Learning Color Names from Real-World Images

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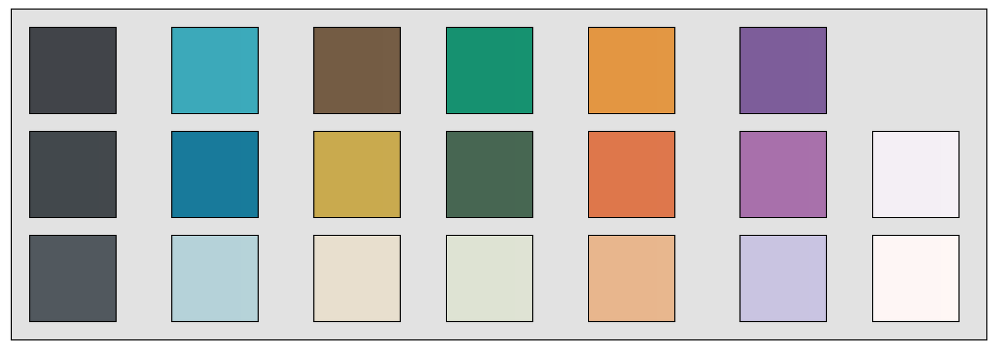
ABSTRACT Within a computer vision context color naming is the action of assigning linguistic color labels to image pixels. In general, research on color naming applies the following paradigm: a collection of color chips is labeled with color names within a well-defined experimental setup by multiple test subjects. The collected data set is subsequently used to label RGB values in real-world images with a color name. In this research we propose to learn color names from real-world images. We avoid test subjects by using Google Image to collect a data set. Due to limitations of Google Image this data set contains a substantial quantity of wrongly labeled data. The color names are learned using a PLSA model adapted to this task. Experimental results show that color names learned from real-world images significantly outperform color names learned from labeled color chips on retrieval and classification.

Research Problem

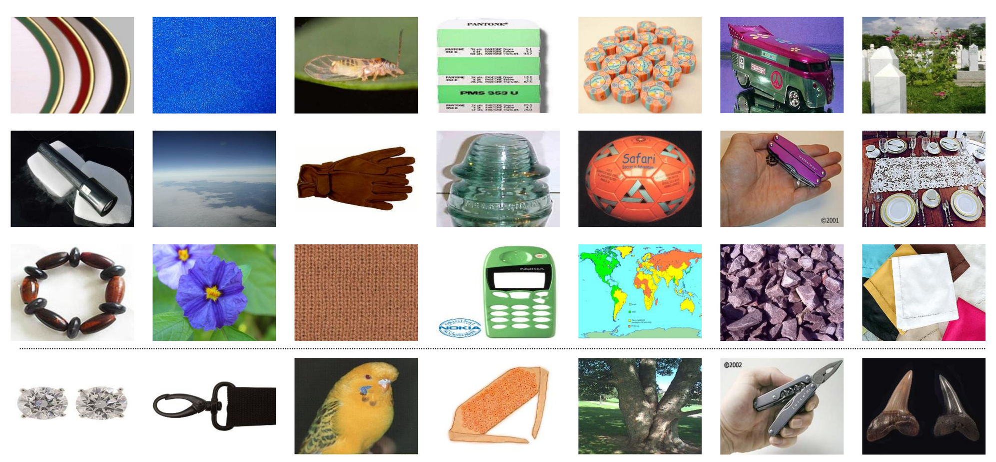
- Is it possible to learn color names from weakly labeled images retrieved from Google Image on the query of ‘color name+”color” ‘, e.g. “red+color”.
- How do learned color names compare to chip-based color names, i.e. the traditional way to compute color names from color chips which are labeled by multiple test subjects in a well-defined experimental setup.

Chip-Based vs. Real-World

Colored Chips named by human test subjects:



“black” “blue” “brown” “green” “orange” “purple” “white”



Images retrieved with Google image:

Basic Color Terms

The English language consists of 11 basic color terms. These basic color terms are defined by the linguistics Berlin and Kay as those color names:

- which are applied to diverse classes of objects.
- whose meaning is not subsumable under one of the other basic color terms.
- which are used consistently and with consensus by most speakers of the language.

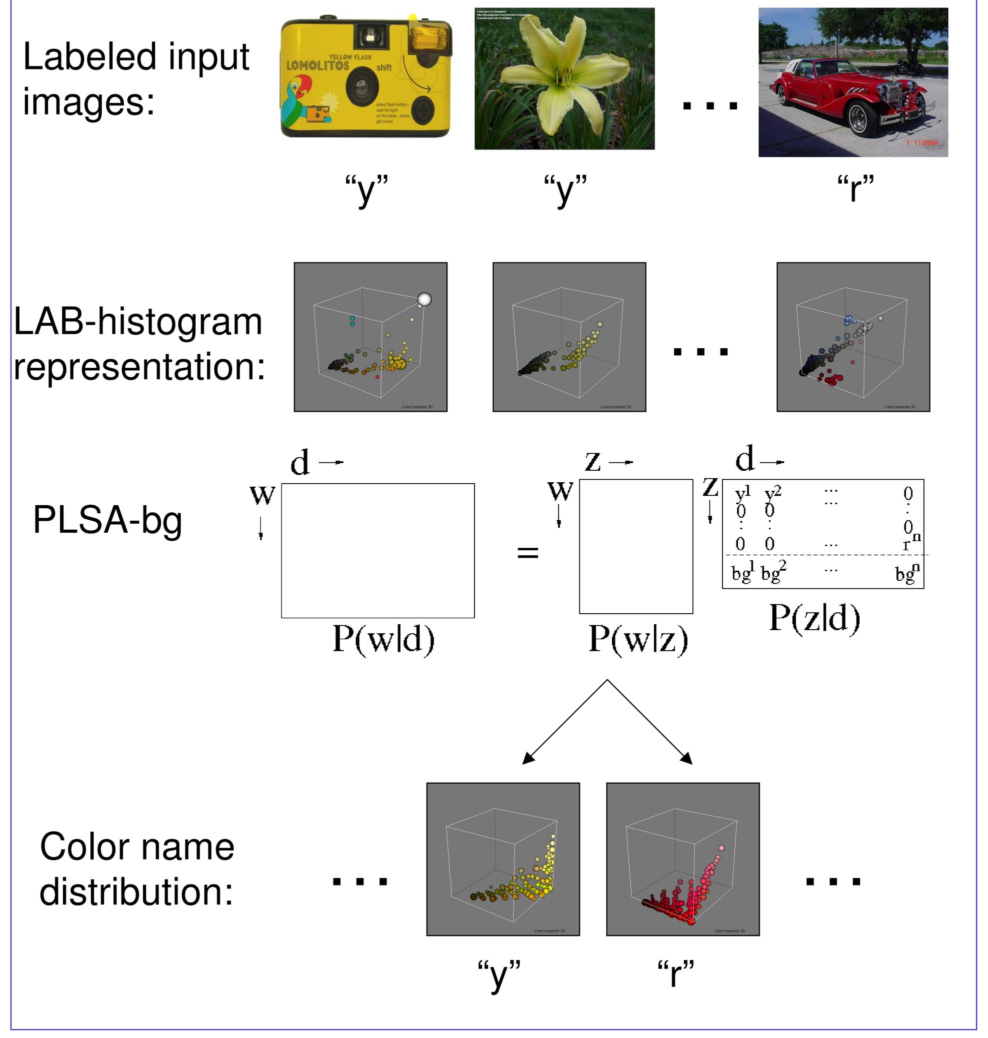
Development color names in languages:

white, black, red, green, yellow, blue, brown, purple, pink, orange, grey

Learning Color Names

Color names are learned with an adapted *Probabilistic Latent Semantic Analysis* (PLSA-bg).

Overview learning approach:



Results

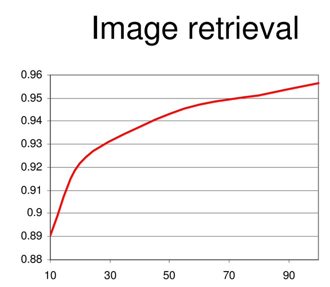
Data Set

A set of 440 images of objects with color names was collected from the **Ebay** auction site. For four categories, cars, dresses, shoes, and pottery.The data is available at:

http://lear.inrialpes.fr/data

Image Retrieval

Image are retrieved (e.g. retrieve ‘brown shoes’) based on the percentage of pixels which has been assigned to the color name.

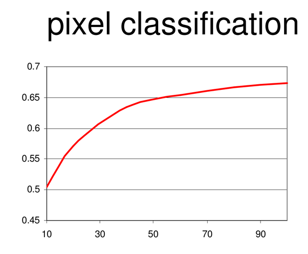


method	train-set	cars	shoes	dresses	pottery	overall
chip-based	cvc	88	93	94	91	92
SVM	Google	91	96	96	91	94
PLSA	Google	89	95	94	92	93
PLSA-bg	Google	92	97	99	95	96
PLSA-bg	Google+Ebay	92	97	100	94	96

retrieval results for ’brown shoes’
ranks:PLSA-bg - chip-based

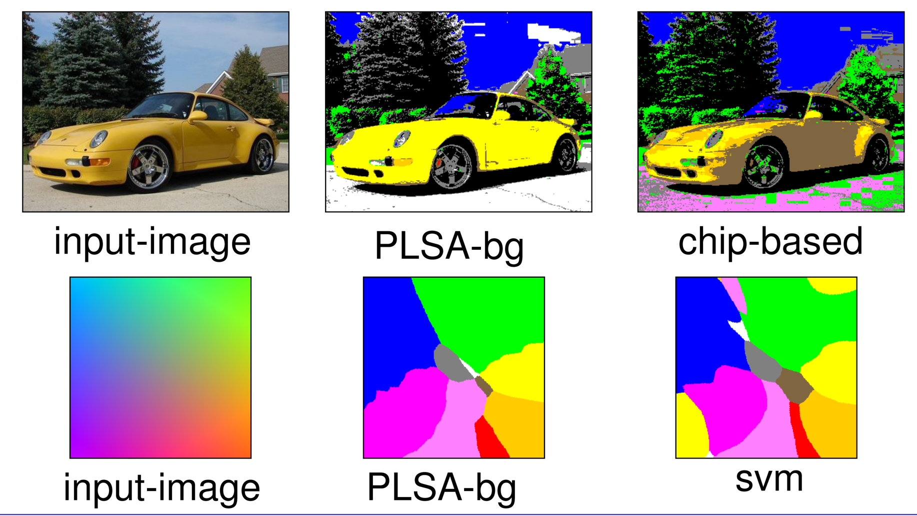
Pixel Classification

Pixels are assigned to their most probable color name.



method	train-set	cars	shoes	dresses	pottery	overall
chip-based	cvc	39	60	62	50	53
SVM	Google	45	61	68	56	62
PLSA	Google	48	69	71	62	63
PLSA-bg	Google	51	71	81	66	67
PLSA-bg	Google+Ebay	53	73	84	71	70

pixel-classification



Flexibility

Learning color names from Google Image search has the additional advantage that the set of basic color terms can easily be varied.

Conclusions

- Results indicate that color names can be learned from weakly labeled images returned from Google Image search.
- Results show that color names returned from Google image outperform color names derived from human-named color chips. Pixel classification results improve by 17 % compared to chip-based color naming.
- We illustrate that color naming based on Google images is flexible in the set of basic color terms.