Lecture 12 Naïve Bayes

- $P(A|C) = \frac{P(A \cap C)}{P(C)}$
- $Bayes\ Theorem: P(A|C) = \frac{P(C|A)P(A)}{P(C)}$
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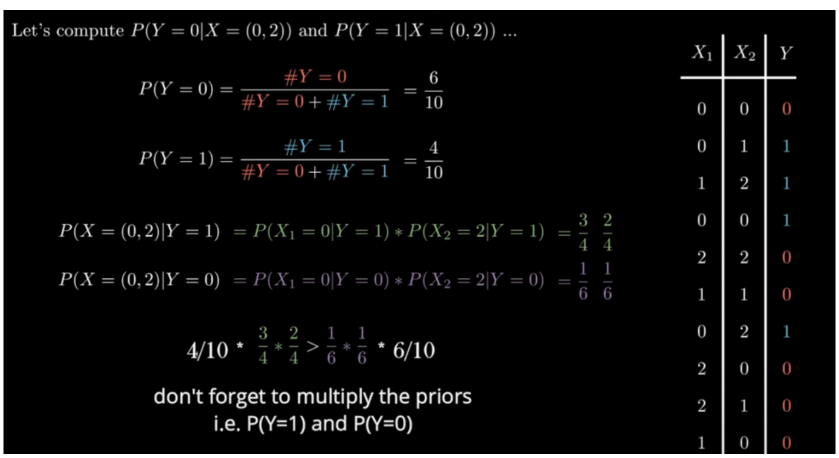
- $P(C|A) = \frac{P(A \cap C)}{P(A)}$
- Bayesian Classifier
    - A Bayesian classifier uses Bayes' Theorem to predict the most likely class for an unknown instance, given its attribute values
- Features X = (X1… Xn) set of features
- Label Y = y
- Find the value of y for which the conditional probability P(Y|X) is maximized so we can say that for a particular value of y that the expression becomes maximized, and the class label should be y
- $Bayes\ Theorem: P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)}$
    - Denominator stays the same no matter the value of y because the evidence (set of features) always remains the same
- Naïve Bayes
    - Need to assume x1 and x2 are independent of each other
        - Allows us to avoid searching for this in our dataset and consider the probability to be a product
        - 

        - So we can see that the class label one maximizes the probability meaning that it is the more desirable category
    - Continuous Attributes
        - Binning / 2-way or multi-way split
            - Create new attribute for each bin
            - Issue is that these attributes are no longer independent
        - Pdf estimation
            - Assume attribute follows a particular distribution (example: normal)

- Use data to estimate the parameters of the distribution