AUGMENTING COLOUR COMMUNICATION IN ENGLISH, GREEK AND THAI

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ABSTRACT

The number of colour names varies across languages. To augment colour communication between speakers of different languages, we need a multilingual method to map how we perceive colours to the words we use to describe them. We evaluate the performance of a supervised colour naming model, Rotated Split Trees (RST), trained by responses from a crowdsourced colour naming experiment in English, Greek and Thai. We assess the generalizability of the model across several colour spaces where it performed best in the CIELUV. A comparison of RST with previous computational colour naming methods using independent psychophysical data in English showed that RST achieves state-of-the-art performance for basic colour categories and identifies five additional categories (n = 16) on the surface of the Munsell system. A demonstration of the performance of RST in segmenting a synthetic image across the colour gamut into colour names in English (n = 30), Greek (n = 28) and Thai (n = 46) further supports earlier findings that speakers can identify 30-50 colour names in their native language.

Keywords: colour, naming, computational, multilingual, communication

INTRODUCTION

Colour naming describes our cognitive capacity to organise millions of discriminable colours into a smaller set of colour categories named, for example, as yellow, turquoise and navy blue. Colour names vary across languages, lexically, in number and in range of reference. To augment colour communication within and across different languages, it is necessary to have a multilingual method for mapping perceptual to cognitive aspects of colour. Computational colour naming methods aim to automate the process of classifying colours to colour names that are meaningful to speakers of various languages across the colour gamut. For example, given the numerical coordinates of a sample in some colour space, what is the best name to describe it in different languages?

Previous efforts [1-7] have predominantly focused on a limited set of 11 basic colour terms (BCTs)[8]. But we [9, 10], and others [11, 12], have shown that BCTs can neither capture the full range of visible colours, nor represent the extensive colour lexicons used by native speakers. In this study, we evaluate a recent supervised machine learning method, namely Random Split Trees (RST) [13], in various colour spaces that not only identifies the basic colours but also captures subtleties of colour nomenclature in wide cultural use in English, Greek and Thai. Our goal is to augment colour communication between speakers of different languages.

METHODOLOGY

In the collection of our behavioural data, we extend previous cross-cultural studies which used only the most saturated colour samples by also sampling the interior of the colour solid. A further methodological improvement includes the departure from usual methods which would use a small number of observers and/or the use of only a restricted set of basic colour terms. Instead, thousands of volunteers from linguistically and demographically diverse populations freely named a large number of colours online (available at: https://colournaming.org). Test stimuli were 2 degree uniformly coloured discs with a black outline of 1 pixel, presented against a neutral grey background. The stimuli consisted of 589 simulated samples approximately uniformly distributed in the Munsell Renotation Data and restricted in the sRGB gamut, plus 11 achromatic samples [14].

We trained RST by 10,000 responses in the crowdsourcing colour naming experiment from 500 participants in English, 10,000 responses from 500 participants in Greek and 5,000 from 250 participants in Thai. RST ensembles a set of random binary decision trees where each tree grows using the full training dataset and splits nodes at random. Tree-based ensembles are essentially a set of hyper-rectangles that can be sensitive to rotations when partitioning the decision space; therefore, prior to any splitting, we randomly rotate the representation space to further induce diversity within the constructed forest and to improve accuracy at determining the form of colour categories in a three-dimensional space.

RESULT AND DISCUSSION

EVALUATION OF COLOUR SPACES

To investigate whether the choice of colour space influences the results of RST, we compared the performance of the model using Leave-One-Out and Leave-Planes-Out cross-validations in RGB-linear, CIE XYZ 1931, CIELAB, CIELUV and CIECAM02-UCS, assuming the sRGB viewing conditions. In the Leave-One-Out mode, we exclude a test chip from the training data and predict its histogram of colour names from the trained model. In the Leave-Planes-Out mode, we exclude the test chip and all the chips with the same, chroma, or lightness or hue dimensions. Each colour space was scored by RMS of Bhattacharyya distances between observed and predicted histograms of colour naming responses shown in Table 1.

Table 1: Comparison of colour spaces for classification in colour names using RST.

Colour Spaces	Leave-One-Out	Leave-Planes-Out
RGB (linear)	0.99	1.03
sRGB	0.99	1.03
$CIEXYZ_{1931}$	0.97	1.14
$CAM02UCS_{sRGB}$	0.95	1.02
$CIELAB_{D65}$	0.92	0.97
$CIELUV_{D65}$	0.91	0.96

Overall, the predictions of the RST algorithm were better in the approximately perceptually uniform colour spaces (CIELAB, CIELUV, CAM02-UCS) than in the non-uniform (RGB, sRGB, CIE XYZ 1931) spaces. The best colour space in terms of accuracy of predictions in both cross-validation modes was CIELUV in agreement with the reports of a recent study on colour clustering [15], although CIELUV’s advantage was slight.

COMPARISON TO EARLIER COMPUTATIONAL COLOUR NAMING MODELS

To compare the performance of RST against previous colour naming models based on the monolexemic psychophysical data of Sturges and Whitfield [16] in British English, we first followed the approach described by Guest & Laar [17] and restricted the responses to their last word resulting in 320 distinct colour terms instead of just the eleven terms of previous colour naming models. We trained the RST with these monolexemic responses and inferred their histograms for the 330 patches of the Munsell array [8] in CIELUV.

In Figure 1, we show the segmentation of the simulated Munsell array by RST against Sturges & Whitfield's distributions of BCTs drawn with black boxes (*n* = 111 chips). The RST model assigned the 330 chips to 16 colour terms: the 11 BCTs with perfect accuracy, as well as additional terms like turquoise, lilac, maroon, peach, mauve, and teal.

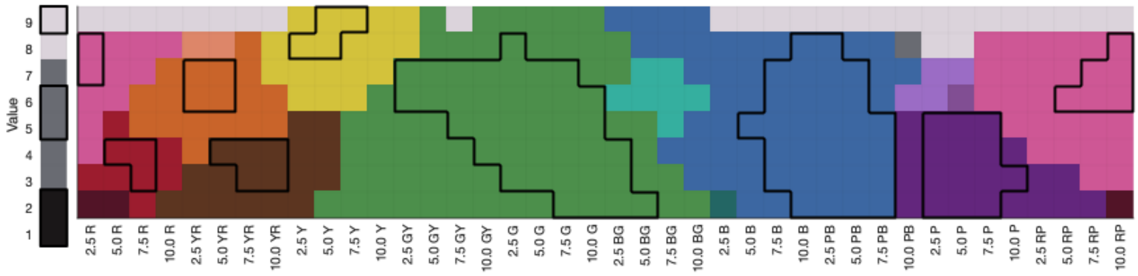

Figure 1. Segmentation of simulated Munsell array into 16 monolexemic colour terms by RST model. Coordinates of their centroids were used to colour each name category. Sturges & Whitfield's mapping of BCTs in British English are drawn with black boxes.

In Table 2., we show the comparison of the performance of the RST model against previous colour naming models of Lammens's Gaussian model (LGM) [3]; MacLaury's English Speaker (MES)[4]; Benavente and Vanrell's Triple Sigmoid model (TSM)[1]; Seaborn's fuzzy k-means model (SFKM) [6]; Benavente et al's Triple Sigmoid- Eliptic Sigmoid model (TSMES) [2]; van de Weijer et al's Probabilistic Latent Semantic Analysis (PLSA)[7]; Parraga & Akbarinia's Neural Isoresponsive Colour Ellipsoids model (NICE) [5]; and Mylonas & MacDonald's Maximum a Posteriori (MAP)[9]. RST achieved the same performance as other state-of-the-art colour naming models (SFKM, TSMES, and NICE), with 100% accuracy for 111 coincidences based on Sturges & Whitfield's results for the 11 basic colour categories. Additionally, RST identified five terms on the Munsell array.

Table 2. Comparison of colour naming models on the Munsell array (n=330 chips) against Sturges & Whitfield (1995) results. The data for LGM, MES, TSM, SFKM, TSEM, PLSA and NICE was obtained from Table 4 in Parrage & Akbarinia (2016).

Models	Coincidences	Errors	%
LGM	92	19	17
MES	107	4	4
TSM	108	3	3
SFKM	111	0	0
TSEM	111	0	0
PLSA	109	2	2
NICE	111	0	0
MAP	110	1	1
RST	111	0	0

COMPUTATIONAL COLOUR NAMING IN ENGLISH, GREEK AND THAI

To automate the colour naming task across different languages, we trained the RST model on unconstrained multilingual datasets in English, Greek, and Thai. Figure 2, shows the performance of the model on segmenting a synthetic image, which includes not only the surface but also the interior of the colour gamut [10], into lexical colour categories.

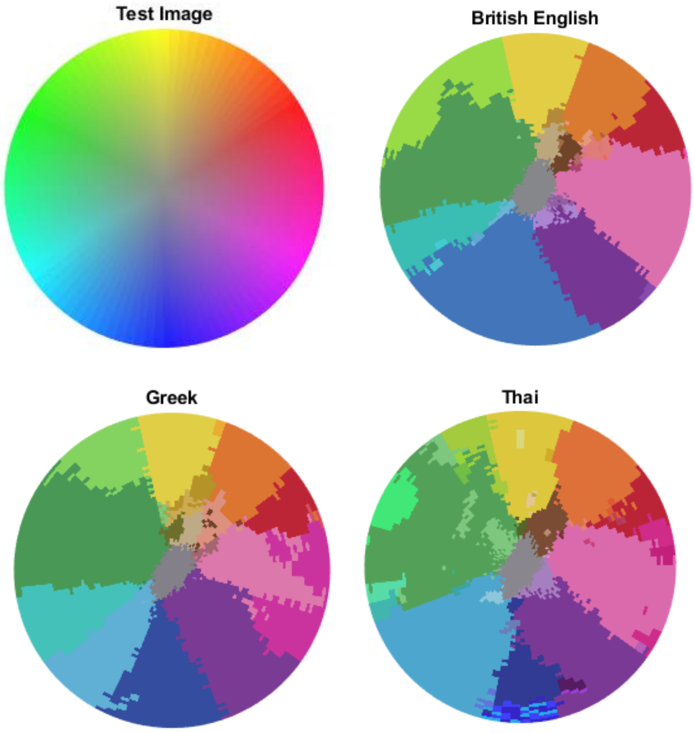

Figure 2. Segmentation of synthetic test image. Test image (1st row – left). Segmentation of test image in British English (1st row – right), Greek (2nd row – left) and Thai (2nd row – right) colour names. Coordinates of their centroids were used to colour each name category.

Learning from British English speakers, the RST algorithm assigned the colour coordinates of the synthetic image into 30 colour names. The seven largest categories were BCTs: *green, blue, grey, pink, purple, yellow* and *orange*. *Red* and *brown* were the 10th and 13th largest categories. *Turquoise* (8th) and *lime green* (9th) were the non-basics with the largest coverage in the test image with *lilac* (11th) and *beige* (12th) found also to cover regions larger than *brown*. *Red* was restricted to the most saturated colours with *salmon*, *peach*, *pink* and *orange* covering the pale region of the same hue angles. *Turquoise* was assigned to pixels all the way from the neutral axis to the limit of the gamut while *lilac* was restricted to the pale regions of *purple*.

With data sourced from Greek speakers, RST identified 28 lexical colour categories in the test image. The five largest categories were the BCTs *green* (*prasino*), *purple* (*mov*), *grey* (*gri*), *blue* (*ble*) and *pink* (*roz*). *Yellow* (*kitrino*) was the 8th, *orange* (*portokali*) was the 10th, *red* (*kokkino*) was the 12th and *brown* (*kafe*) was the 19th largest categories. *Sky blue* (*galazio*), the proposed second blue basic category in Greek, was the 6th largest category covering regions from the neutral axis to the limits of the gamut. Similarly, turquoise (*tirkuaz*) was the 7th most common category. *Lime green* (*lahani*) and *fuchsia* (*fouxia*) were also very popular categories followed by *beige* (*bez*), *salmon* (*somon*) and *olive* (*ladi*). *Lilac* (*lila*) was assigned to >1% of pixels.

Learning colour names from Thai speakers, the RST algorithm identified 46 colour names in the synthetic image. Again, the seven largest categories were the BCTs *green* (*khiaw*), *grey* (*thaw*), *sky blue* (*fa*), *pink* (*chompu*), *purple* (*muang*), *yellow* (*leaung*) and *orange* (*som*). *Brown* (*namtan*) and *red* (*dang*) were the 10th and 12th largest categories. The proposed second basic blue (*namngen*) was the 9th most common category. The largest non-basics were *light green* (*khiawon*) and *light purple* (*muangon*). Compared to all other languages, the *turquoise* category in Thai (*faomkhiaw*) was assigned to a much smaller number of pixels (<1%).

Overall, our results reinforce previous findings that the colour space can be segmented into 30-50 colour categories [10-12]. The large discrepancy in the number of identified colour categories between Thai (n = 46) and both English (n = 30) and Greek (n = 28) is likely due to the more frequent use of modifiers reported in Thai [18]. A more recent study [19] also found that Thai speakers use 20 highly frequent monolexemic colour terms to describe the surface of the Munsell system, compared to the 16 terms reported for English in this study.

CONCLUSION

In conclusion, we present a supervised computational colour naming model, namely Random Split Trees, to automate colour naming in English, Greek and Thai. Our tools and data allowed the analysis of colour names both on the surface and within the colour gamut. Our model performs best in CIELUV and achieves the same level of state-of-the-art performance as earlier models, but goes a step further by identifying 5 additional lexical colour categories in English on the surface of the Munsell system. The performance of the model across the colour gamut in English, Greek and Thai aligns with empirical findings of earlier studies showing that native speakers can identify 30-50 colour names without training.

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