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Article

A Mathematical Structure Underlying Sentences and Its Connection with Short-Term Memory

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Abstract: The mathematical structure underlying a sentence is made of two independent processing units in series. The conditional probability density function of sentence length (measured in words) recordable in the extended short–term memory (E–STM) buffer made of C_F cells is Gaussian. The number of sentences that authors of Italian and English Literatures have written is compared to that theoretically available to them. The multiplicity factor α describes this comparison. $\alpha > 1$ is more likely than $\alpha < 1$ and often $\alpha \gg 1$, therefore the same sentence pattern is reused many times. These texts are easier to read. Very few novels show $\alpha < 1$. In these cases, there are enough diverse sentence patters to convey meaning, but most of them are not used. Texts are more difficult to read, as measured by a universal readability index G_U. A mismatch index I_M synthetically describes the process. α, G_U. and I_M increase with year of publication. Future work will concern other literatures – including ancient ones as Greek and Latin – to confirm what, in our opinion, is general feature of human mind.

Keywords: alphabetical languages; extended short–term memory; human communication; human mind; sentences: mathematical modeling; universal readability index

1. Introduction: Two short–term memory processing units in series

Recently [1], we have proposed a well–grounded conjecture that a sentence – read or pronounced, the two activities are similarly processed by the brain [2] – is elaborated by the short–term memory (STM) with two independent processing units in series, with similar buffer size. The clues for conjecturing this model has emerged by considering many novels belonging to the Italian and English Literatures. We have shown that there are no significant mathematical/statistical differences between the two literary corpora, according to surface deep–language variables. In other words, the mathematical surface structure of alphabetical languages – a creation of human mind – is deeply rooted in humans, independently of the particular language used.

A two–unit STM processing can be justified according to how a human mind seems to memorize "chunks" of information written in a sentence. Although simple and related to the surface of language, the model seems to describe mathematically the input–output characteristics of a complex mental process largely unknown.

The first processing unit is linked to the number of words between two contiguous interpunctions, variable indicated by I_p – termed word interval (Appendix A lists the mathematical symbols used in the present paper) – approximately ranging in Miller's 7 ± 2 law range [3–12]. The second unit is linked to the number M_F of I_p's contained in a sentence, referred to as the extended STM, or E–STM, ranging approximately from 1 to 6. We have shown that the capacity (expressed in words) required to process a sentence ranges from 8.3 to 61.2 words, values that can be converted into time by assuming a reading speed. This conversion gives the range 2.6~19.5 seconds for a fast–reading reader [13], and 5.3~30.1 seconds for a common reader of novels, values well supported by experiments reported in the literature [14–29].

The E–STM must not be confused with the intermediate memory [30, 31]. It is not modelled by studying neuronal activity, but by studying surface aspects of human communication, such as words and interpunctions, whose effects writers and readers have experienced since the invention of writing.

The modeling of the STM processing by two units in series has never been considered in the literature before Reference [32] and [1]. The reader is very likley aware that the literature on the STM and its various aspects is very large

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and multidisciplinary, but nobody, as far as we know, has never considered the connections we have found and discussed in References [32, 1]. Moreover, a sentence conveys meaning, therefore the theory we are further developing might be a starting point to arrive at *the* Information Theory that includes meaning.

Today, some attempts are being made by many scholars trying to arrive at a "semantic communication" theory or "semantic information" theory, but results are still, in our opinion, in their infancy [33–41]. These theories, as those concerning the STM, have not considered the main "ingredients" of our theory as a starting point for including meaning, still a very open issue.

Figure 1 sketches the flow–chart of the two processing units [1]. The words $p_1, p_2, \ldots p_j$ are stored in the first buffer up to j items, approximately in Miller's range, until an interpunction is introduced to fix the length of I_P. The word interval I_P is then stored in the second buffer up to k items, from about 1 to 6, until the sentence ends. The process is then repeated for the next sentence.

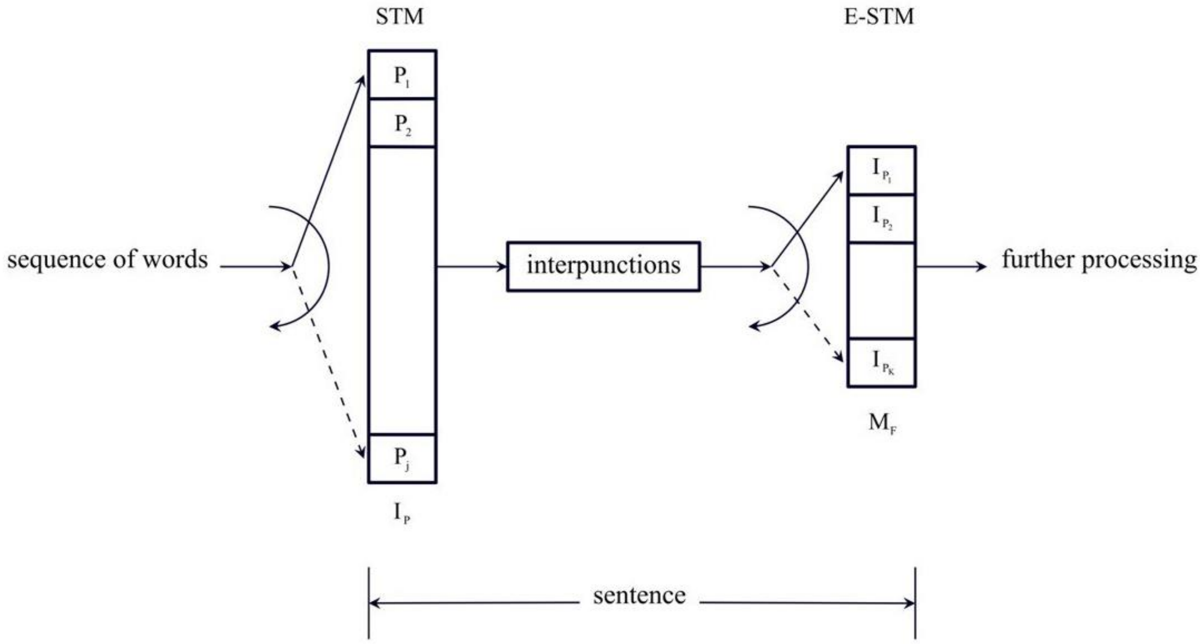

Figure 1. Flow–chart of the two processing units of a sentence. The words $p_1, p_2, \ldots p_j$ are stored in the first buffer up to j items to complete a word interval I_P, approximately in Miller's range, when an interpunction is introduced. I_P is then stored in the E–STM buffer. up to k items, i.e. in M_F cells, approximately 1 to 6, until the sentence ends.

The purpose of the paper is to further investigate the mathematical structure underlying sentences, first theoretically and secondly experimentally, by considering the novels previously mentioned [1], listed in Tables B.1 for Italian Literature and in Table B.2 for English Literature.

After this Introduction, in Section 2 we study the probability distribution function (PDF) of sentence size – measured in words – recordable by an E–STM buffer made of C_F cells (this parameter plays the role of M_F). In Section 3 we study the number of sentences, with the same number of words, that C_F cells can process. In Section 4, we compare the number of sentences that authors of Italian and English Literatures actually wrote for a novel to the number of sentences theoretically available to them, by defining a multiplicity factor. In Section 5 we define a mismatch index, which synthetically measures to what extent a writer uses the number of sentences theoretically available of Section 5. In Section 6 we show that the parameters studied increase with the year of novel publication. Finally, in Section 7, we summarize the main results and propose future work.

2. Probability distribution of sentence length versus E–STM buffer size

First, we study the conditional PDF of sentence length, measured in words W – i.e. the parameter which in long texts, as chapters, gives P_F for each chapter – recordable in an E–STM buffer made of C_F cells – i.e. the parameter which gives M_F in chapters. Secondly, we study the overlap of the PDFs because this overlap gives interesting indications.

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2.1. Probability distribution of sentence length

To estimate the PDF of sentence length, we run a Monte Carlo simulation based on the PDF of I_P obtained in [1] by merging the two literatures recalled in the in the Introduction.

In Reference [1], we have shown that the PDF of I_P, P_F and M_F – as just recalled, these averages refer to single chapters of the novels – can be modelled with a three–parameter log–normal density function (natural logs):

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma_x(x-1)} \exp\left\{-\frac{1}{2}\left[\frac{\ln(x-1)-\mu_x}{\sigma_x}\right]^2\right\} \quad x \geq 1 \qquad (1)$$

In Eq. (1), μ_x and σ_x are, respectively, the mean value and the standard deviation the log–normal PDF. Table 1 reports these values for the three deep–language variables.

Table 1. Mean value μ_x and standard deviation σ_x of the log–normal PDF of the indicated variable [1].

	μ_x	σ_x
I_P	1.689	0.180
P_F	3.038	0.441
M_F	0.849	0.483

The Monte Carlo simulation steps are the following.

1. Consider a buffer made of C_F cells. The sentence contains C_F word intervals: for example, if $C_F = 3$, the sentence contains two interpunctions followed by a full stop, or a question mark, or an exclamation mark.
2. Generate C_F independent values of I_P according to the log–normal model given by Equation (1) and Table 1. The independence of I_P from a cell to another cell is reasonable [1].
3. Add the number of words contained in the C_F cells to obtain W:

$$W = \sum_{i=1}^{C_F} I_{p,i} \qquad (2)$$

4. Repeat steps 1 to 3 many times (we did it 100,000 times, i.e., we simulated 100,000 sentences of different length) to obtain a stable conditional PDF of W.
5. Repeat steps 1 to 4 for another C_F and obtain another PDF.

Figure 2 shows the conditional PDF for several C_F. Each PDF can be very well modelled by a Gaussian PDF $f_{C_F}(x)$ because the probability of getting unacceptable negative values is negligible in any of the PDFs shown in Figure 2. For example, for $C_F = 3$ the mean value and the standard deviation are, respectively, $m_3 = 18.00$ words and $s_3 = 1.79$ words.

In general terms, the mean value of Equation (2) is given by:

$$m_{C_F} = \langle W \rangle = \langle \sum_{i=1}^{C_F} I_{p,i} \rangle = \sum_{i=1}^{C_F} \langle I_{P,i} \rangle = C_F \langle I_p \rangle \qquad (3)$$

Therefore, m_{C_F} is proportional to C_F. As for the standard deviation of W, if the $I_{p,i}$'s are independent – as we assume – then the variance $s_{C_F}^2$ of W is given by:

$$s_{C_F}^2 = \sum_{i=1}^{C_F} \sigma_{I_{P,i}}^2 = C_F \times \sigma_{I_P}^2 \qquad (4)$$

Therefore, the standard deviation s_{C_F} is proportional to $\sqrt{C_F}$. Finally, according to the central limit theory [42], in a significant range about the mean the PDF can be modelled as a Gaussian PDF.

In conclusion, the Monte Carlo simulation produces a Gaussian PDF with mean value proportional to C_F and standard deviation proportional to $\sqrt{C_F}$. These findings are clearly evident in the PDF's shown in Figure 2 in which m_{C_F} and s_{C_F} increase as theoretically expected, therefore, mean values and standard deviations of the other PDF's can be calculated by scaling the values found for $C_F = 3$. For example, for $C_F = 6$, $m_6 = 2 \times 18.00 = 36.00$ words and $s_6 = \sqrt{2} \times 1.79 = 2.53$ words.

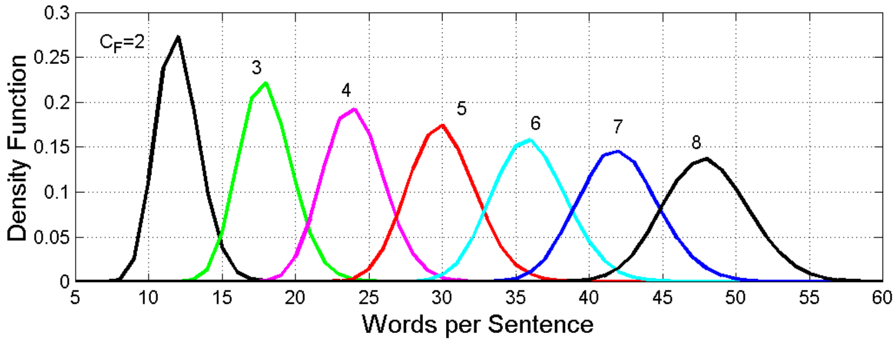

Figure 2. Conditional PDFs of words per sentence versus E–STM buffer of C_F cells from 2 to 8. Each PDF can be modelled with a Gaussian PDF $f_{C_F}(x)$ with mean value proportional to C_F and standard deviation proportional to $\sqrt{C_F}$.

Figure 3 shows the histograms corresponding to Figure 2. The number of samples for each conditional PDF, out of 100,000 considered in the Monte Carlo simulation, are obtained by distributing the samples according to the PDF of M_F given by Eq. (1) and Table 1. The case $C_F = 3$ gives the largest sample size.

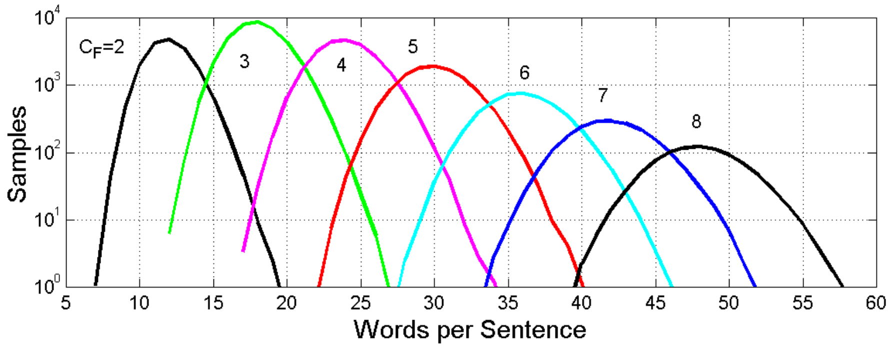

Figure 3. Conditional histograms of words per sentence versus E–STM buffer of C_F cells from 2 to 8, obtained from Figure 1, by simulating 100,000 sentences weighted with the PDF of M_F.

The results shown above have an experimental basis because the relationship between $< P_F >$ – average of words per sentence for the entire novel, calculated by averaging the P_F of single chapters, by weighting single chapters with the fraction of novel total word, as discussed in [32] – versus $< M_F >$ – average of M_F of a novel calculated as P_F – is linear, as Figure 4 shows by drawing $< P_F >$ versus $< M_F >$ concerning the novels mentioned above.

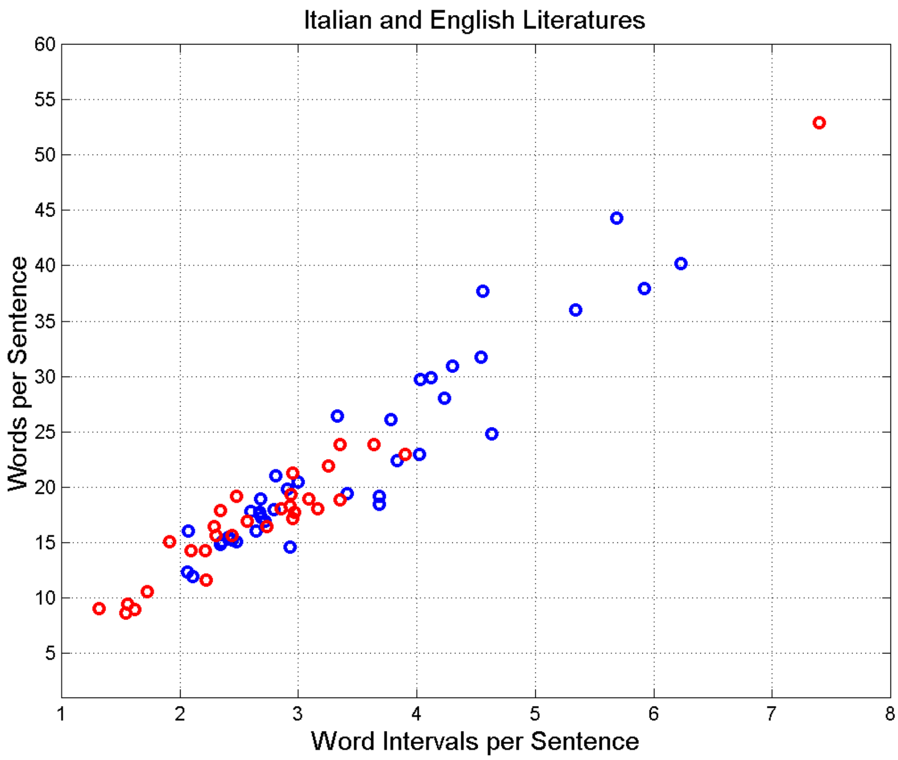

Figure 4. Scatterplot of $< P_F >$ versus $< M_F >$ of Italian novels (blue circles) and English novels (red circles).

2.2. Overlap of the conditional probability distributions

Figure 2 shows that the conditional PDFs overlap, therefore some sentences can be processed by buffers of diverse C_F size, either larger or smaller. Let us define the probability of these overlaps.

Let W_{th} be the intersection of two contiguous Gaussian PDFs, for example $f_{C_F-1}(x)$ and $f_{C_F}(x)$, therefore the probability p_{HL} that a sentence length can be found in the nearest lower Gaussian PDF (going from $C_F \rightarrow C_F - 1$) is given by:

$$p_{HL} = \int_{-\infty}^{W_{th}} f_{C_F}(x)dx \approx \int_{0}^{W_{th}} f_{C_F}(x)dx \quad (5)$$

Similarly, the probability that a sentence length can be found in the nearest higher Gaussian PDF (going from $C_F - 1 \rightarrow C_F$) is given by:

$$p_{LH} = \int_{W_{th}}^{\infty} f_{C_F-1}(x)dx \quad (6)$$

For example, the threshold value between $f_{C_{F=3}}(x)$ and $f_{C_{F=4}}(x)$ is $W_{th} = 20.9$ words and $p_{HL} = 6.6\%$, $p_{LH} = 5.5\%$.

Figure 5 draws these probabilities (%) versus $C_F - 1$ (lower V_F). Because s_{C_F} increases with $\sqrt{C_F}$, therefore $p_{HL} > p_{LH}$. however, this is not only a mathematically obvious result, but it also meaningful because it indicates that: a) a human mind can process sentences of length belonging to the contiguous lower or higher M_F – the probability of going to more distant PDFs is negligible – and b) the number of these sentences is larger in the case $C_F \rightarrow C_F - 1$, which just means that an E–STM buffer can process to a larger extent data matched to a smaller capacity buffer than data matched to a larger capacity buffer.

In general, there is continuity in the length of sentences that a human mind can process as the PDF of P_F shows according to Equation (1), therefore each writer/reader can change the buffer size in a range within the larger range of the log–normal PDF.

Finally, notice that each sentence conveys meaning – theoretically any sequence of words might be meaningful, although this may not be the case, but we do not know their proportion – therefore the PDFs found above are also the PDFs associated with meaning. Moreover, the same numerical sequence of W words can carry different meanings, according to the words used. Multiplicity of meaning, therefore, is "built–in" in a sequence of W words. We will further explore this issue in the next sections by considering the number of sentences that authors of Italian and English Literatures actually wrote.

So far, we have explored the processing of the words of a sentence by simulating sentences of diverse length, conditioned to the E–STM buffer size. In the next section we explore the complementary processing concerning the number of sentences that contain the same number of words.

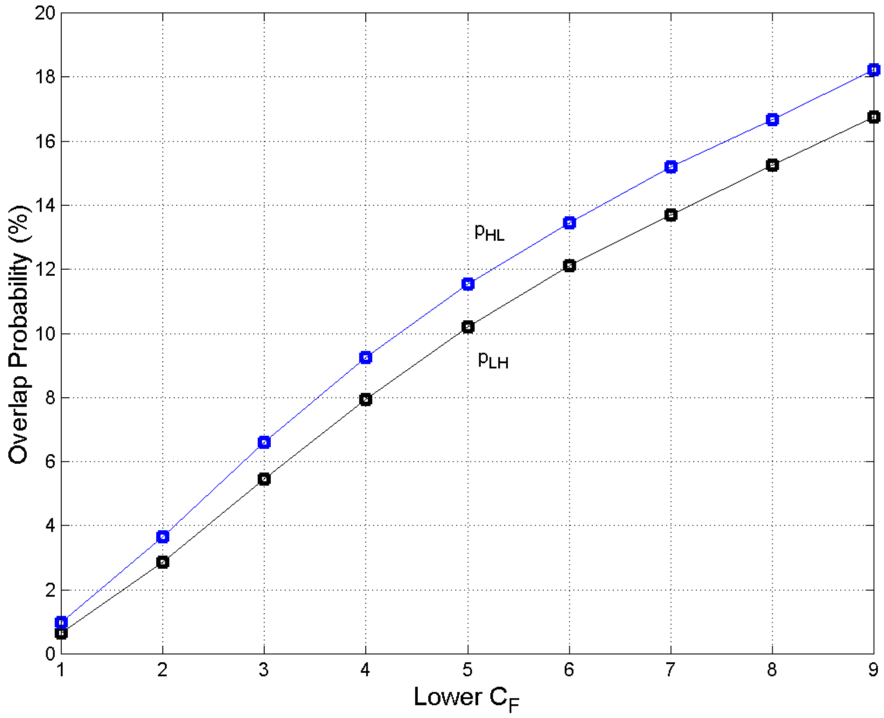

Figure 5. Overlap probability (%) versus $C_F - 1$ (lower C_F); p_{HL} and p_{LH} are given by Equations (5) and (6).

3. Theoretical number of sentences recordable in C_F cells

We study the number of sentences of W words that an E–STM buffer, made of C_F cells, can process. In synthesis, we ask the following question: how many sentences $S_W^{(C_F)}$ containing the same number of words W, Equation (2), can be theoretically written in C_F cells?

Table 2 reports these numbers as a function of W and C_F. We calculated these data first by running a code and then by finding the mathematical recursive formula that generates them, given by:

$$S_W^{(C_F)} = S_{W-1}^{(C_F)} + S_{W-1}^{(C_F-1)} \quad (7)$$

For example, if $W = 20$ words and $C_F = 4$, we read $S_{19}^{(C_F=4)} = 816$, $S_{19}^{(C_F-1=3)} = 153$, therefore $S_{20}^{(C_F=4)} = 816 + 153 = 969$.

Table 2. Theoretical number of sentences $S_W^{(C_F)}$ (columns) recordable in an E–STM buffer made of C_F cells with the same number of words (items) indicated in the first column.

Words W (items storeable)	E–STM buffer made of C_F cells							
	1	2	3	4	5	6	7	8
1	1	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0
3	1	2	1	0	0	0	0	0
4	1	3	3	1	0	0	0	0
5	1	4	6	4	1	0	0	0
6	1	5	10	10	5	1	0	0
7	1	6	15	20	15	6	1	0

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8	1	7	21	35	35	21	7	1
9	1	8	28	56	70	56	28	8
10	1	9	36	84	126	126	84	36
11	1	10	45	120	210	252	210	120
12	1	11	55	165	330	462	462	330
13	1	12	66	220	495	792	1254	792
14	1	13	78	286	715	1287	2046	2046
15	1	14	91	364	1001	2002	3333	4092
16	1	15	105	455	1365	3003	5335	7425
17	1	16	120	560	1820	4368	8338	12760
18	1	17	136	680	2380	6188	12706	21098
19	1	18	153	816	3060	8568	18894	33804
20	1	19	171	969	3876	11628	27462	52698
21	1	20	190	1140	4845	15504	39090	80160
22	1	21	210	1330	5985	20349	54594	119250
23	1	22	231	1540	7315	26334	74943	173844
24	1	23	253	1771	8855	33649	101277	248787
25	1	24	276	2024	10626	42504	134926	350064
26	1	25	300	2300	12650	53130	177430	484990
27	1	26	325	2600	14950	65780	230560	662420
28	1	27	351	2925	17550	80730	296340	892980
29	1	28	378	3276	20475	98280	377070	1189320
30	1	29	406	3654	23751	118755	475350	1566390
31	1	30	435	4060	27405	142506	594105	2041740
32	1	31	465	4495	31465	173971	768076	2635845
33	1	32	496	4960	35960	205436	973512	3403921
34	1	33	528	5456	40920	241396	1178948	4377433
35	1	34	561	5984	46376	282316	1461264	5556381
36	1	35	595	6545	52360	328692	1789956	7017645
37	1	36	630	7140	58905	381052	2118648	8807601
38	1	37	666	7770	66045	439957	2499700	10926249
39	1	38	703	8436	73815	506002	2939657	13425949
40	1	39	741	9139	82251	579817	3519474	16365606
41	1	40	780	9880	91390	662068	4099291	19885080
42	1	41	820	10660	101270	753458	4761359	23984371
43	1	42	861	11480	111930	854728	5514817	29499188
44	1	43	903	12341	123410	966658	6369545	35014005
45	1	44	946	13244	135751	1090068	7336203	41383550
46	1	45	990	14190	148995	1225819	8426271	48719753
47	1	46	1035	15180	163185	1374814	9652090	58371843
48	1	47	1081	16215	178365	1537999	11026904	68023933
49	1	48	1128	17296	194580	1716364	12564903	79050837

50	1	49	1176	18424	211876	1910944	14281267	91615740
51	1	50	1225	19600	230300	2122820	16192211	105897007
52	1	51	1275	20825	251125	2353120	18315031	122089218
53	1	52	1326	22100	273225	2604245	20668151	140404249
54	1	53	1378	23426	296651	2877470	23272396	161072400
55	1	54	1431	24804	320077	3174121	26149866	184344796
56	1	55	1485	26235	344881	3494198	29323987	210494662
57	1	56	1540	27720	371116	3839079	32818185	239818649
58	1	57	1596	29260	398836	4210195	36657264	272636834
59	1	58	1653	30856	428096	4609031	40867459	309294098
60	1	59	1711	32509	458952	5037127	45476490	350161557

Figure 6 draws the data reported in some lines of Table 2 for a quick overview. We see how fast the number of sentences changes with C_F, for constant W. For example, if $W = 20$ words, then $S_{W=20}$ ranges from 1 ($C_F = 1$) to 52,698 sentences ($C_F = 8$). Maxima are clearly visible for $W = 5$ and $W = 10$ words at $C_F = 3$ and $C_F = 5$ or 6, respectively. Values become fantastically large for larger W and C_F, well beyond the ability and creativity of single writers, as we will show in Section 4.

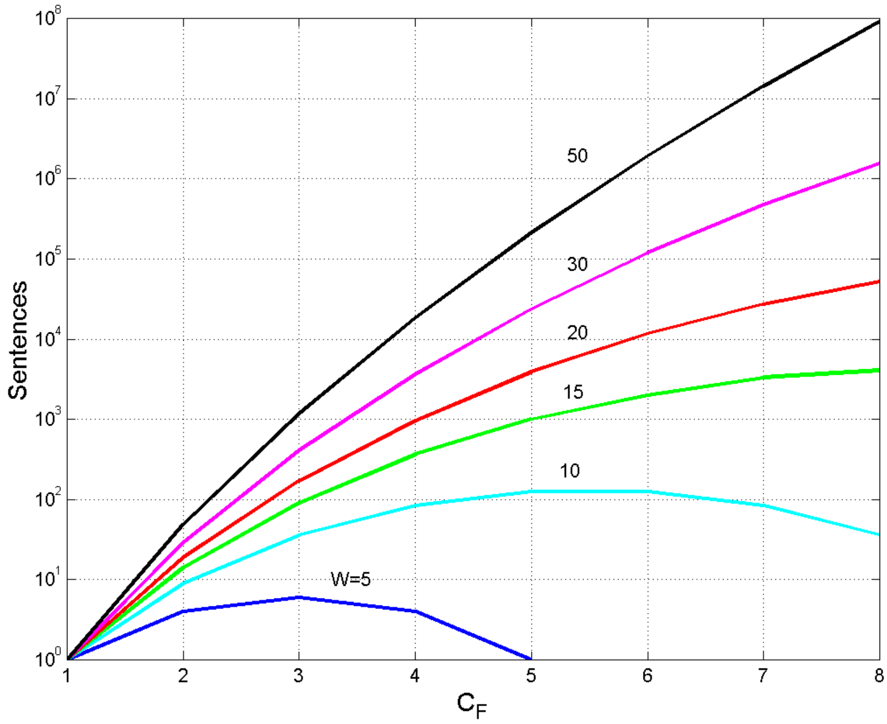

Figure 6. Number of sentences $S_W^{(C_F)}$ made of W words versus E–STM buffer capacity C_F.

Figure 7 draws the data reported in some columns of Table 2, i.e. the number of sentences $S_W^{(C_F)}$ versus W, for fixed C_F. In this case, it is useful to adopt an efficiency factor ε, defined as the ratio between $S_W^{(C_F)}$ and W, for a given C_F:

$$\varepsilon = \frac{S_W^{(C_F)}}{W} \quad (8)$$

This factor says, synthetically, how a buffer of C_F cells is efficient in providing sentences with a given number of words, its units being sentences per word.

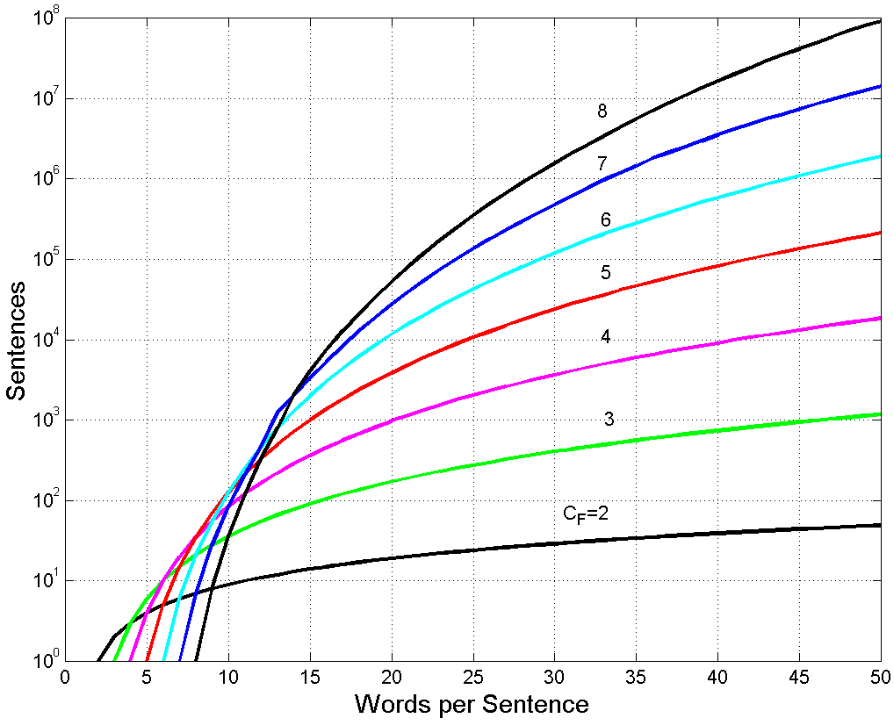

Figure 7. Number of sentences $S_W^{(C_F)}$ recordable in a E–STM buffer capacity C_F versus words per sentence.

Figure 8 shows ε versus W. It is interesting to notice that for $W \lesssim 10$ words, the buffer $C_F = 2$ can be more efficient than the others. Beyond $W = 10$, the larger buffers become very efficient, with very large ε.

If a writer uses short buffers – e.g., deliberately because of his/her style, or necessarily because of reader's E–STM memory size – then he/she has to repeat the same numerical sequence of words many times, according to the number of meanings conveyed. For example, if $C_F = 2$ and $W = 10$ the writer has only 9 different choices, or patterns of two numbers whose sum is 10 (Table 2). Therefore, Table 2 gives the *minimum* number of meanings that can be conveyed. The larger C_F, the larger is the variety of sentences that can be written with W words.

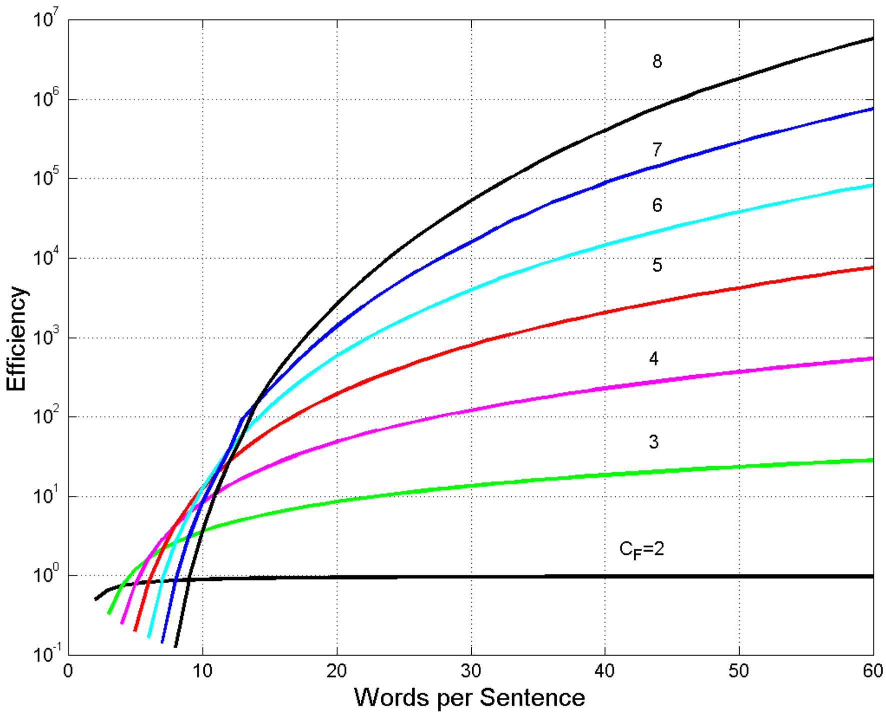

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Figure 8. Efficiency ε, Equation (8), of an E–STM buffer of C_F cells versus words per sentence W.

Now, the following question naturally arises: How many sentences authors do write in their texts, compared to the theoretical number available to them? In the next section we will compare these two sets of data by studying the novels taken from the Italian and English Literatures listed in Appendix B, by assuming their average values $< P_F >$ and $< M_F >$ and by defining a multiplicity factor.

4. Experimental multiplicity factor of sentences

We compare the number of sentences that authors of Italian and English Literatures actually wrote for each novel to the number of sentences theoretically available to them, according to $< P_F >$, $< M_F >$ of each novel. In this analysis, we do not consider the values of P_F and M_F of each chapter of a novel because the detail would be so fine to miss the general trend given, on the contrary, by the average values $< P_F >$, $< M_F >$ of the complete novel.

As is well known, the average value and the standard deviation of integers very likely are not integers – as is always the case for the linguistic parameters – therefore, to apply the mathematical theory of the previous sections, we must do some interpolations and only at the end of the calculation consider integers.

Let us compare the experimental number of sentences $S_{P_F}^{(M_F)}$ of a novel, reported in Tables B.1 and B.2 to the theoretical number $S_W^{(C_F)}$ available to the author, according to the experimental values $< P_F >$ (which plays the role of W) and $< M_F >$ (which plays the role of C_F) of the novel.

By referring to Figure 7, the interpolation between the integers of Table 2 to find the curve of constant C_F – given by the real number $< M_F >$ – is linear along both axes. At the intersection of the vertical line (corresponding to the real number $< P_F >$) and the new curve (corresponding to the real number $< M_F >$), we find the theoretical $S_W^{(C_F)}$ by rounding the value to the nearest integer towards zero. For example, for *David Copperfield*, in Table B.2 we read $S_{P_F}^{(M_F)} = 19{,}610$ and the interpolation gives $S_W^{(C_F)} = 1{,}553$. Figure 9 shows the result of this exercise. We see that $S_W^{(C_F)}$ increases rapidly with $< M_F >$. The most displaced (red) circle is due to *Robinson Crusoe*.

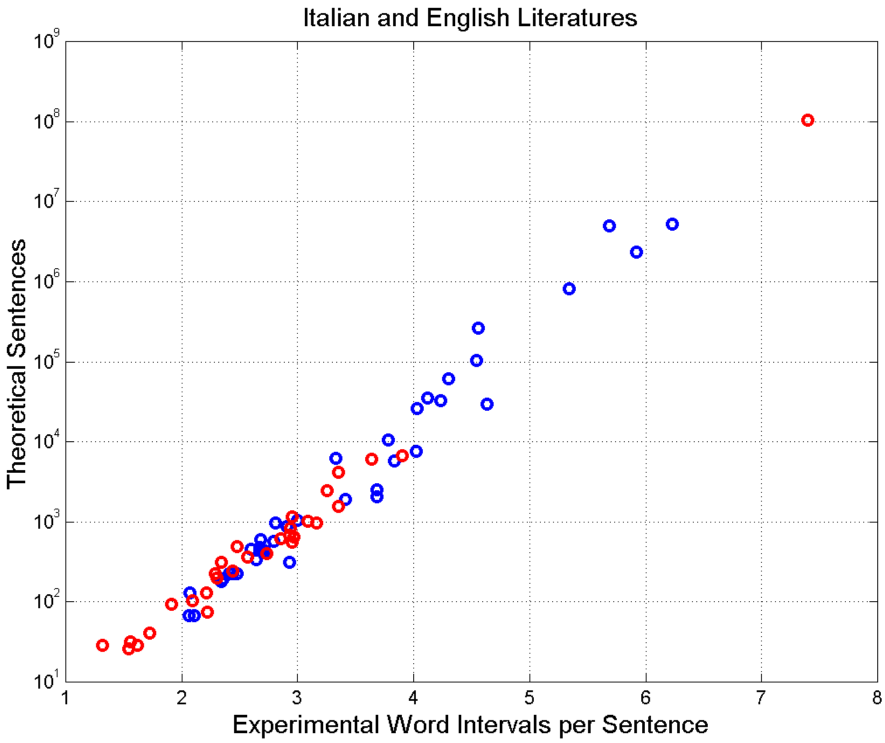

Figure 9. Theoretical number of sentences $S_W^{(C_F)}$ versus $< M_F >$ for Italian (blue circles) and English (red circles) novels.

The comparison between $S_{P_F}^{(M_F)}$ and $S_W^{(C_F)}$ is done by defining a multiplicity factor α, defined as the ratio between $S_{P_F}^{(M_F)}$ (experimental value) and $S_W^{(C_F)}$ (theoretical value):

$$\alpha = \frac{S_{P_F}^{(M_F)}}{S_W^{(C_F)}} \quad (9)$$

The values of α for each novel are reported in Tables B.1, B.2. For example, for *David Copperfield* $\alpha = 19{,}610/1{,}553 = 12.63$. Figure 10 shows α versus $S_{P_F}^{(M_F)}$. We notice a fair increasing trend of α with $S_{P_F}^{(M_F)}$.

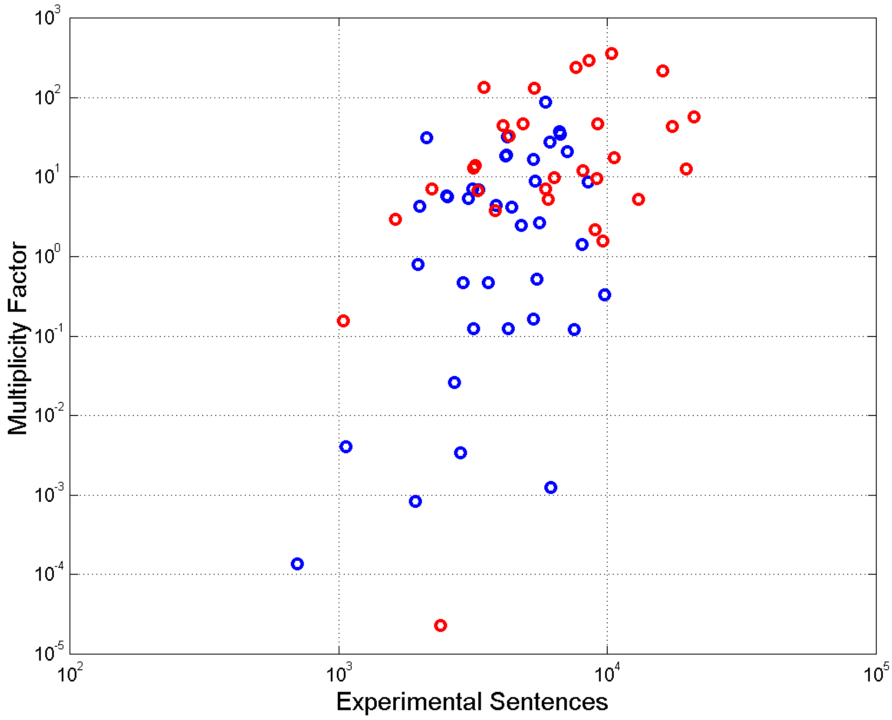

Figure 10. Multiplicity factor versus $S_{P_F}^{(M_F)}$ for Italian (blue circles) and English (red circles) novels.

Figure 11 shows α versus $S_W^{(C_F)}$. An inverse relation power law is a good fit:

$\alpha = 3886/S_W^{(C_F)}$ Italian (10)

$\alpha = 6028/S_W^{(C_F)}$ English (11)

The correlation coefficient of log values is -0.9873.for Italian and -0.9710. for English.

From Equations (10)(11) $\alpha = 1$ when $S_W^{(C_F)} = 3886$ for Italian and $S_W^{(C_F)} = 6028$ for English, therefore, novels with sentences in the range $4000 \sim 6000$ use, on the average, the number of sentences theoretically available for their averages $< P_F >$ and $< M_F >$.

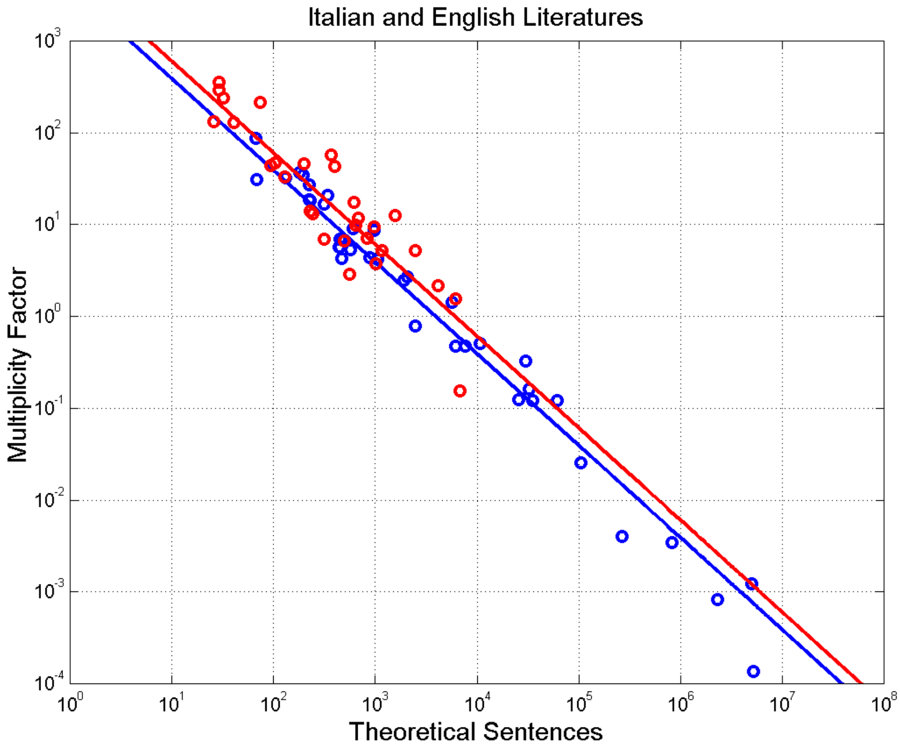

Figure 11. Multiplicity factor α versus theoretical number of words $S_W^{(C_F)}$ for Italian (blue circles and blue line) and English (red circles and red line) novels.

Figure 12 shows α versus $< M_F >$. In this case, an exponential law is a good fit:

$\alpha = 26{,}027 \times e^{-2.923 \times M_F}$ Italian (12)

$\alpha = 15{,}855 \times e^{-2.649 \times M_F}$ English (13)

For Italian Literature (correlation coefficient of linear–log values is -0.9697) $\alpha = 1$ when $M_F = 3.48$, for English Literature (correlation coefficient of linear–log values is -0.9603) $\alpha = 1$ when $M_F = 3.65$. Therefore, novels with sentences in the range $4000 \sim 6000$ use, on the average, the same E–STM buffer size $M_F \approx 3.5$ cells.

From Figures 10–12, we can draw the following conclusion. In general, $\alpha > 1$ is more likely than $\alpha < 1$ and often $\alpha \gg 1$. When $\alpha \gg 1$, the writer reuses many times the same pattern of number of words. The multiplicity factor, therefore, indicates also the *minimum* multiplicity of meaning conveyed by an E–STM, besides, of course, the many diverse meanings conveyed by the same sequence of $I_p's$ obtainable by only changing words. Few novels show $\alpha < 1$. In these cases, the writer has enough diverse patters to convey meaning but most of them are not used.

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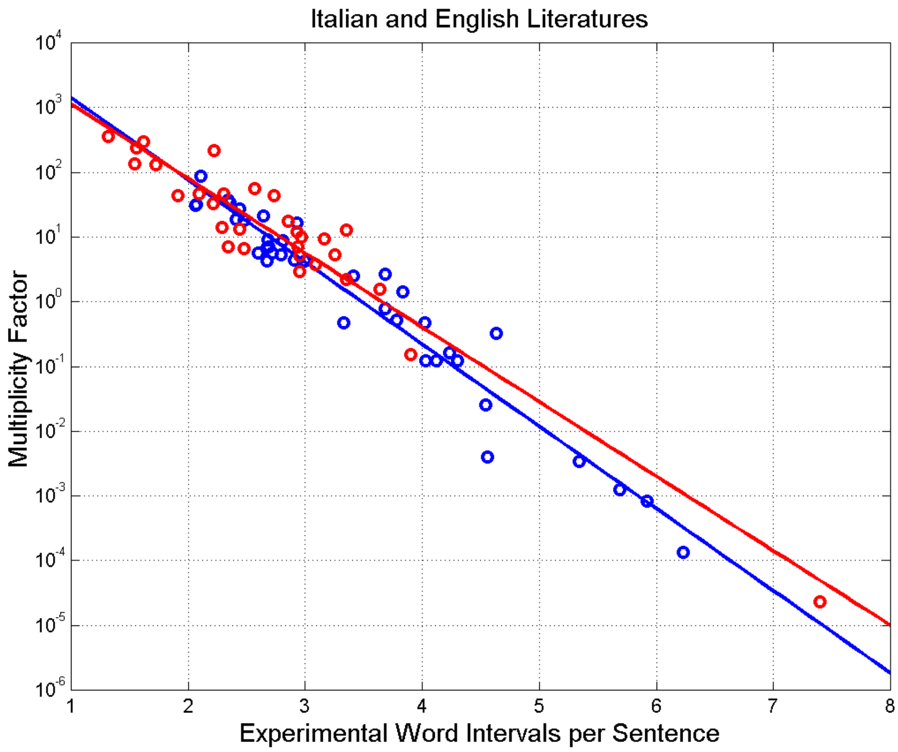

Figure 12. Multiplicity factor α versus M_F for Italian (blue circles and blue line) and English (red circles and red line) novels .

Finally, it is interesting to relate α to a universal readability factor G_U, which is a function of both P_F and I_P [43]. Figure 13 shows α versus G_U. Since readability of a text increases as G_U increases, we can see that the novels with $\alpha < 1$ tend to be less readable than those with $\alpha > 1$. The less readable novels have in general large values of P_F and, therefore, may contain more E–STM cells (large M_F).

In conclusion, if a writer does use the full variety of sentence patterns available, or even overuses them, then he/she writes texts that are easier to read. On the other hand, if a writer does not use the full variety of sentence patterns available, then he/she tends to write texts more difficult to read. In the next section we define a useful index, the mismatch index, which synthetically describes these cases.

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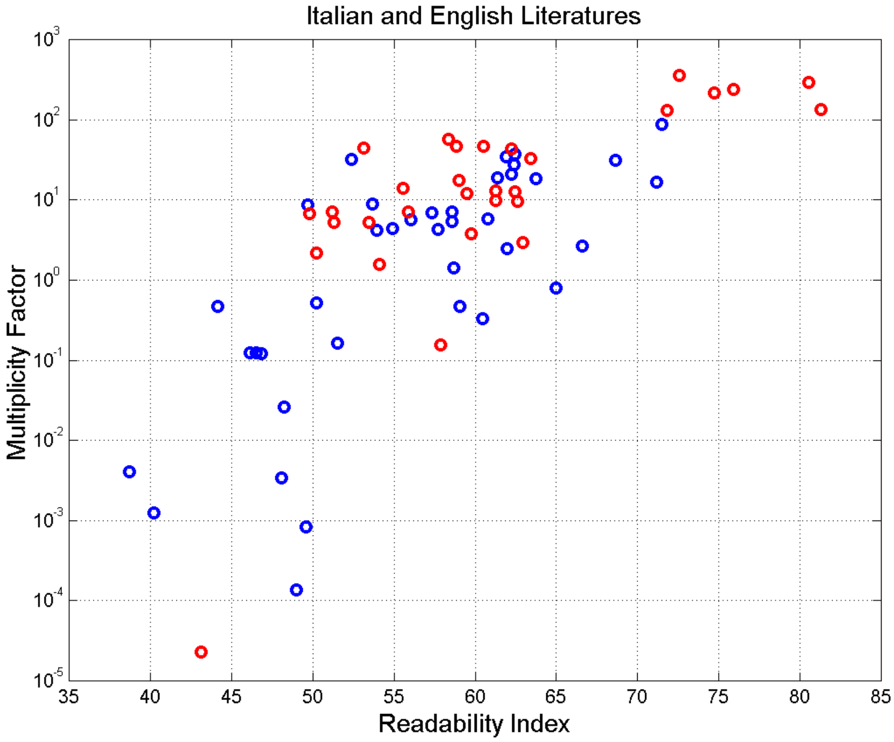

Figure 13. Multiplicity factor α versus readability index G_U for Italian (blue circles) and English (red circles) novels.

5. Mismatch index

We define a useful index, the mismatch index, which measures to what extent a writer uses the number of sentences theoretically available, according to the averages $< P_F >$ and $< M_F >$ of the novel. For this purpose, we define the mismatch index:

$$I_M = \frac{S_{P_F}^{(M_F)} - S_W^{(C_F)}}{S_{P_F}^{(M_F)} + S_W^{(C_F)}} = \frac{\alpha - 1}{\alpha + 1} \quad (14)$$

According to Equation (14), $I_M = 0$ when $S_{P_F}^{(M_F)} = S_W^{(C_F)}$, hence $\alpha = 1$ and in this case experiment and theory are perfectly matched. They are over matched when $I_M > 0$ ($\alpha > 1$) and under matched when $I_M < 0$ ($\alpha < 1$).

Figure 14 shows the scatterplot of I_M versus M_F. The mathematical models drawn are calculated by substituting Equations (12) (13) in Equation (14). We can reiterate that when $I_M > 0$ (over matching, $M_F \lesssim 3.5$) the writer repeats sentence patterns because there are not enough diverse patterns to convey all meanings. Texts are easier to read. When $I_M < 0$ (under matching, $M_F \gtrsim 3.5$) the writer has theoretically many sentence patters to choose from, but he/she uses only few or very few of them. Texts are more difficult to read.

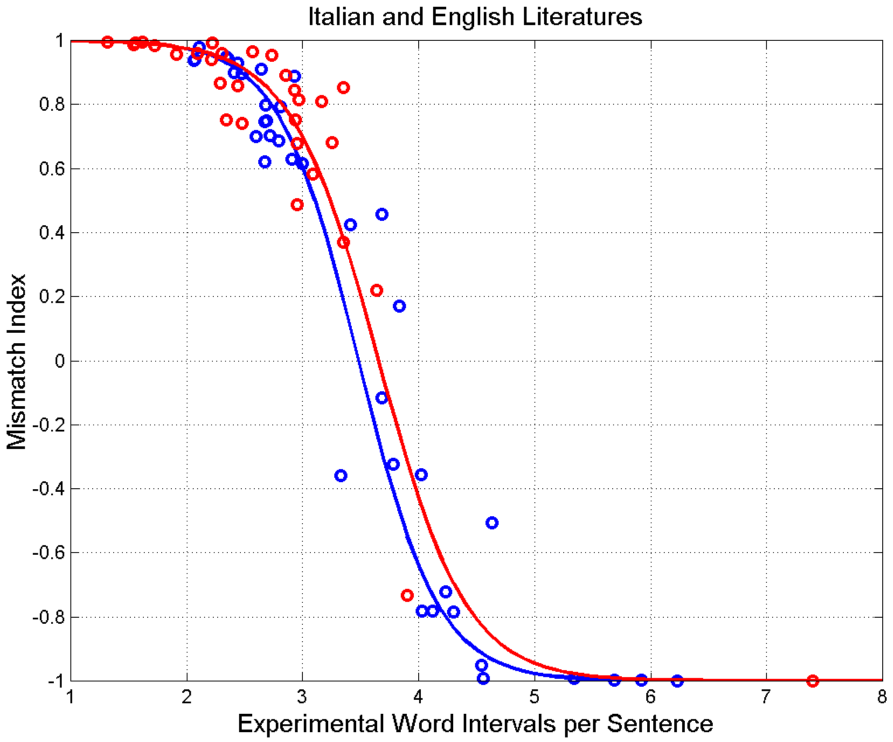

Figure 14. Mismatch index I_M versus M_F for Italian (blue circles and blue line) and English (red circles and red line) novels.

Figure 15 shows the scatterplot of I_M versus $S_W^{(C_F)}$. The mathematical models drawn are calculated by substituting Equations (10) (11) in Equation (14). Over matching is found for $S_W^{(C_F)} < 3886$ for Italian and $S_W^{(C_F)} < 6028$ for English.

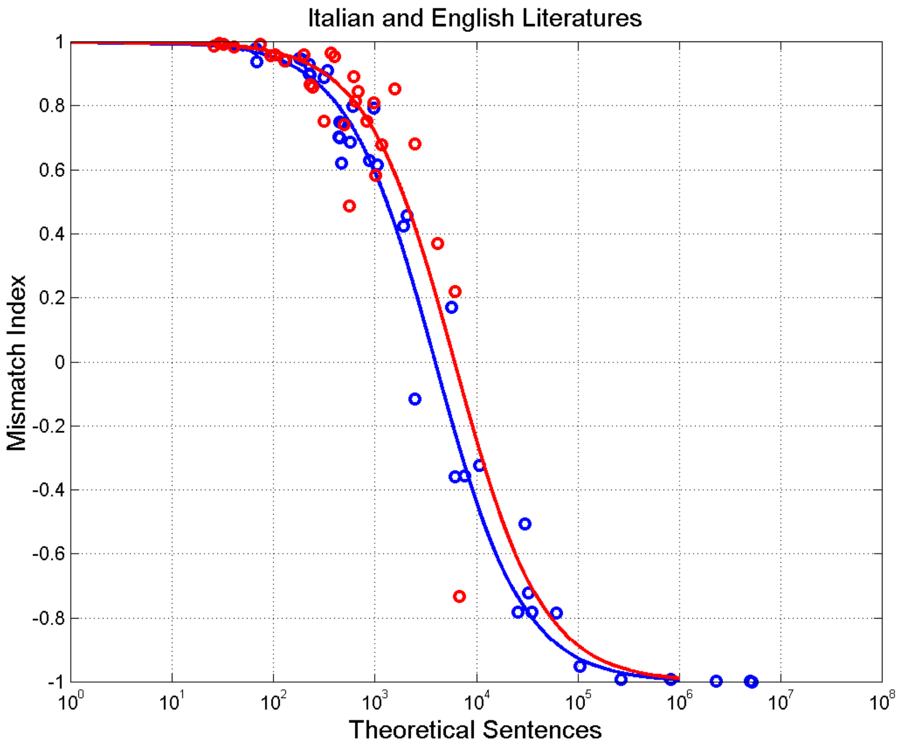

Figure 15. Mismatch index I_M versus theoretical number of sentences $S_W^{(C_F)}$ for Italian (blue circles and blue line) and English (red circles and red line) novels.

Finally Figure 16 shows I_M versus α, Equation (14), a synthetic picture that summarizes the entire analysis of mismatch.

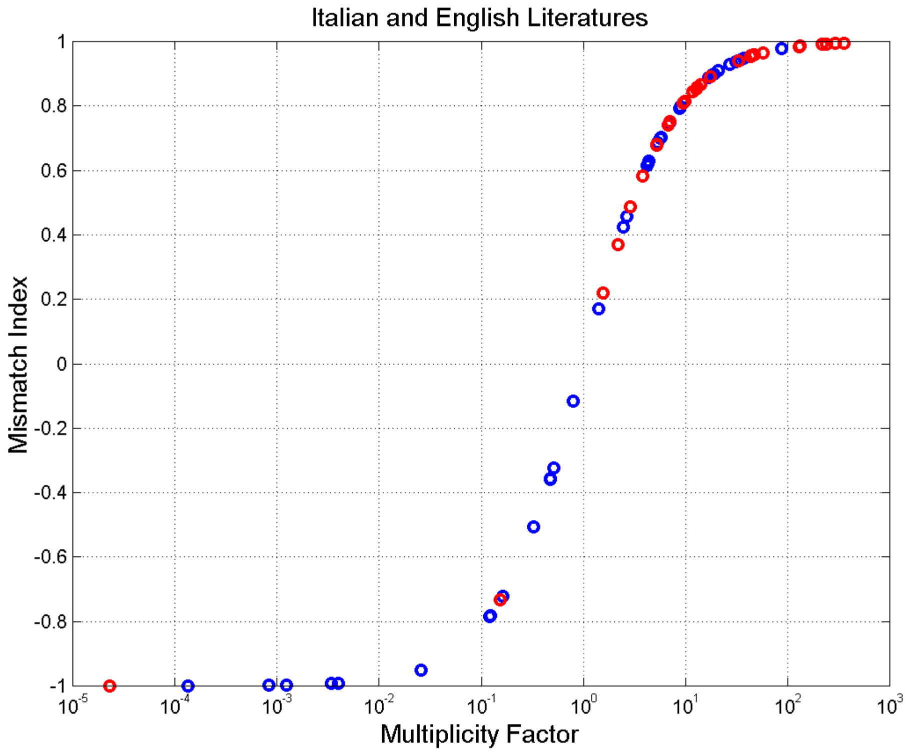

Figure 16. Mismatch index I_M versus the multiplicity factor I_M for Italian (blue circles) and English (red circles) novels.

As we can realize by reading the year of publication in Tables B.1, B.2, the novels span a long period. Do the parameters studied depend on time? In the next section we show that the answer to this question is positive.

6. Time dependence

The novels considered in Tables B.1, B.2 were published in a period spanning several centuries. We show that the multiplicity factor α and the mismatch index I_M do depend on time.

Figure 17 shows the multiplicity factor versus year of publication of the novel since 1800. It is evident that writers tend to use larger values of α – therefore E–STM buffers of small size – as we approach the present epoch, and a possible saturation at $I_M \approx 100$. English shows a stable increasing pattern while Italian seems to contain samples coming from two diverse sets of data, one evolving in agreement with English, the other (given by the novels labelled with "*" in Table B.1), always increasing with time, but with diverse slope.

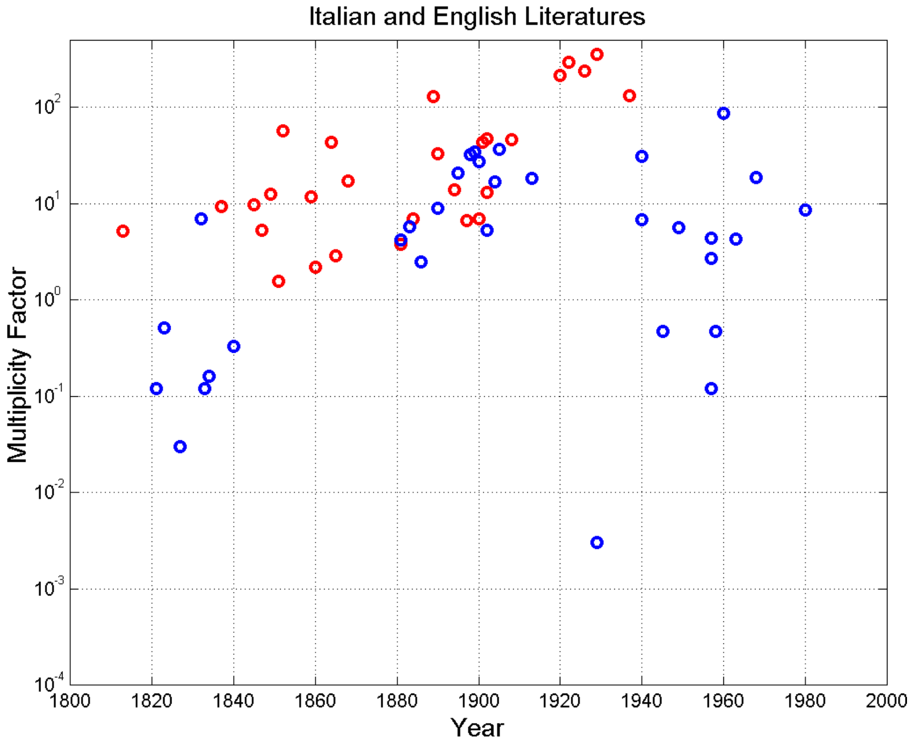

Figure 17. Multiplicity factor I_M versus year of novel publication, for Italian (blue circles) and English (red circles) novels.

Figure 18 shows the mismatch index versus year of novel publication.

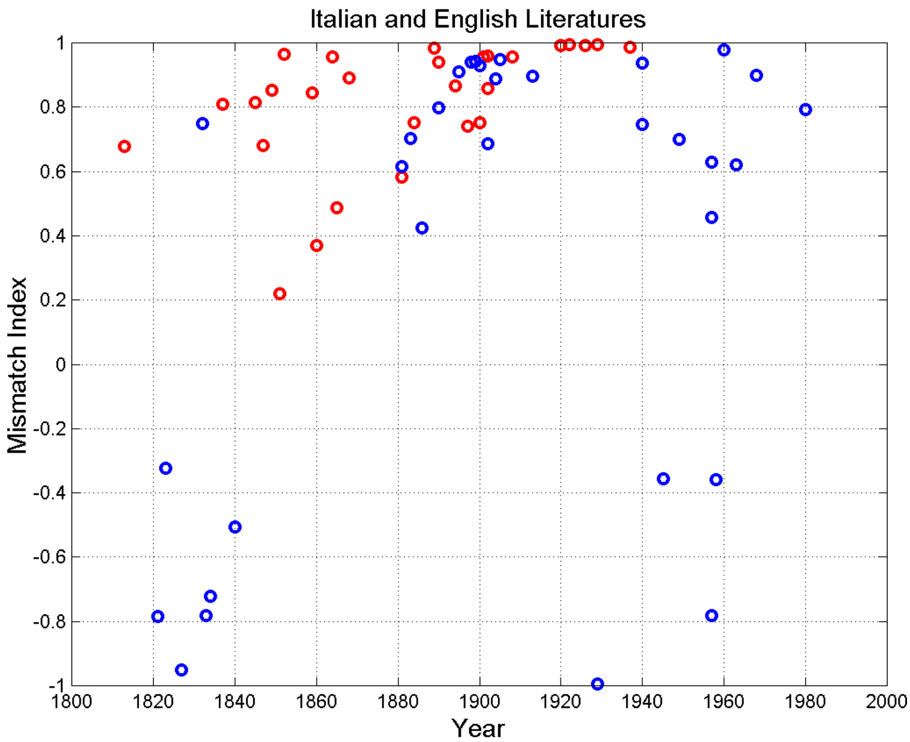

Figure 18. Mismatch factor α versus year of novel publication, for Italian (blue circles) and English (red circles) novels.

Figure 19 shows the universal readability index versus time. In both figures we can notice the same trends shown in Figure 17, therefore reinforcing the conjecture that: (a) writers are partially changing their style with time by making their novels more readable, i.e. more matched to less educated readers, according to the relationship between G_U and the schooling years in Italian school system, as discussed in [43]; (b) a saturation seems to occur in all parameters in the novels written in the second half of the XX century, at least according to the novels of Appendix B.

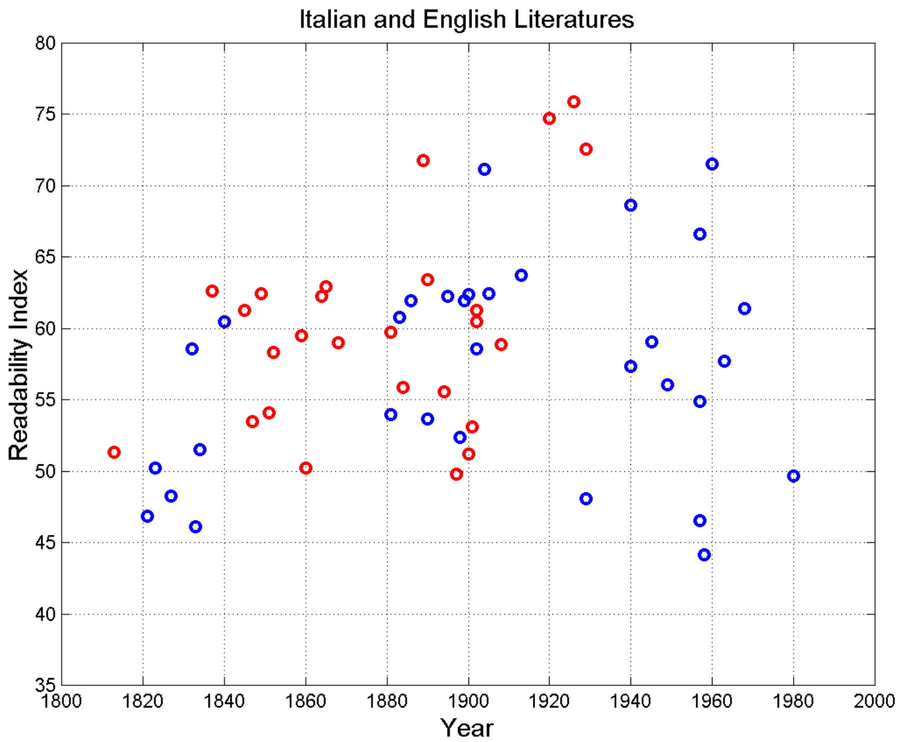

Figure 19. Universal readability index G_U versus year of novel publication, for Italian (blue circles) and English (red circles) novels.

7. Summary and future work

We have investigated the mathematical structure underlying sentences, first theoretically and secondly experimentally by studying a large number of novels of Italian and English Literatures, written down several centuries.

We have studied the conditional PDF of sentence length – measured in words – allowed by an E–STM buffer made of C_F cells, with a Monte Carlo simulation based on the log–normal PDF of the word interval I_P. The simulation produces a conditional Gaussian PDF with mean value proportional to C_F and standard deviation proportional to $\sqrt{C_F}$. These PDFs overlap, indicating, therefore, that some sentences can be processed by buffers of diverse M_F size, either larger or smaller, and that the number of sentences is larger in the overlap case $C_F \rightarrow C_F - 1$ than in the case $C_{F-1} \rightarrow C_F$. This means that an E–STM buffer can process to a larger extent data matched to a smaller buffer capacity than data matched to a larger buffer capacity,

We have also studied the number of sentences with equal number of words that the E–STM buffer of C_F cells can theoretically process. We have then compared this number to the number of sentences that authors of Italian and English Literatures actually wrote for each novel, by defining the multiplicity factor α. In general, $\alpha > 1$ is more likely than $\alpha < 1$ and often $\alpha \gg 1$. When $\alpha \gg 1$ the writer reuses many times the same pattern of number of words in a sentence. The multiplicity factor, therefore, indicates also the minimum multiplicity of meanings conveyed. Few novels show $\alpha < 1$. In these cases, the writer has enough diverse patters to convey meaning but most of them are not used.

We have then defined the mismatch index $-1 \leq I_M \leq +1$, which measures to what extent a writer uses the number of sentences theoretically available. When $I_M = 0$ the match is perfect, the number of sentences theoretically available equals that written in a novel. When $I_M > 0$ (referred to as over matching) the writer repeats sentence patterns because there are not enough diverse patterns to convey all meanings. Texts, however, are easier to read as the universal readability index G_U increases. When $I_M < 0$ (under matching) the writer has theoretically many sentence patterns to choose from, but he/she uses only few of them. Texts are more difficult to read, G_U decreases.

We have shown that α, I_M and G_U increase with year of novel publication. Writers are partially changing their style with time by making their novels more readable, i.e. more matched to less educated readers.

Future work should consider other literatures to confirm what, in our opinion, is general because connected to human mind. The same analysis done on ancient languages, such as Greek and Latin – for which there is a large literary corpus – would show whether these ancient writers/readers displayed similar E–STM.

Appendix A. List of mathematical symbols

Symbol	Definition
C_F	Cells of E–STM buffer
G_U	Universal readability index
I_M	Mismatch index
I_p	Word interval
M_F	Word intervals in a sentence, chapter average
$< M_F >$	Word intervals in a sentence, novel average
P_F	Words in a sentence, chapter average
$< P_F >$	Words in a sentence, novel average
$S_{P_F}^{(M_F)}$	Experimental sentences
$S_W^{(C_F)}$	Theoretical sentences written in C_F cells
W	Words in a sentence
$f(x)$	Three-parameter log-normal density function
$f_{C_F}(x)$	Gaussian PDF
m_{C_F}	Mean value of Gaussian PDF
s_{C_F}	standard deviation of Gaussian PDF
α	Multiplicity factor
ε	Efficiency factor
μ_x	Mean value of log–normal PDF
σ_x	standard deviation of log–normal PDF

Appendix B. List of the novels from Italian and English Literatures considered

Tables B.1 and B.2 list author, title of novel and year of publication of Italian and English Literatures considered in the paper, with deep-language average statistics, multiplicity factor α and mismatch index I_M. The averages $< C_P >$,$< P_F >$,$< I_P >$ $< M_F >$ have been calculated by weighting each chapter value with its fraction of total number of words of the novel, as described in [32].

Table B.1. Authors of the novels of the Italian Literature. Number of total sentences (sentences ending with full–stop, question mark, exclamation mark), average number of characters per word $< C_P >$, average number of words pr sentence, $< P_F >$, average number of word intervals, $< I_P >$, average number word intervals per sentence, $< M_F >$, multiplicity factor α, mismatch index I_M.

Author (Literary Work, Year)	Sentences	$< C_P >$	$< P_F >$	$< I_P >$	$< M_F >$	α	I_M
Anonymous (*I Fioretti di San Francesco*, 1476)	1064	4.65	37.70	8.24	4.56	0.004	-0.99
Bembo Pietro (*Prose*, 1525)	1925	4.37	37.91	6.42	5.92	0.001	-1.00
Boccaccio Giovanni (*Decameron*, 1353)	6147	4.48	44.27	7.79	5.69	0.001	-1.00
Buzzati Dino (*Il deserto dei tartari*, 1940)	3311	5.10	17.75	6.63	2.67	6.90	0.75
Buzzati Dino (*La boutique del mistero*, 1968*)	4219	4.82	15.45	6.37	2.41	18.83	0.90

Calvino (*Il barone rampante*, 1957*)	3864	4.63	19.87	6.73	2.91	4.37	0.63
Calvino Italo (*Marcovaldo*, 1963*)	2000	4.74	17.60	6.59	2.67	4.28	0.62
Cassola Carlo (*La ragazza di Bube*, 1960*)	5873	4.48	11.93	5.64	2.11	87.66	0.98
Collodi Carlo (*Pinocchio*, 1883)	2512	4.60	16.92	6.19	2.72	5.74	0.70
Da Ponte Lorenzo (*Vita*, 1823)	5459	4.71	26.15	6.91	3.78	0.51	-0.32
Deledda Grazia (*Canne al vento*, 1913, Nobel Prize 1926)	4184	4.51	15.08	6.06	2.48	18.35	0.90
D'Azeglio Massimo (*Ettore Fieramosca*, 1833)	3182	4.64	29.77	7.36	4.03	0.12	-0.78
De Amicis Edmondo (*Cuore*, 1886)	4775	4.55	19.43	5.61	3.41	2.48	0.42
De Marchi Emilio (*Demetrio Panelli*, 1890)	5363	4.70	18.95	7.06	2.68	8.95	0.80
D'Annunzio Gabriele (*Le novelle delle Pescara*, 1902)	3027	4.91	17.99	6.38	2.79	5.35	0.68
Eco Umberto (*Il nome della rosa*, 1980*)	8490	4.81	21.08	7.46	2.81	8.70	0.79
Fogazzaro (*Il santo*, 1905)	6637	4.79	14.84	6.33	2.34	37.08	0.95
Fogazzaro (*Piccolo mondo antico*, 1895)	7069	4.79	16.08	6.10	2.64	20.98	0.91
Gadda (*Quer pasticciaccio brutto…* 1957*)	5596	4.76	18.43	4.98	3.68	2.69	0.46
Grossi Tommaso (*Marco Visconti*, 1834)	5301	4.59	28.07	6.56	4.23	0.16	-0.72
Leopardi Giacomo (*Operette morali*, 1827)	2694	4.70	31.78	6.90	4.54	0.03	-0.95
Levi Primo (*Cristo si è fermato a Eboli*, 1945*)	3611	4.73	22.94	5.70	4.02	0.47	-0.36
Machiavelli Niccolò (*Il principe*, 1532)	702	4.71	40.17	6.45	6.23	0.0001	-1.00
Manzoni Alessandro (*I promessi sposi*, 1840)	9766	4.60	24.83	5.30	4.63	0.33	-0.51
Manzoni Alessandro (*Fermo e Lucia*, 1821)	7496	4.75	30.98	7.17	4.30	0.12	-0.78
Moravia Alberto (*Gli indifferenti*, 1929*)	2830	4.81	36.00	6.74	5.34	0.003	-0.99
Moravia Alberto (*La ciociara*, 1957*)	4271	4.56	29.93	7.28	4.12	0.12	-0.78
Pavese Cesare (*La bella estate*, 1940)	2121	4.54	12.37	5.97	2.06	31.19	0.94
Pavese Cesare (*La luna e i falò*, 1949*)	2544	4.47	17.83	6.83	2.60	5.64	0.70
Pellico Silvio (*Le mie prigioni*, 1832)	3148	4.80	17.27	6.50	2.69	7.00	0.75
Pirandello Luigi (*Il fu Mattia Pascal*, 1904, Nobel Prize 1934)	5284	4.63	14.57	4.94	2.93	16.72	0.89
Sacchetti Franco (*Trecentonovelle*, 1392)	8060	4.37	22.43	5.82	3.83	1.41	0.17
Salernitano Masuccio (*Il Novellino*, 1525)	1965	4.40	19.20	5.14	3.68	0.79	-0.12
Salgari Emilio (*Il corsaro nero*, 1899)	6686	4.99	15.09	6.36	2.36	34.46	0.94
Salgari Emilio (*I minatori dell'Alaska*, 1900)	6094	5.01	15.24	6.25	2.44	27.21	0.93
Svevo Italo (*Senilità*, 1898)	4236	4.86	16.04	7.75	2.07	32.34	0.94
Tomasi di Lampedusa (*Il gattopardo*, 1958*)	2893	4.99	26.42	7.90	3.33	0.47	-0.36
Verga (*I Malavoglia*, 1881)	4401	4.46	20.45	6.82	3.00	4.21	0.62

Table B.2. Authors of the novels of the English Literature. Number of total sentences, average number of characters per word $< C_P >$, average number of words pr sentence, $< P_F >$, average number of word intervals, $< I_P >$, average number word intervals per sentence, $< M_F >$, multiplicity factor α, mismatch index I_M. Notice that for Dicken's novels, Table 1 of [44] reported the number of sentences ending only with full–stop; sentences ending with question mark and exclamation mark were not reported, contrarily to all othe literary texts there (and here) reported. Moreover, the analysis conducted in Reference [44] was done by considering only the sentences ending with full–stop, that is why the values of $< P_F >$ and $< M_F >$ there reported are larger (upper bounds) than those listed below.

Literary Work (Author, Year)	Sentences	$< C_P >$	$< P_F >$	$< I_P >$	$< M_F >$	α	I_M

The Adventures of Oliver Twist (C. Dickens, 1837–1839)	9,121	4.23	18.04	5.70	3.16	9.46	0.81
David Copperfield (C. Dickens, 1849–1850)	19,610	4.04	18.83	5.61	3.35	12.63	0.85
Bleak House (C. Dickens, 1852–1853)	20,967	4.23	16.95	6.59	2.57	56.98	0.97
A Tale of Two Cities (C. Dickens, 1859)	8,098	4.26	18.27	6.19	2.93	11.89	0.84
Our Mutual Friend (C. Dickens, 1864–1865)	17,409	4.22	16.46	6.03	2.73	43.41	0.95
Matthew King James (1611)	1,040	4.27	22.96	5.90	3.90	0.15	-0.73
Robinson Crusoe (D. Defoe, 1719)	2,393	3.94	52.90	7.12	7.40	0.00002	-1.00
Pride and Prejudice (J. Austen, 1813)	6,013	4.40	21.31	7.16	2.95	5.20	0.68
Wuthering Heights (E. Brontë, 1845–1846)	6,352	4.27	17.78	5.97	2.97	9.83	0.82
Vanity Fair (W. Thackeray, 1847– 1848)	13,007	4.63	21.95	6.73	3.25	5.26	0.68
Moby Dick (H. Melville, 1851)	9,582	4.52	23.82	6.45	3.64	1.56	0.22
The Mill On The Floss (G. Eliot, 1860)	9,018	4.29	23.84	7.09	3.35	2.17	0.37
Alice's Adventures in Wonderland (L. Carroll, 1865)	1,629	3.96	17.19	5.79	2.95	2.90	0.49
Little Women (L.M. Alcott, 1868–1869)	10,593	4.18	18.09	6.30	2.85	17.34	0.89
Treasure Island (R. L. Stevenson, 1881–1882)	3,824	4.02	18.93	6.05	3.09	3.79	0.58
Adventures of Huckleberry Finn (M. Twain, 1884)	5887	3.85	19.39	6.63	2.94	7.05	0.75
Three Men in a Boat (J.K. Jerome, 1889)	5,341	4.25	10.55	6.14	1.72	130.27	0.98
The Picture of Dorian Gray (O. Wilde, 1890)	4,292	4.19	14.30	6.29	2.21	33.02	0.94
The Jungle Book (R. Kipling, 1894)	3,214	4.11	16.46	7.14	2.29	14.10	0.87
The War of the Worlds (H.G. Wells, 1897)	3,306	4.38	19.22	7.67	2.48	6.72	0.74
The Wonderful Wizard of Oz (L.F. Baum, 1900)	2,219	4.017	17.90	7.63	2.34	7.02	0.75
The Hound of The Baskervilles (A.C. Doyle, 1901–1902)	4,080	4.15	15.07	7.83	1.91	43.87	0.96
Peter Pan (J.M. Barrie, 1902)	31,77	4.12	15.65	6.35	2.44	13.07	0.86
A Little Princess (F.H. Burnett, 1902–1905)	4,838	4.18	14.26	6.79	2.09	46.97	0.96
Martin Eden (J. London, 1908–1909)	9,173	4.32	15.61	6.76	2.30	46.33	0.96
Women in love (D.H. Lawrence, 1920)	16,048	4.26	11.62	5.22	2.22	216.86	0.99
The Secret Adversary (A. Christie, 1922)	8,536	4.28	8.97	5.52	1.62	294.34	0.99
The Sun Also Rises (E. Hemingway, 1926)	7,614	3.92	9.43	6.02	1.56	237.94	0.99
A Farewell to Arms (H. Hemingway,1929)	10,324	3.94	9.05	6.80	1.32	356.00	0.99
Of Mice and Men (J. Steinbeck, 1937)	3,463	4.02	8.63	5.61	1.54	133.19	0.99

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