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Language statistics at different spatial, temporal, and grammatical scales

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Abstract

Statistical linguistics has advanced considerably in recent decades as data has become available. This has allowed researchers to study how statistical properties of languages change over time. In this work, we use data from Twitter to explore English and Spanish considering the *rank diversity* at different scales: temporal (from 3 to 96 hour intervals), spatial (from 3km to 3000+km radii), and grammatical (from monograms to pentagrams). We find that all three scales are relevant. However, the greatest changes come from variations in the grammatical scale. At the lowest grammatical scale (monograms), the rank diversity curves are most similar, independently on the values of other scales, languages, and countries. As the grammatical scale grows, the rank diversity curves vary more depending on the temporal and spatial scales, as well as on the language and country. We also study the statistics of Twitter-specific tokens: emojis, hashtags, and user mentions. These particular type of tokens show a sigmoid kind of behaviour as a rank diversity function. Our results are helpful to quantify aspects of language statistics that seem universal and what may lead to variations.

Keywords: statistical linguistics; culturomics; Twitter; scales

1 Introduction

Statistical linguistics have become a relevant field of research over the last century [1]. In this context, random-text models have been proposed as an explanation for the so-called Zipf's law [2, 3, 4, 5, 6, 7]. Random texts and real texts are compared showing that real texts fill the lexical spectrum much more efficiently and regardless of the word length, suggesting that the meaningfulness of Zipf's law is high. Other studies have focussed on language origins and evolution [8, 9, 10, 11, 12]. The recent availability of data enables further analysis of language usage including dynamics and changes over time [13, 14, 15, 16, 17].

Previous studies consider language variation in timescales of years and centuries [13, 14]. In this article, we study the use and change of language use at the timescales of hours and days. We use geolocalized Twitter data to compare languages at different timescales, as well as at different spatial scales and "grammatical scales". Our motivation was to measure the relevance of each scale in lan-

guage statistics. In other words, does language use vary more with time, space, or structure?

Twitter data has been used for studying language in the context of sentiment and topic analysis, (mis)information spreading, and activity patterns [18, 19, 20, 21, 17, 22]. The information in the meta-data, includes location, time and text, which enables the analysis of dynamics and geography at multiple scales. Previous studies have found differences in the way people use text and interaction mechanisms such as URLs, hashtags, mentions, replies, and retweets by country or culture [23, 24]. Moreover, the usage of Twitter hashtags showed consistencies with the distribution of wealth in urban areas [25].

Our previous research shows that changes in word usage within certain languages follow the same pattern. We measured these changes using a metric we define as *rank diversity*. To calculate it, we consider a corpus of words ranked by their frequency (number of times it appears on a given time interval), and then counting how many different words occupied each rank (see Methods). If a rank is occupied by a single word at all times, the rank diversity is minimum. On the other hand, if in each time interval we have a different word on a given rank, then its rank diversity is maximum. If we plot rank diversity as a function of the rank, we can analyze how word usage changes in time. In [16, 26], we compared the rank diversity of books in different languages. It was shown that rank diversity as a function of the rank can be approximated with a sigmoid, with similar parameters for all languages studied.

Twitter data has unique characteristics that make it an interesting studying subject. Unlike books or other written pieces, people can only publish tweets with a limited number of characters, making interesting the study of use of language in a medium that allows only very short texts and whether it differs statistically from longer texts. Also, Twitter offers a much finer temporal dimensionality than physically published material. And since tweets can be geotagged, we can study geographical differences of language use at very fine scales. Moreover, due to its social network nature, interactions between users (mentions, retweets) and trending topics create a unique language ecosystem. Finally, it provides a big dataset, suitable to perform statistical analysis.

In this work, we analyzed more than 20 million geolocalized tweets from eight different countries. We calculated rank diversity in different spatial, temporal, and grammatical scales. We were interested in measuring the changes in rank diversity for different scales considered. We observed several features. First, higher scales are related to higher rank diversities except in the case of time, which exhibits a concave behavior, where shorter and larger time intervals have higher rank diversity than medium ones. Second, different types of scale affect each other, *i.e.*, they are not independent. Finally, considering the importance of a scale as the rank diversity average dispersion in that scale, we found that the grammatical scale is the most important among the three scales. Temporal and spatial scales have similar importance in the Spanish-speaking countries, while the spatial scale is the least important in English-speaking countries.

2 Methods and Data

We define rank diversity $d(k)$ as the number of words occupying a given rank k during the period of time of the study divided by the number of time intervals T . Therefore, rank diversity is given by:

$$d(k) = \frac{|X(k)|}{T}, \quad (1)$$

where $|X(k)|$ is the cardinality (*i.e.*, number of unique words) that appear at rank k during all time intervals. The time between time “slices” is Δt , so that the total time considered is $T\Delta t$.

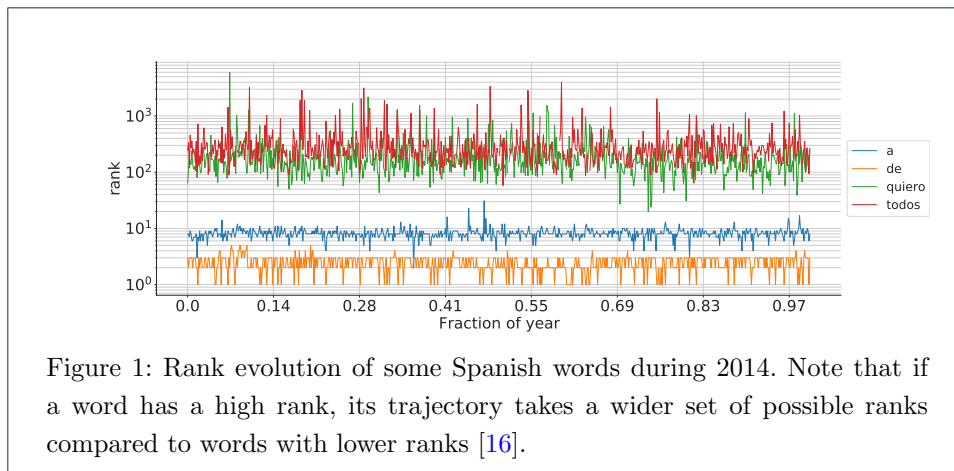
We have found that rank diversity curves for six different Indo-European languages are very similar, as they can be fitted with a sigmoid curve with small differences between languages [16, 26, 27]. This pattern is also present in the rank dynamics of sports [28] and other systems [29].

We use geo-located Twitter data to analyze changes in language usage. The tweets were collected using the Twitter Streaming Application Programming Interface (API). We consider over 20 million geo-located tweets posted from Argentina, Canada, Colombia, India, Mexico, South Africa, Spain and the United Kingdom during 2014 (when each tweet was limited to 140 characters and threads were not as commonly used) and we calculate rank diversity using different time intervals Δt . Geo-located tweets contain precise latitude and longitude coordinates at the moment of their creation. Twitter activity has been previously analyzed to understand patterns of global synchronization [21], spreading mechanisms [20] and political polarization [30].

We define the “grammatical scale” as the length of N -gram blocks used ($N = 1, 2, 3, 4$, and 5) [13]. Single words are monograms or 1-grams, sets of five words are pentagrams or 5-grams, etc. We have previously studied how the grammatical scale affects the rank dynamics of words using the Google Books N -gram dataset [26]. We found that the grammatical scale varies language statistics (rank diversity, change probability, rank entropy and rank complexity) more than changes of the language. In other words, a change in the grammatical scale implies a greater change in the statistics than a change of language (among English, Spanish, French, German, Italian, and Russian).

To define the temporal scale, we need to remember that we define rank diversity $d(k)$ as the number of words occupying a given rank k across all times, divided by the number of time intervals T considered. We can change the time interval Δt and calculate rank diversity for different values of T . It should be noted that if the same dataset is used, as the temporal scale Δt increases, T will decrease.

To illustrate the rank evolution of words (1-grams, but the same applies to any grammatical scale), we show examples of some arbitrarily chosen Spanish words in Figure 1. For example, in this case $d(k = 1)$ is obtained by dividing the number of unique series, which represent words graphically, that at some time passes through the line representing point $k = 1$, over the total number of 3 hourly intervals that divide a year.



We study the effects of the spatial scale tweets from Mexico, Spain, Argentina, and the United Kingdom only, since these countries are the only ones with enough geolocalized data to be statistically significant at different spatial scales (about 3.9, 3.7, 4.6, and 5.6 million tweets from Mexico, Spain, Argentina, and the United Kingdom, respectively). For the first scale, we make a circle with a 3km radius located in the geographical center of the capital city (Mexico City, Madrid, Buenos Aires, and London). For the next scales, we increment the radius of the circle by a power of two each time, *i.e.*, 6km, 12km, 24km, 48km, 98km, ..., until we include the whole country. To avoid biased results, we kept the same number of tweets used in the analysis of the smallest spatial scale for the remaining spatial scales for each country. For example, the number of tweets inside the circle of radius of 3 km for Mexico was 309,792. Therefore, for each of the remaining spatial scales, which in this case are represented as the area inside circles of increasing radius, we took a random sample of tweets of size 309,792 without replacement.

As there are three considered scales, to see any potential differences in the behavior of rank diversity across values of these scales, we generated $I \cdot J \cdot S$ rank diversity curves for each country, where I, J , and S are the number of different values that one particular scale can adopt. So we generated rank diversity curves corresponding to each different combination of values of the considered scales. For example, in the case of Mexico, we have $5 \cdot 6 \cdot 10 = 300$ possible combinations. In order to have a numeric value that quantitatively summarizes the behavior of a rank diversity curve (measuring that behavior as how fast rank diversity increases as a function of rank) and, in consequence, simplify the description of the system and reduce the observed complexity thereof, we used estimations of μ , which is a parameter of the sigmoid curve that indicates the rank where rank diversity curves reach 1/2. The sigmoid is the cumulative of a Gaussian distribution, *i.e.*

$$\Phi_{\mu, \sigma}(\log_{10} k) = \frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{\log_{10} k} e^{-\frac{(y-\mu)^2}{2\sigma^2}} dy, \quad (2)$$

and is given as a function of $\log k$ [16].

The key concept to measure the relevance of changes in scales over rank diversity behavior is to understand that a lower value of μ indicates a greater speed of rank diversity increment as a function of rank.

It is also important to remember that the introduction of both the rank diversity measure and the use of μ as a way of measuring its changes throughout scales implies the use of collective or aggregate measurements, so care must be taken when trying to generate particular conclusions to avoid making incorrect assumptions (ecological fallacy).

To measure the relative importance of a scale in terms of how much a change between two different values of this particular scale influences changes in the behavior of rank diversity, we used the following average:

$$\eta(s) = \frac{\sum_i^I \sum_j^J \sigma_{i,j}^s}{I \cdot J}, \quad (3)$$

where $\sigma_{i,j}^s$ corresponds to the standard deviation of estimated values of μ associated to the scale s given fixed i and j values of the two remaining scales, *i.e.*, if

$$\bar{\mu}_{i,j} = \sum_s \frac{\mu_{i,j}^s}{N}, \quad (4)$$

then

$$\sigma_{i,j}^s = \sqrt{\frac{\sum_s (\mu_{i,j}^s - \bar{\mu}_{i,j})^2}{N - 1}}. \quad (5)$$

In other words, $\eta(s)$ is intended to capture the average dispersion of μ in the scale s . This permits to objectively compare different scales and determine which one is the most important in terms of modifying the speed of rank diversity increment between different values of that scale. In the Results section we show how $\eta(s)$ effectively quantifies what can be visually seen using graphs of μ versus values of scales.

Finally, to statistically support the graphically observed results, we used an additive linear regression model to perform the F -test and assess that at least one of the scales has a significant effect on μ and therefore in rank diversity.

Moreover, the t -test of each coefficient associated to independent variables is used to assess whether or not each individual scale is contributing to explain the variability of μ assuming a linear model, or in the case of the coefficients that represent multiplicative terms in the multiplicative model, to assess if there is a statistically significant interaction between each pair of scales. The effect of interactions between pairs of scales is shown by observing that as one of the scales increases, the behavior of rank diversity depends on the specific value of the remaining scales. In this case, interaction effects are subtle to observe graphically, so a statistical approach is worth the effort to support the hypothesis that interactions exist.

These models were fitted using the \log_{10} scaled values of temporal and grammatical scales as predictors and μ as response. In particular, the multiplicative model is

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_1 X_2 + \beta_5 X_1 X_3 + \beta_6 X_2 X_3. \tag{6}$$

This model is reduced to a linear one discarding the terms that contain products of predictors (X_i). We can understand the coefficients (β_i) as weights that determine the influence of an associated predictor (a particular scale) over the response, which in this case is μ . That is the reason why we use hypothesis tests to evaluate whether there is evidence that a coefficient is different from zero or not. In the products of two scales the coefficients measure the effect of one scale over how the other influences the response. We can note this by factoring a common linear predictor. For example X_1 : $Y = \beta_1 X_1 + \beta_4 X_1 X_2 + \beta_5 X_1 X_3 = (\beta_1 + \beta_4 X_2 + \beta_5 X_3) X_1 = \beta_{145}(X_2, X_3) X_1$, such that now $\beta_{145}(X_2, X_3)$ act as a multivariate function slope of X_1 that determines how X_2 and X_3 influences the relation of X_1 with Y . Specifically, if the associated coefficients β_4 and β_5 of the predictors X_2 and X_3 are statistically different from zero, then there is evidence that this set of predictors interact with X_1 pairwise. β_0 geometrically corresponds to the level of the hyperplane that better fits the observations. In this particular case, it does not give any further information of interest. All our models were fitted via linear least-squares problems solved by the QR factorization method (for numerical stability) using the standard `lm` function of the programming language R.

3 Results

We calculate the rank diversity of N -grams for tweets from eight different countries: half Spanish-speaking and half English-speaking. In Figure 2, we plot the rank diversity using a time interval Δt of 24 hours for $N = 1, 2, \dots, 5$.

First, we note that the sigmoid curve still provides an adequate description of the rank diversity behavior when we consider small time intervals of observation. This is also the case for all the considered combination of scales. Also, we can observe that for $N = 1$, the rank diversity fits are quite similar. However, when we increment N , the fits separate from each other. This difference suggests that 1-grams have a similar rank diversity independently of language and country. However, for 2-grams, 3-grams, and 4-grams, we see a different pattern. The Spanish-speaking countries' curves are close to each other, forming a cluster, whereas the United Kingdom and Canada separate from the rest. This behavior means that there are grammatical and geographical features that make them distinct from the rest. In the next sections, we explore the effects at different scales (grammatical, spatial, and temporal) on rank diversity using estimates of the parameter μ of the sigmoid curves.

3.1 Grammatical Scale

Following the N values in increasing order, Figures 3 and 4 show that as the grammatical scale increases, also the speed of rank diversity increment increases. In general, this stands independently of the country, whether the language is Spanish or English, or which values the other two scales adopt. Note that a larger grammatical scale means an increment in the complexity of the phrases. At the top of

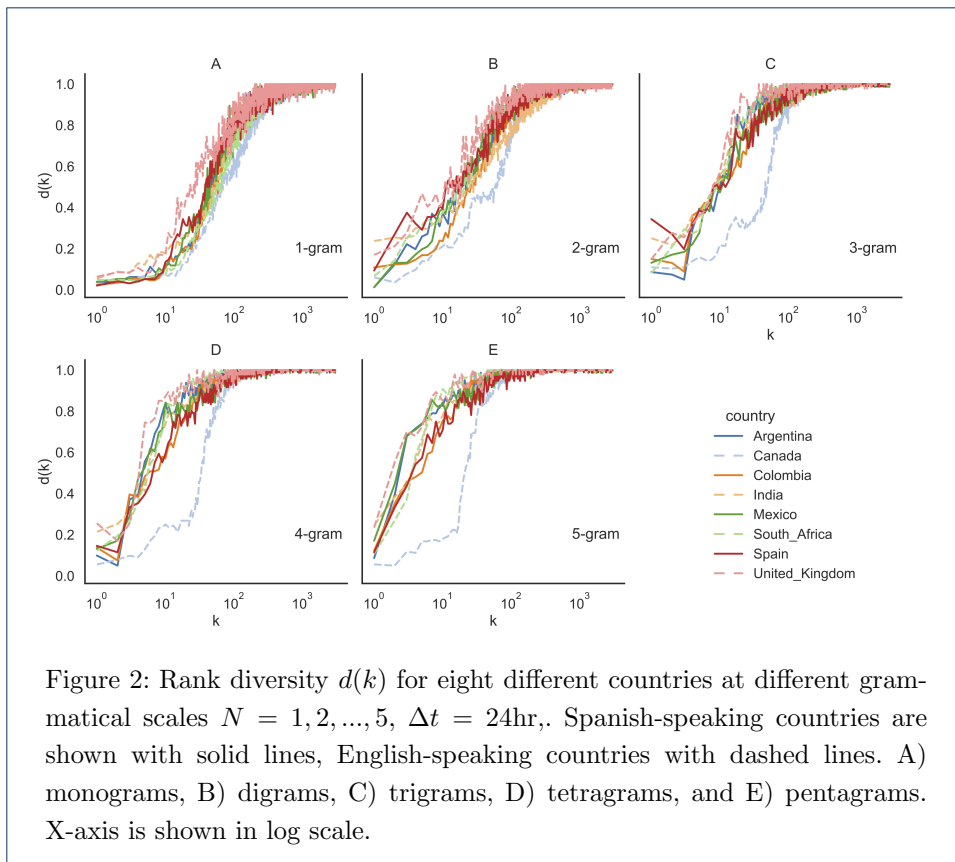


Figure 2: Rank diversity $d(k)$ for eight different countries at different grammatical scales $N = 1, 2, \dots, 5$, $\Delta t = 24\text{hr}$. Spanish-speaking countries are shown with solid lines, English-speaking countries with dashed lines. A) monograms, B) digrams, C) trigrams, D) tetragrams, and E) pentagrams. X-axis is shown in log scale.

the scale (5-grams), we have the rank diversity of blocks formed by five words. The possible combinations of five-word blocks are larger than the ones of four words, and these from the ones of three words. As a consequence, for the initial ranks, we have more diversity than in lower grammatical scales. Moreover, we can confirm that for 1-grams, μ is similar in both Spanish and English and practically independent of the spatial scale. Namely, for words, there are no changes in the speed of rank diversity increment for any area analyzed. Nonetheless, it does vary with respect to the temporal scale as can be seen in the first column of Figure 3. This illustrates the importance of using different scales to analyze the rank diversity of languages.

Also, we can visually identify that changes in the grammatical scale account for the greatest overall increase in speed of rank diversity increment compared to the other two scales. At the end of the results section, we quantify this qualitative observation comparing average dispersions.

3.2 Temporal Scale

In Figure 3 we vary the temporal scale in the x axes to show the relationship between μ and different time intervals Δt . We note that the speed of rank diversity increment is not increasing as in the grammatical or spatial scales, but it has a noticeable concave shape. This nonlinear effect is due to the fact that adding frequencies generates less variable positions for the N -grams in the lists that constitute the total time-span analyzed, therefore, μ increases until a certain time interval. Then, it

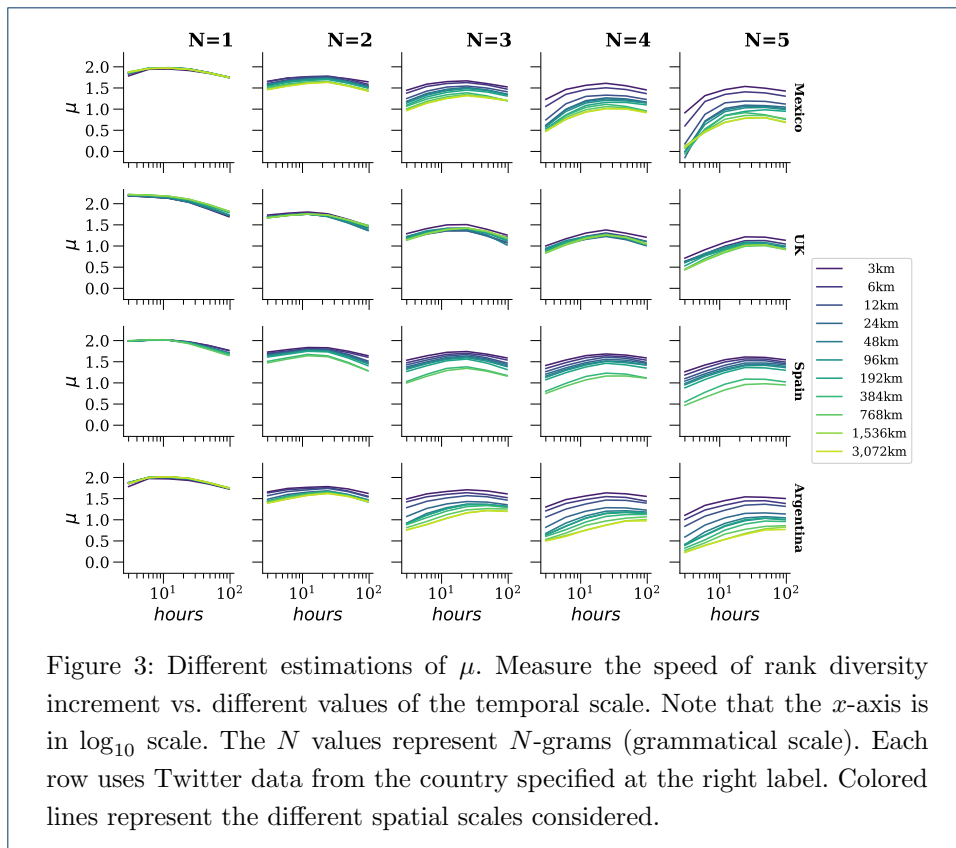
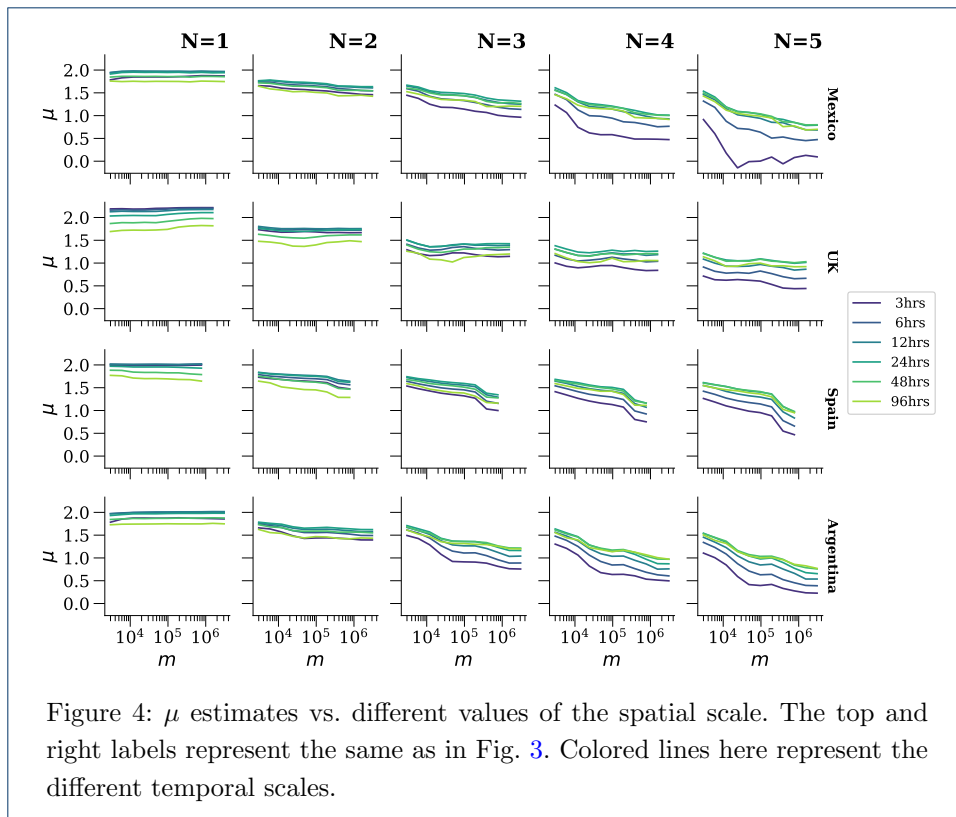


Figure 3: Different estimations of μ . Measure the speed of rank diversity increment vs. different values of the temporal scale. Note that the x -axis is in \log_{10} scale. The N values represent N -grams (grammatical scale). Each row uses Twitter data from the country specified at the right label. Colored lines represent the different spatial scales considered.

starts to decrease, because the number of possible lists that divides the total time-span, which we use as the denominator in the calculation of rank diversity, is lower for higher temporal scales. Furthermore, the relation of the speed of rank diversity increment and the temporal scale is similarly independent of the country and language. Moreover, note how the shape of the relation between μ and time changes in some cases, considering different columns. This represents different grammatical scales, suggesting that the grammatical scale influences on the variation of the temporal scale.

3.3 Spatial Scale

In each plot of Figure 3, specially from the column $N = 3$ to the right, we can already see that given fixed grammatical and temporal scales, the spatial scale also changes the speed of rank diversity increment. Nevertheless, in order to see this relationship more clearly, in Figure 4 we plot μ versus the spacial scale. Note that for the Spanish speaking countries, μ decreases with the spatial scale when the grammatical scale is greater than 1, whereas, in general, μ does not change against the spatial scale for the United Kingdom. More detailed analyses would be required to explore potential explanations, such as whether there exists a greater homogeneity in the United Kingdom compared to the other countries, and/or whether these results reflect a difference between English and Spanish. In general μ also decreases with the grammatical scale.

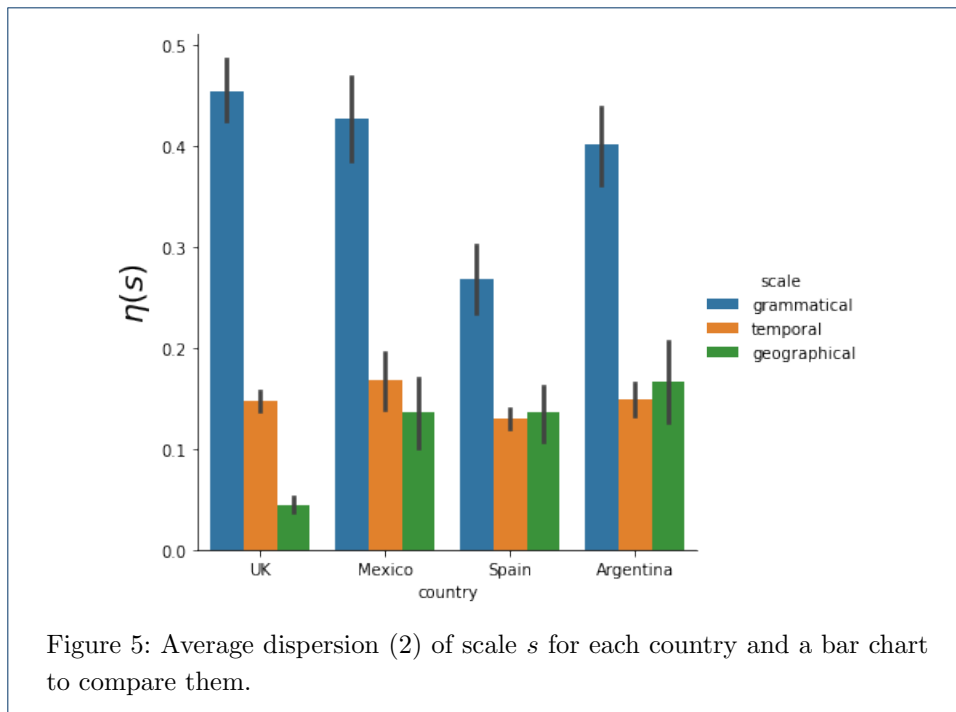


3.4 Relevance of scales

Now we answer the question of which scale is the most important in terms of its effect on the variability of μ and therefore on the behavior of rank diversity itself. To tackle this question, we measure the relative importance of these scales using equations 3, 4, and 5. We show in Figure 5 the results of computing the aforementioned equations for each scale and country. It confirms that the grammatical scale accounts for the maximum dispersion relative to the considered scales. Furthermore, the temporal and spatial scales are both approximately equally important for all the Spanish-speaking countries. For the United Kingdom, the spatial scale seems to have less relevance, although more data.

Finally, the p -values and the associated estimated F -statistic considering the first four terms of model 6 are shown in Table 2. The low p -values indicate that at least one scale is related to μ , assuming that they are approximately linearly correlated. Here we only were interested in supporting the hypothesis that changes in some scale produce changes in the rank diversity behavior, or, in other words, that the linear regression model provides a better fit to the data than a model with no independent variables (with no influence of the scales that could explain the observed variability). Specifically, we can test whether or not a particular scale is related to μ by testing the significance of the associated coefficient. These p -values are in Table 1.

It is worth noticing that for the United Kingdom, the temporal and spatial scales are not so significant according to our test, compared to the grammatical scale. As previously mentioned (Figure 4), the spatial scale seems practically independent



p -value	X_1	X_2	X_3
Mexico	$< 2.0 \times 10^{-16}$	$< 2.0 \times 10^{-16}$	9.8×10^{-16}
United Kingdom	$< 2.0 \times 10^{-16}$	0.125	0.426
Argentina	$< 2.0 \times 10^{-16}$	$< 2.0 \times 10^{-16}$	$< 2.0 \times 10^{-16}$
Spain	$< 2.0 \times 10^{-16}$	$< 2.0 \times 10^{-16}$	0.0183

Table 1: Associated p -values to t -tests of the linear coefficients. X_1, X_2 , and X_3 represent the grammatical, spatial, and temporal scales respectively.

from μ . However, for the temporal scale this means that a linear approximation is not sufficient to capture the relation between these scales and μ . Thus, fitting a quadratic model is enough to find the existence of relations for this scale, also revealing that, for this dataset, the nature of the temporal relation with μ is non-linear, as seen in Figure 3.

Alternatively, to see which interaction between pairs of scales is statistically significant, we can use the p -values associated to t -tests of the estimated coefficients β_4, β_5 , and β_6 in model 6. Results are shown in Table 3. We observe that all the interactions between the grammatical and spatial scales and the grammatical and temporal scales are significant, although for Argentina this is lower. Also there is a higher interaction between grammatical and spatial scales only for the United Kingdom.

3.5 Special tokens

In this section we focus on analyzing special tokens commonly used in Twitter: emojis, hashtags and mentions. We studied the most frequent occurrences within each country and the rank diversity for Argentina, Mexico, Spain and the United Kingdom.

country	Mexico	United Kingdom	Argentina	Spain
$l - 1$	3	3	3	3
$H - l$	326	296	326	266
F -statistic	489.6	631.7	546	261
p -value	$< 2.2 \times 10^{-16}$	$< 2.2 \times 10^{-16}$	$< 2.2 \times 10^{-16}$	$< 2.2 \times 10^{-16}$

Table 2: p -values associated to the F -statistic, which represents the significance of the regression, *i.e.*, that at least one scale is contributing to explain the changes in rank diversity. l is the number of parameters used and H the number of observations.

p -value	$X_1 * X_2$	$X_1 * X_3$	$X_2 * X_3$
Mexico	$< 2.2 \times 10^{-16}$	$< 2.2 \times 10^{-16}$	0.57
United Kingdom	$< 8.2 \times 10^{-5}$	$< 2.2 \times 10^{-16}$	0.12
Argentina	$< 2.2 \times 10^{-16}$	$< 2.2 \times 10^{-16}$	$< 2.6 \times 10^{-4}$
Spain	$< 2.2 \times 10^{-16}$	$< 2.2 \times 10^{-16}$	0.47

Table 3: Associated p -values to t -tests of the interaction coefficients. X_1, X_2 , and X_3 represent the grammatical, spatial, and temporal scales respectively.

An *emoji* is a pictogram, logogram, ideogram, or smiley used in electronic messages and web pages. The primary function of emojis is to fill in emotional cues otherwise missing from typed conversation and refers to pictures that can be represented as encoded characters. Emojis have become widely used to communicate emotion. It is useful to emphasize our communication with body language and facial expressions, which are lacking in texts. Thus, they can be complemented with emojis.

Figure 6 can be read from top to bottom, showing the most frequent emojis in the first rows from the top^[1]. We can see *Smiling Face with Heart-Shaped Eyes* and *Face with Tears of Joy* as the most commonly expressed emotions, followed by other expressions such as happiness, hearts and strength. It is interesting to notice that some emojis are popular across all countries, but also there are some that are prevalent only in some countries. For example, the *Woman Dancing* and *Sun with Face* emojis are popular only in Spain, *Sleeping Face* only in Mexico, *Unamused Face* only in Argentina, while *Fire* appears only in the UK.

We can notice that within the most frequent unicode emoji symbols are some *Emoji Modifier Fitzpatrick*. Emoji characters can be modified to use one of five different skin tone modifiers. Each tone is based on the Fitzpatrick Scale. The Fitzpatrick scale is a numerical classification schema for human skin color [31] developed in 1975 by American dermatologist Thomas B. Fitzpatrick. Argentina only has in its top list *Light Skin Tone*. Spain also includes *Medium-Light Skin Tone*. Mexico and the UK have *Medium Skin Tone* as well. *Medium-Dark Skin Tone* and *Dark Skin Tone* do not appear in any of these lists.

A *hashtag* is a metadata tag that is prefaced by the hash symbol, #. Hashtags are used on platforms such as Twitter and Instagram as a form of user-generated tagging that enables cross-referencing of content, that is, sharing a topic or theme. They are useful for finding content of similar interest.

It is important to note that hashtags are neither registered nor controlled by any one user or group of users. They do not contain any set definitions, meaning that

^[1]Devanagari characters (popular in the UK) were removed as these are not emojis.

Argentina	Mexico	Spain	United Kingdom
😂	😂	😂	😂
27906	20543	21466	19726
😄	👍	😄	😂
20752	14564	14621	18559
👉	😄	👉	👍
12239	12442	13037	15944
💕	👍	👍	👍
11523	9757	10799	14712
👉	😎	👍	B
10428	7851	10743	9610
👉	👉	💕	G
8145	6847	9950	9606
🎵	😄	👉	😄
8133	6090	9926	8283
😂	💕	👉	👉
7594	6079	9326	8261
👉	😄	😂	💕
7196	6006	8776	7111
👉	😄	👉	👍
6624	5567	8643	6807
👉	👉	😄	👍
6284	5551	7581	6499
💕	👉	😄	👉
6133	5009	7339	6457
👉	👉	😎	💕
5669	4622	7104	6109
💕	👉	👉	👉
5662	4054	6926	6022
👍	👉	👉	😂
5218	3944	6891	5609
💕	👍	👉	👉
5217	3803	6590	5475
💕	😄	👉	😎
4488	3540	6460	5300
😄	🎵	ES	👉
4304	3297	6204	4967
💕	M	ES	👉
4113	3255	6162	4909
😄	X	ES	💕
4053	3231	6156	4378

Figure 6: Comparison of the most frequent emojis and modifiers shown in Argentina, Mexico, Spain and the United Kingdom in geolocalized tweets from the year 2014.

a single hashtag can be used for any number of purposes, and that the accepted meaning of a hashtag can change with time.

Table 4 shows that #trndnl is the most common hashtag, which is related to popularity and trending topics. Also important cities of each country are mentioned: Buenos Aires, Cordoba, and Rosario in Argentina; CDMX/Mexico City, Monterrey, Guadalajara, and Puebla in Mexico; Madrid, Barcelona, and Sevilla in Spain; and London and St Albans in the UK. It is interesting that only in Europe weather-related hashtags are popular.

A mention is a tweet that contains another person’s username anywhere in the body of the tweet. User mentions are identified with the @ symbol within tweets.

Table 5 shows the most common user mentions. They highlight meeting places such as shopping centers, cinemas, and airports; and famous companies or people (politicians, artists, sportspeople). Differences can be seen per country, suggesting variations in the usage of Twitter at the time. For example, Argentina has several mentions of artists, Mexico has several mentions of commercial franchises, Spain includes soccer teams and political parties, and the most mentioned account in the UK by far is that of the National Rail network.

It is important to notice that these mentions are from geolocated tweets, which are only a small fraction of all tweets. Thus, these mentions might be biased and the most popular accounts might vary from those listed here.

Argentina		Mexico		Spain		United Kingdom	
#trndnl	9518	#trndnl	10836	#trndnl	19328	#nowplaying	52085
#buenosaires	5022	#cdmx	6951	#madrid	14552	#london	35934
#argentina	2372	#mexico	6540	#barcelona	14167	#job	25486
#me	1646	#mexicocity	3631	#incdgt	13367	#tnc	24897
#cordoba	1502	#job	3508	#dgt	12978	#trndnl	24319
#rosario	1419	#hiring	3135	#meteocat	12260	#areacode	23084
#love	1269	#monterrey	2870	#endomondo	9689	#hiring	22587
#selfie	1088	#endomondo	2626	#meteo	8736	#tides	20236
#friends	1069	#guadalajara	2433	#spain	8649	#ktt	19237
#job	961	#endorphins	2299	#blanco	8644	#weather	12024
#endomondo	939	#friends	2049	#endorphins	8559	#careerarc	11841
#viernes	911	#mexico	1860	#324meteo	8468	#essex	11016
#amigos	891	#love	1758	#meteo	3127	#broadbandcompareuk	10881
#repost	873	#careerarc	1575	#retención	8189	#bestbroadband	10641
#hiring	868	#photo	1486	#precaución	7798	#photo	10492
#night	807	#jobs	1370	#elcatllar	6844	#ukweather	9978
#endorphins	804	#quieremeamame	1333	#obra	5398	#endomondo	9770
#domingo	774	#puebla	1215	#arameteo	4910	#jobs	9375
#sabado	727	#selfie	1183	#sevilla	4890	#endorphins	8988
#carlosrivera	719	#travel	1069	#amarillo	4030	#stalbans	7498

Table 4: Most frequent hashtags in Argentina, Mexico, Spain and United Kingdom in 2014 geolocalized tweets.

Argentina		Mexico		Spain		United Kingdom	
@clubsolotu_arg	724	@aicm3	3965	@canalfiesta	1124	@nationalrailenq	4797
@vale975	649	@cinemex	2629	@aena	1068	@heathrowairport	2088
@pabloalucero	543	@cinopolis	2352	@aenaeropuertos	842	@starbucksuk	1480
@rkartista	432	@germanmontero5	2296	@dominguezja	830	@luythenorth444	1401
@aa2000oficial	417	@grupointocable	2122	@oficialmaki	671	@brewdog	1030
@mauriciomacri	368	@sonadoraeterno	2108	@oficiallamorena	570	@simmons2k	928
@abrahammateomus	339	@mariobautista_	1878	@adif_es	462	@lynnie26blue	903
@lucianopereyra	325	@smartfit_mex	1755	@willylevy29	395	@costacoffee	902
@todonoticias	263	@walmartmexico	1274	@realmadrid	321	@lizbussey	863
@c5n	243	@galeriasmx	1010	@pinedademar	297	@babs200475	819
@infobae	179	@chilismexico	789	@adry60go	288	@shelleym1974	774
@radiomitre	169	@aeropuertodemty	729	@pablo_iglesias_	278	@shelleym1974	774
@rialjorge	163	@aeropuertosgap	695	@sanchezcastejon	273	@luyyorkshire444	693
@cfkargentina	156	@solosanborns	673	@psoe	265	@westendlanegirl	659
@marialuizateodo	153	@banamex	654	@fcbarcelona	242	@feelingpeacenmw	634
@starbucksar	153	@lacasadetono	644	@barcelona_cat	234	@harrods	625
@niallofficial	152	@oasis_coyoacan	625	@ahorapodemos	213	@kathb24	576
@sole_pastorutti	152	@auditoriomx	594	@renfe	202	@selfridges	560
@brigitte2300	144	@perisur	566	@el_pais	199	@visitlondon	481
@lanacion	144	@tuado	559	@mariajosesernas	190	@skynews	466

Table 5: The most frequent users mentioned in Argentina, Mexico, Spain and the United Kingdom in geolocalized tweets from the year 2014.

The rank diversity curves of emojis, hashtags, and user mentions can be approximated with a sigmoid curve, as with many other phenomena [32]. In all cases, user mentions are the most diverse feature of the country and the emojis are the least diverse feature.

4 Conclusions

Analyzing geolocalized Twitter data, we were able to study language use at different spatial, temporal, and grammatical scales. Which scales are more relevant for languages? All of them, but the grammatical is more relevant than the spatial and temporal, at least for the statistical measures considered here. This suggests that the relation of the considered scales with rank diversity cannot be completely understood in detail using just one of the scales, even when the grammatical scale is the most strongly related to changes in the speed of rank diversity increment.

It is interesting that the sigmoid curve correctly describes rank diversity curves in all the considered combinations of spatial and temporal scales. Thus, not only this function adequately fits rank diversity curves for different languages and different *N*-grams as our previous research showed for temporal scales of years, but it also correctly fit rank diversity curves in the smaller temporal scales considered here

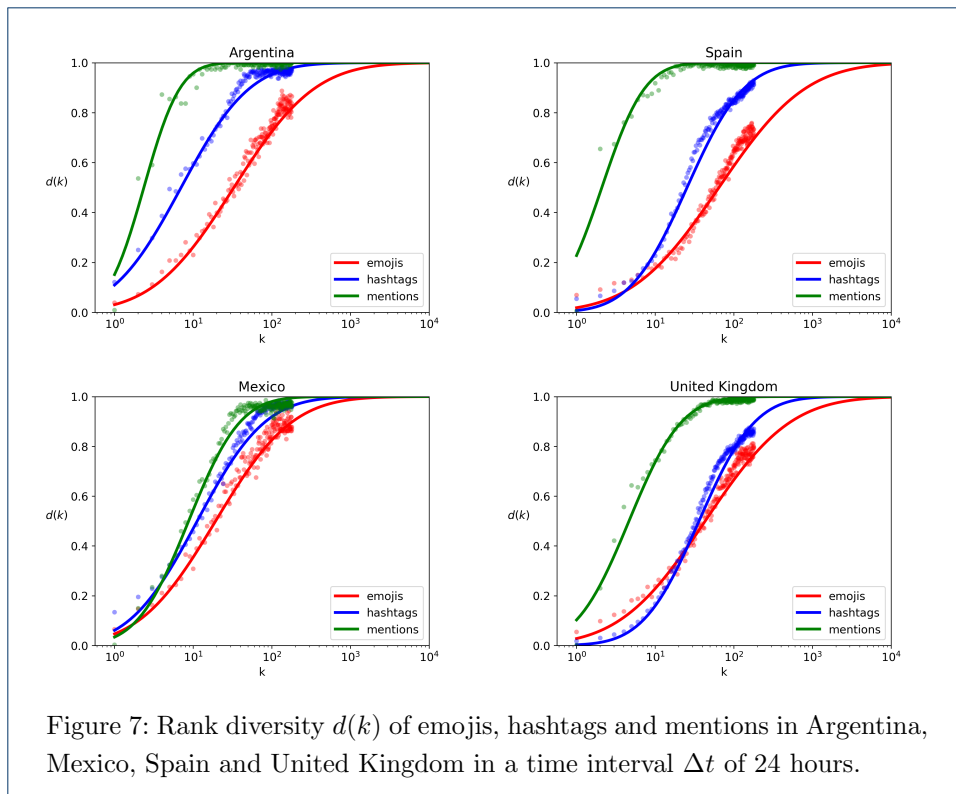


Figure 7: Rank diversity $d(k)$ of emojis, hashtags and mentions in Argentina, Mexico, Spain and United Kingdom in a time interval Δt of 24 hours.

and geographical regions. This suggests that the shape of the rank diversity curve is derived from mechanisms that are not affected by changes in language or scales [32]. Also, notice that the diversity of monograms are not affected by the spatial scale. However, as the grammatical scale increases, the rank diversity curves do change with the spatial scale. This is probably because word usage across regions should be more similar than phrase usage. In other words, language use variability increases at higher grammatical scales.

The evidence of interactions between scales means that rank diversity exhibits different within-scale behavior depending on which values the remaining scales adopt. This effect is clearly noticeable between temporal and grammatical scales and between spatial and grammatical scales. Nonetheless, our results do not support that an interaction exists between the spatial and temporal scales. In general, the speed of increment of rank diversity is greater at higher scales in both grammatical and geographical cases for the Spanish-speaking countries. For example, in terms of 2-grams, this means that the rate of increment of the number of different 2-grams that appear in the ranks during a time span of one year divided into periods of t hours, where t is one of the possible temporal scale values, increments as the spatial scale increases.

We compared the most frequent emojis in different languages and countries, suggesting that emojis are nonverbal symbols that reflect cultural differences between Twitter users and their geographical locations. They can also reflect the collective sentiment [18] of each country and perhaps even certain biases. Hashtags are metadata embedded in a social network, Twitter in this case. The social aspect of it is

in the ability to create communities but also evokes emotions and express feelings. Moreover, hashtags can help recognize the relevant topics and events of a community. Thus, understanding their dynamics can lead to several potential insights. Mentions in Twitter are used to refer to another user account. It shows the most popular business, people or accounts. Their change in time and space reflects how their relevance varies. The use of all of these special tokens also can be approximated with a sigmoid curve in their rank diversity. For different countries, emojis seem the most stable, then hashtags, and mentions are the most volatile.

During the COVID-19 pandemic, the sharing of misinformation on social media has become a major focus in academic studies. For example, Pennycook, *et al.* [22] found that shifting attention to accuracy can reduce misinformation online. An interesting extension of this work would be to study the statistical linguistics of misinformation on Twitter.

Declarations

Availability of data and materials

Data are upon request from the authors.

Competing interests

The authors declare that they have no competing interests.

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Author's contributions

AMG, CG and CP designed research; FSP, RLA, DPM, PR and EC analyzed the data and performed numerical simulations; CG and CP analyzed results and wrote the paper, AMG provided the dataset. All authors read and approved the final manuscript.

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References

1. Zipf, G.K.: *Selective Studies and the Principle of Relative Frequency in Language*. Harvard University Press, Cambridge, MA, USA (1932)
2. Booth, A.D.: A "law" of occurrences for words of low frequency. *Information and Control* **10**(4), 386–393 (1967). doi:[10.1016/S0019-9958\(67\)90201-X](https://doi.org/10.1016/S0019-9958(67)90201-X)
3. Montemurro, M.A.: Beyond the Zipf–Mandelbrot law in quantitative linguistics. *Physica A: Statistical Mechanics and its Applications* **300**(3–4), 567–578 (2001). doi:[10.1016/S0378-4371\(01\)00355-7](https://doi.org/10.1016/S0378-4371(01)00355-7)
4. Ferrer i Cancho, R., Solé, R.V.: Zipf's law and random texts. *Advances in Complex Systems* **05**(01), 1–6 (2002). doi:[10.1142/S0219525902000468](https://doi.org/10.1142/S0219525902000468). <https://doi.org/10.1142/S0219525902000468>
5. Newman, M.E.: Power laws, Pareto distributions and Zipf's law. *Contemporary Physics* **46**(5), 323–351 (2005)
6. Baek, S.K., Bernhardsson, S., Minnhagen, P.: Zipf's law unzipped. *New Journal of Physics* **13**(4), 043004 (2011)
7. Corominas-Murtra, B., Fortuny, J., Solé, R.V.: Emergence of Zipf's law in the evolution of communication. *Phys. Rev. E* **83**, 036115 (2011). doi:[10.1103/PhysRevE.83.036115](https://doi.org/10.1103/PhysRevE.83.036115)
8. Gell-Mann, M., Ruhlen, M.: The origin and evolution of word order. *Proceedings of the National Academy of Sciences* **108**(42), 17290–17295 (2011). doi:[10.1073/pnas.1113716108](https://doi.org/10.1073/pnas.1113716108). <http://www.pnas.org/content/108/42/17290.full.pdf+html>
9. Kirby, S., Dowman, M., Griffiths, T.L.: Innateness and culture in the evolution of language. *Proceedings of the National Academy of Sciences* **104**(12), 5241–5245 (2007). doi:[10.1073/pnas.0608222104](https://doi.org/10.1073/pnas.0608222104). <http://www.pnas.org/content/104/12/5241.full.pdf+html>

10. Steels, L.: Experiments in Cultural Language Evolution. *Advances in interaction studies*. John Benjamins Publishing Company, ??? (2012)
11. Baronchelli, A., Loreto, V., Triá, F.: Language dynamics. *Advances in Complex Systems* **15**(03n04), 1203002 (2012). doi:[10.1142/S0219525912030026](https://doi.org/10.1142/S0219525912030026). <https://doi.org/10.1142/S0219525912030026>
12. Solé, R., Amor, D.R., Duran-Nebreda, S., Conde-Pueyo, N., Carbonell-Ballesteró, M., Montañez, R.: Synthetic collective intelligence. *Biosystems* **148**, 47–61 (2016). doi:[10.1016/j.biosystems.2016.01.002](https://doi.org/10.1016/j.biosystems.2016.01.002). What Synthetic Biology can offer to Artificial Intelligence
13. Michel, J.-B., Shen, Y.K., Aiden, A.P., Veres, A., Gray, M.K., Team, T.G.B., Pickett, J.P., Hoiberg, D., Clancy, D., Norvig, P., Orwant, J., Pinker, S., Nowak, M.A., Aiden, E.L.: Quantitative analysis of culture using millions of digitized books. *Science* **331**(6014), 176–182 (2011). doi:[10.1126/science.1199644](https://doi.org/10.1126/science.1199644). <http://www.sciencemag.org/content/331/6014/176.full.pdf>
14. Perc, M.: Evolution of the most common English words and phrases over the centuries. *Journal of The Royal Society Interface* **9**(77), 3323–3328 (2012). doi:[10.1098/rsif.2012.0491](https://doi.org/10.1098/rsif.2012.0491). <http://rsif.royalsocietypublishing.org/content/9/77/3323.full.pdf+html>
15. Gerlach, M., Altmann, E.G.: Stochastic model for the vocabulary growth in natural languages. *Phys. Rev. X* **3**, 021006 (2013). doi:[10.1103/PhysRevX.3.021006](https://doi.org/10.1103/PhysRevX.3.021006)
16. Cocho, G., Flores, J., Gershenson, C., Pineda, C., Sánchez, S.: Rank diversity of languages: Generic behavior in computational linguistics. *PLoS ONE* **10**(4), 0121898 (2015). doi:[10.1371/journal.pone.0121898](https://doi.org/10.1371/journal.pone.0121898)
17. Alshaabi, T., Adams, J.L., Arnold, M.V., Minot, J.R., Dewhurst, D.R., Reagan, A.J., Danforth, C.M., Dodds, P.S.: Storywrangler: A massive exploratorium for sociolinguistic, cultural, socioeconomic, and political timelines using twitter. *Science Advances* **7**(29) (2021). doi:[10.1126/sciadv.abe6534](https://doi.org/10.1126/sciadv.abe6534). <https://advances.sciencemag.org/content/7/29/eabe6534.full.pdf>
18. Bollen, J., Pepe, A., Mao, H.: Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena. In: *ICWSM11*, Barcelona, Spain, pp. 450–453 (2011). <http://arxiv.org/abs/0911.1583>
19. Dodds, P.S., Harris, K.D., Kloumann, I.M., Bliss, C.A., Danforth, C.M.: Temporal patterns of happiness and information in a global social network: Hedonometrics and twitter. *PLoS ONE* **6**(12), 26752 (2011). doi:[10.1371/journal.pone.0026752](https://doi.org/10.1371/journal.pone.0026752)
20. Morales, A.J., Borondo, J., Losada, J.C., Benito, R.M.: Efficiency of human activity on information spreading on twitter. *Social Networks* **39**, 1–11 (2014). doi:[10.1016/j.socnet.2014.03.007](https://doi.org/10.1016/j.socnet.2014.03.007)
21. Morales, A.J., Vavilala, V., Benito, R.M., Bar-Yam, Y.: Global patterns of synchronization in human communications. *Journal of The Royal Society Interface* **14**(128), 20161048 (2017). doi:[10.1098/rsif.2016.1048](https://doi.org/10.1098/rsif.2016.1048). <https://royalsocietypublishing.org/doi/pdf/10.1098/rsif.2016.1048>
22. Pennycook, G., Epstein, Z., Mosleh, M., Arechar, A.A., Eckles, D., Rand, D.G.: Shifting attention to accuracy can reduce misinformation online. *Nature* **592**(7855), 590–595 (2021). doi:[10.1038/s41586-021-03344-2](https://doi.org/10.1038/s41586-021-03344-2)
23. Hong, L., Convertino, G., Chi, E.H.: Language Matters in Twitter: A Large Scale Study. (2011). <http://alias-i.com/>
24. Weerkamp, W., Carter, S., Tsagkias, M.: How people use Twitter in different languages. *ACM*, ??? (2011)
25. Morales, A.J., Dong, X., Bar-Yam, Y., Pentland, A.: Segregation and polarization in urban areas. *Royal Society Open Science* **6**(10), 190573 (2019). doi:[10.1098/rsos.190573](https://doi.org/10.1098/rsos.190573)
26. Morales, J.A., Colman, E., Sánchez, S., Sánchez-Puig, F., Pineda, C., Iñiguez, G., Cocho, G., Flores, J., Gershenson, C.: Rank dynamics of word usage at multiple scales. *Frontiers in Physics* **6**, 45 (2018). doi:[10.3389/fphy.2018.00045](https://doi.org/10.3389/fphy.2018.00045)
27. Cocho, G., Rodríguez, R.F., Sánchez, S., Flores, J., Pineda, C., Gershenson, C.: Rank-frequency distribution of natural languages: A difference of probabilities approach. *Physica A: Statistical Mechanics and its Applications* **532**, 121795 (2019). doi:[10.1016/j.physa.2019.121795](https://doi.org/10.1016/j.physa.2019.121795)
28. Morales, J.A., Sánchez, S., Flores, J., Pineda, C., Gershenson, C., Cocho, G., Zizumbo, J., Rodríguez, R.F., Iñiguez, G.: Generic temporal features of performance rankings in sports and games. *EPJ Data Science* **5**(1), 33 (2016). doi:[10.1140/epjds/s13688-016-0096-y](https://doi.org/10.1140/epjds/s13688-016-0096-y)
29. Iñiguez, G., Pineda, C., Gershenson, C., Barabási, A.-L.: Dynamics of ranking. *Nature Communications* (2022). doi:[10.1038/s41467-022-29256-x](https://doi.org/10.1038/s41467-022-29256-x)
30. Morales, A.J., Borondo, J., Losada, J.C., Benito, R.M.: Measuring political polarization: Twitter shows the two sides of Venezuela. *Chaos: An Interdisciplinary Journal of Nonlinear Science* **25**(3), 033114 (2015). doi:[10.1063/1.4913758](https://doi.org/10.1063/1.4913758). <https://doi.org/10.1063/1.4913758>
31. Fitzpatrick, T.B.: The validity and practicality of sun-reactive skin types i through vi. *Archives of dermatology* **124**(6), 869–871 (1988)
32. Iñiguez, G., Pineda, C., Gershenson, C., Barabási, A.-L.: Universal dynamics of ranking. *arXiv:2104.13439* (2021)