Supplemental Material for Band-Sifting Decomposition for Image Based Material Editing

Contents

1 Comments on Accompanying Video

1.1 Alternative visualization

Each time we show the alternative visualization, we flip back and forth between the original video and the modified video.

1.2 Masks

We have masked out the foreground objects in most of the videos to separate the region of interest where the effects would be applied. On the video of the Asian male we did not use a mask around the face to demonstrate that our band-sifting operators can be used in settings like that, when the main object of interest occupies most of the frames.

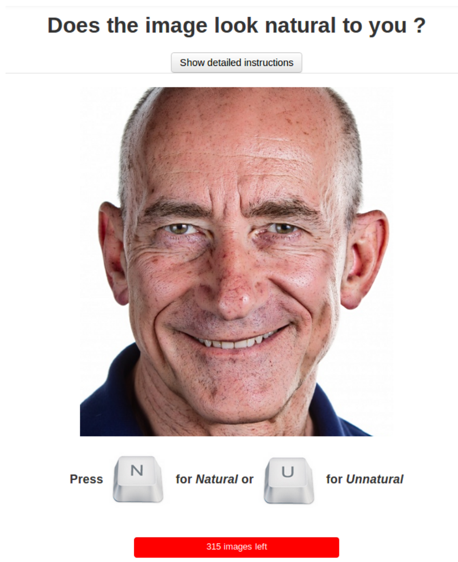
1.3 Over-blurring

On lower resolution videos/images our band-sifting operators that *reduce* high-spatial frequencies can lead to an over-blurred look. We could further post-sharpen results like that to fix this, but we provide all results as generated by our algorithm, aka. we do not do any post-processing.

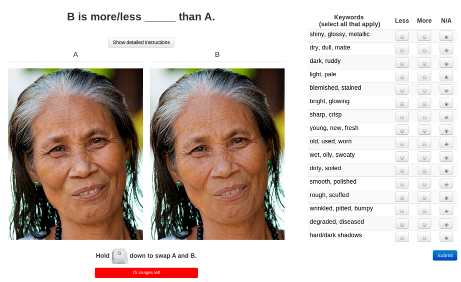
2 Statistical significance formula

To confirm the statistical significance of our second user study results, we assumed a null-hypothesis where for each group of words the users have picked between the three options uniformly at random, i.e. $\frac{1}{3}$ probability for every option. With this settings, the expected mean would be at around 33%. For the average of 30 votes per-category that we got, the standard deviation (in percentage of the votes) would be $\frac{100}{30}\sqrt{30\frac{1}{3}(1-\frac{1}{3})} = 8.6\%$. In order to asses the significance, we measure the distance to the mean in terms of standard deviation steps. Fixing the significance level at $p = 0.1$, it follows that with probability $1 - p = \mathbf{0.9}$, the observations fall in the interval $33\% \pm \mathit{1.64} * 8.6\% = (19\%, 47\%)$. Thus, we can reject the null-hypothesis at a significance level of 0.1 for words that have collected more than **47%** votes. Fixing the significance level at $p = 0.05$, we can reject the null-hypothesis with probability **0.95** for words that have collected more than $33\% + \mathit{1.96} * 8.6\% = 49.8\% \approx$ **50%** votes.

3 Screenshots of Study 1 and Study 2



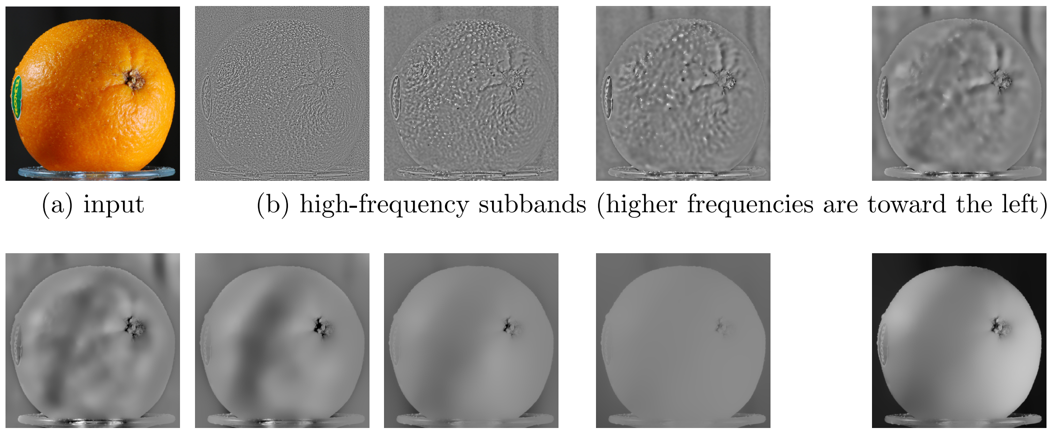
(a) Study 1 interface



(b) Study 2 interface

Figure 1: Web interface for user study 1 and user study 2.

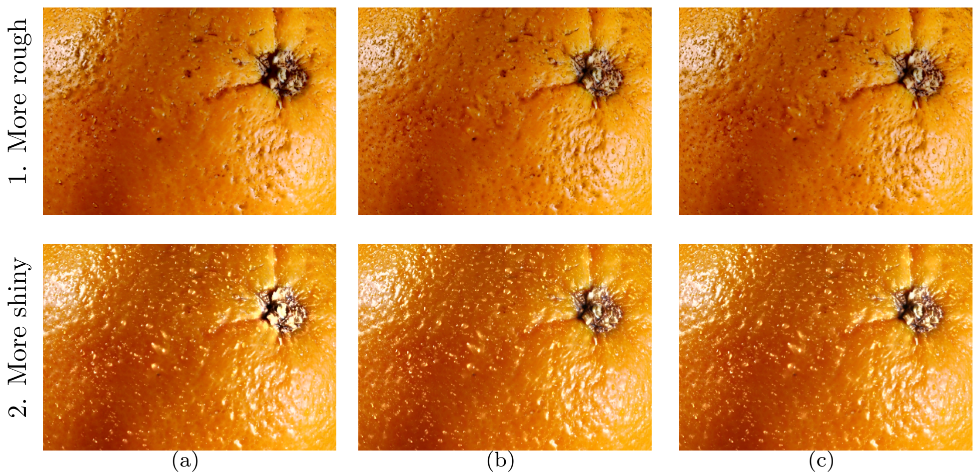
4 Multi-scale decomposition and filter choice



(a) input (b) high-frequency subbands (higher frequencies are toward the left)

(c) low-frequency subbands (lower frequencies are toward the right) (d) low-frequency residual

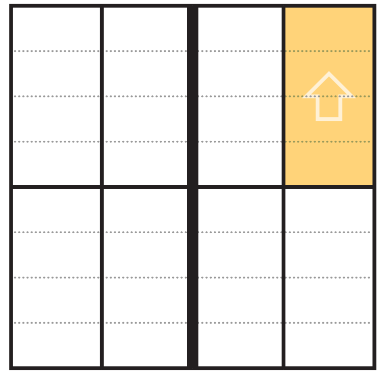
Figure 2: Multiscale decomposition of the luminosity channel of image (a) using the Guided Filter. We set $\sigma_r = 0.1^2$, and we double the spatial extent to build successive levels of the pyramid. By manipulating different subband levels, we are able to capture the multi-scale nature of various features such as gloss, shadows, pores and highlights.



(a) Laplacian pyramid (b) Bilateral Filter pyramid (c) Guided Filter pyramid

Figure 3: Filter choice. Other edge-aware filters can be used to produce similar results. The Laplacian filter, which is non edge-aware, can sometimes be used successfully, as in this example. However it usually starts to show artifacts around edges much quicker than the edge-aware filters we experimented with.

(a) input



(b) our "wet/oily/shiny" effect

(c) using a Laplacian pyramid

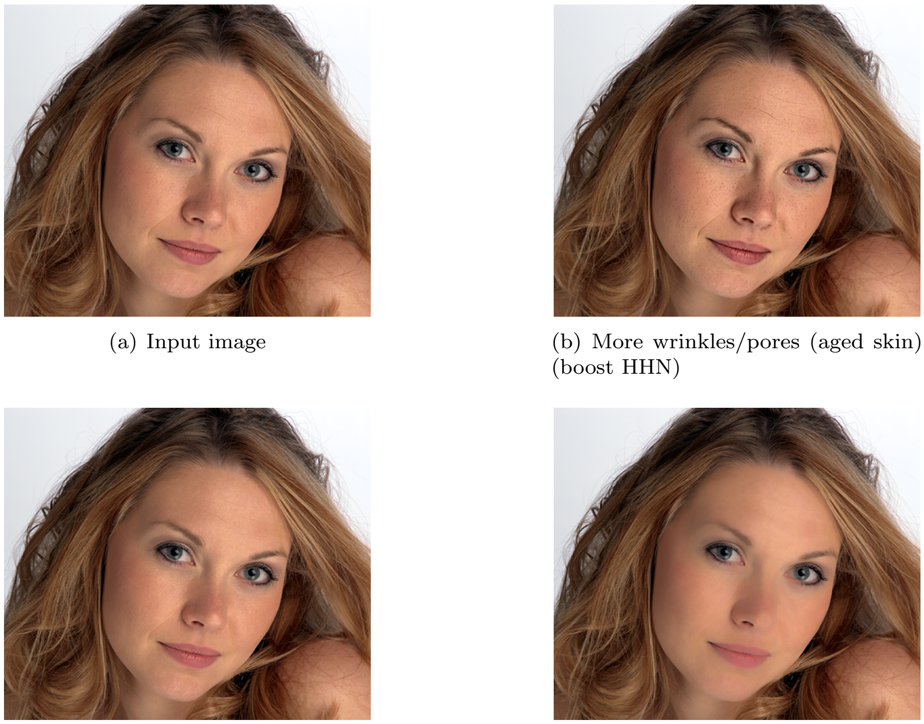
(d) using Bilateral Filtering

(e) using the WLS Filtering

(f) using Guided Filtering

Figure 4: Filter choice. We experimented with pyramid decompositions using different smoothing filters and by tuning their parameters we were able to get roughly similar results. However, in the cases when we manipulate high frequency and high amplitude coefficients, the non-edge aware Laplacian pyramid quickly starts to show artifacts, e.g. around the eyes and the mouth.

5 Evaluation of HHA vs. HHN effects



(a) Input image

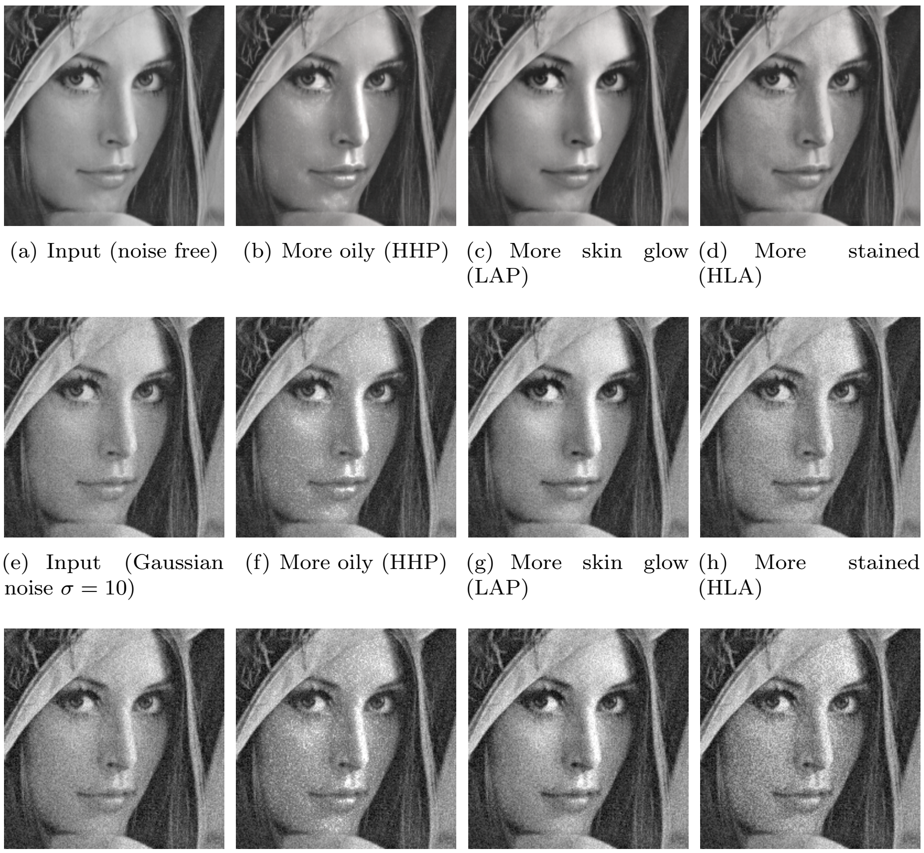
(b) More wrinkles/pores (aged skin) (boost HHN)

(c) Less wrinkles/pores (younger skin) (reduce HHN)

(d) More smooth, but unnatural (reduce HHA)

Figure 5: Showing our “old” (b) and “young” (c) effects, applied to the input image (a). Please zoom on the images to better see the differences . We also demonstrate that by treating the negative and positive coefficients separately we can achieve more natural smoothing of the skin where wrinkles and pores are reduced, but the skin texture is preserved. For comparison, if we simply de-emphasize all the details (d), we would get smooth, but unnatural looking skin. We can also conclude this from the results of our first user study, where for faces users were more willing to accept aggressive smoothing of the negative coefficients, and less aggressive smoothing when both positive and negative were used.

6 Evaluation of the presence of noise and JPEG artifacts



(a) Input (noise free) (b) More oily (HHP) (c) More skin glow (LAP) (d) More stained (HLA)

(e) Input (Gaussian noise $\sigma = 10$) (f) More oily (HHP) (g) More skin glow (LAP) (h) More stained (HLA)

(i) Input (Gaussian noise $\sigma = 15$) (j) More oily (HHP) (k) More skin glow (LAP) (l) More stained (HLA)

Figure 6: The perceptual effects of our band-sifting operators are less convincing in the presence of noise. Further, our HLA operator, that manipulates the high-spatial frequency, low amplitude coefficients is less effective in the presence of strong JPEG artifacts, row 1 column (d).

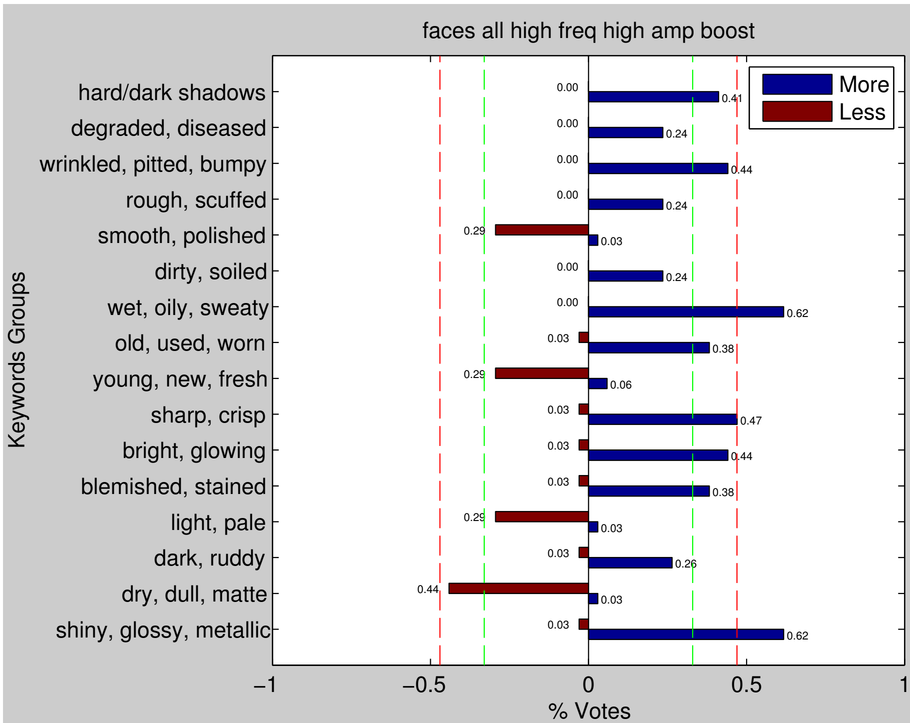
7 Evaluation on a CG image

(a) CG image, alpha = 0.18 (b) CG image, alpha = 0.12 (c) CG image, alpha = 0.06

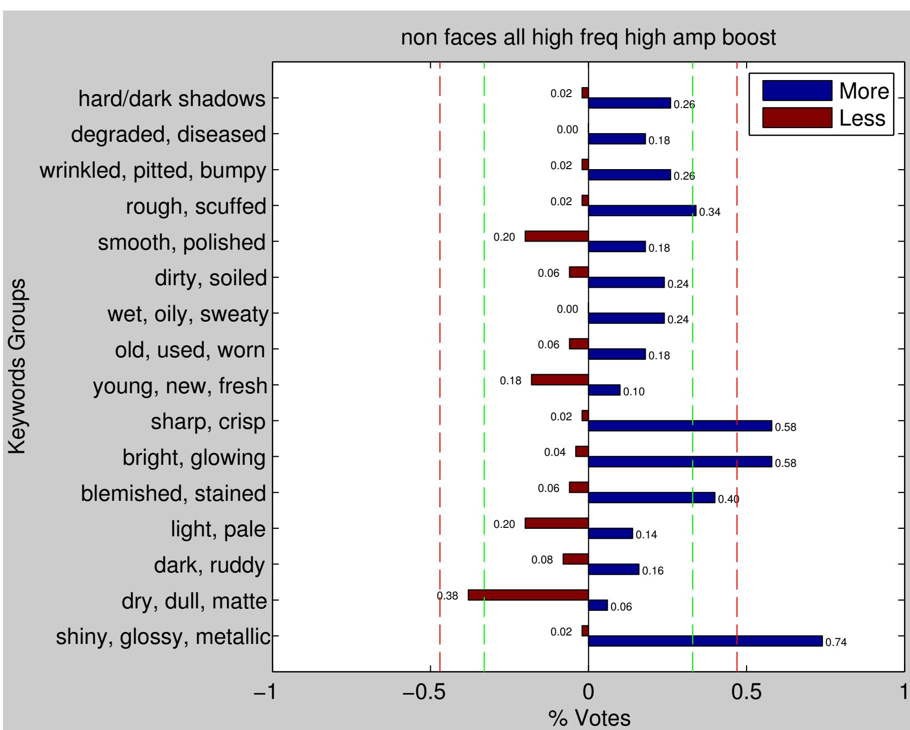
(d) Our result boost 0.18 (e) Our result boost 0.12 (f) Our result reduce 0.06

Figure 7: Result on a photorealistic scanned CG model of a face (courtesy of [Debevec et al.]) with different values for the roughness parameter α. (a), (b) and (c) show physically based rendering of this face with different roughness parameters. In (d) and (e) we show the effect of our “wet/shiny/oily” effect applied to the corresponding images, (a) and (b). This experiment suggests an interesting avenue for future work: try to relate more closely our band-sifting operators to actual material properties, such as the roughness parameter in this case. It also shows that our operators do not hallucinate data: we can make the face looks more shiny, in a natural way, if we have some shininess in the original image.

8 Study 2 “Name the Effects”: votes on all effects

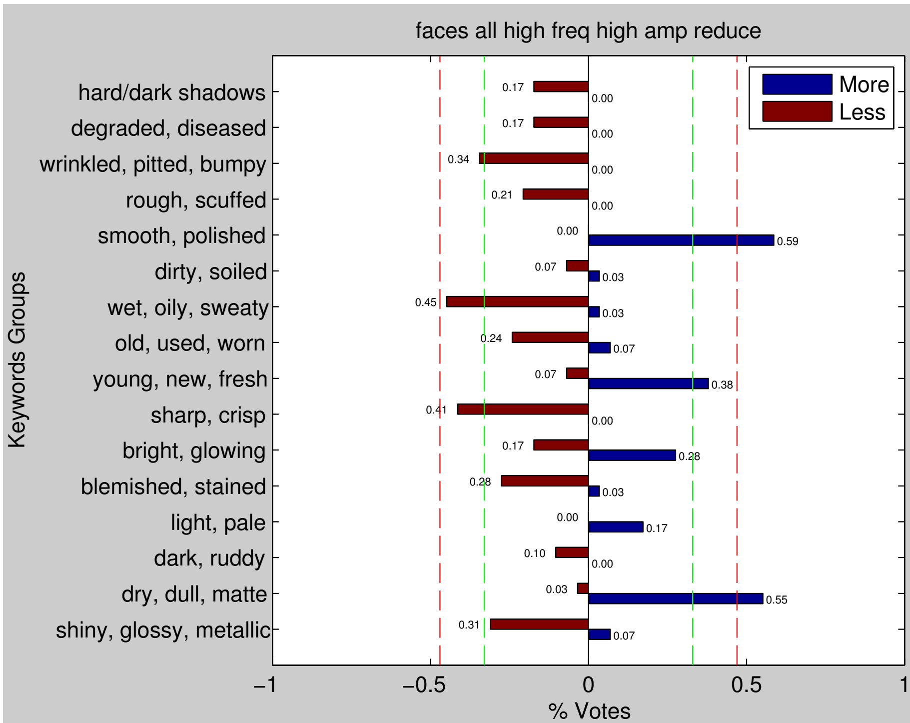


(a) Names for faces

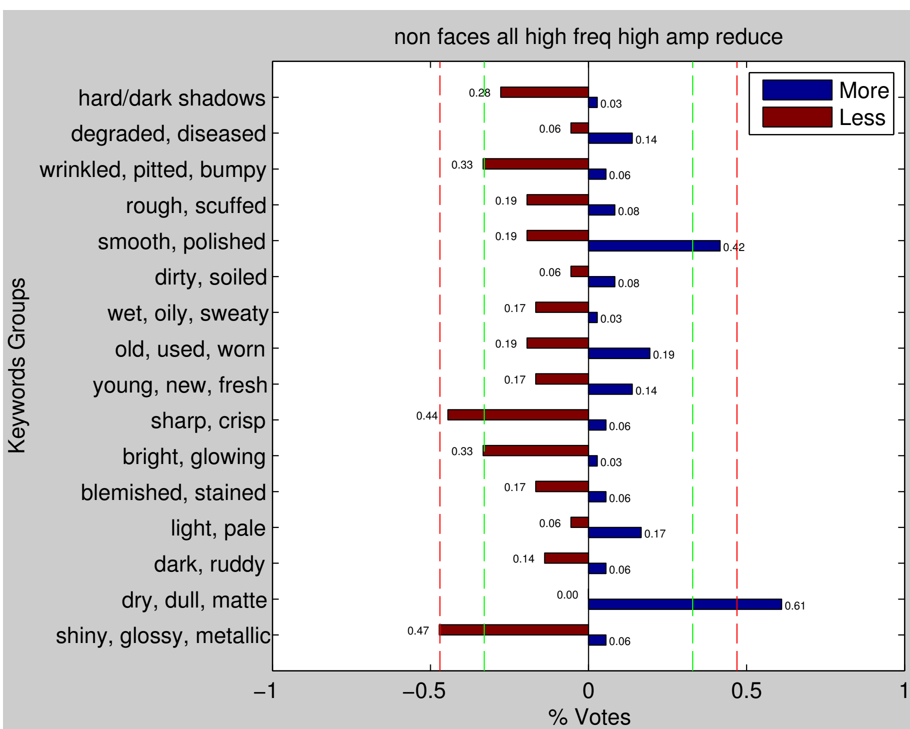


(b) Names for non-face objects

Figure 8: Boost all high-frequency, high-amplitude coefficients (HHA)

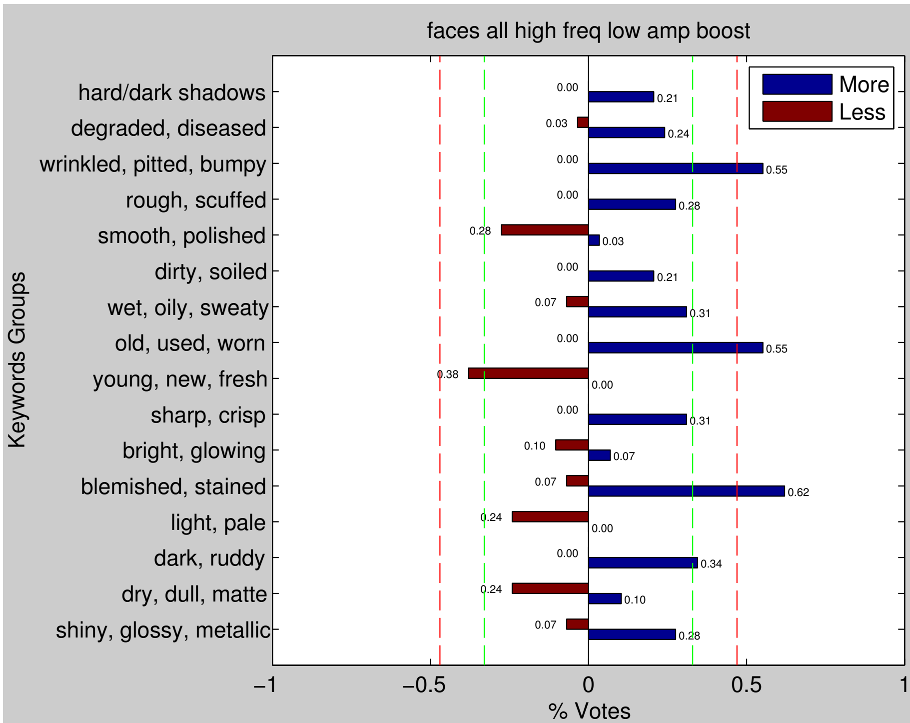


(a) Names for faces

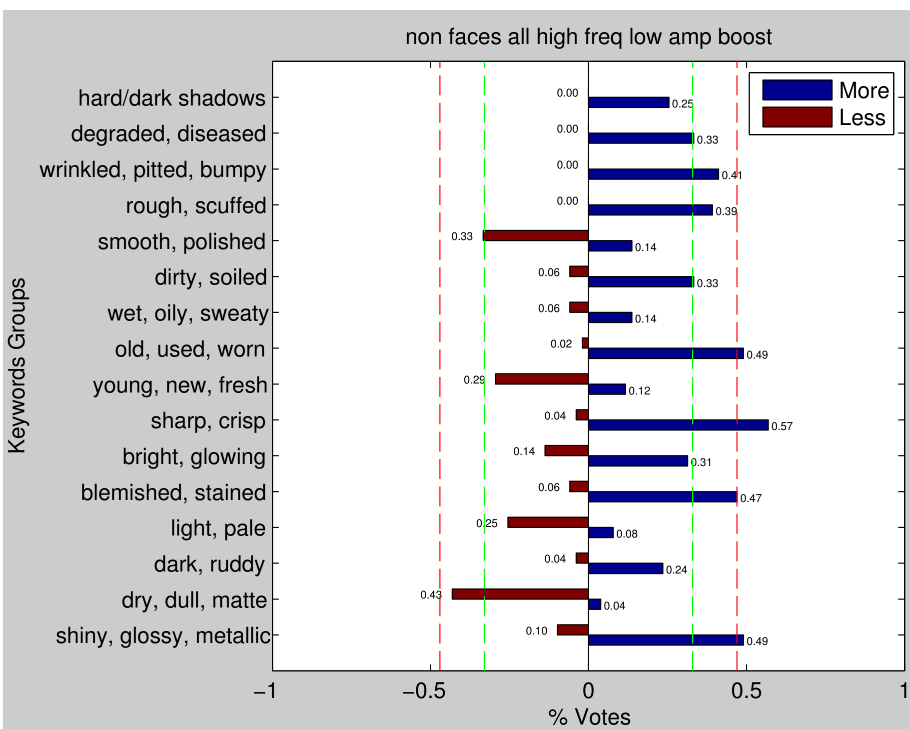


(b) Names for non-face objects

Figure 9: Reduce all high-frequency, high-amplitude coefficients (HHA)

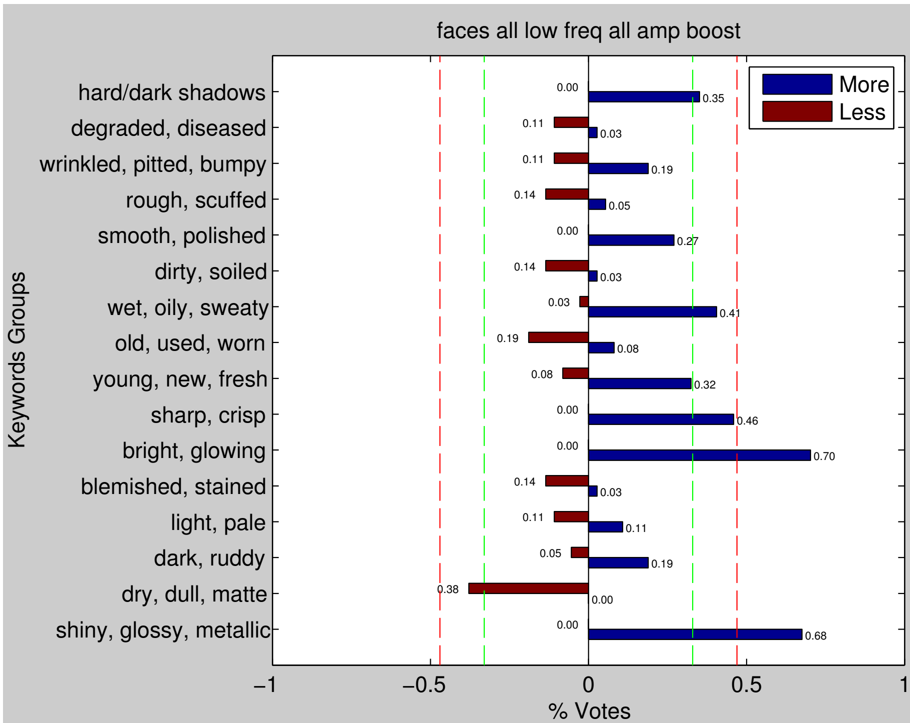


(a) Names for faces

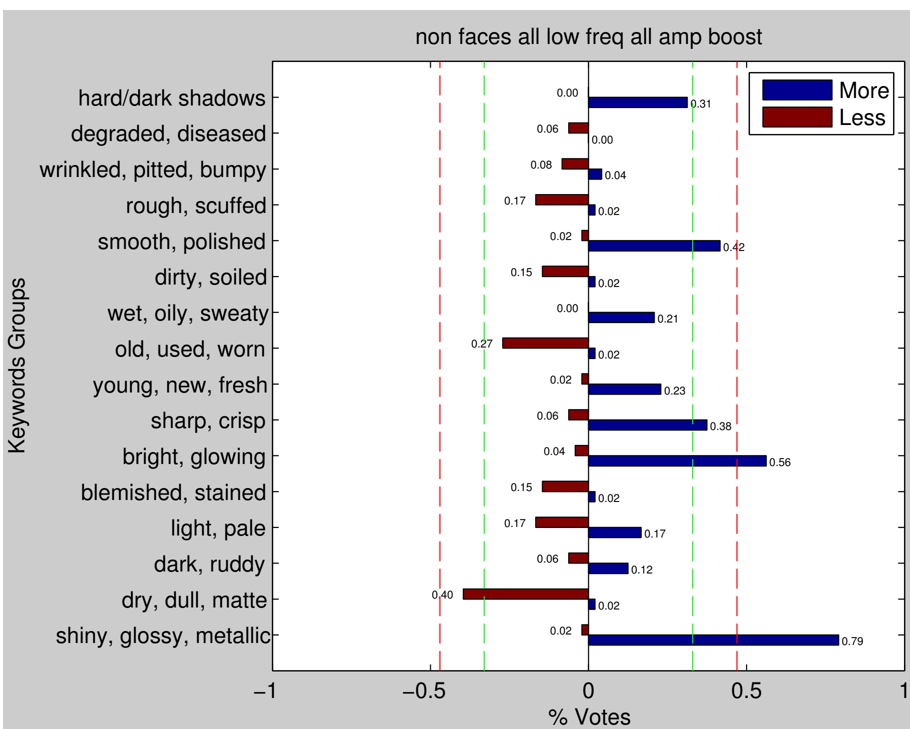


(b) Names for non-face objects

Figure 10: Boost all high-frequency, low-amplitude coefficients (HLA)

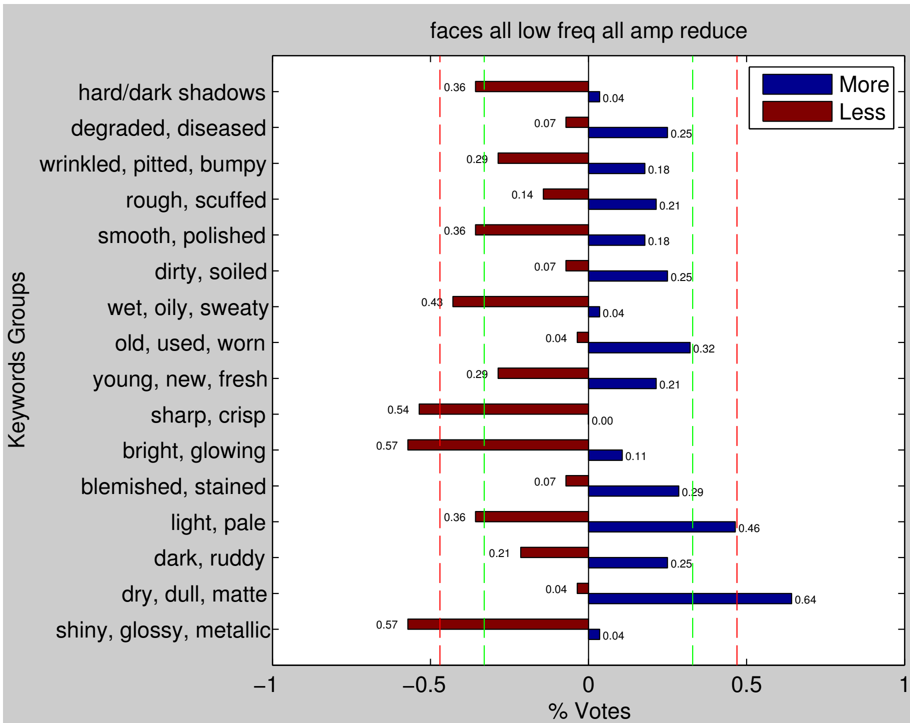


(a) Names for faces

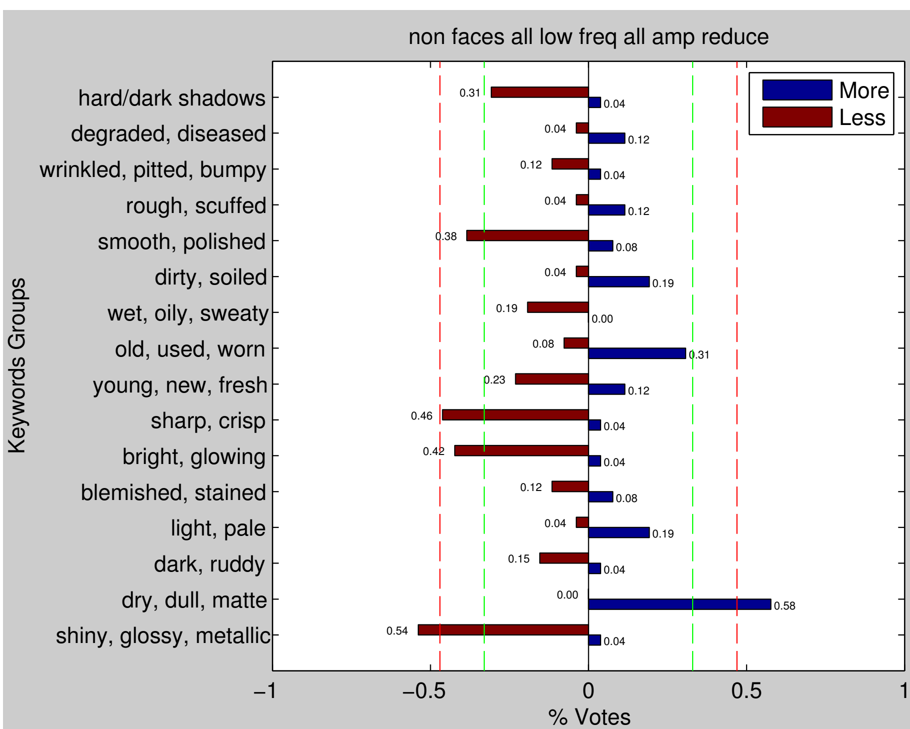


(b) Names for non-face objects

Figure 11: Boost all low-frequency, all-amplitude coefficients (LAA)

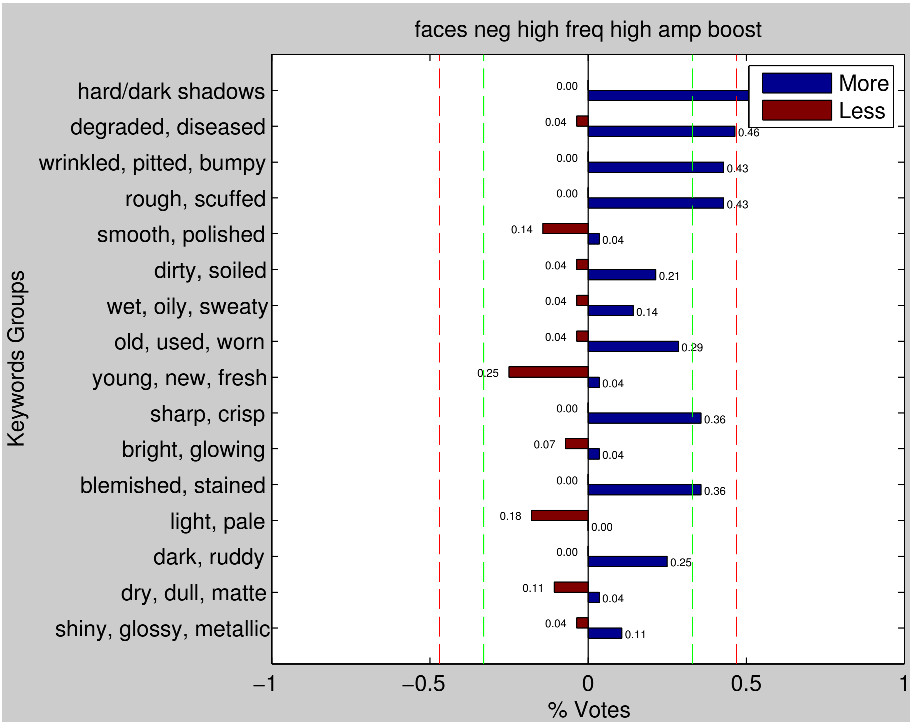


(a) Names for faces

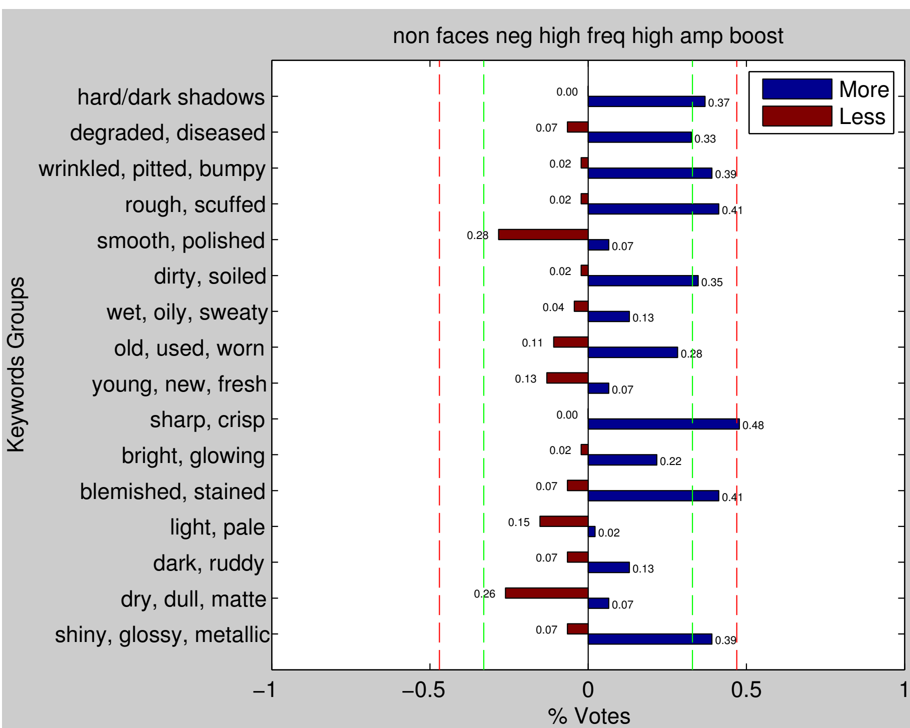


(b) Names for non-face objects

Figure 12: Reduce all low-frequency, all-amplitude coefficients (LAA)

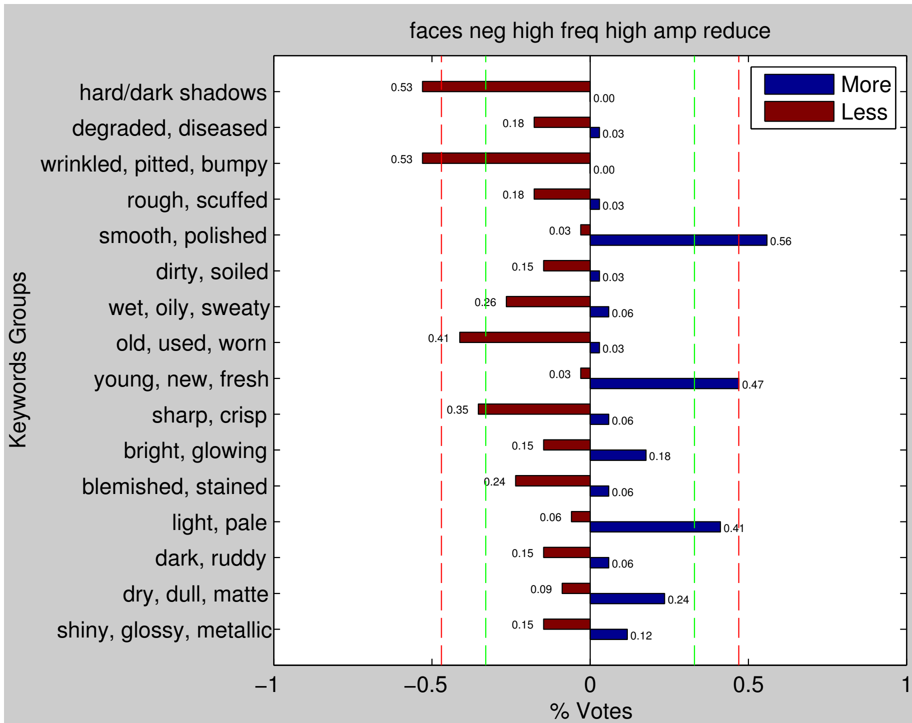


(a) Names for faces

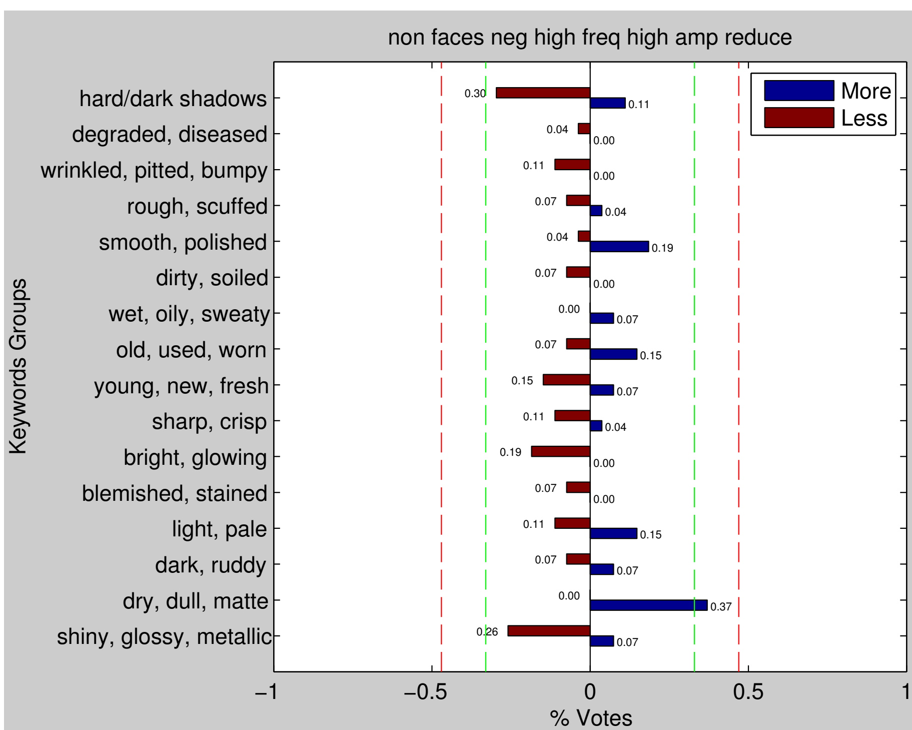


(b) Names for non-face objects

Figure 13: Boost neg high-frequency, high-amplitude coefficients (HHN)

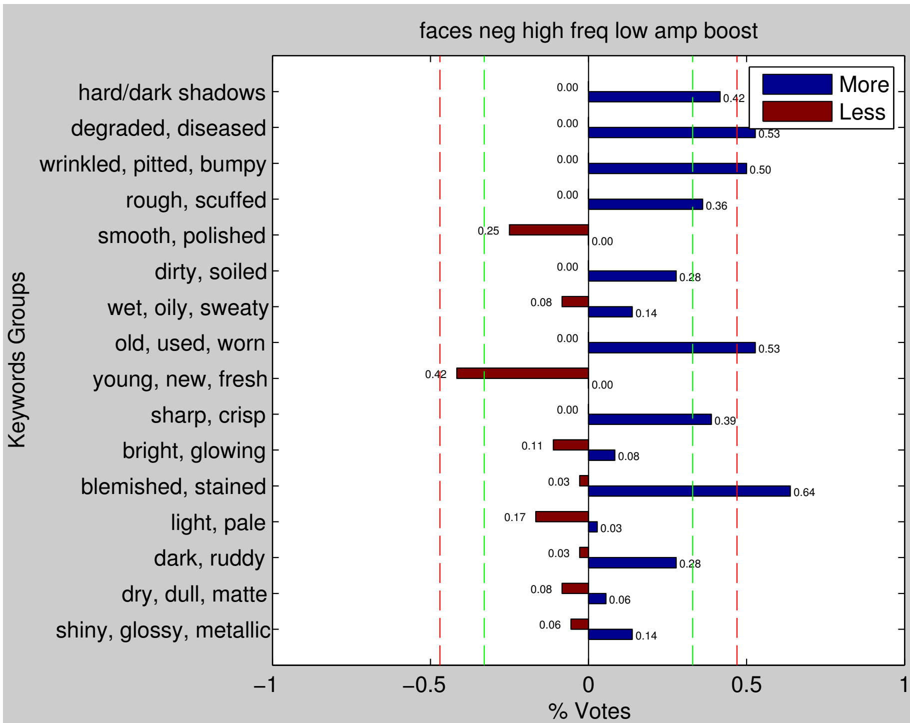


(a) Names for faces

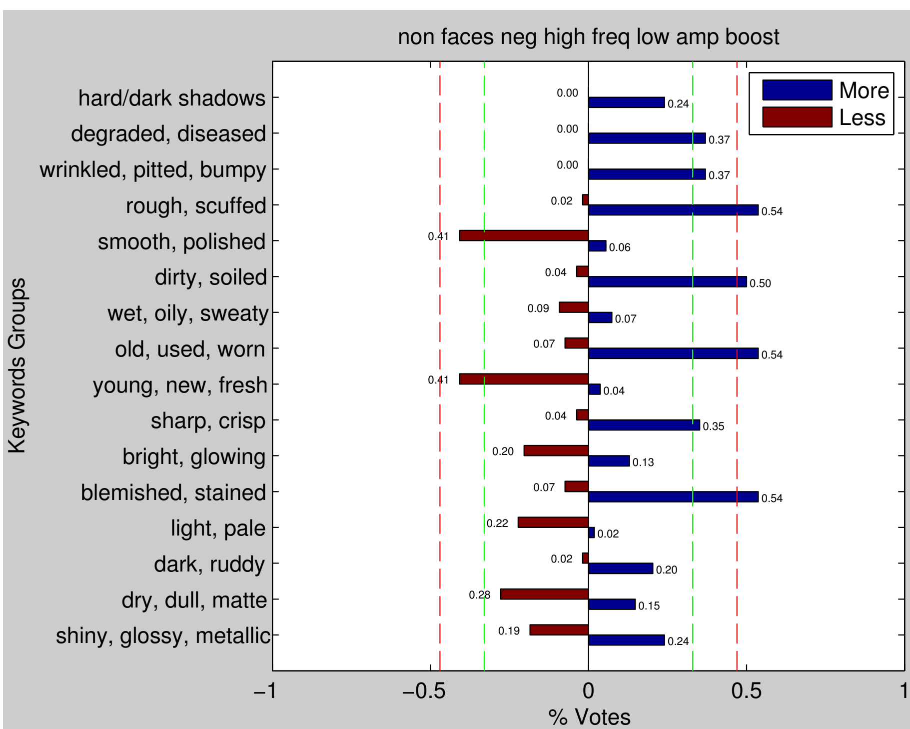


(b) Names for non-face objects

Figure 14: Reduce neg high-frequency, high-amplitude coefficients (HHN)

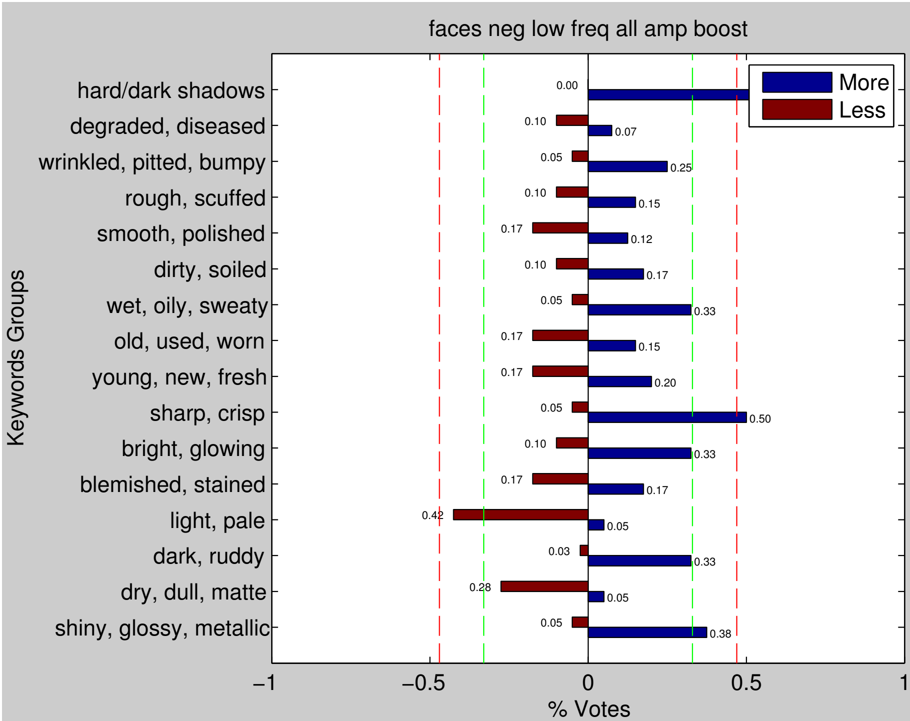


(a) Names for faces

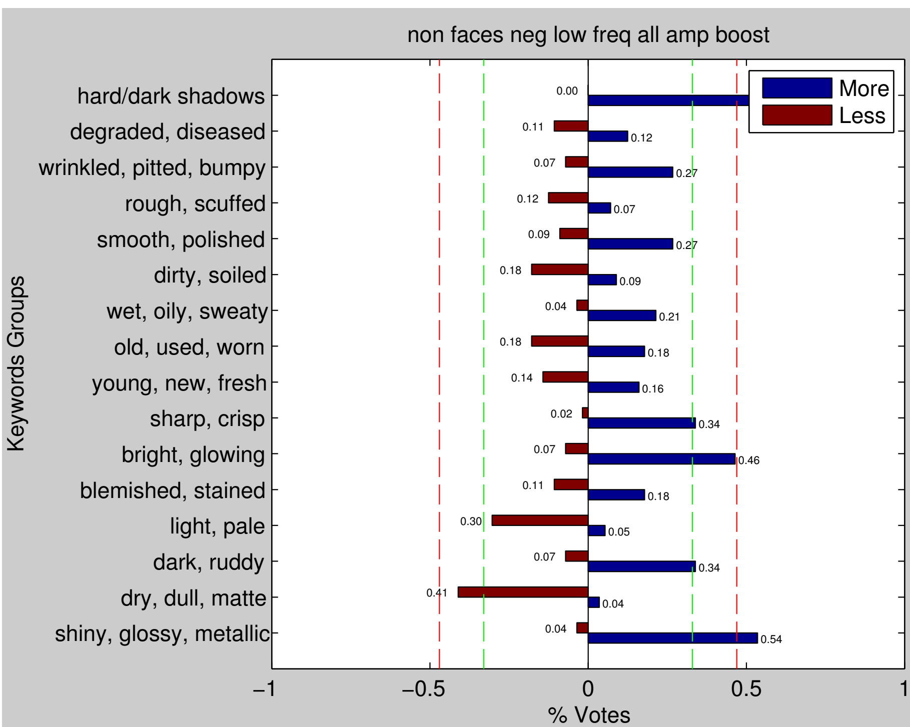


(b) Names for non-face objects

Figure 15: Boost neg high-frequency, low-amplitude coefficients (HLN)

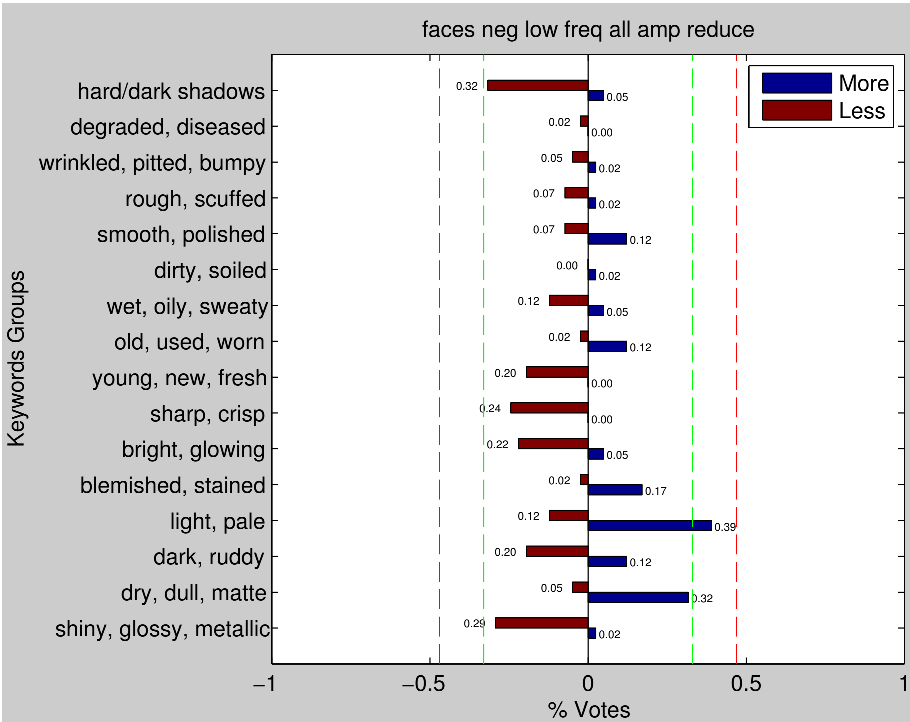


(a) Names for faces

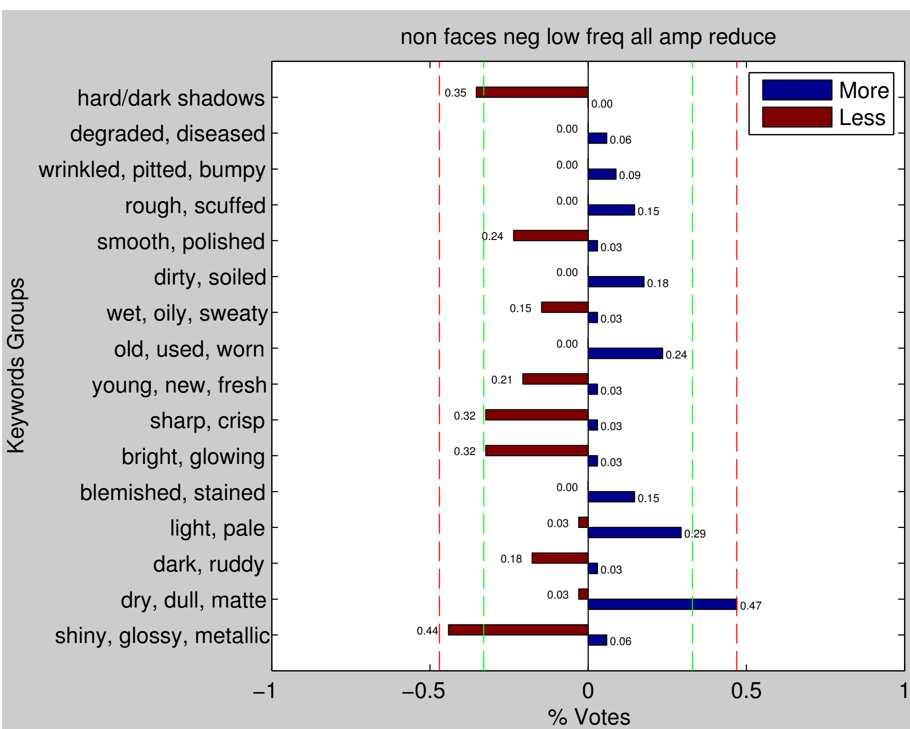


(b) Names for non-face objects

Figure 16: Boost neg low-frequency, all-amplitude coefficients (LAN)

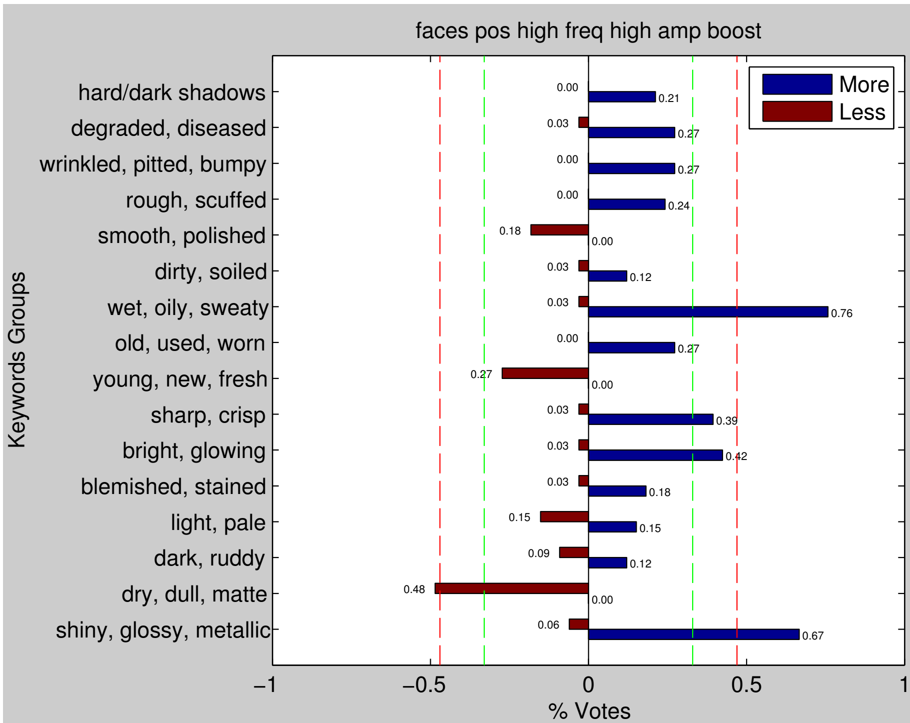


(a) Names for faces

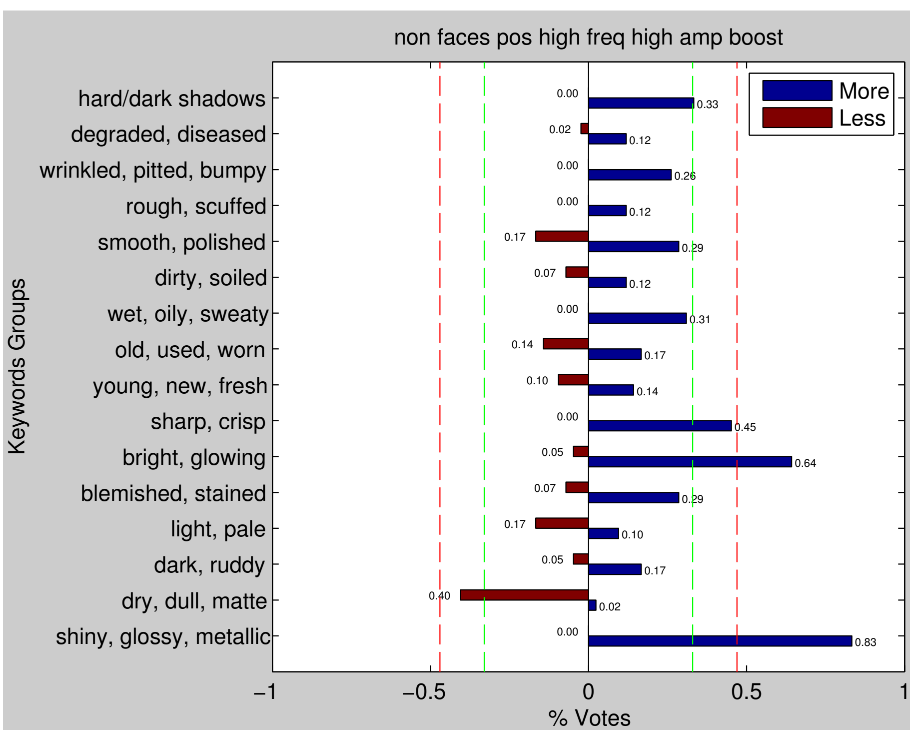


(b) Names for non-face objects

Figure 17: Reduce neg low-frequency, all-amplitude coefficients (LAN)

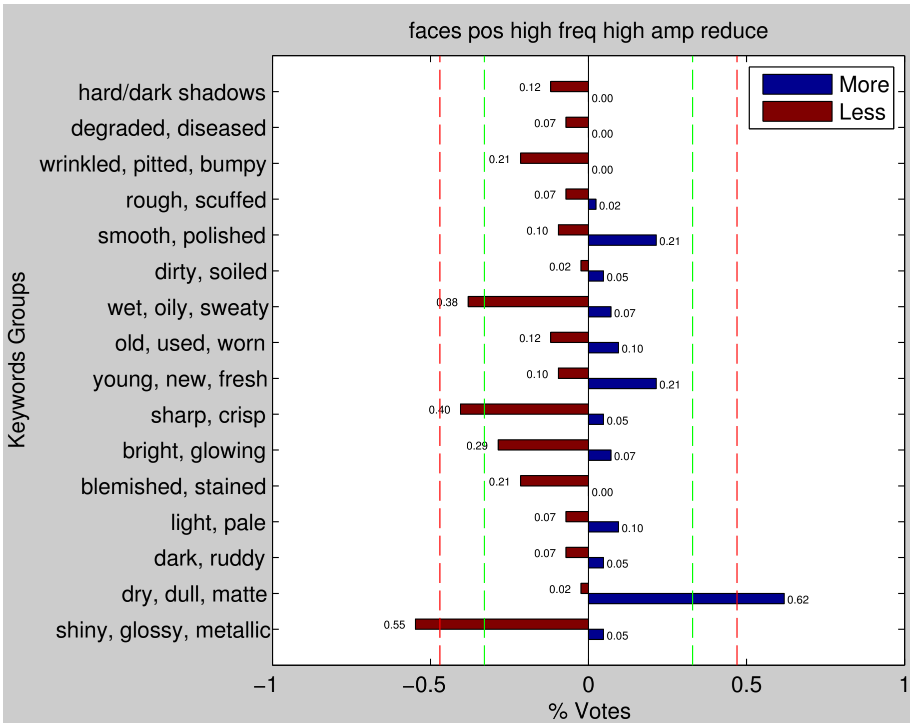


(a) Names for faces

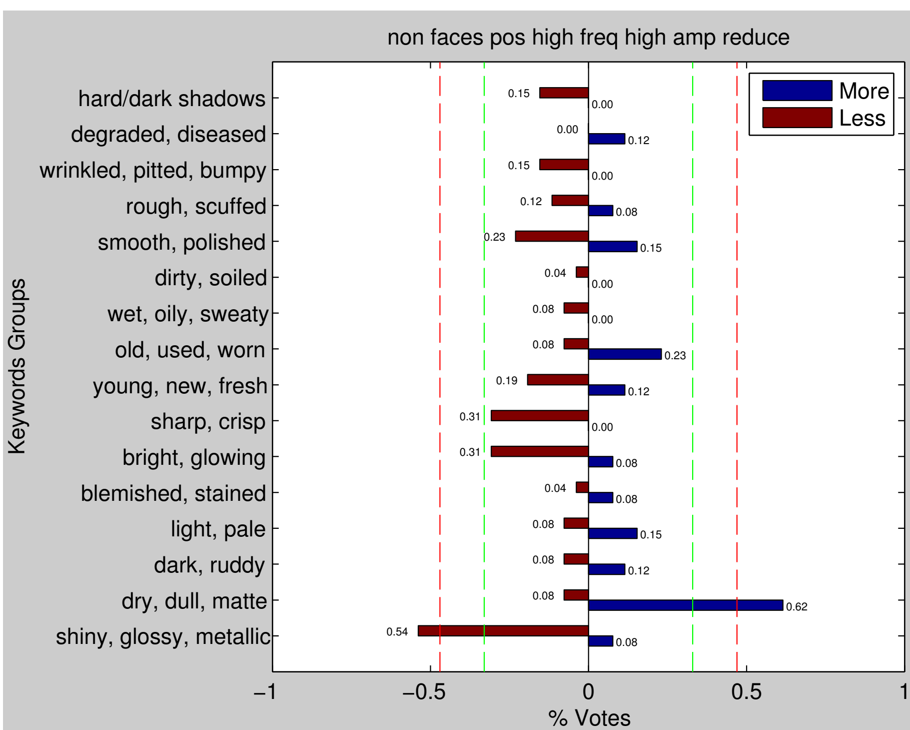


(b) Names for non-face objects

Figure 18: Boost pos high-frequency, high-amplitude coefficients (HHP)

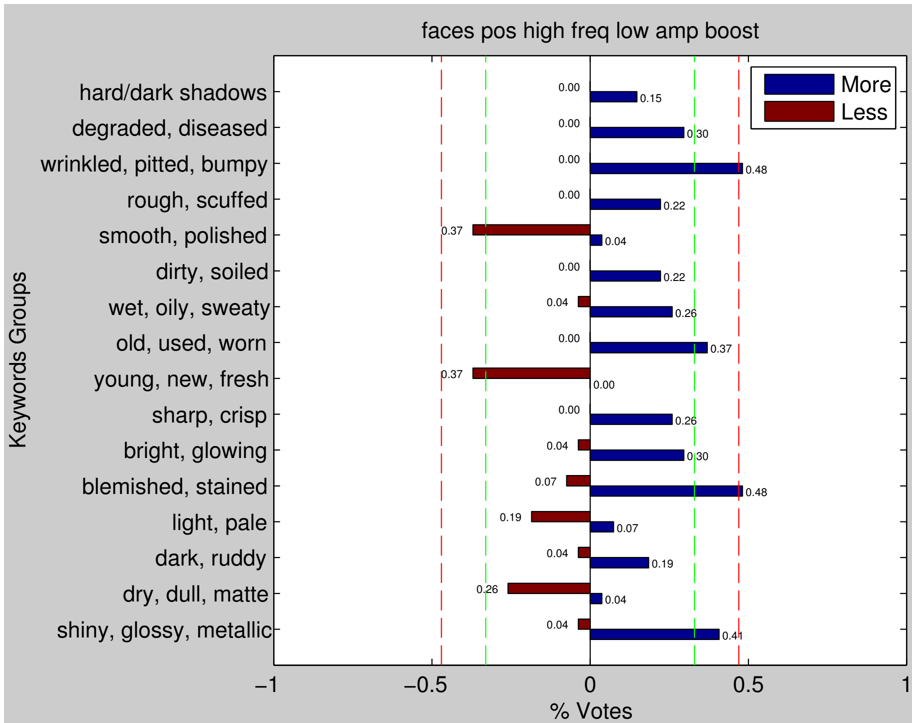


(a) Names for faces

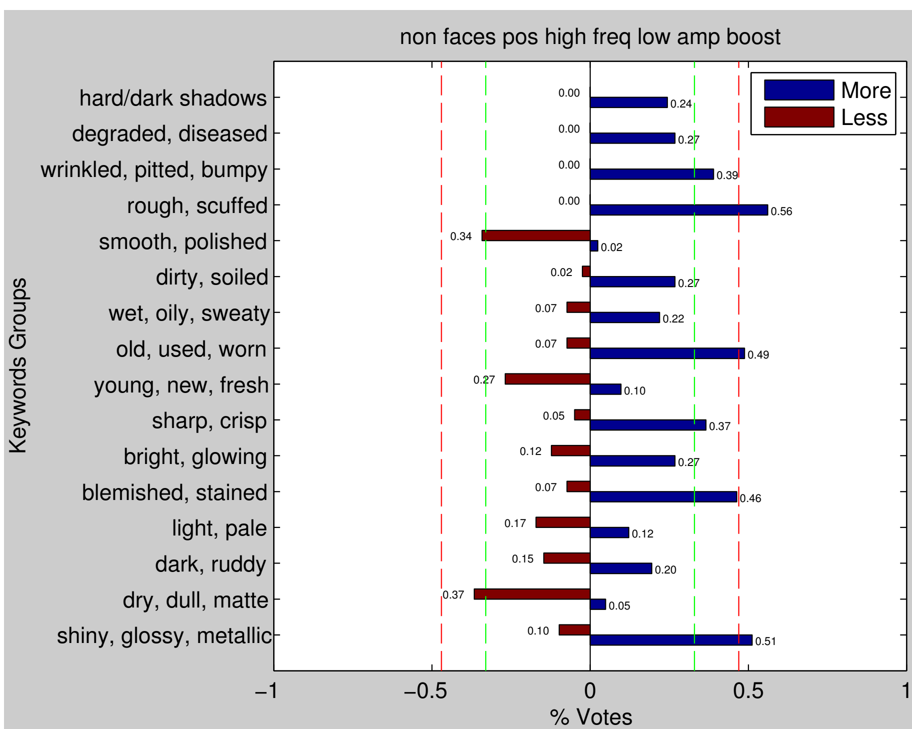


(b) Names for non-face objects

Figure 19: Reduce pos high-frequency, high-amplitude coefficients (HHP)

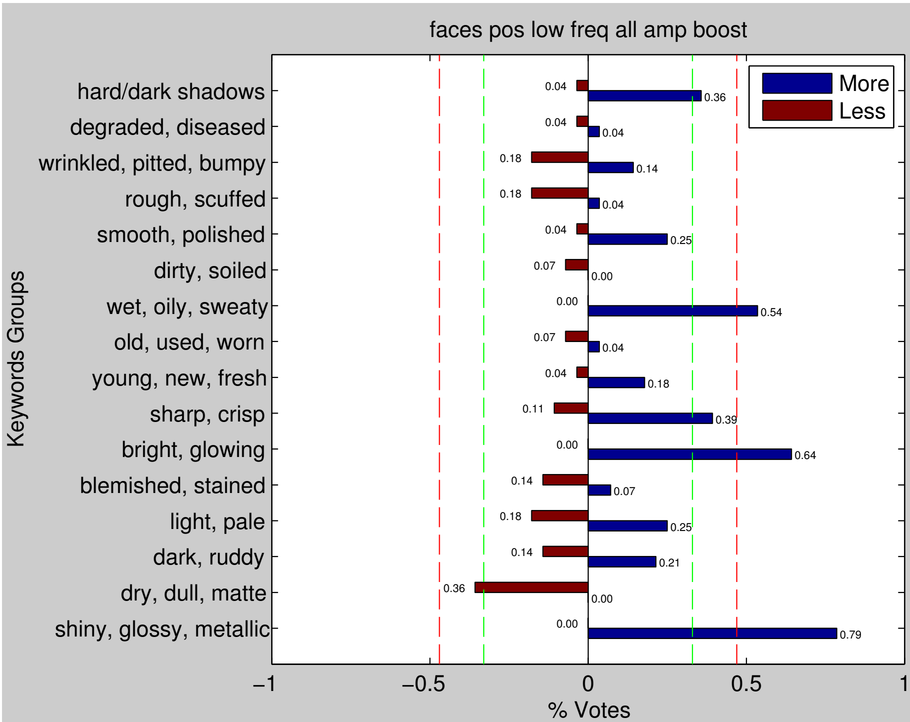


(a) Names for faces

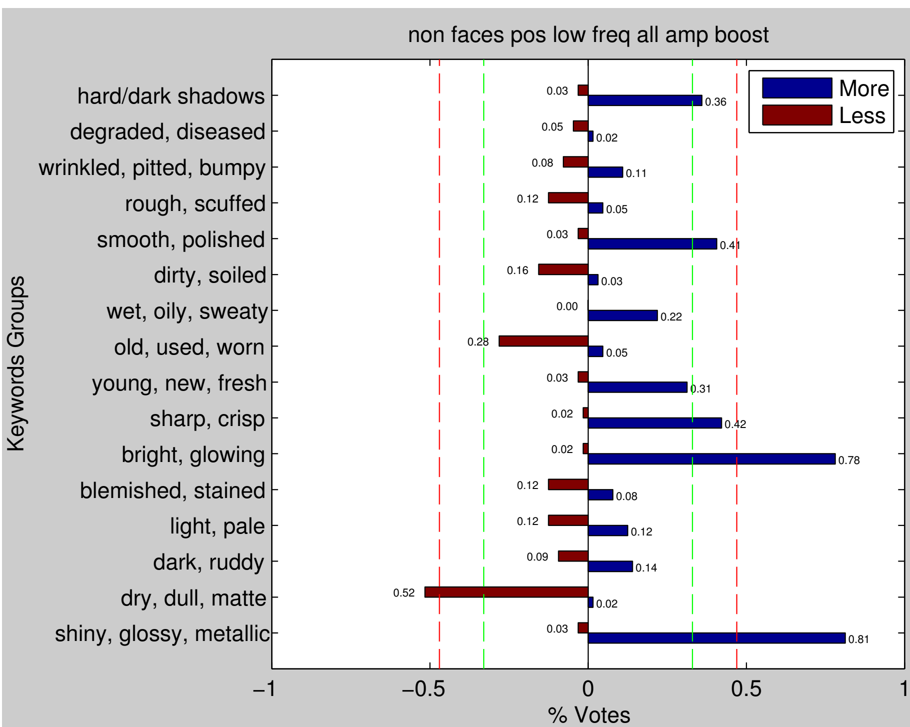


(b) Names for non-face objects

Figure 20: Boost pos high-frequency, low-amplitude coefficients (HLP)

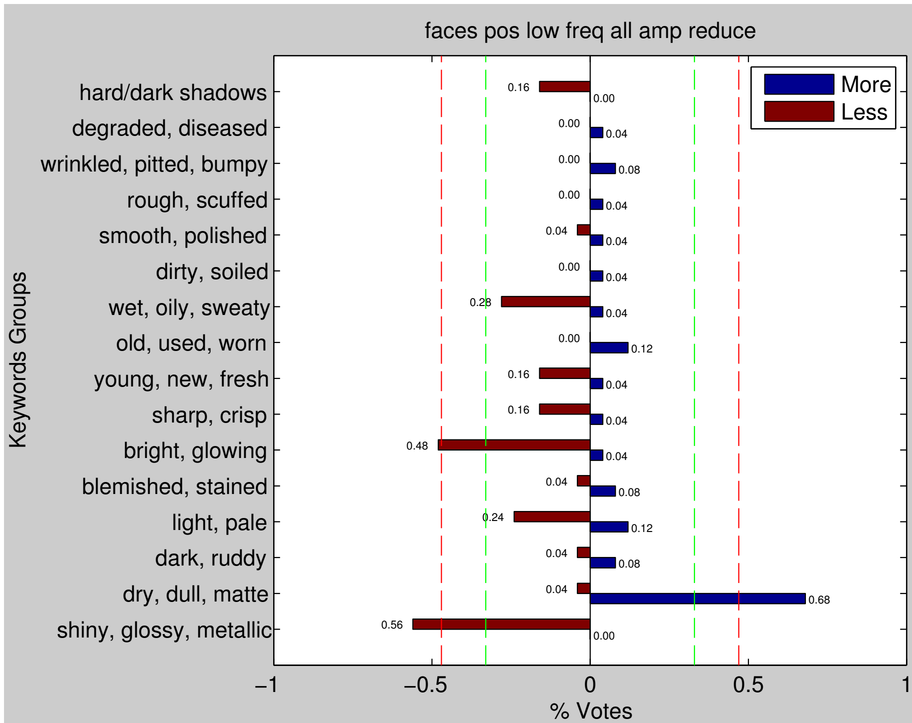


(a) Names for faces

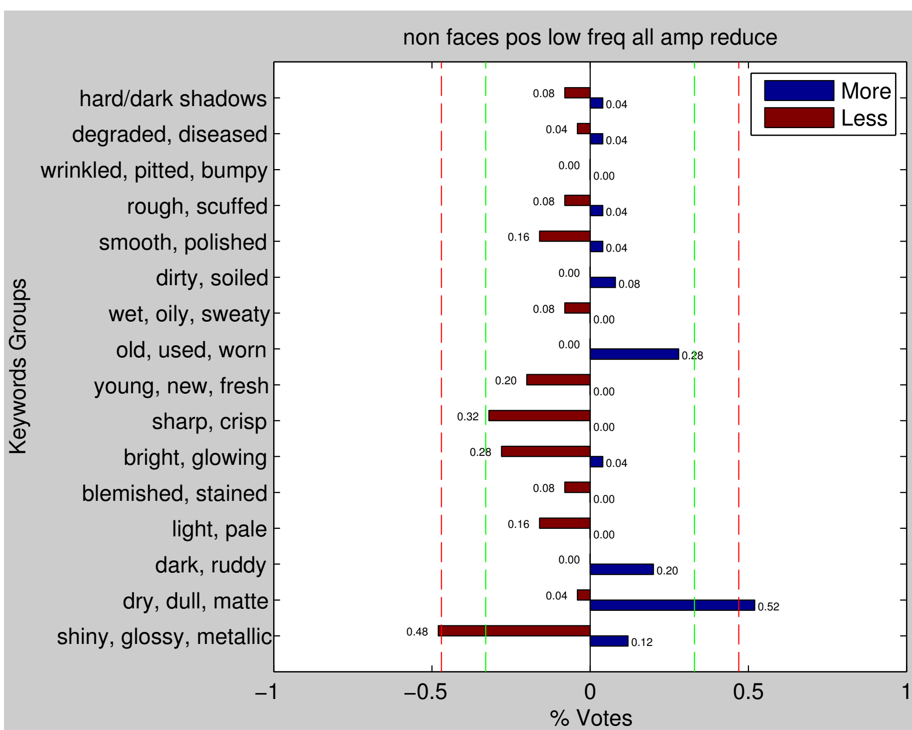


(b) Names for non-face objects

Figure 21: Boost pos high-frequency, all-amplitude coefficients (HAP)

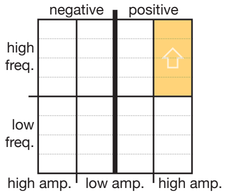
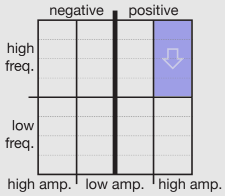
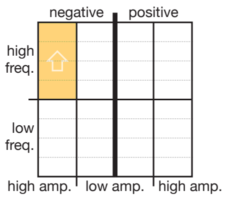
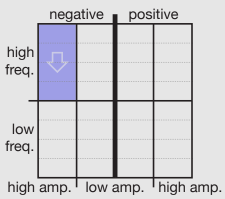
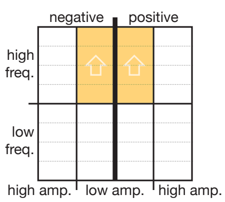
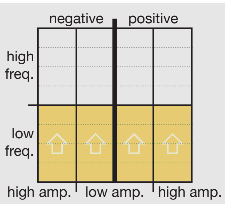
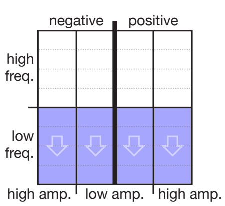


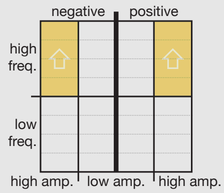
(a) Names for faces



(b) Names for non-face objects

Figure 22: Reduce pos low-frequency, all-amplitude coefficients (LAP)

	coefficient selection	associated properties	input	output
1.		**Objects** (strength: 4) more shiny/glossy/metallic (83%) more bright/glowing (64%) **Faces** (strength: 2) more wet/oily/sweaty (76%) more shiny/glossy/metallic (67%) less dry/dull/matte (48%)		
2.		**Objects** (strength: 2) more dry/dull/matte (62%) less shiny/glossy/metallic (54%) **Faces** (strength: 2) more dry/dull/matte (62%) less shiny/glossy/metallic (55%)		
3.		**Objects** (strength: 3.5) more sharp/crisp (48%) **Faces** (strength: 2) more hard/dark shadows (60%)		
4.		**Objects** (strength: 2) **Faces** (strength: 2) more smooth/polished (56%) less wrinkled/pitted/bumpy (53%) less hard/dark shadows (53%) more young/new/fresh (47%)		
5.		**Objects** (strength: 3.5) more sharp/crisp (57%) more old/used/worn (49%) more blemished/stained (47%) **Faces** (strength: 2) more blemished/stained (62%) more old/used/worn (55%) more wrinkled/pitted/bumpy (55%)		
6.		**Objects** (strength: 5) more shiny/glossy/metallic (79%) more bright/glowing (56%) **Faces** (strength: 4) more bright/glowing (70%) more shiny/glossy/metallic (68%)		
7.		**Objects** (strength: 2) more dry/dull/matte (58%) less shiny/glossy/metallic (52%) **Faces** (strength: 2) more dry/dull/matte (64%) less shiny/glossy/metallic (57%) less bright/glowing (57%) less sharp/crisp (54%)		

<table>
<tr><th></th><th>coefficient selection</th><th>associated properties</th><th>input</th><th>output</th></tr>
<tr><td>8.</td><td>
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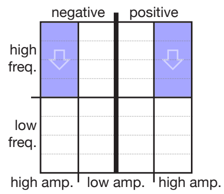
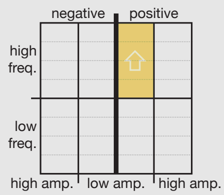
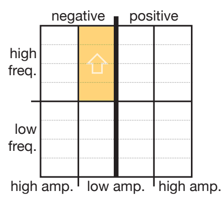
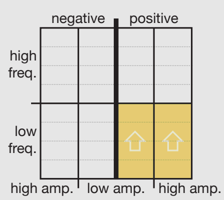
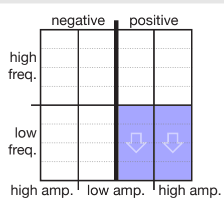
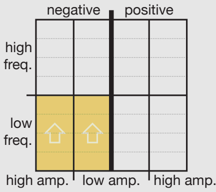
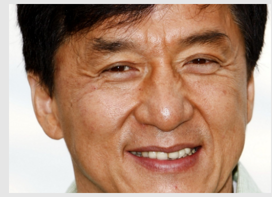
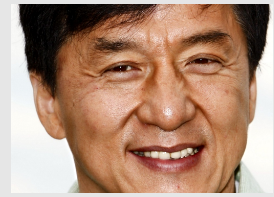
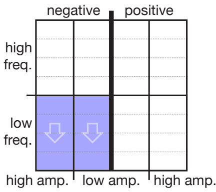
moreshiny/glossy/metallic (74%)
morebright/glowing (58%)
moresharp/crisp (58%)
Faces:
moreshiny/glossy/metallic (62%)
morewet/oily/sweaty (62%)
moresharp/crisp (47%)</td><td></td><td></td></tr>
<tr><td>9.</td><td>
</td><td>Objects:
moredry/dull/matte (61%)
less shiny/glossy/metallic (47%)
Faces:
moresmooth/polished (59%)
moredry/dull/matte (55%)</td><td></td><td></td></tr>
<tr><td>10.</td><td>
</td><td>Objects:
morerough/scuffed (56%)
moreshiny/glossy/metallic (51%)
moreold/used/worn (49%)
Faces:
moreblemished/stained (48%)
morewrinkled/pitted/bumpy (48%)</td><td></td><td></td></tr>
<tr><td>11.</td><td>
</td><td>Objects:
morerough/scuffed (54%)
moreold/used/worn (54%)
moreblemished/stained (54%)
Faces:
moreblemished, stained (64%)
moreold, used, worn (53%)
moredegraded, diseased (53%)</td><td></td><td></td></tr>
<tr><td>12.</td><td>
</td><td>Objects:
moreshiny/glossy/metallic (81%)
morebright/glowing (78%)
less dry/dull/matte (52%)
Faces:
moreshiny/glossy/metallic (79%)
morebright/glowing (64%)
morewet/oily/sweaty (54%)</td><td></td><td></td></tr>
<tr><td>13.</td><td>
</td><td>Objects:
moredry/dull/matte (52%)
less shiny/glossy/metallic (48%)
Faces:
moredry/dull/matte (68%)
less shiny/glossy/metallic (56%)
less bright/glowing (48%)</td><td></td><td></td></tr>
</table>

	coefficient selection	associated properties	input	output
14.		**Objects:** morehard/dark shadows (62%) moreshiny/glossy/metallic (54%) **Faces:** morehard/dark shadows (74%) moresharp, crisp (50%)		
15.		**Objects:** moredry/dull/matte (47%) **Faces:**