

home 24

ZUHAUSE IST, WAS **DIR** GEFÄLLT.

# Calculating Recommendations Based on Product Images

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# home24 “Zuhause ist, was dir gefällt”



**€117b+**

TAM<sup>1</sup> across  
8 markets

**€276m**

Revenue  
FY2017

**85%**

CAGR revenue  
2010-2017

**c.€350**

High  
AOV<sup>2</sup>

**45%**

Gross margin  
FY2017

**First  
order  
profitability**

**<10%**

Low return  
rates<sup>2</sup>

1. Based on Euromonitor data for home24 markets which includes Germany, France, Italy, the Netherlands, Austria, Belgium, Switzerland and Brazil. 2. Including VAT, for Europe only, as of FY2017.

# home24 “code sweet code”



- 1 100+ in tech department
- 2 8 Teams
- 3 16 in Data Team, 14 nationalities
- 4 Data Team working with Scala, Spark, R, ...

[home24.tech.blog](http://home24.tech.blog)



[home24.de/jobs](http://home24.de/jobs)



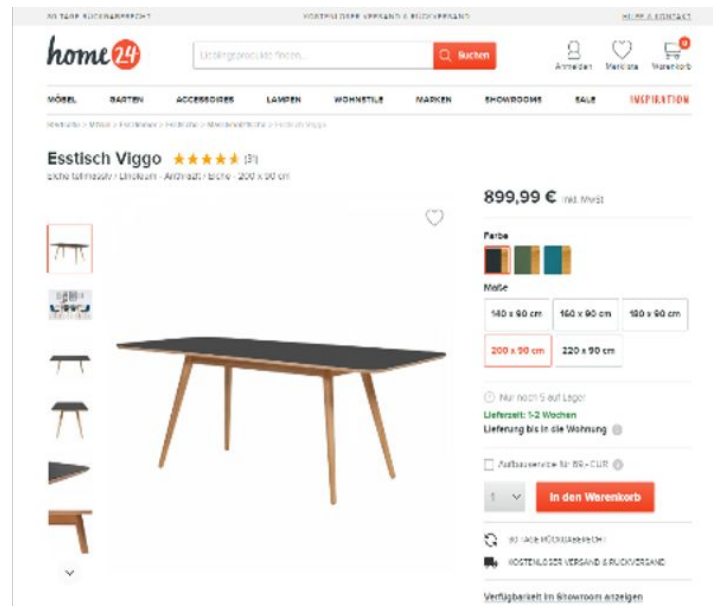
LinkedIn - home24 SE





A modern dining room with a wooden table, white chairs, and a colorful shelving unit. The room is dimly lit, with a blue overlay. The text "How we got the idea to use article images for recommendations" is centered over the image, with a red underline. The background shows a dining table with white chairs, a colorful shelving unit, and framed articles on the wall.

**How we got the idea to use article images for recommendations**



## Best recommender - collaborative filtering

### Advantages:

- Real users shows you exactly what they prefer

### Challenges:

- New products have no user behavior
- Broad assortment of products dilutes collaborative filtering signals

## Improving the system - add attribute-based recommendations

### Advantages:

- Covers all products

### Challenges:

- Let's see...

# Visualising our results

## Attribute-based recommender



Click-through score on recommendations  $\text{score}_A(B) = \frac{\# \text{clicks}_A(B) - \text{expected}_A(B)}{\text{expected}_A(B)}$



# Challenge: Article attributes have limited detail




```
{  
  attributes: {  
    color: "brown",  
    material: "solidwood",  
    ...  
  }  
}
```



```
{  
  attributes: {  
    color: "brown",  
    material: "solidwood",  
    ...  
  }  
}
```

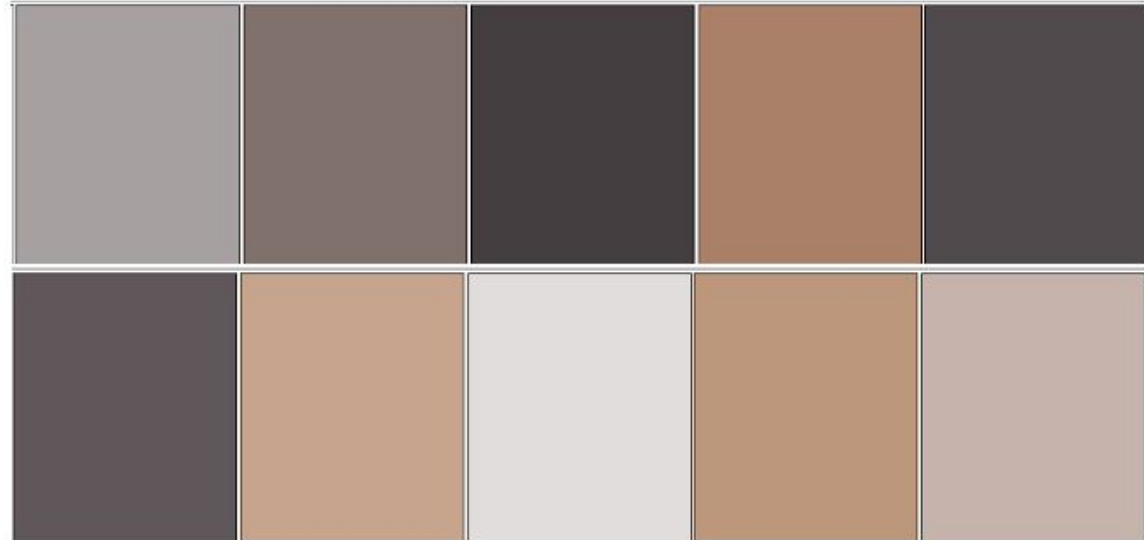


A modern dining room with a wooden table, white chairs, and a colorful shelving unit. The room is dimly lit, with a blue overlay. A floor lamp is visible on the right. The text "Solution: Recommend articles that have similar colors in their images" is overlaid in white, with a red underline.

**Solution: Recommend articles that have similar colors in their images**



## Extracted colors



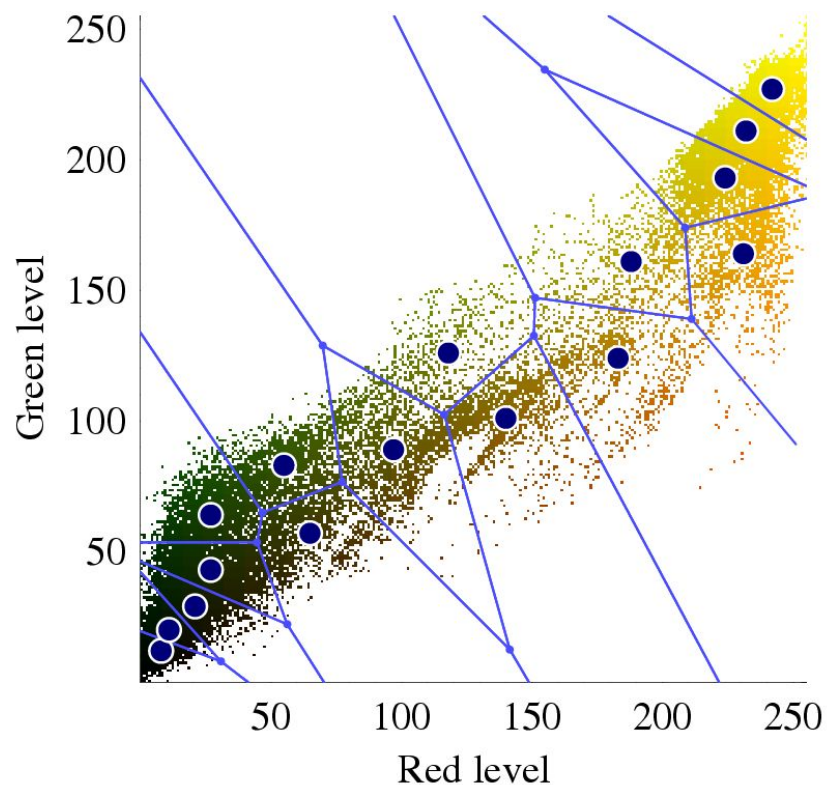
### Extraction process:

- Ignore background pixels
- Cluster remaining pixels to 10 clusters using K-means clustering algorithm, to get a representative sample of colors for each image (color quantization)

# Color quantization



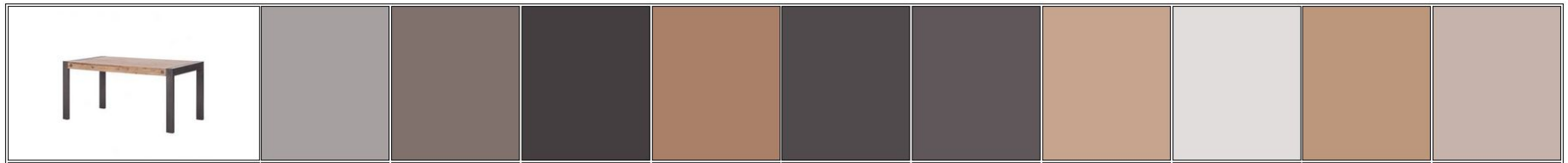
A small photograph that has had its blue channel removed. This means all of its pixel colors lie in a two-dimensional plane in the color cube.



The color space of the photograph to the left, along with a 16-color optimized palette produced by Photoshop. The Voronoi regions of each palette entry are shown.

# Extracted colors

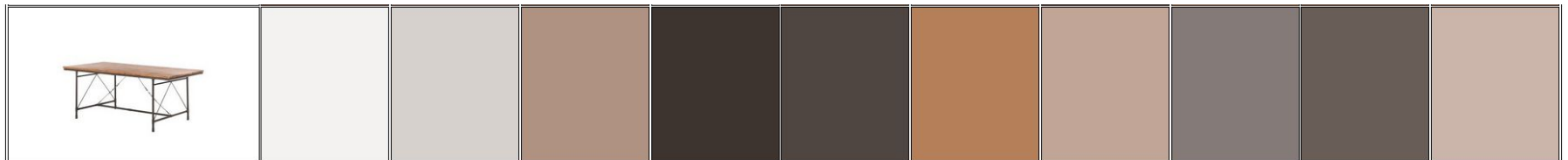
Product that we want recommendations for



Top pick of attribute-based recommender



Most underrated recommendation (based on CTR)



# Calculating the color similarity score



Let  $distance(color_a, color_b)$  be the euclidean distance between the two colors in LAB color space,

and 
$$f(A, B) = \sum_{color_a \in A} \min_{color_b \in B} (distance(color_a, color_b))$$

Then the color similarity score for a pair of products A,B is:

$$score(A, B) = \frac{1}{1 + f(A, B) + f(B, A)}$$



# Final results

## Attribute-based recommender



## + Color Recommender



## = Combined results



# Recognizing clean vs. mood images



## Solution:

Analyse image borders. Standard deviation of color components in RGB  $< 5$  = clean image.

## Dealing with broad assortment of products



### Challenge:

- Calculating color similarity for ALL products of same category is expensive (can be thousands of products, complexity  $O(n^2)$ )

### Our solution:

- Re-using the candidate filtering we have for our attribute-based recommender - locality-sensitive hashing (LSH) based on product attributes

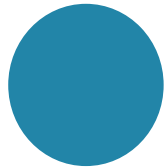
# Locality-sensitive hashing on product attributes

Basic idea: splitting a high-dimensional space to “buckets” based on lower-dimensional projections

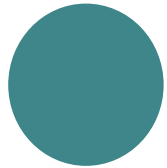
- Products attributes are a high-dimensional space (we consider 14 different attributes)
- LSH hashes the attributes so that similar products map to the same “buckets” with high probability
- This reduces the candidate space from thousands of products to a manageable number



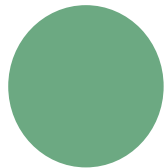
# Results



10% uplift in Click-Through Rate



12% uplift in Click-Through Rate for products with low user behavior



4% conversion rate uplift

# Key Takeaways

- 1 Build tools that let you visualize your results
- 2 Plan to iterate, because you won't get things perfect straight away
- 3 Think about what non-obvious data you have





## ANY QUESTIONS?

Feel free to grab any of us after the talk as well



# Appendix 1 - useful links

**Improving Content-Based Recommendation using Product Images** - Home24 Tech Blog (includes more examples)

<https://home24.tech.blog/2017/05/24/improving-content-based-recommendation-using-product-images/>

**Color quantization**

[https://en.wikipedia.org/wiki/Color\\_quantization](https://en.wikipedia.org/wiki/Color_quantization)

**Color Reduction Using K-Means Clustering**, Mikolov T., 2007 (PDF)

<http://old.cescg.org/CESCG-2007/papers/Brno-Mikolov-Tomas.pdf>

**Locality-sensitive hashing**

[https://en.wikipedia.org/wiki/Locality-sensitive\\_hashing](https://en.wikipedia.org/wiki/Locality-sensitive_hashing)

**LSH.9 Locality-sensitive hashing: how it works**, Victor Lavrenko

<https://www.youtube.com/watch?v=Arni-zkqMBA>