

Sonnet or Not, Bot?

Poetry Evaluation for Large Models and Datasets

Anonymous ACL submission

Abstract

Large language models (LLMs) can now generate and recognize text in a wide range of styles and genres, including highly specialized, creative genres like poetry. But what do LLMs really know about poetry? What *can* they know about poetry? We develop a task to evaluate how well LLMs recognize one aspect of English-language poetry, *poetic form*, which captures many different poetic features, including rhyme scheme, meter, and word or line repetition. We use this task to reflect on LLMs' current poetic capabilities, as well as the challenges and pitfalls of creating NLP benchmarks for poetry and for other creative tasks. In particular, we use this task to audit and reflect on the poems included in popular pretraining datasets. Our findings have implications for NLP researchers interested in model evaluation, digital humanities and cultural analytics research, and cultural heritage collections.

1 Introduction

Writing free verse is like playing tennis with the net down.
- Robert Frost

The poetic capabilities of large language models (LLMs) have been cited prominently by journalists, social media users, and even LLM developers and marketers (Pogue, 2023; Zahn, 2022; Roose et al., 2024). Google named its first chatbot “Bard,” a traditional term for a poet and the nickname of William Shakespeare, and Anthropic named two of its 2024 Claude models after popular poetic forms, “Sonnet” and “Haiku.” Microsoft released an ad that featured its Bing chatbot writing poetry (Bing), as well as an instruction guide for how to write poems with Copilot, including a list of suggested forms to try (Microsoft, 2023). Generated poetry was also one of the first LLM outputs to go viral on social media and remains popular there (Thomas H. Ptacek [@tqbf]). Poetry is a lightning rod for the

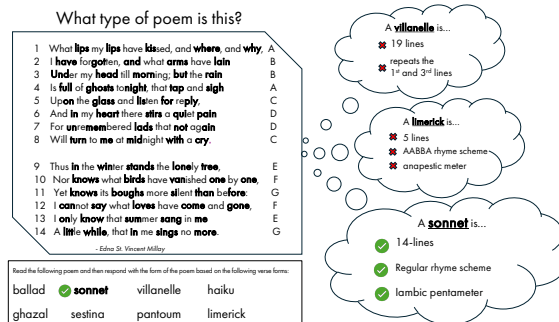


Figure 1: We develop a task to evaluate how well LLMs can identify *poetic form* for more than 20 poetic forms and formal elements in the English language. This is a challenging task because poetic form is determined by a combination of factors: rhyme scheme, meter, repetition, number of lines, and/or subject matter.

marketing and popular imagination of LLM capabilities because it is a signifier of human creativity and complexity, as well as a popular and culturally significant art form with a long history.

But what do LLMs really know about poetry? What *can* they know about poetry? Prior research has focused on computational poetry generation (Zhang and Lapata, 2014), summarization (Mahbub et al., 2023) and detection of individual forms (Abdibayev et al., 2021a), but we need broader evaluation of a wider range of poetic forms and features, and updated audits of LLM capacities and knowledge. Poetic features uniquely combine verbal, aural, and visual elements; the substance, sound, and (in written poetry) appearance of words on the page (e.g., white space) all matter. What’s more, poetry often communicates deep emotion and meaning in non-literal, ambiguous ways, employing figurative language, irony, and allusion.

To measure LLMs’ poetic capabilities, we develop a task to evaluate how well LLMs recognize more than 20 poetic forms and formal elements in the English language. Poetic form captures many different poetic features, including rhyme scheme,

meter, and word or line repetition (see A.8), and it also represents a distinct kind of literary genre. *Sonnets*, *limericks*, and *haiku* are well-known forms, but there are also less-known, more complicated forms like *sestinas* (which repeat the same six end-words in an intricate pattern) or *pantoums* (which repeat the second and fourth lines in an alternating pattern). This task is “difficult”—in some ways inherently so—even for expert human annotators, as we show in a small formative study.

We use this task to reflect on LLMs’ current poetic capabilities, as well as the challenges and pitfalls of creating NLP benchmarks for poetry and for other creative tasks. In particular, we use this task to audit and reflect on the poems included in popular pretraining datasets. A complication is that the circulation of poetry is different from other literary texts, like fiction books and long-form prose, resulting in unmeasured differences in pretraining datasets. Poems are often short and “portable”; on the web and within the publishing industry, individual poems can “travel” across multiple websites and anthologies in ways that previously studied books data (Chang et al., 2023) do not, resulting in increased memorization issues that will affect any poetry evaluation benchmark.

We find that LLMs—particularly GPT-4 and GPT-4o—can successfully identify both common and uncommon *fixed* poetic forms, such as *sonnets*, *sestinas*, and *pantoums*, at surprisingly high accuracy levels when compared to annotations by human experts. But performance varies widely by poetic form and feature; the models struggle to identify *unfixed* poetic forms, especially ones based on topic or visual features. While the LLMs have most success with the poetic forms most commonly found in popular pretraining datasets, we do not see major differences when we compare model performance on poems from major online poetry institutions, popular pretraining datasets, or print books with little to no digital presence.

Our findings have implications for NLP studies of poetry/creative text generation and analysis, digital humanities and cultural analytics research, as well as cultural heritage collections, libraries, and archives that include poetry.

Our contributions include:

- the introduction of the poetic form detection task, with a comparison to formative human study of poetry experts,
- a benchmark evaluation dataset with 1.4k pub-

lic domain poems and form annotations,

- an analysis of poems found in popular pre-training data,
- code and data that we release to the public.¹

2 Poetic Form

Subjective, Fluid, Context-Dependent. Traditionally, “form” refers to “the manner in which a poem is composed as distinct from what the poem is about,” and it can also refer more broadly to “genre or kind of composition” (Preminger et al., 2015). Poetic form can be defined by particular patterns of sound, referred to as prosody, and/or by visual patterns. In scholarship on poetics, forms are fluid and sometimes overlapping. They exist within specific cultural and linguistic contexts, but also travel across them (Ramazani, 2009). They are socially and historically constructed and have been the subject of heated debates (Martin, 2012), while also having remarkable durability across time (a number of the forms we test originated over 1,000 years ago). Since we focus on a corpus of English-language poetry, the forms we focus on are all common in English, although most of them originated in other languages. For “fixed” forms, there are often specific rules and complex patterns of versification, but these rules are also likely to be stretched or broken by poets (Leighton, 2008). Like other literary genres, forms serve as “frameworks of expectation” (Seitel, 2003) that are called up and manipulated in meaningful ways by writers. This makes it inherently difficult and subjective to evaluate poetic form.

Fixed and Unfixed Forms. We divide the poetic forms we consider into three categories: fixed forms, formal elements, and unfixed forms. **Fixed forms** follow particular patterns in terms of number of lines, meter, rhyme, and/or repetition. *Sonnets* and *villanelles* are both fixed forms. **Formal elements**, such as common stanza types and meters, may be component parts of other forms or may define a poem as a whole. For example, there are generally three *quatrains*—or 4-line stanzas—in a Shakespearean sonnet. But a poem made up entirely of *quatrains* is a “quatrain poem.” **Unfixed forms** are defined by particular subject matter or kinds of content, rather than by repetition and sound. These are forms like *elegy* (writing about

¹<https://anonymous.4open.science/r/poetry-eval-D421>

| | | |
|-----|---|-----|
| 163 | loss), which come in a variety of shapes, sizes, and patterns. See A.8 for full definitions and examples. | 212 |
| 164 | | 213 |
| 165 | These categorizations are recognized as imperfect, and they are neither stable nor discrete. A type of poetry like <i>haiku</i> has a common fixed form in English—three lines consisting of 5, 7, and 5 syllables—but <i>haiku</i> can also refer to concise, non-narrative poems with any number of lines that tend to focus on natural imagery (Sato, 2018). Lastly, a single poem can also belong to more than one category. For example, John Keats’s “Ode on a Grecian Urn” is an <i>ode</i> , but it is also an example of <i>ekphrasis</i> (writing about art), since it describes a decorated vase. To address this complexity, we exclude poems with multiple relevant tags in the same “form group,” such as <i>pastoral</i> and <i>elegy</i> (both unfixed forms). We believe that multi-label classification is an important avenue for future work. | |
| 166 | | 214 |
| 167 | | 215 |
| 168 | | 216 |
| 169 | | 217 |
| 170 | | 218 |
| 171 | | 219 |
| 172 | | 220 |
| 173 | | 221 |
| 174 | | 222 |
| 175 | | 223 |
| 176 | | 224 |
| 177 | | 225 |
| 178 | | 226 |
| 179 | | 227 |
| 180 | | 228 |
| 181 | Meta-Discussion of Poetic Form. Like Keats, many authors include the name of the form they are engaged with in the title or text of a poem itself. While in the context of NLP evaluation these explicit mentions of a poem’s form may seem to “give away” the correct answer, they are a fundamental aspect of poetry and are integral to a human reading experience. Thus, we do not exclude this information from our data or task; however, we do include basic statistics about how many poems include the form in the title or text (Figures 4, 5), and we experiment with prompts where the title is and is not included. | 229 |
| 182 | | 230 |
| 183 | | 231 |
| 184 | | 232 |
| 185 | | 233 |
| 186 | | 234 |
| 187 | | 235 |
| 188 | | 236 |
| 189 | | 237 |
| 190 | | 238 |
| 191 | | 239 |
| 192 | | 240 |
| 193 | | 241 |
| 194 | 3 Data | 242 |
| 195 | To test how well LLMs evaluate poetic form, we curate over 4.1k poems, mostly English-language, which have been tagged/categorized with their poetic forms by human annotators, and either published online or collected in books. | 243 |
| 196 | | 244 |
| 197 | | 245 |
| 198 | | 246 |
| 199 | | 247 |
| 200 | 3.1 Poetry Sources | 248 |
| 201 | Poetry Foundation. Poetry Foundation is a non-profit that works “to amplify poetry and celebrate poets” (Foundation, 2024) The organization runs <i>Poetry</i> magazine, and it also hosts an online database of English-language poetry with more than 47k poems. | 249 |
| 202 | | 250 |
| 203 | | 251 |
| 204 | | 252 |
| 205 | | 253 |
| 206 | | 254 |
| 207 | Academy of American Poets. The Academy of American Poets is also a non-profit whose mission is “to support American poets at all stages of their careers and to foster the appreciation of contemporary poetry” (Poets, 2024). The organization hosts | 255 |
| 208 | | 256 |
| 209 | | 257 |
| 210 | | 258 |
| 211 | | |
| | the website Poets.org , which includes more than 10k poems. | |
| | Manually Digitized Poetry Books. We also manually digitize a range of poetry collections and anthologies organized by form that, when searched in the international library database WorldCat, did not have obvious e-books or presences in major databases (e.g. HathiTrust Digital Library). See A.6 for full list of books. | |
| | To our knowledge, the collections from the Poetry Foundation and Academy of American Poets represent the largest collections of human-labeled poetry that extend into the present day. They are both well-respected poetry institutions with significant engagement from poets and poetry scholars. Both institutions have taken great care in formatting their poems with correct white space and line breaks in the HTML of their websites—an aspect of the poems that is essential to understanding both their form and meaning. | |
| | We release 1.4k public domain poems from this dataset with form annotations as well as other accompanying metadata, such as subject tags and author birth and death years, when available. We do not make in-copyright poems available. | |
| | 3.2 Poetry Curation and Processing | |
| | We select poems in the following categories delineated by the Poetry Foundation on their website: verse forms, stanza forms, meters, and types/modes. Conceptually, as discussed in §2, we frame these tag categories as fixed forms , formal elements , and unfixed forms (see Table 1). The Academy of American Poets does not tag poems by meter or stanza form, so for these forms, we only use the Poetry Foundation as our source. | |
| | We scrape up to 400 poems per available form on each of the two websites. We exclude poems that have multiple relevant tags in the same “form group,” but we allow poems that may have multiple relevant tags in different form groups, such as <i>blank verse</i> (formal element) and <i>elegy</i> (unfixed form). We preserve white space and line breaks in our dataset and see this as a central contribution. | |
| | Additionally, we digitize 15 print poetry anthologies and collections tagged with each of the fixed forms that we consider, according to Library of Congress subject headings via WorldCat. | |

| Poetic Form x Source | Poetry Foundation | Academy of American Poets | Both | Manually Digitized | Total |
|------------------------|-------------------|---------------------------|-----------|--------------------|------------------------------|
| <i>Fixed Forms</i> | | | | | |
| Ballad | 96 | 12 | 2 | 25 | 135 |
| Ghazal | 21 | 19 | 0 | 40 | 80 |
| Haiku | 25 | 24 | 1 | 42 | 92 |
| Limerick | 6 | 1 | 0 | 42 | 49 |
| Pantoum | 11 | 14 | 0 | 42 | 67 |
| Sestina | 16 | 23 | 2 | 40 | 81 |
| Sonnet | 376 | 467 | 13 | 40 | 896 |
| Villanelle | 43 | 17 | 3 | 40 | 103 |
| <i>Formal Elements</i> | | | | | |
| Blank Verse | 209 | 0 | 0 | 0 | 209 |
| Free Verse | 387 | 0 | 0 | 0 | 387 |
| Common Measure | 112 | 0 | 0 | 0 | 112 |
| Couplet | 398 | 0 | 0 | 0 | 398 |
| Quatrain | 89 | 0 | 0 | 0 | 89 |
| Tercet | 94 | 0 | 0 | 0 | 94 |
| <i>Unfixed Forms</i> | | | | | |
| Ars Poetica | 23 | 68 | 3 | 0 | 94 |
| Aubade | 11 | 5 | 0 | 0 | 16 |
| Concrete Poetry | 24 | 0 | 0 | 0 | 24 |
| Dramatic Monologue | 158 | 32 | 1 | 0 | 191 |
| Ekphrasis | 81 | 63 | 1 | 0 | 145 |
| Elegy | 193 | 59 | 2 | 10 | 264 |
| Ode | 73 | 43 | 3 | 2 | 121 |
| Pastoral | 75 | 0 | 0 | 0 | 75 |
| Prose Poem | 334 | 141 | 0 | 0 | 475 |
| Total | 2,855 | 988 | 31 | 323 | 4,197 poem/form pairs |

Table 1: The distribution of poems by form and source.

3.3 Auditing Pretraining Data for Poems

Online resources like Poetry Foundation are valuable in large part because they make thousands of poems available on the internet for free. However, this also means that these specific poems are more likely to be present in the training data of LLMs, leading to memorization issues that could affect performance on our form classification task. Prior work has found significant amounts of poetry memorization in large models like GPT-3.5 (D’Souza and Mimno, 2023). We therefore perform initial experiments to probe pretraining datasets for the poems in our datasets. Thanks to new data resources (Soldaini et al., 2024; Elazar et al., 2023), we can search directly for poems in pretraining data rather than probing model outputs.

Dolma. We rely on the Dolma open pretraining dataset (Soldaini et al., 2024). Dolma is a “three-trillion-token English corpus, built from a diverse mixture of web content, scientific papers, code, public-domain books, social media, and encyclopedic materials.” It includes Github, Wikipedia, Wikibooks, Reddit, Semantic Scholar, Project Gutenberg, and Common Crawl texts, resulting in a large pretraining dataset that is open to researchers.

| Domain | N Poems | N Lines | Domain Type |
|---------------------------|---------|---------|-----------------|
| github.com | 740 | 40,724 | content hosting |
| reddit.com | 733 | 9,773 | social media |
| books.google | 545 | 113,373 | books |
| engpoetry.com | 477 | 4,923 | poetry |
| gutenberg.org | 431 | 15,363 | books |
| poets.org | 256 | 2,290 | poetry |
| poemhunter.com | 243 | 1,589 | poetry |
| quotes.yourdictionary.com | 217 | 2,611 | quotes |
| enotes.com | 200 | 872 | study guides |
| poetryexplorer.net | 181 | 649 | poetry |
| poetrysoup.com | 179 | 3,126 | poetry |
| inspirationalstories.com | 171 | 866 | stories |
| free-translator.com | 147 | 2,555 | translation |
| hotfreebooks.com | 145 | 2,110 | books |
| m.poemhunter.com | 142 | 1,218 | poetry |
| rpo.library.utoronto.ca | 132 | 1,026 | books |
| poemine.com | 129 | 835 | poetry |
| semantic scholar.org | 127 | 442 | academic papers |
| internetpoem.com | 125 | 798 | poetry |
| azquotes.com | 121 | 460 | quotes |

Table 2: The source domains with the highest number of detected poems.

We query the Dolma dataset (see §3.3) using the WHAT’S IN MY BIG DATA (WIMBD) platform (Elazar et al., 2023).² WIMBD allows us to search for exact strings and returns all matches along with their associated metadata, including the data source, the original web domain, the surrounding text, and other information. We split each poem into lines, and we remove lines with fewer than four whitespace-delimited tokens (otherwise, the queries are often short and generic, resulting in matches that are not reliably part of a poem). We truncate lines at 20 tokens for query efficiency. We release this data publicly to support future research.

How many poems are in pretraining data? We find that about half of the poems (57%) are *not* present in Dolma (not even one line is detected). This does not guarantee that these poems are not present in the pretraining data for industry models, whose pretraining data is not disclosed and which likely include many in-copyright texts—but this provides us with one publicly available clue. Fig. 2 shows the forms and the proportions of their associated poems that were detected in Dolma, categorized by the Dolma source. About 30% of our poems are found in the Common Crawl data included in Dolma, with the C4 dataset close behind. Wikipedia and Semantic Scholar contain the fewest detected poems. Overall, if at least one line from a poem is detected, it is likely that all the lines will be detected somewhere in Dolma (see Fig. 3).

²<https://github.com/allenai/wimbd>



Figure 2: The proportion of all poems for a given form that were detected (at least one line) in the source data for Dolma. We include only the most frequent forms. We divide by the total number of poems in our dataset, and poems can appear in multiple sources.

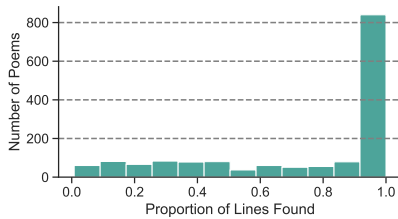


Figure 3: The proportions of lines detected in Dolma per poem (only those with at least one line detected).

Where does poetry pretraining data come from?

Examining the web domains from which the Dolma data was sourced, we find that large websites like Github, Reddit, and Google Books dominate the rankings (Table 2). Many poetry-specific websites like engpoetry.com and poets.org also are present in the top ranked domains, as domains related to books. Figure 2 shows the distribution across data sources, with the Common Crawl dataset dominating, but some sources, e.g., Gutenberg, only containing significant percentages for certain forms like ballads and couplets. Models trained on different mixes of these sources could be more or less capable of recognizing certain forms.

Are these poems memorized?

We additionally replicate the tests from D’Souza and Mimno (2023) by prompting GPT-4 to produce the next five lines of a poem, given its title, author, and first line (see A.7 for our prompt). We then hand-annotate the correctness of the model’s output for 300 random poems. We find that 42% of poems are memorized by GPT-4, and 36% of these memorized poems are also found in Dolma. This indicates that more poetry data is available in the training of closed models like GPT-4 than is available in Dolma, and

memorization is an issue that can be partly but not fully addressed by current open resources.

4 Methods

4.1 Form Classification

We compare the performance of six diverse, state-of-the-art LLMs on the task of identifying more than 20 poetic forms and formal elements from a list of possible options. We test three iterations of the GPT models—**GPT-3.5 Turbo**, **GPT-4** (OpenAI et al.), and **GPT-4o** (OpenAI, 2024)—because we are interested in the evolution of poetic capacities in LLMs over time. We also test **Claude 3 Sonnet** (Anthropic, 2024), **Llama3** (Meta, 2024), and the open-source **Mixtral 8x22B** (AI, 2024).

We experiment with four different zero-shot prompt types, showing the model different amounts of the poem and/or contextual information. We prompt the model with 1) only the text of the poem; 2) only the title and author; 3) only the first line of the poem; 4) only the last line of the poem. We use these different prompts to test for memorization and to better understand how different aspects of a poem, such as a title, may impact performance.

We additionally ask the model to provide both an elaborated and one-word rationale for its choice as well as a confidence score. We show two example templates of the desired response format. An example prompt and response is included in A.5.

4.2 Formative Study with Human Experts

We conduct a small, formative survey with 15 self-identified literature and poetry scholars, asking them to categorize four example poems from our dataset based on text alone. We purposely select four challenging and ambiguous examples based on our own domain expertise: John Crowe Ransom’s “Piazza Piece” (*sonnet*); Robert Browning’s “Prospice” (*ballad*); Natalie Diaz’s “My Brother at 3 A.M.” (*pantoum*); Matthew Rohrer’s “Poem Written with Buson [‘In a minute’]” (*haiku*). We shared the survey in early 2024 on social media, with colleagues, and to scholars associated with the literary studies conference MLA.

5 Results

5.1 Form Classification by LLMs

When prompted with only the text of a poem, the LLMs perform better overall on the *fixed* poetic forms than on the *unfixed* forms or *formal elements*. Classification performance for *sonnets* and *haiku*

| model | Sonnet | | | Limerick | | | Haiku | | | Ballad | | |
|---------|--------|-----------|--------|----------|-----------|--------|-------|-----------|--------|--------|-----------|--------|
| | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall |
| GPT-3.5 | 0.92 | 0.94 | 0.91 | 1.00 | 1.00 | 1.00 | 0.90 | 0.90 | 0.90 | 0.78 | 0.82 | 0.75 |
| GPT-4 | 0.94 | 0.98 | 0.90 | 0.88 | 0.78 | 1.00 | 0.97 | 0.98 | 0.96 | 0.83 | 0.78 | 0.88 |
| GPT-4o | 0.94 | 0.99 | 0.89 | 0.93 | 0.88 | 1.00 | 0.90 | 0.93 | 0.86 | 0.86 | 0.88 | 0.84 |
| Claude | 0.95 | 0.95 | 0.95 | 0.88 | 0.78 | 1.00 | 0.93 | 0.98 | 0.88 | 0.78 | 0.94 | 0.66 |
| Mixtral | 0.92 | 0.96 | 0.89 | 0.88 | 0.78 | 1.00 | 0.79 | 0.94 | 0.68 | 0.74 | 0.72 | 0.75 |
| Llama3 | 0.73 | 1.00 | 0.58 | 0.70 | 0.54 | 1.00 | 0.79 | 0.94 | 0.68 | 0.45 | 0.31 | 0.80 |

| model | Sestina | | | Villanelle | | | Pantoum | | | Ghazal | | |
|---------|---------|-----------|--------|------------|-----------|--------|---------|-----------|--------|--------|-----------|--------|
| | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall |
| GPT-3.5 | 0.17 | 0.80 | 0.10 | 0.62 | 0.46 | 0.94 | 0.20 | 0.60 | 0.12 | 0.57 | 0.51 | 0.65 |
| GPT-4 | 0.87 | 0.86 | 0.88 | 0.93 | 0.98 | 0.89 | 0.81 | 0.71 | 0.96 | 0.65 | 0.51 | 0.92 |
| GPT-4o | 0.73 | 0.63 | 0.88 | 0.92 | 0.90 | 0.95 | 0.82 | 0.74 | 0.92 | 0.51 | 0.36 | 0.90 |
| Claude | 0.41 | 0.31 | 0.61 | 0.58 | 0.58 | 0.57 | 0.53 | 0.54 | 0.52 | 0.54 | 0.59 | 0.50 |
| Mixtral | 0.26 | 1.00 | 0.15 | 0.69 | 0.78 | 0.62 | 0.56 | 0.47 | 0.68 | 0.65 | 0.58 | 0.75 |
| Llama3 | 0.17 | 0.67 | 0.10 | 0.32 | 0.20 | 0.87 | 0.46 | 0.33 | 0.76 | 0.27 | 0.40 | 0.20 |

Table 3: LLM performance by model for the **fixed forms**, where the prompt includes only the poem text.

| Model | Rhyme | | | Repetition | | | Meter | | |
|---------|-------|-----------|--------|------------|-----------|--------|-------|-----------|--------|
| | F1 | Precision | Recall | F1 | Precision | Recall | F1 | Precision | Recall |
| Claude | 0.77 | 0.83 | 0.75 | 0.52 | 0.51 | 0.55 | 0.79 | 0.88 | 0.74 |
| GPT-3.5 | 0.83 | 0.82 | 0.90 | 0.39 | 0.59 | 0.45 | 0.77 | 0.82 | 0.75 |
| GPT-4 | 0.92 | 0.93 | 0.91 | 0.82 | 0.77 | 0.91 | 0.82 | 0.87 | 0.81 |
| GPT-4o | 0.94 | 0.93 | 0.95 | 0.75 | 0.66 | 0.91 | 0.88 | 0.91 | 0.85 |
| Llama3 | 0.64 | 0.61 | 0.85 | 0.31 | 0.40 | 0.28 | 0.67 | 0.71 | 0.66 |
| Mixtral | 0.71 | 0.88 | 0.68 | 0.54 | 0.71 | 0.55 | 0.66 | 0.79 | 0.65 |

| Model | Fixed Topic | | | Fixed Length | | | Visual Form | | |
|---------|-------------|-----------|--------|--------------|-----------|--------|-------------|-----------|--------|
| | F1 | Precision | Recall | F1 | Precision | Recall | F1 | Precision | Recall |
| Claude | 0.58 | 0.61 | 0.61 | 0.65 | 0.72 | 0.71 | 0.39 | 0.56 | 0.31 |
| GPT-3.5 | 0.50 | 0.51 | 0.55 | 0.60 | 0.74 | 0.66 | 0.30 | 0.54 | 0.22 |
| GPT-4 | 0.65 | 0.69 | 0.64 | 0.79 | 0.85 | 0.82 | 0.58 | 0.67 | 0.55 |
| GPT-4o | 0.65 | 0.68 | 0.65 | 0.82 | 0.82 | 0.87 | 0.64 | 0.65 | 0.62 |
| Llama3 | 0.53 | 0.53 | 0.53 | 0.50 | 0.64 | 0.61 | 0.28 | 0.59 | 0.19 |
| Mixtral | 0.57 | 0.60 | 0.60 | 0.60 | 0.80 | 0.60 | 0.34 | 0.51 | 0.28 |

Table 4: LLM performance by model for the **poetic features**, where the prompt includes only the text of the poem

is particularly high, with F1 scores near or over 0.9 for all models except Llama3 (Table 3). This may be attributed to the prevalence of these forms in the training data. Yet when we average model performance by poetic feature (Table 4), it suggests that the models may identify forms with rhyme, meter, and fixed length more easily overall (sonnets typically depend on all three, and haiku on length and syllable count).

The models generally struggle to identify forms based on repetition (see Table 5). However, GPT-4 and GPT-4o do well in this more uncommon poetic category, especially with *sestinas* (F1=0.87; 0.73), *villanelles* (F1=0.93; 0.92), and *pantoums* (F1=0.81; 0.82). This marks significant improvement from GPT-3.5 (F1=0.17, 0.62, 0.20) and is substantially stronger than Claude 3 Sonnet (F1=0.41, 0.58, 0.53), Mixtral 8x22B (F1=0.26, 0.69, 0.56), and Llama3 (F1=0.17, 0.32, 0.46).

Poetic forms based on topic prove more difficult for the models, depending on the topic (Table 5, 6). Forms centered on more concrete subjects like

death (*elegy*) and art (*ars poetica*, *ekphrasis*) are more often recognized, while poems about abstract ideas and styles like *aubades* and *odes* are less so.

There are fewer forms in our dataset that depend on visual features, but most models except GPT-4 and GPT-4o falter with them, namely with *concrete or pattern poetry* (i.e. poems that rely on visual and typographical elements for their structure) and *prose poetry* (i.e. poems that don't have line breaks and look like prose).

5.2 Form Classification by Human Experts

Though the majority of the 15 self-reported literary scholars in our formative study correctly answered sonnet and ballad for poems 1 and 2, respectively (see Figure 8), it was not an overwhelming majority, and answers were split between a wide variety of poetic forms, suggesting that this is not an “easy” task even for trained professionals.

Poems 3 and 4 are even more interesting because they deviate slightly from conventional forms, and the majority of our literary scholar survey respon-

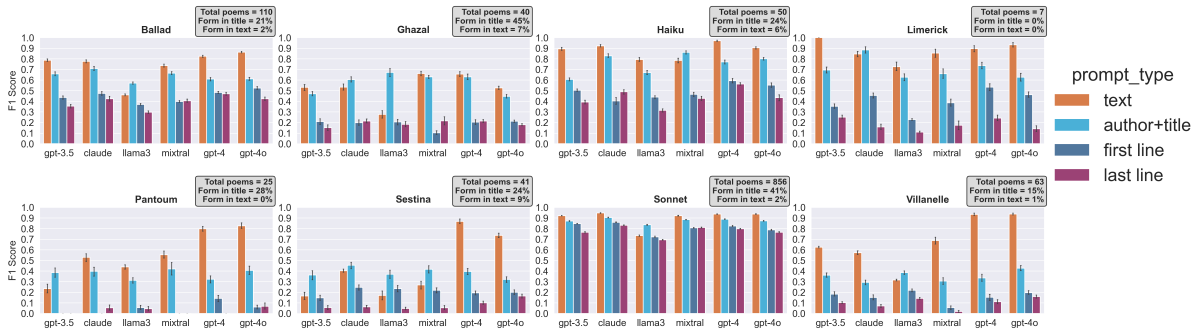


Figure 4: **Fixed Forms — Poetry Foundation and Academy of American Poets.** These figures show LLM performance (F1 scores) on the task of detecting a poem’s *form* (in the same way as the human annotation/institution it was collected from) by prompt type: with only the text of the poem; only the author and title; only the first line; only the last line. Error bars indicate standard deviation across 20 bootstrapped samples of poems.

dents did not accurately identify them. Yet all models except GPT-4o correctly identified Matthew Rohrer’s typically long *haiku* based on the text alone, and GPT-4, GPT-4o, and Llama3 correctly identified Natalie Diaz’s *pantoum* even though Diaz varies the form slightly over the course of the poem. We see these results as promising for more robust studies that compare poetry evaluation between human experts and LLMs.

5.3 Investigating Memorization Issues

When prompted with only the author and title of a poem (and not the text), the models achieve nearly as high or higher classification performance in certain categories (see Figure 4, 5). For sonnets, all the models achieve F1 scores of 0.85 or higher when provided with only the title and author, and scores of 0.75 or higher when provided with only the first or last line. While this result suggests possible memorization issues, at least 40% of the sonnets in our dataset also include the word “sonnet” in their title. Similarly, the models perform better with the author/title only prompt with forms that are often named in their titles, such as *aubade* (56%) and *ode* (48%) (see Figure 5).

We compare model performance for poems from the major online poetry websites with a smaller sample of manually digitized poems found only in print books (see Figure 7), and we see both improvements and declines in classification accuracy across different forms. Detection of *pantoums* improves across all models when shown the poem text, but it decreases considerably (compared to prior performance) when prompted with only the poem’s title and author. This suggests that some *pantoums* from the web may be memorized by the

models, though it’s clear that the models recognize this repetitive structure at high rates, perhaps especially in more conventional iterations (poems from our prestigious online literary sources may be more likely to be experimental than average).

Classification accuracy for *sonnets* drops the most dramatically in our hand-digitized sample, but these sonnets are also unconventional in many ways (it is difficult to identify sonnets that have not reached the digital world), revealing the complexity and ambiguity of this task and the difficulty of curating data in these categories.

When we compare performance between poems that are found and not found in Dolma’s popular pretraining datasets, the results are similarly mixed and inconclusive; we find little obvious impact and believe more work is needed in this area (Table 8).

6 Discussion

6.1 Implications for NLP Researchers

Poetry poses unique challenges to NLP systems. Our form detection task captures many of these complexities, including the need to detect rhyme, meter, topic, and both word and line repetition while allowing for artistic license. This differs from the detection of prose genres, whose delineations mainly rely on topics. Our results emphasize the difficulty of this task, as none of the models tested were able to achieve high test results across the forms, especially the less popular forms. Additionally, our audit of pretraining data holds important lessons for NLP researchers who are designing evaluation benchmarks; most importantly, that memorization is an uneven issue that needs to be quantified.

| | | |
|-----|--|---|
| 499 | 6.2 Implications for Poetry Researchers, Readers, and Digitized Collections | |
| 500 | | |
| 501 | Automatic or computationally-augmented form de- | (poetic form detection), by curating a dataset of |
| 502 | tection has the potential to improve discoverability | poems tagged by form (thus attending to internal |
| 503 | of poems in digital libraries and archives. Poems | differences), and by selecting poems from well- |
| 504 | were often published in periodicals, collections, | respected poetry institutions. |
| 505 | and anthologies, and when these sources are dig- | |
| 506 | itized in full, it makes it difficult to find them as | |
| 507 | individual texts. Consistent detection of structured | |
| 508 | verse forms would aid in the identification of poetic | |
| 509 | texts within digitized historical sources. | |
| 510 | Additionally, LLM evaluations may offer scholar- | |
| 511 | s potential insight into the legibility and durabil- | |
| 512 | ity of different poetic forms, as well as how forms | |
| 513 | relate to each other. For example, LLMs' success- | |
| 514 | ful classification of sonnets may provide further | |
| 515 | evidence for the form's status as "an exceptionally | |
| 516 | transnational poetic design... dispersed throughout | |
| 517 | more of the modern world than any other type of | |
| 518 | Western lyric" (Maxwell, 2004). | |
| 519 | Finally, this research has implications for scholar- | |
| 520 | ship on the circulation and reception of poems | |
| 521 | online. Poems and/or subsections of them often | |
| 522 | circulate widely. Analyzing which lines appear | |
| 523 | in training data offers insight into where poems | |
| 524 | appear on the internet and how they travel online. | |
| 525 | | |
| | 7 Related Work | |
| 526 | | |
| | 7.1 Poetry Generation and Analysis | |
| 527 | Machine-generated poetry has been a focal area in | |
| 528 | NLP for many decades and has received renewed | |
| 529 | interest in the era of LLMs (Manurung et al., 2000; | |
| 530 | Gonçalo Oliveira, 2017; Van de Cruys, 2020; Or- | |
| 531 | mazabal et al.; Lewis et al., 2021; Hu et al., 2023; | |
| 532 | Mélanie-Becquet et al.; Yu et al., 2024). Compu- | |
| 533 | tational analysis of poetry, form, and features like | |
| 534 | rhyme and meter also has a long history, which | |
| 535 | is being transformed by LLMs (Petrick, 1977; | |
| 536 | Yokoyama; Genzel et al., 2010; Haider, 2021; Ab- | |
| 537 | dibayev et al., 2021b,a; de la Rosa et al., 2023). | |
| 538 | Most germane to our study, recent NLP work | |
| 539 | has specifically addressed LLMs' capacity to un- | |
| 540 | derstand poetry. Mahbub et al. (2023) develop a | |
| 541 | task and dataset, "PoemSum," to evaluate how well | |
| 542 | LLMs can summarize poetry. "PoemSum" con- | |
| 543 | tains 3,011 poem summary/poem text pairs, which | |
| 544 | were respectively collected from the website Poe- | |
| 545 | mAnalysis.com and various websites. They con- | |
| 546 | clude that SOTA summarization models are cur- | |
| 547 | rently "not well-suited" for this task. We build on | |
| 548 | this work by focusing on a more specific sub-task | |
| | | 7.2 Literary Genre/Form Classification |
| | | |
| | Automatically classifying literary texts by genre | 554 |
| | has been an active area of research in both NLP and | 555 |
| | the digital humanities. Many studies have focused | 556 |
| | on classifying fictional prose writing genres in nov- | 557 |
| | els (Underwood, 2016; Wilkens, 2016), while other | 558 |
| | work has focused on distinguishing between kinds | 559 |
| | of poetry, such as Greek epic vs. drama (Gianitsos | 560 |
| | et al., 2019) and various styles of spoken free verse | 561 |
| | (Baumann et al., 2018). | 562 |
| | | |
| | In the digital humanities, genre classification has | 563 |
| | often been used to highlight ambiguity. Long and | 564 |
| | So (2016) find that features of English-language | 565 |
| | haiku are statistically distinct, yet they empha- | 566 |
| | size the importance of misclassifications for ex- | 567 |
| | amining how "broadly distributed haiku's influence | 568 |
| | was." Rhody (2012) similarly suggests that compu- | 569 |
| | tational analysis of poetry "works, in part, because | 570 |
| | of its failures." These scholars largely use clas- | 571 |
| | sification to explore the fuzziness, as opposed to | 572 |
| | the rigidity, of genres and poetic forms. This is an | 573 |
| | angle that we do not fully explore in our work and | 574 |
| | view as important for future research. | 575 |
| | | |
| | 8 Conclusion | 576 |
| | | |
| | Our work audits current poetic capacities and train- | 577 |
| | ing data in leading LLMs. We contribute the poetry | 578 |
| | evaluation task and release to the research commu- | 579 |
| | nity a dataset of 1.4k+ annotated public domain | 580 |
| | poems with accompanying metadata about their | 581 |
| | prevalence in popular training datasets. We also | 582 |
| | join Orr and Kang (2024) and others in cautioning | 583 |
| | the benchmark/task as the be-all-end-all framework | 584 |
| | for NLP research. Poetry is a good example of a | 585 |
| | human output that purposely troubles neat cate- | 586 |
| | gorization. We encourage more work that builds | 587 |
| | nuance and ambiguity into humanistic benchmarks | 588 |
| | such as this one, as well as work that places value | 589 |
| | beyond this orientation. Further research is also | 590 |
| | needed to study LLM poetic capacities in languages | 591 |
| | beyond English and to evaluate impacts on human | 592 |
| | creators (we expand on these issues in Limitations | 593 |
| | and Ethical Considerations). | 594 |

9 Limitations

In this study, we focus mostly on English-language poetry that was written and published in Europe and North America. Further, we only consider poems that were tagged by the Poetry Foundation, the Academy of American Poets, or editors of particular poetry collections (see A.6), leaving out many other possible forms as well as poems that do not adhere neatly to forms.

Poetry Foundation and the Academy of American Poets do not have a comprehensive or representative (in terms of gender, race, culture, geography) collections of poems, nor do the print anthologies we digitized. Additionally, most of the poems in these collections are *not* tagged by form, and it is not always clear why some poems have tags and others do not. For example, on the Poetry Foundation website, Etheridge Knight and Sonia Sanchez, two late 20th-century poets associated with the Black Arts Movement, both wrote haiku series that include the word “haiku” in their titles, but they are not tagged as haiku on Poetry Foundation.

While we select these resources because they are well-respected poetry institutions, we do not know how exactly these tags were applied to the poems, or who put them there. From our manual examination of the poems/tags and classification results, we found some examples where tags from either of these institutions were incorrectly applied. We do not believe this problem is extensive, but we have not manually checked every tagged poem.

On these websites, and thus within our dataset, there is also an uneven distribution of poems in each form, reflecting biases related to race, class, language, and culture. For example, the *ghazal* is a poetic form that originated in Arabic and is popular in the Middle East and South Asia; however, *ghazals* are less popular, and less likely to be curated, in English-language contexts. Limericks are another popular and pervasive genre of poetry, yet they are considered a low-brow genre or “light verse” form, and thus there are few of them in this particular dataset.

There are also limitations to conceiving of poetic form as a single-label classification task, as a set of independent categories that a poem can belong to or not. Poetry is often valued for ambiguity, experimentation, and interpretive potential, so fitting neatly into a category is not necessarily what one looks for in poetic analysis. Poets also often mix and merge forms. For example, Gwendolyn

Brooks developed the “*Sonnet-Ballad*,” and Roger Sedarat has created the “*Sonnet Ghazal*” (Sedarat, 2011). Our approach does not account for these kinds of hybrid forms. Further, form only exists in relation to content. As foundational English literary scholars Brooks and Warren (1960) wrote, “the reader, unlike a robot, must be able to recognize the dramatic implications of the form.” These implications only come through when form is considered as part of a broader composition with numerous intertwined elements.

10 Ethical Considerations

Many of the poems that we asked the models to identify are currently under copyright. The poems from Poetry Foundation and Academy of American Poets are freely available online, but this is due to the fact that these institutions pay for copyright and compensate poets for their work, which is crucial for reproduction of recent texts. In the dataset we share, we only include poems that are in the public domain and whose authors died before 1929. In the U.S., copyright extends for 95 years after the date of first publication, so works published before 1929 are in the public domain.

In using LLMs to evaluate poetry, there is a risk of reinforcing dominant understandings of poetic form and prosody. As has been well documented, LLMs can reproduce existing biases related to gender, race, class, and cultural background (Bender et al., 2021), and there is significant existing bias in discourse surrounding poetic form. Strand and Boland (2000) emphasize that “Women were often underrepresented in poetry in the sixteenth, seventeenth, and eighteenth centuries” and were “absent—whether in retrospect or reality... from the festival of form that poetry became in those centuries.” And Shockley (2011) notes that the “discourse around innovative and avant-garde poetry in the U.S.,” which has often emphasized discussions of form, “has historically constructed these categories as implicitly ‘white,’” pointing out that “African American poets, even when they were involved in, perhaps central to, now-canonical avant-garde movements have been marginalized or erased from literary histories.”

These literary histories inform which works are included in anthologies and incorporated into digital collections, and they also influence training data. D’Souza and Mimno (2023) have shown that inclusion in the 1983 edition of the *Norton Anthology*

of Poetry was the best predictor of poem memorization in ChatGPT. This anthology represents a traditional view of the English poetic canon, favoring historical works published in the U.K. and the U.S., and excluding important works by women authors, Black and Indigenous authors and authors of color, and authors working outside Europe and North America. If the performance of LLMs improves in relation to poetic form evaluation, whose versions of form will be reproduced?

Given the complex cultural, historical, and textual conditions from which poetic forms emerge, as well as the centuries-long discourse surrounding how to label, categorize, and analyze form, this work requires domain expertise, and domain experts should be included in discussions about benchmarks for complex creative and interpretive tasks. At the same time, domain experts may have hesitations about this kind of collaboration, given the widespread use of copyrighted material in training data, and the risks LLMs pose to authors, whose work is fundamental to literary studies.

References

Almas Abdibayev, Yohei Igarashi, Allen Riddell, and Daniel Rockmore. 2021a. [Automating the Detection of Poetic Features: The Limerick as Model Organism](#). In *Proceedings of the 5th Joint SIGHUM Workshop on Computational Linguistics for Cultural Heritage, Social Sciences, Humanities and Literature*, pages 80–90, Punta Cana, Dominican Republic (online). Association for Computational Linguistics.

Almas Abdibayev, Allen Riddell, Department of English Indiana University Bloomington, USA, and Daniel Rockmore. 2021b. [BPoMP: The Benchmark of Poetic Minimal Pairs – Limericks, Rhyme, and Narrative Coherence](#). In *Proceedings of the Conference Recent Advances in Natural Language Processing - Deep Learning for Natural Language Processing Methods and Applications*, pages 1–9. INCOMA Ltd. Shoumen, BULGARIA.

Mistral AI. 2024. [Mixtral 8x22B](#). Section: news.

Anthropic. 2024. [The Claude 3 Model Family: Opus, Sonnet, Haiku](#).

Timo Baumann, Hussein Hussein, and Burkhard Meyer-Sickendiek. 2018. [Style detection for free verse poetry from text and speech](#). In *Proceedings of the 27th International Conference on Computational Linguistics*, pages 1929–1940. Association for Computational Linguistics.

Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. [On the](#)

[Dangers of Stochastic Parrots: Can Language Models Be Too Big?](#). In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, FAccT '21*, pages 610–623, New York, NY, USA. Association for Computing Machinery.

Bing. [What will you do with bing | jersey poem](#).

Cleath Brooks and Robert Penn Warren. 1960. *Understanding Poetry. Third edition*. New York : Holt, Rinehart and Winston.

Kent Chang, Mackenzie Cramer, Sandeep Soni, and David Bamman. 2023. [Speak, memory: An archaeology of books known to ChatGPT/GPT-4](#). In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 7312–7327, Singapore. Association for Computational Linguistics.

Javier de la Rosa, Álvaro Pérez Pozo, Salvador Ros, and Elena González-Blanco. 2023. [ALBERTI, a Multilingual Domain Specific Language Model for Poetry Analysis](#). *arXiv preprint*. ArXiv:2307.01387 [cs].

Lyra D’Souza and David Mimno. 2023. [The chatbot and the canon: Poetry memorization in LLMs](#). In *Computational Humanities Research*.

Yanai Elazar, Akshita Bhagia, Ian Helgi Magnusson, Abhilasha Ravichander, Dustin Schwenk, Alane Suhr, Evan Pete Walsh, Dirk Groeneveld, Luca Soldaini, Sameer Singh, Hanna Hajishirzi, Noah A. Smith, and Jesse Dodge. 2023. [What’s in my big data?](#) In *The Twelfth International Conference on Learning Representations*.

Poetry Foundation. 2024. [About Us](#).

Dmitriy Genzel, Jakob Uszkoreit, and Franz Och. 2010. [“Poetic” Statistical Machine Translation: Rhyme and Meter](#). In *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing*, pages 158–166, Cambridge, MA. Association for Computational Linguistics.

Efthimios Gianitsos, Thomas Bolt, Pramit Chaudhuri, and Joseph P. Dexter. 2019. [Stylometric classification of ancient greek literary texts by genre](#). In *Proceedings of the 3rd Joint SIGHUM Workshop on Computational Linguistics for Cultural Heritage, Social Sciences, Humanities and Literature*, pages 52–60. Association for Computational Linguistics.

Hugo Gonçalo Oliveira. 2017. [A Survey on Intelligent Poetry Generation: Languages, Features, Techniques, Reutilisation and Evaluation](#). In *Proceedings of the 10th International Conference on Natural Language Generation*, pages 11–20, Santiago de Compostela, Spain. Association for Computational Linguistics.

Roland Greene and Stephen Cushman. 2016. *The Princeton Handbook of Poetic Terms: Third Edition*, revised, 3 edition. Princeton University Press, Princeton.

| | | |
|-----|---|-----|
| 802 | Thomas Haider. 2021. Metrical Tagging in the Wild: Building and Annotating Poetry Corpora with Rhythmic Features . <i>Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume</i> , pages 3715–3725. | 855 |
| 803 | | 856 |
| 804 | | 857 |
| 805 | | 858 |
| 806 | | 859 |
| 807 | Conference Name: Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume Place: Online Publisher: Association for Computational Linguistics. | 860 |
| 808 | | 861 |
| 809 | | 862 |
| 810 | | 863 |
| 811 | | 864 |
| 812 | Zhiyuan Hu, Chumin Liu, Yue Feng, Anh Tuan Luu, and Bryan Hooi. 2023. PoetryDiffusion: Towards Joint Semantic and Metrical Manipulation in Poetry Generation . <i>arXiv preprint</i> . ArXiv:2306.08456 [cs]. | 865 |
| 813 | | 866 |
| 814 | | 867 |
| 815 | | 868 |
| 816 | Angela Leighton. 2008. <i>On Form: Poetry, Aestheticism, and the Legacy of a Word</i> . Oxford University Press, Oxford. | 869 |
| 817 | | 870 |
| 818 | | 871 |
| 819 | D. Lewis, A. Zugarini, and E. Alonso. 2021. Syllable Neural Language Models for English Poem Generation . In <i>12th International Conference on Computational Creativity (ICCC'21)</i> , pages 350–356, London, UK. Association for Computational Creativity. | 872 |
| 820 | | 873 |
| 821 | | 874 |
| 822 | | 875 |
| 823 | | 876 |
| 824 | Hoyt Long and Richard Jean So. 2016. Literary pattern recognition: Modernism between close reading and machine learning . 42(2):235–267. | 877 |
| 825 | | 878 |
| 826 | | 879 |
| 827 | Ridwan Mahbub, Ifrad Khan, Samiha Anuva, Md Shihab Shahriar, Md Tahmid Rahman Laskar, and Sabbir Ahmed. 2023. Unveiling the essence of poetry: Introducing a comprehensive dataset and benchmark for poem summarization . In <i>Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing</i> , pages 14878–14886, Singapore. Association for Computational Linguistics. | 880 |
| 828 | | 881 |
| 829 | | 882 |
| 830 | | 883 |
| 831 | | 884 |
| 832 | | 885 |
| 833 | | 886 |
| 834 | | 887 |
| 835 | Hisar Manurung, Graeme Ritchie, and Henry Thompson. 2000. Towards A Computational Model Of Poetry Generation . Technical Report, The University of Edinburgh. Accepted: 2010-06-23T14:31:22Z. | 888 |
| 836 | | 889 |
| 837 | | 890 |
| 838 | | 891 |
| 839 | Meredith Martin. 2012. <i>The Rise and Fall of Meter: Poetry and English National Culture, 1860–1930</i> . Princeton University Press, Princeton. | 892 |
| 840 | | 893 |
| 841 | | 894 |
| 842 | William J. Maxwell. 2004. Introduction: Claude Mckay—Lyric Poetry in the Age of Cataclysm . In <i>Complete Poems</i> . University of Illinois Press. | 895 |
| 843 | | 896 |
| 844 | | 897 |
| 845 | Meta. 2024. Llama3 Model Card . | 898 |
| 846 | Microsoft. 2023. How to Write Poetry Using Copilot Microsoft Bing . | 899 |
| 847 | | 900 |
| 848 | Frédérique Mélanie-Becquet, Clément Plancq, Claude Grunspan, Mylène Maignant, Matthieu Raffard, Mathilde Roussel, Fiammetta Ghedini, and Thierry Poibeau. Exploring combinatorial methods to produce sonnets: An overview of the oupoco project . 18(1). | 901 |
| 849 | | 902 |
| 850 | | 903 |
| 851 | | 904 |
| 852 | | 905 |
| 853 | | 906 |
| 854 | OpenAI. 2024. Hello GPT-4o . | 907 |
| | OpenAI, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mohammad Bavarian, Jeff Belgum, Irwan Bello, Jake Berdine, Gabriel Bernadett-Shapiro, Christopher Berner, Lenny Bogdonoff, Oleg Boiko, Madelaine Boyd, Anna-Luisa Brakman, Greg Brockman, Tim Brooks, Miles Brundage, Kevin Button, Trevor Cai, Rosie Campbell, Andrew Cann, Brittany Carey, Chelsea Carlson, Rory Carmichael, Brooke Chan, Che Chang, Fotis Chantzis, Derek Chen, Sully Chen, Ruby Chen, Jason Chen, Mark Chen, Ben Chess, Chester Cho, Casey Chu, Hyung Won Chung, Dave Cummings, Jeremiah Currier, Yunxing Dai, Cory Decareaux, Thomas Degry, Noah Deutsch, Damien Deville, Arka Dhar, David Dohan, Steve Dowling, Sheila Dunning, Adrien Ecoffet, Atty Eleti, Tyna Eloundou, David Farhi, Liam Fedus, Niko Felix, Simón Posada Fishman, Juston Forte, Isabella Fulford, Leo Gao, Elie Georges, Christian Gibson, Vik Goel, Tarun Gogineni, Gabriel Goh, Rapha Gontijo-Lopes, Jonathan Gordon, Morgan Grafstein, Scott Gray, Ryan Greene, Joshua Gross, Shixiang Shane Gu, Yufei Guo, Chris Hallacy, Jesse Han, Jeff Harris, Yuchen He, Mike Heaton, Johannes Heidecke, Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu, Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Łukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Jan Hendrik Kirchner, Jamie Kiros, Matt Knight, Daniel Kokotajlo, Łukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kosic, Gretchen Krueger, Vishal Kuo, Michael Lampe, Ikai Lan, Teddy Lee, Jan Leike, Jade Leung, Daniel Levy, Chak Ming Li, Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan Morikawa, Daniel Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeew Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O’Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael, Pokorny, Michelle Pokrass, Vitchyr H. Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotsted, Henri Roussez, Nick Ry- | 908 |
| | | 909 |
| | | 910 |
| | | 911 |
| | | 912 |
| | | 913 |
| | | 914 |
| | | 915 |
| | | 916 |
| | | 917 |
| | | 918 |

| | | | |
|-----|---|---|------|
| 919 | der, Mario Saltarelli, Ted Sanders, Shibani Santurkar, | Hiroaki Sato. 2018. <i>On Haiku</i> . New Directions Pub- | 975 |
| 920 | Girish Sastry, Heather Schmidt, David Schnurr, John | lishing. | 976 |
| 921 | Schulman, Daniel Selsam, Kyla Sheppard, Toki | | |
| 922 | Sherbakov, Jessica Shieh, Sarah Shoker, Pranav | Roger Sedarat. 2011. <i>Ghazal Games: Poems</i> . Ohio | 977 |
| 923 | Shyam, Szymon Sidor, Eric Sigler, Maddie Simens, | University Press, Athens. | 978 |
| 924 | Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin | | |
| 925 | Sokolowsky, Yang Song, Natalie Staudacher, Fe- | Peter Seitel. 2003. <i>Theorizing Genres—Interpreting</i> | 979 |
| 926 | lipe Petroski Such, Natalie Summers, Ilya Sutskever, | <i>Works</i> . <i>New Literary History</i> , 34(2):275–297. | 980 |
| 927 | Jie Tang, Nikolas Tezak, Madeleine B. Thompson, | | |
| 928 | Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, | Evie Shockley. 2011. <i>Renegade Poetics: Black Aes-</i> | 981 |
| 929 | Preston Tuggle, Nick Turley, Jerry Tworek, Juan Fe- | <i>thetics and Formal Innovation in African American</i> | 982 |
| 930 | lipo Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, | <i>Poetry</i> . University of Iowa Press. | 983 |
| 931 | Chelsea Voss, Carroll Wainwright, Justin Jay Wang, | | |
| 932 | Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, | Luca Soldaini, Rodney Kinney, Akshita Bhagia, Dustin | 984 |
| 933 | C. J. Weinmann, Akila Welihinda, Peter Welin- | Schwenk, David Atkinson, Russell Authur, Ben Bo- | 985 |
| 934 | der, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave | gin, Khyathi Chandu, Jennifer Dumas, Yanai Elazar, | 986 |
| 935 | Willner, Clemens Winter, Samuel Wolrich, Hannah | et al. 2024. Dolma: An open corpus of three tril- | 987 |
| 936 | Wong, Lauren Workman, Sherwin Wu, Jeff Wu, | lion tokens for language model pretraining research. | 988 |
| 937 | Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin | <i>arXiv preprint arXiv:2402.00159</i> . | 989 |
| 938 | Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, | | |
| 939 | Chong Zhang, Marvin Zhang, Shengjia Zhao, Tian- | Mark Strand and Eavan Boland. 2000. <i>The making of a</i> | 990 |
| 940 | hao Zheng, Juntang Zhuang, William Zhuk, and | <i>poem: a Norton anthology of poetic forms</i> . Norton, | 991 |
| 941 | Barret Zoph. <i>GPT-4 technical report</i> . <i>Preprint</i> , | New York. | 992 |
| 942 | arxiv:2303.08774 [cs]. | | |
| 943 | Aitor Ormazabal, Mikel Artetxe, Manex Agirrezabal, | Thomas H. Ptacek [@tqbf]. I’m sorry, i simply cannot | 993 |
| 944 | Aitor Soroa, and Eneko Agirre. <i>PoeLM: A meter-</i> | be cynical about a technology that can accomplish | 994 |
| 945 | <i>and rhyme-controllable language model for unsuper-</i> | this. https://t.co/yj1Y72ez0m . | 995 |
| 946 | <i>vised poetry generation</i> . <i>Preprint</i> , arxiv:2205.12206 | | |
| 947 | [cs]. | Ted Underwood. 2016. <i>The Life Cycles of Genres</i> . | 996 |
| 948 | Will Orr and Edward B. Kang. 2024. <i>AI as a Sport: On</i> | <i>Journal of Cultural Analytics</i> , 2(2). | 997 |
| 949 | <i>the Competitive Epistemologies of Benchmarking</i> . | | |
| 950 | In <i>Proceedings of the 2024 ACM Conference on Fair-</i> | Tim Van de Cruys. 2020. <i>Automatic Poetry Generation</i> | 998 |
| 951 | <i>ness, Accountability, and Transparency</i> , FAccT ’24, | <i>from Prosaic Text</i> . In <i>Proceedings of the 58th An-</i> | 999 |
| 952 | pages 1875–1884, New York, NY, USA. Association | <i>nual Meeting of the Association for Computational</i> | 1000 |
| 953 | for Computing Machinery. | <i>Linguistics</i> , pages 2471–2480, Online. Association | 1001 |
| 954 | Stanley R. Petrick. 1977. <i>Understanding Understanding</i> | for Computational Linguistics. | 1002 |
| 955 | <i>Poetry</i> . <i>Computers and the Humanities</i> , 11(4):217– | | |
| 956 | 221. Publisher: Springer. | Matthew Wilkens. 2016. <i>Genre, Computation, and the</i> | 1003 |
| 957 | Academy of American Poets. 2024. <i>About Us</i> . | <i>Varieties of Twentieth-Century U.S. Fiction</i> . <i>Journal</i> | 1004 |
| 958 | David Pogue. 2023. <i>AI experts on whether you should</i> | <i>of Cultural Analytics</i> , 2(2). | 1005 |
| 959 | be "terrified" of ChatGPT. <i>CBS News</i> . | | |
| 960 | Alex Preminger, Frank J. Warnke, and O. B. Hardison, | Setsuko Yokoyama. <i>Digital Technologies for Exploring</i> | 1006 |
| 961 | Jr. 2015. <i>Princeton Encyclopedia of Poetry and Poet-</i> | <i>Prosody: A Brief Historical Overview</i> . | 1007 |
| 962 | <i>ics</i> . Princeton University Press, Princeton. | | |
| 963 | Jahan Ramazani. 2009. <i>A Transnational Poetics</i> . | Chengyue Yu, Lei Zang, Jiaotuan Wang, Chenyi | 1008 |
| 964 | University of Chicago Press, Chicago. OCLC: | Zhuang, and Jinjie Gu. 2024. <i>CharPoet: A Chinese</i> | 1009 |
| 965 | 435911878. | <i>Classical Poetry Generation System Based on Token-</i> | 1010 |
| 966 | Lisa M. Rhody. 2012. <i>Topic Modeling and Figurative</i> | <i>free LLM</i> . <i>arXiv preprint</i> . ArXiv:2401.03512 [cs]. | 1011 |
| 967 | <i>Language Journal of Digital Humanities</i> . <i>Journal of</i> | | |
| 968 | <i>Digital Humanities</i> , 2(1). | Max Zahn. 2022. <i>What is ChatGPT, the artificial intelli-</i> | 1012 |
| 969 | Kevin Roose, Casey Newton, Rachel Cohn, Whitney | <i>gence text bot that went viral?</i> <i>ABC News</i> . | 1013 |
| 970 | Jones, Jen Poyant, Brad Fisher, Dan Powell, Marion | | |
| 971 | Lozano, Sophia Lanman, Rowan Niemisto, and Di- | Xingxing Zhang and Mirella Lapata. 2014. <i>Chinese</i> | 1014 |
| 972 | ane Wong. 2024. <i>Google Eats Rocks, a Win for A.I.</i> | <i>poetry generation with recurrent neural networks</i> . In | 1015 |
| 973 | <i>Interpretability and Safety Vibe Check</i> . <i>Hard Fork —</i> | <i>Proceedings of the 2014 Conference on Empirical</i> | 1016 |
| 974 | <i>The New York Times</i> . | <i>Methods in Natural Language Processing (EMNLP)</i> , | 1017 |
| | | pages 670–680, Doha, Qatar. Association for Com- | 1018 |
| | | putational Linguistics. | 1019 |

A Appendix

1020

A.1 Poetic Features by Form

1021

| Fixed Forms | Rhyme | Repetition | Meter | Fixed Topic | Fixed Length | Visual Form |
|--------------------|-------|------------|-------|-------------|--------------|-------------|
| Ballad | | | ✓ | | | |
| Ghazal | | ✓ | | | | |
| Haiku | | | | ✓ | ✓ | |
| Limerick | ✓ | | | | ✓ | |
| Pantoum | | ✓ | | | | |
| Sestina | | ✓ | | | ✓ | |
| Sonnet | ✓ | | ✓ | | ✓ | |
| Villanelle | ✓ | ✓ | | | ✓ | |
| Formal Elements | Rhyme | Repetition | Meter | Fixed Topic | Fixed Length | Visual Form |
| Blank Verse | | | ✓ | | | |
| Common Measure | ✓ | | ✓ | | ✓ | |
| Couplet | | | | | ✓ | |
| Free Verse | | | ✓ | | | |
| Quatrain | | | | | ✓ | |
| Tercet | | | | | ✓ | |
| Unfixed Forms | Rhyme | Repetition | Meter | Fixed Topic | Fixed Length | Visual Form |
| Ars Poetica | | | | ✓ | | |
| Aubade | | | | ✓ | | |
| Concrete Poetry | | | | | | ✓ |
| Dramatic Monologue | | | | ✓ | | |
| Ekphrasis | | | | ✓ | | |
| Elegy | | | | ✓ | | |
| Ode | | | | ✓ | | |
| Pastoral | | | | ✓ | | |
| Prose Poem | | | | | | ✓ |

Table 5: Distribution of Poetic Features by Form

A.2 Additional Poetic Form Detection Results

1022

| model | Ars Poetica | | | Aubade | | | Concrete Or Pattern Poetry | | | Dramatic Monologue | | | Ekphrasis | | |
|---------|-------------|-----------|--------|--------|-----------|--------|----------------------------|-----------|--------|--------------------|-----------|--------|-----------|-----------|--------|
| | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall |
| GPT-3.5 | 0.39 | 0.30 | 0.55 | 0.27 | 0.24 | 0.31 | 0.07 | 0.33 | 0.04 | 0.48 | 0.50 | 0.45 | 0.61 | 0.59 | 0.63 |
| GPT-4 | 0.64 | 0.66 | 0.63 | 0.44 | 0.55 | 0.38 | 0.29 | 0.50 | 0.21 | 0.68 | 0.56 | 0.87 | 0.71 | 0.88 | 0.59 |
| GPT-4o | 0.59 | 0.54 | 0.66 | 0.48 | 0.47 | 0.50 | 0.47 | 0.48 | 0.46 | 0.69 | 0.60 | 0.81 | 0.69 | 0.64 | 0.74 |
| Claude | 0.44 | 0.53 | 0.37 | 0.47 | 0.41 | 0.56 | 0.21 | 0.22 | 0.21 | 0.45 | 0.30 | 0.91 | 0.75 | 0.80 | 0.70 |
| Mixtral | 0.43 | 0.69 | 0.31 | 0.51 | 0.41 | 0.69 | 0.15 | 0.14 | 0.17 | 0.47 | 0.34 | 0.77 | 0.65 | 0.79 | 0.55 |
| Llama3 | 0.41 | 0.29 | 0.69 | 0.34 | 0.38 | 0.31 | 0.20 | 0.25 | 0.17 | 0.50 | 0.40 | 0.66 | 0.66 | 0.83 | 0.54 |
| model | Elegy | | | Ode | | | Pastoral | | | Prose Poem | | | | | |
| | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall | | | |
| GPT-3.5 | 0.58 | 0.44 | 0.87 | 0.23 | 0.53 | 0.14 | 0.57 | 0.59 | 0.55 | 0.52 | 0.75 | 0.40 | | | |
| GPT-4 | 0.67 | 0.82 | 0.64 | 0.44 | 0.57 | 0.36 | 0.57 | 0.49 | 0.68 | 0.86 | 0.84 | 0.89 | | | |
| GPT-4o | 0.76 | 0.77 | 0.75 | 0.43 | 0.75 | 0.30 | 0.68 | 0.75 | 0.61 | 0.80 | 0.82 | 0.78 | | | |
| Claude | 0.65 | 0.81 | 0.55 | 0.45 | 0.44 | 0.46 | 0.49 | 0.58 | 0.43 | 0.56 | 0.89 | 0.41 | | | |
| Mixtral | 0.68 | 0.62 | 0.75 | 0.46 | 0.50 | 0.43 | 0.58 | 0.52 | 0.65 | 0.53 | 0.89 | 0.41 | | | |
| Llama3 | 0.67 | 0.59 | 0.76 | 0.40 | 0.32 | 0.55 | 0.44 | 0.46 | 0.43 | 0.35 | 0.92 | 0.22 | | | |

Table 6: LLM performance by model for the **unfixed forms**, where the prompt includes only the poem text.

| model | Couplet | | | Quatrain | | | Tercet | | |
|---------|---------|-----------|--------|----------|-----------|--------|--------|-----------|--------|
| | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall |
| GPT-3.5 | 0.16 | 0.97 | 0.09 | 0.23 | 0.14 | 0.70 | 0.61 | 0.62 | 0.60 |
| GPT-4 | 0.49 | 0.90 | 0.34 | 0.37 | 0.23 | 0.96 | 0.72 | 0.92 | 0.60 |
| GPT-4o | 0.72 | 0.96 | 0.58 | 0.48 | 0.33 | 0.90 | 0.81 | 0.84 | 0.78 |
| Claude | 0.30 | 1.00 | 0.18 | 0.31 | 0.19 | 0.83 | 0.81 | 0.73 | 0.90 |
| Mixtral | 0.51 | 0.99 | 0.35 | 0.27 | 0.18 | 0.56 | 0.69 | 0.55 | 0.90 |
| Llama3 | 0.33 | 0.98 | 0.20 | 0.29 | 0.17 | 0.88 | 0.34 | 0.55 | 0.24 |

| model | Blank Verse | | | Common Measure | | | Free Verse | | |
|---------|-------------|-----------|--------|----------------|-----------|--------|------------|-----------|--------|
| | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall |
| GPT-3.5 | 0.53 | 0.72 | 0.42 | 0.79 | 0.86 | 0.74 | 0.84 | 0.75 | 0.95 |
| GPT-4 | 0.57 | 0.84 | 0.43 | 0.91 | 0.99 | 0.85 | 0.85 | 0.75 | 0.98 |
| GPT-4o | 0.73 | 0.92 | 0.61 | 0.96 | 0.95 | 0.97 | 0.89 | 0.83 | 0.96 |
| Claude | 0.68 | 0.70 | 0.67 | 0.65 | 1.00 | 0.48 | 0.88 | 0.81 | 0.95 |
| Mixtral | 0.46 | 0.54 | 0.41 | 0.36 | 1.00 | 0.22 | 0.83 | 0.72 | 0.97 |
| Llama3 | 0.53 | 0.78 | 0.41 | 0.80 | 0.70 | 0.94 | 0.82 | 0.78 | 0.87 |

Table 7: LLM performance by model for the **formal elements**, where the prompt includes only the poem text.

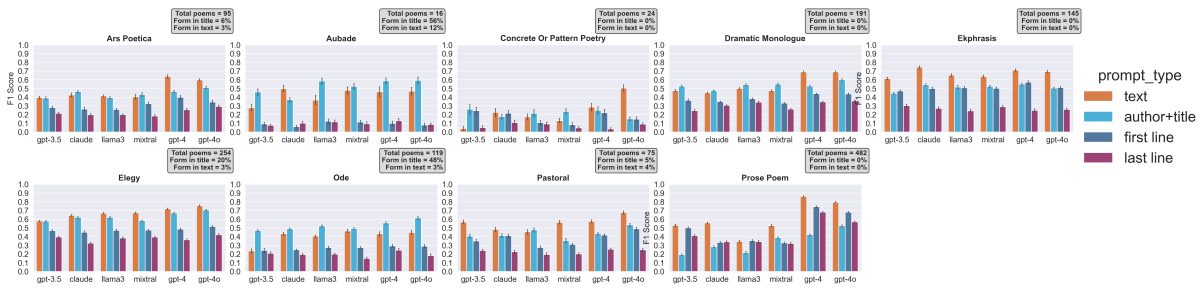


Figure 5: **Unfixed Forms — Poetry Foundation and Academy of American Poets.** These figures show LLM performance (F1 scores) by prompt type on the task of detecting poetic form (in the same way as the human annotation/institution it was collected from) by prompt type: with only the text of the poem; only the author and title; only the first line; only the last line. Error bars indicate standard deviation across 20 bootstrapped samples of poems.

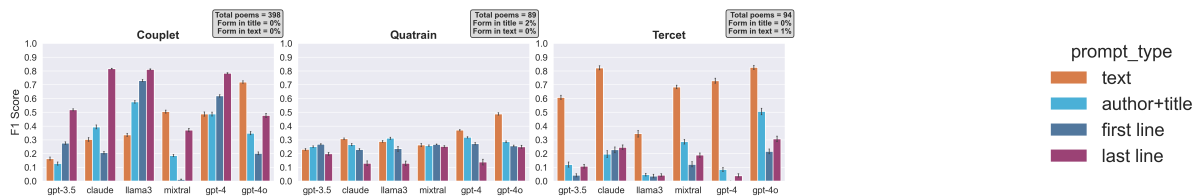


Figure 6: **Formal Elements — Poetry Foundation and Academy of American Poets.** These figures show LLM performance (F1 scores) by prompt type on the task of detecting a poem’s form (in the same way as the human annotation/institution it was collected from) by prompt type: with only the text of the poem; only the author and title; only the first line; only the last line. Error bars indicate standard deviation across 20 bootstrapped samples of poems.

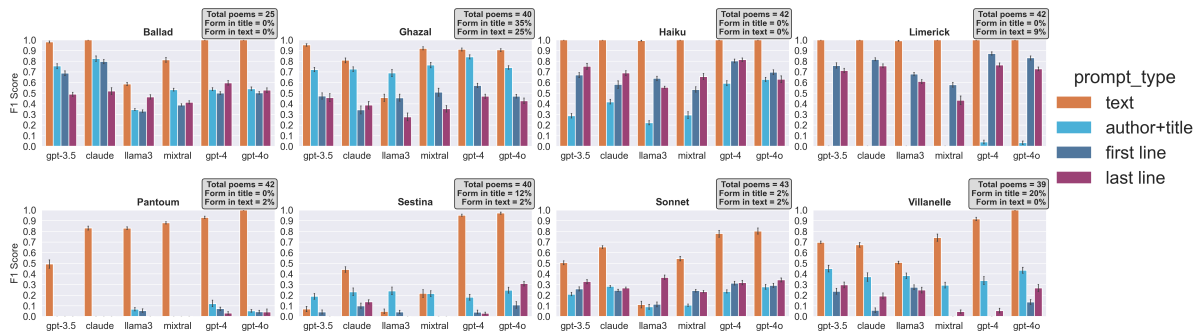


Figure 7: **Fixed Forms — Manually Digitized Poetry Books.** These figures show LLM performance (F1 scores) on the task of detecting a poem’s form (in the same way as the human annotation/institution it was collected from) by prompt type: with only the text of the poem; only the author and title; only the first line; only the last line. Error bars indicate standard deviation across 20 bootstrapped samples of poems. The poems tested in this experiment were included in print books with little to no digital presence and manually digitized/transcribed by our team.

| model | Sonnet | | | Limerick | | | Haiku | | | Ballad | | |
|---------|---------|-----------|--------|------------|-----------|--------|---------|-----------|--------|--------|-----------|--------|
| | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall |
| GPT-3.5 | 0.91 | 0.92 | 0.91 | 1.00 | 1.00 | 1.00 | 0.89 | 0.90 | 0.88 | 0.78 | 0.82 | 0.75 |
| GPT-4 | 0.94 | 0.98 | 0.90 | 0.89 | 0.80 | 1.00 | 1.00 | 1.00 | 1.00 | 0.87 | 0.85 | 0.89 |
| GPT-4o | 0.94 | 0.99 | 0.89 | 1.00 | 1.00 | 1.00 | 0.90 | 0.96 | 0.84 | 0.90 | 0.93 | 0.88 |
| Claude | 0.94 | 0.94 | 0.95 | 0.80 | 0.67 | 1.00 | 0.93 | 1.00 | 0.88 | 0.79 | 0.98 | 0.67 |
| Mixtral | 0.92 | 0.95 | 0.88 | 0.89 | 0.80 | 1.00 | 0.84 | 0.96 | 0.75 | 0.76 | 0.73 | 0.79 |
| Llama3 | 0.74 | 1.00 | 0.58 | 0.67 | 0.50 | 1.00 | 0.84 | 0.96 | 0.75 | 0.49 | 0.35 | 0.82 |
| model | Sestina | | | Villanelle | | | Pantoum | | | Ghazal | | |
| | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall | f1 | precision | recall |
| GPT-3.5 | 0.08 | 1.00 | 0.04 | 0.65 | 0.49 | 0.94 | 0.33 | 0.75 | 0.21 | 0.47 | 0.40 | 0.57 |
| GPT-4 | 0.84 | 0.84 | 0.84 | 0.91 | 0.97 | 0.85 | 0.80 | 0.67 | 1.00 | 0.68 | 0.53 | 0.95 |
| GPT-4o | 0.77 | 0.69 | 0.88 | 0.93 | 0.89 | 0.97 | 0.82 | 0.70 | 1.00 | 0.50 | 0.35 | 0.90 |
| Claude | 0.38 | 0.30 | 0.52 | 0.56 | 0.54 | 0.59 | 0.59 | 0.62 | 0.57 | 0.49 | 0.50 | 0.48 |
| Mixtral | 0.21 | 1.00 | 0.12 | 0.79 | 0.96 | 0.68 | 0.67 | 0.55 | 0.86 | 0.64 | 0.58 | 0.71 |
| Llama3 | 0.14 | 0.67 | 0.08 | 0.31 | 0.19 | 0.88 | 0.59 | 0.44 | 0.86 | 0.25 | 0.36 | 0.19 |

Table 8: **For poems not found in Dolma.** LLM performance by model for the **formal elements**, where the prompt includes only the poem text.

A.4 Formative Study Results

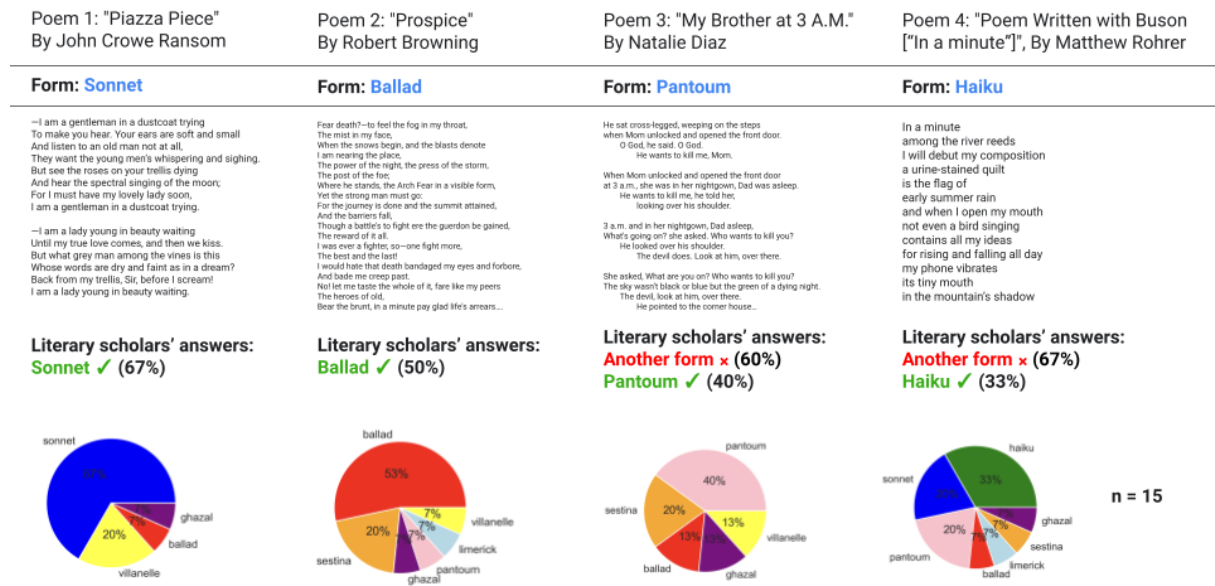


Figure 8: Results from formative study with human experts.

1025 A.5 Example Prompt and LLM Response

1026 Example Prompt:

1027 *Read the following poem and then respond with the form of the poem based on the following*
 1028 *verse forms: ['sonnet', 'ballad', 'villanelle', 'haiku', 'ghazal', 'sestina', 'pantoum', 'limerick'].*
 1029 *All of the poems have been tagged by experts as one of these forms. You must pick one of these*
 1030 *options.*

1031 *Please also provide an elaborated rationale for why you think the poem is in this form, a*
 1032 *one-word summary rationale, and a score ranking your confidence in your answer from 0 to 1.*
 1033 *Please report the single poetic form, elaborated rationale, one-word rationale, and multiple*
 1034 *forms in the following format.*

- 1035 1. Poetic Form: *Ballad*
 1036 2. Elaborated Rationale: *This poem is a ballad because...*
 1037 3. One-Word Summary: *Meter*
 1038 4. Confidence Score : *0.91*

- 1039 1. Poetic Form: *Sonnet*
 1040 2. Elaborated Rationale: *This poem is a sonnet because...*
 1041 3. One-Word Summary: *Meter*
 1042 4. Confidence Score : *0.73*

1043
 1044 *Poem Text (in full): There was an old man of Thermopylae,*
 1045 *Who never did anything properly;*
 1046 *But they said, "If you choose, To boil eggs in your shoes,*
 1047 *You shall never remain in Thermopylae."*

1048
 1049 *Pick ONE of these possible verse forms: ['sonnet', 'ballad', 'villanelle', 'haiku', 'ghazal',*
 1050 *'sestina', 'pantoum', 'limerick'].*

| | |
|--|--------------------------------------|
| Example Response (GPT-4): | 1051 |
| 1. <i>Poetic Form: Limerick</i> | 1052 |
| 2. <i>Elaborated Rationale: This poem is a limerick because it strictly follows the standard limerick rhyme scheme of AABBA. The poem begins with a character and a location (an old man of Thermopylae), and it proceeds in a humorous, light-hearted manner typical of limericks. The first two lines are longer, the next two lines are shorter, and the final line is longer again, also within the parameters of a limerick.</i> | 1053 1054 1055 1056 1057 |
| 3. <i>One-Word Summary: Rhyme</i> | 1058 |
| 4. <i>Confidence Score : 0.98</i> | 1059 1060 |
| | |
| A.6 Manually Digitized Print Poetry Sources | 1061 |
| John Barrell and John Bull. 1975. <i>A Book of English pastoral verse</i> . Oxford University Press, New York. | 1062 |
| Wilmon Brewer. 1937. <i>Sonnets and Sestinas</i> . Cornhill Publishing Co., Boston. | 1063 |
| Fred Cogswell. 1986. <i>Meditations: 50 Sestinas</i> . Ragweed Press. | 1064 |
| Clark Coolidge. 2012. <i>88 Sonnets</i> . Fence Books, Albany, NY. | 1065 |
| Dennis Daly. 2018. <i>Pantoums</i> . Dos Madres Press, Loveland, Ohio. | 1066 |
| Annie Finch, Marie-Elizabeth Mali, Annie Finch, and Julie Kane. 2012. <i>Villanelles</i> . Alfred A. Knopf, New York. | 1067 1068 |
| Sandra M. Gilbert. 2001. <i>Inventions of farewell: a book of elegies</i> . W.W. Norton Co., New York. | 1069 |
| Robert Graves. 1957. <i>English and Scottish ballads</i> . Heinemann, London. | 1070 |
| Scott Gutterman, editor. 2015. <i>Sunlight on the river: poems about paintings, paintings about poems</i> . Prestel, Munich. | 1071 1072 |
| Jim Kacian, Philip Rowland, and Allan Burns. 2013. <i>Haiku in English: the first hundred years</i> . W.W. Norton Company, New York. | 1073 1074 |
| G. Legman. 1969. <i>The Limerick: 1700 examples, with notes, variants, and index</i> . Bell Publishing Co., New York. | 1075 1076 |
| G. Legman. 1977. <i>The New Limerick: 2750 Unpublished Examples, American and British</i> . Crown Publishers. | 1077 1078 |
| Bob Raczka. 2016. <i>Wet cement: a mix of concrete poems</i> . Roaring Brook Press, New York. | 1079 |
| Cor Van den Heuvel. 1986. <i>The haiku anthology: haiku and senryu in English</i> . Simon Schuster, New York. | 1080 1081 |
| Joseph Warton. 1977. <i>Odes on various subjects (1746)</i> . Scholars' Facsimiles Reprints, Delmar, N.Y. | 1082 |
| Eugene Wildman. 1967. <i>The Chicago review anthology of concretism</i> . Swallow Press, Chicago. | 1083 |
| Emmett Williams and Something Else Press. 1967. <i>An anthology of concrete poetry</i> . Something Else Press, New York. | 1084 1085 |
| Seishi Yamaguchi and Sono Uchida. 1993. <i>The essence of modern haiku: 300 poems</i> . Mangajin, Inc., Atlanta, Georgia. | 1086 1087 |
| Kevin Young. 2010. <i>The art of losing: poems of grief and healing</i> . Bloomsbury USA, New York. | 1088 |
| Thomas Perrin Harrison. 1968. <i>The pastoral elegy: an anthology</i> . Octagon Books. | 1089 |
| | |
| A.7 Memorization Prompt | 1090 |
| <i>What are the next five lines of the poem "<POEM_TITLE>" by <AUTHOR_NAME>?</i> | 1091 |
| <i>First Line: <FIRST_LINE></i> | 1092 |
| <i>Next Lines:</i> | 1093 |
| | |
| A.8 Poetic Forms | 1094 |
| Poetic forms can be defined and categorized in various ways. The definitions of forms and formal elements that we offer here are synthesized from information in glossaries of poetic terms available on the Poetry Foundation and Academy of American Poets websites as well as from widely used poetry resources by Strand and Boland (2000) , Greene and Cushman (2016) , and Preminger et al. (2015) . | 1095 1096 1097 1098 |

1099 **A.8.1 Fixed Forms**

1100 **Ballad:** a type of narrative poem with ties to music and oral performance. Traditional ballads often
1101 feature regular meter and stanzas. One conventional pattern is “common measure,” which consists of
1102 quatrains that rhyme ABCB and alternate iambic tetrameter and trimeter.

1103
1104 Example Ballad: from “[Barbara Allen](#)” (by Anonymous)

1105
1106 In Scarlet town, where I was born,
1107 There was a fair maid dwellin’,
1108 Made every youth cry Well-a-way!
1109 Her name was Barbara Allen.

1110
1111 All in the merry month of May,
1112 When green buds they were swellin’,
1113 Young Jemmy Grove on his death-bed lay,
1114 For love of Barbara Allen.

1115
1116 He sent his man in to her then,
1117 To the town where she was dwellin’;
1118 “O haste and come to my master dear,
1119 If your name be Barbara Allen...

1120
1121 **Ghazal:** Originally an Arabic verse form, ghazals consists of a series of couplets usually all ending in
1122 the same word. Poets may include their name in the final couplet.

1123
1124 Example Ghazal: from “[Where did the handsome beloved go?](#)” (by Jalal Al-Din Rumi, translated by
1125 Brad Gooch and Maryam Mortaz)

1126
1127 Where did the handsome beloved go?
1128 I wonder, where did that tall, shapely cypress tree go?

1129
1130 He spread his light among us like a candle.
1131 Where did he go? So strange, where did he go without me?

1132
1133 All day long my heart trembles like a leaf.
1134 All alone at midnight, where did that beloved go?

1135
1136 Go to the road, and ask any passing traveler —
1137 That soul-stirring companion, where did he go?

1138
1139 Go to the garden, and ask the gardener —
1140 That tall, shapely rose stem, where did he go?

1141
1142 Go to the rooftop, and ask the watchman —
1143 That unique sultan, where did he go?

1144
1145 **Haiku:** Originating in Japan, haiku are concise, non-narrative poems that often focus on imagery. In
1146 English, haiku often consist of three unrhymed lines with 5, 7, and 5 syllables respectively.

1147
1148 Example Haiku: “[In Kyoto](#)” (by Bashō, translated by Jane Hirshfield)

| | |
|---|------|
| In Kyoto, | 1150 |
| hearing the cuckoo, | 1151 |
| I long for Kyoto. | 1152 |
| | 1153 |
| Limerick: a light, often comedic verse form consisting of five lines rhymed AABBA. In traditional limericks, lines 1, 2, and 5 are trimeter, while lines 3 and 4 are dimeter, and the dominant meter is anapestic. | 1154 |
| | 1155 |
| | 1156 |
| Example Limerick: “ A Young Lady of Lynn ” (by Anonymous) | 1157 |
| | 1158 |
| There was a young lady of Lynn, | 1159 |
| Who was so uncommonly thin | 1160 |
| That when she essayed | 1161 |
| To drink lemonade | 1162 |
| She slipped through the straw and fell in. | 1163 |
| | 1164 |
| Pantoum: A Malaysian verse form that was adapted into French and later English, which consists of a series of quatrains in which the second and fourth lines of each quatrain serve as the first and third lines of the next quatrain. Pantoums do not have a determined length. | 1165 |
| | 1166 |
| | 1167 |
| | 1168 |
| Example Pantoum: from “ Nocturne ” (by Sadakichi Hartmann) | 1169 |
| | 1170 |
| Upon the silent sea-swept land | 1171 |
| The dreams of night fall soft and gray, | 1172 |
| The waves fade on the jeweled sand | 1173 |
| Like some lost hope of yesterday. | 1174 |
| | 1175 |
| The dreams of night fall soft and gray | 1176 |
| Upon the summer-colored seas, | 1177 |
| Like some lost hope of yesterday, | 1178 |
| The sea-mew’s song is on the breeze. | 1179 |
| | 1180 |
| Upon the summer-colored seas | 1181 |
| Sails gleam and glimmer ghostly white, | 1182 |
| The sea-mew’s song is on the breeze | 1183 |
| Lost in the monotone of night. | 1184 |
| | 1185 |
| Sails gleam and glimmer ghostly white, | 1186 |
| They come and slowly drift away, | 1187 |
| Lost in the monotone of night, | 1188 |
| Like visions of a summer-day. | 1189 |
| | 1190 |
| They shift and slowly drift away | 1191 |
| Like lovers’ lays that wax and wane, | 1192 |
| The visions of a summer-day | 1193 |
| Whose dreams we ne’er will dream again. | 1194 |
| | 1195 |
| Sestina: A complex verse form consisting of six, unrhymed, six-line stanzas followed by a three-line envoi. Each sestet includes the same six endwords in shifting, but specific patterns (below), and all six | 1196 |
| | 1197 |

1198 endwords also appear in the envoi. Endword pattern:
1199

1200 1: ABCDEF

1201 2: FAEBDC

1202 3: CFDABE

1203 4: ECBFAD

1204 5: DEACFB

1205 6: BDFECA

1206 envoi : ECA or ACE
1207

1208 Example Sestina: from “[Sestina: Altaforte](#)” (by Ezra Pound)
1209

1210 I

1211 Damn it all! all this our South stinks peace.

1212 You whoreson dog, Papiols, come! Let’s to music!

1213 I have no life save when the swords clash.

1214 But ah! when I see the standards gold, vair, purple, opposing

1215 And the broad fields beneath them turn crimson,

1216 Then howl I my heart nigh mad with rejoicing.
1217

1218 II

1219 In hot summer have I great rejoicing

1220 When the tempests kill the earth’s foul peace,

1221 And the lightnings from black heav’n flash crimson,

1222 And the fierce thunders roar me their music

1223 And the winds shriek through the clouds mad, opposing,

1224 And through all the riven skies God’s swords clash.
1225

1226 III

1227 Hell grant soon we hear again the swords clash!

1228 And the shrill neighs of destriers in battle rejoicing,

1229 Spiked breast to spiked breast opposing!

1230 Better one hour’s stour than a year’s peace

1231 With fat boards, bawds, wine and frail music!

1232 Bah! there’s no wine like the blood’s crimson!
1233

1234 IV

1235 And I love to see the sun rise blood-crimson.

1236 And I watch his spears through the dark clash

1237 And it fills all my heart with rejoicing

1238 And pries wide my mouth with fast music

1239 When I see him so scorn and defy peace,

1240 His lone might ’gainst all darkness opposing.
1241

1242 V

1243 The man who fears war and squats opposing

1244 My words for stour, hath no blood of crimson

1245 But is fit only to rot in womanish peace

1246 Far from where worth’s won and the swords clash

1247 For the death of such sluts I go rejoicing;

Yea, I fill all the air with my music. 1248

VI 1249

Papiols, Papiols, to the music! 1250

There's no sound like to swords swords opposing, 1251

No cry like the battle's rejoicing 1252

When our elbows and swords drip the crimson 1253

And our charges 'gainst "The Leopard's" rush clash. 1254

May God damn for ever all who cry "Peace!" 1255

VII 1256

And let the music of the swords make them crimson! 1257

Hell grant soon we hear again the swords clash! 1258

Hell blot black for always the thought "Peace!" 1259

Sonnet: A fourteen-line verse form, usually in iambic pentameter, and usually following a set rhyme 1260

scheme. The most common types of sonnets are Shakespearean/English, which consist of three quatrains 1261

followed by a couplet and often rhyme ABABCDCDEFEGG, and Petrarchan/Italian, which consists of 1262

an octave followed by a sestet and often rhyme ABBAABBACDCDCD or ABBAABBACDECDE. 1263

Example Petrarchan sonnet: "When I consider how my light is spent" (John Milton) 1264

When I consider how my light is spent, 1265

Ere half my days, in this dark world and wide, 1266

And that one Talent which is death to hide 1267

Lodged with me useless, though my Soul more bent 1268

To serve therewith my Maker, and present 1269

My true account, lest he returning chide; 1270

"Doth God exact day-labour, light denied?" 1271

I fondly ask. But patience, to prevent 1272

That murmur, soon replies, "God doth not need 1273

Either man's work or his own gifts; who best 1274

Bear his mild yoke, they serve him best. His state 1275

Is Kingly. Thousands at his bidding speed 1276

And post o'er Land and Ocean without rest: 1277

They also serve who only stand and wait." 1278

Example Shakespearean Sonnet: "America" (Claude McKay) 1279

Although she feeds me bread of bitterness, 1280

And sinks into my throat her tiger's tooth, 1281

Stealing my breath of life, I will confess 1282

I love this cultured hell that tests my youth. 1283

Her vigor flows like tides into my blood, 1284

Giving me strength erect against her hate, 1285

Her bigness sweeps my being like a flood. 1286

Yet, as a rebel fronts a king in state, 1287

I stand within her walls with not a shred 1288

Of terror, malice, not a word of jeer. 1289

Darkly I gaze into the days ahead, 1290

And see her might and granite wonders there, 1291

Beneath the touch of Time's unerring hand, 1292

1300 Like priceless treasures sinking in the sand.
1301

1302 **Villanelle:** A 19-line verse form originating in France, made up of five tercets followed by a
1303 quatrain, in which the first and third line of the first stanza are alternately repeated as a refrain in
1304 the following stanzas. Stanza 1 line 1 repeats as the third line of stanzas 2 and 4, and stanza 1 line
1305 3 repeats as the third line of stanzas 3 and 5. These two lines also appear as the closing lines of the quatrain.
1306

1307 Example Villanelle: “Do not go gentle into that good night” (Dylan Thomas)
1308

1309 Do not go gentle into that good night,
1310 Old age should burn and rave at close of day;
1311 Rage, rage against the dying of the light.
1312

1313 Though wise men at their end know dark is right,
1314 Because their words had forked no lightning they
1315 Do not go gentle into that good night.
1316

1317 Good men, the last wave by, crying how bright
1318 Their frail deeds might have danced in a green bay,
1319 Rage, rage against the dying of the light.
1320

1321 Wild men who caught and sang the sun in flight,
1322 And learn, too late, they grieved it on its way,
1323 Do not go gentle into that good night.
1324

1325 Grave men, near death, who see with blinding sight
1326 Blind eyes could blaze like meteors and be gay,
1327 Rage, rage against the dying of the light.
1328

1329 And you, my father, there on the sad height,
1330 Curse, bless, me now with your fierce tears, I pray.
1331 Do not go gentle into that good night.
1332 Rage, rage against the dying of the light.
1333

1334 A.8.2 Stanza Forms

1335 **Couplet:** a two-line stanza or two lines of verse, often but not always rhymed.
1336

1337 Example Couplets: “Interview” by Dorothy Parker
1338

1339 The ladies men admire, I’ve heard,
1340 Would shudder at a wicked word.
1341 Their candle gives a single light;
1342 They’d rather stay at home at night.
1343 They do not keep awake till three,
1344 Nor read erotic poetry.
1345 They never sanction the impure,
1346 Nor recognize an overture.
1347 They shrink from powders and from paints ...
1348 So far, I’ve had no complaints.
1349

| | |
|--|------|
| Tercet: a three-line stanza or three lines of verse, often but not always containing a rhyme. | 1350 |
| | 1351 |
| Example Tercets: from “ The Convergence of the Twain ” (Thomas Hardy) | 1352 |
| | 1353 |
| (<i>Lines on the loss of the “Titanic”</i>) | 1354 |
| | 1355 |
| I | 1356 |
| In a solitude of the sea | 1357 |
| Deep from human vanity, | 1358 |
| And the Pride of Life that planned her, stilly couches she. | 1359 |
| | 1360 |
| II | 1361 |
| Steel chambers, late the pyres | 1362 |
| Of her salamandrine fires, | 1363 |
| Cold currents thrid, and turn to rhythmic tidal lyres. | 1364 |
| | 1365 |
| III | 1366 |
| Over the mirrors meant | 1367 |
| To glass the opulent | 1368 |
| The sea-worm crawls — grotesque, slimed, dumb, indifferent. | 1369 |
| | 1370 |
| IV | 1371 |
| Jewels in joy designed | 1372 |
| To ravish the sensuous mind | 1373 |
| Lie lightless, all their sparkles bleared and black and blind. | 1374 |
| | 1375 |
| V | 1376 |
| Dim moon-eyed fishes near | 1377 |
| Gaze at the gilded gear | 1378 |
| And query: “What does this vaingloriousness down here?” ... | 1379 |
| | 1380 |
| Quatrain: a four-line stanza or unit of verse, often, but not always containing rhyme. | 1381 |
| | 1382 |
| Example Quatrains: from “ Elegy Written in a Country Churchyard ” (Thomas Gray) | 1383 |
| | 1384 |
| The curfew tolls the knell of parting day, | 1385 |
| The lowing herd wind slowly o’er the lea, | 1386 |
| The plowman homeward plods his weary way, | 1387 |
| And leaves the world to darkness and to me. | 1388 |
| | 1389 |
| Now fades the glimm’ring landscape on the sight, | 1390 |
| And all the air a solemn stillness holds, | 1391 |
| Save where the beetle wheels his droning flight, | 1392 |
| And drowsy tinklings lull the distant folds; ... | 1393 |
| | 1394 |
| A.8.3 Meters | 1395 |
| Free Verse: verse that does not follow a particular pattern of meter or rhyme. | 1396 |
| | 1397 |

1398 Example Free Verse: from “[The Waste Land](#)” (T.S. Eliot)

1399
1400 April is the cruellest month, breeding
1401 Lilacs out of the dead land, mixing
1402 Memory and desire, stirring
1403 Dull roots with spring rain.
1404 Winter kept us warm, covering
1405 Earth in forgetful snow, feeding
1406 A little life with dried tubers.
1407 Summer surprised us, coming over the Starnbergersee
1408 With a shower of rain; we stopped in the colonnade,
1409 And went on in sunlight, into the Hofgarten,
1410 And drank coffee, and talked for an hour.
1411 Bin gar keine Russin, stamm’ aus Litauen, echt deutsch.
1412 And when we were children, staying at the archduke’s,
1413 My cousin’s, he took me out on a sled,
1414 And I was frightened. He said, Marie,
1415 Marie, hold on tight. And down we went.
1416 In the mountains, there you feel free.
1417 I read, much of the night, and go south in the winter. ...

1418
1419 **Blank Verse:** Unrhymed iambic pentameter.

1420
1421 Example Blank Verse: from [Paradise Lost](#) (John Milton)

1422
1423 Of Mans First Disobedience, and the Fruit
1424 Of that Forbidden Tree, whose mortal tast
1425 Brought Death into the World, and all our woe,
1426 With loss of Eden, till one greater Man
1427 Restore us, and regain the blissful Seat,
1428 Sing Heav’nly Muse, that on the secret top
1429 Of Oreb, or of Sinai, didst inspire
1430 That Shepherd, who first taught the chosen Seed,
1431 In the Beginning how the Heav’ns and Earth
1432 Rose out of Chaos: or if Sion Hill
1433 Delight thee more, and Siloa’s brook that flow’d
1434 Fast by the Oracle of God; I thence
1435 Invoke thy aid to my adventrous Song,
1436 That with no middle flight intends to soar
1437 Above th’ Aonian Mount, while it pursues
1438 Things unattempted yet in Prose or Rhime.

1439
1440 **Common Measure** : quatrains consisting of alternating lines of iambic tetrameter and trimeter, rhymed
1441 ABAB.

1442
1443 Example Common Measure: from “[It was not death for I stood up](#)” (Emily Dickinson)

1444
1445 It was not Death, for I stood up,
1446 And all the Dead, lie down -
1447 It was not Night, for all the Bells
1448 Put out their Tongues, for Noon.

| | |
|---|------|
| | 1449 |
| It was not Frost, for on my Flesh | 1450 |
| I felt Siroccos - crawl - | 1451 |
| Nor Fire - for just my marble feet | 1452 |
| Could keep a Chancel, cool - | 1453 |
| | 1454 |
| And yet, it tasted, like them all, | 1455 |
| The Figures I have seen | 1456 |
| Set orderly, for Burial | 1457 |
| Reminded me, of mine - ... | 1458 |
| | 1459 |
| A.8.4 Unfixed forms | 1460 |
| Ode: a formal lyric poem, which addresses or celebrates a person, place, object, or concept, usually that is not present. Odes are often longer verse forms, and their stanza patterns vary. | 1461 |
| | 1462 |
| | 1463 |
| Example Ode: from “ Ode on a Grecian Urn ” (John Keats) | 1464 |
| | 1465 |
| Thou still unravish’d bride of quietness, | 1466 |
| Thou foster-child of silence and slow time, | 1467 |
| Sylvan historian, who canst thus express | 1468 |
| A flowery tale more sweetly than our rhyme: | 1469 |
| What leaf-fring’d legend haunts about thy shape | 1470 |
| Of deities or mortals, or of both, | 1471 |
| In Tempe or the dales of Arcady? | 1472 |
| What men or gods are these? What maidens loth? | 1473 |
| What mad pursuit? What struggle to escape? | 1474 |
| What pipes and timbrels? What wild ecstasy? | 1475 |
| | 1476 |
| Heard melodies are sweet, but those unheard | 1477 |
| Are sweeter; therefore, ye soft pipes, play on; | 1478 |
| Not to the sensual ear, but, more endear’d, | 1479 |
| Pipe to the spirit ditties of no tone: | 1480 |
| Fair youth, beneath the trees, thou canst not leave | 1481 |
| Thy song, nor ever can those trees be bare; | 1482 |
| Bold Lover, never, never canst thou kiss, | 1483 |
| Though winning near the goal yet, do not grieve; | 1484 |
| She cannot fade, though thou hast not thy bliss, | 1485 |
| For ever wilt thou love, and she be fair! | 1486 |
| | 1487 |
| Pastoral: a type of poetry and a broader creative tradition idealizing rural life. | 1488 |
| | 1489 |
| Example Pastoral: “ The Passionate Shepherd to His Love ” (Christopher Marlowe) | 1490 |
| | 1491 |
| Come live with me and be my love, | 1492 |
| And we will all the pleasures prove, | 1493 |
| That Valleys, groves, hills, and fields, | 1494 |
| Woods, or steepy mountain yields. | 1495 |
| | 1496 |
| And we will sit upon the Rocks, | 1497 |
| Seeing the Shepherds feed their flocks, | 1498 |

1499 By shallow Rivers to whose falls
1500 Melodious birds sing Madrigals.
1501
1502 And I will make thee beds of Roses
1503 And a thousand fragrant posies,
1504 A cap of flowers, and a kirtle
1505 Embroidered all with leaves of Myrtle;
1506

1507 A gown made of the finest wool
1508 Which from our pretty Lambs we pull;
1509 Fair lined slippers for the cold,
1510 With buckles of the purest gold;
1511

1512 A belt of straw and Ivy buds,
1513 With Coral clasps and Amber studs:
1514 And if these pleasures may thee move,
1515 Come live with me, and be my love.
1516

1517 The Shepherds' Swains shall dance and sing
1518 For thy delight each May-morning:
1519 If these delights thy mind may move,
1520 Then live with me, and be my love.
1521

1522 **Aubade:** A poem or song welcoming or lamenting the arrival of dawn, usually with romantic themes.

1523
1524 Example Aubade: "[Break of Day](#)" (John Donne)

1525
1526 'Tis true, 'tis day, what though it be?
1527 O wilt thou therefore rise from me?
1528 Why should we rise because 'tis light?
1529 Did we lie down because 'twas night?
1530 Love, which in spite of darkness brought us hither,
1531 Should in despite of light keep us together.
1532

1533 Light hath no tongue, but is all eye;
1534 If it could speak as well as spy,
1535 This were the worst that it could say,
1536 That being well I fain would stay,
1537 And that I loved my heart and honour so,
1538 That I would not from him, that had them, go.
1539

1540 Must business thee from hence remove?
1541 Oh, that's the worst disease of love,
1542 The poor, the foul, the false, love can
1543 Admit, but not the busied man.
1544 He which hath business, and makes love, doth do
1545 Such wrong, as when a married man doth woo.
1546

1547 **Dramatic Monologue:** a poem in which a usually fictional speaker addresses a listener, who is also
1548 often imagined.

| | |
|---|------|
| Example Dramatic Monologue: from “ My Last Duchess ” (Robert Browning) | 1549 |
| | 1550 |
| | 1551 |
| That’s my last Duchess painted on the wall, | 1552 |
| Looking as if she were alive. I call | 1553 |
| That piece a wonder, now; Fra Pandolf’s hands | 1554 |
| Worked busily a day, and there she stands. | 1555 |
| Will’t please you sit and look at her? I said | 1556 |
| “Fra Pandolf” by design, for never read | 1557 |
| Strangers like you that pictured countenance, | 1558 |
| The depth and passion of its earnest glance, | 1559 |
| But to myself they turned (since none puts by | 1560 |
| The curtain I have drawn for you, but I) | 1561 |
| And seemed as they would ask me, if they durst, | 1562 |
| How such a glance came there; so, not the first | 1563 |
| Are you to turn and ask thus. Sir, ’twas not | 1564 |
| Her husband’s presence only, called that spot | 1565 |
| Of joy into the Duchess’ cheek; perhaps | 1566 |
| Fra Pandolf chanced to say, “Her mantle laps ... | 1567 |
| | 1568 |
| Elegy: a form of poetry and broader mode of writing expressing grief or loss, often in relation to its subject’s death. | 1569 |
| | 1570 |
| | 1571 |
| Example Elegy: from “ Lycidas ” (John Milton) | 1572 |
| | 1573 |
| | 1574 |
| Yet once more, O ye laurels, and once more | 1574 |
| Ye myrtles brown, with ivy never sere, | 1575 |
| I come to pluck your berries harsh and crude, | 1576 |
| And with forc’d fingers rude | 1577 |
| Shatter your leaves before the mellowing year. | 1578 |
| Bitter constraint and sad occasion dear | 1579 |
| Compels me to disturb your season due; | 1580 |
| For Lycidas is dead, dead ere his prime, | 1581 |
| Young Lycidas, and hath not left his peer. | 1582 |
| Who would not sing for Lycidas? he knew | 1583 |
| Himself to sing, and build the lofty rhyme. | 1584 |
| He must not float upon his wat’ry bier | 1585 |
| Unwept, and welter to the parching wind, | 1586 |
| Without the meed of some melodious tear. | 1587 |
| | 1588 |
| Concrete Poetry: a type of poetry that is structured by visual effect on the page, and often emphasizes nonlinguistic aspects of writing, including typography, layout, whitespace, etc. | 1589 |
| | 1590 |
| | 1591 |
| Example Concrete Poetry: “ Easter Wings ” (George Herbert) | 1592 |
| | 1593 |
| Lord, who createdst man in wealth and store, | 1594 |
| Though foolishly he lost the same, | 1595 |
| Decaying more and more, | 1596 |
| Till he became | 1597 |
| Most poore: | 1598 |
| With thee | 1599 |
| O let me rise | 1600 |

1601 As larks, harmoniously,
1602 And sing this day thy victories:
1603 Then shall the fall further the flight in me.
1604

1605 My tender age in sorrow did beginne
1606 And still with sicknesses and shame.
1607 Thou didst so punish sinne,
1608 That I became
1609 Most thinne.
1610 With thee
1611 Let me combine,
1612 And feel thy victorie:
1613 For, if I imp my wing on thine,
1614 Affliction shall advance the flight in me.
1615

1616 **Prose poem:** a poetic composition that is not broken up into lines.

1617
1618 Example Prose Poem: *Gitanjali*, 14 (by Rabindranath Tagore)

1619
1620 My desires are many and my cry is pitiful, but ever didst thou save me by hard refusals; and this strong
1621 mercy has been wrought into my life through and through.
1622

1623 Day by day thou art making me worthy of the simple, great gifts that thou gavest to me unasked—this
1624 sky and the light, this body and the life and the mind—saving me from perils of overmuch desire.
1625

1626 There are times when I languidly linger and times when I awaken and hurry in search of my goal; but
1627 cruelly thou hidest thyself from before me.
1628

1629 Day by day thou art making me worthy of thy full acceptance by refusing me ever and anon, saving me
1630 from perils of weak, uncertain desire.
1631

1632 **Ars Poetica:** a poem about poetry.

1633
1634 Example Ars Poetica: from “Poetry” (Marianne Moore)

1635
1636 I too, dislike it: there are things that are important beyond all this fiddle.
1637 Reading it, however, with a perfect contempt for it, one discovers that there is in
1638 it after all, a place for the genuine.
1639 Hands that can grasp, eyes
1640 that can dilate, hair that can rise
1641 if it must, these things are important not because a
1642

1643 high-sounding interpretation can be put upon them but because they are
1644 useful; when they become so derivative as to become unintelligible, the
1645 same thing may be said for all of us—that we
1646 do not admire what
1647 we cannot understand. The bat,
1648 holding on upside down or in quest of something to
1649

1650 eat, elephants pushing, a wild horse taking a roll, a tireless wolf under
1651 a tree, the immovable critic twinkling his skin like a horse that feels a flea, the base—
1652 ball fan, the statistician—case after case

| | |
|--|------|
| could be cited did | 1653 |
| one wish it; nor is it valid | 1654 |
| to discriminate against “business documents and | 1655 |
| | 1656 |
| school-books”; all these phenomena are important. One must make a distinction | 1657 |
| however: when dragged into prominence by half poets, the result is not poetry, | 1658 |
| nor till the autocrats among us can be | 1659 |
| “literalists of | 1660 |
| the imagination”—above | 1661 |
| insolence and triviality and can present | 1662 |
| | 1663 |
| for inspection, imaginary gardens with real toads in them, shall we have | 1664 |
| it. In the meantime, if you demand on the one hand, in defiance of their opinion— | 1665 |
| the raw material of poetry in | 1666 |
| all its rawness, and | 1667 |
| that which is on the other hand, | 1668 |
| genuine, then you are interested in poetry. | 1669 |
| | 1670 |
| Ekphrasis: writing that uses vivid language to respond to or describe a work of visual art. | 1671 |
| | 1672 |
| Example Ekphrasis: “ On Seeing the Elgin Marbles ” (John Keats) | 1673 |
| | 1674 |
| My spirit is too weak—mortality | 1675 |
| Weighs heavily on me like unwilling sleep, | 1676 |
| And each imagined pinnacle and steep | 1677 |
| Of godlike hardship tells me I must die | 1678 |
| Like a sick eagle looking at the sky. | 1679 |
| Yet ‘tis a gentle luxury to weep, | 1680 |
| That I have not the cloudy winds to keep, | 1681 |
| Fresh for the opening of the morning’s eye. | 1682 |
| Such dim-conceived glories of the brain | 1683 |
| Bring round the heart an indescribable feud; | 1684 |
| So do these wonders a most dizzy pain, | 1685 |
| That mingles Grecian grandeur with the rude | 1686 |
| Wasting of old Time—with a billowy main— | 1687 |
| A sun—a shadow of a magnitude. | 1688 |
| | 1689 |