

Hafta 4

Bayes Teoremi



DeepLearning.AI

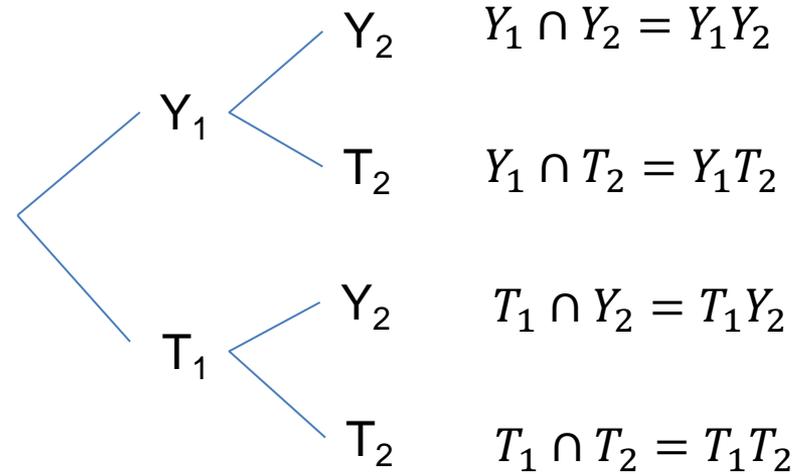
Hafta 3 Tekrar Sorusu

Bağımsız ve Bağıdaşmaz (Ayrık) Olaylar

Örnek: Yazı-Tura deneyi iki kez tekrarlanıyor. $P(Y) = \frac{1}{3}$ (*hileli para*) olduğuna göre en az bir tura gelme olasılığı nedir?

$$P(\Omega) = P\{Y, T\} = 1$$

$$P(Y) = \frac{1}{3}, \quad P(T) = 1 - \frac{1}{3} = \frac{2}{3}$$



$$A = \{Y_1T_2, T_1Y_2, T_1T_2\} = P(A) \neq \frac{|A|}{|\Omega|} \text{ (eşit olasılığa sahip olmadığından)}$$

Bağımsız ve Bağıdaşmaz (Ayrık) Olaylar

$$A = \{Y_1T_2, T_1Y_2, T_1T_2\} = P(A) \neq \frac{|A|}{|\Omega|} \text{ (eşit olasılığa sahip olmadığından)}$$

$$A = \{Y_1T_2, T_1Y_2, T_1T_2\} = P(A) = P\{Y_1T_2, T_1Y_2, T_1T_2\}$$

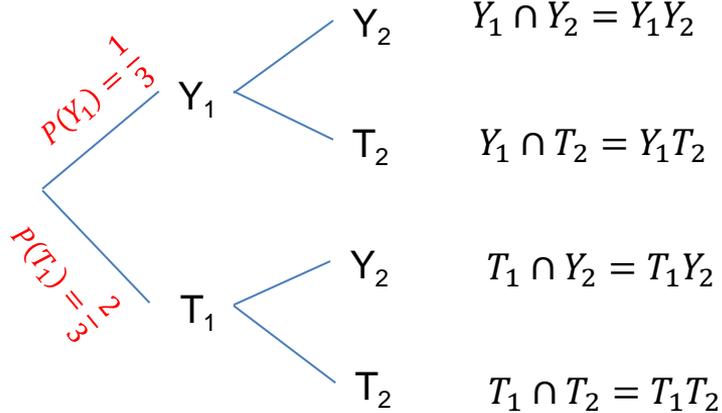
$$P(A) = P\{Y_1T_2\} + P\{T_1Y_2\} + P\{T_1T_2\}$$

?

?

?

Bağımsız ve Bağıdaşmaz (Ayrık) Olaylar



$$P(A) = P\{Y_1T_2\} + P\{T_1Y_2\} + P\{T_1T_2\}$$

? ? ?

$$P(Y_1 \cap Y_2) = P(Y_1Y_2) = \underbrace{P(Y_1)}_{\frac{1}{3}} \cdot \underbrace{P(Y_2|Y_1)}_{P(Y_2) = \frac{1}{3}}$$

$$P(Y_1Y_2) = P(Y_1) \cdot P(Y_2)$$

(Bağımsız Olay)

$$P(Y_1Y_2) = \frac{1}{3} \times \frac{1}{3} = \frac{1}{9}$$

Bağımsız ve Bağıdaşmaz (Ayrık) Olaylar

$$\Omega = \underbrace{\{Y_1Y_2\}}_{\frac{1}{9}}, \underbrace{\{Y_1T_2\}}_{\frac{2}{9}}, \underbrace{\{T_1Y_2\}}_{\frac{2}{9}}, \underbrace{\{T_1T_2\}}_{\frac{4}{9}}$$

$$P(Y_1T_2) = \frac{1}{3} \times \frac{2}{3} = \frac{2}{9}$$

$$A = \{Y_1T_2, T_1Y_2, T_1T_2\} = P(A) \neq \frac{|A|}{|\Omega|} \text{ (eşit olasılığa sahip olmadığından)}$$

$$P(A) = P\{Y_1T_2\} + P\{T_1Y_2\} + P\{T_1T_2\} = \frac{2}{9} + \frac{2}{9} + \frac{4}{9} = \frac{8}{9}$$



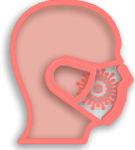
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Bayes Teoremi - Sezgisel

Bayes Teoremi: Sezgisel



1,000,000 insan

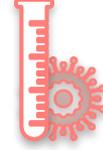


1 / 10,000 insan



100 insan

Hasta Tespit Edildi



99

Sağlıklı Tespit Edildi



1



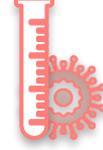
99% Doğruluk



Test Sonucu Hasta



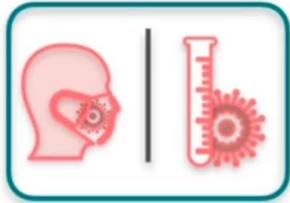
100 insan



1

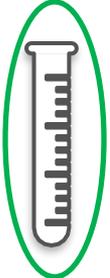


99



Test sonucunuza göre hasta olduğunuz
VERİLDİĞİNDE hasta olma olasılığı?

Bayes Teoremi: Sezgisel



test

Sağlıklı



999,900

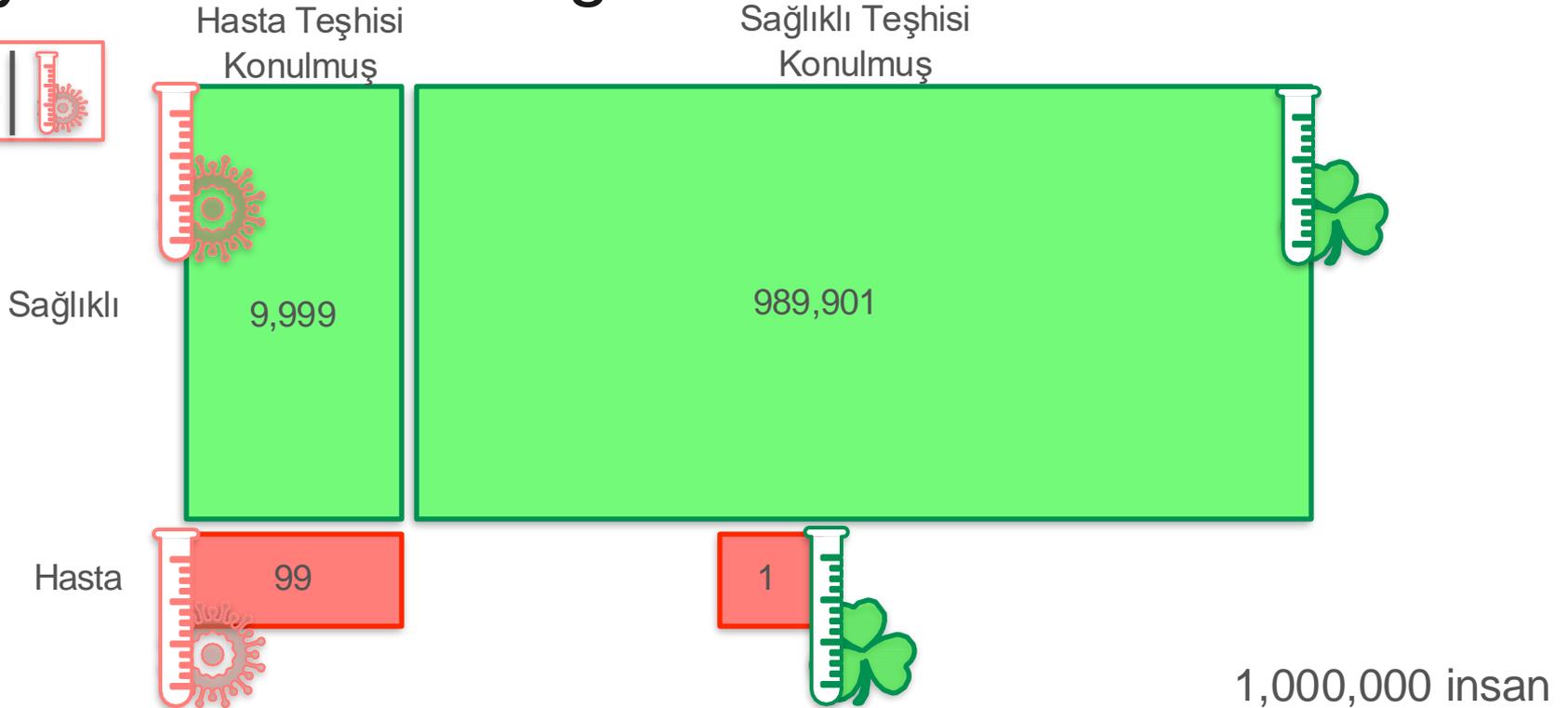
Hasta



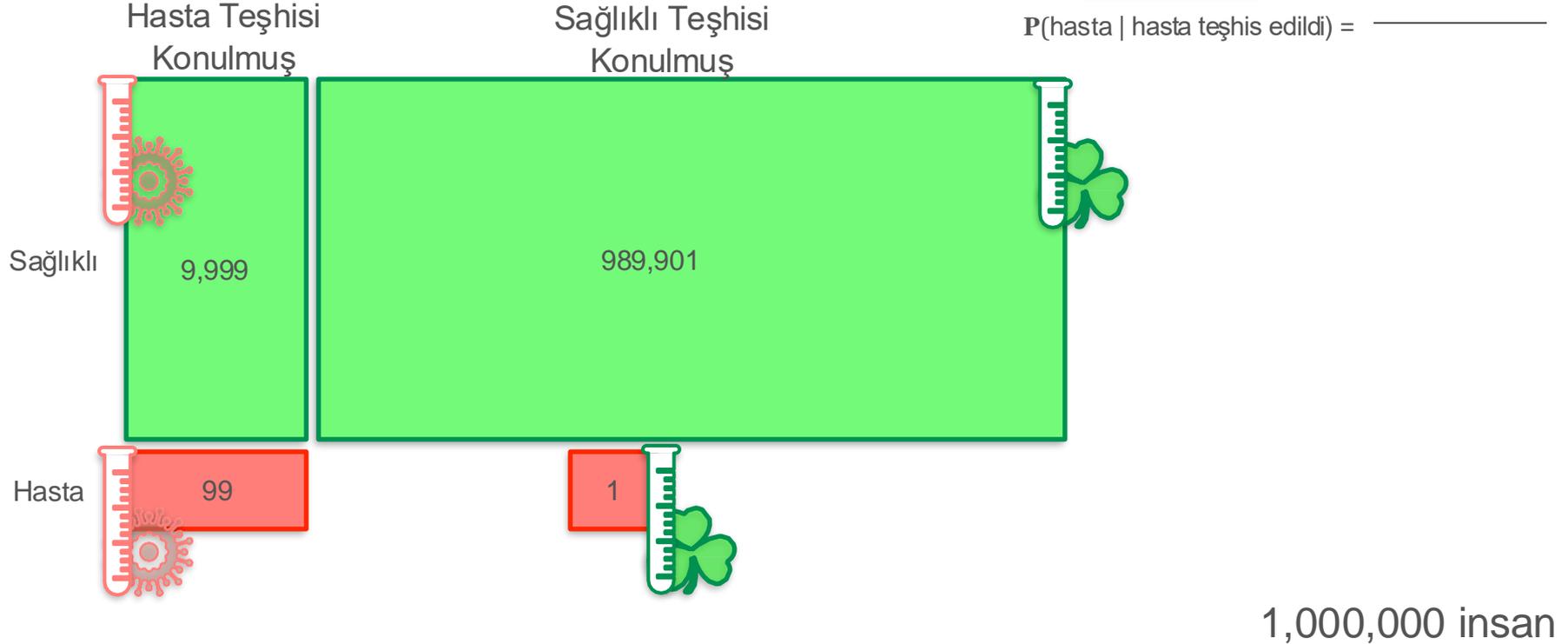
100

1,000,000 insan

Bayes Teoremi: Sezgisel



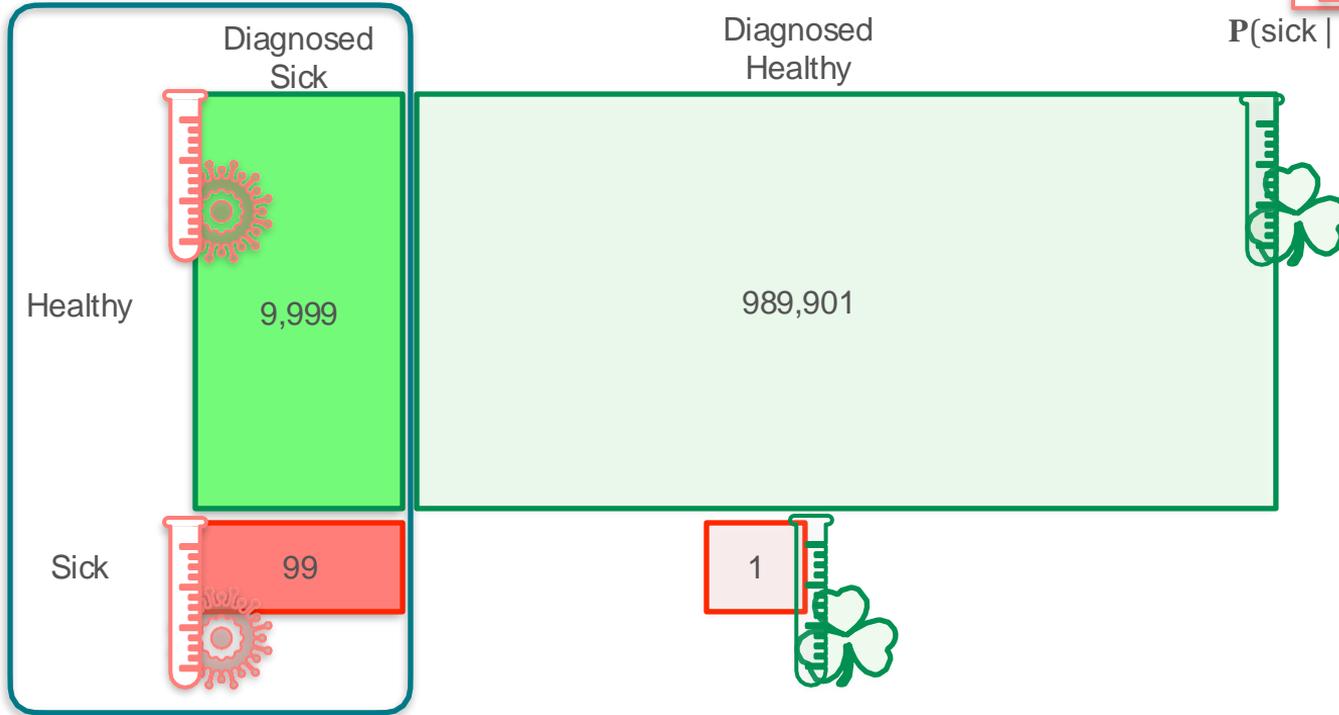
Bayes Teoremi: Sezgisel



Bayes Teoremi: Sezgisel

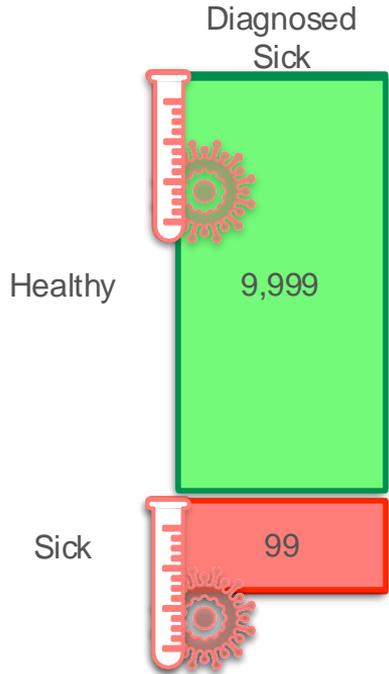


$P(\text{sick} \mid \text{diagnosed sick}) = \text{_____}$



1,000,000 insan

Bayes Teoremi: Sezgisel



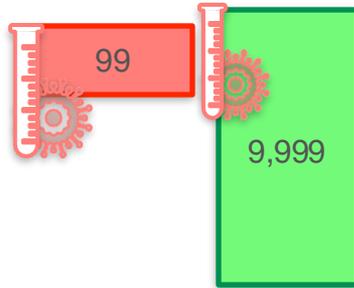
$$\begin{aligned} P(\text{sick} \mid \text{diagnosed sick}) &= \frac{99}{99 + 9999} \\ &= \frac{99}{10098} = 0.0098 \end{aligned}$$

= $\frac{\text{sick and diagnosed sick}}{\text{sick and diagnosed sick} + \text{healthy and diagnosed sick}}$

Bayes Teoremi: Sezgisel



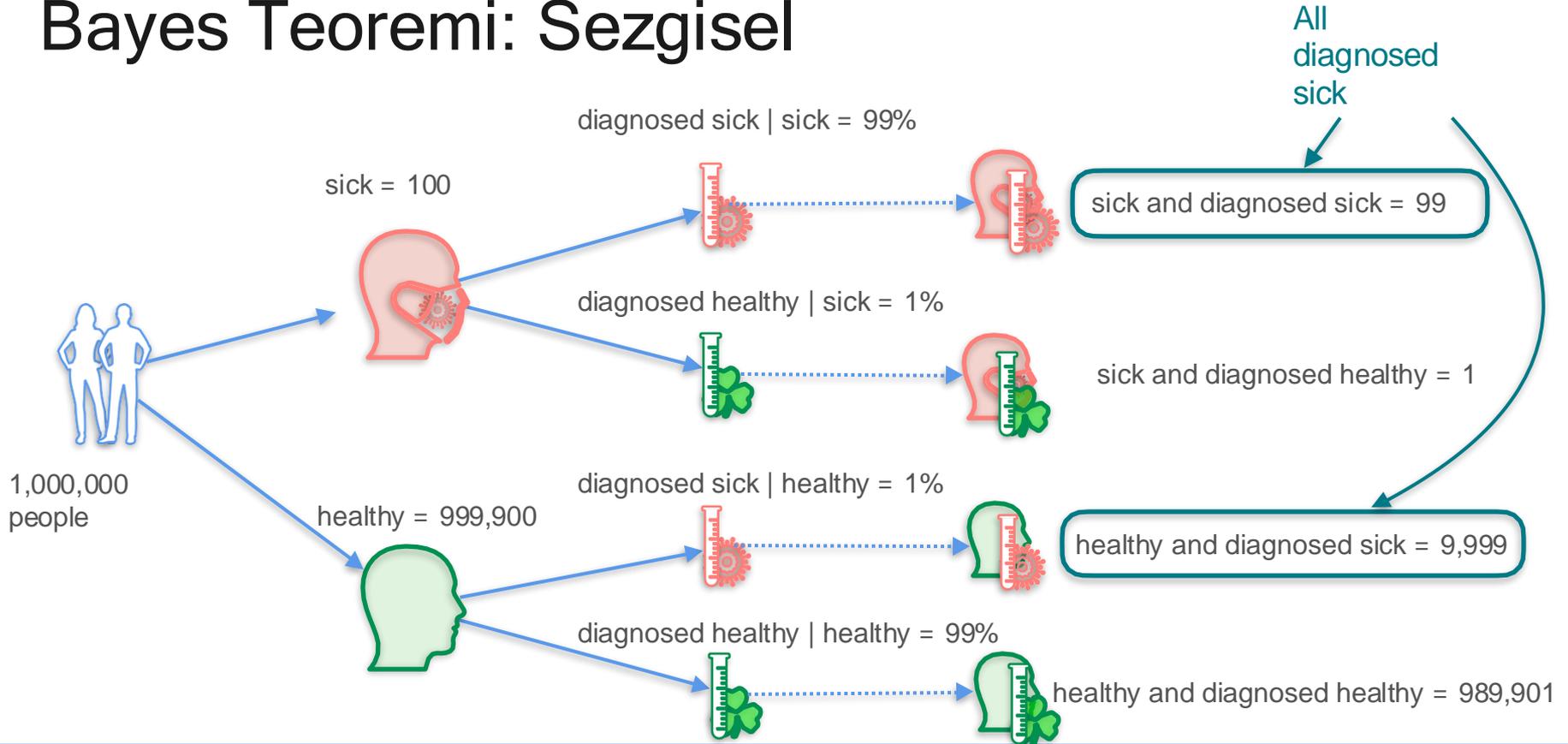
$$P(\text{sick} \mid \text{diagnosed sick}) = \frac{\text{99}}{\text{99} + \text{9,999}}$$



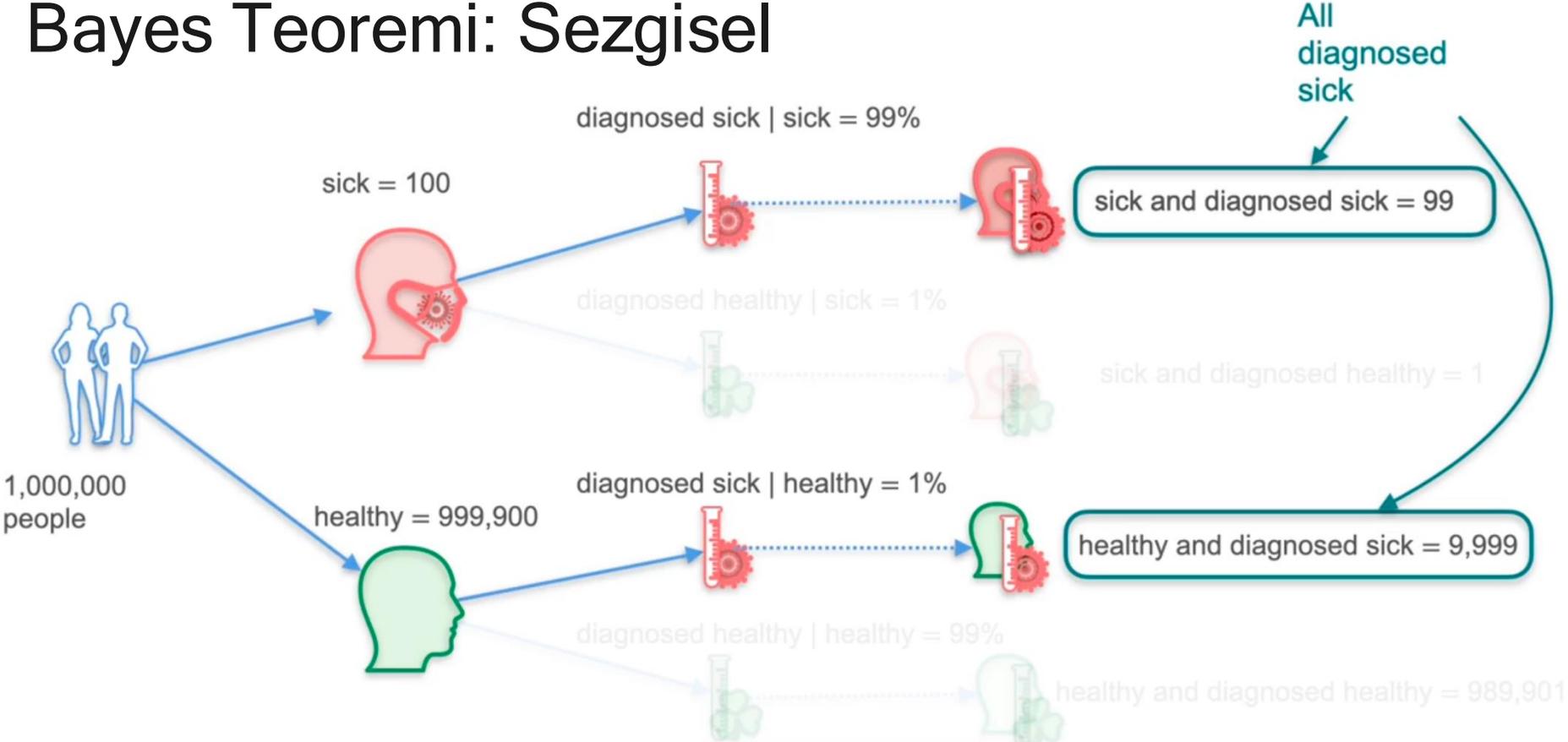
$$= \frac{\text{sick and diagnosed sick}}{\text{sick and diagnosed sick} + \text{healthy and diagnosed sick}}$$

$$= \frac{\text{sick and diagnosed sick}}{\text{everyone diagnosed sick}}$$

Bayes Teoremi: Sezgisel



Bayes Teoremi: Sezgisel



Bayes Teoremi: Sezgisel

$$P(\text{sick} \mid \text{diagnosed sick}) = \frac{\text{Icon: Sick and Diagnosed Sick}}{\text{Icon: Sick and Diagnosed Sick} + \text{Icon: Healthy and Diagnosed Sick}}$$

$$P(\text{sick} \mid \text{diagnosed sick}) = \frac{\text{sick and diagnosed sick} = 99}{\text{healthy and diagnosed sick} = 9,999 + \text{sick and diagnosed sick} = 99}$$

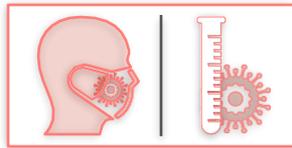
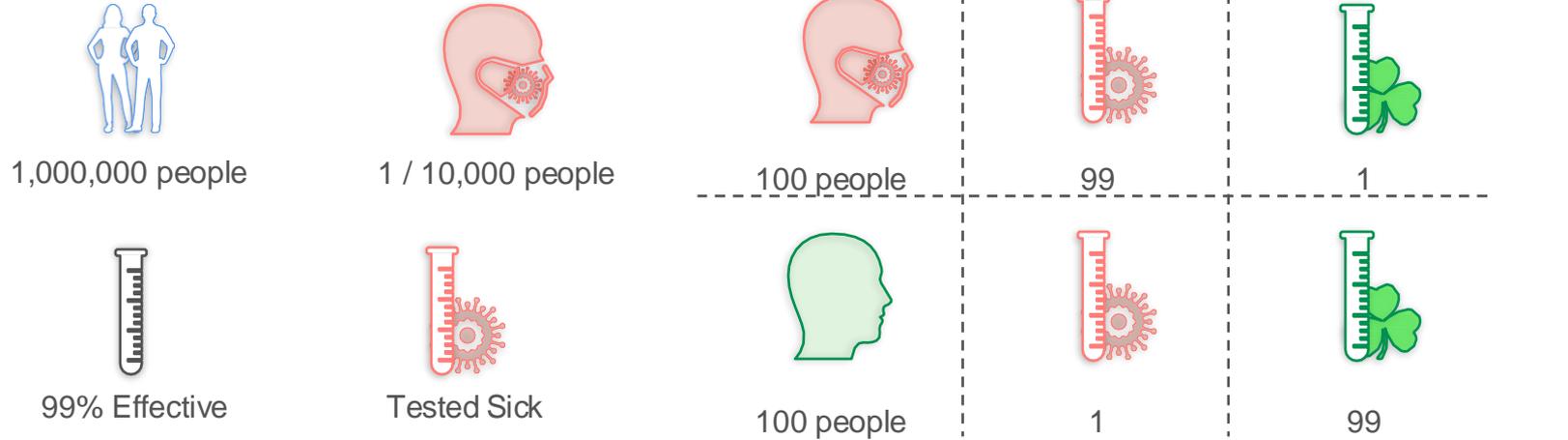
$$P(\text{sick} \mid \text{diagnosed sick}) = \frac{99}{10098} = 0.0098$$



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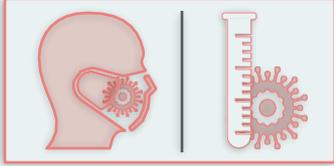
Bayes Teorem – Matematiksel Formül

Bayes Teorem: Formül



Test sonucunuzun pozitif olduğu **VERİLDİĞİNDE** hasta olma olasılığınız nedir

Bayes Teorem: Formül



$$P(\text{sick} \mid \text{diagnosed sick}) = ?$$

$$P(\text{sick}) = 0.01\%$$

$$P(\text{not sick}) = 99.99\%$$

$$P(\text{diagnosed sick} \mid \text{sick}) = 99\%$$

$$P(\text{diagnosed sick} \mid \text{not sick}) = 1\%$$

} teste göre

Test sonucunuzun pozitif olduğu
VERİLDİĞİNDE hasta olma olasılığınız
nedir



1,000,000

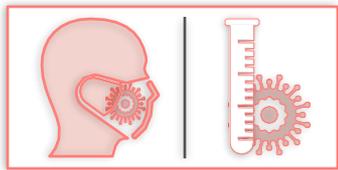


1 / 10,000



99% Effective

Bayes Teorem: Formül



A : sick (hasta)

B : diagnosed sick (hasta teşhisi konmuş)

$P(A | B) = ?$

From Conditional Probability

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

$$P(A | B) = \frac{P(\text{sick and diagnosed sick})}{P(\text{diagnosed sick})}$$

$P(\text{sick} | \text{diagnosed sick}) = ?$

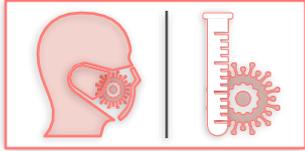
$P(\text{sick}) = 0.01\%$

$P(\text{not sick}) = 99.99\%$

$P(\text{diagnosed sick} | \text{sick}) = 99\%$

$P(\text{diagnosed sick} | \text{not sick}) = 1\%$

Bayes Theorem: Formül



A : sick

B : diagnosed sick

$P(\text{sick} \mid \text{diagnosed sick}) = ?$

$P(\text{sick}) = 0.01\%$

$P(\text{not sick}) = 99.99\%$

$P(\text{diagnosed sick} \mid \text{sick}) = 99\%$

$P(\text{diagnosed sick} \mid \text{not sick}) = 1\%$

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

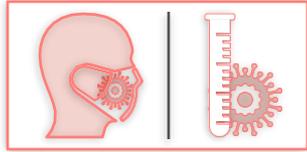
$$P(A \mid B) = \frac{P(\text{sick and diagnosed sick})}{P(\text{diagnosed sick})}$$

$P(\text{sick and diagnosed sick}) = ?$

$P(\text{diagnosed sick}) = ?$

BAYES THEOREM FORMULA CAN HELP

Bayes Theorem: Formül



A : sick

B : diagnosed sick

$$P(\text{sick} \mid \text{diagnosed sick}) = ?$$

$$P(\text{sick}) = 0.01\%$$

$$P(\text{not sick}) = 99.99\%$$

$$P(\text{diagnosed sick} \mid \text{sick}) = 99\%$$

$$P(\text{diagnosed sick} \mid \text{not sick}) = 1\%$$

$$P(A \mid B) = P(\text{sick} \mid \text{diagnosed sick})$$

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

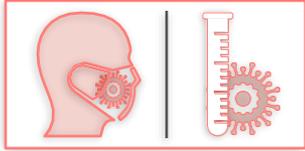
$$P(A \mid B) = \frac{P(\text{sick and diagnosed sick}) = ?}{P(\text{diagnosed sick}) = ?}$$

From Conditional Probability

$$P(A \cap B) = P(A) \cdot P(B \mid A)$$

$$P(\text{sick and diagnosed sick}) = P(\text{sick}) \cdot P(\text{diagnosed sick} \mid \text{sick})$$

Bayes Theorem: Formül



A : sick

B : diagnosed sick

$P(\text{sick} \mid \text{diagnosed sick}) = ?$

$P(\text{sick}) = 0.01\%$

$P(\text{not sick}) = 99.99\%$

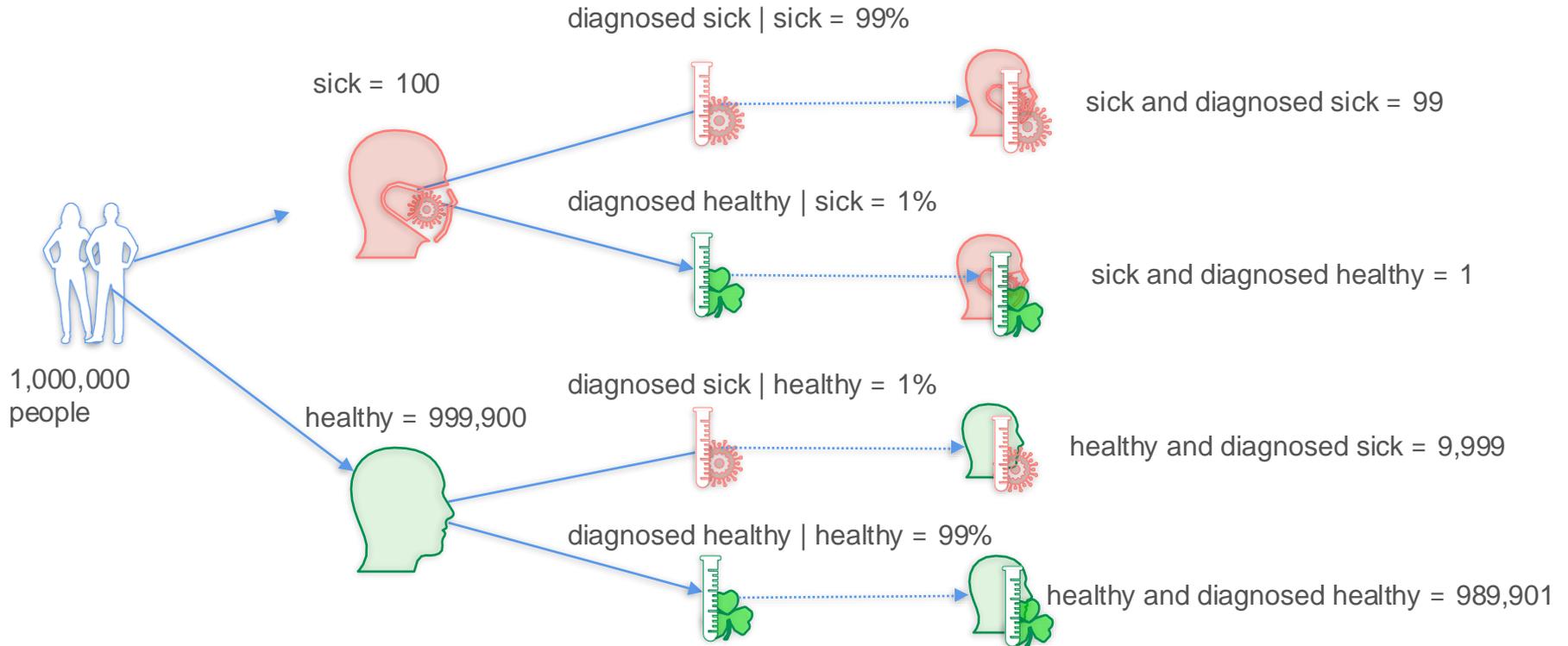
$P(\text{diagnosed sick} \mid \text{sick}) = 99\%$

$P(\text{diagnosed sick} \mid \text{not sick}) = 1\%$

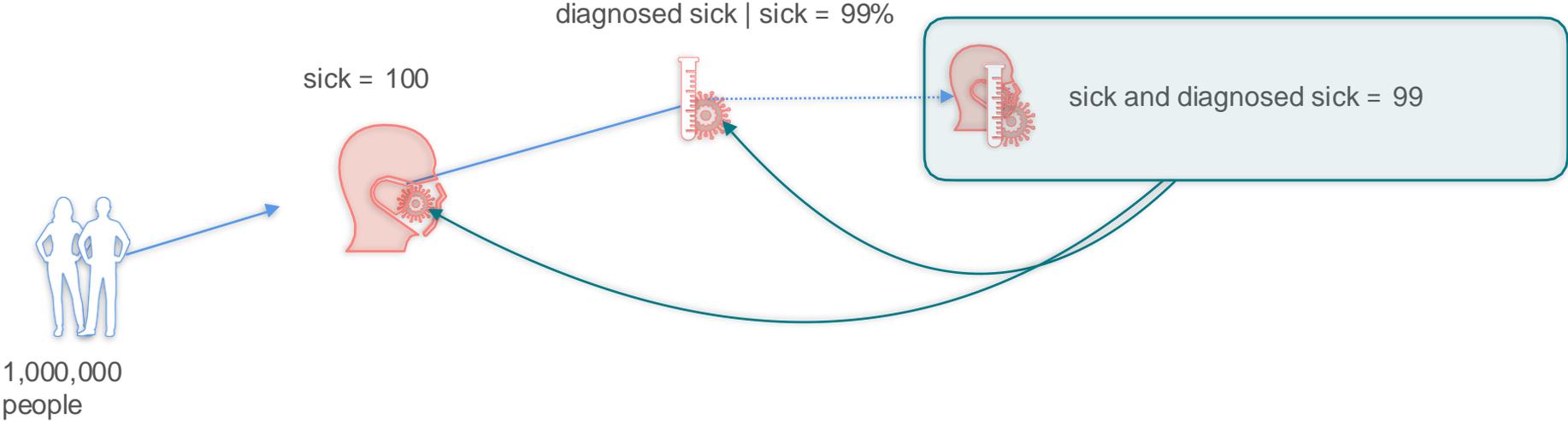
$$P(A \mid B) = \frac{P(A \cap B)}{P(B)}$$

$$P(A \mid B) = \frac{P(\text{sick}) \cdot P(\text{diagnosed sick} \mid \text{sick})}{P(\text{diagnosed sick}) = ?}$$

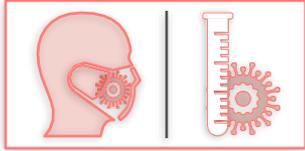
Bayes Theorem: Formül



Bayes Theorem: Formül



Bayes Theorem: Formül



A : sick

B : diagnosed sick

$$P(\text{sick} \mid \text{diagnosed sick}) = ?$$

$$P(\text{sick}) = 0.01\%$$

$$P(\text{not sick}) = 99.99\%$$

$$P(\text{diagnosed sick} \mid \text{sick}) = 99\%$$

$$P(\text{diagnosed sick} \mid \text{not sick}) = 1\%$$

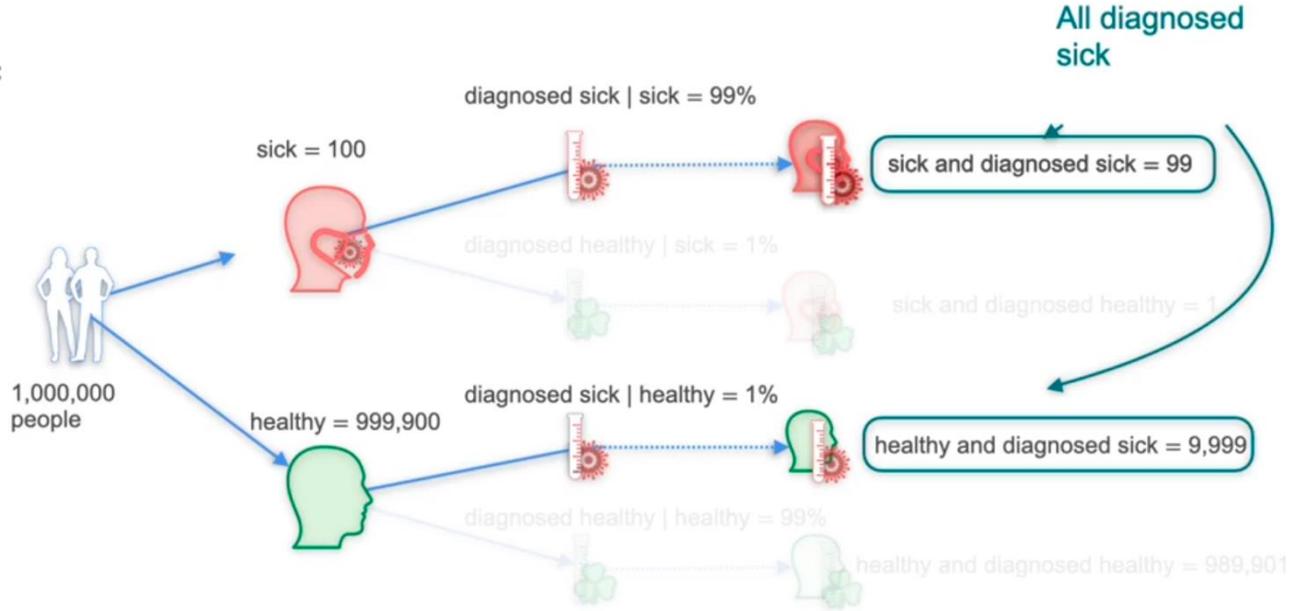
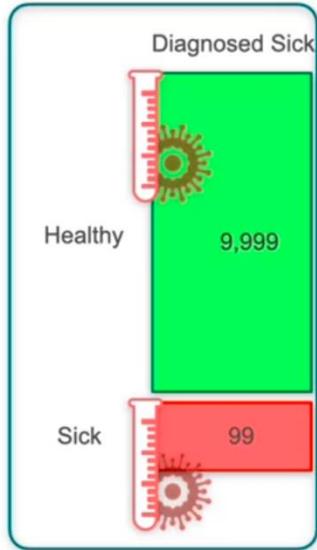
$$P(A \mid B) = \frac{P(A \cap B)}{P(B)}$$

$$P(A \mid B) = \frac{P(\text{sick}) \cdot P(\text{diagnosed sick} \mid \text{sick})}{P(\text{diagnosed sick}) = ?}$$

$$P(\text{diagnosed sick}) =$$

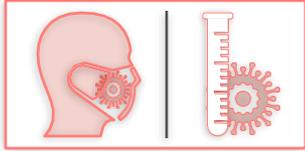
Bayes Teorem: Formül

$P(\text{diagnosed sick}) =$



$$P(\text{sick} \cap \text{diagnosed sick}) + P(\text{not sick} \cap \text{diagnosed sick})$$

Bayes Theorem: Formül



A : sick

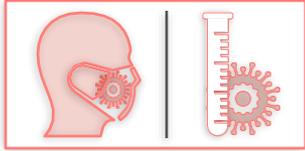
B : diagnosed sick

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

$$P(A | B) = \frac{P(\text{sick}) \cdot P(\text{diagnosed sick} | \text{sick})}{P(\text{diagnosed sick}) = ?}$$

$$P(\text{diagnosed sick}) = P(\text{sick} \cap \text{diagnosed sick}) + P(\text{not sick} \cap \text{diagnosed sick})$$

Bayes Theorem: Formül



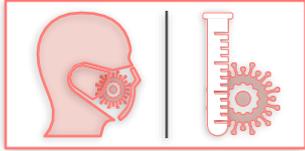
A : sick

B : diagnosed sick

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

$$P(A|B) = \frac{P(\text{sick}) \cdot P(\text{diagnosed sick} | \text{sick})}{P(\text{sick} \cap \text{diagnosed sick}) + P(\text{not sick} \cap \text{diagnosed sick})}$$

Bayes Theorem: Formül



A : sick

B : diagnosed sick

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

$$P(A | B) = \frac{P(\text{sick}) \cdot P(\text{diagnosed sick} | \text{sick})}{P(\text{sick} \cap \text{diagnosed sick}) + P(\text{not sick} \cap \text{diagnosed sick})}$$

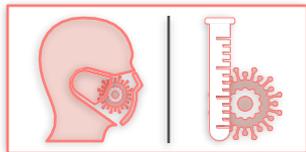
$$P(\text{sick} \cap \text{diagnosed sick}) = P(A \cap B)$$

$$= P(\text{sick}) \cdot P(\text{diagnosed sick} | \text{sick})$$

$$P(\text{not sick} \cap \text{diagnosed sick}) = P(A' \cap B)$$

$$= P(\text{not sick}) \cdot P(\text{diagnosed sick} | \text{not sick})$$

Bayes Theorem: Formül



A : sick

B : diagnosed sick

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

$$P(A | B) = \frac{P(\text{sick}) \cdot P(\text{diagnosed sick} | \text{sick})}{P(\text{sick}) \cdot P(\text{diagnosed sick} | \text{sick}) + P(\text{not sick}) \cdot P(\text{diagnosed sick} | \text{not sick})}$$

$$P(\text{sick}) = 0.01\%$$

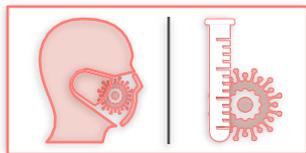
$$P(\text{not sick}) = 99.99\%$$

$$P(\text{diagnosed sick} | \text{sick}) = 99\%$$

$$P(\text{diagnosed sick} | \text{not sick}) = 1\%$$

**BAYES THEOREM
FORMULA**

Bayes Theorem: Formül



A : sick

B : diagnosed sick

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

$$P(A|B) = \frac{P(A) \cdot P(B|A)}{P(A) \cdot P(B|A) + P(A') \cdot P(B|A')}$$

$$P(A) = 0.01\%$$

$$P(A') = 99.99\%$$

$$P(B|A) = 99\%$$

$$P(B|A') = 1\%$$

**BAYES THEOREM
FORMULA**

Bayes Theorem: Formül

$$P(A|B) = \frac{P(A) \cdot P(B|A)}{P(A) \cdot P(B|A) + P(A') \cdot P(B|A')}$$

$$P(A) = 0.01\%$$

$$P(A') = 99.99\%$$

$$P(B|A) = 99\%$$

$$P(B|A') = 1\%$$

Bayes Theorem: Formül

$$P(A|B) = \frac{P(\text{sick}) \cdot P(\text{diagnosed sick} | \text{sick})}{P(\text{sick}) \cdot P(\text{diagnosed sick} | \text{sick}) + P(\text{not sick}) \cdot P(\text{diagnosed sick} | \text{not sick})}$$

$$P(\text{sick}) = 0.01\%$$

$$P(\text{not sick}) = 99.99\%$$

$$P(\text{diagnosed sick} | \text{sick}) = 99\%$$

$$P(\text{diagnosed sick} | \text{not sick}) = 1\%$$

$$P(A|B) = \frac{P(A) \cdot P(B|A)}{P(A) \cdot P(B|A) + P(A') \cdot P(B|A')}$$

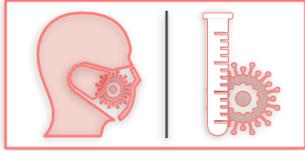
$$P(A) = 0.01\%$$

$$P(A') = 99.99\%$$

$$P(B|A) = 99\%$$

$$P(B|A') = 1\%$$

Bayes Theorem: Formül



A : sick

B : diagnosed sick

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

$$\mathbf{P(A | B)} = \frac{\mathbf{P(A) \cdot P(B | A)}}{\mathbf{P(A) \cdot P(B | A) + P(A') \cdot P(B | A')}}$$

$$\mathbf{P(A)} = 0.01\%$$

$$\mathbf{P(A')} = 99.99\%$$

$$\mathbf{P(B | A)} = 99\%$$

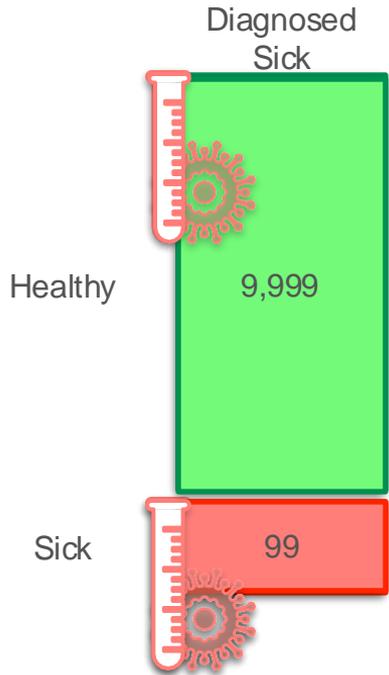
$$\mathbf{P(B | A')} = 1\%$$

$$\mathbf{P(A | B)} = \frac{0.0001 \times 0.99}{(0.0001 \times 0.99) + (0.9999 \times 0.01)}$$

$$\mathbf{P(A | B)} = 0.0098$$

**BAYES THEOREM
FORMULA**

(Hatırlatma) Bayes Teoremi: Sezgisel



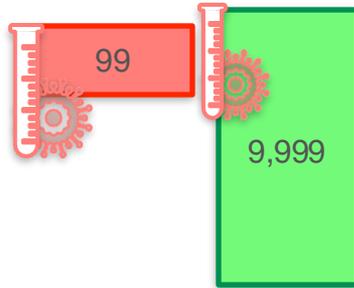
$$\begin{aligned} P(\text{sick} \mid \text{diagnosed sick}) &= \frac{99}{99 + 9999} \\ &= \frac{99}{10098} = 0.0098 \end{aligned}$$

= $\frac{\text{sick and diagnosed sick}}{\text{sick and diagnosed sick} + \text{healthy and diagnosed sick}}$

Bayes Teoremi: Sezgisel



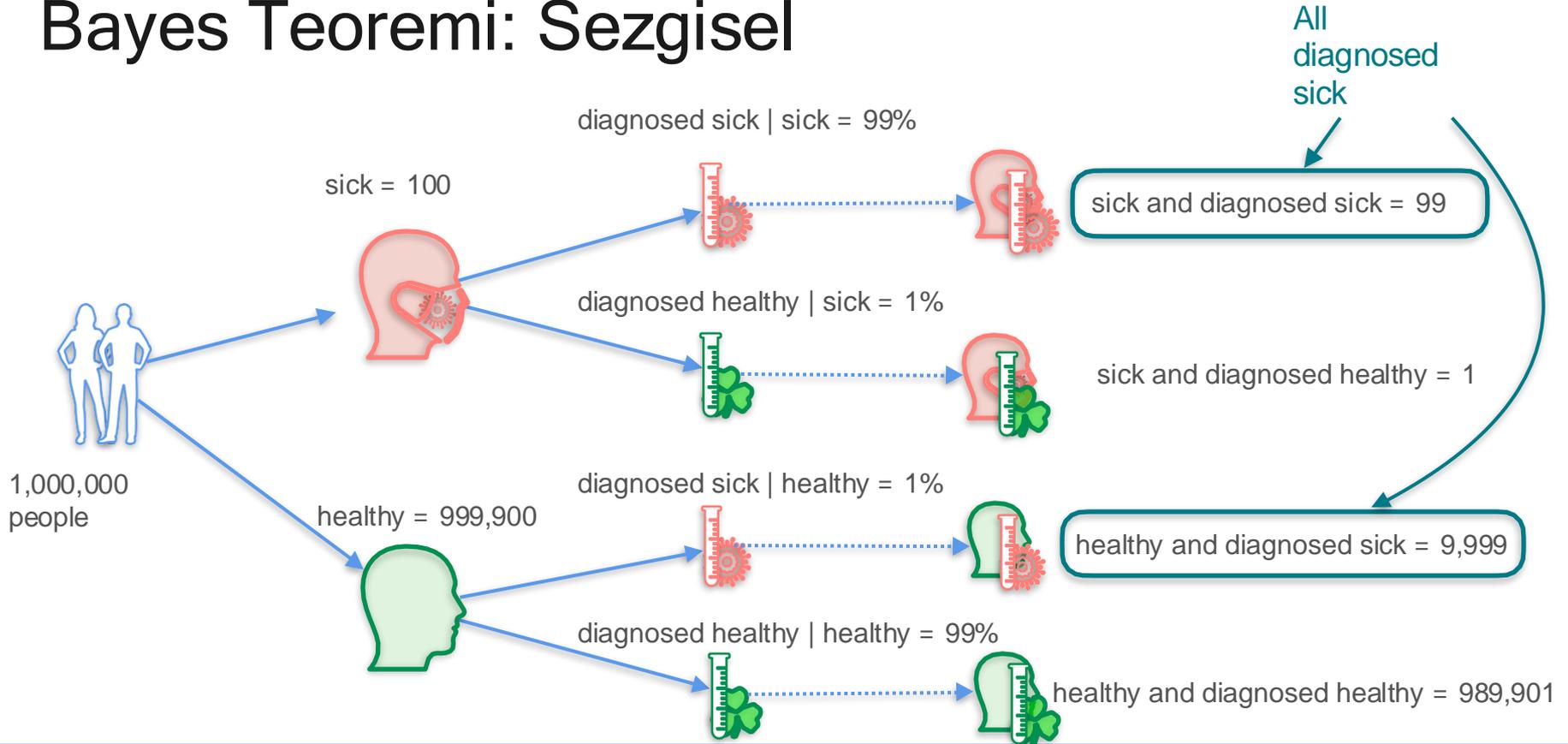
$$P(\text{sick} \mid \text{diagnosed sick}) = \frac{\text{99}}{\text{99} + \text{9,999}}$$



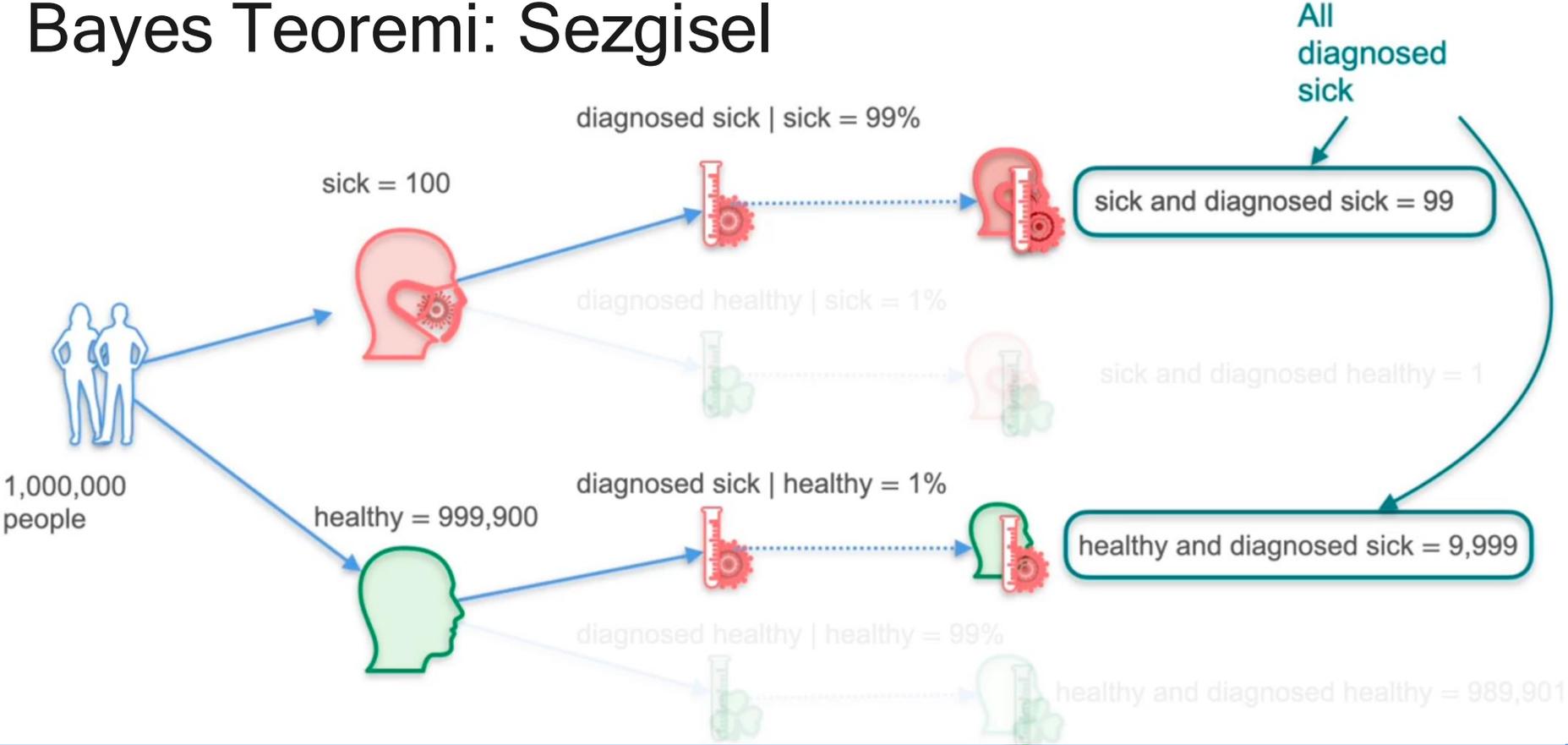
$$= \frac{\text{sick and diagnosed sick}}{\text{sick and diagnosed sick} + \text{healthy and diagnosed sick}}$$

$$= \frac{\text{sick and diagnosed sick}}{\text{everyone diagnosed sick}}$$

Bayes Teoremi: Sezgisel



Bayes Teoremi: Sezgisel



Bayes Teoremi: Sezgisel

$$P(\text{sick} \mid \text{diagnosed sick}) = \frac{\text{Icon: Sick and Diagnosed Sick}}{\text{Icon: Sick and Diagnosed Sick} + \text{Icon: Healthy and Diagnosed Sick}}$$

$$P(\text{sick} \mid \text{diagnosed sick}) = \frac{\text{sick and diagnosed sick} = 99}{\text{healthy and diagnosed sick} = 9,999 + \text{sick and diagnosed sick} = 99}$$

$$P(\text{sick} \mid \text{diagnosed sick}) = \frac{99}{10098} = 0.0098$$



DeepLearning.AI

Bayes Teorem - Spam Örneđi

Bayes Teorem: Spam Örneği



Bayes Teorem: Spam Örneği



20 spam

80 not spam (ham)



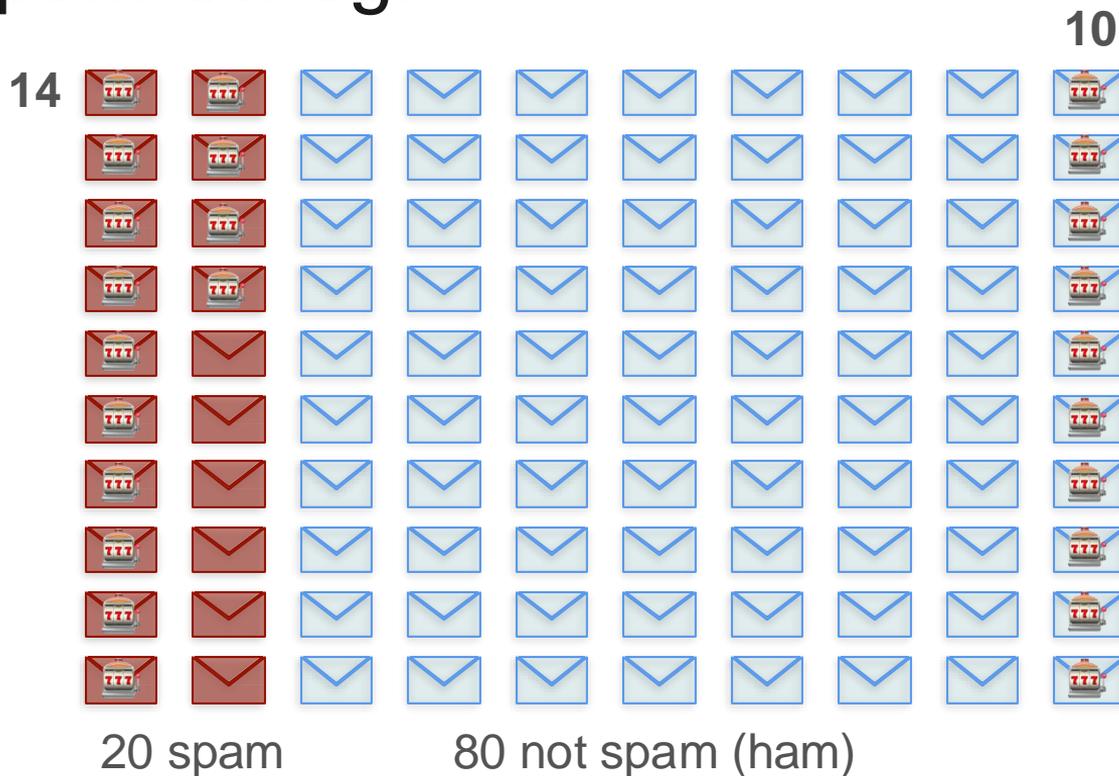
“lottery”
“piyango”

Bayes Teorem: Spam Örneği



Piyango (lottery) kelimesi içeren bir e-postanın spam olma olasılığı nedir?

$P(\text{spam} \mid \text{lottery})$



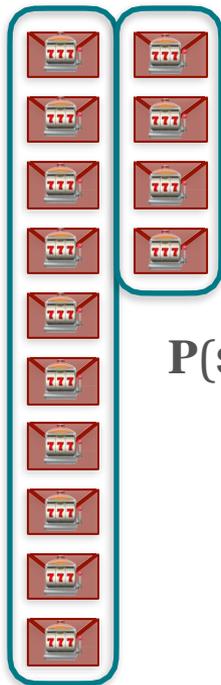
Bayes Teorem: Spam Örneği (Sezgisel Çözüm)



$P(\text{spam} \mid \text{lottery})$

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

A: spam
B: lottery



14

24 emails

containing lottery
(piyango içeriyor)

$$P(\text{spam} \mid \text{lottery}) = \frac{\text{spam and lottery}}{\text{all lottery}}$$

$$\begin{aligned} &= \frac{14}{24} \\ &= \frac{7}{12} = 0.583 \end{aligned}$$



10

Bayes Teorem: Spam Örneği (Formüsel Çözüm)

$P(\text{spam} \mid \text{lottery})$

$$P(A \mid B) = \frac{P(A) \cdot P(B \mid A)}{P(A) \cdot P(B \mid A) + P(A') \cdot P(B \mid A')}$$

A: Email is spam B: Email contains lottery

$$P(\text{spam} \mid \text{lottery}) = \frac{P(\text{spam}) \cdot P(\text{lottery} \mid \text{spam})}{P(\text{spam}) \cdot P(\text{lottery} \mid \text{spam}) + P(\text{not spam}) \cdot P(\text{lottery} \mid \text{not spam})}$$

Bayes Teorem: Spam Örneği (Formüsel Çözüm)

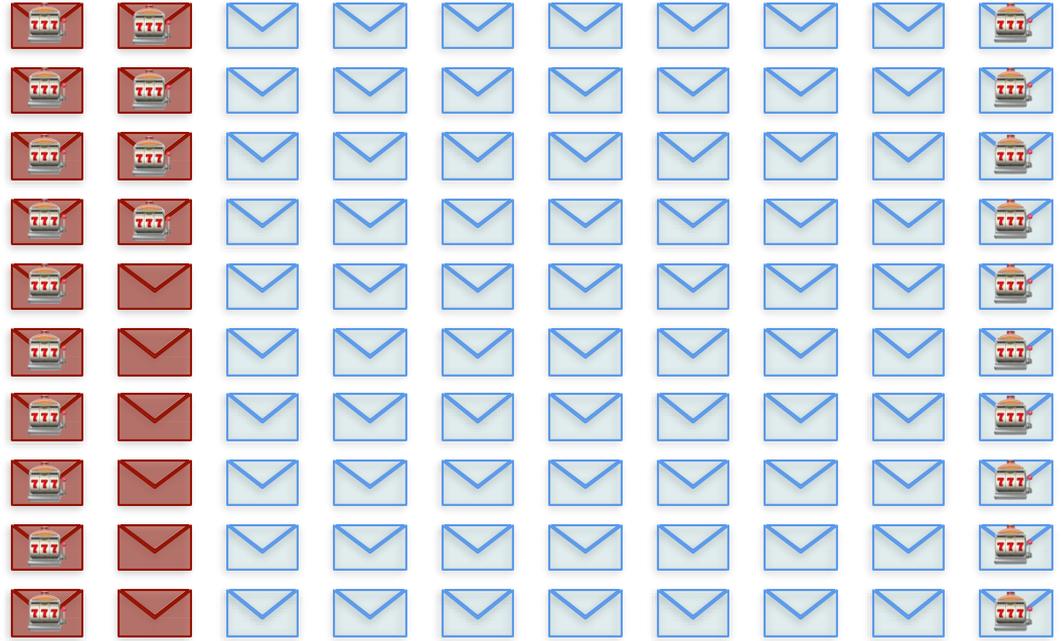
$$P(\text{spam}) = \frac{20}{100} = 0.2$$

$$P(\text{not spam}) = \frac{80}{100} = 0.8$$

$$P(\text{lottery} | \text{spam}) = \frac{14}{20} = 0.7$$

$$P(\text{lottery} | \text{not spam}) = \frac{10}{80} = 0.125$$

14



10

20 spam

80 not spam (ham)

Bayes Teorem: Spam Örneği (Formüsel Çözüm)

$$P(\text{spam}) = 0.2$$

$$P(\text{lottery} | \text{spam}) = 0.7$$

$$P(\text{not spam}) = 0.8$$

$$P(\text{lottery} | \text{not spam}) = 0.125$$

$$P(\text{spam} | \text{lottery}) = \frac{P(\text{spam}) \cdot P(\text{lottery} | \text{spam})}{P(\text{spam}) \cdot P(\text{lottery} | \text{spam}) + P(\text{not spam}) \cdot P(\text{lottery} | \text{not spam})}$$

$$P(\text{spam} | \text{lottery}) = \frac{0.2 \times 0.7}{(0.2 \times 0.7) + (0.8 \times 0.125)} = 0.583$$

Bayes Teorem: Spam Örneği (Formüsel Çözüm)

$$P(\text{spam}) = 0.2$$

$$P(\text{lottery} | \text{spam}) = 0.7$$

$$P(\text{not spam}) = 0.8$$

$$P(\text{lottery} | \text{not spam}) = 0.125$$

$$P(\text{spam} | \text{lottery}) = \frac{P(\text{spam}) \cdot P(\text{lottery} | \text{spam})}{P(\text{spam}) \cdot P(\text{lottery} | \text{spam}) + P(\text{not spam}) \cdot P(\text{lottery} | \text{not spam})}$$

$$P(A | B) = \frac{P(A) \cdot P(B | A)}{P(A) \cdot P(B | A) + P(A') \cdot P(B | A')}$$

Bayes Teorem: Spam Örneği (Formüsel Çözüm)

$$P(\text{spam}) = 0.2$$

$$P(\text{lottery} | \text{spam}) = 0.7$$

$$P(\text{not spam}) = 0.8$$

$$P(\text{lottery} | \text{not spam}) = 0.125$$

$$P(\text{spam} | \text{lottery}) = \frac{P(\text{spam}) \cdot P(\text{lottery} | \text{spam})}{P(\text{spam}) \cdot P(\text{lottery} | \text{spam}) + P(\text{not spam}) \cdot P(\text{lottery} | \text{not spam})}$$

$$P(A | B) = \frac{P(A) \cdot P(B | A)}{P(A) \cdot P(B | A) + P(A') \cdot P(B | A')}$$

$P(A) \cdot P(B | A)$ is labeled $P(A \cap B)$ with a blue arrow pointing to it from the right.

$P(A) \cdot P(B | A) + P(A') \cdot P(B | A')$ is labeled $P(B)$ with a blue arrow pointing to it from the right.



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Bayes Teorem - Prior ve Posterior

Bayes Theorem

PRIOR

$P(A)$

EVENT

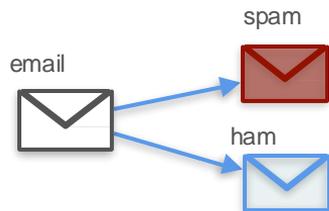
E

POSTERIOR

$P(A | E)$

Prior ve Posterior

PRIOR

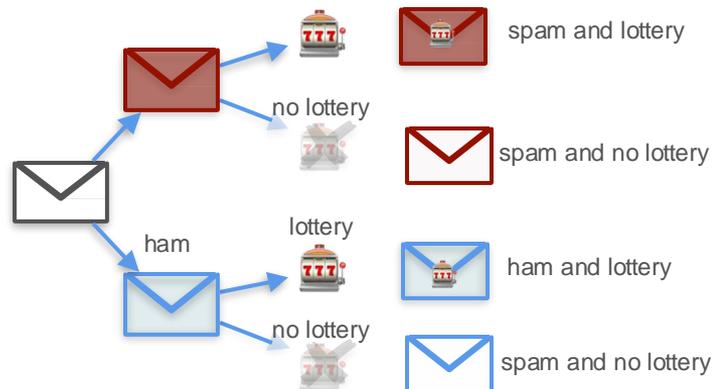


$$P(\text{spam}) = \frac{\text{spam icon}}{\text{spam icon} + \text{ham icon}}$$

EVENT


Email contains lottery

POSTERIOR



$$P(\text{spam} \mid \text{lottery}) = \frac{\text{spam and lottery icon}}{\text{spam and lottery icon} + \text{ham and lottery icon}}$$

Prior ve Posterior

Tıbbi örnekte, bir önceki (prior) ve bir sonraki (posterior) olasılık vardı. Önceki, ilk hasta olma olasılığıydı. Olay pozitif teşhis edildiği gerçeğidir. Sonraki ise, pozitif teşhis koyduğunuz göz önüne alındığında hasta olma olasılığınızdı.

Prior ve Posterior

PRIOR



	1,1	1,2	1,3	1,4	1,5	1,6
	2,1	2,2	2,3	2,4	2,5	2,6
	3,1	3,2	3,3	3,4	3,5	3,6
	4,1	4,2	4,3	4,4	4,5	4,6
	5,1	5,2	5,3	5,4	5,5	5,6
	6,1	6,2	6,3	6,4	6,5	6,6

$$P(\text{sum} = 10) = \frac{3}{36}$$

EVENT



1st dice is 6

olaydan sonra örnek uzay değişir

POSTERIOR

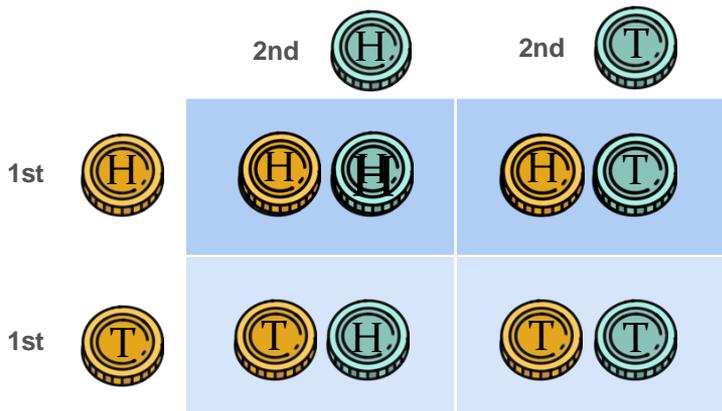


	1,1	1,2	1,3	1,4	1,5	1,6
	2,1	2,2	2,3	2,4	2,5	2,6
	3,1	3,2	3,3	3,4	3,5	3,6
	4,1	4,2	4,3	4,4	4,5	4,6
	5,1	5,2	5,3	5,4	5,5	5,6
	6,1	6,2	6,3	6,4	6,5	6,6

$$P(\text{sum} = 10 \mid \text{1st is 6}) = \frac{1}{6}$$

Prior ve Posterior

PRIOR

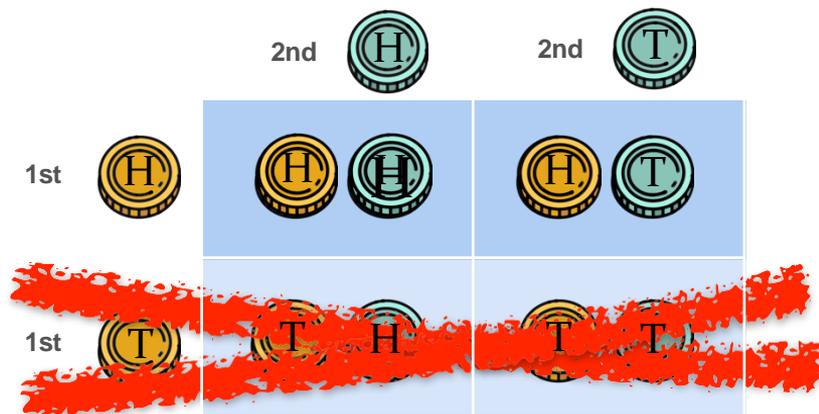


$$P(HH) = \frac{1}{4}$$

EVENT



POSTERIOR



$$P(HH | 1st \text{ is } H) = \frac{1}{2}$$



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Bayes Teorem

Naive Bayes Model

2 Olay?

PRIOR

$$P(\text{spam}) = \frac{\text{Red Envelope}}{\text{Red Envelope} + \text{Blue Envelope}}$$

EVENT



Email contains 'lottery'



Email contains 'winning'



Email contains 'lottery' and 'winning'

POSTERIOR

$$P(\text{spam} \mid \text{lottery}) = \frac{\text{Red Envelope with 777}}{\text{Red Envelope with 777} + \text{Blue Envelope with 777}}$$

$$P(\text{spam} \mid \text{winning}) = \frac{\text{Red Envelope with winning icon}}{\text{Red Envelope with winning icon} + \text{Blue Envelope with winning icon}}$$

?

2 Olay?

EVENT



Email contains 'lottery' and 'winning'

POSTERIOR

$$P(\text{spam} \mid \text{lottery \& winning}) = \frac{\text{[Red envelope with lottery ticket and winning money]} }{\text{[Red envelope with lottery ticket and winning money]} + \text{[Blue envelope with lottery ticket and winning money]}}$$

$$\frac{\text{\# Spam emails with 'lottery' and 'winning'}}{\text{\# Spam emails}}$$

$$P(\text{spam} \mid \text{lottery \& winning}) = \frac{P(\text{spam}) \cdot P(\text{lottery \& winning} \mid \text{spam})}{P(\text{spam}) \cdot P(\text{lottery \& winning} \mid \text{spam}) + P(\text{ham}) \cdot P(\text{lottery \& winning} \mid \text{ham})}$$

A red arrow points from the fraction above to the term $P(\text{lottery \& winning} \mid \text{spam})$ in the denominator, which is circled in red with a red question mark above it.

2 Olaydan Fazla?

EVENT

POSTERIOR

Email contains w_1, w_2, \dots, w_{100}

~~$\frac{\text{\# Spam emails with } w_1, \dots, w_{100}}{\text{\# Spam emails}}$~~ ⁰

$$\mathbf{P}(\text{spam} \mid w_1, \dots, w_{100}) = \frac{\mathbf{P}(\text{spam}) \cdot \mathbf{P}(w_1, \dots, w_{100} \mid \text{spam})}{\mathbf{P}(\text{spam}) \cdot \mathbf{P}(w_1, \dots, w_{100} \mid \text{spam}) + \mathbf{P}(\text{ham}) \cdot \mathbf{P}(w_1, \dots, w_{100} \mid \text{ham})}$$

[?]

Olasılığı daha hızlı hesaplamamanın bir yolu var mı?

Naive assumption



The appearances of 'lottery' and 'winning' are independent
(piyango ve kazanma durumlarının ortaya çıkmasının bağımsız olduğu varsayılır)

$$P(A \cap B) = P(A) \cdot P(B)$$

$$P(\text{spam} \mid \text{lottery \& winning}) = \frac{P(\text{spam}) \cdot P(\text{lottery \& winning} \mid \text{spam})}{P(\text{spam}) \cdot P(\text{lottery \& winning} \mid \text{spam}) + P(\text{ham}) \cdot P(\text{lottery \& winning} \mid \text{ham})}$$

Olasılığı daha hızlı hesaplamamanın bir yolu var mı?

Naive assumption



The appearances of 'lottery' and 'winning' are independent

$$P(A \cap B) = P(A) \cdot P(B)$$

$$P(\text{spam} \mid \text{lottery \& winning}) = \frac{P(\text{spam}) \cdot P(\text{lottery} \mid \text{spam}) \cdot P(\text{winning} \mid \text{spam})}{P(\text{spam}) \cdot P(\text{lottery} \mid \text{spam}) \cdot P(\text{winning} \mid \text{spam}) + P(\text{ham}) \cdot P(\text{lottery} \mid \text{ham}) \cdot P(\text{winning} \mid \text{ham})}$$

Olasılığı daha hızlı hesaplamamanın bir yolu var mı?

Naive assumption

The appearances of the words w_1, w_2, \dots, w_n are independent

$$\mathbf{P}(\text{spam} \mid w_1, \dots, w_n) = \frac{\mathbf{P}(\text{spam}) \cdot \mathbf{P}(w_1 \mid \text{spam}) \cdots \mathbf{P}(w_n \mid \text{spam})}{\mathbf{P}(\text{spam}) \cdot \mathbf{P}(w_1 \mid \text{spam}) \cdots \mathbf{P}(w_n \mid \text{spam}) + \mathbf{P}(\text{ham}) \cdot \mathbf{P}(w_1 \mid \text{ham}) \cdots \mathbf{P}(w_n \mid \text{ham})}$$

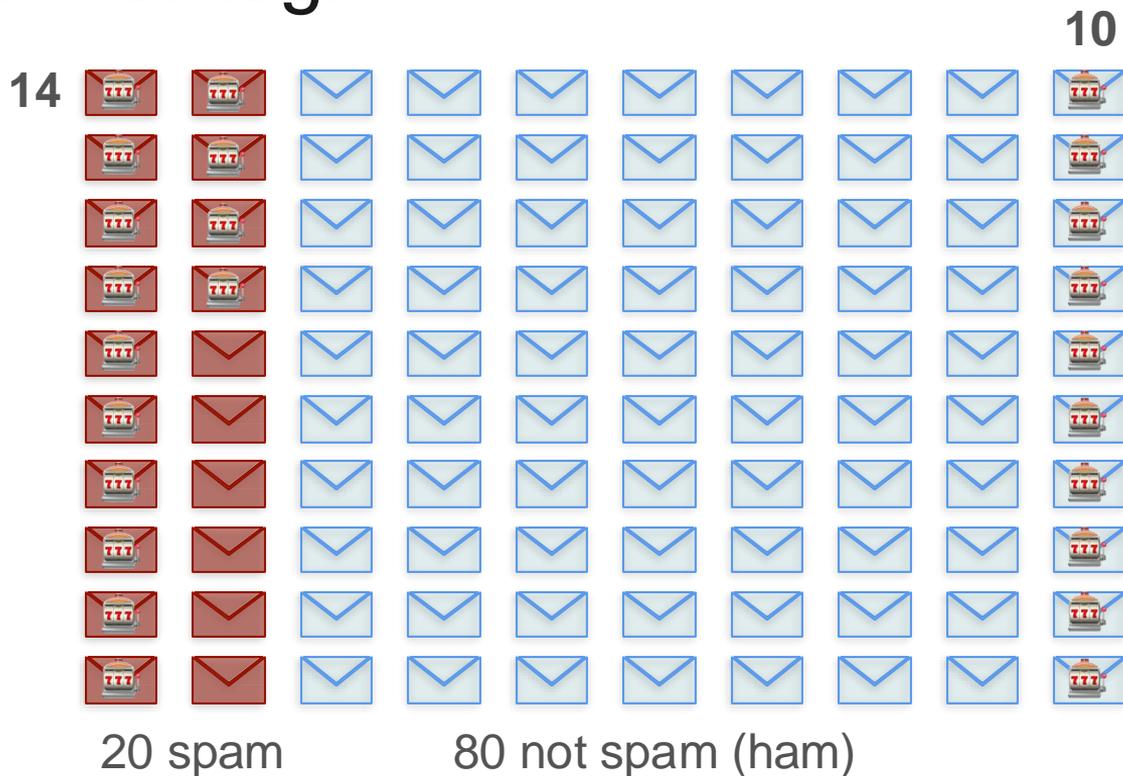
Naive Bayes: Spam Örneği

$$P(\text{spam}) = \frac{20}{100} = 0.2$$

$$P(\text{ham}) = \frac{80}{100} = 0.8$$

$$P(\text{lottery} | \text{spam}) = \frac{14}{20} = 0.7$$

$$P(\text{lottery} | \text{ham}) = \frac{10}{80} = 0.125$$



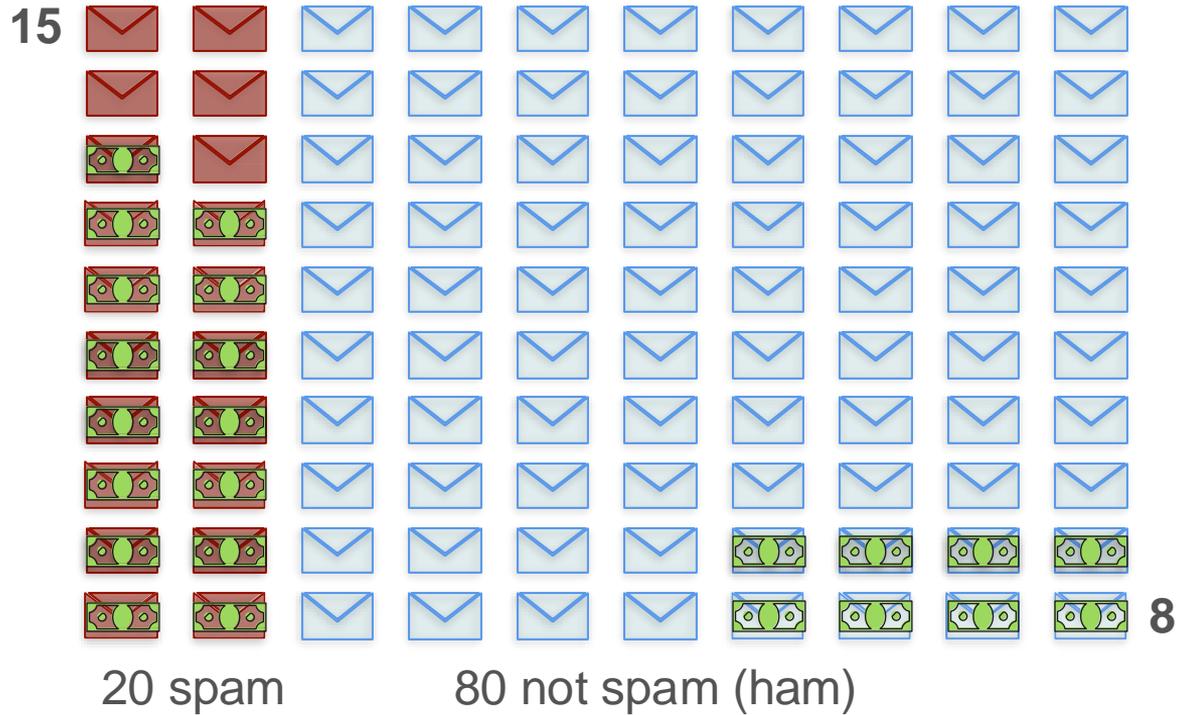
Naive Bayes: Spam Örneği

$$P(\text{spam}) = \frac{20}{100} = 0.2$$

$$P(\text{ham}) = \frac{80}{100} = 0.8$$

$$P(\text{winning} | \text{spam}) = \frac{15}{20} = 0.75$$

$$P(\text{winning} | \text{ham}) = \frac{8}{80} = 0.1$$



Naive Bayes: Spam Örneği

$$P(\text{spam}) = 0.2$$

$$P(\text{lottery} | \text{spam}) = 0.7$$

$$P(\text{winning} | \text{spam}) = 0.75$$

$$P(\text{not spam}) = 0.8$$

$$P(\text{lottery} | \text{ham}) = 0.125$$

$$P(\text{winning} | \text{ham}) = 0.1$$

$$P(\text{spam} | \text{lottery}) = \frac{P(\text{spam}) \cdot P(\text{lottery} | \text{spam}) \cdot P(\text{winning} | \text{spam})}{P(\text{spam}) \cdot P(\text{lottery} | \text{spam}) \cdot P(\text{winning} | \text{spam}) + P(\text{ham}) \cdot P(\text{lottery} | \text{ham}) \cdot P(\text{winning} | \text{ham})}$$

$$P(\text{spam} | \text{lottery} \& \text{winning}) = \frac{0.2 \times 0.7 \times 0.75}{(0.2 \times 0.7 \times 0.75) + (0.8 \times 0.125 \times 0.1)} = 0.913$$

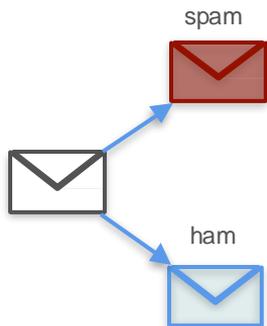


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Makine Öğrenmesinde Olasılık

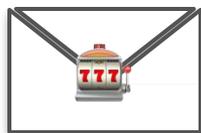
Bayes Theorem

PRIOR

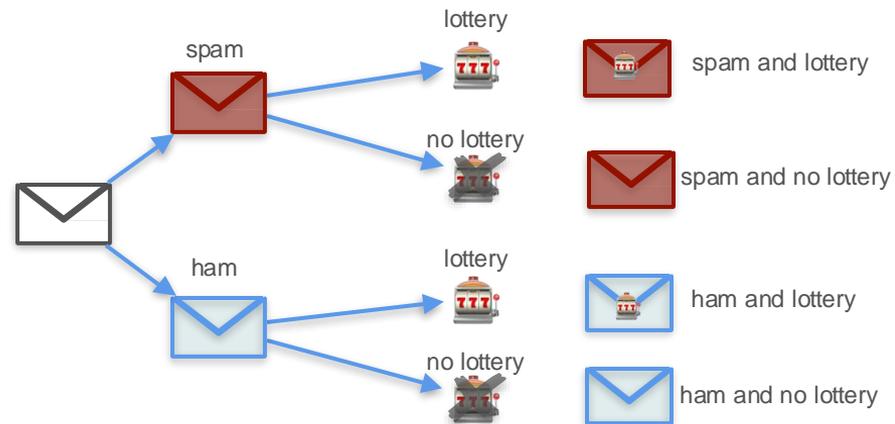


$$P(\text{spam}) = \frac{\text{spam icon}}{\text{spam icon} + \text{ham icon}}$$

EVENT



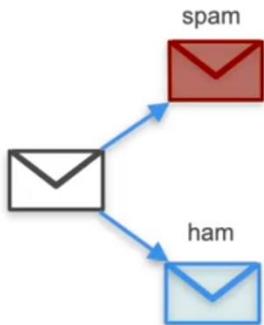
POSTERIOR



$$P(\text{spam} \mid \text{lottery}) =$$

Bayes Theorem

PRIOR

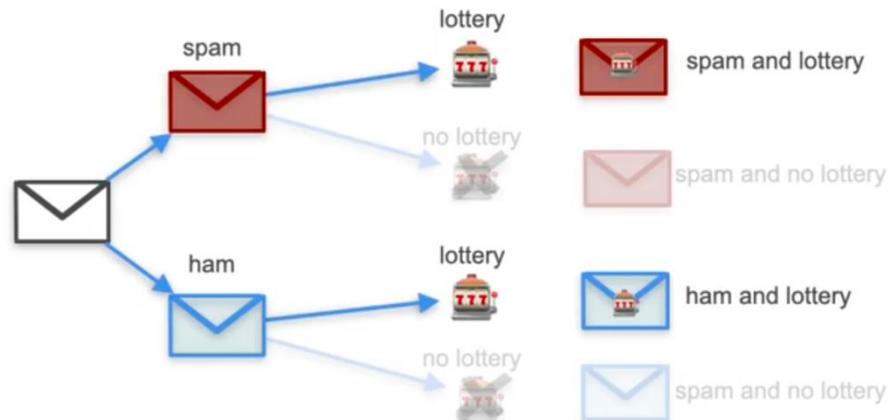


$$P(\text{spam}) = \frac{\text{spam icon}}{\text{spam icon} + \text{ham icon}}$$

EVENT



POSTERIOR



$$P(\text{spam} | \text{lottery}) = \frac{\text{spam and lottery icon}}{\text{spam and lottery icon} + \text{ham and lottery icon}}$$

Örnek

Image recognition (Resim Tanıma)

- Resimde bir kedi olma olasılığı nedir?
- $\mathbf{P}(\text{cat} \mid \text{image}) = \mathbf{P}(\text{cat} \mid \text{pixel}_1, \text{pixel}_2, \dots, \text{pixel}_n)$



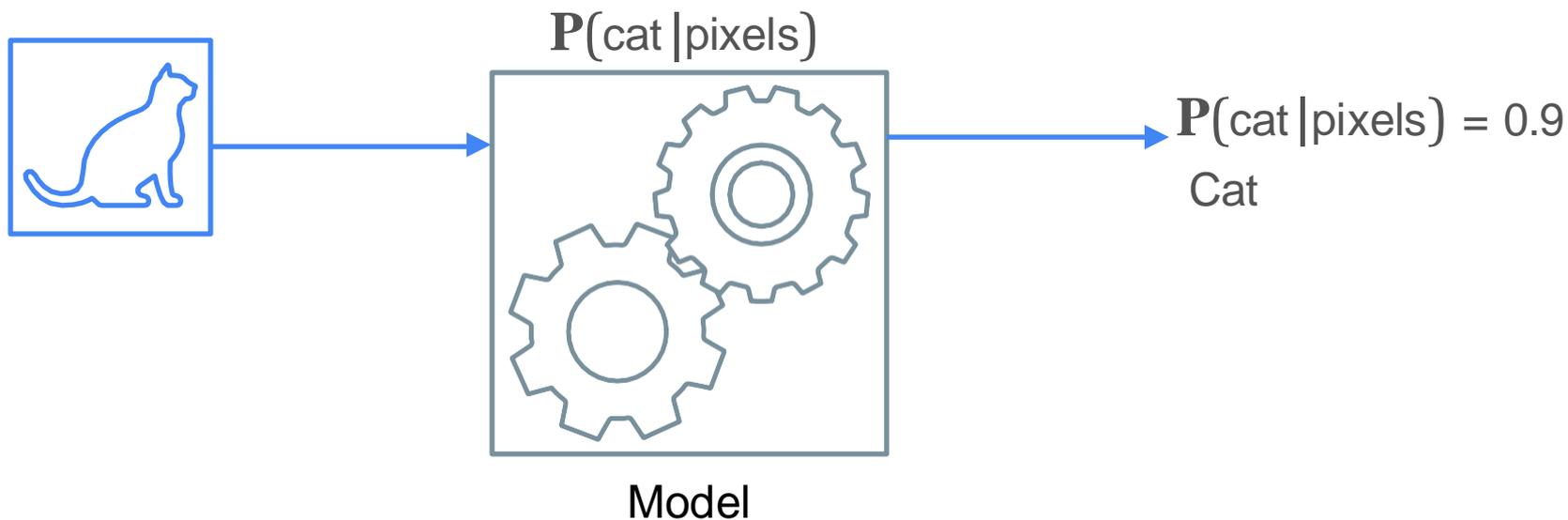
Örnek

Classification (sınıflandırma)

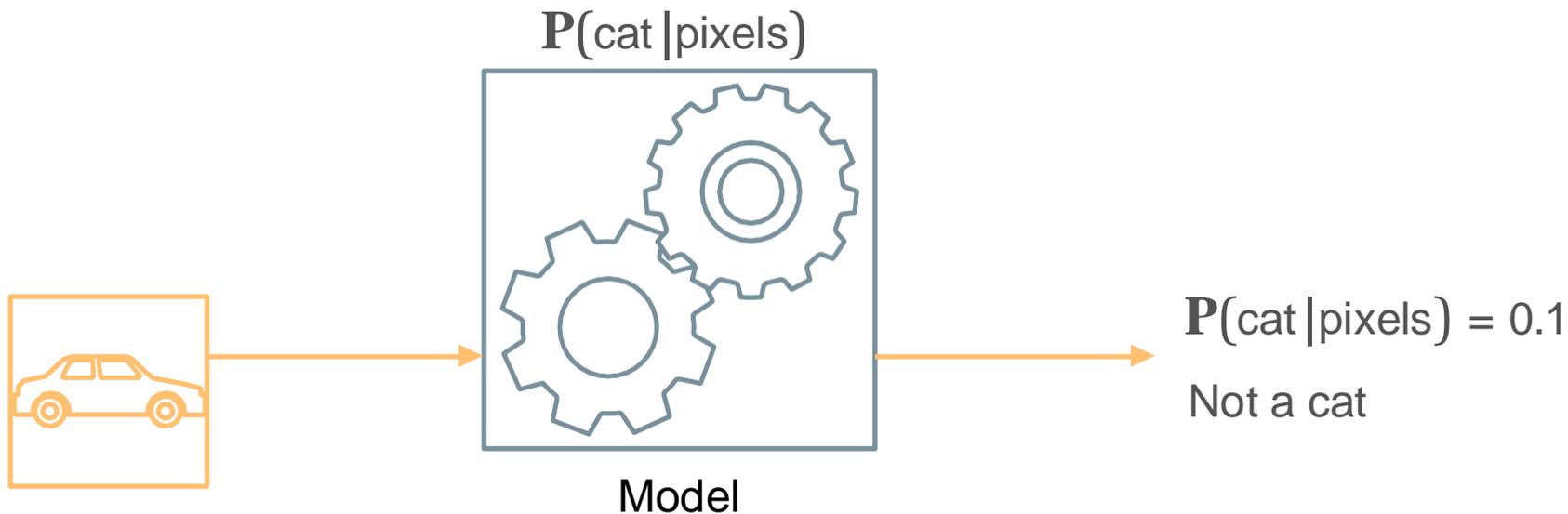
Patient 3		
Patient 2		
Patient 1		
A		
G	Age	29
H	Gender	Female
W	Height	169 cm
S	Weight	62 kg
...	Smoker	No
H
B	Heart rate	63
B	Blood pressure	120 90

- Kişi sağlıklı mı?
- Hesapla $P(\text{healthy} \mid \text{symptoms and history})$
- Hesapla $P(\text{sağlıklı} \mid \text{semptomlar ve hikaye})$

Örnek



Örnek





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Özet

Bayes Teoremi

$P(A|B)$ ve $P(B|A)$ koşullu olasılıkları aşağıdaki gibi yazılabilir.

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

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

!!!

$(A \cap B) = (B \cap A)$ olduğundan

Bayes Teoremi

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

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

veya

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

Bayes Teoremi

Bayes Teoremi

Bir koşullu olasılığı hesaplamak bazen olayla verilen olayı yer değiştirmek işlemleri kolaylaştırır.

Genel Anlamda:



$P(\text{Sonuç} | \text{Sebe})$ Matematiksel Modelimiz (**Hesaplamsı Kolay**)

$P(\text{Sebe} | \text{Sonuç})$ Sonuç çıkarma modelimizi kullanarak bu olasılığı hesaplayabiliriz

Bayes Teoremi

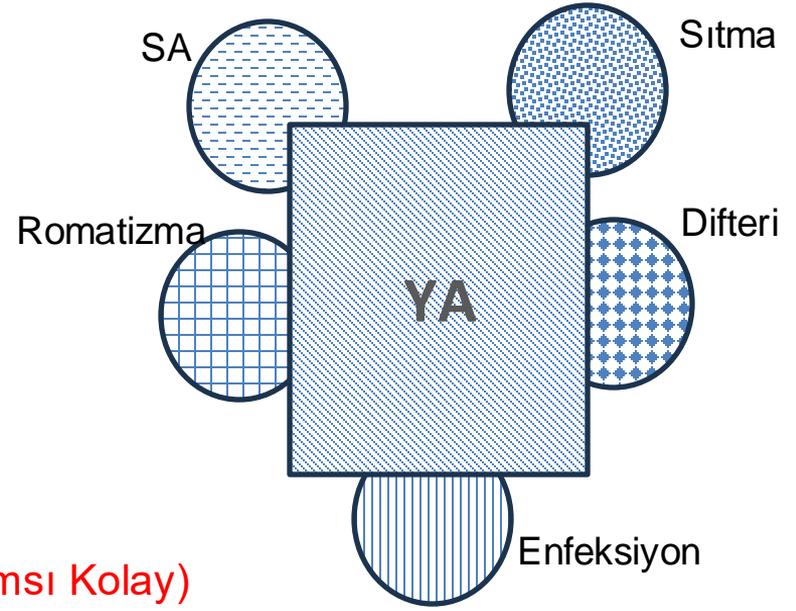
$$P(\text{Sebep} | \text{Sonuç}) = \frac{P(\text{Sonuç} | \text{Sebep}) \cdot P(\text{Sebep})}{P(\text{Sonuç})}$$

$P(\text{Sebep})$: sebeple ilgili önsel olasılık (prior)

$P(\text{Sebep} | \text{Sonuç})$: sebeple ilgili sonsal olasılık (posterior)

Bayes Teoremi

Örnek: Soğuk Algınlığı → Yüksek Ateş
(Hastalık) (Belirti)
Sebeb **Sonuç**
doğrudan gözlemleyemiyoruz doğrudan gözlemliyoruz



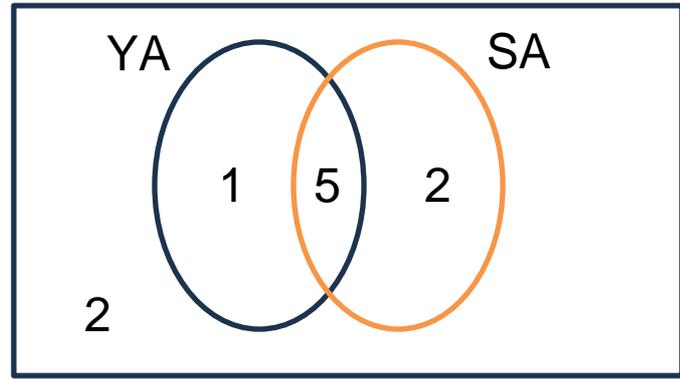
$P(\text{Sonuç} | \text{Sebeb})$ Matematiksel MODEL (Hesaplamsı Kolay)

$P(\text{Yüksek Ateş} | \text{Soğuk Algınlığı})$ Matematiksel MODEL (Hesaplamsı Kolay)
belirti hastalık

$P(\text{Sebeb} | \text{Sonuç})$ Sonuç çıkarma modelimizi kullanarak bu olasılığı hesaplayabiliriz

$P(\text{Soğuk Algınlığı} | \text{Yüksek Ateş}) = ?$ Sonuç çıkarma modelimizi kullanarak bu olasılığı hesaplayabiliriz

Hasta	Soğuk Algınlığı	Yüksek Ateş
1	+	+
2	+	+
3	+	+
4	-	+
5	+	-
6	+	+
7	-	-
8	-	-
9	+	+
10	+	-



$$P(\text{soğuk algınlığı}) = \frac{7}{10}$$

$$P(\text{yüksek ateş}) = \frac{6}{10}$$

$$P(\text{yüksek ateş} \mid \text{soğuk algınlığı}) = \frac{5}{7}$$

$$P(\text{soğuk algınlığı} \mid \text{yüksek ateş}) = \frac{5}{6}$$

$$P(\text{soğuk algınlığı}) = \frac{7}{10}$$

$$P(\text{yüksek ateş}) = \frac{6}{10}$$

$$P(\text{yüksek ateş} \mid \text{soğuk algınlığı}) = \frac{5}{7}$$

$$P(\text{soğuk algınlığı} \mid \text{yüksek ateş}) = \frac{5}{6}$$

$$P(SA \mid YA) = \frac{P(YA \mid SA) \cdot P(SA)}{P(YA)}$$

$$\frac{5}{6} = \frac{5 \cdot 7}{7 \cdot 10}$$

$$P(\text{soğuk algınlığı}) = \frac{7}{10}$$

$$P(\text{yüksek ateş}) = \frac{6}{10}$$

$$P(\text{yüksek ateş} \mid \text{soğuk algınlığı}) = \frac{5}{7}$$

$$P(\text{soğuk algınlığı} \mid \text{yüksek ateş}) = \frac{5}{6}$$

$$P(YA \mid SA) = \frac{P(YA \cap SA)}{P(SA)} = \frac{\frac{5}{10}}{\frac{7}{10}} = \frac{5}{7}$$

$$P(SA \mid YA) = \frac{P(SA \cap YA)}{P(YA)} = \frac{\frac{5}{10}}{\frac{6}{10}} = \frac{5}{6}$$

(zor)

$$P(SA \mid YA) = \frac{P(SA \cap YA)}{P(YA)} = \frac{P(YA \mid SA) \cdot P(SA)}{P(YA)} = \frac{\frac{5}{7} \cdot \frac{7}{10}}{\frac{6}{10}} = \frac{5}{6}$$

(zor)

Marjinal ve Koşul Olasılık

Marjinal olasılık, birden fazla olayın gerçekleştiği bir durumda diğer olaylar dikkate alınmayıp sadece bir olay için bulunan olasılığa marjinal olasılık denir.

Bir A olayının marjinal olasılığı $P(A)$ ile gösterilir.

Örnek

200 öğrencinin cinsiyet ve istatistik dersindeki başarı durumlarına göre dağılımı aşağıda verilmiştir.

Cinsiyet	Başarı durumu		Toplam
	Başarılı	Başarısız	
Erkek	30	50	80
Kadın	80	40	120
Toplam	110	90	200

- Rastgele seçilen bir erkek öğrencinin marjinal olasılığını bulunuz?
- Rastgele seçilen bir kadın öğrencinin marjinal olasılığını bulunuz?
- Rastgele seçilen bir öğrencinin başarılı olmasının marjinal olasılığını bulunuz?
- Rastgele seçilen bir öğrencinin başarısız olmasının marjinal olasılığını bulunuz?

Örnek

200 öğrencinin cinsiyet ve istatistik dersindeki başarı durumlarına göre dağılımı aşağıda verilmiştir.

Cinsiyet	Başarı durumu		Toplam
	Başarılı	Başarısız	
Erkek	30	50	80
Kadın	80	40	120
Toplam	110	90	200

e. Rastgele seçilen bir erkek öğrencinin **başarılı** olması olasılığı? $P(\text{Başarılı}|\text{Erkek})$

f. Rastgele seçilen bir kadın öğrencinin **başarılı** olması olasılığı? $P(\text{Başarılı}|\text{Kadın})$

g. Rastgele seçilen bir erkek öğrencinin **başarısız** olması olasılığı? $P(\text{Başarısız}|\text{Erkek})$

Çözüm-1

Çözüm-2 (Olasılık Ağacı)

Çözüm-3

$$P(B) = P(A).P(B|A) + P(A^c).P(B|A^c)$$

$$P(\text{Başarılı}) = \frac{110}{200}$$

$$P(\text{Başarılı}) \stackrel{?}{=} P(E).P(\text{Başarılı}|E) + P(K).P(\text{Başarılı}|K)$$

Toplam Olasılık Teorisi

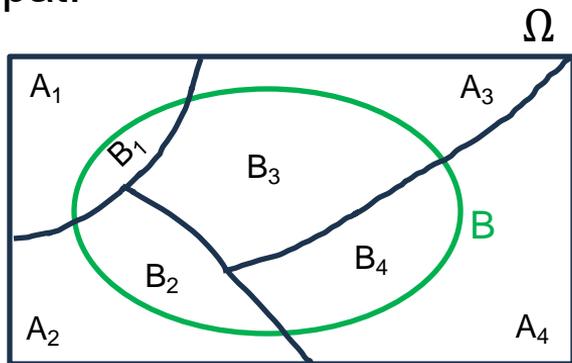
A_1, A_2, \dots, A_n olayları Ω örnek uzayının bölümleri olsun. (Karşılıklı ayrık ve birlikte kapsayıcı) ($A_i \cap A_j = \emptyset$)

B olayı örnek uzayında tanımlı başka bir olay olsun bu durumda B olayının olasılığı ($A_1 \cup A_2 \cup \dots \cup A_n = \Omega$) aşağıdaki gibi hesaplanabilir.

$$P(B) = \sum_{i=1}^n P(A_i) \cdot P(B|A_i)$$

Toplam Olasılık Teorisi

İspat:



$$B = B_1 \cup B_2 \cup B_3 \cup B_4$$

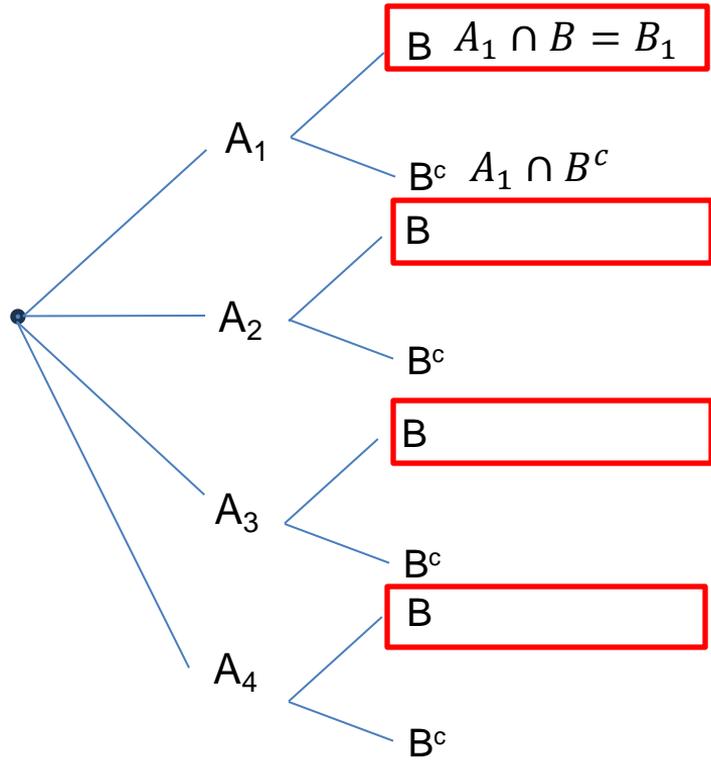
$$B = (A_1 \cap B) \cup (A_2 \cap B) \cup (A_3 \cap B) \cup (A_4 \cap B)$$

$$P(B) = P(A_1 \cap B) + P(A_2 \cap B) + P(A_3 \cap B) + P(A_4 \cap B)$$

$$P(B) = P(A_1)P(B|A_1) + \dots + P(A_4)P(B|A_4)$$

$$P(B) = \sum_{i=1}^4 P(A_i)P(B|A_i)$$

Toplam Olasılık Teorisi



Toplam Olasılık Teorisi

$P(A_i) \rightarrow A_i$ bölümü için ön bilgi (önsel olasılık)

B olayı gözlemlendiğinde A_i 'nin olasılığı

$$\underbrace{P(A_i|B)}_{\text{sonsal olasılık}} = \frac{P(A_i \cap B)}{P(B)}$$

$$= \frac{P(A_i)P(B|A_i)}{P(B)}$$

toplam
olasılık
teorisi

$$= \frac{P(A_i)P(B|A_i)}{\sum_{j=1}^n P(A_j)P(B|A_j)}$$

BAYES TEORİSİ

Genel Bayes Teoremi

Şayet A_1, A_2, \dots, A_n olayları örnek uzayının bölümleri olsun. Örnek uzayında tanımlı herhangi bir B olayı verildiğinde uzayın herhangi bir bölümünün olasılığı aşağıdaki şekilde bulunabilir

$$\begin{aligned} P(A_i | B) &= \frac{P(B | A_i) \cdot P(A_i)}{P(B)} \\ &= \frac{P(B | A_i) \cdot P(A_i)}{\sum_{i=1}^n P(B | A_i) \cdot P(A_i)} \end{aligned}$$

Örnek

Elektirik malzemelerinin olduğu 4 kutumuz olduğunu kabul edelim

- 1. Kutuda 2000 malzemedan %5'i bozuk
- 2. Kutuda 500 malzemedan %40'i bozuk
- 3. Kutuda 1000 malzemedan %10'i bozuk
- 4. Kutuda 1000 malzemedan %10'i bozuk

Rasgele çektiğimiz kutudan bir malzeme aldığımızda bunun bozuk olma olasılığı nedir?

Çözüm

Örnek

Önceki örnekte çekilen malzeme bozuk ise bunun 2.kutundan çekilmiş olma olasılığı nedir?

Çözüm

Ödev

Aynı marka aracın üç farklı yakıt türüne göre kat ettiği yol ve motorun vermiş olduğu arıza oranları belirli bir mesafede incelenmiştir. Buna göre benzinli araç yolun %60'nı, dizel araç yolun %30'nu ve sıvılaştırılmış petrol gazı (LPG) ile %10'unu gittiği gözlenmiştir. Motor arıza oranları ise %2 benzinli araç, %3 dizel araç ve %5 sıvılaştırılmış petrol gazı olduğu belirlenmiştir. Buna göre bu araçlardan rastgele alan bir müşterinin arızalı olma olasılığını bulunuz?