Exemplar-Controllable Paraphrasing and Translation using Bitext

Mingda Chen  Sam Wiseman  Kevin Gimpel
Toyota Technological Institute at Chicago, Chicago, IL, 60637, USA
{mchen,swiseman,kgimpel}@ttic.edu

Abstract
Most prior work on exemplar-based syntactically controlled paraphrase generation relies on automatically-constructed large-scale paraphrase datasets, which are costly to create. We sidestep this prerequisite by adapting models from prior work to be able to learn solely from bilingual text (bitext). Despite only using bitext for training, and in near zero-shot conditions, our single proposed model can perform four tasks: controlled paraphrase generation in both languages and controlled machine translation in both language directions. To evaluate these tasks quantitatively, we create three novel evaluation datasets. Our experimental results show that our models achieve competitive results on controlled paraphrase generation and strong performance on controlled machine translation. Analysis shows that our models learn to disentangle semantics and syntax in their latent representations, but still suffer from semantic drift.

1 Introduction
We consider the task of syntactically-controlled paraphrasing, which seeks to generate sentences that conform to desired syntax, specified either by syntactic templates (Iyyer et al., 2018) or a sentential exemplar (Chen et al., 2019a). Controlled paraphrasing can be used in collaborative and assistive writing technologies, which are deployed technologies used by creative writers (Manjavacas et al., 2017; Miller, 2019), English language learners (Chodorow et al., 2010; Abbas et al., 2020), students in educational settings (Weston-Sementelli et al., 2018), and marketing professionals (Huang and Rust, 2021). Writers use these tools to make their writing more fluent and professional, as well as to gain inspiration from seeing new ways to express their thoughts. Using sentential exemplars can provide a way to tailor the suggestions to match a desired syntactic pattern, without having to specify a linguistic structure such as a constituency tree. In the context of machine translation, controlled translation can be used to customize machine translation outputs in particular ways, such as producing simple sentence structures for ease of understanding. Also, controlled translation can be a way to produce multiple diverse translations which can be used for reranking or for presenting to users to provide a richer sense of the meaning of the original text when the 1-best translation is not useful (Mayhew et al., 2020).

Most prior work on controlled paraphrasing relies on large-scale paraphrase datasets, which are created automatically from bitext (Ganitkevitch et al., 2013; Wieting and Gimpel, 2018; Hu et al., 2019a). However, creating paraphrase datasets is costly (Wieting and Gimpel, 2018; Wieting et al., 2019a), so in this paper we focus on ways of learning to perform exemplar-based syntactically controlled paraphrasing and translation directly from bilingual text (bitext). Inspired by prior work on controlled paraphrase generation (Chen et al., 2019b,a), we use a deep generative sentence model with two latent variables for capturing syntax and semantics. Building on the assumption that the semantics of translation pairs are shared, but syntax varies, we adapt the multi-task objectives proposed by Chen et al. (2019b,a). The model only requires training on bitext, yet it is capable of exemplar-based syntactically controlled paraphrase generation and exemplar-based syntactically controlled machine translation in an almost zero-shot manner.

To evaluate models on these tasks quantitatively, we construct three datasets: one for Chinese controlled paraphrase generation, and the other two for Chinese-to-English and English-to-Chinese controlled machine translation. Similar to the dataset from Chen et al. (2019a), each instance in these datasets contains three items: a
semantic input, a syntactic exemplar, and a reference. Models must generate sentences that combine the semantics of the semantic input with the syntax of the syntactic input. When creating these datasets, we always first automatically construct a large pool of syntactic/semantic paraphrases and then perform heavy manual post-editing to ensure the quality of the dataset and difficulty of the tasks.

Empirically, for English controlled paraphrase generation, we show that (1) our models achieve competitive results compared to prior work that uses English paraphrase pairs and stronger results compared to prior work that uses translation pairs; (2) in order for the models trained on translation pairs to reach similar performance as those trained on paraphrase pairs, the translation-trained models need more training instances than the paraphrase-trained models. We also show that our models are able to perform Chinese controlled paraphrase generation and controlled machine translation without supervision for these tasks. Quantitative analysis shows that the models learn to disentangle semantics and syntax in latent representations. Qualitative analysis shows that our models suffer from semantic drift, especially for long sentences and in the controlled machine translation tasks, showing clear directions for future research.

2 Related Work

Paraphrase generation uses either monolingual parallel corpora (Quirk et al., 2004; Prakash et al., 2016; Gupta et al., 2018; Li et al., 2018) or bilingual parallel corpora by pivoting (Bannard and Callison-Burch, 2005; Ganitkevitch et al., 2013; Mallinson et al., 2017), back-translating (Wieting and Gimpel, 2018; Hu et al., 2019a,b), and more recently language modeling (Guo et al., 2019). Our focus in this work is syntactically-controlled paraphrasing and machine translation based on bitext, whereas most prior work on controlled paraphrase generation relies on English training data (Iyyer et al., 2018; Chen et al., 2019a; Goyal and Durrett, 2020; Kumar et al., 2020; Li et al., 2020; Kazemnejad et al., 2020).

Recently, Liu et al. (2020) show that machine translations can be used as training data for English syntactically-controlled paraphrasing. Relatedly, Wieting et al. (2019a) learn sentence embeddings directly from translations instead of paraphrase pairs, Wieting et al. (2019b) learn disentangled sentence embeddings from translations, and Liu et al. (2019) learn syntactic sentence embeddings through translations and part-of-speech tags.

There is a long history of example-based machine translation (Nagao, 1984; Somers, 1999), and recently researchers find it helpful to build generations upon sentential exemplars (Guu et al., 2018; Weston et al., 2018). Our approach differs from prior work in that we use sentential exemplars for controllability instead of improving generation quality. Part of our evaluation involves syntactically controlled machine translation, relating it to syntax-based machine translation systems (Wu, 1997; Chiang, 2005; Sennrich and Haddow, 2016). Recently, Akoury et al. (2019) found it helpful in speeding up the decoding process.

3 Method and Evaluation

3.1 Method

To perform exemplar-based syntactically controlled generation from bitext, we follow an approach based on the vMF-Gaussian Variational Autoencoder (VGVAE) model (Chen et al., 2019b). VGVAE is a deep generative models with two latent variable models for modelling syntax and semantics, and it is trained with two multi-task losses designed for monolingual paraphrase sentence pairs. To adapt VGVAE and the associated multi-task losses to multilingual settings, we make a few changes, including (1) the use of byte pair encoding (BPE; Sennrich et al., 2016); (2) we use language-specific syntactic encoders, but share the semantic encoder between the two languages; (3) we prepend a language-specific token to each input sentence. Details are in the appendix. We will call this model “mVGVAE”.

The training of the mVGVAE only requires bitext, yet the trained model will contain necessary parameters to perform exemplar-based syntactically controlled paraphrase generation for either language. Moreover, training on bitext also makes the model suitable for cross-lingual tasks, such as exemplar-based syntactically controlled machine translation. In the following sections, we will demonstrate the model’s ability to accomplish these tasks in an almost zero-shot fashion.

3.2 Controllable Paraphrase Generation with a Syntactic Exemplar

To evaluate the syntactic controllability of generation, Chen et al. (2019a) constructed a human-
trained on bitext allows our models to perform generation in languages other than English. To evaluate this capability, we construct a similar dataset in Chinese, as shown in Figure 1. Since there is no large-scale Chinese paraphrase dataset available, we first automatically tag the Chinese sentences obtained from the Chinese-English OpenSubtitles corpus (Lison and Tiedeman, 2016), and then for each sentence, we find a sentence that shares the most similar syntax in the same corpus by computing the edit distance between the part-of-speech tag sequences. After obtaining these syntactic paraphrases, a native Chinese speaker paraphrases the references, following the data construction process described in Chen et al. (2019a) to ensure syntactic mismatch between the semantic input and the syntactic input, and semantic mismatch between the syntactic input and the reference. This contributes 378 instances. We also consider using Chinese instances that are translated from our English controlled paraphrase generation test set, and then we ask the annotator to heavily post edit these instances to ensure the criteria mentioned earlier are met. The final dataset contains 800 instances.

3.3 Controllable Machine Translation with a Syntactic Exemplar

Motivated by the fact that our models are trained on bitext, we create a novel task, where the semantic input is from the source language, and the syntactic input and reference are from the target language. Examples for both English-to-Chinese and Chinese-to-English tuples are shown in Figure 2. Compared to the task of generating paraphrases, this task is more challenging in that it requires translation and syntactic control simultaneously.
We construct evaluation datasets based on the monolingual syntactically-controlled paraphrase datasets described in the previous section. We first use Google Translate to translate the semantic inputs, and then manually go through these sentences to ensure that (1) there is no grammatical error or semantic drift in the translations; and (2) there is strong syntactic mismatch between the translations and the references, so that the task can not be trivially solved by translating the semantic inputs.

When evaluating models on these two datasets, we mostly follow the process used for paraphrase generation except that we use the language-specific syntactic encoders to encode the syntactic inputs. We report BLEU and ST scores for this task.

4 Experiments

4.1 Training

The training of our models uses bitext from OpenSubtitles.\footnote{http://www.opensubtitles.org/} We report results on Chinese-English (Zh-En) sentence pairs. Results on German-English (De-En), Spanish-English (Es-En), and French-English (Fr-En) sentence pairs are in the supplementary material. As baselines, we train models on Czech-English (Cs-En) sentence pairs from the CzEng corpus (Bojar et al., 2016) and English-English (En-En) sentence pairs from the ParaNMT-50M dataset (Wieting and Gimpel, 2018), which is constructed by back-translating the CzEng corpus.

For all these datasets, we first tokenize text with the Stanford CoreNLP toolkit and then use BPE with 30,000 merge operations. Chen et al. (2019a) used several heuristics for additional filtering of the 5-million-pair preprocessed subset of ParaNMT-50M released by Wieting and Gimpel (2018), eventually using half a million paraphrase pairs for training. As these heuristics are not directly applicable to bitext, we use the full 5-million preprocessed subset for En-En. For Zh-En, we randomly sample 5 million sentence pairs. To make the results more comparable to prior work on English controllable paraphrasing, for both settings and the CzEng corpus, we also report results that use 0.5 million sentence pairs, randomly sampled. We use word noising during training (Chen et al., 2019a), and the probability of noising a word is 90%. We perform early stopping based on the BLEU score from the development set. More details, such as runtime and hyperparameters, are in the appendix.

We only have a development set for the English paraphrase generation task, for which we use the dev split from Chen et al. (2019a). For the other tasks, we do not have development sets. We treat our newly-created datasets (described in Sections 3.2 and 3.3) as test sets and report results on them. Therefore, we can consider our results on these tasks to be zero-shot or zero-shot crosslingual results.

4.2 Results

Controlled Paraphrase Generation. For English and Chinese paraphrase generation, we report two groups of baselines. The first group is “return-input”, where we return either the syntactic input or the semantic input as the prediction. As shown in Tables 1 and 2, compared to the semantic input, the syntactic input leads to better ST score but worse semantic-related scores, i.e., BLEU.\footnote{When evaluating Chinese sentences, the metrics are computed at the character-level, following the process described in Ma et al. (2019).} This reflects our consideration about the differences between these two when constructing the dataset.

For English paraphrasing, the second group of baselines is models trained on ParaNMT. The empirical comparison to prior work (Chen et al., 2019a) shows the impact of several changes made when modifying mVGVVAE for use with bitext, such as BPE, as well as the difference in training data filtering. Our model (En-En) achieves worse performance in semantic-related metrics compared to prior work when training on the same amount of data. Using more data partially mitigates the performance gap.

For models trained on bitext, our model obtains stronger performance than Liu et al. (2020) when training on the same amount of data. However, the results for our models and Liu et al. (2020) are not strictly comparable as their models are trained on different datasets. The difference between the results for 0.5M En-En and 0.5M Cs-En shows the advantage of learning from monolingual paraphrase pairs as compared to bitext. Compared to training on 0.5M Cs-En, we are able to obtain slightly better performance when training on 0.5M Zh-En sentence pairs.\footnote{We also experimented with other language pairs in order to make the results more comparable to prior work on English controllable paraphrasing, for both settings and the CzEng corpus, we also report results that use 0.5 million sentence pairs, randomly sampled. We use word noising during training (Chen et al., 2019a), and the probability of noising a word is 90%. We perform early stopping based on the BLEU score from the development set. More details, such as runtime and hyperparameters, are in the appendix.}
increasing the amount of training data to 5M, we are able to match the performance of the 0.5M En-En model. Prior work on learning sentence representations from bitext (Wieting et al., 2019a) also found that training on bitext requires more data than training on English paraphrase data. In light of the strong performance, we will report results that use 5M sentence pairs for the following experiments.

Although models trained on 5M Zh-En bitext perform worse on English paraphrase generation in terms of the BLEU score, they show strong performance on the ST score, suggesting that these generations share similar syntax with the syntactic inputs but they are not faithful to the semantic inputs (e.g., in Sec. 5.4, we find that the model suffers from semantic drift). It is also worth noting that (1) compared to the model trained on ParaNMT, the model trained on Zh-En only trains on half the number of English sentences; (2) during training, the models never get to train on paired monolingual sentences, yet they manage to control the syntax in the generations.

Nonetheless, to offer a competitive baseline for future work, we train a large model with 1000 hidden units per direction on 5 million instances of Zh-En bitext, and report the results as “Zh-En Big” in the tables. As shown in Tables 1 and 2, increasing model size boosts performance significantly.

Controlled Machine Translation. As we do not have semantic inputs in the same language as references in this setting, the “return-input” baseline for the semantic input would score very badly. So, we evaluate standard machine translation systems on these tasks as baselines, simply applying them to the semantic input and ignoring the syntactic input. The systems we consider include (1) a neural sequence-to-sequence model trained on the same 5 million Zh-En bitext using OpenNMT (Klein et al., 2017); and (2) Google Translate.

Test results are shown in Tables 3 and 4. We note that to obtain the OpenNMT results in these two tables, we need to train two separate models on two directions of the Zh-En bitext, whereas we can use a single mVGVAE model for both translation directions (in addition to both paraphrasing tasks). The two tables show that these machine translation systems achieve strong performance on the semantic metric (BLEU), but weak performance on the syntactic metric (ST). This highlights that success of syntactic controllability of generation depends on using the syntactic inputs. Our large model achieves the best results in ST in these two tables and still manages to obtain reasonable BLEU scores.

### 5 Analysis

#### 5.1 Human Evaluation

We conduct a human evaluation to verify the extent to which the syntax of generations matches the syntax of the syntactic inputs. We use Amazon Mechanical Turk and ask human annotators to give scores ranging from 1 to 5 (with 1 being the most dissimilar) for the syntactic similarity between the generated output and the syntactic inputs (details are in the supplementary material).
We report results for the English semantic similarity task in Table 5. We report the best model from Chen et al. (2019a) as “Prior work”. For the Chinese test set, we also benchmark fastText (Bojanowski et al., 2017) on it by using the averaged word vectors as the sentence representation. In comparing to prior work, our En-En model performs worse on the $\Delta$ value, and performs better on the semantic variable.

In general, as suggested by the large $\Delta$ values, our models learn to disentangle the semantic information in the syntactic variable and semantic variable pair. We report the Pearson correlation between the human annotation and the cosine similarity computed based on the sentence representations.

For the syntactic evaluation, we follow the procedure described by Chen et al. (2019b) to automatically parse and tag sentences using the Stanford CoreNLP toolkit for all languages except English. For English, we use the existing dataset provided by Chen et al. (2019b). Then, we randomly pick 300 sentences for each length (up to 30) as test sets, and leave the rest of the sentences with the same length as candidates. We use the sentence representations to retrieve the nearest neighbor in the candidate pool for sentences in the test set, and compute the distance metrics between these two sentences by computing labeled $F_1$ scores for constituency parse (CP) trees or accuracies for part-of-speech (POS) tagging. The syntactic match between the nearest neighbors and the query sentences can illustrate the extent of syntactic information that the sentence representations have captured. This kind of retrieval-based approach has been shown to be effective in sequence labeling (Wiseman and Stratos, 2019).

**Semantic Evaluation.** We report results for the English semantic similarity task in Table 5. We report the best model from Chen et al. (2019a) as “Prior work”. For the Chinese test set, we also benchmark fastText (Bojanowski et al., 2017) on it by using the averaged word vectors as the sentence representation. In comparing to prior work, our En-En model performs worse on the $\Delta$ value, and performs better on the semantic variable.

In general, as suggested by the large $\Delta$ values, our models learn to disentangle the semantic information in the syntactic variable and semantic variables.

### Table 4: English→Chinese controlled translation.

| Representations | English test set |
|----------------|-----------------|
|                | sem. | syn. | $\Delta$ |
| Prior work (En-En) | 74.3 | 7.4 | 66.9 |
| Our work (En-En) | 74.9 | 12.0 | 62.9 |
| Our work (Zh-En) | 73.6 | 16.3 | 57.3 |
| fastText | 67.0 |
| Our work | 76.2 | 23.5 | 52.8 |

### Table 5: Pearson’s correlation (%) for the semantic similarity tasks.

| Evaluation metric | POS Accuracy | CP Labeled $F_1$ |
|-------------------|--------------|-------------------|
|                    | sem. | syn. | $\Delta$ | sem. | syn. | $\Delta$ |
| Oracle | 62.3 | 71.1 |
| Random | 12.9 | 19.2 |
| PW (En-En) | 20.3 | 43.7 | 23.4 | 24.8 | 40.9 | 16.1 |
| En-En | 19.6 | 44.9 | 25.7 | 24.2 | 42.4 | 18.2 |
| Zh-En | 19.7 | 44.4 | 24.7 | 24.4 | 41.7 | 19.5 |
| Chinese test set | | | |
| Oracle | 56.6 | 58.2 |
| Random | 13.4 | 17.8 |
| fastText | 18.7 | 21.7 |
| Zh-En | 15.0 | 36.2 | 21.2 | 19.3 | 32.3 | 12.9 |

### Table 6: POS tagging accuracy (%) and constituent parsing labeled $F_1$ scores (%) for the syntactic evaluation. PW = prior work.
Table 7: The most similar sentences to particular query sentences in terms of the semantic variable and syntactic variable based on the model trained on Zh-En bitext. Each Chinese sentence is followed by a gloss. More examples are in the supplementary material.

| Query Sentence | Semantically Similar | Syntactically Similar |
|----------------|----------------------|-----------------------|
| you from window outside can see it (you almost no possible again close distance see it, use telescope also not work) | 你能从窗户外面看到它也在电视上也会看到它 | 我在国会上讲过我们不会做枪但我们也会靠自己 (i at congress talked we need build a bridge but we can depend on ourselves) |
| with a gun, you feel more dangerous, i would n’t know. | “with a gun ... wouldn’t know.” | all these days, i could n’t work, i could n’t sleep. |
| you from window outside can see it in tv also can see it | 你也几乎不可能再近距离看到它的. 望远镜也不行 | 我们会在电视上看到窗户外面能看到它 (you from window outside can see it in tv also can see it) |

Table 8: Human evaluation results for Chinese-to-English controlled machine translation. We report the average and standard deviation of scores that measures the syntactic similarity between the generations and the syntactic inputs. Higher is better for the average scores.

| Method                  | Avg. | Std. |
|------------------------|------|------|
| OpenNMT                | 2.4  | 1.2  |
| Google Translate       | 2.4  | 1.1  |
| Our model (Zh-En Big)  | 3.5  | 1.4  |

Similar to what we observe in the semantic similarity tasks, our models can disentangle syntactic information in the latent variables, either in the English dataset or the datasets in other languages (see supplementary materials for more results on other languages). On the Chinese test set, fastText is slightly better than the semantic variable of our model, whereas the syntactic variable achieves much better performance.

5.3 Nearest Neighbors

We analyze nearest neighbors based on cosine similarities between query sentences drawn from the test sets and candidates with the same length from the syntactic evaluation candidate set. Table 7 shows the nearest neighbors found by either the semantic variable or the syntactic variable. Similar to Chen et al. (2019a), who trained on paraphrases, models trained on bitext also capture different characteristics for different latent variables. The semantically similar sentences share similar topics with the query sentences, while their syntactic structures are very different. The syntactically similar sentences have similar syntax to the query sentences, while their topics are different. For example, “with a gun … wouldn’t know.” and “i’ll give him … any better” both talk about guns, whereas “all these days … couldn’t sleep” is about working and sleeping, which is topically unrelated to the previous two sentences. However, the syntactic variable still gives it the highest similarity due to the similar syntactic structure. Similar effects can be observed for the Chinese nearest neighbors.

5.4 Generation Samples

In Table 9, we compare generation examples from the “En-En” model to those from the “Zh-En Big” model. Both models are trained on 3 million sentence pairs. In general, we find the models are able to generate sentences that exhibit the expected syntax without changing the semantics. However, for
Table 9: Example outputs from the “En-En” and “Zh-En Big” models for the English controlled paraphrase generation tasks. Both models are trained on 5 million sentence pairs.

Table 10: Example outputs from the “Zh-En Big” model for our three new controlled generation tasks. Each Chinese sentence is followed by a gloss. More examples are in the supplementary material.

long inputs, the outputs from the Zh-En model become more noisy in terms of semantic preservation. For example, see the third instance in the table, where the En-En output is a bit garbled but still uses topically-relevant phrases (e.g., “responsibility of policy”) whereas the Zh-En output has changed the semantics dramatically (“the mayor gets hurt”). In addition, we find that the subword tokenization may have a negative impact on the model performance. In the last example in the table, although the semantic and the syntactic inputs never talk about fish, the outputs from both models contain the word “fish”, which is likely due to the fact that the “wolfish” in the semantic input is tokenized into “wol@@ fish” by the byte pair encoding where “@@” is the separator between non-final subword units.

In Table 10, we demonstrate generation examples from the Zh-En Big model for the other three tasks considered in this paper. In general, the model tends to give higher priority to the syntactic input than the semantic input, even at the cost of faithfulness to the semantic input. For example, in Chinese controlled paraphrase generation, the semantic input “i tired of your late night visits” gets transformed into “your visitor made me tired.”, which shows strong syntactic similarity to the syntactic input, although the word “visit” is replaced by the word “visitor”. This sort of semantic drift occurs more often in controlled machine translation. For example, in English-to-Chinese translation, the instance with similar semantic and syntactic input is translated into “your visitor made me late”, which mistranslates both “visit” and “tired”, although the syntax of the instance remains very similar to that of the syntactic input.

However, it is worth noting that the model manages to transform function words into appropriate words that fit the context. For example, in Chinese-to-English controlled machine translation, the phrase “why can’t i have been drinking or something?” is transformed into “why couldn’t i have been”. It is also interesting to see that the model only needs to be trained once on Zh-En bitext to perform all four of these tasks.

6 Conclusion

We tailored a disentanglement method so that it can be trained on bitext instead of paraphrases, and demonstrated that it can learn to perform exemplar-based syntactically controlled paraphrasing and machine translation in an almost zero-shot fashion. We annotated three new datasets targeting these tasks which will be made available.
titative analysis shows that our model learns to disentangle semantics and syntax in the latent representations, though it still suffers from semantic drift when performing controlled generation, suggesting directions for future work.

References

Muhammad Azeem Abbas, Shiza Hammad, Gwo-Jen Hwang, Sharifullah Khan, and Syed Mushtad Mustuzech Gilani. 2020. An assistive environment for EAL academic writing using formulaic sequences classification. *Interactive Learning Environments*, pages 1–15.

Eneko Agirre, Carmen Banea, Claire Cardie, Daniel Cer, Mona Diab, Aitor Gonzalez-Agirre, Weiwei Guo, Rada Mihalcea, German Rigau, and Janyce Wiebe. 2014. SemEval-2014 task 10: Multilingual semantic textual similarity. In *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014)*, pages 81–91, Dublin, Ireland. Association for Computational Linguistics.

Nader Akoury, Kalpesh Krishna, and Mohit Iyyer. 2019. Syntactically supervised transformers for faster neural machine translation. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1269–1281, Florence, Italy. Association for Computational Linguistics.

Santanjeev Banerjee and Alon Lavie. 2005. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In *Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization*, pages 65–72, Ann Arbor, Michigan. Association for Computational Linguistics.

Colin Bannard and Chris Callison-Burch. 2005. Paraphrasing with bilingual parallel corpora. In *Proceedings of the 43rd Annual Meeting of the Association for Computational Linguistics (ACL’05)*, pages 597–604, Ann Arbor, Michigan. Association for Computational Linguistics.

Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2017. Enriching word vectors with subword information. *Transactions of the Association for Computational Linguistics*, 5:135–146.

Ondřej Bojar, Ondřej Dušek, Tom Kocmi, Jindřich Libovický, Michal Novák, Martin Popel, Roman Sudarikov, and Dušan Vareš. 2016. CzEng 1.6: Enlarged Czech-English Parallel Corpus with Processing Tools Dockered. In *Text, Speech, and Dialogue: 19th International Conference, TSD 2016*, number 9924 in Lecture Notes in Computer Science, pages 231–238, Cham / Heidelberg / New York / Dordrecht / London. Masaryk University, Springer International Publishing.

Daniel Cer, Mona Diab, Eneko Agirre, Itxigo Lopez-Gazpio, and Lucia Specia. 2017. SemEval-2017 task 1: Semantic textual similarity multilingual and crosslingual focused evaluation. In *Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017)*, pages 1–14, Vancouver, Canada. Association for Computational Linguistics.

Mingda Chen, Qingming Tang, Sam Wiseman, and Kevin Gimpel. 2019a. Controllable paraphrase generation with a syntactic exemplar. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5972–5984, Florence, Italy. Association for Computational Linguistics.

Mingda Chen, Qingming Tang, Sam Wiseman, and Kevin Gimpel. 2019b. A multi-task approach for disentangling syntax and semantics in sentence representations. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 2453–2464, Minneapolis, Minnesota. Association for Computational Linguistics.

David Chiang. 2005. A hierarchical phrase-based model for statistical machine translation. In *Proceedings of the 43rd Annual Meeting of the Association for Computational Linguistics (ACL’05)*, pages 263–270, Ann Arbor, Michigan. Association for Computational Linguistics.

Martin Chodorow, Michael Gamon, and Joel Tetreault. 2010. The utility of article and preposition error correction systems for English language learners: Feedback and assessment. *Language Testing*, 27(3):419–436.

Juri Ganitkevitch, Benjamin Van Durme, and Chris Callison-Burch. 2013. PPDB: The paraphrase database. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 758–764, Atlanta, Georgia. Association for Computational Linguistics.

Tanya Goyal and Greg Durrett. 2020. Neural syntactic preordering for controlled paraphrase generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics.

Yinpeng Guo, Yi Liao, Xin Jiang, Qing Zhang, Yibo Zhang, and Qun Liu. 2019. Zero-shot paraphrase generation with multilingual language models. *arXiv preprint arXiv:1911.03597*.

Ankush Gupta, Arvind Agarwal, Prawaan Singh, and Piyush Rai. 2018. A deep generative framework for paraphrase generation. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, (AAAI-18)*, the 30th innovative Applications of Artificial Intelligence (IAAI-18), and the 8th AAAI Symposium on Educational Advances in Artificial Intelligence (EAAI-18), New Orleans, Louisiana, USA, February 2-7, 2018, pages 5149–5156. AAAI Press.
Kelvin Guu, Tatsumori B. Hashimoto, Yonatan Oren, and Percy Liang. 2018. Generating sentences by editing prototypes. Transactions of the Association for Computational Linguistics, 6:437–450.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation, 9(8):1735–1780.

J. Edward Hu, Rachel Rudinger, Matt Post, and Benjamin Van Durme. 2019a. ParaBank: Monolingual bitext generation and sentential paraphrasing via lexically-constrained neural machine translation. In Proceedings of AAAI.

J. Edward Hu, Abhinav Singh, Nils Holzenberger, Matt Post, and Benjamin Van Durme. 2019b. Large-scale, diverse, paraphrastic bitexts via sampling and clustering. In Proceedings of the 23rd Conference on Neural Information Processing Systems (NeurIPS), pages 44–54, Hong Kong, China. Association for Computational Linguistics.

Ming-Hui Huang and Roland T. Rust. 2021. A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49:30–50.

Mohit Iyyer, John Wiebing, Kevin Gimpel, and Luke Zettlemoyer. 2018. Adversarial example generation with syntactically controlled paraphrase networks. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1875–1885, New Orleans, Louisiana. Association for Computational Linguistics.

Amirhossein Kazemnejad, Mohammadreza Salehi, and Mahdieh Soleymani Baghshah. 2020. Paraphrase generation by learning how to edit from samples. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 6010–6021, Online. Association for Computational Linguistics.

Guillaume Klein, Yoon Kim, Yuntian Deng, Jean Senellart, and Alexander Rush. 2017. OpenNMT: Open-source toolkit for neural machine translation. In Proceedings of ACL 2017, System Demonstrations, pages 67–72, Vancouver, Canada. Association for Computational Linguistics.

Ashutosh Kumar, Kabir Ahuja, Raghuram Vadera, and Partha Pratim Talukdar. 2020. Syntax-guided controlled generation of paraphrases. ArXiv, abs/2005.08417.

Yinghao Li, Rui Feng, Isaac Rehg, and Chao Zhang. 2020. Transformer-based neural text generation with syntactic guidance. arXiv preprint arXiv:2010.01737.

Zichao Li, Xin Jiang, Lifeng Shang, and Hang Li. 2018. Paraphrase generation with deep reinforcement learning. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3865–3878, Brussels, Belgium. Association for Computational Linguistics.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In Text Summarization Branches Out, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Pierre Lison and Jörg Tiedemann. 2016. OpenSubtitles2016: Extracting large parallel corpora from movie and TV subtitles. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC 2016), pages 923–929, Portorož, Slovenia. European Language Resources Association (ELRA).

Chen Liu, Anderson De Andrade, and Muhammad Osama. 2019. Exploring multilingual sentence representations. In Proceedings of the 5th Workshop on Noisy User-generated Text (W-NUT 2019), pages 153–159, Hong Kong, China. Association for Computational Linguistics.

Mingtong Liu, Erguang Yang, Deyi Xiong, Yujie Zhang, Chen Sheng, Changjian Hu, Jinan Xu, and Yufeng Chen. 2020. Exploring bilingual parallel corpora for syntactically controllable paraphrase generation. In Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, IJCAI-20, pages 3955–3961. International Joint Conferences on Artificial Intelligence Organization. Main track.

Qingsong Ma, Johnny Wei, Ondřej Bojar, and Yvette Graham. 2019. Results of the WMT19 metrics shared task: Segment-level and strong MT systems pose big challenges. In Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1), pages 62–90, Florence, Italy. Association for Computational Linguistics.

Jonathan Mallinson, Rico Sennrich, and Mirella Lapata. 2017. Paraphrasing revisited with neural machine translation. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers, pages 881–893, Valencia, Spain. Association for Computational Linguistics.

Enrique Manjavacas, Folgert Karsdorp, Ben Burtonshaw, and Mike Kestemont. 2017. Synthetic literature: Writing science fiction in a co-creative process. In Proceedings of the Workshop on Computational Creativity in Natural Language Generation (CC-NLG 2017), pages 29–37, Santiago de Compostela, Spain. Association for Computational Linguistics.

Christopher Manning, Mihai Surdeanu, John Bauer, Jenny Finkel, Steven Bethard, and David McClosky. 2014. The Stanford CoreNLP natural language processing toolkit. In Proceedings of 52nd Annual
Meeting of the Association for Computational Linguistics: System Demonstrations, pages 55–60, Baltimore, Maryland. Association for Computational Linguistics.

Stephen Mayhew, Klington Bicknell, Chris Brust, Bill McDowell, Will Monroe, and Burr Settles. 2020. Simultaneous translation and paraphrase for language education. In Proceedings of the Fourth Workshop on Neural Generation and Translation, pages 232–243, Online. Association for Computational Linguistics.

A.I. Miller. 2019. The Artist in the Machine: The World of AI-Powered Creativity. MIT Press.

Makoto Nagao. 1984. A framework of a mechanical translation between japanese and english by analogy principle. In Proc. of the international NATO symposium on Artificial and human intelligence, pages 173–180.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Aaditya Prakash, Sadid A. Hasan, Kathy Lee, Vivek Datla, Asheel Qadir, Joey Liu, and Oladimeji Farri. 2016. Neural paraphrase generation with stacked residual LSTM networks. In Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers, pages 2923–2934, Osaka, Japan. The COLING 2016 Organizing Committee.

Chris Quirk, Chris Brockett, and William Dolan. 2004. Monolingual machine translation for paraphrase generation. In Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing, pages 142–149, Barcelona, Spain. Association for Computational Linguistics.

Rico Sennrich and Barry Haddow. 2016. Linguistic input features improve neural machine translation. In Proceedings of the First Conference on Machine Translation: Volume 1, Research Papers, pages 83–91, Berlin, Germany. Association for Computational Linguistics.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1715–1725, Berlin, Germany. Association for Computational Linguistics.

Harold Somers. 1999. Example-based machine translation. Machine translation, 14(2):113–157.

Shaonan Wang, Jiajun Zhang, and Chengqing Zong. 2017. Exploiting word internal structures for generic Chinese sentence representation. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 298–303, Copenhagen, Denmark. Association for Computational Linguistics.

Jason Weston, Emily Dinan, and Alexander Miller. 2018. Retrieve and refine: Improved sequence generation models for dialogue. In Proceedings of the 2018 EMNLP Workshop SCAI: The 2nd International Workshop on Search-Oriented Conversational AI, pages 87–92, Brussels, Belgium. Association for Computational Linguistics.

Jennifer L. Weston-Sementelli, Laura K. Allen, and Danielle S. McNamara. 2018. Comprehension and writing strategy training improves performance on content-specific source-based writing tasks. International Journal of Artificial Intelligence in Education, 28:106–137.

John Wieting and Kevin Gimpel. 2018. ParaNMT-50M: Pushing the limits of paraphrastic sentence embeddings with millions of machine translations. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 451–462, Melbourne, Australia. Association for Computational Linguistics.

John Wieting, Kevin Gimpel, Graham Neubig, and Taylor Berg-Kirkpatrick. 2019a. Simple and effective paraphrastic similarity from parallel translations. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4602–4608, Florence, Italy. Association for Computational Linguistics.

John Wieting, Graham Neubig, and Taylor Berg-Kirkpatrick. 2019b. A bilingual generative transformer for semantic sentence embedding. ArXiv, abs/1911.03895.

Sam Wiseman and Karl Stratos. 2019. Label-agnostic sequence labeling by copying nearest neighbors. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 5363–5369, Florence, Italy. Association for Computational Linguistics.

Dekai Wu. 1997. Stochastic inversion transduction grammars and bilingual parsing of parallel corpora. Computational Linguistics, 23(3):377–403.

A Details of Methods

We begin by briefly reviewing the learning objective and parameterization of mVGVAE, and then describe the changes we make to adapt it to the multilingual setting. For more details, please refer to the original papers.
Learning Objectives. mVGVAE is a neural latent-variable sentence model with two latent variables, one for modeling semantics (denoted by $y$ and drawn from a von Mises-Fisher prior) and one for syntax (denoted by $z$ and drawn from a Gaussian prior).

mVGVAE assumes sentences $x$ are generated by independent latent variables $y$ and $z$, leading to a factorized joint probability $p_\theta(x, y, z) = p_\theta(y)p_\theta(z)p_\theta(x | y, z)$. Furthermore, mVGVAE assumes a factorized approximated posterior $q_\phi(y, z | x) = q_\phi(y | x)q_\phi(z | x)$. Combining these two assumptions gives rise to one of the learning of objectives of mVGVAE, the ELBO:

$$
\log p_\theta(x) \geq \mathbb{E}_{y \sim q_\phi(y | x)} \left[ \log p_\theta(x | y, z) \right] - KL(q_\phi(z | x) || p_\theta(z)) - KL(q_\phi(y | x) || p_\theta(y))
$$

(1)

Similar to Chen et al. (2019a), we associate weights with the KL terms. In our experiments, we use $1e^{-3}$ for $z$ and $1e^{-4}$ for $y$. To adapt VGVAE to bitext, we use subword units, i.e., byte-pair encoding (BPE; Sennrich et al., 2016), instead of whole word tokenization.

In addition to Eq. (1), Chen et al. (2019a) introduced other losses for multi-task training: a paraphrase reconstruction loss (PRL) and a word position loss (WPL). We directly apply these two losses to our bitext setting. In particular, PRL for a parallel sentence pair $(x_1, x_2)$ takes the form

$$
\mathbb{E}_{y_2 \sim q_\phi(y | x_2)} \left[ \log p_\theta(x_1 | y_2, z_1) \right] + \mathbb{E}_{y_1 \sim q_\phi(y | x_1)} \left[ \log p_\theta(x_2 | y_1, z_2) \right]
$$

(2)

That is, instead of reconstructing a sentence from its syntactic variable and the semantic variable of its paraphrase, we reconstruct a sentence from its syntactic variable and the semantic variable of its translation.

The WPL loss adds a classifier to explicitly predict word position at each time step $t$ using the concatenation of subword unit embedding $c_t$ and the syntactic variable $z$ produced by the approximated posterior. Formally, WPL is defined as follows:

$$
\mathbb{E}_{z \sim q_\phi(z | x)} \left[ \sum_t \log \text{softmax}(f([c_t; z]))_{w_t} \right]
$$

where $f$ is a 3-layer feedforward neural network, $\text{softmax}(-)$, indicates the probability at position $i$, and $w_t$ is the word boundary at $t$, i.e., the position in $x$ of the original word that contains the $t$-th subword unit. Though we use BPE encoding, we define the ground truth positions for WPL using the original word boundaries. Unlike Chen et al. (2019a), we find the latent code does not help model performance when using subword units, so we do not include it in our models.

Finally, the learning objective for mVGVAE is

$$
\text{ELBO} + \text{PRL} + \text{WPL}
$$

(3)

Parameterization. Similar to Chen et al. (2019a), we parameterize the syntactic encoder $q_\phi(z | x)$ with a bidirectional long short-term memory (LSTM; Hochreiter and Schmidhuber, 1997) network, and the semantic encoder $q_\phi(y | x)$ with a word averaging module. Each is then followed by a 2-layer feedforward neural network for encoding the mean direction of the vMF distribution or the mean and the variance of the Gaussian distribution. The $p_\theta(x | y, z)$ is parameterized with a unidirectional LSTM.

We also allocate language-specific parameters to better model bitext. To indicate the languages of the input sentences, we prepend a language-specific token to each input sentence. Additionally, we use language-specific syntactic encoders, but share the semantic encoder between the two languages as we assume that the semantics between sentence pairs are shared. The syntactic and semantic encoders do not share subword unit embeddings.

The training of the mVGVAE only requires bitext, yet the trained model will contain necessary parameters to perform exemplar-based syntactically controlled paraphrase generation for either language. Moreover, training on bitext also makes the model suitable for cross-lingual tasks, such as exemplar-based syntactically controlled machine translation. In the following sections, we will demonstrate the model’s ability to accomplish these tasks in an almost zero-shot fashion.

B Hyperparameter and Model Size

We follow the hyperparameters used in Chen et al. (2019a) and did not perform any other hyperparameter search for fair comparison. We use 50 as the latent dimension for most of the models, except for the big model, where we use 100. Similarly, we use beam size 10 when evaluating models on test sets.
Our big model has 220.5 million parameters, and the other mVGVAE models each has 30.5 million parameters. OpenNMT baseline has 47.4 million parameters.

C Generation Samples
We show generation examples in Table 11.

D Nearest Neighbors
We show the nearest neighbour examples in Table 12.

E Runtime and Computing Infrastructures
Our models are trained on machines equipped with a single GPU, such as NVIDIA TITAN X or NVIDIA 2080 Ti. We train all of our models for 20 epochs. For the big model, it takes approximately 11.67 hours to finish one epoch. For other mVGVAE models, it takes 6.67 hours to finish one epoch.

F Human Evaluation
During human evaluations, annotators were asked one question: "On a scale of 1-5, how much do you think the structure of sentence 1 and the structure of sentence 2 are similar?", and we show the detailed explanation for each option in Table 13.

G Controlled Paraphrase Generation
We report BLEU, ROUGE-1, ROUGE-2, ROUGE-L, and METEOR. For ST metrics, we report ST-r and ST-s, which are computed between the generations and references, and the generations and syntactic inputs respectively.

We report English controlled paraphrase generation results in Table 14. It is interesting to see that models trained on other language pairs can also learn to perform this task.

We report results for Chinese controlled paraphrase generation in Table 15, Chinese-to-English controlled machine translation in Table 16, and English-to-Chinese controlled machine translation in Table 17.  

H Semantic Disentanglement
We report results for semantic evaluation for other languages in Table 18 and Table 19. For Spanish, we use the Spanish test set from STS 2017 (Agirre et al., 2014). We found that models trained on other language pairs also learn to disentangle latent representations.

I Syntactic Disentanglement
We report results for syntactic evaluation for other languages in Table 20 and Table 21. We found that models trained on other language pairs also learn to disentangle latent representations.

---

6When computing ROUGE scores for Chinese, we map Chinese characters to unique IDs to avoid encoding problems.
| Semantic Input                                           | Syntactic Input                                           | Generation                                           |
|---------------------------------------------------------|-----------------------------------------------------------|------------------------------------------------------|
| 我厌倦了你的深夜探访。 (i tired of your late night visits.) | 他们的耽搁使他发疯了。 (their delay made him crazy.)     | 你的访客让我厌烦了。 (your visitor made me tired.)   |
| 我认为：如果她愿意选择这个坟墓，我们没有理由将她嫁给一个贵族。 (i think, if she willing choose this grave, we no reason will she marry a noble.) | 如果那是他们想要的，你们为什么要这样玩呢？ (if that is they want, you why like this play?) | 如果她们是我们选择的，她就不会结婚了。 (if she is we choose, she will not marry.) |
| 帮助我们学习是布拉德的目的。 (help us learn is brad’s purpose) | 瑞德是去坑害那些百姓的。 (reed is going entrap those common people.) | 布拉德是想帮助我们学习的。 (brad is want help us learn.) |

| **Chinese Controlled Paraphrase Generation** |
|---------------------------------------------|
| 无恶魔可以伤害你，只要你手刃在腰。 as soon as i start the escape sequence, an alarm will sound. as long as you’re a little devil, no one will hurt. |
| 你没有把他的动机写下来？ why not take a look at your verdict？ why not write the letter of his motive？ |
| 不再有毒品给他！ do n’t watch it all day！ do n’t give him any drugs！ |

| **English Controlled Paraphrased Generation** |
|---------------------------------------------|
| Unless nothing happened to him, why would n’t we know？ |
| I’m tired of your late night visits. |
| They succeeded because they found the same rhythm |

| **Chinese-to-English Controlled Machine Translation** |
|------------------------------------------------------|
| 你知道你已经是个死人吗？ (you know you already is a dead man?) |
| 我不能成为一名吸毒者或酗酒者？ (i can not become a drug addict or an alcoholic？ why?) |
| 给史密斯先生买些面包。 (give mr. smith buy some bread.) |

| **English-to-Chinese Controlled Machine Translation** |
|------------------------------------------------------|
| do you need them stopped immediately？ |
| why ca n’t it eat dried peas or something？ |
| let’s take a look at the mechanism. |

Table 11: Example outputs for our four controlled generation tasks. Each Chinese sentence is followed by a gloss.
| Query Sentence | Semantically Similar | Syntactically Similar |
|----------------|----------------------|-----------------------|
| with a gun, you feel more dangerous, I would n’t know. | I’d give him a gun if it makes you feel any better. | all these days, I could n’t work, I could n’t sleep. |
| if you want the loo, it’s just out here in the corridor. | the bathroom’s at the end of the corridor, if you need it. | when you need a car, you pull it right out of the tree. |
| it’s bumpy, but we’ll be past it in a few minutes. | it’s gon na be a little bumpy till we get over the mountains. | it looks negligible, but it will be difficult to get any useful samples. |
| who are you to talk to me like that? | talk to me, just tell me who you are. | what’re you gon na do to me with that? |
| 十五步之远我们的客厅是屋子里最大的房间 (fifteen step away our living room be house inside the biggest room) | 这间客房是更大的，我需要多一点空间，(this guest room be bigger，I need more a little space.) | 如今整个银河中你们的星球是文明程度最低的星球 (now entire Galaxy in you of planet be civilization degree the most low planet) |
| 你从窗户外可以看见它或在电视上也会看到它 (you from window outside can see it or in tv also can see it) | 你几乎不可能再近距离看见它的，用望远镜也不行 (you almost no possible again close distance see it, use telescope also not work) | 我在国会上讲过我们需要建桥但我们会靠自己 (i at congress talked we need build a bridge but we can depend on ourselves) |
| 我们完全有能力为我们的女儿举办一个独特的婚礼 (we absolutely have capability for our daughter hold a unique wedding) | 我们糊弄他们，我们将会举行一个很大的婚礼 (we fool them, we will host a very big wedding) | 我们很可能为我们的驻罗分公选一些管理层的人士 (we very possible can for our zhuoluo branch select some management person) |
| 看它的胸腔在动他正在呼吸大量氧气 (look its chest cavity be move he being breathe great amount oxygen) | Foreman做胸腔穿刺术来排出她肺部的积水 (Forema did chest cavity puncture to discharge she lungs stagnant water) | 闯进她的公寓拿着刀你已经越线太远了 (break into she apartment hold knife you already cross the line too far) |

Table 12: The most similar sentences to particular query sentences in terms of the semantic variable and syntactic variable based on the model trained on Zh-En bitext. Each Chinese sentence is followed by a gloss. More examples are in the supplementary material.
| 1 = The two sentences are completely dissimilar in structure. |
| 2 = The two sentences do not have very similar structure overall, but there are some similarities (e.g., both start with an independent clause that begins with a subject, or both contain a dependent clause introduced by “that”). |
| 3 = The two sentences are roughly equivalent in overall structure, but individual clauses in the sentences have different structures. |
| 4 = The two sentences have similar structure overall, but there are some small differences (e.g., one sentence has more modifiers (adjectives or adverbs) than the other). |
| 5 = The two sentences are completely equivalent, as they have the same sentence structure. |

Table 13: Detailed explanation for each option for human evaluations.
### Table 14: Test set results for English controlled paraphrase generation. The models are trained on 5 million sentence pairs. Lower is better for ST-r and ST-s.

| BLEU | ROUGE-1 | ROUGE-2 | ROUGE-L | METEOR | ST-r | ST-s |
|------|---------|---------|---------|--------|------|------|
| Return-input baselines | | | | | | |
| Syntactic input | 3.3 | 24.4 | 7.5 | 29.1 | 12.1 | 5.9 | 0.0 |
| Semantic input | 18.5 | 50.6 | 23.2 | 47.7 | 28.8 | 12.0 | 13.0 |
| Models trained on the ParaNMT dataset | | | | | | |
| Prior work (En-En) | 13.6 | 44.7 | 21.0 | 48.3 | 24.8 | 6.7 | 3.4 |
| En-En | 13.0 | 44.0 | 20.0 | 47.4 | 23.6 | 6.6 | 3.3 |
| Models trained on bitext (our work) | | | | | | |
| Cs-En | 12.1 | 41.5 | 18.0 | 45.1 | 22.4 | 6.9 | 3.4 |
| Zh-En | 11.5 | 42.7 | 18.3 | 46.1 | 22.2 | 6.7 | 3.4 |
| Zh-En Big | 12.5 | 44.6 | 18.7 | 47.4 | 23.2 | 6.7 | 3.5 |
| De-En | 12.6 | 42.1 | 18.4 | 45.8 | 22.1 | 6.6 | 3.2 |
| Es-En | 11.7 | 41.3 | 17.5 | 44.9 | 21.8 | 6.8 | 3.7 |
| Fr-En | 11.3 | 41.1 | 17.6 | 44.6 | 21.2 | 6.7 | 3.3 |

### Table 15: Test set results for the Chinese controlled paraphrase generation. Lower is better for ST-r and ST-s.

| BLEU | ROUGE-1 | ROUGE-2 | ROUGE-L | METEOR | ST-r | ST-s |
|------|---------|---------|---------|--------|------|------|
| Return-input baselines | | | | | | |
| Syntactic input | 6.2 | 29.9 | 9.2 | 34.4 | 13.2 | 13.9 | 0.0 |
| Semantic input | 49.0 | 77.4 | 57.0 | 65.4 | 42.5 | 18.7 | 22.4 |
| Our work | | | | | | |
| Zh-En | 12.8 | 46.1 | 20.6 | 46.4 | 21.2 | 15.8 | 12.6 |
| Zh-En Big | 16.6 | 52.4 | 26.0 | 50.8 | 24.8 | 15.5 | 12.0 |

### Table 16: Test set performance for Chinese-to-English controlled machine translation. Lower is better for ST-r and ST-s.

| BLEU | ROUGE-1 | ROUGE-2 | ROUGE-L | METEOR | ST-r | ST-s |
|------|---------|---------|---------|--------|------|------|
| Return-input baselines | | | | | | |
| Syntactic input | 3.3 | 24.4 | 7.5 | 29.1 | 12.2 | 5.9 | 0.0 |
| Neural machine translation baselines | | | | | | |
| OpenNMT | 11.0 | 42.4 | 17.0 | 43.1 | 23.4 | 11.5 | 12.0 |
| Google Translate | 14.5 | 47.7 | 20.8 | 46.5 | 27.3 | 11.6 | 12.6 |
| Our work | | | | | | |
| Zh-En | 10.9 | 40.6 | 17.9 | 44.2 | 21.3 | 6.7 | 3.3 |
| Zh-En Big | 12.1 | 42.2 | 18.3 | 45.6 | 22.3 | 6.6 | 3.3 |

### Table 17: Test set performance for English-to-Chinese controlled machine translation. Lower is better for ST-r and ST-s.

| BLEU | ROUGE-1 | ROUGE-2 | ROUGE-L | METEOR | ST-r | ST-s |
|------|---------|---------|---------|--------|------|------|
| Return-input baselines | | | | | | |
| Syntactic input | 6.2 | 29.9 | 9.2 | 34.4 | 13.2 | 13.9 | 0.0 |
| Neural machine translation baselines | | | | | | |
| OpenNMT | 12.3 | 40.4 | 20.0 | 39.9 | 17.7 | 19.2 | 20.4 |
| Google Translate | 30.3 | 63.2 | 37.7 | 56.6 | 32.0 | 18.5 | 21.3 |
| Our work | | | | | | |
| Zh-En | 9.6 | 40.2 | 16.1 | 41.4 | 18.1 | 16.1 | 11.0 |
| Zh-En Big | 11.9 | 44.3 | 19.1 | 44.5 | 20.4 | 15.7 | 10.0 |

### Table 18: Pearson’s correlation (%) for the English semantic similarity task.

| | En-En | Fr-En | De-En | Es-En | Zh-En |
|---|---|---|---|---|---|
| sem. | syn. | Δ | sem. | syn. | Δ | sem. | syn. | Δ | sem. | syn. | Δ |
| Prior work | 74.3 | 7.4 | 66.9 | - | - | - | - | - | - | - | - |
| Our work | 74.9 | 12.0 | 62.9 | 73.2 | 10.4 | 62.8 | 68.6 | 12.1 | 56.5 | 72.6 | 12.9 | 59.7 | 73.6 | 16.3 | 57.3 |
Table 19: Pearson’s correlation (%) for the Spanish semantic similarity and Chinese semantic similarity tasks.

|         | POS Accuracy | CP Labeled F₁ |
|---------|--------------|---------------|
|         | sem. | syn. | Δ   | sem. | syn. | Δ   |
| Fasttext| 48.0 |       |     | 74.0 |       |     |
| Our work| 76.3 | 49.0  | 27.3| 76.2 | 23.5 | 52.8|

Table 20: POS tagging accuracy (%) and constituent parsing labeled F₁ scores (%) for the English syntactic evaluation. The models are trained on 5 million sentence pairs.

|         | POS Accuracy | CP Labeled F₁ |
|---------|--------------|---------------|
|         | sem. | syn. | Δ   | sem. | syn. | Δ   |
| Oracle Fr| 62.3 |       |     | 71.1 |       |     |
| Random Fr| 12.9 |       |     | 19.2 |       |     |
| Prior work| 20.3 | 43.7 | 23.4| 24.8 | 40.9 | 16.1|
| En-En | 19.6 | 44.9 | 25.3| 24.2 | 42.4 | 18.2|
| Fr-En | 19.9 | 41.8 | 21.9| 24.2 | 41.8 | 17.6|
| De-En | 20.1 | 44.7 | 24.6| 24.4 | 42.0 | 17.6|
| Es-En | 19.7 | 44.0 | 24.4| 24.1 | 41.5 | 17.4|
| Zh-En | 19.7 | 44.4 | 24.7| 24.4 | 41.7 | 17.3|

Table 21: POS tagging accuracy (%) and constituent parsing labeled F₁ scores (%) for the multilingual syntactic evaluation. The models are trained on 5 million sentence pairs.

|         | POS Accuracy | CP Labeled F₁ |
|---------|--------------|---------------|
|         | sem. | syn. | Δ   | sem. | syn. | Δ   |
| Oracle Fr| 71.7 |       |     | 92.8 |       |     |
| Random Fr| 18.2 |       |     | 31.0 |       |     |
| fastText Fr-En| 28.5 |       |     | 34.7 |       |     |
| Oracle De Random De| 67.7 |       |     | 99.9 |       |     |
| fastText De-En| 17.7 |       |     | 46.5 |       |     |
| Oracle Es Random Es| 27.0 |       |     | 51.7 |       |     |
| fastText Es-En| 21.5 | 47.4 | 25.9| 50.3 | 58.1 | 7.8 |
| Oracle Zh Random Zh| 56.8 |       |     | 64.2 |       |     |
| fastText Zh-En| 9.7 |       |     | 16.8 |       |     |
| Oracle Fr| 21.7 |       |     | 23.2 |       |     |
| Random Fr| 15.7 | 34.9 | 21.2| 19.0 | 34.0 | 15.0|
| fastText Es-En| 13.4 |       |     | 17.8 |       |     |
| Oracle Zh Random Zh| 15.0 | 36.2 | 21.2| 19.3 | 32.3 | 12.9|