# Exercise_1

April 26, 2022

## Probabilistic Machine Learning

**Machine Learning in Science, University of Tübingen, Summer Semester 2022**

## 1 EXAMple

### a

For any two events $A, B \in \Omega$

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

$$P(A,B) \geq 0; P(B) \geq 0 \implies \frac{P(A,B)}{P(B)} \geq 0 \tag{1}$$

$$\begin{aligned} P(\Omega \mid B) &= \frac{P(\Omega, B)}{P(B)} \\ &= \frac{1 \cdot P(B)}{P(B)} \\ &= 1 \end{aligned} \tag{2}$$

Let $A_1, A_2, A_3, \dots \in \Omega$ be disjoint:

$$\begin{aligned} P(A_1, A_2, A_3, \dots \mid B) &= \frac{P(A_1, A_2, A_3, \dots)}{P(B)} \\ &= \frac{P(A_1) + P(A_2) + P(A_3) + \dots}{P(B)} \\ &= \frac{P(A_1)}{P(B)} + \frac{P(A_2)}{P(B)} + \frac{P(A_3)}{P(B)} + \dots \\ &= P(A_1 \mid B) + P(A_2 \mid B) + P(A_3 \mid B) + \dots \end{aligned} \tag{3}$$

### b

**i**

Yes!
$P(H_1, H_2 \mid B) = P(H_1 \mid B) \cdot P(H_2 \mid B) = 0.01 \cdot 0.01$

**ii**

No!
$P(H_1, H_2) \neq P(H_1) \cdot P(H_2)$

**c**

Let $W_i$ be the event of winning in the $i$th "round"

**i**

$$P(W_1) = \frac{2}{3}$$

**ii**

$$P(W_2 \mid W_1) = \frac{1}{2}$$

**iii**

$$P(W_2 \mid \neg W_1) = 1$$

**iv**

$$\begin{aligned} P(W_2) &= P(W_1) \cdot P(W_2 \mid W_1) + P(\neg W_1) \cdot P(W_2 \mid \neg W_1) \\ &= \frac{2}{3} \cdot \frac{1}{2} + \frac{1}{3} \cdot 1 \\ &= \frac{2}{3} = P(W_1) \end{aligned}$$

It doesnt have any impact on my winning chances

**v**

$$\begin{aligned} P(W_1 \mid W_2) &= \frac{P(W_2 \mid W_1) P(W_1)}{P(W_2)} \\ &= \frac{\frac{1}{2} \cdot \frac{2}{3}}{\frac{2}{3}} \\ &= \frac{1}{2} \end{aligned}$$

# 2 Theory

$$P(A) = \frac{|A|}{p}$$

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

Assume $A$ and $B$ are independent, then

$$\begin{aligned} P(A,B) &= P(A) \cdot P(B) \\ &= \frac{|A|}{p} \cdot \frac{|B|}{p} \end{aligned}$$

$$\begin{aligned} \implies \frac{|A|}{p} \cdot \frac{|B|}{p} &= \frac{|A \cap B|}{p} \\ |A \cap B| \cdot p &= |A| \cdot |B| \end{aligned}$$

Because $p$ is a prime, this can only be true when:
1. $|A \cap B| = 0 \implies |A| = 0$ or $|B| = 0 \implies A = \emptyset$ or $B = \emptyset$
2. $|A| = p$ or $|B| = p \implies A = \Omega$ or $B = \Omega$

# 3 Practical Question

### Exercise 01

**hand in before 29.04.2022, 12:00 p.m. (noon)**

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In the lecture, we calculated the probability of someone having COVID given a positive COVID test. In this exercise, we ask you to code up a method that performs this calculation, given the sensitivity and specificity of a COVID test, depending on the prevalence of COVID.

#### 1) COVID Prevalence

The 7 Day Incidence Rate per 100,000 people in Germany (as of 19.04.2022) is 698.9. How would you convert this number into the probability of someone having COVID in Germany? (Hint: Ignore the length of time for which people remain sick, and simply assume that the incidence rate represents the total number of people with COVID per 100,000 people on a given day)

[5]:
```
inc = 698.9

prevalence = inc / 1e5
prevalence
```

[5]:
```
0.0069889999999999996
```

### 2) Sensitivity and Specificity

Several "Schnell-tests' ' are available on the market for COVID self-testing. Their diagnosic accuracy is measured by their sensitivity and specificity. 1. How are the sensitivity and specificity of a test defined? 2. How would you compute the probabilities of a false positive test and a false negative test, given its sensitivity and specificity?

**Answer 2)** 1. sensitivity is the probability of a true positive: $P(\text{'test: covid'} \mid \text{'covid'})$
specificity is the probability of a true negative: $P(\text{'test: no covid'} \mid \text{'no covid'})$

2. false pos: $P(\text{'test: covid'} \mid \text{'no covid'}) = 1 - P(\text{'test: no covid'} \mid \text{'no covid'}) = 1 - \text{specificity}$
   false neg: $P(\text{'test: no covid'} \mid \text{' covid'}) = 1 - P(\text{'test: covid'} \mid \text{'covid'}) = 1 - \text{sensitivity}$

### 3) Probability of Infection

1. Which probabilities would you need to compute the probability of an infection given a positive test?
2. Which mathematical theorem would you use to compute this quantity?

**Answer 3)** 1. - Probability of infection (without test) - Sensitivity - Specificity

2. Bayes' Theorem

### 4) Function definition

Write a function that returns the probability of having COVID given a positive test. The function should take as inputs the sensitivity and specificity of a test, and the COVID prevalence.

[2]:
```python
# Your code here
def covid_prob(sens, spec, prev = 698.9 / 1e5):
    p_positive = sens * prev + (1-spec) * (1-prev)
    return sens * prev * 1/p_positive
```

### 5) Test your code

Using the function you wrote above, compute the probability of having COVID, given a positive COVID test with sensitivity = 0.9652 and specificity = 0.9968 for prevalence: 1. 0.016319 (Korea, South) 2. 0.006989 (Germany) 3. 0.000613 (Norway)

(Prevalence based on https://oscovida.github.io/countries-incidence-rate.html, date of access: 19.04.22)

[3]:
```python
sens = 0.9652
spec = 0.9968

countries = ['South Korea', 'Germany', 'Norway']
prevs = [0.016319, 0.006989, 0.000613]

for country, prev in zip(countries, prevs):
```

```
    print(f'In {country} the Probability of having covid after a positive test␣
↪is {round(covid_prob(sens, spec, prev)*100, 2)}%')
```

```
In South Korea the Probability of having covid after a positive test is 83.34%
In Germany the Probability of having covid after a positive test is 67.98%
In Norway the Probability of having covid after a positive test is 15.61%
```

### 6) Plot of infection probability

Plot how the probability of infection given a positive COVID test changes, depending on COVID prevalence.

[4]:
```
import numpy as np
from matplotlib import pyplot as plt
prev_space = np.linspace(0,1, 100)
p_infection = covid_prob(sens, spec, prev_space)

plt.plot(prev_space, p_infection)
plt.show()
```