Abstract

Our software system simulates the classical collaborative Japanese poetry form, renga, made of linked haikus. We used NLP methods wrapped up as web services. Our experiments were only a partial success, since results fail to satisfy classical constraints. To gather ideas for future work, we examine related research in semiotics, linguistics, and computing.

1 Introduction

Extensions of a haiku generation system via concept blending and collaborative AI allow us to return to some of the classical ideas in Japanese poetry. As we will discuss below, the classic haiku is a carefully composed juxtaposition of two concepts – and it traditionally formed the starting verse of a longer poetry jam, resulting in a poem called a renga. Computer haikus have been explored in practice at least since Lutz (1959). More recently, haikus have been used by Ventura (2016) as the testbed for a thought experiment on levels of computational creativity.

Ventura’s creative levels range from randomisation to plagiarism, memorisation, generalisation, filtration, inception and creation. Further gradations and criteria could be advanced, for example, the fitness function used for filtration could be developed and refined as the system learns.

Imitation, pastiche, and apprenticeships are often used by humans who are learning a new task: while the first two are relatively easy to simulate with computers, the third is less straightforward. And while self-play was a good way for AlphaGo to transcend its training data (Silver et al., 2016), we need qualitative evaluation measures in the poetry domain, where there is no obvious “winning condition.”

We began by creating a program for generating haikus, trained on a small corpus. Code for this system is available as is an API for the haiku generator. Our main experiment involved connecting the haiku generation system into a general-purpose flowchart-based scripting system, FloWr, which has been extended with its own API allowing programmatic use and manipulation of flowcharts. Our technical aim was to simulate the collaborative creation of linked haikus. This was a success (Figure 1), although the rengas we produced fail to satisfy classical constraints. Our discussion considers the aesthetics of the generated poems and outlines directions for future research.

Figure 1: Two rengas being composed in parallel with FloWr

1 “Inject[ing] knowledge into a computationally creative system without leaving the injector’s fingerprints all over the resulting artifacts.”
2 Background

Coleridge considered poetry to be “the blossom and the fragrance of all human knowledge.” AI researcher Ruli Manurung defines poetry somewhat more dryly: “A poem is a natural language artefact which simultaneously fulfils the properties of meaningfulness, grammaticality and poeticness” (Manurung, 2004, p. 8).

The haiku as we know it was originally called hokku – 発句, literally the “starting verse” of a collaboratively written poem, the renga. Each of the links in a renga traditionally take the familiar 5/7/5 syllable form. Classical rengas vary in length from two to 100 links (and, rarely, even 1000). The starting verse is traditionally comprised of two images, with a kireji – a sharp cut – between them. The term haiku introduced by the 19th Century poet Masaoka Shiki supersedes the older term both in the context of rengas and as a label for the stand-alone poem. Stylistically, a haiku captures a moment.

- Autumn moonlight –
  A worm digs silently
  Into the chestnut
  Matsuo Basho (1644-1694)

Computer generated haikus have a ways to go before they can match the aesthetics of the masters, but some are quite readable.

- all green in the leaves
  I smell dark pools in the trees
  crash the moon has fled
  (Masterman and McKinnon Wood, 1968)

- early dew
  the water contains
  teaspoons of honey
  (Netzer et al., 2009)

- Mount Moiwa
  is this the view of yellow gingko leafs?
  (Rzepka and Araki, 2015)

In classical renga, all of the verses after the first have further complex constraints, such as requiring certain images to be used at certain points, but disallowing repetition, with various proximity constraints. The setting in which rengas were composed is also worth commenting on. A few poets would compose together in party atmosphere, with one honoured guest proposing the starting haiku, then the next responding, and continuing in turn, subject to the oversight of a scribe and a renga master. These poetry parties were once so popular and time-consuming that they were viewed as a major decadence. Jin’Ichi et al. (1975) offers a useful overview.

Because of the way we’ve constructed our haiku generating system, it can take an entire haiku as its input topic – we just add the word vectors to make a topic model – and compose a response. This affords AI-to-AI collaboration, or AI-human collaboration. It can also blend two inputs – for example, the previous haiku and the current constraint from the renga ruleset (e.g., the requirement to allude to “cherry blossoms” or “the moon”).

3 Example

Here is a haiku our system wrote in response to the two prompts “frog pond” and “moon.” Most of the system’s haikus are not this clever or on-topic: odds against finding one of this quality are at least 100/1.

- that gull in the dress –
  vivacious in statue
  from so many ebbs

4 Implementation

Working with a small haiku corpus, we used a POS tagger to reveal the grammatical structure typical to haikus. The CMU Pronouncing Dictionary is used to count syllables of words that fill in this structure. Wikipedia provides a general text corpus, which we used to generate n-grams, preferring more common constructions in haikus. The Wikipedia data was also processed with GloVe to create a semantic vector space model of topics, based on word co-occurrences in short:

1. Haiku corpus → POS tagger → grammatical skeleton fragments.
2. General text corpus → n-gram model.
3. General text corpus → topic vectors.
4. Combine skeleton fragments to make a haiku template.
5. Assign syllable counts to slots.
6. Fill in the template, preferring n-grams and close topic matches.
Adding a web API turned the haiku generating system into a haiku server, and facilitated subsequent work with FloWr. FloWr provides its own API, so rengas can also be generated on demand.

5 Experiments

I. Initial evaluation of haikus Following Manurung’s definition of poetry, above, we would like to assess: (1) whether a given haiku makes sense and how well it fits the topic, (2) whether it fits the form, i.e., is it a valid haiku?, and (3), the beauty of the writing, the emotion it evokes. Note that (2) is guaranteed in our case, since the software constructs poems by filling in a grammatical skeleton extracted from existing haikus with words that have the correct number of syllables. Accordingly, our initial evaluation focused on sense, topic, and beauty. Details were written up by Aji (2015). The system was then extended with multiple inputs, in some cases producing interesting blends: e.g., the word “ebb” in our Example is a convincing blend of the aquatic and lunar prompts. This motivated Experiment II.

II. Generation of rengas Here are two rengas generated using FloWr together with the haiku API.

| fertile forefingers | that vase in the quilt – |
| took orchard for my lather | the effeminate of names |
| brackish was cherished | with a colored juice |
| toddler of strong bet | cases of sibyl |
| foaling feels to a good tooth | and a stylish curators |
| thriving like a paw | from downed in the aim |
| a drawer straight inside | figures of digress |
| under the slicked interim | and a sumac excises |
| to shrink the safe cute | from key in the ribbed |
| readjusted blots | cluster for icebergs – |
| in the creativity – | and a waging everglades |
| one child at a love | from huge in the drug |

In each case, the prompt for the first haiku is “flower blossom” and the secondary prompt for the following links are “moon,” “autumn,” and “love,” respectively. For the first renga, FloWr selects the “most positive” haiku from the ten that the API returns, using the AFINN word list. In the second renga, FloWr selects the haiku with the lowest word variety (computed in terms of Levenshtein distance).

6 Discussion and Related Work

Towards automated evaluation Some of the evaluation dimensions are built into the way the poems are constructed. As above, Form is explicitly considered for haikus. To some degree, so are Sense and Topic.

Sense: we used an n-gram model of text likelihood, which will yield a higher score for constructions that match frequently observed phrases.

Topic: we used a vector model of the topic word(s), and can measure the distance to the vector given by the sum of the words in the poem.

Results could certainly be improved in these respects: furthermore, in comparison to reading a single haiku, our rengas ask for a lot more interpolation of meaning on the part of the reader. Issues with Form resurface here: our generated rengas fail to satisfy the classical constraints. Results should improve with the addition of “audio equaliser-style” parameters such as priority, dither, and saturation. These could be used to identify the high-priority terms (or with dither, concepts) to use in a link.

Emotion: In our experiment with FloWr, we used a quite simple method. Mohammad (2016) surveys more recent work in this area.

Beauty: Waugh (1980) points out that language is based on a “hierarchy of signs . . . of ascending complexity, but also one of ascending freedom or creativity,” and also remarks that a “poem provides its own ‘universe of discourse.’” To some extent these criteria pull in opposite directions: towards complexity, and towards coherence, respectively.

Some paths forward Wiggins and Forth (2015) use hierarchical models in a system that builds a formative evaluation as it composes or reads sentences, judging how well they match learned patterns. While this seems to have more to do with constraints around typicality, per Waugh, there is room for creativity within hierarchies. Hoey (2005) makes a convincing argument that satisfying lexical constraints while violating some familiar patterns may come across as interesting and creative.

Word similarities can be found using GloVe: this would presumably produce links with more coherent
meanings, compared to the edit distance-based measure we used. Ali Javaheri Javid et al. (2016) use information gain to model the aesthetics of cellular automata. Can these ideas be combined to model evolving topic salience, complexity, and coherence?

If the system provided a razo (the troubadours’ jargon for “rationale”; see Agamben (1999, p. 79)), we could debug that, and perhaps involve additional AI systems in the process (Corneli et al., 2015).

7 Conclusion

In terms of Ventura’s hierarchy of creative levels, the haiku system appears to be in the “generalisation” stage. Our renga-writing experiments with FloWr brought in a “filtration” aspect. The research themes discussed above point to directions for future work in pursuit of the “inception” and “creativity” stages.

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