

# Agenda

- Data Simulation
- Paper
- E. Schnitzer & R. Platt

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exposed

non-exposed

Y

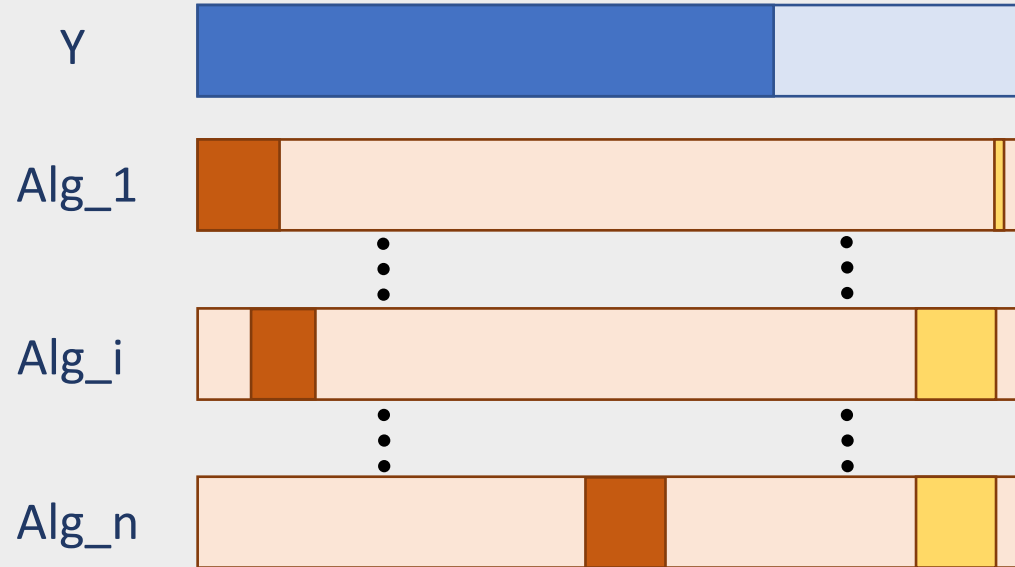


 Y = 0

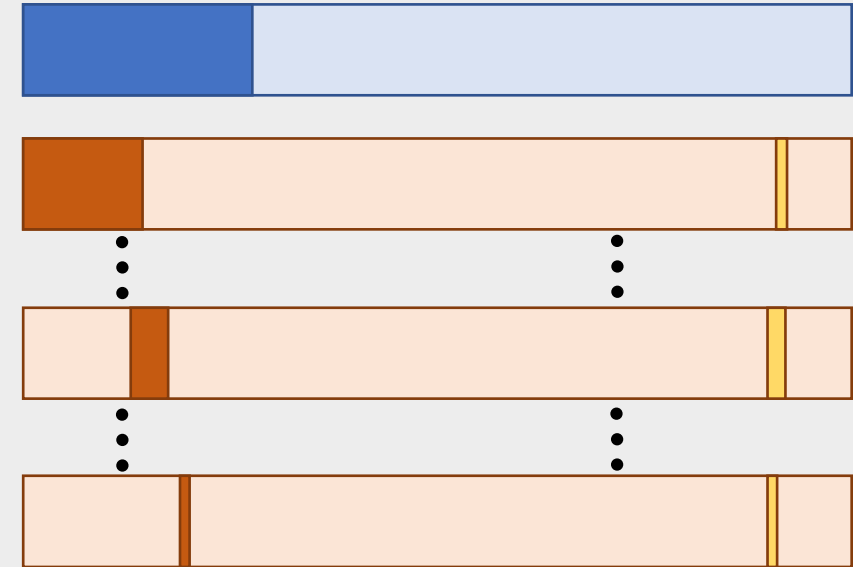
 Y = 1

- Y could be different between groups

exposed



non-exposed



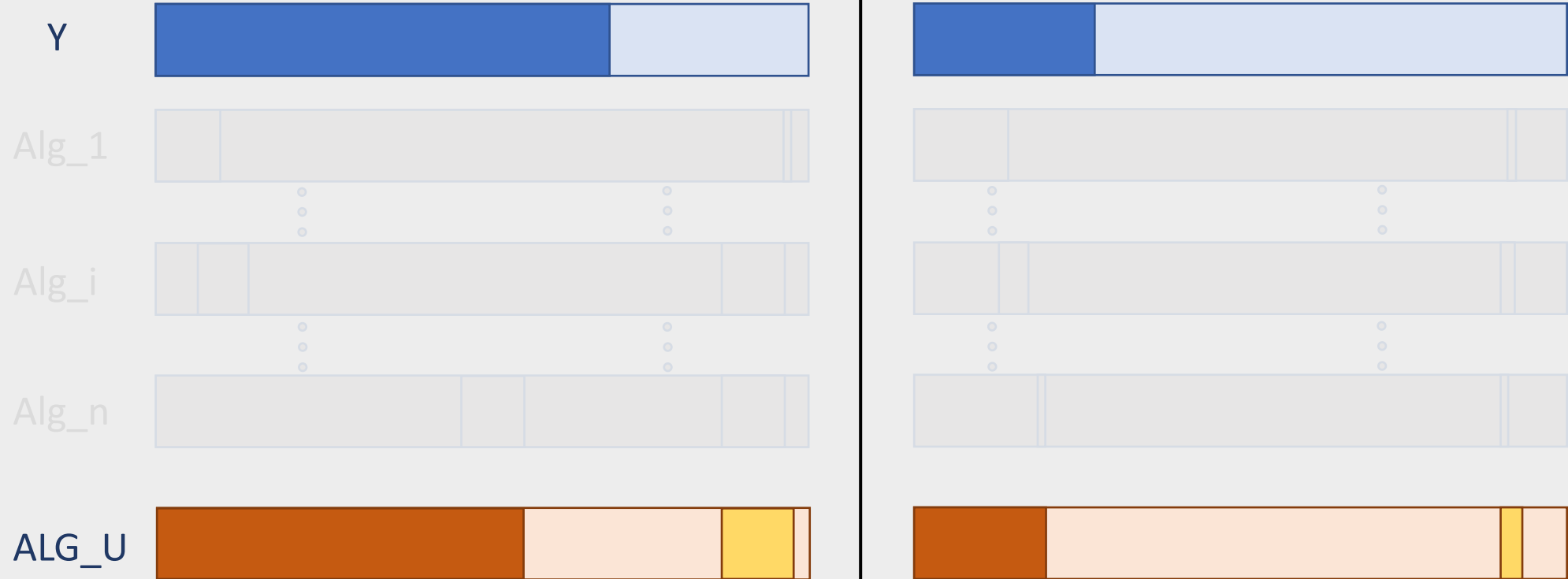
$Y = 0$   
 $Y = 1$

FP  
TP  
Alg = 0

- Many algorithms can be combined, each one finding a part of the positives
- The validation indices of the individual algorithms can be non-differential

exposed

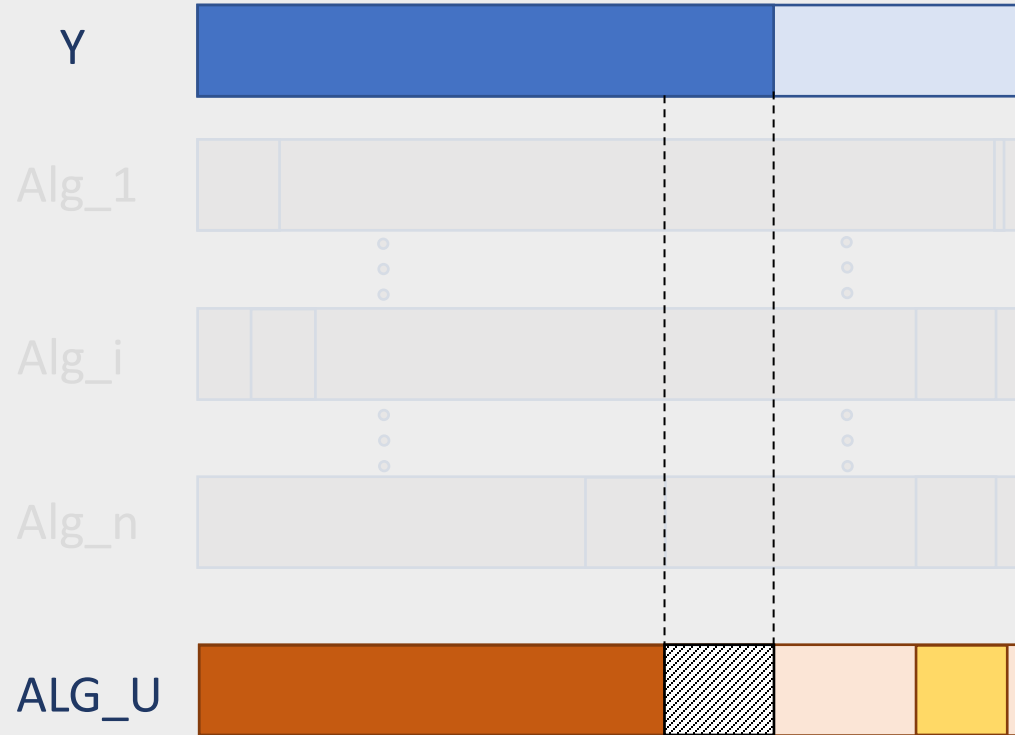
non-exposed



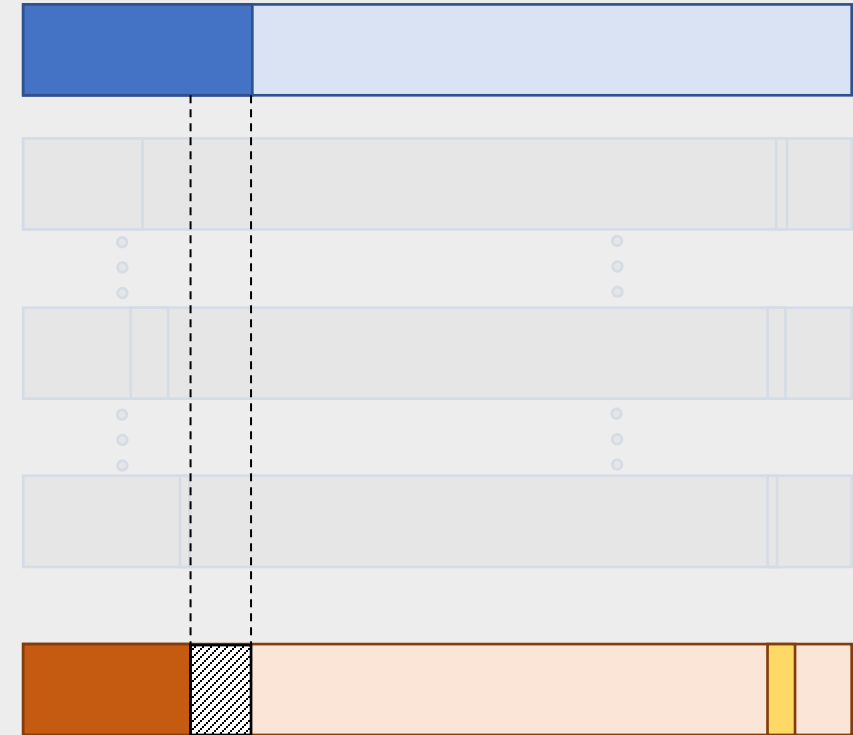
- $Y = 0$
- $Y = 1$
- FP
- TP
- $Alg = 0$

- $ALG_U$  corresponds to  $Alg_1 \cup \dots \cup Alg_n \cup \dots \cup Alg_n$

## exposed



## non-exposed



- Y = 0
- Y = 1
- FP
- TP
- Alg = 0

FN

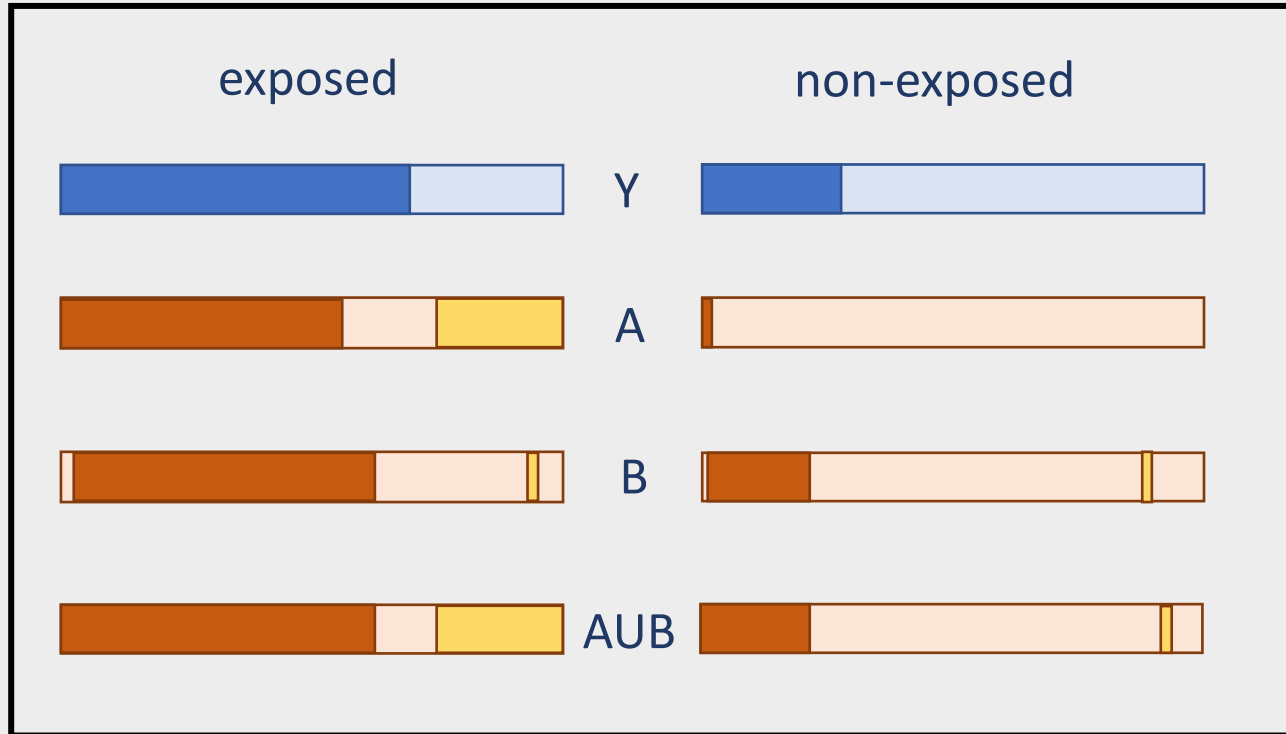
The proportion of false negative of **ALG\_U** (so the sensitivity), is assumed to be the equal in both groups, and it must be due to 'MAJOR' cause:

- Non-sistematic errors
- Private medicine
- ...

All the others cases must detected in al least one algorithm.

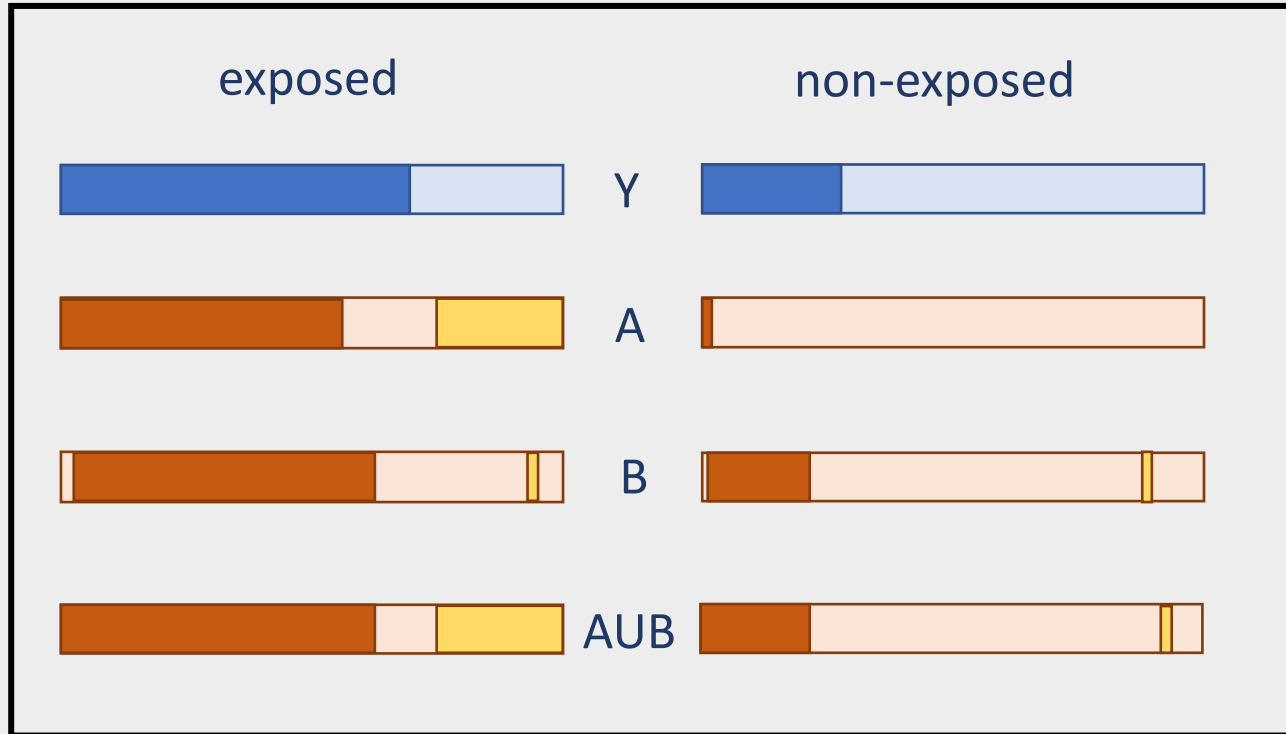
# Example

Some events are certainly found in a patient's medical history (e.g. lung cancer), unless there are ' **MAJOR** ' causes. We can think of an exposure positively correlated with the event (e.g. smoking), and a first algorithm A including all subjective diagnoses and a second algorithm B including all objective diagnoses.



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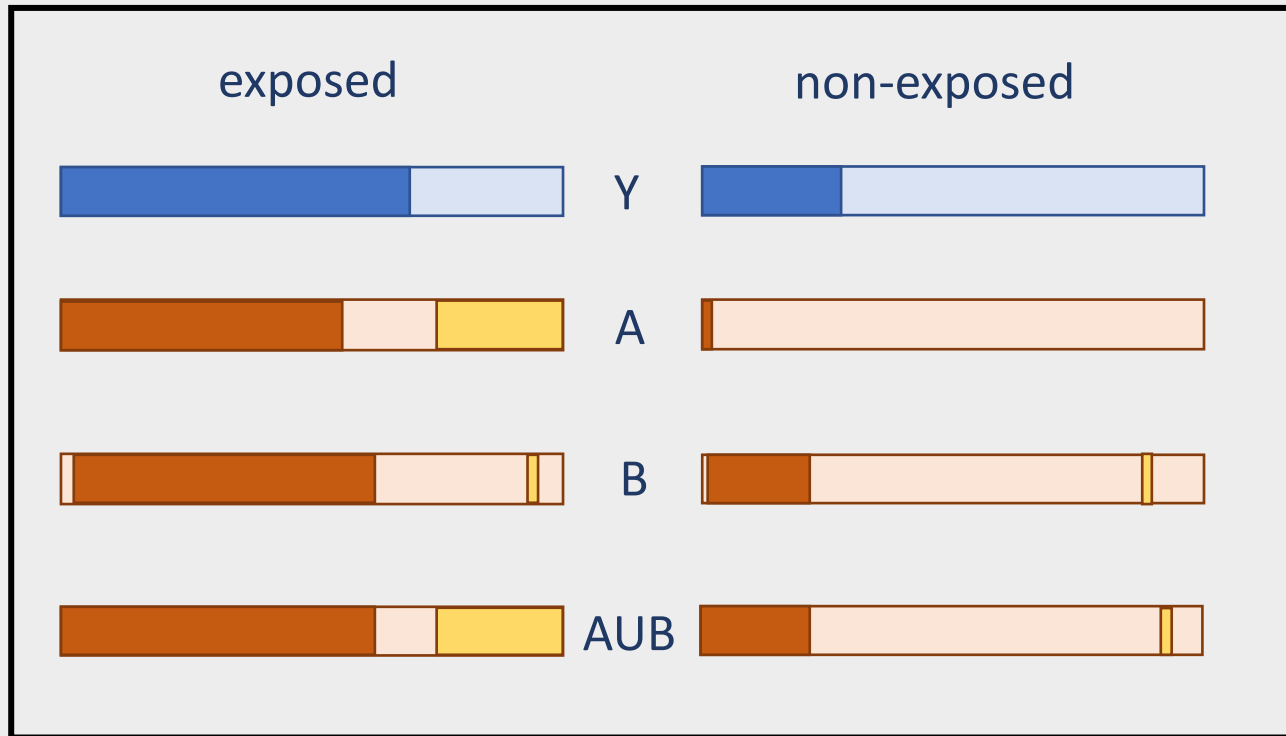


- events are higher among the exposed group



# Example

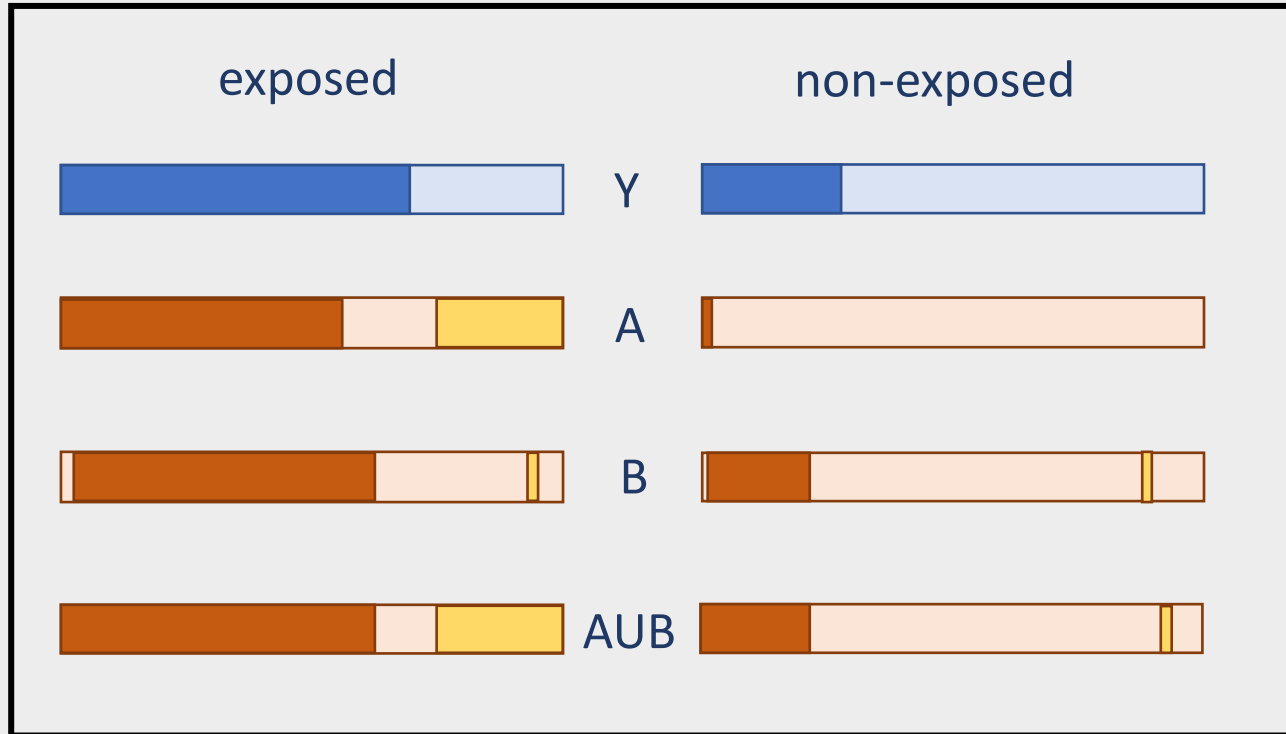
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- events are higher among the exposed group
- a subjective diagnosis would result in A having a higher SE in the exposed group, but also a lower SP, due to the influence of exposure
- A may have a higher SP in the non-exposed group, but also a lower SE

# Example

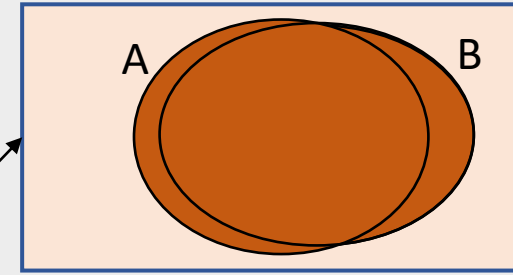
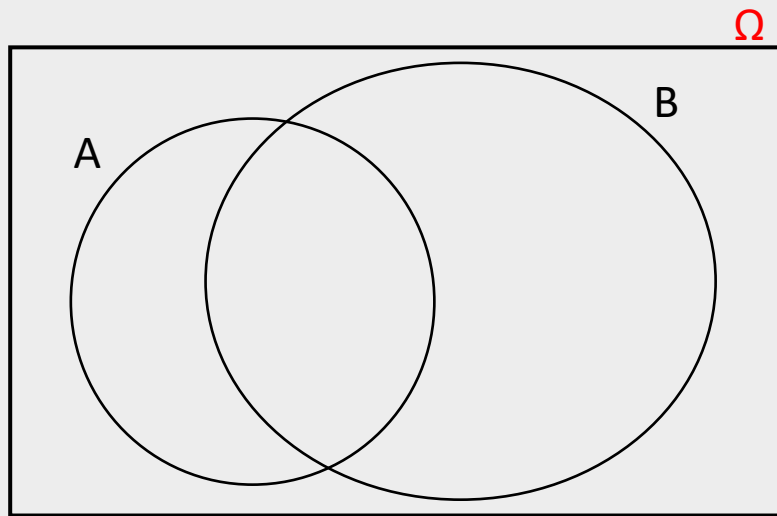
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- events are higher among the exposed group
- a subjective diagnosis would result in A having a higher SE in the exposed group, but also a lower SP, due to the influence of exposure
- A may have a higher SP in the non-exposed group, but also a lower SE
- the proportion of FP in AUB should not depend on the exposure group (**MAJOR** causes  $\perp$  E)

# Venn diagram

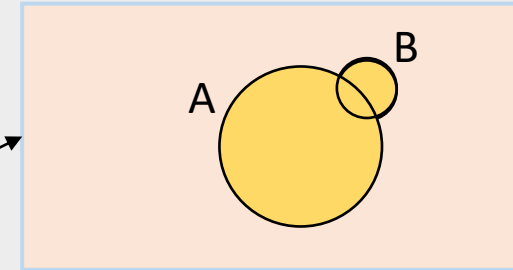
The venn diagram makes it easier to see the probability dependencies, but it requires four different sample spaces ( $\Omega$ )



$\Omega: Y == 1 \ \& \ E == 1$

$$P(A) = SE_A^e$$

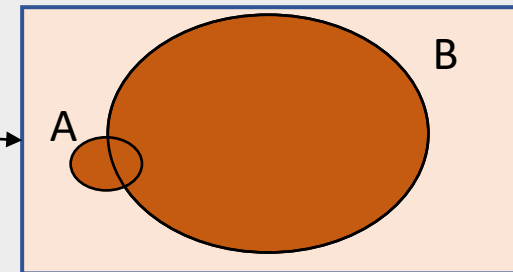
$$P(B) = SE_B^e$$



$\Omega: Y == 0 \ \& \ E == 1$

$$P(A) = 1 - SP_A^e$$

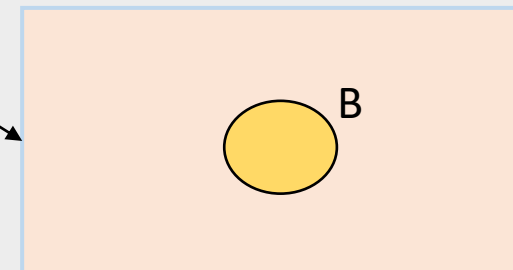
$$P(B) = 1 - SP_B^e$$



$\Omega: Y == 1 \ \& \ E == 0$

$$P(A) = SE_A^{\bar{e}}$$

$$P(B) = SE_B^{\bar{e}}$$

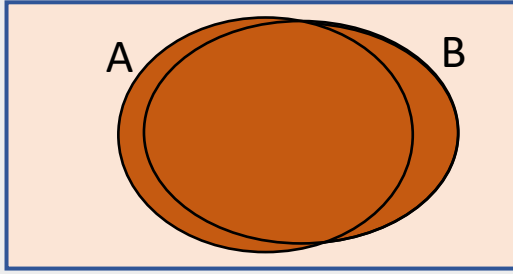


$\Omega: Y == 0 \ \& \ E == 0$

$$P(A) = 1 - SP_A^{\bar{e}}$$

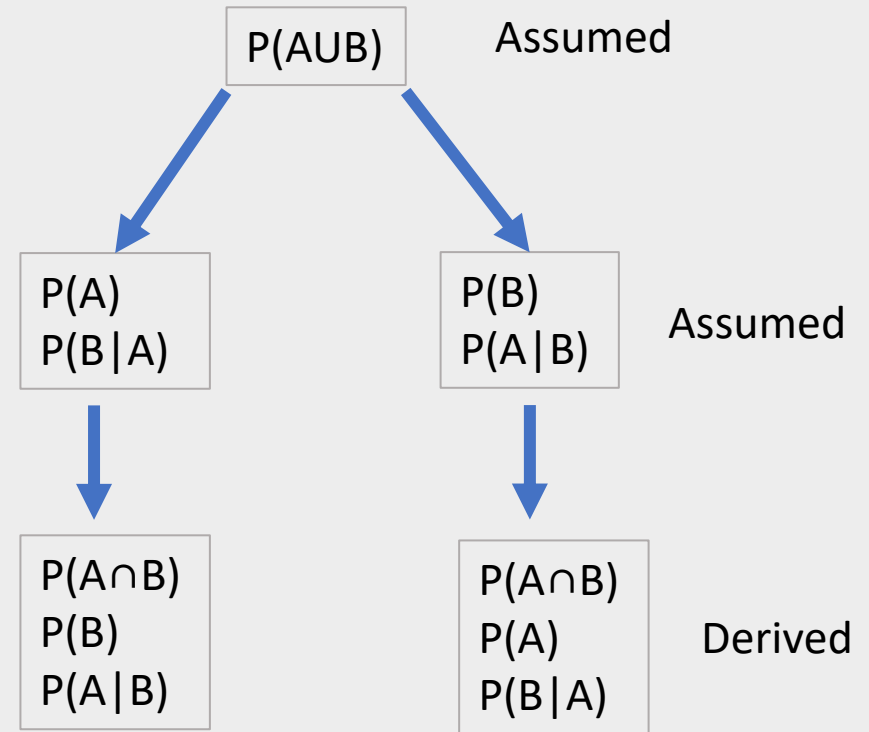
$$P(B) = 1 - SP_B^{\bar{e}}$$

# Venn diagram

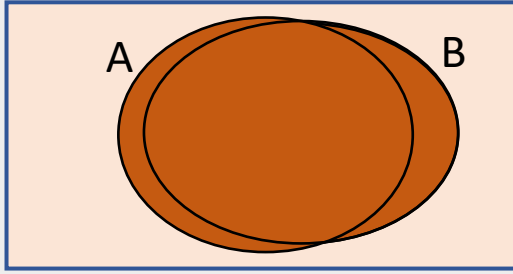


For each  $\Omega$  six different probabilities exist:

- $P(A)$
- $P(B)$
- $P(A \cup B)$
- $P(A \cap B)$
- $P(A|B)$
- $P(B|A)$

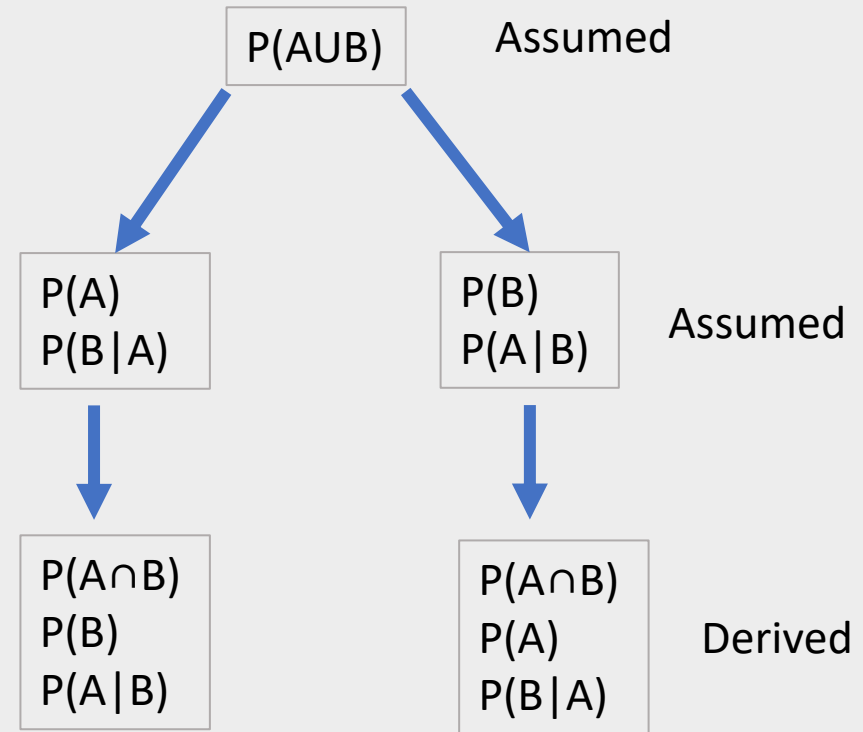


# Venn diagram



For each  $\Omega$  six different probabilities exist:

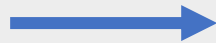
- $P(A)$
- $P(B)$
- $P(A \cup B)$
- $P(A \cap B)$
- $P(A|B)$
- $P(B|A)$



$$P(A \cup B) = 0.80$$

$$P(A) = 0.7$$

$$P(B|A) = 0.9$$



$$P(A \cap B) = P(A) * P(B|A)$$

$$P(B) = P(A \cup B) - P(A) + P(A \cap B)$$

$$P(A|B) = P(A \cap B) / P(B)$$



$$P(A \cap B) = 0.7 * 0.9 = 0.63$$



$$P(B) = 0.8 - 0.7 + 0.63 = 0.73$$



$$P(A|B) = 0.63 / 0.73 = 0.86$$

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# E. Schnitzer & R. Platt

	E. Schnitzer & R. Platt	Pregnancy Algorithm	Non-differentility test
Data	<ul style="list-style-type: none"><li>Defined cohort of pregnancies</li></ul>	<ul style="list-style-type: none"><li>Cohort of pregnancies defined by multiple components</li></ul>	<ul style="list-style-type: none"><li>Simulated data</li></ul>
Exposure	<ul style="list-style-type: none"><li>Gestational age-specific exposure</li></ul>		<ul style="list-style-type: none"><li>Binary exposure</li></ul>
Causal Inference	<ul style="list-style-type: none"><li>Target trials (ITT):<ul style="list-style-type: none"><li>IPW</li><li>G-computation</li><li>TMLE</li></ul></li></ul>		<ul style="list-style-type: none"><li>Differential misclassification</li><li>Risk Ratio</li></ul>
Possible developement		<ul style="list-style-type: none"><li>Can missed pregnancies affect causal effects?</li></ul>	