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# Diverse Diffusion: Enhancing Image Diversity in Text-to-Image Generation

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## Abstract

Latent diffusion models excel at producing high-quality images from text. Yet, concerns appear about the lack of diversity in the generated imagery. To tackle this, we introduce Diverse Diffusion, a method for boosting image diversity beyond gender and ethnicity, spanning into richer realms, including color diversity.

Diverse Diffusion is a general unsupervised technique that can be applied to existing text-to-image models. Our approach focuses on finding vectors in the Stable Diffusion latent space that are distant from each other. We generate multiple vectors in the latent space until we find a set of vectors that meets the desired distance requirements and the required batch size.

To evaluate the effectiveness of our diversity methods, we conduct experiments examining various characteristics, including color diversity, LPIPS metric, and ethnicity/gender representation in images featuring humans.

The results of our experiments emphasize the significance of diversity in generating realistic and varied images, offering valuable insights for improving text-to-image models. Through the enhancement of image diversity, our approach contributes to the creation of more inclusive and representative AI-generated art.

## 1 Introduction

Latent diffusion models have gained significant attention for text-to-image generation, with DALL-E [18] and Stable Diffusion [19] being some of the most prominent examples. While they have shown impressive results in generating high-quality images from textual descriptions, there have been concerns regarding potential causes of their usage for various sensitive applications.

To prevent the potential misuse of these models, a few recent efforts have been made. For instance, [6] investigated the efficacy of Stable Diffusion for the medical imaging. Additionally, [24] explored image-retrieval frameworks to detect content replication in generated images. [21] developed a classifier to trace back generated images to their source models, ensuring accountability

for creators. Furthermore, [13] created faithful diffusion that selects images corresponding to a prompt.



Figure 1: Images generated with standard Stable Diffusion and our method for the prompt “rose”, batch size = 5. Here, our method is shown to select images not only diverse in colors, but also in ideas, compared to Stable Diffusion.

Bias can arise from various sources, such as the training data or the algorithmic biases inherent in the model architecture. [25] shows that text-to-image models pick up cultural biases linked to various Unicode scripts. While increasing training data quality remains a significant concern and solutions such as [23] have been proposed to tackle dataset level bias, it is also important to ensure that the diffusion-based methods do not amplify any biases present in the training data.

The lack of diversity problem was addressed in [11], [5] and [8]. There, the authors notice that images generated by Stable Diffusion lack diverse cultural representation and are prone to gender stereotypes. [4] highlights the need for algorithmic adjustments in generative models to increase the diversity of their output for multi-solution tasks. It also proposes a framework that integrates automated machine learning with computational creativity to automate key tasks in artistic pipelines and increase the creative autonomy of computational agents. Further, [27] argues that Stable Diffusion v1-4 violates demographic parity in generating images of a doctor given a gender- and skin-tone-neutral prompt. The author observed that the model is biased towards generating images of perceived male figures with lighter skin, with a significant bias against figures with darker skin, as well as a notable bias against perceived female figures. According to [3], AI image generators often display gender and cultural biases. Stable Diffusion as other models has inherent biases from the training datasets. It was found, for instance, that Stable Diffusion depicts all engineers as male despite women making up around 20% of people in engineering professions. According to [7] Stable Diffusion bears the nontrivial biases due to learned relations between not necessarily related concepts like “millennials” and “drinking”.

There are recent methods focusing on diversity for Stable Diffusion generated images as well. Most of them focus on specific domains to broaden the image variability. For instance, [22] and [2] report that adding supporting context to text-to-image models prompts increases diversity in

both general and human-specific fashion. In [20] the authors report increase in generation of rare-concept images following the seed manipulation. [14] trains prompt embeddings that would guide to generate images fairly according to the set of sensitive attributes such as gender and ethnicity.

Promoting novelty and diversity is a challenge that exists both for image and text generation. In [28] the authors emphasize the importance of producing novel and diverse textual outputs. By leveraging a language-model-based discriminator, their model DP-GAN assigns high rewards to text that exhibits both novelty and fluency. Our approach for image generation also goes beyond addressing sensitive fairness concerns and opens new avenues for creative expression, as we focus not only on representation of people with different ethnicities and genders, but also, as our approach is unsupervised, on diversity of color and other dissimilarities of images in a batch.

It is common to generate multiple image versions using latent diffusion models. Even in non-sensitive scenarios, having diverse outputs is essential. A collection of similar images holds little advantage over a single image. Therefore, we propose a method that encompasses various domains, including faces, cars, animals and more to enhance diversity in text-to-image generation. By increasing diversity within batches, we can reduce the number of required generation iterations. For instance, by increasing the probability of obtaining satisfactory images from 1% with a vanilla Stable Diffusion to 5% using our method, the expected number of generated batches before satisfaction decreases by a factor 5.

Overall, in this article, we present Diverse Diffusion, *i.e.*, modifications to the Stable Diffusion algorithm that facilitate the generation of diverse images and thereby help to create more inclusive art within a limited number of Stable Diffusion generations (and therefore less computational power) in unsupervised fashion. Images generated with and without our approach are illustrated in Figure 1.

We highlight the following contributions: (i) A general unsupervised technique that can be applied to existing text-to-image models to increase image diversity, which is essential for generating realistic and varied images. (ii) Experiments that demonstrate the diversity advantages of our proposed approach.

## 2 Diversity algorithms

There are different approaches to generating diverse point sets in an unsupervised manner. For example, Latin Hypercube Sampling [16], low discrepancy methods [1][10][17] and low dispersion. Here, we focus on low dispersion, optimized by a very limited random search for staying in the domain of validity of our latent variables. We aim to find vectors in the latent space of Stable Diffusion that are distant from one another. To accomplish this, we generate multiple vectors in the latent space until we obtain a set that contains the required number of vectors (determined by the batch size) and satisfies a specific distance requirement.

In the “**baseline**” setting, we generate images using the standard, unmodified version of Stable Diffusion without imposing any distance requirements on the latent space.

In the “**cap**” setting, we enforce a minimum requirement of  $d_{\min}$  on the vectors corresponding to all pairs of images within a batch. We illustrate the procedure of choosing a set of latent vectors  $V$  for batch size  $B$  and minimum distance requirement  $d_{\min}$  in algorithm 1.

In the “**max**” setting, we impose a maximum number of iterations on searching for a new vector that would have a maximal minimal distance to all the already selected vectors in the batch. We illustrate the procedure of choosing a set of latent vectors  $V$  for batch size  $B$  and a maximum number of iterations requirement  $N_{\max}$  in algorithm 2.

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**Algorithm 1** Generating diverse vectors in the “cap” setting

---

**Require:** batch size  $B$ , minimum distance  $d_{\min}$ **Ensure:** Set of diverse vectors  $V$ 

```
1:  $V \leftarrow \emptyset$  {Initialize an empty set of vectors}
2: while  $|V| < B$  do
3:    $v_{\text{new}} \leftarrow \text{GenerateNewVector}()$  {Generate a new vector in the latent space of stable diffusion}

4:   if  $\text{MinDistance}(v_{\text{new}}, V) \geq d_{\min}$  then
5:      $V \leftarrow V \cup \{v_{\text{new}}\}$  {Add the new vector to the set}
6:   end if
7: end while
8: return  $V$  {Return the set of diverse vectors}
```

---

---

**Algorithm 2** Generating diverse vectors in the “max” setting

---

**Require:** batch size  $B$ , maximum iterations number  $N_{\max}$ **Ensure:** Set of diverse vectors  $V$ 

```
1:  $V \leftarrow \emptyset$  {Initialize an empty set of vectors}
2: for  $b = 1$  to  $B$  do
3:    $v_{\text{farthest}} \leftarrow \text{GenerateNewVector}()$ 
4:   for  $N = 1$  to  $N_{\max} - 1$  do
5:      $v_{\text{new}} \leftarrow \text{GenerateNewVector}()$  {Generate a new vector in the latent space of stable diffusion}
6:     if  $\text{MinDistance}(v_{\text{new}}, V) > \text{MinDistance}(v_{\text{farthest}}, V)$  then
7:        $v_{\text{farthest}} \leftarrow v_{\text{new}}$ 
8:     end if {Find the vector with the maximum minimum distance to the existing set}
9:      $V \leftarrow V \cup \{v_{\text{farthest}}\}$  {Add the farthest vector}
10:  end for
11: end for
12: return  $V$  {Return the set of diverse vectors}
```

---

In setting “**pooling\_cap**” and “**pooling\_max**” we apply the same exact methods as in “cap” and “max” but the distance is calculated differently. Specifically, the distance is computed between the vectors that were initially processed by average pooling  $8 \times 8$  which down-samples the vector size to  $4 \times 8 \times 8$ .

We use two different settings for generating diverse image batches: **standard experiment** and **long experiment**.

The parameters of a standard experiment are the following: in setting “cap” the minimal distance between latent vectors should be at least 182, while in the setting “pooling\_cap” it should be at least 3.1, in setting “max” and “pooling\_max” the number of iterations after which the farthest vector is found is 100.

The parameters of a long experiment are the following: (i) in setting “cap” the minimal distance between latent vectors should be at least 183, while in setting “pooling\_cap” it should be at least 3.1. In the setting “max” and “pooling\_max” the number of iterations after which the farthest vector is found is 10000.

The choice of settings provides variable diversity levels and variable computational complexity. In the current paper for small batch sizes (3, 5, 10), we create both standard and long experiments, and for the big batch sizes (50) we create only standard experiments. In the cap and pooling cap setting, due to the distance limitations and no limit on a number of iterations, the experiment for big batches becomes increasingly slower. That is why, for purposes of limiting computational cost, we recommend the “pooling\_max” method for batch sizes more than 50.

### 3 Evaluation Methods

In order to evaluate diversity of generated images, we use both quantitative and human evaluation methods. For quantitative methods, we focus primarily on color diversity image similarity metric LPIPS [29]. Increasing image color diversity is an important aspect of ensuring general diversity of the images: we would like to get representation for people, animals, and objects of all colors.

#### 3.1 Color diversity

To assess the color diversity in an image batch  $b$ , we employ a method that involves extracting color information from each image in the batch using the RGB color model, which represents colors as a combination of red, green, and blue channels. Specifically, we compute the mean value for each channel ( $R_i, B_i, G_i$ ) in the given image  $i$ , and identify whether one of these colors is predominantly present in the image  $i$ .

To determine the dominant color in image  $i$  with respect to a coefficient  $K$ , we define the image as having a dominant color of Red if  $R_i > K \times \max(G_i, B_i)$ , as Green if  $G_i > K \times \max(R_i, B_i)$ , as Blue if  $B_i > K \times \max(G_i, R_i)$ , and as None if none of these inequalities are true. We denote the dominant color of image  $i$  with respect to the coefficient  $K$  as  $D_K(i)$ .

To evaluate color diversity of an image batch  $b$ , we compute a number of dominant colors in that batch with respect to a coefficient  $K$ ,  $N_K(b)$ .

$$\begin{aligned}
 N_K(b) = 3 - & \prod_{i \in b} (1 - I(D_K(i) == Red)) \\
 & - \prod_{i \in b} (1 - I(D_K(i) == Green)) \\
 & - \prod_{i \in b} (1 - I(D_K(i) == Blue)), \tag{1}
 \end{aligned}$$

where  $I$  is an indicator function and  $D_K(i)$  is a dominant color of an image  $i$  with respect to the coefficient  $K$ .

The first color diversity metric across the batches set  $B$  is an average number of dominant colors present in the batches of that set with respect to a coefficient  $K$ .

$$Avg_K(B) = \frac{\sum_{b \in B} N_K(b)}{\|B\|}, \tag{2}$$

where  $\|B\|$  is the total number of batches in the set  $B$ .

The second color diversity metric aims to compute proportion of batches that contain at least one image predominantly exhibiting red, blue or green color, considering RGB image encoding. This allows for the quantification of color variability within a batch.

Specifically, for various values of a coefficient  $K$  and batch set  $B$  we compute the proportion

$$C3_K(B) = \frac{\sum_{b \in B} I(N_K(b) == 3)}{\|B\|}, \quad (3)$$

where  $\|B\|$  is the total number of batches in the set  $B$  and  $I$  is an indicator function.

Another color diversity metric is the proportion of batches containing images with different dominant colors (not all the images in a batch are predominantly red, blue or green).

Specifically, for various values of a coefficient  $K$  and batch  $b$  we compute the proportion

$$C2_K(B) = \frac{\sum_{b \in B} I(N_K(b) >= 2)}{\|B\|}, \quad (4)$$

where  $\|B\|$  is the total number of batches in the set  $B$  and  $I$  is an indicator function.

### 3.2 LPIPS metric

Similarly to [9] and [12], we use LPIPS (Learned Perceptual Image Patch Similarity) [29] to evaluate the diversity of the images generated by Stable Diffusion. We measure the pairwise similarity between images in a batch and compare the obtained values for different modifications of Stable Diffusion generation algorithm.

### 3.3 Ethnicity and gender classification for images portraying humans

As mentioned in [27], Stable Diffusion may lack diversity in ethnicity representation. That is why, for the prompts that we use for the human face generation, we compare ethnic diversity in between our methods and basic version of Stable Diffusion. In order to identify the ethnicity of a person present on an image, we use DeepFace ethnicity recognition [26]. In particular, we identify the following groups of ethnicities: (i) Black, (ii) Asian, (iii) Hispanic, (iv) White or Middle Eastern. For gender classification (male/female), we also use DeepFace. We compute the percentage of batches where all pairs of genders and ethnicities are present or at least 3 out of 4 ethnicities are present (similarly to colors).

### 3.4 Multiplicative improvement

Our method aims to increase representation of underrepresented groups. That is why for all the metrics mentioned above we compute percentage versus multiplicative improvement score. Here percentage stands for the percentage of batches that follow some characteristic  $C$  (for example, contain images of Asian men) and multiplicative improvement stands for multiplicative increase in this percentage for our preferred method (“**pooling\_cap**”) compared to the baseline method (**standard Stable Diffusion**). By using this metric, we can evaluate our efforts in promoting the inclusivity of underrepresented classes.

## 4 Experiment setting

As a baseline, we use Stable Diffusion v-5 with PNDM Scheduler. We measure diversity using LPIPS or artificial classes (image hue) or human-centered criteria (gender/ethnicity) and check

various batch sizes. We use machines with 8 Tesla V100-SXM2-32GB GPUs and 80 x86\_64 CPUs. The full code is (anonymously) provided in <https://anonymous.4open.science/r/DiverseDiffusion-1012>. See supplementary material for reproducibility details.

#### 4.1 Experiments on small batches

For our small batch experiment setup, we choose the following list of prompts: “face”, “rose”, “butterfly”, “cat”, “horse”, “car”, “ornament”, “bird”, “color”, “a professional photograph of an adult person face”, “photo of an animal in the grass” and “octane, hyperrealistic, backlit”.

In each experiment, we consider batches of 3, 5 and 10 images in order to compute diversity metrics in each of these batches, and to compare our modifications with original Stable Diffusion. For each batch size and each modification, we create at least 2500 batches.

#### 4.2 Experiments on big batches

For our big batch experiment setup, we choose the following list of prompts: “a professional photograph of a man face”, “a photograph of a person with different colored eyes”, “a passport-style photograph of a person’s face”, “a professional photograph of an adult person face”, “a close-up photograph of an elderly person’s face” and “a beauty shot of a model’s face”. These prompts are all centered on human photos and thus allow us to evaluate not only LPIPS and color diversity but also gender and ethnicity variation, which are crucial to ensure in any human-centered applications of diffusion models. In each experiment, we consider batches of 50 images in order to compute diversity metrics in each of these batches and compare our modifications with the baseline: original Stable Diffusion. For each modification, we create at least 900 batches.

### 5 Experiments and results

An example of image batches generated with our method “pooling\_cap” and original Stable Diffusion is presented in Figure 2. In two randomly chosen examples among all batches generated by the baseline and “pooling\_cap” for the prompt “a photograph of a person with different colored eyes” and batch size 50, we can see that while getting images corresponding to the prompt remains difficult for our chosen method, we still get improvement both in number of images corresponding to the prompt and ethnic diversity.

Further, we present the experimental evaluation of our proposed methods for promoting diversity in generated image batches. We assess the color diversity, gender and ethnicity representation, and image diversity using the LPIPS metric. The experiments are conducted on various prompts and compared against the baseline Stable Diffusion method.

#### 5.1 Color evaluation

In this subsection, we evaluate the color diversity of the generated image batches. We present multiplicative improvement results, summarizing the color diversity improvement for various values of the coefficient  $K$  across different prompts specified in Section “Experiments on small batches”. Other experiment results are provided in the supplementary material.

In Figure 3, we can see that in majority of the cases using pooling\_cap method does not decrease the representation of batches with all 3 colors dominance. We also can see that we get very high





Figure 2: Examples of images generated with the prompt “a photograph of a person with different colored eyes”: pooling\_cap against baseline Stable Diffusion, batch size=50. Images corresponding to the “expected output” of the prompt are highlighted in red.

(> 2.5) improvement coefficient numbers in cases where color dominance is defined using coefficient  $k = 1.1$ , which significantly increases the number of batches featuring this rare characteristic.

In Figure 4, we can see that in majority of the cases using pooling\_cap method does not decrease the representation of batches featuring at least 2 dominant colors. Similar to figure 3, we observe very high (> 2.5) improvement coefficient numbers only in cases where color dominance is defined

using coefficient  $K > 1$ , which significantly increases the number of batches featuring this rare characteristic. We also can see that for modes where having at least 2 dominant colors per batch is a rare characteristic (less than 50% of batches feature it), we always have improvement coefficient  $> 1$ , thus increasing the color diversity.

## 5.2 Gender and ethnicity evaluation

Here, we evaluate the impact of our proposed method on the diversity of gender and ethnicity representation in the generated image batches.

Our results, as illustrated in Figure 5, demonstrate a remarkable enhancement in the representation of underrepresented categories. This improvement is consistently observed across all ethnicity/gender pairs that initially appeared in less than 60% of the batches. Notably, our cap pooling technique has led to a substantial increase in their presence, with certain categories being up to 2.4 times more prevalent than in the standard Stable Diffusion version.

While we see some detrimental results for Hispanics representation, it is important to note that ethnicity identification based solely on a person’s image is not always accurate for artificial intelligence methods. In this research, we primarily focus on the diversity between white and black individuals, as they can be visually distinguished with minimal ambiguity [15]. In Figure 5, we observe a positive improvement in the representation of black individuals, both male and female, compared to the baseline results for Stable Diffusion.

Overall, these findings highlight the effectiveness of our approach in promoting diversity and addressing underrepresentation in gender and ethnicity across various image batches.

## 5.3 LPIPS evaluation

In this subsection, we evaluate the generated image diversity using the LPIPS metric. LPIPS measures the perceptual similarity between images based on deep neural network representations. A lower pairwise LPIPS score indicates greater diversity among the generated images.

Here we compare the performance of different methods, including the baseline and our proposed “pooling\_cap” method, across different batch sizes.

Figure 6 presents the average batch pairwise LPIPS distance for a batch size of 3. We can see that for most of the experiments “pooling\_cap” method proves to be more diverse than the baseline, while for certain cases such as “face”, baseline outperforms “pooling\_cap”. We also notice that “pooling\_cap” is not the single method that performs well. Others, such as “cap”, prove to be the best for various prompts as well. For example: “rose”, “ornament” and “car”.

Figure 7 illustrates the average batch pairwise LPIPS distance for a batch size of 5. We can see that for most of the experiments “pooling\_max” method proves to be most diverse among all the methods outperforming “pooling\_cap”, while “pooling\_cap” is still better than the baseline for most of the cases. Similarly to Figure 6, we can also notice that for the cases where baseline had a small average LPIPS distance (for instance “octane” and “photo of an animal”), all the proposed methods significantly outperform the baseline. This fact shows that even for small batches, our methods provide diversity benefits in cases when it was really lacking.

Figure 8 showcases the average batch pairwise LPIPS distance for a batch size of 10. Here, we can see that for most of the experiments “pooling\_max” is the most diverse among all the methods, while “pooling\_cap” is still better than the baseline for most of the cases. We again notice that in cases where the baseline had a small average LPIPS distance (for instance “octane”), all of

the proposed methods significantly outperform the baseline. This fact shows that even for small batches, our methods provide diversity benefits in cases when it was really lacking. In contrast to the results presented in Figure 6, in Figure 8 “pooling\_max” method shows to always outperform the baseline. This observation indicates that our methods provide better diversity guaranties for the bigger batch sizes.

In contrast to the results shown in Figures 6, 7 and 8, in Figure 9 we can see that the “pooling\_cap” method is consistently highlighted as the most diverse across all experiments. This emphasizes that larger batch sizes lead to better diversity due to the increased availability of reference points for each new image. This experiment strengthens our earlier observations on color diversity and solidifies the superiority of the “pooling\_cap” variant over the standard Stable Diffusion approach in terms of diversity.

Table 1: Average pairwise LPIPS value across different batches with the same prompt.

Method	average LPIPS
Baseline	$0.354 \pm 0.004$
ENTIGEN	$0.325 \pm 0.004$
<b>Pooling_cap</b>	<b><math>0.294 \pm 0.005</math></b>

For the experiment presented in Table 1, we compute LPIPS distance between several image pairs for the same prompt (not necessarily in the same batch) and then average it between different prompts. We do this experiment across standard Stable Diffusion, our preferred method “pooling\_cap” and another diversity method and ENTIGEN [2] diversity method applied to the same prompts as in subsection “Experiments on big batches”. More precisely, to each prompt, we add either “irrespective of their gender” or “irrespective of their color”. We can see that even though our generation is focused mainly on batch setting, our method achieves better diversity both than Stable Diffusion and ENTIGEN, that was specifically designed to eliminate human-centered biases such as gender and ethnicity.

Multiplicative improvement of percentage of image batches that contain at least one image with dominance of each color (Red, Green, Blue)

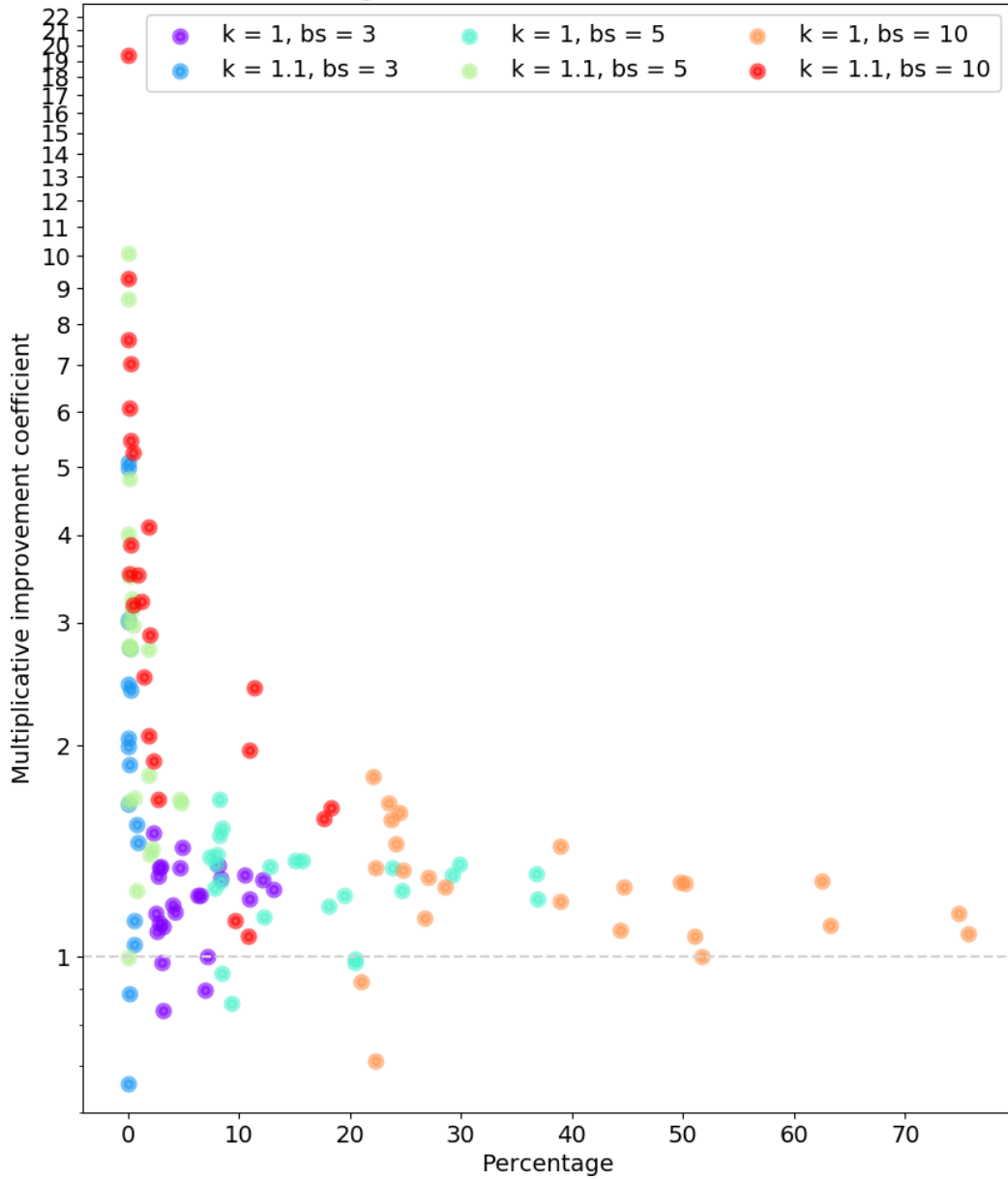


Figure 3: Multiplicative improvement of percentage of batches containing images with all 3 dominant colors: pooling\_cap against baseline Stable Diffusion, depending on  $K$  as specified in the text and batch size  $bs$ . Improvements are greater on the left, *i.e.* more difficult cases.

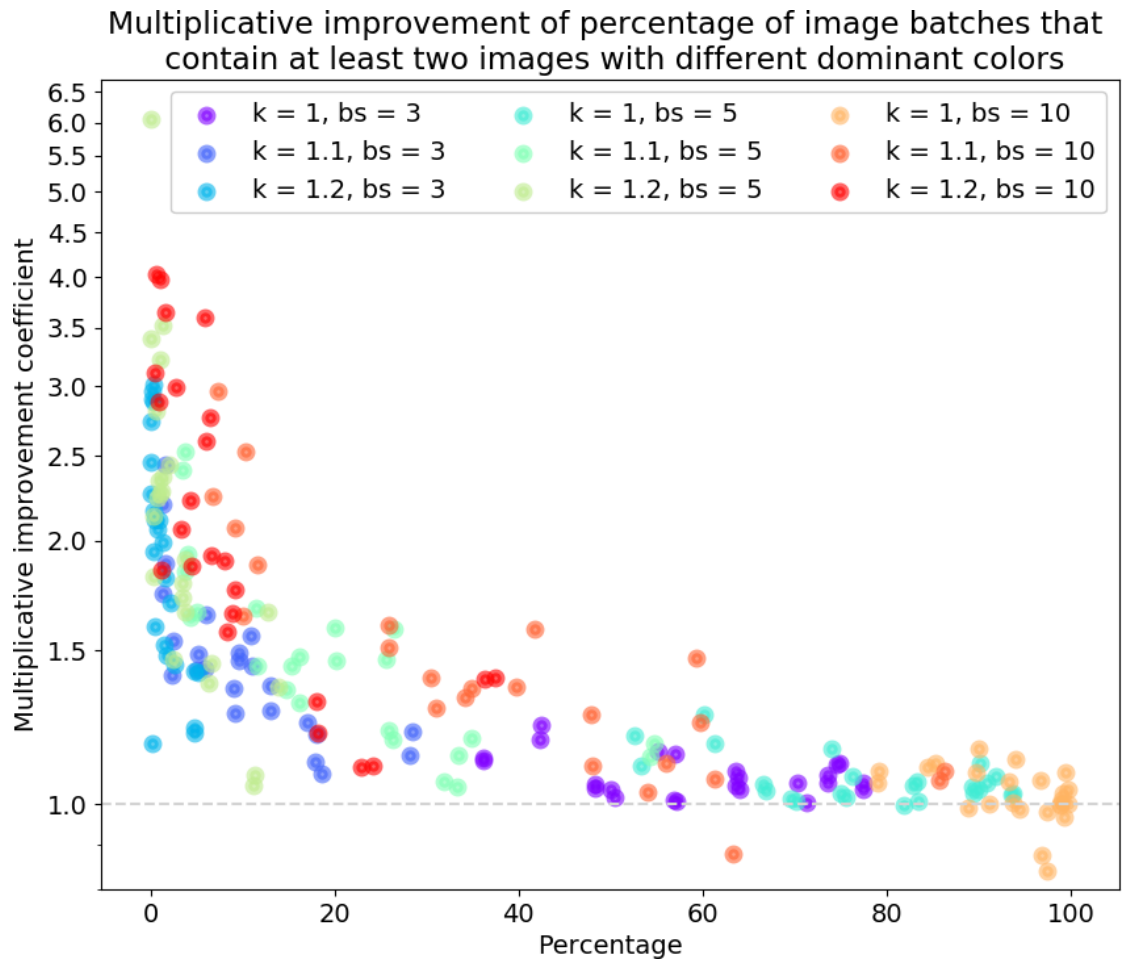


Figure 4: Multiplicative improvement for the percentage of batches containing images of at least 2 of the 3 categories: the improvement is greater for more difficult cases, which are on the left (pooling\_cap against baseline Stable Diffusion method).

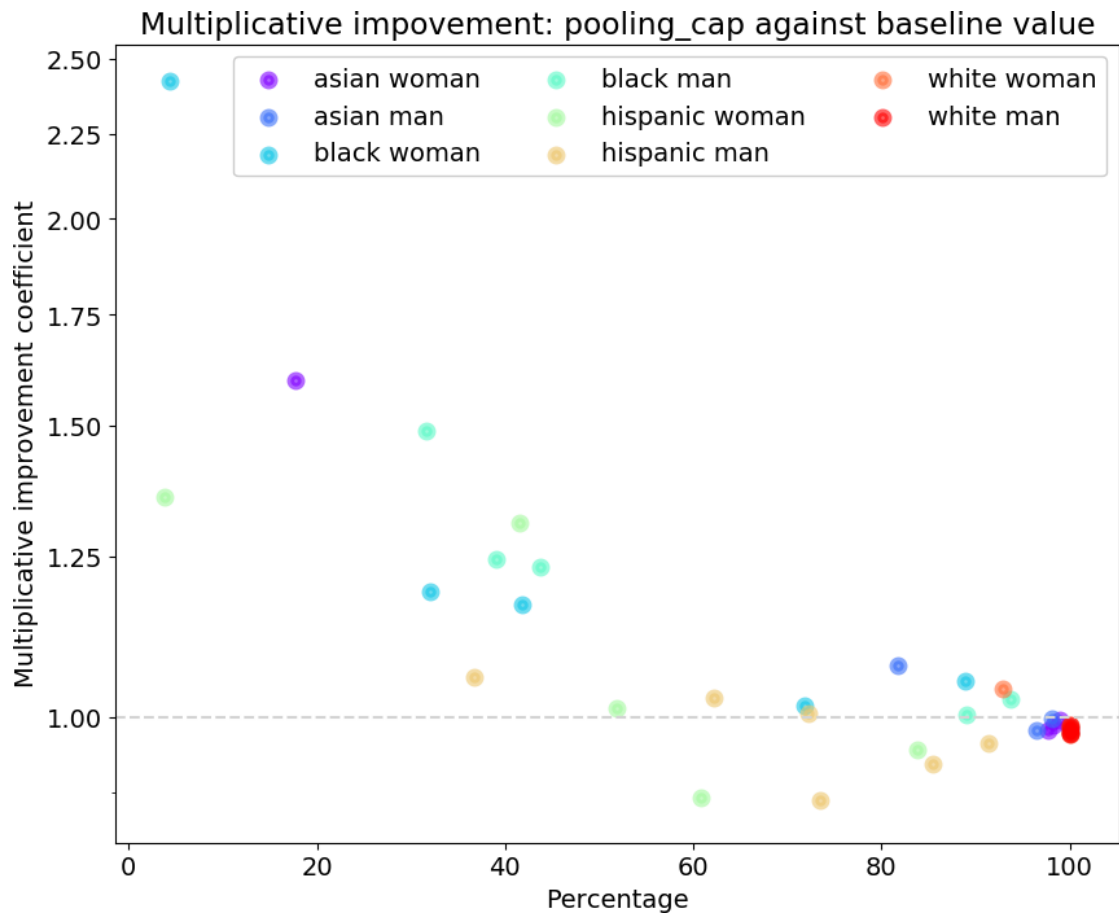


Figure 5: Multiplicative improvement (increase) of percentage of batches containing various ethnicity + gender pairs: we get a greater improvement for more difficult cases (pooling\_cap against baseline Stable Diffusion method).

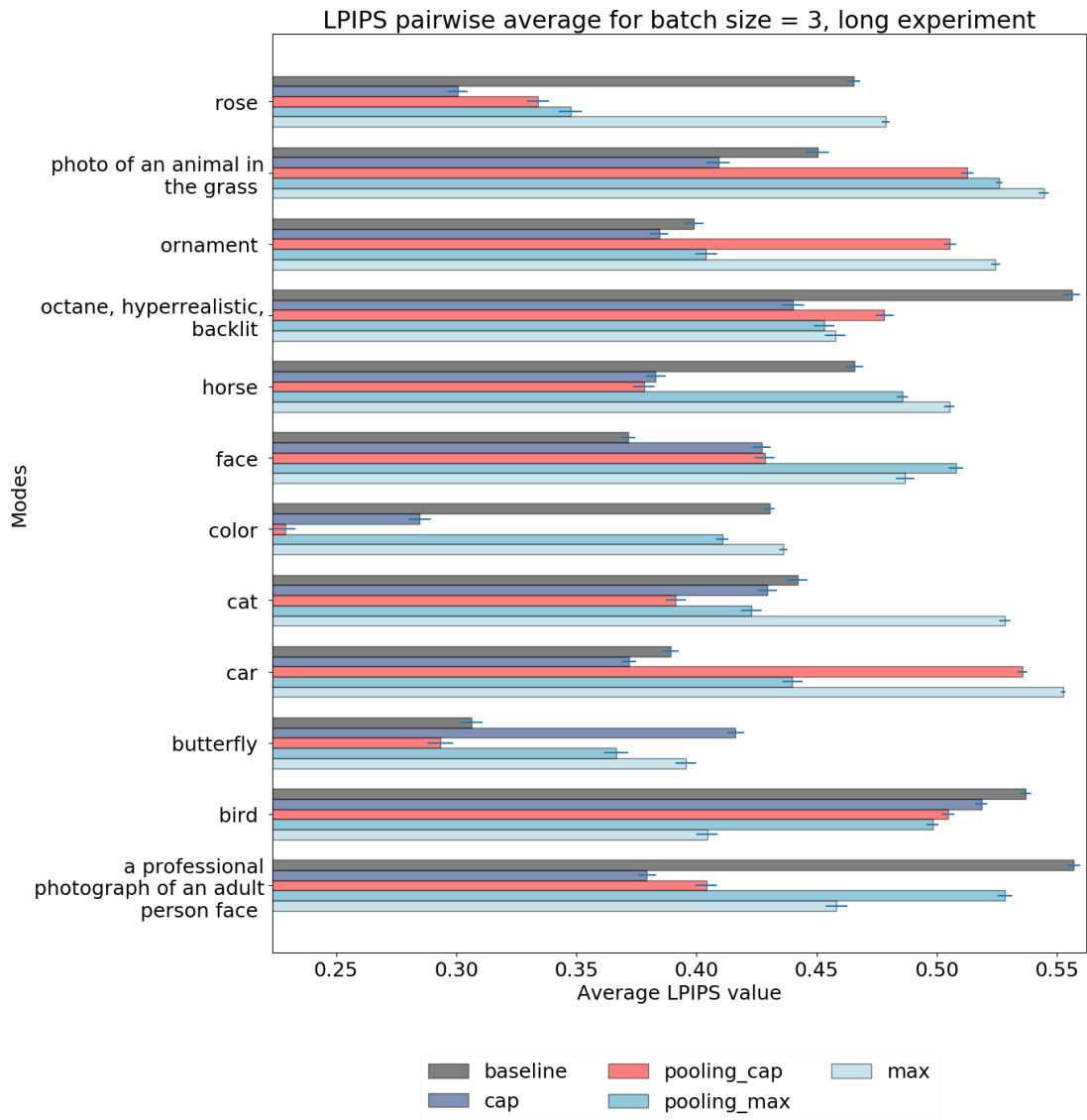


Figure 6: Average batch pairwise LPIPS, batch size=3: no clear conclusion overall, due to the small batch size.

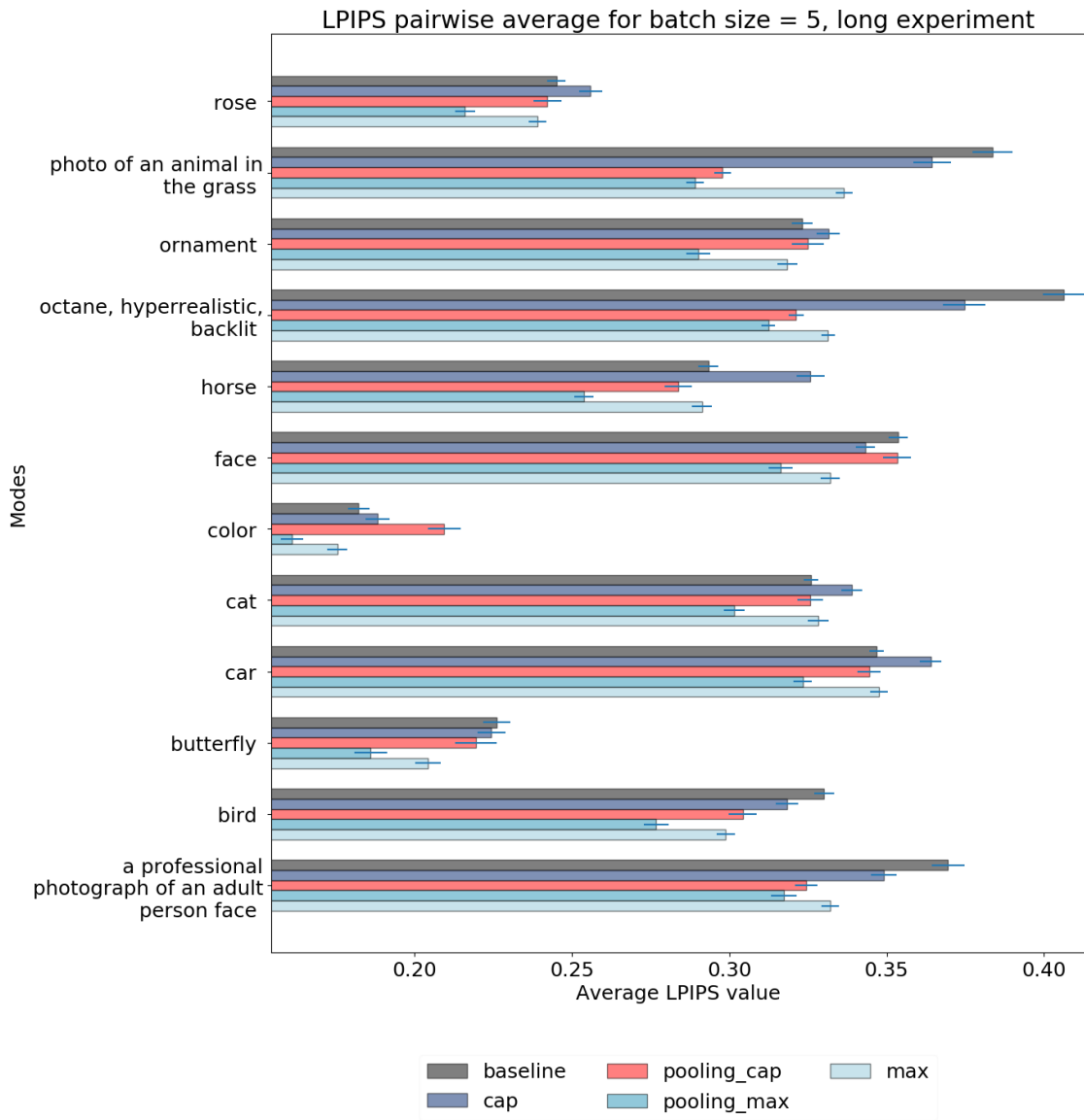


Figure 7: Average batch pairwise LPIPS, batch size=5: the two Pooling methods are often better than the baseline, though results are clearer for batch size 50.



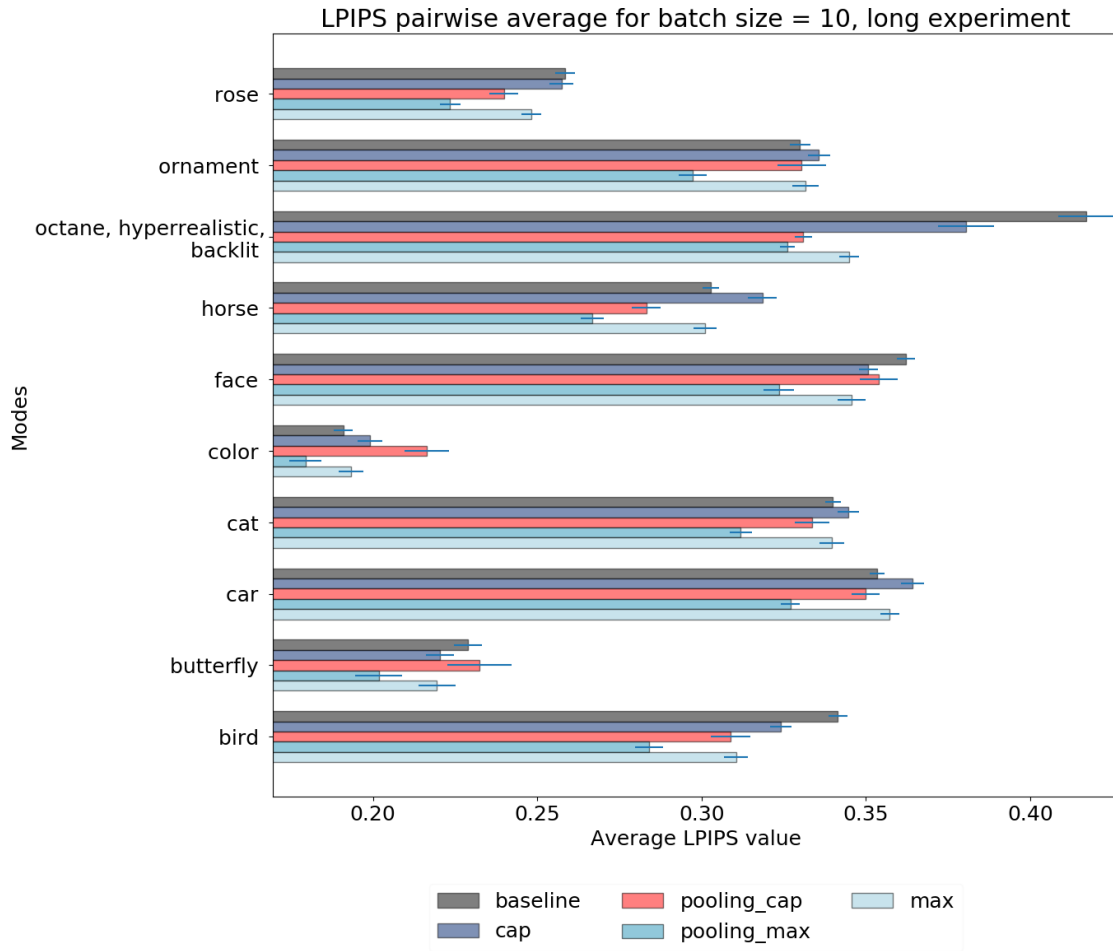


Figure 8: Average batch pairwise LPIPS, batch size=10. The two Pooling methods are often better than the baseline, though results are clearer for batch size 50.

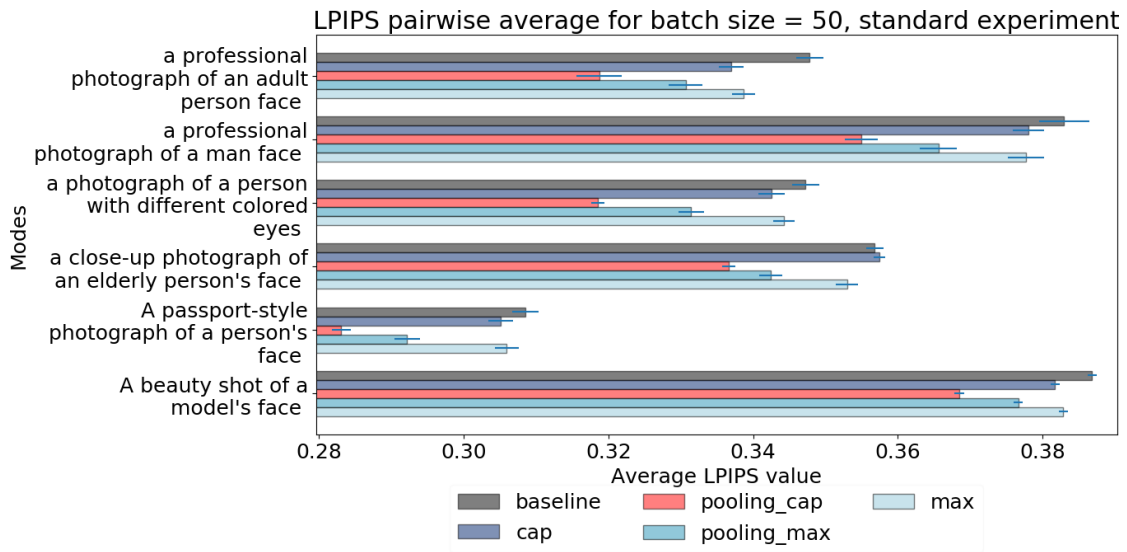


Figure 9: Average batch pairwise LPIPS, batch size=50. For this batch size, in all cases pooling methods (both max and cap) are beneficial to diversity as measured by LPIPS.

## 6 Conclusions

In conclusion, our contributions include (i) a general technique that can be applied to existing text-to-image models to increase image diversity, which works in an unsupervised manner with a negligible overhead and (ii) experiments that showcase the diversity advantages of our proposed approach applied to Stable Diffusion, through classification (both image hue and gender/ethnicity) and LPIPS measurements.

Experimental results highlight the impact of our proposed method on color diversity. By analyzing the multiplicative improvement in the batches containing images with dominant colors, we observe that the “pooling\_cap” method consistently maintains or increases the representation of batches with all three dominant colors. Additionally, we notice significant enhancement when using the color dominance coefficient  $K > 1$  (*i.e.*, cases in which success is rarer, hence the problem is more difficult). These findings validate the effectiveness of our approach in promoting diverse color compositions in generated images.

Our experimental results consistently demonstrate the superiority of our “pooling\_max” and “pooling\_cap” methods over the baseline (standard Stable Diffusion) in terms of average pairwise LPIPS distance within batches. This evaluation metric serves as a reliable measure of image diversity, and our methods consistently outperform the baseline, showcasing their ability to generate more diverse images. These findings highlight the effectiveness of our approach in expanding the range of image variations and improving overall diversity.

Furthermore, the results show a notable improvement in the representation of underrepresented categories across different ethnicity/gender pairs. The “pooling\_cap” method led to a substantial increase in the presence of these categories, with some categories being up to 2.4 times more frequent, compared to the baseline. It is important to acknowledge the inherent limitations of ethnicity identification based solely on visual cues, but our focus on improving the representation of underrepresented categories, particularly between white and black individuals, aligns with the goal of promoting diversity and inclusion in image generation.

In the future, we intend to assess the generalizability of our approach by applying it to different text-to-image models. This will allow us to determine the extent to which our technique can be adapted and utilized in various contexts. We also intend to integrate our method into the Stable Diffusion image generation. Our ultimate goal is to advance the field of text-to-image generation by pushing the boundaries of diversity and realism, enabling the creation of visually varied and inclusive images for a wide range of applications.

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## 7 Appendix – Diverse Diffusion: Enhancing Image Diversity in Text-to-Image Generation

### 8 Additional results for color diversity

Here, we provide additional experimental results to further illustrate the color diversity improvement achieved by our proposed approach. The results are organized based on different coefficient values ( $K$ ) and batch sizes. The figures presented below showcase the multiplicative improvement of batches featuring certain color dominance characteristics using the “pooling\_cap” and “pooling\_max” methods compared to the baseline Stable Diffusion.

#### 8.1 $K=1$

##### **Batch size = 3**

Figures 10 and 11 display the results for the  $K = 1$  coefficient and a batch size of 3 in both long and standard experiments.

##### **Batch size = 5**

Figures 10 and 13 present the results for the  $K = 1$  coefficient and a batch size of 5 in both long and standard experiments.

##### **Batch size = 10**

Figures 14 and 15 illustrate the results for the  $K = 1$  coefficient and a batch size of 10 in both long and standard experiments.

##### **Batch size = 50**

Figure 16 illustrates the results for the  $K = 1$  coefficient and a batch size of 50 in the standard experiment.

#### 8.2 $K=1.1$

##### **Batch size = 3**

Figures 17 and 18 display the results for the  $K = 1.1$  coefficient and a batch size of 3 in both long and standard experiments.

##### **Batch size = 5**

Figures 19 and 20 present the results for the  $K = 1.1$  coefficient and a batch size of 5 in both long and standard experiments.

##### **Batch size = 10**

Figures 21 and 23 showcase the results for the  $K = 1.1$  coefficient and a batch size of 10 in both long and standard experiments.

##### **Batch size = 50**

Figure 24 illustrates the results for the  $K = 1$  coefficient and a batch size of 50 in the standard experiment.

#### 8.3 $K=1.2$

##### **Batch size = 3**

Figures 25 and 26 display the results for the  $K = 1.2$  coefficient and a batch size of 3 in both long and standard experiments.

**Batch size = 5**

Figures 27 and 28 present the results for the  $K = 1.2$  coefficient and a batch size of 5 in both long and standard experiments.

**Batch size = 10**

Figures 22 and 29 illustrate the results for the  $K = 1.2$  coefficient and a batch size of 10 in both long and standard experiments.

**Batch size = 50**

Figure 30 illustrates the results for the  $K = 1$  coefficient and a batch size of 50 in the standard experiment.

These supplementary results provide an evaluation of the color diversity improvement achieved by our proposed approach across various coefficient values and batch sizes. The figures demonstrate the effectiveness of the “pooling\_cap” method in enhancing color diversity compared to the baseline Stable Diffusion method.

## 9 Additional results for LPIPS evaluation

In the main paper for the small batch sizes, we provide the LPIPS evaluation results only for the “long experiment”. Here, we provide missing results for the “standard experiment” setting.

Figure 31 presents the average batch pairwise LPIPS distance for a batch size of 3 for the “standard experiment” setting. Here, same as in Figure 6 it is hard to see what method is the best for diversity due to the small batch size

Figure 32 illustrates the average batch pairwise LPIPS distance for a batch size of 5 in the “standard experiment” setting. We can see that the results presented in Figure 32 are less conclusive than the results in Figure 7, which demonstrates that the “long experiment” setting is better suited for the small batch sizes.

Figure 33 illustrates the average batch pairwise LPIPS distance for a batch size of 10 in the “standard experiment” setting. We can see that similarly to the results for batch size 5, the results presented in Figure 33 are less conclusive than the results in Figure 8, which again demonstrates that the “long experiment” setting is better suited for the small batch sizes.

## 10 Reproducibility details

In this section, we provide additional details on reproducibility.

- In this paper, we do not provide any theoretical contributions, which is why the theoretical contribution section does not apply to the current work.
- No external dataset is used, as the code generates all necessary data.
- The GPU/CPU requirements are specified at the beginning of section “Experiment setting”.
- All results of all tested hyperparameters are included in the paper. There is no preliminary hyperparameter optimization conducted as part of the experimentation process.
- The code is and available online. It includes both the image generation attached and the evaluation methods that are discussed in this paper. In addition, we have included supplementary examples of images generated by both our preferred method and the standard stable diffusion in the attachment. All these examples are structured similarly to Figure 2 and 1.



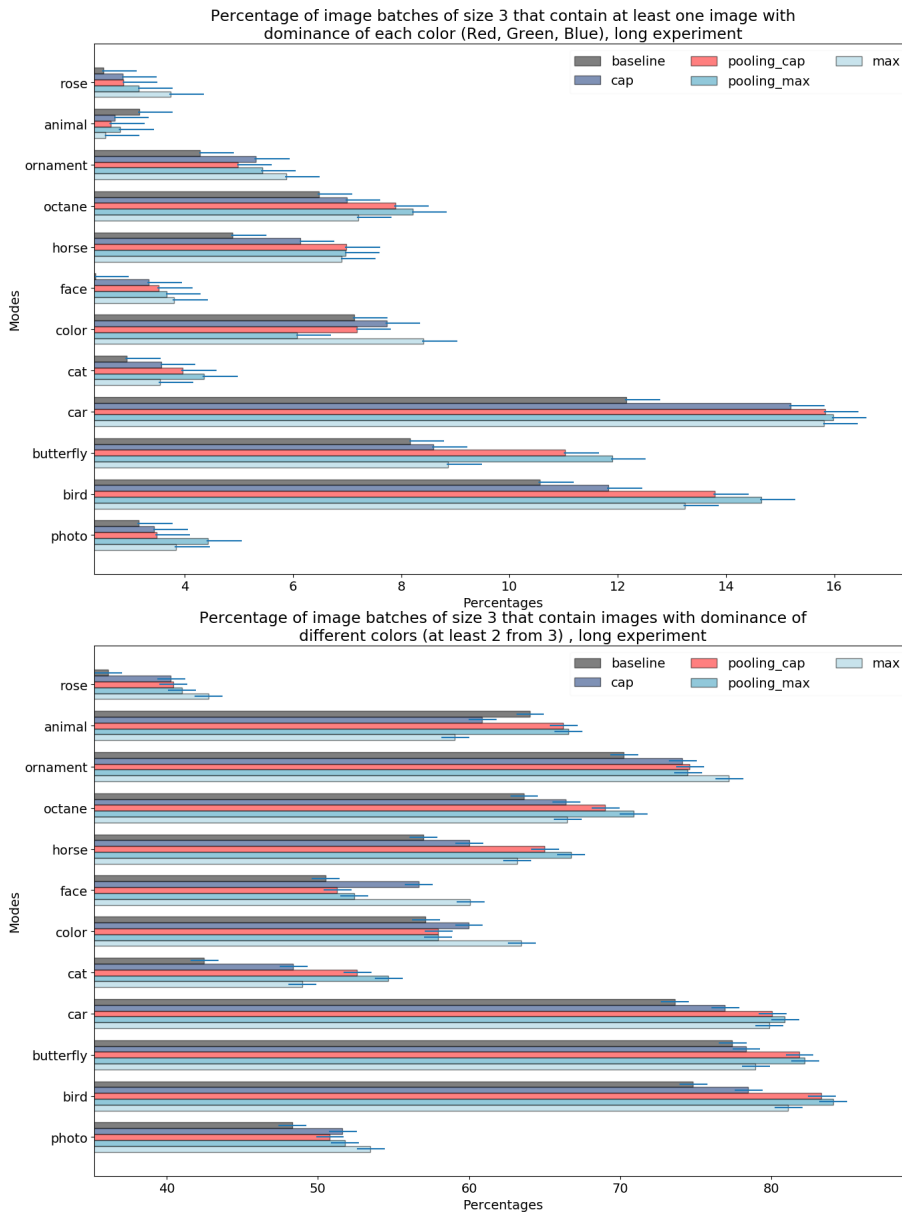


Figure 10: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1$ , batch size = 3, long experiment

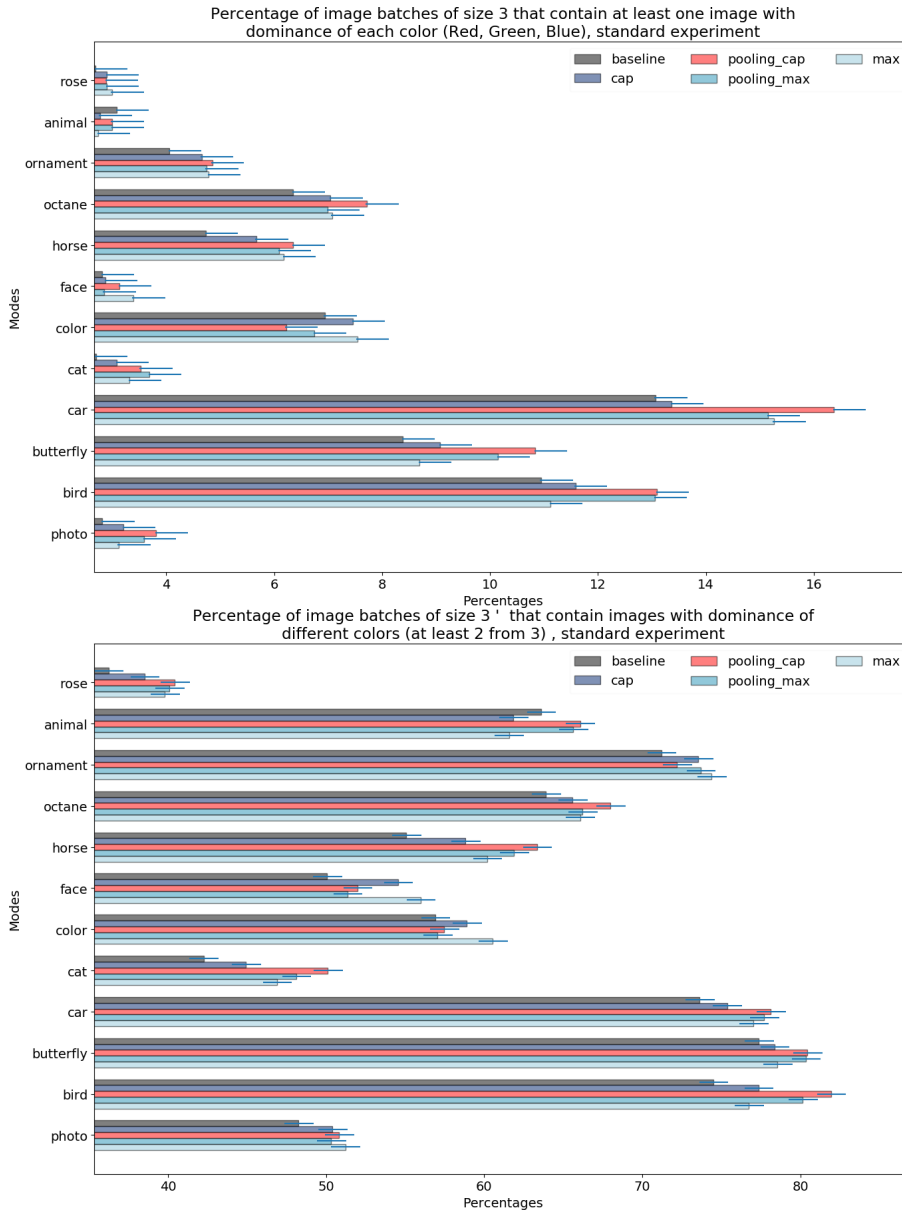


Figure 11: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1$ , batch size = 3, standard experiment

## 11 Ethics statement

Our research is conducted with a commitment to ethical principles. The imagery used in this study comprises AI-generated faces, removing any potential ethical concerns related to real individuals.

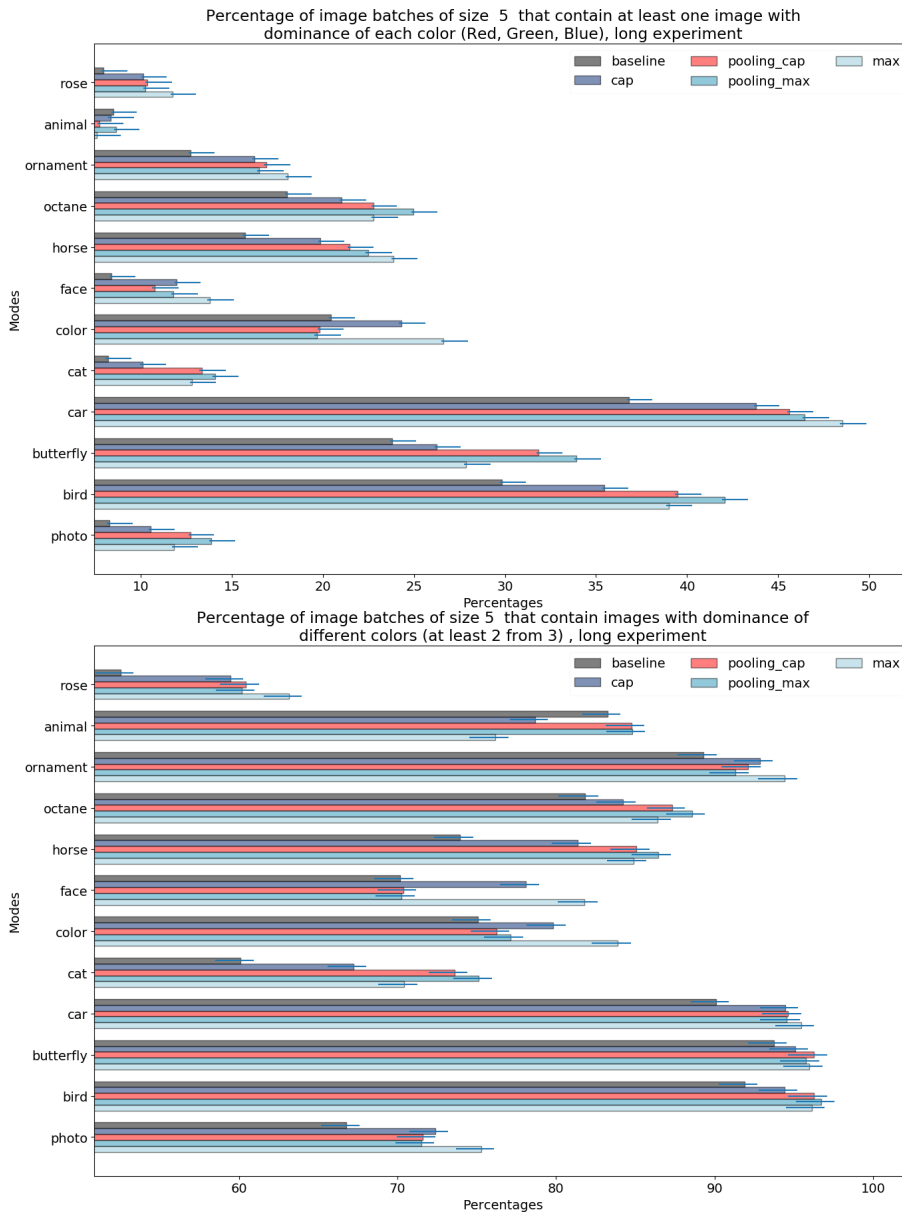


Figure 12: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1$ , batch size = 5, long experiment

The code for generating images and the evaluation methods are made openly available, enhancing transparency and facilitating reproducibility. To make our results statistically sound, we provide results with the 95% confidence interval error bars.

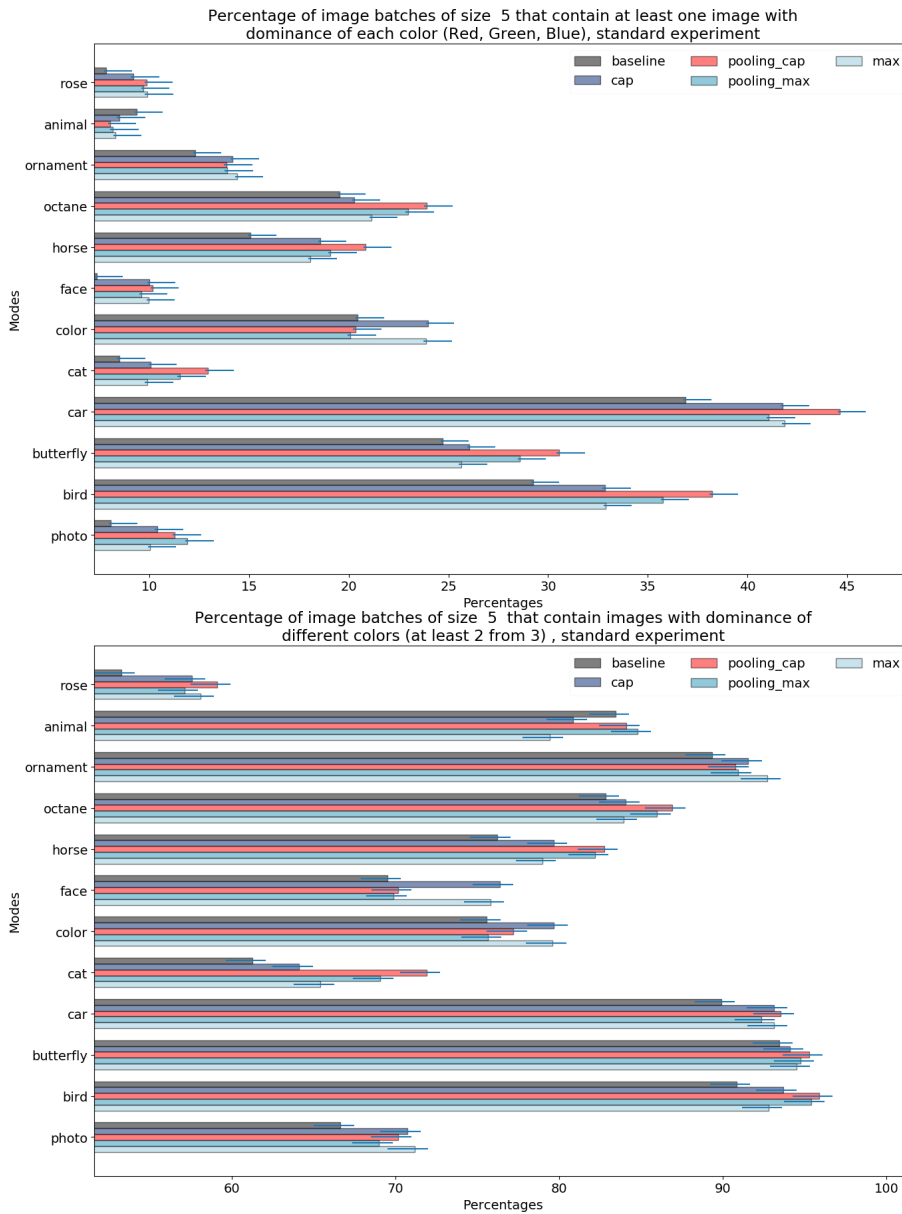


Figure 13: Multiplicative improvement of batches containing all 3 dominant colors with  $K = 1$ , batch size = 5, standard experiment

Our core objective centers on enhancing image diversity within the AI framework, promoting inclusivity, and expanding the spectrum of artistic expression. With our research, we would like to contribute meaningfully to the advancement of AI-generated art while adhering to ethical standards.

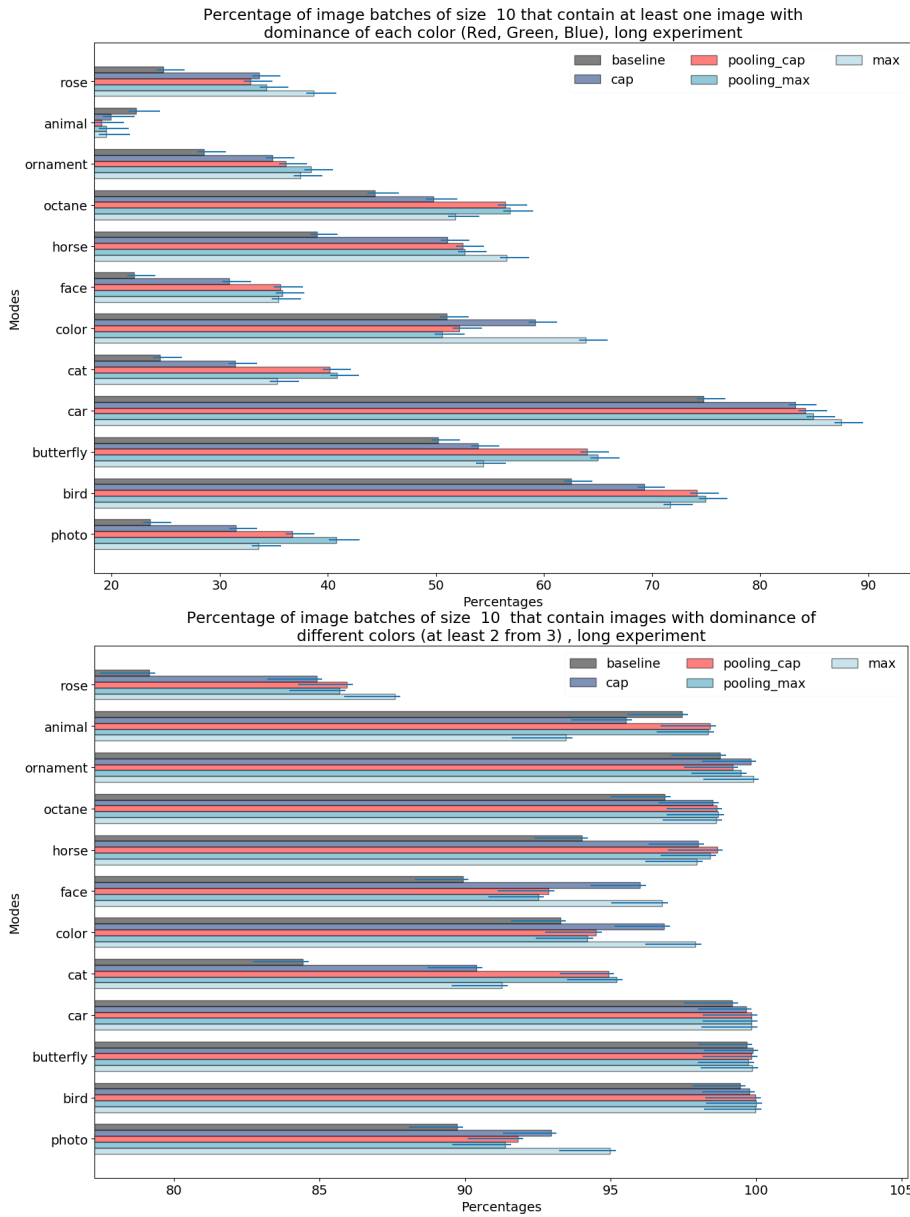


Figure 14: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1$ , batch size = 10, long experiment

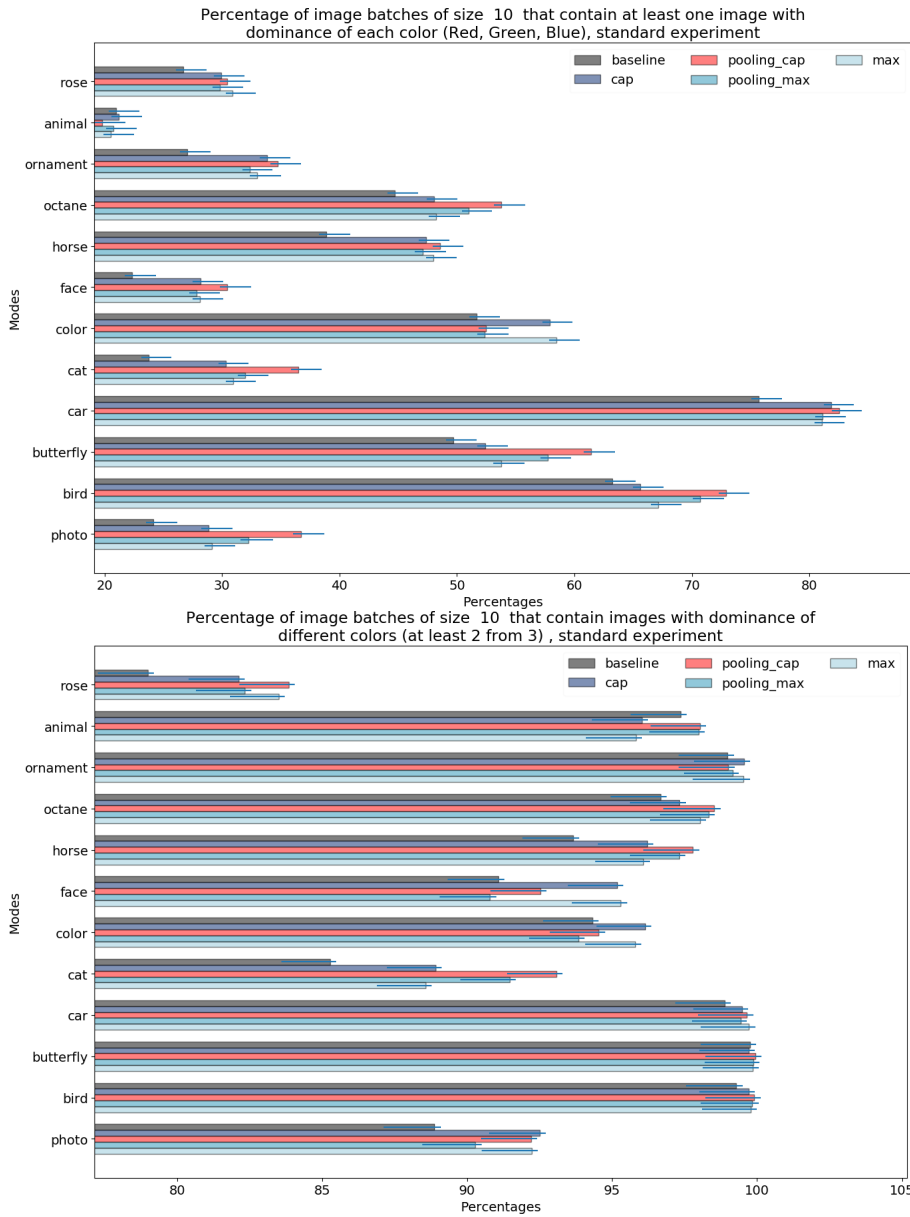


Figure 15: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1$ , batch size = 10, standard experiment

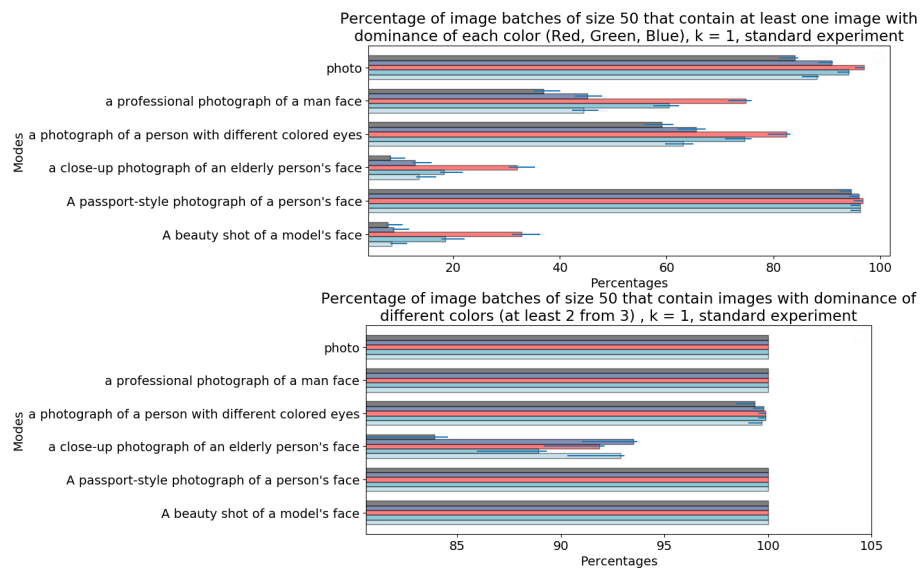


Figure 16: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1$ , batch size = 50, standard experiment

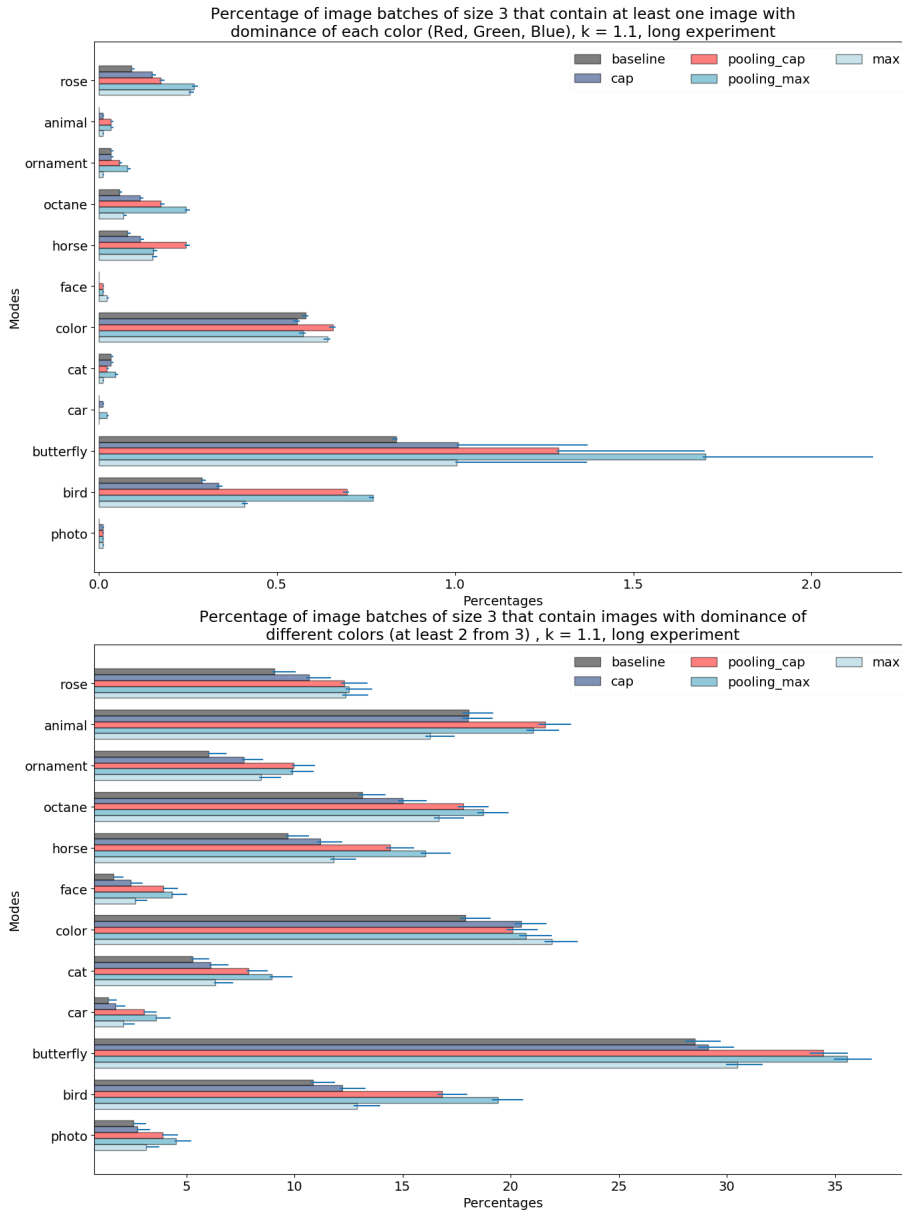


Figure 17: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1.1$ , batch size = 3, long experiment



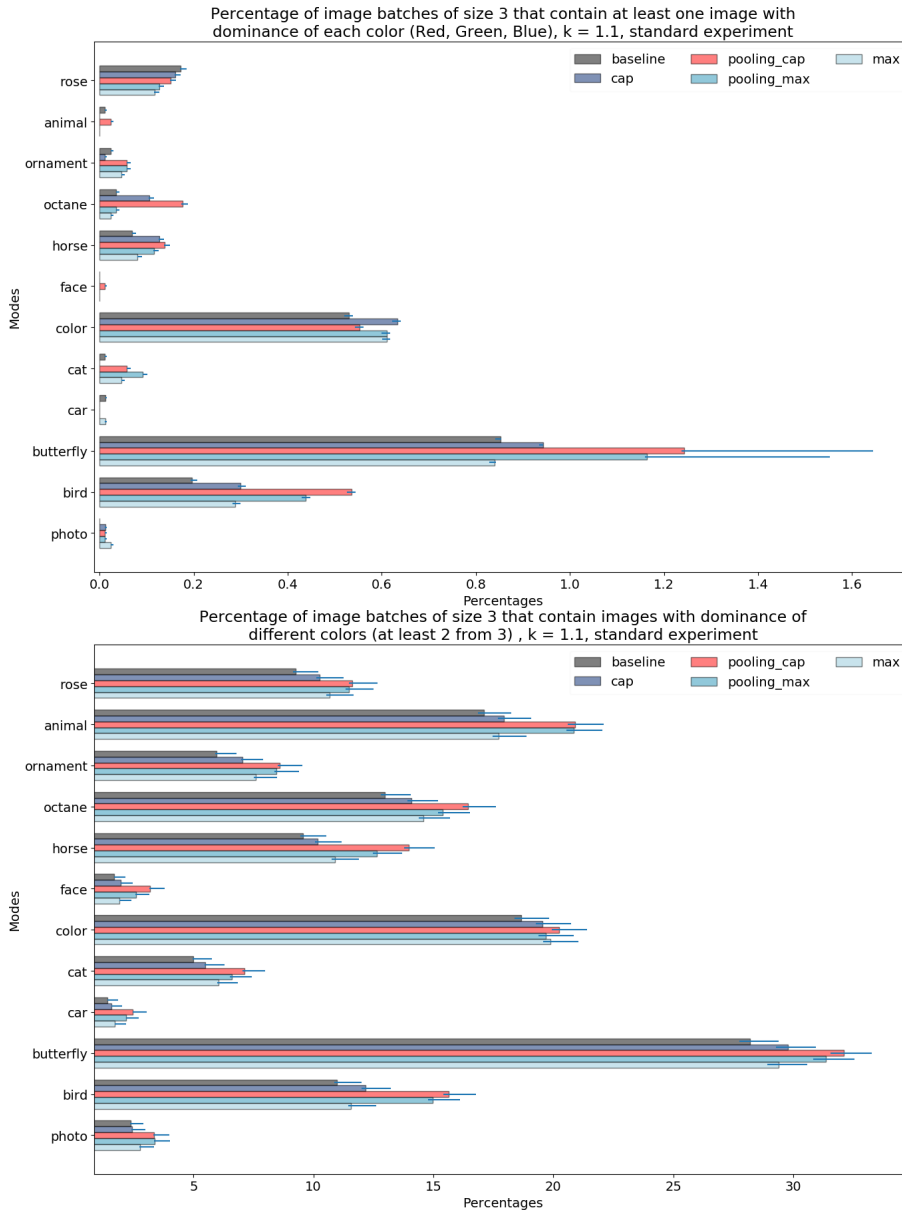


Figure 18: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1.1$ , batch size = 3, standard experiment

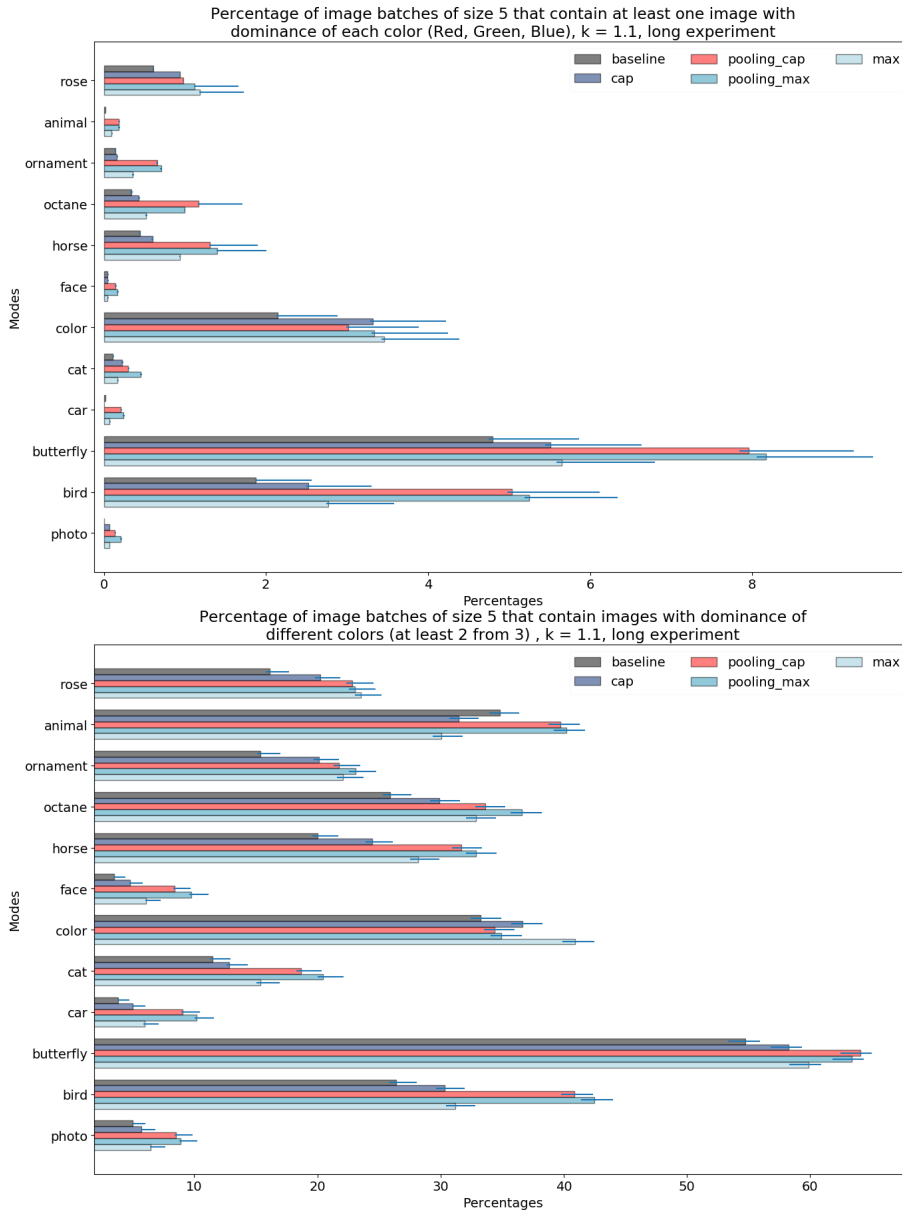


Figure 19: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1.1$ , batch size = 5, long experiment

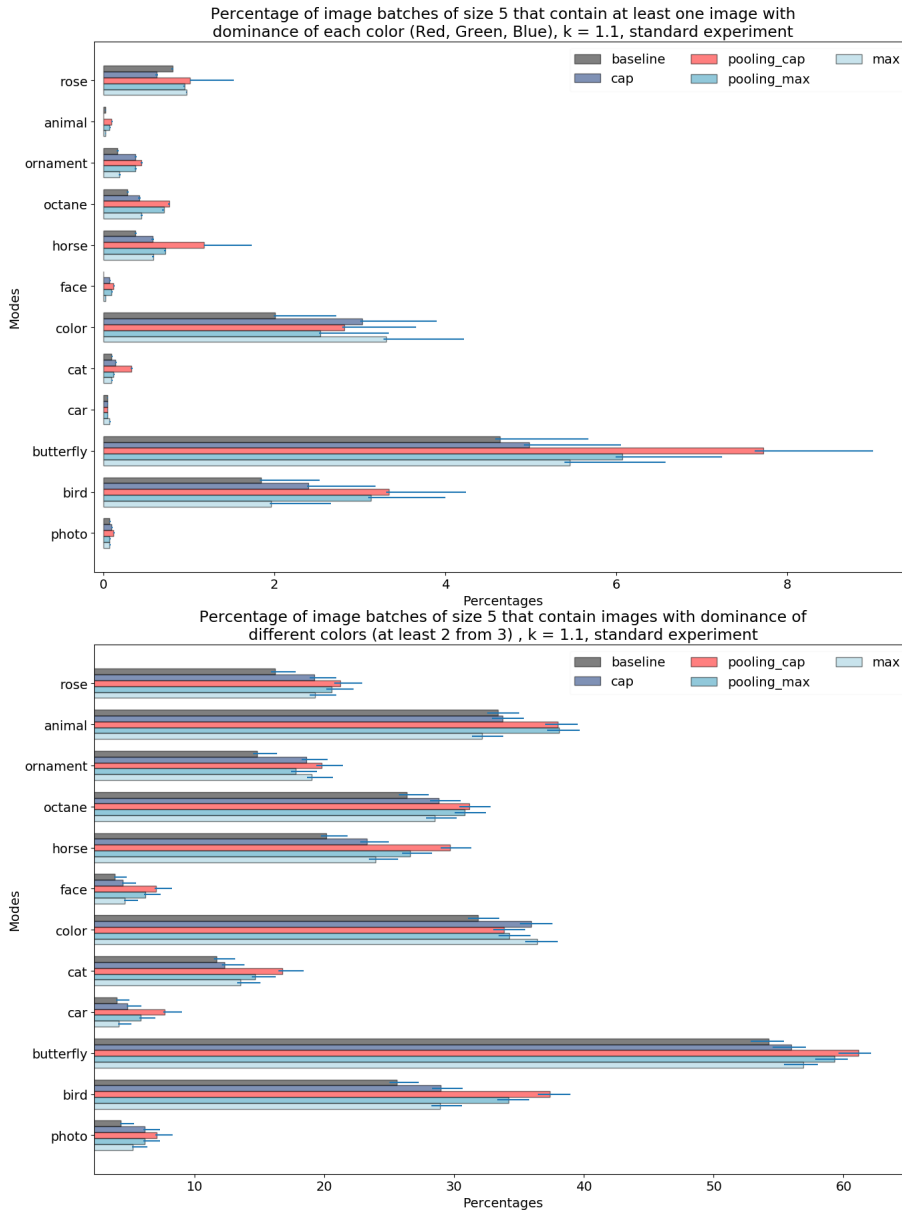


Figure 20: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1.1$ , batch size = 5, standard experiment

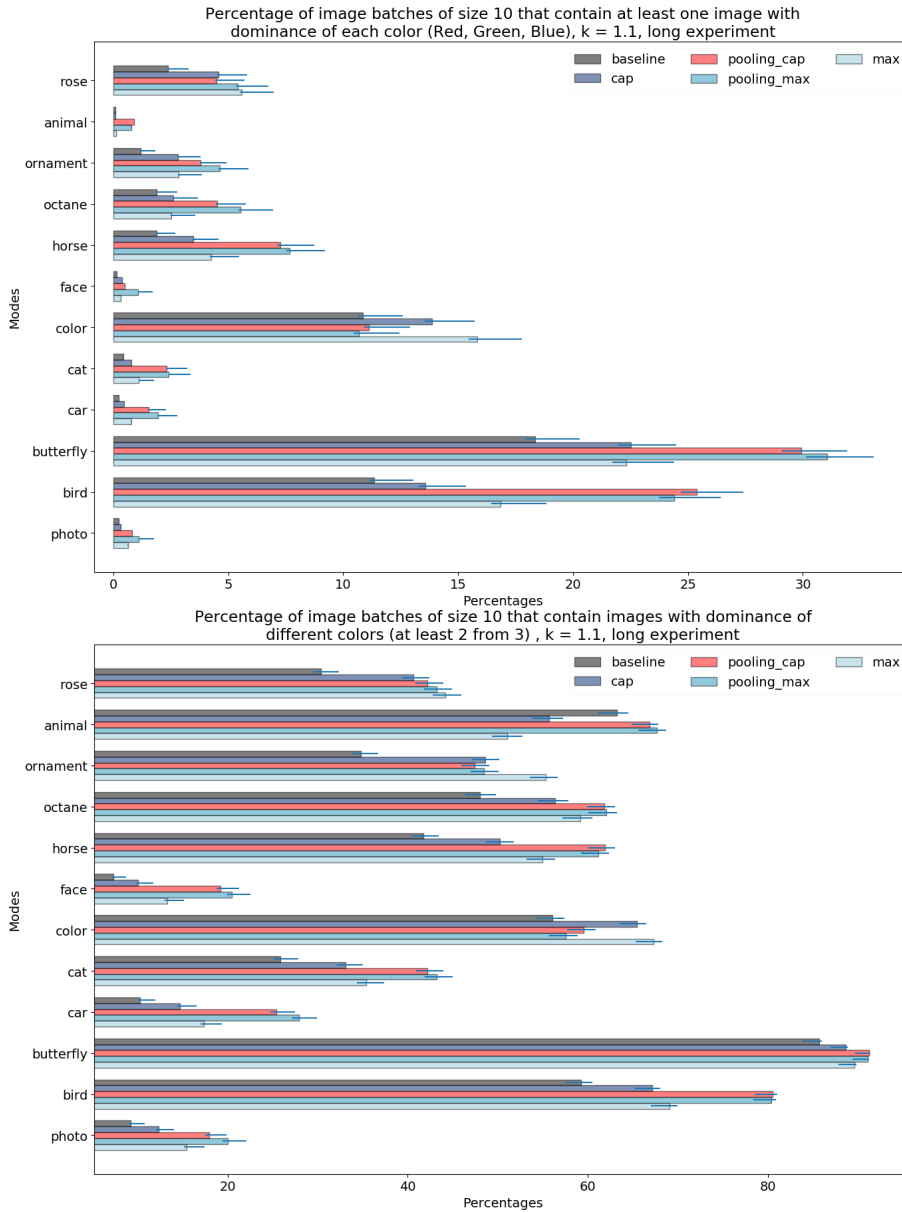


Figure 21: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1.1$ , batch size = 10, long experiment.

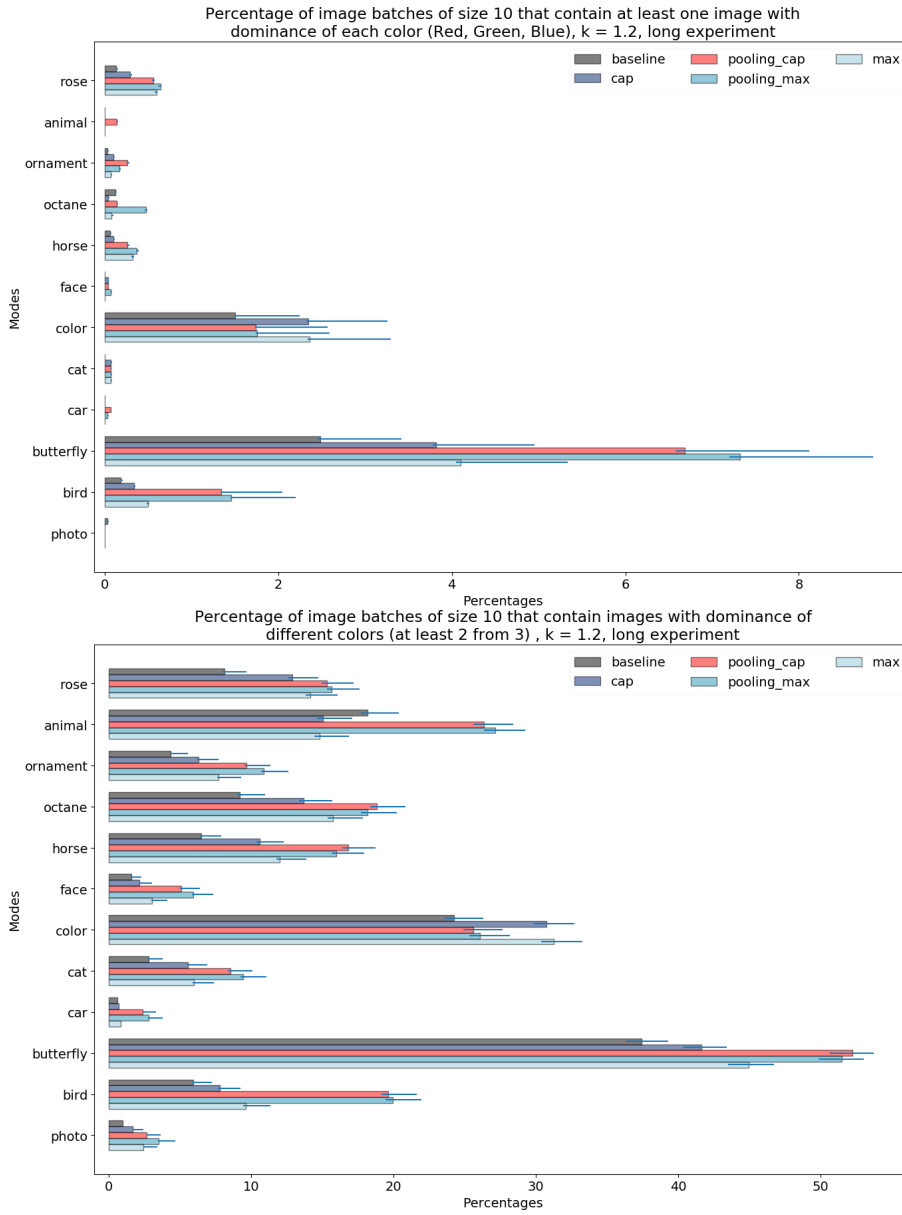


Figure 22: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1.2$ , batch size = 10, long experiment.

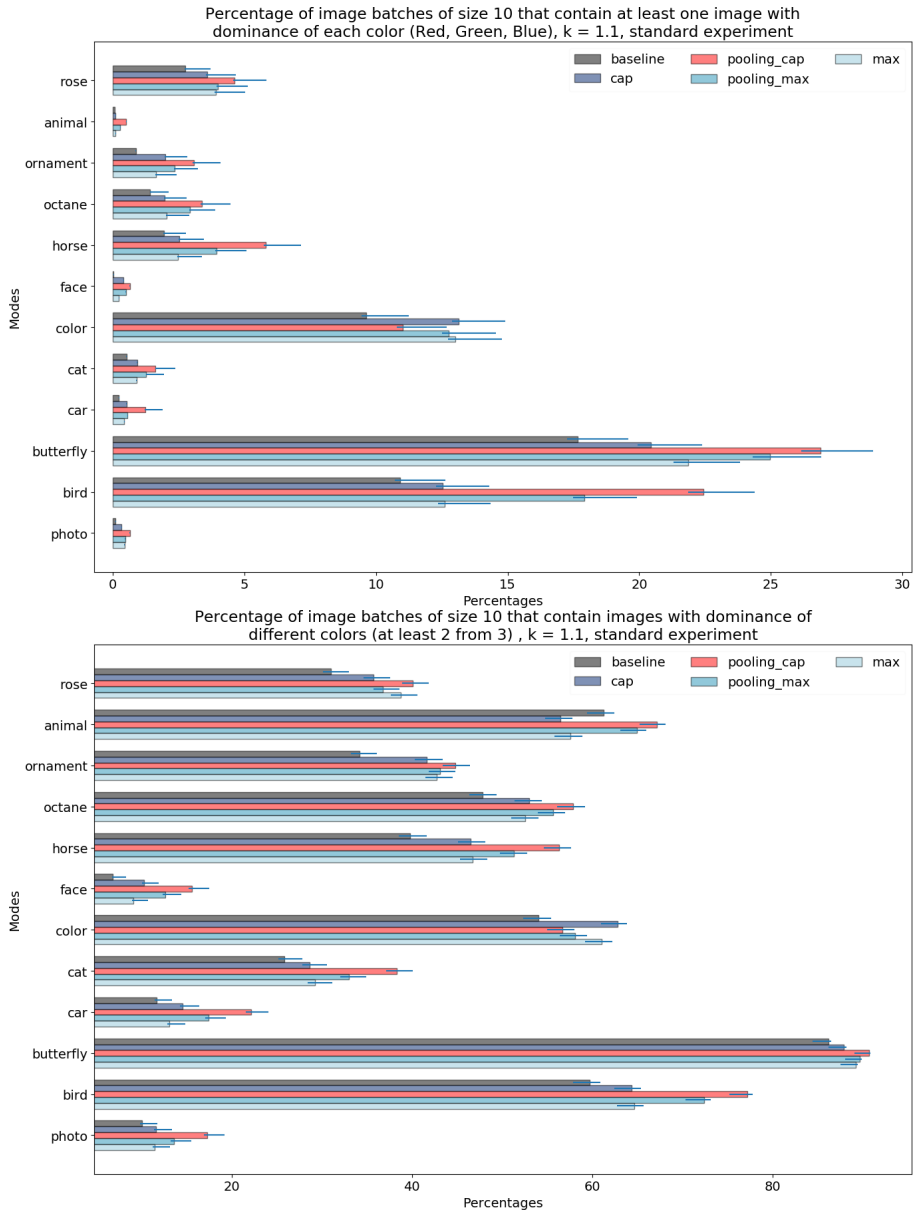


Figure 23: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1.1$ , batch size = 10, standard experiment.

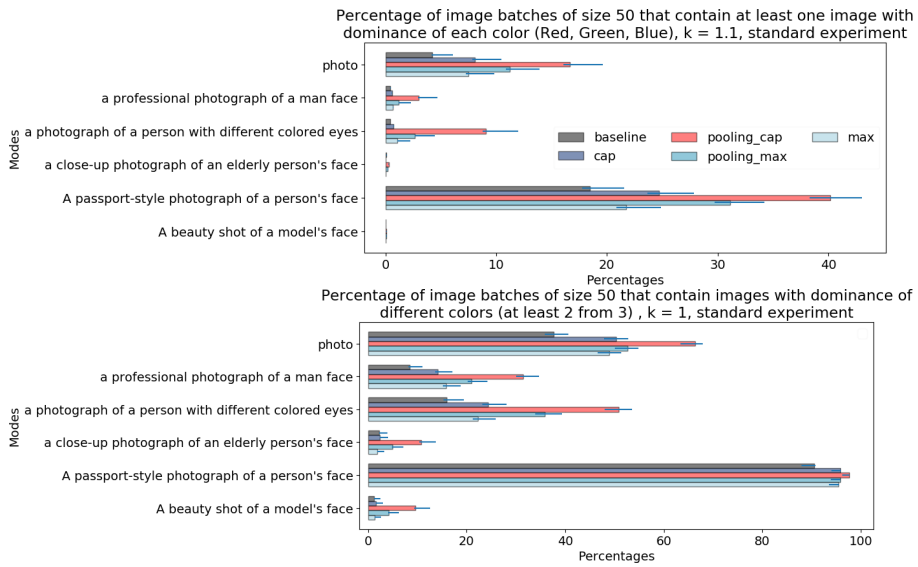


Figure 24: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1.1$ , batch size = 50, standard experiment.

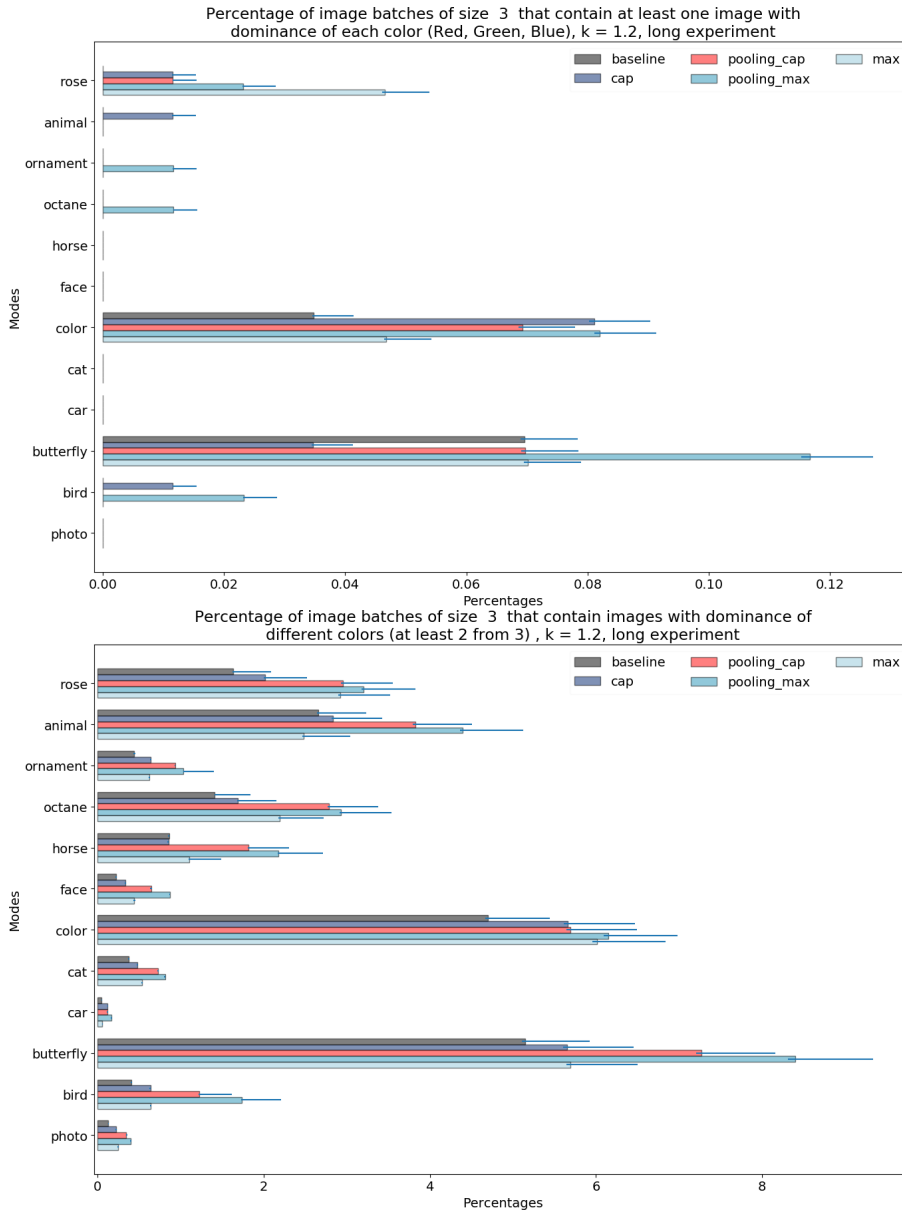


Figure 25: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1.2$ , batch size = 3, long experiment.



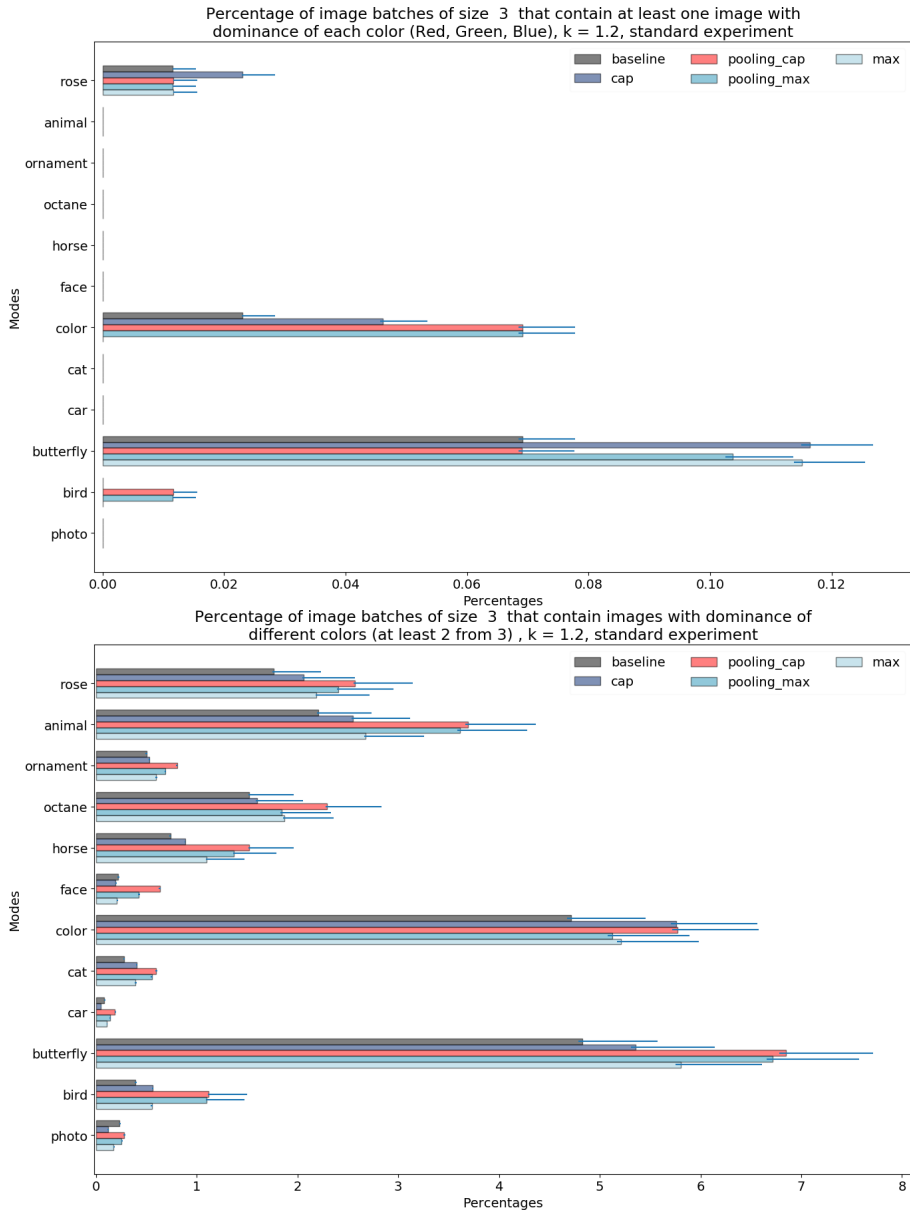


Figure 26: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1.2$ , batch size = 3, standard experiment.

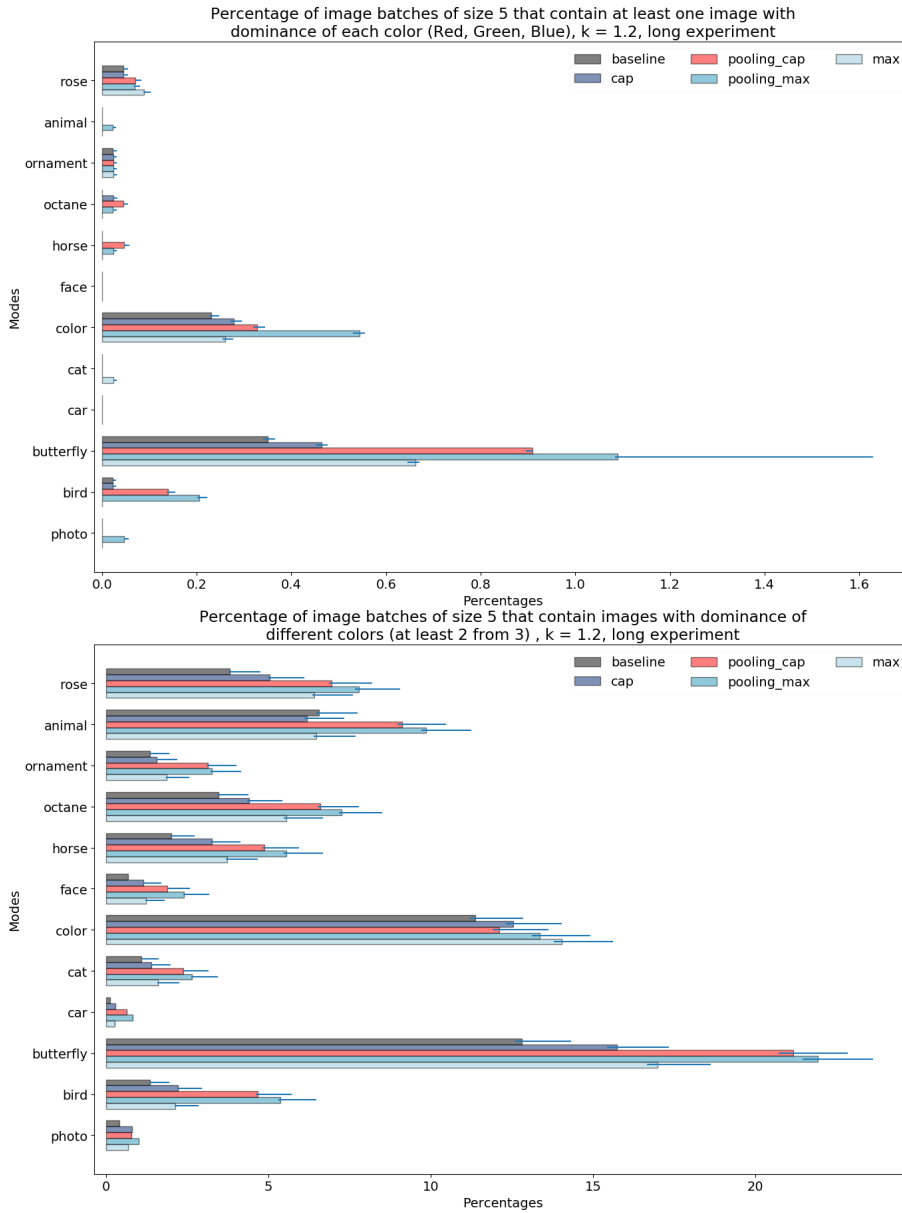


Figure 27: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1.2$ , batch size = 5, long experiment.

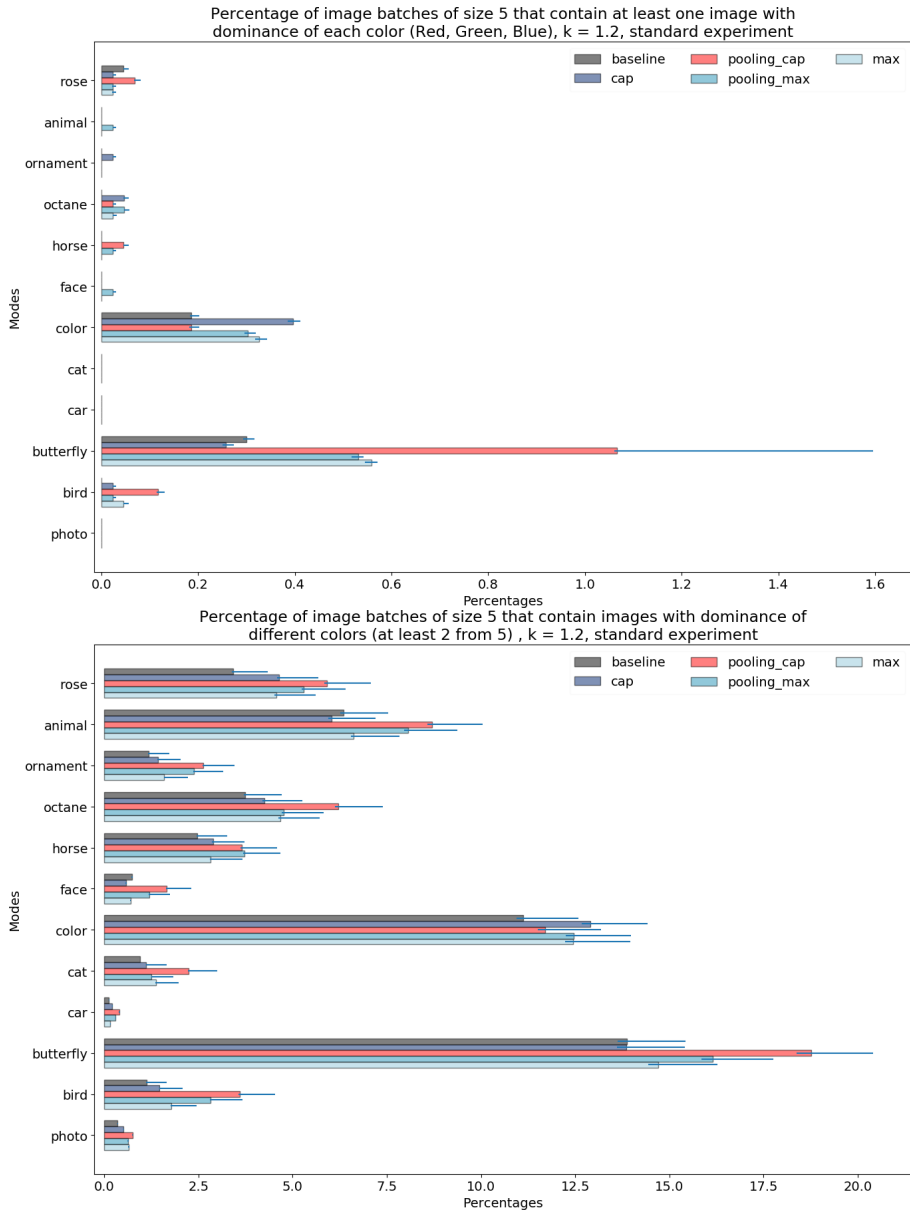


Figure 28: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1.2$ , batch size = 5, standard experiment.

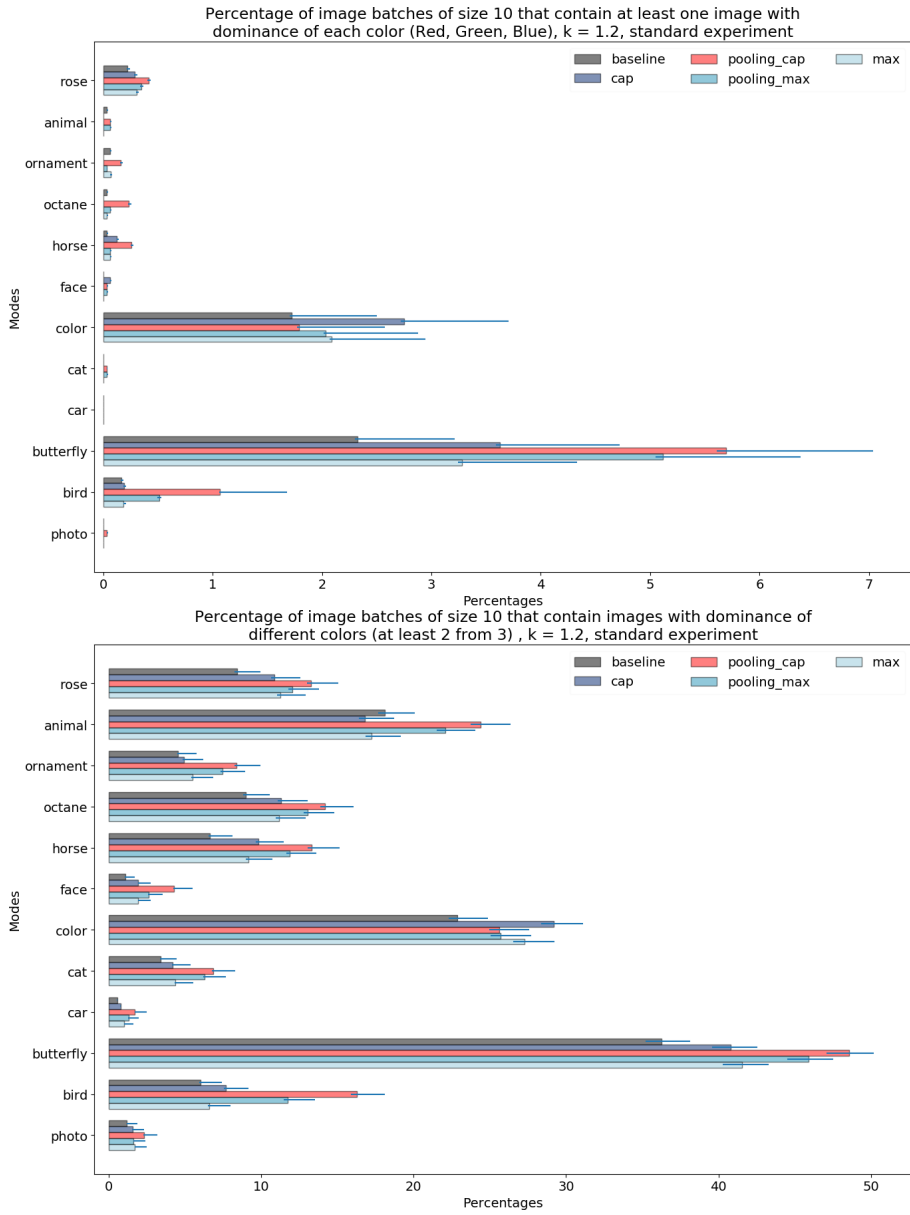


Figure 29: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1.2$ , batch size = 10, standard experiment.

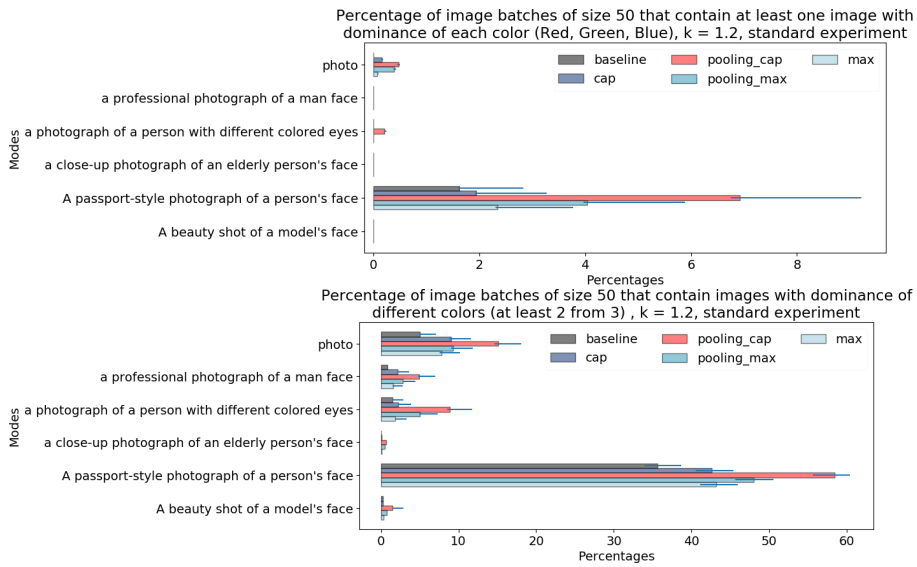


Figure 30: Comparison of different modes for various prompts in regard to the percentage of batches containing images with different dominant colors for the following parameters:  $K = 1.2$ , batch size = 50, standard experiment.

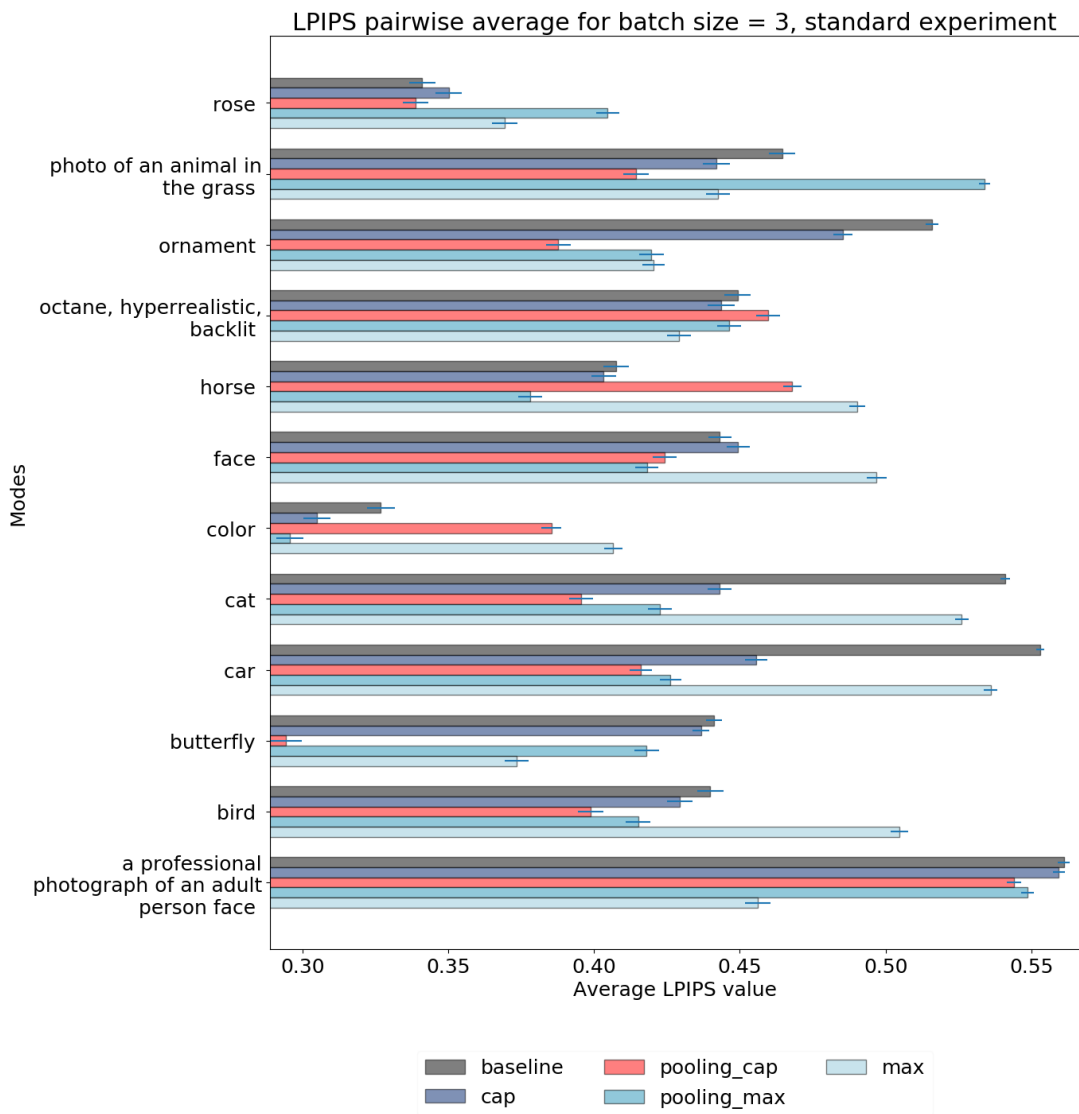


Figure 31: Average batch pairwise LPIPS, batch size=3, standard experiment : no clear conclusion overall,

due to the small batch size.

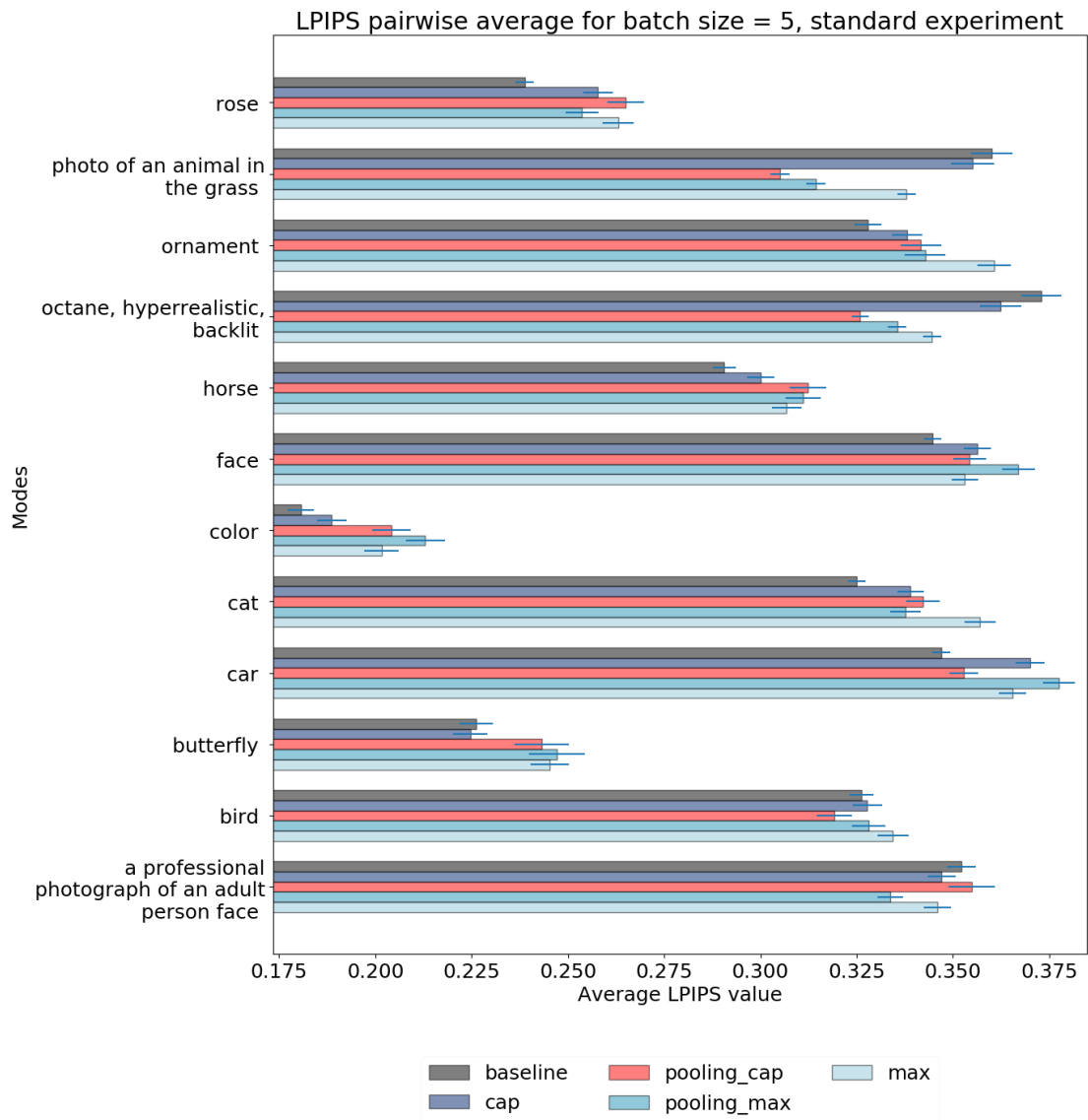


Figure 32: Average batch pairwise LPIPS, batch size=5, standard experiment

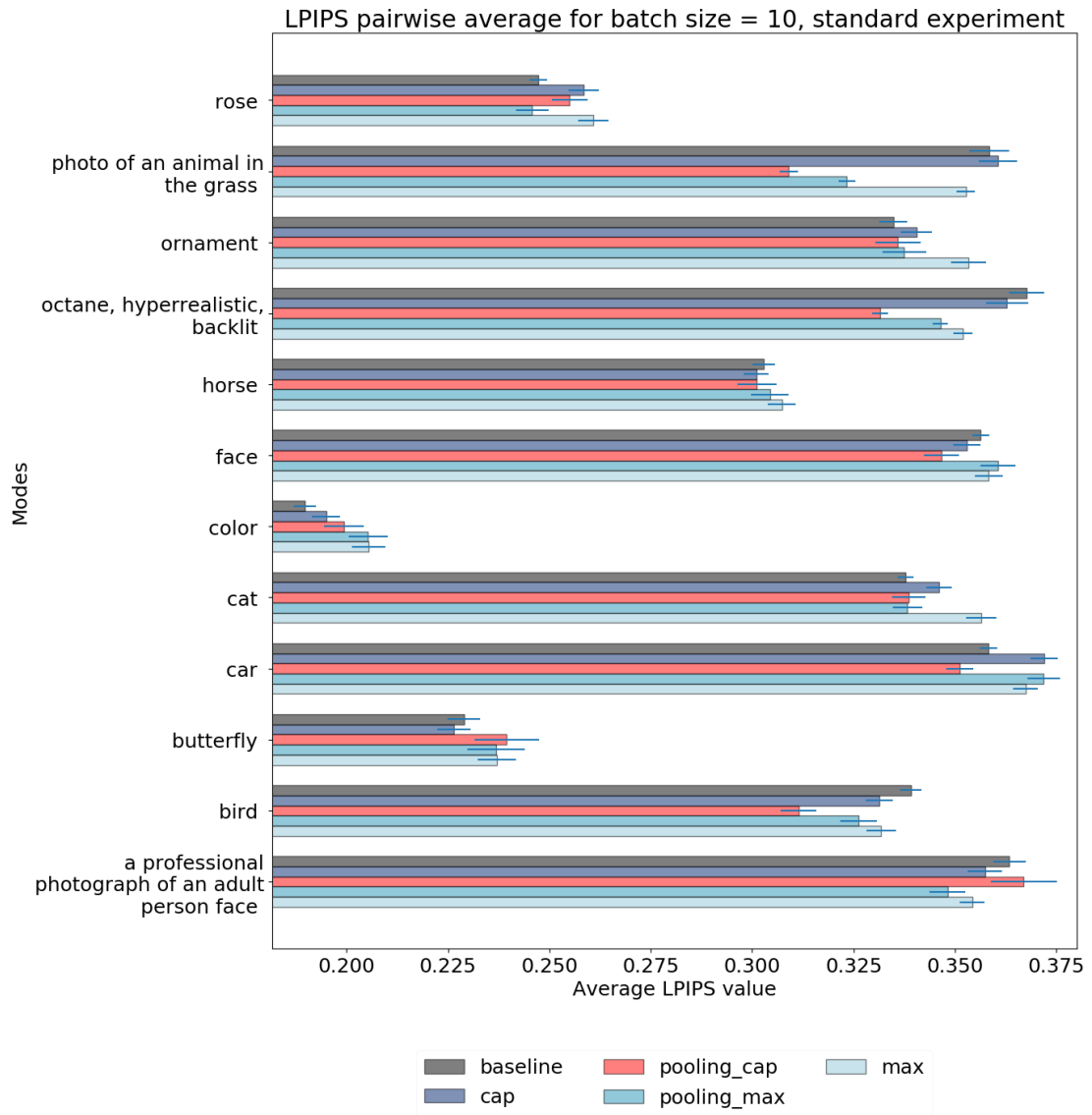


Figure 33: Average batch pairwise LPIPS, batch size=10