Conditional Rap Lyrics Generation with Denoising Autoencoders

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Abstract

We develop a method for automatically synthesizing a rap verse given an input text written in another form, such as a summary of a news article. Our approach is to train a Transformer-based denoising autoencoder to reconstruct rap lyrics from content words. We study three different approaches for automatically stripping content words that convey the essential meaning of the lyrics. Moreover, we propose a BERT-based paraphrasing scheme for rhyme enhancement and show that it increases the average rhyme density of the lyrics by 10%. Experimental results on three diverse input domains – existing rap lyrics, news, and movie plot summaries – show that our method is capable of generating coherent and technically fluent rap verses that preserve the input content words. Human evaluation demonstrates that our approach gives a good trade-off between content preservation and style transfer compared to a strong information retrieval baseline.

1 Introduction

Automatic lyrics generation is a challenging language generation task for any musical genre, requiring story development and creativity while adhering to the structural constraints of song lyrics. Here we focus on the generation of rap lyrics, which poses three additional challenges specific to the rap genre: (i) a verse in rap lyrics often comprises multiple rhyme structures which may change throughout a verse (Bradley, 2017), (ii) the number of words in a typical rap verse is significantly larger when compared to other music genres (Mayer et al., 2008), requiring modeling of long-term dependencies, and (iii) the presence of many slang words.

Prior approaches to rap generation typically use unconditional generation (Potash et al., 2015; Malmi et al., 2016). This approach synthesizes lyrics without providing any context that could be useful to guide the narrative development into a coherent direction (Dathathri et al., 2020). For example, generating rap lyrics on a specific topic, e.g., “cooking,” is not possible with unconditional generation. Motivated by this, in this paper, we propose a novel approach for conditional generation of rap verses, where the generator is provided a source text and tasked with transferring the style of the text into rap lyrics. Compared to unconditional generation, this task can support the human creative process more effectively as it allows a human writer to engage with the generator by providing the content of the lyrics while receiving automatic suggestions on how to improve the style of the lyrics to resemble the rap domain.

Our approach is to train sequence-to-sequence models (Vaswani et al., 2017) to reconstruct existing rap verses conditioned on a list of content words extracted from the verses (see Figure 1). By
learning a mapping from content words to complete verses, we implicitly learn the latent structure of rap verses given content, while preserving the target output style of the rap lyrics. We compare three different approaches to extracting content words (Section 3.1) that offer different trade-offs between content preservation and style.

The flexibility of our method allows us to input content words extracted from texts written in any style during inference to generate novel rap lyrics about a given topic. We evaluate our models on short summaries of news articles from the CNN/DailyMail dataset (Hermann et al., 2015) and movie plot summaries from the CMU corpus (Bamman et al., 2013). We also test providing existing rap lyrics as input since a model trained to paraphrase existing lyrics can serve as a useful tool for a writer wanting to explore different ways of expressing the same ideas. Our model outputs are further enhanced by a novel post-processing step (Section 3.2) that substitutes non-rhyming end-of-line words with suitable rhyming alternatives.

Automatic and human evaluations (Sections 5 and 6) suggest that our method gives a better trade-off between content preservation and style than a strong information retrieval baseline. In summary, our work makes an important first step towards content-controlled generation of song lyrics with creativity and rhyme.

2 Background

2.1 Rap Lyrics Generation

The majority of previous work on rap lyrics generation focuses on unconditional generation. Potash et al. (2015) use a recurrent neural network language model which estimates \( p(y) = \prod_{i=1}^{t} p(y_i|y_1, ..., y_{i-1}) \) over sequences of words \( y = (y_1, ..., y_i, ..., y_t) \) coming from rap lyrics. Instead of relying on sequence models, Malmi et al. (2016) take an information retrieval approach, stitching together lines from existing rap lyrics to form novel rhyming verses. One advantage of their approach is that it directly optimizes against a rhyme density metric, resulting in lyrics of high technical quality. However, since each line is picked independently from existing lyrics, there is no guarantee that the output lyrics will be coherent. Moreover, the generator is inherently limited to presenting the ideas that can be formulated as a combination of the input lines.

There are two main drawbacks of unconditional generation of rap lyrics. First, the open-ended nature of the task is too unconstrained for generating lyrics with more specific content: ideally, we may want to have control over at least some aspects of the model during inference, such as the topic of the lyrics, or their sentiment. This can be achieved by modelling \( p(y|a) \) (Dathathri et al., 2020), where \( a \) is some desirable attribute. Second, although frequent rhyming is an essential feature of fluent rap verses (Malmi et al., 2016), language models have no built-in incentive to learn to consistently generate rhymes at the end of each line, prompting researchers to invent techniques to promote rhyming in their models separately (Potash et al., 2015; Hopkins and Kiela, 2017).

Rap lyrics generation is also related to work in poetry generation (Hopkins and Kiela, 2017; Lau et al., 2018). Poetry is similar to rap in the sense that it also contains rhythmic verses that consist of a formal structure (Bradley, 2017), which provides a good flow to an accompanying piece of music. Unlike for rap lyrics, there is some work on poetry generation conditioned on a topic (Yang et al., 2018), keywords (Kantosalo et al., 2014; Oliveira et al., 2017), or an image (Liu et al., 2018). In contrast to these works, we condition the model on a longer input text and systematically evaluate the model using both automatic and human evaluation.

2.2 Text Rewriting and Style Transfer

Recent work on style transfer of text (Fu et al., 2018; Shen et al., 2017; Prabhumoye et al., 2018), focuses on transfer from one text attribute to another, such as gender (male to female) or political (democratic to republican). The main difference between such studies and our work is that our setting is more lenient with respect to meaning preservation: our focus here is on generating creative and fluent verses that match the overall topic of the input and also preserve some of the content. Generating outputs that match the meaning of the input perfectly is difficult without a parallel dataset, which does not exist for synthesizing lyrics from other types of texts.

Our approach to conditional text generation is also related to recent work on self-supervised pre-training objectives for text-to-text generation tasks (Raffel et al., 2019; Lewis et al., 2019). Such studies apply simple noise objectives, such as word masking, deletion, or shuffling, to large quantities of raw training data, generating text pairs for train-
ing. Pre-training on such datasets has been beneficial for many tasks in NLP, such as automatic text summarization (Zhang et al., 2019), question answering (Raffel et al., 2019), and data-to-text generation (Freitag and Roy, 2018).

3 Approach

Our approach to conditional generation of rap verses consists of three steps (see Figure 1). First, given a dataset of rap verses, we apply a stripping approach to extract a set of content words \( c = \{c_1, ..., c_i\} \) from each of the texts, omitting words that carry any specific stylistic information. The content words aim to resemble the topic and the main meaning of the original text. Second, we train a sequence-to-sequence model to reconstruct the original rap verses \( r \) conditioned on the content words, estimating \( p(r|c) \). The model learns to generate a verse that is as close as possible to the original verse, filling in any stylistic information that is needed to generate a realistic rap verse. Third, during inference, we can input content words extracted from a text written in any style, resulting in novel output rhyme verses. In this work, we experiment with news article summaries, as well as with short movie plot summaries.

After generation, we optionally apply a rhyme enhancement step (Section 3.2) that introduces additional end-of-line rhymes to the output rap lyrics, further enhancing their technical quality.

3.1 Stripping Approaches

Given a dataset of original rap verses, our base approach to extracting content words involves preprocessing each verse to remove all stop words\(^1\), numbers and punctuation. To promote greater novelty\(^2\) and variability in the outputs produced by our models, we additionally apply one of three noise types to the stripped content words:

**Shuffle.** We shuffle all of the content words on the sentence level (line level for rap verses). This type of noise forces our models to learn to rearrange the location of the input content words when generating the output rap lyric, rather than to merely copy words from the input in an identical order.

\(^1\)We use the list of English stopwords defined in NLTK.
\(^2\)In early experiments, we tested training models using only this base approach. The models performed very well at reconstructing existing rap lyrics, however when the input was from a different domain, we observed very conservative outputs.

A similar noising approach has been recently employed by Raffel et al. (2019).

**Drop.** We randomly remove 20% of the input content words. This type of noise promotes our models to generate novel words during generation, rather than only copying content words from the input.

**Synonym.** We replace 20% of the content words with synonyms obtained from WordNet (Miller, 1995). We pick words randomly and replace them with a random synonym. This type of noise promotes our models to learn to replace content words with synonyms, which might fit better in the context or style of the current output rap verse.

3.2 Rhyme Enhancement with BERT

To further improve the rhyming fluency of our models, we implement a post-processing step for rhyme enhancement (RE). The step iterates through the lines produced for an output verse to introduce additional end-of-line rhymes where possible.

Given two lines from a generated verse, such as:

\[
\text{where were you?}
\]
\[
\text{last year i was paid in a drought with no beginners}
\]

our rhyme enhancement approach (Algorithm 1) iterates over each of the lines in the verse, replacing the ending words with a MASK token, e.g.:

\[
\text{where were you?}
\]
\[
\text{last year i was paid in a drought with no MASK}
\]

The verse is then passed through a BERT model\(^3\) (Devlin et al., 2018) which predicts the \( K \) most likely replacement candidates\(^4\) for the MASK token. For example, the replacement candidates for \( you \) might be \( \{they, we, I, it\} \), and for \( beginners \) might be \( \{food, fruit, you, rules\} \). We pick the candidate that leads to the highest increase in rhyming, determined by the length of the longest overlapping vowels in the two words (Malmi et al., 2016).

Here, the highest rhyme length is obtained by pairing \( you \) with \( food \), therefore \( food \) is selected as a word replacement for \( beginnings \), and the example becomes:

\[
\text{where were you?}
\]
\[
\text{last year i was paid in a drought with no food}
\]

\(^3\)Devlin et al., 2018
\(^4\)We use the list of English stopwords defined in NLTK.
Algorithm 1: Rhyme enhancement with BERT.

```
input : lyrics verse V = \{l_0, ..., l_N\} consisting of N tokenized lines; number of BERT predictions K to consider.
output : modified V with enhanced rhyming.

Function get_rhyming_replacement (V, src_idx, tgt_idx, mask):
    src ← V[src_idx][1] // get last word
tgt ← V[tgt_idx][1]
    // Predict most likely words.
preds ← bert.predictions(mask, K)
    // Compute original rhyme length.
rl_orig ← rhyme_length(src, tgt)
    for pred ∈ preds do
        rlnew ← rhyme_length(pred, tgt)
        if rlnew > rl_orig then
            // return replacement
            return pred, rlnew
    return target, rl_orig // return original

for i ← 1, 3, ..., N // for each odd line
    // Create two masks for the two consecutive lines.
    mask[l] ← mask.text(V, i)
    mask[l+1] ← mask.text(V, i+1)
    // Generate replacement candidates.
cand[1], r limbs ← get_rhyming_replacement (V, i + 1, i, mask[1]) // replace last word at i
    cand[2], r limbs ← get_rhyming_replacement (V, i + 1, i, mask[2]) // replace last word at i + 1
    if rlims ≥ rl[1] // update lines in V
        V[i + 1][-1] ← cand[2]
    else
        V[i][-1] ← cand[1]
return V
```

4 Experimental Setup

Datasets. We conduct experiments using three datasets. As our rap dataset, we use 60k English rap lyrics provided by Musixmatch\(^5\). We split each lyric into verses, remove verses shorter than 4 lines, and reserve 2k verses for validation and testing.

We use two datasets as our out-of-domain inputs. First, we use the CNN/DailyMail automatic summarization dataset (Hermann et al., 2015), which is in the news domain. We only use the summaries from this dataset. Second, we also experiment with inputting a subset of the CMU movie plot summary corpus (Bamman et al., 2013). Since some of the

\(^5\)https://www.musixmatch.com/

movie summaries are very long, for this dataset, we filter summaries longer than 140 tokens and shorter than 40 tokens. Table 1 contains additional statistics on our datasets.

Model details. As our sequence transducer, we use a standard 6-layer Transformer encoder-decoder model (Vaswani et al., 2017). We train all of our models on the subword level (Sennrich et al., 2016), extracting a common vocabulary of 50k tokens from a joint collection of news summaries and rap lyrics. We use the same vocabulary for both our encoders and decoders.

Training regime. In order to promote a smoother transfer between the styles, we follow a training regime for each of our models. We initially train our models on news articles for 20 epochs, after which we finetune them on rap verses for an additional 20 epochs, using the same stripping approach for both.\(^6\)

Generation details. During inference, we generate outputs using diverse beam search (Vijayakumar et al., 2016) to promote greater diversity across the hypothesis space. We use a beam with a size of 24 and 6 diverse beam groups. Furthermore, we limit the maximum output sequence length to two times the length of the input content words and penalize repetitions of bigrams in the outputs.

To select our final output, we additionally implement a simple hypothesis reranking method. For each of the 24 final predictions on the beam, we compute two scores: the rhyme density (RD) of the text, following (Malmi et al., 2016), as well as its repetition score, rep:

\[
rep(s) = \frac{\sum_i overlap(\bar{s}_i, s_i)}{|s|}. \tag{1}
\]

rep measures the average unigram overlap (see Equation 2) of each sentence \(s_i\) in the text \(s\) with

\(^6\)In future work, it would be interesting to experiment with larger, pretrained models, such as T5 (Raffel et al., 2019) and BART (Lewis et al., 2019).

| Dataset | # Pairs | Sent. p.d. | Tok. p.d. | Tok. p.s. |
|---------|---------|------------|-----------|-----------|
| News    | 28k/11k/11k | 3.7 ± 1.2  | 35.9 ± 1.6 | 10.5 ± 4.5 |
| Movies  | 165k/1k/1k  | 15.1 ± 4.7  | 22.4 ± 11  | 9.5 ± 4.25 |
| Rap     | 10.5 ± 2.4  | 57.9 ± 24.3 | 90.0 ± 27.6 | 91.8 ± 49.1 |

Table 1: Statistics of our datasets. # Pairs denotes the number of pairs used for training/validation/testing; p.d. is per document; p.s. is per sentence.
all other sentences of the text concatenated into a single string (denoted as \( R \)). We pick the hypothesis that maximizes: \( \text{score}(s) = RD(s) - rep(s) \). Afterwards, we optionally apply our rhyme enhancement step (Section 3.2), to further increase the frequency of rhymes in our outputs.

**Bias mitigation.** Rap lyrics, like other human-produced texts, may contain harmful biases and offensive content which text generation models should not propagate further. Our conditional lyrics generation setup is less susceptible to this issue since the user provides the content, and the generator is supposed to modify only the style of the text. Yet, the model may learn to use inappropriate individual terms that are common in rap lyrics. To alleviate this, we maintain a blacklist of words that the model is not able to generate.

### 5 Automatic Evaluation

#### 5.1 Evaluation Metrics

**Content preservation.** We test the capacity of our models to preserve the content words by computing a unigram overlap score:

\[
\text{overlap}(x, y) = \frac{|\{y\} \cap \{x\}|}{|\{y\}|}
\]

(2)

between unique unigrams from an input text \( x \) and the generated output rap verse \( y \). Additionally, we report the BLEU score (Papineni et al., 2002) between the original and reconstructed lyrics.

**Rhyming fluency.** We measure the technical quality of our rap verses using the rhyme density (RD) metric (Malmi et al., 2016). The metric is based on computing the longest matching vowel sound sequence for adjacent words in a verse, which resembles multisyllabic assonance rhymes.

As a reference, RD values above 1 can be considered high, with some rap artists reaching up to 1.2 (Malmi et al., 2016). In our rap training dataset, we observe a large variability of RD values (0.84 ± 0.38 on average) because it contains a wide range of rap subgenres.

#### 5.2 Results

Our results are shown in Table 2, where we include all of our stripping approaches (Shuffle, Drop, Replace). We report the results of applying the additional rhyme enhancement step separately (* + RE).

| Baseline | BLEU | Overlap | RD | BLEU | Overlap | RD | BLEU | Overlap | RD |
|----------|------|---------|----|------|---------|----|------|---------|----|
| IR NEWS BASELINE | -    | -       | 0.84 ± 0.38 | -    | 0.73 ± 0.2 | -    | 0.72 ± 0.21 |
| IR RAP BASELINE | -    | -       | -    | -    | -       | -    | -    | -       | -    |
| Shuffle | 10.27 | 0.63 ± 0.13 | 1.01 ± 0.31 | 0.51 ± 0.11 | 0.90 ± 0.23 | 0.45 ± 0.12 | 0.89 ± 0.26 |
| Shuffle + RE | 12.72 | 0.60 ± 0.12 | 1.10 ± 0.32 | 0.49 ± 0.10 | 0.96 ± 0.27 | 0.43 ± 0.11 | 0.98 ± 0.27 |
| Drop   | 11.06 | 0.52 ± 0.11 | 1.03 ± 0.32 | 0.43 ± 0.10 | 0.90 ± 0.24 | 0.38 ± 0.10 | 0.93 ± 0.25 |
| Drop + RE | 09.81 | 0.50 ± 0.11 | 1.13 ± 0.33 | 0.40 ± 0.09 | 0.99 ± 0.27 | 0.36 ± 0.10 | 1.03 ± 0.26 |
| Replace | 14.30 | 0.57 ± 0.15 | 1.00 ± 0.30 | 0.43 ± 0.14 | 0.86 ± 0.28 | 0.34 ± 0.13 | 0.95 ± 0.27 |
| Replace + RE | 12.72 | 0.54 ± 0.15 | 1.10 ± 0.31 | 0.40 ± 0.13 | 0.98 ± 0.24 | 0.31 ± 0.12 | 1.05 ± 0.28 |

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**Baselines.** For reference, we also report the result of an information retrieval baseline (IR BASELINE), which retrieves the closest text from our training dataset given an input from the news or movies test sets. To implement the baseline, we use sentence embedding similarity\(^7\) instead of computing a hard lexical overlap score, because we want to retrieve training examples whose overall meaning matches the inputs. This approach fits the task more naturally and better suits our human evaluation in Section 6.

We report two variants of the IR BASELINE. First, we retrieve the closest summary from the CNN/DailyMail news training set (IR NEWS BASELINE), which resembles a lower bound for our target task of style transfer from news to rap lyrics. Second, we retrieve the closest verse from our rap training set (IR RAP BASELINE). This baseline is potentially very strong, because all of its outputs perfectly match the style of original rap verses, giving us an upper bound for rap style, while still maintaining some degree of lexical and

\(^7\)We use a 600-dimensional Sent2Vec model (Pagliardini et al., 2018), which is pretrained on Wikipedia.
semantic overlap with the input texts.

Rap reconstruction. In the left part of Table 2, we evaluate the reconstruction capacity of our models, which tests if they are capable of reliably regenerating original rap lyrics given extracted content words from them. All of our models performed very well on this task, generating fluent lyrics which incorporate a large part of the input content words, yet are still novel and may have a slightly different meaning compared to the original lyrics. The SHUFFLE stripping approach achieved the highest content overlap, most likely because it does not change or delete any of the content words, while the DROP approach achieved the highest rhyme density, significantly surpassing the average rhyme density observed in the training dataset (INPUT).

When using our rhyme enhancement step (* + RE), we observe a slight decrease in overlap due to potential replacement of content words. However, the rhyme density increases by 0.1 on average, and the rhymes also look better qualitatively (see Section 7).

Style transfer from movie/news summaries. In the right part of Table 2, we evaluate the capacity of our models to generate rap lyrics using content words extracted from movie plot summaries or news article summaries. For these inputs, our models generated outputs with lower content overlap on average than for rap reconstruction, with movies retaining slightly more content than news. This gap is potentially due to the large general differences in style, vocabulary, and topic of the inputs, prompting our models to ignore some of the content words in favor of words that better fit the style of rap lyrics. Still, our generation methods manage to achieve similar rhyme density while significantly outperforming the strong IR BASELINE in terms of content overlap.

6 Human Evaluation

Due to the limitations of automatic metrics for text generation, we also perform an evaluation using human raters. We asked three raters, who are trained to translate lyrics, to rate 100 rap verses produced by three of our systems, using news article summaries as input. We evaluate our SHUFFLE + RE conditional generation approach, as well as the two variants of the IR BASELINE, which return the closest rap lyrics or news articles from our training datasets. As discussed in Section 5, the two baselines provide good approximate performance bounds for content and style.

The three raters were asked the following questions:

1. How much do the lyrics presented resemble rap lyrics on a scale from 1 (not at all) to 5 (this could be from existing rap lyrics)? This question measures the style preservation capacity of our models (Style).

2. How well do the lyrics preserve the content of the original news article on a scale from 1 (not at all) to 5 (very well)? This question measures the meaning preservation of our models (Meaning).

3. Do these lyrics look like a song you know (yes or no)? For the IR RAP BASELINE, this question measures the familiarity of raters with the real lyrics that were selected (Familiarity), while for the other two systems it measures the capacity to fool the raters.

Our results are in Table 3, while in Tables 4 and 5, we compute the inter-rater agreements for the
We note that, although rater 2 is in slight disagreement with the other two raters for the second question, using Cohen’s Kappa (Cohen, 1960). We note that, although rater 2 is in slight disagreement with the other two raters for the second question, in overall, all reported averaged ratings are always consistent.

Our method outperforms both baselines in terms of meaning preservation, demonstrating that it is capable of better preserving the content of the input. In terms of style, we outperform the IR NEWS BASELINE, demonstrating that there is a change in style towards rap verses. There is still a large gap to reach the fluency of original rap verses retrieved by the IR RAP BASELINE. However, it is worth noting that the content preservation of IR RAP BASELINE is significantly lower, as shown in Table 2, and simply the fact that the content of the generated lyrics is closer to the news domain might encourage the raters to rate the generated lyrics as having a lower rap resemblance score. In other words, the style score of IR RAP BASELINE might be unrealistic to attain even with a perfect conditional rap lyrics generator.

In overall, the results indicate that our method provides a trade-off between the two baselines in terms of style, while outperforming both of them in terms of meaning preservation. Furthermore, 8% of the time, our conditional generation model is able to fool our experienced raters to think that our synthetic rap lyrics originate from real rap songs.

### 7 Qualitative Evaluation

In Tables 6, 7 and 8, we also display a few manually selected example model outputs (additional examples are available in the Appendix) produced after inputting content words extracted from each of our input text styles (existing rap lyrics, movie plot summaries and news article summaries).

When using existing rap lyrics as input, many outputs seem coherent and of higher quality in comparison to outputs produced using news/movie inputs. For news/movie inputs, the models are still capable of integrating the input content words into a rhyming verse that preserves some of the overall meaning of the original text (e.g., “the film also follows the adventures of lucius the slave escaping via the underground railroad to freedom” → “slave, run from lucius slavery; battle of freedom and liberty”).

### 8 Conclusion

We have proposed a novel approach to generation of rap verses conditioned on a list of content words.
We showed that our method is capable of generating coherent and technically fluent synthetic verses using diverse text types as input, including news articles, movie plot summaries, or original rap verses. The fluency of our outputs is further improved through a novel rhyme enhancement step. Our approach is particularly effective when rephrasing the content of existing rap lyrics in novel ways, making it a potentially useful tool for creative writers wishing to explore alternative expressions of their ideas.

The generality of our approach to conditional text generation makes it applicable to generation of creative texts in other domains, such as poetry or short stories. Future work could explore other approaches to extracting content words, and could extend our work to end-to-end generation of whole rap songs, rather than of individual verses. Moreover, the task of generating coherent verses from a set of content words could be naturally modeled as a text-editing task (Dong et al., 2019; Mallinson et al., 2020; Malmi et al., 2019) instead of a sequence-to-sequence task.

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References

David Bamman, Brendan O’Connor, and Noah A. Smith. 2013. Learning latent personas of film characters. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 352–361, Sofia, Bulgaria. Association for Computational Linguistics.

Adam Bradley. 2017. Book of rhymes: The poetics of hip hop. Civitas Books.

Jacob Cohen. 1960. A coefficient of agreement for nominal scales. Educational and psychological measurement, 20(1):37–46.

Sumanth Dathathri, Andrea Madotto, Janice Lan, Jane Hung, Eric Frank, Piero Molino, Jason Yosinski, and Rosanne Liu. 2020. Plug and play language models: A simple approach to controlled text generation. In International Conference on Learning Representations.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Yue Dong, Zichao Li, Mehdi Rezagholizadeh, and Jackie Chi Kit Cheung. 2019. Editsnts: An neural programmer-interpreter model for sentence simplification through explicit editing. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 3393–3402.

Markus Freitag and Scott Roy. 2018. Unsupervised natural language generation with denoising autoencoders. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing.

Zhenxin Fu, Xiaoye Tan, Nanyun Peng, Dongyan Zhao, and Rui Yan. 2018. Style transfer in text: Exploration and evaluation. In Thirty-Second AAAI Conference on Artificial Intelligence.

Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. Teaching machines to read and comprehend. In Advances in neural information processing systems, pages 1693–1701.

Jack Hopkins and Douwe Kiela. 2017. Automatically generating rhythmic verse with neural networks. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 168–178.

Anna Kantosalo, Jukka M Toivanen, Ping Xiao, and Hannu Toivonen. 2014. From isolation to involvement: Adapting machine creativity software to support human-computer co-creation. In ICCC, pages 1–7.
Eric Malmi, Sebastian Krause, Sascha Rothe, Daniil Pyry Takala, Hannu Toivonen, Tapani Hugo Gonçalo Oliveira, Tiago Mendes, and Ana Rudolf Mayer, Robert Neumayer, and Andreas Rauber. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. arXiv preprint arXiv:1910.13461.

Bei Liu, Jianlong Fu, Makoto P Kato, and Masatoshi Yoshikawa. 2018. Beyond narrative description: Generating poetry from images by multi-adversarial training. In Proceedings of the 26th ACM international conference on Multimedia, pages 783–791.

Jonathan Mallinson, Aliaksei Severyn, Eric Malmi, and Guillermo Garrido. 2020. Felix: Flexible text editing through tagging and insertion. arXiv preprint arXiv:2003.10687.

Eric Malmi, Sebastian Krause, Sascha Rothe, Danii Mirylenka, and Aliaksei Severyn. 2019. Encode, tag, realize: High-precision text editing. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 5057–5068.

Eric Malmi, Pyry Takala, Hannu Toivonen, Tapani Raiko, and Aristides Gionis. 2016. Dopelearning: A computational approach to rap lyrics generation. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pages 195–204. ACM.

Rudolf Mayer, Robert Neumayer, and Andreas Rauber. 2008. Rhyme and style features for musical genre classification by song lyrics. In Proceedings of the 9th International Conference on Music Information Retrieval, pages 337–342.

George A Miller. 1995. Wordnet: a lexical database for english. Communications of the ACM, 38(11):39–41.

Hugo Gonçalo Oliveira, Tiago Mendes, and Ana Boavida. 2017. Co-poetryme: a co-creative interface for the composition of poetry. In Proceedings of the 10th International Conference on Natural Language Generation, pages 70–71.

Matteo Pagliardini, Prakhar Gupta, and Martin Jaggi. 2018. Unsupervised Learning of Sentence Embeddings using Compositional n-Gram Features. In NAACL 2018 - Conference of the North American Chapter of the Association for Computational Linguistics.
A Additional Model Outputs

Tables 9, 10 and 11 contain additional example model outputs for each of our domains (rap lyrics, movie summaries and news article summaries) and each of our stripping approaches (DROP, SHUFFLE, and SYNONYM).
Table 9: Additional model outputs for rap reconstruction.
**INPUT:** hoping to improve his financial lot, petty thief hawk chovinski hires a dancing instructor to teach him how to bear himself like a gentleman. His lessons completed, hawk then poses as a european nobleman, intending to trap a wealthy wife. yolande cowles sees through hawk’s pose but falls in love with him anyway.

**DROP + RE:** i improve a grizzly lot of petty thief times dancing in the middle of the night i am the man who can teach you how to bear it like a gentleman with diamonds i’m a superheroic, i can be your wife yolande cowles tonight falls in love anyway

**SHUFFLE + RE:** you teach me petty dancing like bear thief chovinski, intersect, be a lot of financial gentleman hoping he can improve somebody wife, nobleman, the trap is so polished wealthy hawk lessons, european hawk lessons yolande cowles anyway, sees him pose when he says hawk love!

**SYNONYM + RE:** hoping that you can improve a financial lot of petty use mortarboard chovinski engage dancing with the snake teach her how to settle like a gentleman lessons are shackled by a bullet sit in european imagine in the trap with a wealthy wife yolande hood sees the sky when the pose falls in line anyway, no, not me

**INPUT:** a novelist who has abandoned her writing career tracks down the details of a true story from the last days of the spanish civil war. the writer and falangist rafael schne oz mazas faced a firing squad along with fifty other prisoners, but managed to escape into the woods. a republican soldier, apparently one of those searching the area for the escaped prisoner, found him but allowed him to escape. the novelist pieces together the fragments of the story, plagued by contradictions and mysterious characters, and comes to realize that her search for the truth is a personal quest of self-discovery.

**DROP + RE:** i was born to be the one who had been abandoned in a career with details of a true path spanish civil writer only with his own mind and his owning. he was in the back of the streets, and the s.i.s. and he had a few faced firing squad prepared fifty designers managed to escape, through the woods of his heart he has been a renegade apparently no one is searching for an exchange but he escaped from a prisoner, found himself allowed to escape into pieces of himself together in his mind. his story was an unfolder, but now he is in love with life so i am the only one who’s been found in which he does not realize that the truth is that he died

**SHUFFLE + RE:** abandoned career for the last days of the military civil war, writing my spanish story details the details writer tracks in the woods faced, firing squad, fal-and-st, and fifty sdat so managed to escape, along with these prisoners, no escape escaped area, apparently i was one of those who was a case searching for a soldier, allowed to be found by these imma pieces of my story is self-rantional, this is not a story that comes out of hand on a quest to search for personal characters who were not for me together we realize the truth, we are not the same, these are the mysteries, this

**SYNONYM + RE:** this is for all of my shows and to all my explodements. i had to reload, my career, tracks and reaction. true story for the last days, spanish civil war writers. falg-a-st, and the cluck, the sall, and the kass, of the most of players all the same as faced firing squad, all along with fifty driller. we escape, escape through the woods of our owners! soldier apparently one in the searching room, escaped by a prisoner who found allowed to escape from our own creators’ our together we are the understatement, our story is overflows; our overstanding, over our our over and over again and overborn. come and make a search for truth in our personal quest for more

| Table 10: Additional model outputs for style transfer from movie plot summaries to rap lyrics. |
INPUT (NEWS): police in lucknow, northern india, have bought four drones to help control crowds. the unmanned aerial vehicles are being fitted with cameras and pepper spray to subdue angry protesters. some indians have questioned why police are resorting to “authoritarian and forceful methods.”

DROP + RE: and the police lucknow me
i be on the northern mission
and i keep it on my own
i’m in the ghetto, i help control folks
they be only, fitted for play
pepper spray on your face
we be off

SHUFFLE + RE: four northern police help me out of my body
lucknow, i just bought some crowds to control all my faults,
my fitted is angry and my cameras spray in pepper in melia, tanials, cameras, rici, genies!
police say

SYNONYM + RE: police have no lucknow
i was simply on my own
in my own, i bought a four of ours
they were on their owners, they help control the crowds
and they was on our owned, airy in a briefcase
fitted cameras, pepper spray and we say
we had to do it, we did go
but we was in our own hood, wild as the most
so i had

INPUT (NEWS): elizabeth sedway posted to video to facebook showing her removal from a plane. she was forced off a flight in hawaii and told she could n’t head home to california. alaska airlines later apologized, saying it could have handled the situation differently.

DROP + RE: and i was on my own for a while, sedway
posted in the video showing up on a plane
forced me to be deported
i couldn’t get my head home, california
from alaska to alaska
later on i had me a few of demands
that i could have handled my situation

SHUFFLE + RE: posted at sedway 32
video, plane, showing up on a plane with some of my own issues
told me i wasn’t forced to be home
but i could head a flight to california to hawaii mexico
and have a situation later on, saying that i could, handled it in alaska

SYNONYM + RE: on my iphone
i was sitting at the m-m-way posted in a video,
in the gps showing up on a kitchen plane driving flying to detroit
told me i couldn’t head home to california
to alaska
and i been at it for a while, later on i had an allowance saying i could have last

Table 11: Additional model outputs for style transfer from news articles to rap lyrics.