $A$ die $B \quad$ winner | probability |
| :---: |
| of outcome |

Identify Outcomes: Each leaf is an outcome and $\mathcal{S}=$ $\{(2,1),(2,5),(2,9),(6,1),(6,5),(6,9),(7,1),(7,5),(7,9)\}$.

Identify Event: $E=\{(2,5),(2,9),(6,9),(7,9)\}$.
Compute probabilities: $\operatorname{Pr}[$ Dice 1 is 6$]=\frac{1}{3}$.
$\operatorname{Pr}[(6,5)]=\operatorname{Pr}[$ Dice 2 is $5 \cap$ Dice 1 is 6$]=$
$\operatorname{Pr}[$ Dice 2 is $5 \mid$ Dice 1 is 6$] \operatorname{Pr}[$ Dice 1 is 6$]=\frac{1}{3} \frac{1}{3}=\frac{1}{9}$.
$\operatorname{Pr}[E]=\operatorname{Pr}[(2,5)]+\operatorname{Pr}[(2,9)]+\operatorname{Pr}[(6,9)]+\operatorname{Pr}[(7,9)]=\frac{4}{9}$.
Meaning that there is less than $50 \%$ chance of winning.

## Conditional Probability - Examples

Q: We get another chance - this time we know that die A is good (since we lost to it previously), we choose die A and the other player chooses die C . What is our probability of winning?


Now, $E=\{(3,6),(3,7),(4,6),(4,7)\}$ and hence $\operatorname{Pr}[E]=\frac{4}{9}$. Meaning that there is less than $50 \%$ chance of winning.

## Conditional Probability - Examples

We get yet another chance, and this time we choose die $C$, because we reason that die $A$ is better than B , and C is better than A .

We can construct a similar tree diagram to show that the probability that we win is again $\frac{4}{9}$.

- A beats $B$ with probability $\frac{5}{9}$ (first game).
- C beats A with probability $\frac{5}{9}$ (second game).
- B beats C with probability $\frac{5}{9}$ (third game).

Since A will beat B more often than not, and B will beat C more often than not, it seems like A ought to beat C more often than not, that is, the "beats more often" relation ought to be transitive. But this intuitive idea is false: whatever die we pick, the second player can pick one of the others and be likely to win. So picking first is actually a disadvantage!

This is the topic of some recent research and was covered in this article:
https://www.quantamagazine.org/
mathematicians-roll-dice-and-get-rock-paper-scissors-20230119/

## Conditional Probability - Examples

Q: A test for detecting cancer has the following accuracy - (i) If a person has cancer, there is a $10 \%$ chance that the test will say that the person does not have it. This is called a "false negative" and (ii) If a person does not have cancer, there is a $5 \%$ chance that the test will say that the person does have it. This is called a "false positive". For patients that have no family history of cancer, the incidence of cancer is $1 \%$. Person X does not have any family history of cancer, but is detected to have cancer. What is the probability that the Person X does have cancer?

## Conditional Probability - Examples

$\mathcal{S}=\{($ Healthy, Positive $),($ Healthy, Negative $),($ Sick, Positive $),($ Sick, Negative $)\}$.
$A$ is the event that Person X has cancer. $B$ is the event that the test is positive.


## Questions?

## Conditional Probability

Conditional probability for complement events: For events $E, F, \operatorname{Pr}\left[E^{c} \mid F\right]=1-\operatorname{Pr}[E \mid F]$. Proof: Since $E \cup E^{c}=\mathcal{S}$, for an event $F$ such that $\operatorname{Pr}[F] \neq 0$,

$$
\begin{aligned}
\left(E \cup E^{c}\right) \cap F & =\mathcal{S} \cap F=F \\
\left(E \cup E^{c}\right) \cap F & =(E \cap F) \cup\left(E^{c} \cap F\right) \quad \text { (Distributive Law) } \\
\Longrightarrow \operatorname{Pr}\left[(E \cap F) \cup\left(E^{c} \cap F\right)\right] & =\operatorname{Pr}[F]
\end{aligned}
$$

Since $E \cap F$ and $E^{c} \cap F$ are mutually exclusive events,

$$
\begin{aligned}
& \operatorname{Pr}[E \cap F]+\operatorname{Pr}\left[E^{c} \cap F\right]=\operatorname{Pr}[F] \Longrightarrow \frac{\operatorname{Pr}\left[E^{c} \cap F\right]}{\operatorname{Pr}[F]}=1-\frac{\operatorname{Pr}[E \cap F]}{\operatorname{Pr}[F]} \\
& \Longrightarrow \operatorname{Pr}\left[E^{c} \mid F\right]=1-\operatorname{Pr}[E \mid F] \quad \text { (By def. of conditional probability) }
\end{aligned}
$$

## Bayes Rule

Bayes Rule: For events $E$ and $F$ if $\operatorname{Pr}[E] \neq 0$ and $\operatorname{Pr}[F] \neq 0$, then, $\operatorname{Pr}[F \mid E]=\frac{\operatorname{Pr}[E \mid F] \operatorname{Pr}[F]}{\operatorname{Pr}[E]}$. Proof: Using the formula for conditional probability,

$$
\begin{aligned}
\operatorname{Pr}[E \mid F] & =\frac{\operatorname{Pr}[E \cap F]}{\operatorname{Pr}[F]} ; \quad \operatorname{Pr}[F \mid E]=\frac{\operatorname{Pr}[F \cap E]}{\operatorname{Pr}[E]} \\
\Longrightarrow \operatorname{Pr}[E \cap F] & =\operatorname{Pr}[E \mid F] \operatorname{Pr}[F] \quad ; \quad \operatorname{Pr}[F \cap E]=\operatorname{Pr}[F \mid E] \operatorname{Pr}[E] \\
\Longrightarrow \operatorname{Pr}[E \mid F] \operatorname{Pr}[F] & =\operatorname{Pr}[F \mid E] \operatorname{Pr}[E] \\
\Longrightarrow \operatorname{Pr}[F \mid E] & =\frac{\operatorname{Pr}[E \mid F] \operatorname{Pr}[F]}{\operatorname{Pr}[E]}
\end{aligned}
$$

Allows us to compute $\operatorname{Pr}[F \mid E]$ using $\operatorname{Pr}[E \mid F]$. Later in the course, we will see an application of the Bayes rule to machine learning.

