

A spam classifier based on Bayes network

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FRAME 1

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 - ▶ Subitem 1
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FRAME 2

FRAME 3

THE BAYESIAN APPROACH

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- This has led to two different interpretations of the theorem.

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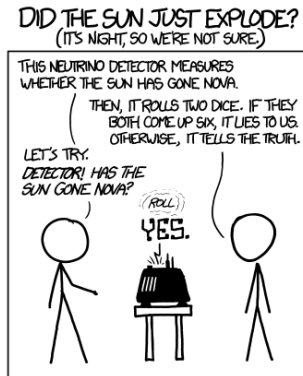
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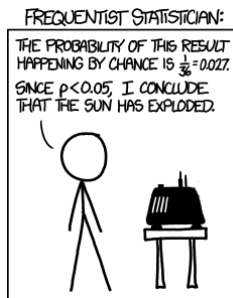
- ▶ $P(A|B)$ is the *a posteriori* probability
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- ▶ $P(B|A)P(A)$ is the *prior* probability
- ▶ $P(B) = \sum_{a \in A} P(B|A = a)P(A = a)$ is the *total* probability



from <http://xkcd.com/1132>, see also http://en.wikipedia.org/wiki/Sunrise_problem

THE BAYESIAN APPROACH

Frequentists vs. Bayesians



from <http://xkcd.com/1132>, see also
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The frequentist relies on the theoretical probability of the events.

THE BAYESIAN APPROACH

Frequentists vs. Bayesians



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The bayesian observes the past events occurred,
and adapts the probability accordingly.

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EXPLAINING AWAY

If we know that one possible cause of the event has happened, this may *explain away* the event, being all the other causes less probable once we know the one that happened.

CONDITIONAL INDEPENDENCE

1- If

$$P(A|B, C) = P(A|B)$$

then we say that B and C are *conditionally independent*. 2- Note that *conditional independence* \neq *independence*

NAIVE BAYES

If, in a spam mail, we read the words “buy replica”, likely we’ll also read “watches”. This suggests to us to try all the possible subsets of words: this is $O(2^{|mail|})$...

Hence, we assume that every word is independent with respect to all the other ones, and each word brings its own contribute to the “spamminess” of the mail without being part of some longer locution. Surprisingly, this works very well in practice, and fast, since it can be done in linear time. This approach is called *naive*.

SPAMBAYES

Python, to use Ply and BeautifulSoup
dataset: SpamAssassin archive

FRAME 1