The Dostoyevskian Trope
State Incongruence in Danish Textual Cultural Heritage

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Abstract

In the history of prolific authors, we are confronted with the figure of the suffering author. Setting aside metaphysical theories, the central claim seems to be that a state incongruent dynamic is an intricate part of the creativity process. Two propositions can be derived this claim, 1: the creative state is inversely proportional to the emotional state, and 2: the creative state is causally predicted by the emotional state. We call this creative-emotional dynamic 'The Dostoyevskian Trope'. In this paper we present a method for studying the Dostoyevskian trope in prolific authors. The method combines Shannon entropy as an indicator of lexical variability with fractal analysis in order to measure creative dynamics over multiple documents. We generate a sentiment time series from the same documents and test for asymmetric directed dependencies between the creative and sentiment time series. We illustrate the method by searching for the Dostoyevskian trope in Danish textual cultural heritage, specifically three highly prolific authors from the 19th century, namely, N.F.S. Grundtvig, H.C. Andersen, and S.A. Kierkegaard.

Keywords— Creativity, Fractal Analysis, Information Theory, Sentiment Analysis

Introduction

There is a popular belief among both laymen and researchers that suffering can promote creative production (1; 2). This belief has multiple names 'the suffering artist', 'the tortured artist' as well as 'the wisdom of suffering'. The validity of this belief is however debatable (3; 4). Setting aside various metaphysical theories about the clarity and humility inherent in pain, there is a central claim pertaining to the dynamic of the creative process, namely that, state incongruent dynamics are an intricate to the creativity process. We derive two testable propositions from this dynamic that we collectively call 'The Dostoyevskian Trope' with a reference to the paradigmatic life of Fodor Dostoyevsky: Firstly *the creative state is inversely proportional to the emotional state*, and secondly *the creative state is causally predicted by the emotional state*. If we can find empirical support both propositions, we argue that there is evidence favoring the Dostoyevskian trope. In order to implement this, we propose a two step procedure: first, we combine information theory with fractal analysis in order to model creativity; second, we test for causal-like directed asymmetric relations between creativity and emotional states using average work sentiment as a proxy.

In this paper, creativity is modeled as *persistent trends in lexical variability*, estimated by the time varying Hurst exponent of Shannon's source entropy, for the collected writings of a prolific author. While entropy and information theory are widely used for studying variability in discrete time series such as characters and words (5; 6; 7), fractal analysis is less common in the humanities. Methods for fractal analysis are used in many areas of science to study self-similarity of complex dynamic systems (8). With self-similarity we simply mean that small parts of a system, in this case patterns of fluctuations at shorter time scales, are scaled copies of the larger parts of the system, that is, fluctuations at longer time scales. Reading, for instance, is a dynamic system that displays self-similarity across multiple time scales, because reading fluency and word comprehension are affected by the immediate word context (i.e. shorter time scales) as well as the larger text context (i.e., longer time scales) (9). Many culturally relevant complex systems display self-similarity in psychology (10), economy (11), sociology (12), and health (13), language (14) and music (15). In all these domains we find an important class of fractal objects called $1/f^{\alpha}$ noise, which is characterized by a power-law decaying power spectral density as well as power-law decaying rank-ordered eigenvalue spectrum. $1/f^{\alpha}$ noise has attracted considerably attention due to findings of so-called 'pink noise', where $\alpha = 1$, in a range of natural and man-made processes. In the present study we are targeting a subclass of $1/f^{\alpha}$ noise called a $1/f^{2H+1}$ process where H is the Hurst exponent that takes the values $0 < H < 1$. For $1/f^{2H+1}$ processes the following heuristic (16): For $0 < H < 0.5$, the time series is an anti-persistent process (i.e., increments are followed by decreases and decreases by increments), for $H = 0.5$, the time series only has short-range correlations also called short memory, and when $0.5 < H < 1$, the time series is a persistent process (i.e. increments are followed by increases and decreases by further decreases) characterized by long memory (Fig. 1). Returning the reading example, we can say that the reading is a persistent process because because it has been shown that for reading speed $0.5 < H < 1$.

With the massive data accumulation in almost every text domain, dictionary-based lexical matching has reemerged as a corpus independent approach to automated sentiment analysis. Sentiment content can be used to identify affective states and preferences of authors (17; 18; 19; 20), profile authors (21; 22), and construct narrative arcs (23; 24; 25). In accordance with this development, we use a Danish sentiment dictionary to estimate the average work sentiment in order to create a author-specific sentiment time series. This time series reflects fluctuations in expressive sentiment content relative to the individual author and can function as a limited proxy for the variability in his/her underlying emotional states. Multiple techniques can be used to compare asymmetric similarities between time varying creative and emotional states. In this paper we apply Granger causality (26), which tests for the existence and directionality of causal-like relations between temporally disjunctive time series. Granger causality, which originates in econometrics, is based on the assumption that causality is more than temporal disjunction, it involves directionality or predictability between time series. At its core Granger causality tests whether values of one time series X contains information that is uniquely predictive of subsequent values in a different time series Y. The relation tested by Granger causality is often characterized as predictive causality and represented as $X\ Granger\ cause\ Y$ (27).

Methods

In this section we describe the method components of our approach focusing particularly on fractal analysis since it, in comparison to other analysis of lexical variability and sentiment, is less common in the humanities.

Entropy and Adaptive Fractal Analysis

In discrete cases with K distinct values, classical source entropy h of Shannon, or just entropy, is a measure of the variability. We measure h at the word level with a lexicon of K distinct types accordingly:

$$h = -\sum_{i=1}^{K} p_i \times \log_2(p_i) \tag{1}$$

With p being defined as:

$$p_i = Fr(w_i)/\sum_{i}^{K} Fr(w_i) \tag{2}$$

where Fr is the absolute frequency of word w. Word-level entropy measures the lexical variability of a tokenized string and will result in $0 \leqslant h \leqslant \log K$ with $h = \log K$ if the words in the string are uniformly distributed (i.e., a string where each type equally likely) and $h = 0$ if the string is perfectly predictable (i.e., a string with repetitions of only one type). For time series analysis in general, entropies are indicative of complexity such that larger values of h indicates greater complexity (28). Using entropy to model creativity in natural language is motivated by several studies (29; 30; 31; 7).

In fractal processes and time series analysis, detrended fluctuation analysis (DFA) (32) is a method for determining the statistical self-similarity (i.e. self-affinity) of a signal and can be used to analyze time series that appear to be long memory processes or $1/f$ noise. DFA is a widely used methods for estimating the Hurst parameter. It involves (1) constructing a random walk process

$$u(n) = \sum_{k=1}^{n}(x_k - \overline{x}), \quad n = 1, 2, \cdots, N, \tag{3}$$

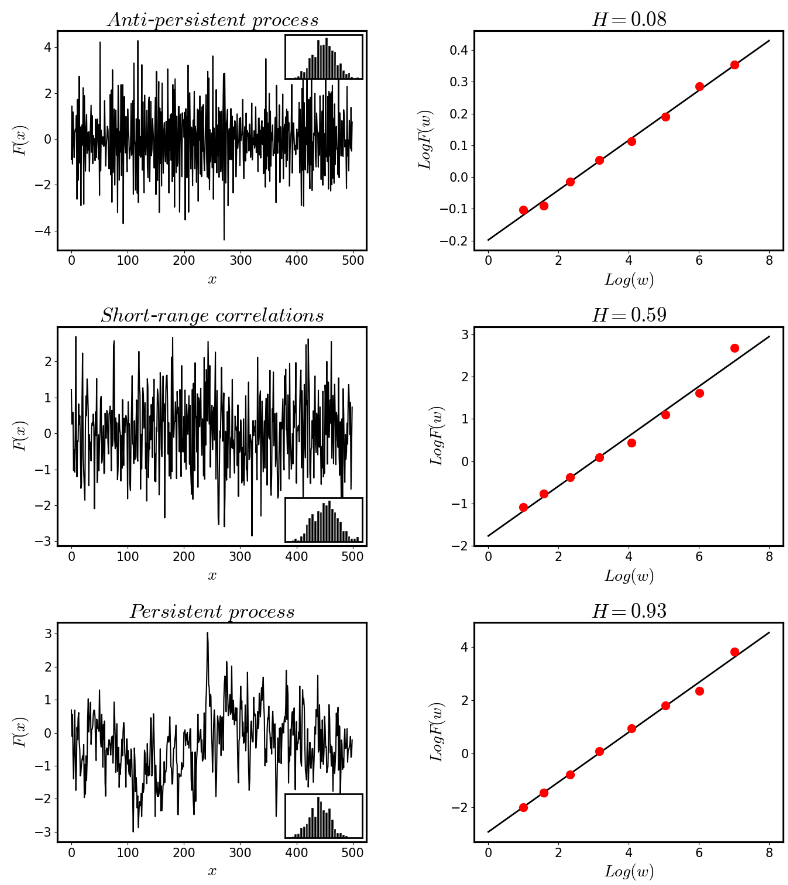

Fig. 1: Left: Time series that exhibit anti-persistent (top), short memory (middle), and persistent (bottom) behavior. Right: Estimation of the Hurst exponent for matching time series in the left column.

where $\overline{x}$ is the mean of the series $x(k)$, $k = 1, 2, \cdots, N$, (2) dividing the constructed random walk process into non-overlapping segments, (3) determining the best linear or polynomial fits in each segment as the local trends, (4) getting the variance of the differences between the random walk process and the local trends, and (5) averaging them over all the segments. Therefore, DFA may involve discontinuities at the boundaries of adjacent segments. Such discontinuities could be detrimental when the data contain trends (33), non-stationarity (34), or nonlinear oscillatory components such as signs of rhythmic activity (35; 36). To overcome this weakness adaptive fractal analysis (AFA) has been proposed (16). AFA is an improvement of DFA. The main advantage of AFA over DFA is that AFA identifies a global smooth trend, which is obtained by optimally combining local linear or polynomial fitting, and thus no longer suffers from DFA's problem of discontinuities or even large, abrupt changes at the boundary of adjacent segments. As a result, AFA can automatically deal with arbitrary, strong nonlinear trends, which is not shared by any other methods, including DFA (16; 36).

AFA is based on a nonlinear adaptive multi-scale decomposition algorithm (16). The first step involves partitioning an arbitrary time series under study into overlapping segments of length $w = 2n + 1$, where neighboring segments overlap by $n + 1$ points. In each segment, the time series is fitted with the best polynomial of order M, obtained by using the standard least-squares regression; the fitted polynomials in overlapped regions are then combined to yield a single global smooth trend. Denoting the fitted polynomials for the $i-th$ and $(i + 1) - th$ segments by $y^i(l_1)$ and $y^{(i+1)}(l_2)$, respectively, where $l_1, l_2 = 1, \cdots, 2n + 1$, we define the fitting for the overlapped region as

$$y^{(c)}(l) = w_1 y^{(i)}(l + n) + w_2 y^{(i+1)}(l), \quad l = 1, 2, \cdots, n + 1, \tag{4}$$

where $w_1 = \left(1 - \frac{l-1}{n}\right)$ and $w_2 = \frac{l-1}{n}$ can be written as $(1 - d_j/n)$ for $j = 1, 2$, and where d_j denotes the distances between the point and the centers of $y^{(i)}$ and $y^{(i+1)}$, respectively. Note that the weights decrease linearly with the distance between the point and the center of the segment. Such a weighting is used to ensure symmetry and effectively eliminate any jumps or discontinuities around the boundaries of neighboring segments. As a result, the global trend is smooth at the non-boundary points, and has the right and left derivatives at the boundary (37). The global trend thus determined can be used to maximally suppress the effect of complex nonlinear trends on the scaling analysis. The parameters of each local fit is determined by maximizing the goodness of fit in each segment. The different polynomials in overlapped part of each segment are combined using Equation (3) so that the global fit will be the best (smoothest) fit of the overall time series. Note that, even if $M = 1$ is selected, i.e., the local fits are linear, the global trend signal will still be nonlinear. With the above procedure, AFA can be readily described. For an arbitrary window size w, we determine, for the random walk process $u(i)$, a global trend $v(i), i = 1, 2, \cdots, N$, where N is the length of the walk. The residual of the fit, $u(i) - v(i)$, characterizes fluctuations around the global trend, and its variance yields the Hurst parameter H according to the following scaling equation:

$$F(w) = \left[\frac{1}{N}\sum_{i=1}^{N}(u(i) - v(i))^2\right]^{1/2} \sim w^H. \tag{5}$$

Thus, by computing the global fits, the residual, and the variance between original random walk process and the fitted trend for each window size w, we can plot $\log_2 F(w)$ as a function of $\log_2 w$. The presence of fractal scaling amounts to a linear relation in the plot, with the slope of the relation providing an estimate of H (Fig. 1).

Sentiment Analysis and Causal-like Dependencies

Dictionary-based (or lexicon-based) sentiment analysis is simple lexical matching utilizing a dictionary of words annotated for their sentiment value. Dictionaries are typically full form word lists and available dictionaries vary widely in terms of design, sentiment range, word classes, domains and languages [1]. Because analysis of social media and consumer behavior is an influential driver in the development of sentiment analysis, most dictionaries are developed for contemporary English. The present study uses the AFINN dictionary (38), which was developed contemporary Danish and English. In order to apply the dictionary to 19th century Danish, we normalized all text by 'modernizing' them using a combination of statistical and rule-based approaches to spelling correction. The average sentiment score for each work was then computed by averaging sentiment scores over slices of 1000 words (see Data).

Finally, a test for Granger causality was applied to sentiment time series and time-varying Hurst exponent for entropy. To test if variation in creativity (Y) at time t is predicted by emotional states (X) at earlier time steps $t-1\ldots t-k$, that is if $X\ Granger\ cause\ Y$, we compared the nested ('creativity only') model:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \ldots + \beta_k y_{t-k} + \epsilon \tag{6}$$

with the full ('creativity and emotional states') model:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \ldots + \beta_k y_{t-k} + \alpha_1 x_{t-1} + \ldots + \alpha_k x_{t-k} + \epsilon \tag{7}$$

to see which one does the better job at explaining y_t based on th residuals. The zero-model for the hypothesis then is $H_0 : \alpha_i = 0$ for each i of the element $[1, k]$ with the alternative hypothesis being $H_1 : \alpha_i \neq 0$ for at least one i of the element $[1, k]$. We applied the test bi-directionally such that the Dostoyevskian Trope finds support iff we can confirm that '$X\ Granger\ cause\ Y$' and reject that '$Y\ Granger\ \ cause\ X$'.

Data

We illustrate the applicability of the method on a corpus ($N = 1329$ documents) by N.F.S. Grundtvig ($n_1 = 921$), H.C. Andersen ($n_2 = 194$), and S.A. Kierkegaard ($n_3 = 214$). Before analysis the corpus was reduced to alpha-numeric characters and each document was length normalized in windows of 1000 words.[2]. The entropy and sentiment scores for each document were then estimated as an average over windows. Time-varying estimation of H was computed maximally overlapping windows of entropy for 256 works.

[1]For an overview see: Reagan, A., Tivnan, B., Williams, J. R., Danforth, C. M., & Dodds, P. S. (2015). Benchmarking sentiment analysis methods for large-scale texts: A case for using continuum-scored words and word shift graphs. ArXiv Preprint ArXiv:1512.00531.

[2]Normalizing to windows of 250 and 500 words results in qualitatively similar results.

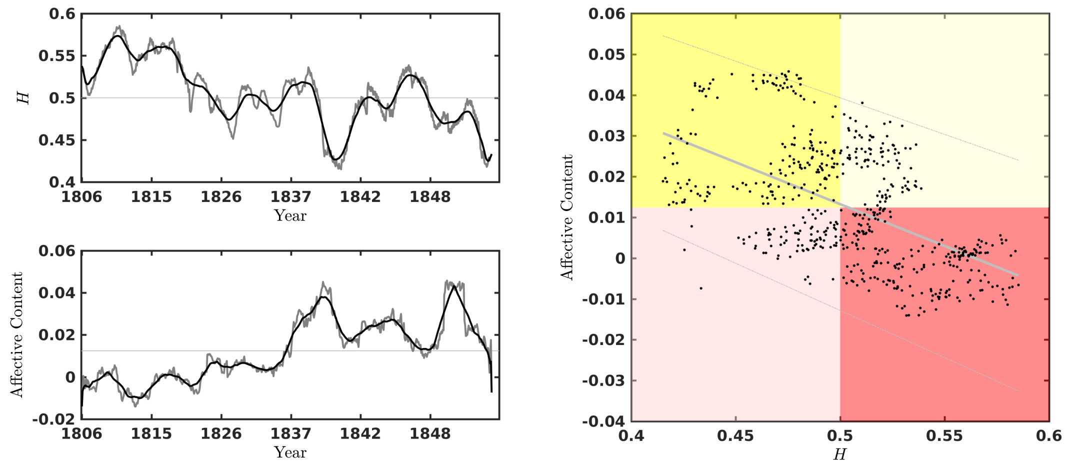

Fig. 2: Left: Time varying H(urst) exponent (upper) and sentiment (lower) for N.F.S. Grundtvig. Right: Inverse linear relation between H and sentiment (boundaries are 95Notice that only

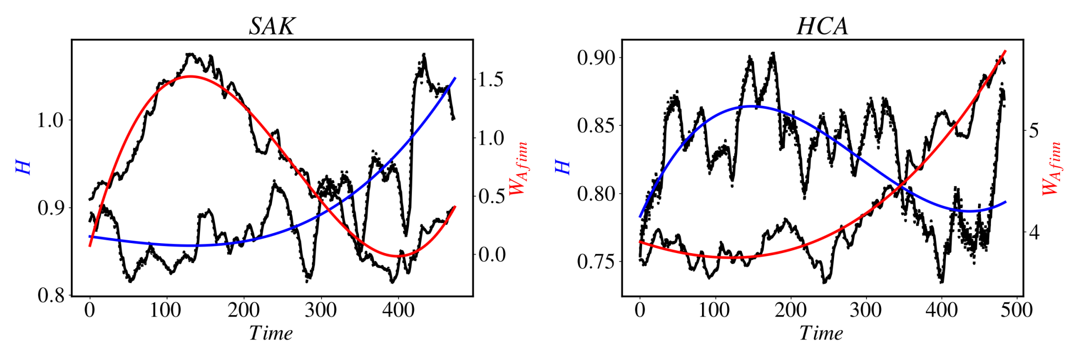

Fig. 3: Time varying H(urst) exponent (blue) and sentiment (red) for H.C. Andersen (HCA) (right) and S.A. Kierkegaard (SAK) (left). Red and blue lines are cubic fits to the raw signals. Both HCA and SAK show evidence of the first part of the Dostoyevskian trope, but only SAK displays a time delay in the hypothesized direction. HCA's Entropy exhibits persistent behavior ($0.5 < H_e \leq 1$) for his entire career

Results

We summarize the result as follows: First, all authors, N.F.S. Grundtvig (NFSG), H.C. Andersen (HCA) and S.A. Kierkegaard (SAK), show an inverse relation between creative and emotional states (Fig. 2 and 3). In accordance with previous studies on creativity and mood, this result is indicate an association between negative mood and artistic creativity (39; 40; 41). Second, only NFSG and

SAK show an asymmetric causal-like relation between in the hypothesized direction. We do in other words find support for the Dostoyevskian trope in Danish textual cultural heritage, but since HCA is propablt the most successful of the three, not for all authors have to be suffering[3] in order to be creatively successful.

For further research it is worth noticing that both NFSG and HCA display a general negative creativity trend, which might reflect aging. SAK died relatively young at the age of 42, which is roughly similar to the age at which NFSG and HCA's creativity decreases. Another interesting detail is that HCA's was creatively optimal in the sense that his creativity shows persistent trends throughout his career. NFSG's creatvity on the other hand becomes anti-persistent or rigid with age. SAK finally displays on-off intermittency for his later years switching between states of persistent behavior and "bursts" of chaotic behavior (42).

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