Exponential Differential Document Count

A Feature Selection Factor for Improving Bayesian Filters

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What is it?

The EDDC, aka Confidence Factor, is an intuitively and empirically derived factor for automatically detecting and reducing the influence of features with low class separation power.

Motivation

To mimic what we, humans, do when inspecting a message to tell if it is spam or not:

- Consider mainly the features which carry strong indications;
- Discard or reduce the importance of those which occur approximately equally in both classes.

How is the Confidence Factor used?

It is used to adjust the ***local probability*** of a feature towards the don't care value (0.5), in the Bayes formula, inversely to its class separation power:

$$P(C|F) = \frac{\boldsymbol{P_a(F|C)} \times P(C)}{P(F)}$$

$P_a(F|C)$ is the adjusted value of $P(F|C)$, after applying the Confidence Factor:

$$\boldsymbol{P_a(F|C)} = 0.5 + CF(F) * (P(F|C) - 0.5)$$

Where $CF(F)$ is the Confidence Factor of the feature F.

How is it calculated?

- Goal: to derive a factor to reduce the influence of features with approximately the same frequency in both classes, *spam* and *ham*;
- First attempt: to use the difference of the normalized counts in both classes because it's zero when the frequencies are equal:

$$CF(F) = ND_{f,h} - ND_{f,s}$$

$ND_{f,h}$ - Normalized count of ham messages containing the feature *f*

$ND_{f,s}$ - Normalized count of spam messages containing the feature *f*

Problem:

CF(F) must be in the interval [0,1] because the adjusted *local* ***probability***, $P_a(F|C)$, must also be in that interval!

How is it calculated?

- The previous problem can be fixed with two simple steps:
  - dividing by the sum of the normalized counts: keep <= 1;
  - taking the square to avoid negative values: keep >= 0;

$$CF(F) = \left(\frac{ND_{f,h} - ND_{f,s}}{ND_{f,h} + ND_{f,s}} \right)^2$$

Or, in a simplified notation:

$$CF(F) = \frac{N\Delta_f^2}{N\Sigma_f^2}$$

But we still have problems when $ND_{f,h}$ and $ND_{f,s}$ are small:

For $ND_{f,h} = 1$ and $ND_{f,s} = 0$, the confidence factor is 1, completely unrealistic!

How is it calculated?

- A new term is then subtracted from the numerator to smooth the results for small counts – the inverse of the sum of the *observed* (not normalized) counts in both classes:

$$CF(F) = \frac{N\Delta_f^2 - \frac{1}{D_{f,h} + D_{f,s}}}{N\Sigma_f^2}$$

$D_{f,h}$ - Count of ham messages containing the feature *f*

$D_{f,s}$ - Count of spam messages containing the feature *f*

Or, using the simplified notation: $$CF(F) = \frac{N\Delta_f^2 - \frac{1}{\Sigma_f}}{N\Sigma_f^2}$$

which is the *core* of the EDDC formula.

OSB Features and Intrinsic Weight

Orthogonal Sparse Bigrams (OSB) is a technique for feature generation that produces bigrams like the four below for the sentence "OSBF is a Bayesian filter":

Bigram				Distance
OSBF	**is**			**0**
OSBF	<skip>	**a**		**1**
OSBF	<skip>	<skip>	**Bayesian**	**2**
OSBF	<skip>	<skip>	<skip> **filter**	**3**

For a 5-token sliding window the intrinsic weight of the feature, in OSBF, is given experimentally by $(5-d)^{(5-d)}$ where ***d*** is the number of skipped tokens in the bigram. The closer the tokens, the greater the weight.

Generic EDDC formula

Finally, adding a term to take into account the intrinsic weight of the feature, we have the generic EDDC formula:

$$CF(F) = \left(\frac{N\Delta_f^{\,2} - \frac{K_1}{\Sigma_f}}{N\Sigma_f^{\,2}} \right)^{K_2} \times \frac{W_f \Sigma_f}{1 + K_3 W_f \Sigma_f}$$

$N\Delta_f$ - Difference of the normalized counts, in both classes, of documents containing f

$N\Sigma_f$ - Sum of the normalized counts, in both classes, of documents containing f

Σ_f - Sum of the counts, in both classes, of documents containing f

Wf - Intrinsic weight of the feature

K1, K2, K3 – Constants empirically defined

Variant implemented in CRM114- OSBF and in OSBF- Lua

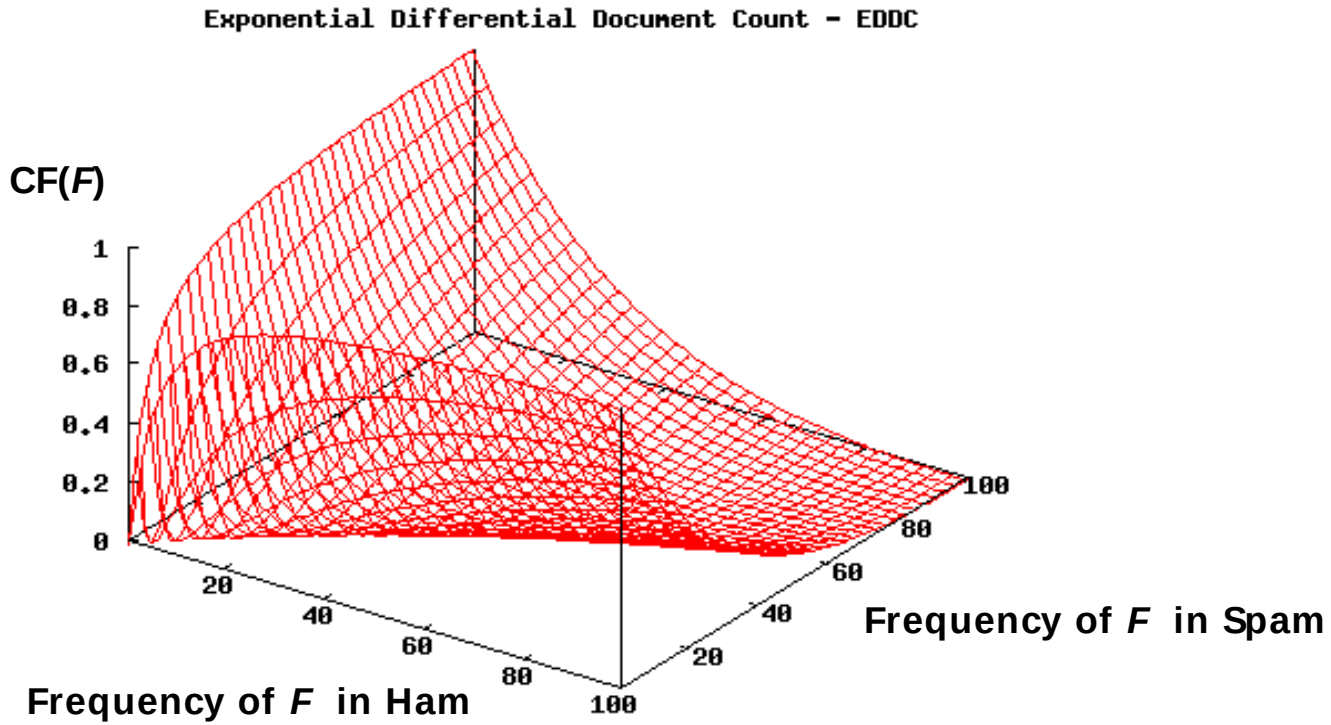
$$CF(F) = \left(\frac{N\Delta_f^{\,2} + ND_{f,s} \times ND_{f,h} - \frac{K_1}{N\Sigma_f}}{N\Sigma_f^{\,2}} \right)^{K_2} \times \frac{W_f \times N\Sigma_f}{1 + K_3 \times W_f \times N\Sigma_f}$$

$ND_{f,s}$ - Normalized number of documents containing f in class spam

$ND_{f,h}$ - Normalized number of documents containing f in class ham

- Slower decay of the confidence factor as $N\Delta_f^2$ decreases
- Requires higher K_2 (best experimental value = 10, while only 2 in the original formula)

Visualization of the Confidence Factor



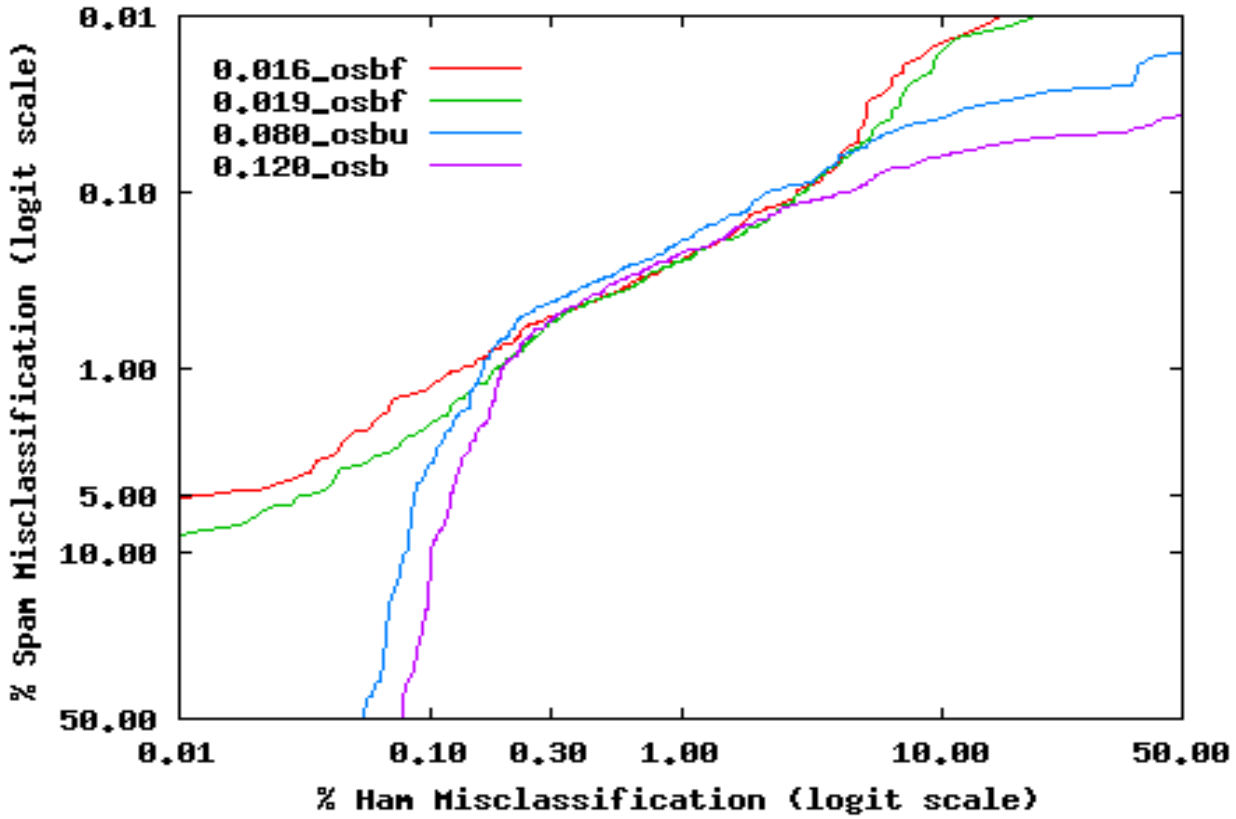
- Function of the difference between the frequencies of the feature in both classes;
- Features with small differences in frequency are strongly de-emphasized.

Classifiers: OSB, OSB Unique and OSBF

The three classifiers examined in this work have in common that they are all Bayesian and use Orthogonal Sparse Bigrams for feature generation.

- The OSB classifier takes its name from the feature generating technique - it's the standard CRM114 with OSB features;
- OSB Unique is a variant of the OSB classifier that ignores duplicate features;
- OSBF is similar to OSBU Unique but uses EDDC as a Confidence Factor for feature selection.

ROC Curves for the Full Corpus



- The 0.016 OSBF curve was generated using the original formula;
- The 0.019 OSBF with the variant in the previous slide;
- The original formula has been showing better performance as the code improves
  - better pruning, bugs removed.

Conclusions

- The EDDC factor clearly improved the overall performance of the OSB Bayesian filters presented;

- More importantly, it highly improved the performance in the most critical region for spam filtration, that where ham% <= 0.1;

- It doesn't impact speed – all 3 filters are really fast. Even with the large database used in these tests (2x46 Mbytes), they were able to process the Full corpus (92.189 messages) in 60-70 minutes on an AMD Athlon(TM) XP 2400+.

Thanks!

The CRM114-OSBF source is available at

http://crm114.sourceforge.net

The OSBF-Lua source is available at

http://osbf-lua.luaforge.net