

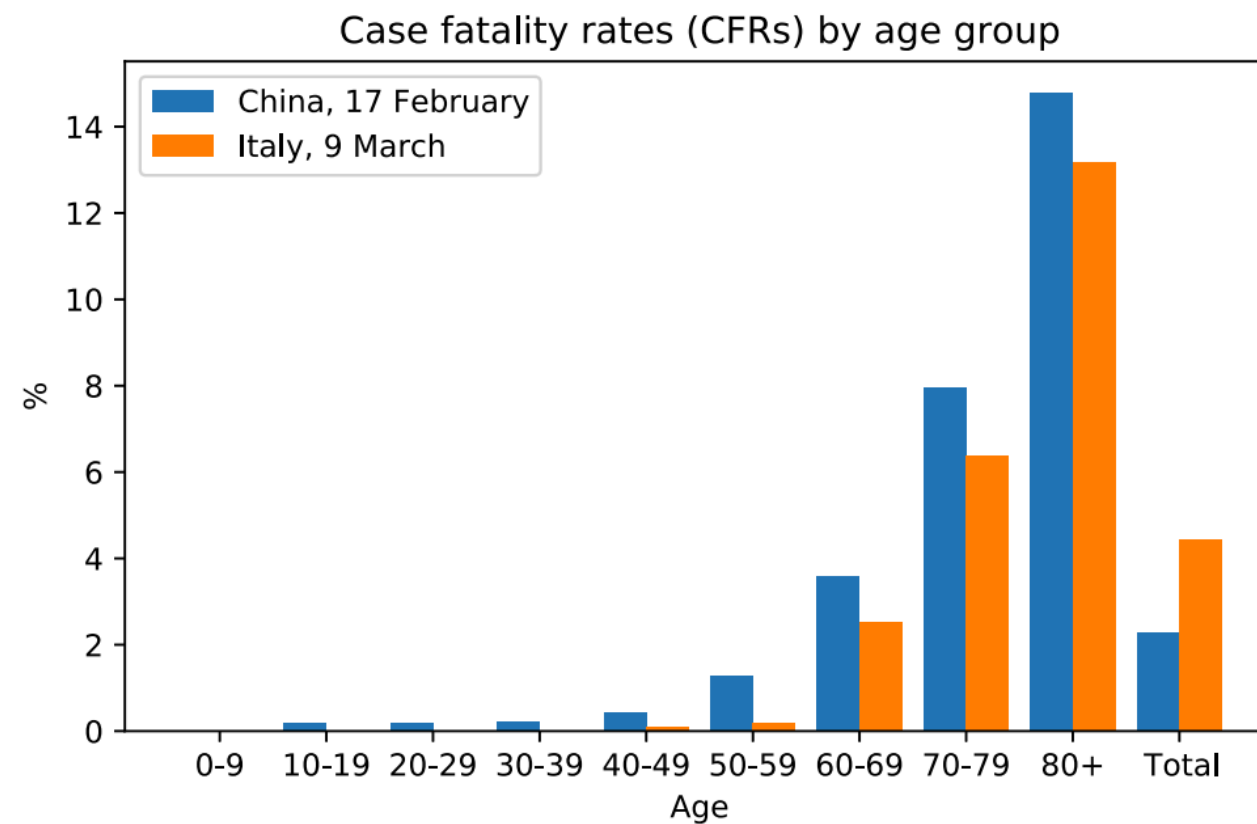
# Epidemiology - Part 1

Feb. 11, 2025

# Recap question:

Feb. 11, 2025

1. Critique the following incorrect statement: in the Israeli ICU, 515 people are hospitalized due to COVID. Of these, 214 were not vaccinated and 301 were vaccinated. Therefore, the vaccines do not work (data from Sept. 2021)
2. Explain why the last bar of this graph does not contradict the rest of the bars



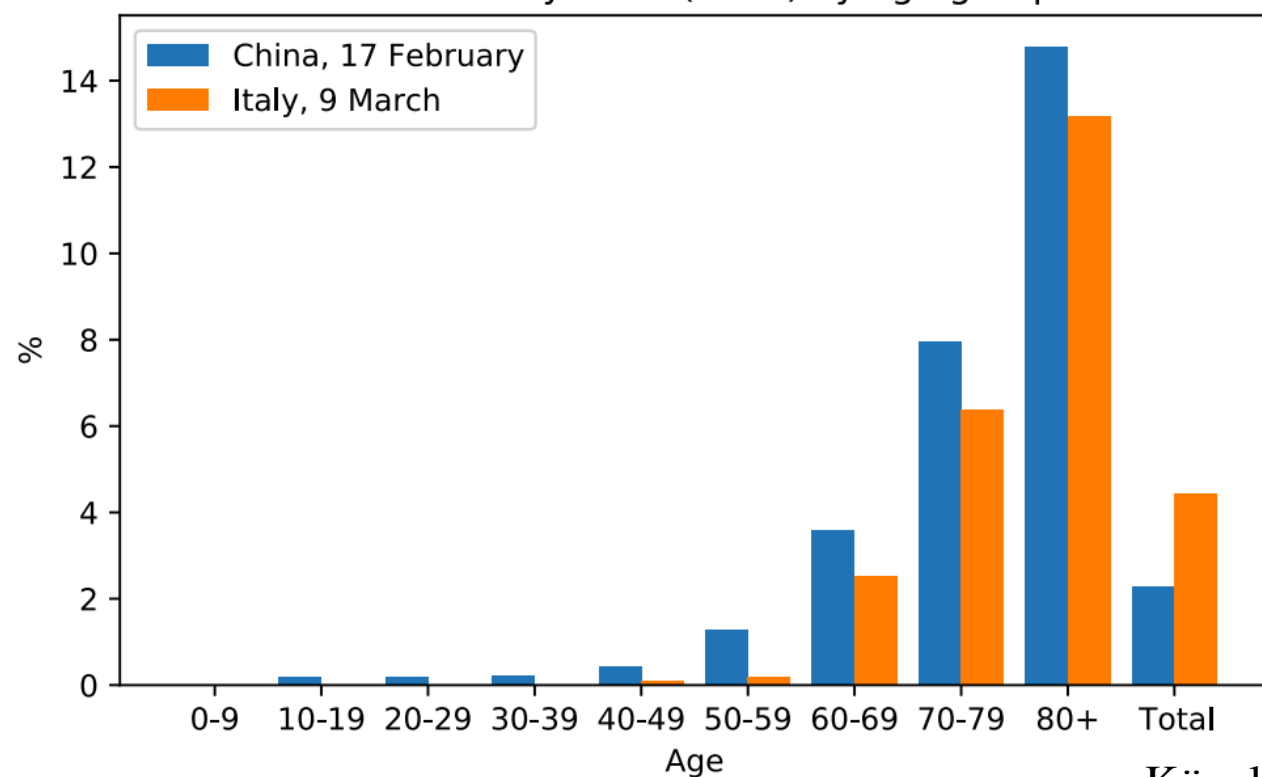
von Kügelgen et al (2021)

# Recap question:

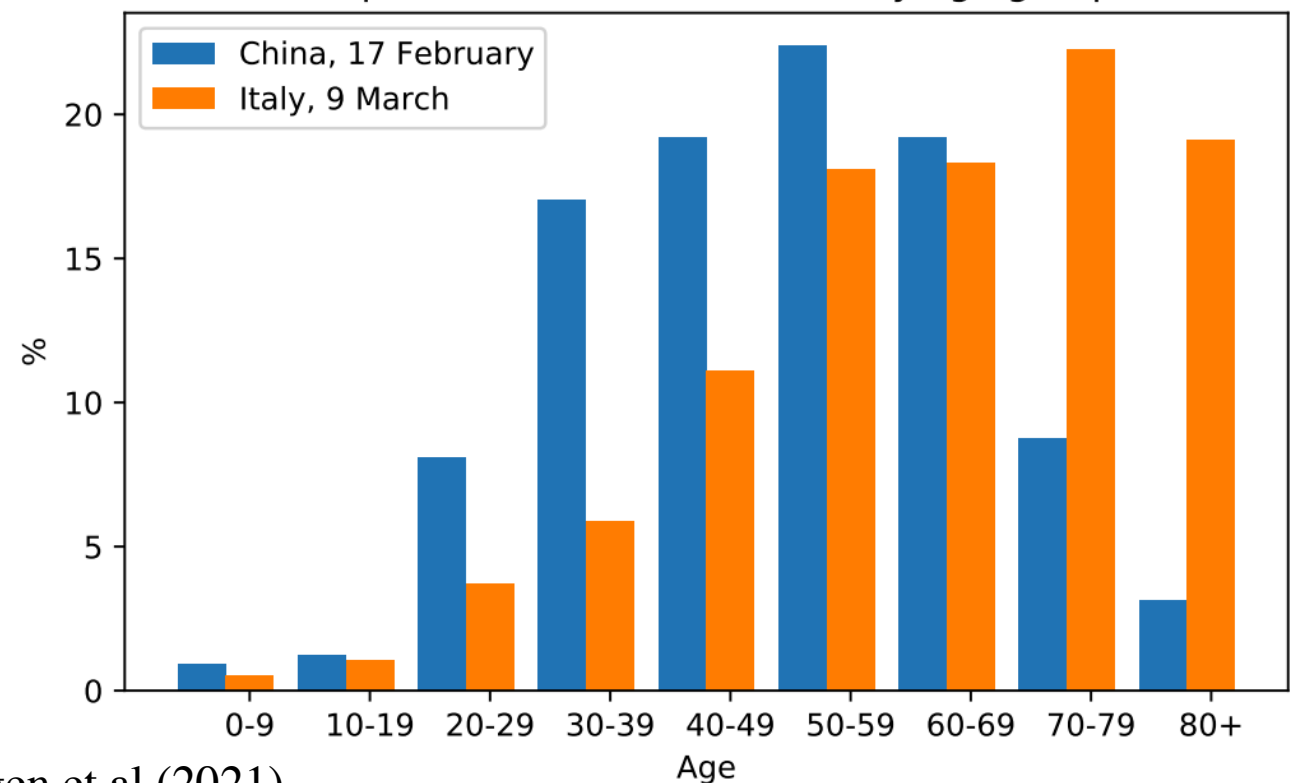
Feb. 11, 2025

1. There could be a Simpson's paradox lurking behind the numbers, ...
2. This is Simpson's paradox: there were more infected in the oldest age group in Italy, which raised overall mortality levels

Case fatality rates (CFRs) by age group



Proportion of confirmed cases by age group



von Kügelgen et al (2021)

# Epidemiology - Part 1

Feb. 11, 2025

By the end of this lecture, you will be able to:

1. Recap **p-values**
2. Explain **Dorfman's testing method**
3. Calculate **sensitivity and specificity** of repeated COVID tests

# Last bits of hypothesis testing

# Hypothesis testing

Consider the following example:

48 bank supervisors (all male) were given the same personnel file and asked whether the person should be promoted or not. The files are identical, except that 24 of the files were assigned to belong to male employees and 24 to females. Of the 48 files, 35 were promoted, 21 of which belonged to males and the rest belonged to females.

The percentage of men promoted =  $\frac{21}{24} = 88\%$

The percentage of women promoted =  $\frac{14}{24} = 58\%$

So there is a 30% difference between men and women promoted. Could this have been due to chance?

## Terminology:

$H_0$  : null hypothesis that there is no discrimination, i.e. each person is equally likely to get promoted.

$H_A$  : alternative hypothesis, i.e., there is some sort of discrimination. Ofter this is just the complement of  $H_0$ .

$p$ -value: probability of obtaining results that are at least as extreme as the observed results, if the null hypothesis were correct, i.e.,

$$p = P(\text{difference at least } 30\% | H_0) \approx 0.01$$



# What value of the $p$ - value is significant?

This is a value judgement and differs between fields, depending on how serious it would be to draw the wrong conclusion. Given a level  $\alpha$  of significance, we reject the null hypothesis if we witness the  $p$  - value is smaller than  $\alpha$  .

$\alpha = 0.05$  or  $\alpha = 0.01$  is common in biomedical research

$\alpha = 0.00000003$  was used when discovering the Higgs boson

	$H_0$ is true	$H_0$ is false
Do not reject $H_0$	Correct inference	Type II error
Reject $H_0$	Type I error	Correct inference

## **Example 2:**

Tom has two roommates: Ryan and Hugo. Every week, Tom draws a name out of a bucket to randomly select the roommates to take the trash out that week. Hugo suspects that Tom is cheating, so he starts keeping track of the draws, and he finds that out of 12 draws, Tom didn't get picked even once!

$H_0$  : Tom is not cheating so each roommate gets  
picked 1/3 of the time

$H_A$  : Tom is cheating

$P(\text{Tom not picked in a given draw} \mid H_0) =$

$P(\text{Tom not picked in 12 consecutive draws} \mid H_0)$

$=$



Hint: the probabilities of **independent** events multiply  $P(A \text{ and } B) = P(A) \cdot P(B)$

$p =$

$$P(\text{Tom not picked in a given draw} \mid H_0) = \frac{2}{3}$$

$$P(\text{Tom not picked in 12 consecutive draws} \mid H_0)$$

=



Hint: the probabilities of **independent** events multiply  $P(A \text{ and } B) = P(A) \cdot P(B)$

$$p =$$

$$P(\text{Tom not picked in a given draw} \mid H_0) = \frac{2}{3}$$

$$P(\text{Tom not picked in 12 consecutive draws} \mid H_0) \\ = \left(\frac{2}{3}\right)^{12} \approx 0.8\%$$

$$p =$$

$$P(\text{Tom not picked in a given draw} | H_0) = \frac{2}{3}$$

$$P(\text{Tom not picked in 12 consecutive draws} | H_0) \\ = \left(\frac{2}{3}\right)^{12} \approx 0.8\%$$

$$p = P(\text{Tom not picked in at least 12 draws} | H_0)$$

$$P(\text{Tom not picked in a given draw} | H_0) = \frac{2}{3}$$

$$P(\text{Tom not picked in 12 consecutive draws} | H_0) \\ = \left(\frac{2}{3}\right)^{12} \approx 0.8\%$$

$$p = P(\text{Tom not picked in at least 12 draws} | H_0) \\ = P(\text{Tom not picked in 12 draws} | H_0) \approx 0.008$$



because there were 12 draws in total

# What value of the $p$ - value is significant?

This is a value judgement and differs between fields, depending on how serious it would be to draw the wrong conclusion

$p = 0.05$  or  $p = 0.01$  is common in biomedical research

$p = 0.00000003$  was used when discovering the Higgs boson

	$H_0$ is true	$H_0$ is false
Do not reject $H_0$	Correct inference	Type II error
Reject $H_0$	Type I error	Correct inference

**Do not reject  $\neq$  Accept!!!**



# **Drawbacks of the Framework of Hypothesis Testing**

- More inclined towards not rejecting the null hypothesis
- The result depends on the choice of null hypothesis



**Epidemiology** is the study and analysis of the incidence, distribution, and possible control of diseases and other factors relating to health.

# Types of COVID-19 tests

**Diagnostic tests:** show if you have an active coronavirus infection.

- molecular tests
- antigen tests

**Antibody tests:** show if you have been infected by coronavirus in the past

# Used at Princeton

↙  
Molecular tests  
(Ex: RT-PCR)

Antigen tests

saliva, nasal or throat swab

nasal or throat swab

detect genetic materials of  
the virus

detect specific proteins of  
the virus

highly sensitive and  
specific

highly specific but less  
sensitive

a few hours to days

less than an hour

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# Challenges in testing

**Resources:** having an adequate number of trained health professionals to collect and process samples along with an adequate supply of reagents and testing machines

**Time:** having the test results available promptly to avoid infected people from unknowingly spreading the virus to others.

# At Princeton

## Undergraduate Student Data

Week Ending ▾	Tests	Positive Cases	Positivity Rate	Change in Positivity Rate
Feb 25, 2022	5,870	326	5.55%	0.66%
Feb 18, 2022	6,131	300	4.89%	4.51%
Feb 11, 2022	5,537	21	0.38%	0.09%
Feb 4, 2022	8,015	23	0.29%	-1.03%
Jan 28, 2022	9,344	123	1.32%	-0.57%

51 - 55 / 129 < >

## Graduate Student Data

Week Ending ▾	Tests	Positive Cases	Positivity Rate	Change in Positivity rate
Feb 18, 2022	2,141	5	0.23%	-0.07%
Feb 11, 2022	2,319	7	0.3%	0.07%
Feb 4, 2022	3,408	8	0.23%	-0.25%
Jan 28, 2022	3,491	17	0.49%	-0.38%
Jan 21, 2022	2,641	23	0.87%	-0.17%

51 - 55 / 128 < >

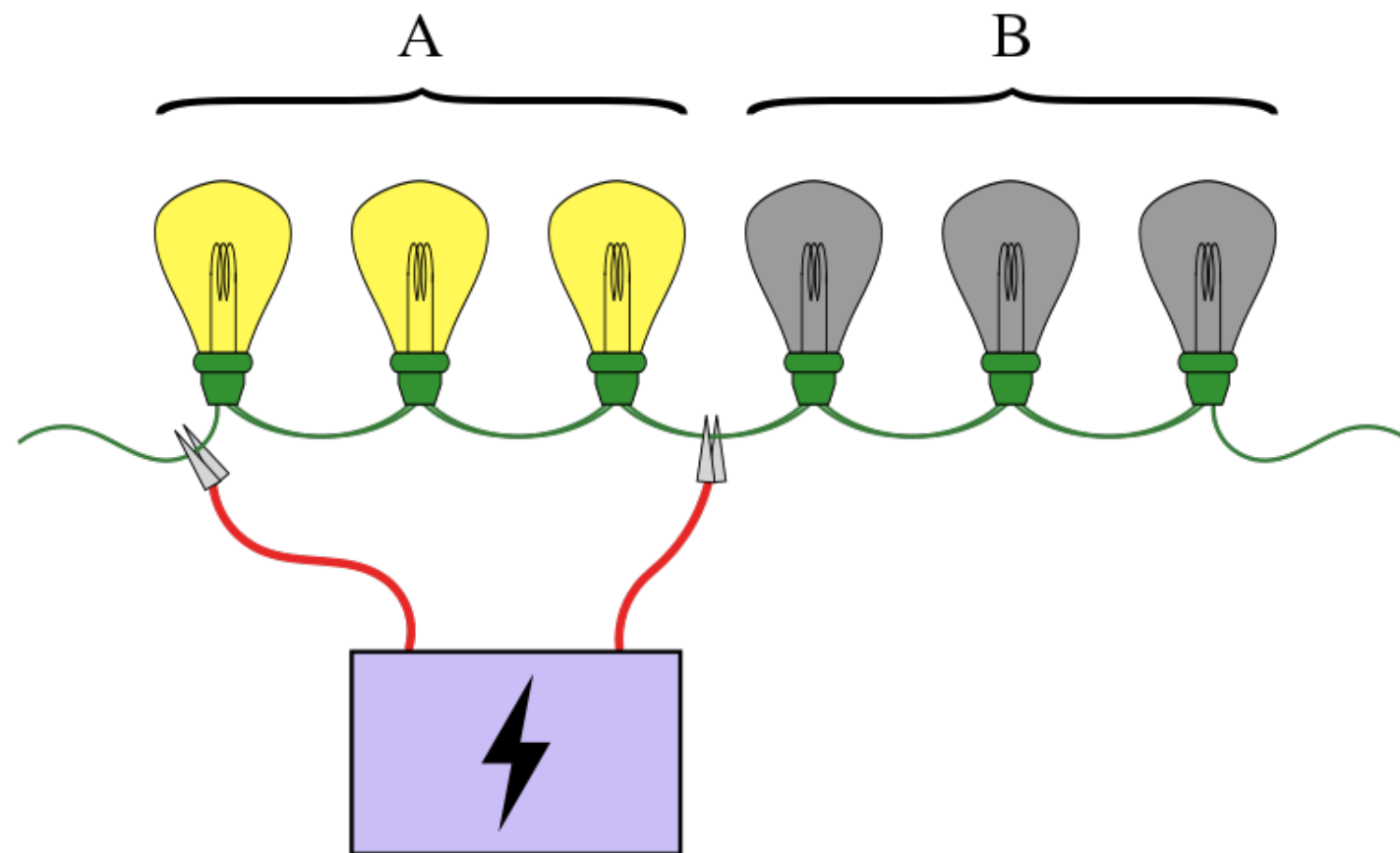
## Faculty, Staff & Other Data

Week Ending ▾	Tests	Positive Cases	Positivity Rate	Change in Positivity Rate
Feb 25, 2022	5,360	15	0.28%	0.02%
Feb 18, 2022	5,477	14	0.26%	-0.01%
Feb 11, 2022	5,593	15	0.27%	-0.28%
Feb 4, 2022	5,445	30	0.55%	-0.37%
Jan 28, 2022	4,025	37	0.92%	-0.85%

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# Pool testing

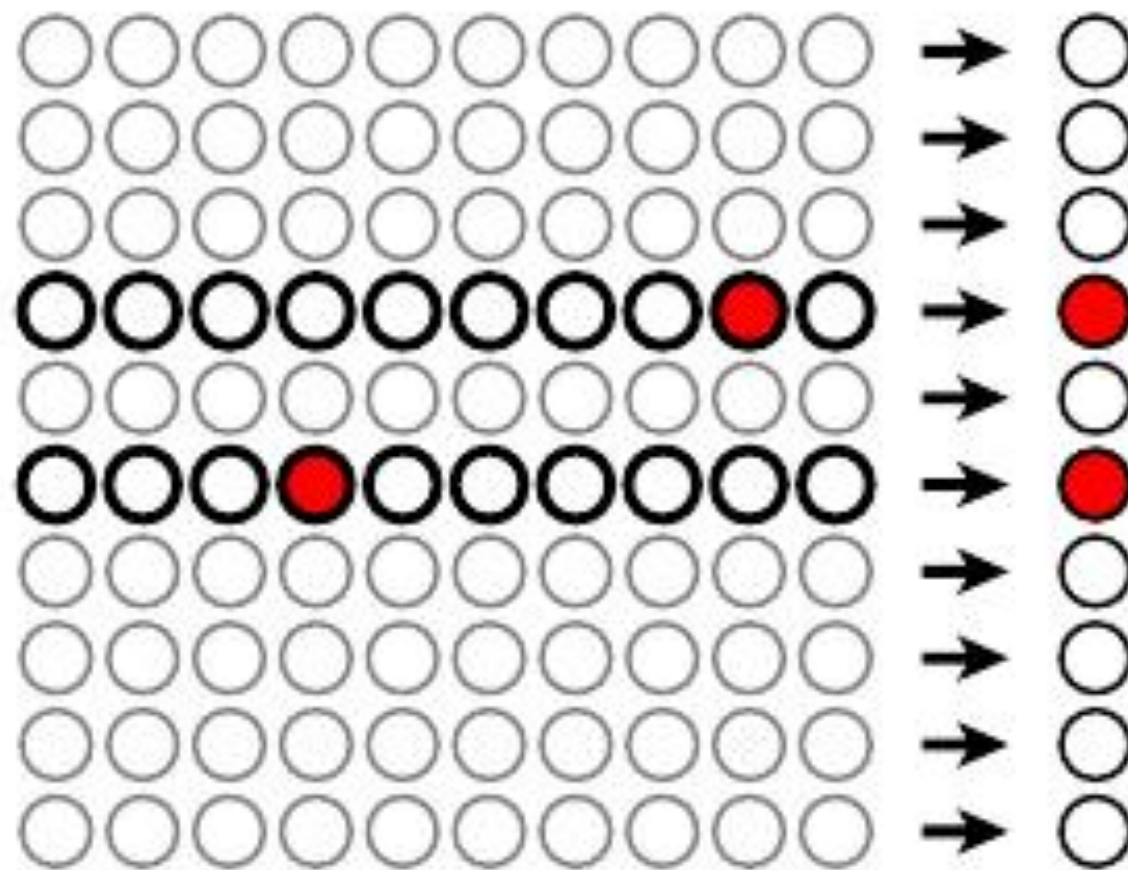
combine samples from many patients into testing pools strategically rather than testing samples from each individual patient separately





# Dorfman's method

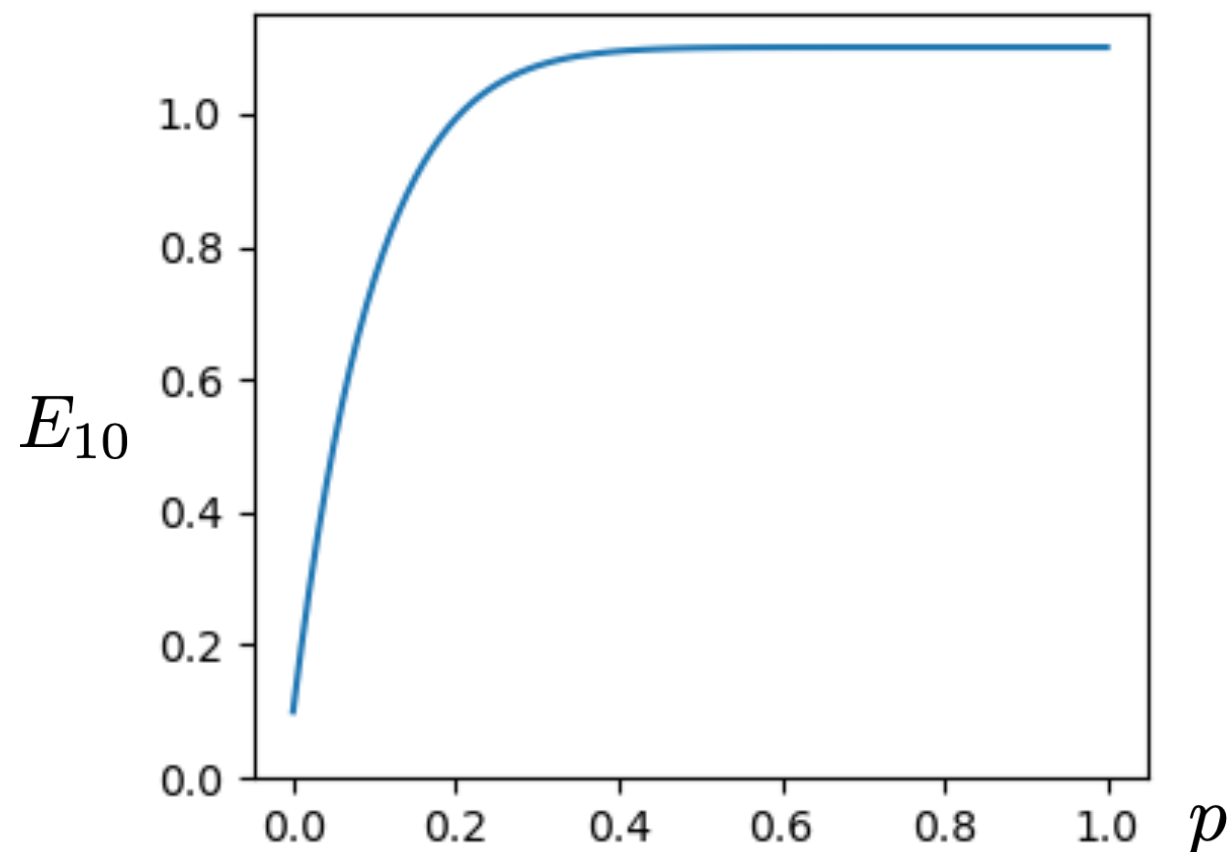
If the test result of a pool is negative, everyone in that pool is free of infection. If a pool tests positively, each individual in the pool is then tested.



Dorfman's method is useful when the population infection rate, or **prevalence**, is low. Consider the scenario that there is an infected person in every pool instead. How many tests are needed?

If  $k^2$  samples are grouped into  $k$  pools with  $k$  samples each, with prevalence  $p$ , the expected number of tests per person is

$$E_k(p) = \frac{1}{k} + (1 - q^k), \quad q = 1 - p$$



Asymptomatic weekly positivity rate at PU less than 10% at the peak

# At Princeton, pooling was used starting Feb 2021

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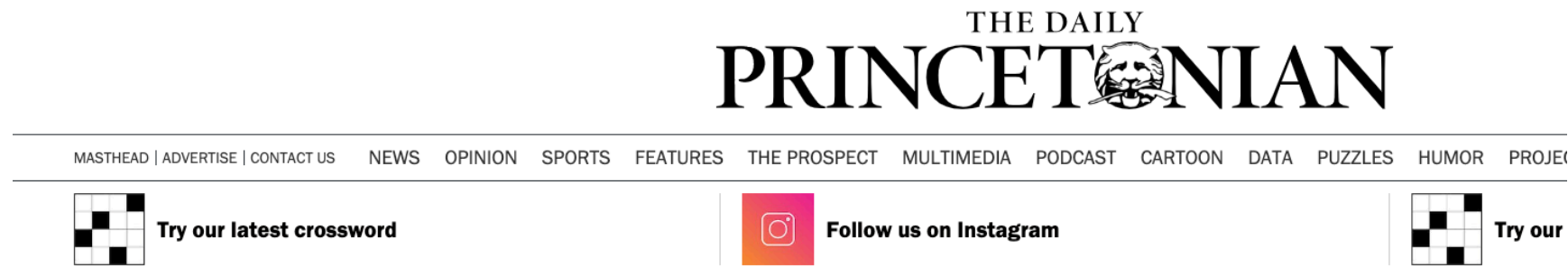
## NEWS

# Princeton's COVID-19 lab approved to begin “pooling” samples

**Evelyn Daskoch**

February 16, 2021 | 7:24pm EST

At Princeton, pooling was used starting Feb 2021



NEWS

## Princeton's COVID-19 lab approved to begin "pooling" samples

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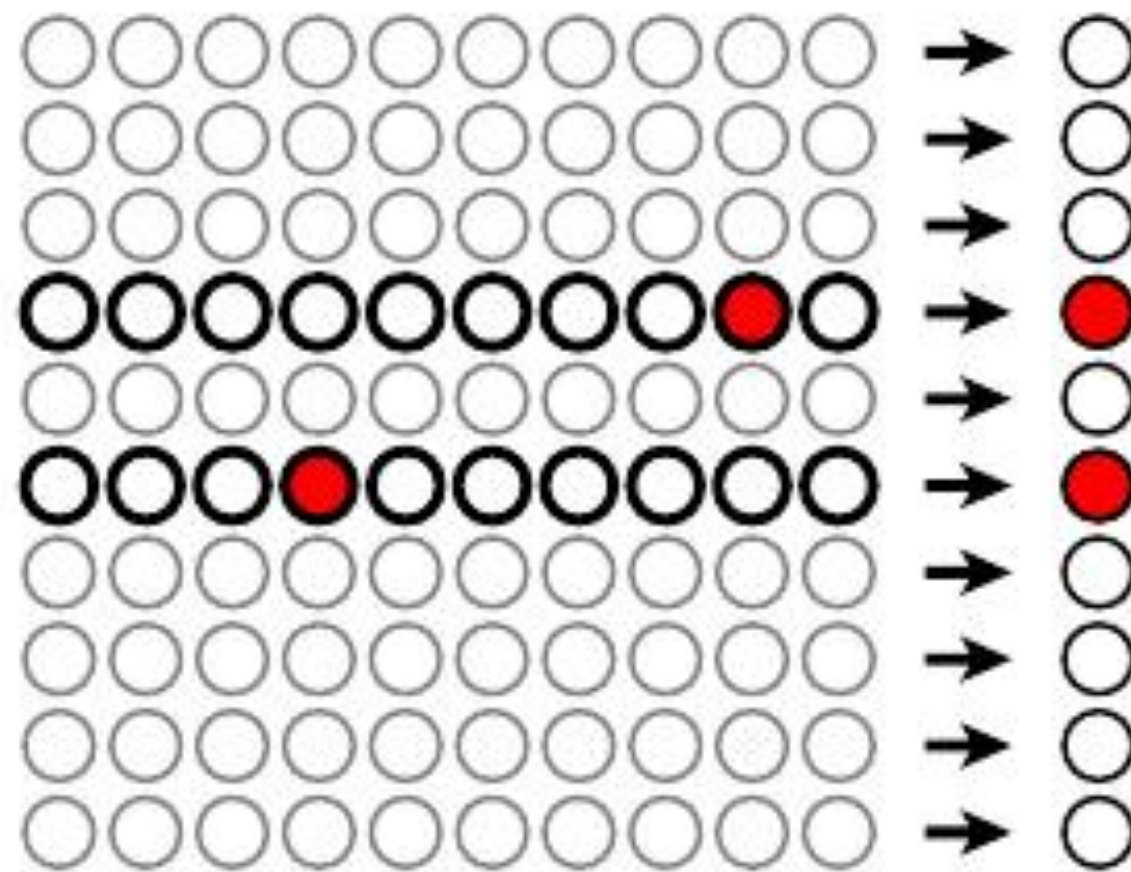
After some experiments, settled on 4 individual samples combined into one pool, and a positive result of the pool triggered individual tests of the 4 samples.

Saves work when there are less than ~10% positive cases

# Non-perfect tests

When the test has sensitivity  $S_e$  and specificity  $S_p$ , the expected number of tests per person is

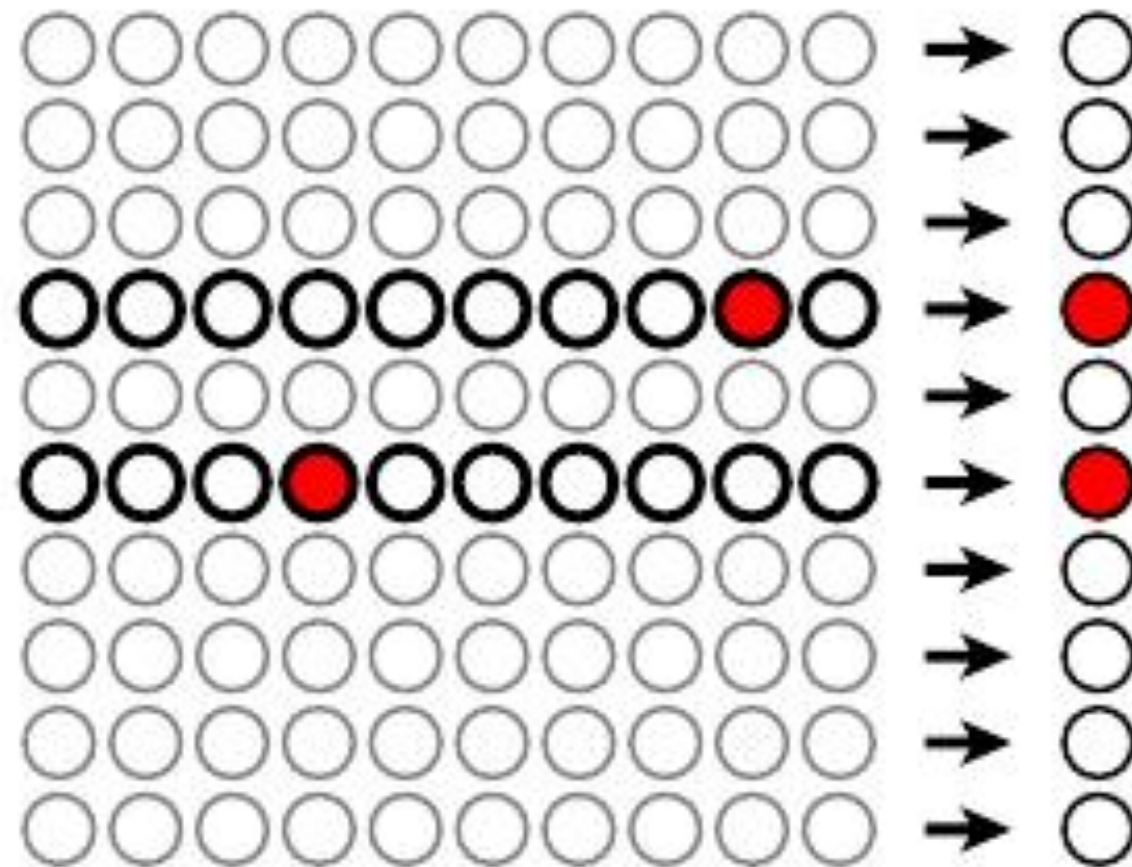
$$E_k(p) = \frac{1}{k} + S_e(1 - q^k) + (1 - S_p)q^k$$



Sensitivity = probability that test shows positive given that you are infected

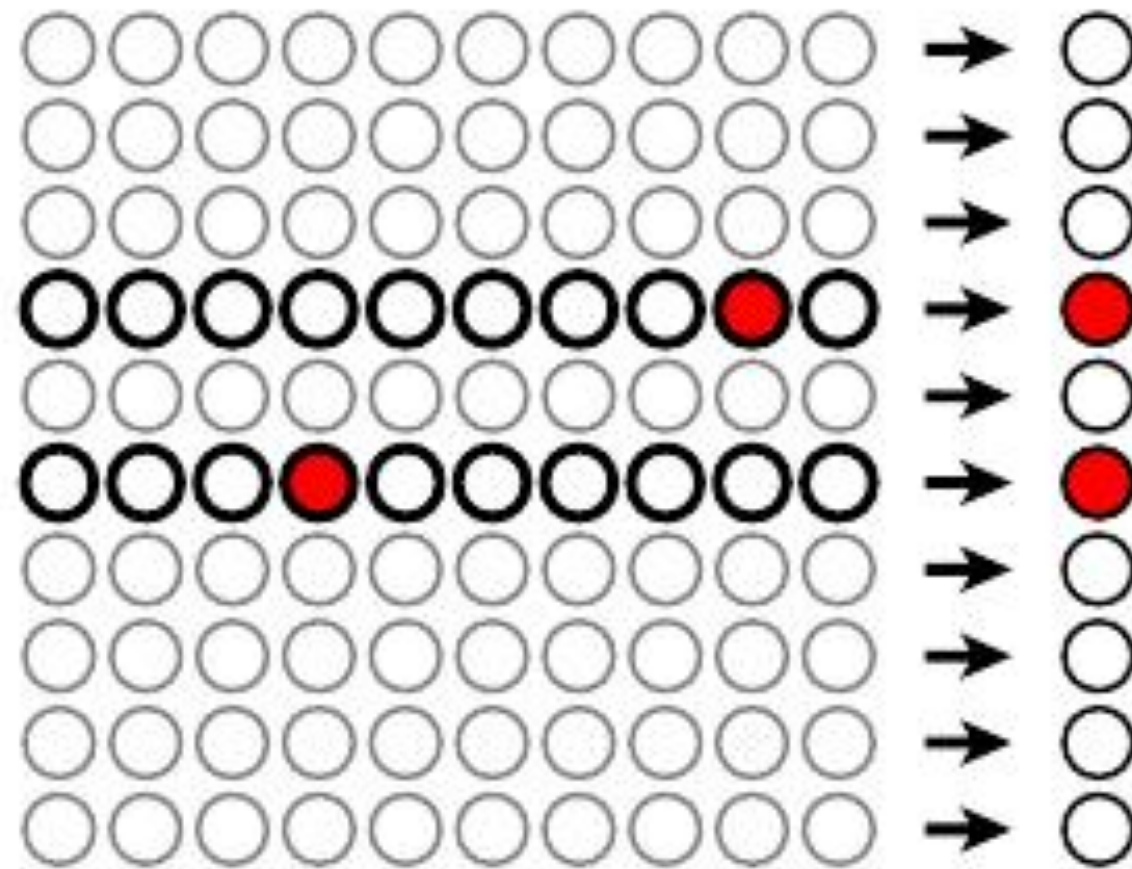
Specificity = probability that test shows negative given that you are not infected

**What happens to sensitivity and specificity for each individual?**





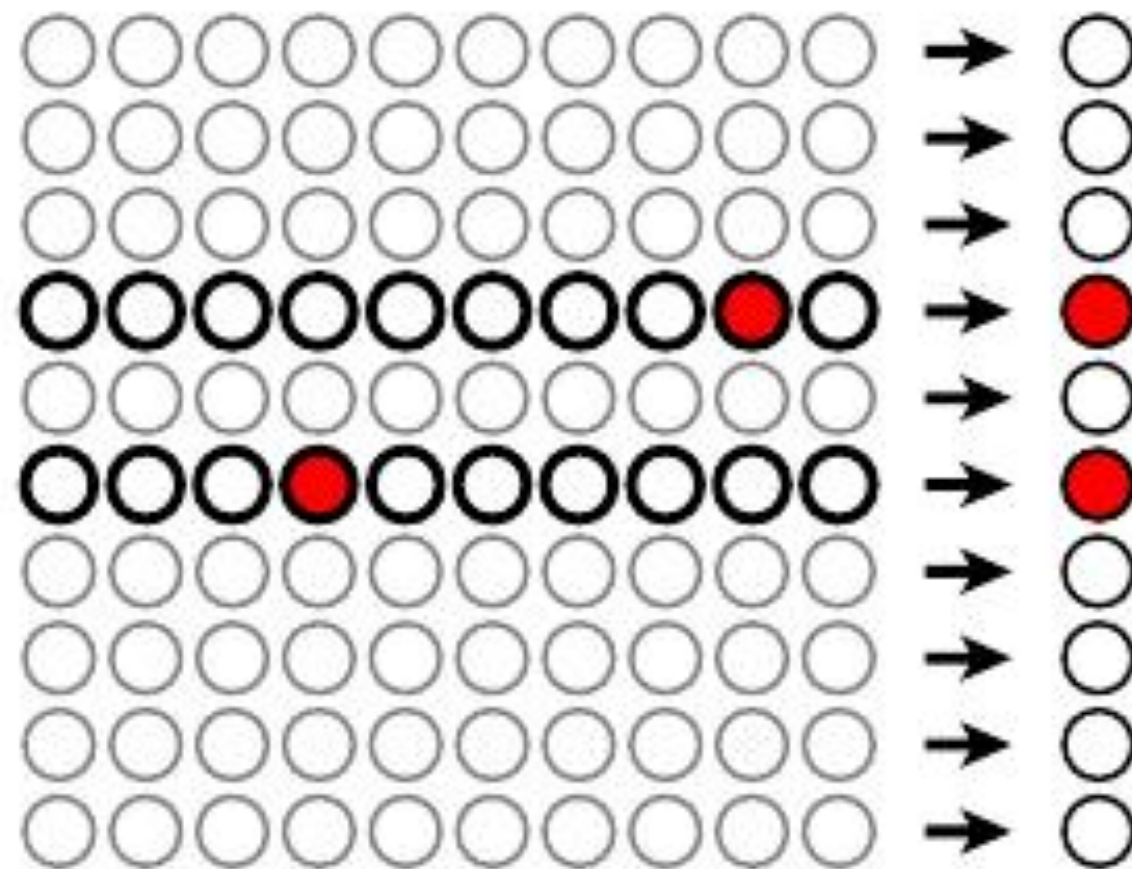
**What happens to sensitivity and specificity for each individual?**



An infected person needs two tests (pool and subsequent individual test) to be positive to be correctly shown as positive.



**What happens to sensitivity and specificity for each individual?**



An infected person needs two tests (pool and subsequent individual test) to be positive to be correctly shown as positive.

Expect sensitivity to decrease, but specificity to increase!

The sensitivity and specificity of Dorfman's method is

$$S'_e = S_e^2$$

and

$$S'_p = 1 - (1 - S_p)P_{k-1}, \text{ where}$$

$$P_{k-1} = S_e(1 - q^{k-1}) + (1 - S_p)q^{k-1}$$

For  $S_e = S_p = 0.95$ ,  $p = 0.01$ , we have

$$S'_e = 0.90, \quad S'_p = 0.99$$

# Repeated testing

## Repeated testing

**Recall what we did for a single test:** Consider one COVID test with 84% **sensitivity** and 99% **specificity**. ( $I$  = infected), and assume 10% of the population is infected

$$P(\text{positive} | I) = 0.84$$

True positive

$$P(\text{negative} | I) = 0.16$$

False negative

$$P(\text{negative} | nI) = 0.99$$

True negative

$$P(\text{positive} | nI) = 0.01$$

False positive

We used Bayes' rule to get the formula:

$$P(I|\text{positive}) = \frac{P(\text{positive}|I)P(I)}{P(\text{positive}|I)P(I) + P(\text{positive}|nI)P(nI)} \quad 36$$

## Example 1:

$$P(\text{test positive} \mid I) = 0.84$$

True positive

$$P(\text{test negative} \mid I) = 0.16$$

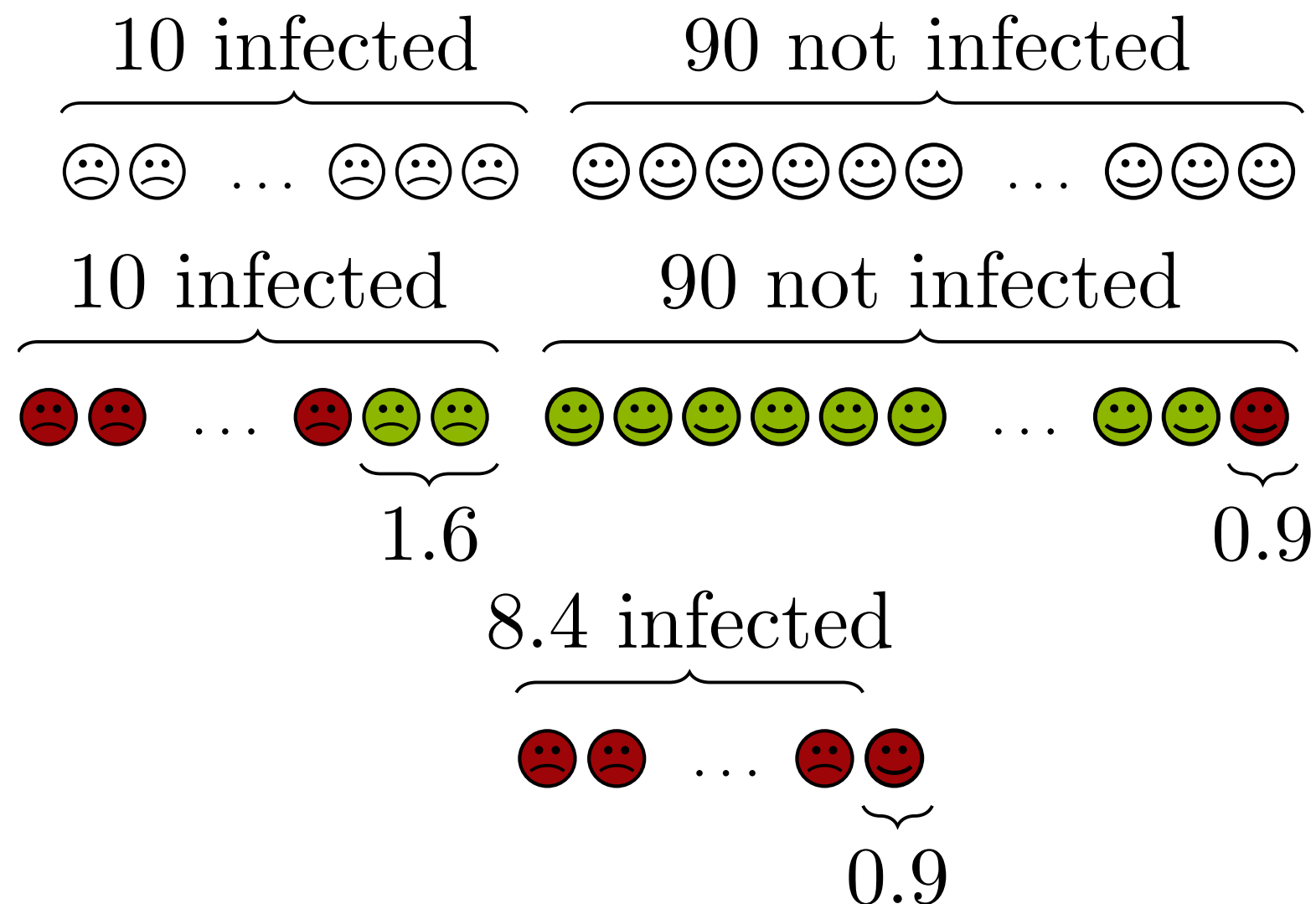
False negative

$$P(\text{test negative} \mid nI) = 0.99$$

True negative

$$P(\text{test positive} \mid nI) = 0.01$$

False positive



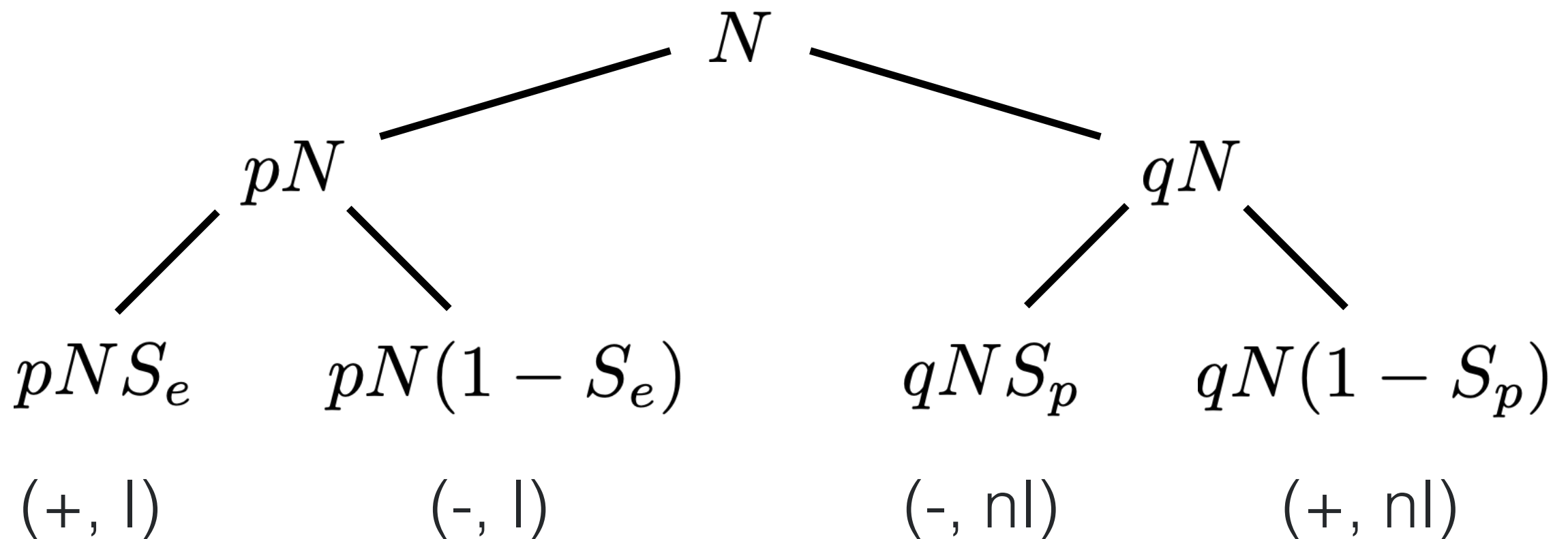
# Repeated testing

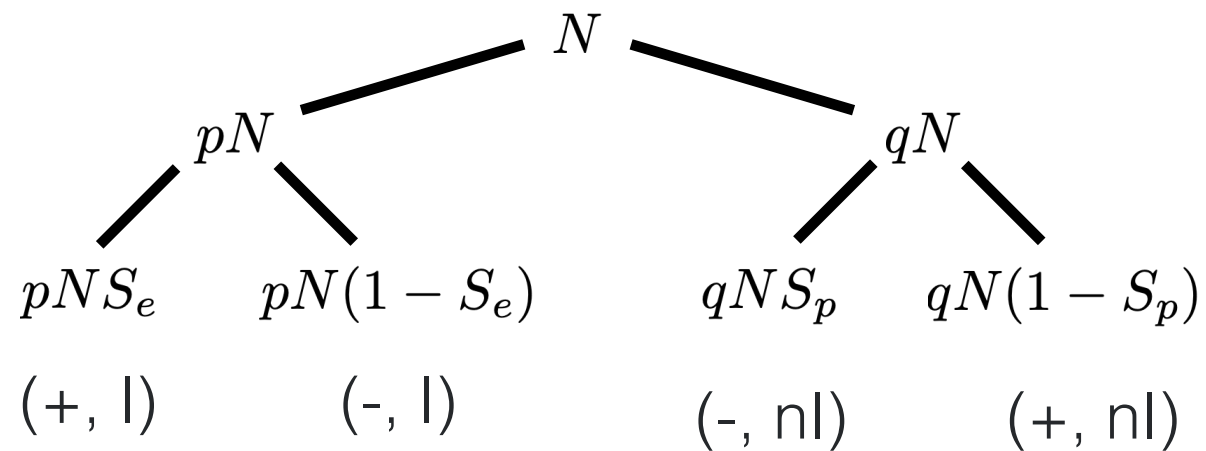
Graphical illustration of the math:

$S_e$  : sensitivity,  $S_p$  : specificity,  $N$  : population size

$p$  : prevalence,  $q = 1 - p$ ,

After the first test,

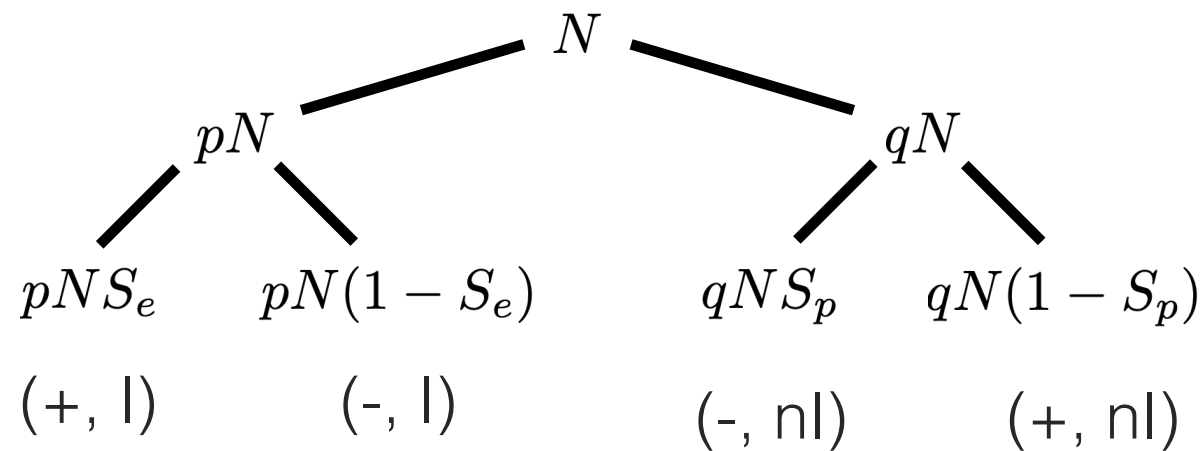




$$N_+ = pNS_e + qN(1 - S_p)$$

$$P(I|+) = \frac{pNS_e}{pNS_e + qN(1 - S_p)} = \frac{pS_e}{pS_e + q(1 - S_p)}$$

$$P(nI|+) = \frac{q(1 - S_p)}{pS_e + q(1 - S_p)}$$



$$N_+ = pNS_e + qN(1 - S_p)$$

$$P(I|+) = \frac{pNS_e}{pNS_e + qN(1 - S_p)} = \frac{pS_e}{pS_e + q(1 - S_p)}$$

$$P(nI|+) = \frac{q(1 - S_p)}{pS_e + q(1 - S_p)}$$

For  $S_e = 0.9$ ,  $S_p = 0.95$ ,  $p = 0.05$ ,

$$P(I|+) \approx 0.49$$



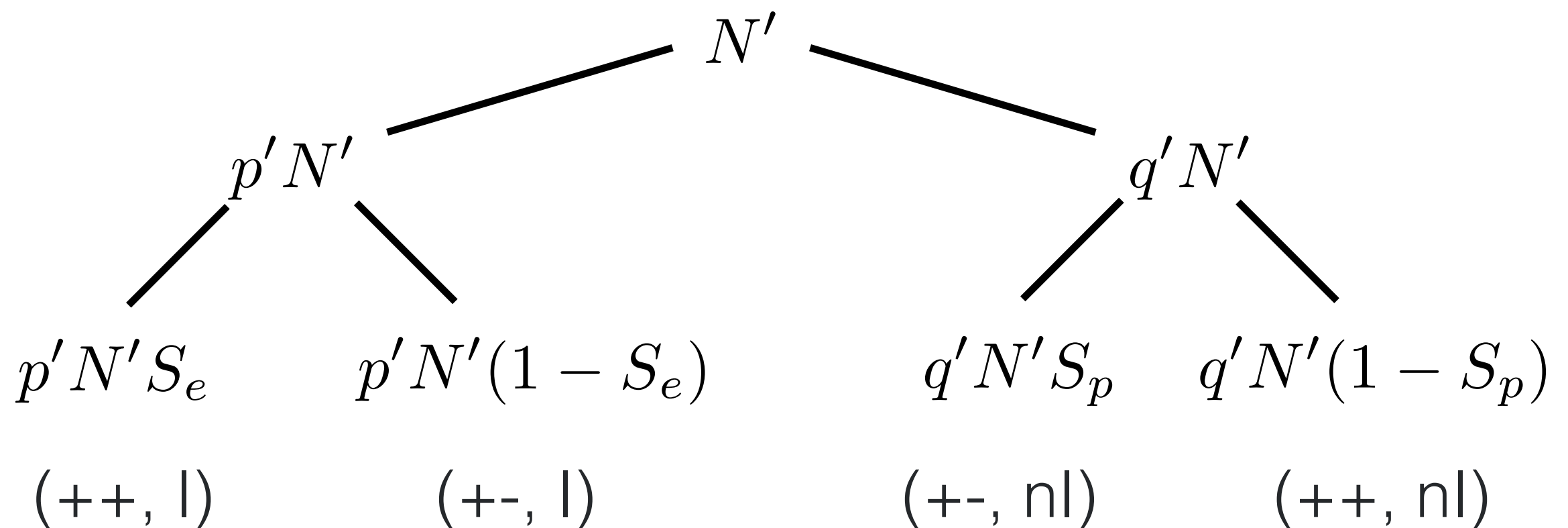
When testing again we do the same math, but only look at the individuals who tested positive in the first test, so the probability to be infected is now  $p(I|+)$   
In other words, we replace:

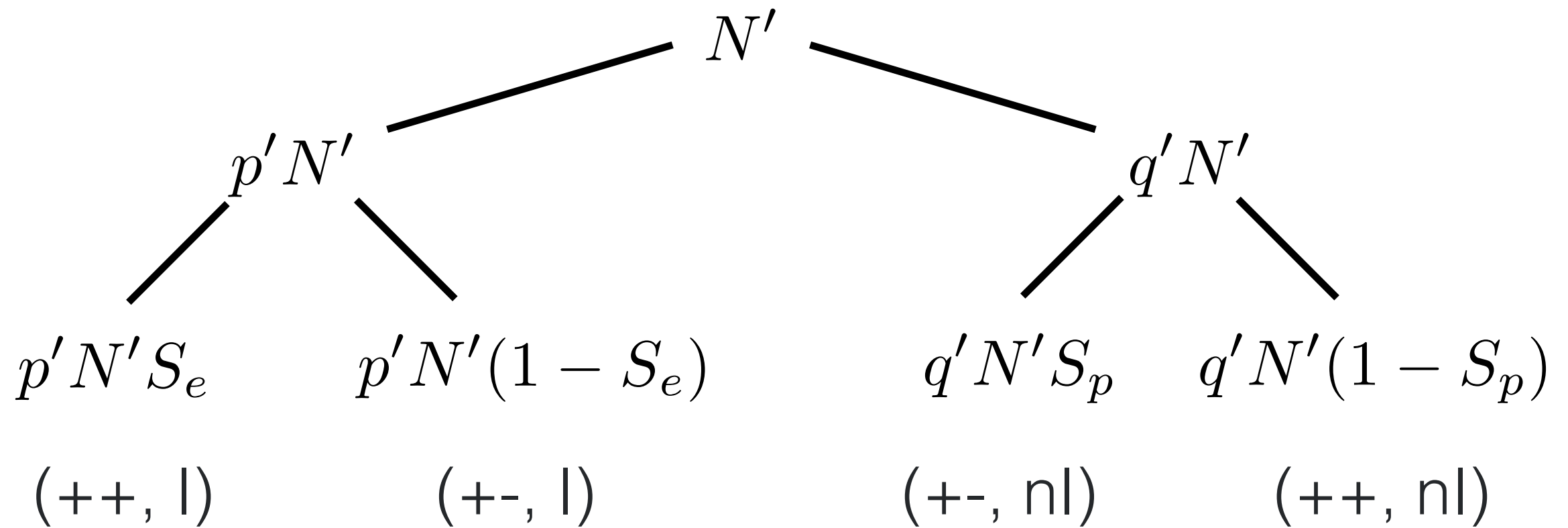
$$N \rightarrow N' = N_+ \text{ and } p \rightarrow p' = p(I|+)$$
$$q \rightarrow q' = 1 - p'$$

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$$q \rightarrow q' = 1 - p'$$





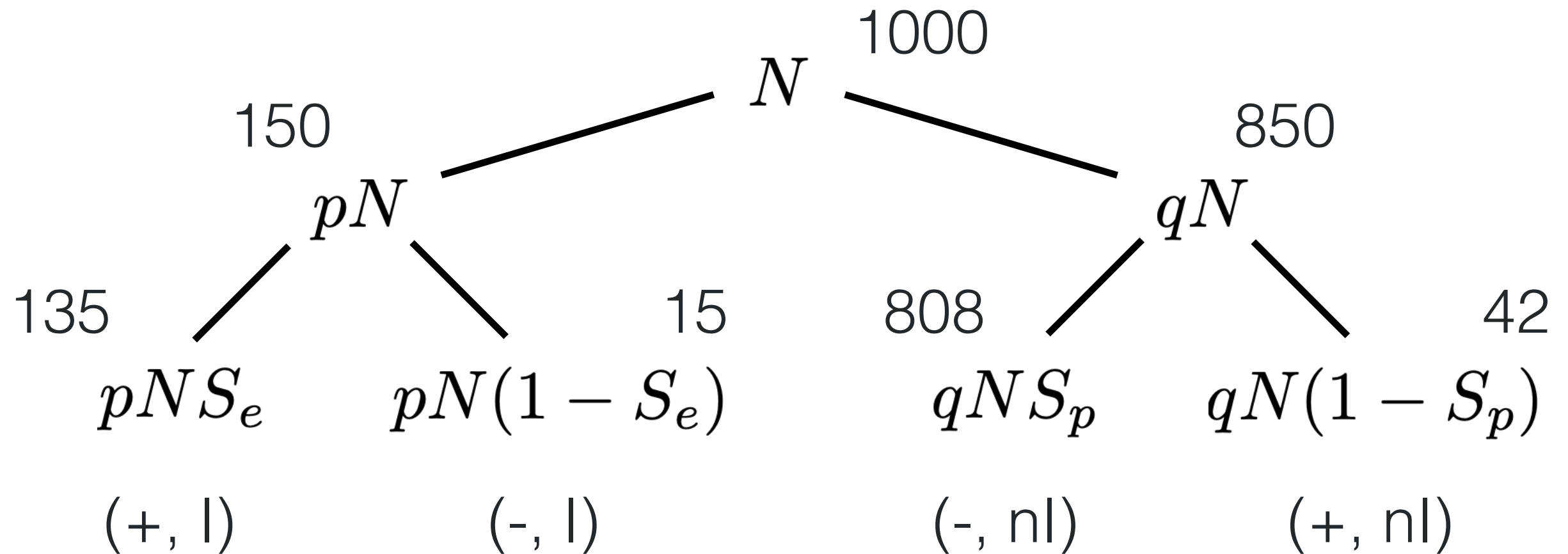
$$\begin{aligned}
 P(I|++) &= \frac{p'N'S_e}{p'N'S_e + q'N'(1 - S_p)} = \frac{p'S_e}{p'S_e + q'(1 - S_p)} \\
 &= \frac{pS_e^2}{pS_e^2 + q(1 - S_p)^2} \approx 0.94
 \end{aligned}$$

If we perform a third test, we test the samples whose first two test results are positive, and the same calculations give

$$p(I|+++) = \frac{pS_e^3}{pS_e^3 + q(1 - S_p)^3} \approx 0.997$$

# Estimating prevalence

$$S_e = 0.9, \quad S_p = 0.95, \quad p = 0.15$$



test number	number of positives $N_+$	ratio $r$	$N_+/r$
1	177	0.9	197
2	124	0.81	152
3	109	0.729	150

If we neglect the number of false positives, the number of positives after  $k$  tests should be approximately  $S_e^k$  times the number of positive cases in the population, which can be used to estimate the total number of positives.

# References

1. <http://www.ams.org/publicoutreach/feature-column/fc-2020-10>
2. <http://www.ams.org/publicoutreach/feature-column/fc-2020-09>