The Effects of Human Variation in DUC Summarization Evaluation

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Abstract

There is a long history of research in automatic text summarization systems by both the text retrieval and the natural language processing communities, but evaluation of such systems' output has always presented problems. One critical problem remains how to handle the unavoidable variability in human judgments at the core of all the evaluations. Sponsored by the DARPA TIDES project, NIST launched a new text summarization evaluation effort, called DUC, in 2001 with follow-on workshops in 2002 and 2003. Human judgments provided the foundation for all three evaluations and this paper examines how the variation in those judgments does and does not affect the results and their interpretation.

1 Introduction

Research in summarization was one of the first efforts to use computers to "understand" language. Work was done back in the 1950s by many groups, including commercial services, to automatically produce abstracts or lists of pertinent keywords for documents. The interest in automatic summarization of text has continued, and currently is enjoying increased emphasis as demonstrated by the numerous summarization workshops held during the last five years. The DUC summarization evaluations (2001 – 2004)(`http://duc.nist.gov`) sponsored by the DARPA TIDES project (Translingual Information Detection, Extraction, and Summarization) are prominent examples. DUC has been guided by a roadmap developed by members of the summarization research community.

Along with the research has come efforts to evaluate automatic summarization performance. Two major types of evaluation have been used: *extrinsic* evaluation, where one measures indirectly how well the summary performs by measuring performance in a task putatively dependent on the quality of the summary, and *intrinsic* evaluation, where one measures the quality of the created summary directly.

Extrinsic evaluation requires the selection of a task that could use summarization and measurement of the effect of using automatic summaries instead of the original text. Critical issues here are the selection of a real task and the metrics that will be sensitive to differences in the quality of the summaries.

This paper concerns itself with intrinsic evaluations. Intrinsic evaluation requires some standard or model against which to judge summarization quality and usually this standard is operationalized by finding an existing abstract/text data set or by having humans create model summaries (Jing et al., 1998).

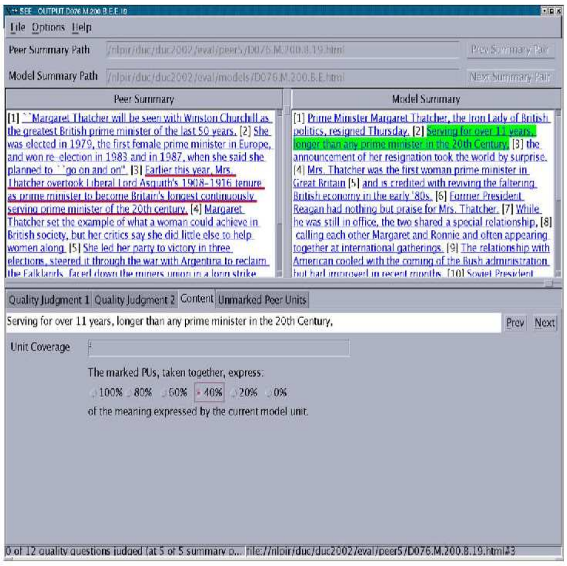
Intrinsic evaluations have taken two main forms: *manual*, in which one or more people evaluate the system-produced summary and *automatic*, in which the summary is evaluated without the human in the loop. But *both* types involve human judgments of some sort and with them their inherent variability. Humans vary in what material they choose to include in a summary and in how they express the content. Humans judgments of summary quality vary from one person to another and across time for one person.

In DUC 2001 - 2003 human judgments have formed the foundation of the evaluations and information has been collected each year on one or more sorts of variation in those judgments. The following sections examine this information and how the variation in human input affected or did not affect the results of those evaluations.

2 Initial Design – DUC-2001

Since the roadmap specified testing in DUC-2001 of both single and multi-document summarization, the data sets and tasks were designed as follows.

Sixty sets of approximately 10 documents each were provided as system input for this task. Given such a set of documents, the systems were to automatically create a 100-word generic summary for each document. Additionally they were to create a generic summary of the entire set, one summary at each of four target lengths (approximately 400, 200,



Peer Summary Path: /nlpir/duc/duc2002/eval/peer5/D076.M.200.B.19.html

Model Summary Path: /nlpir/duc/duc2002/eval/models/D076.M.200.B.E.html

Peer Summary: [1] ``Margaret Thatcher will be seen with Winston Churchill as the greatest British prime minister of the last 50 years. [2] She was elected in 1979, the first female prime minister in Europe, and won re-election in 1983 and in 1987, when she said she planned to ``go on and on''. [3] Earlier this year, Mrs. Thatcher overtook Liberal Lord Asquith's 1908-1916 tenure as prime minister to become Britain's longest continuously serving prime minister of the 20th century. [4] Margaret Thatcher set the example of what a woman could achieve in British society, but her critics say she did little else to help women along. [5] She led her party to victory in three elections, steered it through the war with Argentina to reclaim the Falklands, faced down the miners union in a long strike

Model Summary: [1] Prime Minister Margaret Thatcher, the Iron Lady of British politics, resigned Thursday. [2] Serving for over 11 years, longer than any prime minister in the 20th Century, [3] the announcement of her resignation took the world by surprise. [4] Mrs. Thatcher was the first woman prime minister in Great Britain [5] and is credited with reviving the faltering British economy in the early '80s. [6] Former President Reagan had nothing but praise for Mrs. Thatcher. [7] While he was still in office, the two shared a special relationship, [8] calling each other Margaret and Ronnie and often appearing together at international gatherings. [9] The relationship with American cooled with the coming of the Bush administration but had improved in recent months. [10] Soviet President

Serving for over 11 years, longer than any prime minister in the 20th Century,

Unit Coverage: 4

The marked PUs, taken together, express:

○ 100% ○ 80% ○ 60% ● 40% ○ 20% ○ 0%

of the meaning expressed by the current model unit.

0 of 12 quality questions judged (at 5 of 5 summary p... file://nlpir/duc/duc2002/eval/peer5/D076.M.200.B.19.html#3

Figure 1: SEE interface for judging per unit coverage

100, and 50 words).

The sets of documents were assembled at NIST by 10 retired information analysts. Each person selected six document sets, and then created a 100-word manual abstract for each document, and for the entire document set at the 400, 200, 100 and 50 word lengths. Thirty of the sets (documents and manual abstracts) were distributed as training data and the remaining thirty sets of documents (without abstracts) were distributed as test data.

Fifteen groups participated in DUC-2001, with 11 of them doing single document summarization and 12 of them doing the multi-document task.

The evaluation plan as specified in the roadmap was for NIST to concentrate on manual comparison of the system results with the manually-constructed abstracts. To this end a new tool was developed by Chin-Yew Lin at the Information Sciences Institute, University of Southern California (`http://www.isi.edu/~cyl/SEE/`). This tool allows a summary to be rated in isolation as well as compared to another summary for content overlap. Figure 1 shows one example of this interface. Human evaluation was done at NIST using the same personnel who created the manual abstracts (called model summaries).

One type of evaluation supported by SEE was coverage, i.e., how well did the peer summaries (i.e., those being evaluated) cover the content of the documents (as expressed by the model summary). A pairwise summary comparison was used in this part of the evaluation and judges were asked to do detailed coverage comparisons. SEE allowed the judges to step through predefined units of the model summary (elementary discourse units/EDUs) (Soricut and Marcu, 2003) and for each unit of that summary, mark the sentences in the peer summary that expressed [all(4), most(3), some(2), hardly any(1) or none(0)] of the content in the current model summary unit. The resulting ordered category scale[0-4] is treated as an interval scale in the coverage score based on feedback from the judges on how it was used. The coverage score for a given peer summary is the mean of its scores against the EDUs of the associated model ($\sim$ 4 EDUs per summary for the 50-word model summaries). This process is much more complex than doing a simple overall comparison using the entire summary but past evaluation experiences indicated that judges had more difficulty making an overall decision than they did making decisions at each EDU.

2.1 DUC-2001 Results - Effect of Variability in Models

Recall that there are two very different sources of human variation in DUC-2001, as in all the DUC evaluations. The first is the disagreement among judges as to how well a system summary covers the model summary. This is similar to what is seen in relevance assessment for IR evaluations. To the extent that different judges are consistently more lenient or strict, this problem has been handled in DUC by having the same judge look at all summaries for a given document set so that all peer summaries are affected equally and by having enough document sets to allow averaging over judges to mitigate the effect of very strict or very lenient judges. If a judge's leniency varies inconsistently in a way dependent on which system is being judged (i.e., if there is an *interaction* between the judge and the system), then other strategies are needed. (Data was collected and analyzed in DUC-2002 to assess the size of these interactions.)

Summarization has a second source of disagreement and that is the model summaries themselves. People write models that vary not only in writing style, but also in focus, i.e., what is important to summarize in a document or document set.

To shed light on variability in creation of models and their use, each of the 30 document sets in the test set (plus the 300 individual documents) were summarized independently by three summarizers - the one who had selected the documents plus two others. These extra summaries were used as additional peer human summaries in the main evaluation and also in a special study of the model effects on evaluation.

This special study worked with a random subset of 20 document sets (out of 30). Each peer was judged twice more by a single person who had not done the original judgment. This person used the two extra models, neither of which had been created by the person doing the judgments. There was only time to do this for the multi-document summaries at lengths 50 and 200.

2.2 Model Differences

A first question is how much did the two models differ. One way of measuring this is by a simple n-gram overlap of the terms. This was done based on software in the MEAD toolkit (`http://www.summarization.com`), without omitting the commonwords, nor doing any stemming, and the n-grams were allowed to span sentence boundaries. The average unigram overlap (the number of unique unigrams in the intersection/the number of unique unigrams in the union) for the two extra 50-word model summaries was 0.151 and there were only 6 out of the 20 sets that had any tri-gram overlap at all. For the 200-word summaries, the average unigram overlap was 0.197, with 16 out of the 20 sets having tri-gram overlaps. These numbers seem surprisingly low, but an examination of the summaries illustrates some of the reasons. What follows are the two model pairs with the greatest and least unigram overlap in the two extra 50-word document set group.

Document set 32, Judge G "In March 1989, an Exxon oil tanker crashed on a reef near Valdez, Alaska, spilling 8.4 million gallons of oil into Prince William Sound seriously damaging the environment. The cleanup was slow and Exxon was subject to severe compensation costs and indictment by a federal jury on five criminal charges."

Document set 32, Judge I "On March 24, 1989, the Exxon Valdez spilled 11.3 million gallons of crude oil in Prince William Sound, Alaska. Cleanup of the disaster continued until September and cost almost $2 billion, but 117 miles of beach remained oily. Exxon announced an earnings- drop in January 1990 and was ordered to resume cleaning on May 1."

Document set 14, Judge B "U.S. military aircraft crashes occur throughout the world more often than one might suspect. They are normally reported in the press; however, only those involving major damage or loss of life attract extensive media coverage. Investigations are always conducted. Flight safety records and statistics are kept for all aircraft models."

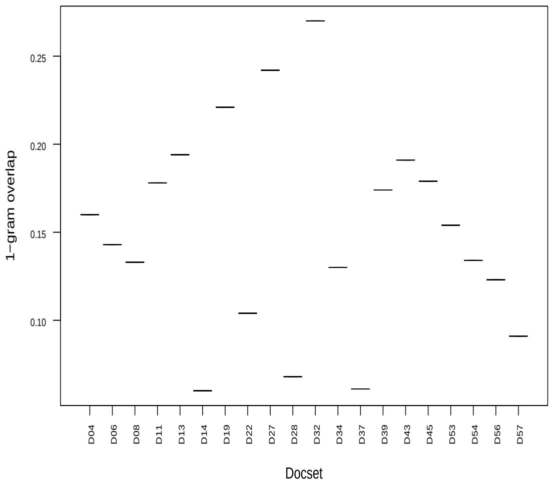


Figure 2: DUC-2001 unigram overlap by document set for the two extra 50-word models

Document set 14, Judge H "1988 crashes included four F-16s, two F-14s, three A-10s, two B-52s, two B-1Bs, and one tanker. In 1989 one T-2 trainer crashed. 1990 crashes included one F-16, one F-111, one F-4, one C-5A, and 17 helicopters. Other plane crashes occurred in 1975 (C-5B), 1984 (B-52), 1987 (F-16), and 1994 (F-15)."

For document set 32, the two model creators are covering basically the same content, but are including slightly different details (and therefore words). But for document set 14, the two models are written at very different levels of granularity, with one person writing a very high-level analysis whereas the other one gives only details. Note that these are only examples of the variation seen across the models; many other types of variations exist.

Additionally there is a wide variation in overlap across the 20 document sets (see Figure 2). This document set variation is confounded with the human variation in creating the models since there were 6 different humans involved for the 20 document sets.

2.3 Effects of Model Differences on Document Set Coverage Scores

Figure 3 shows the absolute value of the coverage score differences between the two extra models for each of the 20 document sets for the 50-word summaries. The middle bar shows the median, the black

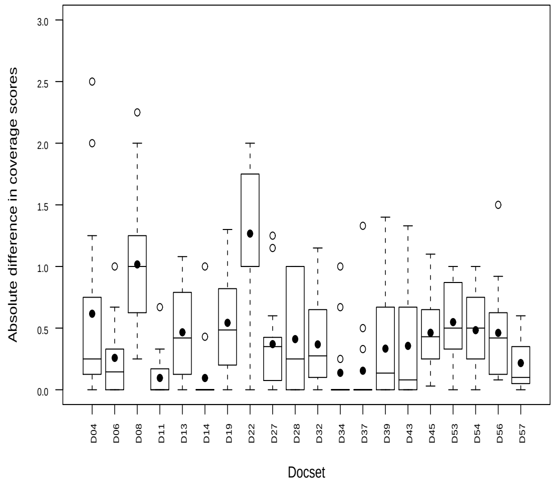


Figure 3: DUC-2001 absolute coverage differences by document set for the two extra 50-word models

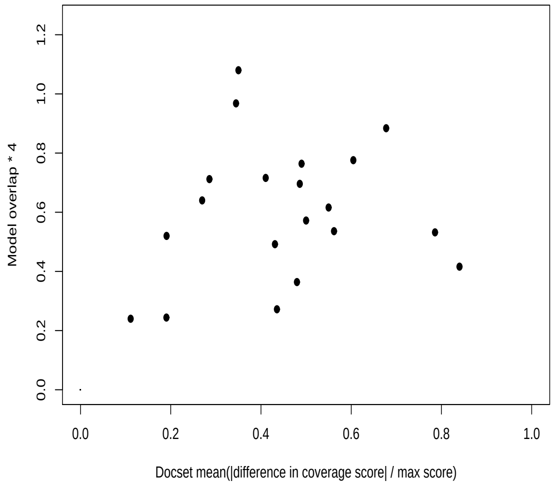


Figure 4: DUC-2001 absolute coverage differences vs overlap for two extra 50-word models

dot the average, and the box comprises the middle 2 quartiles. The open circles are outliers.

There is a large variation across document sets, with some sets having much wider ranges in coverage score differences based on the two different models. Looking across all 20 document sets, the average absolute coverage difference is 0.437 or 47.8% of the highest scoring model for the 50-word summaries and 0.318 (42.5%) for the 200-word summaries. This large difference in scores is coming solely from the model difference since judgment is being made by the same person (although some self-inconsistency is involved (Lin and Hovy, 2002)).

2.4 Relationship between Model Differences and Coverage Scores

Does a small unigram overlap in terms for the models in a given document set predict a wide difference in coverage scores for peers judged against the models in that document set? Comparing Figures 2 and 3, or indeed graphing overlap against coverage (Figure 4) shows that there is little correlation between these two. One suspects that the humans are able to compensate for different word choice and that the coverage differences shown in Figure 3 represent differences in *content* in the models.

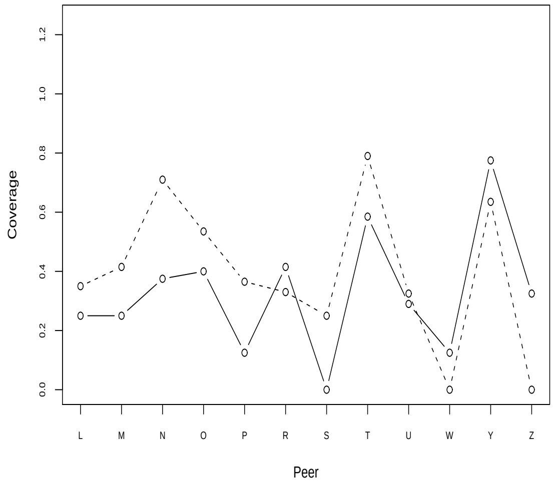


Figure 5: DUC-2001 median coverage by systems using extra model sets (50-word summaries)

2.5 Effects of Model Differences on per System Coverage Scores

How does the choice of model for each document set affect the absolute and relative coverage score for each system averaged across all document sets? Figure 5 shows the median coverage scores (50-word summaries) for the 12 systems using each of the two extra model sets. The points for the coverage scores are connected within a given model to make changes in rank with neighbors more obvious. It can be seen that the scores are close to each other in absolute value and that the two lines track each other *in general*. (The same type of graph could be shown for the 200-word summaries, but here there were even smaller differences between system rankings.)

What is being suggested (but not proven) by Figure 5 is that the large differences seen in the model overlap are not reflected in the absolute or relative system results for the DUC-2001 data examined. Most of the systems judged better against one set of models are still better using different models. The correlation (Pearson's) between median coverage scores for the systems using the two extra model sets is 0.641 ($p < 0.05$). This surprising stability of system rankings clearly needs further analysis beyond this paper, but implies that the use of enough instances (document sets in this case) allows an averaging effect to stablize rankings.

There are many system judgments going into these averages, basically 20 document sets times the average number of model units judged per document set ($\sim$ 4). These 80 measurements should make the means of the extra scorings better estimates of the "true" coverage and hence more alike. More importantly, Figure 5 suggests that there is minimal model/system interaction. Although no analysis of variance (ANOVA) was run in DUC-2001, the ANOVAs for DUCs 2002 and 2003 verify this lack of interaction.

3 DUC-2002

DUC-2002 was designed and evaluated in much the same manner as DUC-2001 to allow continuity of research and evaluation. There were 60 more document sets with manual abstracts created in the same way as the first 60 sets. The target lengths of the summaries were shortened to eliminate the 400-word summary and to include a headline length summary. The SEE GUI was modified to replace the five-point intervals [All, most, some, hardly any, or none] with percentages [0, 20, 40, 60, 80, 100] to reflect their perception by judges and treatment by researchers as a ratio scale. Seventeen groups that took part in DUC-2002, with 13 of them tackling the single document summary task (at 100 words) and 8 of them working on the multi-document task.

3.1 DUC-2002 Results - Effect of Variability in Judges

Beyond the main evaluation, it was decided to measure the variability of the coverage judgments, this time holding the models constant. For six of the document sets, each peer was judged three additional times, each time by a different judge but using the same model (not a model created by any of the judges). Whereas the judgment effect does not change the relative ranking of systems in the TREC information retrieval task (Voorhees, 1998), the task in coverage evaluation is much more cognitively difficult and needed further exploration. In DUC the question being asked involves finding a shared meaning between the content in each model summary unit and in the peer summary sentence, and determining how much meaning is shared – a very subjective judgment.

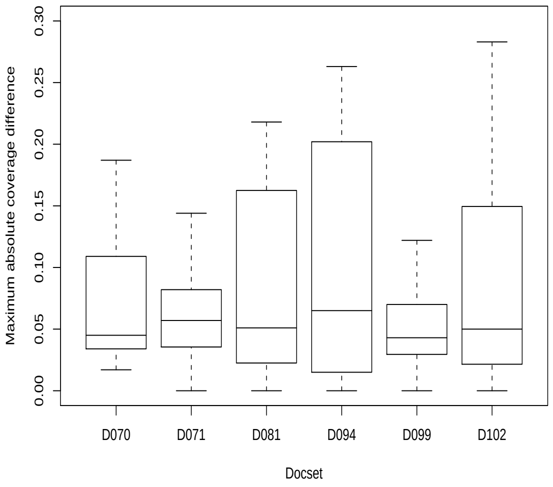


Figure 6: DUC-2002 maximum absolute coverage differences by document set for 50-word models

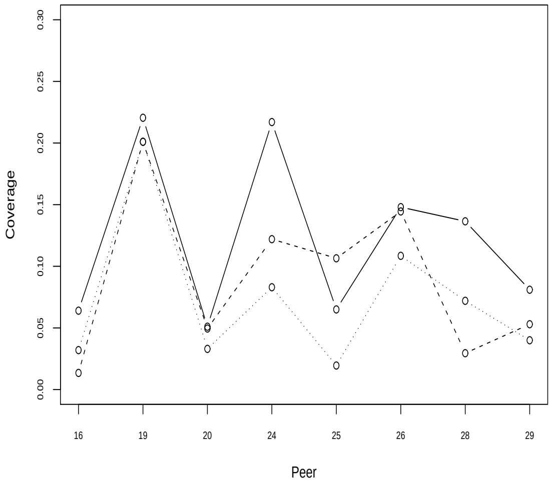


Figure 7: DUC-2002 median coverage by systems using extra judgment sets (50-word summaries)

3.2 Differences in the Coverage Judgments Using the Same Model

The average absolute coverage score difference between the highest and lowest of the three extra scorings of each peer summary for the 50-word summaries was 0.079, which is a 47.6% difference (0.070 for the 200-word, or 37.1%). This is about the same percentage differences seen for the coverage differences based on using different models in DUC-2001.

Once again, there is a wide variation across the six document sets (see Figure 6). Even though the median is similar across these sets, the variation is much larger for two of the document sets, and much smaller for two others. The variation in coverage score for the 200-word summaries is much less, similar to what was found in DUC-2001.

3.3 Effects of Judgment Differences on per System Coverage Scores

Figure 7 shows how the extra judgment variations affected the average system coverage scores. The lines plotted are similar to those shown for the DUC-2001 model variations, one line for each set of extra judgments. The scores again are very close together in absolute value and in general the systems are ranked similarly. In this case, the pairwise correlations (Pearson's) were 0.840, 0.723, and 0.801 ($p < 0.05$). With only six document sets involved in the averaging, versus the 20 used in DUC-2001, it is surprising that there is still so little effect.

3.4 ANOVA Results

The extra three judgments per peer allowed for analysis of variance (ANOVA) and estimates of the sizes of the various main effects and interactions. While the main effects (the judge, system, and document set) can be large, they are by definition equally distributed across all systems. Although still significant, the three interactions modeled – judge/system, judge/docset, and system/docset, are much smaller (on the order of the noise, i.e., residuals) and so are not likely to introduce a bias into the evaluation. Due to lack of space, only the ANOVA for DUC-2003 is included (see Table 1).

4 DUC-2003

For DUC-2003 it was decided to change the tasks somewhat. In an effort to get the human summaries closer to a common focus, each of the multi-document summary tasks had some constraining factor. There were four different tasks for summarization, one very short ”headline” task for single documents (300 single documents in the test set), and three different multi-document summary tasks (each task had 30 document sets used in testing). There were 21 groups that participated in DUC-2003, with 13 of them doing task 1, 16 doing task 2, 11 doing task 3 and only 9 trying task 4.

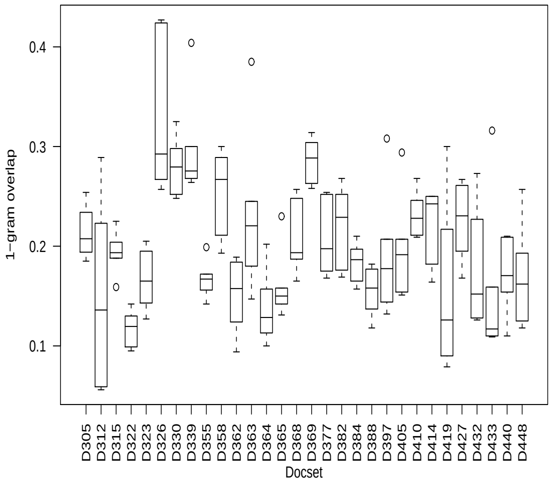


Figure 8: DUC-2003 unigram overlap by document set for 100-word models

4.1 DUC-2003 Results - Effect of Variability in Judges and Models

Beyond the main evaluation it was decided to do further investigation into the effects of model and judgment variation, in particular to focus on task 4 (create short summaries of 10 documents that were relevant to a given question). Each of the 30 document sets in task 4 had four different model summaries built by four different people, and four judgments made where the judge in each case was the model creator. The two types of variations were deliberately confounded for several reasons. The first was that the variations had already been investigated separately and it was important to investigate the combined effect. The second related issue is that this confounding mimics the way the evaluation is being run, i.e. the judges are normally using their own model, not someone else's model. The third reason was to provide input to the proposed automatic evaluation (ROUGE) to be used in DUC-2004 in which multiple models would be used but with no human judgments.

4.2 Differences in Model/Judgment Sets

The n-gram overlap for the 30 document sets is shown in Figure 8 with six possible pairwise comparisons for each set of four model summaries. The average unigram overlap is 0.200, but again a wide variation in overlap across the different document sets.

4.3 Effects of Model/Judgment Differences

Looking only at the maximum and minimum score in each set of four, the coverage score differences

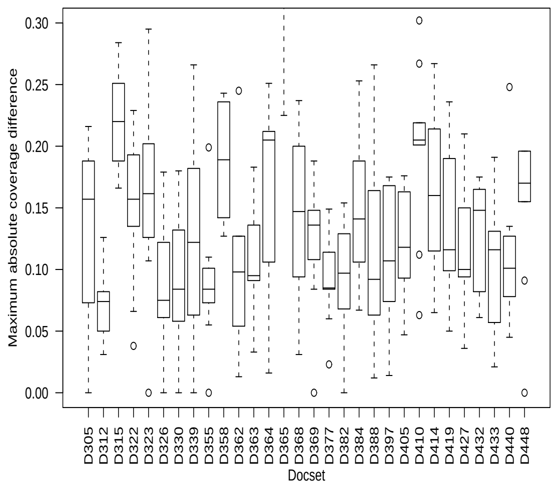


Figure 9: DUC-2003 maximum absolute coverage differences by document set for 100-word models

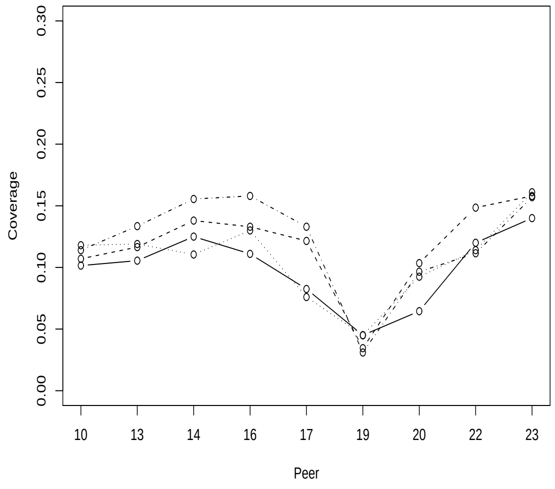


Figure 10: DUC-2003 median coverage by systems using extra judgment sets (100-word summaries)

are still high, with an average absolute coverage difference of 0.139 or 69.1% difference. Again there is a wide variation across document set/judge pair (see Figure 9).

Figure 10 shows the absolute coverage scores for each system for each of the four model/judgment pairs. The difference in absolute scores is small, and the relative ranking of the systems is mostly unchanged. For DUC-2003, the pairwise correlations (Pearson's) are 0.899, 0.894, 0.837, 0.827, 0.794, and 0.889 ($p < 0.05$). Additionally the scores are lower and closer than in earlier DUCs; this is probably because task 4 was a new task and systems were in a learning curve.

<table>
<tr><td colspan="6">coverage = grand mean
+ judge + system + docset
+ judge/system + judge/docset
+ system/docset</td></tr>
<tr><td>Source</td><td>Df</td><td>SS</td><td>MS</td><td>F</td><td>Pr(F)</td></tr>
<tr><td>judge</td><td>9</td><td>1.243</td><td>0.138</td><td>47.66</td><td>&lt;.0001</td></tr>
<tr><td>system</td><td>10</td><td>0.941</td><td>0.094</td><td>32.49</td><td>&lt;.0001</td></tr>
<tr><td>docset</td><td>29</td><td>1.313</td><td>0.045</td><td>15.62</td><td>&lt;.0001</td></tr>
<tr><td>jud/sys</td><td>90</td><td>0.282</td><td>0.003</td><td>1.08</td><td>0.2939</td></tr>
<tr><td>jud/ds</td><td>79</td><td>1.010</td><td>0.012</td><td>4.41</td><td>&lt;.0001</td></tr>
<tr><td>sys/ds</td><td>289</td><td>3.087</td><td>0.010</td><td>3.68</td><td>&lt;.0001</td></tr>
<tr><td>resid</td><td>787</td><td>2.281</td><td>0.002</td><td></td><td></td></tr>
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Table 1: Analysis of Variance for DUC-2003

4.4 ANOVA Results

An analysis of variance was also run on the DUC-2003 task 4 multiple models and judgments study, and results are presented in Table 1. The abbreviations for the column headings are as follows: Df (degrees of freedom), SS (sum of squares), MS (mean square), F (F value), Pr(F) (probability of F under the null hypothesis). The judge, system, and document set effects predominate as expected. Although still significant, the three interactions modeled - judge/system (jud/sys), judge/docset (jud/ds) and system/docset (sys/ds) are smaller than any of the main effects.

5 Conclusions

The secondary experiments described in this paper were by necessity small in scope and so are not conclusive. Still they consistently suggest stability of the SEE-based coverage results reported in the first three DUCs, i.e., despite large variations in the human-generated model summaries *and* large variations in human judgments of single-model coverage, the ranking of the systems remained comparatively constant when averaged over dozens of document sets, dozens of peer summaries, and 10 or so judges.

Note that this is only *on average*, i.e. there will be variations reflected in the individual document sets and the scoring cannot be used reliably at that level. However, variation in human summaries reflects the real application and one can only aim at improved performance on average for better summary methodology.

Attempts to reduce or incorporate variability in summarization evaluation will and should continue, e.g., by use of "factoids" (van Halteren and Teufel, 2003) or "summarization content units" (Passonneau and Nenkova, 2004) as smaller units for generating model summaries. The use of constraining factors such as in DUC-2003 is helpful, but only in some cases since there are many types of summaries that do not have natural constraints. Variability issues will likely have to be dealt with for some time and from a number of points of view.

In manual evaluations the results of this study need to be confirmed using other data. In ROUGE-like automatic evaluations that avoid variability in judgments and exploit variation in models, the question of how the number of models and their variability affect the quality of the ROUGE scoring needs study.

Beyond laboratory-style evaluations, system builders need to attend to variability. The averages hide variations that need to be analysed; systems that do well on average still need failure and success analysis on individual test cases in order to improve. The variations in human performance still need to be studied to understand better why these variations are occurring and what this implies about the acceptability of automatic text summarization for real end-users. The effect of variability in training data on the machine learning algorithms used in constructing many summarization systems must be understood.

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