# Evaluating Summaries Automatically – a system proposal

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**Abstract**

We propose in this paper an automatic evaluation procedure based on a metric which could provide summary evaluation without human assistance. Our system includes two metrics, which are presented and discussed. The first metric is based on a known and powerful statistical test, the $\chi^2$ goodness-of-fit test, and has been used in several applications. The second metric is derived from three common metrics used to evaluate Natural Language Processing (NLP) systems, namely *precision*, *recall* and *f-measure*. The combination of these two metrics is intended to allow one to assess the quality of summaries quickly, cheaply and without the need of human intervention, minimizing though, the role of subjective judgment and bias.

## 1. Introduction

The summarization of a text consists in extracting the chief points of an original document in terms of its key sentences and/or clauses, and displaying the summary in a readable form. In general terms, this definition leads to a very important question: what constitutes a good summary? Or, more simply: how to evaluate a summary?

Research on summary evaluation over the last decades has tried to respond to these complex questions. In acknowledgment of this fact, a series of conferences like Text Retrieval Conferences (TREC) (Voorhees and Harman, 1999), Message Understanding Conferences (MUC) (Chinchor et al, 1993), TIPSTER SUMMAC Text Summarization Evaluation (Mani et al, 1998), Document Understanding Conference (DUC) (DUC, 2004), and Text Summarization Challenge (TSC) (Fukushima and Okumura, 2001), have attested the importance of this topic. The main difficulty in evaluating a summarization system is that there is not as yet, a clear definition for what constitutes a good summary. Another difficulty related to summary evaluation comes from the fact that each text can have more than one correct summary as may be seen in the work of Edmundson (1969), Hand (1997) and Paice (1990). The majority of evaluation methods developed so far have depended on human intervention, and therefore have the drawbacks of being time consuming and expensive. On the other hand, if a researcher, for example, needs an evaluation method which is fast and is not influenced by human error or subjectivity, an automatic evaluation method could be the answer. Many approaches have been developed on this topic, using a variety of metrics such as sentence recall, sentence ranking, content-based, and so on (e.g. Donaway et al (2000); Radev et al (2000); Saggion et al (2002)).

In this paper, we present an efficient automatic summary evaluation procedure. The fundamental characteristic of such a procedure is that primarily it should be based on a new metric which could provide summary evaluation without human assistance. Second, it should be based on insights derived from research in summary evaluation, statistics and NLP. To sum up, our intention is to establish a novel automatic procedure which may be used to evaluate the content of a summary, quickly, cheaply and without the need of human intervention.

This paper is organized as follows: Section 2 describes the development of our evaluation procedure. Section 3 presents the performance analysis of our procedure. Finally, the conclusions are summarized in Section 4.

## 2. Method´s description

We have developed a system called VERT[1], which has two methods or metrics: one deals with content bearing words in both the reference text and candidate summaries using correlation and $\chi^2$ statistics. The second deals with the matching between sentences, based again in content words using a graph theory method. This graph theory method, based on bipartite matching, leads to the well-known precision and recall that form the basis of Information Retrieval (IR)-metrics. The first method is called VERT-C and the second is called VERT-F. The idea for the name is derived from two previous systems, namely BLEU[2] (Papineni et al, 2001) and ROUGE[3] (Lin, 2004).

### 2.1 VERT-C: Chi-Square ($\chi^2$) Statistics

This metric is based on the Chi-Square ($\chi^2$) goodness-of-fit test. This test measures whether or not

[1] VERT stands for **V**aluation using **E**nhanced **R**ationale **T**echnique

[2] BLEU stands for **BiL**ingual **E**valuation **U**nderstudy

[3] ROUGE stands for **R**ecall-**O**riented **U**nderstudy for **G**isting **E**valuation

observed events in a data sample are close to those that would be expected if the null hypothesis were true. The test evaluates the degree of correspondence between the observed and expected values, measuring then the fit of the model (Pedersen et al, 1996).

This test has been used extensively in text analysis (Butler, 1985). Butler has described a number of instances where uses the $\chi^2$ test to compare the similarity/dissimilarity between speech and text samples produced by different language users. A comparative study of literary styles of different authors based on the usage of orthographic markers of given categories of words, used the $\chi^2$ test.

The oft-repeated citation is of Church and Gale (1991), where pairs of words in source and target texts were identified using the same test for a text of aligned corpora in source and target language. More recently Kilgarriff (2001) has used the test to compare two corpora.

We have used the $\chi^2$ test to measure similarity between a text and its surrogate summary, following the procedure proposed by Siegel and Castellan (1988):

We begin stating the null hypothesis ($H_0$): the summary is a good representation of its parent/full text, i.e. the distribution of content bearing words in the summary is the same as in its parent/full text; and the alternative hypothesis ($H_1$): the summary is not a good representation of its parent/full text, i.e. the distribution of content bearing words in the summary is different from its parent/full text.

After the hypotheses statement, the steps that we performed were:

1. Produce a word frequency list for a text and its summary.
2. Normalize the list to headwords by reducing all words when possible to their stems so that all lexical variants of a particular word are counted as a single word (e.g. *analyze*, *analyzed*, *analyzing* will be reduced to analyz).
3. Arrange the data (observed frequencies) by using an array consisting of *r* rows and *c* columns called contingency table. See Figure 1 for an example. Generally speaking, the columns represent groups and each row represents a category of a measured variable. In our case, the contingency table will have two columns. One column for the full text (hereafter, FT) and other column for the summary (hereafter, SP10, SP30, ABS). The rows ($r_1$, $r_i$ ,..., $r_k$) of the table contain the frequency of the keywords in the original document (column $c_1$) and in the summary (column $c_2$).
4. Sum up cell frequencies across columns (see Figure 1).
5. Compute $E_i = n \times p_i \ (i = 1,2,\ldots,k)$, where *n* denotes the sample size in the summary and $p_i$ denotes the probability specified for the $i_{th}$ category in the null hypothesis and *k* is the number of lexical words (stems). For example, the calculation for the word **ambassador** in the SP10 column will be as follows:

   Expected Cell Frequency = 35*(5/57) = 3.1

All the expected cell frequencies are calculated in this way (see Figure 1).

6. Compute $\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i}$, where *O* represents the observed frequency and *E* represents the expected frequency.
7. Compute $df = number\ of\ lexical\ words\ (stems) - 1$.
8. Compute the *p-value* at the selected level of significance (e.g. $\alpha$= 0.05).

| | **Document** | |
|---:|---:|---:|
| **Word** | FT | SP10 |
| | | $O_i$ ($E_i$) |
| spiers | 8 | 5 (4.9) |
| affairs | 6 | 4 (3.7) |
| ambassador | 5 | 3 (3.1) |
| general | 5 | 3 (3.1) |
| state | 4 | 2 (2.5) |
| political | 4 | 3 (2.5) |
| director | 3 | 3 (1.8) |
| department | 3 | 2 (1.8) |
| undersecretary | 3 | 1 (1.8) |
| pakistan | 2 | 2 (1.2) |
| appoint | 2 | 1 (1.2) |
| turkey | 2 | 1 (1.2) |
| embassy | 2 | 1 (1.2) |
| london | 2 | 1 (1.2) |
| charge | 2 | 1 (1.2) |
| bahamas | 2 | 1 (1.2) |
| secretary | 2 | 1 (1.2) |
| **Total** | **57** | **35** |

Figure 1: An example of a contingency table

## 2.2 VERT-F: *N-gram* Matching

*N-gram* matching procedures are used typically in linguistic pattern recognition models (e.g. ROUGE (Lin, 2004) and BLEU (Papineni et al, 2001)). Also, there is a considerable interest in machine translation in this context when cross-lingual patterns between source and target translation are matched to assess the effectiveness of a translation system.

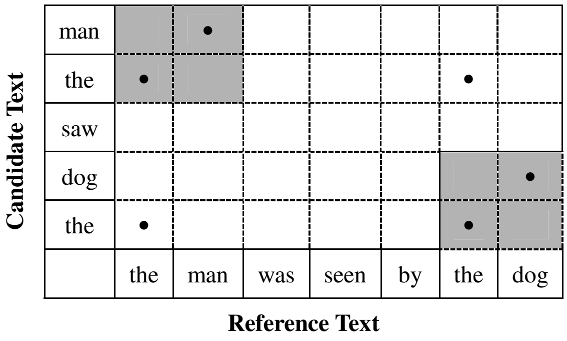
Turian, et al (2003), for instance, proposed an interesting machine translation evaluation procedure which inspired us in the development of VERT-F. The idea is based on the intersection of two texts[4] (the reference and the candidate) and what these texts have in common. A comparison is then carried out using a grid which shows the commonality between these two texts. In order to illustrate this comparison, consider two texts:

[4] *Bitext* is the employed term used by Turian *et al.*

```
Reference text: the man was seen by the dog
Candidate text: the dog saw the man
```

The common unigrams are: the, man, dog; and the bigrams are: the man, the dog.

This is shown in the bitext grid in Figure 2. If a word appears in the reference text and in the candidate text, there is a *hit*; represented as a bullet in Figure 2.



Candidate Text

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| man | | ● | | | | | |
| the | ● | | | | | ● | |
| saw | | | | | | | |
| dog | | | | | | | ● |
| the | ● | | | | | ● | |
| | the | man | was | seen | by | the | dog |

Reference Text

Figure 2: Bitext grid showing the relationship between a reference text (X axis) and its corresponding candidate text (Y axis)

The first suggestion then would be to count the number of hits in the grid. However, there is a risk of double-counting, that is, words that appear more than once in both texts. See the word '*the*' in Figure 2, for instance. In order to avoid double-counting, a subset of the hits is taken such that there are no hits in the same row or column. Double-counting is avoided through the use of the "*maximum bipartite matching problem*" (MBMP), which is discussed in graph theory (Open University (2001), Cormen, et al (2001)). In graph theory, a bipartite graph is a special graph where the set of vertices can be divided into two disjoint sets with two vertices of the same set never sharing an edge (Cormen, et al., 2001).

So, the bitext grid for the candidate and reference text represented in Figure 2 can be represented using MBMP as in Figure 3.

From the definition of the '*maximum bipartite matching problem*', the maximum match size (MMS) of a bitext is the size of any maximum matching for that bitext. The MMS in Figure 3 includes two vertices between the four instances for the nodes in the graph, together with one vertex each for man and dog nodes.

One can show that the MMS value divided by the length of the candidate text (*C*) or divided by the length of the reference text (*R*) will lead to the recall and precision metrics. Recall and precision are the most common metrics used to evaluate NLP systems (Salton and McGill (1983), van Rijsbergen (1979)). According to these authors, when one compares a set of candidate items *Y* to a set of reference items *X*, we will have:

$$recall\ (Y \mid X) = \frac{|X \cap Y|}{|X|} \qquad precision\ (Y \mid X) = \frac{|X \cap Y|}{|Y|}$$

Taking the idea of the intersection of a pair of texts described earlier, and applying the recall and precision definition to it, we will obtain, respectively:

$$recall\ (Candidate \mid Reference) = \frac{MMS\ (Candidate, Reference)}{|Reference|},$$

$$precision\ (Candidate \mid Reference) = \frac{MMS\ (Candidate, Reference)}{|Candidate|}$$

We will use the *f-measure*, as our proposed metric, which is a combination of *precision* and *recall*:

$$F_\beta = \frac{(1+\beta^2) \times precision\ \times recall}{\beta^2 \times precision + recall},$$

and for $\beta = 1$ we will have:

$$F_\beta = \frac{2 \times precision\ \times recall}{(precision\ + recall)}$$

In fact, *f-measure* is the harmonic mean of the *recall* and *precision* metrics.

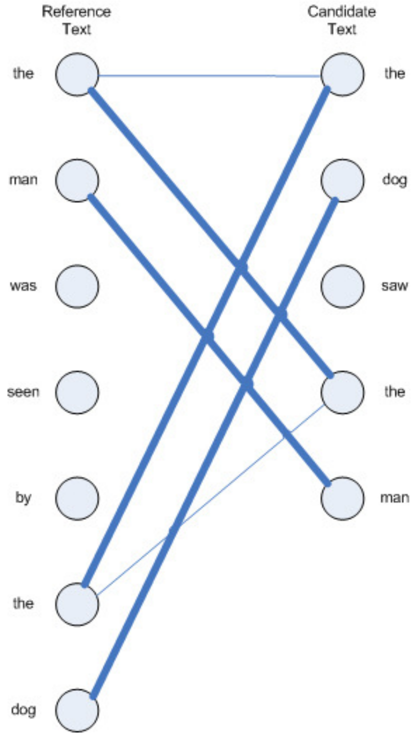


Figure 3. Graph representation of the example shown in Figure 2

We then have implemented the two metrics described above and incorporated them into a computational framework.

## 3. DOING THE EVALUATION OF EVALUATION

The major goal of the experiment reported in this section, is to investigate the performance of a new automatic summary evaluation system, called VERT. In addition, the evaluation procedure must not depend on human intervention; it should be carried out automatically.

For us, the efficacy of an automatic evaluation metric must be assessed through correlation comparison between the automatic metric scores and human scores. This means that the automatic scores should correlate highly with human scores (Lin, 2004). If they do correlate, we can affirm that the automatic metric can be used to evaluate summaries. We believe that this criterion forms the fundamental 'ground-truth' for the evaluation of our two metrics (VERT-C and VERT-F).

We have used DUC data in order to evaluate VERT, because such a corpus contains 3 years of human judgements, and this would make our efficacy assessment possible and feasible. From DUC data we have used the following corpus for this study:

- Summaries of single documents of about 100 words for DUC 2001 and DUC 2002. In total, 15 systems submitted 3,304 summaries for DUC 2001. For DUC 2002, 17 systems submitted 7,359 summaries.
- Very short summaries of single documents of about 10 words for DUC 2003, where 14 systems submitted in total 8,050 summaries.

As we said earlier, the assessment of an automatic evaluation metric should be carried out through correlation analysis. In the statistical literature, this type of analysis makes use of measures of correlation, which are, according to Sheskin (2000), 'descriptive statistical measures that represent the degree of relationship between two or more variables'. These descriptive measures are known as *correlation coefficients*. Those coefficients, when calculated, produce a value within the range of –1 to +1. If a value of +1 is obtained, there is a perfect positive correlation; if a value of –1 is obtained, there is a perfect negative correlation, and a value of zero indicates no correlation at all. This range (–1 to +1), in fact, denotes the strength of the relationship between the two variables.

A question arises at this point: is it possible to determine if one metric is "better" than another through correlation analysis? In other words, how to proceed in comparative evaluations, like ROUGE versus VERT, for instance? In comparative evaluations we believe that the answer is ranking correlation (Voorhees (2000); Voorhees and Tice (2000)). What we mean is the rankings produced by a particular scoring method (an evaluation metric, in our context) are more important than the scores themselves. This insight is given by Kendall's Tau ($\tau$) correlation coefficient (Sheskin, 2000). Kendall's $\tau$ calculates the "distance" between two rankings as the minimum number of pairwise adjacent swaps necessary to convert one ranking into the other. The "distance" value, which is normalized by the number of items being ranked, is the correlation coefficient. In other words, Kendall's $\tau$ depends on the number of inversions in the rank order of one variable when the other variable is ranked in order. If the correlation is 1.0, we have two identical rankings; if it is -1.0, we have a correlation between a ranking and its perfect inverse; and if it is 0.0, there is no correlation.

We then computed, for each set of DUC data (i.e. 2001, 2002 and 2003), the Kendall's $\tau$ correlation coefficient. This correlation coefficient was computed between the systems' average VERT-C and VERT-F scores, and their respective mean coverage scores as assigned by NIST assessors. The mean coverage scores were assigned by human judges, where they examined the percentage of content overlap between a manual summary and the candidate summary using Summary Evaluation Environment[5] developed by the University of Southern California's Information Sciences Institute.

Table 1 shows the Kendall's $\tau$ correlation coefficient of VERT-C and VERT-F scores versus human judgements on DUC 2001 and 2002 data, which consist of single summaries of 100 words, and also on DUC 2003 data, which consist of very short summaries of 10 words.

As can be seen in Table 1, VERT-F achieved a good correlation with human scores compared to VERT-C. A possible explanation for the difference in terms of performance between VERT-C and VERT-F is due to the difference of the approaches. VERT-F is based on the matching of all words between a reference text and a candidate text; that is, each text is split in clauses (a word is the minimum clause in this case), and the matching is carried out. On the other hand, VERT-C is word frequency based, that is, only the most frequent words in the reference and in the candidate text are considered in the calculation, resulting then, in less similarity.

| DUC | VERT-C vs Humans | VERT-F vs Humans |
|---|---|---|
| 2001 | 0.78 | 0.91 |
| 2002 | 0.52 | 0.89 |
| 2003 | 0.59 | 0.95 |

Table 1. Kendall's $\tau$ correlation coefficient of VERT scores versus human scores for DUC 2001, 2002 and 2003 data

One might ask: what about the comparative evaluations? What about ROUGE and BLEU against VERT? Similarly, we computed Kendall's $\tau$ between ROUGE, BLEU and human scores. These values are shown in Table 2 below.

| DUC | BLEU vs Human | ROUGE vs Human |
|---|---|---|
| 2001 | 0.64 | 0.85 |
| 2002 | 0.54 | 0.99 |
| 2003 | 0.05 | 0.97 |

Table 1. Kendall's $\tau$ correlation coefficient of BLEU and ROUGE scores versus human scores for DUC data

[5] SEE is available at http://www.isi.edu/~cyl/SEE

We decided to put all the results into a chart in order to illustrate better the metrics performances. Looking at Figure 4, we observe that the best performance was achieved by ROUGE, which outperforms our metric VERT-C, and BLEU. On the other hand, VERT-F and ROUGE comparatively presented almost the same performance. BLEU showed the poorest performance amongst the other metrics. These results also highlight the achievement of our proposed metric VERT; or more specifically VERT-F.

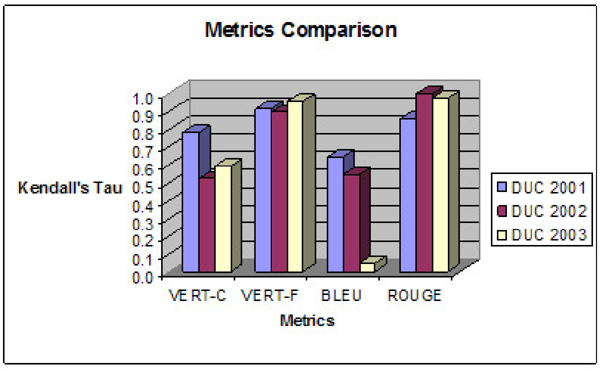


Figure 4. Comparative Chart

## 4. Conclusion

The previous section has presented the experiments conducted in order to test VERT's performance. We have utilized correlation analysis, a kind of statistical investigation which makes use of correlation coefficients. These coefficients quantify the degree of relationship between two or more variables. Kendall's $\tau$ correlation coefficient has been used. The outcomes of the experiment revealed that VERT-F outperformed VERT-C due to a difference between the rationales of the methods. The rationale behind VERT-F is based on the matching of all words (*n-gram* matching) contained in the reference and the candidate text, and the rationale behind VERT-C is based on choosing only content words, i.e. the most frequent words in the reference and the candidate text. We believe that VERT-C rationale tended to worsen its performance.

We found a high and positive statistically significant correlation between VERT scores and human scores. This can be considered as a significant achievement because three years of human evaluation data have been used to perform the correlation analysis.

We also have found that doing a comparative evaluation (ranking correlation) amongst BLEU, ROUGE and VERT against human scores, ROUGE outperformed the other two. However, VERT-F had a similar performance in relation to ROUGE, the official metric used by NIST. The results suggest that VERT-F can be used as a reliable summary evaluation metric, since it presented performance results similar to ROUGE, which is the official metric utilised by NIST in two editions of DUC (2004 and 2005).

In conclusion, we believe that the notion of ranking correlation, that is, comparative evaluation, is central to summary evaluation research; or more specifically, evaluation of evaluation. Using, as background, a mature discipline like statistics, we can confirm that our evaluation experiments are significant and their results are consistent. Moreover, our work contributed to solid advance in the state of the art.

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