FracTale: Assessing the Correlation Between Narrative Beauty and Self-Similarity in Grimm's Folktales*

Cosimo Palma[1,2,*], Florentina Armaselu[3,†]

[1] University of Naples "L'Orientale", Via Duomo, 219, 80139 Napoli, Italy
[2] University of Pisa, Lungarno Antonio Pacinotti, 43, 56126 Pisa, Italy
[3] University of Luxembourg, 2, place de l'Université, L-4365 Esch-sur-Alzette, Luxembourg

Abstract

This work presents an assessment of the correlation between self-similarity and literary quality in Grimm's folktales. It examines text patterns at multiple levels (episodes, sentences, clauses) using homothety to evaluate similarity distributions across scales. The research employs Moran's I for spatial autocorrelation analysis and the Hurst Exponent to quantify the long-term memory of informativeness values based on Dependency Distance and Eventfulness, thus modeling texts as both spatial objects and time-series. The study defines literary quality by a tale's presence in the "Best fairytales" list from the corpus source website. The results are validated against randomly generated- and Europeana stories.

Keywords

Self-similarity in Texts, Computational Narratology, Grimm's folktales, Literary Quality Assessment

1. Introduction

The automatic assessment of literary quality remains an open challenge in Natural Language Processing [1, 2]. This challenge stems not only from the complexity of computational modeling, but also from the ongoing debate about what constitutes literary beauty as such [3].

Existing metrics for evaluating *automatic* story generation, largely designed for machine translation tasks, fail to capture the semantic aspects and creative elements essential to literary quality [4]. Recent studies confirm that literary quality is multifaceted [1], suggesting that addressing individual aspects separately may prove more effective.

In this work, we investigate the relationship between self-similarity and literary beauty.

Self-similarity (the property of a system whose components match the shape of its general structure [5]) has been strongly correlated with aesthetic pleasure in various domains including art, architecture, and music, suggesting a potential parallel also at the textual level.

Furthermore, a significant aspect of literary quality derives from structure and component relationships rather than content alone [6].

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*Corresponding author. He conducted the experiments and wrote the initial manuscript.
† She contributed to the general conceptual framework and to the critical revision of the manuscript.
cosimo.palma@phd.unipi.it (C. Palma)
0000-0002-8161-9782 (C. Palma)

1.1. Related Work

The observations in the introduction point at self-similarity as a content-agnostic, task-independent metric that could potentially serve as a component of literary quality assessment frameworks. Cordeiro et al. [7] employ the Kolmogorov-Smirnov goodness-of-fit and Hurst parameter[1] to evaluate self-similarity and long-range correlation behavior in an English corpus of literature, news stories, and blogs. Their analysis of lexical features, including word and sentence length and lexical diversity, suggests a potential correlation between perceived text quality and degree of self-similarity. Complementing this work, Mohseni et al. [8] apply multi-fractal detrended fluctuation analysis to differentiate between canonical and non-canonical fiction, while Drożdż et al [9] use Fourier-based power spectra to analyze sentence length patterns, suggesting that aesthetic optimization involves self-similar alternation of sentence lengths. In [10], an experiment with similar setting as in [9] is carried out for Chinese prose. Although fractality appears to be a fundamental feature of prose writing, Chinese literature shows weaker long-range correlations compared to Western literature, with fewer instances of multifractal structures. Furthermore, no significant differences are detected therein between fictional and non-fictional books.

Other studies such as [11] investigate the relationship between *sentiment dynamics in narratives*, selected among the fairy-tales of Andersen, and readers' appreciation of literary quality approximated by *GoodReads scores*. According to their hypothesis, an optimal balance between predictability and surprise in a sentiment arc's structure may contribute to a narrative's perceived quality, as suggested by a slight correlation between Hurst Exponent and readers' rating. Bringing about similar conclusions, in [12], a formalism used for the representation of recursive shapes is applied to fairy-tales. Several studies consider various types of literary genres: for instance, [13] asserts that the basic form of narratives is fractal in nature, by combining, at different scales, thousands of *objective-obstacle pairs*, while [14] proposes an integrated approach combining *z-text* modeling, topic analysis, and fractal geometry techniques such as box counting and fluctuation analysis to study information granularity and argument development.

1.2. Questions and Challenges

The cited literature opens up a series of questions some of which we address in this paper. In [7] the link between fractality and beauty is assumed, not proven.

In [11], GoodReads [2] reviews of Andersen's tales are used. However, these do not refer to the folktales themselves, but rather to illustrated books available in online shops. In our investigation, the *uniqueness of the medium* is regarded as a key factor for an unbiased assessment. In theory, a worse folktale could be regarded as better just because of better illustrations or even because of a better "quality-price" ratio. Finally, the measurement of self-similarity is principally based on the *length* of the text unit. Alternative dimensions, such as *informativeness*, are not considered. We argue that text complexity, which we take into account through the informativeness and readability dimensions (see section 2.2), is an aspect that should be investigated as well, as part of the correlation analysis of folktale fractality[3] and its aesthetic appeal.

[1] See section 2 for a definition of this concept.

[2] https://www.goodreads.com/shelf/show/folktales.

[3] The particular approach on fractality selected for the present study.

2. Methodology

To address these questions, we developed the *FracTale* project (for a diagrammatic overview of the conducted experiment, refer to Figure 1)[4]. The analysis of text length fractality has been explored, among others, in [15], referencing the Minkowski–Bouligand dimension [16]: $D_h = \frac{\ln(N)}{\ln(1/h)}(0)$ [5] where N represents the number of structures within a given scope (in our case three), and h is the *homothety* (the ratio of a structure's size to a similar structure at the previous higher level). For each tale, the average homothety is calculated as:

$$\bar{H} = \frac{\left[\left(\frac{\text{avg. size of episodes}}{\text{size of tale}}\right) + \left(\frac{\text{avg. size of sentences}}{\text{avg. size of episodes}}\right) + \left(\frac{\text{avg. size of clauses}}{\text{avg. size of sentences}}\right)\right]}{3} \quad (1)$$

To also have an account of *spatial* autocorrelation, we use Moran's I [17] to analyze spatial dependencies across different textual levels. For each level (clauses, sentences, episodes), we:

- Define the spatial units with values x_i representing their properties: $x_i = \text{length}(\text{unit}_i)$
- Establish a weighting matrix: $w_{ij} = 1$ if units i and j are adjacent, otherwise $w_{ij} = 0$
- Calculate the global mean: $\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$
- Compute the covariance term: $\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})$
- Calculate the variance: $\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2$
- Derive Moran's $I = \frac{N}{S_0}\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{N}(x_i-\bar{x})^2}$ (2) where $S_0 = \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}$

Values of Moran's I range from -1 to 1, with positive values indicating spatial clustering (similar values appear together), values near zero suggesting random distribution, and negative values showing spatial dispersion.

For assessing self-similarity in time series related to individual textual dimensions, we implemented the method used in [7], [8] and [9], estimating the *Hurst Exponent*.

The Hurst exponent quantifies time series long-term memory (autocorrelation) on a 0-1 scale: 0.5 indicates randomness, above 0.5 indicates trend persistence, and below 0.5 indicates trend reversal patterns. Given the short size of our time series, unlike [7], we estimate it using Rescaled Range analysis (R/S) [18].

Specifically, for each sentence-level measure (dependency distance, eventfulness, informativeness. In the following: X), we:

- Compute cumulative deviations from the mean: $Y(t,n) = \sum_{i=1}^{t}(X_i - \bar{X}_n)$ for $t = 1, 2, \ldots, n$
- Find range $R(n) = \max_{1\leq t\leq n} Y(t,n) - \min_{1\leq t\leq n} Y(t,n)$
- Calculate standard deviation $S(n) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X}_n)^2}$
- Determine $R(n)/S(n)$ ratio for increasing time intervals
- Plot $\log(R/S)$ against $\log(n)$ where n is the interval length
- Derive the Hurst exponent H as the slope of this line: $\frac{R(n)}{S(n)} \propto n^H$ (3)[6].

[4]The codebase of this paper can be accessed at https://github.com/Glottocrisio/FracTale.

[5]In our case, D_h values are always positive because $N > 1$ and $h < 1$ (positive numerator, positive denominator).

[6]If this relationship does not follow perfect scaling, as commonly happens in real data, the regression might produce a slope greater than 1. This can also be the case if data has strong trends, as it occurs in our case study with the time-series of *Eventfulness* values.

Experiment Framework Overview

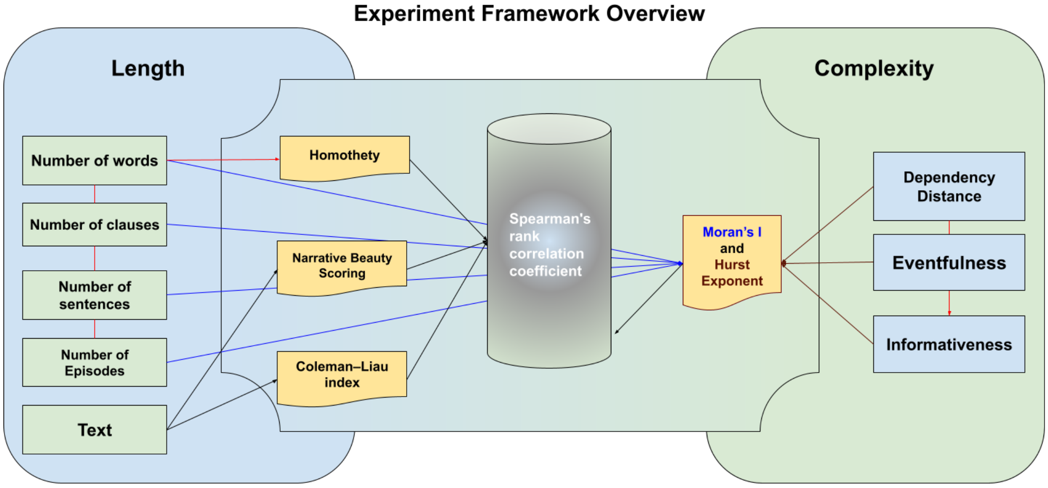

Figure 1: A diagrammatic overview of the experiment setting.

2.1. Corpus Selection

Fairytales offer an ideal starting point for our inquiry due to their simplicity and structured text, presenting both "proppian" *narrative functions* [19] and *episodes* (clusters of functions comparable to scenes, visually rendered as paragraphs). They serve as archetypal templates for understanding more complex texts, allowing verification and scaling of results to larger literary corpora. Our analysis used a subset of Grimm's folktales. We selected *GrimmStories*[7] for corpus harvesting due to its multilingual content, folktale ranking, and episode divisions. In *GrimmStories*, rankings vary by language ("most beautiful" in some languages versus "most famous" in others), suggesting view-based popularity rather than preference — assumption that seems to be confirmed by ranking fluctuations[8]. We utilized these rankings as a popularity metric, representing a significant component of *narrative beauty*.

The selected languages (*English*, *German*, and *Italian*) already featured episode divisions. Initially, we ranked 25 stories per language with identical beauty scores for five-story batches, but due to observed ranking volatility, we ultimately classified all "Best fairytales" equally as "top" with all others (namely, circa fifteen tales per language) labeled as "bottom". This approach was validated by the localized nature of ranking volatility, as tales outside the top 25 rarely entered it. To assess correlation between self-similarity and stories fundamentally, we compared with Europeana Stories [9]. We also generated random pseudo-stories as a control group using Python's *random* package, creating text units structurally similar to human-authored texts.

[7]https://www.grimmstories.com/.
[8]The "best fairy-tales" corpus for our analysis has been harvested on 08/07/2024. The "not best" ones, along with Europeana Stories and the randomly generated corpus have been collected in January 2025.
[9]Cultural heritage narratives with both journalistic and narrative elements. Their paragraphs are therefore not episodes in the strict sense of the term.

2.2. Dataset Features

To examine text self-similarity, we approach complexity through *Informativeness*, comprised of *Dependency Distance*[10] [20] and *Eventfulness*[11] [21], and the Coleman-Liau Index[12] [22].

For Grimm's tales and Europeana stories, we computed the following features:

- Tale composition: Episodes, Sentences, Clauses, Words
- Average lengths: Episode, Sentence, Clause[13]
- Complexity measures: **ADD** (Average Dependency Distance), **AEv** (Average Eventfulness), **I**[14] (Informativeness = ADD $\times$ AEv), **CLI** (Coleman-Liau Index)
- Self-similarity metrics: D_h (Minkowski–Bouligand dimension, see Equation 0), **Average Homothety** (see Equation 1), **Hurst Exponent** (for vectors of sentence-based DD, Ev and I values, see Equation 3), **Moran's I** (for sentences and episodes, see Equation 2).

3. Visualization and Discussion of Results

Some of the most relevant[15] among the above-mentioned computed metrics have been displayed in a correlation matrix (rank-based, with Spearman coefficient [23]), with the aim of capturing the correlation among the different features and their overall relation to the quality category the related tales belong to ("top" or "bottom") (Figure 2). Random tales' correlation matrices are indeed colder, which indicates that all the individuated features, including the ones for self-similarity, are related to *meaning*. Generally, in Italian, *readibility* and *informativeness* are strictly correlated, while the opposite happens for German. In general, we can appreciate similar patterns for same language tales, that are in turn significantly different between "top" and "bottom" tales: surprisingly, "top" tales are overall colder than "bottom" ones, for every language; the features are less correlated between each other, on average, corroborating the theory that beauty also arises from surprise and unexpectedness. Moreover, for "bottom" stories it is easier to detect patterns (they are more similar to each other, according to the extracted features, than the "top" ones).

A striking correlation between self-similarity and literary quality (as they were measured) cannot be traced. From Table 2, however [16], we notice that the Hurst Exponent for Dependency Distance, Eventfulness and Informativeness is generally higher for the "bottom" stories. The only measure for self-similarity proven to be consistently higher for best tales over all languages is the Moran's I of episode series. Averagely, Hurst Exponent of combined informativeness values are

[10] Dependency Distance measures the average linear distance between words that are syntactically related in a sentence. Higher values indicate more complex sentence structures that place greater demands on working memory.

[11] Eventfulness quantifies how much narrative action occurs in a sentence, essentially measuring the density of plot developments or "happenings" within a textual unit. It is approximated as number of episodes per sentence.

[12] The Coleman-Liau Index is a readability formula that estimates the years of formal education in the U.S. needed to understand a text in English on a first reading. It relies on characters per word and words per sentence rather than syllable counting. Since its adaptation for other languages only slightly differs from the English-based model, we opted to use the same for all other languages investigated in the present study.

[13] Length is consistently measured in number of words throughout our analysis.

[14] Informativeness combines syntactic complexity (ADD) with narrative density (AEv) to produce a composite measure of information load.

[15] In order from left to right: ADD, AEv, Avg_I, CLI, avg_H, Hrst_Ev, Hrst_I, M_I (sentence), M_I (episodes).

[16] CV_H in Table 2 stands for *Coefficient of variation of the harmonic mean.*

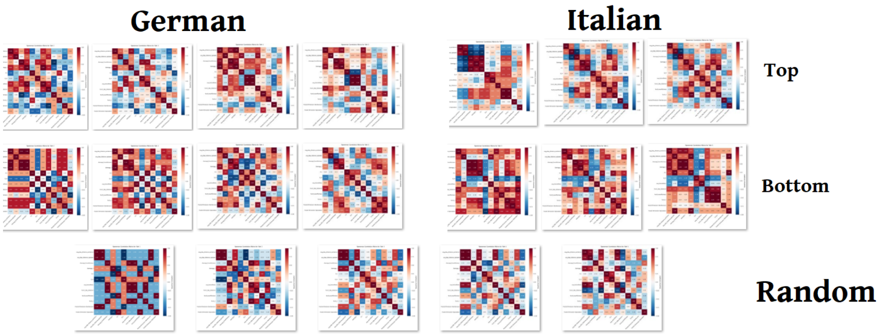

Figure 2: Spearman's correlation matrices for German and Italian Grimm's folkstale, as well as randomly generated ones. Features are from left to right the same as listed in section 2.2.

Europ_EN_DE	1	2	3	4	5	6	Avg	Var	1	2	3	4	5	6	Avg	Var
ADD	13.2	0.2	0.1	1.0	1.2	10.8	4.4	35	0.3	3.9	1.9	0.3	0.2	0.3	1.1	2.3
Avg_E	0.6	0.6	0.6	0.7	0.7	0.8	0.7	0.0	0.6	0.6	0.6	0.6	0.6	0.5	0.6	0.0
Avg_I	7.3	0.1	0.1	0.7	0.9	8.6	3.0	15	0.2	2.3	1.2	0.2	0.1	0.1	0.7	0.8
CLI	12.6	9.5	10.9	10.4	13.1	10.5	11.2	1.9	16.9	16.2	15.7	18	16	14.5	16.1	1.2
D_h	1	1	1	1.4	1.4	2	1.3	0.2	1	1	1.1	1	1	0.9	1	0
avg_H	0.3	0.3	0.3	0.3	0.3	0.4	0.3	0	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.0
hrst_DD	0.4	0.4	0.4	0.5	0.3	0.8	0.5	0.0	0.6	0.6	0.3	0.7	0.6	0.9	0.6	0.0
hrst_Ev	0.5	0.8	0.8	0.8	1.2	1.2	0.9	0.1	0.8	0.7	0.6	1.0	0.5	0.7	0.7	0.0
hrst_I	0.4	0.4	0.5	0.5	0.6	0.3	0.4	0.0	0.4	0.7	0.6	0.7	0.6	0.8	0.6	0.1
M_I (Sent)	0.2	0.2	0.2	-0.3	-0.1	-0.2	0	-0.9	-0.1	-0.1	0.2	0.3	0.3	0.1	0.1	-1
M_I (Ep)	0.4	-0.2	0.4	0	-0.1	0.4	0.2	-1	0	-0.2	0	0.2	-0.1	0.2	0	-1
Grimm_EN_DE	**1**	**2**	**3**	**4**	**5**	**6**	**Avg**	**Var**	**1**	**2**	**3**	**4**	**5**	**6**	**Avg**	**Var**
ADD	8.9	10.8	3.3	3.4	28	36.2	15.1	188	3.4	11.2	3.5	9.4	4.7	8.4	6.8	11
Avg_E	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.2	0.1	0.1	0.1	0.2	0.1	0.0
Avg_I	0.5	2.5	0.4	0.3	2.8	4.1	1.7	2.5	0.3	2.4	0.3	1.2	0.6	2.0	1.1	0.8
CLI	5.1	6.5	6.3	6.8	5.8	6.3	6.1	0.3	9.7	10.1	10.5	10.8	10.0	9.4	10.1	0.3
D_h	0.5	0.6	0.5	0.5	0.7	0.5	0.5	0	0.5	0.6	0.5	0.7	0.5	0.6	0.6	0
avg_H	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0	0.1	0.2	0.1	0.2	0.1	0.1	0.1	0
hrst_DD	0.3	0.7	0.5	0.6	0.5	0.6	0.5	0.0	0.7	0.7	0.5	0.7	0.7	0.6	0.6	0.0
hrst_Ev	0.7	0.7	0.5	0.6	1.1	0.7	0.7	0.0	0.6	0.7	0.5	0.2	0.9	0.9	0.6	0.1
hrst_I	0.5	0.6	0.9	0.5	0.7	0.8	0.7	0.0	0.6	0.8	0.7	0.8	0.7	1.0	0.8	0.1
M_I (Sent)	0.0	0.3	0.1	-0.2	0.1	0.1	0.1	-1.0	0.1	0.5	-0.1	0.4	0.1	0.2	0.2	-1
M_I (Ep)	0.3	-0.9	0.3	-0.8	0.8	-0.4	-0.1	-0.5	-0.7	-0.9	-0.2	0.9	-0.6	0.7	-0.1	-0.5

Table 1
Extracted features comparison across Europeana Stories and Grimm Stories in English and German. Values shown for six (casual) tales, their average (Avg), and variance (Var). All values rounded to one decimal place.

in folktales higher than the ones computed for only DD or E. From Table 1, we can notice that self-similarity values (both spatial and time-series based) do not vary significantly across the two corpora. In all languages, best tales show the worst correlation between spatial and time-series based computations of self-similarity; the opposite happens for the other ones.

In Table 1, Hurst_I is averagely higher than Hurst_eventfulness for folktales. Moreover, Europeana stories show higher readibility (CLI) and lower average dependency distance per sentence. A potential connection can be made with the Dalen-Oskam's study [3, pp. 56-57] that showed a certain correlation between books highly rated as "literary" characterised by longer and more complex sentences than more popular books rated as possessing less "literary" quality but more "readability and accessibility" quality, related also to the "pleasure of reading."

Grimm_DE_top			Grimm_DE_bottom		Grimm_EN_top		Grimm_EN_bottom		Grimm_IT_top		Grimm_IT_bottom	
Metric	H_Mean	CV_H	H_Mean	CV_H	H_Mean	CV_H	H_Mean	CV_H	H_Mean	CV_H	H_Mean	CV_H
ADD	3.87	0.97	4.20	0.66	3.99	0.96	5.09	0.72	4.45	1.61	3.46	1.38
Avg_E	0.13	0.46	0.10	0.40	0.16	0.44	0.11	0.50	0.13	0.48	0.08	0.61
Avg_I	0.39	1.36	0.39	1.07	0.55	1.14	0.53	0.88	0.41	2.39	0.22	1.55
CLI	9.35	0.12	9.76	0.06	5.81	0.09	5.86	0.13	8.54	0.1	8.46	0.09
hrst_DD	0.59	0.19	0.64	0.14	0.55	0.30	0.54	0.26	0.47	0.45	0.59	0.28
hrst_Ev	0.62	0.35	0.60	0.57	0.67	0.23	0.69	0.24	0.57	0.37	0.8	0.33
hrst_I	0.66	0.22	0.75	0.18	0.67	0.2	0.67	0.2	0.64	0.18	0.66	0.24
M_I (Sent)	0.02	0.23	0.10	0.17	-0.06	0.24	0.02	0.19	0.04	0.15	0.1	0.13
M_I (Ep)	-0.01	0.42	-0.19	2.36	-0.01	0.39	-0.08	4.56	-0.05	11	-0.54	1.51

Table 2
Inter-language overview for German, English and Italian folktales (with harmonic mean).

4. Conclusion and Future Work

In this study, we investigated the correlation between self-similarity (measured as both Hurst exponent and Moran's I) in narratives and "beauty" ranking in a selection of Grimm's folktales across three languages. The results, while encouraging to a certain degree, need to be confirmed through more extensive experiments. Surprisingly, no strong correlations could be observed for "top" tales, while certain patterns have been discerned for "bottom" ones. This observation may be aligned with the assumption that beauty and unpredictability are not incompatible. However, the randomly generated stories showed a lower degree of correlation, which suggests that these metrics are able to capture, to a certain extent, textual features related to meaning. The "beauty" of a fairy tale may thus involve a middle ground between correlated and uncorrelated structural mechanisms, including various forms of self-similarity.

Future research directions may elaborate on multifractal behaviour as in [8, 9], computing a more accurate scoring of narrative beauty through platforms like Amazon Mechanical Turk's SageMaker or a generative AI-based functionality (with beauty broken down into sub-components such as, for example, *interestingness* or *readability*), and exploring surprisal-based perspectives by calculating n-grams of Propp functions for episodes. Given the challenges of precise annotation, developing more effective guidelines for beauty scoring would be crucial to enhance reliability. Additional research avenues include expanding to more languages and diverse corpora (novels), considering further theoretical modeling of self-similarity to assess appropriate measurement approaches and potential fractality variations between original versions and their translations.

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