Rapformer: Conditional Rap Lyrics Generation with Denoising Autoencoders

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Abstract

The ability to combine symbols to generate language is a defining characteristic of human intelligence, particularly in the context of artistic story-telling through lyrics. We develop a method for synthesizing a rap verse based on the content of any text (e.g., a news article), or for augmenting pre-existing rap lyrics. Our method, called Rapformer, is based on training a Transformer-based denoising autoencoder to reconstruct rap lyrics from content words extracted from the lyrics, trying to preserve the essential meaning, while matching the target style. Rapformer features a novel BERT-based paraphrasing scheme for rhyme enhancement which increases the average rhyme density of output lyrics by 10%. Experimental results on three diverse input domains show that Rapformer is capable of generating technically fluent verses that offer a good trade-off between content preservation and style transfer. Furthermore, a Turing-test-like experiment reveals that Rapformer fools human lyrics experts 25% of the time.1

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). That 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 to conditional generation 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 (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. Model outputs are enhanced by a post-processing step (Section 3.2) that substitutes non-rhyming end-of-line words with suitable rhyming alternatives.

We test our method on three diverse input domains: short summaries of news articles, movie plot summaries, and existing rap lyrics. Automatic and human evaluations (Sections 5 and 6) suggest that our method provides a trade-off between content preservation and style compared to a strong information retrieval baseline.

2 Background

2.1 Rap Lyrics Generation

Prior work on rap lyrics generation often focuses on unconditional generation, either using language models (Potash et al., 2015) or by stitching together lines from existing rap lyrics using information retrieval methods (Malmi et al., 2016). 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. 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 (Hopkins and Kiela, 2017).

More recently, Manjavacas et al. (2019) propose a conditional approach to rap lyrics generation, which extracts high-level features from the lyrics, such as their sentiment, mood, or tense, to provide a template during generation. Although their approach allows for some control during generation, it is limited in terms of generating lyrics with more specific content. The work that is closest to ours is (Lee et al., 2019) who propose an approach to sentence style transfer based on text denoising, and test their approach on style transfer from pop to rap lyrics. In contrast to these works, we condition the model on longer input text and also introduce a novel method for enhancing the rhymes of our output verses. We also perform extensive automatic and human evaluations on style transfer from diverse input domains to rap lyrics.

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; Lample et al., 2019; Liu et al., 2019), focuses on transfer from one text attribute to another, such as gender or political inclination. 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. Our conditional lyrics generation based on denoising autoencoders is also related to recent work on self-supervised pre-training objectives for text-to-text generation tasks, which have been beneficial for many NLP tasks, such as automatic text summarization (Zhang et al., 2020), question answering (Lewis et al., 2020; Raffel et al., 2019), and data-to-text generation (Freitag and Roy, 2018).

3 Conditional Generation of Lyrics

Our approach to conditional generation of rap verses consists of three steps (Figure 1).

1. Given a dataset of rap verses, we apply a stripping approach to extract from each verse a set of content words that aim to resemble the main content of the original text, omitting any specific stylistic information.

2. We train a Transformer model (Vaswani et al., 2017) to reconstruct the original rap verses conditioned on the content words. The model learns to generate the original verse, filling in missing stylistic information.

3. At inference time, we can input content words extracted from a text written in any style, such as a news article, resulting in novel output rhyme verses. After generation, we optionally apply a rhyme enhancement step (Section 3.2).

3.1 Stripping Approach

Given a dataset of original rap verses, our base approach to extracting content words involves pre-
processing each verse to remove all stop words\(^2\), numbers, and punctuation. To promote greater novelty\(^3\) 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. A similar noising approach has been recently employed by Raffel et al. (2019).

Drop. We randomly remove 20% of the input content words for the purpose of promoting generation of novel words, 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 improve the rhyming fluency of our models, we implement a post-processing step for rhyme enhancement (RE) which modifies a generated verse to introduce additional end-of-line rhymes. Given two lines from a generated verse, such as:

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

RE iterates over each of the lines in the verse, replacing the ending words with a MASK token. The verse is then passed through a BERT model\(^4\) (Devlin et al., 2019) which predicts the \(K = 200\) most likely replacement candidates for MASK. 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). In the example above, replacing beginners with food maximizes the rhyme length, and the example becomes:

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

Algorithm 1 contains a detailed implementation of our approach.

![Algorithm 1: Bert Rhyme Enhancement](image)

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\(^2\)We use the list of English stopwords defined in NLTK.

\(^3\)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.

\(^4\)We finetune a BERT base model on our rap verse dataset for 20 epochs.

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## 5 Automatic Evaluation

We conduct an automatic evaluation of RAPEFORMER, using the test sets of each of our three datasets. Our focus is on measuring two components that are important for generating fluent conditional rap verses: preserving content from the input text to the output, and maintaining rhyming fluency during generation.

### 5.1 Evaluation Metrics

#### Content preservation.

We test the capacity of our models to preserve content words from the input by computing a unigram overlap score:

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

between unique unigrams from an input text $x$ and the generated output rap verse $y$. We also report the BLEU score (Papineni et al., 2002) when training a model to reconstruct original 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 a phonetic transcription of the
lyrics and finding the average length of matching vowel sound sequences which resemble multisyllabic assonance rhymes. As a reference, RD values above 1 can be considered high, with some rap artists reaching up to 1.2.

5.2 Baselines
For reference, we report the result of an information retrieval baseline, which retrieves the closest text from our training dataset given input from the news or movies test sets, using sentence embedding similarity.\(^8\) We report two variants of the IR baseline. First, we retrieve the closest summary from the CNN/DailyMail news training set (IR NEWS), 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). The outputs of the strong IR Rap baseline perfectly match the style of original rap verses, giving us an upper bound for rap style, while maintaining some degree of lexical and semantic overlap with the input texts.

5.3 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 (model names ending with "+ RE").

Rap reconstruction. In the left part of Table 2, we evaluate our model’s capacity to reliably regenerate original rap lyrics given extracted content words from them. RAPFORMER performed well on this task, generating fluent lyrics that incorporate a large part of the input content words and surpassing the average rhyme density observed in the training dataset (INPUTS). When using our rhyme enhancement step, we observe a slight decrease in overlap due to the potential replacement of content words. However, RD increases by 10% on average.

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

6 Human Evaluation
Due to the limitations of automatic metrics for text generation, we also perform four human evaluation experiments using three raters, who are trained to translate lyrics. Due to limited resources, we evaluate only the RAPFORMER variant with the Shuffle stripping approach and rhyme enhancement, which achieved the highest content overlap in our automatic evaluation.

The first two human experiments (in Table 3) focus on style transfer using news articles as input. Each rater inspected 100 verses produced by either the RAPFORMER, or the two IR baselines, answering the following three questions:

1. How much do the lyrics presented resemble rap lyrics? On a scale from 1 (not at all),

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\(^8\)We use a 600-dimensional Sent2Vec model (Pagliardini et al., 2018), which is pretrained on Wikipedia.
Table 3: Human evaluation results of RAPFORMER (using the SHUFFLE stripping approach, and news articles as input). The average inter-rater agreement for Style is 0.3, and for Meaning is −0.1, measured using Cohen’s Kappa (Cohen, 1960).

| Method    | Style | Meaning | Familiarity |
|-----------|-------|---------|-------------|
| IR NEWS   | 1.18  | 2.01    | 1%          |
| IR RAP    | 4.27  | 1.33    | 31%         |
| RAPFORMER | 2.03  | 2.55    | 8%          |

1. Recalling the lyrics of a song you know (yes or no)? For IR RAP, this question measures the Familiarity of the raters with the lyrics; for the other two methods, it measures the capacity to fool the raters.

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 IR RAP, this question measures the Familiarity of the raters with the lyrics; for the other two methods, it measures the capacity to fool the raters.

Table 4: Turing-like evaluation, reporting the percentage of lyrics generated by RAPFORMER (using the SHUFFLE stripping approach, and rap lyrics as input) that human experts incorrectly label as existing rap lyrics. The average inter-rater agreement for Side-by-Side is 0.8, and for Random is 0.4, measured using Cohen’s Kappa (Cohen, 1960).

| Method    | Side-by-Side | Random |
|-----------|--------------|--------|
| RAPFORMER | 7%           | 25%    |

The other two human experiments (in Table 4) focus on our rap reconstruction task, performing two Turing-test-like comparisons between 100 real and synthetic verses:

1. Side-by-Side: the original rap lyrics and RAPFORMER lyrics are presented side-by-side, in a random order, and a rater is asked, Which of these lyrics was written by a human? (see the Appendix for examples).

2. Random: a verse is shown and the rater is asked, "Do you think these rap lyrics are: (a) AI-generated or (b) human-created?".

In terms of style (Table 3), we outperform IR NEWS, 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 IR RAP. However, it is worth noting that the content preservation of IR RAP is considerably lower, as shown in Tables 2 and 3, 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 might be unrealistic to attain even with a perfect conditional generator.

Overall, the results indicate that our method provides a trade-off between the two baselines in terms of style while outperforming them in terms of content overlap. Furthermore, 8% of the time, our conditional generation model fooled experienced raters to think that our synthetic rap lyrics generated from news articles originate from real rap songs. Our rap lyrics augmentation approach also proved to be robust in the Turing-style evaluation of rap reconstruction (Table 4), where RAPFORMER fooled the raters 25% of the time when lyrics from a random source are presented one-by-one, and 7%...
7 Example Model Outputs

In Tables 5, 6 and 7, 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").

Furthermore, in Table 8 we present examples from our side-by-side Turing test, where we asked raters to choose which of two lyrics was generated (augmented) by RAPFORMER, and which was written by a human. For the selected outputs, two of the three raters incorrectly guessed that the lyrics generated by RAPFORMER were actually human-created.

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, including combining several stripping approaches, and could explore the utility of large-scale pretrained models (e.g., (Raffel et al., 2019; Lewis et al., 2020)) for this task. Another direction is to extend our
Table 8: Examples of lyrics generated by RAPFORMER that fooled the majority (at least two out of three) human raters in a side-by-side comparison with human created lyrics. Inappropriate words are replaced by a single dash.

Table: 8 Examples of lyrics generated by RAPFORMER that fooled the majority (at least two out of three) human raters in a side-by-side comparison with human created lyrics. Inappropriate words are replaced by a single dash.

| Question 45 of 100 | Correct answer: (B) |
|--------------------|---------------------|
| LYRICS (A)        |                     |
| waka waka:        | i say na correct eye i take waka this waka |
| they say na blind eye, take it far | but after i’ve got you i blind pata pata |
| i’ve got it on my own, my own | oche du no dum no oda du num doka |
| oche num, oda du, doka dum so | anybody try you i go shoot the murderer |
| if anybody ever try go shoot the almighty | ever blazing you amazing |
| blazing so amazing |                     |
| Which of these lyrics was written by a human? |                     |

| Question 72 of 100 | Correct answer: (B) |
|--------------------|---------------------|
| LYRICS (A)        |                     |
| vegas on the third floor, like lamar with the cardio | out in vegas like lamar, third floor tropicana |
| fascinated by the cars smokin’ dope in the casino | fascinated with the cars, smokin’ dope in the phantom |
| despise the propaganda rise, higher | telfon’s on the rise, i despise propaganda |
| mac-11 camouflage for example, that’s why i never set fires | camouflag mac-11, i should set an example |
| i walk with a flame that never match my desires | never baptized, as i walk through the fires |
| take a pic, cause the pain is higher | the pain and the flame never match my desires |
| i’m rich as a coupe, light it up with kelly | crucified cause i’m rich, in the coupe, take a pic |
| phone sucker, my friend, it’s a blessing | on the phone at the light, kelly rowland’s a friend |
| benz, plaques, wall, and go’s | cattish in the benz, manti treo’s a sucker |
| - ‘em all, hustler say the victim | plaques on the wall, hustler so i can say “- ‘em” |
| cirroc and bel air - | bel air for the - , cirroc in the pool |
| april -’s -, her name so | my - is a -, her name is april’s a fool |
| Which of these lyrics was written by a human? |                     |

| Question 74 of 100 | Correct answer: (A) |
|--------------------|---------------------|
| LYRICS (A)        |                     |
| she cut the call when she was on ma phone | i picked up the phone and cut the line and call |
| when you picked up the line | i asked what’s up girl, why you got so long |
| you got so mad and asked me who’s the girl | i’m sleeping behind you |
| i’m sleeping with behind | baby, i guess i try to say the truth |
| baby, i had no words to say | but... it’s time to lie... |
| so i guess i will try |                     |
| not to lie... it’s the time... |                     |
| Which of these lyrics was written by a human? |                     |

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### A Additional Model Outputs

In Tables 9, 10 and 11 we display a few additional manually selected model outputs for each of our input domains (rap lyrics, movie summaries and news article summaries) and each of our stripping approaches (SHUFFLE (RAPFORMER), DROP, and SYNONYM).

### B Demo Song

We generated lyrics for a demo song by using the abstract of this paper as the input to RAPFORMER. We generated multiple samples, by reshuffling the content words of the abstract multiple times. We sent all sample lyrics to a rap artist, and asked them to record a song using a subset of those lyrics. We allowed for re-arranging and deletion, but no addition of human-created lyrics. The resulting audio file is included in the supplementary material, while the final lyrics of the song are in Table 12.

We also tested the recently released Jukebox algorithm (Dhariwal et al., 2020) for end-to-end synthesis of a rap song conditioned on the abstract lyrics. However, our preliminary results were unsatisfactory since it was impossible to tell individual words apart from the generated audio.

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Also available at [https://bit.ly/3kXGItD](https://bit.ly/3kXGItD).
| Input | Control the whole domain, and then show no shame. Make rappers go? And they so lame, playing with no game. Put em on the lil plane til they can’t claim no fame. I got, the range, better, stay in the slow lane. I make the flow change from hurricanes to a slow rain. Your thoughts are so plane, i rearrange your whole frame until my whole name grow out your brain like rogaine. |
|-------|--------------------------------------------------|
| Drop + RE | Like propane in control, my whole objective show no shame. I can make it playin’ the game. Put em in a lil’ game, til they don’t claim fame range. You better stay in your lane, and make the flow change. I be on a plane to rearrange your own frame. Your whole name grow in my brain, rogaine letter. |
| Synonym + RE | Control the whole domain just to show it no shame. Make these rappers go lame, they playin’ the game. Put em on a lil’ plane til they can’t title the fame. If you got a range, you better stay in a slow lane. Name run change hurricane slow rain. Thoughts on the ground and rearrange your whole frame. Whole name grow brain like a rogaine cane. |
| Shuffle + RE (Transformer) | Aim dough like propane came with a whole blow shame how you control the whole show. Lame rappers playin’ the game, make your domain go can’t claim em til you put a lil fame on a show. Slow down, stay in your lane, got a better range. Make it rain, change your flow, slow rain. Rearrange your whole frame, plane change. Grow like rogaine, put my whole name on your brain. |

| Input | Now comes our turn. We step in, you burn. You got something to learn. And bring a breath of fresh air. This is how we go. You check this mode. Ride da best you know. And still want more. |
|-------|--------------------------------------------------|
| Drop + RE | When it comes to turn to step. I got something to bring in my breath. Go check my mode. Ride with da so. You know I still want to be your own. |
| Synonym + RE | When it comes to turn my step to burn. I got something to learn. Bring your breath to new light. Go check the way i ride. Da best i know. You still want so. |
| Shuffle + RE (Transformer) | When it comes to my turn. Step up and learn something to burn. I got fresh air on my breath. Go check da best mode, bring it yeah. You know I still want a ride. |

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

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

SHUFFLE + RE (RAPFORMER): 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!

INPUT: The film follows the lives of several West Point cadet classmates who find themselves on opposite sides of the war. The film also follows the adventures of Lucius the slave escaping via the underground railroad to freedom with the first battle of Bull Run and the birth of a Lucius’ child born in slavery.

DROP + RE: Film of the West Point where they can find the opposite sides of ours
Film also and they will be a slave escaping me from the underground,
And we will not be the same if we are not the maker
This is a film cutting first bull from birth to child’s slaver.

SYNONYM + RE: Film to succeed our lives in several zones
Our head is the most likely to find our own
We are not the same as the other side of ever
Film also follows adventure
The Lucius slave, the escaping via underground
Motorical, Freedom, film out
First battle Bull, then feed him birth
Golden child, born in order

SHUFFLE + RE (RAPFORMER): this is the opposite of war follows lives on both sides
Several point film from the west to the light
Find a child born escaping via immigration
Film the underground cutting off the film of all the complications
Slave, run from Lucius slavery
Battle of Freedom and liberty
Also the first bull follows Luc-up!

Table 10: Additional model outputs for style transfer from movie plot summaries to rap lyrics.
INPUT (NEWS): temperatures dipped into the mid-30s during 4 days man lay in woods of philadelphia park. mom told police son was with her in maryland, but he was found friday with blanket, bible. victim being treated for malnutrition, dehydration; mother faces host of charges after extradition.

DROP + RE: i've been dipped for days, lay in woods in the park with the crook my son from pittsburgh found friday blanket, bible victim i was born to be a victim of my reality with no faces host charges, i had to do it everything

SYNONYM + RE: dipped in mid-a.t. days, man i dwell in ways UNK 3: gs, park mom told the police son that he was from illegal found him on friday, he had a blanket with a bible a victim of how he treated him as a

SHUFFLE + RE (RAPFORMER): man i was dipped up in a lay up with some of them from an old mid-30s days in the home mom told me to be in michigan anyway police blanket friday i found my son a bible he was a host for the trial my mother treated him as an alien a victim of faces

INPUT (NEWS): jordan spieth won the 2015 masters by four shots on sunday. the 21-year-old american led all week at the augusta national golf club. he shot final-round 70 to finish on 18 under par and take the green jacket.

DROP + RE: to all of my masters, four sunday morning, american led alert national golf club, final-round time take a green jacket

SYNONYM + RE: jordan, we are not the same, no masters! four shots of the sun, the laughter we were the most likely american led in a week at the first club shot last finish, hey get the green cap

SHUFFLE + RE (RAPFORMER): masters, four shots on sunday jordan, led me to the national club, the american way golf week, green dine, par finish my jacket, take my final-round start

INPUT (NEWS): the dallas native will play alongside justin rose in the final pairing. has set a scoring record for the first 54 holes of 16 under par. finished runner-up last year and is now determined to win. is first player since greg norman in 1996 to have lead after each round.

DROP + RE: dallas native play i was born to be a slave but now i’m on my own and i’ll be the first so justin final scoring holes in par last year determined to start been a player, since greg the only way to tell

SYNONYM + RE: dallas, c4, i play with the same g6, justin rose to the place c1, ready to scoring the record first holes in the firearm, then i remember this is the first year determined to win, first player, since marc ellen went here

SHUFFLE + RE (RAPFORMER): justin rose, native gold final par, scoring holes, set it off, play it again, justin rose determined to win the first record, last year i was finished greg player, he was a player from the beginning since first i lead the worldball.

Table 11: Additional model outputs for style transfer from news articles to rap lyrics.
Table 12: Lyrics of our demo song, described in Appendix B.