- Our task is to classify new classes as they arrive i.e decide to which class label belong, based on the currently existing objects.
- Since, there are twice as many Brown cookies as white.

- So the new case will be twice as likely to have membership of brown cookies than white.
- In Bayesian analysis, this belief is known as the prior probability.

- Prior probabilities are based on previous experience, in this case the percentage of Brown and white cookies.

- It is often used to predict outcomes before they actually happen.

- Prior Probability of Brown cookies, i.e. P() = $\frac{Number\ of\ brown\ cookies}{Total\ number\ of\ cookies} = \frac{12}{20}$ = 0.6

- Prior Probability of white cookies, i.e. P() = $\frac{Number\ of\ white\ cookies}{Total\ number\ of\ cookies} = \frac{8}{20}$ = 0.4

Agenda

- Why Naive Bayes?
- Classification --
  Naive Bayes classifier
- Independent Features
- Prior Probability
- **Likelihood**
- Posterior Probability
- Relationship between Posterior, prior and likelihood
- Applications --
  1. Face Recognition
  2. Spam Filtering
  3. Weather Prediction
  4. Text Classification
- Advantages
- Limitations

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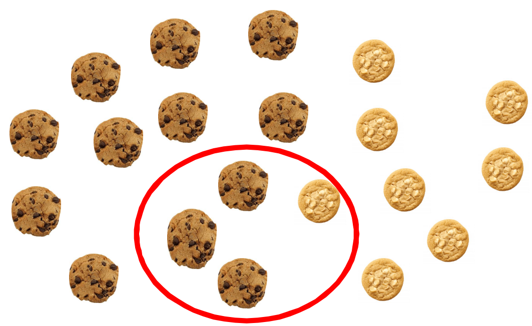
Likelihood

Lets calculate Likelihood for this example



Let’s calculate probability for X given it is either Brown or White.

- Probability of (X | Brown cookie) : $\frac{3}{20}$ = 0.15
- Probability of (X | white cookie) : $\frac{1}{20}$ = 0.05


CAN I HAVE SOME...
PRETTY PLEASE?

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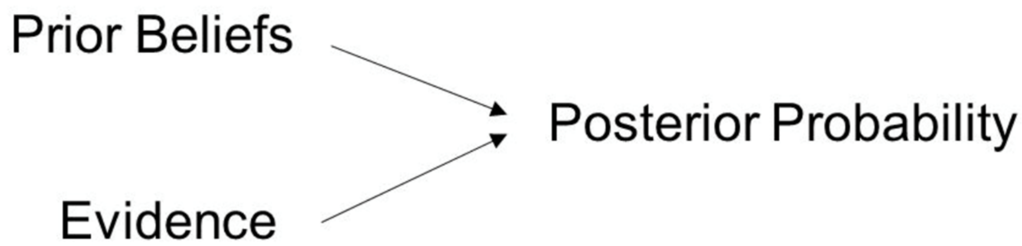
Posterior Probability

- It represents the updated prior probability after taking into account some new piece of information.



Posterior Probability

- In the Bayesian analysis, the final classification is produced by combining both sources of information, i.e., the prior and the likelihood, to form a posterior probability using the Bayes.

Posterior Probability = Prior Probability X Likelihood

Posterior Probability

- Posterior Probability, P(Brown cookie | X) = Prior X Likelihood

$$= \frac{12}{20} \times \frac{3}{20}$$

$$= \frac{36}{400} = \frac{9}{100} = 0.09$$

- Posterior Probability, P(white cookie | X) = Prior X Likelihood

$$= \frac{8}{20} \times \frac{1}{20}$$

$$= \frac{8}{400} = \frac{2}{100} = 0.02$$

- Finally, we classified **X** as Brown cookie since its class membership achieves the largest Posterior probability.

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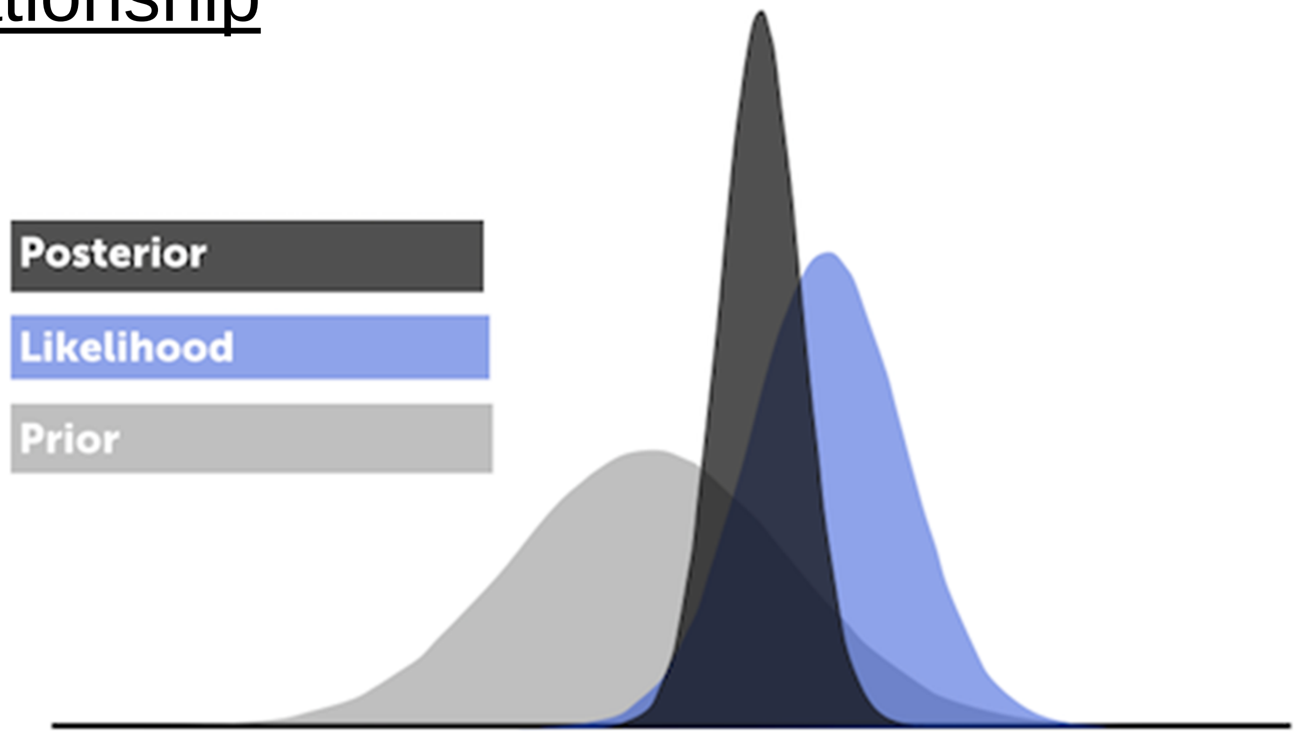
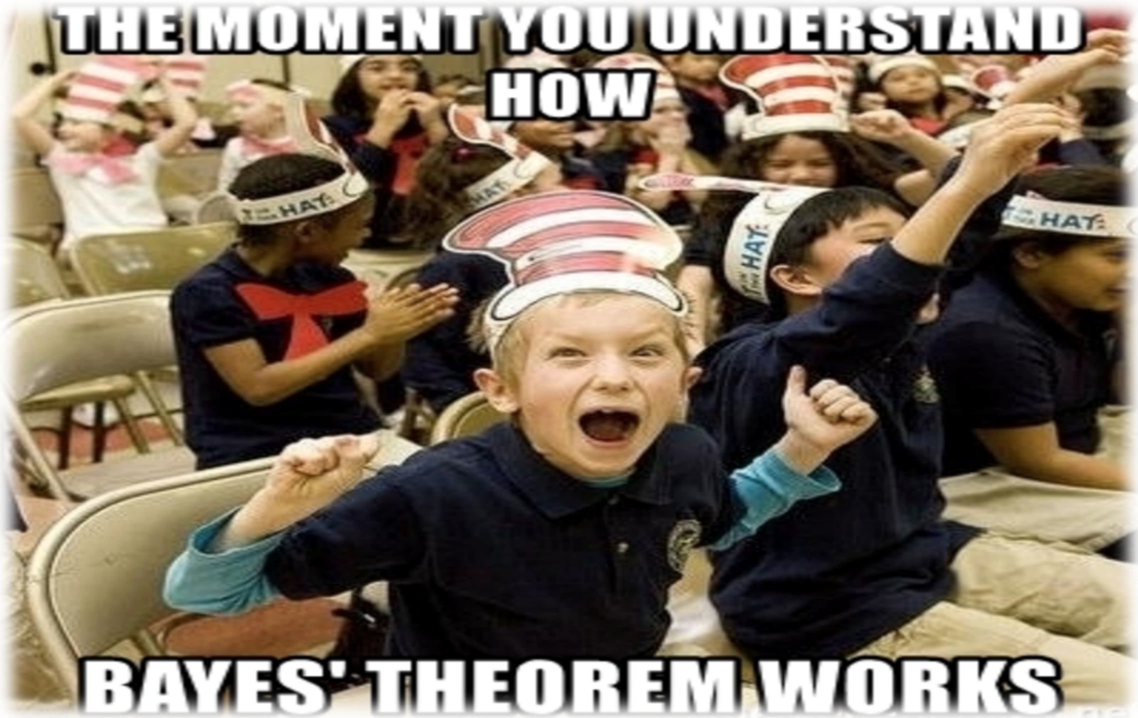
Relationship




THE MOMENT YOU UNDERSTAND HOW
BAYES' THEOREM WORKS

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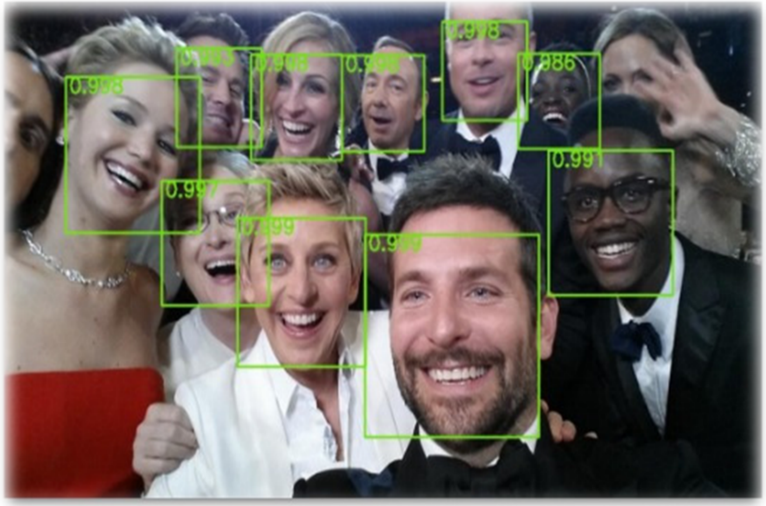
Applications

Face Recognition

- It is considered as automated approach to verify the identification of the human being based on his characteristics like, fingerprint, iris pattern, or face.



Spam Filtering

- It is used to mark an email as **spam**, or **not spam** ?