A spam classifier based on Bayes network

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Sistemi Intelligenti

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Introduction

The Bayesian approach

Bayes rule:

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

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

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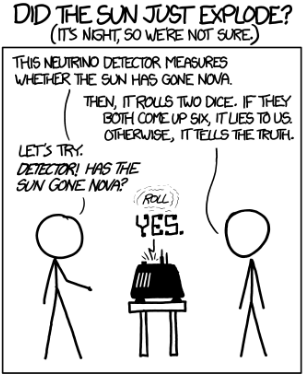
- In other words, we can estimate the probability of an hypothesis, given that we know the consequences.
- This has led to two different interpretations of the theorem.

The Bayesian approach

Frequentists vs. Bayesians



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

The Bayesian approach

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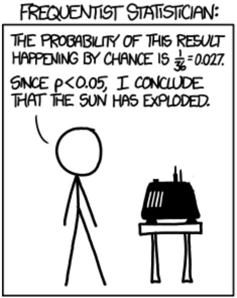

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The frequentist relies on the theoretical probability of the events.

The Bayesian approach

Frequentists vs. Bayesians

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

Bayesian networks

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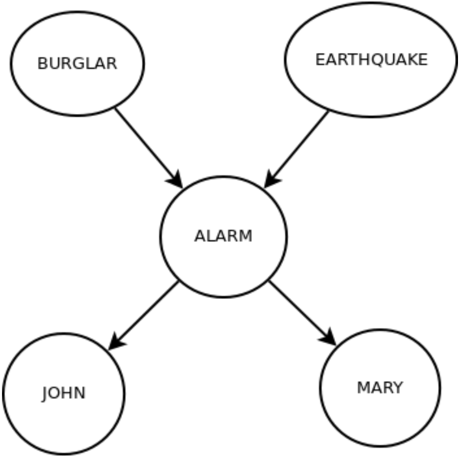
- Nodes = events
- (Directed) Edges = causal relationship
- Two nodes are connected by an edge: the child of an arc is influenced by its ancestor in a probabilistic way

AN EXAMPLE



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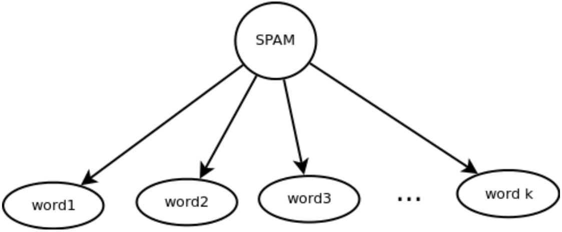
- It is called *naive*, since it's often unrealistic, but it yields good results.
- In spam classification:



Naive Bayes for spam classification

We want to build a classifier that distinguishes good mails from undesired mails:

- good mails: *ham*
- undesired mails: *spam*

ALGORITHM

Algorithm:

- Training

Algorithm

Algorithm:

- Training
- Validation

Algorithm

Algorithm:

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- Testing

Naive Bayes for spam classification

Formulas:

- For each word:

$$P_{word|spam} = \frac{\text{\# occurrences of word in spam mails}}{\text{\# total occurrences of word}}$$

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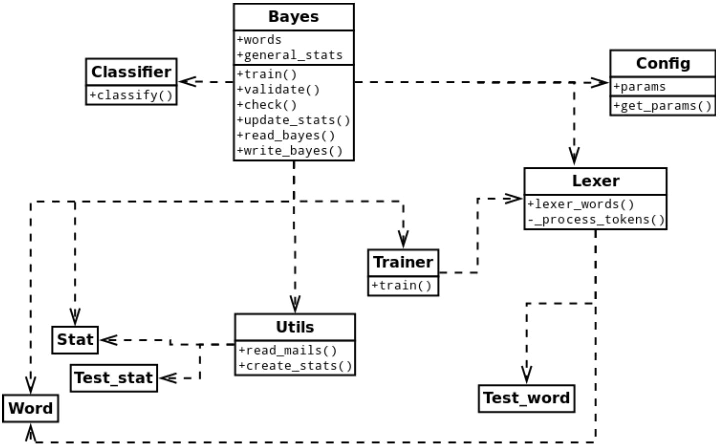
- Outcome is the class that maximizes the probability of belonging to that class.

SpamBayes

- SpamBayes: applying Naive Bayes to spam classification
- Python with Ply and BeautifulSoup
- dataset: SpamAssassin archive
- Code and documentation available at `http://code.google.com/p/sist-int-2012project/`

SpamBayes


Bayes
+words
+general_stats
+train()
+validate()
+check()
+update_stats()
+read_bayes()
+write_bayes()
Classifier
+classify()
Config
+params
+get_params()
Lexer
+lexer_words()
-_process_tokens()
Trainer
+train()
Utils
+read_mails()
+create_stats()
Stat
Test_stat
Word
Test_word

Notes on implementation

- Smoothing:

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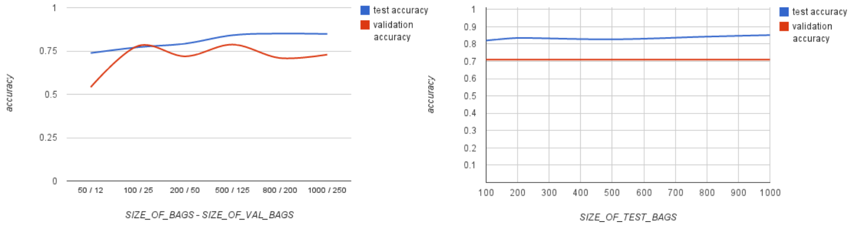
- Several mail features detected
- Several parameters to be tuned: we describe the more relevant ones

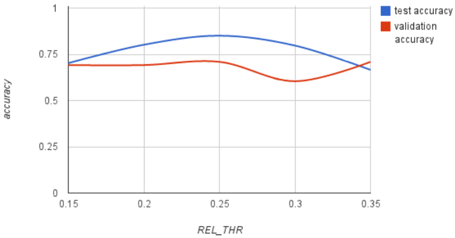
PARAMETERS

Size of training/validation/test sets:



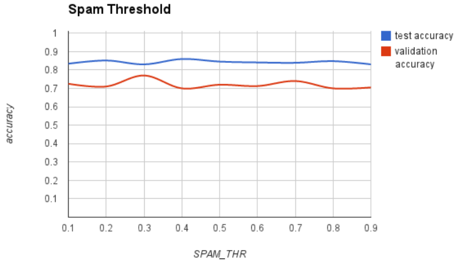
PARAMETERS

Relevance threshold:



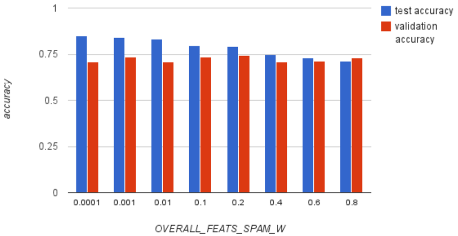
Parameters

"Spamicity" threshold:



PARAMETERS

Feature statistic threshold:



RESULTS

- About the dataset:

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  - How to improve?