

# Who is Bayes? What is Bayes?

BAYESIAN DATA ANALYSIS IN PYTHON



Michał Oleszak

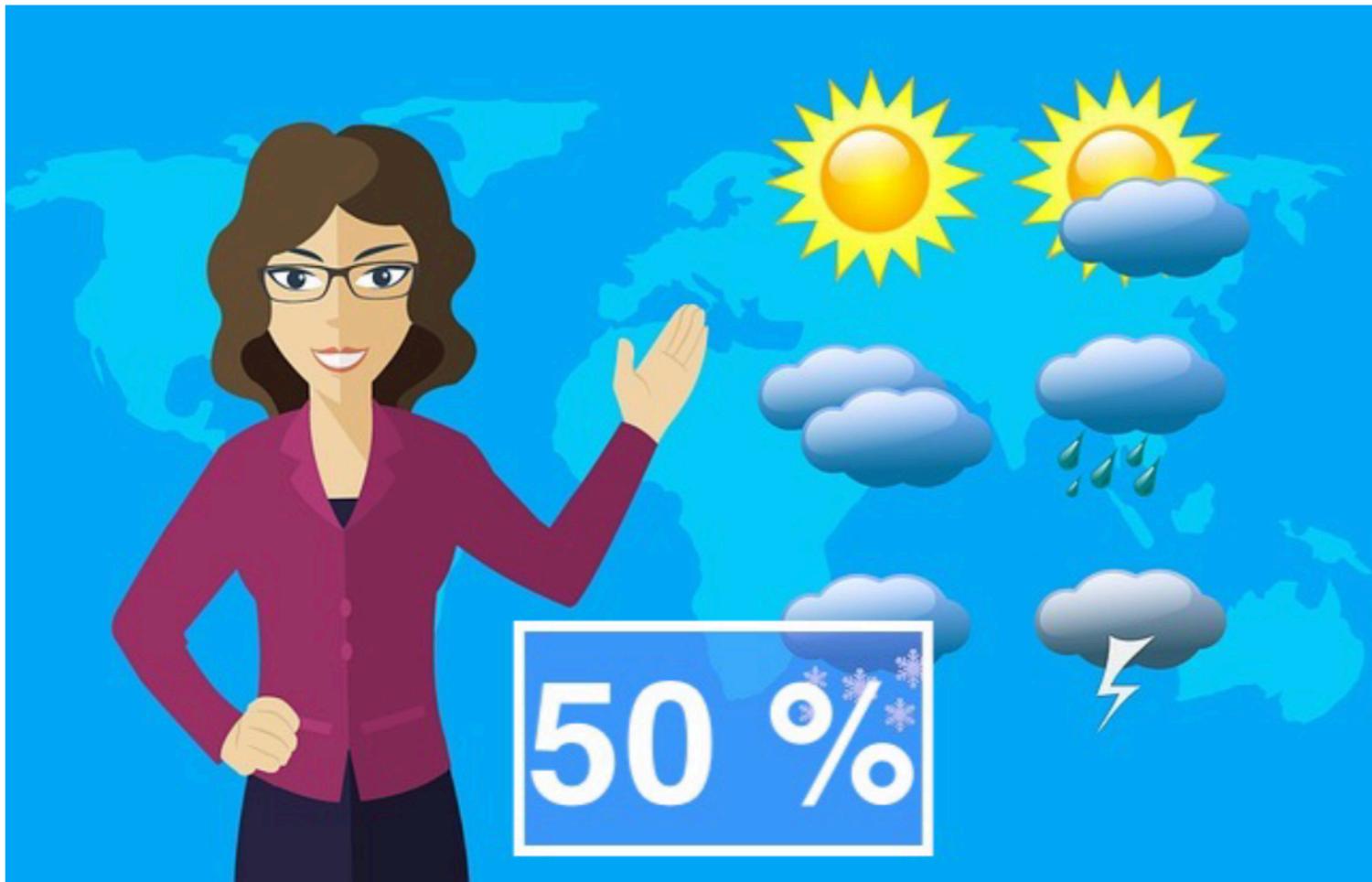
Machine Learning Engineer

# Who is Bayes?



<sup>1</sup> Public Domain, <https://commons.wikimedia.org/w/index.php?curid=14532025>

# Should you take your umbrella?



# What is Bayes?

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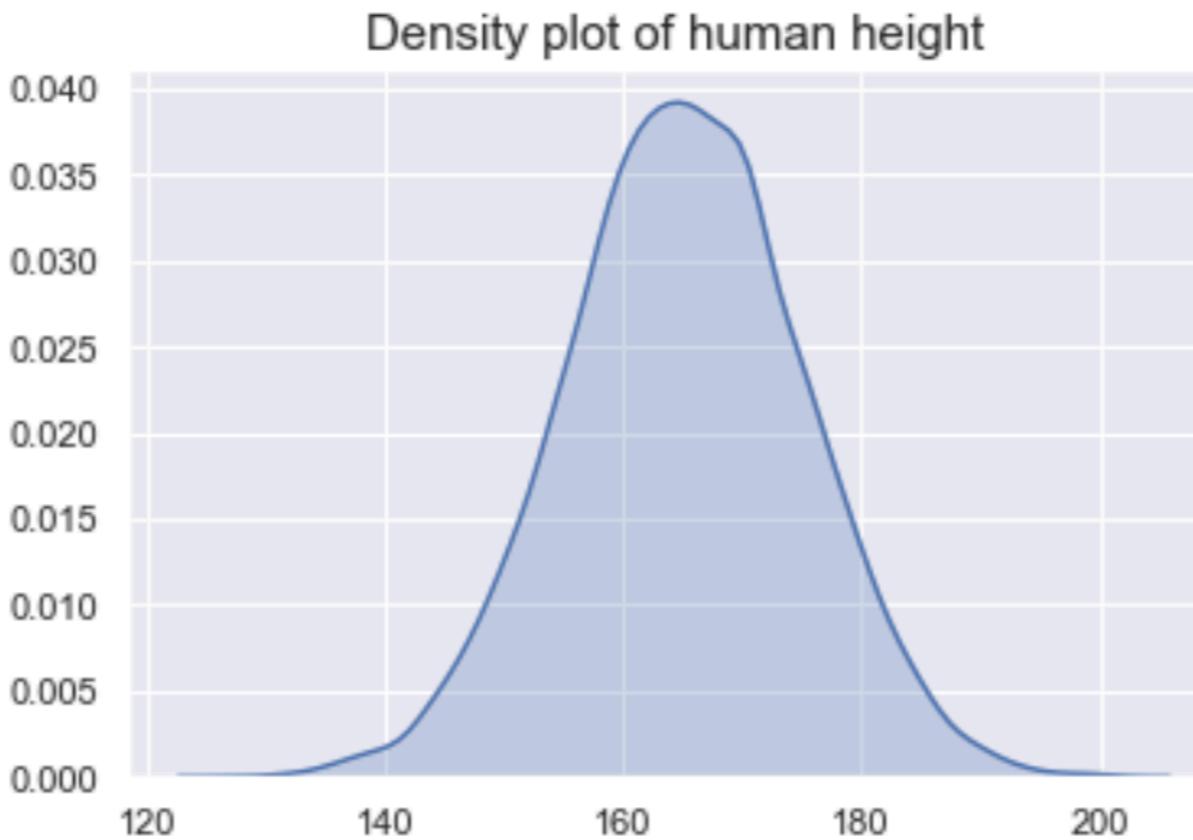
	Frequentist (classical) approach	Bayesian approach
<b>probability</b>	proportion of outcomes	degree of belief
<b>parameters</b>	fixed values	random variables

# It pays to go Bayes!

- Natural handling of uncertainty (because parameters have distributions!).
- Possibility to include expert opinion or domain knowledge in the model (because probability means the degree of belief!).
- No need to rely on fixed constants such as p-values.
- Statistically correct even with little data.
- Often coincides with frequentist results, but offers more flexibility to build custom models.

# Probability distributions

- A distribution of a random variable specifies what values this variable can take, and with what probabilities.
- Can be discrete (finite set of possible values) or continuous (infinitely many possible values)
- Continuous distributions can be visualized on a density plot.



# Distributions in Python

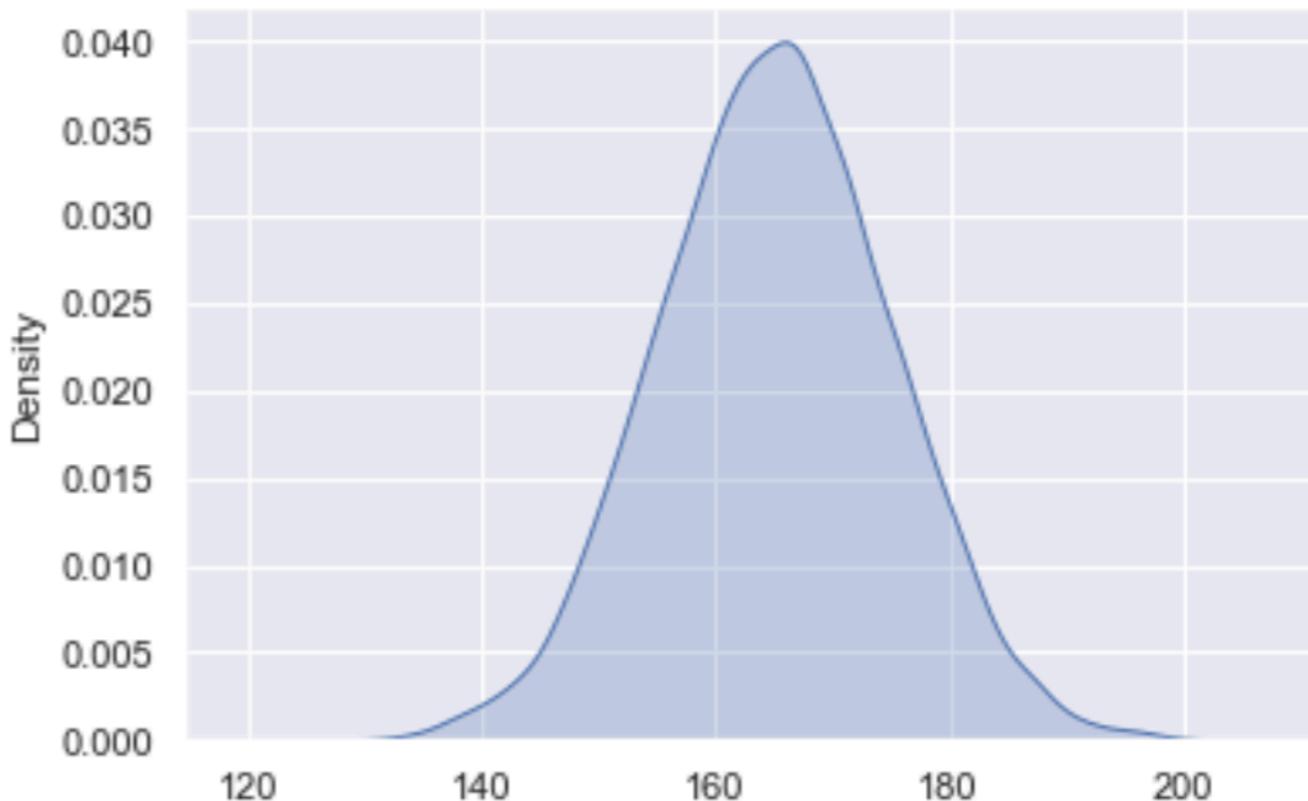
```
print(draws)
```

```
[146.58686154393, 159.40688614250, ..., ]
```

```
print(len(draws))
```

```
10000
```

```
import matplotlib.pyplot as plt  
import seaborn as sns  
sns.kdeplot(draws, shade=True)  
plt.show()
```



# Probability and Bayes' Theorem

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# Probability theory

- Statement of uncertainty.
- A number between 0 and 1.
  - $P = 0 \rightarrow$  impossible
  - $P = 1 \rightarrow$  certain
  - $P = 0.5 \rightarrow$  50/50 chance
- $P(\text{rain tomorrow}) = 0.75 \rightarrow$  75% chance of rain tomorrow

# Probability rules

## Sum rule

- Probability of A **or** B (independent events)
- OR = addition
- Probability of rolling 2 or 4 with a die

$$P(2 \text{ or } 4) = 1/6 + 1/6 = 0.33333\ldots = 33.3\%$$

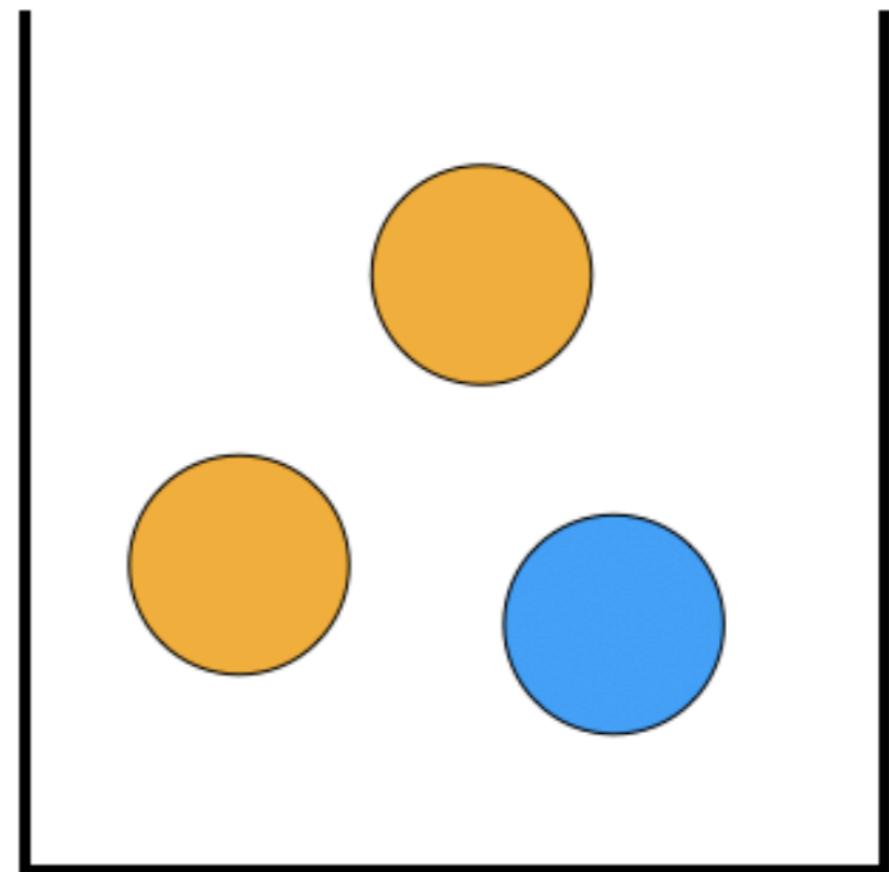
## Product rule

- Probability of A **and** B (independent events)
- AND = multiplication
- Probability of rolling 2 and then 4 with a die

$$P(2 \text{ and } 4) = 1/6 * 1/6 = 0.02777\ldots = 2.8\%$$

# Conditional probability

- Probability of some event occurring, **given that** some other event has occurred.
- $P(A | B)$
- $P(\text{orange}) = 2/3 \rightarrow \text{unconditional}$
- $P(\text{blue}) = 1/3 \rightarrow \text{unconditional}$
- $P(\text{blue} | \text{orange}) = 1/2 \rightarrow \text{conditional}$
- $P(\text{orange} | \text{blue}) = 1 \rightarrow \text{conditional}$



# Bayes' Theorem

- A way to calculate conditional probability when we know some other probabilities.

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

# Bayes' Theorem

- A way to calculate conditional probability when we know some other probabilities.

$$P(\text{accident}|\text{slippery}) = \frac{P(\text{slippery}|\text{accident}) * P(\text{accident})}{P(\text{slippery})}$$

```
road_conditions.head()
```

```
    accident  slippery
0      False     True
1      True      True
2      False    False
3      False    False
4      False    False
```

# Bayes' Theorem in practice

$$P(\text{accident}|\text{slippery}) = \frac{P(\text{slippery}|\text{accident}) * P(\text{accident})}{P(\text{slippery})}$$

```
# Unconditional probability of an accident
p_accident = road_conditions["accident"].mean() # 0.0625

# Unconditional probability of the road being slippery
p_slippery = road_conditions["slippery"].mean() # 0.0892

# Probability of the road being slippery given there is an accident
p_slippery_given_accident = road_conditions.loc[road_conditions["accident"]]["slippery"].mean() # 0.7142

# Probability of an accident given the road is slippery
p_accident_given_slippery = p_slippery_given_accident * p_accident / p_slippery # 0.5
```

# Tasting the Bayes

## BAYESIAN DATA ANALYSIS IN PYTHON



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# Binomial distribution

- A discrete distribution, can only take one of two values:
  - Success (1)
  - Failure (0)
- One parameter: probability of success.
- Task: given a list of draws (successes and failures), estimate the probability of success.

# Binomial distribution in Python

Number of successes in 100 trials:

```
import numpy as np  
np.random.binomial(100, 0.5)
```

51

```
np.random.binomial(100, 0.5)
```

44

Get draws from a binomial:

```
import numpy as np  
np.random.binomial(1, 0.5, size=5)
```

```
array([1, 0, 0, 1, 1])
```

# Heads probability

- `get_heads_prob()` - a custom function
- input: a list of coin tosses
- output: a list, the distribution of the probability of success

```
import numpy as np  
tosses = np.random.binomial(1, 0.5, size=1000)  
print(tosses)
```

```
[1 0 0 0 1 1 0 1 1 ... ]
```

# Heads probability

```
heads_prob = get_heads_prob(tosses)  
print(heads_prob)
```

```
[0.47815295 0.51679212 0.51684779 ... ]
```

```
import matplotlib.pyplot as plt  
import seaborn as sns  
  
sns.kdeplot(heads_prob,  
            shade=True,  
            label="heads probility")  
plt.show()
```

