Chap4#5#1: Machine Learning for Anomaly-based Spam Detection

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Topics to study in Chapter 4

- Machine learning for Anomaly Detection: Definition of an anomaly. Types of Anomalies or outliers in machine learning. Motivation for machine learning for anomaly detection.
  Data Visualization. Supervised, Unsupervised and Semi-supervised Learning methods for Anomaly Detection.
  Applications of Anomaly Detection: Intrusion detection, Fraud detection, Health monitoring, Defect detection, and lastly Spam detection. Intrusion Detection with Heuristics.Goodness-of-fit. Host Intrusion Detection. Network Intrusion Detection. Web Application Intrusion Detection.
  Overview of Machine learning Approaches for Anomaly Detection: Distance-based, Clustering-based and Model-based Approaches. Algorithms for Distance and Density-based approaches, Rank-based approaches, Ensemble Methods Algorithms for Time Series Data. Deep Learning for Anomaly Detection. Behavioural-based Anomaly Detection [8 hours]

Topics in Handouts#1, #2, #3

1. Email Basics, Spam Detection Basics, and ML-based Spam Detection Basics
   - Background & Basics: Email architecture
   - Basic Spam Detection Mechanism
   - Basic Categories of Spam Detection Mechanisms
   - Spam Detection: Historical aspects and impact of Spam
   - Spam Detection: How Gmail, Yahoo and Outlook ... work
   - Basic ML-based Spam Detection Architecture, Building Blocks
   - Categories Spam Detection Mechanisms
   - Basic ML-based Spam Filtering process
   - Performance evaluation measures
2. Classical ML-based Spam Filtering
3. Deep Learning-based Spam Filtering

Background & Basics: Email architecture

Background: Typical Email architecture

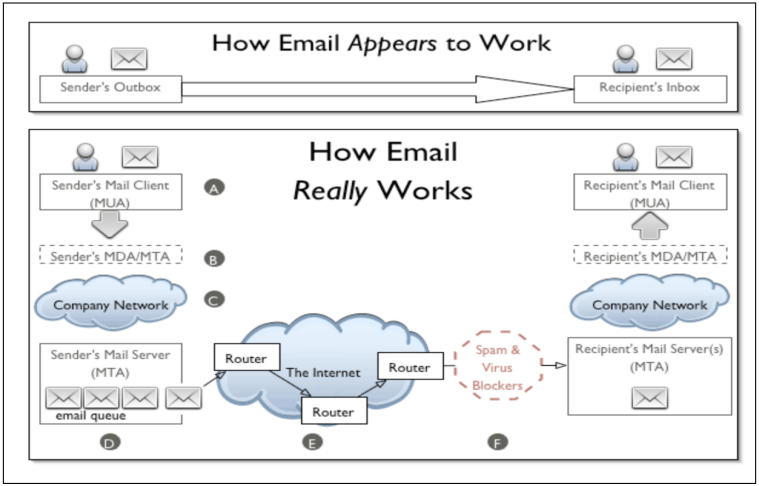
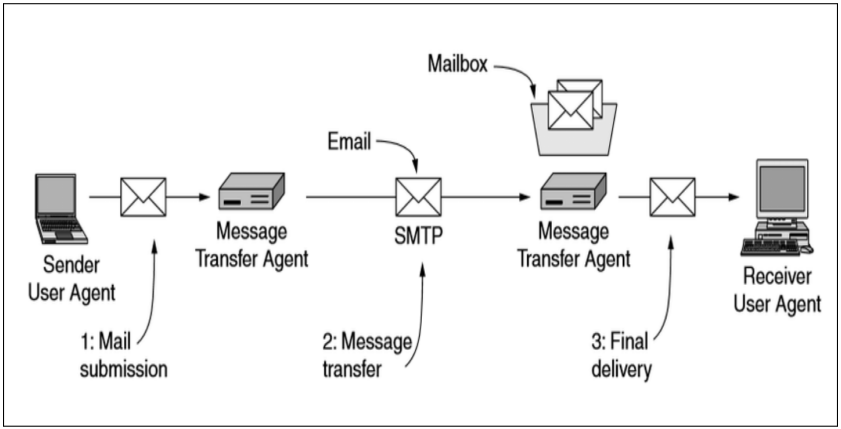


Figure: Basic Email Architecture[1]

[1]:Source: https://www.oasis-open.org/khelp/kmlm/user_help/html/how_email_works.html

Background: Typical Email architecture...



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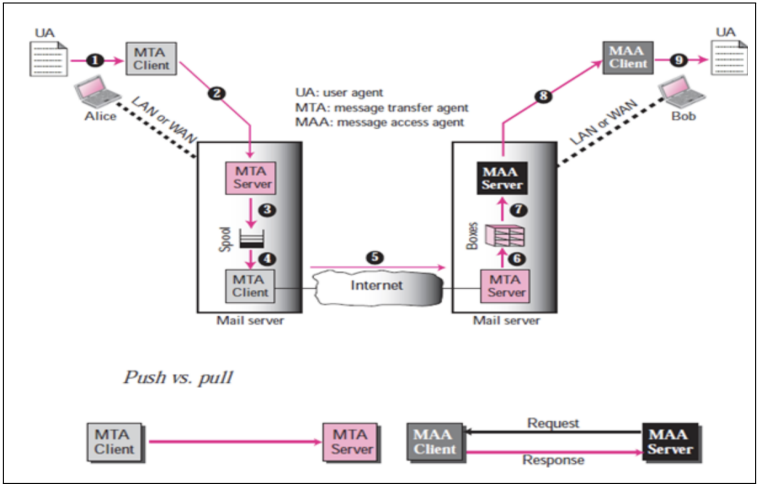

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[1]:Source: Forouzan

Basic Spam Detection Mechanism

Fundamental Spam Detection approaches

Fundamental Spam Detection may work at either of the two levels

- an individual level

[1] Src: https://www.analyticsvidhya.com/blog/2020/10/what-is-the-convolutional-neural-network-architecture/

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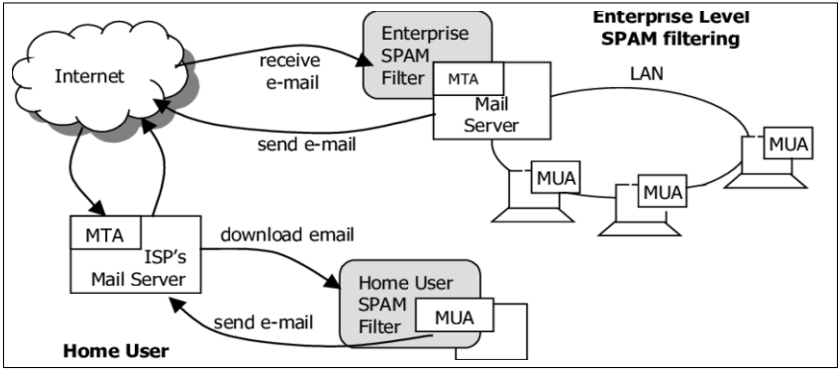

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Figure: Spam Filtering Mechanism

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Basic Categories of Spam Detection Mechanisms

Spam Detection Fundamental Approaches

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Our focus shall be on the latter, but vital to learn about what are different Spam detection approaches of interest - to understand their basic characteristics.

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- drawback is it requires feature extraction and the associated processes.

Self-reading & preparation topics start...

Spam Detection: Historical aspects and impact of Spam

Historical aspects and impact of Spam

Kaspersky lab's survey on 2022. [1]

- 48.63% of all emails around the world were Spam, whereas 52.78% of all emails in the Russian segment of the internet were Spam

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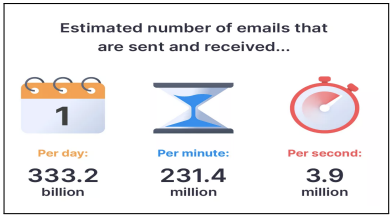
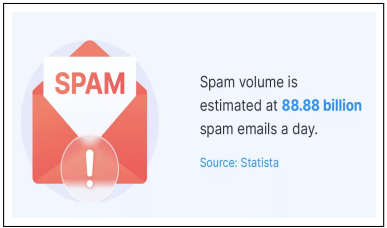


Figure: Src: www.mackeeper.com



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Spam Detection: How Gmail, Yahoo and Outlook emails Spam filters work

How Gmail, Yahoo and Outlook emails Spam filters work ?

- X

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Self-reading & preparation topics end...

Basic ML-based Spam Detection Architecture, Building Blocks

Email Spam filtering architecture

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- Filters block unsolicited or suspicious emails that are a threat to the security of network.
- In order to identify an email as a Spam, various ML-based approaches could be employed - a broad schematic of which is shown in the next slide.....

Spam Detection background: Conventional ML-based approach

Generally consists of four major steps:

- Dataset collection,
- Pre-processing the dataset,
- Training and Testing models and
- Comparing and Analyzing results.

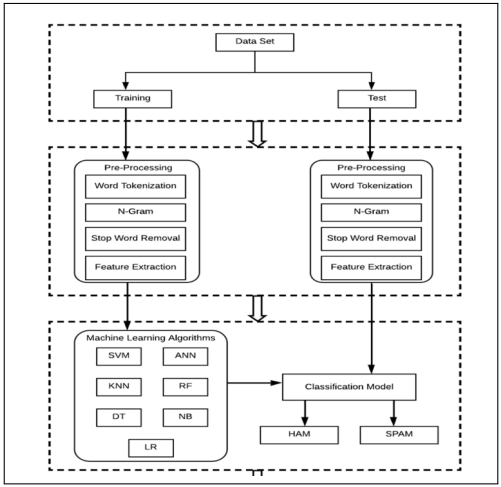

Figure: ML-based Spam filtering

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Categories Spam Detection Mechanisms: Another View

Filtering of email Spam used to follow one of the following approaches viz.

- Content Based Filtering Technique

Spam Detection Approaches Classification/Alternative Mechanisms

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- Heuristic OR Rule Based OR Knowledge engineering-based approach
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- Adaptive Spam Filtering Technique

Spam Detection Approaches: Content-based filtering

- used to create automatic filtering rules and to classify emails using ML approaches, using classifiers such as

Naïve Bayesian classification	Neural Networks,
K Nearest Neighbor	Decision-tree
Artificial immune systemm	Support Vector Machine,
or other classifiers	-

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- Spammers insert random characters into messages to foil hash-based signatures
- hence, flexible and adaptive signatures are needed.

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Case base or Sample based filtering

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- lastly, the machine learning algorithm is used to train datasets and test them to decide whether the incoming mails are Spam/non-Spam.

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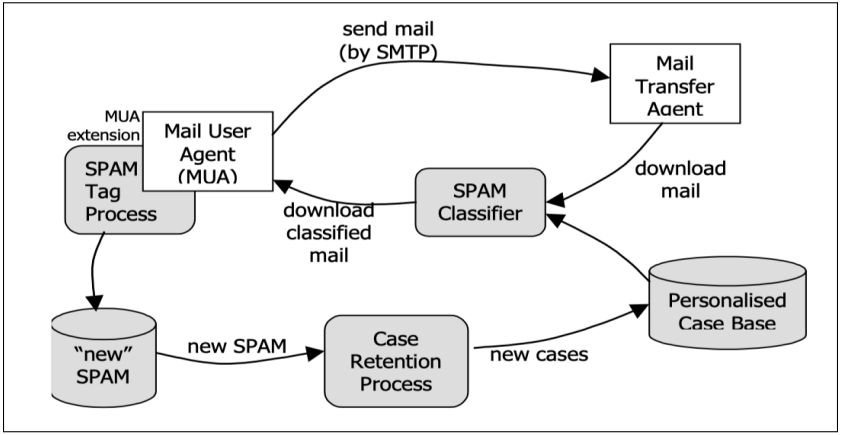

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- A good example of a rule based Spam filter is SpamAssassin - tagged as the #1 Enterprise Open-Source Spam Filter (Ref: https://Spamassassin.apache.org/)

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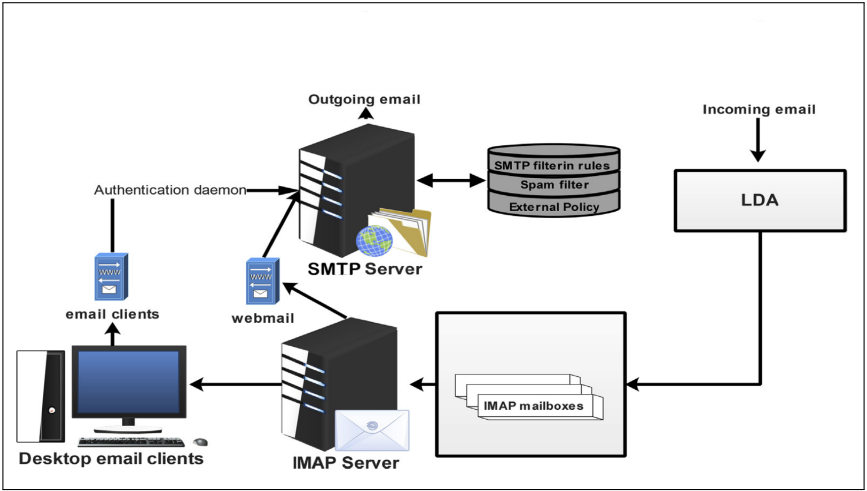
Basic ML-based Spam Filtering process

Fundamental Spam Detection: Basic Architecture



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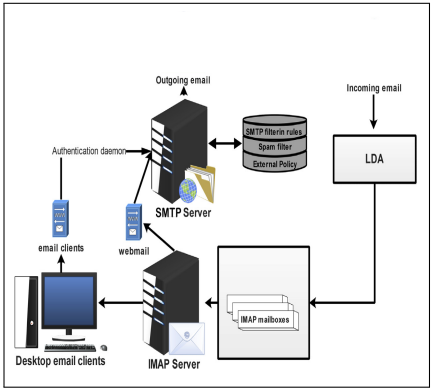

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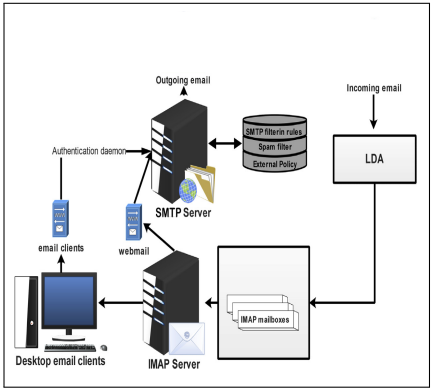

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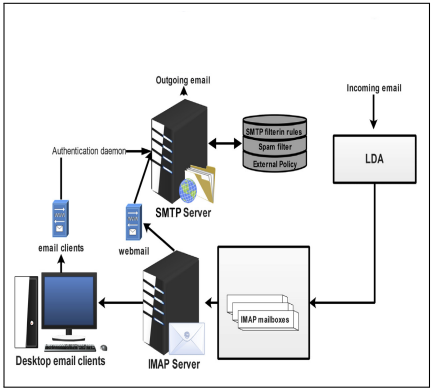

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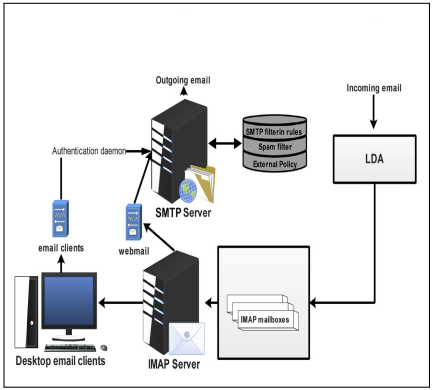

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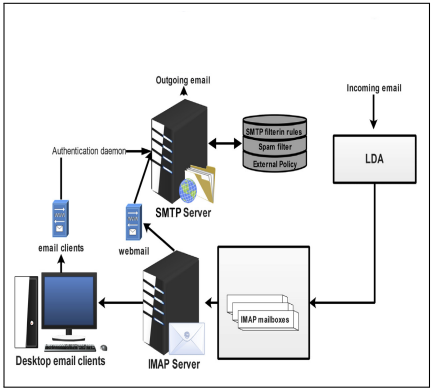

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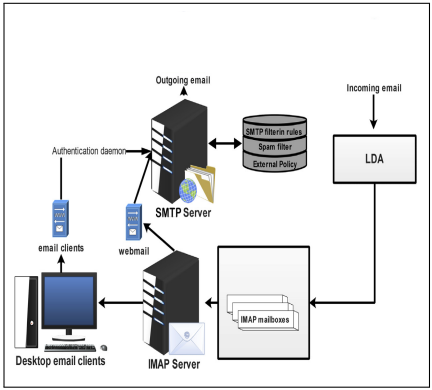
- this information can be used by an ML classifier for detecting Spam and filtering mails.



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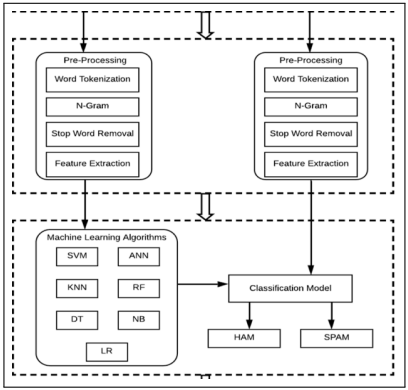

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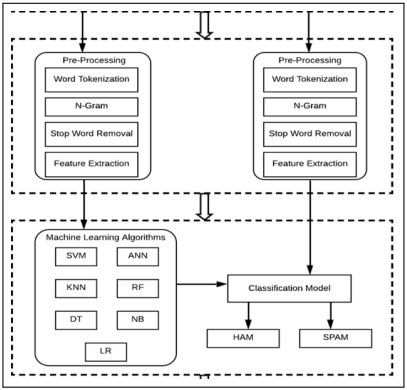

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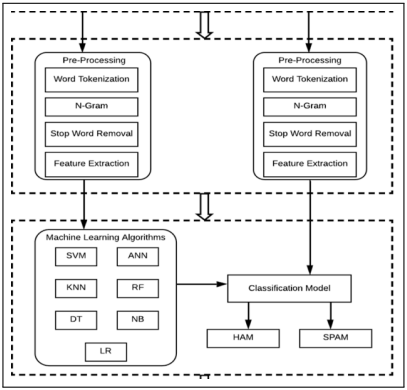

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[1] Emmanuel Gbenga Dada et al, Machine learning for email Spam filtering: review, approaches and open research problems, Heliyon, 5(6), 2019

Basic ML-based Spam Filtering process...

The necessary stages that must be observed in the mining of data from an email message can be:

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  - divides the email into a sequence of representative symbols called tokens.
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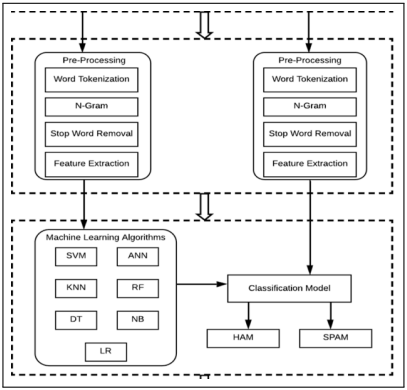

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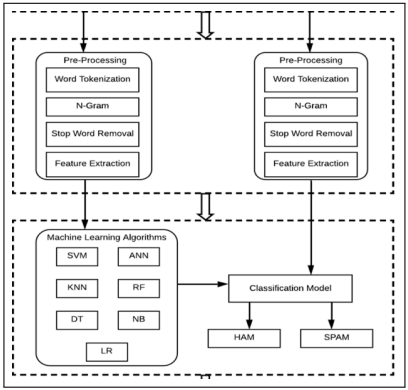
  - at times, the symbols are replaced with distinctive identification symbols to extricate all the characteristics and words from the email exclusive of taking into account the meaning.

[1]



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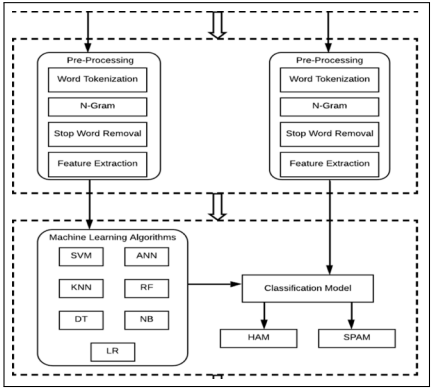

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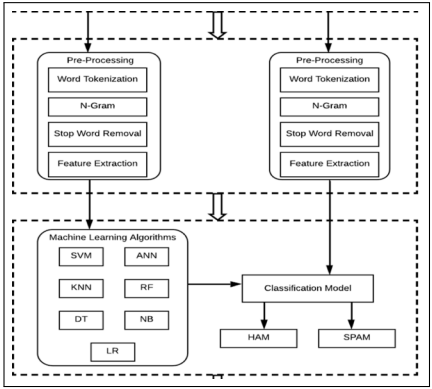

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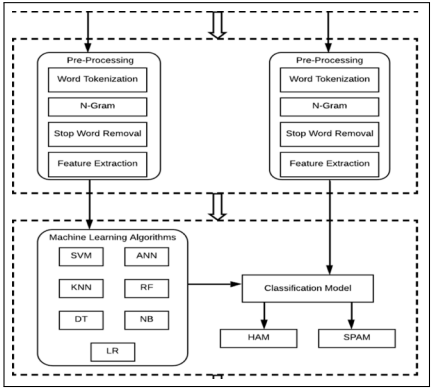

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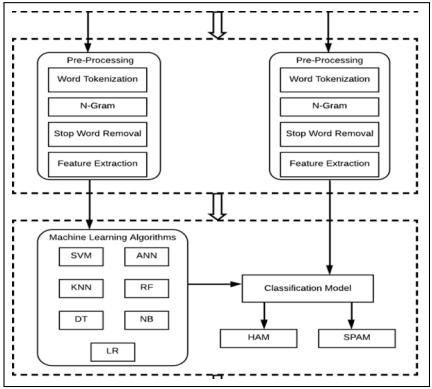

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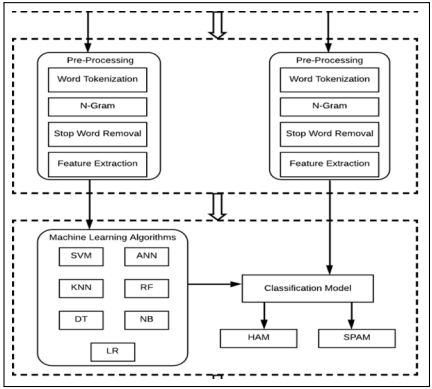
- the indicate types of messages/features shown on the next slide.



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Basic ML-based Spam Filtering process...

Typical messages that can be classified as Spam

Advance fee fraud, including inheritance, lottery, visa and customs-clearance scams

Romance scams, including marketing sex enhancement drugs to cure erection dysfunctional, online dating,

Military scams, Ads for porn sites, Ads for miscellaneous external sites, earning big money through "work-from-home" jobs,

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Some of the most important features for Spam filtering include:

1. Message body and subject,
2. Adult content
3. Recipient age, Sex and country
4. Volume of the message, Occurrence count of words
5. Recipient replied (indicates whether the recipient replied to the message),
6. Circadian patterns of the message (Spam messages usually have many semantic discrepancies),
7. Bag of words from the message content

Basic ML-based Spam Filtering process...

Some of the Sender Account Features used for Spam filtering are: include:

1. Sender Country (from IPA),
2. Sender IP address,
3. Username of the sender,
4. Sender & Recipient Age,
5. Sender Reputation.
6. Sender's date of birth,
7. Sender Email,
8. Account lifespan,
9. Sex of sender
10. Age of recipient.
11. Geographical distance between sender & receiver,

1

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Publicly available email Spam corpus

A comprehensive list of the corpora made available to the public in the different techniques are as follows:

Table 2
Publicly available email spam corpus.

Dataset name	Number of messages		Rate of spam	Year of creation	References
	Spam	Non-spam			
Spam archive	15090	0	100%	1998	Almeida and yamakami [32]
Spambase	1813	2788	39%	1999	Sakkis et al [33]
Lingspam	481	2412	17%	2000	Sakkis et al [33]
PU1	481	618	44%	2000	Attar et al [34]
Spamassassin	1897	4150	31%	2002	Apache spamassassin [35]
PU2	142	579	20%	2003	Zhang et al [36]
PU3	1826	2313	44%	2003	Zhang et al [36]
PUA	571	571	50%	2003	Zhang et al [36]
Zh1	1205	428	74%	2004	Zhang et al [36]
Gen spam	31,196	9212	78%	2005	Cormack and lynam [37]
Trec 2005	52,790	39,399	57%	2005	Androutsopoulos et al [38]
Biggio	8549	0	100	2005	Biggio et al [39]
Phishing corpus	415	0	100	2005	Abu-nimeh et al [40]
Enron-spam	20170	16545	55%	2006	Koprinska et al [41]
Trec 2006	24,912	12,910	66%	2006	Androutsopoulos et al [42]
Trec 2007	50,199	25,220	67%	2007	Debarr and wechsler [43]
Princeton spam image Benchmark	1071	0	100%	2007	Wang et al [44]
Dredze image spam Dataset	3297	2021	62%	2007	Dredze, gevaryahu and elias-bachrach [45]
Hunter	928	810	53%	2008	Gao et al [46]
Spamemail	1378	2949	32%	2010	Csminninggroup [47]

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Performance Evaluation Measures

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  - What would be the classifier's accuracy value if a setting is lopsided, that is, one where the number of Spam messages utilized for testing the performance of the filter is very much higher than that of ham messages ?
- Can one have a zero probability of wrongly categorizing a ham message in the real world ? Therefore the other metrices.....

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Let use now use the following notations:

- NH: the Number of non-Spam messages to be classified
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- True Negatives:
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Performance evaluation...: False/True Positives/Negatives

True Positive: Cases when we **predicted spam** and our **prediction is true** that means **actual value is also spam.**

True Negatives: Cases when we **did not predict spam** and our **prediction is true** that means **actual value is not spam.**

False Positives: Cases when we **predicted spam** and our **prediction is false** that means **actual value is not spam.**

False Negatives: Cases when we **did not predict spam** and our **prediction is false** that means **actual value is spam.**

Figure: False/True Positives/Negatives

1

[1] https://thatascience.com/learn-machine-learning/Precision-and-Recall/

Performance evaluation measures: Acc and Err...

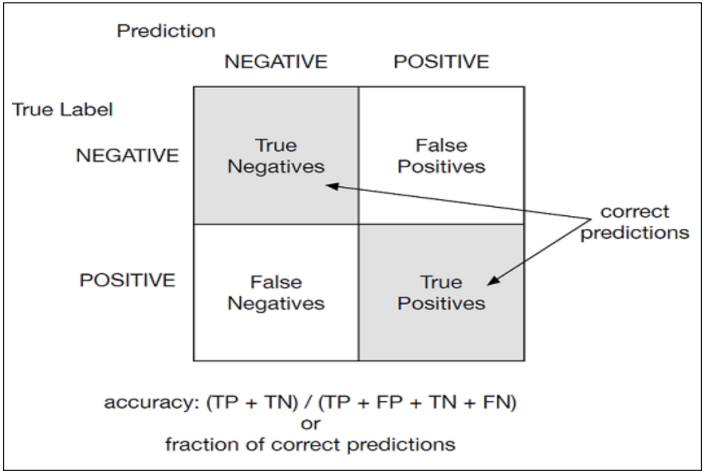

Figure: Accuracy

[1] https://freecontent.manning.com/evaluating-a-classification-model-with-a-Spam-filter/

Performance evaluation measures: Acc and Err...

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$$A_{cc} = \frac{|H \rightarrow H| \ + \ |S \rightarrow S|}{N_H \ + \ N_S} \qquad (1)$$

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Now, we can formally define the *Acc* and *Err*, as follows:

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Let use now use the following notations:

- NH: the Number of non-spam messages to be classified
- NS: the Number of spam messages to be classified
- H - a message actually classified as HAM message,
- S - a message actually classified as SPAM message,

Then,

- False Positives:
  - the number of HAM messages wrongly classified as the spam messages, denoted by $|H \rightarrow S|$
- False Negatives:
  - the number of Spam messages wrongly classified as the HAM messages, denoted by $|S \rightarrow H|$
- True Positives:
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- Here, do A_{cc} and E_{rr} mutually **assume** equal cost of a False Positive $|H \rightarrow S|$ and a False Negative $|H \rightarrow S|$ events OR assume different costs ?
- Is it a realistic assumption ?
- this is the proof of our earlier hypothesis that A_{cc} and E_{rr} are necessary but not sufficient metrices to measure the performance of a classifier ?
- hence, now we shall introduce one more expression viz. the false positive rate (FPR) - defined as the ratio of ham or valid e-mails that are classified as Spam....

next slide.

Performance evaluation measures:FPR, FNR

The False Positive Rate (FPR) is expressed as follows:

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$$FPR = \frac{|S \rightarrow S|}{|H \rightarrow S|\ +\ |S \rightarrow S|}$$

e.g. if it is 0.843, or when it predicts that an email is a Spam, the classifier is correct around 84% of the time.

Performance evaluation measures: Precision

Thus, graphically the Precision is....

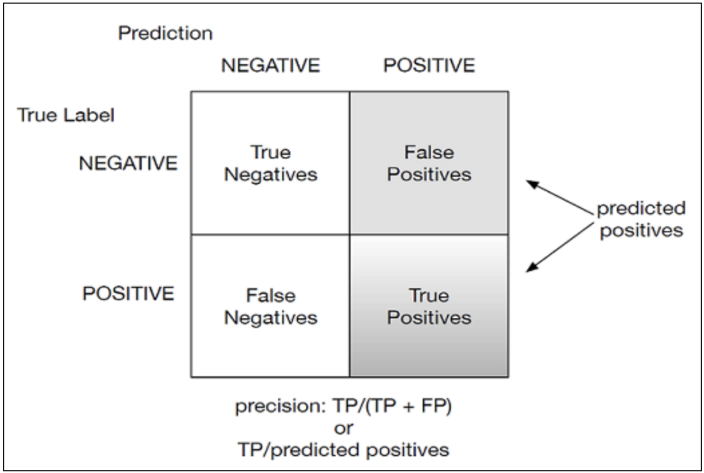

Figure: Precision

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- that is, Recall is the percentage of correctly ruled positives (as Spam) out of all of the actual positives - the term actual meaning, even if a mail is termed as false negative, it IS actually a Spam and hence is an actual positive.

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- Recall is also envisaged to indicate sensitivity of a model

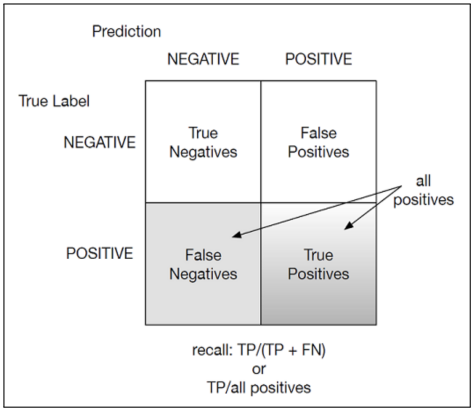

Figure: Recall, graphically

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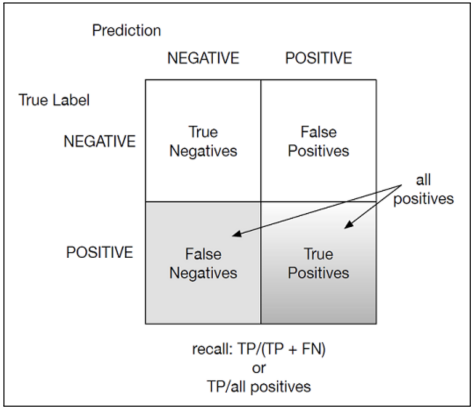

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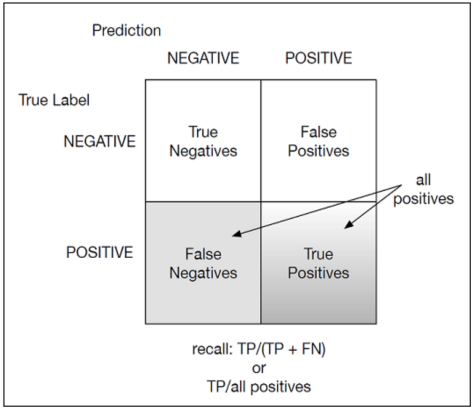

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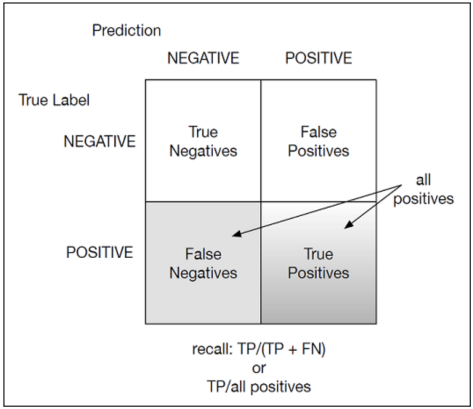
- And, the occurrence of such situation would be conveyed with a low Recall because the denominator in above expression would be high !



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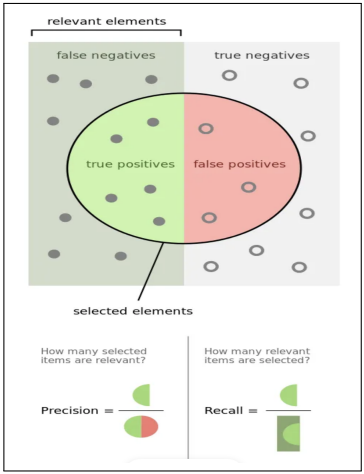
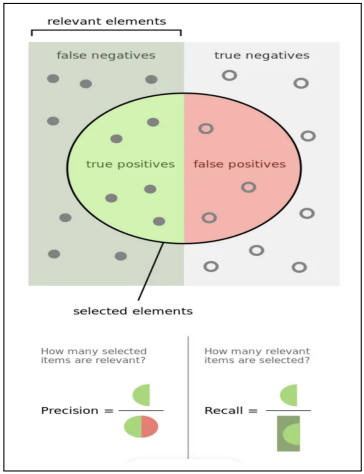


Figure: Recall & Precision

[1] https://commons.wikimedia.org/w/index.php?curid=36926283



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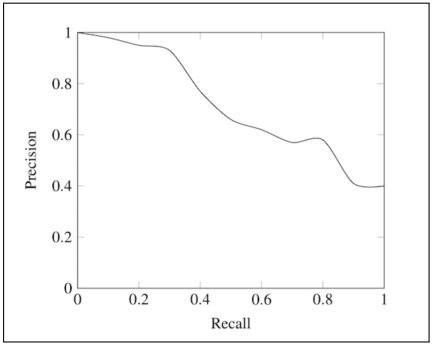

Figure: Recall & Precision: inversely proportional to each other

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Performance evaluation measures: An Example

- Consider that out of 100 emails, only 2 are Spams and 98 are HAMs. IClassifier predicts all as HAM. Then Acc = ?. But is that acceptable?
- Now look at other data as follows:
  - True Positives = $|S \rightarrow S| = 221$
  - True Negatives = $|H \rightarrow H| = 1414$
  - False Positives = $|H \rightarrow S| = 20$
  - False Negatives = = $|S \rightarrow H| = 17$
- Acc = ?
- Err = ?
- Pr = ?
- Rr= ?

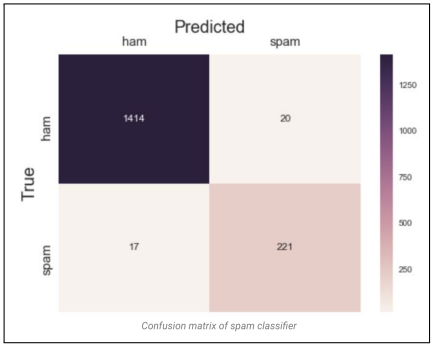

Figure: Confusion Matrix of Spam Classifier

Performance evaluation measures: Relating Pr and Rr

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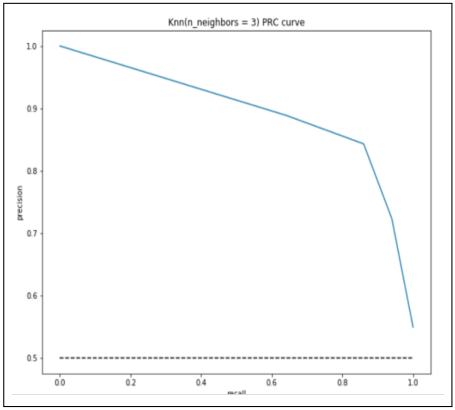

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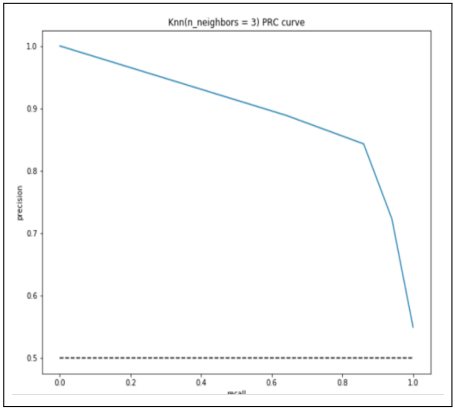

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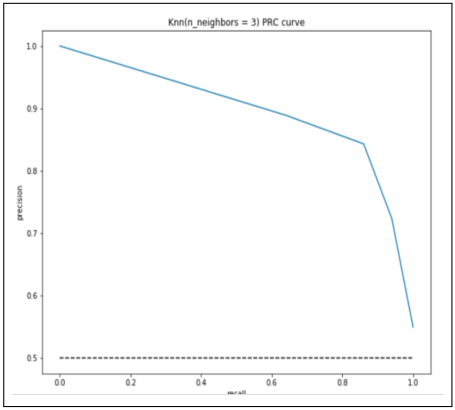

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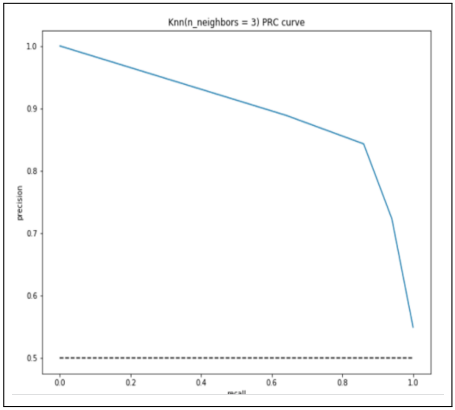

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- The ROC curve is generated by plotting the true positive rate (TPR) against the false positive rate (FPR) at different threshold settings.

Performance evaluation measures: Receiver Operating Characteristics curve

- Spam filters with a drastically reduced FPR and FNR are said to have a better performance.
- FNR & FPR represent the efficiency of filters that directly aim at the classification decision borderline devoid of generating the probability estimate.
- On the other hand, the efficiency of filters that explicitly estimate the group conditional probabilities and then
  - execute classification based on estimated probabilities, can be represented by a curve called ROC (Receiver Operating Characteristics) curve.
- ROC curve, is a graphical plot that demonstrates the analytical capability of a Spam filter as its bias level is modified.
- The ROC curve is generated by plotting the true positive rate (TPR) against the false positive rate (FPR) at different threshold settings.
- When the ROC curve of a Spam filter closely sits on top of another, such filter can be classified a filter with superior performance in all implementation setups.

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- RoC curve makes these aspects clearer.....see next slide...

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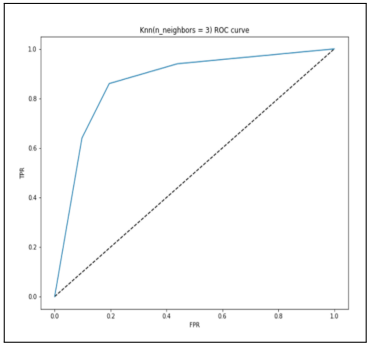

Figure: Relating TPR and FPR

Source:
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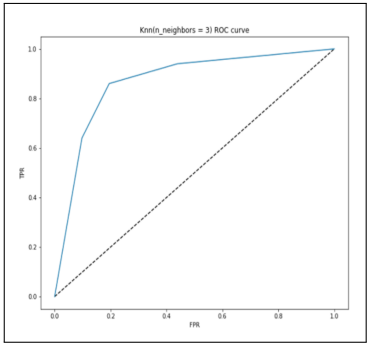

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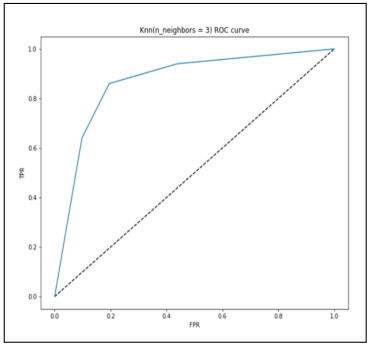

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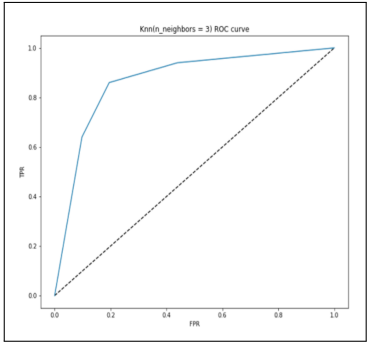

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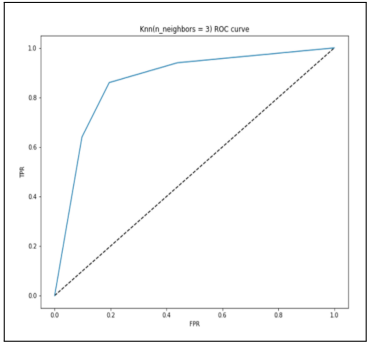

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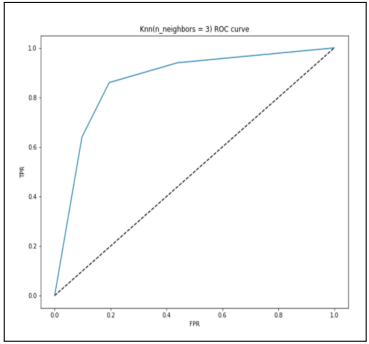

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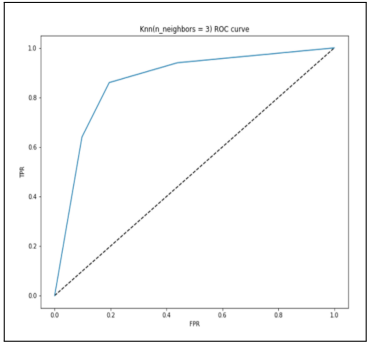

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- In Spam filtering, Precision is emphasized over Recall. This is appropriate, because it's more important to not lose non-Spam email than it is to filter every single piece of Spam out of inbox.

Performance evaluation measures: Motivation for F1 Score

Thus, important to remember

Precision is a measure of confirmation (when the classifier indicates positive, how often it's correct), and Recall is a measure of utility (how much the classifier finds of what there is to find).

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In situations like this, it is preferable to have one number to compare all the different choices by. Such score is the F1 score.
The F1 score measures a tradeoff between Precision and Recall.
It's defined as the harmonic mean of the Precision and Recall. This is most easily shown with an explicit calculation.

Performance evaluation measures: F-measure OR F_1 Score

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- If the filter's Recall falls too low as its Precision increases, this results in a lower F1. IT signifies that one has traded off too much Recall for better Precision.

Performance evaluation measures: Total Cost Ratio (TCR)

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- higher the value implies better performance. When the value of TCR ¡ 1, the filter performance is said to be very poor, to the extent its use is not advisable i.e. the baseline (not using the filter) is better.

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  - $\lambda = 999$ implies that $C_{FP} = 999 * C_{FN}$..... tthe Spam messages are deleted immediately.

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Performance evaluation measures: Sensitivity with λ values

- In computing cost sensitivity of filters, λ decides the strictness of penalty for wrongly classifying a non-Spam email as Spam.
- Table shows different strata of cost sensitivity of model that have been taken into consideration, seen as follows:
  - the efficiency of a filter for a given λ is compared with a baseline case by means of total cost ratio as explained in.
  - λ is used for fine-tuning the weight of false positive and its performance is assessed by the cost sensitivity.
  - the three values used for λ and their significance is as discussed before, shown again here.

Table 3
Levels of cost sensitivity of model.

λ	Maximum Tolerance Level $T = \lambda/(1+\lambda)$	Significance of having such cost sensitivity?
999	0.999	Filtered messages are thrown away and no additional processing is carried out.
99	0.9	Filtering a non-spam message is slightly penalized above allowing a spam message to go through. It is used to demonstrate that it is cumbersome re-sending a filtered spam message than deleting it manually.
1	0.5	If the receiver is not concerned as regards missing a non-spam message.

Source: Emmanuel Gbenga Dada et al, Machine learning for email Spam filtering: review, approaches and open research problems, Heliyon, 5(6), 2019

ML-based Methods used for Email Spam filtering

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