1. What is prior probability? Give an example.

#### Ans: Prior probability, in Bayesian statistics, is the probability of an event before new data is collected. This is the best rational assessment of the probability of an outcome based on the current knowledge before an experiment is performed.

#### Example 1: Fair Dice Roll

A six-sided fair dice is rolled. What is the a priori probability of rolling a 2, 4, or 6, in a dice roll?

The number of desired outcomes is 3 (rolling a 2, 4, or 6), and there are 6 outcomes in total. The a priori probability for this example is calculated as follows:

A priori probability = 3 / 6 = 50%. Therefore, the a priori probability of rolling a 2, 4, or 6 is 50%.

Example 2: Deck of Cards

In a standard deck of cards, what is the a priori probability of drawing an ace of spades?

The number of desired outcomes is 1 (an ace of spades), and there are 52 outcomes in total. The a priori probability for this example is calculated as follows:

A priori probability = 1 / 52 = 1.92%. Therefore, the a priori probability of drawing the ace of spades is 1.92%.

1. What is posterior probability? Give an example.

Ans: Posterior probability is a conditional probability conditioned on randomly observed data. Hence it is a random variable. Suppose an individual is chosen from a high school population at random.  The probability of choosing a female individual is 50%.  The probability of choosing an individual with brown hair is 40%.  The conditional probability that the individual is female and with brown hair is 20%.  If the individual extracted at random from the high school population is female, what is the conditional probability that she also has brown hair?  This is an example of posterior probability and it can be calculated using Bayes’ Formula.

* P(female) = 0.5
* P(brown hair) = 0.4
* P(female/brown hair) = 0.2

Probability(female/brown hair) = {P(brown hair/female) x P(female)} / P(brown hair)

P(female/brown hair) = (0.2 x 0.5) / (0.4).

The posterior probability of choosing a female with brown hair = 0.25 or a 1 in 4 chance.

3. What is likelihood probability? Give an example.

Ans: Likelihood is the probability that an event already been occurred would give a specific outcome. Whereas, probability is for event that will occur in future. Suppose we have a coin that is assumed to be fair. If we flip the coin one time, the probability that it will land on heads is 0.5. Now suppose we flip the coin 100 times and it only lands on heads 17 times. We would say that the likelihood that the coin is fair is quite low. If the coin was actually fair, we would expect it to land on heads much more often.

4.What is Naïve Bayes classifier? Why is it named so?

Ans: A Naive Bayes classifier is a classification algorithm in machine learning included in supervised learning. Naive Bayes classifiers are a family of probabilistic classifiers based on applying Bayes’ theorem.

Its named Naive Bayes because

1. Naive — Due to the assumption that all predictors (or features) are independent, and its a naive assumption as it rarely happens in real life.
2. Bayes — Since it utilizes Bayes Theorem to classify data to any of the classes

5. What is optimal Bayes classifier?

Ans: The Bayes optimal classifier is a probabilistic model that makes the most probable prediction for a new example, given the training dataset. The Bayes Theorem, which provides a systematic means of computing a conditional probability, is used to describe it. It’s also related to Maximum a Posteriori (MAP), a probabilistic framework for determining the most likely hypothesis for a training dataset.

 Take a hypothesis space that has 3 hypotheses h1, h2, and h3.

 The posterior probabilities of the hypotheses are as follows:

h1 -> 0.4

h2 -> 0.3

h3 -> 0.3

Hence, h1 is the MAP hypothesis. (MAP => max posterior)

Suppose a new instance x is encountered, which is classified negative by h2 and h3 but positive by h1. Taking all hypotheses into account, the probability that x is positive is .4 and the probability that it is negative is therefore .6. The classification generated by the MAP hypothesis is different from the most probable classification in this case which is negative.

 The most probable classification of the new instance is obtained by combining the predictions of all hypotheses, weighted by their posterior probabilities.

 If the new example’s probable classification can be any value vj from a set V, the probability P(vj/D) that the right classification for the new instance is vj is merely

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UUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABSBFDFgoDHqccmiigBaKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKAP/2Q==)

The denominator is omitted since we’re only using this for comparison and all the values of P(vj/D) will have the same denominator.

 The value vj, for which P (vj/D) is maximum, is the best classification for the new instance.

6. Write any two features of Bayesian learning methods.

Ans:

* Each observed training example can incrementally decrease or increase the estimated probability that a hypothesis is correct
* Prior knowledge can be combined with observed data to determine the final prob. Of a hypothesis.
* Bayesian methods can accommodate hypotheses that make probabilistic predictions.

7. Define the concept of consistent learners.

Ans: A learner L using a hypothesis H and training data D is said to be a consistent learner if it always outputs a hypothesis with zero error on D whenever H contains such a hypothesis. • By definition, a consistent learner must produce a hypothesis in the version space for H given D. Therefore, to bound the number of examples needed by a consistent learner, we just need to bound the number of examples needed to ensure that the version-space contains no hypotheses with unacceptably high error.

8. Write any two strengths of Bayes classifier.

Ans:

* To begin, Bayesian learning algorithms compute explicit probabilities for hypotheses.
* The second reason is that they aid comprehension of various learning methods that do not involve probability manipulation.

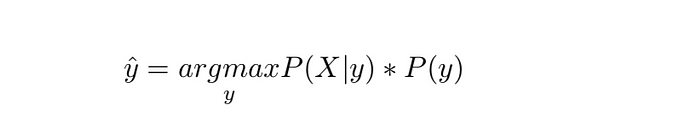
9. Write any two weaknesses of Bayes classifier.

Ans:

* Requires initial knowledge of many prob.
* Significant computational cost is required to determine the optimal hypothesis

10. Explain how Naïve Bayes classifier is used for

1. Text classification: steps for text classification
   * + Represent a document X as a set of (w, a frequency of w) pairs.
     + For each label y, build a probabilistic model P(X| Y = y) of documents in class y.
     + To classify, select label y which is most likely to generate X:



Assumptions:

1. The order of the words in document X makes no difference but repetitions of words do.
2. Words appear independently of each other, given the document class.

Based on these assumptions, equations to estimate P(X|y):

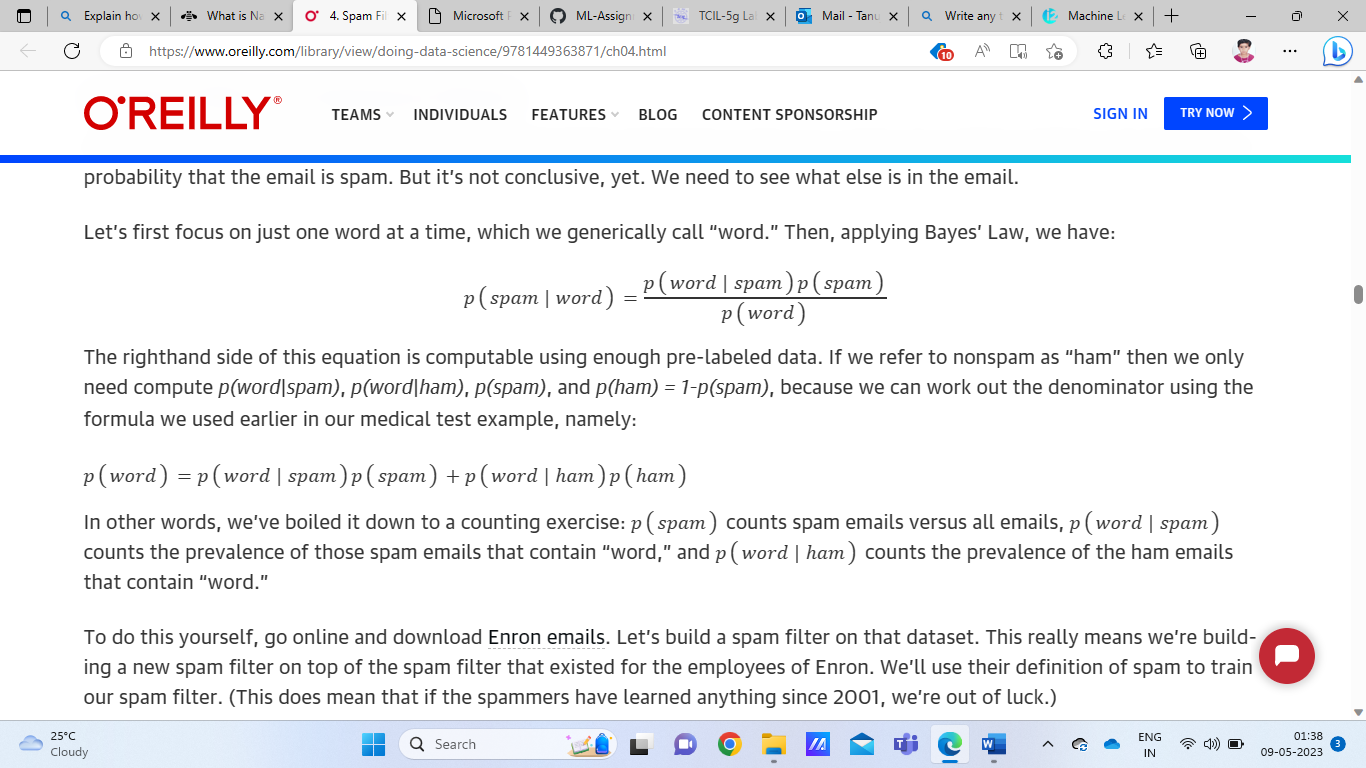
A picture containing text, font, receipt, white

Description automatically generated

For equation (2), if we have a new word*w* in the new text that we need to classify, P(W = w | Y = y) = 0 as *w* has never appeared in our training data. => one solution is to smooth the probabilities

2. Spam filtering: Naïve Bayes classifier ,uses Bayes’ Law to create a good spam filter? if the word “Viagra” appears, this adds to the probability that the email is spam. Check the mail contents.

Let’s first focus on just one word at a time, which we generically call “word.” Then, applying Bayes’ Law, we have:



The righthand side of this equation is computable using enough pre-labeled data. If we refer to nonspam as “ham” then we only need compute *p(word|spam)*, *p(word|ham)*, *p(spam)*, and *p(ham) = 1-p(spam)*, because we can work out the denominator using the formula we used earlier in our medical test example, namely:

A screenshot of a computer

Description automatically generated

P(spam) counts spam emails versus all emails, P(word|spam) counts the prevalence of those spam emails that contain “word,” and p(word|ℎam) counts the prevalence of the ham emails that contain “word.”

3. Market sentiment analysis

For Market sentiment analysis text classification is required. We can use ‘bag of words (BOW)’ model for the analysis. BOW model is used for feature extraction in text data. It returns a vector with all the words and the number of times each word is repeated. It is known as BOW because it is only concerned with the number of times a word is repeated rather than the order of words. Document term matrix (DTM) is calculated. Doc vectors would be a sparse vector if documents are too large. Sparse vectors need a lot of memory for storage and due to length, even computation becomes slow. To reduce the length of the sparse vectors, one may use the technique like stemming, lemmatization, converting to lower case or ignoring stop-words e.t.c.