Universality and diversity in word patterns

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Words are fundamental linguistic units that connect thoughts and things through meaning. However, words do not appear independently in a text sequence. The existence of syntactic rules induce correlations among neighboring words. Further, words are not evenly distributed but approximately follow a power law since terms with a pure semantic content appear much less often than terms that specify grammar relations. Using an ordinal pattern approach, we present an analysis of lexical statistical connections for eleven major languages. We find that the diverse manners that languages utilize to express word relations give rise to unique pattern distributions. Remarkably, we find that these relations can be modeled with a Markov model of order 2 and that this result is universally valid for all the studied languages. Furthermore, fluctuations of the pattern distributions can allow us to determine the historical period when the text was written and its author. Taken together, these results emphasize the relevance of time series analysis and information-theoretic methods for the understanding of statistical correlations in natural languages.

I. INTRODUCTION

Despite its complexity, language seems to be organized with a few structural principles [1]. For example, every language has a lexicon of thousands of words. These are basic elements with a particular meaning which can be combined in utterances to transmit a full idea. Therefore, the potential number of word combinations can be overwhelming large. However, a statistical analysis of lexical frequencies shows a scaling behavior (Zipf’s law [2]) that establishes an inverse proportion with respect to word rankings. This probability distribution holds for large corpora and many different languages [3] and has been linked to a cognitive principle of least effort in human communication [4, 5].

Yet, the Zipf’s law yields no information on the selection rules that govern grammatical arrangements within a sentence. Indeed, words with the highest frequencies often operate with a purely syntactic purpose, such as determiners (e.g., the in English), prepositions (of), conjunctions (and) or pronouns (I), but unigram distributions like the Zipf’s law cannot provide insight into the deep relationships formed between function and content words to produce meaningful sentences. What is desirable, thus, is to investigate distributions of bigrams, trigrams, etc. [6] to have a complete picture of the statistical patterns that underlie human language.

At first sight the task looks formidable. If \( N \) is the vocabulary cardinality, the number of distinct \( n \)-grams is \( N^n \). For a rough estimate of \( N = 10^4 \), the possible combinations become exceedingly large already for \( n = 3 \) and cannot hence be statistically analyzed with the largest available resources (e.g., the Google Books corpus [7] includes around \( 10^{11} \) tokens). Even if one takes into account syntactic rules that forbid certain combinations, the number would continue to be enormous. Here, we take an approach that significantly simplifies the problem while revealing at the same time interesting linguistic patterns.

Our approach is based on an ordinal analysis [8, 9]. A text is viewed as a time series where the time dimension corresponds to the discrete position of the word inside the text. This perspective is accurate because language, with very few exceptions, is linear: one word comes after the other. Let us consider the beginning of the The Man Who Was Thursday, a 1908 novel by G. K. Chesterton: “A cloud was on the mind of men and wailing went the weather...”. In Fig. 1 we plot the ranking of these words calculated from their absolute frequencies within the novel as a function of position. It follows that the is the top word type and appears at the bottom of the time
series while content words (*cloud, mind, men*) possess a much lower occurrence and come into the high part of series. As a consequence, any text portion in the book consists of a succession of ups and downs as the story unfolds. Our aim is to study this dynamics rather than the particular ranking value as the Zipf’s law does. Below, we show that the distribution of increasing and decreasing patterns contains extremely valued information not only about the language itself but also about its history and the speaker (or the writer) who generates the speech.

II. METHOD

Let \( W \) be the number of words in a given text. We rank its words according to their absolute frequency and render the text a sequence of rankings: \( S_r = \{r_1, r_2, \ldots, r_W\} \). This way, the \( i \)-th word in the sequence is replaced with its frequency ranking \( r_i \). The rankings are calculated from each text separately. This guarantees that each word is assigned with a ranking. Another possibility is to use a common ranking for all works under consideration (see the Supplementary Information (SI)), but our results are not significantly altered because \( W \gg 1 \) is large for the texts considered in this work. A word of caution is necessary for rare words [10] since it may be that two words with very low frequency share the same ranking. Whenever this happens we modify randomly the rankings of the affected words to make sure that in \( S_r \), two neighboring terms are never equal. In the SI we give details of this procedure and prove that this modification does not affect the final results.

Our objective is to obtain the pattern distribution for the text. Depending on the embedding dimension \( D \) in the time series [11] there exist \( D! \) ordinal patterns. For instance, if \( D = 2 \) we have either an increasing or a decreasing pattern between two consecutive words with rankings \( r_i < r_{i+1} \) in the first case and \( r_i > r_{i+1} \) in the second case. We plot a sketch of these in the top-left panel of Fig. 2. Then, for the data in Fig. 1 the pattern sequence becomes \( S_p = \{1, 2, 2, 1, 2, 1, 2, 1, 2, 1\} \), where we have assigned the symbols 1 (2) to the increasing (decreasing) pattern. For \( D = 3 \) we have six possibilities, namely, 1 (\( r_i < r_{i+1} < r_{i+2} \)), 2 (\( r_i < r_{i+2} < r_{i+1} \)), 3 (\( r_{i+1} < r_i < r_{i+2} \)), 4 (\( r_{i+2} < r_i < r_{i+1} \)), 5 (\( r_{i+1} < r_{i+2} < r_i \)) and 6 (\( r_{i+2} < r_{i+1} < r_i \)), see top-right panel in Fig. 2. As a result, the sequence in Fig. 1 can be symbolized as \( S_p = \{2, 6, 6, 3, 2, 5, 2, 3, 2, 6, 5\} \). The procedure can be straightforwardly generalized to higher dimensions (see bottom panel in Fig. 2 for the 24 ordinal patterns with \( D = 4 \)).

Additionally, one may consider the embedding delay \( \tau \in \mathbb{N} \) that defines the time separation between the elements [11]. In the remainder of this paper, we take \( \tau = 1 \), which implies consecutive data, thus fulfilling the linear property of language. As a consequence, the embedding dimension agrees with the number of items in an \( n \)-gram. Another remark is in order. The pattern sequences \( S_p \) are generated allowing for overlaps between frequency rankings. Linguistically, this implies that our method probes the phrase structure of the sentence. This can be understood as follows. Quite generally, the pattern distributions show text correlations between segments of length \((D - 1)\tau \). We have checked that for \( \tau = 3 \) the results do not differ from a random sequence obtained by shuffling the text words. It follows that the method is sensitive to short-ranged correlations, which occur at the phrase (syntagmatic) level. Below, we provide further evidence for this.

We perform an analysis in three different levels. In the macroscale, we contrast the different pattern distributions across major language families [12]: Indo-European (English, Spanish, French, German, Latin and Russian), Afro-Asiatic (Somali), Niger-Congo (Xhosa), Turkic (Turkish), Austroasiatic (Vietnamese) and Austronesian (Tagalog). Our choice also allows for a broad variety of linguistic typologies. Since word order plays a crucial role in our findings (see Sec. III), we concentrate on the most common subject-verb-object (SVO) arrangements found in human language: SVO (English, Spanish, French, Russian, Vietnamese, Xhosa), SOV (German, Latin, Somali, Turkish) and VSO (Tagalog), which amount to 96% of the existing typologies. We only exclude East Asian families (Sino-Tibetan, Japonic, Koreanic) because word boundaries are not clearly depicted in their written samples and linear ordering is not fulfilled. However, the number of selected languages suffices to support our findings. To avoid possible differences due to the distinct nature of the analyzed texts and allow for

![FIG. 2. Ordinal patterns employed in this work for embedding dimensions \( D = 2 \) (top left), \( D = 3 \) (top right) and \( D = 4 \) (bottom). Each dot represents a value in a word ranking diagram such as the one in Fig. 1.](image)
FIG. 3. Relative frequency for pattern 1, as defined in Fig. 2 for embedding dimension $D = 2$, as a function of the text position for the Bible and the languages indicated above. Each frequency is calculated for a temporal window of $10^4$ words. Then, the window is shifted $10^3$ time units until the text finishes. Labels in the horizontal axis indicate the different, consecutive, window series. Whereas the blue curves correspond to the original text, the red dots indicate a shuffled (random) realization generated by randomly varying the token positions.

In the mesoscale, we focus on one language (English) and examine the pattern distribution along time. For definiteness, we bring our attention to the four periods into which scholars traditionally divide the history of English: Old English, Middle English, Early Modern English and Modern English [15]. We pick representative works for each period (see Table S1 in the SI). It is worth mentioning here that Sigaki et al. [16] have recently shown that physics-inspired measures estimated from ordinal patterns distributions are able to capture relevant information about paintings, their style and their temporal evolution. Moreover, these measures can be consistently connected with qualitative canonical concepts proposed by art historians to distinguish artworks.

Finally, the microscale is concerned with individual authors. We fix both the language and the period (Modern English) and analyze a literary corpus [17] corresponding to four writers: G. K. Chesterton, A. C. Doyle, H. P. Lovecraft and E. A. Poe. Notice that the two most important varieties of English (British and American) are equally represented with these authors. In Table S1 in the SI we quote the five book titles for each of these writers employed for our microscale analysis.

We start our analysis by showing with blue curves in Fig. 3 the normalized frequencies of the first $D = 2$ pattern for the different Bibles. (The frequency for the second pattern can be simply derived from probability normalization.) Each frequency is calculated for a temporal window of $10^4$ words. Then, the window is shifted $10^3$ time units until the book finishes. For all languages, the signals appear stochastic but clearly differ from a random sequence obtained by shuffling all the words (red curves). In the latter case, the series also fluctuate but their mean is 0.5 as should be. In contrast, the expectation value for the original text is above or below 0.5, depending on the language, suggesting that the stationary probabilities contain correlations entirely due to the word ordering dictated by the syntactic rules that operate in human language. Note that we depict two sequences for German, each corresponding to a different Bible translation, showing that their dynamical behavior do not show significant changes.

We now compare in Fig. 4 (blue curves) the probability distributions for the observed stationary patterns. Here, we choose a representative value for $D$ ($D = 4$ but the same conclusion is achieved for any other value provided that $D! \ll W$). Quite remarkably, we find that every language has its own fingerprint. Admittedly, a few languages display almost equal histograms, such as French and Spanish (both Romance languages), but this should not make us think that the distributions are determined by the linguistic family. For instance, English and German are both Germanic languages and show distinct probability functions. On the other hand, Xhosa (and possibly Turkish) shows a uniform distribution close to the shuffled case, the latter shown as a red band with $3\sigma$. 

III. RESULTS

a fair comparison, we need a single work, long enough, translated to the previously mentioned languages. The Bible fulfills all these requirements, is publicly available for natural language processing purposes [13] and has already been employed in quantitative linguistics [14].
limits obtained after 100 independent realizations. We attribute this result to the fact that Xhosa is a strongly agglutinative language where articles and prepositions are not typically independent words but morphemes that join to root words. We further discuss this particular effect in the SI. Finally, we do not observe any connection between the SVO order and the pattern probabilities. The linguistic reason underlying the divergences must be sought for somewhere else.

To gain further insight, we include in Table I the most frequent bigrams and their $D = 2$ associated pattern for both English and Spanish. Whereas in English the pattern 2 is more common, in Spanish the pattern with the highest probability is 1. What is the rationale for this difference? If we examine the top bigrams we find that their parsing is preposition + determiner (of the in English or de la in Spanish) or determiner + noun (the Lord in English or la tierra in Spanish). Therefore, their deep structures (in the generative grammar language sense [18]) do not differ. It is instead the surface structure that determines the mean values for each pattern. Since the is the top word type in English, we find more instances of pattern 2 corresponding to the group preposition + determiner. Contrarily, this structure is built in Spanish with the preposition de, which is the top word type in this language and, as a consequence, pattern 1 appears more often. It is therefore not surprising that, as compared with Spanish, we derive an almost equal distribution in French, which employ similar words for these functions and with similar frequencies. Thus, the concrete pattern distributions are not only caused by the syntactic rules but also by the diverse strategies that languages employ to express these rules with the vocabulary at their disposal. Importantly, our results do no invalidate the existence of a universal grammar. We will unveil in Sec. IV a true universal feature that is not observable in the patterns’ mean values but surprisingly in their statistical distribution through short-ranged correlations.

Let us now discuss the mesoscale level. It is well known that language changes with time. Then, we expect that pattern distributions will evolve along history. We illustrate this phenomenon in Fig. 5. We take representative works for each historical period. In the Old English case [Fig. 5a)], we plot the probability distribution function for Andreas (curve 1), Anglo-Saxon Chronicle (2), Beowulf (3), Christ (4), Genesis (5) and Guthlac (6). Despite the fact that these texts are quite short, the distributions appear similar (with fluctuations due to the different lengths and genre). For the Middle English [Fig. 5b]) we use Layamon’s Brut (to have texts of similar lengths we split this work in curves 7 and 8), Canterbury Tales (9, 10 and 11), Confession Amantis (12, 13 and 14), Book of the Knight of La Tour-Landry (15) and Mandeville’s Travels (16). It is nice to see the evolution in the patterns from the Old [Fig. 5a]) to the Middle periods [Fig. 5b]]. The latter distributions appear more uniform because of both the smaller time range of their period and a higher language standardization, a process that began in the Late Middle Ages. The Early-Modern English corpus [Fig. 5c)] comprises works of Ben Jonson and those of Christopher Marlowe, Milton’s Paradise Lost, and Shakespeare’s Tragedies and Comedies (see Table S1 in the SI for their number identification). Finally, those chosen authors living in the Modern English period [Fig. 5d)] were aforementioned in Sec. II and their works are also enumerated in Table S1 of the SI. Clearly, there is an overall coherence among patterns belonging to the same time, which suggests that the traditional classification in periods has a lexical support.

This is better seen when one calculates the permutation Jensen-Shannon distance [19] between distributions and plots this distance for $D = 4$ as in Fig. 6. We observe four dark areas that well correspond to the four historical periods. The distinction is clear between Old, Modern and the cluster formed by Middle English and Early-Modern English, between which the transition is less clear. This is because the Early-Modern English spans a period between the Renaissance, when the medieval
forms were still popular, and the 17th century, when English conventions were approaching those of the Modern period. Interestingly, there exist individual deviations from the historical pattern. For instance, Anglo-Saxon Chronicle (work 2) appears to be close to the Middle English cluster whereas Paradise Lost (work 22) would be more suitable to be classified in the previous stage (Middle English), probably due to Milton’s intentionally archaic style. Another exception is Jonson (works 17, 18 and 19), whose style is better categorized within the Modern period. We highlight that despite the method’s simplicity we are not only able to correctly place literary works in their composition period but also detect singular departures assignable to particular style features.

Previous results are encouraging because they show that on top of a common background that characterizes written works in a given language there may exist fluctuations large enough to allow us to determine the author of a set of texts. In fact, a few subclusters with smaller distances can be distinguished in Fig. 6 for works of the same writers. This is particularly evident for Layamon’s, Gower’s, Jonson’s and Shakespeare’s works. We now pursue this idea by further analyzing the last historical period (microscale). In Fig. 7 we depict the ordinal patterns and their probability frequencies for $D = 4$. Fluctuations are seen in the slight differences within the histogram. Then, we assess the pairwise distribution distance and plot the resulting matrix in Fig. 8. To obtain a more efficient discrimination between the texts, thus amplifying the fluctuations shown in Fig. 7, we set the embedding dimension to $D = 6$, which allows for 720 patterns. Strikingly, we observe in Fig. 8 that each writer forms a cluster of his own, with the largest distance taking place between Poe (works numbered between 16 and 20) and the rest, perhaps due to Poe’s highly mixed style. Here, we add an important caveat: the microscale is the most sensitive situation and Fig. 8 is only a proof of concept. To use this technique in author attribution tasks would require better refined analyses that fall beyond the scope of the present work.

IV. DISCUSSION

We have seen that the analysis of ordinal patterns is a powerful method that allows to identify (i) language, (ii) historical period and (iii) single authors. These results have their origin in the greatly diverse procedures with which human languages embody abstract formal relationships. We now discuss a universal trait, common to all languages studied in this work, which is unearthed after a closer look at the dynamical properties of the pattern series.

Let $x$ denote an ordinal pattern, which as discussed in Sec. II can take on $D!$ possible values. The probability to find a block of size $n \geq 1$ in the pattern sequence $S_p$ is $P(x_{i+n-1} = y_k, \ldots, x_{i+1} = y_j, x_i = y_l)$ where $t$ is the time (or position) index and $y$ designates the pattern values with $i, j, k$ running from 1 to $D!$. For a sufficiently long text ($W \gg 1$) we can faithfully compute these block probabilities from their occurrences as long as $n \ll W$. Notably, $P$ contains the complete information on the possible correlations between adjacent patterns. In Sec. III we calculated the expectation $E(x_i)$ which in the long term becomes stationary and consequently independent of $t$. However, to investigate pattern-pattern correlations one needs to find the covariance $E(x_i, x_{i+1})$. The issue is that this autocorrelation function depends on the employed symbolization for $D \geq 2$. (We discuss this in more detail in the SI). To overcome this important difficulty,
we resort to the approach discussed in Ref. [21], where a method is presented to determine the order of a Markov chain.

That language can be modeled as a Markov chain is an old subject. Markov himself proposed this technique [22] for his pattern analysis of vowels and consonants in A. Pushkin’s novel Eugene Onegin. In a Markovian system with a discrete space of states, the probability to find at time \( t \) the random variable \( x \) in state \( y \) depends on the state at time \( t - 1 \). This correlation is captured by the conditional probability. In general, a Markov chain has memory (or order) \( m \) if the conditional probabilities satisfy

\[
P(x_t = y_k | x_{t-1} = y_j, \ldots, x_{t-m} = y_l, \ldots, x_0 = y_l) = P(x_t = y_k | x_{t-1} = y_j, \ldots, x_{t-m} = y_l).
\]

This means that one would need to check \((D!)^{m+2}\) equalities even assuming that memory decreases with time [23]. Luckily, there is an equivalent, much shorter scheme, which consists of calculating the block entropy

\[
H_n = - \sum_{i,j,...,k=1}^{D!} P(x_{t+n-1} = y_k, \ldots, x_{t+1} = y_j, x_t = y_i) \times \log P(x_{t+n-1} = y_k, \ldots, x_{t+1} = y_j, x_t = y_i),
\]

where \( H_n \) is independent of \( t \) due to time homogeneity. Applying the condition given by Eq. (1), the entropy becomes a linear function of \( n \) [24]:

\[
H_\mu(n) = (H_{\mu+1} - H_{\mu})(n - \mu) + H_\mu,
\]

for \( n \geq \mu > 0 \) and \( H_0(n) = n H_1 \) for \( n \geq 1 \) with \( \mu \in \mathbb{N}_0 \) a trial memory. Therefore, the parameter

\[
\Delta_\mu = \frac{1}{n_{\text{max}} - \mu + 1} \sum_{n=\mu}^{n_{\text{max}}} (H_\mu(n) - H_n)^2
\]

vanishes if \( \mu \geq m \) for all values of \( n_{\text{max}} \). Thus, the memory \( m \) can be found from the condition

\[
m = \min(\mu : \Delta_\mu = 0).
\]

In practice, we define a small threshold for the vanishing of the order parameter. This method can then provide the \( m \) value that better fits the sequences \( S_p \) for the languages considered in Sec. III.

In Fig. 9a) and b) we plot the entropy as a function of the block size for the English Bible at \( D = 2 \) and \( D = 3 \), respectively. We find in both cases that the sequences \( S_p \) can be described with a Markov model of memory \( m = 2 \) since the data (red dots) are well fitted with Eq. (3) for \( \mu = 2 \) (blue curve overlapping with the red line). Interestingly, the entropy is smaller than that of the shuffled realization (green line). Therefore, the deviation with the random case is entirely due to correlations among words.

We also show in the insets of Fig. 9 the behavior of \( \Delta_\mu \) for a set of trial memories. For the two \( D \) values, the parameter \( \Delta_\mu \) attains 0 at \( \mu = 2 \) (within a tiny numerical error). We have checked that this is true for all the studied languages. Naturally, each language has its own transition probabilities given by Eq. (1). What is remarkable is that every lexical pattern distribution can be modeled with a Markov chain of order 2 independently of the considered language.

Even further, the deviations of these sequences from an \( m = 1 \) model are all of the same order, as can be seen in Table II, where we present the Markovity parameter \( \delta \) defined as

\[
\delta = \frac{|H_1 - \mathcal{H}(1)|}{a}.
\]

Here, \( \mathcal{H}(n) = a n + b \) with coefficients \( a \) and \( b \) obtained from linear regression. This fitting is done for \( n > 1 \) in order that \( H_1 \) and \( \mathcal{H}(1) \) be independent. Then, \( \delta \) quantifies the departure of the entropy curves from a pure Markovian model of memory \( m = 1 \). In all cases, \( \delta \) enhances as \( D \) increases because the number of possible blocks grows as \((D!)^3\) and the calculation becomes less reliable due to finite size effects. Strikingly enough, \( \delta \) is approximately
the same for all languages. Therefore, a $m=2$ Markov model appears to be an accurate modelization for ordinal sequences of human language, the deviations from $m=1$ being worldwide established. In the SI, we provide a further proof for this finding using an alternative method based on autocorrelation functions.

We emphasize that our results are not in contradiction with recent claims that point to long-range correlations in texts [25–29]. Recalling that our ordinal analysis replaces a huge number of words with a few ranking-based patterns, it is natural to expect that pattern-pattern correlations quickly vanish after a few Markov steps. This is consistent with our method being responsive to interrelations inside a phrase, which are typically much shorter than a sentence, and whose syntactic structure puts constraints on the parts of speech to which its elements may belong. We quantify that these constrains act between maximum 3 adjacent patterns and that this is a universal feature of human communication, possibly due to the few grammar rules (in comparison with the number of words) that govern all languages. In the SI we recalculate the pattern statistical distributions shuffling the sentences and obtain exactly the same distributions, which is another indication that pattern correlations are established above single words but below the sentence level.

### V. CONCLUSIONS

In short, we have demonstrated that every language has a characteristic fingerprint in terms of a statistical distribution for symbolic patterns. The observed patterns emerge from a combination of the syntactic rules that shape each language and the way that this language articulate those rules. A careful view of the pattern distribution provides useful information on the historical period when the text was produced and the author that wrote it. These findings bode well for possible applications of our method. We envisage implementations in stylometry studies that seek a correct authorship attribution, as mentioned above, or in forensic linguistics for legal cases where linguistic data play a decisive role. Another interesting application would aim at the detection of speech impairments in individuals.

The procedure discussed here has obvious limitations, the most important of which concerns semantics. Since every word is replaced with its ranking value in a table of frequencies, the symbolic patterns are agnostic with regard to meaning. However, this is the same limitation that takes place in all information-theoretic approaches to language, like Shannon’s theory of communications [30]. This does not preclude our analysis from being capable of finding a novel linguistic universal [31] in relation with a common memory value that determines short-ranged correlations in phrase structures.

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1. M. D. Hauser, N. Chomsky, and W. T. Fitch, “The faculty of language: What is it, who has it, and how did it evolve?” Science 298, 1569–1579 (2002).
2. George Kingsley Zipf, The Psychobiology of Language (Houghton-Mifflin, New York, NY, 1935).
3. S. T. Piantadosi, “Zipf’s word frequency law in natural language: A critical review and future directions,” Psychon. Bull. Rev. 21, 1112–1130 (2014).
4. B. Mandelbrot, “On the theory of word frequencies and on related Markovian models of discourse,” in Structure of Language and its Mathematical Aspects, Vol. XII (1953) pp. 190–210.
5. R. Ferrer i Cancho and R. V. Solé, “Least effort and the origins of scaling in human language,” Proceedings of the National Academy of Sciences 100, 788–791 (2003).
6. Le Quan Ha, Philip Hanna, Ji Ming, and Francis Jack Smith, “Extending Zipf’s law to n-grams for large cor-
por，“Artificial Intelligence Review 32, 101–113 (2009).

[7] Jean-Baptiste Michel, Yuan Kui Shen, Aviva Presser Aiden, Matthew K. Gray, The Google Books Team, Joseph P. Pickett, Dale Hoiberg, Dan Clancy, Peter Norvig, Jon Orwant, Steven Pinker, Martin A. Nowak, and Erez Lieberman Aiden, “Quantitative analysis of culture using millions of digitized books,” Science 331, 176–182 (2011).

[8] Christoph Bandt and Bernd Pompe, “Permutation entropy: A natural complexity measure for time series,” Phys. Rev. Lett. 88, 174102 (2002).

[9] Massimiliano Zanin and Felipe Olivares, “Ordinal patterns-based methodologies for distinguishing chaos from noise in discrete time series,” Communications Physics 4, 1–14 (2021).

[10] Kumiko Tanaka-Ishii and Armin Bunde, “Long-range memory in literary texts: On the universal clustering of the rare words,” PLOS ONE 11, 1–14 (2016).

[11] Anastasios A. Tsonis, Chaos: From Theory to Applications (Plenum Press, New York, NY, 1992).

[12] Raymond G. (Ed.) Gordon, Ethnologue. Languages of the World, 15th ed. (SIL International, Dallas, TX, 2005).

[13] C. Christodouloupoulos and M. A. Steedman, “A massively parallel corpus: the Bible in 100 languages,” Lang. Resources & Evaluation 49, 375–395 (2015).

[14] Ali Mehri and Maryam Jamaati, “Variation of Zipf’s exponent in one hundred live languages: A study of the holy bible translations,” Physics Letters A 381, 2470–2477 (2017).

[15] George Sampson, The Concise Cambridge History of English Literature, 3rd ed. (Cambridge University Press, Cambridge, UK, 1970).

[16] Higor Y. D. Sigaki, Matjaž Perc, and Haroldo V. Ribeiro, “History of art paintings through the lens of entropy and complexity,” Proceedings of the National Academy of Sciences 115, E8585–E8594 (2018).

[17] Project Gutenberg (Urbana, IL, 2021) https://www.gutenberg.org/.

[18] David Crystal, The Cambridge Encyclopedia of Language, 2nd ed. (Cambridge University Press, Cambridge, UK, 1997).

[19] Luciano Zunino, Felipe Olivares, Haroldo V. Ribeiro, and Osvaldo A. Rosso, “Permutation Jensen-Shannon distance: A versatile and fast symbolic tool for complex time-series analysis,” Phys. Rev. E 105, 045310 (2022).

[20] Jack Grieve, “Quantitative authorship attribution: An evaluation of techniques,” Literary and Linguistic Computing 22, 251 (2007).

[21] J. De Gregorio, D. Sánchez, and R. Toral, “An improved estimator of Shannon entropy with applications to systems with memory,” arXiv:2205.11931 (unpublished).

[22] Alain Schenkel, Jun Zhang, and Zhang Yi-Cheng, “Long range correlations in human writings,” Fractals 1, 47–57 (1993).

[23] Peter Grassberger, “Toward a quantitative theory of self-generated complexity,” International Journal of Theoretical Physics 25, 907–938 (1986).

[24] J. H. Greenberg, “Some universals of grammar with particular reference to the order of meaningful elements,” in Universals of Language, Vol. 298, edited by J. H. Greenberg (MIT Press, 1963) pp. 79–113.
S1. COMMON RANKING

In this section, we calculate the ranking sequences differently. We consider a large corpus and arrange its words based on their occurrences. The corresponding rankings are then used to determine the ordinal patterns. The advantage of this approach is that all literary works are symbolized using the same ranking. The limitation is that word types that do not appear in the corpus cannot be assigned to a definite ranking and therefore not all patterns consist of consecutive words. However, we do not see a significant difference with the method employed in the main text.

It suffices to illustrate this fact with a single language (e.g., English). We have checked that our conclusions are unaltered for different languages. The English word frequency list contains the 1/3 million most frequent words [1] built from the Google Books Corpus (GBC) [2]. In Fig. S1a) we depict the symbol dynamics for \(D = 2\) obtained from the GBC ranking, comparing with the original series, which is reproduced in Fig. S1b) from top left panel in Fig. 3 of the main text. We find that the dynamical patterns resemble each other although the peak amplitudes differ. This is expected because the strength of the fluctuations depend on the word frequencies, which in turn are calculated from different corpora. However, the probability distributions are almost unaltered. We show this in Fig. S1c) for the GBC side by side with Fig. S1d), which is replicated from top left panel in Fig. 4 of the main text. This demonstrates the robustness of our method for alternative corpora provided that the size of the corpus is sufficiently large.
FIG. S1. Dynamical behavior of the first $D = 2$ pattern (blue curves) for the English Bible when the ranking sequences are generated by using a) a common and b) its own corpus. The corresponding ordinal pattern probability distributions for $D = 4$ are displayed in c) and d), respectively. Results obtained when words are shuffled (red curves) are also included only for reference purpose. As in the main text, in the dynamical panels we only include a single shuffling realization to avoid finite size effects but in the distribution panels the red curves are indeed bands with $3\sigma$ limits calculated after 100 realizations.

S2. SEQUENCES WITH EQUAL RANKINGS

If a sequence of $k$ words have the same ranking $r_i < r_{i+1} = r_{i+2} = \cdots = r_{i+k} < r_{i+k+1}$, then we modify randomly those rankings by adding to each of $r_{i+1}, \ldots, r_{i+k}$ a uniform random number in the interval $(-r_{i+1} - r_i, r_{i+k+1} - r_{i+k})$. Here, we provide evidence that our procedure of breaking ranking ties does not affect the main results except for a case that deserves attention. In Fig. S2 we plot with solid blue lines the pattern distributions when two consecutive words are allowed to have the same ranking. If this happens, an ordinal pattern cannot form but this will occur mostly for rare words. In addition, in Fig. S2 we reproduce with red dashed lines the case as in Fig. 4 of the main text. Clearly, adding a small random number preserves the general structure of the probability distributions with the advantage that the number of generated patterns is the maximum possible. The case where the two distributions seriously differ is Xhosa (and, to a smaller degree, Turkish). This is caused by the large number of word types that have occurrence 1 or 2 in the text. Therefore, it is likely that two consecutive words have the same ranking and adding a small random number is now not negligible. We ascribe this effect to the agglutinative nature of Xhosa. Unlike, e.g., English, which expresses most of its syntactic functions with isolated words, Xhosa displays agglutinated morphological complexes. It is thus natural to expect in the Xhosa Bible a large amount of hapax legomena. Any random shift will then represent a significant perturbation to the original series, as observed in our data.

S3. LIST OF LITERARY WORKS

Table S1 shows the full list of literary works employed in the mesoscale and microscale analyses in Sec. III of the main text.
| Number | Title                                                      | Author                      |
|--------|------------------------------------------------------------|-----------------------------|
| 1      | Andreas                                                   | Anonymous                   |
| 2      | Anglo-Saxon Chronicle                                    | Anonymous                   |
| 3      | Beowulf                                                   | Anonymous                   |
| 4      | Christ                                                    | Anonymous and Cynewulf      |
| 5      | Genesis                                                   | Anonymous                   |
| 6      | Guthlac                                                   | Anonymous                   |
| 7      | Brut I                                                    | Layamon                     |
| 8      | Brut II                                                   | Layamon                     |
| 9      | Canterbury I                                              | Chaucer                     |
| 10     | Canterbury II                                             | Chaucer                     |
| 11     | Canterbury III                                            | Chaucer                     |
| 12     | Confessio Amantis I                                       | Gower                       |
| 13     | Confessio Amantis II                                      | Gower                       |
| 14     | Confessio Amantis III                                     | Gower                       |
| 15     | The Book of the Knight of La Tour-Landry                  | Caxton                      |
| 16     | The Travels of Sir John Mandeville                        | Mandeville                  |
| 17     | Every Man in His Humor. The Poetaster                     | Jonson                      |
| 18     | Epicoene. Cynthia’s Revels                               | Jonson                      |
| 19     | Bartholomew Fair. The Alchemist                           | Jonson                      |
| 20     | Tamburlaine the Great. Hero and Leander                   | Marlowe                     |
| 21     | The Jew of Malta. The Massacre at Paris                   | Marlowe                     |
| 22     | Paradise Lost                                             | Milton                      |
| 23     | Tragedies I                                               | Shakespeare                 |
| 24     | Tragedies II                                              | Shakespeare                 |
| 25     | Comedies I                                                | Shakespeare                 |
| 26     | Comedies II                                               | Shakespeare                 |
| 27     | The Innocence of Father Brown (1)                         | Chesterton                  |
| 28     | The Man Who Know Too Much (2)                             | Chesterton                  |
| 29     | The Napoleon of Notting Hill (3)                          | Chesterton                  |
| 30     | The Man Who Was Thursday (4)                              | Chesterton                  |
| 31     | The Wisdom of Father Brown (5)                            | Chesterton                  |
| 32     | Memoirs of Sherlock Holmes (6)                            | Conan Doyle                 |
| 33     | The Return of Sherlock Holmes (7)                         | Conan Doyle                 |
| 34     | The Sign of Four (8)                                      | Conan Doyle                 |
| 35     | The Hound of the Baskervilles (9)                         | Conan Doyle                 |
| 36     | The Adventures of Sherlock Holmes (10)                    | Conan Doyle                 |
| 37     | The Randolph Carter Stories (11)                          | Lovecraft                   |
| 38     | The Dream Cycle (12)                                      | Lovecraft                   |
| 39     | Twenty-Nine Tales (13)                                    | Lovecraft                   |
| 40     | Twenty-Nine Collaborative Stories (14)                    | Lovecraft et al.            |
| 41     | At the Mountains of Madness (15)                          | Lovecraft                   |
| 42     | The Works of Edgar Allan Poe I (16)                       | Poe                         |
| 43     | The Works of Edgar Allan Poe II (17)                      | Poe                         |
| 44     | The Works of Edgar Allan Poe III (18)                     | Poe                         |
| 45     | The Works of Edgar Allan Poe IV (19)                      | Poe                         |
| 46     | The Works of Edgar Allan Poe V (20)                       | Poe                         |

**TABLE S1.** Literary works considered in the mesoscale and microscale analyses. The numerical identification of the left column is used in the axes of Figs. 5 and 6 of the main text while the numbers in parentheses are employed for the axes of Fig. 8 of the main text.
S4. AUTOCORRELATION ANALYSIS

Let us consider a two-state system with values $z_i \in \{1, 2\}$. This corresponds to the $D = 2$ case for ordinal patterns discussed in the main text. A Markov process or order $m = 2$ is defined by the following 8 (of which 4 are independent) transition probabilities

$$p_{ij} = \text{Prob}(z_{n+2} = 1 | z_n = i, z_{n+1} = j), \quad i, j = 1, 2 \quad (S1)$$
$$q_{ij} = \text{Prob}(z_{n+2} = 2 | z_n = i, z_{n+1} = j) = 1 - p_{ij}, \quad i, j = 1, 2 \quad (S2)$$

Given a sequence $\{z_0, z_1, z_2, \ldots\}$ we can form a new series by concatenating two consecutive values $x_0 = (z_0, z_1)$, $x_1 = (z_1, z_2)$, etc. For instance the series in the $z$ variable $\{1, 1, 2, 1, 2, 1, 2, 2\}$ yields the series $\{11, 12, 21, 12, 21, 11, 12, 22\}$ in the $x$ variable. Note that the length of the $x$ series is one unit less than the original length of the $z$ variable series. The key point is that in the new $x$ variable space the process is Markovian with the matrix of transition probabilities $W_{ij} = P(x_n = X_i | x_{n-1} = X_j)$ with $X_1 = 11, X_2 = 12, X_3 = 21, X_4 = 22$:

$$W = \begin{pmatrix}
p_{11} & 0 & p_{21} & 0 \\
q_{11} & 0 & q_{21} & 0 \\
0 & p_{12} & 0 & p_{22} \\
0 & q_{12} & 0 & q_{22}
\end{pmatrix} \quad (S3)$$

If we denote by $\vec{P}_n = \begin{pmatrix}
P(x_n = 11) \\
P(x_n = 12) \\
P(x_n = 21) \\
P(x_n = 22)
\end{pmatrix}$ the probability vector whose components are the probability that the value of $x_n$ at time step $n$ is equal to $ij, i, j = 1, 2$, we can write down the evolution equation $\vec{P}_n = W\vec{P}_{n-1}$, of general solution
\[ \vec{P}_{n+\ell} = W^n \vec{P}_\ell \] valid for all values of \( n \) and \( \ell \). The steady state \( \vec{P}_{\text{st}} = \lim_{n \to \infty} \vec{P}_n \) satisfies

\[
\begin{pmatrix}
P_{\text{st}}(x = 11) \\
P_{\text{st}}(x = 12) \\
P_{\text{st}}(x = 21) \\
P_{\text{st}}(x = 22)
\end{pmatrix} = \frac{1}{q_{11}q_{12} + (2q_{11} + p_{21})p_{22}} \begin{pmatrix}
p_{21}p_{22} \\
q_{11}p_{22} \\
q_{11}p_{22} \\
q_{11}q_{12}
\end{pmatrix}
\] (S4)

where the right hand side is the, conveniently normalized, eigenvector associated to the eigenvalue \( \lambda_0 = 1 \) of the matrix of transition probabilities \( W \). Note that \( P_{\text{st}}(x = 12) = P_{\text{st}}(x = 21) \), as in a given \( \{z_n\} \) series there are always as many transitions \( 1 \to 2 \) than \( 2 \to 1 \) with the possible exception arising from the last term of the series being equal to the first one. In addition to \( \lambda_0 = 1 \), the matrix \( W \) has three further eigenvalues, \( \lambda_1, \lambda_2, \lambda_3 \), different from 1 that can be obtained as the roots of the characteristic equation:

\[ \lambda^3 + (p_{22} - p_{11})\lambda^2 + (p_{22}q_{11} - p_{12}q_{21})\lambda + (p_{12} - p_{22})(p_{11} - p_{21}) = 0, \]

(S5)

whose explicit solutions are too cumbersome to be written down here.

All statistical properties of the \( z \) series can be derived from those of the series in the \( x \) variables. For example,

\[ P(z_n = i) = \sum_{j=1,2} P(x_n = ij), \]

(S6)

\[ P(z_n = i, z_{n+1} = j) = P(x_n = ij) \]

(S7)

\[ P(z_n = k, z_{n+2} = i) = \sum_{j=1,2} P(z_n = k, z_{n+1} = j, z_{n+2} = i) \]

\[ P(z_n = k, z_{n+1} = j, z_{n+2} = i) = P(z_{n+2} = i|z_n = k, z_{n+1} = j)P(z_n = k, z_{n+1} = j) \]

\[ = \begin{cases} 
p_{ki}P(x_n = kj) & i = 1 \\
q_{ki}P(x_n = kj) & i = 2
\end{cases} \] (S8)

\[ P(z_n = i, z_{n+\ell} = j) = \sum_{k_1=1,2, k_2=1,2} P(x_{n-1} = ik_1, x_{n+\ell} = jk_2), \quad \ell > 2 \] (S9)

valid for all values \( i, j, k = 1, 2, \) etc.

We are interested in the correlation function \( C_\ell \) of the original \( \{z_n\} \) series as a function of the time lag \( \ell \) between values in the series. This is defined as

\[ C_\ell = \frac{\langle z_{n+\ell}z_n \rangle_{\text{st}} - \langle z_n \rangle_{\text{st}}^2}{\langle z_n \rangle_{\text{st}}^2 - \langle z_n \rangle_{\text{st}}^2}. \] (S10)

All averages are performed in the steady-state where all dependence on the initial condition has been lost. Note that \( C_0 = 1 \), and that this definition is independent on the actual values assigned to the variables \( z_n \) since any linear transformation \( z_n \to az_n + b \) with arbitrary \( a,b \) would give the same result. This is a particular result valid only for a series whose elements take only two values. For an ordinal analysis with \( D > 2 \) we would have to face the issue that different assignments to the values of the \( z \) variable would yield different numerical values to the autocorrelation function.

The averages in the steady state are computed as:

\[ \langle z_n \rangle_{\text{st}} = \sum_{z_n=1,2} z_n P_{\text{st}}(z_n), \]

(S11)

\[ \langle z_{n+\ell}z_n \rangle_{\text{st}} = \sum_{z_n=1,2; z_{n+\ell}=1,2} z_n z_{n+\ell} P_{\text{st}}(z_n, z_{n+\ell}), \]

(S12)

using Eqs. (S6-S9) and the steady-state solution given by Eq. (S4).

Based on Eqs. (S11-S12) and the general solution \( \vec{P}_{n+\ell} = W^\ell \vec{P}_n \) of the recurrence relation, we can write the correlation function in terms of the eigenvalues of the matrix \( W \) as:

\[ C_\ell = \alpha \lambda_1^\ell + \beta \lambda_2^\ell + (1 - \alpha - \beta) \lambda_3^\ell, \] (S13)

(note the fulfilment of the condition \( C_0 = 1 \)).
Using the definition given by Eq.(S10) and the previous relations, a long but straightforward calculation yields $C_1$ and $C_2$ in terms of the transition probabilities:

$$C_1 = Z^{-1}(p_{21}q_{12} - q_{11}p_{22}),$$

$$C_2 = Z^{-1}(p_{21}q_{21} - p_{22}q_{11} + (p_{12} - p_{21})(-p_{21}q_{22} + q_{11}(2p_{22} + q_{12}))).$$

Setting $\ell = 1, 2$ in Eq. (S13) we can connect $\alpha$ and $\beta$ with the values of $C_1$ and $C_2$:

$$\alpha = \frac{C_2 - C_1(\lambda_2 + \lambda_3) + \lambda_2\lambda_3}{(\lambda_1 - \lambda_2)(\lambda_1 - \lambda_3)},$$

$$\beta = \frac{C_2 - C_1(\lambda_1 + \lambda_3) + \lambda_1\lambda_3}{(\lambda_2 - \lambda_1)(\lambda_2 - \lambda_3)}.$$  

In practise, we proceed as follows: Given the series $\{z_n\}$ obtained from the lexical pattern analysis explained in the main text for $D = 2$, we numerically compute the probabilities $p_{11}, p_{12}, p_{21}, p_{22}$ using Eq. (S1), i.e., counting the frequency with which a value $z_n = 1$ follows a pair $z_{n-2} = i, z_{n-1} = j$. Once these values have been obtained, we compute the correlation function $C_\ell$ using Eq. (S13) with values of $\lambda_1, \lambda_2, \lambda_3$ following from Eq. (S5) and values of $\alpha, \beta$ from Eqs. (S14,S15,S16,S17). We then compare the obtained values of $C_\ell$ with the ones computed numerically from the original series.

The results for the analysis of the Bible in English, French, German and Spanish are displayed in Fig. S3. It can be seen that the autocorrelation function $C_\ell$ for $\ell \geq 0$ is rather well represented by the memory-2 Markov model introduced here and is consistent with the results shown in Fig. 9 of the main text. The agreement is much better for the French and Spanish versions of the Bible, while the English and, mostly, the German versions show some discrepancy for large values of $\ell$.

If we had used a purely Markovian model of memory $m = 1$, then the transition probabilities for the $z$ variables are

$$p_1 = P(z_{n+1} = 1|z_n = 1), \quad q_1 = P(z_{n+1} = 2|z_n = 1) = 1 - p_1,$$

$$p_2 = P(z_{n+1} = 1|z_n = 2), \quad q_2 = P(z_{n+1} = 2|z_n = 2) = 1 - p_2.$$  

A standard analysis concludes that the correlation function decays exponentially, $C_\ell = (\lambda)^\ell$, where $\lambda = p_1 - p_2$ is the eigenvalue different from 1 of the transition probability matrix. This functional form is totally excluded from the numerical data.

## S5. Shuffled Sentences

The shuffled realizations of Figs. 3 and 4 in the main paper and Fig. S1 of this SI are obtained by randomly shuffling all the words in the original text. A different shuffled realization shuffles the sentences instead of the individual words. Remarkably, our results obtained for shuffled sentences are the same than those obtained for the original sequences. For definiteness, we select four languages and plot in Fig. S4 both the original pattern dynamics for $D = 2$ (blue dots), reproduced from Fig. 3 of the main text, and the ordinal pattern when the sentences are shuffled (red dots). Obviously, the dynamics do not agree because the relative frequencies are calculated over time windows and these windows contain texts with totally different sentences in both cases. However, the stationary values and their probability distributions are not modified. This is shown in Fig. S5 for $D = 4$, where one can note that there is exact match between the original Bible (blue lines as replicated from Fig. 4 of the main text) and the Bible with shuffled sentences (red dots). Since the short memory encountered in our analysis is based on these statistical distributions, we can safely conclude that our method detects short-ranged correlations that typically occur inside a sentence.

[1] P. Norvig, Natural language corpus data, in *Beautiful Data*, edited by T. Segaran and J. Hammerbacher (O’Reilly Media, 2009) pp. 219–242.

[2] Y. Lin, J.-B. Michel, E. Lieberman Aiden, J. Orwant, W. Brockman, and S. Petrov, Syntactic annotations for the Google Books Ngram corpus, in *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics* (Association for Computational Linguistics, 2012) pp. 169–174.
FIG. S3. Autocorrelation function (ACF), defined in Eq. (S10), of the series generated from the lexical pattern analysis of the Bible in four languages, as discussed in the main text for $D = 2$. Blue dots with error bars show the numerical values while the red line is the theoretical expression given by Eq. (S13), which is obtained after computing the transitions probabilities $p_{11}, p_{12}, p_{21}, p_{22}$ from the series. Four top panels show that an $m = 2$ Markov chain correctly captures the original series correlations. Four bottom panels are zoomed versions that point to small discrepancies when the time lag $\ell$ is large.
FIG. S4. Dynamical behavior for $D = 2$ as in Fig. 3 of the main text but comparing the original Bible (blue dots) and the Bible with shuffled sentences (red dots). In both cases, the curves differ from the case with shuffled words (the red curve in Fig. 3 of the main text), which corresponds to the trivial dynamics.

FIG. S5. Pattern probability distributions for $D = 4$ for the original Bible (blue lines as in Fig. 4 of the main text) and the Bible with shuffled sentences (red dots).