Corroborating Text Evaluation Results with Heterogeneous Measures

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1 Introduction

The automatic evaluation of textual outputs is a core issue in many Natural Language Processing (NLP) tasks such as Natural Language Generation, Machine Translation (MT) and Automatic Summarization (AS). State-of-the-art automatic evaluation methods all operate by rewarding similarities between automatically-produced candidate outputs and manually-produced reference solutions, so-called human references or models.

Over the last decade, a wide variety of measures, based on different quality assumptions, have been proposed. Recent work suggests exploiting external knowledge sources and/or deep linguistic annotation, and measure combination (see Section 2). However, original measures based on lexical matching, such as BLEU (Papineni et al., 2001a) and ROUGE (Lin, 2004) are still preferred as de facto standards in MT and AS, respectively. There are, in our opinion, two main reasons behind this fact. First, the use of a common measure certainly allows researchers to carry out objective comparisons between their work and other published results. Second, the advantages of novel measures are not easy to demonstrate in terms of correlation with human judgements.

Our goal is not to answer which is the most reliable metric or to propose yet another novel measure. Rather than this, we first analyze in depth the state of the art in order to clarify this issue. After this, we formalize and verify empirically a set of properties that every text evaluation measure based on similarity to human-produced references satisfies. These properties imply that corroborating system improvements with additional measures always increases the overall reliability of the evaluation process. In addition, the greater the heterogeneity of the measures (which is measurable) the higher their combined reliability. These results support the use of heterogeneous measures in order to consolidate text evaluation results.
the measures (which is measurable) the higher their reliability. The practical implication is that, corroborating evaluation results with measures based on higher linguistic levels increases the heterogeneity, and therefore, the reliability of evaluation results.

2 State of the Art

2.1 Individual measures

Among NLP disciplines, MT probably has the widest set of automatic evaluation measures. The dominant approach to automatic MT evaluation is, today, based on lexical metrics (also called \(n\)-gram based metrics). These metrics work by rewarding lexical similarity between candidate translations and a set of manually-produced reference translations. Lexical metrics can be classified according to how they compute similarity. Some are based on edit distance, e.g., WER (Nießen et al., 2000), PER (Tillmann et al., 1997), and TER (Snover et al., 2006). Other metrics are based on computing lexical precision, e.g., BLEU (Papineni et al., 2001b) and NIST (Doddington, 2002), lexical recall, e.g., ROUGE (Lin and Och, 2004a) and CDER (Leusch et al., 2006), or a balance between the two, e.g., GTM (Melamed et al., 2003; Turian et al., 2003b), METEOR (Banerjee and Lavie, 2005), BLANC (Lita et al., 2005), SIA (Liu and Gildea, 2006), MAXSIM (Chan and Ng, 2008), and \(O_1\) (Giménez, 2008).

The lexical measure BLEU has been criticized in many ways. Some drawbacks of BLEU are the lack of interpretability (Turian et al., 2003a), the fact that it is not necessary to increase BLEU to improve systems (Callison-Burch and Osborne, 2006), the over-scoring of statistical MT systems (Le and Przybocki, 2005), the low reliability over rich morphology languages (Homola et al., 2009), or even the fact that a poor system translation of a book can obtain higher BLEU results than a manually produced translation (Culy and Riehemann, 2003).

The reaction to these criticisms has been focused on the development of more sophisticated measures in which candidate and reference translations are automatically annotated and compared at different linguistic levels. Some of the features employed include parts of speech (Popovic and Ney, 2007; Giménez and Márquez, 2007; Owczarzak et al., 2007a; Owczarzak et al., 2007b; Owczarzak et al., 2008; Chan and Ng, 2008; Kahn et al., 2009), CCG parsing (Mehay and Brew, 2007), syntactic constituents (Liu and Gildea, 2005; Giménez and Márquez, 2007), named entities (Reeder et al., 2001; Giménez and Márquez, 2007), semantic roles (Giménez and Márquez, 2007), discourse representations (Giménez, 2008), and textual entailment features (Padó et al., 2009). In general, when a higher linguistic level is incorporated, linguistic features at lower levels are preserved.

The proposals for summarization evaluation are less numerous. Some proposals for AS tasks are based on syntactic units (Tratz and Hovy, 2008), dependency triples (Owczarzak, 2009) or convolution kernels (Hirao et al., 2005) which reported some reliability improvement over ROUGE in terms of correlation with human judgements.

In general, however, it is not easy to determine clearly the contribution of deeper linguistic knowledge in those proposals. In the case of MT, improvements versus BLEU have been reported (Liu and Gildea, 2005; Kahn et al., 2009), but not over a more elaborated metric such as METEOR (Mehay and Brew, 2007; Chan and Ng, 2008). Besides, controversial results on their performance at sentence vs system level have been reported in shared evaluation tasks (Callison-Burch et al., 2008; Callison-Burch et al., 2009; Callison-Burch et al., 2010).

2.2 Combined measures

Several researchers have suggested integrating heterogeneous measures. Some of them optimize the measure combination function according to the metric’s ability to emulate the behavior of human assessors (i.e., correlation with human assessments). For instance, using linear combinations (Padó et al., 2009; Liu and Gildea, 2007; Giménez and Márquez, 2008), Decision Trees (Akiba et al., 2001; Quirk, 2004), regression based algorithms (Paul et al., 2007; Albrecht and Hwa, 2007a; Albrecht and Hwa, 2007b) or a variety of supervised machine learning algorithms (Quirk et al., 2005; Corston-Oliver et al., 2001; Kulesza and Shieber, 2004; Gamon et al., 2005; Amigó et al., 2005).

Some of these works report evidence on the contribution of combining heterogeneous measures. For instance, Albrecht and Hwa included syntax-based
measures together with lexical measures, outperforming other combination schemes (Albrecht and Hwa, 2007a; Albrecht and Hwa, 2007b). Liu and Gildea, after examining the contribution of each component metric, found that “metrics showing different properties of a sentence are more likely to make a good combined metric” (Liu and Gildea, 2007). Akiba et al., which combined multiple edit-distance features based on lexical, morphosyntactic and lexical semantic information, observed that their approach improved single editing distance for several data sets (Akiba et al., 2001). More evidence was provided by Corston and Oliver. They showed that results on the task of discriminating between manual and automatic translations improve when combining linguistic and \( n \)-gram based features. In addition, they showed that this mixed combination improved over the combination of linguistic or \( n \)-gram based measures alone (Corston-Oliver et al., 2001). (Padó et al., 2009) reported a reliability improvement by including measures based on textual entailment in the set. In (Giménez and Márquez, 2008), a simple arithmetic mean of scores for combining measures at different linguistic levels was applied with remarkable results in recent shared evaluation tasks (Callison-Burch et al., 2010).

2.3 Meta-evaluation criteria

Meta-evaluation methods have been gradually introduced together with evaluation measures. For instance, Papineni et al. (2001b) evaluated the reliability of the BLEU metric according to its ability to emulate human assessors, as measured in terms of Pearson correlation with human assessments of adequacy and fluency at the document level. The measure NIST (Doddington, 2002) was meta-evaluated also in terms of correlation with human assessments, but over different document sources and for a varying number of references and segment sizes. Melamed et al. (2003) argued, at the time of introducing the GTM metric, that Pearson correlation coefficients can be affected by scale properties. They suggested using the non-parametric Spearman correlation coefficients instead. Lin and Och meta-evaluated ROUGE over both Pearson and Spearman correlation over a wide set of metrics, including NIST, WER, PER, and variants of ROUGE, BLEU and GTM. They obtained similar results in both cases (Lin and Och, 2004a). Banerjee and Lavie (2005) argued that the reliability of metrics at the document level can be due to averaging effects but might not be robust across sentence translations. In order to address this issue, they computed the translation-by-translation correlation with human assessments (i.e., correlation at the sentence level).

However, correlation with human judgements is not enough to determine the reliability of measures. First, correlation at sentence level (unlike correlation at system level) tends to be low and difficult to interpret. Second, correlation at system and segment levels can produce contradictory results. In (Amigó et al., 2009) it is observed that higher linguistic levels in measures increases the correlation with human judgements at the system level at the cost of correlation at the segment level. As far as we know, a clear explanation for these phenomena has not been provided yet.

Third, a high correlation at system level does not ensure a high reliability. Culy and Riehemann observed that, although BLEU can achieve a high correlation at system level in some test suites, it over-scores a poor automatic translation of “Tom Sawyer” against a human produced translation (Culy and Riehemann, 2003). This meta-evaluation criterion based on the ability to discern between manual and automatic translations have been referred to as human likeness (Amigó et al., 2006), in contrast to correlation with human judgements which is referred to as human acceptability. Examples of meta-measures based on this criterion are ORANGE (Lin and Och, 2004b) and KING (Amigó et al., 2005). In addition, many of the approaches to metric combination described in Section 2.2 take human likeness as the optimization criterion (Corston-Oliver et al., 2001; Kulesza and Shieber, 2004; Gamon et al., 2005). The main advantage of meta-evaluation based on human likeness is that, since human assessments are not required, metrics can be evaluated over larger test beds. However, the meta-evaluation in terms of human likeness is difficult to interpret.

2.4 The use of evaluation measures

In general, the state of the art includes a wide set of results that show the drawbacks of \( n \)-gram based measures as BLEU, and a wide set of proposals for new single and combined measures which are meta-
evaluated in terms of human acceptability (i.e., their ability to emulate human judges, typically measured in terms of correlation with human judgements) or human-likeness (i.e., their ability to discern between automatic and human translations) (Amigó et al., 2006). However, the original measures BLEU and ROUGE are still preferred.

We believe that one of the reasons is the lack of an in-depth study on to what extent providing additional evaluation results with other metrics contributes to the reliability of such results. The state of the art suggests that the use of heterogeneous measures can improve the evaluation reliability. However, as far as we know, there is no comprehensive analysis on the contribution of novel measures when corroborating evaluation results with additional measures.

### 3 Similarity Based Evaluation Measures

In general, automatic evaluation measures applied in tasks like MT or AS are similarity measures between system outputs and human references. These measures are related with precision, recall or overlap over specific types of linguistic units. For instance, ROUGE measures n-gram recall. Other measures that work at higher linguistic levels apply precision, recall or overlap of linguistic components such as dependency relations, grammatical categories, semantic roles, etc.

In order to delimit our hypothesis, let us first define what is a similarity measure in this context. Unfortunately, as far as we know, there is no formal concept covering the properties of current evaluation similarity measures. A close concept is that of “metric” or “distance function”. But, actually, measures such as ROUGE or BLEU are not proper “metrics”, because they do not satisfy the symmetry and the triangle inequality properties. Therefore, we need a new definition.

Being $\Omega$ the universe of system outputs $s$ and gold-standards $g$, we assume that a similarity measure, in our context, is a function $x : \Omega^2 \rightarrow \mathbb{R}$ such that there exists a decomposition function $f : \Omega \rightarrow \{e_1, \ldots, e_n\}$ (e.g., words or other linguistic units or relationships) satisfying the following constraints: (i) maximum similarity is achieved only when then the decomposition of the system output resembles exactly the gold-standard decomposition; and (ii) growing overlap or removing non overlapped elements implies growing $x$. Formally, if $x$ ranges from 0 to 1:

$$f(s) = f(g) \Leftrightarrow x(s, g) = 1$$

$$(f(s) = f(s') \cup \{e \in f(g) \setminus f(s')\}) \rightarrow x(s, g) > x(s', g)$$

$$(f(s) = f(s') \setminus \{e \in f(s') \setminus f(g)\}) \rightarrow x(s, g) > x(s', g)$$

For instance, a random function and the reversal of a similarity function ($f'(s) = \frac{1}{f(s)}$) do not satisfy these constraints. While the F measure over Precision and Recall satisfies these constraints\(^1\), precision and recall in isolation do not satisfy all of them: maximum recall can be achieved without resembling the goldstandard text decomposition; and maximum precision can be achieved with only a few overlapped elements.

BLEU (Papineni et al., 2001a) computes the n-gram precision while the metric ROUGE (Lin and Och, 2004a) computes the n-gram recall. However, in general, both metrics satisfy all the constraints, given that BLEU includes a brevity penalty and ROUGE penalizes or limits the system output length. The measure METEOR creates an alignment between the two strings (Banerjee and Lavie, 2005). This overlap-based measure satisfies also the previous constraints. Measures based on edit distance over n-grams (Tillmann et al., 1997; Nießen et al., 2000) or other linguistic units (Akiba et al., 2001; Popovic and Ney, 2007) match also our definition of similarity measure. The editing distance is minimum when the two compared text are equal. The more the evaluated text contains elements from the gold-standard the more the editing distance is reduced (higher similarity). The word ordering can be also expressed in terms of a decomposition function. A similar reasoning applies to every relevant measure in the state-of-the-art.

### 4 Data Sets and Measures

#### 4.1 Data sets

In this paper, we provide empirical results for MT and AS. For MT, we use the data sets from the Arabic-to-English (AE) and Chinese-to-English (CE) NIST MT Evaluation campaigns in 2004 and

\(^1\)There is an exception. In an extreme case, when recall is zero, removing non overlapped elements does not modify the F measure.
Both include two translations exercises: for the 2005 campaign we contacted each participant individually and asked for permission to use their data\(^3\). In our experiments, we take the sum of adequacy and fluency, both in a 1-5 scale, as a global measure of quality (LDC, 2005). Thus, human assessments are in a 2-10 scale. For AS, we have used the AS test suites developed in the DUC 2005 and DUC 2006 evaluation campaigns\(^4\). This AS task was to generate a question focused summary of 250 words from a set of 25-50 documents to a complex question. Summaries were evaluated according to several criteria. Here, we will consider the responsiveness judgements, in which the quality score was an integer between 1 and 5. See Tables 1 and 2 for a brief quantitative description of these test beds.

\(^2\)http://www.nist.gov/speech/tests/mt

\(^3\)We are grateful to a number of groups and companies who responded positively: University of Southern California Information Sciences Institute (ISI), University of Maryland (UMD), Johns Hopkins University & University of Cambridge (JHU-CU), IBM, University of Edinburgh, University of Aachen (RWTH), National Research Council of Canada (NRC), Chinese Academy of Sciences Institute of Computing Technology (ICT), Instituto Trentino di Cultura - Centro per la Ricerca Scientifica e Tecnologica(ITC-IRST), MITRE.

\(^4\)http://duc.nist.gov/

\(^5\)http://www.lsi.upc.edu/~nlp/Asiya

### 4.2 Measures

As for evaluation measures, for MT we have used a rich set of 64 measures provided within the ASIYA Toolkit (Giménez and Márquez, 2010)\(^5\). This includes measures operating at different linguistic levels: lexical, syntactic, and semantic. At the lexical level this set includes variants of 8 measures employed in the state of the art: BLEU, NIST, GTM, METEOR, ROUGE, WER, PER and TER. In addition, we have included a basic measure \(O\) that computes the lexical overlap without considering word ordering. All these measures have similar granularity. They use \(n\)-grams of a varying length as the basic unit with additional information provided by linguistic tools. The underlying similarity criteria include precision, recall, overlap, or edit rate, and the decomposition functions include words, dependency tree nodes (DP,HWC, DP-Or, etc.), constituency parsing (CP-STM), discourse roles (DR-Or), semantic roles (SR-Or), named entities, etc. Further details on the measure set may be found in the ASIYA technical manual (Giménez and Márquez, 2010).

According to our computations, our measures cover high and low correlations at both levels. Correlation at system level spans between 0.63 and 0.95. Correlations at sentence level ranges from 0.18 up to 0.54. We will discriminate between two subsets of
measures. The first one includes those that decom-
pose the text into words, n-grams, stems or lexical
semantic tags. This set includes BLEU, ROUGE,
NIST, GTM, PER and WER families. We will re-
fer to them as “lexical” measures. The second set
are those that consider deeper linguistic levels such
as parts of speech, syntactic dependencies, syntactic
constituents, etc. We will refer to them as “linguis-
tic” measures.

In the case of automatic summarization (AS), we
have employed the standard variants of ROUGE
(Lin, 2004). These 7 measures are ROUGE-{1..4},
ROUGE-SU, ROUGE-L and ROUGE-W. In addi-
tion we have included the reversed precision ver-
cion for each variant and the F measure of both. Notice
that the original ROUGE measures are oriented to
recall. In total, we have 21 measures for the sum-
marization task. All of them are based on n-gram
overlap.

5 Additive reliability

As discussed in Section 2, a number of recent pub-
llications address the problem of measure combi-
nation with successful results, specially when het-
erogeneous measures are combined. The following
property clarifies this issue and justifies the use of
heterogeneous measures when corroborating evalua-
tion results. It asserts that the reliability of system
improvements always increases when the evaluation
result is corroborated by an additional similarity
measure, regardless of the correlation achieved by
the additional measure in isolation.

For the sake of clarity, in the rest of the paper,
we will denote the similarity \( x(s, g) \) between sys-
tem output \( s \) and human reference \( g \) by \( x(s) \).
The quality of a system output \( s \) will be referred to as
\( Q(s) \). Let us define the reliability \( R(X) \) of a mea-
sure set as the probability of a real improvement (as
measured by human judges) when a score improve-
ment is observed simultaneously for all measures in
the set \( X \).

\[
R(X) \equiv P(Q(s) \geq Q(s') | x(s) \geq x(s') \forall x \in X)
\]

According to this definition, we may not be able
to predict the quality of any system output (i.e. a
translation) with a highly reliable measure set, but
we can ensure a system improvement when all mea-
sures corroborate the result. Then the additive relia-
bility property can be stated as:

\[
R(X \cup \{x\}) \geq R(X)
\]

We could think of violating this property by
adding, for instance, a measure consisting of a ran-
don function \( x'(s) = \text{rand}(0..1) \) or a reversal of
the original measure \( x'(s) = 1/x(s) \). These kind
of measures, however, would not satisfy the con-
straints defined in Section 3.

This property is based on the idea that similarity
with human references according to any aspect
should not imply statistically a quality decrease. Al-
though our test suites includes measures with low
correlation at segment and system level, we can con-
firm empirically that all of them satisfy this property.

We have developed the following experiment:
taking all possible measure pairs in the test suites,
we have compared their reliability as a set versus the
maximal reliability of any of them (by computing
the difference \( R(X) - \text{max}(R(x_1), R(x_2)) \)). Figure
1 shows the obtained distribution of this difference
for our MT and AS test suites. Remarkably, in al-
most every case this difference is positive.

This result has a key implication: Corroborating
evaluation results with a new measure, even when
it has lower correlation with human judgements,
increases the reliability of results. Therefore, if the
correlation with judgements is not determinant, the
question is now what factor determines the contri-
bution of the new measures. According to the fol-
lowing property, this factor is the heterogeneity of
measures.

6 Heterogeneity

This property states that the reliability of any mea-
sure combination is lower bounded by the hetero-
genecity of the measure set. In other words, a single
measure can be more or less reliable, but a system
improvement according to all measures in an het-
erogeneous set is reliable.

Let us define the heterogeneity \( H(X) \) of a set of
measures \( X \) as, given two system outputs \( s \) and \( s' \)
such that \( g \neq s \neq s' \neq g \) (\( g \) is the reference
text), the probability that there exist two measures that
contradict each other. That is:

\[
H(X) \equiv P(\exists x, x' \in X. x(s) > x(s') \land x'(s) < x'(s'))
\]
Thus, given a set $X$ of measures, the property states that there exists a strict growing function $F$ such that:

$$R(X) \geq F(H(X)) \quad \text{and} \quad H(X) = 1 \rightarrow R(X) = 1$$

In other words, the more the similarity measures tend to contradict each other, the more a unanimous improvement over all similarity measures is reliable. Clearly, the harder it is that measures agree, the more meaningful it is when they do.

The first part is derived from the Additive Reliability property. Intuitively, any individual measure has zero heterogeneity. Increasing the heterogeneity implies joining measures or measure sets progressively. According to the Additive Reliability property, this joining implies a reliability increase. Therefore, the higher the heterogeneity, the higher the minimum Reliability achieved by the corresponding measure sets.

The second part is derived from the Heterogeneity definition. If $H(X) = 1$ then, for any distinct pair of outputs that differ from the reference, there exist at least two measures in the set contradicting each other. That is, $H(X) = 1$ implies that:

$$\forall s \neq s' \neq g(\exists x, x' \in X.x(s) > x(s') \land x'(s) < x'(s'))$$

Therefore, if one output improves the other according to all measures, then the output must be equal than the reference.

$$\neg(\exists x, x' \in X.x(s) > x(s') \land x'(s) < x'(s')) \rightarrow g = s \lor g = s'$$

According to the first constraint of similarity measures, a text that is equal to the reference achieves the maximum score:

$$g = s \rightarrow f(g) = g(s) \rightarrow \forall x.x(s) \geq x(s')$$

Finally, if we assume that the reference (human produced texts) has a maximum quality, then it will have equal or higher quality than the other output.

$$g = s \rightarrow Q(s) \geq Q(s')$$

Therefore, the reliability of the measure set is maximal. In summary, if $H(X) = 1$ then:

$$R(X) = P(Q(s) \geq Q(s') | x(s) \geq x(s') \forall x \in X) = \left[ P(Q(s) \geq Q(s') | s = g) = 1 \right]$$

Figures 2 and 3 show the relationship between the heterogeneity of randomly selected measure sets and their reliability for the MT and summarization test suites. As the figures show, the higher the heterogeneity, the higher the reliability of the measure set. The results in AS are less pronounced due to the redundancy in ROUGE measure.

Notice that the heterogeneity property does not necessarily imply a high correlation between reliability and heterogeneity. For instance, an ideal single measure would have zero heterogeneity and
achieve maximum reliability, appearing in the top left area. The property rather brings us to the following situation: let us suppose that we have a set of single measures available which achieve a certain range of reliability. We can improve our system according to any of these measures. Without human assessments, we do not know what is the most reliable measure. But if we combine them, increasing the heterogeneity, the minimal reliability of the selected measures will be higher. This implies that combining heterogeneous measures (e.g. at high linguistic levels) that do not achieve high correlation in isolation, is better than corroborating results with any individual measure alone, such as ROUGE and BLEU, which is the common practice in the state of the art.

The main drawback of this property is that increasing the heterogeneity implies a sensitivity reduction. For instance, if $H(X) = 0.9$, then only for 10% of output pairs in the corpus there exists an improvement according to all measures. In other words, unanimous evaluation results from heterogeneous measures are reliable but harder to achieve for the system developer. The next section investigates on this issue.

Finally, Figure 4 shows that linguistic measures increase the heterogeneity of measure sets. We have generated sets of metrics of size 1 to 10 made up by lexical or lexical and linguistic metrics. As the figure shows, in the second case, the measure sets achieve a higher heterogeneity.

7 Score thresholds vs. Additive Reliability

According to the previous properties, corroborating evaluation results with several measures increases the reliability of evaluation results at the cost of sensitivity. On the other hand, increasing the score threshold of a single measure should have a similar effect. Which is then the best methodology to improve reliability? In this section we provide experimental evidence on the relationship between both ways of increasing reliability: we have found that, corroborating evaluation results over single texts with additional measures is more reliable than requiring higher score differences according to any individual measure in the set. More specifically, we have found that the reliability of a measure set is higher than the reliability of each of the individual measures at a similar level of sensitivity.

Formally, we define the sensitivity $S(X)$ of a metric set $X$ as the probability of finding a score improvement within text pairs with a real (i.e. human assessed) quality improvement:

$$S(X) = P(x(s) \geq x(s') \forall x \in X | Q(s) \geq Q(s'))$$

Being $R_{th}(x)$ and $S_{th}(x)$ the reliability and sensitivity of a single measure $x$ for a certain increase score threshold $th$: 
The property that we want to check is that, at the same sensitivity level, combining measures is more reliable than increasing the score threshold of single measures:

\[ S(X) = S_{th}(x), x \in X \rightarrow R(X) \geq R_{th}(x) \]

Note that if we had a perfect measure \( x_p \) such that \( R(x_p) = S(x_p) = 1 \), then combining this measure with a low reliability measure \( x_l \) would produce a lower sensitivity, but the maximal reliability would be preserved.

In order to confirm empirically this property, we have developed the following experiment: (i) We compute the reliability and sensitivity of randomly chosen measure sets over single text pairs. We have generated sets of 2, 3, 5, 10, 20 and 40 measures. In the case of summarization corpora we have combined up to 20 measures. In addition, we compute also the heterogeneity \( H(X) \) of each measure set; (ii) Experimenting with different values for the threshold \( th \), we compute the reliability of single measures for all potential sensitivity levels; (iii) For each measure set, we compare the reliability of the measure set versus the reliability of single measures at the same sensitivity level. We will refer to this as the Reliability Gain:

\[ \text{Reliability Gain} = R(X) - \max \{ R_{th}(x) / x \in X \land S_{th}(x) = S(X) \} \]

If there are several reliability values with the same sensitivity for a given single measures, we choose the highest reliability value for the single measure.

Figures 5 and 6 illustrate the results for the MT and AS corpora. The horizontal axis represents the Heterogeneity of measure sets, while the vertical axis represents the reliability gain. Remarkably, the reliability gain is positive for all cases in our test suites. The maximum reliability gain is 0.34 in the case of MT and 0.08 for AS (note that summarization measures are more redundant in our corpora). In both test suites, the largest information gains are obtained with highly heterogeneous measure sets.

In summary, given comparable measures in terms of reliability, corroborating evaluation results with several measures is more effective than optimizing systems according to the best measure in the set. This empirical property provides an additional evidence in favour of the use of heterogeneous measures and, in particular, of the use of linguistic measures in combination with standard lexical measures.

8 Conclusions

In this paper, we have analyzed the state of the art in order to clarify why novel text evaluation measures
are not exploited by the community. Our first conclusion is that it is not easy to determine the reliability of measures, which is highly corpus-dependent and often contradictory when comparing correlation with human judgements at segment vs. system levels.

In order to tackle this issue, we have studied a number of properties that suggest the convenience of using heterogeneous measures to corroborate evaluation results. According to these properties, we can ensure that, even when if we can not determine the reliability of individual measures, corroborating a system improvement with additional measures always increases the reliability of the results. In addition, the more heterogeneous the measures employed (which is measurable), the higher the reliability of the results. But perhaps the most important practical finding is that the reliability at similar sensitivity levels by corroborating evaluation results with several measures is always higher than improving systems according to any of the combined measures in isolation.

These properties point to the practical advantages of considering linguistic knowledge (beyond lexical information) in measures, even if they do not achieve a high correlation with human judgements. Our experiments show that linguistic knowledge increases the heterogeneity of measure sets, which in turn increases the reliability of evaluation results when corroborating system comparisons with several measures.

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