

# A spam classifier based on Bayes network

Alberto Franzin, Fabio Palese

Sistemi Intelligenti

January 4, 2013

# INTRODUCTION

Introduction

Bayesian networks

Definition

Naive Bayes

SpamBayes

RESULTS

Frame 1

# THE BAYESIAN APPROACH

- Bayes rule:

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

defines the *a posteriori* probability of event  $A$ , knowing the event  $B$  has already occurred.

# THE BAYESIAN APPROACH

- Bayes rule:

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

defines the *a posteriori* probability of event  $A$ , knowing the event  $B$  has already occurred.

- In other words, we can estimate the probability of an hypothesis, given that we know the consequences.

# THE BAYESIAN APPROACH

- Bayes rule:

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

defines the *a posteriori* probability of event  $A$ , knowing the event  $B$  has already occurred.

- In other words, we can estimate the probability of an hypothesis, given that we know the consequences.
- This has led to two different interpretations of the theorem.

# THE BAYESIAN APPROACH

- Bayes rule:

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

# THE BAYESIAN APPROACH

- Bayes rule:

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

- $P(A|B)$  is the *a posteriori* probability

# THE BAYESIAN APPROACH

- Bayes rule:

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

- $P(A|B)$  is the *a posteriori* probability
- $P(B|A)$  is the *likelihood*



# THE BAYESIAN APPROACH

- ▶ Bayes rule:

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

- ▶  $P(A|B)$  is the *a posteriori* probability
- ▶  $P(B|A)$  is the *likelihood*
- ▶  $P(B|A)P(A)$  is the *prior* probability

# THE BAYESIAN APPROACH

- Bayes rule:

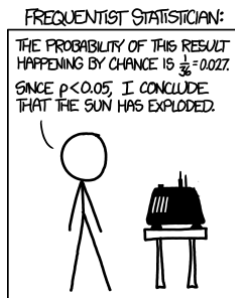
$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B|A)P(A)}{P(B)}$$

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



# THE BAYESIAN APPROACH

## Frequentists vs. Bayesians



from <http://xkcd.com/1132>, see also  
[http://en.wikipedia.org/wiki/Sunrise\\_problem](http://en.wikipedia.org/wiki/Sunrise_problem)

The frequentist relies on the theoretical probability of the events.

# THE BAYESIAN APPROACH

## Frequentists vs. Bayesians



from <http://xkcd.com/1132>, see also

[http://en.wikipedia.org/wiki/Sunrise\\_problem](http://en.wikipedia.org/wiki/Sunrise_problem)

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

# WHAT IT IS

A Bayes network is a way to describe causal relationships between events.

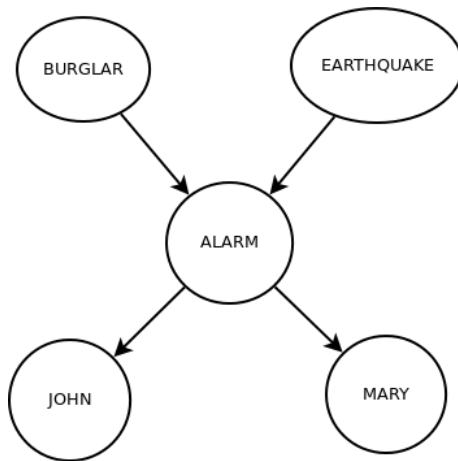
- ▶ Nodes = events
- ▶ (Directed) Edges = causal relationship

# WHAT IT IS

A Bayes network is a way to describe causal relationships between events.

- ▶ Nodes = events
- ▶ (Directed) Edges = causal relationship
- ▶ Two nodes are connected by an edge: the child of an arc is influenced by its ancestor in a probabilistic way

# AN EXAMPLE





# CONDITIONAL INDEPENDENCE

- If

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

then we say that  $B$  and  $C$  are *conditionally independent*.

# CONDITIONAL INDEPENDENCE

- If

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

then we say that  $B$  and  $C$  are *conditionally independent*.

- Note that *conditional independence*  $\neq$  *independence*

# CONDITIONAL INDEPENDENCE

- ▶ If

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

then we say that  $B$  and  $C$  are *conditionally independent*.

- ▶ Note that *conditional independence*  $\neq$  *independence*
- ▶ 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.

# NAIVE BAYES

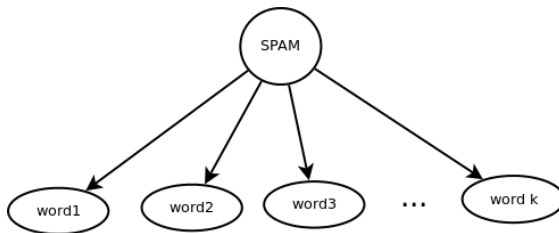
- ▶ Computing all the probabilities in a Bayesian network requires exponential time. We introduce the assumption of independence among variables.

# NAIVE BAYES

- ▶ Computing all the probabilities in a Bayesian network requires exponential time. We introduce the assumption of independence among variables.
- ▶ It is called *naive*, since it's often unrealistic, but it yields good results.

# NAIVE BAYES

- ▶ Computing all the probabilities in a Bayesian network requires exponential time. We introduce the assumption of independence among variables.
- ▶ It is called *naive*, since it's often unrealistic, but it yields good results.
- ▶ In spam classification:



# SPAMBAYES

Python, to use Ply and BeautifulSoup  
dataset: SpamAssassin archive

# FRAME 1