RESEARCH ARTICLE

Complexity Measurement of Natural and Artificial Languages

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We compared entropy for texts written in natural languages (English, Spanish) and artificial languages (computer software) based on a simple expression for the entropy as a function of message length and specific word diversity. Code text written in artificial languages showed higher entropy than text of similar length expressed in natural languages. Spanish texts exhibit more symbolic diversity than English ones. Results showed that algorithms based on complexity measures differentiate artificial from natural languages, and that text analysis based on complexity measures allows the unveiling of important aspects of their nature. We propose specific expressions to examine entropy related aspects of tests and estimate the values of entropy, emergence, self-organization, and complexity based on specific diversity and message length. © 2014 Wiley Periodicals, Inc. Complexity 20: 25–48, 2015

Key Words: Information; entropy; emergence; self-organization; complexity; natural language; artificial language; computer code; software; power law

1. INTRODUCTION

The study of symbol frequency distribution for English was initially addressed by Zipf [1] in 1949 and Heaps during the 70s [2], giving rise to Zipf's and Herdan-Heaps' laws, respectively (frequently referred to as Heaps' law). Zipf [1] suggested that the scale free shape of the word frequency distribution, typically found for English long texts, derives from his *Principle of Least Effort*. As in many other large scale phenomena, the origin of the tendency of natural languages to organize around scale free structures, remains controversial [3] and a plentiful source of hypothesis and comparisons with other "laws of nature" [4–6]. The relationship between both Laws has been studied [7] and their validity for various natural alphabetic languages tested [8–10]. Yet, a generally accepted mechanism to explain this behavior is still lacking, as Zipf's and Heaps' laws have been traditionally applied only to probabilistic consequences of grammar structure and language size.

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Language grammar has been addressed in the study of basic grammar rules and the mechanisms to buildup English phrases, initiated by Chomsky [11] in the late 50's.

Later Jackendoff developed the X-bar theory [12], fostering the idea of underlying effects driving human communication processes to produce grammar properties common to all natural languages. Yet clear descriptions of the fundamental sources of such a behavior, remains a matter of discussion, perhaps because it is a problem too complex to be completely understood using only theoretical methods.

Important differences arise from the nature and content of message than is transmitted. Yet, languages viewed as describing tools, have their own capacity to deliver a message more effectively or more efficiently. Therefore, languages are susceptible of being evaluated. As George Markowsky [13] expressed:

"An important point to stress here... is that the algorithmic complexity[1] of an object depends very much on the language in which the object is described! We can make the complexity of any particular object as small or as large as we choose by picking the appropriate language or by modifying an existing language."

In this article, we treat languages as complex systems made of large sets of symbols, and following other authors' suggestion [14, 15], we compare messages expressed in natural and artificial languages using metrics developed to quantify complexity. Our comparison is based on measurements of message symbol diversity, entropy and symbol frequency distributions. Zipf's distribution profiles and Heaps' functions are identified for different messages samples. We evaluate the impact of these measures over emergence, self-organization and complexity of messages expressed in natural and artificial languages.

Our strategy is to evaluate a wide range of texts for each language studied, including text pieces from a variety of writers distributed over a timespan of more than 200 years. All texts were recorded in a computer file directory and analyzed with purposely developed software called *MoNet* [16] (see section 2.10), as explained in sections 2.1 to 2.6.

2. METHODS

We compared three aspects of English, Spanish, and artificial languages: symbol diversity D, entropy h, and the symbol frequency distribution f. For the available measures of diversity and information, we follow Gershenson and Fernandez [17] to evaluate emergence and self-organization for natural and artificial languages. For complexity, we use the definition of Lopez-Ruiz et al. [18], which sees complexity as a balance between chaotic and stable regimes.

[1]The concept of Algorithmic Complexity is not rigorously the same concept of Complexity, Emergence or Information we apply in this study. Still, Markowsky's point of view justifies perfectly our study.

All computations are directed to the symbolic analysis. We have made an effort to recognize slight differences in the way words or punctuation signs are presented in a text. Nevertheless our analysis disregards any syntactical meaning.

2.1. Text Length L and Symbolic Diversity d

The length of a text L is measured as the total number of symbols or words used and the diversity D as the number of different symbols that appear in the text. We define the specific diversity d as the ratio of diversity D and length L, that is

$$d = \text{ specific diversity } = D/L. \tag{1}$$

In this study, symbols are considered at the scale of words. Here a word is a considered as a sequence of characters delimited by some specific characters such as a blank space (see section 2.9). Most recognized symbols were natural and artificial language words. Nevertheless some single character symbols, such as periods and commas, appeared by themselves with complete meaning and function and therefore playing a role comparable to that of normal words.

2.2. Entropy h

Entropy calculations are based on Shannon's information [19], which is equivalent to Boltzmann-Gibbs entropy. Message information is estimated by the entropy equation is based on the probability of appearance of symbols within the message. Symbols (words) are treated all with the same weight, ignoring any information that might be associated to meanings, length or context. Shannon's entropy expression for a text with a symbol probability distribution $P(p_i)$ is:

$$h(p_i) = -\sum_{i=1}^{2} p_i \log_2 p_i \ . \tag{2}$$

Shannon was interested in evaluating the amount of information and its transmission processes; therefore his entropy expression was presented for a binary alphabet formed by the symbols "0" and "1." Entropy measurement in this study is at the scale of words, where each word is a symbol, extending the original Shannon's expression for a D-symbol alphabet:

$$h(f_r) = -\sum_{r=1}^{D} \frac{f_r}{L} \log_D \frac{f_r}{L} \ , \tag{3}$$

where we have replaced the term p_i with its equivalent in terms of the symbol frequency distribution $F(f_r)$ and the text length L measured as the total number of symbols.

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The values for the symbol frequency distribution $F(f_r)$ are ordered on r, the symbol rank place ordered by their number of appearances in the text. Since there are D different symbols, r takes integer values from 1 to D. Notice the base of the logarithm is the diversity D and hence h is bounded between zero and one.

2.3. Emergence e

As a system description is based on different scales—the number of different symbols used—the quantity of information of the description varies. Emergence measures the variation of the quantity of information needed to describe a system as the scale of the description varies, thus, emergence can be seen as a profile of quantity of information for a range of system scales. Therefore, we express emergence e as a function of the quantity of information respect to the description length L (total number of symbols) and the specific symbol diversity d. This is given Shannon's information (3), so we have:

$$e(F(f_r))=h(F(f_r)) \,. \tag{4}$$

2.4. Self-Organization s

The self-organization of a system can be seen as the capacity to spontaneously limit the tendency of its components to fill the system space—symbols in our case—in a homogenous, totally random distributed fashion. Since entropy reaches a maximum when the system components are homogeneously randomly dispersed, self-organization s is measured as the difference of the maximum entropy level $h_{\max}=1$, and the actual system entropy [14].

$$s(F(f_r))=h_{\max}-h(F(f_r))= 1-e(F(f_r)) \,. \tag{5}$$

2.5. Complexity c

Message entropy calculations are based on Shannon's expression [19]. Message information is estimated by the entropy equation based on the probability of appearance of symbols within the message. Symbols (words) have all the same weight here, ignoring putative differences in information associated to the word's meanings, length, or context. We used the complexity definition proposed by López-Ruiz et al. [18], and its quantifying expression proposed by Fernández et al. [14]

$$c(F(f_r))=4 \cdot e(F(f_r)) \cdot s(F(f_r))=4 \cdot h(F(f_r)) \cdot [\, 1-h(F(f_r))]. \tag{6}$$

In this definition, complexity is high when there is a balance between emergence (entropy, chaos) and self-organization (order). If either is maximal, then complexity is minimal. Equations (4)–(6) depend on Shannon's information and can be reduced to it [14]. Still, it is explanatory to study each of these separately, as it will be seen in our results below, emergency e is a measure of "disorder," entropy s measures order and complexity c their balance.

2.6. Symbol Frequency Distribution *f*

For any message or text the number of words in a rank segment $[a, b]$ may computed as:

$$L_{a,\ b}=\sum_{r=a}^{b} f_r \ , \tag{7}$$

where a and b are the start and the end of the segment where symbol were ranked, respectively. For any segment, $a=1$ and $b=\mathrm{D}$.

Zipf's law states that any sufficiently long English text will behave according to the following rule [3, 8]:

$$f(r)= \frac{f_a}{(r-a)^g} \ , \tag{8}$$

where r is the ranking by number of appearances of a symbol, $f(r)$ a function that retrieves the numbers of appearances of word ranked as r, f_a the number of appearances of the first ranked word within the segment considered, and g a positive real exponent.

For any message, we define Zipf's reference $Z_{a,b}$ as the total number of symbol appearances in the ranking segment $[a, b]$ assuming that it follows Zipf's Law. Therefore $Z_{a,b}$ is

$$Z_{a,b}=\sum_{r=\mathrm{a}}^{b} f_r= \sum_{r=a}^{b}\frac{f_a}{r^g} \,. \tag{9}$$

Equation (8) allows us to determine the Zipf's reference Z for any segment within the symbol rank dominion. We computed versions of Zipf's reference Z for the complete message, specifically named $Z_{1,\ D}$, and for the tail of the message frequency distribution (see Figure 1), named $Z_{\theta,\ \ D}$. The subindex θ is used to indicate the ranking position r_θ where the head-tail transition occurs.

Head-tail transition location can be a difficult parameter to set and is often considered to be among a range of possibilities. We used the following definition: for a discrete symbol ranked frequency or probability distribution, the region of the lowest frequency of ranked symbols starts where the symbols with a unique frequency (or probability = 1) end. Figure 1 illustrates an example of symbol frequency profile. The point signaled with the arrow corresponds to the 20th rank position and has seven occurrences, and no other symbol shares the same number of appearances. At that point we define the start of the tail which includes the distribution domain shadowed in yellow in the figure.

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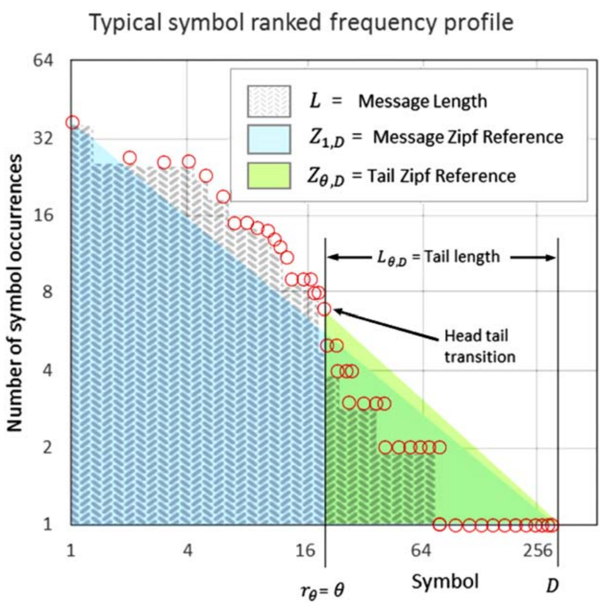
FIGURE 1



Typical symbol ranked profile. Red dots indicate the number of occurrences and the ranking position of the symbols of a given text. Message Zipf's and tail Zipf's references are the blue and yellow shadowed areas, respectively.

2.7. Zipf's Deviation *J* for a Ranked Distribution

The complete message Zipf's reference is determined by expression (8). The corresponding Zipf's deviations $J_{1,D}$ from a Zipfian distribution and the deviation of its tail $J_{\theta,D}$ are

$$J_{1,D} = (L - Z_{1,D})/Z_{1,D}, \quad (10a)$$

$$J_{\theta,D} = (L_{\theta,D} - Z_{\theta,D})/Z_{\theta,D}. \quad (10b)$$

Identifying the starting point for the tail of each message or code profile is a search intensive task. We included in the software *MoNet*, the capability of locating within a frequency profile the points with properties characterizing the start of the tail and to split messages and codes in heads and tails. Once the tail starting rank r_θ is determined, Zipf's tail deviation was obtained by applying Eqs. (10a) and (10b).

2.8. Message Selection

We built text libraries containing consisting of large text fragments, obtained from English and Spanish speeches, segments of stories and novels, and computer codes written in high level programming languages (C, C#, Basic, Matlab, Java, HTML, and PHP). The program then produced descriptive indices and attributes for each of these. Each message could be analyzed as an individual object or as a part of a collective group of objects.

2.8.1. Natural Language Message Selection

Natural language messages were collected from historic speeches available in on the web as texts expressed in English or Spanish. Natural language texts include speeches from politicians, human rights defenders, and literature Nobel Laureates. The language used to write the original speech was not a selection criterion. There are speeches in our selection originally written in English, Spanish, French, Russian, Italian, German, Arabic, Portuguese, Chinese, and Japanese. Translated speeches and texts are indicated as such, providing data for studying translations. Novel fragments were authored in English or Spanish by popular writers and by some Nobel laureates in literature.

We collected 156 texts in English and 158 in Spanish. The shortest speech was 87 words long, whereas the longest speech contained more than 20,000 words.

2.8.2. Artificial Language Message Selection

We included 49 computer codes devoted to perform recognizable tasks. Artificial text lengths go from a C# code which generates Fibonacci numbers with just 62 symbols, to computer logs with more than 160,000 symbols. This selection of artificial texts include codes written in *C*, *C#*, Basic, Java, MatLab, HTML, and PHP. The Table in Appendix A gives details of codes and their fragments used here.

2.9. Symbol Treatment

Special treatment of certain character strings or symbols were considered as follows:

Word: A word is any character string isolated by the characters "space" or "line return." The word is the symbolic unit.

Space: The space works as a delimiter for symbols or words.

Line Return or Line Feed: Is a delimiter for paragraphs.

Punctuation Signs: Any sign is considered as a complete independent symbol. In natural languages, the punctuation signs have specific meaning that, with very few exceptions, are not sensitive to other surrounding characters. When located next to numeric characters, if a punctuation sign appeared attached to another symbol, the sign was handled as being separated by the space character to keep it as a single symbol. This rule provides a coherent solution to the very frequent case where words appear attached to punctuation symbols.

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Numbers: For natural languages, a digitally written number might be a unique sequence of characters. Numbers express quantities and work as adjectives or modifiers of an idea. All numbers in a natural language message are then considered as different symbols.

Synonyms: Since ours is a symbolic analysis, synonyms are considered as different words.

Capital letters: Words are case sensitive. In English and Spanish, a word with its first letter written with a capital letter, refers to a specific name. Therefore, a name appropriately written with a first capital letter is different from the same character sequence written with all letters in lower case. But when the word starting with capital letter comes after a period sign, we assume it is a common lower case word, unless other appearances of the same word indicates it certainly is a proper name that should keep its first capital letter.

For Spanish messages

Accents: in Spanish, vowels are sometimes marked with an accent over it to indicate where the sound stress or emphasis should be. Rules to indicate when the accent mark should be present and when it should not, are easy to apply and are part of what any Spanish speaker should know from elementary school. Forgetting accent marks when they should appear is associated with poor writing abilities; it is unacceptable in any serious literary work. We consider that any accented word is different, and has some different meaning, from the same character sequence without accents.

For artificial languages (computer code)

Comments: in artificial languages comments do not affect any action of the interpreter or compiler. Additionally, comments are intended to convey ideas to the human programmer, administrator or maintenance personnel, hence most comments are written in phrases dominated by natural languages. Comments were thus excluded from any code analyzed.

Computer Messages: Most computer codes rely on the possibility of informing the user or operator about execution parameters. This information is normally expressed in different languages to that of the code. Computer message contained in a code were converted to a single word by extracting all spaces.

Numbers: Differently from natural languages, in artificial languages sequences of digits may represent variable names or memory addresses, which are objects with different meaning. In artificial languages, any difference in a digit is considered to result in a different word.

Capital letters: We considered artificial language symbols as case sensitive.

Variables: When in different parts of the code, two or more variable names were presented as the same symbol or characters string, but we know that sometimes they could have a totally different meaning since they could be pointing to a different memory address. This may introduce some deviation in the results.

2.10. Software

Two software programs were developed to analyze the texts. First, we built a file directory structure containing, and classifying the messages each with its inherent and invariant text-object properties. We refer to the file directory as the library. The second software program, called *MoNet*, manages the library and produced the data for our study.

2.10.1. Library

The library holds descriptions of each existing text-object with its attribute values. The scope of each object description can be adjusted adding attributes or even modifying their data representation nature and dimensionality. We built a text library containing hundreds of these text-objects. Libraries can be updated by deleting or adding text-objects.

2.10.2. MoNet

MoNet is a bundle of scripts, interpretations, programs, and visual interfaces designed to analyze complex systems descriptions at different scales of observation. *MoNet* describes a system as a collection of objects and object families connected by hierarchical and functional relationships.

MoNet can treat every text included in a library as well as the library itself, offering results for text-objects as independent elements or as groups. For every component of the system modeled, descriptions at different scales can coexist. Individual objects can be selected combining logical conditions based on properties or attribute values.

3. RESULTS

3.1. Diversity for Natural and Artificial Languages

Figure 2 shows how diversity varies with the message length in texts written in English, Spanish, and computer code. Diversity increases as messages grow in length, but there seems to be an upper bound of diversity for each message length. For English this upper bound is slightly lower than for Spanish. As message length increases, English also shows a wider dispersion toward lower diversities of words. Artificial messages represented by computer code showed a much lower diversity than the natural languages. The regression models of Heaps' law [9] for message diversities and message length are:

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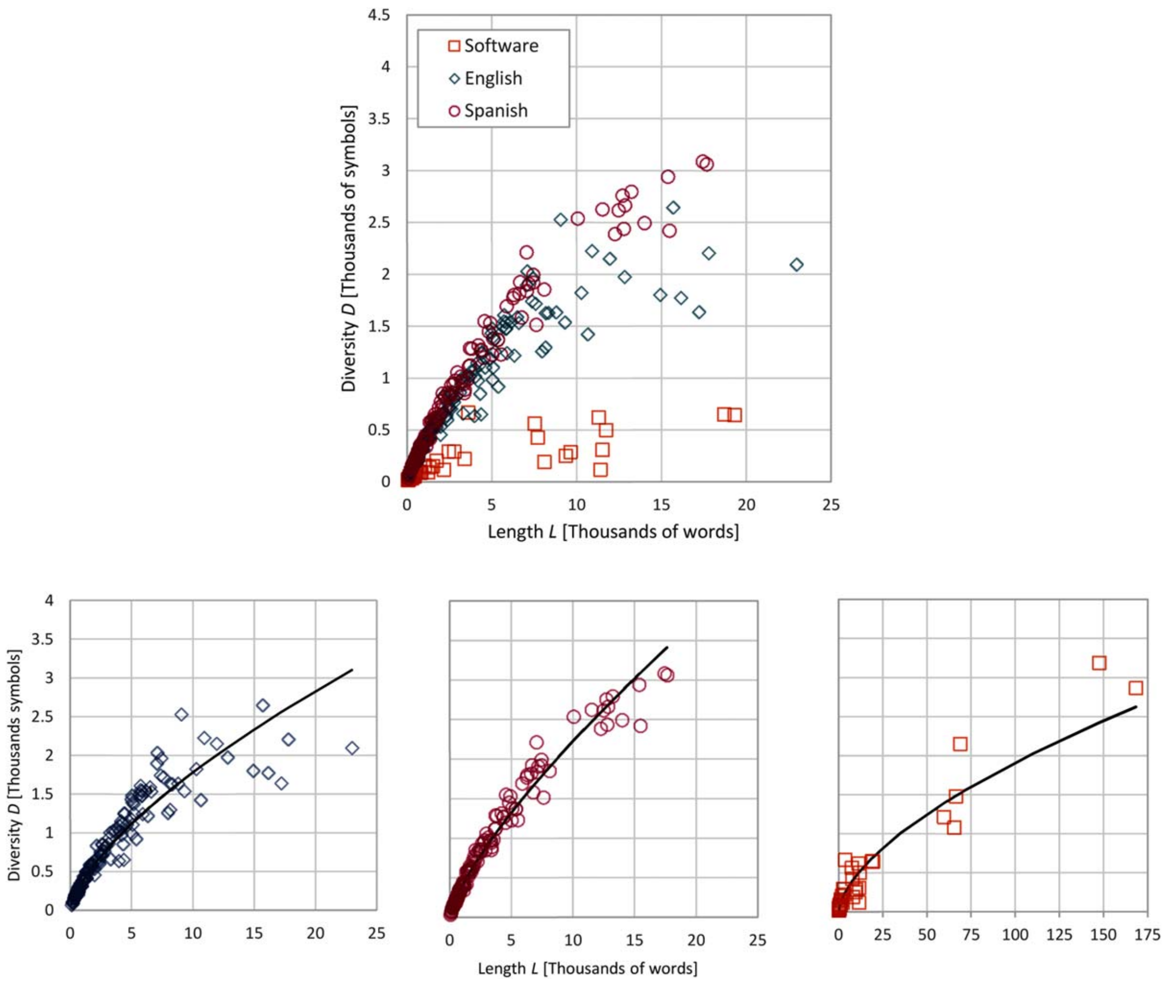
FIGURE 2



Diversity for messages expressed in English, Spanish, and computer code. Lower row presents fit dots (black) for messages expressed in English (left), Spanish (center), and Software (right).

$$\begin{aligned} \text{English}: &\quad D= 3.766 \cdot L^{0.67}. &\quad (11a)\\ \text{Spanish}: &\quad D= 2.3 \cdot L^{0.75}. &\quad (11b)\\ \text{Software}: &\quad D= 2.252 \cdot L^{0.61}. &\quad (11c) \end{aligned}$$

3.2. Entropy for Natural and Artificial Languages

Figure 3 shows entropy h values for texts expressed in natural languages and computer code programs as a function of specific diversity d (see section 2.1). Extreme values of entropy are the same for messages expressed in all languages; entropy drops down to zero when diversity decreases to zero and tends to a maximum value of 1 as specific diversity approaches 1. For artificial messages entropy is dispersed over a wider range of values, perhaps as a consequence of the many different computer languages included in this work's sample. Natural languages show less dispersion in entropy levels, nevertheless differences among languages show up in the areas they cover over the plane of entropy-diversity with few overlapping shared areas over that space. See Figure 3.

The entropy expression shown in Eq. (3) is a function with $D-1$ degrees of freedom; there are $D-1$ different ways of varying the variable F that affect the resulting value of entropy h. Nevertheless, when specific diversity is at extreme values $d=0$ and $d=1$, the distribution F becomes homogenous and function $h(F)$ adopts the following predictable behavior.

$$h(F \mid d \to 0) = 0 \quad (12a)$$
$$h(F \mid d \to 1) = 1 \quad (12b)$$

Having these extreme conditions for $h(F)$, we propose a real function $h(d)$ to characterize the entropy distribution

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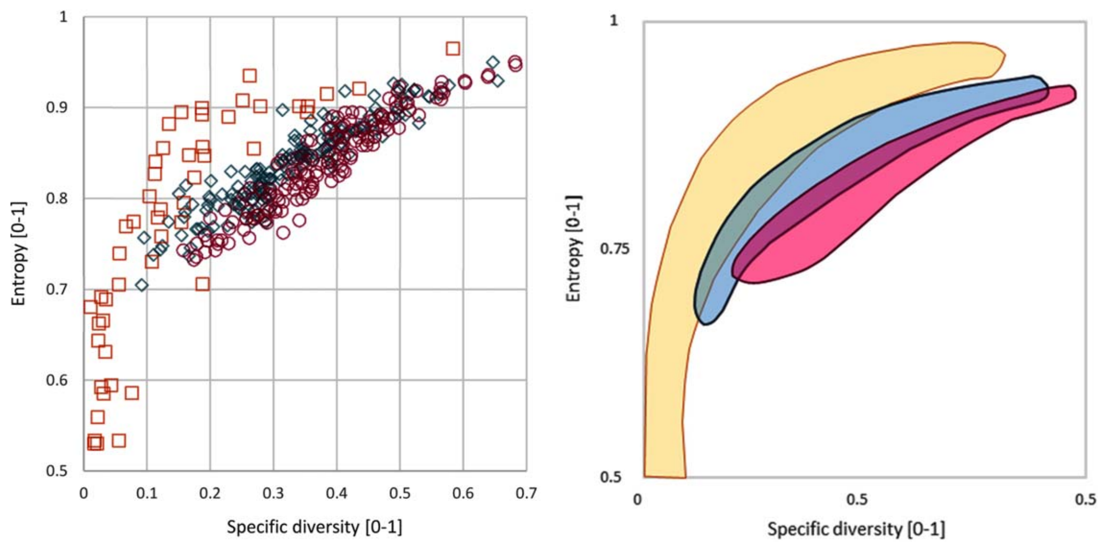
FIGURE 3



Messages entropy vs. specific diversity for English (blue rhomboids), Spanish (red circles) and computer code (orange squares). On the left graph each dot represents a message. The right graph shows the area where most messages lie upon its corresponding language.

of a language over the range of specific diversity. The dispersion of the points is due to the fact that none of the texts obeys perfectly a Zipf's law, yet each language tends to fill a particular area of the space entropy-specific diversity.

To model the curves along the core of these clusters of dots, that is entropy as a function of specific diversity, we refer to the so called Lorenz curves [20] which can be used to describe the fraction of edges W of a scale-free network with one or two ends connected to a node which belongs to the fraction P of the nodes with highest degree [5]. The family of Lorentz curves is expressed by

$$W = P^{(\alpha-2)/(\alpha-1)}. \tag{13}$$

Now consider the network associated to a text where the nodes represent words or symbols and the edges represent the relation between consecutive words. In a network like this, all nodes, except those corresponding to the first and the last words, will have a degree of connectivity that doubles the number of appearances of the represented word. Thus, the resulting ranked node degree distribution will be analogous to a Zipf's distribution and therefore, the network as defined, will have a scale-free structure. Conversely, entropy can be interpreted as the cumulative uncertainties that every symbol adds or subtracts from the total uncertainty or entropy. Viewing entropy h of a ranked frequency distribution as the cumulative uncertainty after adding up the contributions of the D most frequent symbols, we should expect this entropy h to have a scale-free behavior with respect to changes D. After the analogies between these conditions and those needed to expect a behavior like the Lorentz curves dictate, we propose the use of the one-parameter expression (13) to describe any language's entropy as a function of d and the parameterα. So that:

$$h = \left(\frac{D}{L}\right)^{(\alpha-2)/(\alpha-1)} = d^{(\alpha-2)/(\alpha-1)}. \tag{14}$$

Figure 4 compares the data using the entropy model for the languages studied. Values of α were obtained to minimize square errors between the entropy model and the experimental results obtained from each text of the library. Numerical results were α=2.123 for English, α=2.178 for Spanish and α=2.1 for artificial. The figure shows a much wider range of entropy values for artificial languages compared to the natural languages studied. Equations (15a)–(15c) present specific cases of function $h(d)$ for each language studied:

$$\text{English}: \quad h = d^{0.1511} \tag{15a}$$
$$\text{Spanish}: \quad h = d^{0.1756} \tag{15b}$$
$$\text{Software}: \quad h = d^{0.09091} \tag{15c}$$

3.3. Emergence, Self-Organization, and Complexity

Starting with functions for entropy, obtaining expressions for emergence, self-organization and complexity is straightforward using results of Eqs. (15a)–(15c) with Eqs. (4)–(6). Figure 5 illustrates these results.

To obtain expressions of emergence, self-organization as functions of the message length L, we combined Eqs.

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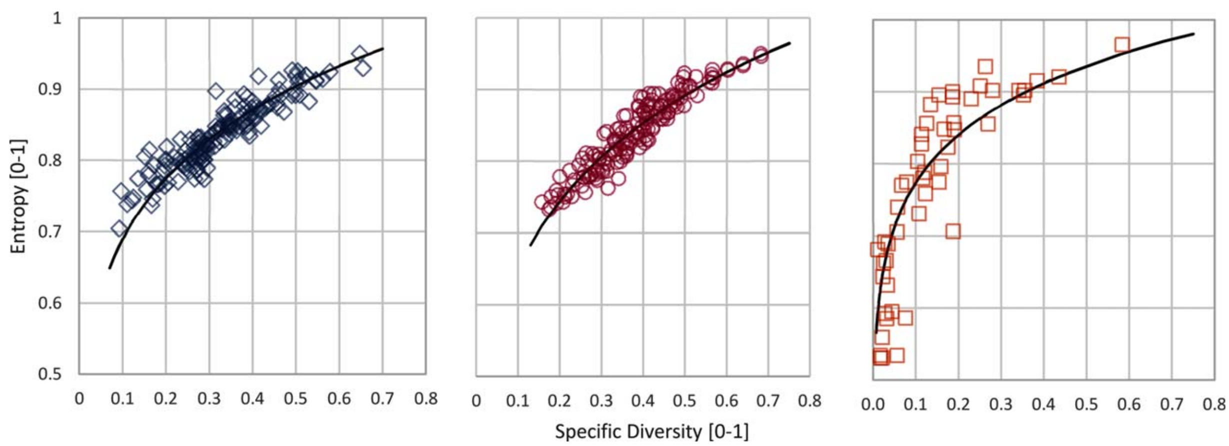
FIGURE 4



Messages entropy vs. specific diversity for English (left), Spanish (center). and artificial languages (right).

(15a)–(15c) with (11a)–(11c), respectively. See the results in Figure 6. For all languages, emergence increases with specific diversity and decreases with length. Self-organization follows opposite tendencies, decreasing with specific diversity and increasing with length. Complexity is maximal for low specific diversities and then decreases, although much less for natural languages. Complexity increases with length for all languages.

The most conspicuous result here is that artificial languages show a different pattern in complexity depending on specific diversity, as the maximum complexity for artificial languages is close to zero and then decreases faster than natural languages. This might reflect fundamental differences in organizing the symbols (grammar) between both types of languages.

3.4. Symbol Frequency distributions

Profile of symbol frequency distributions were inspected in two ways: first by a qualitative analysis of their shapes and second by characterizing each profile with its area deviation J with respect to a Zipfs distributed profile.

A sample of symbol frequency distributions profiles for the considered languages is represented in Figure 7. Each sequence of markers belongs to a message and each marker corresponds to a word or symbol within the message. While no important differences are observed among messages profiles expressed in the same language, a noticeable tendency to a faster decreasing frequency profile appears for messages expressed in artificial languages, perhaps a consequence of the limited number of symbols these types of languages have.

By building these frequency profiles, we could obtain a list of the most used words in English and Spanish. An equivalent list for artificial languages is also obtainable; however it is difficult to interpret due to the diversity of programming languages used in our artificial text sample. Table 1 shows statistics about the use of symbols for English and Spanish. Table 1 was constructed overlapping symbol frequency profiles of English and Spanish messages contained in our working library. After these calculations, two frequency profiles (probability distributions) were obtained: one for English, the other for Spanish. The first 25 rows of Table 1 correspond to the 25 most used symbols. After this high ranked symbols, rows in Table 1 show groups of symbols sharing ranges with the same or approximate percentage of use. In accordance with our definition of tail form this study, head-tail transition occurs at rankings 40 and 35 for English and Spanish, respectively.

Joining the text messages in three sets, according to the language they are written with, we obtained an approximation of the symbol frequency profiles for the “active” fraction of the languages studied (see Discussion). Figure 7 shows these profiles. Natural languages exhibit a wide range of ranks where the symbol frequency decays with an approximately constant slope g, sustaining Zipf’s law for English and extending its validity to Spanish, at least up to certain range of the symbol rank dominion. Even though we included many programming languages and artificial code as if they were all part of a unique language, which they are not, artificial languages do not show a range where we can consider slope g a constant, evidencing the fact that artificial languages are much smaller than natural ones. The values of exponent g were calculated for the three profile tails and included in Figure 7; profile slopes are all negative but g values are shown positive to be consistent with Eq. (8). Notice that Spanish has,

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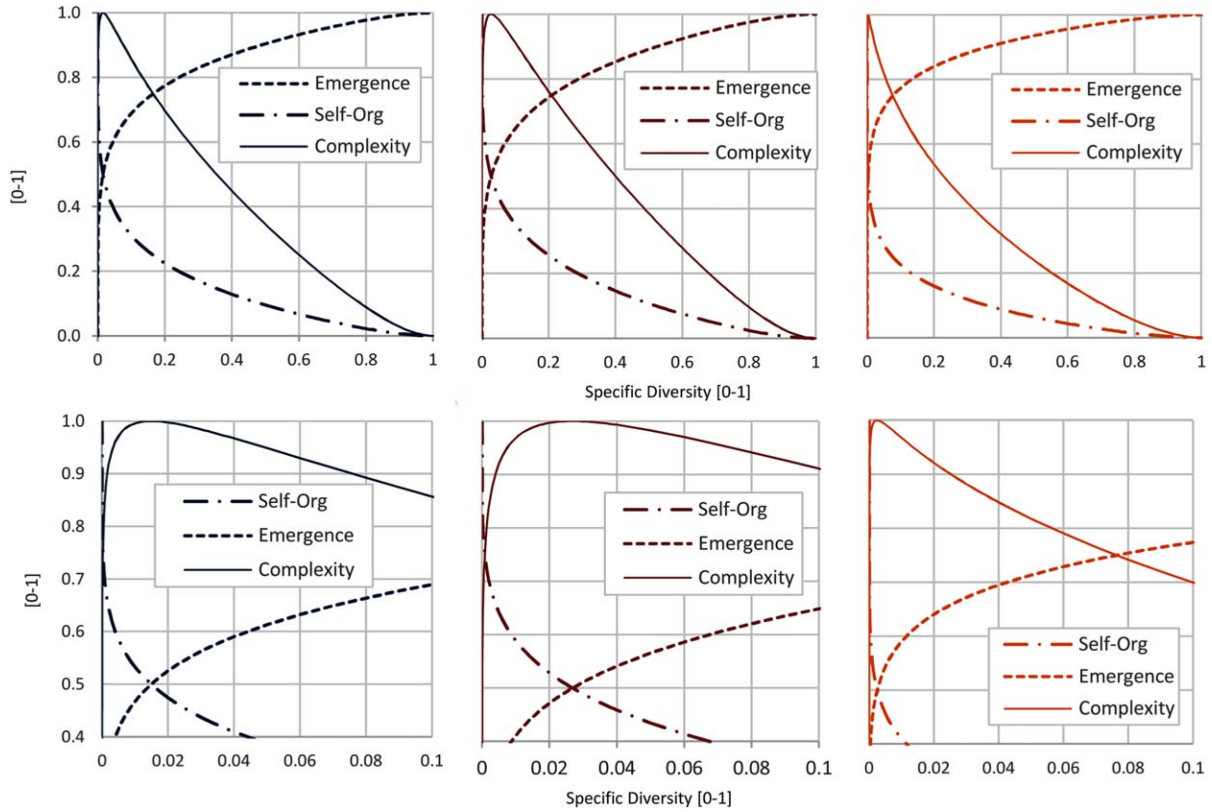
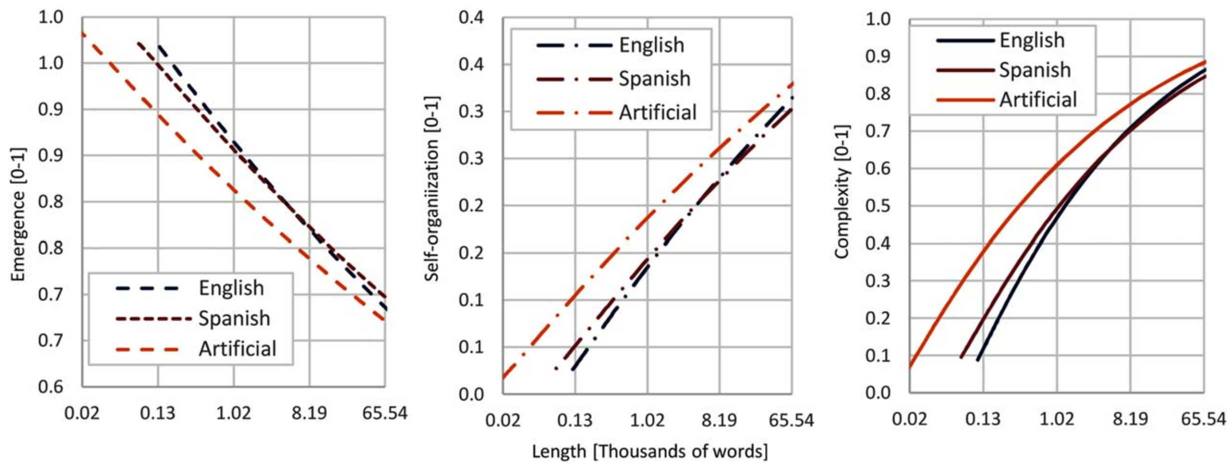
FIGURE 5



Emergence, self-organization, and complexity for English (left), Spanish (center), and computer code (right). Vertical axis is dimensionless [0−1]. Graphs placed on the lower row correspond to the detail very near the value zero for horizontal axis. These plots are based on Eqs. (4)−(6) combined with Eqs. (15a)−(15c).

FIGURE 6



Emergence (left), self-organization (center), and complexity (right) for English, Spanish, and computer code. Vertical axis is dimensionless [0−1]. These plots are based on Eqs. (4)−(6) combined with Eqs. (15a)−(15c), (11a)−(11c).

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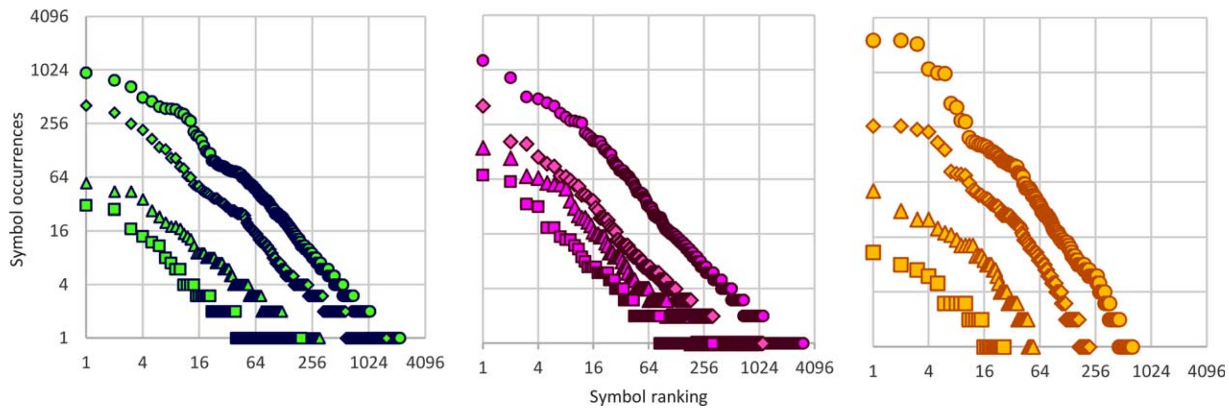
FIGURE 7



Ranked symbol frequency distribution for English (left), Spanish (center), and computer code (right). A sample of three or four messages for each language is shown. English: square: 1945.BS.Eng.GabrielaMistral; triangle: 1921.MarieCurie; rhombus: 1950.NL.Eng.BertrandRussell; circle: 1890.RusselConwell. Spanish: square: 1936.DoloresIbarruri; triangle: 1982.Gabriel García Márquez; rhombus: JoseSaramago.Valencia; circle: CamiloJoseCela.LaColmena.Cap1. Artificial: square: FibonacciNumbers.CSharp; triangle: QuickSort.CSharp; rhombus: Sociodynamica.Module3; circle: WebSite.Inmogal.php.

among the languages studied here, the smallest tail slope, meaning the heaviest tail; an indication of the variety of words included in all the Spanish messages. At the other end of our sample, artificial languages present the fastest decaying slope and the most limited number of symbols.

Direct measurement of differences between profile shapes is not straight forward. We converted the symbol frequency distributions into probability distributions and graph their corresponding cumulative function distribution (CDF) shown in Figure 8. As expected, artificial languages' CDF grow faster than the others; the 500 most frequently used symbols are enough to comprise almost 90% of all symbols included in our list of more than 13,000 artificial symbols. The first 500 words cover 74% of the 23,398 English words included in our library and 70% for the 33,249-word Spanish library.

The profile heads also reflect some differences between languages. In spite of the general faster growing English's CDF as compared with Spanish, the latter's CDF is higher up to symbol ranked about 56, where the two curves cross. This Spanish faster growing CDF within the head region implies a more intensive use of the close-words group and consequently the tendency of a more structured use of this particular language.

3.4.1. Zipf's Deviation $J_{1,\ D}$ for Ranked Distribution

We computed Zipf's deviations $J_{1,D}$ for natural and artificial languages. Figure 9 shows the result of these calculations on the plane Zipf's deviation $J_{1,D}$ vs. Length L. Dependence between Zipf's deviation $J_{1,D}$ and length L was evaluated with standard deviation and correlations. We also performed two tests with Student-t distributions to compare the Zipf's deviations $J_{1,D}$. The first tests the hypothesis of English and Spanish Zipf's distribution being the same. The second tests the hypothesis for natural and artificial languages to be the same. Results for all tests show that p-values are very small indicating that Zipfs deviation differed statistically in very significant ways between the three different languages studied. Table 2 summarizes these results.

3.4.2. Tail Zipf's Deviation $J_{1,\ D}$ for Ranked Tail Distributions

Zipf's deviation was also inspected for the tails of the ranked frequency distributions as described in Section 2.6. This evaluation provides some further understanding of the tails shapes and relates some tendencies to other variables associated to the messages and the languages. Figure 10 shows the Zipf's deviation $J_{\theta,\ D}$ based on the messages tails for the three languages included in this study. The incidence of language and different group of writers over the tail of ranked frequency distributions was evaluated by performing a Student-t test which results are included in Table 3. Student-t tests to compare the distributions of the texts tail Zipf's deviations $J_{\theta,D}$ show very small p-values, indicating that tail Zipfs deviation differed statistically in very significant ways between the three different languages studied.

4. DISCUSSIONS

4.1. Diversity for Natural and Artificial Languages

Setting a precise number for the total number of words of a natural language is impossible, as words appear and disappear constantly. However it has been estimated that

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TABLE 1

Most Frequently Used Symbols in English and Spanish.

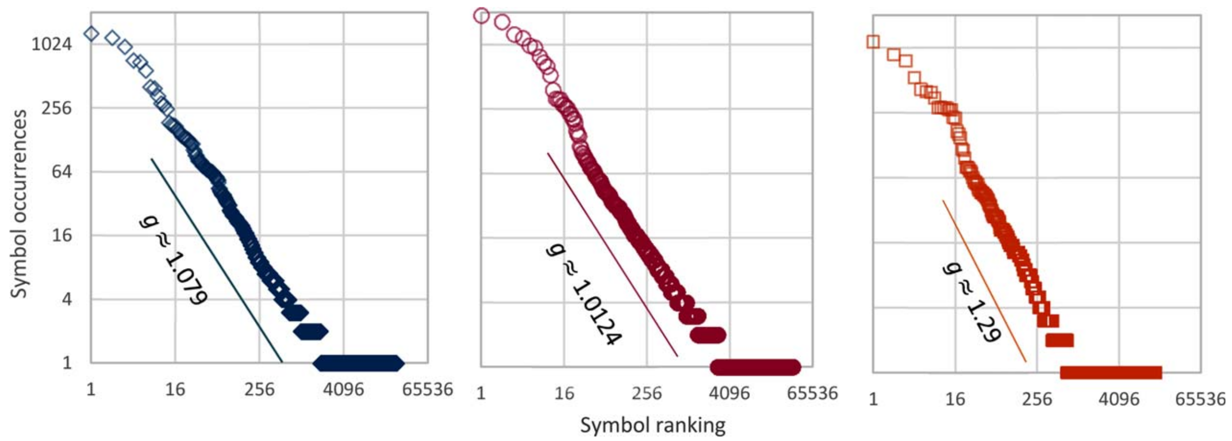
Natural Languages Symbol Frequency					
English. Total Symbols = 23,398			Spanish. Total Symbols = 33,249		
Rank	Word (Symbol)	Use (%)	Rank	Word (Symbol)	Use (%)
1	the	5.51921	1		5.7697
2	,	4.96449	2	de	5.0643
3	.	4.58479	3		3.8664
4	of	2.96836	4	la	3.5446
5	and	2.89258	5	que	3.0410
6	to	2.39816	6	y	2.8992
7	a	1.71795	7	el	2.3789
8	in	1.63451	8	en	2.0957
9	that	1.42234	9	a	1.9270
10	i	1.33711	10	los	1.5953
11	is	1.29327	11	no	1.1690
12	it	1.09772	12	las	0.9659
13	we	1.09103	13	un	0.9562
14	not	0.79216	14	se	0.9486
15	“	0.78874	15	con	0.8530
16	for	0.73284	16	del	0.8395
17	he	0.70253	17	por	0.7923
18	have	0.70204	18	una	0.7836
19	was	0.63881	19	para	0.6962
20	be	0.62708	20	es	0.6939
21	this	0.55440	21	-	0.6241
22	as	0.54185	22	lo	0.6229
23	you	0.53549	23	su	0.5637
24	are	0.53370	24	al	0.4811
25	with	0.52637	25	mas	0.4503
26	they	0.50694	26	como	0.4330
. . .	. . .	. . .	. . .	. . .	. . .
58	***man***	***0.24761***	*58*	***pueblo***	***0.1435***
. . .	. . .	. . .	*59*	***mundo***	***0.1408***
62	***people***	***0.23883***	*60*	sobre	0.1344
. . .	. . .	. . .	. . .	. . .	. . .
71	***world***	***0.17423***	*67*	***vida***	***0.1256***
. . .			. . .	. . .	. . .
500. . .	*indeed. . .*	0.01867...	*500. . .*	*poeta. . .*	0.01749...
. . .8000	*. . .yard*	. . .0.000732	*. . .7339*	*. . .flujo*	. . .0.000843
8002 - 9920	*adapt - vitiated*	*0.00055*	*7340-8841*	*funda. . .insurgimos*	0.000843
9923 - 13505	*actress - Zemindars*	*0.00037*	*8842-11,736*	*adictos . . .zumbido*	0.000632
13506 - 23398	*Aaron-Zulu*	*0.00018*	*11,737-15,622*	*abastecimientos . . . Zelli*	0.000419
			15,783-33,249	*abanderado . . . Xavier*	0.000209

Open-class words are shown with italic characters. Closed-class words are shown with normal characters. Top ranked open-class words are shown with italic-bold letters.

English contains more words than Spanish [21–23]. Living languages evolve over time and structural differences make it difficult to compare figures of language size measure. Nevertheless the numbers of lemmas in dictionaries provide us a reference to compare language sizes. The dictionary of the Real Academia Española contains 87.718 Spanish lemmas [24] while the Oxford English dictionary includes about 600.000 words [25]. Despite the larger size of English dictionaries, Spanish texts showed higher and less dispersed symbol diversity than English.

The higher word diversity of Spanish may thus be due to factors such as syntactical rules or grammar which affect both languages differently. Verb tenses and conjugations, for example, are all considered as one word when

FIGURE 8



Ranked symbol frequency distribution for English (left), Spanish (center) and artificial languages (right).

included in a dictionary, but each of them was recognized as a different symbol here.

For Spanish, most articles, pronouns and subject genres vary from masculine to feminine while for English this only happens for particular cases like his/her. These grammar characteristics may increase the number of different symbols used in any Spanish texts, but considering the relative size of closed and open word groups, this effect should be marginal with regard to general text symbol diversity. Conversely, verbs, which belong to the open group of words, have more tenses and conjugations for Spanish and therefore increase Spanish word diversity in ways not accounted for in dictionaries. Grammar is then one feature that explains greater Spanish word diversity compared to English.

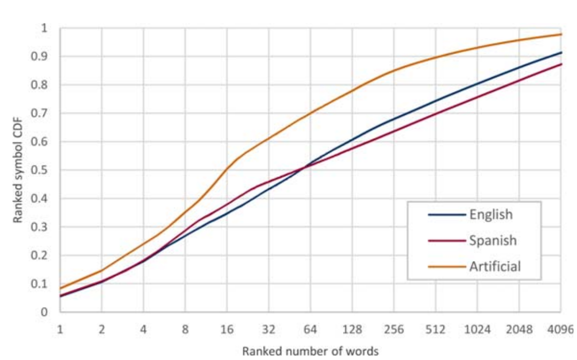
These differences might explain only parts of the results shown here. A wider use of words in Spanish, compared to English, despite a larger number of words in English dictionaries, cannot be excluded.

4.2. Entropy for Natural and Artificial Languages

There is no qualitative difference for this property between English and Spanish, perhaps a consequence of the similar structure and functionality both natural languages share. Nevertheless entropy appears slightly higher for messages expressed in English than for those in Spanish; being English a larger language in terms of words, this result might be explained as consequence of a more elaborated grammar in Spanish allowing for lower entropy levels. The topic also has an impact over the properties we measured. For example, religious speeches in English and political speeches in Spanish show a lower symbol diversity than those texts influenced by other topics. Clearly, the semantic speech content has an incidence over the text properties as the symbolic diversity and entropy. In addition to these theme-associated differences, there are however, overlapping differences between the languages themselves. We think the number of messages considered and the wide range of natural language themes and computer code functions included in our library of study, suffice to avoid any important bias in our comparison between natural and artificial languages caused by the differences in the semantic content of texts.

Natural languages have developed to express concepts and complex ideas. Natural languages can express many

FIGURE 9



CDF of symbols ranked by frequency. Horizontal axis is scaled to show the curves for the 4096 most frequently used words for English, Spanish, and artificial language. Note the logarithmic scale in horizontal axis.

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TABLE 2

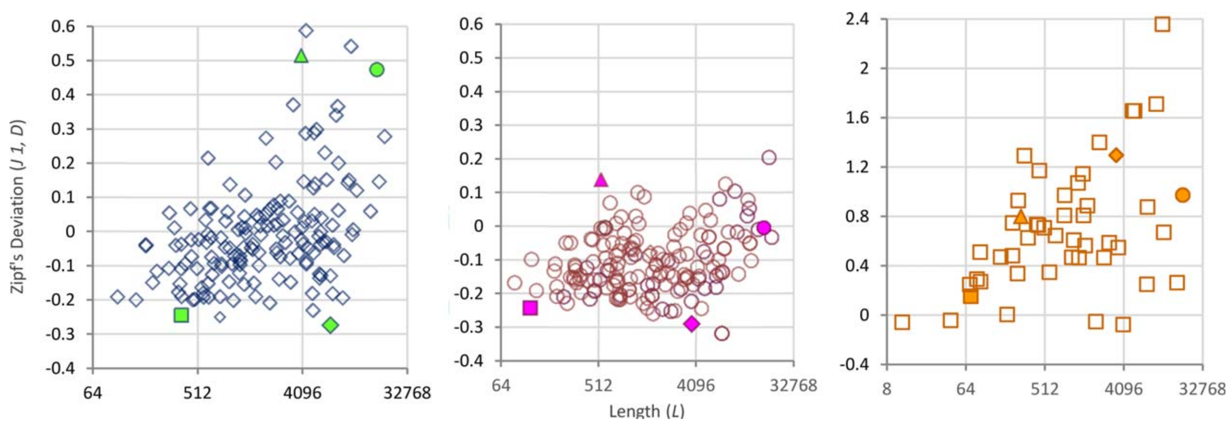
Zipf's Deviation $J_{1,D}$ and its Correlation with Length L for English, Spanish, and Artificial Messages.

Zipfs' Deviation $J_{1,D}$ for Natural and Artificial Languages				
	n	$J_{1,D}$ average	$J_{1,D}$ Std. Dev	Correlation $J_{1,D}$:L
English	156	0.0045	0.1719	0.560
Spanish	158	−0.1074	0.0943	0.351
Computer Code	49	0.6944	0.4961	0.102
t-test	*n*1-*n*2	*p*-value		
English-Spanish	156-158	6.58E-12		
Natural-Software	314-49	9.47E-64		

different types of messages such as information, persuasion, inspiration, instruction, distraction, and joy. Artificial languages, in contrast, are designed to give precise instructions; they are more formal than natural ones [26] as they must convey precise and unequivocal information to machines. Artificial languages are represented by computer programs; collections of instructions having extensive number of symbols and commands. The number of symbols that an artificial language usually contains is very small when compared to natural ones. Connecting and auxiliary words like prepositions and articles are limited to conditional and logical expressions. Adjectives are replaced by numeric variables which may quantify some aspects modeled. With these limitations, computer languages have little room for style compared to natural languages. Computer code is valued for its effectiveness rather than its beauty. The limited structure to form sentences in artificial languages leads to a relatively flatter frequency distribution and therefore higher entropy levels.

Since emergence is defined as equivalent to Shannon's information (entropy), the higher emergence for artificial languages implies that less symbols are used to produce "more meaning." In other words, there is less redundancy in artificial than in natural languages. Redundancy can lead to robustness [27], which is desirable in natural languages where communication may be noisy. However, artificial languages are created for formal, deterministic compliers or interpreters, so there is no pressure to develop robustness.

FIGURE 10



Zipf's deviation $J_{1,D}$ of symbol ranked frequency distributions depending on text length L. English (left), Spanish (center), and software (right). English: square: 1945.BS.Eng.GabrielaMistral; triangle: 1921.MarieCurie; rhombus: 1950.NL.Eng.BertrandRussell; circle: 1890.RusselConwell. Spanish: square: 1936.DoloresIbarruri; triangle: 1982.Gabriel García Márquez; rhombus: JoseSaramago.Valencia; circle: CamiloJoseCela.LaColmena.Cap1. Artificial: square: FibonacciNumbers.CSharp; triangle: QuickSort.CSharp; rhombus: Sociodynamica.Module3; circle: WebSite.Inmogal.php

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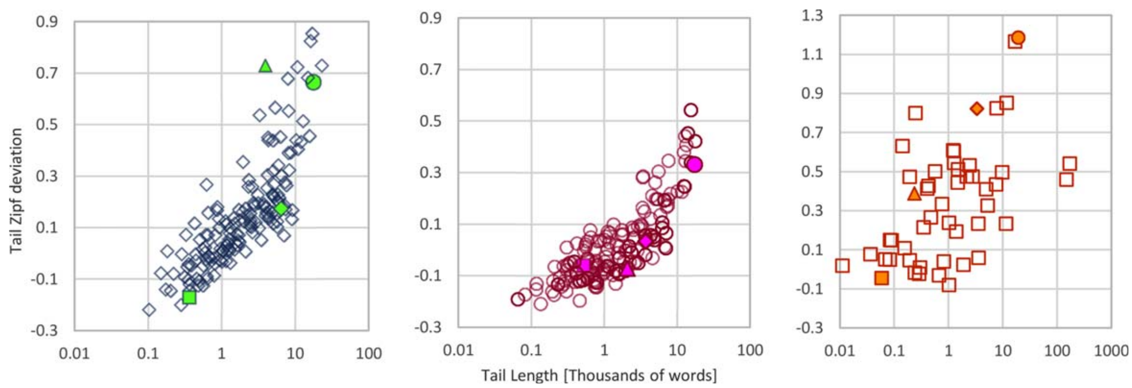
FIGURE 11



Tail Zipf's deviation J_(θ,D) for symbol ranked frequency distributions vs. text tail length L. English (left), Spanish (center), and software (right). Reference texts are highlighted with filled markers. English: square —1945.BS.Eng.GabrielaMistral; triangle: 1921.MarieCurie; rhombus: 1950.NL.Eng.BertrandRussell; circle: 1890.RusselConwell. Spanish: square: 1936.DoloresIbarruri; triangle: 1982.Gabriel García Márquez; rhombus: JoseSaramago.Valencia; circle: CamiloJoseCela.LaColmena.Cap1. Artificial: square: FibonacciNumbers.CSharp; triangle: QuickSort.CSharp; rhombus: Sociodynamica.Module3; circle: WebSite.Inmogal.php.

Self-organization, as opposed to emergence, is higher in artificial than in natural languages. This is because of the same reason explained above: artificial languages require more structure to be more precise, which fulfills their purpose. Natural languages are less organized because they require flexibility and adaptability for their purpose, which includes the ability of having different words with the same meaning (synonymy) and words with different meanings (polysemy).

For the same specific diversity d, complexity is higher for natural languages (Figure 5). However, for the same length L, complexity is higher for artificial languages, as emergence dominates the properties of all languages ($e > 0.5$) (Figure 6). Artificial languages are slightly more regular, but all languages have a relatively high entropy and thus emergence.

4.3. Symbol Frequency Distributions

Intuition may suggest that the symbol frequency profile of a symbol limited language will decay faster than a richer language in terms of number of available symbols. Figures 8 illustrates how, for the natural languages considered here, the points of each message rank distribution profile lay close to a straight line connecting the first with the last ranked word. This indicates that g values for natural languages are approximately constant over the range of symbol ranking. For artificial texts, on the contrary, symbol-frequency vs. symbol-ranking does not show a constant decay value. The slope of the graph is low for most used symbols and increases its decay rate as the symbols considered approach the least used ones, giving the rank symbol profile of artificial language the concave downward shape characteristic of an approximation to the

TABLE 3

Tail Zipf's Deviation $J_{\theta,D}$ and its Correlation with Message Tail Length L_θ for English, Spanish, and Artificial Messages.

Tail Zipfs' Deviation $J_{\theta,D}$ for Natural and Artificial Languages				
	n	$J_{\theta,D}$ average	$J_{\theta,D}$ Std. Dev	Correlation J_θ:L_θ
English	156	0.1502	0.2108	0.809
Spanish	158	0.0235	0.1493	0.856
Computer Code	49	0.3528	0.3062	0.640
t-test	n1-n2	p-value		
English-Spanish	156-158	2.34E-09		
Natural-Software	314-49	2.79E-15		

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cut-off region [28]. This increasing slope g that artificial messages exhibit over ranges of the ranking dominion indicate these languages are close to the physical limit of their total number of symbols. For natural languages g values are not only lower but also closer to a constant, denoting that natural language profiles are within the scale-free region and therefore far from the physical limit [28] imposed by the number of symbols they are constituted with. Natural languages are significantly larger than the artificial languages all together.

There is a qualitative difference of the symbol frequency distributions for natural and artificial languages; texts written in natural languages correlate with a power law distribution for all the symbol ranking ranges while artificial texts show an increasing decay slope for ranges of least used symbols. This difference may be related to the fact that for natural languages any message uses only a tiny fraction of the whole set of words of the language, while any reasonable long computer code will use a large fraction of the whole set of symbols available in the computer language.

The most conspicuous difference between natural and artificial languages was revealed using ZIpf's deviation $J_{1,\ D}$. Statistical analysis revealed highly significant differences between natural and artificial languages in this variable. Tail Zipf's deviation $J_{\theta,\ D}$, confirmed these differences, focusing only on the tails of these distributions. No loss of information was evidenced when focusing our analysis only on the tails, compared with analysis using the complete frequency profile of the ZIpf's deviation $J_{1,\ D}$.

Another interesting aspect of this list of symbols is where the words of open and close classes lay according to their frequency of use; close and open word classes are also known as core and noncore word types. As Moore explained [29], English grew by adding new words to its open-word class consisting of nouns, verbs, and qualifiers, (adjectives and adverbs). The close-word class contains determiners, pronouns, prepositions, and conjunctions; words that establish functionality and language structure. The dynamic process of word creation and the "flow" of words from one class to the other have been recently modeled [30]. Changes over time are slow, thus for our purpose of this study, we considered the open and close classes as invariant groups. Being the open-class the sustained faster growing type of words of natural languages, it is reasonable to expect the open words class to be much larger than the group of closed words. The smaller size of the closed-word class and the highly restricted character of its components (most of them do not even have synonyms), explain the high frequency of their use and their tendency to be placed near the top of the ranked list shown in Table 1, letting the open-class words to sink down to lower ranked positions of the list. There are formal indications of this tendency of close words to group near the top of frequency ranked list in a study by Montemurro and Zanette [31], where pronouns are presented as the most frequently used word-function in Shakespeare's Hamlet.

Besides being necessary to understand the structure of English and Spanish, the classification of words as members of the open and closed groups is important because analyzing the ranking among the open-class words may lead to some practical uses as the recognition of message subject or theme. The highest ranked open-class words are represented using italic-bold characters. For the messages included in this study, the most used open-class words were "man," "people" and "world" for English, and "pueblo," "mundo" and "vida" for Spanish; all of them are terms with strong connection to government, religion, and human rights as the main theme treated by the majority of the messages.

5. CONCLUSIONS

Diversity is higher for Spanish messages than for English ones, suggesting that there is influence of cultural constraints over message diversity. Being more restricted to very specific uses and less dependent on writing style, artificial languages showed a considerably lower diversity than natural languages.

Entropy measures for natural languages are higher than those for artificial. The larger symbolic diversity for natural languages dominates the resulting text entropies, leaving frequency profiles to a more subtle influence. When comparing English and Spanish, however, symbolic diversities are closer to each other while entropy differences become relevant. Future work could include sets of legal, clinical, or technical documents. Since these seem to be more specific, they should have properties in between the natural and artificial sets studied here.

We have shown that important differences among languages become evident by experimentally measuring symbolic diversity, emergence, and complexity in collections of texts. The differences detected are the result of the combination of the current status of their respective evolution as well as cultural aspects that affect the style of communicating and writing. These differences among languages are evidenced measuring symbolic diversity, emergence, and complexity in collections of texts. Yet the most reliable measure was the symbolic diversity. Applying this procedure over the basis of a "grammar scale complexity" would provide a deeper sense of languages nature and behavior.

From a wider scope, the results obtained constitute a strong indication that languages can be regarded beyond a large set of words and grammar rules, and as a collections

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of interacting organisms to which the concepts of complexity, emergence, and self-organization apply.

We believe that the present study showed that complexity analysis can add to our understanding of features of natural languages. For example, automatic devises to differentiate text written by computers from text produced by real persons might be feasible using this knowledge. Yet our study also revealed that complexity science is in a very incipient state regarding its capacity to extract meaning from the analysis of texts. Much interesting work lies ahead.

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Appendix A: Artificial texts

Artificial texts:

http://www.gfebres.com/F0IndexFrame/F132Body/F132BodyPublications/NatArtifLangs/Whole/Artificial.Properties.htm

Artificial language texts properties

L Text Length
D Diversity
d Specific diversity [0-1]
h Entropy [0-1]
g Zipf's exponent
$J_{1,D}$ Zipf's diviation
$J_{\vartheta,D}$ Tail Zipf's diviation

Text Name	*L*	*D*	*d*	*h*	*g*	$J_{1,D}$	$J_{\vartheta,D}$
FibonacciNumbers.CSharp	62	27	0.435	0.921	0.788	0.100	-0.045
Math.Mime2d.MathLab	11376	120	0.011	0.681	1.599	2.334	0.249
Levenberg.MathLab	567	99	0.175	0.823	0.993	0.376	0.502
IsPrime.C	158	56	0.354	0.902	0.823	0.146	0.108
InsertAfterBefore.CSharp	141	37	0.262	0.935	0.738	0.615	0.632
MathLab.Fr.MathLab	1707	207	0.121	0.788	1.041	0.561	0.583
MathLab.pplane8.MathLab	68788	2157	0.031	0.586	1.252	0.435	1.751
MatrixLUDecomp.CSharp	416	52	0.125	0.856	1.007	1.011	0.413
MatrixFuncts.CSharp	8069	194	0.024	0.663	1.487	0.704	0.565
MathLab.Taller.MathLab	2162	122	0.056	0.740	1.190	1.383	0.472
MathLab.programa2.MathLab	9324	254	0.027	0.692	1.345	1.555	0.476
HeapSort.Java	314	59	0.188	0.857	0.956	0.534	0.010
HeapSort.CSharp	247	46	0.186	0.900	0.894	0.721	0.388
HanoiTowers.Java	484	92	0.190	0.847	0.892	0.624	0.266
CopyFolderNContent.CSharp	195	49	0.251	0.908	0.800	0.488	0.473
ChainedScatterTable.CSharp	201	46	0.229	0.890	0.842	0.570	0.046
BoolFunctWithMultiplexerLogic.C	1030	163	0.158	0.796	1.000	0.479	0.238
BlowfishEncryption.C	3574	669	0.187	0.706	1.254	-0.181	0.058
ExtendedEuclidean.C	86	24	0.279	0.902	0.846	0.443	0.149
GameOfLife.C	247	46	0.186	0.893	0.864	0.882	0.799
FTPFunctions.CSharp	11505	312	0.027	0.593	1.467	0.286	1.184
FiniteElements.MathLab	2748	295	0.107	0.731	1.079	0.551	0.467
Factorial.CSharp	36	21	0.583	0.965	0.578	0.063	0.078
MatrixLUDecomp.Phyton	298	40	0.134	0.882	0.956	1.250	-0.023
MetaWords.FormsAnsClasses.CSharp	1279	144	0.113	0.828	0.963	1.065	0.544
Sociodynamica.Module1	9617	290	0.030	0.666	1.271	1.705	0.496
Sociodynamica.Forms	2428	297	0.122	0.759	1.075	0.461	0.532
SnakeGame.C	1515	157	0.104	0.803	1.061	0.816	0.512
QuickSort.CSharp	364	56	0.154	0.896	0.882	0.934	0.216
Sociodynamica.Module2	7672	428	0.056	0.706	1.176	0.873	0.824
Sociodynamica.Module3	3363	223	0.066	0.770	1.086	1.288	0.822
Sumation.CSharp	71	25	0.352	0.895	0.850	0.208	0.051
WebSite.TiempoReal.Html	7495	565	0.075	0.586	1.264	0.250	0.434
WebSite.RistEuropa.Html	11713	503	0.043	0.595	1.321	0.668	0.852
WebSite.Inmogal.php	19299	647	0.034	0.632	1.261	0.966	1.185
ViscomSoft.ScannerActivex.CSharp	11275	623	0.055	0.534	1.405	-0.084	0.471
QuadraticPrograming.CSharp	433	72	0.166	0.848	0.927	0.713	0.427
Polinom.CSharp	86	33	0.384	0.916	0.760	0.228	0.049
PermutationAlgorithm.Java	1227	96	0.078	0.775	1.149	1.032	0.610
NetPlexMainForm.CSharp	59496	1218	0.020	0.531	1.432	0.232	1.449
NetPlex.Forms.CSharp	66281	1482	0.022	0.644	1.226	1.492	1.449
NetPlex.Classes.CSharp	18662	652	0.035	0.689	1.139	1.880	1.416
ModularInverse.C	91	31	0.341	0.902	0.865	0.248	0.148
MetaWordsMainForm.CSharp	65492	1081	0.017	0.531	1.462	0.279	1.478
PartDifEqtnsHeatEq.MathLab	677	104	0.154	0.774	1.053	0.613	-0.041
PartDifEqtnsLaplaceEq.MathLab	825	96	0.116	0.780	1.131	0.741	0.030
PermutationAlgorithm.Csharp	777	88	0.113	0.841	1.015	1.041	0.334
PartDifEqtnsWaveEqtn.MathLab	249	67	0.269	0.855	0.897	0.336	-0.017
mail.log.2	147418	3195	0.022	0.560	1.297	1.297	0.460
Apache.Access.log	168355	2870	0.017	0.534	1.464	0.445	0.542

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English texts (1/3):
http://www.gfebres.com/F0IndexFrame/F132Body/F132BodyPublications/NatArtifLangs/Whole/English.Properties.htm

English texts properties

L	Text Length	***d***	Specific diversity [0-1]	$J_{1,D}$	Zipf's diviation
D	Diversity	***h***	Entropy [0-1]	$J_{\vartheta,D}$	Tail Zipf's diviation
		g	Zipf's exponent		

Text Name	*L*	*D*	*d*	*h*	*g*	$J_{1,D}$	$J_{\vartheta,D}$
1381.JohnBall	227	117	0.5154	0.9143	0.7680	-0.1156	-0.0788
1588.QueenElizabethI	359	156	0.4345	0.8786	0.9376	-0.1528	-0.0414
1601.Hamlet	150	97	0.6467	0.9501	0.7449	-0.1987	-0.0760
1601.QueenElizabethI	1140	388	0.3404	0.8647	0.8467	0.0056	0.1264
1606.LancelotAndrewes	9285	1540	0.1659	0.7374	1.0936	-0.0690	0.1691
1814.NapoleonBonaparte	182	95	0.5220	0.9202	0.7380	-0.0406	-0.1394
1833.ThomasBabington	15668	2647	0.1689	0.7460	0.9988	0.0602	0.4564
1849.LucretiaMott	7575	1720	0.2271	0.7705	0.9759	-0.0457	0.2653
1851.ErnestineLRose	8301	1630	0.1964	0.7643	0.9851	0.0630	0.3239
1851.SojournerTruth	436	180	0.4128	0.9185	0.7197	0.0651	0.1175
1861.AbrahamLincoln	4007	1018	0.2541	0.8077	0.9268	0.0116	0.1815
1863.AbrahamLincoln	292	143	0.4897	0.9270	0.6524	0.0557	-0.0018
1867.ElizabethCadyStanton	5847	1481	0.2533	0.7846	0.9869	-0.1277	0.2027
1873.SusanBAnthony	626	255	0.4073	0.8617	0.9043	-0.1505	-0.0215
1877.ChiefJoseph	183	92	0.5027	0.9257	0.7401	-0.0375	0.0102
1890.RusselConwell	17766	2207	0.1242	0.7483	0.9861	0.4742	0.6646
1892.FrancesEWHarper	4395	1244	0.2830	0.8053	0.9417	-0.0930	0.1430
1901.MarkTwain	660	255	0.3864	0.8889	0.7560	0.0641	0.0714
1903.BS.Eng.BjornstjerneBjornson	1651	573	0.3471	0.8496	0.8244	0.0487	0.0336
1906.MaryChurch	1558	585	0.3755	0.8524	0.8963	-0.1499	0.0423
1909.BS.SelmaLagerlof	2296	626	0.2726	0.8247	0.9300	0.0186	0.1479
1915.AnnaHoward	10633	1425	0.1340	0.7747	0.9506	0.5420	0.7245
1916.CarrieChapman	6120	1542	0.2520	0.7943	0.9360	-0.0303	0.2165
1916.HellenKeller	2557	854	0.3340	0.8294	0.9202	-0.1370	0.1029
1918.WoodrowWilson	2753	769	0.2793	0.8177	0.9053	-0.0112	0.1972
1920.CrystalEastman	2131	669	0.3139	0.8482	0.8341	0.0675	0.1753
1921.MarieCurie	921	307	0.3333	0.8642	0.8356	0.0582	0.1353
1923.BS.Eng.WilliamButlerYeats	320	167	0.5219	0.9197	0.6626	0.0119	-0.0906
1923.JamesMonroe	1178	417	0.3540	0.8493	0.8830	-0.0816	0.0324
1923.NL.Eng.WilliamButlerYeats	4257	1127	0.2647	0.8194	0.9079	0.0306	0.3058
1925.MaryReynolds	4300	852	0.1981	0.8022	0.9134	0.2870	0.4510
1930.NL.Eng.SinclairLewis	5707	1609	0.2819	0.7986	0.9534	-0.1360	0.1034
1932.MargaretSanger	1162	399	0.3434	0.8468	0.9113	-0.1212	0.1130
1936.EleanorRoosvelt	1966	457	0.2325	0.8301	0.8796	0.2744	0.3562
1936.KingEdwardVIII	596	243	0.4077	0.8747	0.7740	0.0342	0.0039
1936.NL.Eng.EugeneOneill	1177	407	0.3458	0.8381	0.8972	-0.0955	0.0109
1938.BS.PearlBuck	520	197	0.3788	0.8935	0.8255	-0.0226	0.0538
1938.NL.PearlBuck	10270	1825	0.1777	0.7666	0.9751	0.1511	0.4402
1940.05.WinstonChurchill	703	292	0.4154	0.8730	0.8546	-0.0931	-0.0164
1940.06.A.WinstonChurchill	3762	1067	0.2836	0.8228	0.9142	-0.0642	0.1929
1940.06.B.WinstonChurchill	4899	1189	0.2427	0.8022	0.9318	0.0320	0.2297
1941.AdolfHitler	10901	2228	0.2044	0.7691	0.9748	-0.0076	0.4059
1941.FranklinDRoosvelt	574	261	0.4547	0.8806	0.9119	-0.1906	-0.0467
1941.HaroldIckes	2448	720	0.2941	0.8221	0.8930	0.0248	0.1185
1942.MahatmaGandhi	1234	428	0.3468	0.8554	0.8496	0.0138	0.0437
1944.DwightEisenhower	208	120	0.5769	0.9248	0.7615	-0.1486	-0.1436
1944.GeorgePatton	873	313	0.3585	0.8861	0.8021	0.0323	0.1694
1945.BS.Eng.GabrielaMistral	370	196	0.5297	0.8833	0.9373	-0.2446	-0.1705

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English texts (cont. 2/3):

1946.WinstonChurchill	1285	498	0.3875	0.8496	0.9141	-0.1538	0.0101
1947.GeorgeCMarshall	1606	582	0.3624	0.8422	0.9275	-0.1892	0.0749
1947.HarryTruman	2445	716	0.2928	0.8218	0.9296	-0.0612	0.1564
1948.BS.Eng.ThomasEliot	1467	504	0.3436	0.8448	0.8791	-0.0470	0.1376
1949.BS.Eng.WilliamFaulkner	622	248	0.3987	0.8838	0.7906	-0.0064	0.0733
1950.MargaretChase	1717	561	0.3267	0.8450	0.8948	-0.0602	0.0507
1950.NL.Eng.BertrandRussell	6476	1590	0.2455	0.7893	0.9457	-0.0280	0.1745
1953.DwightEisenhower	2906	830	0.2856	0.8108	0.9130	-0.0310	0.1212
1953.NelsonMandela	4967	1433	0.2885	0.8010	0.9572	-0.1801	0.1607
1954.BS.Eng.ErnestHemingway	367	183	0.4986	0.9195	0.7180	-0.0366	-0.1006
1957.MartinLutherKing	7952	1261	0.1586	0.7797	0.9508	0.3431	0.6792
1959.RichardFeynman	8135	1300	0.1598	0.7855	0.9460	0.3665	0.5540
1961.01.JohnFKennedy	1519	529	0.3483	0.8523	0.8439	-0.0371	0.1181
1961.04.JohnFKennedy	1715	605	0.3528	0.8454	0.8870	-0.0980	0.0729
1961.05.JohnFKennedy	6584	1535	0.2331	0.7991	0.8770	0.1528	0.3033
1961.11.JohnFKennedy	680	316	0.4647	0.8922	0.8045	-0.1246	-0.0369
1962.09.JohnFKennedy	2428	751	0.3093	0.8272	0.8962	-0.0497	0.1076
1962.10.JohnFKennedy	2772	811	0.2926	0.8287	0.8727	0.0344	0.1864
1962.12.MalcomX	17199	1640	0.0954	0.7573	1.0099	0.7080	0.8545
1962.BS.Eng.JohnSteinbeck	952	385	0.4044	0.8589	0.8830	-0.1454	-0.0257
1963.06.10.JohnFKennedy	3680	1019	0.2769	0.8149	0.8815	0.0568	0.1859
1963.06.26.JohnFKennedy	662	237	0.3580	0.8752	0.8416	-0.0101	0.1583
1963.09.20.JohnFKennedy	3986	1089	0.2732	0.8043	0.9247	-0.0233	0.1468
1963.MartinLutherKing	1731	527	0.3044	0.8366	0.8858	0.0428	0.1703
1964.04.MalcomX	3288	660	0.2007	0.8198	0.8880	0.3468	0.5379
1964.05.LyndonBJohnson	1168	430	0.3682	0.8484	0.8902	-0.0695	-0.0292
1964.LadybirdJohnson	818	353	0.4315	0.8762	0.8278	-0.1008	-0.0384
1964.MartinLutherKing	1266	498	0.3934	0.8616	0.8238	-0.0458	0.0172
1964.NelsonMandela	11929	2152	0.1804	0.7667	0.9602	0.1212	0.4337
1965.03.LyndonBJohnson	4166	975	0.2340	0.8052	0.9006	0.1485	0.2551
1965.04.LyndonBJohnson	1286	419	0.3258	0.8486	0.8581	0.0454	0.0569
1967.BS.Eng.MiguelAngelAsturias	1039	435	0.4187	0.8489	0.8953	-0.2004	0.0091
1967.MartinLutherKing	7360	1743	0.2368	0.7939	0.9337	0.0198	0.2773
1967.NL.Eng.MiguelAngelAsturias	5026	1479	0.2943	0.7899	0.9974	-0.2295	0.1170
1968.MartinLutherKing	5022	986	0.1963	0.7928	0.9192	0.2791	0.4393
1968.RobertFKennedy	627	197	0.3142	0.8978	0.7639	0.2170	0.2682
1969.IndiraGhandi	1058	408	0.3856	0.8674	0.8591	-0.0709	0.0118
1969.RichardNixon	5056	1105	0.2186	0.8048	0.9198	0.1308	0.3209
1969.ShirleyChisholm	966	382	0.3954	0.8671	0.8312	-0.0465	0.0192
1971.BS.Eng.PabloNeruda	503	209	0.4155	0.8701	0.8653	-0.1067	-0.1051
1971.NL.Eng.PabloNeruda	4114	1150	0.2795	0.8115	0.9101	-0.0349	0.1604
1972.JaneFonda	792	340	0.4293	0.8741	0.8661	-0.1875	-0.0853
1972.RichardNixon	5362	920	0.1716	0.7938	0.9442	0.3032	0.5676
1974.RichardNixon	1959	536	0.2736	0.8331	0.8944	0.0518	0.1618
1976.BS.Eng.SaulBellow	395	199	0.5038	0.9118	0.7613	-0.0981	-0.0452
1976.NL.Eng.SaulBellow	5625	1499	0.2665	0.7990	0.9128	-0.0142	0.1551
1977.NL.Eng.VicenteAleixandre	2618	845	0.3228	0.8267	0.9052	-0.0723	0.0825
1979.MargaretThatcher	3217	1002	0.3115	0.8204	0.9330	-0.1461	0.0988
1979.MotherTeresa	4349	652	0.1499	0.8055	0.9244	0.5909	0.4403
1981.RonaldReagan	1175	448	0.3813	0.8553	0.8701	-0.0838	0.0317
1982.NL.Eng.GabrielGarciaMarquez	2132	833	0.3907	0.8401	0.9209	-0.2080	0.0088
1982.RonaldReagan	5037	1392	0.2764	0.8062	0.9200	-0.0617	0.2275
1983.BS.Eng.WilliamGolding	369	201	0.5447	0.9131	0.8124	-0.1896	-0.1445
1983.NL.Eng.WilliamGolding	5140	1375	0.2675	0.8124	0.8904	0.0502	0.2202
1983.RonaldReagan	5160	1257	0.2436	0.8137	0.8787	0.1348	0.2692
1986.BS.Eng.WoleSoyinka	482	245	0.5083	0.8925	0.8611	-0.1972	-0.1240
1986.NL.Eng.WoleSoyinka	9033	2530	0.2801	0.7783	0.9740	-0.1930	0.1335

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English texts (cont. 3/3):

1986.RonaldReagan	784	305	0.3890	0.8603	0.8460	-0.0231	0.0221
1987.RonaldReagan	3160	935	0.2959	0.8218	0.9151	-0.0794	0.1962
1988.AnnRichards	3109	863	0.2776	0.8265	0.8720	0.0951	0.2281
1989.BS.Eng.CamioJoseCela	464	227	0.4892	0.8917	0.8719	-0.1957	-0.0973
1989.NL.Eng.CamioJoseCela	5826	1541	0.2645	0.8058	0.9200	-0.0364	0.2301
1990.BS.Eng.OctavioPaz	636	300	0.4717	0.8686	0.8820	-0.1903	-0.0978
1990.NL.Eng.OctavioPaz	5704	1549	0.2716	0.7870	0.9619	-0.1224	0.1249
1991.BS.Eng.NadineGordimer	562	280	0.4982	0.8924	0.8368	-0.1779	-0.1242
1991.GeorgeBush	1771	582	0.3286	0.8438	0.8640	-0.0115	0.0453
1991.NL.Eng.NadineGordimer	4384	1254	0.2860	0.8021	0.9389	-0.0878	0.1359
1992.BS.Eng.DerekWalcott	104	68	0.6538	0.9300	0.8842	-0.1905	-0.2184
1992.NL.Eng.DerekWalcott	7403	1965	0.2654	0.7743	0.9897	-0.1805	0.1731
1993.BS.Eng.ToniMorrison	368	201	0.5462	0.9122	0.7638	-0.1078	-0.1185
1993.MayaAngelou	794	311	0.3917	0.8349	0.9974	-0.2499	-0.0170
1993.NL.Eng.ToniMorrison	3486	1023	0.2935	0.8116	0.9188	0.0002	0.0533
1993.SarahBrady	949	316	0.3330	0.8697	0.7814	0.1311	0.1014
1993.UrvashiVaid	1315	414	0.3148	0.8399	0.8832	0.0114	0.0994
1994.MotherTeresa	3953	638	0.1614	0.8150	0.9124	0.5166	0.7301
1994.NelsonMandela	1010	388	0.3842	0.8479	0.8798	-0.0936	-0.0319
1995.BS.Eng.SeamusHeaney	287	161	0.5610	0.9150	0.7679	-0.1065	-0.1995
1995.ErikaJong	2356	601	0.2551	0.8298	0.8624	0.1873	0.2864
1995.HillaryClinton	2483	715	0.2880	0.8225	0.8776	0.0696	0.1309
1995.NL.Eng.SeamusHeaney	7050	1897	0.2691	0.7871	0.9577	-0.1276	0.1895
1997.BillClinton	1302	417	0.3203	0.8451	0.8357	0.1107	0.0794
1997.EarlOfSpencer	1327	508	0.3828	0.8574	0.8216	-0.0041	-0.0359
1997.NancyBirdsall	2312	644	0.2785	0.8328	0.8783	0.0783	0.2596
1997.PrincessDiana	1753	602	0.3434	0.8498	0.8286	0.0174	0.1282
1997.QueenElizabethII	449	207	0.4610	0.8998	0.7511	-0.0231	-0.0017
1999.AnitaRoddick	2012	634	0.3151	0.8420	0.8630	0.0101	0.1252
2000.CondoleezzaRice	1510	517	0.3424	0.8540	0.8794	-0.0503	0.0159
2000.CourtneyLove	8166	1627	0.1992	0.8000	0.9275	0.1890	0.3911
2000.PopeJohnPaulII	823	327	0.3973	0.8747	0.8438	-0.0937	0.0713
2001.09.11.GeorgeWBush	670	296	0.4418	0.8807	0.7944	-0.0727	-0.0107
2001.09.13.GeorgeWBush	550	251	0.4564	0.8744	0.8626	-0.1634	0.0185
2001.BS.Eng.VSNaipaul	347	172	0.4957	0.8982	0.8301	-0.1708	-0.0516
2001.HalleBerry	636	219	0.3443	0.8496	0.8505	0.0575	-0.0875
2001.NL.Eng.VSNaipaul	6303	1220	0.1936	0.7873	0.9287	0.2345	0.4531
2002.OprahWinfrey	603	226	0.3748	0.8653	0.8559	-0.0308	0.0252
2003.BethChapman	877	334	0.3808	0.8764	0.8497	-0.0435	0.1807
2003.BS.Eng.JMCoetzee	329	151	0.4590	0.9138	0.7498	-0.0398	0.0728
2003.NL.Eng.JMCoetzee	4593	1105	0.2406	0.7934	0.9693	-0.0467	0.1642
2005.NL.Eng.HaroldPinter	5787	1478	0.2554	0.8023	0.9161	-0.0002	0.2048
2005.SteveJobs	2584	706	0.2732	0.8321	0.8750	0.0857	0.2561
2007.NL.Eng.DorisLessing	5881	1244	0.2115	0.7924	0.9689	0.0405	0.3426
2010.BS.Eng.MarioVargasLlosa	452	204	0.4513	0.8911	0.7897	-0.0722	-0.0271
2010.NL.Eng.MarioVargasLlosa	7073	2034	0.2876	0.7740	1.0218	-0.2736	0.0711
ErnestHemingway.TheOldManAndThe	14915	1804	0.1210	0.7438	1.0362	0.3077	0.6836
ErnestHemingway.TheOldManAndThe	16130	1775	0.1100	0.7385	1.0420	0.3865	0.8258
ErnestHemingway.TheSunAlsoRises.E	22951	2099	0.0915	0.7049	1.0839	0.4104	0.7308
IsaacAsimov.IRobot.Cap2	8772	1636	0.1865	0.7678	0.9552	0.1894	0.3930
IsaacAsimov.IRobot.Cap6	12812	1977	0.1543	0.7597	0.9808	0.2709	0.5145

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Spanish texts (1/3):

http://www.gfebres.com/F0IndexFrame/F132Body/F132BodyPublications/NatArtifLangs/Whole/Spanish.Properties.htm

Spanish texts properties

L Text Length
D Diversity
d Specific diversity [0-1]
h Entropy [0-1]
g Zipf's exponent
J $_{1,D}$ Zipf's diviation
J $_{\vartheta,D}$ Tail Zipf's diviation

Text Name	*L*	*D*	*d*	*h*	*g*	$J_{1,D}$	$J_{\vartheta,D}$
1755.PatrickHenry	313	151	0.482	0.910	0.817	-0.131	-0.057
1805.Simón Bolívar	462	230	0.498	0.878	0.942	-0.190	-0.196
1813.Simón Bolívar	739	332	0.449	0.864	0.835	-0.086	-0.122
1819.Simón Bolívar	11502	2629	0.229	0.751	0.962	-0.030	0.226
1830.Simón Bolívar	201	121	0.602	0.930	0.745	-0.112	-0.120
1863.AbrahamLincoln	305	152	0.498	0.923	0.760	-0.115	0.010
1868.CarlosMCespedes	1457	591	0.406	0.836	0.945	-0.214	-0.082
1873.SusanBAnthony	594	237	0.399	0.870	0.829	-0.005	-0.042
1899.Vladimir Lenin	1920	644	0.335	0.817	0.948	-0.140	-0.002
1912.Emiliano Zapata	2590	935	0.361	0.811	0.974	-0.251	-0.051
1917.Emiliano Zapata	1619	653	0.403	0.826	0.985	-0.260	-0.094
1918.Emiliano Zapata	1438	593	0.412	0.830	0.987	-0.243	-0.131
1918.WoodrowWilson	303	171	0.564	0.909	0.813	-0.158	-0.160
1919.Georges Clemenceau	209	126	0.603	0.928	0.792	-0.179	-0.174
1919.Lloyd George	135	92	0.681	0.950	0.746	-0.191	-0.209
1921.MarieCurie.Esp	563	239	0.425	0.895	0.785	-0.010	0.022
1931.Manuel Azaña	297	152	0.512	0.906	0.832	-0.153	-0.118
1933.JAntonioPrimoDeRivera	3190	972	0.305	0.803	0.963	-0.158	0.099
1934.Adolf Hitler	347	163	0.470	0.893	0.870	-0.146	-0.100
1936.Dolores Ibarruri	537	193	0.359	0.864	0.807	0.138	-0.061
1936.José Buenaventura Durruti	690	305	0.442	0.877	0.796	-0.049	-0.065
1938.Dolores Ibarruri	774	318	0.411	0.846	0.962	-0.218	-0.042
1938.Leon Trotsky	1023	416	0.407	0.860	0.835	-0.063	-0.044
1938.Neville Chamberlain	638	302	0.473	0.883	0.827	-0.131	-0.077
1940.B.Winston Churchill	68	36	0.529	0.892	1.048	-0.136	-0.191
1940.Benito Mussolini	736	338	0.459	0.868	0.924	-0.221	-0.115
1940.Charles de Gaulle	122	69	0.566	0.928	0.756	-0.098	-0.153
1940.Winston Churchill	395	195	0.494	0.900	0.819	-0.123	-0.046
1941.Franklin Roosevelt	280	158	0.564	0.922	0.803	-0.151	-0.131
1941.Joseph Stalin	880	341	0.388	0.878	0.832	-0.021	0.036
1942.08.Mahatma Gandhi	2588	864	0.334	0.825	0.864	-0.025	0.049
1943.Heinrich Himmler	350	184	0.526	0.919	0.806	-0.197	-0.048
1943.Joseph Goebbels	1173	414	0.353	0.864	0.798	0.101	0.031
1945.Harry Truman	768	315	0.410	0.869	0.890	-0.110	-0.125
1945.Hirohito	766	352	0.460	0.868	0.871	-0.163	-0.144
1945.Juan Domingo Perón	1059	414	0.391	0.865	0.851	-0.069	0.053
1946.Jorge Eliécer Gaitán	3544	986	0.278	0.811	0.893	0.039	0.150
1947.George Marshall	754	328	0.435	0.867	0.871	-0.128	-0.051
1948.David Ben Gurion	1178	417	0.354	0.826	0.977	-0.149	-0.064
1950.Robert Schuman	998	385	0.386	0.840	0.956	-0.211	-0.076
1950.William Faulkner	533	233	0.437	0.895	0.761	-0.006	-0.002
1952.Eva Perón	1124	344	0.306	0.839	0.899	0.030	0.071
1953.Dwight D Eisenhower	1732	622	0.359	0.847	0.886	-0.115	0.058
1956.Gamar Abdel Nasser	839	337	0.402	0.868	0.821	-0.050	-0.059
1959.Fidel Castro	2892	853	0.295	0.810	0.908	-0.012	0.090
1959.Fulgencio Batista	85	58	0.682	0.947	0.783	-0.168	-0.172
1959.Nikita Kruschev	404	198	0.490	0.889	0.870	-0.161	-0.123
1961.J F Kennedy	1613	602	0.373	0.838	0.894	-0.136	0.014
1961.Nelson Mandela	5350	1373	0.257	0.778	0.945	-0.032	0.198
1962.J F Kennedy	319	160	0.502	0.905	0.836	-0.168	-0.061
1963.J F Kennedy	651	256	0.393	0.891	0.738	0.070	0.077

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Spanish texts (cont. 2/3):

1963.Martin Luther King Jr	1746	578	0.331	0.828	0.945	-0.114	0.077
1964.Ernesto Che Guevara	7172	1911	0.266	0.779	0.961	-0.135	0.168
1964.Malcom X	824	321	0.390	0.877	0.776	0.028	0.034
1964.Nelson Mandela	5347	1372	0.257	0.778	0.944	-0.032	0.198
1964.Ronald Reagan	1062	450	0.424	0.875	0.789	-0.049	-0.026
1967.BS.Esp.MiguelAngelAsturias	804	339	0.422	0.845	0.959	-0.203	-0.127
1967.Ernesto Che Guevara	5868	1696	0.289	0.788	0.937	-0.120	0.135
1967.Fidel Castro	5519	1232	0.223	0.788	0.953	0.019	0.304
1967.Martin Luther King	7418	1924	0.259	0.786	0.944	-0.067	0.197
1967.NL.Esp.MiguelAngelAsturias	4901	1533	0.313	0.787	0.967	-0.184	0.038
1969.Richard Nixon	4501	1200	0.267	0.800	0.925	-0.026	0.210
1970.Salvador Allende	1865	718	0.385	0.834	0.898	-0.147	-0.044
1971.BS.Esp.PabloNeruda	468	209	0.447	0.859	0.946	-0.193	-0.120
1971.Pablo Neruda	3683	1290	0.350	0.806	0.948	-0.223	-0.019
1972.Salvador Allende	10046	2540	0.253	0.766	0.971	-0.141	0.228
1973.Augusto Pinochet	4191	1318	0.314	0.797	0.935	-0.121	0.040
1973.Bando Nro 5	801	366	0.457	0.860	0.925	-0.209	-0.143
1973.Salvador Allende	700	314	0.449	0.868	0.893	-0.174	-0.093
1974.Richard Nixon	741	302	0.408	0.879	0.775	0.009	0.002
1976.Jorge Videla	604	264	0.437	0.875	0.916	-0.183	-0.034
1977.BS.Esp.VicenteAleixandre	241	137	0.568	0.917	0.850	-0.209	-0.134
1977.NL.Esp.VicenteAleixandre	2379	859	0.361	0.818	0.988	-0.253	-0.010
1978.Juan Carlos I	973	411	0.422	0.848	0.925	-0.188	-0.092
1979.Adolfo Suárez	13201	2799	0.212	0.751	0.990	-0.102	0.407
1979.Ayatolá Jomeini	254	126	0.496	0.918	0.762	-0.049	-0.106
1979.Fidel Castro	12832	2668	0.208	0.743	0.989	-0.049	0.345
1981.Adolfo Suárez	1348	420	0.312	0.842	0.818	0.088	0.099
1981.Roberto Eduardo Viola	3823	1288	0.337	0.799	0.929	-0.174	0.043
1982.BS.Esp.GabrielGarciaMarquez	522	251	0.481	0.876	0.892	-0.157	-0.118
1982.Felipe González	6592	1818	0.276	0.782	0.940	-0.099	0.192
1982.Gabriel García Márquez	2095	856	0.409	0.831	0.949	-0.242	-0.073
1982.Leopoldo Galtieri	119	76	0.639	0.934	0.896	-0.243	-0.130
1982.Margaret Thatcher	586	242	0.413	0.895	0.776	-0.003	0.034
1983.Raúl Alfonsín	3309	976	0.295	0.805	0.896	0.010	0.094
1984.Ronald Reagan	790	339	0.429	0.864	0.825	-0.073	-0.059
1986.Ronald Reagan	729	323	0.443	0.879	0.862	-0.153	-0.091
1987.Camilo José Cela	1591	621	0.390	0.830	0.944	-0.205	-0.092
1987.Ronald Reagan	3150	1016	0.323	0.816	0.924	-0.144	0.083
1988.Gorbachov	1017	416	0.409	0.859	0.847	-0.093	-0.085
1989.Carlos Saúl Menem	1199	404	0.337	0.845	0.864	0.008	0.067
1989.NL.Esp.CamiloJoseCela	6291	1803	0.287	0.777	0.965	-0.148	0.085
1990.BS.Esp.OctavioPaz	613	284	0.463	0.878	0.850	-0.131	-0.109
1990.George H. W. Bush	654	269	0.411	0.881	0.854	-0.114	0.049
1990.NL.Esp.OctavioPaz	4804	1452	0.302	0.788	0.933	-0.076	0.050
1991.Boris Yeltsin	466	219	0.470	0.889	0.865	-0.160	-0.070
1991.Gorbachov	197	126	0.640	0.936	0.715	-0.133	-0.161
1992.Rafael Caldera	2504	832	0.332	0.810	0.932	-0.150	0.048
1992.Severn Suzuki	1001	403	0.403	0.869	0.876	-0.157	0.040
1993.Bill Clinton	2010	703	0.350	0.827	0.914	-0.098	-0.002
1996.Jose María Aznar	5069	1383	0.273	0.782	0.951	-0.104	0.197
1998.José Saramago	6235	1775	0.285	0.781	0.978	-0.182	0.106
1999.Elie Wiesel	806	328	0.407	0.854	0.971	-0.218	-0.068
1999.Hugo Chavez	12766	2441	0.191	0.760	1.002	-0.051	0.442
2000.Vicente Fox	7417	1998	0.269	0.778	0.929	-0.066	0.173
2001.Fernando de la Rúa	1129	436	0.386	0.853	0.825	-0.042	0.004
2001.George W. Bush	340	173	0.509	0.905	0.808	-0.155	-0.049
2001.Osama Bin Laden	455	215	0.473	0.891	0.801	-0.105	-0.062
2002.A.George W. Bush	590	271	0.459	0.887	0.820	-0.095	-0.032
2002.Barack Hussein Obama	983	379	0.386	0.840	0.900	-0.068	-0.073
2003.B.George W. Bush	564	237	0.420	0.886	0.823	-0.056	0.013
2003.George W. Bush	741	352	0.475	0.879	0.854	-0.164	-0.140
2003.José Saramago	1110	441	0.397	0.849	0.870	-0.083	-0.062

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Spanish texts (cont. 3/3):

2004.Pilar Manjón	209	118	0.565	0.917	0.867	-0.209	-0.065
2005.Daniel Ortega	7593	1516	0.200	0.779	0.943	0.125	0.347
2005.Gerhard Schroeder	1547	559	0.361	0.843	0.875	-0.076	-0.011
2005.Steve Jobs	2524	832	0.330	0.831	0.880	-0.061	0.077
2006.Alvaro Uribe	4555	1552	0.341	0.776	0.969	-0.244	-0.030
2006.Dianne Feinstein	1503	525	0.349	0.841	0.888	-0.088	0.018
2006.Evo Morales	3391	890	0.262	0.812	0.981	-0.154	0.287
2006.Gastón Acurio	4348	1276	0.293	0.803	0.953	-0.148	0.122
2006.Hugo Chavez	3353	948	0.283	0.808	0.969	-0.150	0.164
2007.Al Gore	1319	580	0.440	0.859	0.903	-0.228	-0.097
2007.Cristina Kirchner	5004	1228	0.245	0.795	0.918	0.047	0.262
2007.Daniel Ortega	3373	857	0.254	0.805	0.969	-0.082	0.282
2008.Barack Hussein Obama	309	159	0.515	0.897	0.843	-0.120	-0.078
2008.J. L. Rodriguez Zapatero	449	204	0.454	0.886	0.803	-0.040	-0.120
2008.Julio Cobos	280	138	0.493	0.907	0.768	-0.049	-0.062
2008.Randy Paush	1817	624	0.343	0.847	0.875	-0.080	0.062
2009.Barack Hussein Obama	2834	978	0.345	0.817	0.894	-0.089	-0.002
2010.BS.Esp.MarioVargasLlosa	424	204	0.481	0.888	0.882	-0.217	-0.091
2010.Hillary Clinton	2426	832	0.343	0.831	0.874	-0.107	0.088
2010.NL.Esp.MarioVargasLlosa	7034	2215	0.315	0.763	1.035	-0.318	0.007
2010.Raúl Castro	260	145	0.558	0.912	0.877	-0.229	-0.141
2010.Sebastian Piñera Echenique	432	173	0.400	0.890	0.819	-0.037	0.025
CamiloJoseCela.LaColmena.Cap1	17409	3089	0.177	0.736	1.021	0.003	0.332
CamiloJoseCela.LaColmena.Cap2	15370	2943	0.191	0.741	1.000	-0.006	0.339
CamiloJoseCela.LaColmena.Cap6	3629	1117	0.308	0.798	0.990	-0.223	0.056
CamiloJoseCela.LaColmena.Notas4E	1623	596	0.367	0.829	0.954	-0.171	-0.031
ErnestHemingway.ElViejoYElMar.Par	13979	2498	0.179	0.751	0.975	0.116	0.452
ErnestHemingway.ElViejoYElMar.Par	15446	2424	0.157	0.743	0.993	0.186	0.542
ErnestHemingway.Fiesta.Libro1	17642	3064	0.174	0.733	1.016	0.018	0.422
GabrielGMarquez.CronMuerteAnunc	12454	2621	0.210	0.754	0.948	0.080	0.248
GabrielGMarquez.CronMuerteAnunc	12680	2760	0.218	0.754	0.944	0.058	0.246
GabrielGMarquez.CronMuerteAnunc	6751	1586	0.235	0.774	0.933	0.088	0.193
GabrielGMarquez.DicursoCartagena	1443	579	0.401	0.844	0.910	-0.175	-0.081
GabrielGMarquez.MejorOficioDelMu	2949	1059	0.359	0.808	0.948	-0.186	-0.051
IsaacAsimov.YoRobot.Cap2	8080	1856	0.230	0.767	0.967	-0.020	0.220
IsaacAsimov.YoRobot.Cap6	12235	2391	0.195	0.754	0.968	0.075	0.380
JorgeLuisBorges.ElCongreso	6656	1926	0.289	0.774	0.963	-0.140	0.014
JorgeLuisBorges.ElMuerto	2109	753	0.357	0.814	0.950	-0.174	-0.067
JorgeLuisBorges.ElSur	2746	948	0.345	0.800	0.984	-0.193	-0.044
JorgeLuisBorges.LasRuinasCirculare:	2238	824	0.368	0.826	0.920	-0.138	-0.046
JoseSaramago.Valencia	3711	1126	0.303	0.786	1.045	-0.290	0.033
MarioVargasLlosa.DiscursoBuenosAi	1984	776	0.391	0.819	0.967	-0.246	-0.081
MiguelAAsturias.SrPresidente.Parte	4352	1269	0.292	0.786	0.975	-0.143	0.057
OctavioPaz.DiscursoZacatecas	2238	711	0.318	0.810	0.949	-0.101	0.013
OctavioPaz.LaberintoSoledad.Part3	7054	1843	0.261	0.757	0.991	-0.143	0.065

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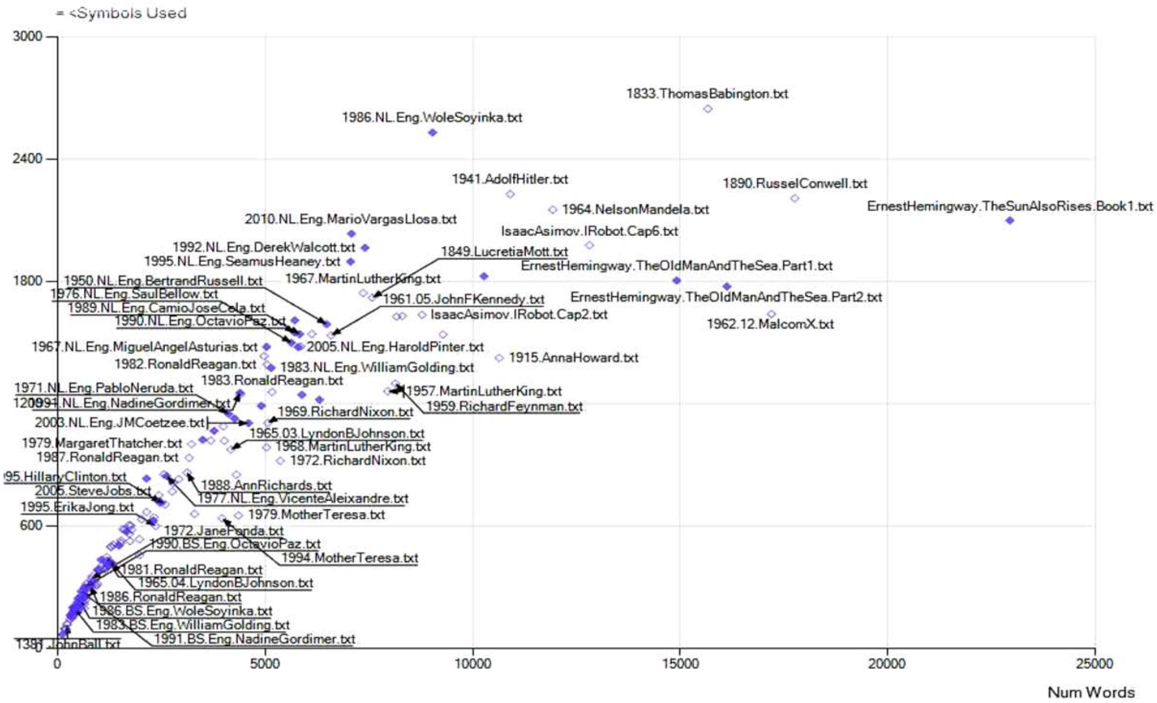
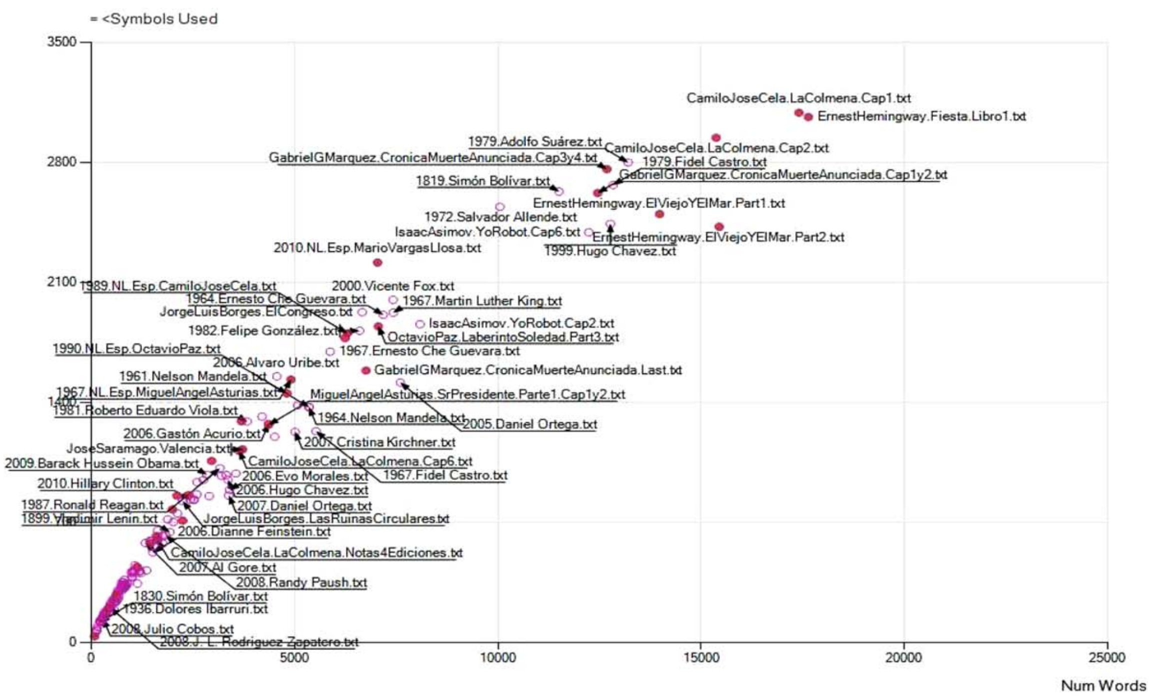
Appendix B

English: Diversity vs. Length



Spanish: Diversity vs. Length



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