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# System Supporting Poetry Generation Using Text Generation and Style Transfer Methods

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**Abstract**

The paper presents the *Bairon* system that supports the automatic generation of poetry. The proposed system allows generating a poem in the literary style of the selected writer using the user's input as the first line, and translating the given text into Shakespearean English. To accomplish that, GPT-2 and T5 language models were fine-tuned. We also propose easy to understand metrics to evaluate the quality of the generated poems and their similarity to the corresponding poet's original work, and to present the results. Additionally, the Poetry Turing Test with human participants was conducted to get another measure of quality of the generated poetry.



*Keywords:* poetry generation; text generation; style transfer; Poetry Turing Test; emotion analysis; BLEU score

## 1. Introduction

Abstract and creative thinking are some of the key features of human intelligence that allow humans to create art, including, among others, poetry, literature, music, and painting. For example, it is not a trivial task to attempt to create a set of rules needed to be followed in order to create a poem. We can distinguish some characteristics of a poem, like rhyming or rhythm, but they can be — and often are — broken. However, in recent years, artificial intelligence has also made its way into areas such as art [3], including poetry [26, 1, 21] and music composition [17, 18, 28], which until now have been dominated by humans.

With the dynamic development of artificial intelligence, in particular natural language processing, we are faced with new challenges — for example distinguishing the fake news generated by a language model. It is possible not only to generate a coherent text indistinguishable from human work, but also to imitate a literary style or create an article about a specific topic.

We think that it is important for people with and without experience with artificial intelligence to be aware of the possibilities of current language models. We created a user-friendly system for people with no natural language pro-

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cessing knowledge who want to understand the possibilities of current language models through poetry. The proposed system allows generating a poem in the literary style of either Shakespeare, Whitman, or Cummings, based on the first line written by the user. We fine-tuned the GPT-2 [34] model using each poet's works as training data. The system also provides the possibility to "translate" user's input into Shakespearean style using style transfer approach. For that task, we used the T5 [35] model to generate paraphrases using Shakespeare's sonnets and their translations to modern English as parallel training data. Users can also write a poem interacting with the model. During such process, the user writes the first line, then the model generates a line based on the current text, next the user can write another line, and so on. The system also provides metrics to compare the generated poems with poems of the corresponding poet. As objective metrics, we chose emotion analysis and word percentages for text generation evaluation, and BLEU score for style transfer evaluation. We also carried out the Poetry Turing Test, in which a single line of text was presented to the users, and they have to decide whether it was written by a human or generated by a model. Furthermore, subjective ratings of three factors of a poem: general quality, grammatical correctness, along with comprehensibility and resemblance to the poet's literary style were collected and analyzed.

## 2. Related Research Works

There have been many attempts to create a poetry generation system — for example, a system that generates poems based on user's input parameters [29, 20] or allows creating a poem collaboratively with a model [37]. The field of text generation was revolutionized by introducing the transformers architecture [38]. Radford et al. proposed Generative Pretrained Transformer 2 model, known as GPT-2, that creates high quality free text [34]. An abundance of publications that use fine-tuned GPT-2 models to create poetry has arisen, for example based on work of a specific poet [41] or that are trained to elicit particular emotions in a reader [1]. There are also systems that use Recurrent Neural Networks with Finite State Acceptor that build the poem around rhyme words [20] or that use Gated Recurrent Units with encoder-decoder architecture [6]. Li et al. [27] use transformers-based auto-regressive model to create text with rigid formats — specifically sonnets and classical Chinese poetry. The task of text style transfer is a less popular research topic, but there exist some research works that explore it — specifically for paraphrase generation [25, 40].

The mentioned systems focus on either building a set of rules for creating a poem or to generate a poem in a specific style or different literary styles (highbrow, imaginative or poetic [19]). There is no work that directly compares models trained on texts of different poets with distinctive styles. Moreover, although some publications use metrics, they are mostly not very comprehensible to a user with no knowledge regarding natural language processing. For example, Misztal-Radecka and Indurkhya [29] use FACE descriptive model [5] that attempts to quantitatively evaluate a creative piece of text by providing a framing that is a kind of natural language commentary. However, as stated in [21], this framing "does not make a big difference in human assessment of the creativity, meaningfulness or general quality of computer-generated poems". Bena and Kalita [1] use the Coh-Metrix tool [22] that measures text readability, word imageability, narrativity, referential cohesion, syntactic simplicity and lexical diversity — they seem more suited for people with linguistic knowledge. Poetry Turing Test [4] is a test where a person judges whether a poem was written by a human or generated by a machine. Köbis and Mossink [26] analyze the results of the Poetry Turing Test in different settings, where users are incentivized or where the model-generated samples are picked by people rather than chosen randomly.

In this paper, we present *Bairon*[1] — a system that allows users to:

- generate poems in the style of William Shakespeare, Walt Whitman or Edward Estlin Cummings with the first line provided by the user;
- translate texts into Shakespearean style or write a poem collaboratively with a model;
- perform a Poetry Turing Test and compare the results of each model;
- compare emotion analysis and word percentages analysis results of each model.

[1] https://github.com/magdalena-b/Bairon

In our work, we analyze results of a model fine-tuned on three different poets, each with a unique style, and propose user-based along with objective measurements. We explore criteria of evaluating poetry generation that are comprehensible for users with no natural language processing or linguistic knowledge.

The main contributions of the research presented in this paper are as follows:

1. fine-tuning of the three 124M GPT-2 models based on poetry of William Shakespeare, Walt Whitman and Edward Estlin Cummings;
2. providing experimental results of Poetry Turing Test and performing comparison of how well the model works on different poetic styles,
3. using emotion analysis and word percentages as measures of quality for generated poems and BLEU [31] score along with user ratings as measures of style transfer.

## 3. The System: Models, Metrics and Architecture

This section presents the models and metrics used in the developed system. The architecture and functionalities of the system are also discussed.

### 3.1. Poetry Generation

As the model for poetry generation, we chose *Generative Pretrained Transformer 2* with 124 million parameters with 3000 training steps and batch size 1. Temperature (a parameter that controls the randomness in the generated text) was set to 0.7. We used all 154 Shakespeare's sonnets (about 2300 lines) for fine-tuning Shakespeare model. For Whitman model fine-tuning, all of his poems available in public domain were used (about 11600 lines). Cummings model was fine-tuned with the use of all of his poems available in public domain (about 4700 lines).

### 3.2. Style Transfer

To realize style transfer, we trained T5 model used for paraphrase generation. T5-small model with 60 million parameters, and with learning rate 0.0003 was used. The model was trained using parallel data of 70 Shakespeare's sonnets (about 870 lines) along with their translations to modern English acquired from *No Sweat Shakespeare* [30] — each original line corresponding to a line in modern English.

### 3.3. BLEU Metrics

BLEU score [31] is a metric used to evaluate machine translation. We chose to use it experimentally, to evaluate translations of users' inputs to Shakespearean English. While the desired BLEU score for machine translation is 1.0, it can't be exactly determined what is the ideal score for style transfer — in our case handled as paraphrase generation. The overall meaning of the line cannot change, but we expect the line to have a different form or contain different words. Citing the work *Paraphrase Generation as Monolingual Translation: Data and Evaluation* [40]: "Automatic evaluation metrics in related fields such as machine translation operate on around achieving dissimilarity." We used BLEU-4, which calculates the collective BLEU score for 1-grams, 2-grams, 3-grams and 4-grams.

### 3.4. Poets

We chose William Shakespeare, Walt Whitman and Edward Estlin Cummings as we wanted a range of distinctly different literary styles. Shakespeare uses Elizabethan English, Whitman, and Cummings both write in modern English, but theirs styles are quite different. Whitman writes in free form, he often uses enumerations and anaphora. Cummings experiments a lot with syntax and uses a lot of punctuation marks: colons and parentheses.

### 3.5. Architecture

The system for poetry generation was realized as a web application that allows users to:

1. generate poems based on the provided input with various methods, such as collaborative writing or style transfer (Fig. 1),
2. save generated poem and browse other archived poems (Fig. 2),
3. view metrics (such as emotion analysis, users' rating or BLEU scores) of a particular poem or all generated texts,
4. perform a Poetry Turing Test.

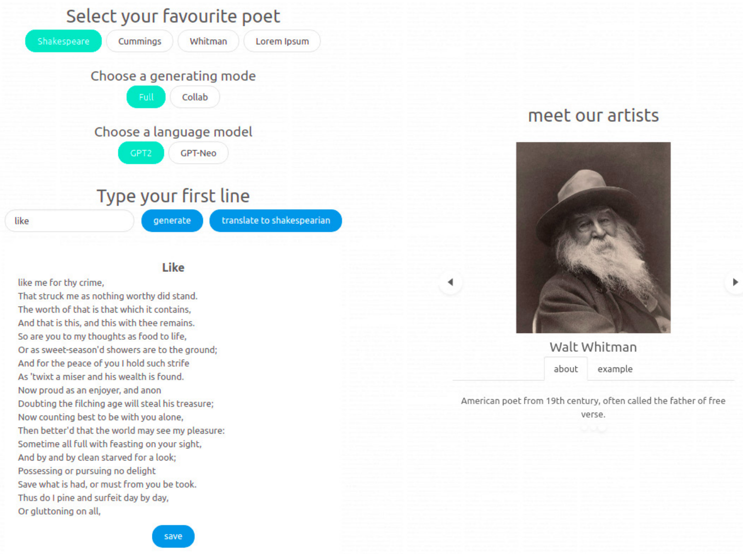


Fig. 1. Poem generation.

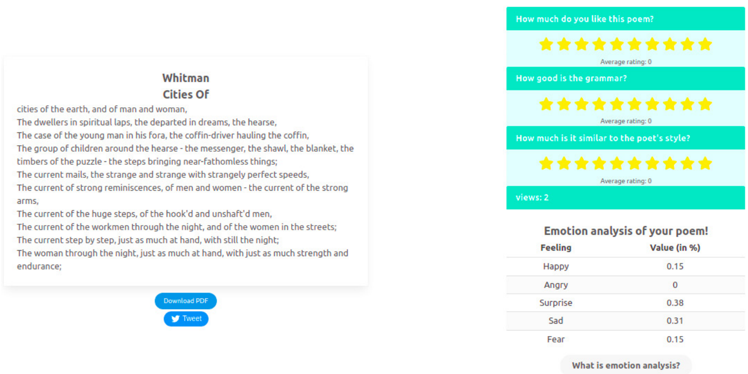


Fig. 2. Detailed view of an archived poem.

The architecture of the system is presented in Fig. 3. The front-end of the application was implemented using Vue.js [39] — a modern framework that helps in building small web applications in SPA architecture. In addition, we used CSS library Bulma [2], which allows for creating consistent and good-looking GUI. The back-end of the application was implemented with the use of a Python [33] framework: Django [7]. This choice made it easier to integrate the back-end with language models and the database. Additionally, we used the Django REST Framework [8]

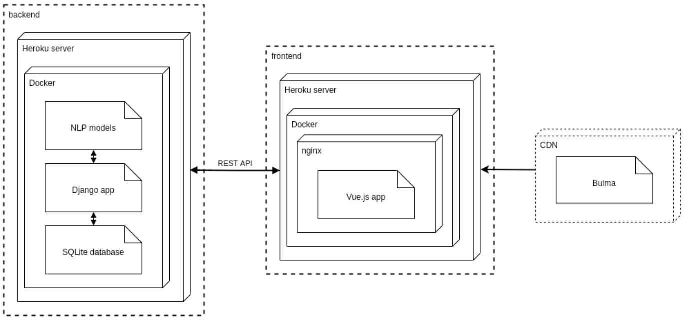


Fig. 3. System's architecture and communication between components.

extension for the API and SQLite [36] for the database where user votes, and generated as well as original poems are stored (which is convenient for delivering texts to the poetry Turing Test). The realized application is based on microservice architecture, which made its deployment easier. We created Docker [9] containers of parts of the realized application — the images can be installed on any system architecture (in our case — a cloud platform Heroku [24] was used).

## 4. Experimental Results

In this section, the results of experiments carried out with the use of the system for poetry generation are presented and analyzed.

### *4.1. Poetry Generation — Cummings*

The maximum length for the generated text was set to 200 words. An example of a poem generated by the Cummings-trained model based on the user line "From" is presented in Fig. 4 — we can observe the use of parentheses typical for Cummings poems.

### *4.2. Poetry Generation — Whitman*

An example of a poem generated by the Whitman-trained model based on the user line "Cities of" is presented in Fig. 5 — the text contains anaphora, a literary technique characteristic for Whitman.

### *4.3. Poetry Generation — Shakespeare*

The Shakespeare-trained model did not successfully generate original content — after a line or two, it was producing the source material line by line. It is possible that the corpus of texts used for training was not big enough or the training time was too short. It might also be the case of GPT-2 being pretrained on modern English, so fine-tuning with 2300 lines of Shakespeare's sonnets and given parameters was not enough for the model to learn to generate a long text in Shakespearean English.

An example of a poem generated by Shakespeare-trained model based on user line "like a summer breeze" is presented in Fig. 6.

The first three generated lines are original. Lines from 5 to 16 are taken from Sonnet 86, and the last two lines come from Sonnet 87.

```
from
the Hair & The Brain
of Music
each
Hand
Human
(this
is
the consummation
of day,the hour)
Human
(with a little harder
for it moistly upon
my lips
)
putting on stars and the
expensive cheap
moon
dear girl
How i was crazy how i cried when i heard
```

Fig. 4. An example of a poem generated by Cummings-trained model.

```
cities of the earth, and of man and woman,
The dwellers in spiritual laps, the departed in dreams, the hearse,
The case of the young man in his fora, the coffin-driver hauling the coffin,
The group of children around the hearse - the messenger, the shawl, the blanket, the timbers of the
puzzle - the steps bringing near-fathomless things;
The current mails, the strange and strange with strangely perfect speeds,
The current of strong reminiscences, of men and women - the current of the strong arms,
The current of the huge steps, of the hook’d and unshaft’d men,
The current of the workmen through the night, and of the women in the streets;
The current step by step, just as much at hand, with still the night;
The woman through the night, just as much at hand, with just as much strength and endurance;
```

Fig. 5. An example of a poem generated by Whitman-trained model.

### 4.4. *Poetry Turing Test*

The Poetry Turing Test was performed with the participation of 5 people with different knowledge of English (one native speaker, and four people for whom English is a second language — two of them used the language on a daily basis, and the other two only studied the language at school). Samples of model-generated texts were chosen randomly. During the experiment, we gathered 135 votes. The system indicated users whether the given answer was right or wrong. Table 1 presents the results.

Table 1. Detailed Poetry Turing Test results.

| **Model** | **true human** | **false human** | **true machine** | **false machine** |
|---|---|---|---|---|
| Cummings | 34 % | 10 % | 24 % | 31 % |
| Whitman | 29 % | 39 % | 12 % | 20 % |

There are 4 classes of results:

```
like a summer breeze,
Cannot take away, but makes worse:
So thou, to whom my love doth dwell,
My most full flame should bide,
That did my ripe thoughts in my brain inhearse,
Making their tomb the womb wherein they grew?
Was it his spirit, by spirits taught to write
Above a mortal pitch, that struck me dead?
No, neither he, nor his compeers by night
Giving him aid, my verse astonished.
He, nor that affable familiar ghost
Which nightly gulls him with intelligence,
As victors of my silence cannot boast;
I was not sick of any fear from thence:
But when your countenance filled up his line,
Then lacked I matter; that enfeebled mine.


Farewell! thou art too dear for my possessing,
And like enough thou know'st thy estimate,
```

Fig. 6. An example of a poem generated by Shakespeare-trained model.

1. true human — sampled line is from an original poem and the user classified it as such,
2. false human — sampled line is generated by the model and the user classified it as written by the poet,
3. true machine — sampled line is generated by the model and user classified it as such,
4. false machine — sampled line is written by the poet and the user classified it as generated by the model.

We can see that the Cummings-trained model got the most *true human* and *false machine* votes — as Cummings was known for experimenting with syntax in his poems, it is not much of a surprise. Whitman-trained model had a high rate of *false human* votes. It appears that the model was good at imitating the corresponding poet's original work.

Some participants expressed the opinion that the samples were too short to make choice. In future work, it would be interesting to compare the results with one line samples and multiple line samples.

### *4.5. Word Percentages*

Word frequency percentages were used as a measure to compare texts generated by the model with the original poet's works. We conducted word pre-processing — deleting punctuation and stop words (words like "I", "myself", "off"). Table 2 shows the top 10 words in each set of texts. We can see that none of the models got exactly the same top words that appeared in the corresponding author's works.

Table 2. Most frequent words in each set of texts.

| **Whitman** | **Whitman GPT-2** | **Cummings** | **Cummings GPT-2** |
|---|---|---|---|
| see | current | thy | whose |
| one | men | whose | around |
| shall | much | like | hair |
| love | take | little | little |
| soul | would | eyes | grace |
| yet | cities | upon | infinite |
| thee | man | love | lips |
| life | women | one | slowly |
| day | night | lips | deep |
| night | yet | body | one |

### *4.6. Emotion Analysis*

Emotion analysis [23] is a technique used to extract emotions corresponding to a text. We conducted emotion analysis of original works of each author, and of corresponding model's generated texts using `text2emotion` library [32], which extracts emotion based on keywords. There are five different feelings distinguished:

1. happiness,
2. sadness,
3. anger,
4. surprise, and
5. fear.

The bar graphs showing the results are presented in Fig. 7 and Fig. 8.

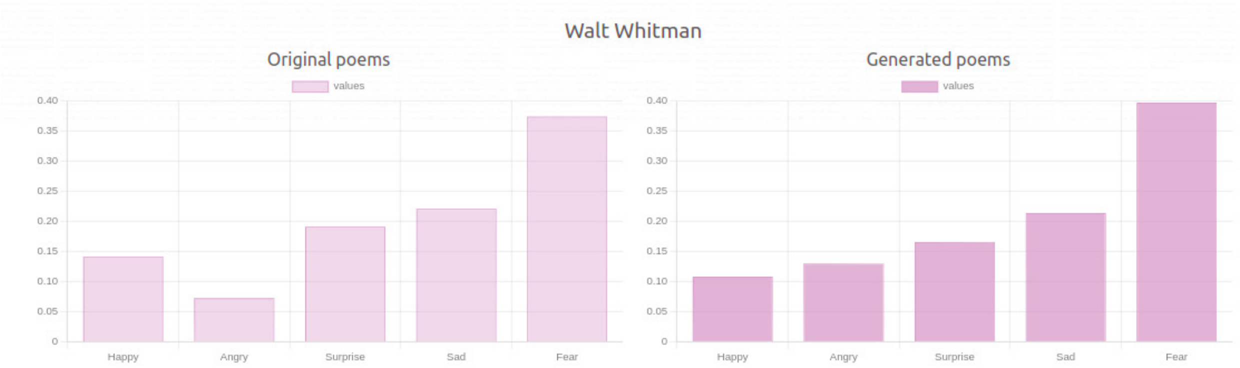


Fig. 7. Emotion analysis — Whitman.

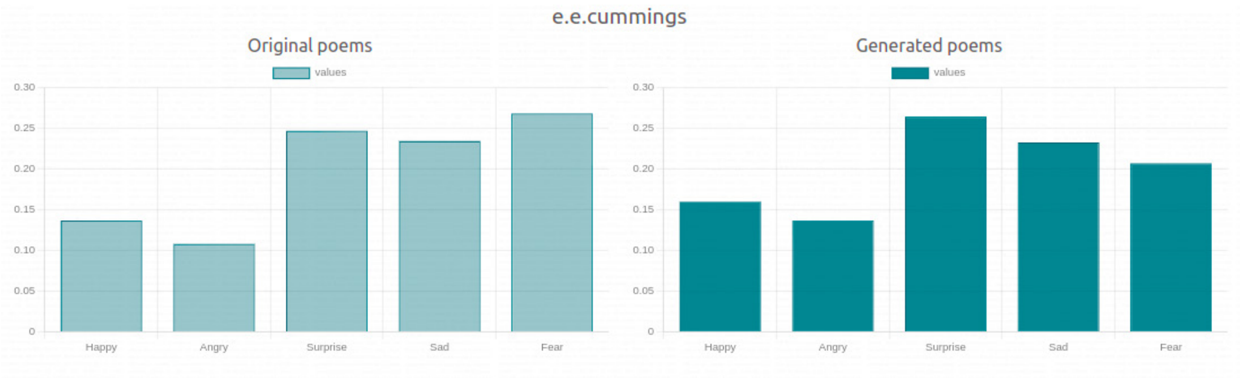


Fig. 8. Emotion analysis — Cummings.

### *4.7. BLEU Score*

An example of Shakespearean translations generated by T5 model of a line “life is beautiful” provided by the user are presented in Table 3.

Table 3. Style transfer of user’s line “life is beautiful” to Shakespearean literary style.

| |
|---|
| What is life’s beautiful |
| Life’s beautiful |
| The world is bright |
| The love of life is rich |
| Lord is beautiful |

Collective BLEU score for these translations was 0.23.

## 5. Conclusions

In this paper, the system that supports poetry generation along with style transfer and presents different metrics of the generated texts was introduced. The system can be used by people with no natural language processing knowledge and by people who want to evaluate the results of the given models. We posed research questions regarding the metrics and evaluation methods of texts generated by language models in different literary styles. The results of the carried out experiments showed that the models trained on Whitman and Cummings poetry can produce texts that are hard to distinguish from the original work on a line-by-line basis.

Future work could include gathering more votes for the Poetry Turing Test and getting more data to further analyze the results. It would be beneficial to compare the poems with the first line provided by the user with the poems in which the first line is translated into a poet's style from the text provided by the user. It would also be interesting to try out different language models with or without transformers architecture — for example, XLNet or GPT-3. Other evaluation metrics could be added, such as the TF-IDF index to compare word frequencies in the generated texts and in poet's body of works against frequencies of words from a corpus of texts in modern English — formal or colloquial, for example from Wikipedia or Reddit pages. A comparison of BLEU scores of a translation to Shakespearean style with the users' ratings would give a valuable insight into how to interpret this metric in the case of paraphrase generation.

The application of bio-inspired artificial intelligence algorithms as adaptation and optimization mechanisms for machine learning models could possibly be another research direction. It appears that the use of agent-based evolutionary algorithms as the basis for the adaptation and optimization mechanisms would bring particularly great benefits because this approach has already been successfully used in multimodal optimization [10, 11], multi-objective optimization [14, 15, 16], decision support [13], and neural networks optimization [12].

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