

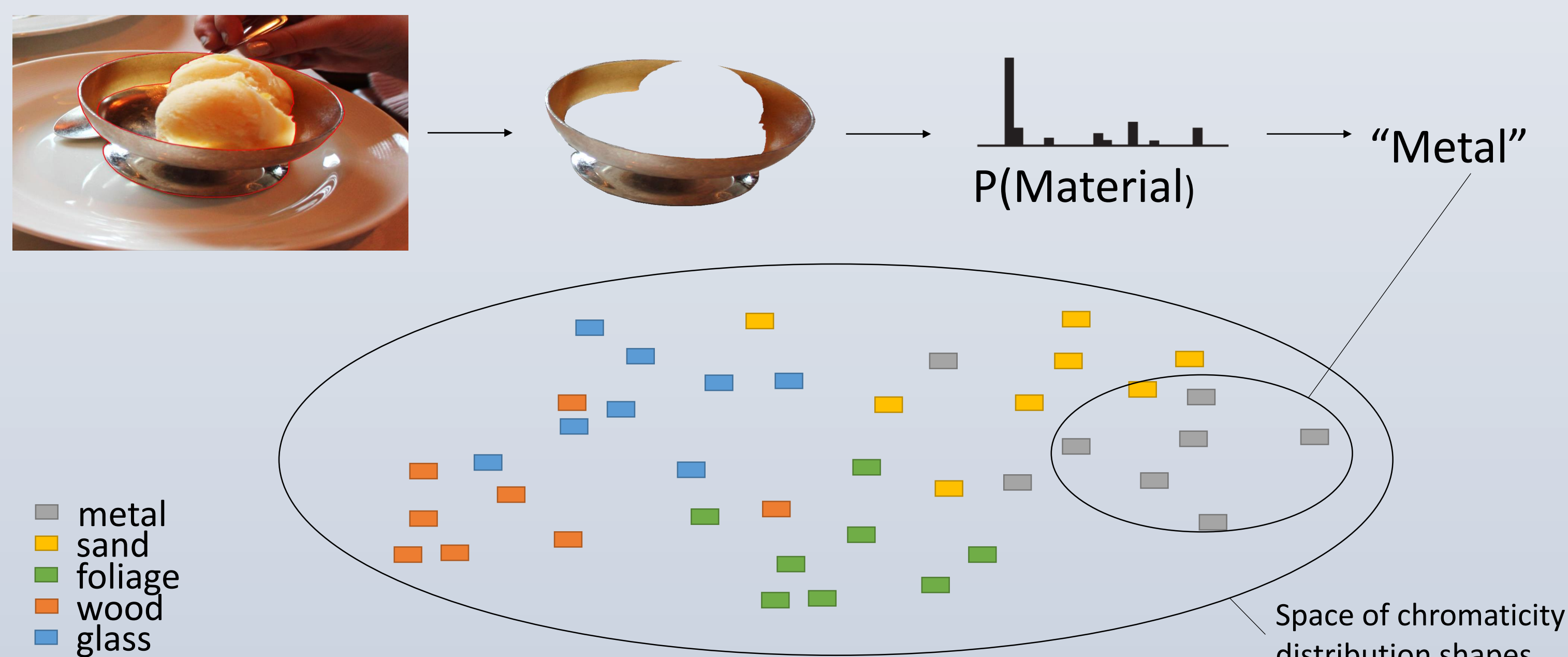
Material-Specific Chromaticity Priors

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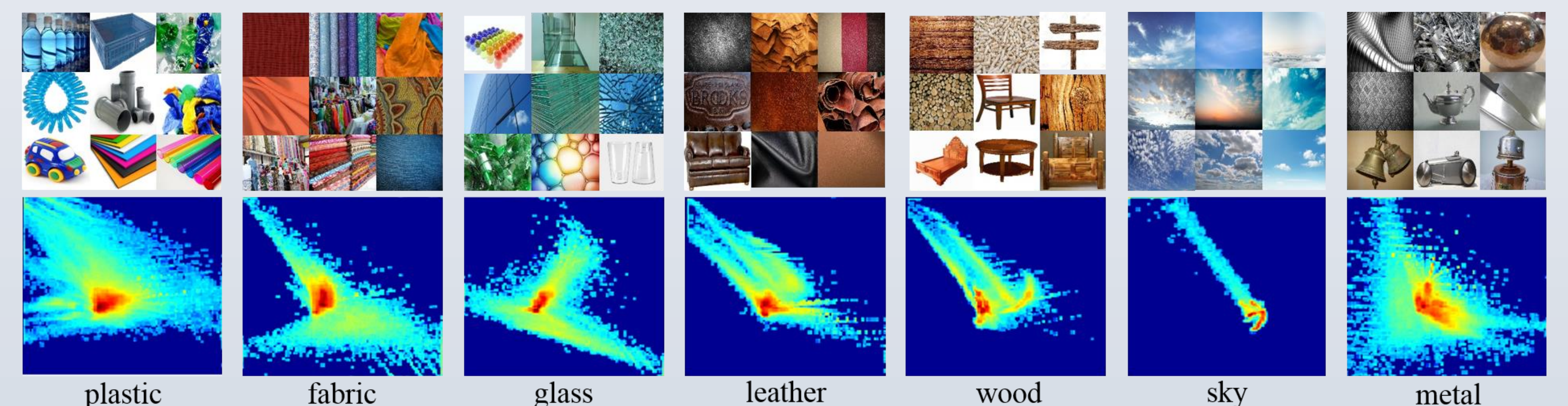
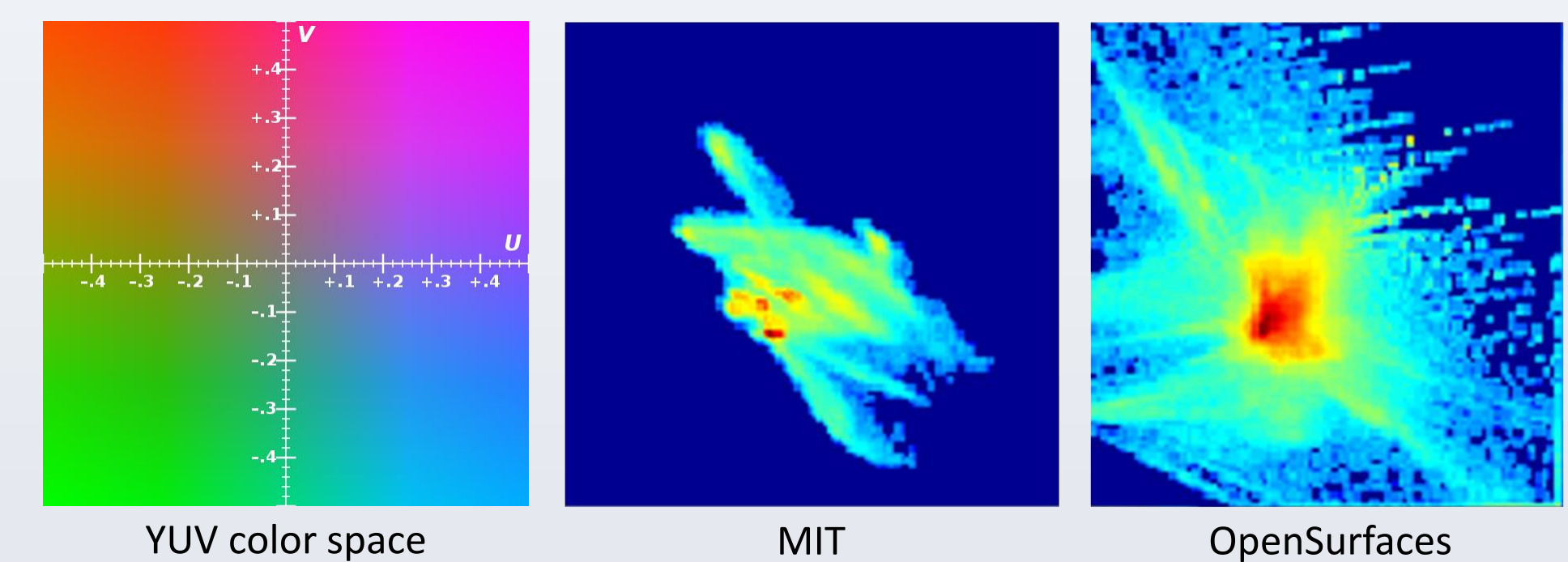
Problem

Recent advances in machine learning have enabled the recognition of high-level categories of materials with a reasonable accuracy. With these techniques, we can construct a per-pixel material labeling from a single image. We observe that groups of high-level material categories have distinct chromaticity distributions. This fact can be used to predict the range of the absolute chromaticity values of objects, provided the material is correctly labeled. We explore whether these constraints are useful in the context of the intrinsic images problem. This poster describes how to leverage material category identification to boost estimation results in state-of-the-art intrinsic images datasets.



Overview

Heatmap plots of chromaticities in YUV color space from random samples of training datasets. Blue represents UV values that are the least frequent, red those that are the most frequent. The OpenSurfaces dataset is a more accurate representation of real-world materials.



Various subgroups of materials have different characteristics. Plastic has a much wider range of chromaticity values than sky. Wood spans a limited range of unsaturated colors, while metal has quite a few outliers due to strong specular reflections.

Contributions

- The observation that areas with different materials form distinct subsets within the space of chromaticity distributions.
- A prior that relates a chromaticity distribution, associated with a specific material category, with possible reflectance values of an object.
- A novel combination of existing techniques: we use material classification to construct a material-specific chromaticity prior. This is useful for intrinsic image decomposition to improve the estimation of reflectance values.

Related work

Recent deep learning techniques can predict material labels at every pixel using a combination of a sliding convolutional neural network and a fully connected conditional random field [1]. They achieve a mean class accuracy of 85.9%. We use the open source framework of Barron et al. [3] to implement our chromaticity prior in an intrinsic image decomposition framework. A lot of work has been put into constructing large and diverse material databases, such as MINC [1] and OpenSurfaces [2]. However, these do not contain ground truth intrinsic image data, which is extremely hard to come by. We evaluate our prior on the only dataset known to us that has ground truth intrinsic decomposition data for real objects [4].

Evaluation

	MSE with prior trained on all materials	MSE with prior trained on specific material	Improvement
Cup2	0.2583	0.2248	14.92%
Deer*	0.2848	0.2848	0.00%
Frog2	0.3547	0.2986	18.77%
Paper2	0.3333	0.3009	10.75%
Pear	0.3188	0.2769	15.11%
Potato	0.2924	0.2625	11.37%
Raccoon	0.2755	0.2425	13.59%
Sun	0.3616	0.3279	10.28%
Teabag1	0.4351	0.3768	15.48%
Squirrel	0.4014	0.3541	13.34%

* material not correctly classified

Results

Results with prior trained on all materials



Results with specialized priors



Input images courtesy of Barron et al. [3]

References

- [1] Sean Bell, Paul Upchurch, Noah Snavely, and Kavita Bala. Material recognition in the wild with the materials in context database. CVPR, 2015.
- [2] Sean Bell, Paul Upchurch, Noah Snavely, and Kavita Bala. OpenSurfaces: A richly annotated catalog of surface appearance. ACM Trans. on Graphics (SIGGRAPH), 32 (4), 2013.
- [3] Jonathan T Barron and Jitendra Malik. Shape, illumination, and reflectance from shading. TPAMI, 2015.
- [4] Roger Grosse, Micah K. Johnson, Edward H. Adelson, and William T. Freeman. Ground-truth dataset and baseline evaluations for intrinsic image algorithms. In ICCV, pages 2335–2342, 2009.