Advances in Complex Systems
Vol. 15, Nos. 3 & 4 (2012) 1150016 (13 pages)

DOI: 10.1142/S0219525911003426

WHY ARE BASIC COLOR NAMES "BASIC"?

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Received 26 May 2011
Revised 25 July 2011
Published 13 March 2012

It is widely known that color names across the world's languages tend to be organized into a neat hierarchy with a small set of "basic names" featuring in a comparatively fixed order across linguistic societies. However, to date, the basic names have only been defined through a set of linguistic principles. There is no statistical definition that quantitatively separates the basic names from the rest of the color words across languages. Here we present a rigorous statistical analysis of the World Color Survey database hosting color word information from 110 non-industrialized languages. The central result is that those names for which a population of individuals show a larger overall agreement across languages turn out to be the basic ones exactly reproducing the color name hierarchy and, thereby, providing, for the first time, an empirical definition of the basic color names.

Keywords: Computational cognitive science; world color survey; basic color names; statistical physics; term agreement.

1. Introduction

Brent Berlin and Paul Kay performed a classic study on world-wide color naming [3] showing for the first time that color names can be arranged into a coherent hierarchy with a limited number of "basic color names" that individual cultures started to use in a relatively fixed order. The authors defined a color word in a language as a basic color name based on eight linguistic principles (see [3]). This seminal work was further advanced by the construction of the World Color Survey (WCS) database [7] that contains color names supplied by 2616 informants for 330 chips on the Munsell Color System. These speakers belong to 110 mostly unwritten languages spoken by non-industrialized societies. Color naming in the WCS languages is thought to be relatively uncontaminated by contact with highly industrialized cultures whose color lexicons closely resemble patterns similar to English. Repeated scientific investigations of this database have now established a link between linguistic conventions [29] and socio-cognitive capabilities of the categorizing subjects. The existence of the universal tendencies have been reported by various researchers [10, 15, 19, 27] although there is a strong debate still continuing against this hypothesis [1, 8, 13, 24–26]. Despite these objections, there is a constant flow of publications related to the WCS database [1, 13, 16, 18, 21, 22] and it certainly plays a pivotal role in all color naming experiments.

Two very important observations made by Berlin and Kay in [3] while defining the basic color names were that they (i) have a very high frequency, and (ii) are agreed upon by speakers of a language. However, no rigorous statistical analysis have been made so far to make these observations quantitative, thereby paving the way to a precise empirical definition of the basic color names. In this article, we shall focus on quantifying the idea that certain names in a population of individuals are basic compared to others. Some of the questions that we would attempt to answer in the course of the article are whether there exists meaningful statistical properties that makes the basic color names different from the rest of the color words and, if so, what is the principal phenomena that forms the basis of this characteristic difference. The central finding is that those names for which a population of individuals show a larger overall agreement across languages turn out to be the basic ones exactly reproducing the hierarchy reported in [3]. Note that this hierarchy suggested by Berlin and Kay [3] might not be alone considered as a determinant of the "basic color terms" of a language (see [9] and the references therein for a detailed discussion on this issue). However, our idea here has been to mainly present a solid statistical method to extract certain meaningful information from the WCS database. One natural question that seems to be very relevant and not so far well-investigated, is how much do the speakers agree among each other in naming the color chips on the Munsell chart. We attempt to check if there is a difference in the way speakers in a language agree over using certain terms as compared to the rest of the terms. To this end, we perform an appropriate statistical analysis of the WCS data, whereby, we define different agreement measures among the speakers across the languages archived in the database. We observe that indeed there is a difference and one has to actually resort back to the empirical findings reported in [3] in order to meaningfully interpret this difference. Remarkably, the agreement values for the basic color names cited in [3] are significantly larger than the rest of the color words across the different languages, thereby, pointing to the presence of the color name hierarchy, however, this time, in a more principled and quantitative fashion.

The rest of the paper is structured as follows. In Sec. 2, we present a detailed statistical analysis of the database reporting (i) the frequency distribution of color words across languages and (ii) agreement of the speakers in a language on using a color word for naming a particular color. Finally, in Sec. 3 we discuss the impact of these results, present reasons for their origins as well as outline certain future directions.

2. Statistical Analysis of the WCS Database

The World Color Survey is a large-scale field study that was started in 1976 to collect cross-linguistic color naming data from 110 unwritten, geographically-distributed languages representing a wide range of language families (http://www.icsi.berkeley.edu/wcs). Owing to the setup of the survey the color terms recorded in the database can be both basic as well as non-basic. The WCS contains data from roughly 20–25 speakers per language who were interviewed by the field linguists. Two types of experiments were performed as follows.

(i) Each speaker was shown a color chip from the Munsell chart (consisting 330 chips) in a pre-defined random order and was asked to name this chip using a color term of his/her language. The speakers were instructed to use words which they themselves consider simple (not inflected) and can be used to name any color in their language but their responses were not otherwise restricted to a pre-determined set of vocabulary. The experiment was repeated for all the 330 chips in the chart and for all the speakers. One important issue that deserves a mention here is how to resolve which terms across different languages have the same semantic content, i.e. roughly refer to the same region in the visible spectrum. For the purpose of our analysis, the "sameness" of the terms across different languages have been determined from the term abbreviations provided by the field linguists in the WCS database. For instance, the same abbreviation "LB" is used to refer to the terms: (a) "lobu" in the language Abidji, (b) "lokban" in the language Casiguran Agta and (c) "libi-lib" in the language Mampruli. We have used these abbreviations for identifying similar terms across languages since every single abbreviation is used in such a way as to denote those terms that roughly correspond to the same region of the color spectrum. We shall call this data WCS_1.

(ii) In this experiment, the stimulus array was shown as before and the speakers were asked to indicate the best example(s) from the array for every color term collected from the first experiment outlined in (i). We shall call this data WCS_2.

2.1. *Frequency statistics and markedness hierarchy*

Markedness is a classical concept in linguistics where a "marked" form is a non-basic and less natural form while an "unmarked" form is a basic/default form. This concept initially developed from phonology (see [5, 28] for references) and was later extended to all other branches of linguistics including morphology, syntax and semantics. A typical example from phonology is as follows: if the phoneme /g/ is present in a language then the phoneme /k/ is almost surely present in the language but not vice versa. In other words, /k/ [voiceless, velar, plosive] is a less marked phoneme than /g/ [voiced, velar, plosive]. The psycholinguistic reason for this is that the articulatory effort required for voicing a velar phoneme (i.e. the case of

/g/) is much higher in comparison to that required if the phoneme is devoiced (i.e. the case of /k/) [4, 6].

Now coming back to the color problem. A similar hierarchy has been noted by Berlin and Kay [3] showing that if a linguistic society has two color names then it corresponds to "bright" and "dark" while if it has three then the third one is always red. Additional names get added in a fixed order as a language evolves: first "green" and/or "yellow" and then blue. Once again, the principle of markedness applies here: if "green" is present in a language then "red" is almost surely present in it but not vice versa.

A widely accepted method among linguists to quantify markedness is through the statistical frequency of occurrence of the terms across the languages. In the following, we study this cross-linguistic frequency distribution of the unique color terms[a] documented in the WCS. In particular, we define the cross-linguistic frequency as the total number of times a particular term has been used to name different color chips for all the speakers across all the languages. Figure 1 shows the rank versus frequency distribution. Clearly, one can observe that there are a few terms with a very high frequency that in principle correspond to the names that are "cross-linguistically" most basic followed by the rest of the low frequency color words. In the inset we plot the number of unique color terms present in a language (color inventory size) for all the 110 languages documented in WCS. Note that while most of the languages have around 9–10 color words, there are languages that have as low as 3 unique terms (Yacouba) and as high as 79 unique words (Mampruli).

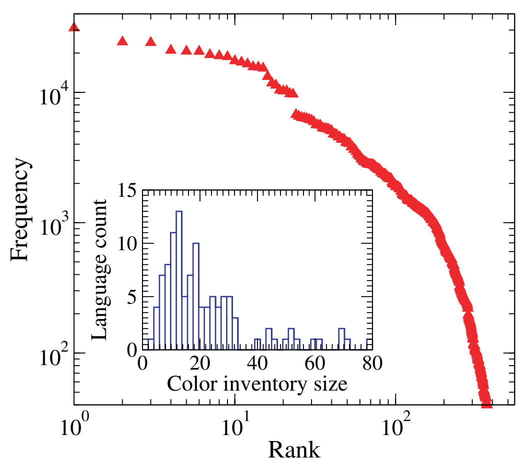


Fig. 1. Cross-linguistic rank-frequency distribution of the terms. The inset shows the distribution of color inventory sizes for the 110 languages of WCS. We use the data obtained from WCS_1 for producing these results.

[a]In this case and in all the statistical analysis that follow, we exclusively refer to the unique term abbreviations found in WCS_1.

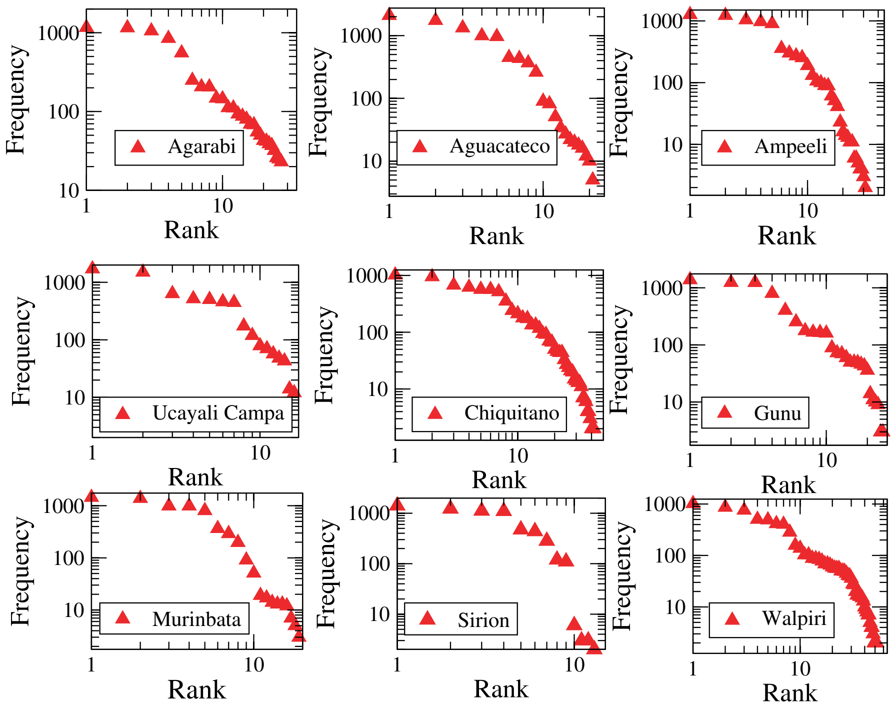


Fig. 2. Rank versus frequency of the color terms within a language for nine different languages. We use the data obtained from WCS_1 for producing these results.

One can further study the frequency of occurrence of a particular term within a language. For each language, we define this intra-linguistic frequency for a specific term as the total number of times this term was used by the different speakers of the considered language to name the different chips. In Fig. 2, we report the rank-frequency distribution of the terms for nine different languages. Note that these results are representative and all the other languages behave similarly. The most striking feature for these plots is that there are a few terms with a very high frequency (corresponding to the basic color names), subsequently, followed by the rest of the very low frequency terms as has been already observed in case of the cross-linguistic frequency distribution in Fig. 1.

In the following section, we take a further step and analyze the overall agreement among the speakers in relation to the use of a term by defining suitable statistical measures and, thereby, empirically reproduce the exact hierarchy as has been noted in [3].

2.2. *Agreement among the speakers*

Here we shall attempt to measure the agreement of the speakers of a language in naming a color chip using the color terms. In particular, we compute the average similarity of term usage across the speakers for each term in a language which, in a way, defines the agreement among them. The average similarity is calculated as follows.

2.2.1. *Similarity measures*

Let us consider a particular term t for a specific language l. Let us further consider a binary vector with 330 entries each corresponding to the color chips (say $c_1, c_2, \ldots, c_{330}$) of the Munsell chart. For each speaker s in l, we can construct one such binary vector from WCS_1 as follows. If the speaker s uses the term t to name a particular color chip i then the entry $(c_i)_s^t$ of the vector $\mathbf{c}_s^t$ is set to 1 and otherwise it is set to 0. We define the pairwise similarity $((S_{s_1 s_2})^t)$ of the speakers s_1 and s_2 on the term t as

$$(S_{s_1 s_2})^t = \mathbf{c}_{s_1}^t \wedge \mathbf{c}_{s_2}^t = \sum_{i=1}^{330} (c_i)_{s_1}^t \wedge (c_i)_{s_2}^t, \tag{1}$$

where $\wedge$ refers to the binary AND operation. Figure 3 shows a real example taken from WCS_1 illustrating the process of calculating $(S_{s_1 s_2})^t$ for the snippet $c_{101}, c_{102}, \ldots, c_{130}$ of the binary vector. If there are N speakers in l then we define the overall similarity on the term t as the average $S_{s_1 s_2}$ across all the $N(N-1)/2$ pairs of speakers.

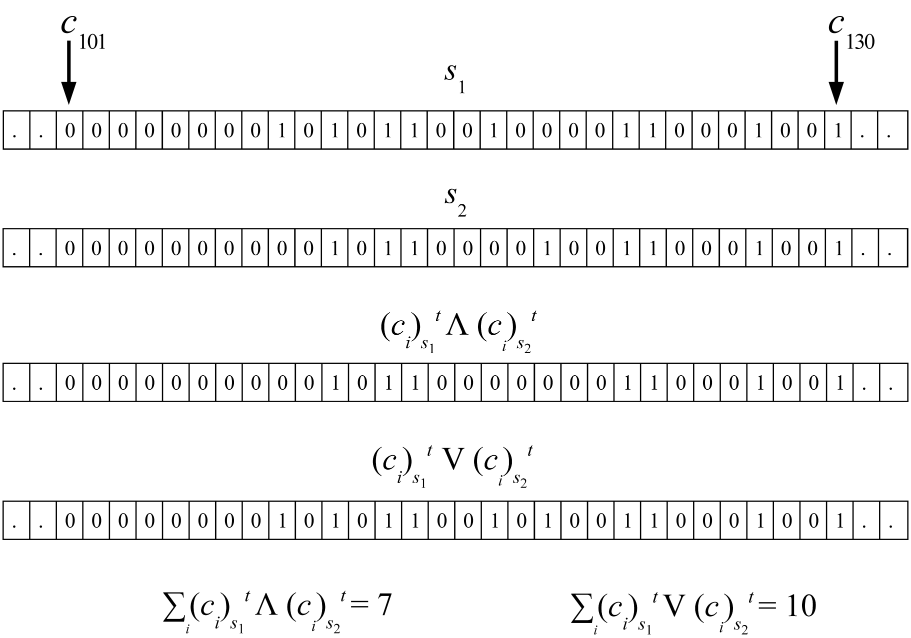


Fig. 3. A real example taken from WCS_1 illustrating the process of calculating $(S_{s_1 s_2})^t$ and $(OR_{s_1 s_2})^t$ for the snippet $c_{101}, c_{102}, \ldots, c_{130}$ of the binary vector. The language considered is Abidji and the term t considered is “lobu” (term abbreviation: LB).

We consider two normalization schemes that rescale the similarity measure within the $[0, 1]$ range. Both schemes are adopted in order to reduce the bias due to different term frequencies.

Scheme I: We normalize the overall similarity by f/N where f is the frequency of usage of t by the speakers in l.

Scheme II: We use here a local normalization for each pair of speakers. In particular, we normalize each pairwise similarity $((S_{s_1 s_2})^t)$ first by $(OR_{s_1 s_2})^t$ where $(OR_{s_1 s_2})^t = \mathbf{c}^t_{s_1} \vee \mathbf{c}^t_{s_2}$ and then compute the overall similarity (see Fig. 3 for an example). Here $\vee$ is the binary OR operation and $(OR_{s_1 s_2})^t$ counts the number of Munsell chips for which at least one of the speakers adopted the term t.

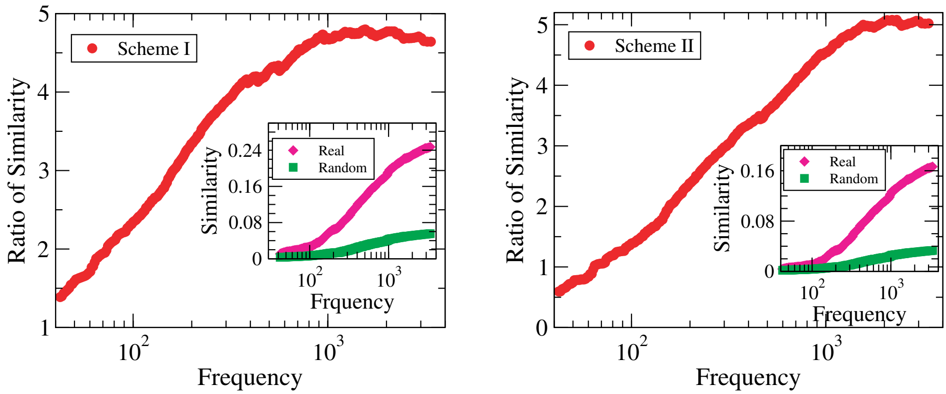
If there are N speakers in l then we define the overall similarity on the term t as the average $S_{s_1 s_2}$ across all the $N(N-1)/2$ pairs of speakers. We compute the overall similarity for each term present in l. The *average cross-linguistic similarity* for a term t is the average overall similarity of t across all the languages in which it is found.

2.2.2. *Control experiment*

As a control experiment, we further compute the similarity as if these terms were randomly used by the speakers of a language to name the different chips as many times as their real frequency of usage in that language. The idea is to replace the values $(c_i)^t_s$ in the binary vector randomly by 0/1, keeping, however, the frequency of usage (f) of t in l unchanged. If the number of speakers speaking language l is N then we can imagine a matrix $M \times N$ constructed in the following way. We randomly choose f entries of the matrix and set their value to 1; the other entries are fixed to 0. In this way, although the frequency of t remains intact, the pairwise similarity among the speakers (i.e. binary AND of the rows of the matrix) and consequently, the overall similarity should change given the data collected in WCS_1 does not have arbitrary origins.

2.2.3. *Average cross-linguistic similarity*

Figures 4(a) and (b) respectively shows for Scheme I and Scheme II, the ratio of the average cross-linguistic similarity of real data (WCS_1) to the randomly generated data (control set) versus the frequency of the term. Clearly, for both the schemes, one observes an increasing ratio with the frequency indicating that in WCS_1 the speakers show a significantly higher agreement for the very frequent terms (i.e. those corresponding to the basic color names) and (almost) no agreement for the low frequency terms. The insets in both the figures separately show the real and the randomly generated similarity values further pointing to the fact that this result is not merely an outcome of the frequency effect, i.e. the higher similarity



(a) (b)

Fig. 4. Average cross-linguistic similarity for the different terms. (a) Ratio of the real to randomly generated average cross-linguistic similarity (Scheme I). (b) Ratio of the real to randomly generated average cross-linguistic similarity (Scheme II). In both cases, the inset shows the real and the random similarity values separately. The results are presented as sliding window averages with a window size of 250. We use the data obtained from WCS_1 for producing these results.

signaled by the frequent terms is not by the virtue of their high frequency of usage because then this effect would have been also reflected in the randomly generated data.

2.2.4. *Correlation among speakers*

Furthermore, along similar lines, one can compute the overall correlation among the speakers for the different terms. For our purpose, we compute the Pearson's correlation coefficient (σ)[b] across the speakers for using a particular term which indicates how the naming pattern of a speaker for a particular term is related to another speaker. In particular, we measure the Pearson's correlation between each pair of binary vectors made of the $(c_i)_s^t$ entires and then average the quantity over all the $N(N-1)/2$ pairs of speakers. The cross-linguistic correlation for t is the average correlation over all languages where t is found. By definition, this value is bounded in the range $[-1, 1]$. Once again we observe that for real data taken from WCS_1, σ is high for the high frequency terms and is close to zero for the low frequency terms (see Fig. 5). If we perform the same control experiment as outlined above and compute the cross-linguistic correlation for the randomly generated data, we observe that it is always close to zero irrespective of the frequency of the terms (see Fig. 5).

[b] If we have n entries for each of the two vectors $\mathbf{X}$ and $\mathbf{Y}$ numbered as $x_1, x_2 \cdots x_n$ and $y_1, y_2 \cdots y_n$ respectively, then the Pearson's correlation is defined as $\sigma = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\sqrt{n\sum y_i^2 - (\sum y_i)^2}}$.

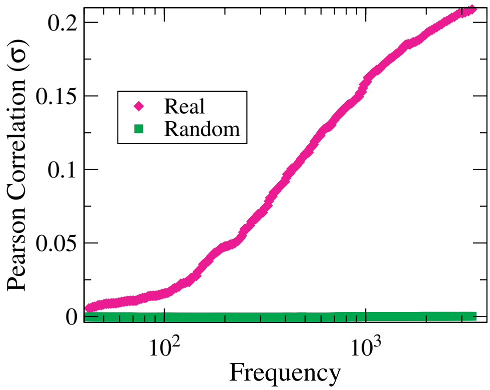


Fig. 5. Cross-linguistic Pearson's correlation for the different terms. The results are presented as sliding window averages with a window size of 250. We use the data obtained from WCS_1 for producing these results.

2.2.5. *Cross-linguistic similarity based inverse rank sum*

As a final step, we investigate how the average cross-linguistic similarity of a term is related to the basic colors. The proportion of the chips on the Munsell chart that correspond to the basic colors (i.e. "black", "white", "red", "green", "yellow", "blue")[c] is shown in Fig. 6 (adapted from [12, 14]). The objective here is to investigate how the terms ranked by their average cross-linguistic similarity (obtained from WCS_1) are related to the basic color names. To this purpose, we rank all the terms across all the languages with their average cross-linguistic similarity (using both Scheme I and Scheme II). Next, we search the most representative color chip for each term in the rank list using the results from WCS_2. We consider the chip that is related to a term the largest number of times (i.e. by maximum number of speakers) as the representative color chip for that term. Thus, we are able to obtain a mapping of each term in the rank list to a color chip. Note that in this way the chip corresponding to a term inherits the rank of the term. Let r^c denote the rank of a particular chip c. Consequently, the inverse rank sum for a basic color B is given by $\sum_{\forall c \in B} \frac{1}{r^c}$ where the chips constituting B on the Munsell chart are adapted from references [12, 14]. A hypothetical example is shown in Fig. 7 to illustrate this calculation. We calculate this quantity for all the basic colors.

The average cross-linguistic similarity based inverse rank sum for the chips corresponding to the basic color names are presented in Fig. 8(a) (Scheme I) and (b) (Scheme II) in comparison to rest of the colors. These results immediately show that although the portion of the total chip area covered by the basic colors is quite small, the majority of the top ranking color terms correspond to them. In fact, if

[c]Since it is hard to differentiate the grayscale monochromatic colors, i.e. the different shades of "black" and "white" from the term abbreviations used in WCS_1, we have kept it as a single entity in the rest of our analysis.

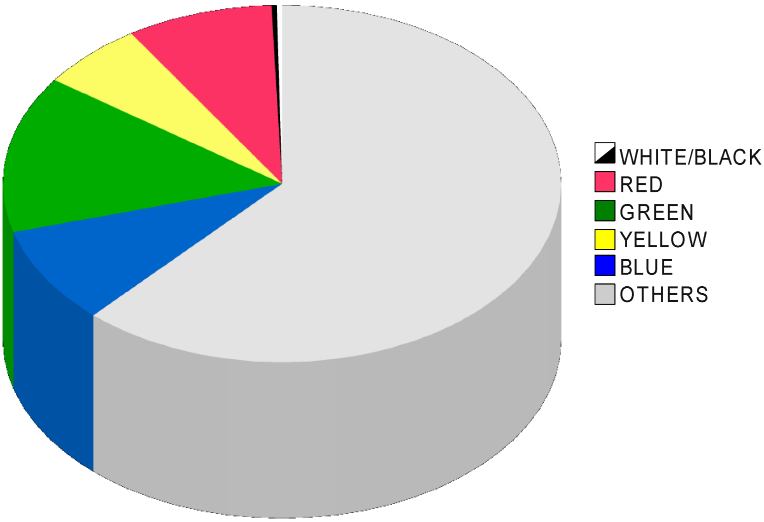


Fig. 6. The proportion of color chips occupied by the terms corresponding to the basic color names. Each color on the pie-graph represents the percentage area it covers on the Munsell chart.

Term	Rank	Chip
YX	1	G17
TSA	2	G2
IA	3	F17
YB	4	G2
ER	5	G1
OX	6	A18
FE	7	C9
TSO	8	G8

Maps to RED on Munsell chart

$$\sum_{c \in \mathrm{RED}} (1/r^c) = 1/2 + 1/4 + 1/5 = .95$$

Fig. 7. A hypothetical example illustrating the process of average cross-linguistic similarity based inverse rank sum calculation. r^c denotes the rank of a particular chip c. The chips "G1" and "G2" actually belong to the "RED" area of the Munsell chart according to [12, 14].

one arranges the color names in a decreasing order of their inverse rank sum, the following is the outcome: $[black, white] < [red] < [green] < [yellow] < [blue]$ which perfectly corresponds to the implicational hierarchy reported in [3]. Hence, it is reasonable to conclude that those terms on which a population tends to agree more correspond to (cross-linguistically) the basic color names which in turn presents a solid empirical definition of the basic color names. It is important to mention here

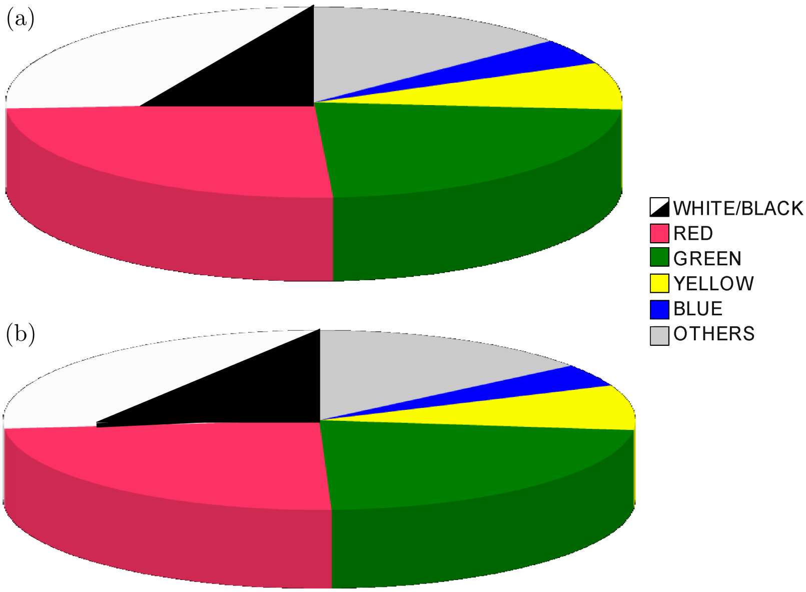


Fig. 8. Average cross-linguistic similarity based inverse rank sum for the chips corresponding to basic colors. Each color on the pie-graph represents the percentage of the total inverse rank sum corresponding to the chip(s) used to name the color. In order to produce these results, the rank list is obtained from WCS_1 and the "color chip-to-rank" correspondence is obtained using WCS_2.

that various exceptions have been reported by the past researchers in connection to this hierarchy. For instance, six languages studied by Berlin and Kay [3] do not conform to this hierarchy. In some cases this is because there is no basic color name that can be consistently identified with certain parts of the visible spectrum. Dowman [9], in this context, notes that the Kuku-Yalanji (Australia) language has no consistent name for green. While some speakers identify either just green or both green and blue with the term *kayal*, most of them do not use it at all for green. In addition, certain other languages studied by Berlin and Kay are found to be in a transition between the evolutionary stages and therefore deviating from the hierarchy mainly since some speakers (especially younger speakers) are found to use more color names than the others (see [9] and the references therein).

3. Discussion

We view the results presented here as signaling an universal tendency for the named color categories across the languages of the world. It is interesting to note how a simple measure of similarity among the individuals implying their agreement neatly separates out the basic color terms from the rest of the color words. The universality of agreement can be — as pointed out by various researchers — an outcome of the human perceptual (e.g. visual) factors that can be assumed to be roughly similar across individuals [11, 23]. In this perspective, an heterogeneity in the way humans perceive and detect colors across the whole visible spectrum can make certain perceptual regions across the color space more favored than others by the individuals, as already hypothesized in [21]. Some of us have been able to show that a purely cultural negotiation process among a population of individuals sharing an elementary perceptual bias, namely the Just Noticeable Difference (JND) [2, 17], is sufficient to trigger the emergence of the universal tendencies observed in human color categorization [1].

In summary, through a rigorous statistical analysis of the World Color Survey database we have shown that the color names for which a larger overall agreement across languages is observed turn out to be the basic ones, providing, for the first time, a statistical definition of the basic color names. Furthermore, if one ranks the basic color names according to the overall agreement across languages, one recovers the color name hierarchy reported in literature [3] as for the order of their emergence in different populations. We believe that the results presented here not only contribute to the ongoing debate related to the universals in color categorization, but also stimulate new efforts towards the growth of statistical approaches in cognitive science. Finally, an important future direction could be to test whether this universal hierarchy can be recovered through a cultural route, for instance, through the model introduced in [20] and further reused in [1].

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