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Capacity of Linguistic Communication Channels in Literary Texts: Application to Charles Dickens' Novels

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Abstract: In the first part of the article, we recall our general theory of linguistic channels—based on regression lines between deep language parameters—and study their capacity and interdependence. In the second part, we apply the theory to novels written by Charles Dickens and other authors of English literature, including the Gospels in the King James version of the Bible. In literary works (or in any long texts), there are multiple communication channels. The theory considers not only averages but also correlation coefficients. The capacity of linguistic channels is a Gaussian stochastic variable. The similarity between two channels is measured by the likeness index. Dickens' novels show striking and unexpected mathematical/statistical similarity to the synoptic Gospels. The Pythagorean distance, defined in a suitable Cartesian plane involving deep language parameters, and the likeness index correlate with an inverse proportional relationship. A similar approach can be applied to any literary corpus written in any alphabetical language.

Keywords: alphabetical languages; English literature; Information; likeness index; linguistic channels; signal-to-noise ratio



Citation: Matricciani, E. Capacity of Linguistic Communication Channels in Literary Texts: Application to Charles Dickens' Novels. *Information* **2023**, *14*, 68. <https://doi.org/10.3390/info14020068>

Academic Editor: David Bawden

Received: 5 October 2022

Revised: 28 December 2022

Accepted: 20 January 2023

Published: 26 January 2023



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1. Linguistic Communication Channels in Literary Texts

In recent papers [1–4], we have developed a new and general statistical theory on the deep mathematical structure of literary texts (or any long text) written in alphabetical languages—including translations—based on Shannon's communication theory [5], which involves linguistic stochastic variables and communication channels suitably defined. In the theory, “translation” means not only the conversion of a text from one language to another—which is properly understood, of course, as translation—but also how some linguistic parameters of a text are related to those of another text, either in the same language or in another language. “Translation”, therefore, in the general theory, refers also to the case in which a text is compared (metaphorically “translated” into) to another text, regardless of the language of the two texts.

The theory, whose features are further developed in the present article, has important limitations because it gives no clues as to the correct use of words and grammar, the variety and richness of the literary expression, or its beauty or efficacy. It does not measure the quality and clearness of ideas. The comprehension of a text is the result of many other factors, the most important being the reader's culture and reading habits, besides the obvious understanding of the language. In spite of these limitations, the theory can be very useful, because it can be applied to any alphabetical language, such as those studied in [3], because it deals with the underlying mathematical structure of texts, which can be very similar from language to language, therefore defeating the apparent scattering due to the mythical Babel Tower event.

The theory does not follow the actual paradigm of linguistic studies. Most studies on the relationships between texts concern translation because of the importance of automatic (i.e., machine) translation. Translation transfers meaning from one set of sequential symbols into another set of sequential symbols and was studied as a language learning

methodology, or as part of comparative literature, with theories and models imported from other disciplines [6,7]. References [8–14] report results not based on the mathematical analysis of texts, as the theory here further developed does. However, when a mathematical approach is used, as in References [15–27], most of these studies neither consider Shannon’s communication theory nor the fundamental connection that some linguistic variables seem to have with the reading ability and short-term memory capacity of readers [1–4]. In fact, these studies are mainly concerned with automatic translations, not with the high-level direct response of human readers. Very often, they refer only to one very limited linguistic variable, e.g., phrases [26], and not to sentences, which convey a completely developed thought, rather than deep language parameters, as our theory does.

As stated in [26], statistical automatic translation is a process in which the text to be translated is “decoded” by eliminating the noise by adjusting lexical and syntactic divergences to reveal the intended message. In our theory, what is defined as “noise”—given by quantitative differences between the source text (input) and translated text (output)—must not be eliminated because it makes the translation readable and matched to the reader’s short-term memory capacity [3], a connection never considered in [15–45], references that represent only a small part of the vast literature on machine translation.

Besides the total numbers of characters, words, sentences, and interpunctuations (punctuation marks), the theory considers the number of words n_W , the number of sentences n_S per chapter, or any chosen subdivision of a literary text, large enough to provide reliable statistics, e.g., a few hundred words. Moreover, it also considers what we have termed the deep language variables, namely the number of characters per word C_P , words per sentence P_F , words per interpunctuations I_P (this parameter, called also the “word interval” [1], is linked to the short-term memory capacity of readers), and interpunctuations per sentence M_F (this parameter gives also the number of I_{Ps} contained in a sentence).

To study the apparently chaotic data that emerge from literary texts in any language, the theory compares a text (the reference, or input text) to another text (output), with a complex communication channel—composed of several parallel channels [4], one of which is explicitly considered in the present article—in which both the input and output are affected by “noise”, i.e., by the different scattering of the data around an average relationship, namely a regression line.

In [3], we have shown how much the mutual mathematical relationships of a literary work written in a language are saved or lost in translating it into another language. To make objective comparisons, we have defined the likeness index I_L , based on the probability and communication theory of noisy digital channels.

We have shown (see Section 4 of [3]) that two linguistic variables, e.g., the variables n_S and n_W , can be linearly linked by regression lines. This is a general feature of texts. For example, if we consider the regression line linking n_S to n_W in a reference text and that found in another text, it is possible to link the n_S of the first text to the n_S of the second text with another regression line without explicitly calculating its parameters (slope and correlation coefficient) from the samples, because the mathematical problem has the same structure of the theory developed in Section 1 of [2].

In [4], we have applied the theory developed in [1–3] to compare how a literary character speaks to different audiences by diversifying and adjusting (“fine tuning”) two important linguistic communication channels, namely the “sentences channel”—this channel links the sentences of the input text to the sentences of the output text for the same number of words—and the “interpunctuations channel”—this channel links the word intervals of the two texts for the same number of sentences. We have shown that the theory can “measure” how an author shapes a character’s speaking to different audiences by modulating the deep language parameters.

In the present article, we have developed the theory of linguistic channels further. The article is structured in two parts. In the first part, we study the capacity of linguistic channels and show their interdependence. In the second part, to show some features and usefulness of the theory, we apply it to novels written by Charles Dickens (1812–1870)

and compare their statistical/mathematical features to those of a few novels of English literature. Moreover, a comparison with the King James version of the Gospels shows a striking and unexpected similarity to Dickens' novels.

After this introduction, Section 2 deals with the fundamental relationships in linguistic channels; Section 3 deals with their experimental signal-to-noise ratios (Monte Carlo simulations) and recalls the meaning of self- and cross-channels; Section 4 deals with the Shannon capacity and its probability distribution. In the second part of the article, paralleling the theoretical Sections 2–5 deals with Charles Dickens' novels and their deep language variables; Section 6 reports the experimental signal-to-noise ratio of the self- and cross-channels in Dickens' novels and in the Gospel of Matthew; Section 7 deals with the Shannon capacity of the self- and cross-channels and the likeness index; Section 8 deals with the likely influence of the Gospels on Dickens' novels; Section 9 reports some final remarks, and Section 10 concludes. Appendix A reports some numerical tables on the channels involving the Gospels.

2. Fundamental Relationships in Linguistic Communication Channels

In this section, we recall the general theory of linguistic channels [1–4]. In a literary work, an independent (reference) variable x (e.g., the number of words per chapter n_W) and a dependent variable y (e.g., the number of sentences in the same chapter n_S) can be related by the regression line passing through the origin of the Cartesian coordinates:

$$y = mx \quad (1)$$

In Equation (1), m is the slope of the line.

Let us consider two different text blocks Y_k and Y_j , e.g., the chapters of work k and work j . Equation (1) does not give the full dependence of the two variables because it links only average conditional values. We can write more general linear relationships, which consider the scattering of the data—measured by the correlation coefficients r_k and r_j , respectively, not considered in Equation (1)—around the average values (measured by the slopes m_k and m_j):

$$y_k = m_k x + n_k \quad (2a)$$

$$y_j = m_j x + n_j \quad (2b)$$

The linear model Equation (1) connects x and y only on the average, while the linear model Equation (2) introduces additive “noise” through the stochastic variables n_k and n_j , with zero mean value [2–4]. The noise is due to the correlation coefficient $|r| \neq 1$, not considered in Equation (1).

We can compare two literary works by eliminating x . In other words, we compare the output variable y for the same number of the input variable x . In the example previously mentioned, we can compare the number of sentences in two works—for an equal number of words—by considering not only the average relationship, Equation (1), but also the scattering of the data, measured by their correlation; see Equation (2). We refer to this communication channel as the “sentences channel” and to this processing as “fine tuning” because it deepens the analysis of the data and can provide more insight into the relationship between two literary works, or more general texts.

By eliminating x from Equation (2), we obtain the linear relationship between, now, the input number of sentences in work Y_k (now, the reference, input work) and the number of sentences in text Y_j (now, the output work):

$$y_j = \frac{m_j}{m_k} y_k - \frac{m_j}{m_k} n_k + n_j \quad (3)$$

Compared to the new reference work Y_k , the slope m_{jk} is given by

$$m_{jk} = m_j / m_k \quad (4)$$

The noise source that produces the correlation coefficient between Y_k and Y_j is given by

$$n_{jk} = -\frac{m_j}{m_k}n_k + n_j = -m_{jk}n_k + n_j \quad (5)$$

The “regression noise-to-signal ratio”, R_m , due to $|m_{jk}| \neq 1$, of the new channel is given by [2]

$$R_m = (m_{jk} - 1)^2 \quad (6)$$

The unknown correlation coefficient r_{jk} between y_j and y_k is given by [46]

$$r_{jk} = \cos|\arcsin(r_j) - \arcsin(r_k)| \quad (7)$$

The “correlation noise-to-signal ratio”, R_r , due to $|r_{jk}| < 1$, of the new channel from text Y_k to text Y_j is given by [1]

$$R_r = \frac{1 - r_{jk}^2}{r_{jk}^2} m_{jk}^2 \quad (8)$$

Because the two noise sources are disjoint and additive, the total noise-to-signal ratio of the channel connecting text Y_k to text Y_j is given by [2]

$$R = (m_{jk} - 1)^2 + \frac{1 - r_{jk}^2}{r_{jk}^2} m_{jk}^2 \quad (9)$$

Notice that Equation (9) can be represented graphically [2]. Finally, the total signal-to-noise ratio is given by

$$\Gamma = 1/R \quad (10a)$$

$$\Gamma_{dB} = 10 \times \log_{10} \Gamma \quad (10b)$$

Of course, we expect, and it is so in the following, that no channel can yield $|r_{jk}| = 1$ and $|m_{jk}| = 1$; therefore, $\Gamma_{dB} = \infty$, a case referred to as the ideal channel, unless a text is compared with itself (self-comparison, self-channel). In practice, we always find $|r_{jk}| < 1$ and $|m_{jk}| \neq 1$. The slope m_{jk} measures the multiplicative “bias” of the dependent variable compared to the independent variable; the correlation coefficient r_{jk} measures how “precise” the linear best fit is.

In conclusion, the slope m_{jk} is the source of the regression noise; the correlation coefficient r_{jk} is the source of the correlation noise of the channel.

3. Experimental Signal-to-Noise Ratios in Linguistic Channels

Because of the different sample size used in calculating a regression line, its slope m and correlation coefficient r —being stochastic variables—are characterized by average values and standard deviations, which depend on the sample size [46]. Obviously, the theory would yield more precise estimates of Γ —see Equation (10)—for a larger sample size. With a small sample size—as is the case with the number of chapters of a literary text—the standard deviations of m and r can give too large a variation in Γ (see the sensitivity of this parameter to the slope m and the correlation coefficient r in [3]). To avoid this inaccuracy—due to a small sample size, not to the theory of Section 2—we have defined [3] and discussed [3,4] a “renormalization” based on Monte Carlo simulations, whose results can be considered “experimental”. Therefore, the results of the simulation can replace, as discussed in [3], the theoretical values.

Let us recall the steps of the Monte Carlo simulation by explicitly considering the sentences channel [3].

Let the literary work Y_j be the “output”, of which we consider n disjoint block texts (e.g., chapters), and let us compare it with a particular input literary work Y_k characterized by a regression line, as detailed in Section 2. The steps of the Monte Carlo simulation are the following:

1. Generate n independent numbers (the number of disjoint block texts, e.g., chapters) from a discrete uniform probability distribution in the range 1 to n , with replacement, i.e., a text can be selected more than once.
2. “Write” another possible “work Y_j ” with new n disjoint texts, e.g., the sequence 2; 1; n ; $n - 2$; hence, take text 2, followed by text 1, text n , text $n - 2$ up to n texts. A block text can appear twice (with probability $1/n^2$), three times (with probability $1/n^3$), etc., and the new “work Y_j ” can contain a number of words greater or smaller than the original work, on average (the differences are small and do not affect the final statistical results and analysis).
3. Calculate the parameters m_j and r_j of the regression line between words (independent variable) and sentences (dependent variable) in the new “work Y_j ”, namely Equation (1).
4. Compare m_j and r_j of the new “work Y_j ” (output, dependent work) with any other work (input, independent work, m_k and r_k), in the “cross-channels” so defined, including the original work Y_j (a particular case referred to as the “self-channel”).
5. Calculate m_{jk} , r_{jk} , and Γ_{dB} of the cross-channels (linking sentences to sentences), according to the theory of Section 2.
6. Consider the values of Γ_{dB} so obtained, in Equation (10), as “experimental” results $\Gamma_{dB,ex}$.
7. Repeat Steps 1 to 6 many times to obtain reliable results (we have done so 5000 times because this number of simulations ensures reliable results down to two decimal digits in $\Gamma_{dB,ex}$).

In conclusion, the Monte Carlo simulation should eliminate the inaccuracy in estimating the slope and correlation coefficient due to a small sample size. However, besides the usefulness of the simulation as a “renormalization” tool to avoid small sample size inaccuracy, as shown in [3,4], there is another property—very likely more interesting—of the new generated literary works. In fact, as the mathematical theory does not consider meaning, the new works obtained in Step 2 might have been “written” by the author, because they maintain the main statistical properties of the deep language parameters of the original text. In other words, they are “literary works” that the author might have written at the time that he wrote the original work.

4. Capacity of Self- and Cross-Channels and Its Probability Distribution

In Reference [3] (see Figure 7 of [3]), we have shown that the probability density function of $\Gamma_{dB,ex}$ in both self- and cross-channels can be approximately modeled as Gaussian, with average value M (dB) and standard deviation S (dB), i.e., the values reported, for example, in Tables 4 and 5 of [3], or below.

In this section, we determine the probability density function of the Shannon capacity of self- and cross-channels, starting from the Gaussian probability density function of $\Gamma_{dB,ex}$. For this calculation, we need to apply the theory of variable transformation [46].

First, it can be shown that the probability density function of the linear signal-to-noise ratio

$$\Gamma = 10^{\Gamma_{dB,ex}/10} \quad (11)$$

is given by the log-normal probability density function with average value $\mu = M \times \log(10)/10$ and standard deviation $\sigma = S \times \log(10)/10$:

$$f_{\Gamma}(\Gamma) = \frac{1}{\sqrt{2\pi}\sigma\Gamma} \times \exp\left\{-\frac{(\Gamma - \mu)^2}{2\sigma^2}\right\} \quad (12)$$

Now, each channel has capacity C (bits per symbol), which can be conservatively (see the discussion in [2]) calculated according to Shannon [5]:

$$C = 0.5 \times \log_2(1 + \Gamma) \quad (13)$$

Therefore, the capacity of linguistic self- and cross-channels, as those relating to the sentences channel, can be calculated from Equation (13), in which C has a probability density function to be determined from the log-normal probability density function, as in Equation (12).

By setting $k = 0.5 / \log(2) \approx 0.72$, the theory of variable transformation applied to Equations (12) and (13) gives the following probability density function of C/k (natural logs):

$$f_{C/k}(C/k) = \frac{\exp(C/k)}{k\sigma\sqrt{2\pi}(\exp(C/k) - 1)} \times \exp\left\{-\frac{[\log(\exp(C/k) - 1) - \mu]^2}{2\sigma^2}\right\} \quad (14)$$

Now, if $\exp(C/k) \gg 1$, (as $C \geq 0$, $\exp(C/k) \geq e \approx 2.78$)—a condition that applies to all cases studied below—it can be approximated, in a large range of C/k , with

$$f_{C/k}(C/k) \approx \frac{1}{k\sigma\sqrt{2\pi}} \times \exp\left\{-\frac{[C/k - \mu]^2}{2\sigma^2}\right\} \quad (15)$$

Finally, by setting

$$\alpha = k\mu \quad (16a)$$

$$\delta = k\sigma \quad (16b)$$

the probability density function $f_C(C)$ is given by

$$f_C(C) = \frac{1}{\delta\sqrt{2\pi}} \times \exp\left\{-\frac{(C - \alpha)^2}{2\delta^2}\right\} \quad (17)$$

In other words, if $\exp(C/k) \gg 1$, then the probability distribution function of channel capacity C is Gaussian in a large range ($C \geq 0$, of course), with average value α and standard deviation δ given by Equation (16).

In [3], we explored a means of comparing the signal-to-noise ratios $\Gamma_{dB,ex}$ of self- and cross-channels objectively, and possibly also obtaining more insight into texts' mathematical likeness. In comparing a self-channel with a cross-channel, the probability of mistaking one work for another is a binary problem because a decision must be taken between two alternatives. The problem is classical in binary digital communication channels affected by noise, as recalled in [3]. In digital communication, "error" means that bit 1 is mistaken for bit 0 or vice versa; therefore, the channel performance worsens as the error frequency (i.e., the probability of error) increases. However, in linguistics, self- and cross-channel "error" means that a text can be more or less mistaken, or confused, with another text; consequently, two texts are more similar as the probability of error increases. Therefore, as in [3], a large error probability means that two literary works are mathematically similar in the considered channel.

As with the likeness index defined in [3] for the $\Gamma_{dB,ex}$ of self- and cross-channels, we could define also the "capacity likeness index" I_C . Again, $0 \leq I_C \leq 1$; $I_C = 0$ means totally independent texts, and $I_C = 1$ means totally dependent texts. However, if Equation (16) holds—as is the case in the literary works here considered and shown below—then the capacity likeness index I_C of the self- and cross-channels and the likeness index concerning $\Gamma_{dB,ex}$, I_L coincide, because the two Gaussian densities of C are obtained from those of $\Gamma_{dB,ex}$ by rigidly shifting them to the left in the x - axis of the same quantity. Therefore, in the following we do not distinguish between the two indices.

In the following second part of the article, we apply the theory to literary works belonging to the English literature by mainly studying Dickens' novels, including the Gospels of the classical King James translation.

5. Charles Dickens' Novels and Deep Language Variables

The novels of Charles Dickens that are studied are listed in Table 1. They range from one of the earliest ones, *The Adventures of Oliver Twist* (1837–1839), to the last one, *Our Mutual Friend* (1864–1865). This particular choice may be useful to study the possible time dependence of their mathematical characteristics.

Table 1. Charles Dickens' novels. Number of chapters (i.e., the number of samples considered in calculating the regression lines of the theory), total number of characters contained in the words, total number of words and sentences, deep language parameters C_P , P_F , I_P , M_F , with standard deviation reported in the second line.

Novel	Chapters	Characters	Words	Sentences	C_P	P_F	I_P	M_F
<i>The Adventures of Oliver Twist</i> (1837–1839)	53	679,008	160,604	6712	4.228 0.013	24.321 0.427	5.695 0.071	4.279 0.065
<i>David Copperfield</i> (1849–1850)	64	1,469,251	363,284	15,000	4.044 0.152	24.398 0.264	5.613 0.038	4.349 0.040
<i>Bleak House</i> (1852–1853)	64	1,480,523	350,020	16,350	4.230 0.180	21.638 0.288	6.590 0.062	3.284 0.031
<i>A Tale of Two Cities</i> (1859)	45	607,424	142,762	6207	4.255 0.018	23.656 0.650	6.192 0.069	3.806 0.075
<i>Our Mutual Friend</i> (1864–1865)	67	1,394,753	330,593	15,327	4.219 (0.014)	21.867 0.323	5.997 0.046	3.650 0.050

Tables 2 and 3 list the other English literary works—including the Gospel according to *Matthew* in the King James version of the Bible—studied and compared to Dickens' novels. The novels belong to the XIX and XX centuries and have been chosen because their texts are freely available in digital format in the internet.

Table 2. English literature. Literary works are ordered according to publication years. Number of chapters (i.e., the number of samples considered in calculating the regression lines of the theory), total number of characters related only to words, total number of words and sentences. The order number is useful to identify the single literary works in Figure 2.

Literary Work	Order	Chapters	Characters	Words	Sentences
<i>Matthew King James</i> (1611)	1	28	99,795	23,397	1040
<i>Robinson Crusoe</i> (D. Defoe, 1719)	–	20	479,249	121,606	2393
<i>Pride and Prejudice</i> (J. Austen, 1813)	2	61	537,005	121,934	6013
<i>Wuthering Heights</i> (E. Brontë, 1845–1846)	3	32	470,820	110,297	6352
<i>Vanity Fair</i> (W. Thackeray, 1847–1848)	4	66	1,285,688	277,716	13,007
<i>Moby Dick</i> (H. Melville, 1851)	5	132	922,351	203,983	9582
<i>The Mill On The Floss</i> (G. Eliot, 1860)	6	57	888,867	207,358	9018
<i>Alice's Adventures in Wonderland</i> (L. Carroll, 1865)	7	12	107,452	27,170	1629
<i>Little Women</i> (L.M. Alcott, 1868–1869)	8	47	776,304	185,689	10,593
<i>Treasure Island</i> (R.L. Stevenson, 1881–1882)	9	34	273,717	68,033	3824
<i>Adventures of Huckleberry Finn</i> (M. Twain, 1884)	10	42	427,473	110,997	5887

Table 2. Cont.

Literary Work	Order	Chapters	Characters	Words	Sentences
<i>Three Men in a Boat</i> (J.K. Jerome, 1889)	11	16	235,362	55,346	5341
<i>The Picture of Dorian Gray</i> (O. Wilde, 1890)	12	13	229,118	54,656	4292
<i>The Jungle Book</i> (R. Kipling, 1894)	13	9	209,935	51,090	3214
<i>The War of the Worlds</i> (H.G. Wells, 1897)	14	27	265,499	60,556	3306
<i>The Wonderful Wizard of Oz</i> (L.F. Baum, 1900)	15	22	156,973	39,074	2219
<i>The Hound of The Baskervilles</i> (A.C. Doyle, 1901–1902)	16	15	245,327	591,32	4080
<i>Peter Pan</i> (J.M. Barrie, 1902)	17	17	194,105	47,097	31,77
<i>A Little Princess</i> (F.H. Burnett, 1902–1905)	18	20	278,985	66,763	4838
<i>Martin Eden</i> (J. London, 1908–1909)	19	45	601,672	139,281	9173
<i>Women in Love</i> (D.H. Lawrence, 1920)	20	31	785,240	184,393	16,048
<i>The Secret Adversary</i> (A. Christie, 1922)	21	29	324,635	75,840	8536
<i>The Sun Also Rises</i> (E. Hemingway, 1926)	22	18	270,867	69,166	7614
<i>A Farewell to Arms</i> (H. Hemingway, 1929)	23	41	352,251	89,396	10,324
<i>Of Mice and Men</i> (J. Steinbeck, 1937)	24	16	119,604	29,771	3463

Table 3. English literature. Literary works are ordered according to publication years. Deep language parameters C_p , P_F , I_p , M_F , with standard deviation reported in the second line. The order number is useful to identify the single literary works in Figure 2.

Literary Work	Order	C_p	P_F	I_p	M_F
<i>Matthew King James</i> (1611)	1	4.266 0.011	23.510 4.402	5.906 0.549	3.981 0.625
<i>Robinson Crusoe</i> (D. Defoe, 1719)	–	3.941 0.016	57.747 2.448	7.119 0.077	8.081 0.282
<i>Pride and Prejudice</i> (J. Austen, 1813)	2	4.404 0.017	24.856 0.5661	7.156 0.090	3.459 0.049
<i>Wuthering Heights</i> (E. Brontë, 1845–1846)	3	4.269 0.015	25.822 0.628	5.969 0.060	4.313 0.075
<i>Vanity Fair</i> (W. Thackeray, 1847–1848)	4	4.630 0.010	25.744 0.478	6.733 0.077	3.830 0.063
<i>Moby Dick</i> (H. Melville, 1851)	5	4.522 0.014	31.1769 0.5719	6.447 0.086	4.870 0.080
<i>The Mill On The Floss</i> (G. Eliot, 1860)	6	4.287 0.018	28.026 0.727	7.089 0.092	3.942 0.076
<i>Alice's Adventures in Wonderland</i> (L. Carroll, 1865)	7	3.955 0.024	30.920 3.1676	5.790 0.159	5.709 0.423
<i>Little Women</i> (L.M. Alcott, 1868–1869)	8	4.181 0.016	21.083 0.4700	6.302 0.068	3.333 0.048
<i>Treasure Island</i> (R. L. Stevenson, 1881–1882)	9	4.023 0.016	21.893 0.7709	6.050 0.159	3.611 0.071
<i>Adventures of Huckleberry Finn</i> (M. Twain, 1884)	10	3.851 0.016	24.886 0.822	6.633 0.103	3.797 0.147

Table 3. Cont.

Literary Work	Order	C_p	P_F	I_P	M_F
<i>Three Men in a Boat</i> (J.K. Jerome, 1889)	11	4.253 0.023	13.707 0.398	6.137 0.166	2.241 0.053
<i>The Picture of Dorian Gray</i> (O. Wilde, 1890)	12	4.192 0.040	16.563 1.959	6.292 0.191	2.560 0.195
<i>The Jungle Book</i> (R. Kipling, 1894)	13	4.109 0.295	21.516 1.308	7.145 0.178	2.997 0.130
<i>The War of the Worlds</i> (H.G. Wells, 1897)	14	4.384 0.035	20.850 0.650	7.667 0.177	2.712 0.046
<i>The Wonderful Wizard of Oz</i> (L.F. Baum, 1900)	15	4.017 0.021	20.547 0.496	7.627 0.136	2.692 0.042
<i>The Hound of The Baskervilles</i> (A.C. Doyle, 1901–1902)	16	4.149 0.030	17.793 0.611	7.832 0.242	2.273 0.038
<i>Peter Pan</i> (J.M. Barrie, 1902)	17	4.121 0.023	18.1953 0.939	6.348 0.223	2.856 0.085
<i>A Little Princess</i> (F.H. Burnett, 1902–1905)	18	4.179 0.113	16.377 0.574	6.795 0.168	2.405 0.051
<i>Martin Eden</i> (J. London, 1908–1909)	19	4.320 0.020	16.941 0.389	6.764 0.095	2.501 0.040
<i>Women in Love</i> (D.H. Lawrence, 1920)	20	4.259 0.017	13.709 0.198	5.215 0.065	2.631 0.028
<i>The Secret Adversary</i> (A. Christie, 1922)	21	4.281 0.020	11.020 0.158	5.522 0.082	2.001 0.027
<i>The Sun Also Rises</i> (E. Hemingway, 1926)	22	3.916 0.025	10.698 0.497	6.016 0.188	1.771 0.039
<i>A Farewell to Arms</i> (H. Hemingway, 1929)	23	3.940 0.015	10.120 0.370	6.802 0.184	1.480 0.018
<i>Of Mice and Men</i> (J. Steinbeck, 1937)	24	4.017 0.018	9.669 0.169	5.606 0.079	1.726 0.021

Tables 1 and 2 report also the number of chapters (i.e., the number of samples considered in calculating the regression lines of the theory), the total number of characters contained in the words, and the total number of words and sentences, followed by the deep language parameters, namely C_p , P_F , I_P , M_F . These data have been calculated manually as described in [1–3].

For Dickens' novels, besides their different sizes—from the shortest (*A Tale of Two Cities*) to the longest (*David Copperfield*)—it is interesting to note the very similar average structure of sentences in terms of words per sentence P_F , approximately $22 \sim 24$. These average values, however, give rise to significant differences when the sentences channel is studied in Section 6 (fine tuning) by considering also the spreading of the data due to correlation coefficients.

The average values reported in Tables 1 and 2 can be analyzed in two interesting ways: (a) by studying the relationship between I_P and P_F , and its very likely connection with Miller's law 7 ± 2 [47]; (b) by showing a high-level overall view of the literary works in a Cartesian plane.

5.1. Relationship between I_P and P_F , Miller's Law

An interesting observation of the averages reported in Table 3 is the range of the word interval I_P from approximately 5.2 (*Women in Love*) to 7.8 (*The Hound of The Baskervilles*), a significant interval in Miller's law 7 ± 2 . Because I_P is very likely an estimate of the capacity

of the short-term memory buffer, the short-term memory of the intended readers of *David Copperfield* ($I_P = 5.6$) is less engaged than that of the readers of *Bleak House* ($I_P = 6.6$).

Figure 1 shows the scatter plot between the average values of I_P and P_F , for the works listed in Table 3, together with the non-linear regression line (least-square best-fit) that models, as in [1], the average value of I_P versus the average value of P_F , given by

$$I_P = (I_{P\infty} - 1) \times \left[1 - e^{-\frac{(P_F-1)}{(P_{F0}-1)}} \right] + 1 \quad (18)$$

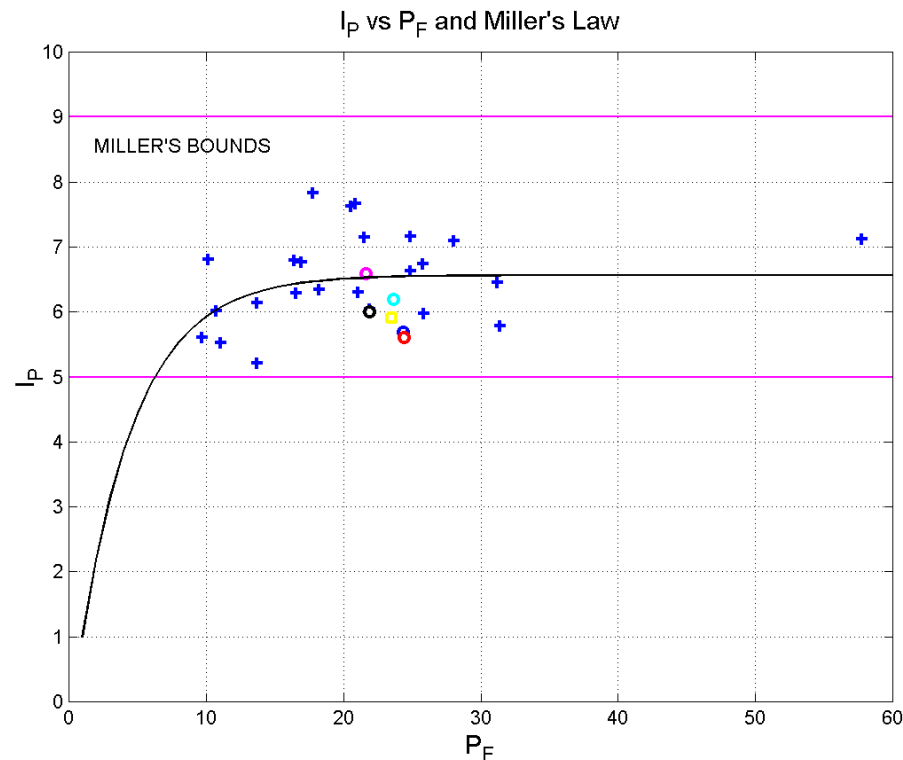


Figure 1. Scatter plot between I_P and P_F of the literary works of Tables 1 and 2, together with the non-linear regression line (best-fit line) that models, on average, I_P versus P_F for these works, Equation (1), and Miller's bounds. Dickens' novels are represented by the circles: *The Adventures of Oliver Twist*, blue; *David Copperfield*, red; *Bleak House*, magenta; *A Tale of Two Cities*, cyan; *Our Mutual Friend*, black. *Matthew*: yellow square. The blue crosses refer to the other works listed in Table 2. The mark on the far right refers to *Robinson Crusoe*.

In Equation (18), $I_{P\infty} = 6.57$ (words per inter-punctuations) is the horizontal asymptote, and $P_{F0} = 4.16$ (words per sentence) is the value of P_F at which the exponential in Equation (18) falls at $1/e$ of its maximum value. Notice that the asymptotic value 6.57 is very close to its center value 7, and all data fall within Miller's range 7 ∓ 2 , the same as the literary works in the Italian literature [1].

The trend modeled by Equation (18) can be justified as follows. As the number of words in a sentence, P_F , increases, the number of word intervals, I_P , can increase but not linearly, because the short-term memory cannot hold, approximately, a number of words larger than that empirically predicted by Miller's law; therefore, saturation must occur [1]. This is clearly shown by the right-most couple (57.747, 7.119) in Figure 1 due to *Robinson Crusoe*.

In other words, scatter plots, such as that shown in Figure 1, drawn also for other literature [1], should give an insight into the short-term memory capacity engaged in reading the texts. The values found for each author set the average size of the short-

term memory capacity that their readers should have in order to read the literary work more easily.

The average value of the deep language parameters can be used to provide a first assessment of how much the literary works are similar, or “close”, by reporting them in a Cartesian plane as vectors, a graphical representation discussed in detail in [1–3] and here briefly recalled.

5.2. The Vector Plane

Let us consider the following six vectors of the indicated components $\vec{R}_1 = (C_P, P_F)$, $\vec{R}_2 = (M_F, P_F)$, $\vec{R}_3 = (I_P, P_F)$, $\vec{R}_4 = (C_P, M_F)$, $\vec{R}_5 = (I_P, M_F)$, $\vec{R}_6 = (I_P, C_P)$ and their resulting vector:

$$\vec{R} = \sum_{k=1}^6 \vec{R}_k \quad (19)$$

The choice of which parameter represents the component in the abscissa and ordinate axes is not important because, once the choice is made, the numerical results will depend on it, but not the relative comparisons and general conclusions.

Figure 2 shows the resulting vector (19). The Cartesian coordinates reported have been “normalized” so that *Of Mice and Men* is located at (0,0) (blue pentagon) and *Moby Dick* is located at (1,1) (green triangle with vertex pointing down). This normalized representation allows us to maintain the relative distances by assuming the same unit in the two coordinates.

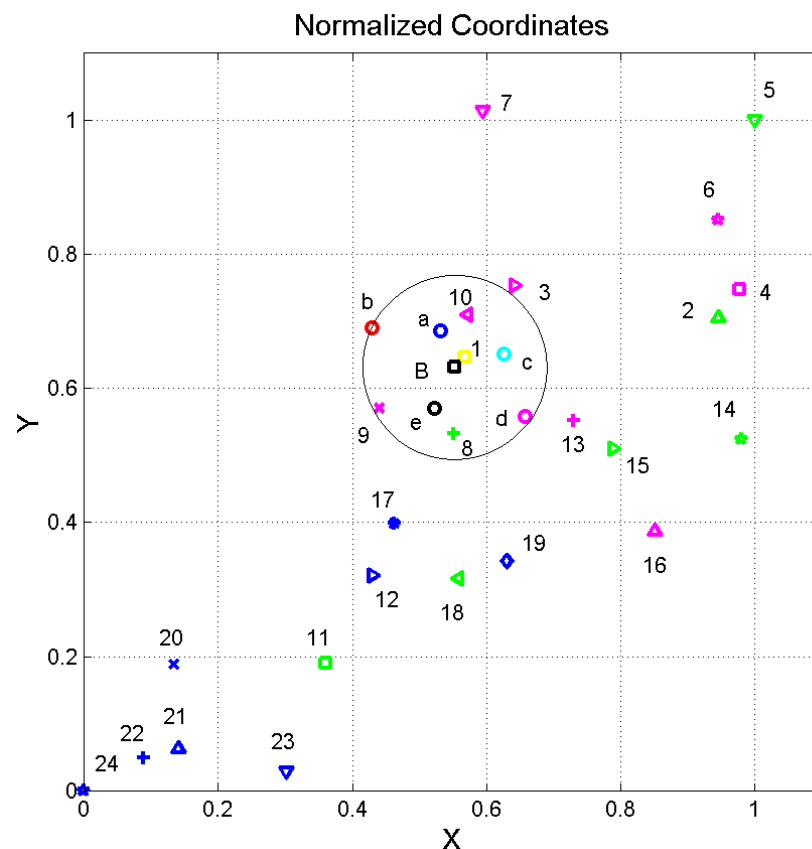


Figure 2. Normalized coordinates x and y of the resulting vector (18) of the literary works listed in Tables 1 and 2, normalized so that *Of Mice and Men* is located at the origin (0,0) and *Moby Dick* is located at (1,1). Dickens’ novels are represented by the circles: *The Adventures of Oliver Twist*, a , blue; *David Copperfield*, b , red; *Bleak House*, d , magenta; *A Tale of Two Cities*, c , cyan; *Our Mutual Friend*, e , black. *Matthew*: 1, yellow square. The black square B is the barycenter of Dickens’ works. The other novels are numbered according to the order reported in Table 2.

It can be noted that, compared to the other English works, Dickens's novels are all very near to each other, within the circle drawn from their barycenter (black square) with the radius reaching *David Copperfield* (red circle). It can also be noted that there is a clear distinction between XIX century (magenta and green marks) and XX century novels (blue marks), therefore introducing a time arrow in the development of the English literature, at least for the sampled works. The outlying vector (1.443, 2.211) of *Robinson Crusoe* (1719) is not reported due to space constraints.

Curiously, the Gospel of *Matthew* in the King James version of the Bible (yellow square, see Table 3) is very near to Dicken's barycenter. This is an unexpected coincidence, which requires further investigation. Did the classical New Testament books available at that time—namely the King James translations—affect the mathematical structure of Dickens' writings? In Section 8, we propose a likely answer to this question by considering also the other three Gospels (*Mark, Luke, John*).

As stated before, all these findings and observations refer to a high-level comparison because they involve only average values. In literary works, however, there are multiple communication channels [2,3], one of which is the so-called “sentences channel”, a channel that linearly links the sentences of two literary works for an equal number of words. The theory of these channels includes not only averages, such as regression lines, but also correlation coefficients, as recalled in the first part of this article; therefore, in the next section, we apply the theory to Dickens' works.

6. Experimental Signal-to-Noise Ratio of Self- and Cross-Channels

As discussed in Section 3, we consider the values of $\Gamma_{dB,ex}$ concerning the sentences channel. Table 4 lists the slope m and the correlation coefficient r of the regression line between the number of sentences n_s (dependent variable) and the number of words n_W (independent variable) per chapter in Dickens' works and in *Matthew*. Four decimal digits are reported because some values differ only from the third digit. These data are the parameters of the input literary works k required by the theory.

Table 4. Slope m and correlation coefficient r of the regression line between the number of sentences n_s (dependent variable) and the number of words n_W (independent variable). Four decimal digits are reported because some values differ only from the third digit.

Literary Work	m	r
<i>Oliver Twist</i>	0.0417	0.9307
<i>David Copperfield</i>	0.0411	0.9704
<i>Bleak House</i>	0.0466	0.9391
<i>A Tale of Two Cities</i>	0.0447	0.9680
<i>Our Mutual Friend</i>	0.0463	0.9149
<i>Matthew</i>	0.0447	0.9499

We can notice, for example, that the slopes of *Matthew* and *A Tale of Two Cities* are equal to the forth decimal digit, but not so the correlation coefficients—recall the sensitivity of the signal-to-noise ratio to this parameter, discussed in [3]. Therefore, in this case, $\Gamma_{dB,ex}$ is practically given by the regression noise; see Equation (8). In other words, a comparison based only on averages would conclude that the two texts are mathematically identical: only a “fine tuning” study of the sentences channel would show, as we do below, that similarity does exist but not to this extent.

Table 5 shows the average value M (dB) and standard deviation S (dB) of $\Gamma_{dB,ex}$ (dB) in the self- and cross-channels, the correlation coefficient r_{jk} , and the slope m_{jk} of the regression line between the number of sentences n_s of *Oliver Twist* (output channel) versus the number of sentences n_s in the other Dickens novels (input channels), for an equal number of words.

Table 5. Average value M (dB) and standard deviation S (dB) of $\Gamma_{dB,ex}$ (dB) in self- and cross-channels, average value and standard deviation of correlation coefficient r_{jk} , and slope m_{jk} of the regression line between the number of sentences n_S of *Oliver Twist* (channel output) versus the number of sentences n_S in the other Dickens novels (channel input), for equal number of words, in the sentences channel. Four decimal digits are reported because some values differ only from the third digit.

Novel	Signal-to-Noise Ratio $\Gamma_{dB,ex}$ (dB)		Correlation Coefficient r_{jk}		Slope m_{jk}	
	M	S	Ave	Dev	Ave	Dev
<i>Oliver Twist</i> (self-channel)	29.45	6.66	0.9988	0.0019	1.0000	0.0151
<i>David Copperfield</i>	18.18	3.98	0.9904	0.0070	1.0161	0.0155
<i>A Tale of Two Cities</i>	17.71	2.34	0.9916	0.0064	0.9334	0.0141
<i>Bleak House</i>	18.92	1.31	0.9985	0.0024	0.8960	0.0136
<i>Our Mutual Friend</i>	19.09	1.67	0.9979	0.0025	0.9015	0.0136

Tables 6–9 show the results when the output channel is *David Copperfield*, *Bleak House*, *A Tale of Two Cities*, *Our Mutual Friend*. For example, according to Table 4, in *David Copperfield*, 100 words give $n_S = 0.0411 \times 100 = 4.11$ sentences on average; therefore, from Table 5, this number of sentences is “translated” into $(1.0161 \pm 0.0155) \times 4.11 \approx 4.18 \pm 0.06$ sentences in *Oliver Twist*, with correlation coefficient $r_{jk} = 0.9904 \pm 0.0070$. Of course, the largest statistical value cannot exceed 1.

Table 6. Average value M (dB) and standard deviation S (dB) of $\Gamma_{dB,ex}$ (dB) in self- and cross-channels, correlation coefficient r_{jk} , and slope m_{jk} of the regression line between the number of sentences n_S of *David Copperfield* (channel output, self-channel) versus the number of sentences n_S in the other Dickens novels (channel input, cross-channels), for equal number of words, in the sentences channel.

Novel	Signal-to-Noise Ratio $\Gamma_{dB,ex}$ (dB)		Correlation Coefficient r_{jk}		Slope m_{jk}	
	M	S	Ave	Dev	Ave	Dev
<i>David Copperfield</i> (self-channel)	32.02	6.32	0.9994	0.0009	0.9996	0.0120
<i>Oliver Twist</i>	17.87	2.63	0.9906	0.0045	0.9842	0.0117
<i>A Tale of Two Cities</i>	21.24	1.31	0.9993	0.0010	0.9191	0.0110
<i>Bleak House</i>	16.22	1.11	0.9933	0.0038	0.8816	0.0103
<i>Our Mutual Friend</i>	14.32	1.15	0.9843	0.0059	0.8874	0.0106

Table 7. Average value M (dB) and standard deviation S (dB) of $\Gamma_{dB,ex}$ (dB) in self- and cross-channels, correlation coefficient r_{jk} , and slope m_{jk} of the regression line between the number of sentences n_S of *Bleak House* (channel output, self-channel) versus the number of sentences n_S in the other Dickens novels (channel input, cross-channels), for equal number of words, in the sentences channel.

Novel	Signal-to-Noise Ratio $\Gamma_{dB,ex}$ (dB)		Correlation Coefficient r_{jk}		Slope m_{jk}	
	M	S	Ave	Dev	Ave	Dev
<i>Bleak House</i> (self-channel)	29.86	6.72	0.9988	0.0018	1.0007	0.0126
<i>Oliver Twist</i>	17.75	1.39	0.9985	0.0018	1.1175	0.0143
<i>David Copperfield</i>	19.57	3.55	0.9942	0.0053	1.0436	0.0133
<i>A Tale of Two Cities</i>	19.62	3.50	0.9943	0.0052	1.0439	0.0135
<i>Our Mutual Friend</i>	24.46	6.20	0.9968	0.0031	1.0075	0.0129

Table 8. Average value M (dB) and standard deviation S (dB) of $\Gamma_{dB,ex}$ (dB) in self- and cross-channels, correlation coefficient r_{jk} , and slope m_{jk} of the regression line between the number of sentences n_S of *A Tale of Two Cities* (channel output, self-channel) versus the number of sentences n_S in the other Dickens novels (channel input, cross-channels), for equal number of words, in the sentences channel.

Novel	Signal-to-Noise Ratio $\Gamma_{dB,ex}$ (dB)		Correlation Coefficient r_{jk}		Slope m_{jk}	
	M	S	Ave	Dev	Ave	Dev
<i>A Tale of Two Cities</i> (self-channel)	26.01	6.85	0.9974	0.0036	0.9955	0.0297
<i>Oliver Twist</i>	18.57	5.84	0.9921	0.0068	1.0666	0.0316
<i>David Copperfield</i>	19.23	2.74	0.9972	0.0039	1.0829	0.0323
<i>Bleak House</i>	19.72	3.39	0.9943	0.0053	0.9548	0.0281
<i>Our Mutual Friend</i>	16.72	3.68	0.9868	0.0096	0.9611	0.0285

Table 9. Average value M (dB) and standard deviation S (dB) of $\Gamma_{dB,ex}$ (dB) in self- and cross-channels, correlation coefficient r_{jk} , and slope m_{jk} of the regression line between the number of sentences n_S of *Our Mutual Friend* (channel output, self-channel) versus the number of sentences n_S in the other Dickens novels (channel input, cross-channels), for equal number of words, in the sentences channel.

Novel	Signal-to-Noise Ratio $\Gamma_{dB,ex}$ (dB)		Correlation Coefficient r_{jk}		Slope m_{jk}	
	M	S	Ave	Dev	Ave	Dev
<i>Our Mutual Friend</i> (self-channel)	29.89	6.66	0.9989	0.0017	1.0004	0.0139
<i>Oliver Twist</i>	18.00	1.58	0.9981	0.0028	1.1101	0.0154
<i>David Copperfield</i>	12.67	1.61	0.9841	0.0085	1.1272	0.0155
<i>Bleak House</i>	25.22	6.58	0.9968	0.0038	0.9942	0.0138
<i>A Tale of Two Cities</i>	15.47	2.39	0.9858	0.0078	1.0358	0.0144

Finally, notice the asymmetry typical of linguistic channels [1–4]. For example, from Table 5, in the cross-channel of *David Copperfield*, $\Gamma_{dB,ex} = 18.18 \pm 3.98$ (dB), while, from Table 6, in the cross-channel of *Oliver Twist*, $\Gamma_{dB,ex} = 17.87 \pm 2.63$ (dB).

Notice that the standard deviation of $\Gamma_{dB,ex}$ in self-channels is approximately 6 ~ 7 dBs, independently of the average value, and when the average value M of a cross-channel moves closer to that of the self-channel, also its standard deviation tends to assume the same value (e.g., *Our Mutual Friend* in Table 7), a typical feature of cross-channels being very similar to self-channels [2–4].

Now, as discussed in Section 3, self-channels can describe all possible literary works that, by maintaining the same statistical properties of the original work, the author might have written at the same time as the original one. Therefore, the closer the parameters of the cross-channels to those of the self-channel, the more similar are the input and output works. In other words, the Gaussian probability density function of a cross-channel can largely overlap with that of the self-channel. This superposition is quantified by the likeness index, as shown in [3] for $\Gamma_{dB,ex}$. In the next section, we show this overlap for the channel capacity C and calculate the likeness index.

7. Capacity of Self- and Cross-Channels and Likeness Index

In this section, we calculate the capacity C of self- and cross-channels. We assume that the signal-to-noise ratio $\Gamma_{dB,ex}$ of these channels is Gaussian, with the average value and standard deviation given in Tables 5–10, and calculate C from Equation (13), by running a Monte Carlo simulation (100,000 simulations).

Table 10. Average value M (dB) and standard deviation S (dB) of $\Gamma_{dB,ex}$ (dB) in self- and cross-channels, correlation coefficient r_{jk} , and slope m_{jk} of the regression line between the number of sentences n_S of *Matthew* (channel output, self-channel) versus the number of sentences n_S in Dickens' novels (channel input, cross-channels), for equal number of words, in the sentences channel.

Novel	Signal-to-Noise Ratio $\Gamma_{dB,ex}$ (dB)		Correlation Coefficient r_{jk}		Slope m_{jk}	
	M	S	Ave	Dev	Ave	Dev
<i>Matthew</i> (self-channel)	26.75	6.57	0.9979	0.0036	1.0008	0.0258
<i>Oliver Twist</i>	20.02	4.19	0.9964	0.0041	1.0721	0.0273
<i>David Copperfield</i>	17.71	2.74	0.9948	0.0073	1.0885	0.0281
<i>Bleak House</i>	23.72	6.32	0.9956	0.0064	1.0000	0.0260
<i>A Tale of Two Cities</i>	22.97	3.99	0.9974	0.0037	0.9596	0.0251
<i>Our Mutual Friend</i>	19.83	3.95	0.9934	0.0060	0.9653	0.0252

Figure 3 shows the results for *Bleak House* (Table 7), together with the theoretical Gaussian probability density function calculated according to the approximation given by Equations (16) and (17). The simulated data show a probability density function that agrees extremely well with the theoretical model. In fact, the average value and standard deviation of the simulated data agree to the forth digit with those calculated with Equations (16) and (17), therefore confirming the validity of the hypotheses assumed for the Gaussian model, in Equation (17).

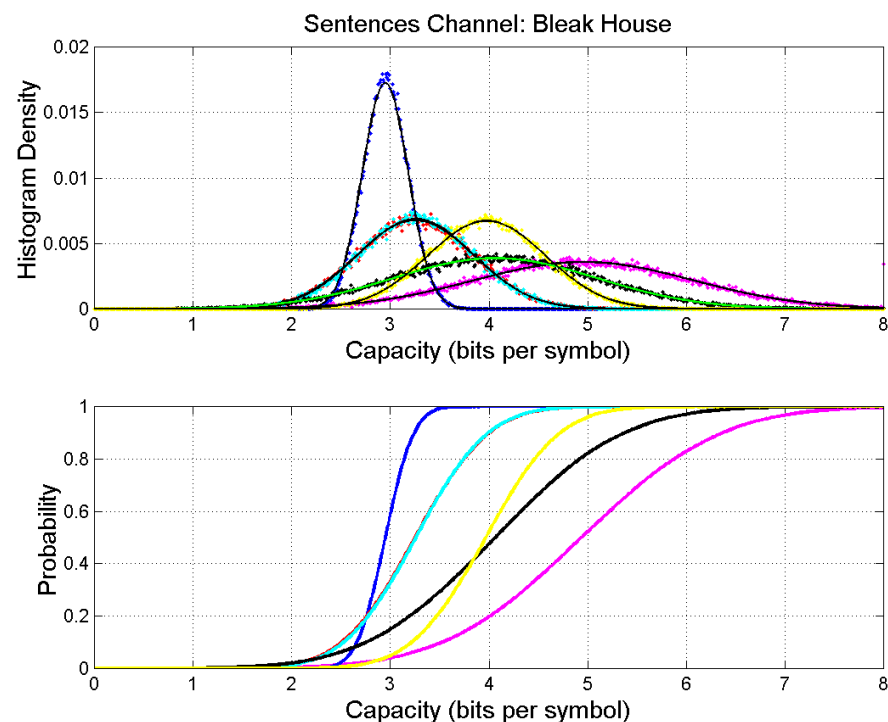


Figure 3. Upper panel: Probability density histograms of self- and cross-channel capacity. *Bleak House*: magenta (output); *The Adventures of Oliver Twist*: blue; *David Copperfield*: red; *A Tale of Two Cities*: cyan; *Our Mutual Friend*: black. *Matthew*: yellow. The continuous black lines are the theoretical densities given by Equation (17). Lower panel: Probability distribution functions.

Figures 4–8 show the Monte Carlo results for the channels listed in Tables 5–9. We see a further confirmation that the capacity of all self- and cross-channels can be very well modeled as Gaussian. This result applies also to the case in which *Matthew* is the

output text (Figure 8). Moreover, the average value of the worst cross-channels tends to be approximately half of that of the self-channel.

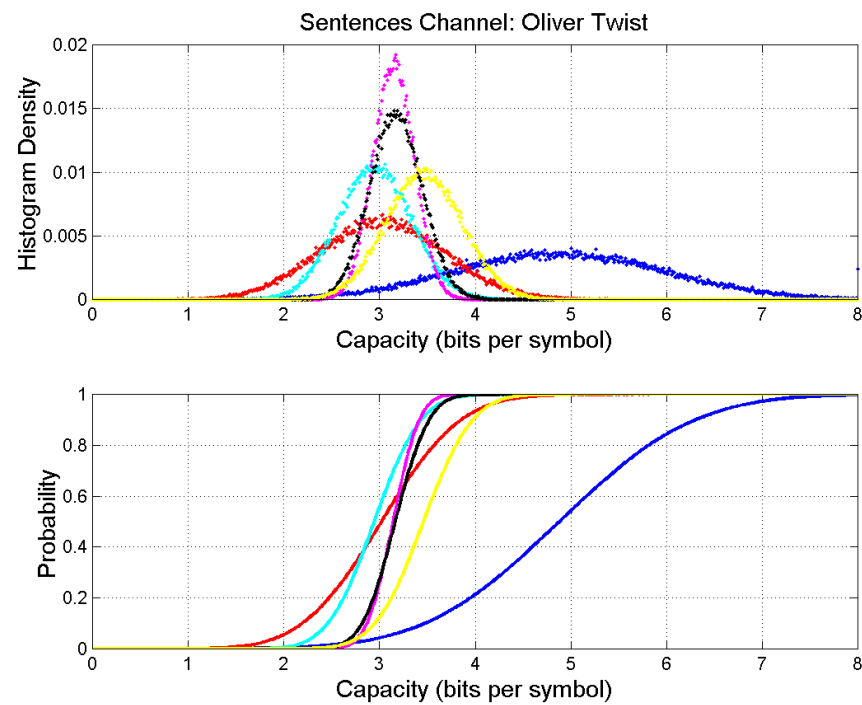


Figure 4. Upper panel: Probability density histograms of self- and cross-channel capacity. *The Adventures of Oliver Twist*: blue (output); *David Copperfield*: red; *Bleak House*: magenta; *A Tale of Two Cities*: cyan; *Our Mutual Friend*: black. *Matthew*: yellow. Lower panel: Probability distribution functions.

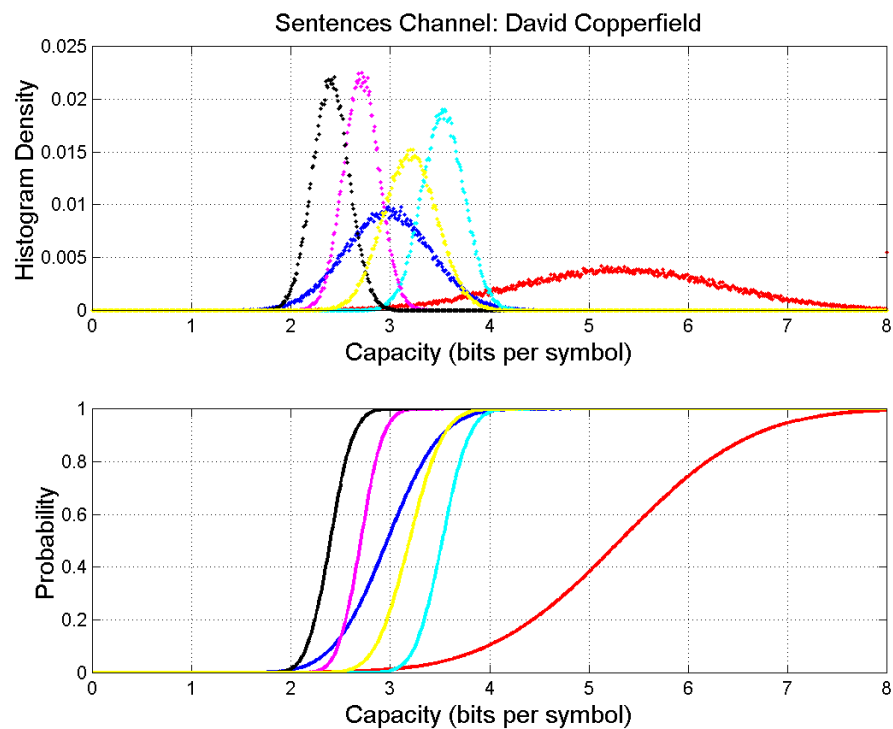


Figure 5. Upper panel: Probability density histograms of self- and cross-channel capacity. *David Copperfield*: red (output); *The Adventures of Oliver Twist*: blue; *Bleak House*: magenta; *A Tale of Two Cities*: cyan; *Our Mutual Friend*: black. *Matthew*: yellow. Lower panel: Probability distribution functions.

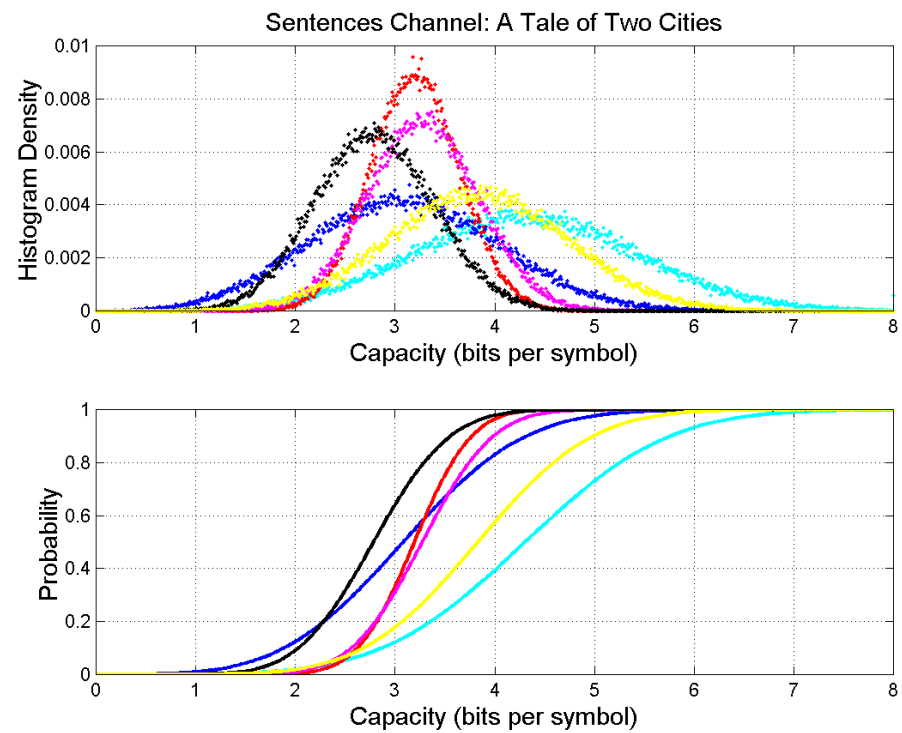


Figure 6. Upper panel: Probability density histograms of self- and cross-channel capacity. *A Tale of Two Cities*; cyan (output); *David Copperfield*: red; *The Adventures of Oliver Twist*: blue; *Bleak House*: magenta; *Our Mutual Friend*: black. *Matthew*: yellow. Lower panel: Probability distribution functions.

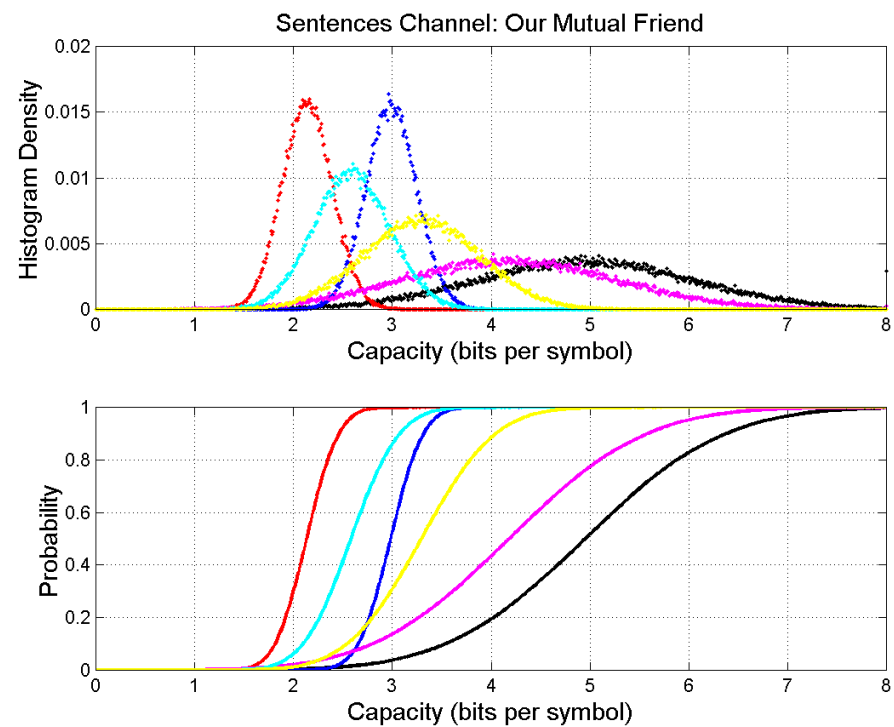


Figure 7. Upper panel: Probability density histograms of self- and cross-channel capacity. *Our Mutual Friend*: black (output); *A Tale of Two Cities*; cyan; *David Copperfield*: red; *The Adventures of Oliver Twist*: blue; *Bleak House*: magenta; *Matthew*: yellow. Lower panel: Probability distribution functions.

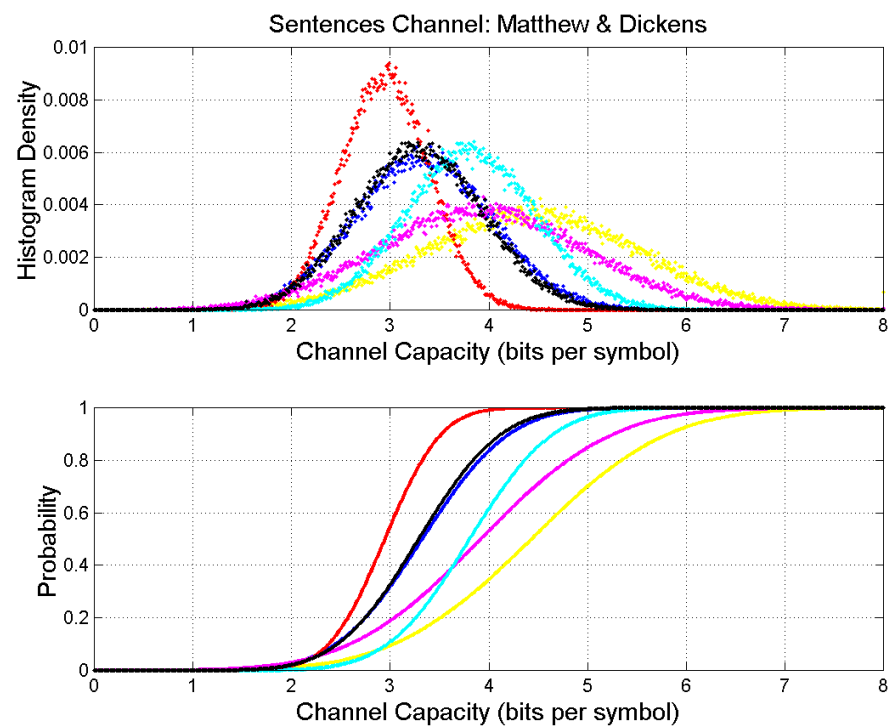


Figure 8. Upper panel: Probability density histograms of self- and cross-channel capacity. ; *Matthew*: yellow (output); *Our Mutual Friend*: black; *A Tale of Two Cities*: cyan; *David Copperfield*: red; *The Adventures of Oliver Twist*: blue; *Bleak House*: magenta. Lower panel: Probability distribution functions.

In conclusion, if the stochastic variable $\Gamma_{dB,ex}$ of a linguistic channel is Gaussian, then also its capacity (bits per symbol) is Gaussian.

Now, from the Gaussian probability density functions shown in Figures 3–8, the likeness index I_C can be calculated. As discussed in Section 4, this index coincides with the likeness index I_L ; therefore, we do not distinguish between them in the following. Table 11 reports the results for Dickens' works. The title in the first line indicates the output novel, and the title in the first column indicates the input novel (regression line given in Table 4). The output novel is the work that produces the regression lines in Step 2 of the Monte Carlo simulation, and the input work (with fixed regression line, Table 4) produces the cross-channel.

Table 11. Likeness index $I_L = I_C$ between the indicated literary works, sentences channel. The work in the first line indicates the output text; the text in the first column indicates the input text (regression line given in Table 3). For example, in the channel *Our Mutual Friend* \rightarrow *Bleak House*, $I_L = 0.675$, while in the reverse channel, *Bleak House* \rightarrow *Our Mutual Friend*, $I_L = 0.724$.

Novel	<i>Oliver Twist</i>	<i>David Copperfield</i>	<i>Bleak House</i>	<i>A Tale of Two Cities</i>	<i>Our Mutual Friend</i>	<i>Matthew</i>
<i>Oliver Twist</i>	1	0.102	0.103	0.554	0.116	0.508
<i>David Copperfield</i>	0.277	1	0.295	0.415	0.030	0.293
<i>Bleak House</i>	0.139	0.025	1	0.488	0.724	0.813
<i>A Tale of Two Cities</i>	0.165	0.120	0.294	1	0.097	0.671
<i>Our Mutual Friend</i>	0.168	0.013	0.675	0.353	1	0.483

For example, in the channel *Our Mutual Friend* \rightarrow *Bleak House*, $I_L = 0.675$. In the reverse channel, *Bleak House* \rightarrow *Our Mutual Friend*, $I_L = 0.724$. The meaning of these results is the following: in the channel *Bleak House* \rightarrow *Our Mutual Friend*, the regression line between the sentences and words in every new *Our Mutual Friend* simulated in Step 2 of the Monte Carlo algorithm of Section 3 is very similar to that of the input text *Bleak House* (regression given in Table 4), so that the theory of Section 2 produces, in the end, this large I_L . In other words, the regression of *Bleak House* belongs to the set of regression lines (self-channel) of *Our Mutual Friend*, a “belonging” described by the two Gaussian densities and measured by $I_L = 0.724$.

Now, similarly, in the channel *Our Mutual Friend* \rightarrow *Bleak House*, the regression line between the sentences and words in every new *Bleak House* is quite similar to that of the input text *Our Mutual Friend* (Table 3), so that $I_L = 0.675$. However, in this case, this asymmetry may indicate a time arrow, because *Bleak House* (written earlier) seems to be more “contained” in *A Mutual Friend* (written later) than the reverse, because $0.724 > 0.675$. The time arrow, however, is not evident in other cases.

It is very interesting and surprising to compare them with *Matthew*. It can be noticed, in fact, that *Bleak House* ($I_L = 0.813$) and *A Tale of Two Cities* ($I_L = 0.671$) are more similar to *Matthew* than the other novels. In other words, *Matthew* seems to have affected the statistics of the sentences in these two Dickens works more than those found in *Our Mutual Friend*, *Oliver Twist*, and *David Copperfield*. Appendix A reports the tables for the other Gospels.

Now, let us consider in more depth the likely influence of the Gospels of the King James translation on Dickens’ writing.

8. The Likely Influence of the Gospels on Dickens’ Novels

The very similar values of the deep language parameters in Dickens’ novels and in the Gospel according to *Matthew* (Figures 1 and 2) may be a trace of the influence unconsciously left in Dickens’ style after researching the life of Jesus of Nazareth and writing *The Life of Our Lord* for his children, published only in 1934 [48]. Dickens felt the need to impart some religious instruction to his children by writing a simplified version of the Gospels. According to scholars [49–51], in his novels, all the strongest illustrations are derived from the New Testament because he gave priceless value to its Books.

Figure 9 shows a detail of Figure 2, with the insertion of the other Gospels, whose deep language parameters are reported in Table 12. Notice that only the three synoptic Gospels (*Matthew*, *Mark*, *Luke*) fall within the circle of Dickens’ novels, while *John* is clearly further away. In other words, John does not seem to have notably influenced Dickens’ writing.

Table 12. Gospels statistics, King James version. Number of chapters (i.e., the number of samples considered in calculating the regression lines of the theory), total number of characters contained in the words, total number of words and sentences, deep language parameters C_P , P_F , I_P , M_F , with standard deviation reported in the second line.

Gospel	Chapters	Characters	Words	Sentences	C_P	P_F	I_P	M_F
<i>Matthew</i>	28	99,795	23,397	1040	4.266 0.011	23.510 4.402	5.906 0.549	3.981 0.625
<i>Mark</i>	16	61,355	15,166	688	4.046 0.022	22.297 0.5969	5.847 0.073	3.816 0.100
<i>Luke</i>	24	102,726	25,469	1127	4.033 0.015	22.883 0.544	6.104 0.178	3.789 0.096
<i>John</i>	21	75,635	19,094	968	3.961 0.029	19.971 0.496	5.838 0.134	3.443 0.092

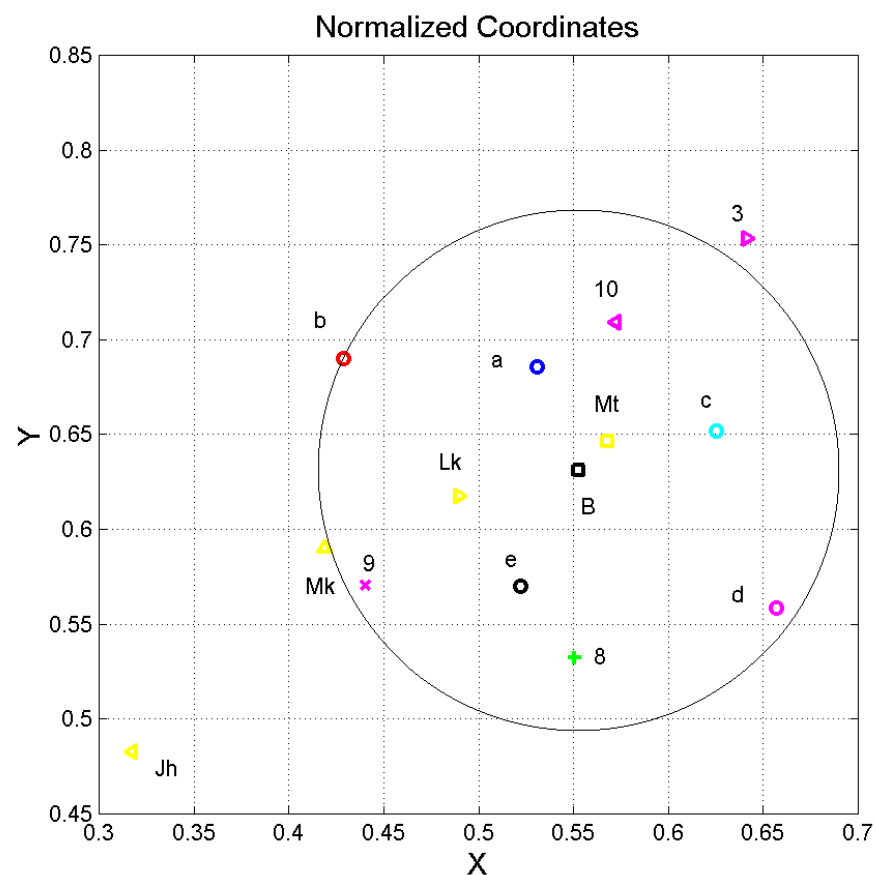


Figure 9. Normalized coordinates x and y of the resulting vector (18) of the literary works listed in Tables 1 and 2 (detail) and the canonical Gospels (*Matthew*, *Mark*, *Luke*, *John*, yellow marks), normalized so that *Of Mice and Men* is located at the origin (0,0) and *Moby Dick* is located at (1,1). Dickens' novels are represented by the circles: *The Adventures of Oliver Twist*, a , blue; *David Copperfield*, b , red; *Bleak House*, d , magenta; *A Tale of Two Cities*, c , cyan; *Our Mutual Friend*, e , black. The other novels are numbered according to the order reported in Table 2.

Table 13 reports the slope m and correlation coefficient r of the regression line between the number of sentences n_S (dependent variable) and the number of words n_W (independent variable) per chapter, in the Gospels. Four decimal digits are reported because some values differ only from the third digit. Notice that *Matthew* and *Luke* almost coincide, as already observed in the general study reported in [52] on the original Greek texts. *Mark* is not far, therefore distinguishing the synoptic Gospels from *John*.

Table 13. Slope m and correlation coefficient r of the regression line between the number of sentences n_S (dependent variable) and the number of words n_W (independent variable) per chapter, in the canonical Gospels. Four decimal digits are reported because some values differ only from the third digit.

Gospel	m	r
<i>Matthew</i>	0.0447	0.9499
<i>Mark</i>	0.0459	0.9541
<i>Luke</i>	0.0446	0.9329
<i>John</i>	0.0511	0.9441

Table 14 summarizes the likeness index between the indicated Gospel (output) and Dickens' novels (input). This table shows that Dickens' novels have been likely influenced

by the synoptic Gospels, especially the last three novels, which were written shortly after *The Life of Our Lord*.

Table 14. Likeness index $I_L = I_C$ between the indicated Dickens novels and the four Canonical Gospels in the King James translation (output), sentences channel. The Gospel in the first line indicates the output text; the text in the first column indicates the input text (regression line given in Table 10). For example, in the channel *Our Mutual Friend* → *Bleak House*, $I_L = 0.675$, while in the reverse channel, *Bleak House* → *Our Mutual Friend*, $I_L = 0.724$.

Input Novel	<i>Matthew</i>	<i>Mark</i>	<i>Luke</i>	<i>John</i>
<i>Oliver Twist</i>	0.508	0.429	0.545	0.045
<i>David Copperfield</i>	0.293	0.384	0.325	0.045
<i>Bleak House</i>	0.671	0.851	0.767	0.314
<i>A Tale of Two Cities</i>	0.813	0.890	0.643	0.170
<i>Our Mutual Friend</i>	0.483	0.641	0.707	0.227

In conclusion, we conjecture that the synoptic Gospels, read and studied by Dickens, affected and shaped, unconsciously, the deep language parameters of his writing style.

9. Final Remarks

We can now link the results shown in Figure 2 (vectors) with the likeness index I_L . We have noticed that Dickens' novels are concentrated within a circle, which includes very few novels by other authors.

In the Cartesian plane, we can calculate the Pythagorean distance \uparrow between a literary work and a reference work, and correlate \uparrow with the corresponding I_L . Such an exercise is shown in Figure 10, as an example, where the reference (output) is *Bleak House*. It is clearly evident that I_L decreases sharply as \uparrow increases.

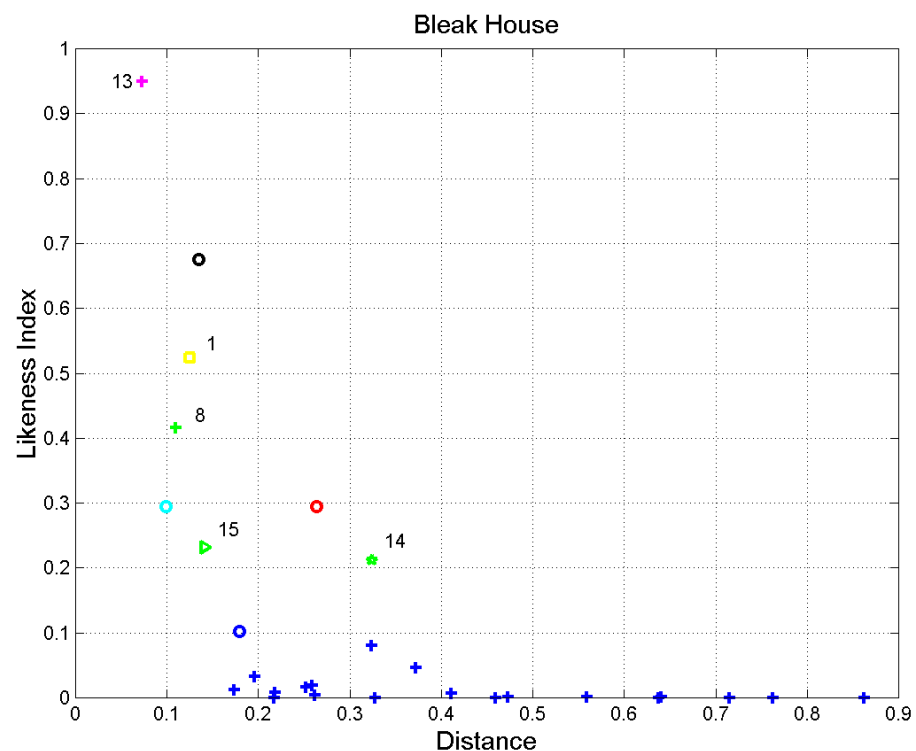


Figure 10. Likeness index I_L versus Pythagorean distance \uparrow between a literary work and a reference (output) work (*Bleak House*).

For small distances ($\downarrow \lesssim 0.15$), I_L and \downarrow show a tight inverse relationship. The closest work to *Bleak House* is *The Jungle Book* (13), followed by *Little Women* (8), *Treasure Island* (9), and *The Adventures of Huckleberry Finn* (10). Although these novels fall within the circle, they could not have influenced Dickens' style because they were published later than *Bleak House* (Tables 2 and 3); therefore, a small distance is a necessary but not a sufficient condition for two literary works being mathematically similar.

10. Conclusions

In the first part of the article, we have recalled our general theory of linguistic channels and have studied the Shannon capacity and interdependence of these channels. In the second part, to show some features and usefulness of the theory, we have applied it to novels written by Charles Dickens and other authors of English literature, including the Gospels of the classical King James version of the Bible.

In literary works (or in any long texts), there are multiple communication channels, one of which is the channel that linearly links the sentences of two literary works for an equal number of words, as explicitly studied in the article. The theory of these channels considers not only averages, such as regression lines, but also correlation coefficients.

A Monte Carlo simulation addresses the inaccuracy in estimating the slope and correlation coefficient of regression lines due to the small sample size (i.e., given by the number of chapters of each literary work). However, besides the usefulness of the simulation as a “renormalization” tool shown in the article, there is another very likely more interesting property concerning the new generated literary works. In fact, because the mathematical theory does not consider meaning, the simulated texts might have been “written” by the author, as they maintain the main statistical properties of the deep language parameters of the original text. In other words, they are “literary works” that the author might have written at the time that he wrote the original work.

We have shown that the probability density function of the capacity of self- and cross-channels (defined and studied in the article) is a Gaussian stochastic variable. The closer the parameters of the cross-channels are to those of the self-channel, the more similar are the two literary works. The similarity is measured by the likeness index.

We have found that Dickens' novels show striking and unexpected mathematical/statistical similarity to the synoptic Gospels. The similarity may be a trace of the influence unconsciously left in Dickens' deep language style after researching the life of Jesus of Nazareth and writing *The Life of Our Lord* for his children.

We have shown that the Pythagorean distance \downarrow (in a suitably defined Cartesian plane involving the deep language parameters) and the likeness index, for a reference literary work compared to all others, correlates with the corresponding likeness index with a tight inverse proportional relationship.

A similar approach can be applied, of course, to any literary corpus written in any alphabetical language, and this would allow us to compare different texts, even in translation.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A Statistics of Gospels of *Mark*, *Luke*, *John* in the King James Translation

Tables A1–A3 report the statistics concerning the Gospels of *Mark*, *Luke* and *John*. The King James translation necessary to calculate the likeness index is reported in Table 12. All Gospels have been downloaded from <https://www.biblegateway.com/versions/King-James-Version-KJV-Bible/#booklist> (accessed on 4 October 2022).

Table A1. Average value M (dB) and standard deviation S (dB) of $\Gamma_{dB,ex}$ (dB) in self- and cross-channels, correlation coefficient r_{jk} , and slope m_{jk} of the regression line between the number of sentences n_S of *Mark* (channel output, self-channel) versus the number of sentences n_S in Dickens' novels (channel input, cross-channels), for equal number of words, in the sentences channel.

Novel	Signal-to-Noise Ratio $\Gamma_{dB,ex}$ (dB)		Correlation Coefficient r_{jk}		Slope m_{jk}	
	M	S	Ave	Dec	Ave	Dev
<i>Mark</i> (self-channel)	24.57	6.74	0.9957	0.0089	0.9968	0.0292
<i>Oliver Twist</i>	17.09	3.51	0.9936	0.0075	1.0960	0.0322
<i>David Copperfield</i>	16.47	3.31	0.9931	0.0137	1.1130	0.0321
<i>Bleak House</i>	22.33	5.89	0.9947	0.0081	0.9816	0.0285
<i>A Tale of Two Cities</i>	22.70	6.60	0.9935	0.0135	1.0237	0.0298
<i>Our Mutual friend</i>	19.05	5.41	0.9902	0.0089	0.9888	0.0287

Table A2. Average value M (dB) and standard deviation S (dB) of $\Gamma_{dB,ex}$ (dB) in self- and cross-channels, correlation coefficient r_{jk} , and slope m_{jk} of the regression line between the number of sentences n_S of *Luke* (channel output, self-channel) versus the number of sentences n_S in Dickens' novels (channel input, cross-channels), for equal number of words, in the sentences channel.

Novel	Signal-to-Noise Ratio $\Gamma_{dB,ex}$ (dB)		Correlation Coefficient r_{jk}		Slope m_{jk}	
	M	S	Ave	Dec	Ave	Dev
<i>Luke</i> (self-channel)	26.39	6.21	0.9978	0.0030	0.9984	0.0245
<i>Oliver Twist</i>	21.07	3.54	0.9977	0.0033	1.0676	0.0268
<i>David Copperfield</i>	16.98	3.67	0.9920	0.0080	1.0838	0.0269
<i>Bleak House</i>	23.70	4.45	0.9979	0.0032	0.9562	0.0237
<i>A Tale of Two Cities</i>	20.87	5.75	0.9930	0.0072	0.9967	0.0246
<i>Our Mutual friend</i>	22.38	4.96	0.9960	0.0047	0.9615	0.0239

Table A3. Average value M (dB) and standard deviation S (dB) of $\Gamma_{dB,ex}$ (dB) in self- and cross-channels, correlation coefficient r_{jk} , and slope m_{jk} of the regression line between the number of sentences n_S of *John* (channel output, self-channel) versus the number of sentences n_S in Dickens' novels (channel input cross-channels), for equal number of words, in the sentences channel.

Novel	Signal-to-Noise Ratio $\Gamma_{dB,ex}$ (dB)		Correlation Coefficient r_{jk}		Slope m_{jk}	
	M	S	Ave	Dec	Ave	Dev
<i>Luke</i> (self-channel)	26.88	6.67	0.9977	0.0040	0.9986	0.0206
<i>Oliver Twist</i>	12.40	1.08	0.9970	0.0040	1.2227	0.0257
<i>David Copperfield</i>	11.30	1.51	0.9936	0.0086	1.2412	0.0255
<i>Bleak House</i>	18.74	2.40	0.9975	0.0045	1.0951	0.0227
<i>A Tale of Two Cities</i>	15.12	2.44	0.9942	0.0083	1.1421	0.0236
<i>Our Mutual friend</i>	16.77	2.40	0.9946	0.0054	1.1023	0.0229

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