

ECE 528 – Introduction to Random Processes in ECE Lecture 3: Conditional Probability & Independent Events

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September 9 and 16, 2020

Note

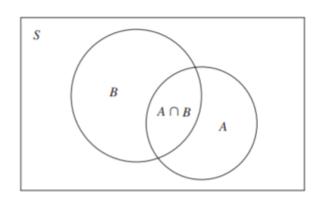
- These slides cover material partially presented in class. They are provided to help students to follow the textbook. The material here are partly taken from the book by A Leon-Garcia, Probability and Random Processes for Electrical Engineering, 3rd edition, whom I am thankful.
- There are many other topics which have been covered in class using the blackboard as step-by-set derivation and detailed discussions were need.

Additional Stuff Covered

- Chapter 2
- Problems 2.4 and 2.29 and 2.54
- The Balls and Boxes
- Tree diagram for Conditional probability
- BSC using conditional
- More on Bayes' Rule
- Application and use cases
- Covid-19 Testing and Bayes' Rule
- From Bernoulli to Binomial to Poisson
- Derivation of Poisson distribution

Conditional Probability

- Are events A & B interrelated?
- If we know that B occurred, how does probability of A change?



$$\frac{n_{A \cap B}}{n_B} = \frac{n_{A \cap B}/n}{n_B/n} \to \frac{P[A \cap B]}{P[B]}$$

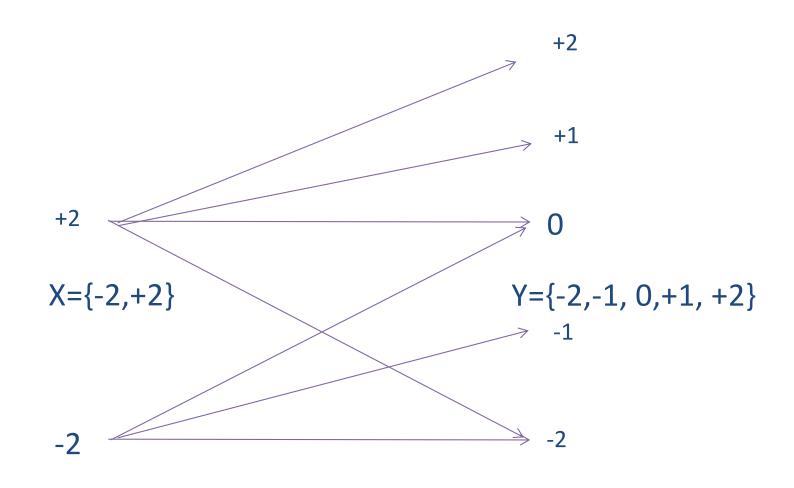
FIGURE 2.9 If B is known to have occurred, then A can occur only if $A \cap B$ occurs.

$$P[A|B] = \frac{P[A \cap B]}{P[B]}$$
 for $P[B] > 0$.

Problem 2.4

- A binary communication system transmits a signal X that is either a voltage signal +2 or a voltage signal -2. A malicious channel reduces the magnitude of the received signal by the number of heads it counts in two tosses of a coin. Let Y be the resulting signal.
- (a) Find the sample space.
- (b) Find the set of outcomes corresponding to the event "transmitted signal was definitely +2."
- (c) Describe in words the event corresponding to the outcome

Binary Communication System



 $X=\{-2, +2\}$ and $Y=\{-2, -1, 0, +1, +2\}$

Problem 2.4 Solution

A)

Y -2 -1 0 1 2

+2 -- (2,0) (2,1) (2,2)

-2 (-2,-2) (-2,-1) (-2,0) -- --

- **b**) "X definitely + 2" : {(2,1),(2,2)}
- c) $\{Y=0\} = \{(2,0),(-2,0)\}$ Observed output is Zero. Cannot determine Input

Problem 2.29

- Let M be the number of message transmissions in Problem 2.7. Find the probabilities of the events A, B,C,C..... Assume the probability of successful transmission is 1/2.
- Problem 2.7: Let M be the number of message transmissions in Experiment E6. (a) What is the set A corresponding to the event "M is even"? (b) What is the set B corresponding to the event "M is a multiple of 3"? (c) What is the set C corresponding to the event "6 or fewer transmissions are required"? (d) Find the sets and describe the corresponding events in words

Problem 2.29 Solution

Each Transmission is equivalent to tossing a fair coin. If outcome is heads, the transmission is successful. If tails, another transmission is required. Let's find the probability that j transmissions are required:

$$P[j] = \left(\frac{1}{2}\right)^{j}$$

$$P[A] = P[j \text{ even}] = \sum_{k=1}^{\infty} \left(\frac{1}{2}\right)^{2k} = \sum_{k=1}^{\infty} \left(\frac{1}{4}\right)^{k} = \sum_{k=0}^{\infty} \left(\frac{1}{4}\right)^{k} - 1 = \frac{1}{1 - \frac{1}{4}} - 1 = \frac{1}{3}.$$

$$P[B] = P[j \text{ multiple of 3}] = \sum_{k=1}^{\infty} \left(\frac{1}{2}\right)^{3k} = \frac{1}{1 - \frac{1}{8}} - 1 = \frac{1}{7}.$$

Problem 2.29 Solution

$$P[C] = \sum_{k=1}^{6} \left(\frac{1}{2}\right)^{k} = \frac{1}{2} \sum_{k=0}^{5} \left(\frac{1}{2}\right)^{k} = \frac{1}{2} \frac{1 - \left(\frac{1}{2}\right)^{6}}{1 - \frac{1}{2}} = \frac{63}{64}.$$

$$P[C^c] = 1 - P[C] = \frac{1}{64}.$$

$$P[A \cap B] = \sum_{k=1}^{\infty} \left(\frac{1}{2}\right)^{6k} = \frac{1}{1 - \frac{1}{64}} - 1 = \frac{1}{63}$$
 since a multiple of 2 and 3 is a multiple of 6.

$$P[A-B] = P[A] - P[A \cap B] = \frac{1}{3} - \frac{1}{63} = \frac{20}{63}$$
 since

$$A = (A - B) \cup (A \cap B)$$
 and $(A - B) \cap (A \cap B) = \emptyset$.

$$P[A \cap B \cap C] = \left(\frac{1}{2}\right)^6 = \frac{1}{64} \text{ since } A \cap B \cap C = \{6\}.$$

Problem 2.54

• A lot of 100 items contains k defective items. M items are chosen at random and tested. (a) What is the probability that m are found defective? This is called the hypergeometric distribution. (b) A lot is accepted if 1 or fewer of the M items are defective. What is the probability that the lot is accepted?

Problem 2.54 Solution

The number of ways of choosing M out of 100 is $\binom{100}{M}$. This is the total number of equiprobable outcomes in the sample space.

We are interested in the outcomes in which m of the chosen items are defective and M-m are nondefective.

The number of ways of choosing m defectives out of k is $\binom{k}{m}$.

The number of ways of choosing M-m nondefectives out of 100 k is $\begin{pmatrix} 100-k \\ M-m \end{pmatrix}$.

The number of ways of choosing m defectives out of k

 $\frac{and}{\binom{k}{m}} \frac{M-m \text{ non-defectives out of } 100-k \text{ is} }{\binom{k}{m} \binom{100-k}{M-m}}$

 $P[m \text{ defectives in } M \text{ samples}] = \frac{\# \text{ outcomes with } k \text{ defective}}{\text{Total } \# \text{ of outcomes}}$ $= \frac{\binom{k}{m} \binom{100 - k}{M - m}}{\binom{100}{M}}$

This is called the Hypergeometric distribution.

(b)
$$P[lot accepted] = P[m=0 \text{ or } m=1] = \frac{\binom{100-12}{M}}{\binom{100}{M}} + \frac{le}{\binom{100-12}{M}}$$

The number of ways of choosing m defectives out of k is $\binom{k}{m}$.

The number of ways of choosing M-m nondefectives out of 100-k is $\binom{100-k}{M-m}$.

The number of ways of choosing m defectives out of k

and M-m non-defectives out of 100-k is

$$\binom{k}{m}\binom{100-k}{M-m}$$

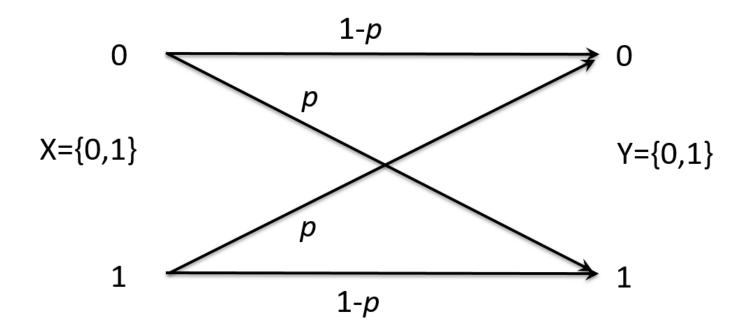
 $P[m \text{ defectives in } M \text{ samples}] = \frac{\# \text{ outcomes with } k \text{ defective}}{\text{Total } \# \text{ of outcomes}}$

$$= \frac{\binom{k}{m} \binom{100-k}{M-m}}{\binom{100}{M}}$$

This is called the Hypergeometric distribution.

b)
$$P[\text{lot accepted}] = P[m = 0 \text{ or } m = 1] = \frac{\binom{100 - k}{M}}{\binom{100}{M}} + \frac{k \binom{100 - k}{M - 1}}{\binom{100}{M}}.$$

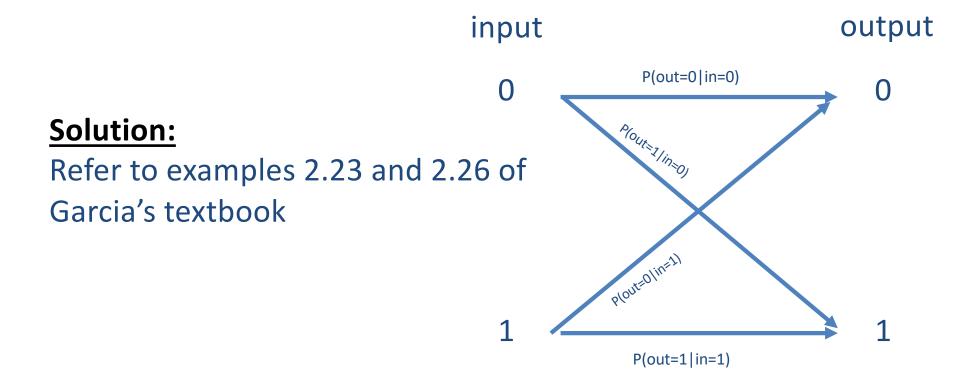
Binary Communication Channel



- Binary Symmetric Channel (BSC) model and noisy channel
- binary {0,1}
- symmetric means prob $(0 \rightarrow 1)$ = prob $(1 \rightarrow 0)$

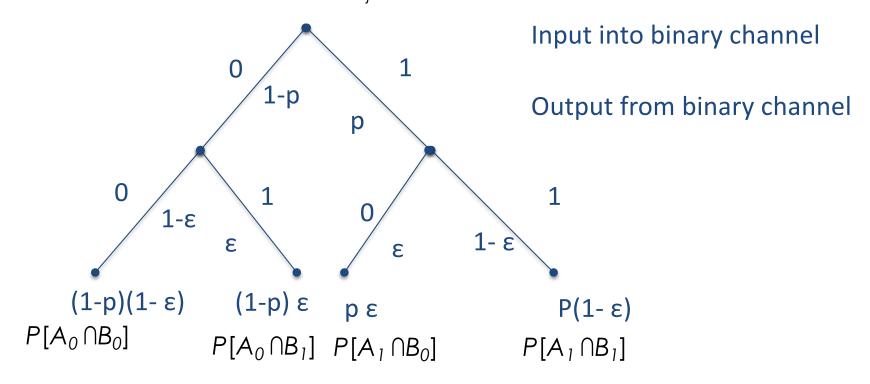
Example 1: Binary (Symmetric) Channel

 Given the binary symmetric channel depicted in figure, find P(input = j | output = i); i,j = 0,1. Given that P(input = 0) = 0.4, P(input = 1) = 0.6.



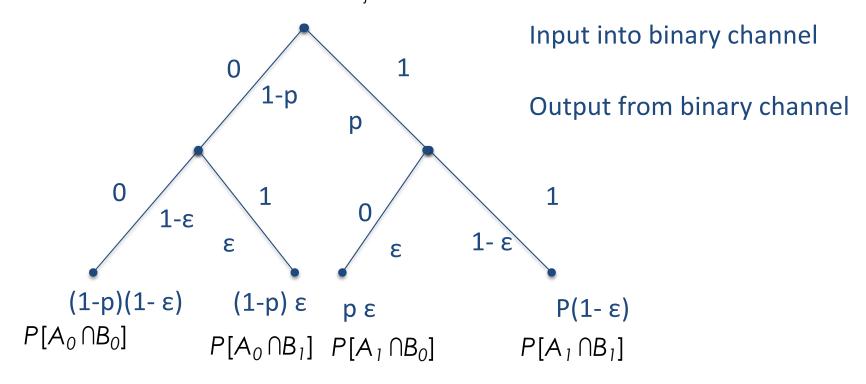
Binary Tree Diagram

Let A_i be the event "input was i," and let B_j be the event "receiver decision was i." Find the probabilities for $P[A_i \cap B_i]$ i=0, 1 and j=0,1.



Binary Tree Diagram (2)

Let A_i be the event "input was i," and let B_j be the event "receiver decision was i." Find the probabilities for $P[A_i \cap B_i]$ i=0, 1 and j=0,1.



Find which input is more probable given that the receiver has output 1.

Assume that, a priori, the input is equally likely to be 0 or 1.

$$P[B_1] = P[B_1 | A_0] P[A_0] + P[B_1 | A_1] P[A_1]$$

Probability of Joint Occurrence

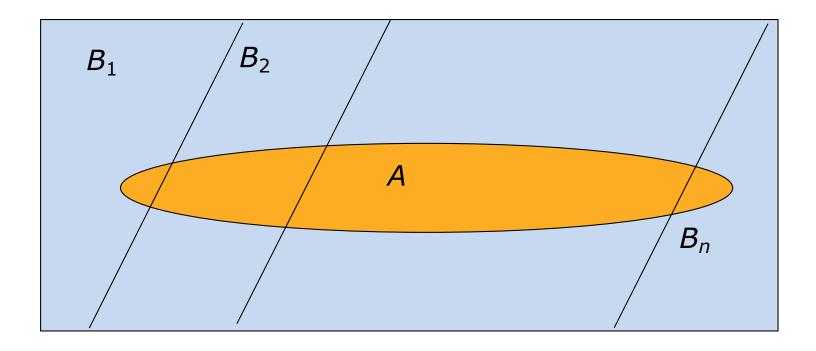
$$P[A|B] = \frac{P[A \cap B]}{P[B]}$$
 for $P[B] > 0$.

$$P[A \cap B] = P[A \mid B] P[B]$$
$$= P[B \mid A] P[A]$$

$$P[A \cap B \cap C] = P[A \mid B \cap C] P[B \cap C]$$
$$= P[A \mid B \cap C] P[B \mid C] P[C]$$

Theorem on Total Probability

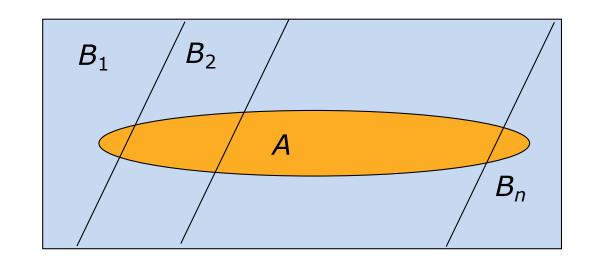
$$P[A] = \sum_{i=1}^{n} P[A \cap B_i] = \sum_{i=1}^{n} P[A \mid B_i] P[B_i]$$



Bayes' Rule

Suppose A occurs, what is the probability of B_i ?

$$B[B^{i} \mid A] = \dot{s} \dot{s} \dot{s}$$



$$P[B_{j} | A] = \frac{P[B_{j} \cap A]}{P[A]} = \frac{P[A | B_{j}]P[B_{j}]}{\sum_{i=1}^{n} P[A | B_{i}]P[B_{i}]}$$

Event Independence

 Intuition: Knowledge that A occurred does not change the probability of B.

$$P[A \cap B] = P[A]P[B]$$

$$P[A|B] = \frac{P[A \cap B]}{P[B]} = \frac{P[A]P[B]}{P[B]} = P[A]$$

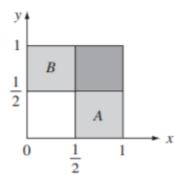
$$P[B|A] = \frac{P[A \cap B]}{P[A]} = \frac{P[A]P[B]}{P[A]} = P[B]$$

Example: Random Pair in Unit Square

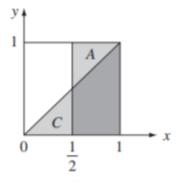
$$A = \{x > y\}, B = \{x > 0.5\} C = \{y < 0.5\}$$

$$P[A|B] =$$

$$P[B|C] =$$



(a) Events A and B are independent.



(b) Events A and C are not independent.

FIGURE 2.13 Examples of independent and nonindependent events.

Independence of Three Events

 Definition: A, B, & C are independent if they are pairwise independent

$$P[A \cap B] = P[A]P[B], P[A \cap C] = P[A]P[C],$$

and $P[B \cap C] = P[B]P[C]$

 and if knowledge of 2 of them does not affect the probability of the 3rd

$$P[C \mid A \cap B] = \frac{P[A \cap B \cap C]}{P[A \cap B]} = P[C]$$

 Therefore, A, B, & C are independent if probability of ∩ of pairs & triplets = product of individual probabilities:

$$P[A \cap B \cap C] = P[A \cap B]P[C] = P[A]P[B]P[C]$$

Independence of Multiple Events

• Similarly, A_1 , ..., A_n are independent if for k = 2, ..., n:

$$P[A_1 \cap A_k] = P[A_1] P[A_k]$$

Exercise: Random Pair in Unit Square

$$A = \{x < 0.5\}, B = \{y > 0.5\}$$

 $F = \{x < 0.5 \text{ and } y < 0.5\} \cup \{x > 0.5 \text{ and } y > 0.5\}$

Sequences of Independent Experiments

- Definition: Two experiments are independent if all of their respective events are independent.
- Suppose that a random experiment E involves performing n subexperiments: E_1 , E_2 , E_3 , ..., E_n .
- S is Cartesian product of individual sample spaces:

$$S = S_1 \times S_2 \times S_3 \times ... \times S_n$$

An outcome of random experiment consists of an n-tuple

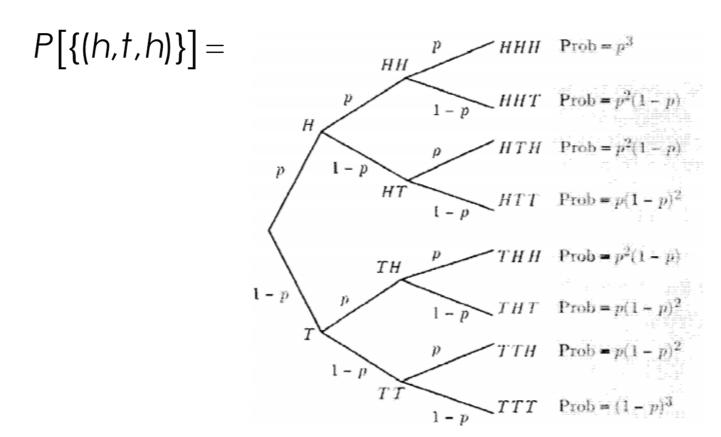
$$\xi = (\xi_1, \xi_2, ..., \xi_n)$$
 where ξ_i is an outcome of E_i

• If the subexperiments are independent, and if A_k only concerns the outcome E_k , then probabilities of events involving intersections of A_k are given by:

$$P \left[A_1 \cap A_2 \cap \cdots \cap A_n \right] = P \left[A_1 \right] P \left[A_2 \right] \dots P \left[A_n \right]$$

Example: Independent Coin Tosses

- Toss a fair coin three times.
- Assume tosses are independent.



Example: Sequence of Bernoulli Trials

- Bernoulli trial involves performing an experiment once and noting whether an event A occurred.
 - "Success" or "1" if A occurs;
 - "Failure" or "0" otherwise
 - Suppose P[A] = p
- Perform n independent Bernoulli trials, what is probability of k successes in n trials?

Example: Sequence of Bernoulli Trials II

The probability of a sequence with exactly k 1s in n trials:

$$p_n(k) = \binom{n}{k} p^k (1-p)^{n-k}$$
 for $k = 0, \dots, n$,

• The number of distinct sequences with k 1s and (n - k) 0s is:

$$p_n(k) = N_n(k)p^k(1-p)^{n-k}.$$

• The probability of *k* successes in *n* trials is:

$$\binom{n}{k} = \frac{n!}{k! (n-k)!}$$

Approximating Binomial Probabilities

• If *n* is large and *p* is small, then for $\alpha = np$

$$p_{k} = \binom{n}{k} p^{k} (1-p)^{n-k} \square \frac{\alpha^{k}}{k!} e^{-\alpha} \quad \text{for } k = 0,1,...$$

$$\frac{p_{k+1}}{p_{k}} = \frac{\binom{n}{k+1} p^{k+1} q^{n-k-1}}{\binom{n}{k} p^{k} q^{n-k}} = \frac{k! (n-k)! p}{(k+1)! (n-k-1)! q}$$

$$= \frac{(n-k)p}{(k+1)q} = \frac{(1-k/n)\alpha}{(k+1)(1-\alpha/n)} \to \frac{\alpha}{k+1} \quad \text{as } n \to \infty$$

See the derivation in class how p_k approaches Poisson

Interpreting the Test Result for Covid-19

- NEW SLIDES FOR LECTURE 3
- Interpreting the result of a test for covid-19 depends on:
 - The accuracy of the test
 - The pre-test probability or estimated risk of disease before testing

Recent Federal Reserve Inflation Policy

- On August 27, 2020 Jerome Powel announced a major change to the current inflation policy
- The old policy kept the inflation below target of 2%
- The new policy keeps the average inflation rate is at 2%
- It means FED will let the inflation rate vary and go above 2% target before considering raising the interest rate
- So the new policy makes the inflation as a random variable

More on Bayes' Theorem

- Bayes' Theorem is a way of finding a probability when we know certain other probabilities.
 - The formula is: P(A|B) = P(A) P(B|A)/P(B)
 - Which tells us: how often A happens given that B happens, ie, P(A|B)
 - When we know: how often B happens given that A happens, ie, P(B|A)
 - and how likely A is on its own, ie, P(A)
 - and how likely B is on its own, ie, P(B)
- Let's say
 - P(Fire) means how often there is fire, and
 - P(Smoke) means how often we see smoke, then:
 - P(Fire | Smoke) means how often there is fire when we can see smoke
 - P(Smoke | Fire) means how often we can see smoke when there is fire
 - So the formula kind of tells us "forwards" P(Fire|Smoke) when we know "backwards" P(Smoke|Fire)

California WiFi

- Last few days (Sept 2020) California WiFi (Wild Fires) have killed more than 36 people
- Wild fires are rare (1%)
- But smoke is fairly common (10%) and 90% of wild fires make smoke
- We can then discover the probability of wild fires when there is Smoke:

P(Wild Fire|Smoke) = P(Fire) P(Smoke|Fire)/P(Smoke) =
$$1\% \times 90\%/10\% = 9\%$$

Example: Picnic Day

- You are planning a picnic today, but the morning is cloudy
- 50% of all rainy days start off cloudy!
- But cloudy mornings are common (about 40% of days start cloudy)
- And this is usually a dry month (only 3 of 30 days tend to be rainy, or 10%)
- What is the chance of rain during the day?
- Use Rain to mean rain during the day, and Cloud to mean cloudy morning.
- The chance of Rain given Cloud is written P(Rain|Cloud)
- P(Rain|Cloud) = P(Rain) P(Cloud|Rain)/P(Cloud)
- P(Rain) is Probability of Rain = 10%
- P(Cloud|Rain) is Probability of Cloud, given that Rain happens = 50%
- P(Cloud) is Probability of Cloud = 40%
- $P(Rain | Cloud) = 0.1 \times 0.5/0.4 = .125$
- Or a 12.5% chance of rain. Not too bad! So, let's go for it!

COVID-19 Pandemic

- Original Covid-19
- Mutated Virus (second wave) lingers longer (is smart!)
- Covid-19 Testing
- Antibody
- Interpreting the test result for Covid-19

Antibody Tests and Potential Shortcomings

- We have Developed tests that detect antibodies in the blood of people who have previously been infected with the COVID-19.
- These serology tests can provide important data on how COVID-19 is spreading through a population.
- There is also hope that the presence of certain antibodies may signify immunity to future infection
- Antibody shortcomings (just to be aware)
 - They may detect ineffective antibodies
 - They do not indicate if an infection is still active
 - They fail to detect infection if administered before antibodies develop

Testing Measures

- Two statistical measures of the testing performance widely used in medicine are Sensitivity and specificity
- Sensitivity measures the probability of testing Positive for those who are infected with Covid
 - That is, P(Test+|Covid+)
 - Those infected correctly identified as having Covid
- Specificity measures the probability of testing negative for those who are not infected with Covid
 - That is, P(Test-|Covid-)
 - Those healthy correctly identified as not having Covid

COVID-19: Probability of at least one Positive

- Initial screening for Covid-19 tests antibody in the blood
- Even if an individual is Covid-negative, the testing probability of p = 0.1 gives a positive result
- Suppose 100 people are tested who are all Covid-negative.
- What is probability that at least one will show positive on the test?
- Using complement rule:P(at least one positive) = 1 P(all negative)
- Assuming that each individual is independent (independent events), then we can write P(all negative)= $(1-p)^{100}$

P(at least one positive) = $1 - 0.99^{100} = 0.9999$

Health Status and Testing

- A person is Positive (has Covid) given Tests Positive P(Test+|Covid+)
- A person is Negative given Tests Negative P(Test-|Covid-)
- A person is Positive but Tests Negative P(Test-|Covid+) (False Negative)
- A person is Negative but Tests Positive P(Test+|Covid-) (False Positive)
- High Sensitivity (more accurate) → Low rate of False Negative
- High Specificity → Low rate of False Positive
- For 80% sensitivity, among 100 people with Covid-19, 80 would have positive tests
- For 90% specificity, among 100 people without Covid-19, 90 would have negative tests

Covid-19 Testing Illustration (1)

- Infection rate of 10%
 - ie, Covid- = Green Box=90% (90), Covid+ =Red Box=10% (10)
- Testing Sensitivity of 80 % (relates to False Negative of 20%)
 - Among 10 people with Covid-19, 8 would be identified as positive and 2 as negative (False Negative)
- Testing Specificity of 90 % (relates to False Positive of 10%)
 - Among 90 people without Covid-19, 81 would be identified as negative and 9 as positive (False Positive)
- Legend:

Cases:

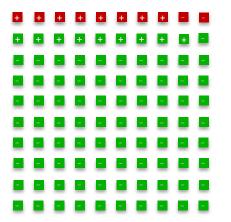
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+ = Test + - = Test -

= Covid - (not infected)

= Covid + (infected)
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Covid-19 Testing Illustration (2)

- What is the probability of having Covid given Test was positive?
- What is the probability of not having Covid given Test was negative?



Testing\Status	Covid +	Covid -	Total
Test +	8	9	17
Test -	2	81	83
Total	10	90	100

Covid-19 Testing Illustration (3)

- What is probability that a person is infected with Covid? From the Table we find P(Covid+)=10/100 = 0.10
- Now we ask, given that a person has tested positive, what is the probability that the person indeed has Covid, ie, P(Covid+|Test+)?
 - This is 8/17 (from the Table), called positive predictive value
- What is the probability of not having Covid if test is negative?
 - This is 81/83 (from the Table), called negative predictive value
- Later, we will use the Conditional Probability and the Bayes'
 Rule for calculations to answer the same questions.

Using the Bayes' Rule to Compute Covid Testing

- We want to know the chances of having Covid when test indicates positive, ie, P(Covid|Test+)
- Also we want to know the chances of not having Covid when test indicates negative, ie, P(Covid-|Test-)
- Let's try to formulate this using what we have learned:

Use iPad to show the calculation

Conditional Probability and Bayes' Rule (1)

What is the probability of having Covid given test was positive, ie, *P*(Covid+ |Test+)?

- Denote Event A for Covid infection with outcomes Covid+ and Covid-
- Denote Event B for Testing with outcomes Test+ and Test-
- A and B are two events in sample space

Note that we use the conditional probability of event B given that event A has occurred ie, P (B|A), to calculate P (A|B) by $P[A|B] = P[A \cap B]/P[B]$ $P(\text{Covid+} \text{ and Test+}) = P[\text{Covid+} \cap \text{Test+}] = P(\text{Covid+}) \times P(\text{Test+}|\text{Covid+})$ $= 0.1 \times 0.8 = 0.08$

P[Test+] is probability of test indicating Positive to anyone (w or w/o Covid)

P[Test+] = P(Covid+)xP(Test+|Covid+)+P(Covid-)xP(Test+|Covid-)

 $P[Test+] = 0.1 \times 0.8 + 0.9 \times 0.1 = 0.17$

P(Covid+ |Test+)=0.08/0.17=0.47

Conditional Probability and Bayes' Rule (2)

What is the probability of not having Covid given test was negative, ie, *P*(Covid- | Test-)?

P[not A | not B] is P(Covid-| Test-)

 $P[\text{not } A | \text{not } B] = [\text{not } A \cap \text{not } B]/P[\text{not } B]$

 $P(\text{Covid- and Test-}) = P[\text{Covid-} \cap \text{Test-}] = P(\text{Covid-}) \times P(\text{Test-} | \text{Covid-}) = 0.9 \times 0.9 = 0.81$

P[Test-] is probability of test indicating Negative to anyone (w or w/o Covid)

P[Test-] = P(Covid-)xP(Test-|Covid-)+P(Covid+)xP(Test-|Covid+)

P[Test-] = 0.9x0.9+0.1x0.2 = 0.83

P(Covid-|Test-)=0.81/0.83=0.976

Conditional Probability and Bayes' Rule (3)

- Now assume an Infection rate of 30%
- Keep the Testing Sensitivity and Specificity as before 80% and 90% respectively
- Using the method just described we compute P(Covid+ | Test+) and P(Covid-| Test-)
- P(Covid+ | Test+) = P(Covid+∩Test+)/P(Test+)= P(Covid+)xP(Test+|Covid+)/P(Test+)=0.3x0.8=0.24/P(Test+)
- P[Test+] = P(Covid+)xP(Test+|Covid+) +P(Covid-)xP(Test+|Covid-)
- P[Test+] = 0.3x0.8+0.7x0.1 = 0.31
- P(Covid+ | Test+)=0.24/0.31=0.774

Similarly we compute P(Covid-|Test-)=0.7x0.9/(0.7x0.9+0.3x0.2)=0.912

Dependency on Infection Rate*

- The accuracy of screening tests is highly dependent on the infection rate
- For infection rate of 10% we had
 - P(Covid+|Test+)=0.47
 P(Covid-|Test-)=0.976
- For infection rate of 30% we had
 - P(Covid+|Test+)=0.774 P(Covid-|Test-)=0.912

^{*:} Sara Lewin Fraser, "Coronavirus Antibody Tests Have a Mathematical Pitfall," Scientific American, July 1, 2020

Generalization - Bayes' Rule for Covid-19 Calculation

- We can write a special version of the Bayes' formula P(A|B) = P(A)P(B|A)/{P(A)P(B|A)+P(not A)P(B|not A)} This is for "A" with two cases (A and not A)
- Extending to "A" with three (or more) cases

When "A" has 3 or more cases we include them all in the denominator:

$$P(A1|B) = P(A1)P(B|A1)/{P(A1)P(B|A1) + P(A2)P(B|A2) + P(A3)P(B|A3) + ...}$$

Note that we have been using the following:

$$P[A \cap B] = P[A \mid B] P[B] = P[B \mid A] P[A]$$

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Poisson Distribution

Derivation of Poisson distribution

$$\Pr[X=k] = \frac{\alpha^k}{k!} e^{-\alpha}$$

Wrote 3 assumptions and derived the probabilities in class using iPad