

CS6462

Probabilistic and Explainable AI

Lesson 6

Bayes' Theorem

$$P(A | B) = \frac{P(A \cap B)}{P(B)}$$

Probability of event A
given B has occurred
Probability of event A occurred
and event B occurred
Probability of event B

Calculating Conditional Probability

Definition (recall):

- the "likelihood of an event occurring, based on the occurrence of another event":
the *conditional probability* $P(E|F)$ of an event E given an event F , is the probability that E occurs given that F has occurred

$$P(E|F) = \frac{P(E \cap F)}{P(F)}, \text{ iff } P(F) > 0$$

Alternative way to calculate conditional probability:

- one conditional probability can be calculated using the other conditional probability
 $P(E|F) = P(F|E) * P(E) / P(F)$ – useful when $P(E \cap F)$ is challenging to calculate
- reverse

$$P(F|E) = P(E|F) * P(F) / P(E)$$

Bayes' Theorem

$$P(A | B) = \frac{P(A \cap B)}{P(B)}$$

Probability of event A
given B has occurred

Probability of event A occurred
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Probability of event B

Bayes' Theorem:

- principled way of calculating a conditional probability without the composite probability $P(E \cap F)$

$$P(E | F) = \frac{P(F | E) * P(E)}{P(F)}$$

- if we do not have access to the denominator $P(F)$ directly, we can calculate it:

$$P(F) = P(F | E) * P(E) + P(F | E^c) * P(E^c)$$

- new form:

$$P(E | F) = \frac{P(F | E) * P(E)}{P(F | E) * P(E) + P(F | E^c) * P(E^c)}$$

Bayes' Theorem (cont.)

$$P(A | B) = \frac{P(A \cap B)}{P(B)}$$

Probability of event A
given B has occurred

Probability of event A occurred
and event B occurred

Probability of event B

General form of Bayes' Theorem:

if E_1, \dots, E_k are mutually exclusive events and $E_1 \cup E_2 \dots E_k = S$, then

$$P(E_i | F) = \frac{P(F | E_i) * P(E_i)}{P(F | E_1) * P(E_1) + \dots + P(F | E_k) * P(E_k)}$$

Terms:

- $P(A | B)$: Posterior probability
- $P(A)$: Prior probability
- $P(B | A)$: Likelihood probability
- $P(B)$: Evidence probability
- this allows Bayes Theorem to be restated as:

$$\textbf{Posterior} = \textbf{Likelihood} * \textbf{Prior} / \textbf{Evidence}$$

$$P(A | B) = \frac{P(A \cap B)}{P(B)}$$

Probability of event A
given B has occurred
Probability of event A occurred
and event B occurred
Probability of event B

Bayes' Theorem for Independent Events

Independent Events E and F:

- if two events **E** and **F** are independent, then:

$$P(E | F) = P(E)$$

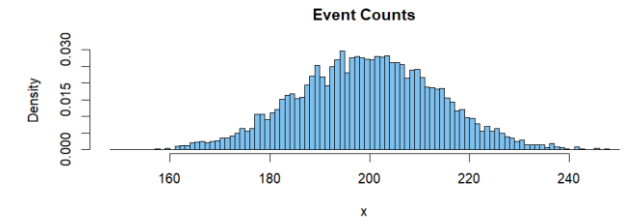
$$P(F | E) = P(F)$$

$$P(F | E^c) = P(F)$$

$$P(E | F) = P(E) = \frac{P(F | E) * P(E)}{P(F | E) * P(E) + P(F | E^c) * P(E^c)} = \frac{P(F) * P(E)}{P(F) * P(E) + P(F) * P(E^c)} = \frac{P(E)}{P(E) + P(E^c)} = P(E)$$

Bayes' Theorem cannot be used for independent events as *we need to determine the total probability and there is no dependency of events.*

Bayes' Theorem - Example



Example 1:

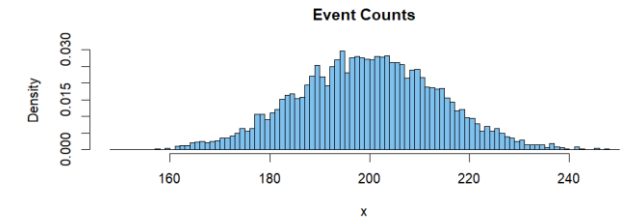
Finding out a patient's probability of having liver disease if they are an alcoholic. "Being an alcoholic" is the **test** (kind of like a litmus test) for liver disease.

PCR test for Covid-19:

- $P(A) = 0.10$ (past data tells you that 10% of patients entering your clinic "have liver disease" - **A**)
- $P(B) = 0.05$ (5% of the clinic's "patients are alcoholics" - **B**)
- $P(B|A) = 0.07$ (among those patients diagnosed with liver disease, 7% are alcoholics)
- $P(A|B) = ?$

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)} = \frac{0.07 * 0.1}{0.05} = 0.14 = 14\%$$

Bayes' Theorem – Example (cont.)



Example 2: Testing for Covid-19

Antibody Test for Covid-19:

- $P(T+|I+) = 0.98$ (sensitivity - positive test $T+$ for infected $I+$)
- $P(T-|I-) = 0.995$ (specificity - negative test $T-$ for non-infected $I-$)
- $P(I+) = 0.0003$ (prevalence)

Testing on large scale not sensible (too many false positives).

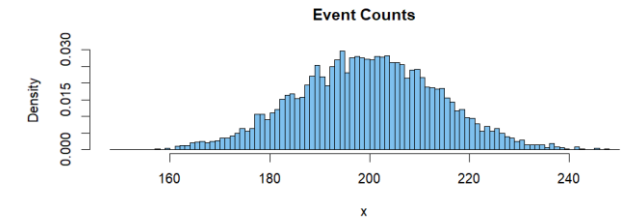
What is the probability that the tested person is infected if the test was positive?

$$P(I+|T+) = \frac{P(T+|I+)*P(I+)}{P(T+|I+)*P(I+) + P(T+|I-)P(I-)} = \frac{0.98 * 0.0003}{0.98 * 0.0003 + 0.005 * 0.9997} = 0.05556$$

Considering different population with $P(I+) = 0.1$ (greater risk):

$$P(I+|T+) = \frac{P(T+|I+)*P(I+)}{P(T+|I+)*P(I+) + P(T+|I-)P(I-)} = \frac{0.98 * 0.1}{0.98 * 0.1 + 0.005 * 0.9997} = 0.956$$

Bayes' Theorem – Example (cont.)



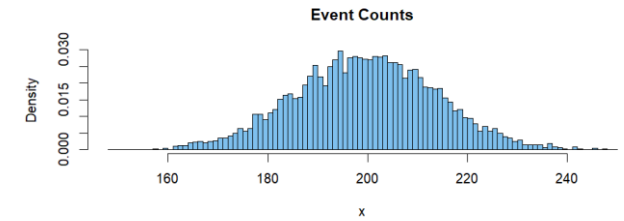
Example 3:

There are two bags. Bag I has 7 red and 4 blue balls and bag II has 5 red and 9 blue balls. We draw a ball at random and it turns out to be red. Determine the probability that the ball was from the bag I using the Bayes' Theorem.

- X – ball is from bag I
- Y – ball is from bag II
- A – red ball
- $P(X) = P(Y) = \frac{1}{2}$
- $P(A|X) = 7/11, P(A|Y) = 5/14$

$$P(X|A) = \frac{P(A|X)*P(X)}{P(A|X)*P(X) + P(A|Y)*P(Y)} = \frac{7/11*1/2}{7/11*1/2 + 5/14*1/2} = \frac{0.31818181818}{0.49675324675} = 0.64052287581$$

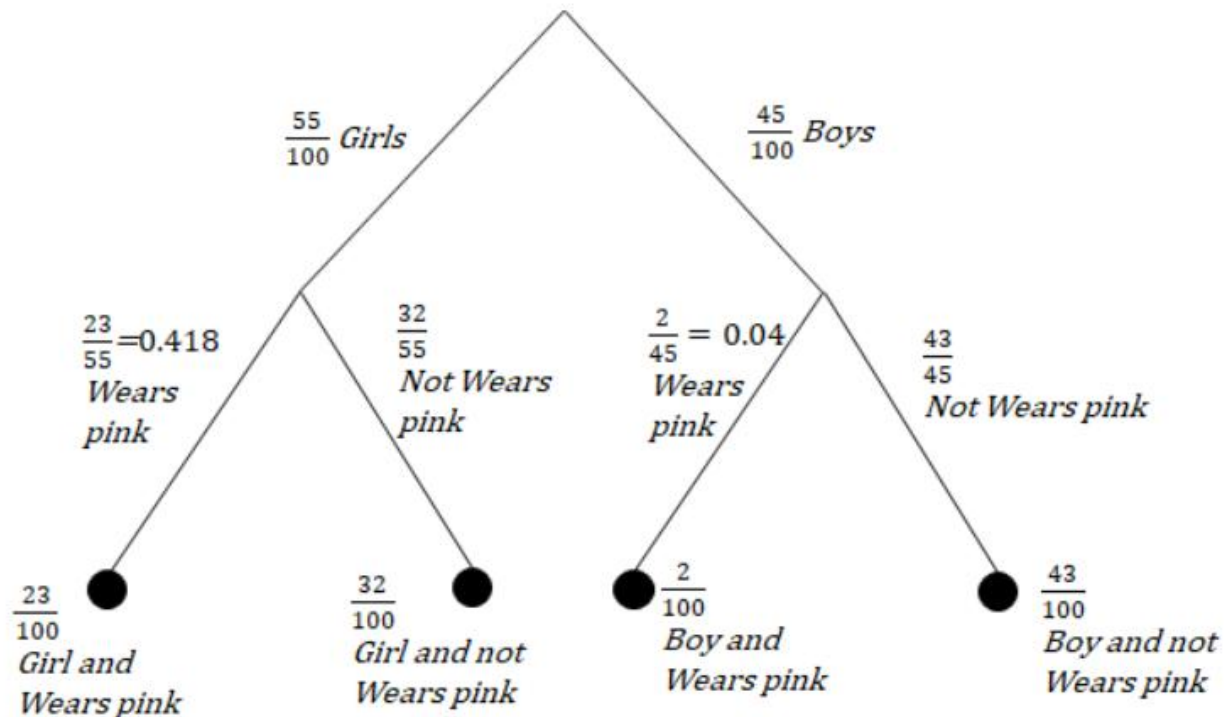
Graphical Representation



Example 4:

Calculate the probability that the student is a girl and she wears pink, **$P(\text{Wearing pink} \cap \text{Girl})$** or **$P(\text{Girl} \cap \text{Wearing pink})$** . Girls are 55 out of 100. Girls wearing pink are 23. Boys wearing pink are 2.

Tree Diagram for Bayesian Probability:



conditional probability of she wears pink given that the student is a girl

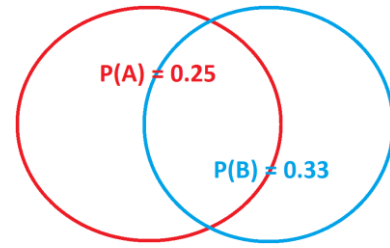
$$P(\text{Wearing pink} | \text{Girl}) = \frac{\text{count}(\text{Wearing pink} \cap \text{Girl})}{\text{count}(\text{Girl})}$$

$$= \frac{23}{55}$$

$$= \frac{\text{count}(\text{Wearing pink} \cap \text{Girl})/100}{\text{count}(\text{Girl})/100}$$

$$= \frac{P(\text{Wearing pink} \cap \text{Girl})}{P(\text{Girl})}$$

Summary



Conditional Probability:

- the “likelihood of an event occurring, based on the occurrence of another event”

Bayes’ Theorem

- principled way of calculating a conditional probability without the composite probability $P(E \cap F)$

$$P(E|F) = \frac{P(F|E) * P(E)}{P(F)}$$

- if we do not have access to the denominator $P(F)$ directly, we can calculate it:

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- new form:

$$P(E|F) = \frac{P(F|E) * P(E)}{P(F|E) * P(E) + P(F|E^c) * P(E^c)}$$

Graphical representation of Bayesian probabilities

Next Lesson – Model-Based Reasoning

Thank You!

Questions?