Abstract

Limerick generation exemplifies some of the most difficult challenges faced in poetry generation, as the poems must tell a story in only five lines, with constraints on rhyme, stress, and meter. To address these challenges, we introduce LimGen, a novel and fully automated system for limerick generation that outperforms state-of-the-art neural network-based poetry models, as well as prior rule-based poetry models. LimGen consists of three important pieces: the Adaptive Multi-Templated Constraint algorithm that constrains our search to the space of realistic poems, the Multi-Templated Beam Search algorithm which searches efficiently through the space, and the probabilistic Storyline algorithm that provides coherent storylines related to a user-provided prompt word. The resulting limericks satisfy poetic constraints and have thematically coherent storylines, which are sometimes even funny (when we are lucky).

1 Introduction

A limerick is a short and catchy 5-line poem that tells a funny, crude, or ironic story. It has strict structural constraints such as an AABBA rhyming scheme, a 99669 syllable count, and an anapestic meter pattern (Legman, 1988). Writing limericks is a challenging task even for human poets, who have to carefully choose, optimize, and even invent new words to satisfy all of the constraints while incorporating creativity and humor.

Prior to this paper, there has not been a successful attempt at realistic automatic limerick generation. Perhaps this is because the task is challenging: Large-scale neural networks often fail to generate decent limericks because the amount of available human-written limericks to learn from is much smaller than other forms of poetry, and because limericks must follow strict structural, meter, and rhyming constraints. Traditional methods for generating limericks instead hard-code the constraints into a template, so that the constraints are obeyed but the generated poems are all extremely similar (resembling Mad Libs, where one fills words into a single template).

In this paper, we introduce a novel system of algorithms for automatic limerick generation, denoted as LimGen. LimGen takes a user-specified prompt word and produces a creative and diverse set of limericks related to the prompt. Table 1 shows some of LimGen’s output.

LimGen is a rule-based search method. Its main components are: (1) Adaptive Multi-Templated Constraints (AMTC), which constrain LimGen’s search to a space of realistic limericks, leveraging knowledge from limerick sentence structures extracted from human poets; (2) the novel Multi-Templated Beam Search (MTBS), which searches the space in a way that fosters diversity in generated poems; and (3) the probabilistic Storyline algorithm, which provides coherent storylines that are thematically related to the prompt word.

LimGen relies on the part-of-speech (POS) limerick templates extracted from a small training set and uses a pre-trained language model to fill words into the templates. We used the 345M version of pre-trained GPT-2 (Radford et al., 2019), which performs extremely well in unconstrained text generation. However, it is important to note that a language model such as GPT-2, powerful though it may be, is only a plugin module for LimGen. Without LimGen, GPT-2 alone is completely incapable of generating limericks.

Through our experiments, we demonstrate that LimGen creates a new benchmark for limerick generation, outperforming both traditional rule-based algorithms and encoder-decoder style neural networks across a variety of metrics, including...
There was a greedy man named Todd,
Who lost all his money in a fraud.
When he returned to work,
He was robbed by his clerk,
And never could buy a cod.

There was a magician named Nick,
Who fooled all his family in a trick.
When he returned to hide,
He was found by his bride,
And killed with a magical lipstick.

Table 1: LimGen examples.

 emotional content, grammar, humor, sensibleness
and storyline quality. Furthermore, although Lim-
Gen is not yet on par with human poets, our
experiments show that 43% of LimGen’s output
cannot be distinguished from human-written lim-
ericks even when directly compared with actual
human limericks.

The main contributions of this paper are the
multi-template-guided LimGen system and its
MTBS search algorithm. Equipped with AMTC,
LimGen is the first fully automated limerick gen-
eration system that has the ability to write creative
and diverse limericks, outperforming existing
state-of-the-art methods. Our diversity-fostering
beam search (MTBS) is on par with some of
the best beam search algorithms in terms of its
ability to optimize limerick quality, and it does a
significantly better job at fostering diversity than
other methods. The code for LimGen as well as the
complete list of machine-generated limericks used
in our experiments are available online (Wang
et al., 2020).

From a broader perspective, we have shown that
rule-based poetry generation systems that follow a
multi-templated approach, as implemented via the
AMTC in this work, can perform better than large-
scale neural network systems, particularly when
the available training data are scarce. Our work
indicates that a computational system can exhibit
(what appears to be) creativity using domain-
specific knowledge learned from limited samples
(in our case, POS templates extracted from
human-written poems). Although we only use
templates to capture the part-of-speech structure
of limericks, in general, templates can represent
any explicit or latent structures that we wish to
leverage. Other NLP applications (e.g., biography
generation, machine translation, image caption-
ing, machine translation) have also seen revived
interest in template-guided approaches (Wiseman
et al., 2018; Yang et al., 2020; Deshpande et al.,
2019; Wang et al., 2019). Thus, it is conceivable
that the general framework of LimGen, including
AMTC and the MTBS algorithm, can be applied
to other forms of poetry generation, as well as
broader domains in NLP.

2 Related Literature

To the best of our knowledge, Poevolve (Levy,
2001), which combines an RNN with an evolu-
tionary algorithm, and the stochastic hill climbing
algorithm proposed by Manurung et al. (2000)
are the only other serious attempts at limerick
generation in the past 20 years. Unfortunately,
their implementations did not result in readable
limericks, as can be seen in Section 4.3.

Traditional rule-based methods in poetry gener-
ation are able to enforce hard constraints, such as
rhyming dictionaries or POS templates (Gervás,
2000, 2001; Colton et al., 2012; Yan et al., 2016).
LimGen is also rule-based, though it has substan-
tially more flexibility and diversity than Colton
et al.’s (2012) approach, which follows a single
POS template during poetry generation. Needless
to say, the use of adaptive multi-templates makes
AMTC the bedrock of LimGen.

Neural language models have recently been
able to produce free-style (unconstrained) English
poetry with moderate success (Hopkins and Kiela,
2017; Liu et al., 2018). In Chinese poetry gener-
ation (Zhang and Lapata, 2014; Yi et al., 2018b;
Wang et al., 2016; Yi et al., 2018a), research
has been so successful that it has spurred further
efforts in related areas such as sentiment and style-
controllable Chinese quatrain generation (Yi et al.,
2020; Yang et al., 2018; Chen et al., 2019). How-
ever, their large-scale neural network models take
advantage of the Chinese quatrain database, which
has more than 150k training examples. In contrast,
LimGen uses less than 300 limericks. Most modern
poetry-generation systems are encoder-decoder
style recurrent networks (e.g., character-level and
word-level LSTMs) with modifications such as
various forms of attention mechanisms. Lau et al.
(2018) integrated these techniques and proposed
Deep-speare, which represents the state-of-the-
art for Shakespearean sonnet generation. In our


experiments, we have adapted and re-trained Deep-speare for limerick generation. Empirically, it cannot compete with LimGen.

For handling rhyming constraints, unlike Ghazvininejad et al. (2016) and Benhart et al. (2018), who generate the last word of each line before generating the rest of the line, our proposed Storyline algorithm selects a probability distribution for the last word of each line.

Beyond poetry generation, templates are often used in other NLP tasks. For biography generation, Wiseman et al. (2018) noted that a template-guided approach is more interpretable and controllable. Yang et al. (2020) stated that templates are beneficial for guiding text translation. For fostering diversity in generated text, Deshpande et al. (2019) found that a part-of-speech template-guided approach is faster and can generate more diverse outputs than the non-templated diverse beam search of Vijayakumar et al. (2018). LimGen’s MTBS generates diverse results by design; it also addresses the problem of degradation of performance when beam size grows larger, which has been a challenge noted in several prior works (Cohen and Beck, 2019; Vinyals et al., 2016; Koehn and Knowles, 2017).

Since all rule-based constraints in LimGen are easily enforced by a filtering function, it does not need to borrow any advanced techniques from the area of constrained text generation (e.g., Hokamp and Liu, 2017; Anderson et al., 2017; Post and Vilar, 2018; Yan et al., 2016) where constraints are more complicated.

3 Methodology

We first introduce terminology in Section 3.1. We present LimGen along with AMTC in Section 3.2. We present the MTBS algorithm in Section 3.3, and present our Storyline algorithm in Section 3.4.

3.1 Terminology

We first introduce some useful notation for the concepts of (partial) line, (partial) template, language model, filtering function, and scoring function.

LimGen’s entire vocabulary is $\mathcal{W}$ with size $|\mathcal{W}|$. For word $w \in \mathcal{W}$, its POS is $w.pos$. The first $t$ words of a complete line $s_i$ forms a partial line $s_i^{(t)}$. We store many partial lines $s_i^{(t)}$ with length $t$ in a set $S^{(t)} = \{s_i^{(t)}\}_i$. A new word $w$ concatenated to $s_i^{(t)}$ becomes $s_i^{(t+1)} = (s_i^{(t)}, w)$. A (partial) template is a sequence of POS tags. The (partial) template of line $s$ is $s.pos = (w_1.pos, \ldots, w_n.pos)$. A language model $L$ processes a (partial) line and gives a probability distribution for the next word. We use $\mathcal{D}^{(t)}$ to denote the probability distribution at step $t$. The filtering function $\mathcal{F}$ filters out words that do not satisfy meter and stress constraints by setting the probability mass of these words in $\mathcal{D}^{(t)}$ to zero. Since limericks have a specific meter and stress pattern, words that break this pattern are filtered out by $\mathcal{F}$.

The scoring function for lines is denoted $H(\cdot)$, which is the average negative log likelihood given by the language model. Although our search algorithm generally aims to maximize $H(\cdot)$, the language model’s scoring mechanism may not be aligned with poetic quality; sometimes a slightly lower scoring poem has better poetic qualities than a higher scoring one. Thus we may find a better poem by sifting through LimGen’s output, rather than choosing the highest scoring poem.

3.2 Adaptive Multi-Templated Constraint (AMTC)

Because the number of limericks that exist in available databases is so limited, we cannot expect that a neural network would learn the POS constraints for a valid limerick. Instead, we use rule-based POS constraints, which are useful in that they ensure the output adheres to the known structure of poetry. The use of adaptive multi-templates makes the poems more diverse and interesting by providing LimGen with greater flexibility in pursuing many different templates.

It may seem natural to choose multiple templates and have the limerick generation process follow each one of them in parallel, but this is inefficient; instead, we start generating from one template, keeping also the set of templates that agree with what we have generated so far. This way, we generate each line by combining a set of related templates. Specifically, AMTC constrains LimGen to consider word $w$ for partial line $s^{(t)}$ only if the template of $s^{(t+1)} = (s^{(t)}, w)$ matches with a human-written template up to the first $t + 1$ tokens. Therefore, the more templates we extract from real poems, the higher the degree of freedom we offer LimGen.
In Section 3.4 the Storyline Algorithm describes how storylines are integrated with LimGen to generate last words of each line.

Initialize $S^{(0)} \leftarrow \{\}$. For $t = 0, 1, 2, \ldots$

1. $S^{(t+1)}$ will store all candidate partial lines of length $t + 1$.
2. $S^{(t+1)}$ will store the chosen partial lines by MTBS.

Initialize $S^{(t+1)} \leftarrow \varnothing, \tilde{S}^{(t+1)} \leftarrow \varnothing$.

For $s^{(t)}_i \in S^{(t)}$

1. Filter the distribution $L(s^{(t)}_i)$ given by GPT-2.
2. For meter and stress match $D^{(t+1)}_1 \leftarrow \mathcal{F}(L(s^{(t)}_i))$.
3. For $w_k \in \mathcal{W}$ with $D^{(t+1)}_1(w_k) > 0$
   - AMTC ensures partial template is always the prefix of a viable human template.
   - If $[s^{(t)}_i, w_k]$ satisfies AMTC:
     - $w_k$ is the last word (i.e., $[s^{(t)}_i, w_k]$’s template matches a human template), where Storyline Algorithm contributes to generation of $w_k$
     - Concat $[s^{(t)}_i, w_k]$, union with $\tilde{S}^{(t+1)}$.

End for

End for

Find top $N$ lines using multi-templated beam search $\tilde{s}^{(t+1)}_1, \ldots, \tilde{s}^{(t+1)}_{N} \leftarrow \text{MTBS}(\tilde{S}^{(t+1)})$;

Union with $S^{(t+1)}$;

Output $S^{t+1}$.

We present the entire LimGen system with AMTC in Algorithm 3.1.

We illustrate LimGen with the example in Figure 1. At the 3rd step of generating the second line, set $S^{(3)}$ contains partial lines $s^{(3)}_1 = \{ ‘who \ ate \ a’ \}$ and $s^{(3)}_2 = \{ ‘who \ bought \ a’ \}$, which share the same partial template “WHO VBD A”. The probability distributions for the fourth words are $D^{(4)}_1 = L(s^{(3)}_1)$ and $D^{(4)}_2 = L(s^{(3)}_2)$. One can see how LimGen with AMTC does not follow a single template using the example in Figure 1 since the partial template “WHO VBD A” branches into two distinct partial templates “WHO VBD A JJ” and “WHO VBD A NN”.

After $\mathcal{F}$ filters out all unsatisfactory words that break the syllable or stress pattern, we obtain two filtered distributions $\tilde{D}^{(4)}_1 = \mathcal{F}(D^{(4)}_1)$ and $\tilde{D}^{(4)}_2 = \mathcal{F}(D^{(4)}_2)$. We then filter out words that do not satisfy the AMTC. The concatenation step in LimGen saves all possible partial lines into a temporary set $S^{(4)}$.

The MTBS algorithm then finds $N$ diverse and high-scoring candidate lines from $\tilde{S}^{(4)}$ and saves them into $\tilde{S}^{(4)}$. In the next section, we present the MTBS algorithm in detail.

### 3.3 Multi-Templated Beam Search (MTBS)

At iteration $t$, suppose we have a set of partial lines $\tilde{S}^{(t)}$ with size $N$. Let $\hat{S}^{(t+1)}$ be the set of all possible one-word extensions of these partial lines. Given the scoring function $H(\cdot)$, a standard beam search would sort $\hat{S}^{(t+1)}$ in descending order and keep the top $N$ elements. In limerick generation using standard beam search, we also observed the phenomenon documented by Li and Jurafsky (2016) that most of the completed lines come from a single highly-valued partial line. As mentioned before, the innovation of MTBS over previous diverse beam search papers (Li and Jurafsky, 2016; Vijayakumar et al., 2018) is that it calculates a diversity score between (partial) templates (runtime $O(N^2)$), which is more computationally efficient than an approach that assigns a notion of diversity between individual lines (runtime $O(N|\mathcal{W}|)$, $N \ll |\mathcal{W}|$, where $N$ is the total number of templates and $|\mathcal{W}|$ is the vocabulary size). Our proposed diversity score also more accurately captures the diversity between generated lines. The intuition is that if two generated lines have very different templates, they are usually fundamentally different in terms of the progression of the story.

We use a weighted hamming distance to measure the difference between (partial) templates of the same length, denoted as “diversity score.” Before formally defining diversity score, we calculate the weights of each POS category. For each POS category, we take the inverse of its percentage of occurrence within all those $n$th line templates (e.g., second line templates) extracted from the $n$th line of one of our human-written limericks from the database. (The POS weights are only calculated once, before we start generating the $n$th line.) We then use the softmax to transform them into weights for each POS, which measure how rare these POS categories are. The softmax nonlinear transformation softly clips the large weights of outlier POS categories that appear only once or twice. More formally we have:

**Definition 1 (Part-of-Speech Weight).** Let $P$ be the set of all POS categories that occur in all the $n$th line complete-line templates extracted from the limerick database, $|P|$ is its size. For $p_i \in P$, the proportion of $p_i$ is $q_i = \frac{\#p_i \text{ occurrences}}{\sum_{p_j \in P} \#p_j \text{ occurrences}}$, and the weights of $\{p_i\}_{1 \leq i \leq |P|}$ are defined as

$$\{w(p_i)\}_{1 \leq i \leq |P|} = \text{softmax}\left(\left\{\frac{1}{q_i}\right\}_{1 \leq i \leq |P|}\right).$$

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Algorithm 3.2 Multi-Templated Beam Search (MTBS)

▷ The following describes MTBS at iteration $t$

1. Input $\tilde{S}^{(t+1)}$ ← $\emptyset$, $A$ ← $\emptyset$;
2. $A$ will hold the templates we have chosen
3. Split $\tilde{S}^{(t+1)}$ by templates into $m$ subsets: $\{T_1 : \tilde{S}_1^{(t+1)}, \ldots, T_m : \tilde{S}_m^{(t+1)}\}$,
4. Lines in the same subset share the same template
5. For each $\tilde{S}_i^{(t+1)}$, we calculate score $h_i$ by averaging its top $n$ lines according to $H(\cdot)$
6. $B$ ← $\{T_1 : h_1, \ldots, T_i : h_i, \ldots, T_m : h_m\}$;
7. In $B$, each template corresponds to an aggregate score $h$
8. Assume $h = \max B$, append top $n$ lines according to $H(\cdot)$ from $\tilde{S}_j^{(t+1)}$ to $S^{(t+1)}$;
9. Delete $h_i$ from $B$, append $T_i$ into $A$;
10. while $|S^{(t+1)}| \leq N - n$ and $B \neq \emptyset$ do
11. $x \in \arg\max_i \left( h_i \sum_{T_k \in A} \|T_i - T_k\|_{div} \right)$;
12. Append top $n$ lines from $\tilde{S}_2^{(t+1)}$ to $S^{(t+1)}$;
13. Delete $h_x$ from $B$, append $T_x$ into $A$;
14. end while
15. Return $S^{(t+1)}$;

Definition 2 (Diversity Score). For (partial) templates $T_1 = \{pos_{11}, \ldots, pos_{1i}\}$ and $T_2 = \{pos_{21}, \ldots, pos_{2j}\}$, assume index set $A = \{i | pos_{1i} \neq pos_{2i}\}$, then we define the diversity score (weighted hamming distance) between $T_1$ and $T_2$ as

$$\|T_1 - T_2\|_{div} = \sum_{i \in A} \max(w(pos_{1i}), w(pos_{2i})).$$

Consider a scenario where (partial) templates $T_1$ and $T_2$ have different POS categories at index $i$ but both categories are fairly common (for instance, one noun and one verb), and where (partial) templates $T_1$ and $T_3$ also have different POS categories at index $j$ but one or both are rare. Our proposed diversity score will ensure that the diversity between $T_1$ and $T_3$ is greater than the diversity between $T_1$ and $T_2$, which aligns with our intuition.

In short, given the set of partial lines $\tilde{S}^{(t+1)}$, MTBS will choose $N$ lines, denoted as $S^{(t+1)}$, such that they are high-scoring and generated using many diverse templates. Specifically, we divide $\tilde{S}^{(t+1)}$ into $m$ subsets $\{T_1 : \tilde{S}_1^{(t+1)}, \ldots, T_m : \tilde{S}_m^{(t+1)}\}$, where each subset corresponds to a unique (partial) template of length $t + 1$. According to scoring function $H(\cdot)$, for each of these subsets $\tilde{S}_i^{(t+1)}$, we calculate its aggregate score $h_i$ by averaging its $n$ highest-scoring lines. For ease of notation, we let $B = \{T_1 : h_1, \ldots, T_i : h_i, \ldots, T_m : h_m\}$, and we initialize $A = \emptyset$ to be the set of previously chosen templates. At this point, we shall iteratively determine the order by which lines from these $m$ subsets will be included into $S^{(t+1)}$.

We select the first subset that has the highest aggregate score within $\{h_1, \ldots, h_m\}$. Assume it is $\tilde{S}_j^{(t+1)}$ with score $h_j$. We then delete $T_j : h_j$ from $B$, add $T_j$ to $A$, and add the top $n$ lines from $\tilde{S}_j^{(t+1)}$ to $S^{(t+1)}$. Then, for each iteration $> 1$, we calculate a set of temporary new scores $\tilde{B} = \{T_1 : h_1, \ldots, T_i : h_i, \ldots, T_m : h_m\}$ where each $h_i$ is the original score $h_i$ multiplied by $\sum_{T_k \in A} \|T_i - T_k\|_{div}$, which is the sum of the diversity scores between $T_i$ and all previously chosen templates in $A$. These scores are designed to strike a balance between finding high probability lines (as approximated by $h$) and lines whose templates have high diversity from the previously chosen templates (as measured by $\sum_{T_k \in A} \|T_i - T_k\|_{div}$). Afterwards, we repeat the process of choosing the template with the highest $\tilde{h}$ score, delete it from $B$, add it to $A$, and add the top $n$ lines from its corresponding subset to $S^{(t+1)}$. We stop the iteration before the size of $S^{(t+1)}$ exceeds $N$.  

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Empirically, MTBS does not favor the templates with the rarest POS (largest distance from the rest), since those will have very low scores from $H(\cdot)$. It turns out MTBS picks templates that are reasonably different from each other while ensuring their generated lines have enough high scores.

3.4 Storyline Algorithm

We define the storyline of a limerick to be the last words of each line, denoted as $Y = (y_1, y_2, y_3, y_4, y_5)$, where $y_1$ is traditionally a name or place. In addition to making sure $Y$ has an “AABBA” rhyming pattern, our storyline algorithm also helps LimGen to maintain a consistent theme throughout its process of limerick generation.

We define the probabilistic distribution of storyline $Y$ given a prompt word $y_0$ as:

$$p(Y|y_0) = p(y_2|y_0)p(y_3|y_0)p(y_4|y_0,y_2,y_3) \cdot p(y_5|y_0,y_2,y_3)p(y_1|y_5),$$

(1)

$$p(y_2|y_0) \propto \text{Sim}(y_2, y_0),$$

$$p(y_3|y_0) \propto \text{Sim}(y_3, y_0),$$

$$p(y_4|y_0,y_2,y_3) \propto \sum_{l_1, l_2} \text{Sim}(y_1, y_l),$$

$$p(y_5|y_0,y_2,y_3) \propto \sum_{l_1, l_2} \text{Sim}(y_5, y_l),$$

$$p(y_1|y_5) \propto \sum_{l_1, l_2} \text{Sim}(y_1, y_l),$$

(2)

where the conditional distribution of each storyline word $y_l$ is a multinomial distribution over $\mathbb{W}$. Sim($w_1, w_2$) calculates the semantic similarity between words $w_1, w_2 \in \mathbb{W}$, which is their distance in a pretrained word embedding space. Indicator function $1_{w_1, w_2}^{(r)}$ denotes whether $w_1$ rhymes with $w_2$ and $1_{w_1}^{(p)}$ denotes whether $w_1$ is a person’s name. By sampling the storyline from $p(Y|y_0)$, we guarantee the following:

- $y_2$ and $y_3$ are semantically related to $y_0$;
- $y_4$ rhymes with $y_3$; $y_5$; $y_1$ and $y_2$ rhyme;
- $y_4$, $y_5$ are semantically related to $y_0$, $y_2$, $y_3$.

Examples of samples from Storyline’s distribution are provided in Table 2.

During the process of generating a limerick, the Storyline algorithm will sequentially generate many storylines in the order of $y_2, y_3, y_4, y_5, y_1$, each of which satisfies not only the rhyming constraint but also the constraints on POS template, syllable count, and anapestic meter pattern. Figure 2 shows the directed acyclic graph for the Storyline algorithm when the beam size of MTBS is 1.

In general, given a prompt word $y_0$, we start by generating the first line $l_1$, which has a canonical form, with a random name filled at its end as a placeholder for $y_1$ (otherwise, a pre-specified name will limit the options for $y_2$, $y_3$). Following $l_1$, we use LimGen to generate a set of second lines $\{\ldots, l_2, \ldots\}$ (as described in Algorithm 3.1) with last word left blank. We use $l_1'$ to denote a limerick generated up to this point (i.e., $l_1$ concatenated with an almost-finished $l_2$). For each $l_1'$, we repeatedly sample $y_2$ from the conditional Storyline distribution $p(y_2|y_0)$ in (2) until it satisfies constraints on POS, syllable and meter. $[l_1', y_2]$ together form the complete first two lines of a limerick. Continuing to generate lines, we use MTBS (described in Algorithm 3.2) to maintain a set of high-scoring and diverse second lines $\{\ldots, l_2', y_2, \ldots\}$. Note that our language model also assigns a probability score for each $y_2$. We can continue generating $l_1''$ with LimGen and sampling $y_k$ from the conditional Storyline distribution for $k = 3, 4, 5$ in a similar fashion. Finally, we sample $y_1$ from $p(y_1|y_5)$ and replace the random name at the end of $l_1$ by it. The result is a set of limericks $\{\ldots, L, \ldots\}$, from which we choose the highest scoring one.

<table>
<thead>
<tr>
<th>Prompt</th>
<th>Storyline</th>
</tr>
</thead>
<tbody>
<tr>
<td>war</td>
<td>(Wade, raid, campaign, again, stayed)</td>
</tr>
<tr>
<td>sports</td>
<td>(Pete, street, school, pool, athlete)</td>
</tr>
<tr>
<td>monster</td>
<td>(Skye, guy, scary, carry, pie)</td>
</tr>
<tr>
<td>forest</td>
<td>(Shea, day, friend, end, way)</td>
</tr>
</tbody>
</table>

Table 2: Examples of storyline samples.
small limerick dataset of 200 human-written limericks from Cicchi (2019) and Limericks (2019). For a full list of our modified POS categories see Wang et al. (2020). Since the filtering function $F$ requires knowing each word’s syllable and stress pattern, we use CMU (2019) for information on syllable and stress.

As for the implementation of the Storyline algorithm, there are several existing technologies to indicate whether two words rhyme with each other. For example, Deep-speare (Lau et al., 2018) proposed a character-level LSTM to learn rhyming. For the sake of simplicity and accuracy, we used a rhyming dictionary curated from Beeferman (2016). We also used a dictionary of names (Namepedia, 2019) from which the Storyline algorithm can choose $y_1$, the name in the poem’s first line. To calculate the semantic similarity between two words, we use the pre-trained word embedding space from spaCy’s model (Honnibal et al., 2020).

Note that Algorithm 3.1 is only responsible for generating the last four lines of a limerick. Since first lines of limerick usually have a canonical form, we generate the first lines separately.

The outline of this section is as follows. We first show why GPT-2—or even retrained GPT-2—cannot produce limericks without LimGen. We then show the low-quality output from prior attempts at limerick generation. We have also designed five experiments to compare the quality of LimGen’s output with limericks from human poets, baseline algorithms, and other state-of-the-art poetry systems re-purposed for limerick generation. All five experiments were evaluated on Amazon Mechanical Turk by crowd-workers, following a protocol similar to that of Lau et al. (2018) and Hopkins and Kiela (2017) (see Section 4.4 for details). Additionally, an “Expert Judgment” experiment was conducted where more experienced judges directly evaluated the performance of LimGen’s output and human-written limericks across a variety of metrics (See Section 4.8 for details).

Since LimGen has three major components: AMTC, MTBS, and Storyline, we designed three baseline algorithms for an ablation analysis in order to investigate the effectiveness of each of them.

- **Single-Template**: MTBS+Storyline but without AMTC
- **No-Story**: AMTC+MTBS but without pre-selected storylines
- **Candidate-Rank**: AMTC+Storyline but we have replaced the MTBS algorithm with another modified beam search algorithm Candidate-Rank (Cohen and Beck, 2019).

In our experiments, LimGen and all baseline algorithms use a total beam size of $N = 360$ at each step, MTBS algorithm’s individual beam size per template is $n = 12$, and we take the highest scoring poem from the set of output poems. For implementation details please refer to our online GitHub repository (Wang et al., 2020).

### 4.2 GPT-2 Cannot Generate Poems by Itself

A naïve implementation of GPT-2 simply cannot produce original and valid limericks. GPT-2 tends
There was a kind girl whose name is Jane,
A girl who I did not know,
He then added,
She had tons of luggage,
It seemed I could walk where she.

(b) This output is an exact replica of a human limerick (Vaughn, 1904) in the training corpus of GPT-2.

Wait, there was a young lady in china,
Who was quite a greedy young diner.
She feasted on snails,
Slugs, peacocks and quails,
‘No mixture,’ she said, ‘could be finer.’

Table 3: Two examples of Naïve GPT-2.

to generate long sentences that exceed the syllable limit for limericks. To meet a syllable constraint, we would need to truncate the generated sentences, which creates lines that do not end correctly. Rhyming is insurmountable if we do not utilize additional algorithms, as evidenced by Example (a) of Table 3. The output lacks poetic quality since the training corpus of GPT-2 does not mainly consist of limericks or other kinds of poetry.

If we try to re-train the last few layers of a GPT-2 model on our entire limerick dataset, it does not solve the problem. To our knowledge, our entire dataset is the largest and most comprehensive limerick dataset, consisting of more than 2000 limericks from several sources (Cicchi 2019; Limericks, 2019; Lear, 2010; Parrott, 1984; Haynes, 2010). Even though this dataset is much larger than the subset of data (≈300) from which we extracted templates, it is still insufficient to retrain GPT-2. The result of re-training is that GPT-2 severely overfits. It only regurgitates limericks from the training corpus, as seen in Example (b) of Table 3.

Terminating training early (in order to avoid memorization or overfitting) leads only to an awkward merge of problems shown in the two examples of Figure 3 in which the model has not learned enough to faithfully reproduce the form of a limerick, but also often loses coherence abruptly or regurgitates the training set.

Just as LimGen needs a powerful pre-trained language model such as GPT-2, without LimGen’s algorithms, GPT-2 by itself is unable to accommodate the constraints of limerick generation due to the deficiency of training data.

4.3 Prior Attempts at Limerick Generation

Levy (2001) stated that ‘‘the current system produces limericks that in many ways seem random.’’ We have re-run their implementation, and it only produced meaningless verses with serious grammatical issues. Manurung et al. (2000) stated that their work is unfinished and stated that their results ‘‘can hardly be called poems’’ (see examples in Table 4). Empirically, LimGen has a clear advantage over both prior works. Therefore, the low-quality output from these systems do not warrant an extensive comparison with LimGen’s poems.

On the other hand, popular internet poem generators (PoemGenerator, 2019; PoemOfQuotes, 2019) have a set of human-written half-finished sentences that are assembled with user input words to create limericks (see Table 5). However, because so little of the resulting limerick is generated by a machine, we cannot consider these internet poem generators as automatic limerick generation systems.

4.4 Experiment 1: LimGen vs. No-Story

As we have mentioned before, the No-Story baseline still utilizes the AMTC and MTBS algorithms. This experiment demonstrates the importance of having pre-selected storylines in poetry generation.

We randomly selected 50 pairs of limericks, in which each pair of limericks consists of one generated by LimGen and another generated by No-Story using the same prompt word. For each pair of limericks, 5 different crowd-workers (each with an approval rate ≥90%) answered a list of 6 questions on different evaluation metrics (humor, sensibleness, storytelling, emotional content, grammar, thematic relatedness to prompt) and an additional sanity-check question to filter out illogical responses. Figures 3 and 4 show the side-by-side comparison of a pair of limericks and the list of questions exactly as they appeared on the Amazon Mechanical Turk survey. Note that the output of LimGen has a 50% chance of being either Limerick A or B to avoid any left–right bias.

A total of 250 response were recorded, and a small number of responses were filtered out since they did not answer the sanity check question correctly, which asks crowd-workers to count the number of 3-letter words in the fourth line of Limerick B. We have transformed the response such that a response of 5 always means that the poem is

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Figure 3: Side-by-side comparison of two limericks generated from different methods.

(a) Example of Levy’s (2001) system
Ears christmas new throat boat apparel,
Plain always obsessed deal idea,
Attempt blast work many,
Mercator aghast,
Kathleen mind revealed barge bugs humor.

(b) Example of Manurung et al.’s (2000) system
The bottle was loved by Luke,
a bottle was loved by a dog
A warm distinctive season humble mellow,
smiled refreshingly slowly. Ran.

Table 4: Two prior attempts at limerick generation.

(a) Example of PoemGenerator (2019)
There once was a man called Liam.
He said, "See the coliseum!",
It was rather young,
But not very zedong,
He couldn’t resist the mit im.

(b) Example of PoemOfQuotes (2019)
There was a man from White
Who liked to fly his kite
On each sunny day
The man would say ‘Oh, how I miss White!’

Table 5: Examples of internet poem generators. Underlined parts are human-written half sentences and bold parts are user inputs.

Which limerick has more emotional contents (e.g., happiness, sadness, scariness,)
5: Definitely A; 4: Probably A; 3: The same; 2: Probably B; 1: Definitely B

Which limerick has better grammar?
5: Definitely A; 4: Probably A; 3: The same; 2: Probably B; 1: Definitely B

Which limerick is more related to the keyword “fall”?
5: Definitely A; 4: Probably A; 3: The same; 2: Probably B; 1: Definitely B

Which limerick is more humorous?
5: Definitely A; 4: Probably A; 3: The same; 2: Probably B; 1: Definitely B

Which limerick makes more sense?
5: Definitely A; 4: Probably A; 3: The same; 2: Probably B; 1: Definitely B

Which limerick does a better job at telling a story?
5: Definitely A; 4: Probably A; 3: The same; 2: Probably B; 1: Definitely B

Figure 4: The list of questions on Amazon Mechanical Turk survey.

is > 3, we run a one-sided t-test with the null-hypothesis being ‘‘metric ≤ 3, i.e., LimGen is not doing better than baseline.’’ If the mean of a metric is < 3, suggesting the baseline is probably doing better, we run the complementary one-sided t-test with the null-hypothesis being ‘‘metric ≥ 3, i.e., baseline is not doing better than LimGen.’’

From Table 6, the p-value of grammar, humor, relatedness to prompt, and storytelling are all small enough to reject the null hypothesis, which shows that LimGen was better than No-Story in all four categories. We can weakly reject the null hypothesis for the sensibleness metric, which shows that LimGen also may outperform No-Story with respect to sensibleness. However, the p-value of emotion is 0.38, therefore we cannot
Table 6: LimGen vs. No-Story.

<table>
<thead>
<tr>
<th>Metrics</th>
<th>mean</th>
<th>sd</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>emotion</td>
<td>3.03</td>
<td>1.22</td>
<td>0.38</td>
</tr>
<tr>
<td>grammar</td>
<td>3.18</td>
<td>1.27</td>
<td>0.03</td>
</tr>
<tr>
<td>humor</td>
<td>3.14</td>
<td>1.20</td>
<td>0.05</td>
</tr>
<tr>
<td>relatedness</td>
<td>3.32</td>
<td>1.22</td>
<td>2.0×10^{-4}</td>
</tr>
<tr>
<td>storytelling</td>
<td>3.35</td>
<td>1.38</td>
<td>3.0×10^{-4}</td>
</tr>
<tr>
<td>sensibleness</td>
<td>3.14</td>
<td>1.42</td>
<td>0.09</td>
</tr>
</tbody>
</table>

Table 7: LimGen vs. Single-Template.

<table>
<thead>
<tr>
<th>Metrics</th>
<th>mean</th>
<th>sd</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>emotion</td>
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<tr>
<td>grammar</td>
<td>3.06</td>
<td>1.14</td>
<td>0.25</td>
</tr>
<tr>
<td>humor</td>
<td>2.91</td>
<td>1.15</td>
<td>0.15</td>
</tr>
<tr>
<td>relatedness</td>
<td>3.03</td>
<td>1.22</td>
<td>0.37</td>
</tr>
<tr>
<td>storytelling</td>
<td>3.06</td>
<td>1.31</td>
<td>0.28</td>
</tr>
<tr>
<td>sensibleness</td>
<td>3.19</td>
<td>1.27</td>
<td>0.034</td>
</tr>
</tbody>
</table>

Table 8: LimGen vs. Candidate-Rank.

From Table 8, the only statistically significant result is that LimGen outperforms Candidate-Rank with respect to sensibleness, which is due to the diversity fostering beam search MTBS. Since in our left-to-right limerick generation procedure, LimGen picks the next word that not only satisfies POS, meter, syllable and rhyming constraints but also flows naturally with the preceding lines, it is beneficial to maintain a diverse set of preceding partial lines to choose from. This ensures coherency and sensibleness in the output limericks. We can see the role of MTBS in fostering diversity more explicitly by counting distinct POS templates and by calculating the repetition (in terms of n-grams) within a fixed number of output limericks. For both LimGen and Candidate-Rank, a maximum of 360 sentences can be processed in parallel. We ran both methods 200 times (using 100 prompt words, each with one female and one male name). LimGen has an average of 27 different templates per ∼200 poem run, whereas Candidate-Rank only used 6 templates on average. For each run, to measure diversity, we randomly selected 50 limericks from the output set and calculated the “mean popularity of each n-gram” (e.g., 2-gram, 3-gram, 4-gram, 5-gram) in their last lines. Specifically, for each n-gram (n consecutive words) within those 50 last lines, we record its number of occurrences within those 50 lines. We then average all those recorded
numbers and denote it as the ‘‘mean popularity of $n$-gram.’’ For instance, ‘‘mean popularity of 3-gram’’ = 2.0 indicates that, on average, each 3-gram within those 50 lines repeats twice. A high value of the ‘‘mean popularity of $n$-gram’’ indicates heavy phrase repetition. As we can see from Figure 5, MTBS has a significantly lower ‘‘mean popularity of $n$-gram’’ than the Candidate-Rank beam search, which indicates more sentence diversity within MTBS’s output.

4.7 Experiment 4: LimGen vs. Deep-speare

Similar to GPT-2, Deep-speare’s language model was trained on 2000 limericks for 30 epochs until validation loss stopped decreasing using the optimal hyper-parameters provided by Lau et al. (2018). Since the pentameter model for stress and the rhyming model in the full Deep-speare are not guaranteed to adhere to limericks’ stress, syllable, and rhyming constraints, especially when the training data are scarce, we replaced these two models (pentameter and rhyming) with constraints to ensure the output from Deep-speare meets the requirements of limericks. Compared to GPT-2, Deep-speare is a much smaller model. In the original paper, it was trained on only 7000 quatrains of sonnets. After training on our limerick dataset, it was able to produce some form of limerick that warrants a comparative experiment.

We can clearly see from Table 9 that for the task of limerick generation, LimGen outperforms this adapted version of Deep-speare (which is considered a state-of-the-art neural network for English poetry generation) across all metrics. It remains to be seen whether Deep-speare will improve given more training data. However, it is unclear where more data would come from.

4.8 Experiment 5: LimGen vs. Human Poets

In this experiment, 50 human limericks were chosen randomly from our database. Although not completely homogeneous in their poetic qualities, they were all well-thought-out and well-written, and represent genuine effort from their authors.

In Table 11, we added a column that records the percentage of limerick pairs with an average response $> 3$, that is, the percentage of LimGen’s limericks that are better than human’s on a specific metric according to crowd-workers. Clearly, human poets outperform LimGen on several metrics. It is not statistically conclusive which method is better with respect to grammar, presumably due to the template-guided approach that ensures grammatical correctness. Upon careful inspection, we noticed that for several metrics, there is actually a significant portion of LimGen’s output that were rated more highly than human-written limericks. For example, 43% of the machine-generated limericks had better emotional content than human poems. Another observation is that humor seems to be the hardest attribute for LimGen to emulate and master. Even though LimGen does output humorous limericks at times, they usually do not have the highest score according to our scoring function $H(\cdot)$; in other words, even though humorous poems were generated, our scoring mechanism could not recognize them as humorous.

In this same experiment, we asked crowd-workers a Turing test question for each limerick pair (one by a human and one by LimGen) (Figure 6): whether Limerick A or B is more likely to be written by a human. Recall that in our analysis we have transformed the data such that a score of 5 indicates the crowd-worker thinks that the poem was surely written by machine. The recorded score distribution is

<table>
<thead>
<tr>
<th>Metrics</th>
<th>mean</th>
<th>sd</th>
<th>p-value</th>
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</thead>
<tbody>
<tr>
<td>emotion</td>
<td>3.46</td>
<td>1.18</td>
<td>2.96×10^{-7}</td>
</tr>
<tr>
<td>grammar</td>
<td>4.02</td>
<td>1.35</td>
<td>≈ 0</td>
</tr>
<tr>
<td>humor</td>
<td>3.36</td>
<td>1.24</td>
<td>6.74×10^{-5}</td>
</tr>
<tr>
<td>storytelling</td>
<td>3.98</td>
<td>1.11</td>
<td>≈ 0</td>
</tr>
<tr>
<td>sensibleness</td>
<td>3.99</td>
<td>1.18</td>
<td>≈ 0</td>
</tr>
</tbody>
</table>

Table 9: LimGen vs. Deep-speare.
There once was a brave soldier named Wade
Who led a small army on his raid.
He died on the campaign,
But he kept his promises and stayed.

(a) Prompt word: war

There was a loud waitress named Jacque,
Who poured all her coffee in a shake.
But the moment she stirred,
She was struck by a bird,
Then she saw it fly towards the lake.

(c) Prompt word: shaken

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Statistics</th>
<th>mean</th>
<th>sd</th>
<th>p-value</th>
<th>&gt; 3</th>
</tr>
</thead>
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<tr>
<td>emotion</td>
<td></td>
<td>2.84</td>
<td>1.41</td>
<td>0.04</td>
<td>43%</td>
</tr>
<tr>
<td>grammar</td>
<td></td>
<td>2.97</td>
<td>1.41</td>
<td>0.29</td>
<td>58%</td>
</tr>
<tr>
<td>humor</td>
<td></td>
<td>2.21</td>
<td>1.41</td>
<td>≈ 0</td>
<td>22%</td>
</tr>
<tr>
<td>storytelling</td>
<td></td>
<td>2.55</td>
<td>1.49</td>
<td>≈ 0</td>
<td>37%</td>
</tr>
<tr>
<td>sensibleness</td>
<td></td>
<td>2.58</td>
<td>1.47</td>
<td>≈ 0</td>
<td>35%</td>
</tr>
</tbody>
</table>

| Table 11: LimGen vs. human poets. |

5 : 11%, 4 : 14%, 3 : 18%, 2 : 29%, 1 : 27%.
Scores 4 and 5 are when LimGen’s limericks are mistaken as human-written when directly compared with actual human-written poems. Score 3 is when judges cannot differentiate between LimGen’s output and human poems. Overall, the crowd-workers cannot differentiate LimGen’s output from human-written poems 43% of the time.

Table 10: More Example limericks from LimGen.

<table>
<thead>
<tr>
<th>(b) Prompt word: loss</th>
</tr>
</thead>
</table>
| There was a honest man named Dwight
Who lost all his money in a fight.
His friends were so upset,
They were willing to bet,
And they did not like feeling of spite. |

<table>
<thead>
<tr>
<th>(d) Prompt word: violent</th>
</tr>
</thead>
</table>
| There once was a nice man named Theodore
Who killed all his family in a war.
He came back from the dead,
With a scar on his head,
But he lost his memories and more. |

Figure 6: The Turing test question.

Which limerick is written by human?
5: Definitely A; 4: Probably A; 3: The same; 2: Probably B; 1: Definitely B

from humans) across the same metrics on an absolute scale from 1 to 5 (1 being the worst and 5 being the best). Each panelist completed at least one assignment, which consists of 6 poems randomly chosen from the set of 60 limericks. We ensured that each limerick was evaluated at least twice and the panelists did not see repeated limericks. None of these panelists knew anything about how the automated poems were generated. They were only notified that they would see a mixture of machine and human-written limericks.

The scores in this survey are absolute values rather than relative values. We interpret an average over 3 on a metric as a decent level of performance. From Table 12, although expert judgment confirms that human poets outperform LimGen, it still shows that LimGen performs decently according to several metrics: LimGen has decent grammar and can tell a story well with its verses. It seems that grammar and storytelling are the easiest poetic attributes to master, since both human poets and LimGen have the highest scores on these metrics. Emotion and sensibleness are harder to learn. But what really differentiates human poets and LimGen is poets’ ability to consistently make jokes.

Overall, we find our results encouraging, as they not only show that LimGen outperforms all prior baselines by a clear margin, but also shows that LimGen has the potential to approach human level performance in the future. More outputs from LimGen are in Table 10.
### Table 12: Expert judges: LimGen vs. humans.

<table>
<thead>
<tr>
<th>emotion</th>
<th>Human</th>
<th>LimGen</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>grammar</td>
<td>3.79 ± 0.98</td>
<td>2.93 ± 0.99</td>
<td>0.006</td>
</tr>
<tr>
<td>humor</td>
<td>4.22 ± 0.99</td>
<td>3.65 ± 0.96</td>
<td>0.068</td>
</tr>
<tr>
<td>storytelling</td>
<td>3.92 ± 1.01</td>
<td>2.21 ± 0.92</td>
<td>≈ 0</td>
</tr>
<tr>
<td>sensibleness</td>
<td>4.44 ± 0.74</td>
<td>3.68 ± 0.85</td>
<td>0.009</td>
</tr>
</tbody>
</table>

Table 13: Additional limericks from LimGen.

There was a shy actor named Dario,  
Who played a big role on our show.  
He came back from the break,  
And we went to the lake,  
And he sat down and took his photo.

(a) Prompt word: Season

There was an artist named Cole,  
Who made a huge impact on my soul.  
He was a musician,  
He was on a mission,  
And that is the beauty of this role.

(b) Prompt word: Art

There once was a liar named Kai,  
Who fooled a grand jury on her lie.  
I had a suspicion,  
I was on a mission,  
I was ready to fight and to die.

(c) Prompt word: Cunning

There was a bright cleaner named Dot,  
Who put all her money in a pot.  
When she started to smoke,  
She was struck by a stroke,  
She has a severe case of a clot.

(d) Prompt word: Water

There was a funky chef named Dwight,  
Who cooked a great meal on our night.  
We got back from the bar,  
And we walked to the car,  
And we sat down and had our bite.

(e) Prompt word: Beer

There was a cruel judge named Lyle,  
Who killed a young girl on his trial.  
It was like a nightmare,  
I was scared by his stare,  
But I knew his intentions and smile.

(f) Prompt word: Death

Table 13: Additional limericks from LimGen.

5 Conclusion

LimGen is the first fully automated limerick generation system. Using human judgements, we have shown that our adaptive multi-templated constraints provide LimGen with a combination of quality and flexibility. We have shown the value of our diversity-fostering multi-templated beam search, as well as the benefits of our Storyline algorithm.

Acknowledgments

We would like to extend our sincere appreciation to all people involved in this research project, especially our colleagues Matias Benitez, Dinesh Palanisamy, and Peter Hasse for their support and feedback in the initial stage of our research. We would also like to thank Alstadt for funding. We have included a few more poems from LimGen in Table 13. Please refer to our online GitHub repository (Wang et al., 2020) for implementation details and more poems.

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