

# You can be Shakespeare!

## A Case Study in Paraphrase Targeting Writing Styles

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### ABSTRACT

We present initial investigation into the task of paraphrasing language while targeting a particular writing style. The plays of William Shakespeare and their modern translations are used as a testbed for evaluating paraphrase systems targeting a specific style of writing. We show that even with a relatively small amount of parallel training data available, it is possible to learn paraphrase models which capture stylistic phenomenon, and these models outperform baselines based on dictionaries and out-of-domain parallel text. In addition we present an initial investigation into automatic evaluation metrics for paraphrasing writing style. To the best of our knowledge this is the first work to investigate the task of paraphrasing text with the goal of targeting a specific style of writing.

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KEYWORDS: Paraphrase, Writing Style.

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## 1 Introduction

Identical meaning can be expressed or *paraphrased* in many different ways; automatically detecting or generating different expressions with the same meaning is fundamental to many natural language understanding tasks (Giampiccolo et al., 2007), so much previous work has investigated methods for automatic paraphrasing (Barzilay and Lee, 2003; Dolan et al., 2004; Shinyama and Sekine, 2003; Das and Smith, 2009; Bannard and Callison-Burch, 2005). Although two utterances may be semantically equivalent, they can still be stylistically quite different. For example, the same information is likely to be conveyed using very different lexical and grammatical patterns in advertising materials v.s. technical manuals, or in Shakespearean plays v.s. Hollywood movies.

In this paper, we investigate the task of automatic paraphrasing when targeting a writing style, focusing specifically on the style of Early Modern English employed by William Shakespeare. We exploit modern translations of 17 plays written to help students better understand Shakespeare's work. A parallel corpus is extracted from these modern translations, which is then used to train phrase-based translation models which are capable of automatically paraphrasing ordinary sentences into Shakespearean English. In addition we develop several baseline systems which do not make use of this source of parallel text and instead rely on manually compiled dictionaries of expressions commonly found in Shakespearean English, or out of domain parallel monolingual text gathered through Amazon's Mechanical Turk (Chen and Dolan, 2011).

We evaluate these models both through human judgements and standard evaluation metrics from the Machine Translation and paraphrase literature, however no previous work has inves-

tigated the ability of automatic evaluation metrics to capture the notion of writing style. We propose several new metrics for evaluating paraphrases targeting a specific writing style, and measure correlation with human judgements showing promising preliminary results.

Systems which are capable of automatically paraphrasing literary writing styles could be directly beneficial for educational applications. For example, a system which generates paraphrases targeting a specific style of writing could help students to experiment with writing literature in that style. In addition, out of the 37 surviving plays written by William Shakespeare only 17 currently have modern translations available. Though we have not yet formally evaluated paraphrasing Shakespeare’s plays into modern English, we believe it should be possible to make the other 20 plays more accessible to students of Shakespeare by automatically generating high-quality modern translations.

## 2 Shakesperean Paraphrasing

We propose to use Shakespeare’s plays as a testbed for the task of paraphrasing while targeting a specific writing style. Because these plays are some of the highest regarded examples of English literature and are also very unique in style, many linguistic resources are available such as parallel corpora of modern translations and dictionaries of stylistically representative words and their modern equivalents.

We compare 3 different stylistic paraphrase systems targeting Shakesperean English. One which leverages parallel corpora of modern translations, another which makes use of dictionaries of stylistically representative expressions, and another which leverages out-of-domain monolingual parallel data.

### 2.1 Modern Translations

Having access to parallel text in the target style allows us to train statistical models for generating paraphrases, and also perform automatic evaluation of semantic adequacy using BLEU, which requires access to a set of reference translations. For this purpose we scraped modern translations of 17 Shakespeare plays from <http://nfs.sparknotes.com>, and an additional 8 translations of overlapping plays from <http://enotes.com>, giving us two reference translations for 8 out of the 17 plays.

After tokenizing and lowercasing, the plays were aligned using Bob Moore’s bilingual sentence (Moore, 2002) aligner, which produced about 21,079 alignments out of 31,718 sentences in the Sparknotes data, and 10,365 sentence pairs out of 13,640 sentences in the enotes data. The modern translations from each source are qualitatively quite different. The Sparknotes paraphrases tend to differ significantly from the original text, whereas the enotes translations are much more conservative, making fewer changes. To illustrate these differences empirically and provide an initial paraphrase baseline, we computed BLEU scores of the unchanged modern translations against Shakespeare’s original text; the Sparknotes paraphrases result in a BLEU score of 24.67, whereas the Enotes paraphrases prouce a much higher BLEU of 52.30 indicating their similarity to the original text. These corpus statistics are summarized in table 1.

We apply a typical phrase-based Statistical Machine Translation pipeline, performing word alignment on the data described in table 1 using GIZA++ (Och and Ney, 2003), then extracting phrase pairs and performing decoding using Moses (Koehn et al., 2007).

| corpus  | initial size | aligned size | No-Change BLEU |
|---|--------------|--------------|----------------|
| <a href="http://nfs.sparknotes.com">http://nfs.sparknotes.com</a> | 31,718       | 21,079       | 24.67          |
| <a href="http://enotes.com">http://enotes.com</a>                 | 13,640       | 10,365       | 52.30          |

Table 1: Parallel corpora generated from modern translations of Shakespeare’s plays

| target | source  | target   | source   |
|--------|---------|----------|----------|
| ABATE  | shorten | ANIGHT   | by night |
| CAUTEL | deceit  | CHILDING | pregnant |
| FOIL   | defeat  | MORTAL   | deadly   |

Table 2: Exaple dictionary entries

## 2.2 Baselines

Phrase-based translation has been demonstrated to be an effective approach to generating paraphrses (Chen and Dolan, 2011; Quirk et al., 2004), however this approach does require the existence of parallel corpora which may not be available for many writing styles. For this reason we were motivated to investigate alternative approaches.

### 2.2.1 Dictionary Based Paraphrase

Several dictionaries of stylistically representative words of Shakesperean English and their modern equivelants are available on the web. These dictionaries can be used to define a translation model which is used in combination with a language model as in standard phrase-based MT (Koehn and Knight, 2000).

We gathered a set of 20,138 dictionary entries which were scraped from <http://www.shakespeareswords.com/>, then used heuristic rules to extract 68,709 phrase/word pairs. Example dictionary entries are presented in table 2. As described in (Koehn and Knight, 2000), we estimate phrase translation probabilities based on the frequencies of the translation words/phrases in the target language - the Shakespearean English.

For instance, if we look at the modern English (\*probably define EME, Shakespearean, modern/ordinary etc ... I don’t know what words to use) word *maybe*, our dictionary lists 4 possible Shakespearean translations. We can obtain the following conditional probabilities for each translation according to the n-gram back off model built on Shakespeare’s 36 plays by SRILM toolkit (\*ref "SRILM an Extensible Language Modeling Toolkit":

**TODO:** need to describe how parameters were learned and combined with LM

| conditional probability | target       | source |
|-------------------------|--------------|--------|
| 0.0000790755            | PERCHANCE    | maybe  |
| 0.00003691883           | PERADVENTURE | maybe  |
| 0.00007524298           | HAPPLY       | maybe  |
| 0.00007141065           | HAPPILY      | maybe  |

Table 3: Word frequency in target language

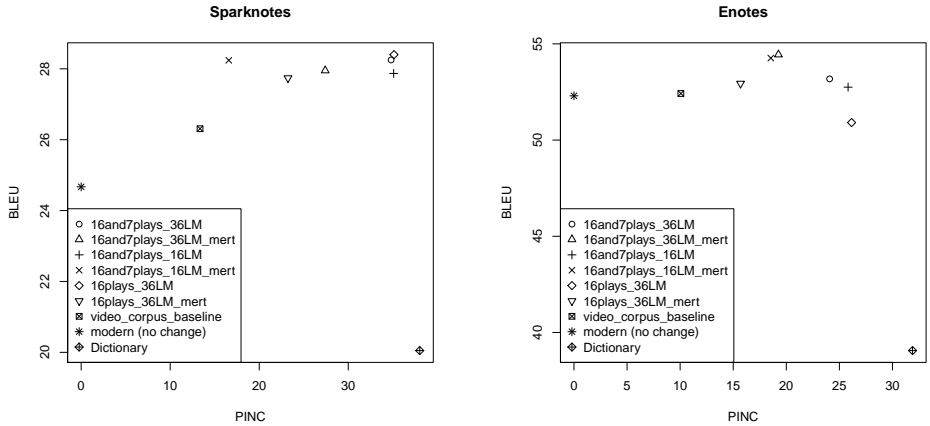


Figure 1: Various Shakespearean Paraphrase systems compared using BLEU and PINC. A brief description of each system is presented in table 4.

### 2.2.2 Out of Domain Monolingual Parallel Data

As a final baseline we consider a paraphrase system which is trained on out-of-domain data gathered by asking users of Amazon’s Mechanical Turk Service (Snow et al., 2008) to describe videos (Chen and Dolan, 2011). We combine a phrase table extracted from this out of doimain parallel text, with an in-domain language model consisting of Shakespeare’s 37 plays. Although this monolingual parallel data does not include text in the target writing style, the in-domain language model does bias the generated sentences towards Shakespeare’s writing style.

### 2.3 Comparison Using Existing Automatic Evaluation Metrics

Figure 1 compares a variety of systems targeting Shakespearean English using previously the previously proposed BLEU (Papineni et al., 2002) and PINC (Chen and Dolan, 2011) automatic evaluation metrics. A summary of each system is presented in table 4. Notice that the enotes data is quite similar to the original translations, obtaining a BLEU score of 52.3 when compared against the original text. Our goal is to produce paraphrases which make many changes to the input, therefore in the remainder of this paper, we focus on the Sparknotes data for evaluation.

Two main trends emerge from figure 1. First, notice that all of the systems which are trained using parallel text achieve higher BLEU scores than the baseline of not making any changes to the modern translations. While the dictionary baseline achieves a competitive PINC score, indicating it is making significant changes to the input, it’s BLEU is lower than the *no changes* baseline. Secondly, it seems apparent that the systems whose parameters are learned using Minimum Error Rate training tend to be more conservative, making fewer changes to the input and thus achieving lower PINC scores, but not seeing any BLEU improvements on the test data. Finally we note that using the larger language model seems to yield a slight improvement in BLEU score.

Several example paraphrases generated by our system, both from Romeo and Juliet and several Hollywood movies are presented in table ??.

| System                | Description   |
|-----------------------|---|
| 16and7plays_36LM      | Phrase table learned from all 16 Sparknotes plays (other than R&J) and language model built from all 36 of Shakespeare’s plays, excluding R&J. Uses default Moses parameters. |
| 16and7plays_36LM_MERT | Same as 16and7plays_36LM except parameters are tuned using Minimum Error Rate Training (?) instead of using the default Moses parameters.                                     |
| 16and7plays_16LM      | Phrase table is built from both Sparknotes and Enotes data, and Language model is built from the 16 with modern translations  |
| 16and7plays_16LM_MERT | Same as 16and7plays_16LM except parameters are tuned using MERT.  |
| 16plays_36LM          | Only Sparknotes modern translations are used. All 36 plays are used to train Shakesperean language model. a   |
| 16plays_36LM_MERT     | Same as 16plays_36LM except parameters are tuned using MERT.  |
| modern (no change)    | No changes are made to the input, modern translations are left unchanged.   |
| Dictionary            | Dictionary baseline described in section 2.2.1  |

Table 4: Descriptions of various systems for Shakesperean Paraphrase. Romeo and Juliet is held out for testing.

### 3 Human Evaluation

Figure 1 provides some insight into the performance of the various systems, however it is initially unclear how well the BLEU and PINC automatic evaluation metrics perform when applied to evaluating paraphrases targeting a specific style of writing. BLEU and PINC have previously been shown to have high correlation with human judgements of semantic adequacy and lexical dissimilarity of paraphrase candidates, however no previous work has evaluated automatically generated paraphrases which target a specific style of writing (Chen and Dolan, 2011).

While BLEU is typically used to measure semantic adequacy, it seems reasonable to assume that it may also depend on style, since utterances are more likely to contain overlapping ngrams if they are both semantically and stylistically similar. What BLEU doesn’t tell us, however is what portion of it’s improvements are due to stylistic similarity or semantic equivalence. For this reason, we were motivated perform an evaluation based on human judgements of semantic adequacy, lexical dissimilarity and stylistic similarity.

For this purpose, we randomly sampled 100 lines from Romeo and Juliet, then two of the authors annotated each sentence and it’s Shakesperean translation with semantic adequacy, lexical dissimilarity, stylistic similarity, and overall quality. The aggregate results of the human evaluation are displayed in figure 2.

Based on the human evaluation, it appears that the baseline combining paraphrases collected

| Source                  | Speaker     | Input  | Output  |
|-------------------------|-------------|--|---|
| Romeo & Juliet          | Benvolio    | he killed your relative , brave mercutio , and then young romeo killed him .                                     | he slew thy kinsman , brave mercutio , and then young romeo kill him .                                  |
| Romeo & Juliet          | Romeo       | i can read my own fortune in my misery .   | i can read mine own fortune in my woes .  |
| Star Wars               | Palpatine   | If you will not be turned, you will be destroyed!  | if you will not be turn 'd , you will be undone !   |
| Star Wars               | Luke        | Father, please! Help me!   | father , i pray you , help me !   |
| The Matrix              | Agent Smith | Good bye, Mr. Anderson.  | fare you well , good master anderson .  |
| The Matrix              | Morpheus    | I'm trying to free your mind, Neo. But I can only show you the door. You're the one that has to walk through it. | i 'll to free your mind , neo. but i can but show you the door. you 're the one that hath to tread it . |
| Raiders of the Lost Ark | Belloq      | Good afternoon, Dr. Jones.   | well met , dr. jones .  |
| Raiders of the Lost Ark | Jones       | I ought to kill you right now.   | i should kill thee straight .   |

Table 5: Example Shakesperean paraphrases generated by the best overall system.

from mechanical turk (Chen and Dolan, 2011) with a Shakesperean language model has the highest semantic adequacy, however it is also fairly conservative making few changes to the input. The dictionary baseline, and system trained on parallel modern translations make a roughly comparable number of changes to the input sentences, but the system trained on modern translations achieves higher semantic adequacy, while being rated higher on style and overall.

These results seem roughly in line with the automatic evaluation metrics presented in figure 1, however with several important differences. Although the video baseline achieves the highest semantic adequacy in the human evaluation, it's BLEU score is significantly lower than 16plays\_36LM on the Sparknotes data.<sup>1</sup> It would appear that in this case BLEU is conflating semantic adequacy with writing style. Although the paraphrases produced by the video baseline have high semantic adequacy, their style tends to differ from the reference translations resulting in fewer ngram matches, and thus a lower BLEU score.

## 4 Automatic Metrics Evaluating Writing Style

While PINC and BLEU do seem useful for automatically evaluating paraphrases targeting a writing style, BLEU tends to conflate the notions of semantic adequacy with writing style. When comparing various systems using automatic metrics, however, it would seem useful to separate

<sup>1</sup> Note that the BLEU score of 16plays\_36LM is significantly lower when evaluated on the Enotes data. This makes sense, because the 16 plays come from Sparknotes. This system is not trained on the 7 Enotes plays which, whose modern translations tend to be slightly different in style.

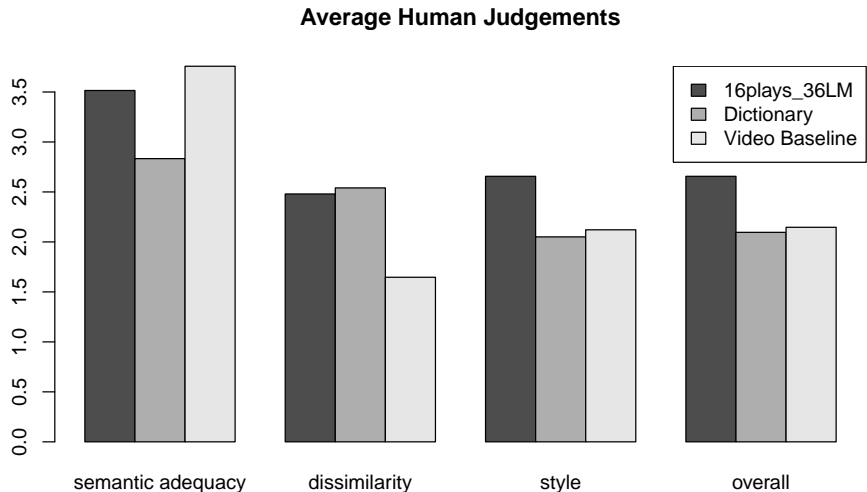


Figure 2: Average human judgements evaluating semantic adequacy, lexical dissimilarity, stylistic similarity, and overall quality of Shakesperean paraphrase systems

these two criteria. It would seem desirable for our automatic evaluation metrics to be able to distinguish between a system which generates perfect paraphrases which don't match the target style of writing and a system which generates sentences in the correct style, but which convey different meaning.

To help address this issue we propose two new automatic evaluation metrics whose goal is to measure the degree to which automatic paraphrases match the target style. Both metrics assume existence of large corpora in both the source and target style, but do not require access to any parallel text, or human judgements.

We present a preliminary evaluation of these metrics by measuring their correlation with human judgements, however we emphasize that here we are only evaluating these metrics with respect to one specific writing style. We are cautiously optimistic that these results will generalize across writing styles, however, as they are based entirely on ngram statistics.

## 4.1 Cosine Similarity Style Metric

As a first approach automatic evaluation of writing style, we propose a vector-space model of similarity between the system output and a large corpus of text in both the source and target style. The intuition is that if there is a large ngram overlap between the system's output and a large corpus of text in the target style, then the output is more likely to be stylistically appropriate.

More concretely, we extract ngrams from both the source and target corpus which are then represented as binary vectors  $\vec{s}$ , and  $\vec{t}$ ; similarly the output sentence is represented using a vector of ngrams  $\vec{o}$ . The proposed metric is the normalized cosine similarity between the source

|                   |                 | Pearson's $\rho$ |
|-------------------|-----------------|------------------|
| semantic adequacy | BLEU            | 0.35             |
| dissimilarity     | PINC            | 0.78             |
| style             | BLEU            | 0.07             |
| style             | PINC            | 0.20             |
| style             | Cosine          | 0.37             |
| style             | Maximum Entropy | 0.47             |

Table 6: Correlation between various human judgements and automatic evaluation metrics and target corpora:

$$S_{\text{Cosine}}(\vec{o}) = \frac{\frac{\vec{o} \cdot \vec{t}}{\|\vec{o}\| \times \|\vec{t}\|}}{\frac{\vec{o} \cdot \vec{t}}{\|\vec{o}\| \times \|\vec{t}\|} + \frac{\vec{o} \cdot \vec{s}}{\|\vec{o}\| \times \|\vec{s}\|}}$$

## 4.2 Logistic Regression Style Metric

We also consider a Logistic Regression based approach as an alternative to evaluating writing style. The idea here, is to estimate the probability that each sentence belongs to the target style, by using a large source and target training corpus to learn the parameters of a logistic regression model. This probability is estimated as follows:

$$P(\text{style} = \text{target} | \text{sentence}) = \frac{1}{1 + e^{-(\vec{\theta} \cdot f(\text{sentence}))}}$$

Where  $f(\text{sentence})$  is a vector of ngrams, and  $\vec{\theta}$  is a vector of weights. The parameters,  $\vec{\theta}$ , are optimized on the source and target corpus, where the assumption is that the target corpus is in the target style, whereas the source corpus is not.<sup>2</sup>

## 4.3 Evaluation

We trained both Logistic Regression and Cosine Similarity evaluation metrics using the original Shakespeare plays and modern translations as the source and target corpus respectively (holding out Romeo and Juliet), then measured Pearson's Correlation Coefficient between the automatic evaluation metrics and human judgements reported in section 3. These results are reported in table 6.

As can be seen in table 6, the correlation between semantic adequacy and BLEU appears smaller than that reported in previous work (Chen and Dolan, 2011). Presumably this is due to the conflation of stylistic differences and semantic adequacy discussed in section 3, however the correlation between BLEU and human style judgements seems too low to be of practical use. PINC has very high correlation with judgments on dissimilarity, however we note that it is also highly correlated with human style judgements. To understand why PINC is highly correlated with human style judgements, notice that because the systems we are evaluating are targeting Shakespearean English, when changes are made to the input they are likely to be in the target style. Although PINC has high correlation with human judgements, it is

<sup>2</sup> Parameters were optimized using MEGAM <http://www.cs.utah.edu/~hal/megam/>.



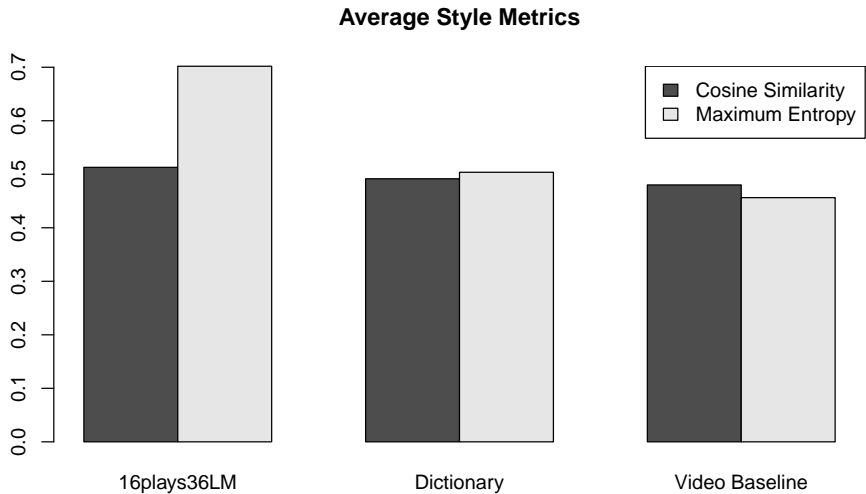


Figure 3: Overall results from comparing automatic style metrics. Note that the automatic metrics agree with results from human judgements in figure 2.

likely not a useful measure of style in practice, because for example a paraphrase system which makes many changes to the input, but targets a completely different style will also get a high PINC score. Both the Cosine and Maximum Entropy style metrics achieve the highest overall correlation with human writing style judgements, with the Maximum Entropy score performing significantly better.

Finally we note that overall the average automatic metrics seem to agree with human judgements as displayed in figure 3.

## 5 Related Work

Although no previous work has investigated paraphrasing modern text into Shakesperean English, or the more general task of paraphrasing while targeting a specific writing style, there are several strands of related work.

Perhaps most relevant is recent work generating and translating rhythmic poetry (Greene et al., 2010). This work focused on generating text in an appropriate meter (e.g. iambic pentameter) using finite-state transducers. In contrast our work does not address the issue of meter, however it should be possible to combine our translation models with their weighted FSTs to produce Shakesperean paraphrase models which produce output in an appropriate meter.

Much previous work has addressed the task of automatically generating paraphrases (Barzilay and Lee, 2003; Dolan et al., 2004; Shinyama and Sekine, 2003; Das and Smith, 2009; Bannard and Callison-Burch, 2005; Callison-Burch, 2008; Kok and Brockett, 2010). In addition several authors have previously proposed automatic paraphrase evaluation metrics (Chen and Dolan, 2011; Callison-Burch et al., 2008; Bangalore et al., 2000; Liu et al., 2010). We are not

aware, however, of any previous work that has addressed the task of generating or evaluating paraphrases targeting a specific style of writing.

Finally we highlight related work on authorship classification which can be seen as detecting a specific style of writing (Gamon, 2004; Raghavan et al., 2010). This work has not specifically addressed the task of automatically generating or evaluating paraphrases in a specific style, however.

## 6 Conclusions

We have presented initial investigation into the task of automatic paraphrasing while targeting a specific style of writing. We proposed Shakespeare's plays and their modern translations as a testbed for this task, and developed a series of paraphrase systems targeting Shakesperean English. We showed that while existing evaluation metrics are useful for evaluating paraphrases in this context, BLEU tends to conflate semantic equivalence with writing style giving an incomplete picture of which systems perform better according to each of these criteria.

To address the issues with previous evaluation metrics applied to this task, we have introduced two new metrics for evaluating writing style. We measured correlation between automatic metrics and human judgements in the context of paraphrasing writing style, and showed that our new metrics have better correlation with human judgements than existing metrics in the context of our data. While this evaluation is limited to one specific style of writing, we are optimistic that these or similar metrics will also perform well when evaluating other writing styles.

Future work could include automatically translating the remaining 20 of Shakespeare's plays into modern English, which could be beneficial to students of Shakespeare's plays and also to future human translators.

## References

- Bangalore, S., Rambow, O., and Whittaker, S. (2000). Evaluation metrics for generation. In *Proceedings of the first international conference on Natural language generation - Volume 14*.
- Bannard, C. and Callison-Burch, C. (2005). Paraphrasing with bilingual parallel corpora. In *Proceedings of the 43rd Annual Meeting of the Association for Computational Linguistics (ACL05)*.
- Barzilay, R. and Lee, L. (2003). Learning to paraphrase: an unsupervised approach using multiple-sequence alignment. In *Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology - Volume 1*, NAACL '03.
- Callison-Burch, C. (2008). Syntactic constraints on paraphrases extracted from parallel corpora. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*.
- Callison-Burch, C., Cohn, T., and Lapata, M. (2008). Parametric: an automatic evaluation metric for paraphrasing. In *Proceedings of the 22nd International Conference on Computational Linguistics - Volume 1*.
- Chen, D. L. and Dolan, W. B. (2011). Collecting highly parallel data for paraphrase evaluation. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics (ACL-2011)*, Portland, OR.

- Das, D. and Smith, N. A. (2009). Paraphrase identification as probabilistic quasi-synchronous recognition. In *Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP: Volume 1 - Volume 1*, ACL '09.
- Dolan, B., Quirk, C., and Brockett, C. (2004). Unsupervised construction of large paraphrase corpora: Exploiting massively parallel news sources. In *Proceedings of Coling 2004*.
- Gamon, M. (2004). Linguistic correlates of style: authorship classification with deep linguistic analysis features. In *Proceedings of the 20th international conference on Computational Linguistics*.
- Giampiccolo, D., Magnini, B., Dagan, I., and Dolan, B. (2007). The third pascal recognizing textual entailment challenge. In *Proceedings of the ACL-PASCAL Workshop on Textual Entailment and Paraphrasing*, RTE '07.
- Greene, E., Bodrumlu, T., and Knight, K. (2010). Automatic analysis of rhythmic poetry with applications to generation and translation. In *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing*.
- Koehn, P., Hoang, H., Birch, A., Callison-Burch, C., Federico, M., Bertoldi, N., Cowan, B., Shen, W., Moran, C., Zens, R., Dyer, C., Bojar, O., Constantin, A., and Herbst, E. (2007). Moses: open source toolkit for statistical machine translation. In *Proceedings of the 45th Annual Meeting of the ACL on Interactive Poster and Demonstration Sessions*.
- Koehn, P. and Knight, K. (2000). Estimating word translation probabilities from unrelated monolingual corpora using the em algorithm. In *Proceedings of the Seventeenth National Conference on Artificial Intelligence and Twelfth Conference on Innovative Applications of Artificial Intelligence*.
- Kok, S. and Brockett, C. (2010). Hitting the right paraphrases in good time. In *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*.
- Liu, C., Dahlmeier, D., and Ng, H. T. (2010). PEM: A paraphrase evaluation metric exploiting parallel texts. In *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing*.
- Moore, R. C. (2002). Fast and accurate sentence alignment of bilingual corpora. In *Proceedings of the 5th Conference of the Association for Machine Translation in the Americas on Machine Translation: From Research to Real Users*, AMTA '02.
- Och, F. J. and Ney, H. (2003). A systematic comparison of various statistical alignment models. *Comput. Linguist.*
- Papineni, K., Roukos, S., Ward, T., and Zhu, W.-J. (2002). Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics*.
- Quirk, C., Brockett, C., and Dolan, W. (2004). Monolingual machine translation for paraphrase generation. In *Proceedings of EMNLP 2004*.

Raghavan, S., Kovashka, A., and Mooney, R. (2010). Authorship attribution using probabilistic context-free grammars. In *Proceedings of the ACL 2010 Conference Short Papers*.

Shinyama, Y. and Sekine, S. (2003). Paraphrase acquisition for information extraction. In *Proceedings of the second international workshop on Paraphrasing - Volume 16, PARAPHRASE '03*.

Snow, R., O'Connor, B., Jurafsky, D., and Ng, A. Y. (2008). Cheap and fast—but is it good?: evaluating non-expert annotations for natural language tasks. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing, EMNLP '08*.