

# NAÏVE BAYES

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# DATA SCIENCE PROCESS

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1. Define problem.
2. Gather data.
3. Explore data.
4. Model with data.
5. Evaluate model.
6. Answer problem.

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# AGENDA

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- Probability
- Bayes' Theorem
- Naïve Bayes

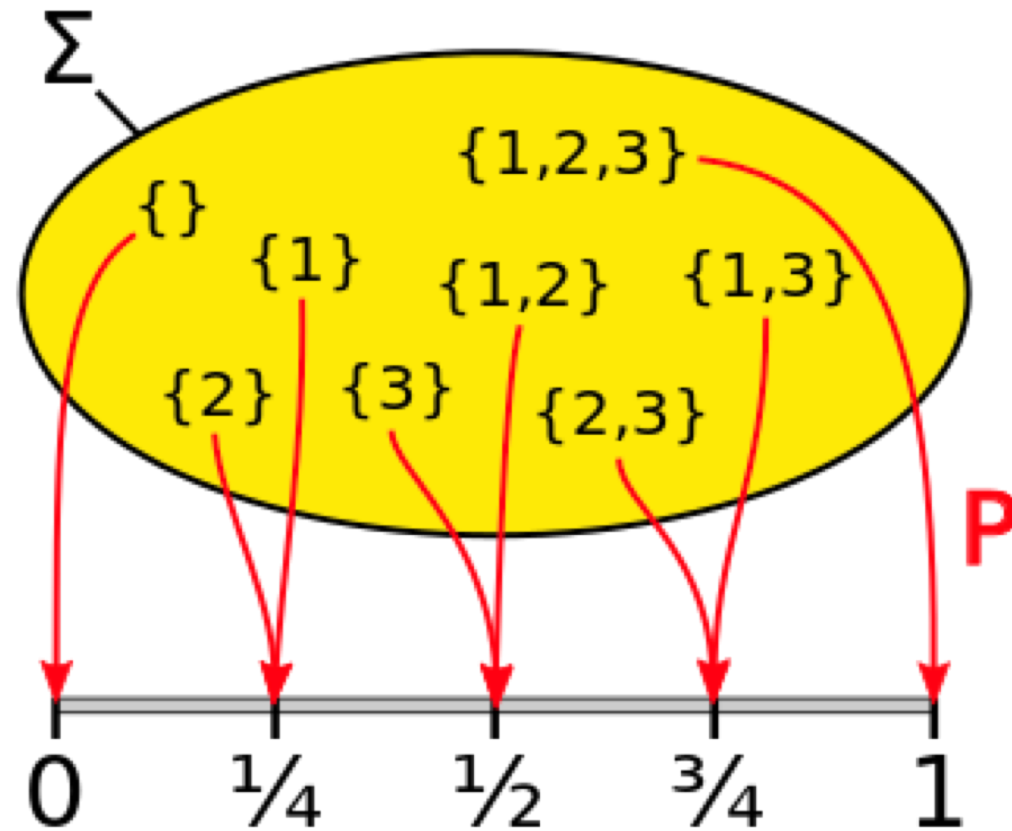
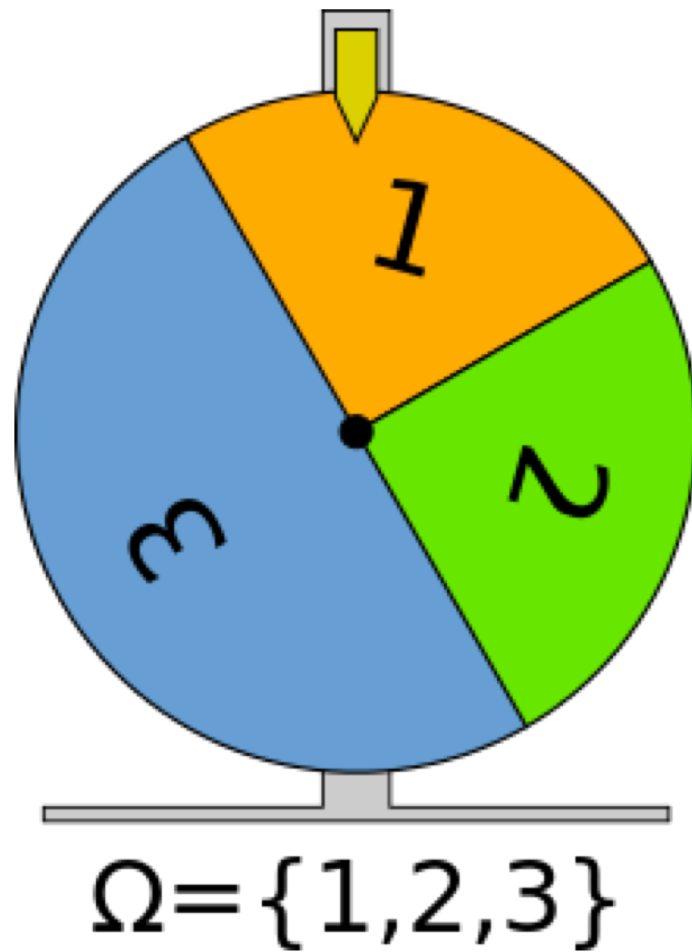
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## DEFINITIONS

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- Experiment: A procedure that can be repeated infinitely many times and has a well-defined set of outcomes.
- Event: Any collection of outcomes of an experiment.
- Sample Space: The set of all possible outcomes of an experiment, denoted  $\mathcal{S}$ .

# PROBABILITY BASICS



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# PROBABILITY RULES

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- $P(\emptyset) = 0$ 
  - Note:  $\emptyset$  indicates the “empty set,” or the event containing zero outcomes from the experiment.

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# PROBABILITY RULES

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- $P(A \cup B) = P(A) + P(B) - P(A \cap B)$ 
  - Venn diagrams can help to illustrate this – but remember that Venn diagrams are not proofs!
  - If  $A$  and  $B$  are disjoint, then  $P(A \cap B) = 0 \Rightarrow P(A \cup B) = P(A) + P(B)$ .

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# PROBABILITY RULES

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- $P(A|B) = \frac{P(A \cap B)}{P(B)}$ 
  - Note:  $A|B$  means “ $A$  given  $B$ ” or “ $A$  conditional on the fact that  $B$  happens.”



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# PROBABILITY RULES

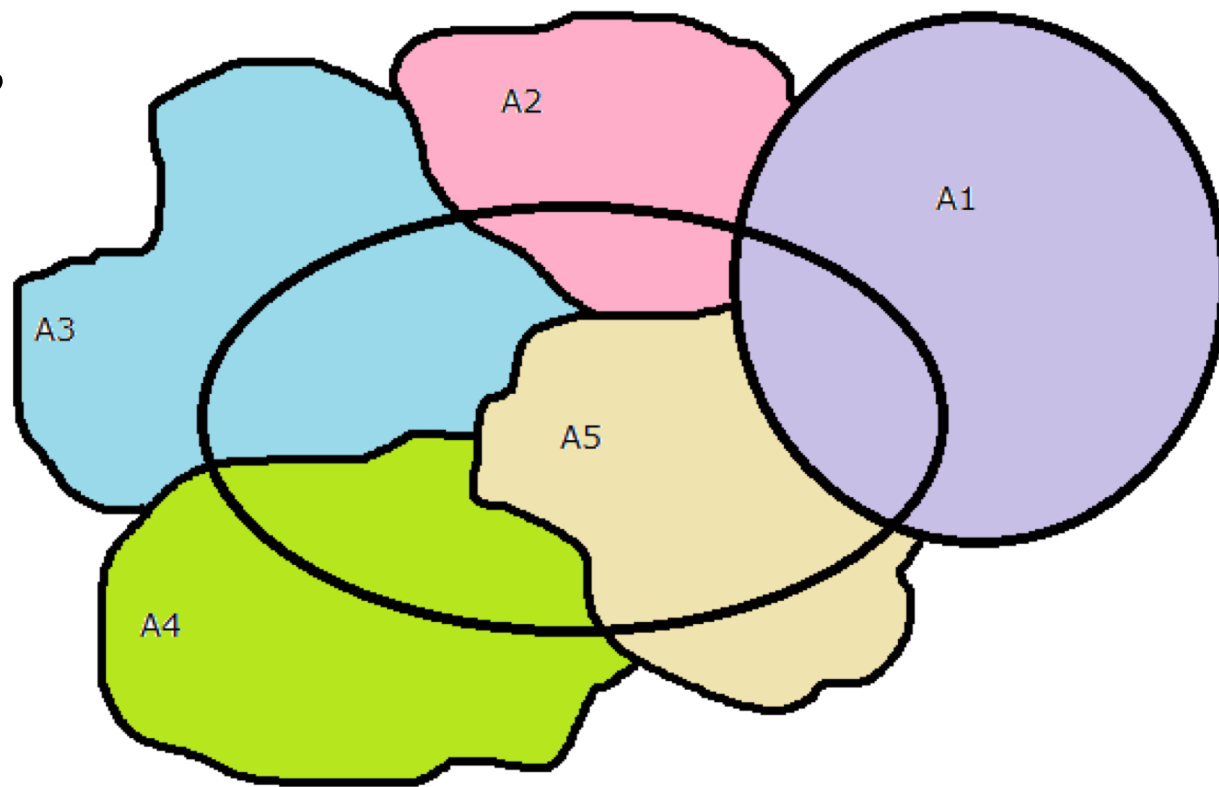
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- $P(A \cap B) = P(A|B)P(B)$ 
  - We took the last rule, multiplied both sides of  $P(B)$ , and voila!

# PROBABILITY RULES

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- $P(B) = \sum_{i=1}^n P(B \cap A_i)$ 
  - “Law of Total Probability”



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## PROBABILITY RULES – SUMMARY

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- $P(\emptyset) = 0$
- $P(A \cup B) = P(A) + P(B) - P(A \cap B)$
- $P(A|B) = \frac{P(A \cap B)}{P(B)}$
- $P(A \cap B) = P(A|B)P(B)$
- $P(B) = \sum_{i=1}^n P(B \cap A_i)$

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# BAYES' THEOREM

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- Bayes' Theorem (Bayes' Rule) relates  $P(A|B)$  to  $P(B|A)$ .

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## BREAKING DOWN BAYES' THEOREM

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

- $P(A)$  is the probability that  $A$  occurs given no supplemental information.
- $P(B|A)$  is the likelihood of seeing evidence (data)  $B$  assuming that  $A$  is true.
- $P(B)$  is the probability that  $B$  occurs given no supplemental information.
  - $P(B)$  what we scale  $P(B|A)P(A)$  by to ensure we are only looking at  $A$  within the context of  $B$  occurring.

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# APPLYING BAYES' THEOREM TO SPAM CLASSIFICATION

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

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## APPLYING BAYES' THEOREM TO SPAM CLASSIFICATION

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$$P(\text{spam}|\text{words in email}) = \frac{P(\text{words in email}|\text{spam})P(\text{spam})}{P(\text{words in email})}$$

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## APPLYING BAYES' THEOREM TO SPAM CLASSIFICATION

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$$P(\text{spam}|\text{words}) = \frac{P(w_1|\text{spam})P(w_2|w_1 \cap \text{spam})P(w_3|w_2 \cap w_1 \cap \text{spam}) \cdots P(\text{spam})}{P(w_1)P(w_2|w_1)P(w_3|w_2 \cap w_1) \cdots}$$

- This gets **really** complicated. Can we simplify this?



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# NAÏVE BAYES

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- The Naïve Bayes classification algorithm is a:
  - classification modeling technique
  - that relies on Bayes Theorem
  - that makes one simplifying (*and often unrealistic*) assumption
- **We assume that our features are independent of one another.**

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# APPLYING BAYES' THEOREM TO SPAM CLASSIFICATION

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$$P(\text{spam}|\text{words}) = \frac{P(w_1|\text{spam})P(w_2|w_1 \cap \text{spam})P(w_3|w_2 \cap w_1 \cap \text{spam}) \cdots P(\text{spam})}{P(w_1)P(w_2|w_1)P(w_3|w_2 \cap w_1) \cdots}$$

$$P(\text{spam}|\text{words}) = \frac{P(w_1|\text{spam})P(w_2|\text{spam})P(w_3|\text{spam}) \cdots P(\text{spam})}{P(w_1)P(w_2)P(w_3) \cdots}$$

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# NAÏVE BAYES

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- **Advantages** of making this assumption of feature independence:
  - Easier to calculate probabilities.
  - Empirically, our classifications are surprisingly accurate.
- **Disadvantages** of making this assumption of feature independence:
  - It's so incredibly unrealistic, especially in the case of text data.
  - While our classifications are accurate, our predicted probabilities are usually quite bad.

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# PROCESS OF NAÏVE BAYES

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1. Decide which Naïve Bayes model to use.
  - BernoulliNB
  - MultinomialNB
  - GaussianNB
2. Decide what your priors will be.
  - Based on your data. (*default*)
  - Manually set.
3. `.fit()`, `.predict()`!

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## WHICH NAÏVE BAYES MODEL SHOULD I USE?

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- BernoulliNB
- MultinomialNB
- GaussianNB

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## WHAT SHOULD MY PRIORS SHOULD BE?

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$$P(\text{spam}|\text{words in email}) = \frac{P(\text{words in email}|\text{spam})P(\text{spam})}{P(\text{words in email})}$$

- Estimated from data.
- Manually set.

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# PROCESS OF NAÏVE BAYES

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# WHERE DOES NAÏVE BAYES FIT IN OUR MENTAL SET OF MODELS?

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## INTERVIEW QUESTION

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- Suppose we want to detect whether Amazon reviews are spam or ham. How would you do this?