Combining Coherence Models and Machine Translation Evaluation Metrics for Summarization Evaluation

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Abstract

An ideal summarization system should produce summaries that have high content coverage and linguistic quality. Many state-of-the-art summarization systems focus on content coverage by extracting content-dense sentences from source articles. A current research focus is to process these sentences so that they read fluently as a whole. The current AESOP task encourages research on evaluating summaries on content, readability, and overall responsiveness. In this work, we adapt a machine translation metric to measure content coverage, apply an enhanced discourse coherence model to evaluate summary readability, and combine both in a trained regression model to evaluate overall responsiveness. The results show significantly improved performance over AESOP 2011 submitted metrics.

1 Introduction

Research and development on automatic and manual evaluation of summarization systems have been mainly focused on content coverage (Lin and Hovy, 2003; Nenkova and Passonneau, 2004; Hovy et al., 2006; Zhou et al., 2006). However, users may still find it difficult to read such high-content coverage summaries as they lack fluency. To promote research on automatic evaluation of summary readability, the Text Analysis Conference (TAC) (Owczarzak and Dang, 2011) introduced a new subtask on readability to its Automatically Evaluating Summaries of Peers (AESOP) task.

Most of the state-of-the-art summarization systems (Ng et al., 2011; Zhang et al., 2011; Conroy et al., 2011) are extraction-based. They extract the most content-dense sentences from source articles. If no post-processing is performed to the generated summaries, the presentation of the extracted sentences may confuse readers. Knott (1996) argued that when the sentences of a text are randomly ordered, the text becomes difficult to understand, as its discourse structure is disturbed. Lin et al. (2011) validated this argument by using a trained model to differentiate an original text from a randomly-ordered permutation of its sentences by looking at their discourse structures. This prior work leads us to believe that we can apply such discourse models to evaluate the readability of extract-based summaries. We will discuss the application of Lin et al.'s discourse coherence model to evaluate readability of machine generated summaries. We also introduce two new feature sources to enhance the model with hierarchical and Explicit/Non-Explicit information, and demonstrate that they improve the original model.

There are parallels between evaluations of machine translation (MT) and summarization with respect to textual content. For instance, the widely used ROUGE (Lin and Hovy, 2003) metrics are influenced by BLEU (Papineni et al., 2002): both look at surface n-gram overlap for content coverage. Motivated by this, we will adapt a state-of-the-art, linear programming-based MT evaluation metric, TESLA (Liu et al., 2010), to evaluate the content coverage of summaries.

TAC's overall responsiveness metric evaluates the

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quality of a summary with regard to both its content and readability. Given this, we combine our two component coherence and content models into an SVM-trained regression model as our surrogate to overall responsiveness. Our experiments show that the coherence model significantly outperforms all AESOP 2011 submissions on both initial and update tasks, while the adapted MT evaluation metric and the combined model significantly outperform all submissions on the initial task. To the best of our knowledge, this is the first work that applies a discourse coherence model to measure the readability of summaries in the AESOP task.

2 Related Work

Nenkova and Passonneau (2004) proposed a manual evaluation method that was based on the idea that there is no single best model summary for a collection of documents. Human annotators construct a *pyramid* to capture important Summarization Content Units (SCUs) and their weights, which is used to evaluate machine generated summaries.

Lin and Hovy (2003) introduced an automatic summarization evaluation metric, called ROUGE, which was motivated by the MT evaluation metric, BLEU (Papineni et al., 2002). It automatically determines the content quality of a summary by comparing it to the model summaries and counting the overlapping n-gram units. Two configurations – ROUGE-2, which counts bigram overlaps, and ROUGE-SU4, which counts unigram and bigram overlaps in a word window of four – have been found to correlate well with human evaluations.

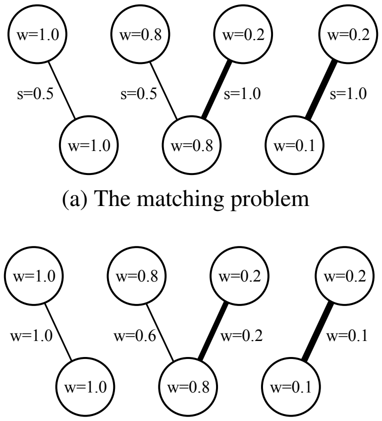
Hovy et al. (2006) pointed out that automated methods such as ROUGE, which match fixed length n-grams, face two problems of tuning the appropriate fragment lengths and matching them properly. They introduced an evaluation method that makes use of small units of content, called Basic Elements (BEs). Their method automatically segments a text into BEs, matches similar BEs, and finally scores them.

Both ROUGE and BE have been implemented and included in the ROUGE/BE evaluation toolkit[1], which has been used as the default evaluation tool in the summarization track in the Document Understanding Conference (DUC) and Text Analysis Conference (TAC). DUC and TAC also manually evaluated machine generated summaries by adopting the Pyramid method. Besides evaluating with ROUGE/BE and Pyramid, DUC and TAC also asked human judges to score every candidate summary with regard to its content, readability, and overall responsiveness.

DUC and TAC defined linguistic quality to cover several aspects: grammaticality, non-redundancy, referential clarity, focus, and structure/coherence. Recently, Pitler et al. (2010) conducted experiments on various metrics designed to capture these aspects. Their experimental results on DUC 2006 and 2007 show that grammaticality can be measured by a set of syntactic features, while the last three aspects are best evaluated by local coherence. Conroy and Dang (2008) combined two manual linguistic scores – grammaticality and focus – with various ROUGE/BE metrics, and showed this helps better predict the responsiveness of the summarizers.

Since 2009, TAC introduced the task of Automatically Evaluating Summaries of Peers (AESOP). AESOP 2009 and 2010 focused on two summary qualities: content and overall responsiveness. Summary content is measured by comparing the output of an automatic metric with the manual Pyramid score. Overall responsiveness measures a combination of content and linguistic quality. In AESOP 2011 (Owczarzak and Dang, 2011), automatic metrics are also evaluated for their ability to assess summary readability, *i.e.*, to measure how linguistically readable a machine generated summary is. Submitted metrics that perform consistently well on the three aspects include Giannakopoulos and Karkaletsis (2011), Conroy et al. (2011), and de Oliveira (2011). Giannakopoulos and Karkaletsis (2011) created two character-based n-gram graph representations for both the model and candidate summaries, and applied graph matching algorithm to assess their similarity. Conroy et al. (2011) extended the model in (Conroy and Dang, 2008) to include shallow linguistic features such as term overlap, redundancy, and term and sentence entropy. de Oliveira (2011) modeled the similarity between the model and candidate summaries as a maximum bipartite matching problem, where the two summaries are represented as two sets of nodes and precision and recall are cal-

[1] `http://berouge.com/default.aspx`



(a) The matching problem

(b) The matching solution

Figure 1: A BNG matching problem. Top and bottom rows of each figure represent BNG from the model and candidate summaries, respectively. Links are similarities. Both n-grams and links are weighted.

culated from the matched edges. However, none of the AESOP metrics currently apply deep linguistic analysis, which includes discourse analysis.

Motivated by the parallels between summarization and MT evaluation, we will adapt a state-of-the-art MT evaluation metric to measure summary content quality. To apply deep linguistic analysis, we also enhance an existing discourse coherence model to evaluate summary readability. We focus on metrics that measure the average quality of machine summarizers, *i.e.*, metrics that can rank a set of machine summarizers correctly (human summarizers are not included in the list).

3 TESLA-S: Evaluating Summary Content

TESLA (Liu et al., 2010) is an MT evaluation metric which extends BLEU by introducing a linear programming-based framework for improved matching. It also makes use of linguistic resources and considers both precision and recall.

3.1 The Linear Programming Matching Framework

Figure 1 shows the matching of bags of n-grams (BNGs) that forms the core of the TESLA metric. The top row in Figure 1a represents the bag of n-grams (BNG) from the model summary, and the bottom row represents the BNG from the candidate summary. Each n-gram has a weight. The links between the n-grams represent the similarity score, which are constrained to be between 0 and 1. Mathematically, TESLA takes as input the following:

1. The BNG of the model summary, X, and the BNG of the candidate summary, Y. The ith entry in X is x_i and has weight x_i^W (analogously for y_i and y_i^W).
2. A similarity score $s(x_i, y_j)$ between all n-grams x_i and y_j.

The goal of the matching process is to align the two BNGs so as to maximize the overall similarity. The variables of the problem are the allocated weights for the edges,

$$w(x_i, y_j) \qquad \forall i, j$$

TESLA maximizes

$$\sum_{i,j} s(x_i, y_j) w(x_i, y_j)$$

subject to

$$\begin{array}{rcll} w(x_i, y_j) & \geq & 0 & \forall i, j \\ \sum_j w(x_i, y_j) & \leq & x_i^W & \forall i \\ \sum_i w(x_i, y_j) & \leq & y_j^W & \forall j \end{array}$$

This real-valued linear programming problem can be solved efficiently. The overall similarity S is the value of the objective function. Thus,

$$\begin{array}{rcl} \text{Precision} & = & \frac{S}{\sum_j y_j^W} \\ \text{Recall} & = & \frac{S}{\sum_i x_i^W} \end{array}$$

The final TESLA score is given by the F-measure:

$$F = \frac{\text{Precision} \times \text{Recall}}{\alpha \times \text{Precision} + (1 - \alpha) \times \text{Recall}}$$

In this work, we set $\alpha = 0.8$, following (Liu et al., 2010). The score places more importance on recall than precision. When multiple model summaries are provided, TESLA matches the candidate BNG with each of the model BNGs. The maximum score is taken as the combined score.

3.2 TESLA-S: TESLA for Summarization

We adapted TESLA for the nuances of summarization. Mimicking ROUGE-SU4, we construct one matching problem between the unigrams and one between skip bigrams with a window size of four. The two F scores are averaged to give the final score.

The similarity score $s(x_i, y_j)$ is 1 if the word surface forms of x_i and y_j are identical, and 0 otherwise. TESLA has a more sophisticated similarity measure that focuses on awarding partial scores for synonyms and parts of speech (POS) matches. However, the majority of current state-of-the-art summarization systems are extraction-based systems, which do not generate new words. Although our simplistic similarity score may be problematic when evaluating abstract-based systems, the experimental results support our choice of the similarity function. This reflects a major difference between MT and summarization evaluation: while MT systems always generate new sentences, most summarization systems focus on locating existing salient sentences.

Like in TESLA, function words (words in closed POS categories, such as prepositions and articles) have their weights reduced by a factor of 0.1, thus placing more emphasis on the content words. We found this useful empirically.

3.3 Significance Test

Koehn (2004) introduced a bootstrap resampling method to compute statistical significance of the difference between two machine translation systems with regard to the BLEU score. We adapt this method to compute the difference between two evaluation metrics in summarization:

1. Randomly choose n topics from the n given topics with replacement.
2. Summarize the topics with the list of machine summarizers.
3. Evaluate the list of summaries from Step 2 with the two evaluation metrics under comparison.
4. Determine which metric gives a higher correlation score.
5. Repeat Step 1 – 4 for 1,000 times.

As we have 44 topics in TAC 2011 summarization track, $n = 44$. The percentage of times metric a gives higher correlation than metric b is said to be the significance level at which a outperforms b.

	Initial			Update		
	P	S	K	P	S	K
R-2	0.9606	0.8943	0.7450	0.9029	0.8024	0.6323
R-SU4	0.9806	0.8935	0.7371	0.8847	0.8382	0.6654
BE	0.9388	0.9030	0.7456	0.9057	0.8385	0.6843
4	0.9672	0.9017	0.7351	0.8249	0.8035	0.6070
6	0.9678	0.8816	0.7229	0.9107	0.8370	0.6606
8	0.9555	0.8686	0.7024	0.8981	0.8251	0.6606
10	0.9501	0.8973	0.7550	0.7680	0.7149	0.5504
11	0.9617	0.8937	0.7450	0.9037	0.8018	0.6291
12	0.9739	0.8972	0.7466	0.8559	0.8249	0.6402
13	0.9648	0.9033	0.7582	0.8842	0.7961	0.6276
24	0.9509	0.8997	0.7535	0.8115	0.8199	0.6386
TESLA-S	**0.9807**	**0.9173**	**0.7734**	0.9072	**0.8457**	0.6811

Table 1: Content correlation with human judgment on summarizer level. Top three scores among AESOP metrics are underlined. The TESLA-S score is bolded when it outperforms all others. ROUGE-2 is shortened to R-2 and ROUGE-SU4 to R-SU4.

3.4 Experiments

We test TESLA-S on the AESOP 2011 content evaluation task, judging the metric fitness by comparing its correlations with human judgments for content. The results for the initial and update tasks are reported in Table 1. We show the three baselines (ROUGE-2, ROUGE-SU4, and BE) and submitted metrics with correlations among the top three scores, which are underlined. This setting remains the same for the rest of the experiments. We use three correlation measures: Pearson's r, Spearman's ρ, and Kendall's τ, represented by P, S, and K, respectively. The ROUGE scores are the recall scores, as per convention. On the initial task, TESLA-S outperforms all metrics on all three correlation measures. On the update task, TESLA-S ranks second, first, and second on Pearson's r, Spearman's ρ, and Kendall's τ, respectively.

To test how significant the differences are, we perform significance testing using Koehn's resampling method between TESLA-S and ROUGE-2/ROUGE-SU4, on which TESLA-S is based. The findings are:

- Initial task: TESLA-S is better than ROUGE-2 at 99% significance level as measured by Pearson's r.
- Update task: TESLA-S is better than ROUGE-SU4 at 95% significance level as measured by Pearson's r.
- All other differences are statistically insignificant, including all correlations on Spearman's

ρ and Kendall's τ.

The last point can be explained by the fact that Spearman's ρ and Kendall's τ are sensitive to only the system rankings, whereas Pearson's r is sensitive to the magnitude of the differences as well, hence Pearson's r is in general a more sensitive measure.

4 DICOMER: Evaluating Summary Readability

Intuitively, a readable text should also be coherent, and an incoherent text will result in low readability. Both readability and coherence indicate how fluent a text is. We thus hypothesize that a model that measures how coherent a text is can also measure its readability. Lin et al. (2011) introduced discourse role matrix to represent discourse coherence of a text. W first illustrate their model with an example, and then introduce two new feature sources. We then apply the models and evaluate summary readability.

4.1 Lin et al.'s Discourse Coherence Model

First, a free text in Figure 2 is parsed by a discourse parser to derive its discourse relations, which are shown in Figure 3. Lin et al. observed that coherent texts preferentially follow certain relation patterns. However, simply using such patterns to measure the coherence of a text can result in feature sparseness. To solve this problem, they expand the relation sequence into a discourse role matrix, as shown in Table 2. The matrix essentially captures term occurrences in the sentence-to-sentence relation sequences. This model is motivated by the entity-based model (Barzilay and Lapata, 2008) which captures sentence-to-sentence entity transitions. Next, the discourse role transition probabilities of lengths 2 and 3 (*e.g.*, Temp.Arg1→Exp.Arg2 and Comp.Arg1→nil→Temp.Arg1) are calculated with respect to the matrix. For example, the probability of Comp.Arg2→Exp.Arg2 is $2/25 = 0.08$ in Table 2.

Lin et al. applied their model on the task of discerning an original text from a permuted ordering of its sentences. They modeled it as a pairwise ranking model (*i.e.*, original vs. permuted), and trained a SVM preference ranking model with discourse role transitions as features and their probabilities as values.

S_1 Japan normally depends heavily on the Highland Valley and Cananea mines as well as the Bougainville mine in Papua New Guinea.
S_2 Recently, Japan has been buying copper elsewhere.
$S_{3.1}$ But as Highland Valley and Cananea begin operating,
$S_{3.2}$ they are expected to resume their roles as Japan's suppliers.
$S_{4.1}$ According to Fred Demler, metals economist for Drexel Burnham Lambert, New York,
$S_{4.2}$ "Highland Valley has already started operating
$S_{4.3}$ and Cananea is expected to do so soon."

Figure 2: A text with four sentences. $S_{i.j}$ means the jth clause in the ith sentence.

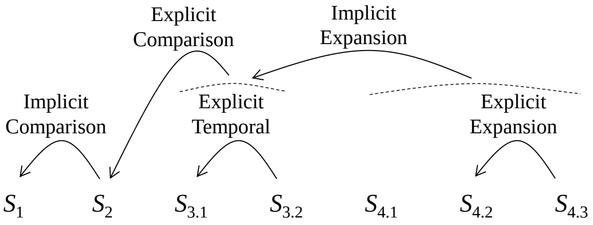


Figure 3: The discourse relations for Figure 2. Arrows are pointing from Arg2 to Arg1.

S#	Terms				
	copper	cananea	operat	depend	…
S_1	nil	Comp.Arg1	nil	Comp.Arg1	
S_2	Comp.Arg2 Comp.Arg1	nil	nil	nil	
S_3	nil	Comp.Arg2 Temp.Arg1 Exp.Arg1	Comp.Arg2 Temp.Arg1 Exp.Arg1	nil	
S_4	nil	Exp.Arg2	Exp.Arg1 Exp.Arg2	nil	

Table 2: Discourse role matrix fragment extracted from Figure 2 and 3. Rows correspond to sentences, columns to stemmed terms, and cells contain extracted discourse roles. Temporal, Contingency, Comparison, and Expansion are shortened to Temp, Cont, Comp, and Exp, respectively.

4.2 Two New Feature Sources

We observe that there are two kinds of information in Figure 3 that are not captured by Lin et al.'s model. The first one is whether a relation is Explicit or Non-Explicit (Lin et al. (2010) termed Non-Explicit to include Implicit, AltLex, EntRel, and NoRel). Explicit relation and Non-Explicit relation have different distributions on each discourse relation (PDTB-Group, 2007). Thus, adding this information may further improve the model. In addition to the set of the discourse roles of "Relation type . Argument tag", we introduce another set of "Explicit/Non-Explicit . Relation type . Argument tag". The cell $C_{cananea,S_3}$ now contains Comp.Arg2, Temp.Arg1, Exp.Arg1, E.Comp.Arg2, E.Temp.Arg1, and N.Exp.Arg1 (E for Explicit and N for Non-Explicit).

The other information that is not in the discourse role matrix is the discourse hierarchy structure, *i.e.*, whether one relation is embedded within another relation. In Figure 3, $S_{3.1}$ is Arg1 of Explicit Temporal, which is Arg2 of the higher relation Explicit Comparison as well as Arg1 of another higher relation Implicit Expansion. These dependencies are important for us to know how well-structured a summary is. It is represented by the multiple discourse roles in each cell of the matrix. For example, the multiple discourse roles in the cell $C_{cananea,S_3}$ capture the three dependencies just mentioned. We introduce intra-cell bigrams as a new set of features to the original model: for a cell with multiple discourse roles, we sort them by their surface strings and multiply to obtain the bigrams. For instance, $C_{cananea,S_3}$ will produce bigrams such as Comp.Arg2↔Exp.Arg1 and Comp.Arg2↔Temp.Arg1. When both the Explicit/Non-Explicit feature source and the intra-cell feature source are joined together, it also produces bigram features such as E.Comp.Arg2↔Temp.Arg1.

4.3 Predicting Readability Scores

Lin et al. (2011) used the SVM^{light} (Joachims, 1999) package with the preference ranking configuration. To train the model, each source text and one of its permutations form a training pair, where the source text is given a rank of 1 and the permutation is given 0. In testing, the trained model predicts a real number score for each instance, and the instance with the higher score in a pair is said to be the source text.

In the TAC summarization track, human judges scored each model and candidate summary with a readability score from 1 to 5 (5 means most readable). Thus in our setting, instead of a pair of texts, the training input consists of a list of model and candidate summaries from each topic, with their annotated scores as the rankings. Given an unseen test summary, the trained model predicts a real number score. This score essentially is the readability ranking of the test summary. Such ranking can be evaluated by the ranking-based correlations of Spearman's ρ and Kendall's τ. As Pearson's r measures linear correlation and we do not know whether the real number score follows a linear function, we take the logarithm of this score as the readability score for this instance.

We use the data from AESOP 2009 and 2010 as the training data, and test our metrics on AESOP 2011 data. To obtain the discourse relations of a summary, we use the discourse parser[2] developed in Lin et al. (2010).

4.4 Experiments

Table 3 shows the resulting readability correlations. The last four rows show the correlation scores for our coherence model: LIN is the default model by (Lin et al., 2011), LIN+C is LIN with the intra-cell feature class, LIN+E is enhanced with the Explicit/Non-Explicit feature class. We name the LIN model with both new feature sources (i.e., LIN+C+E) DICOMER – a DIscourse COherence Model for Evaluating Readability.

LIN outperforms all metrics on all correlations on both tasks. On the initial task, it outperforms the best scores by 3.62%, 16.20%, and 12.95% on Pearson, Spearman, and Kendall, respectively. Similar gaps (4.27%, 18.52%, and 13.96%) are observed on the update task. The results are much better on Spearman and Kendall. This is because LIN is trained with a ranking model, and both Spearman and Kendall are ranking-based correlations.

Adding either intra-cell or Explicit/Non-Explicit features improves all correlation scores, with Explicit/Non-Explicit giving more pronounced improvements. When both new feature sources are in-

[2] http://wing.comp.nus.edu.sg/~linzihen/parser/

	Initial			Update		
	P	S	K	P	S	K
R-2	0.7524	0.3975	0.2925	0.6580	0.3732	0.2635
R-SU4	0.7840	0.3953	0.2925	0.6716	0.3627	0.2540
BE	0.7171	0.4091	0.2911	0.5455	0.2445	0.1622
4	0.8194	0.4937	0.3658	0.7423	0.4819	0.3612
6	0.7840	0.4070	0.3036	0.6830	0.4263	0.3141
12	0.7944	0.4973	0.3589	0.6443	0.3991	0.3062
18	0.7914	0.4746	0.3510	0.6698	0.3941	0.2856
23	0.7677	0.4341	0.3162	0.7054	0.4223	0.3014
LIN	**0.8556**	**0.6593**	**0.4953**	**0.7850**	**0.6671**	**0.5008**
LIN+C	**0.8612**	**0.6703**	**0.4984**	**0.7879**	**0.6828**	**0.5135**
LIN+E	**0.8619**	**0.6855**	**0.5079**	**0.7928**	**0.6990**	**0.5309**
DICOMER	**0.8666**	**0.7122**	**0.5348**	**0.8100**	**0.7145**	**0.5435**

Table 3: Readability correlation with human judgment on summarizer level. Top three scores among AESOP metrics are underlined. Our score is bolded when it outperforms all AESOP metrics.

		Initial			Update		
	vs.	P	S	K	P	S	K
LIN	4	∗	∗∗	∗∗	∗∗	∗∗	∗∗
LIN+C		∗∗	∗∗	∗∗	∗∗	∗∗	∗∗
LIN+E		∗∗	∗∗	∗∗	∗	∗∗	∗∗
DICOMER		∗∗	∗∗	∗∗	∗∗	∗∗	∗∗
DICOMER	LIN	–	∗	∗	∗	–	–

Table 4: Koehn's significance test for readability. ∗∗, ∗, and – indicate significance level >=99%, >=95%, and <95%, respectively.

corporated into the metric, we obtain the best results for all correlation scores: DICOMER outperforms LIN by 1.10%, 5.29%, and 3.95% on the initial task, and 2.50%, 4.74%, and 4.27% on the update task.

Table 3 shows that summarization evaluation Metric 4 tops all other AESOP metrics, except in the case of Spearman's ρ on the initial task. We compare our four models to this metric. The results of Koehn's significance test are reported in Table 4, which demonstrates that all four models outperform Metric 4 significantly. In the last row, we see that when comparing DICOMER to LIN, DICOMER is significantly better on three correlation measures.

5 CREMER: Evaluating Overall Responsiveness

With TESLA-S measuring content coverage and DICOMER measuring readability, it is feasible to combine them to predict the overall responsiveness of a summary. There exist many ways to combine two variables mathematically: we can combine them in a linear function or polynomial function, or in a way similar to how precision and recall are combined in F measure. We applied a machine learning approach to train a regression model for measuring responsiveness. The scores predicted by TESLA-S and DICOMER are used as two features. We use SVM^{light} with the regression configuration, testing three kernels: linear function, polynomial function, and radial basis function. We called this model CREMER – a Combined REgression Model for Evaluating Responsiveness.

	Initial			Update		
	P	S	K	P	S	K
R-2	0.9416	0.7897	0.6096	0.9169	0.8401	0.6778
R-SU4	0.9545	0.7902	0.6017	0.9123	0.8758	0.7065
BE	0.9155	0.7683	0.5673	0.8755	0.7964	0.6254
4	0.9498	0.8372	0.6662	0.8706	0.8674	0.7033
6	0.9512	0.7955	0.6112	0.9271	0.8769	0.7160
11	0.9427	0.7873	0.6064	0.9194	0.8432	0.6794
12	0.9469	0.8450	0.6746	0.8728	0.8611	0.6858
18	0.9480	0.8447	0.6715	0.8912	0.8377	0.6683
23	0.9317	0.7952	0.6080	0.9192	0.8664	0.6953
25	0.9512	0.7899	0.6033	0.9033	0.8139	0.6349
CREMER$_{LF}$	0.9381	0.8346	0.6635	0.8280	0.6860	0.5173
CREMER$_{PF}$	**0.9621**	**0.8567**	**0.6921**	0.8852	0.7863	0.6159
CREMER$_{RBF}$	**0.9716**	**0.8836**	**0.7206**	0.9018	0.8285	0.6588

Table 5: Responsiveness correlation with human judgment on summarizer level. Top three scores among AESOP metrics are underlined. CREMER score is bolded when it outperforms all AESOP metrics.

We train the regression model on AESOP 2009 and 2010 data sets, and test it on AESOP 2011. The DICOMER model that is trained in Section 4 is used to predict the readability scores on all AESOP 2009, 2010, and 2011 summaries. We apply TESLA-S to predict content scores on all AESOP 2009, 2010, and 2011 summaries.

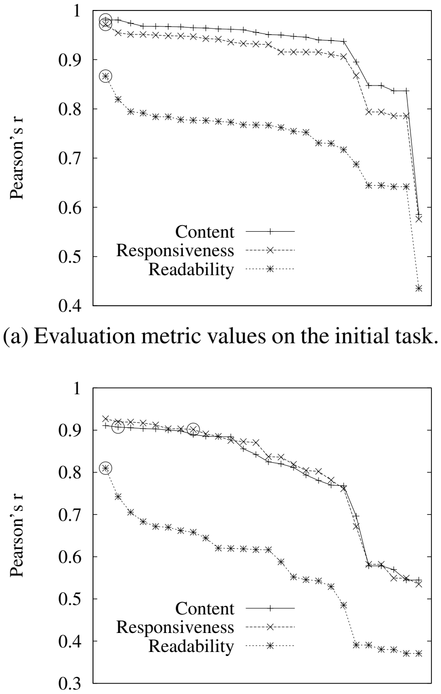
5.1 Experiments

The last three rows in Table 5 show the correlation scores of our regression model trained with SVM linear function (LF), polynomial function (PF), and radial basis function (RBF). PF performs better than LF, suggesting that content and readability scores should not be linearly combined. RBF gives better performances than both LF and PF, suggesting that RBF better models the way humans combine content and readability. On the initial task, the model trained with RBF outperforms all submitted metrics. It outperforms the best correlation scores by 1.71%, 3.86%, and 4.60% on Pearson, Spearman, and Kendall, respectively. All three regression models do not perform as well on the update task. Koehn's significance test shows that when trained with RBF, CREMER outperforms ROUGE-2 and ROUGE-SU4 on the initial task at a significance level of 99% for all three correlation measures.

6 Discussion

The intuition behind the combined regression model is that combining the readability and content scores will give an overall good responsiveness score. The function to combine them and their weights can be obtained by training. While the results showed that SVM radial basis kernel gave the best performances, this function may not truly mimic how human evaluates responsiveness. Human judges were told to rate summaries by their overall qualities. They may take into account other aspects besides content and readability. Given CREMER did not perform well on the update task, we hypothesize that human judgment of update summaries may involve more complicated rankings or factor in additional input that CREMER currently does not model. We plan to devise a better responsiveness metric in our future work, beyond using a simple combination.

Figure 4 shows a complete picture of Pearson's r for all AESOP 2011 metrics and our three metrics on both initial and update tasks. We highlight our metrics with a circle on these curves. On the initial task, correlation scores for content are consistently higher than those for responsiveness with small gaps, whereas on the update task, they are almost overlapping. On the other hand, correlation scores for readability are much lower than those for content and responsiveness, with a gap of about 0.2. Comparing Figure 4a and 4b, evaluation metrics always correlate better on the initial task than on the update task. This suggests that there is much room for improvement for readability metrics, and metrics need to consider update information when evaluating update summarizers.



(a) Evaluation metric values on the initial task.

(b) Evaluation metric values on the update task.

Figure 4: Pearson's r for all AESOP 2011 submitted metrics and our proposed metrics. Our metrics are circled. Higher r value is better.

7 Conclusion

We proposed TESLA-S by adapting an MT evaluation metric to measure summary content coverage, and introduced DICOMER by applying a discourse coherence model with newly introduced features to evaluate summary readability. We combined these two metrics in the CREMER metric – an SVM-trained regression model – for automatic summarization overall responsiveness evaluation. Experimental results on AESOP 2011 show that DICOMER significantly outperforms all submitted metrics on both initial and update tasks with large gaps, while TESLA-S and CREMER significantly outperform all metrics on the initial task. [3]

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[3] Our metrics are publicly available at `http://wing.comp.nus.edu.sg/~linzihen/summeval/`.

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