A large-scale computational study of content preservation measures for
text style transfer and paraphrase generation

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Abstract

Text style transfer and paraphrasing of texts are actively growing areas of NLP, dozens of
methods for solving these tasks have been recently introduced. In both tasks, the system is
supposed to generate a text which should be semantically similar to the input text. There-
fore, these tasks are dependent on methods of measuring textual semantic similarity. How-
ever, it is still unclear which measures are the best to automatically evaluate content preserva-
tion between original and generated text. According to our observations, many researchers
still use BLEU-like measures, while there exist more advanced measures including neural-
based that significantly outperform classic approaches. The current problem is the lack of a
thorough evaluation of the available measures. We close this gap by conducting a large-scale
computational study by comparing 57 measures based on different principles on 19 annotated
datasets. We show that measures based on cross-encoder models outperform alternative
approaches in almost all cases. We also introduce the Mutual Implication Score (MIS), a
measure that uses the idea of paraphrasing as a bidirectional entailment and outperforms all
other measures on the paraphrase detection task and performs on par with the best measures in
the text style transfer task.

1 Introduction

Text style transfer (TST) and paraphrases genera-
tion (PG) are active areas of research in NLP, with
dozens of papers proposing new methods. These
methods could be applied for practical purposes,
such as supporting human writers, personalizing
digital assistants, or even creating artificial person-

Research and development of TST models re-
quire fast feedback loops, and they require fast and
reliable automatic quality measures. TST is hard
to evaluate for several reasons. First, golden an-
swers, even if available, are not the only valid way
to rewrite the text. Second, parallel corpora with
different styles do not emerge naturally and are
hard to find. This means that reference-based eval-
uation is often prohibitive and creates a need for
manual evaluation of TST or for clever automatic
measures.

The basic desired properties of TST are style
accuracy, content preservation, and fluency (Mir
et al., 2019). For many methods of unsupervised
TST, keeping the content of the original text and
automatically measuring its preservation is one of
the most difficult tasks (see e.g. Dale et al. (2021)).

During development, the only way to control
content preservation is to use automatic measures.
Such measure takes two sentences and return the
value which indicates the similarity of their con-
tent. More formally, the measure $\text{sim}$ quantifies
semantic relatedness of two utterances, an original
text $x$ and a style-transferred or paraphrased text $y$
: $\text{sim}(x, y) \rightarrow [0; 1]$. The measure $\text{sim}$ yields high
score for the pairs with similar content and low
score for ones with different content.

As Krishna et al. (2020) and Yamshchikov et al.
(2021) show, most TST works evaluate the content
preservation with BLEU (Papineni et al., 2002) or
similar measures based on word overlap between
two texts. The situation in PG is almost identical.
Most works including the most recent ones (Sun
et al., 2021; Fu et al., 2020) also still rely on BLEU.

Even though measures like BLEU, based on a
word or character-level n-grams are pretty intuitive
and straightforward, they don’t take into account
synonyms and distributively related words. More-
over, there already exist several pieces of evidence
that correlation of standard BLEU-like automatic
measures is relatively low (Briakou et al., 2021).
The recent development of vector representations
of textual information (Mikolov et al., 2013; Zhang
et al., 2019) and various ways to handle these vec-
tors provides room for improvement of the ap-
proaches to scoring the content preservation. It
is, therefore, crucial to perform a thorough analysis of all existing content preservation measures and to gather best practices from the top-performing approaches to create a new approach that could demonstrate stable performance in terms of both PG and TST tasks.

In this work, we further extend a comprehensive study of Yamshchikov et al. (2021) by analyzing a much more diverse set of measures including recently developed transformers-based ones, and also by proposing a new measure specially developed for TST and PG content preservation scoring. The contributions of our paper are as follows:

- We perform a large-scale evaluation of automatic content preservation measures for text style transfer and paraphrase generation tasks, which includes 57 measures applied to 9 paraphrasing datasets and 10 text style transfer datasets. To the best of our knowledge, this is the largest and the most comprehensive evaluation of this kind;
- We introduce Mutual Implication Score (MIS): a measure of content preservation based on predictions of NLI models in two directions. We show that it outperforms all known measures in paraphrase detection and shows consistently high results for TST. We opensource the model on Huggingface Model Hub.¹

The code for measures and experiments is released publicly.²

2 Related work

2.1 Measures of content preservation

There exists a large number of content preservation measures that can be classified into several groups. In this section, we describe all of these approaches. Refer to Figure 1 for a schematic description of all approaches.

Words or characters n-grams (ngram) The most simple and intuitive way to compare two texts is based on the overlap of word or character n-grams. The standard method used to evaluate the quality of a generated text is to compare it with a human-written reference text via BLEU score (Papineni et al., 2002), which is the precision of word n-grams. In TST and PG papers, BLEU is often used to evaluate content preservation relative to the original text or a reference. Other popular measures based on words or n-grams are ROUGE (Lin, 2004), METEOR (Banerjee and Lavie, 2005), chrF (Popović, 2015). Such approaches as Levenshtein distance (Levenshtein et al., 1966), Jaro-Winkler distance (Jaro, 1989) also work at the subword level by calculating the edit distance between two sequences, so we also refer them to the ngram group. Panchenko and Morozova (2012) provided a comparative study of classic word similarity measures and their combinations. The ngram measures are simple and intuitive but do not handle well such linguistic phenomena as synonyms, negation, and issues with word order.

Similarity between static embeddings (emb-static) Another family of measures partially overcomes these difficulties by representing texts with their embeddings and calculating the distance (e.g. cosine similarity) between the embeddings of two texts. This group of measures can be further divided by the way the embeddings are generated. The basic way of obtaining the embedding of a text is by averaging across static word embeddings: Word2vec (Mikolov et al., 2013), GloVe (Pennington et al., 2014), FastText (Bojanowski et al., 2017).

Similarity between contextualized embeddings (emb-context) Special distance function (e.g. WMD (Kusner et al., 2015), POS-distance (Tian et al., 2018a)) can be also applied to context-dependent vectors: BERTScore (Zhang et al., 2019), MoverScore (Zhao et al., 2019).

Similarity between embeddings from bi-encoders (emb-bi-enc) Embeddings of a text can be generated by encoding a text with a pre-trained encoder. If the two texts are encoded separately, and then we compute the cosine similarity between their embeddings, we refer to such models as bi-encoders. This group of models is usually trained in a supervised manner. The encoders can be trained on the translation task (Laser (Artetxe and Schwenk, 2019), LaBSE (Feng et al., 2020)), paraphrase identification task (SIMILE (Wieting et al., 2019)), or text generation task (BARTScore (Yuan et al., 2021)). They potentially can compare the meanings of texts that are very different in terms of structure and vocabulary.

¹https://huggingface.co/SkolkovoInstitute/Mutual_Implication_Score
²https://github.com/skoltech-nlp/mutual_implication_score
Symmetric and asymmetric cross-encoders (sym/asym-cross-enc) The models called cross-encoders process both texts simultaneously using cross-attention and directly predict the relationship between the texts. They can perform symmetrically (score is independent of the order of the texts being compared) or asymmetrically (score strongly depends on the order of the texts). Due to their supervised nature, such models can reflect content preservation more accurately than word-based approaches, but they depend on labeled data and may not generalize well to new domains. The presence of symmetry is defined by the task the model was trained on. Thus, models trained on the Natural Language Inference (NLI) task data (such as BLEURT (Sellam et al., 2020) or NUBIA (Kane et al., 2020)) are asymmetric, while cross-stsb-base model trained solely on STS-B dataset (Cer et al., 2017) for semantic textual similarity, or APD model (Nighojkar and Licato, 2021) trained on paraphrase datasets perform symmetrically.

Two-folded asymmetric cross-encoders (2x-asym-cross-enc) A textual entailment model can be used for scoring semantic relations between two phrases. Nighojkar and Licato (2021) propose to use a natural language inference (NLI) model for paraphrase identification, and Deng et al. (2021) suggest a similar model for evaluation of summarization and text style transfer. The main idea of these works is to use NLI models in a two-fold manner (direct and reverse). NLI models are generally asymmetric cross-encoders, so we classify this group of approaches as a two-fold asymmetric encoder.

As shown in Figure 2, despite the wide variety of measures, n-gram-based measures are still used most often, while embedding-based measures and cross-encoders are much less popular. In some papers, no automatic content preservation measures are used.

2.2 Evaluation of content preservation measures

Our work in many respects follows the setup of Yamshchikov et al. (2021) and extends it in several directions. In this work, the authors collected crowdsourc estimates of content preservation for 14,000 sentence pairs from 14 sources and compared these estimates with 13 automatic
measures. They evaluated the quality of automatic measures by the correlation between rankings provided by these measures and rankings created by human scores. This scoring showed that the WMD over GloVe embeddings and L2 distance between the ELMo embeddings outperform other measures. However, no supervised sentence encoders or cross-encoders were considered in this work.

In the work by Briakou et al. (2021), the authors evaluated measures of formality transfer in four languages. The main subject of this work is a thorough analysis of multilingual formality style transfer, including a high-level analysis of all aspects of style transfer quality: style accuracy, content preservation, and fluency. The authors used chrF and a cross-encoder (XLM-R) trained on a semantic text similarity dataset to calculate content preservation. They also cautioned against using BLEU in this context, because it has a lower correlation with human judgments than many other measures. However, automatic measures of content preservation were not the main focus of this work, so we extend its results by applying more diverse measures on the English part of their dataset, among others.

3 Datasets used in comparative study

We run our analysis of measures on parallel datasets manually labeled for semantic similarity or content preservation. To make the comparison more generalizable, we fetch a large number of datasets generated by different models.

3.1 Text style transfer datasets

The text style transfer task is aimed at transforming a text to change its style (a particular attribute of its text) while keeping the content intact. Since in some cases the style cannot be separated from the content (e.g. if the style is positive/negative sentiment), strict preservation of all content is sometimes impossible in the TST task. Therefore, we consider the parallel TST datasets separately from other data used for the analysis.

In many TST works, outputs were evaluated with human judgments, but the raw similarity labels are rarely published. We managed to find datasets that include human similarity scores for various TST tasks:

- **Detoxification:**
  - Tox600 (Dale et al., 2021),
  - CAE (Laugier et al., 2021)

- **Formality transfer:**
  - xformal-FoST (Briakou et al., 2021),
  - STRAP_form, (Krishna et al., 2020)
  - Yam. GYAFC (Yamshchikov et al., 2021)

- **Sentiment transfer:**
  - PG-YELP (Pang and Gimpel, 2019)
  - Yam. Yelp (Yamshchikov et al., 2021)

- **Transfer to Old English:**
  - Yam. Bible (Yamshchikov et al., 2021),
  - STRAP_coha (old American English), (Krishna et al., 2020)
  - STRAP_SP (Shakespearean English) (Krishna et al., 2020)

3.2 Paraphrases datasets

Unlike TST, the paraphrase generation task requires full preservation of content. There exist a large number of parallel datasets of paraphrases manually labelled for content preservation. The majority of them have binary labels (“same”/“different”). We use the following datasets in our analysis:

- **MSRP** (Dolan and Brockett, 2005),
- **Twitter-URL** (Lan et al., 2017),
- **PIT** (Xu et al., 2014),
- **PAWS** (Yang et al., 2019b),
- **ETPC** (Kovatchev et al., 2018),

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\(^3\)We use the datasets collected and/or used in the analysis by Yamshchikov et al. (2021). For clarity, we prepend their names with “Yam.” prefix.
4 Mutual Implication Score (MIS)

The goal of our research is not only to analyze the existing measures of content preservation but also to suggest a new measure that can outperform the existing ones. We devise a new measure that is based on measuring content similarity with NLI, as described by Nighojkar and Licato (2021). In this work, the authors exploit the assumption that implies the two sentences with the same meaning should be equivalent in their inferential properties, i.e. each sentence should textually entail the other. This means that the NLI model is supposed to return similar entailment scores when applied to semantically equal sentences regardless of the sequence these sentences are sent to the input of the model. The authors used this assumption to propose an adversarial method of dataset creation for paraphrase identification.

NLI models predict whether one text logically entails another, and are, therefore, asymmetric. High entailment probability in the forward direction means that the second text accurately follows the first one and does not contain hallucinated information. A high entailment score in the backward direction means that all the information from the first text is retained in the second text.

The most natural way to aggregate scores from both directions is to multiply them or compute their arithmetic or harmonic mean. We use this approach as a baseline. We yield NLI scores from the following models:

- RobNLI (Nie et al., 2020) — RoBERTA-Large (Zhuang et al., 2021) pre-trained on SNLI (Bowman et al., 2015), MNLI (Williams et al., 2018), FEVER-NLI (Nie et al., 2019), and ANLI (Nie et al., 2020),
- FBrobNLI (Liu et al., 2019) — RoBERTA-Large pre-trained only on MNLI,
- DeBERTa (He et al., 2021) pre-trained on the MNLI dataset.

Although these NLI models are a good starting point, they might not be fully suitable for measuring content preservation, because they were trained for a different task. We suggest that further fine-tuning them on the data annotated with content preservation scores might yield better models.

Thus, we modify the RoBERTA architecture used for NLI. Namely, we use the original encoder in both forward and backward directions, concatenate the last hidden states, and then send them to the classification module which is tuned on data annotated with content preservation scores. We refer to this model as Mutual Implication Score (MIS). The scheme of our model is given in Figure 3.

We initialize the model with pre-trained weights from the RobNLI model. We tune it on Quora Question Pairs dataset (Sharma et al., 2019) for 2 epochs with a learning rate $4e^{-6}$ and all but the last encoder layer and classifier layer frozen.

We evaluate the model with the Spearman rank correlation coefficient of the automatic content preservation scores with human judgments. We evaluate all TST and PG datasets introduced in Section 3. We evaluate MIS and baseline NLI-based measures (we aggregate the NLI scores for both directions with the arithmetic mean because it showed the best results in our preliminary experiments).

The results are shown in Table 1. Fine-tuning the (slightly modified) NLI model on content preser-
ivation data slightly improves its performance on datasets generated by paraphrasing models and yields significantly higher correlation on TST datasets.

5 Measures analysis

We compute the content preservation scores for paraphrasing and style transfer datasets using measures of different types. We analyze the performance of individual measures and compare the performance of different groups of measures. We also look into the difference in measures performance on PG and TST tasks and analyze the individual datasets.

5.1 Experimental setting

We analyze 57 content preservation measures of different types. As described in Section 2.1, the measures can be divided into the following groups: a word or character n-gram based (ngram), the measures based on the distance between static (emb-static) or contextualized (emb-context) embeddings, or embeddings from bi-encoders (emb-bi-enc), or different groups of encoders-based measures: symmetric (sym-cross-enc), asymmetric (asym-cross-enc) or two-fold asymmetric (2x-asym-cross-enc) cross-encoders. This grouping is used explicitly during analysis. The full list of measures is given in Table 8.

We compute the content preservation scores for 19 datasets listed in Section 3. The full information about the datasets is given in Appendix Tables 5 and 6.

We evaluate measures using the Spearman rank correlation coefficient of the automatic scores with human judgments. Since we use a large number of measures and datasets, we report only aggregated results. The full results are available in the Appendix Figures 7 and 8.

5.2 Measure-level analysis

Figure 4 shows the correlations of the best-performing measures from different groups for individual datasets. The last columns of the plots show the performance of each measure averaged across datasets. The plot shows that MIS and similar measures based on two-folded asymmetric cross-encoders have the best average performance on the paraphrase datasets. For TST datasets, there is no clear winner: symmetric cross-encoders (cross-stsb-large/base), bi-encoders (SIMCSE-SL/SB), asymmetric cross-encoders (BLEURT, NUBIA), and two-folded asymmetric cross-encoder (MIS) demonstrate almost equal performance.

The performance of content preservation measures on TST datasets varies from style to style. The TST datasets we use contain style transformations of four types: detoxification, formal to informal, positive to negative sentiment, and modern to old-style English. Thus, it seems natural to average the measures performance not only by all TST datasets but also by TST datasets of different styles. The averaged scores are shown in Table 2. There is no clear winner for old-style English and formality transfer: MIS and SIMCSE-SL show almost equal performance. However, we can see that BLEURT measures are clear leaders in detoxification and sentiment transfer.

| Measure     | Toxic | Old_Eng | Form | Sent |
|-------------|-------|---------|------|------|
| BLEURT-B128 | 0.47  | 0.52    | 0.61 | 0.39 |
| BLEURT-L128 | 0.54  | 0.57    | 0.64 | 0.35 |
| MIS         | 0.50  | 0.60    | 0.69 | 0.28 |
| NUBIA       | 0.43  | 0.60    | 0.66 | 0.33 |
| SIMCSE-SL   | 0.46  | 0.60    | 0.69 | 0.36 |

Table 2: Mean Spearman correlation of measures which perform best on different text style transfer tasks. Tasks: Toxic — detoxification, Old_Eng — old-style to modern English, Form — formal to informal, Sent — sentiment transfer. The best scores are shown in bold.

| Measure            | Paraphrase Generation (PG) | Text Style Transfer (TST) |
|--------------------|-----------------------------|---------------------------|
|                    | 2x-asym-cross-enc | sym-cross-enc | asym-cross-enc | emb-bi-enc | emb-context | ngram | emb-static | sym-cross-enc | emb-bi-enc | asym-cross-enc | 2x-asym-cross-enc | emb-context | ngram |
| \( \rho_{\text{max}} \) | 0.61 | 0.55 | 0.54 | 0.54 | 0.47 | 0.42 | 0.42 | 0.55 | 0.55 | 0.54 | 0.54 | 0.54 | 0.54 | 0.41 |
| \( \rho_{\text{avg}} \) | 0.56 | 0.51 | 0.49 | 0.45 | 0.42 | 0.34 | 0.27 | 0.51 | 0.49 | 0.46 | 0.45 | 0.45 | 0.45 | 0.35 |
| #wins             | 3   | 5   | 2   | 2   | 0   | 0   | 0   | 3   | 3   | 3   | 0   | 1   | 1   |

Table 3: Spearman correlations of measures belonging to different groups: \( \rho_{\text{max}} \) — correlation of the best-performing in the group, \( \rho_{\text{avg}} \) — correlation averaged over the group, #wins — the number of times the model from the group performs best on any of the datasets.
Figure 4: Correlation of measures of different classes with human judgments on paraphrase and text style transfer datasets. The text above each dataset indicates the best-performing measure. The rightmost columns show the mean performance of measures across the datasets.

5.3 Group-level analysis

To get more generalizable results of the analysis, we perform a group-level comparison of measures in Table 3. We report the Spearman correlation scores averaged over datasets of PG and TST tasks (as before, we do not merge all datasets and consider the two tasks separately). We report the mean and maximum correlations of all measures of a group. We also compute the number of times when a measure of a group performs best on the particular dataset. This indicator can be somewhat biased due to the nature of each dataset, however, it can still serve as an additional source of information. If the difference between correlations is not significant (by Williams test (Graham and Baldwin, 2014)) we assign one winning time to each group.

From this point of view, we can even better see that two-folded asymmetric models are the best choice for paraphrases detection because the mean correlation outperforms the next best-performing group by 0.05. Symmetric cross-encoders can also be an alternative option for this task because they show the largest number of wins. Symmetric cross-encoders show the highest mean correlation on the TST task. At the same time, the number of wins and correlations of the best models from this class are similar for all encoder-based classes.

Finally, from the measure-level and group-level perspective, we can see that encoder-based measures outperform ngrams-based measures in the absolute majority of datasets on TST and PG tasks.

5.4 Data-level analysis

So far we relied on the correlations averaged across different datasets. However, it is also natural to have a closer look at how the behavior of different measures changes across datasets.

For this purpose, we represent each dataset as a vector of correlations of each measure with the human judgments and plot a dendrogram (see Figure 5) to show the clustered structure of the obtained vectors. The dendrogram should be interpreted as follows. The height at which each dataset is connected to another dataset or group of datasets indicates the distance between the dataset vectors. We additionally plot a heatmap of cosine similarities of these datasets vectors in Appendix Figure 9.

Datasets related to sentiment transfer (PG-YELP, Yam. Yelp) look different from others, thus, they form a separate cluster in the dendrogram. The reason for this dissimilarity is probably the fact that in this type of TST task (sentiment transfer) the content of the utterance changes more significantly than in other tasks. Moreover, PG-YELP is originally distributed as a pairwise comparison dataset. To yield sentence-level scores, we apply Luce Spectral Ranking (Maystre and Grossglauser, 2016). This preprocessing might affect the quality of labels.

In general, the datasets are clustered into two rather dense groups and this clustering does not match the separation of the datasets among TST and PG tasks. The different behavior of the tested
measures might be explained by the way the data is annotated. For example, the PAWS datasets were collected in an adversarial manner (by shuffling the words in sentences), STRAP datasets were generated with TST models, and Yam. datasets were annotated by a similar group of workers — these three sets form clusters in the dendrogram.

6 Using automatic measures to rank text style transfer systems

While above we compared automatic and human ranking of individual text pairs, our final goal is to find a measure to rank TST or PG systems. Six TST datasets used in our analysis were created by running several TST models on the same dataset and manually assessing the degree of content preservation in the resulting text pairs. They cover diverse tasks: formality transfer (xformal-FoST and STRAP_form datasets), text detoxification (Tox600 and CAE datasets), Shakespeare style transfer (STRAP_SP), and sentiment transfer (PG-YELP). We use the human judgments on content preservation from these datasets to rate the ability of various measures to rank text style transfer systems.

For brevity and clarity, we do not report the results of this analysis for all measures. Instead, we select the best-performing measure from each group:

- **cross-encoders:** MIS, RobNLI/mean, BLEURT-L128 and cross-stsb-base,
- **bi-encoders:** LaBSE and SIMCSE-SL (supervised, using ROBERTa-large),
- **embedding-based models:** SIMILE, BERTScore (with microsoft/deberta-xlarge-mnli model), and WMD,
- **ngram-based measures:** BLEU and ChrF.

We show the results aggregated across the datasets in Table 4. The scores for individual datasets and measures and a list of measures managed to identify the best-performing model for a given dataset are given in Appendix C.

No measure can fully match the system rankings produced by humans. However, our MIS measure and BLEURT have the highest correlations with human judgments. BLEURT performs best on this task because it correctly identifies the winner on 5 datasets out of 6. The popular measures BLEU, ChrF, and WMD identify the best system only on the xformal-FoST dataset.

7 Computational efficiency of the measures

While the correlation of measures with human judgments is important, the usability of the measure in real tasks can not be treated in isolation from its computational efficiency. The main capabilities of such measures are robustness and inference speed.

One of the key functions of content preservation measures is to compare different TST or PG approaches with each other and ensure that different runs of the learning-based measure yield similar results. This problem does not apply to words or character n-grams-based models. However, this could yield some issues with trainable model-based measures. That is why it is crucial for all such measures to open-source trained weights. Moreover, when using such measures for comparison it is nec-
necessary to put the model into inference mode and freeze all layers. In such a case the model-based measures yield similar scores to similar text pairs regardless of the number of attempts or any hardware properties.

Another blocker to the usage of a certain measure could be a long inference time. We conduct additional experiments by calculating the average inference time per sample for a subset of measures representing each class w.r.t. the average correlation of the measure on the task. We concatenate texts from both tasks into two united datasets. For trainable measures, we use a data loader with a batch size equal to eight. We load all trainable models to NVIDIA GeForce RTX 2080 Ti. All other measures are calculated sample-wise on Intel(R) Xeon(R) Gold 5217 CPU @ 3.00GHz. We plot the results on Figure 6.

The most optimal measures are located at the bottom right corner of these plots, which means that the measure requires the least possible computational time and at the same time demonstrates a high correlation with human judgments. For the PG task, the MIS measure demonstrates the best performance and its average inference time is at the approximately same level as most of the other model-based measures. For TST task symmetric and asymmetric cross-encoders are the most optimal.

8 Conclusions

As our experiments show, encoder-based measures of content preservation correlate with human judgments much better than the traditional word or character-based measures such as BLEU on a wide range of datasets. In all paraphrase datasets and 9 out of 10 text style transfer datasets, the best-performing measures are based on the cross-encoder or bi-encoder architecture.

We suggest a measure called MIS which is based on the idea that texts with similar meanings mutually entail each other. We show that the proposed architecture outperforms other measures in the evaluation of paraphrases and performs on par with the top-performing measures in the evaluation of text style transfer. More specifically, it is particularly successful in transferring between contemporary and old English and between formal and informal styles. Thus, we recommend using this measure for content preservation scoring for paraphrases and TST tasks in the aforementioned tasks and to use BLEURT for other TST tasks.

While the best measures in our analysis improve over the popular ones (e.g. BLEU) by a large margin, their correlation with human judgments is still far from perfect. We expect that even better measures of content preservation will be proposed in the nearest future. We also hope that the MIS measure and the performed large scale computational study could be applied to other NLP tasks, such as machine translation, text summarization, etc.

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A Datasets

| Name       | Comment                                      | Size  |
|------------|----------------------------------------------|-------|
| ETPC       | all data from textual_np_pos and textual_np_neg files | 6004  |
| PAWS-qqp   | dev_and_test.tsv from qqp part used          | 677   |
| PAWS-wiki  | Test split from PAWS-Wiki Labeled (Final)    | 8000  |
| Twitter-URL| Test split used                               | 10120 |
| PIT        | Test split used                               | 972   |
| MSR        | Test split used                               | 1630  |
| APT        | Test split used (ap-h-test)                   | 1252  |
| Yam. para  | Data from Paralex,Parphrase folder used       | 3223  |
| SICK       | Test split form SICK_test.annotated used      | 4927  |

Table 5: Paraphrase generation (PG) datasets used in the experiments.

| Name       | Comment                                      | Size  | Style |
|------------|----------------------------------------------|-------|-------|
| Tox600     | All data used                                | 600   | Toxic |
| Yam. Yelp  | Yelp subset of annotated data                | 2000  | sentiment |
| Yam. GYAFC | GYAFC subset of annotated data               | 6000  | Formality |
| Yam. Bible | Bible subset of annotated data               | 2000  | Old-style |
| xformal-FoST| English subset of annotated data use (meta_gyafc_en.tsv) | 2458  | Formality |
| CAE        | All data used                                | 500   | Toxic |
| PG         | All data used. Individual ranks were induced from side-by-side comparisons using the Luce spectral ranking model. The dataset was obtained by direct request to Pang and Gimpel (2019). | 886   | Sentiment |
| STRAP_coha | For each sentence pair, the mean human score was used. All data used | 100   | Historical American English |
| STRAP_form | 684   | Formality |
| STRAP_SP   | 550   | Old-style |

Table 6: Text style transfer (TST) datasets used in the experiments.

B Measures analysis
| Citation               | Measure                                                                 | Task   |
|------------------------|-------------------------------------------------------------------------|--------|
| Hu et al. (2017)        | Automatic content preservation measures are not used                   | CG     |
| Shen et al. (2017)      | Automatic content preservation measures are not used                   | TST    |
| Mueller et al. (2017)   | Edit distance                                                         | CG     |
| Jhamtani et al. (2017)  | PINC (Chen and Dolan, 2011), BLEU                                      | TST    |
| Radford et al. (2017)   | Only style accuracy analyzed                                          | TST    |
| Logeswaran et al. (2018)| round-trip BLEU                                                        | CG     |
| Subramanian et al. (2018)| self-BLEU                                                              | TST    |
| Zhang et al. (2018b)    | BLEU                                                                   | TST    |
| Prabhumoye et al. (2018)| Manual pairwise comparison only                                       | TST    |
| Tian et al. (2018b)     | self-BLEU, POS-distance - noun difference between the original and transferred sentences | TST    |
| Yang et al. (2018)      | self-BLEU                                                              | TST    |
| Rao and Tetreault (2018)| STS CNN model (He et al., 2015)                                       | TST    |
| Carlson et al. (2018)   | PINC, BLEU                                                             | TST    |
| Zhao et al. (2018)      | BLEU                                                                   | TST    |
| Fu et al. (2018)        | Cosim between averaged or max/min-pooled GloVe (Pennington et al., 2014) embeddings | TST    |
| Xu et al. (2018)        | BLEU                                                                   | TST    |
| Zhang et al. (2018a)    | BLEU                                                                   | TST    |
| Gupta et al. (2018)     | BLEU, ROUGE, METEOR                                                   | PG     |
| Pang and Gimpel (2019)  | Cosim between GloVe (Pennington et al., 2014) embeddings weighted by inverse document frequency | TST    |
| Li et al. (2018)        | BLEU                                                                   | TST    |
| Smith et al. (2019)     | self-BLEU                                                              | TST    |
| Sudhakar et al. (2019)  | self-BLEU                                                              | TST    |
| Wu et al. (2019b)       | BLEU                                                                   | TST    |
| John et al. (2019)      | Cosim between averaged or max/min-pooled GloVe (Pennington et al., 2014) embeddings | TST    |
| Luo et al. (2019)       | BLEU                                                                   | TST    |
| Dai et al. (2019)       | self-BLEU                                                              | TST    |
| Jain et al. (2019)      | BLEU, spacy.docsim                                                     | TST    |
| Lai et al. (2019)       | self BLEU                                                              | TST    |
| Wang et al. (2019)      | BLEU                                                                   | TST    |
| Xu et al. (2019)        | BLEU                                                                   | TST    |
| Kajiwara (2019)         | BLEU, F1-score over added, deleted, adn kept words                    | PG     |
| Wu et al. (2019a)       | Case insensitive BLEU                                                  | TST    |
| Li et al. (2019a)       | BLEU                                                                   | TST    |
| Li et al. (2019b)       | BLEU, ROUGE                                                            | PG     |
| Chen et al. (2019)      | BLEU, ROUGE, METEOR                                                   | PG     |
| Yang et al. (2019a)     | BLEU, METEOR, TER (Snover et al., 2006)                                | PG     |
| Egomnwan and Chali (2019)| BLEU, ROUGE, METEOR, GMS                                               | PG     |
| Wang et al. (2018)      | BLEU, METEOR, TER (Snover et al., 2006)                                | PG     |
| Krishna et al. (2020)   | SIMILEWieting et al. (2019)                                            | TST    |
| Shen et al. (2020b)     | self-BLEU                                                              | CG     |
| Li et al. (2020)        | self-BLEU                                                              | TST    |
| Xu et al. (2020)        | self-BLEU                                                              | TST    |
| Gong et al. (2020)      | Cosim between averaged or max/min-pooled GloVe embeddings              | TST    |
| Zhang et al. (2020)     | BLEU                                                                   | TST    |
| Shen et al. (2020a)     | BLEU                                                                   | CG     |
| He et al. (2020)        | self-BLEU                                                              | TST    |
| Goyal and Durrett (2020)| BLEU                                                                   | PG     |
| Fu et al. (2020)        | BLEU, ROUGE                                                            | PG     |
| Laugier et al. (2021)   | BLEU, cosine similarity of USE (Cer et al., 2018)                     | TST    |
| Lai et al. (2021)       | BLEU, BLEURT (Sellam et al., 2020)                                    | TST    |
| Shi et al. (2021)       | WMD (Kusner et al., 2015), BLEU, BERTScore (Zhang et al., 2019)       | TST    |
| Riley et al. (2021)     | self-BLEU                                                              | TST    |
| Krause et al. (2021)    | Only detoxification and fluency analyzed                               | CG     |
| Lee et al. (2021)       | BLEU, BERTScore (Zhang et al., 2019)                                   | TST    |
| Cao et al. (2020)       | BLEU                                                                   | TST    |
| Rane et al. (2021)      | BLEU                                                                   | TST    |
| Hu and He (2021)        | Word Overlap, BLEU, cosine similarity between averaged or max/min-pooled GloVe (Pennington et al., 2014) embeddings | TST    |
| Sun et al. (2021)       | BLEU, ROUGE, METEOR                                                   | PG     |

Table 7: Automatic content preservation measures used in recent works on text style transfer (TST), paraphrase generation (PG), and controllable generation (CG).
| Measure name in report | Comment | Article |
|------------------------|---------|---------|
| RobNLI/*               | Combination or separate use of NLI scores in direct or reverse direction | Nie et al. (2020) |
| SIMILE                 | Cosine similarity between embeddings generated with LSTM-based model | Wieting et al. (2019) |
| w2v_wmd_norm           | Word mover distance with word2vec normalized | Kusner et al. (2015) |
| w2v_wmd               | Word mover distance with word2vec |          |
| w2v_l2               | Euclidean distance between word2vec |          |
| w2v_cossim            | Cosine similarity over word2vec |          |
| USE                   | Cosine similarity between embeddings generated with Universal Sentence Encoder | Cer et al. (2018) |
| SIMCSE-UL              | Unsupervised and supervised version of SIMCSE:Simple Contrastive Learning of Sentence Embeddings | Gao et al. (2021) |
| SIMCSE-UBu             | Supervised version trained to produce embeddings on NLI data in contrastive manner using entailing sample as positive sample and contradiction as negative. |          |
| SIMCSE-SL              |          |          |
| SIMCSE-SB              |          |          |
| SIMCSE-SBertUnc        |          |          |
| LaBSE                  | Cosine similarity between language-agnostic cross-lingual sentence embeddings | Feng et al. (2020) |
| BERT-base-NLI-STSB     |          | Reimers and Gurevych (2019) |
| ROUGE                  | ROUGE Longest Common Subsequence | Lin (2004) |
| ROUGE3                 | ROUGE with trigram |          |
| ROUGE2                 | ROUGE with bigram |          |
| ROUGE1                 | ROUGE with unigram |          |
| NUBIA                  | Multi-module pipeline consisting of Feature Extraction, Aggregation and Calibration for semantic similarity scoring | Kane et al. (2020) |
| MoverScore             | Combination or separate use of Facebook roberta NLI model’s scores in direct or reverse direction | Liu et al. (2019) |
| METEOR                 | Special case of Earth Mover’s Distance applied to BERT embeddings | Zhao et al. (2019) |
| Levenshtein            | The measure is based on the harmonic mean of unigram precision and recall | Banerjee and Lavie (2005) |
| Jaro_winkler           | The minimum number of single-character edits | Levenshtein et al. (1966) |
| fasttext_wmd_norm      | Normalized word mover distance over fasttext vectors | Kusner et al. (2015) |
| fasttext_wmd           | Word mover distance over fasttext vectors |          |
| fasttext_l2            | Euclidean distance between fasttext vectors |          |
| fasttext_cossim        | Cosine similarity between fasttext vectors |          |
| facebook/bart-large-cnn | Weighted log probability of one text y given another text x. The weights are used to put different emphasis on different tokens | Lewis et al. (2020) |
| BLEURT-L512            | BERT fine-tuned for semantic similarity evaluation task in cross-encoder manner on synthetic data | Sellam et al. (2020) |
| BLEURT-L128            |          |          |
| BLEURT-B512            |          |          |
| BLEURT-B128            |          |          |
| deberta/*              | Combination or separate use of NLI scores from deberta model in direct or reverse direction | He et al. (2021) |
| cross-stsb-large       | Base and Large version of CrossEncoder trained on STSb | Reimers and Gurevych (2019) |
| cross-stsb-base        |          | Nighojkar and Licato (2021) |
| APD                   | Paraphrase detector trained on the Adversarial Paraphrasing dataset from the corresponding paper |          |
| chrf                  | Character n-gram F-score | Popović (2015) |
| BLEU                   | Modified unigram precision score | Papineni et al. (2002) |
| bertscore/roberta-large | F1-score over BERT-embeddings between tokens from initial and target sentences. The packages are: roberta-large, Bert base multilingual cased, microsoft/deberta-xlarge-mnli correspondingly | Zhang et al. (2019) |
| bertscore_Bert-bmc     |          |          |
| bertscore-Mic-Deberta  |          |          |

Table 8: The full list of the automatic measures of content preservation used in the analysis.
Figure 7: Spearman correlations of all the evaluated measures with human judgments for paraphrase generation (PG) datasets. The measures are sorted by the mean correlation across all datasets. The top correlations for individual datasets are marked with *. The color palette of the heatmap is based on the regret, which is the difference between the correlation of the measure on a particular dataset and the best correlation on this dataset. The lower the value of regret, the higher the quality.
| Model                  | SIMCSE-SL       | BERENT, GIN       | SPM-Deberta        | UNIMA              | SIMCSE-3L           | mean             |
|-----------------------|-----------------|-------------------|-------------------|-------------------|--------------------|------------------|
| facebook/bart-large-cnn (emb-bi-enc) | 0.66, 0.54, 0.48 | 0.29, 0.23, 0.18 | 0.98, 0.90, 0.86 | 0.98, 0.90, 0.86  | 0.98, 0.90, 0.86  | 0.98, 0.90, 0.86  |
| bertscore-Mic-Deberta (emb-context) | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  |
| FBrobNLI/prod (2x-asym-cross-enc) | 0.59, 0.46, 0.32 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  |
| bertscore_Bert-bmc (emb-context) | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  |
| deberta/prod (2x-asym-cross-enc) | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  |
| BERT-base-NLI-STSB (emb-bi-enc)  | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  |
| FBrobNLI/direct (asym-cross-enc) | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  |
| RobNLI/reverse (asym-cross-enc)   | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  |
| fasttext_wmd_norm (emb-static)    | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  |
| w2v_l2 (emb-static)         | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  |
| ROUGE1 (ngram)               | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  |
| METEOR (ngram)               | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  |
| chrF (ngram)                 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27 | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  | 0.60, 0.39, 0.27  |

Figure 8: Spearman correlations of all the evaluated measures with human judgments for text style transfer (TST) datasets. The measures are sorted by the mean correlation across all datasets. The top correlations for individual datasets are marked with *. The color palette of the heatmap is based on the regret, which is the difference between the correlation of the measure on a particular dataset and the best correlation on this dataset. The lower the value of regret, the higher the quality.
Figure 9: Cosine similarities of vectors of measures’ correlations on individual datasets. The last column shows the mean cosine similarity of a dataset vector and vectors of all other dataset (excluding self-similarity). Postfixes ‘p’ and ‘t’ indicate datasets for to PG and TST tasks, respectively.
## C  System-level ranking

### Table 9: System ranking on Tox600 (Dale et al., 2021), text detoxification.

| system                  | human | MIS | RobNLI/mean | BLEURT-L128 | cross-stsb-base | LaBSE | SIMCSE-SL | bertscore-Mic-Deberta | SIMILE | w2v_wmd | BLEU | chef |
|-------------------------|-------|-----|-------------|-------------|-----------------|-------|-----------|-----------------------|--------|---------|------|------|
| paragaphy               | 0.65  | 0.52| 0.39        | -0.25       | 0.82            | 0.95  | 0.68      | 0.76                  | 0.67   | -0.67   | 0.48 | 0.41|
| condbert                | 0.64  | 0.41| 0.27        | -0.26       | 1.07            | 0.96  | 0.75      | 0.83                  | 0.76   | -0.34   | 0.72 | 0.73|
| mask_infill             | 0.59  | 0.39| 0.29        | -0.29       | 0.96            | 0.99  | 0.82      | 0.87                  | 0.82   | -0.21   | 0.79 | 0.80|

### Table 10: System ranking on xformal-FoST (Briakou et al., 2021), formality transfer.

| system                  | human | MIS | RobNLI/mean | BLEURT-L128 | cross-stsb-base | LaBSE | SIMCSE-SL | bertscore-Mic-Deberta | SIMILE | w2v_wmd | BLEU | chef |
|-------------------------|-------|-----|-------------|-------------|-----------------|-------|-----------|-----------------------|--------|---------|------|------|
| nmt_combined            | 4.67  | 0.91| 0.90        | 0.78        | 4.35            | 0.98  | 0.96      | 0.95                  | 0.93   | -0.15   | 0.88 | 0.85|
| pbmt                    | 4.64  | 0.89| 0.88        | 0.71        | 4.08            | 0.98  | 0.95      | 0.94                  | 0.91   | -0.17   | 0.85 | 0.81|
| ref                     | 4.56  | 0.87| 0.84        | 0.32        | 2.98            | 0.95  | 0.89      | 0.86                  | 0.76   | -0.44   | 0.64 | 0.59|
| nmt_copy                | 3.99  | 0.74| 0.72        | 0.40        | 3.04            | 0.97  | 0.88      | 0.88                  | 0.82   | -0.26   | 0.77 | 0.73|
| nmt_baseline            | 3.90  | 0.73| 0.70        | 0.40        | 3.00            | 0.96  | 0.87      | 0.89                  | 0.82   | -0.25   | 0.77 | 0.74|

### Table 11: System ranking on CAE (Laugier et al., 2021), text detoxification.

| system                  | human | MIS | RobNLI/mean | BLEURT-L128 | cross-stsb-base | LaBSE | SIMCSE-SL | bertscore-Mic-Deberta | SIMILE | w2v_wmd | BLEU | chef |
|-------------------------|-------|-----|-------------|-------------|-----------------|-------|-----------|-----------------------|--------|---------|------|------|
| CAET rephrasing         | 2.63  | 0.34| 0.28        | -0.63       | 0.56            | 0.92  | 0.62      | 0.70                  | 0.56   | -0.66   | 0.47 | 0.44|
| IE rephrasing           | 2.20  | 0.37| 0.36        | -0.73       | 0.55            | 0.96  | 0.60      | 0.73                  | 0.56   | -0.56   | 0.56 | 0.56|
| ST (multi) rephrasing   | 2.10  | 0.26| 0.22        | -1.16       | -0.22           | 0.91  | 0.52      | 0.63                  | 0.60   | -0.67   | 0.46 | 0.46|
| ST (cond) rephrasing    | 2.08  | 0.25| 0.23        | -1.11       | -0.07           | 0.92  | 0.53      | 0.66                  | 0.62   | -0.65   | 0.49 | 0.47|
| CA rephrasing           | 1.88  | 0.05| 0.08        | -1.54       | -2.22           | 0.90  | 0.18      | 0.51                  | 0.16   | -0.95   | 0.23 | 0.18|

### Table 12: System ranking on PG-YELP (Pang and Gimpel, 2019), sentiment transfer.

| system                  | human | MIS | RobNLI/mean | BLEURT-L128 | cross-stsb-base | LaBSE | SIMCSE-SL | bertscore-Mic-Deberta | SIMILE | w2v_wmd | BLEU | chef |
|-------------------------|-------|-----|-------------|-------------|-----------------|-------|-----------|-----------------------|--------|---------|------|------|
| paraphrase_base         | 0.79  | 0.64| 0.53        | -0.39       | 1.19            | 0.94  | 0.77      | 0.74                  | 0.65   | -0.69   | 0.45 | 0.39|
| paraphrase_0.0          | 0.76  | 0.73| 0.64        | -0.08       | 1.91            | 0.94  | 0.82      | 0.77                  | 0.71   | -0.63   | 0.50 | 0.43|
| paraphrase_0.5          | 0.59  | 0.56| 0.44        | -0.45       | 1.04            | 0.93  | 0.73      | 0.71                  | 0.61   | -0.74   | 0.42 | 0.35|
| unmt                    | 0.31  | 0.23| 0.19        | -0.95       | -0.31           | 0.93  | 0.50      | 0.69                  | 0.51   | -0.64   | 0.51 | 0.43|
| he_2020                 | 0.26  | 0.21| 0.19        | -0.99       | -0.82           | 0.90  | 0.45      | 0.67                  | 0.46   | -0.65   | 0.45 | 0.40|

### Table 13: System ranking on STRAP_form, (Krishna et al., 2020), formality transfer.

| system                  | human | MIS | RobNLI/mean | BLEURT-L128 | cross-stsb-base | LaBSE | SIMCSE-SL | bertscore-Mic-Deberta | SIMILE | w2v_wmd | BLEU | chef |
|-------------------------|-------|-----|-------------|-------------|-----------------|-------|-----------|-----------------------|--------|---------|------|------|
| paraphrase_base         | 0.81  | 0.62| 0.58        | -0.11       | 1.48            | 0.95  | 0.79      | 0.76                  | 0.72   | -0.69   | 0.44 | 0.37|
| paraphrase_0.0          | 0.58  | 0.44| 0.43        | -0.52       | 0.77            | 0.94  | 0.69      | 0.70                  | 0.62   | -0.79   | 0.37 | 0.31|
| he_2020                 | 0.35  | 0.19| 0.21        | -1.07       | -0.28           | 0.93  | 0.49      | 0.68                  | 0.49   | -0.65   | 0.46 | 0.40|
| unmt                    | 0.26  | 0.12| 0.13        | -1.23       | -0.92           | 0.93  | 0.41      | 0.66                  | 0.41   | -0.72   | 0.42 | 0.34|

### Table 14: System ranking on STRAP_SP (Krishna et al., 2020), Shakespeare style transfer.

| dataset                | measures                                                                 |
|------------------------|--------------------------------------------------------------------------|
| Tox600                 | MIS, BLEURT-L128                                                         |
| xformal-FoST           | BLEURT-L128, cross-stsb-base, SimCSE, BERTScore, and all other models    |
| CAE                    | BLEURT-L128, cross-stsb-base, SimCSE                                     |
| PG-YELP                | BLEURT-L128, LabSE, BERTScore                                            |
| STRAP_form             | LabSE, SimCSE, BERTScore, SIMILE                                         |
| STRAP_SP               | MIS, BLEURT-L128, cross-stsb-base, LabSE, SimCSE, BERTScore, SIMILE      |

### Table 15: The measures that correctly identify the best text style transfer system for each dataset.