# **MAVias: Mitigate any Visual Bias**

# Supplementary Material

# 1. Theoretical Justification

### 1.1. Impact on Gradients

Let us consider a bias-aligned  $\mathbf{x}^{(a)}$  and a bias-conflicting sample  $\mathbf{x}^{(c)}$  with targets  $y^{(a)} = y^{(c)} = \kappa$ . The logits produced by  $f_{\theta}$  and  $g_{\phi}$  for each class  $k \in \mathcal{Y}$ , are then  $\mathbf{z}^{(a)}_{\text{main}}(k)$ ,  $\mathbf{z}^{(c)}_{\text{main}}(k)$ ,  $\mathbf{z}^{(a)}_{\text{main}}(k)$ ,  $\mathbf{z}^{(a)}_{\text{tag}}(k)$ , and  $\mathbf{z}^{(c)}_{\text{tag}}(k)$ , respectively.  $g_{\phi}$  encodes visual bias, being irrelevant to class  $\kappa$ , thus we expect  $\mathbf{z}^{(a)}_{\text{tag}}(\kappa) \gg \mathbf{z}^{(c)}_{\text{tag}}(\kappa)$ . Also, bias-aligned samples that contain shortcuts are easier to learn by  $f_{\theta}$  and therefore it is expected that  $\mathbf{z}^{(a)}_{\text{main}}(\kappa) \geq \mathbf{z}^{(c)}_{\text{main}}(\kappa)$ . These imply:

$$\mathbf{z}_{\text{main}}^{(a)}(\kappa) + \mathbf{z}_{\text{tag}}^{(a)}(\kappa) \gg \mathbf{z}_{\text{main}}^{(c)}(\kappa) + \mathbf{z}_{\text{tag}}^{(c)}(\kappa) \Rightarrow$$

$$\sigma^{(\kappa)}(\mathbf{z}_{\text{main}}^{(a)} + \mathbf{z}_{\text{tag}}^{(a)}) \gg \sigma^{(\kappa)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \Rightarrow$$

$$\frac{1}{\sigma^{(\kappa)}(\mathbf{z}_{\text{main}}^{(a)} + \mathbf{z}_{\text{tag}}^{(a)})} \ll \frac{1}{\sigma^{(\kappa)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)})}$$
(3)

where  $\sigma^{(k)}$  denotes the kth class' softmax score.

Additionally,  $f_{\theta}$  after a few iterations learns biasaligned samples (based either on relevant or irrelevant class features) indicating  $\arg\max_{k\in\mathcal{Y}}\mathbf{z}_{\mathrm{main}}^{(a)}(k)=\kappa$ , while  $\arg\max_{k\in\mathcal{Y}}\mathbf{z}_{\mathrm{tag}}^{(a)}(k)=\kappa$ , by definition. Hence,  $\sigma^{(\kappa)}(\mathbf{z}_{\mathrm{main}}^{(a)}+\mathbf{z}_{\mathrm{tag}}^{(a)})\approx 1$  leading to diminished gradients  $\frac{\partial}{\partial\theta_0}[\sigma^{(\kappa)}(\mathbf{z}_{\mathrm{main}}^{(a)}+\mathbf{z}_{\mathrm{tag}}^{(a)})]\approx 0$ . On the other hand,  $\sigma^{(\kappa)}(\mathbf{z}_{\mathrm{main}}^{(c)}+\mathbf{z}_{\mathrm{tag}}^{(c)})\in (0,1)$  leading to gradients  $\frac{\partial}{\partial\theta_0}[\sigma^{(\kappa)}(\mathbf{z}_{\mathrm{main}}^{(c)}+\mathbf{z}_{\mathrm{tag}}^{(c)})]>0$ . Hence:

$$\frac{\partial}{\partial \theta_0} \left[ \sigma^{(\kappa)} (\mathbf{z}_{\text{main}}^{(a)} + \mathbf{z}_{\text{tag}}^{(a)}) \right] \le \frac{\partial}{\partial \theta_0} \left[ \sigma^{(\kappa)} (\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right]$$
(4)

Combining Eq. (3) and Eq. (4) we get:

$$\begin{split} \frac{1}{\sigma^{(\kappa)}(\mathbf{z}_{\text{main}}^{(a)} + \mathbf{z}_{\text{tag}}^{(a)})} \cdot \frac{\partial}{\partial \theta_0} [\sigma^{(\kappa)}(\mathbf{z}_{\text{main}}^{(a)} + \mathbf{z}_{\text{tag}}^{(a)})] \ll \\ \frac{1}{\sigma^{(\kappa)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)})} \cdot \frac{\partial}{\partial \theta_0} [\sigma^{(\kappa)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)})] \Rightarrow \\ \frac{\partial}{\partial \theta_0} [\log \sigma^{(\kappa)}(\mathbf{z}_{\text{main}}^{(a)} + \mathbf{z}_{\text{tag}}^{(a)})] \ll \\ \frac{\partial}{\partial \theta_0} [\log \sigma^{(\kappa)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)})] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(a,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(a)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \ll \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^{(c)} + \mathbf{z}_{\text{tag}}^{(c)}) \right] \Rightarrow \\ \frac{\partial}{\partial \theta_0} \left[ \sum_k \mathbbm{1}(c,k) \cdot \log \sigma^{(k)}(\mathbf{z}_{\text{main}}^$$

where

$$\mathbb{1}(i,k) = \begin{cases} 1 & \text{if } y_i = k \\ 0 & \text{otherwise} \end{cases}$$
 (6)

which indicates that through our framework, the main model  $f_{\theta}$  is enforced to update its weights based mainly on the gradients corresponding to the bias-conflicting samples  $\mathbf{x}^{(c)}$ . This essentially means that  $f_{\theta}$  will eventually ignore the visual cues prevalent in  $\mathbf{x}^{(a)}$  samples corresponding to irrelevant information encoded by the tag model  $g_{\phi}$ .

## 1.2. Unbiased Distribution Learning

Let  $p_{tr}(X,Y,B)$  be the training data distribution where X, Y, B are random variables associated with the data, the label, and the bias attribute, respectively. From Theorem 1 of [16] we know that if  $P_u$  is a shift of  $p_{tr}$  such that the distribution  $P_u(Y|B)$  is uniform (and therefore unbiased), then for a model  $f_{\theta} = p_u(y|\mathbf{x})$  that estimates the conditional probability over  $P_u$ , its probability over  $p_{tr}$  will be

$$p_{tr}(y|\mathbf{x}) = \frac{\exp\left(\mathbf{z}_{\text{main}}(y) + \log p_{tr}(y|b)\right)}{\sum_{y'} \exp\left(\mathbf{z}_{\text{main}}(y') + \log p_{tr}(y'|b)\right)}$$
(7)

In the case of MAVias, let the probability  $p_{tr}(y|b)$  be estimated through the projection and classification layers,  $\mathbf{z}_{\text{tag}} = f_{\boldsymbol{\theta}_c}(g_{\boldsymbol{\phi}}(\mathbf{e}))$ , which use the visual bias embeddings  $\mathbf{e}$  (encoding the irrelevant tags) to produce logits  $\mathbf{z}_{\text{tag}}$ . As a result,

$$\log p_{tr}(y|b) = \log \frac{e^{\mathbf{z}_{tag}(y)}}{\sum_{y''} e^{\mathbf{z}_{tag}(y'')}}$$

$$= \mathbf{z}_{tag}(y) - \log \left(\sum_{y''} e^{\mathbf{z}_{tag}(y'')}\right)$$

$$= \mathbf{z}_{tag}(y) - A(\mathbf{z}_{tag})$$
(8)

where  $A(\mathbf{z}_{\text{tag}}) = \sum_{y''} e^{\mathbf{z}_{\text{tag}}(y'')}$ . Replacing (8) to (7) gives

$$p_{tr}(y|\mathbf{x}) = \frac{\exp\left(\mathbf{z}_{\text{main}}(y) + \mathbf{z}_{\text{tag}}(y) - A(\mathbf{z}_{\text{tag}})\right)}{\sum_{y'} \exp\left(\mathbf{z}_{\text{main}}(y') + \mathbf{z}_{\text{tag}}(y') - A(\mathbf{z}_{\text{tag}})\right)}$$

$$= \frac{\exp\left(-A(\mathbf{z}_{\text{tag}})\right) \exp\left(\mathbf{z}_{\text{main}}(y) + \mathbf{z}_{\text{tag}}(y)\right)}{\exp\left(-A(\mathbf{z}_{\text{tag}})\right) \sum_{y'} \exp\left(\mathbf{z}_{\text{main}}(y') + \mathbf{z}_{\text{tag}}(y')\right)}$$

$$= \frac{e^{(\mathbf{z}_{\text{main}}(y) + \mathbf{z}_{\text{tag}}(y))}}{\sum_{y'} e^{(\mathbf{z}_{\text{main}}(y') + \mathbf{z}_{\text{tag}}(y'))}}$$
(9)

thus leading to the logit addition of Eq. (1).

For this approach to work, however, one must ensure that models  $g_{\phi}$  and  $f_{\theta_c}$  are successfully trained to produce logits  $\mathbf{z}_{\text{tag}}$  that predict  $p_{tr}(y|b)$  and are not dominated by  $\mathbf{z}_{\text{main}}$ . This is achieved by the logit alignment term of Eq. (2) which controls the magnitude differences of  $\mathbf{z}_{\text{main}}$  and  $\mathbf{z}_{\text{tag}}$ .

### 2. Experimental Setup

### 2.1. Prompting

To ensure accurate tag classification, we provide the LLM with a detailed system prompt. Tags are processed in batches of 100, as testing has shown that longer lists can lead to some tags being overlooked. Since relevant tags are significantly fewer than irrelevant ones, we instruct the LLM to return only the relevant tags, allowing us to deduce the irrelevant ones. The exact system prompt is presented in Fig. 4

### **System Prompt**

I will provide you with the name of a target class and a large list of tags. Your task is to evaluate the tags and identify only those directly related to the target class. A tag is considered relevant if it describes or is an essential part of the object associated with the class name. This includes tags that refer to: physical components, defining features, inherent characteristics, and essential behaviors or functions of the object.

For example, if the target class is "bee", tags like "insect", "wing", and "buzz" are relevant because they describe core aspects of what a bee is or does. Conversely, a tag is irrelevant if it refers to elements that are not an intrinsic part of the object. Irrelevant tags may include: background details, environmental context, colors (unless a defining characteristic), lighting, textures, other objects, or other non-essential contextual elements.

For example, in the case of the class "bee", tags like "sky", "flower", or "blue" would be irrelevant, as they describe the environment or background rather than the bee itself.

Please output only the relevant tags in JSON format only (i.e., { relevant\_tags: [the list of tags]}).

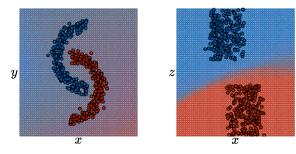
Figure 4. LLM system prompt for deriving the relevant tags.

### 3. Two-moon Distribution Experiment

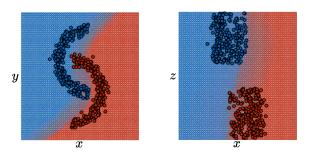
To demonstrate the capability of MAVias in mitigating biased features, we extend the classic two-moon distribution into a 3-dimensional setting. In this scenario, we con-

sider a dataset  $\mathcal{D}=\{(\mathbf{x}^{(i)},y^{(i)})\}_{i=1}^N$ , where each input  $\mathbf{x}^{(i)}=(x_1^{(i)},x_2^{(i)},x_3^{(i)})$  consists of two relevant features  $x_1^{(i)},x_2^{(i)}$  and an additional irrelevant feature  $x_3^{(i)}$  that introduces bias. The target label  $y^{(i)}$  should be determined based on the features  $x_1^{(i)},x_2^{(i)}$ , following the typical two-moon structure, while the feature  $x_3^{(i)}$  represents the bias (e.g., samples are linearly separable with respect to  $x_3^{(i)}$ , even though it should not be used for classification).

In this setup, the main model  $f_{\theta}(\mathbf{x}^{(i)})$  receives the full input  $\mathbf{x}^{(i)} = (x_1^{(i)}, x_2^{(i)}, x_3^{(i)})$ , while the projection layer  $g_{\phi}(x_3^{(i)})$  is provided only with the irrelevant feature  $x_3^{(i)}$ . The projection layer helps the system to explicitly account for this bias by incorporating  $x_3^{(i)}$  in a controlled manner, while the main model is encouraged to focus on the relevant features  $x_1^{(i)}$  and  $x_2^{(i)}$  for classification. As shown in Fig. 5, MAVias enables the main model to effectively learn the underlying two-moon distribution based on the features  $x_1^{(i)}, x_2^{(i)}$ , while the vanilla model relies only on the biased feature  $x_3^{(i)}$ , treating it as a shortcut that prevents the model from learning the proper distribution.



(a) Vanilla outputs on axes x and y. (b) Vanilla outputs on axes x and z.



(c) MAVias outputs on axes x and y. (d) MAVias outputs on axes x and z.

Figure 5. Two-moon problem on 3 dimensions. The distributions are linearly separable on axis z (i.e., z feature introduces bias), while the actual target is to learn the distributions defined by the features x and y.

Table 13. Bias-conflict and Unbiased accuracy comparison on CelebA with *BlondHair* and *gender* as biased attribute and target, respectively. Bold denotes the best-performing bias label-unaware (BU) method and underlined denotes the best-performing bias label-aware method.

|              |    | Bias BlondHair             |                  |  |
|--------------|----|----------------------------|------------------|--|
| Methods      | BU |                            |                  |  |
|              |    | Unbiased                   | Bias-conflict    |  |
| LNL [20]     | X  | $80.1 \pm 0.8$             | $61.2 \pm 1.5$   |  |
| DI [48]      | X  | $90.9 \pm 0.3$             | $86.3 \pm 0.4$   |  |
| EnD [44]     | X  | $86.9 \pm 1.0$             | $76.4 \pm 1.9$   |  |
| BC-BB [16]   | X  | $91.4 \pm 0.0$             | $87.2 \pm 0.2$   |  |
| FairKL [2]   | X  | $81.7 \pm 1.7$             | $69.9 \pm 2.4$   |  |
| FLAC [41]    | X  | $91.2{\scriptstyle\pm0.3}$ | $88.7 \pm 0.5$   |  |
| LfF [32]     | 1  | 84.2±0.3                   | 81.2±1.4         |  |
| SoftCon [16] | /  | 84.1                       | 74.4             |  |
| FLAC-B [41]  | /  | $87.0 \pm 0.6$             | $84.9 \pm 2.2$   |  |
| MAVias       | ✓  | <b>89.7</b> $\pm$ 0.6      | <b>87.1</b> ±1.7 |  |

## 4. Comparative Analysis

In this section, we compare the performance of MAVias with other competitive methods on closed-set (i.e., predefined bias) scenarios. The reported results encompass both bias-label aware (BA) and bias-label unaware (BU) methods. However, it should be noted that MAVias can be directly compared only with the BU approaches. Table 13 presents the performance of MAVias on CelebA with gender as target and the BlondHair as the biased attribute. The performance on unbiased and bias-conflicting samples indicates the ability of MAVias to reduce reliance on spurious correlations between the target and the corresponding biased attributes. Specifically, MAVias achieves 87.1% accuracy on bias-conflicting samples, surpassing state-of-theart BU methods such as FLAC-B [41] and LfF [32], while maintaining high unbiased accuracy (89.7%). Table 14 evaluates MAVias on Waterbirds, a well-known benchmark for spurious correlation problems between bird type and background environment. Notably, MAVias attains 93.7% Worst-Group accuracy, outperforming all compared BU methods (+5%), while slightly improving the average accuracy (+0.7%). The results on UrbanCars in Tab. 15 further validate the efficacy of MAVias in mitigating multiple biases introduced by co-occurring objects and background features. While the in-distribution accuracy (I.D. Acc) of MAVias is marginally lower than that of LfF [32] or Debian [24], it achieves substantial improvements in reducing the BG Gap (4.1) and CoObj Gap (2.4), as well as their combined effects (BG+CoObj Gap: 6.7).

Table 14. Evaluation on Waterbirds.

| Method        | BU | WG Acc.                                | Avg. Acc.                              |
|---------------|----|--|--|
| GroupDro [38] | X  | $90.6 \pm 1.1$                         | 91.8±0.3                               |
| BAdd [42]     | X  | $92.9 \pm 0.3$                         | $93.6{\scriptstyle\pm0.2}$             |
| DFR [36]      | X  | $\underline{92.9{\scriptstyle\pm0.2}}$ | $\underline{94.2{\scriptstyle\pm0.4}}$ |
| JTT [27]      | /  | $86.7 \pm 1.5$                         | $93.3 \pm 0.3$                         |
| DISC [49]     | ✓  | $88.7{\scriptstyle\pm0.4}$             | $93.8 \pm 0.7$                         |
| MAVias        | ✓  | $93.7 \pm 0.4$                         | $94.5 \pm 0.4$                         |

Table 15. Evaluation on UrbanCars.

| Method        | BU              | I.D. Acc                   | BG Gap          | CoObj Gap       | BG+CoObj Gap    |
|---------------|-----------------|----------------------------|-----------------|-----------------|-----------------|
| GroupDro [38] | X               | 91.6                       | 10.9            | 3.6             | 16.4            |
| DFR [36]      | X               | 89.7                       | 10.7            | 6.9             | 45.2            |
| LLE [25]      | X               | 96.7                       | <u>2.1</u>      | 2.7             | 5.9             |
| BAdd [42]     | X               | $91.0{\scriptstyle\pm0.7}$ | $4.3 \pm 0.4$   | $1.6 \pm 1.0$   | $3.9 \pm 0.4$   |
| LfF [32]      | \ \ \ \ \ \ \ \ | 97.2                       | 11.6            | 18.4            | 63.2            |
| JTT [27]      |                 | 95.9                       | 8.1             | 13.3            | 40.1            |
| Debian [24]   |                 | 98.0                       | 14.9            | 10.5            | 69.0            |
| MAVias        |                 | 92.8±0.8                   | <b>4.1</b> ±0.6 | <b>2.4</b> ±1.4 | <b>6.7</b> ±1.4 |

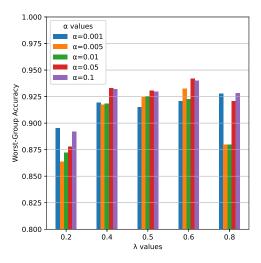


Figure 6. Impact of hyperparameters  $\alpha$  and  $\lambda$  on the worst-group accuracy (closed-set protocol) on the Waterbirds dataset.

## 5. Ablations & Hyperparameter Tuning

Tab. 16 reports the performance of MAVias when computing individual embeddings for each tag and then averaging them compared to the one computing a single embedding for all tags combined. As one may observe, although both are highly effective, the latter can provide more representative features.

Fig. 6 illustrates the impact of different values of hyperparameters  $\alpha$  and  $\lambda$  on the MAVias performance. The hyperparameters for all datasets were tuned through the same grid search. Overall, optimal  $\lambda$  values are close to 0.5 -

Table 16. Comparison of MAVias performance on Waterbirds using different approaches for computing embeddings from tags. "separately" denotes computing individual embeddings for each tag and then averaging them, while "collectively" denotes computing a single embedding for all tags combined.

| Туре         | WG Acc.                    | Avg. Acc.                  |
|--------------|----------------------------|----------------------------|
| separately   | $93.0 \pm 0.2$             | $93.6 \pm 0.2$             |
| collectively | $93.7{\scriptstyle\pm0.4}$ | $94.5{\scriptstyle\pm0.4}$ |

we noticed that values >0.5 work better for less biased datasets and <0.5 for datasets with extreme bias rates.  $\alpha$  is a much less sensitive hyperparameter, and any value between 0.001-0.1 does not have a severe impact on the results.

# 6. Irrelevant Tags

Tables 17,18,19, and 20 report the lists of irrelevant tags for CelebA, Waterbirds, UrbanCars, and ImageNet9 datasets, respectively.

### Table 17. CelebA irrelevant tags.

#### class tags

#### non-blond

32 glasses, Eiffel tower, accordion, adjust, advortisement, alarm clock, album cover, alcohal, musement park, antler, apple two, parcon, aguarium, archey, arena, arm, arm, art chibition, artist, aspangus, assembly, actroaut, athletic, am, attach, attend, andi, adultivirum, relator sunglasses, tooks, backedrop, backge badminns had based ball puber, basedull game, basedull game, basedull game, basedull game, basedull game, basedull game, basedull player, backbedull team, base, base guitar, but, bathroom accessory, bathroom sink, latter, battery, beach, beach ball, beach chaile, beach beach berown berown and beach and a control of the part of the pa

#### blonde

CD, Eiffel tower, Wii, Wii controller, actor, adjust, album, album cover, alley, apron, army, award, baby, backdrop, balustrade, bandeau, barber, barbie, bartender, baseball bat, bathroom mirror, beach ball, beautiful, beauty salon, bed, bedcover, bikini top, birth, bite, blender, blow, boat, bobfloat, bookshelf, bookstore, bouquet, bow, box, brace, bracelet, braid, bride, bridle, brush, bubble, bust, camera, candy, car seat, cardigan, carpet, casino, cat, catwalk, chiluahua, christmas hat, cigar, city, clip, clock, cloth, clothing store, coach, coat, comb, comfort, convention, cosmetic, crochet, crowd, curl, cut, daisy, dashboard, debate, deliver, denim jacket, diamond, diri feld, doll, dress, dressing room, drive, dye, earring, eat, engagement ring, equestrian, exhaust hood, eyebrow, eyeliner, fan, fashion show, father, fawn, figure skater, flag, flash, flight attendant, flip, floor, flower, folder, freckle, fur, fur coat, game controller, gathering, gift, gift box, girl, graduate, grass, greenery, guitar, headboard, headdress, hearing, hedge, hip, home appliance, hood, horse, hospial bed, hug, hydrant, interview, ivy, jacuzzi, jockey, kangaroo, khaki, kitchen, kitchen counter, knit, lamp, laptop, lash, ledge, ledorad, lick, lighthouse, lightning, lipstick, lolliplop, lush, makewap aritst, microscope, mirror, moete, mother, motorcycle, mouth, necklace, enon light, newborn, news, nose, office building, office window, officer, owen, overall, package, palm tree, pastry, pearl, pen, pencil, pet, phone, photo, picture frame, pigtail, pillar, pillow, pilot, pink, podium, poinsettia, pole, ponytail, pool, pop arist, pose, premiere, prom, pug, purple, python, raceway, ramp, razor, relax, ribbon, ring, sailor, salon, savanna, scarf, scooter, screen, seashell, sea belt, selfie, shampoo, shawl, shopping bag, short, shower curtain, slice, smartphone, smell, smile, sparkle, sparrow, speech bubble, sports ball, sports coat, spray, stable, stack, stering wheel, sterings on the submy suinding pool, syringe, tabby, take, tape

#### Table 18. Waterbirds irrelevant tags.

#### class

#### tags

landbird

accordion, ainplane window, airship, alcohol, algae, amphilheater, amusement park, amenone, ant, apple, apple tree, aquarium, area, arm, armochair, armor, army, arrow, aspuragus, atrium, attach, atv, aurora, author, autumn leave, autumn park, ax, baby, baby carriage, back, backdrop, backpack, backyard, bag, balance, balcony, ball, balastrade, bamboo, bamboo forest, banana, banana tree, bandeau, bangs, banyan tree, barge, bark, barrel, basrier, baseball bat, basch lat, basch lat, basch ball, beach ball, beach bouse, beach towel, beam, bear, bear cut, beautiful, beer, beer bottle, belily, bench, bengal tiger, beret, berry, beverage, bicycle, bicycle helmet, biker, bikini bikini top, bin, birch, birch brich, birch, brich, b

#### waterbird

Border collie, aircraft carrier, album, album cover, algae, amusement park, antler, appear, apple, apple tree, apron, aquarium, army, arrow, aurora, autumn park, ball, ballerina, ballet, ballet dancer, ballet skirt, balustrade, banana tree, barbie, bark, barrier, baseball hat, basket, battleship, beach, beach chair, beach hut, beach towel, beam, beautiful, beaver, belty, bench, berry, bicycle, bikini, bikini top, birch, bird bath, bird feeder, blossom, board, boardwalk, boat, boat house, boat ride, bottle, boy, bridge, brown, brown, brunette, bubble, building, buoy, bus, bus window, bus, to abana, cactus, calm, camera, camp, camper, campsite, can, canoe, car, car mirror, car window, cargo ship, carp, carvot, carvy, cave, chain, chair, chase, cheetah, chest, child, chimney, chopstick, cinema, city, city skyline, city view, city wall, cliff, climb, clotd, cloud, cloudy, coast, coat, coconut tree, collage, collect, concept car, cone, corn field, couple, course, crash, crest, crowd, crowded, cruise, cruise ship, curb, cycle, daffodil, dam, dance, dancer, dark, dashboard, daybed, deck, deer, den, denim jacket, destruction, dirt field, dirt road, dirt track, disco ball, diving board, dock, doll, donkey, doorway, driftwood, drive, dry, eel, cuclayptus tree, cyergreen, eye, fall, fawn, fence, fern, ferry, fift, flighter jet, fin, fishing, fishing pole, fjord flag, fleet, flip, float, flood, flooder, f

#### Table 19. UrbanCars irrelevant tags.

#### class

tags

urban-car

advertisement, alley, apartment, archway, atm, attach, back, backyard, balcony, balustrade, bear, bin, binocular, bird, black, brick building, buss top, bush, cage, canopy, carpet, catch, ceiling, ceiling fan, charge, chase, chimney, city, city skyline, city street, city view, cliff, cloth, collage, corn field, corridor, country lane, countryside, courthouse, crane, crash, creek, crop, crosswalk, curb, cut, cut, dark, destruction, display, dog house, doodle, door, doorway, dune, dust, enclosure, evergreen, exit, explosion, fence, fill, fire truek, fireplace, filp, flood, floor, fuel, garage, garage door, gas, gas station, gravel, green, greenery, gun, hand, hang, hay, head, headlight, hedge, home, bood, horseback, house, house exterior, hurdle, hut, hydrant, ice skating, illuminate, intersection, jockey, jump, lake, lamp, lamp post, lawn, ledge, lift, lighthouse, line, living room, mat, meter, miniature, mountain, narrow, neon light, night, night view, number, office building, out, outdoor, outhouse, overpass, paling, palm tree, park, parking garage, parking sien, s

#### country-car

advertisement, animal, apartment, arrow, atv, autumn forest, autumn tree, back, balustrade, bamboo forest, barrier, bat, bear, bed, bend, bicycle, black, boardwalk, boulder, bride, bridge, brown, brown bear, buffalo, build, bull, bus top, bush, eage, calf, cart, cattle, chase, chimney, city street, cliff, climb, cloud, cloudy, coach, construction site, corridor, country lane, couple, cow, cowboy, crane, crop, cross, curve, daffodil, dam, deer, desert road, dirt bick, dirt field, dirt road, dirt track, dog, donkey, door, dust, elephant, enclosure, evergreen, farmland, fence, field, fire escape, fire hose, fire truck, flag, flower, forest, forest path, forest road, gas station, gasmask, goat, goggles, grass, grasvy, grave, gravestone, gravygard, gray, graze, green, gun, hallway, handstand, head, hedge, highway, hill, hillside, hook, horse, hose cart, horseback, hut, ice cream cone, jump, lamb, land, lay, leash, lift, fighthouse, line, log, lush, milk, milk, emister, moose, mountain path, mud, mural, night sky, out, parachute, parking, path, peak, pig, pine, pine forest, pine, pine, pine forest, pine, pine, pine, pine forest, pine, pine, pine forest, pine, pine, pine forest, pine, pine, pine forest, pine, pine, pine, pine forest, pine, pine, pine, pine, pine, pine, pine, pine, pine forest, pine, pine, pine forest, pine, pine forest, pine, pine,

| class      | tags   |
|------------|--|
| Dog        | CD, French bulldog, antler, appliance, area, arm, armchair, back, backdrop, backyard, bag, balance, barn, barrel, barricade, barrier, basseball hat, basin, basket, bath, bathroom, bathroom sink, bead, bed, bed, bed, bed, bedcover, belt, bench, beret, bib, black, blanket, blood, blue, boardwalk, boat, bookcase, bookshelf, boulder, bow ite, bowl, boxer, boy, break, broom, brown, brush, bubble, building, bureau, bush, cabinet, cap, car, car seat, car window, carpet, carrot, carry, car, cat food, cement, chair, child, christmas hat, cloth, cocktail dress, comfort, computer chair, computer monitor, concrete, cone, contest, corridor, counter top, course, court, crack, cube, curb, dachshund, daisy, dandelion, deck, dirt field, dirt road, dirt track, dish washer, dock, doll, door, doorway, dot, drawer, dress, dresser, drink, duffel, eat, enclosure, eye, face, fairy, farm, feed, fence, fern, finish line, fireplace, flower, flower bode, floding chair, football, footprint, forest, fridge, frishee, frost, frosty, garden, gift, girl, glass door, goggles, gravel, green, greyhound, guinea pig, hair, hallway, hand, handkerchief, hardwood, hardwood floor, hassock, hay, head, headscarf, hide, hillside, home appliance, hose, house exterior, hug, hurdle, jeans, judge, kiss, kitchen, kitchen cabinet, kitchen floor, kitchen island, kitchen sink, lamb, lap, laundry basket, lawn, leather jacket, ledge, living room, log, lollipop, lush, magnet, man, measuring tape, milk, miniature, moose, motorbike, motorboat, motorcycles, motorcyclist, mound, neck, necklace, obstacle course, office, office chair, office supply, open, out, paling, paper towel, park, pasture, patch, path, pavement, pen, pencil, person, photo frame, picnic table, picture frame, plant, plate, pointer, pole, polke dot, poodle, porch, pot, quilt, racket, rail, ramp, red, reindeer, river, road, rocking chair, rocky, roll, room, round table, rural, scarf, screen door, seat, seat belt, shadow, shake, shirt, sking, sign, sink, sik, sik, pole, sky, sleeping bag, syele, seat, lil |
| Fish       | window sill, wine glass, winter, woman, wood, wood floor, wood wall, wool, wrap, wrapping paper, wrestle, yellow algae, appear, aquarium, attach, bag, bait, ball, banana, baseball hat, basin, bass, bat, bath, bathroom, bathroom accessory, bathroom sink, beach, beach chair, bean, beard, beautiful, beetle, billiard table, bin, bite, black, blade, blood, blue, boat, bowl, boy, brush, bubble, bug, buoy, cactus, cake, calm, camouflage, camp, campfire, campsite, canoe, cat, catch, caterpillar, cave, ceiling, chair, child, chocolate cake, clear, cliff, cloth, coast, color, comb, container, coral, coral reef, couple, coverall, cowboy hat, crack, creek, dark, display, dive, diver, dock, doll, dolphin, dress, dry, dye, enclosure, entertainment center, eye, fang, fedora, fin, fish market, fisherman, fishing net, fishing pole, flat, float, folding chair, foot, footprint, frosting, frying pan, gasmask, gecko, girl, glass bowl, glass table, grampus, gray, green, hairbruah, and, hat, head, hole, humpback whale, ice, image, jacket, joker, jumpsuit, kayak, koi, lagoon, lake, land, laugh, ledge, lid, life jacket, lush, machete, man, market, mask, mine, mound, mouse, mud, muscle, net, night, overall, package, pad, paddle, pancake, peak, pearl, peel, penguin, pepper, person, pet, pharmacy, phone, photo, pink, plant, plastic, plate, platter, pod, pole, polk dot, polo shirt, pond, pool, pose, profile, puddle, purple, raincoat, ram, reel, river, rock formation, rocky, sack, safety vest, sale, sandal, sea, sea cave, sea lion, sea urchin, seabed, seal, seashell, shine, shirt, shirtless, shore, shoreline, showcase, silver, sit, skate, smile, snorkel, snow, spike, sponge, squat, squid, stab, stand, stern, stingray, stone, stool, strainer, strap, stream, stuff, sun, sun hat, sunglasses, surface, suspenders, sweatshirt, swin, swimming pool, swimwear, swordfish, table, tail, tank, tape, tarp, teddy, tent, toe, toilet bowl, toilet seat, tool, torch, tortoise, toy, tree, tripod, tropic, trumpet, tube, turquoise, turtle, tusk, twig, underwater |
| Bird       | area, attack, bath, balay, balustrade, bark, beach, bean, bed, bend, berry, bill, birch tree, bird bath, bird cage, bird feeder, bird house, bird nest, birdbath, blanket, bloom, blossom, blue, boulder, branch, brown, brush, bud, building, bunk bed, bureau, bush, cabinet, calm, car mirror, car window, catch, ceiling, chase, cherry blossom, cherry tree, circle, clear, climb, close-up, cloud, coast, comb, cone, counter top, couple, creek, crest, cross, debris, diri field, dock, driftwood, drink, dry, enclosure, evergreen, eye, face, feed, fence, field, fir tree, fish, flap, flight, float, flood, flower, flower bed, fly, food, foot, forehead, forest, garbage, grain, grassland, grassy, gravel, gray, graze, greenery, gull, hand, hay, head, hide, hillsdide, house finch, kitchen counter, kitc, ladder, lake, land, landing, lap, laugh, lavender, ledge, leg, lizard, metal, mollymawk, mound, mouth, mud, mulch, neck, nectar, nest, night, nose, nut, open, osprey, ostrich, out, paling, paper, patch, peak, peanut, pen, penguin, perch, pillar, pillow, pine, pine cone, pink, plain, plank, plant, plow, portrait, post, power line, puddle, purple, raft, rapid, rearview mirror, red, reflection, relax, rice field, ripple, river, rock formation, rocky, roof, room, rope, sand, savanna, sea, seabird, seal, seaweed, seed, shirt, shore, shoreline, sip, sit, sky, smile, snowy, spread, spruce, stem, stick, still, stone, stretch, string, sunflower seed, swim, table, tail, teal, telegraph pole, thistle, tile, tile roof, toy, tree, tree branch, tropic, turkey, twig, vegetation, view mirror, walk, water, water llly, wave, weed, wet, wetland, wildflower, window sill, windshield, wing, wire, wood, yard, yellow, zoo   |
| Vehicle    | advertisement, air field, alcohol, alley, ambulance, amusement ride, animal, antique, approach, arena, armor, auto show, baby, back, balance, barn, barrel, barricade, barrier, basin, beach, beach chair, beautiful, bench, bend, bicycle helmet, bicker, bin, bird cage, black, blow, blue, boat, boot, bottle, box, box, by, brick building, bridge, broom, brown, brunette, building, building, buil, builet, bumper, cabin, cabin car, cage, camper, campsie, car, eac, aconopy, car show, cardboard box, carpet, cat, catch, cattle, ceiling, eement, chair, check, child, city, city square, city street, classic, cliff, ocl, cloudy, coast, cock, commuter, cone, construction worker, container, cooler, countryside, coupe, couple, course, cow, cowboy boot, cowboy bat, crane, crate, crop, cross, crowd, crowded, curb, curve, cycle, cylinder, dark, dashboard, decker bus, decorate, desert road, destruction, dirt bike, dirt field, display, dock, dog house, donkey, doodle, door, doormat, doorway, dozer, dress, drift, driveway, dust, elephant, emergency, emergency service, enclosure, envelope, equipment, evergreen, excavator, face, fence, field, figurine, fill, fire department, fire hose, fire station, fire truck, fireman, flag, flame, flip, flood, floor mat, flower, fly, food truck, forest, garage, garage door, garbage, garbage truck, garden, garden hose, generator, girl, go, goat, goggles, gold, golf cart, grass, grassland, grassy, gravel, gray, green, handcart, hangar, hat, hay, headlight, heart, hedge, helmet, hide, highway, hill, hiliside, hip, hood, hose, house, house exterior, hut, intersection, jacket, job, jockey, jump, jumpsuit, karting, kayak, ladder, lake, lamp,  |
| Reptile    | algae, amusement park, aquarium, arm, armadillo, baby elephant, back, bag, balloon, banana banana tree, bank, bark, barrel, baseball glove, baseball hat, basin, bath, bathroom sink, beach, beak, bin, bird, black, blanket, blowfish, blue, bottle, boulder, box, bracelet, branch, break, brick, bronze statue, brown, bubble, bug, building, bull, bush, cage, car, car window, cardboard box, carnival, carp, cat, ceiling, cement, chair, chase, eigarette, claw, clear, climb, cloth, clown fish, coast, coconut tree, coin, computer, computer desk, concrete, container, coral, coral reef, crack, creek, crochet, cross, curl, dart, dashboard, desert, dinosaur, dip, dirt field, dirt road, dirt track, display, diver, draw, driftwood, dry, duckling, dune, eagle, enclosure, eye, fang, fern, field, figurine, fish, float, floor, flower, flow |
| Carnivore  | tube, twig, underwater, unicorn, up, vegetable, vegetation, walk, walk, watch, water, wave, weed, wetsuit, whale, white, window sill, windshield, wood, wood floor, world, wrap, wristband, yellow, zoo CD, appear, apple, apple tree, aquarium, area, arm, backrop, bag, balance, ball, bamboo, bamboo forest, bank, basket, balh, balthroom accessory, balthroom sink, beach, beak, beac rub, baever, belly, bin, birch tree, bird cage, bite, blanket, blood, boat, bottle, boulder, break, brush, bureau, bush, cabinet, cage, can, car, car window, catamount, catch, cave, chair, chase, chopstick, cigarette, claw, close-up, closet, cloth, container, counter top, cowboy hat, crane, crate, cub, cub, cub, cub, cub, cub, cut, dairy, dandelion, dark, deer, den, dir field, diir road, dirt track, dog breed, dog house, dough, old, officer, drink, dry, eat, enclosure, evergeren, eve, fall, fang, faucet, fence, field, fir tree, fish, flower, flower bed, foot, footstall, forest, frosty, fruit, fur, grass, grassland, grassy, grazze, green, greenery, greet, ground squirrel, guard, habitat, hamster, hand, hay, hide, hill, hillside, hole, ice floe, iceberg, illuminate, image, jaw, jump, jungle, lake, lamb, land, lap, laugh, lay, ledge, lick, log, lush, mammal, man, mane, meat, mound, mountain stream, mouth, mud. mulch, nects, night, night view, open, paper bag, path, pavement, peak, pen, pencil, perch, photo, pine, pink, plaint, plant, plastic, play, pole, pond, pool, portrait, post, posterad, profile, raft, rail, and, ever, ever, level bank, riverbed, rood, rock face, rock formation, rocky, roof, run, rural, savanna, screen door, sea, sea lino, seal, shadow, sheepe, shelter, shirt, sink, sky, sleep, smile, snow, snowball, snowy, spruce, squat, squirrel, stand, stem, stick, stone, straw, stream, street dog, stretch, stripe, stuff, stump, sun, swamp, swim, tabby, tank, terrain, tiger, tire, toe, tree, tree trunk, trout, trunger, tub, tube, tundrat, tug's, v |
| Insect     | acorn, alcohol, apple, apple tree, asphalt road, attach, autumn leave, ball, banana leaf, banana tree, bark, bat bathroom, bathroom sink, beautiful, berry, bird, bird nest, bite, black, blackberry, bloom, blossom, blue, boulder, break, brick, broom, brown, brush, bumblebee, bush, butterfly bouse, cactus, candy cane, cane, cardboard, cardboard box, carpet, cat, ceiling, cement, chestnut, climb, close-up, cloth, cloudy, color, concrete, container, couple, crack, cricket, curb, daisy, dandelion, dirt field, dot, dry, evergreen, eye, feather, fence, fern, field, figurine, flap, floor, foot, forest floor, froug, fruit, fruit tree, garden, gasmask, glass bead, glass jar, glass vase, goggles, gold, grain, grass, gravel, gray, green, greenery, hand, hang, head, hide, homet, hummingbird, image, ivy, jar, jump, land, larva, lavender, leaf, ledge, lemon, lid, lilac, limb, lush, maple leaf, marble, mat, measuring tape, microscope, mud, mulch, napkin, needle, nest, night, nose, nut, orange, orange tree, pad, paint brush, paper towel, parrot, patch, pavement, peel, peony, perch, person, pest, pet, petal, photo, pillar, pillow, pine, pink, plastic, pole, polka dot, pond, poppy, post, pot, puddle, rail, red, reed, road, rock face, rocky, roll, rope, rose, ruler, sand, scale, screen door, sea, seed, shadow, sign, sit, skin, sky, slug, spider web, spruce, stab, stand, stare, stem, stick, stone, stool, string, stripe, stump, swab, swallowail butterfly, swirl, tabby, tank, thistle, tile wall, tissue, toilet paper, toilet seat, tool, tree, tree branch, tree frog, tree trunk, vegetation, violet, walk, wall, water, water drop, wave, wb, white, wildflower, window, wire, wood wall, writing, yellow  |
| Instrument | CD, Eiffel tower, alcohol, alley, altar, amplifer, animal, antique, arch, armchair, army, art artifact, assembly line, autumn leave, baby, backdrop, bag, balcony, ball, balustrade, band, bangs, banjo, bar stool, barrel, baseball glove, baseball hat, basement, bassist, bat, bath, bathroom accessory, bathroom sink, battery, beach, bead, beam, beard, bedroom, beer beer can, belt, beret, beverage, billard, billiard table, bird, birthday, birthday cake, bite, blade, blanket, blender, blowfish, boardwalk, boat, boiler, book, bookshelf, boot, bottle, bottle screw, bouquet, bow, bow tie, bowling ball, braid, brass, brick, brick, brick building, brooch, broom, brown, brunette, brush, bubble, bullet, bundle, bureau, bust, cabinet, cage, cake, camp, can, cane, canopy, cape, camival, carpet, carrot, carry, carve, cat, cathedral, ceiling, ceiling fan, chain, chandelier, chapel, check, chestnut, chicken, chocolate cake, choir, chopstick, christmas hat, church bench, cigar, cigarette, clay, cloak, close-up, closet, cloth, cloudy, club, clutch, clutch bag, cock, cockail dises, comb, computer, concert, concert hall, conductor, connect, container, copper, corner, cosmetic, cosplay, costume, cotton candy, couch, counter top, cowboy hat, crowd, crowded, crumb, cue, cup, curb, curtain, cylinder, dam, dance, dark, dart, dayligh, decorate, design, dirt field, disco ball, display, doll, door, door handle, draw, drawer, dress, dress hat, dress shirt, dresser, drink, dumbbell, eagle, carphone, carring, elastic band, electronic, equipment, face, fair, fan, faucet, feather, fedora, festival, field, figurine, flag, flap, floa, flower, folding chair, fondant, foot, football field, football game, footrest, footstall, fountain pen, frosting, fruit, frying pan, garment, gathering, geisha, glass bead, glass bowl, glass vase, glass window, glasses, goggles, gold, grass, grassy, green, hair, hall, hallowede, hand, handle,  |
| Primate    | window, wine bottle, wine glass, wing, wire, witch, wok, woman, wood, wood floor, wood wall, wooden spoon, workbench, workshop, wristband, writing, yellow appear, apple, attach, baby, baby elephant, back, balance, ball, balustrade, bannan tree, bandage, barrel, basin, basket, bata, balk, bench, berry, bird cage, bire, black, blade, blanket, blue, boardwalk, bookshelf, bottle, boulder, branch, broccoli, brown, brown bear, building, canopy, car, car window, card, carrot, cat, catch, cement, chair, chase, clarinet, claw, cliff, close-up, cob, coconut, computer, container, couple, cub, curb, dinning table, dirt road, dirt track, display, dog, dog house, drink, dry, eat, enclosure, eye, face, fang, field, flower, flute, fruit, fur, grassland, greet, greeting card, hair, hammock, hand, hang, hat, hay, head, hedge, book, hot, howler, huddle, hug, husky, hyaena, impala, jump, karate, koala, land, lap, laptop, laugh, lay, leash, hedge, leprecham, lick, log, mammal, man, mammal, man, mane, martial, mill, motorbike, motorcycle, motorcyclist, mound, mountain, mouth, neck, neckband, night, nose, open, only palm tree, panda, park bench, parrot, patch, peak, peel, perch, person, pet, picnic table, pillar, plain, plank, plant, play, pole, pool, poppy, power line, profile, rail, ramp, red, red panda, relax, ride, rock face, rock formation, roll, rope, rope bridge, sale, sand, savanna, scooter, sea, shadow, shirtless, shoulder, showcase, sin esse, sit, sky, sleep, sloth, smile, squat, stab, stare, steam, stem, stick, stone, stool, strap, straw, stretch, string, stuff, stump, sun hat, swing, swinge, table, tablecloth, tassel, telegraph pole, fie, tile wall, toy, treat, tree, tree branch, tree trunk, trumpet, tub, tusk, twig, wear, weed, white, window, window sill, wire, wood, yellow   |