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A Computational Approach to Style in American Poetry

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Abstract

We develop a quantitative method to assess the style of American poems and to visualize a collection of poems in relation to one another. Qualitative poetry criticism helped guide our development of metrics that analyze various orthographic, syntactic, and phonemic features. These features are used to discover comprehensive stylistic information from a poem's multi-layered latent structure, and to compute distances between poems in this space. Visualizations provide ready access to the analytical components. We demonstrate our method on several collections of poetry, showing that it better delineates poetry style than the traditional word-occurrence features that are used in typical text analysis algorithms. Our method has potential applications to academic research of texts, to research of the intuitive personal response to poetry, and to making recommendations to readers based on their favorite poems.

1 Introduction

There is considerable ongoing research in natural language processing to extract semantic content from prose texts. The more mystical (if less lucrative) realm of poetry, however, has gone largely unexplored. The meek tradition of quantitative poetry analysis, dating back at least 60 years to Josephine Miles's examination of frequent adjectives by hand [12], can profit from modern computational techniques. In particular, computers can give insight into the latent structures that together form a poem's style.

Here, we attempt to computationally capture a comprehensive scope of poetic style. Further, we aim to make the results of the analysis readily accessible through visualization of stylistic similarity among poems in a collection.

This method has many potential applications, such as: a personal recommendation system based on style; academic exploration of how particular poets differ from or influence one another; assessment of how different elements affect readers' intuitive perception of a poem's overall style; and how important style is compared to semantic content in overall reader preference.

To achieve these goals, we embed each poem in a vector space that was developed from an extensive survey of literary scholarship. We then use principal components analysis (PCA) to visualize collections. With many poetry collections, our method showed success in a variety of areas: differentiating poems from poets with different styles; verifying consistency within a single long poem; showing evidence of known mentoring relationships; and more. These results were taken from both the colorful visual projections and the statistical analysis of poem distances in the stylistic feature space.

In Section 2, we describe the approach that we took to map poems into a quantitative vector space and visualize them. Section 3 details analysis covering 81 poems by 18 poets, and a comparison to traditional vector-space models. Section 4 reviews the previous work from various fields of study that laid the foundation for this research. Section 5 provides further discussion and possibilities for the future.

2 A Vector Space for Poetry

Our first contribution is embedding poetry into a vector space for analysis. We focused on stylistic elements of poetry, foregoing semantic content. Our goal was to map any poem text to a multi-dimensional vector that accurately represents the poem's place in stylistic space.

Predominant approaches of modern text analysis focus on word occurrence [11, 1], which is not appropriate to our goals. Word occurrence is used primarily to determine semantic content, while we are concerned with style. Moreover, collapsing text into a "bag of words" loses the structural information that is critical to style. Diction per se can certainly have a stylistic element, for instance affecting the formality of tone by choosing the word "egregious" over "very bad," but poetic style mostly derives from relationships among words on multiple levels.

Instead, we identified different features that comprise a poem's style and subsequently implemented them as com-

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putational functions of the text. The computation of these metrics maps the poem text to a high-dimensional vector, with the computed value of each metric providing the coordinate location in the corresponding dimension: where $f_i(p)$ for $(1 \leq i \leq N)$ are the metrics taking text p as input and producing scalar values, $p \mapsto (f_1, f_2, \ldots, f_N)$.

2.1 Features of style

A mix of ideas from the existing literature of poetry criticism and personal intuition informed our decisions regarding which features to consider. In total, we had 84 metric dimensions available, each falling under one of the features discussed here. Features are divided into three categories: orthographic, based on the letters or words as written (without higher-level interpretation); syntactic, based on word function; and phonemic, based on sound.

Orthographic Our orthographic features were motivated by intuition and Miles's statement, "The poetic line is the unit of measure" [12]. The primary features that we analyze are word count, number of lines, number of stanzas, average line length (in words), average word length, and average number of lines per stanza. We also calculate the frequencies of the most frequent noun, adjective, and verb (respectively) in each poem as proxies for repetition.

Syntactic The frequencies of parts of speech (POS) reflect a poet's mode of discourse. Miles [14] examined the adjective-noun-verb-connective (A-N-V-C) ratio for notable English-language poets. Miles [13] also examined phrasal versus clausal type, a distinction partly manifested in POS frequencies: phrasal type has an "abundance of adjectives and nouns, in heavy modifications and compounding of subjects, in a variety of phrasal constructions, including verbs turned to participles," while clausal type has more "relative and adverbial clauses, action [i.e., tensed verbs]." Miles also discussed the dichotomy of "adjectival" versus "predicative" style, where predicative manifests itself in "the dominance of verb over adjective" [14].

Heylighen and Dewale [6] found that POS frequencies reflect the level of formality in different languages including English. Biber [2] cites contractions as reflecting formality, stating, "contractions and first and second person pronouns share a colloquial, informal flavor."

We include both frequencies of contractions and of parts of speech aggregated to different levels of specificity, e.g. pronoun as well as first person singular pronoun.

Phonemic Sound is vital to the experience of a poem. Miles [12] wrote, "All patterns of repetition in sound [including] assonance... provide indeed some basis in the poetic material." Repetition is useful in poetry especially with sound, and the major poetic sound devices are all analyzed.

Rhyme is the most well-known feature of poetry, prominent in nursery rhymes that children hear growing up. Much modern poetry, though, abandons a formal rhyme scheme, if not rhyme altogether. This actually increases the potential explanatory power of rhyme frequency since its use is voluntary and subsequently more varied by poet. There are different types of end rhyme, too, which we define as: identity rhyme, identical phoneme sequences; perfect rhyme, the same phoneme sequence from the ultimate stressed vowel onward, but differing in the preceding consonant; semirhyme, a perfect rhyme where one word has an additional syllable at the end, such as "stick" and "picket"; and slant rhyme, either identical ultimate stressed vowels or phoneme sequences following the ultimate stressed vowel, but not both. All four types of rhyme and certain combinations thereof are considered as features.

The next most prominent sound devices used in poetry are alliteration (repetition of consonant sounds beginning words), assonance (repetition of vowel sounds), and consonance (repetition of consonant sounds), all of which are features that we compute.

2.2 Computation of metrics

We implemented each of the features above as a computational metric, mapping each poem text into a feature vector, as described above. We set weights for each metric by which the raw value is multiplied, with a setting of zero effectively turning off the metric. Thus we could cause certain metrics to contribute relatively more towards the total stylistic distance between poems, either to reflect a personal sense of the relative importance of metrics or to focus on specific features of style.

To determine parts of speech, we used a rule-based POS tagger based on [5]. It was acquired already trained (on a *Wall Street Journal* corpus). While POS tagging is an area for improvement, our comparison of the tagger's results with manual tagging of a few real poems showed enough accuracy to produce meaningful results. We used the CMU Pronouncing Dictionary for North American English to translate words into phoneme sequences for analysis of sound devices.

2.3 Visualization with PCA

The high-dimensional poem vectors are projected onto two dimensions to present as accurate a depiction of relative poem similarity as possible. We used PCA, which reduces dimensionality while preserving the greatest variance in the data. The complexity of PCA is determined by the singular value decomposition (SVD). It took 5.7 minutes to run SVD with 50,000 poems and 11.3 minutes for 100,000 poems; a more realistically sized sample of 80 poems took under 0.05 seconds. All runs were performed on a 1.80GHz Pentium 4 with 512MB RAM. Presentational accuracy decreases with more poems; a calculation of "stress," or reconstruction error, is available to indicate the overall correctness of the visualization.

3 Results

In this section, we describe our analyses of poems by prominent American poets covering a variety of periods and styles.[1] The poets were selected from several sources, including the *Oxford Anthology of Modern American Poetry* [15] and Wikipedia [16].

We set the weights trying to ensure that no individual metric(s) drowned out the explanatory power of the others. This was admittedly ad hoc, and can be improved/automated in the future. We used the same weights for all analyses.

3.1 Feature analysis

To give a better sense of the full computational process, we provide below excerpts from three poems along with their computed values for a few salient feature metrics: frequencies of perfect end rhyme, first person singular pronouns, and coordinating conjunctions. These feature values reflect the poems' overall relationships, which are in turn reflected in the visualization.

First, the opening five lines of the famous "The Road Not Taken" by Robert Frost are: "Two roads diverged in a yellow wood, / And sorry I could not travel both / And be one traveler, long I stood / And looked down one as far as I could / To where it bent in the undergrowth." Here, the perfect end rhyme of wood/stood/could and both/growth figures prominently. Frost rhymes not only pairs of lines but triplets; he follows this *abaab* rhyme scheme throughout the 20-line poem. The first person perspective is also noteworthy; these are not objective descriptions but subjective musings. That three lines begin with "And" is perhaps the first feature noticed by a quick glance; this use of coordinating conjunctions continues through the poem.

Second, the opening two stanzas of Louise Gluck's more modern "Parable of Faith" are: "Now, in twilight, on the palace steps / the king asks forgiveness of his lady. / / He is not / duplicitous; he has tried to be / true to the moment; is there another way of being / true to the self?" In contrast to Frost, Gluck has no formal rhyme scheme. Also unlike Frost, Gluck writes in third person (appropriate for a "Parable"). Finally, there are no conjunctions here.

[1]The full source and data are freely available from the first author for non-commercial use.

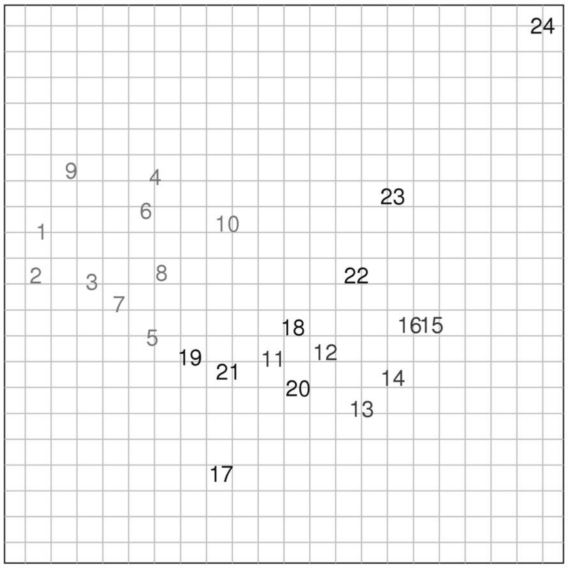
Third, the closing sestet of a sonnet by Edna St. Vincent Millay, entitled "Love Is Not All," is: "It well may be that in a difficult hour, / Pinned down by pain and moaning for release, / Or nagged by want past resolution's power, / I might be driven to sell your love for peace, / Or trade the memory of this night for food. / It well may be. I do not think I would." Millay's work is between Frost's and Gluck's. She follows the traditional English sonnet form, yielding plenty of perfect end rhymes, though only two lines per rhyme to Frost's three (or two), and the final couplet has a slant rhyme instead; her poem's perfect rhyme metric value is 0.139, to Frost's 0.278 and Gluck's zero. Although not shown by the excerpt, Millay's opening octave is (traditionally) an objective setup of the suggestion that "Love Is Not All." While she comes around to a first person statement in the final twist, this is balanced by a complete lack of first person in the preceding lines; her first person pronoun metric value is 0.032, to Frost's 0.063 and Gluck's zero. Millay's poem flows differently than Gluck's, partly from extensive use of coordinating conjunctions and partly from the sonnet's iambic meter, which Frost uses less strictly. Millay's coordinating conjunction metric value is 0.104 and Frost's 0.063, against Gluck's zero.

PCA places Millay's poem about in between Frost's and Gluck's; see Fig. 2 (Frost's is 6, Millay's 37, and Gluck's 43). This reflects their overall computed distances: Frost and Gluck are the farthest apart, at 234.6, while Millay is almost equidistant from both, 182.9 from Frost and 178.5 from Gluck.

3.2 Sample analysis

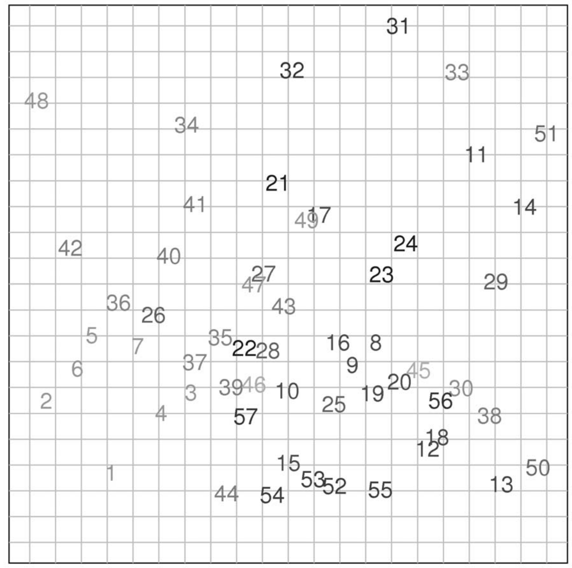
We compared selected poems from Robert Frost's *North of Boston* (1915), poems written by Marianne Moore, and selections from Frank O'Hara's famous *Lunch Poems* (1964). As the plot shows (Fig. 1), our method identifies a division between the styles of these poets and represents this difference visually. O'Hara's work lies "in between" Frost's and Moore's; or, at least, O'Hara's poems are more similar to Frost's and Moore's, respectively, than are Frost's and Moore's to each other. From the plot, O'Hara's "Song (Is it dirty)" (24) appears to be an outlier; this is supported by the computed values.

While using a limited number of poets simplifies the relationships present in the data and tends to result in more accurate visualization, using a larger number of poets still yields significant results. The works of 16 poets from the *Oxford Anthology of Modern American Poetry* [15] (plus Tracy K. Smith) yielded Fig. 2. As expected, the accuracy of the visualization drops (the display "stress" increases by 50%), but much clustering can still be seen. For instance, the Robert Frost poems (1-7) are grouped in the lower-left area; Louise Gluck's three "Circe" poems (40-42) lie in



Legend: 1-10, Moore; 11-16, Frost; 17-24, O'Hara.

Figure 1. Similarity among poems from Moore, Frost, and O'Hara



Legend: 1-7, Frost; 8-10, Whitman; 11-14, Williams; 15-20, Stevens; 21-24, Sexton; 25-29, Plath; 30, Pinsky; 31-32, Pound; 33-37, Millay; 38, Ginsberg; 39-44, Gluck; 45-46, Eliot; 47-49, Dickinson; 50-51, Cummings; 52-55, Bishop; 56-57, Smith.

Figure 2. Similarity among poems from the *Oxford Anthology of Modern American Poetry*.

the area above Frost; Walt Whitman's three poems (8-10) sit slightly below and right of center; and the four poems from Elizabeth Bishop (52-55) are adjacent in the middle of the bottom edge of the screen. From the true, higher-dimensional distance data, we constructed a chart (Fig. 3) showing the observed degree of clustering by poet. The first data series (white columns) shows the mean "self-distance" for each poet and in aggregate, calculated by taking the mean of the Euclidean distances of all poem pairs for a given poet. The second data series (gray columns) shows the mean "inter-poet" distance for each poet and in aggregate. Here, all pairs containing one and only one poem of a poet are considered when calculating mean distance. All poets (and the aggregate) showed smaller mean intra-poet distances than inter-poet distances. The short length of both Dickinson's and Williams's poems may account for their high variance. From the visualization and the statistical analysis, Elizabeth Bishop, Robert Frost, and Walt Whitman seem to have the most consistent styles. The chart shows values normalized by a scalar factor, such that mean aggregate inter-poet distance is 1, and standard error of the mean error bars.

3.3 Comparison with word occurrence

As a quantitative gauge of performance, we implemented a bag of words cosine distance algorithm using term frequency (TF) and inverse document frequency (IDF) weights [1]. A bag of words approach, though not stylistically oriented, provides a modern standard for document similarity. We applied it to the two sets of poetry analyzed above plus a set of only Moore and Frost, once with just TF weights and once with TF and IDF for each set. While our method calculates a lower intra-poet than inter-poet distance for every poet, the bag of words approach does not; when it does, our method usually reports a more statistically significant differential.

For the following two examples, we examined the difference of inter- and intra-poet distance. To compare fairly, we scaled this value by the standard error of the mean for the inter-poet distance (per poet). Thus, an algorithm—primarily TF-IDF is affected—is not penalized for producing more similar absolute values if the differentials are just as statistically significant. The second example shows aggregates across all poets within the selections indicated, normalized the same way. In both cases, bigger bars indicate more ability to differentiate style by poet.

Comparing performance by poet in the *Oxford Anthology* selection of poems (Fig. 4 Left), there are a few instances where the bag of words algorithm ("TF" or "TF-IDF") per-

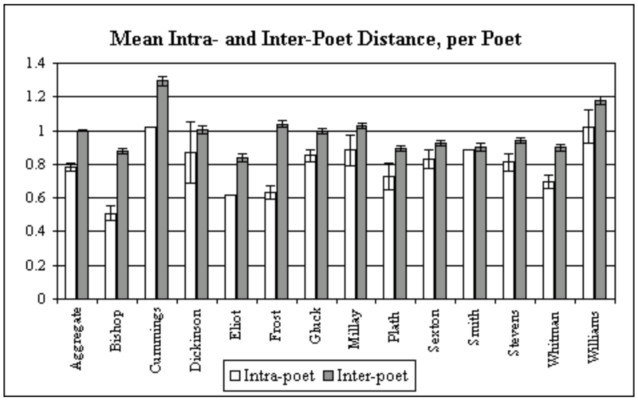


Figure 3. Comparison of intra- and inter-poet distances for selections from the *Oxford Anthology of Modern American Poetry*, **using Euclidean distances calculated from the features described in Section 2.1.**

forms better than ours ("Style"). For these poets, perhaps the algorithm is picking up the plethora of personal pronouns in Frost, or the "bee" themed words in Plath's "The Bee Meeting," "Stings," "The Swarm," and "The Arrival of the Bee Box." Overall, our technique performed better, showing greater differentials in 10 of the 13 poets.

Comparing aggregate performance on three poetry selections (Moore and Frost; Moore, Frost, and O'Hara; and the *Oxford Anthology*-based collection), the advantage of our method over the bag of words algorithm is significant (Fig. 4 Right). This provides further quantitative evidence that our method indeed captures latent stylistic features of poems, enough to discover poem clustering by poet better than an existing method.

3.4 Additional analysis

The preceding examples were drawn from a much larger set of explorations that included comparing well-known atypical poems such as Whitman's "O Captain! My Captain!" with their more typical counterparts and comparing sections within one long poem (e.g., Whitman's "Song of Myself") to check its consistency. Additionally, we ran sensitivity tests to ensure that metrics other than parts of speech and length still showed poet clustering; this was especially encouraging since the remaining metrics (rhyme, etc.) are arguably the least similar to the word frequency used in most current quantitative textual analysis.

We also examined known poet mentoring relationships, particularly those of Williams and Creeley, Stevens and Ashbery, and Moore and Bishop. These were identified by L. Keller in her book *Re-Making It New: Contemporary American Poetry and the Modernist Tradition* [7], although she singled out Creeley-Williams as more personal support than stylistic influence. Of 55 poet pairs that we examined—all combinations of Ashbery, Bishop, Creeley, Dickinson, Frost, Ginsberg, Gluck, Millay, Moore, Stevens, and Williams—the mean inter-poet distance was 94 (SD=25). The Creeley-Williams distance was 104, while the other two pairs picked out by Keller were among the closest: Ashbery-Stevens was 50, and Bishop-Moore 59.

Interestingly, poems from Williams's *Spring and All* (1923) were very close (distance 54) to his other volume, *The Wedge* (1944), when merging poems from each volume into a single "poem." This suggests that the variability seen in his individual poems may be largely due to their short length, while collectively the poems may gravitate around a consistent Williams style.

4 Previous Work

The two main contributors to statistical poetry analysis are Josephine Miles and Marina Tarlinskaja, both of whom had to collect data by hand. Miles examines frequently used adjectives in English-language poetry and studies adjective-noun-verb-connective proportions across different eras [12, 13, 14]. Tarlinskaja statistically analyzes poetry across many languages, specializing in meter and prosody [17, 18].

There has been less research in automated poetry analysis. Contributions include the use of a connectionist model [4], a Chinese poem classifier [10], determination of Slavic textual genre by word length distribution [3], and the prevalent use of word frequencies [8].

5 Discussion

Our method was able to distinguish poetry texts based on a combination of features not traditionally used in prose text analysis but traditionally relied upon for poetry analysis. We examined clustering by poet as one proxy for performance, assuming that poets have relatively consistent styles. The results, both statistical and visual, show that our method can discern stylistic similarity in poetry. Further, this ability is significantly greater than that of a bag of words cosine distance algorithm with TF-IDF weights.

One area of future work is to explore other features of poetry. The one major stylistic area that went altogether untouched is prosody, the rhythmic variations in stress and intonation, which offers many challenges. Great progress has been made in text-to-speech algorithms for prose, but their accuracy in poetic prosody is unknown. Another area left unexplored is visual style, important to such notable poets as ee cummings. Additional metrics that we did not use include additional amalgamated metrics such as a full stop

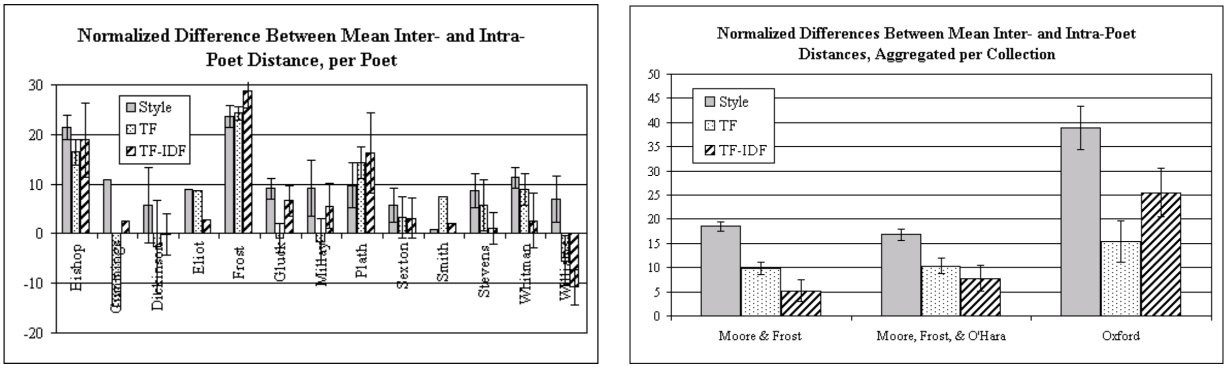


Figure 4. Comparison to term frequencies. Our algorithm is "Style"; larger values indicate clustering by poet. (Left) *Oxford Anthology* **selections. (Right) Three collections.**

frequency; additional measures of length; and a breakdown of verbs into transitive, intransitive, and copula (linking).

A second area of future work is to look into other methods of dimensionality reduction. Possibilities include non-negative matrix factorization [9] and variants of topic models such as the author-topic model [1].

We developed a computational method of feature analysis for poetry, guided by traditional qualitative and quantitative approaches. We enhanced this analytical engine with visualization and a graphical interface. Our analyses demonstrate considerable potential for this approach.

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