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Evaluating systematic errors and biases in generative image models

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I hereby declare that I have written this thesis independently without any help from others and without the use of documents or aids other than those stated. I have mentioned all used sources and cited them correctly according to established academic citation rules.

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Abstract

Generative models have gained in importance over the last years and are likely going to become even more present in fields such as stock image production. If used in advertising, potentially discriminatory biases could reinforce those present in society and further reduce equality for multiple minority groups. Prejudices indicating that individuals with dark skin are criminals and that higher paying occupations are more fitting for white men, remain an issue in modern society. Seeing the images by the models displaying for example (e.g.) a black woman as a lawyer will help normalising their presence in such professions. Increasing the visibility of underrepresented groups signifies to both themselves and the wider population that they belong. Therefore it is essential to eliminate biases whenever possible.

In order to do that it is crucial to understand the outputs of the models and document what kind of biases and errors exist, as well as to get an idea of the quality of the images and their understanding of what they generate. This thesis investigates systematic biases and errors in the image generation models Stable Diffusion and min(Dalle). It looks at the gender and skin type distributions of specific societal roles a person can take on. This includes multiple professions in different classes perceived as low, middle or high income or status and roles such as victims or attackers. It is also looked at biases regarding different relationship models and sexualities. Furthermore, the spatial understanding of the models is tested to see whether they actually create meaningful images or only statistically good looking ones. Both of these concepts can affect the usability of the models and the potential negative consequences if they are used. There is a significant gap in existing research regarding the spatial understanding of the models, despite the contribution to the potential accuracy of the structure of the generated images.

This work did a semi-quantitative evaluation and subsequently, when it was possible, the results were compared to actual statistical data. It was demonstrated that neither model exhibited a substantial spatial comprehension or reliably produced spatial relations. Both models had clear biases regarding the gender, skin types and relationship models or sexuality of the generated people. However, especially with regards to relationship models and sexualities, these biases somewhat aligned with reality. Both models struggled more with the skin type distributions, but Stable Diffusion was rather accurate when it came to the gender distribution of the different professions. The min(Dalle) model in general had a strong bias towards white males.

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Chapter 1

Introduction

Generative models have gained in importance over the last years and are likely going to further grow in popularity. Training these models uses huge data sets derived from the internet [1] [2]. These data sets are then filtered to exclude violent and pornographic content and generally become "aesthetic" and "safe for work" [1], while there is a lack of data set curation and documentation practices [2]. This can lead to biases and errors in the training data, which then is reinforced in the models output [3]. As these models can be used commercially, e.g. by generating images for advertisement, as well as privately, these biases can have a negative impact on individuals as well as the general public and therefore lead to amplified discrimination such as racism, ableism, sexism or homophobia.
As Heather Hiles, the chair of Black Girls Code [1], said: "People learn from seeing or not seeing themselves that maybe they don't belong." [4]. This thesis will look at two generative models for image generation called Stable Diffusion [5] [6] and min(Dalle) [7] in two ways to address the same overall question. Are there systematic errors and biases in generative image models that could lessen the usability of such models because of their negative impact or incorrectness? More specifically, the following two subquestions will be addressed.

1. Can modern generative models understand objects in relation to each other and therefore have a spatial concept or do the models merely generate stochastic good looking, but not meaningful images?

These spatial reasoning abilities have not been thoroughly researched, despite their possible implications on the practical use of the models, and their part in gaining a deeper understanding of the representations learned by the models.

2. Do the models show signs of systematic biases leading to discrimination against gender, ethnicity and others?

[1] A non-profit organisation supporting black girls and non-conforming youth of colour to engage in computer programming education. Link: https://www.wearebgc.org/, accessed on: 2023-11-05

Instead of adopting the perspective presented in the work by Luccioni et. al. (2023) [1], a more qualitative approach which involves a different set of biases was chosen. Namely, in order to find systematic biases in the generative models Stable Diffusion and min(Dalle), this thesis examines generated images regarding family and relationship models, different roles a person can have and specifically different occupations and their diversity representation. The first objective is to classify gender and skin type and analyse the images with regards to stereotypes concerning the perceived gender, ethnicity, sexuality and societal class. Understanding inherent biases can help understanding how generative models support racism, misogyny, homophobia and other kinds of discrimination.

This thesis consists of the five main parts foundation and methods of evaluating the generative image models, the results in regard to the two research objectives and a discussion of these results and this work. The next two chapters establish a theoretical basis for the relevant research, models, and prompting and apply the theory to this work specifically. They detail the methodology employed to assess the biases and errors of the models and verify the outcomes. In the following chapter the resulting distributions regarding the gender, the skin type, the relationship model and sexuality and the level of spatial understanding are presented. Lastly these results are discussed and put into perspective to obtain an overview of existing systematic biases and errors of both models. In the conclusion the findings are summarised and an outlook for potential further work is given.

Chapter 2

Foundations

2.1 Related work

To counteract issues regarding errors and biases induced by the training data, work has been done to find methods for better data collection to create well documented data sets covering not only majorities but also minorities as well [2]. Further work has focused on analysing existing models to better understand the extend of their inherent biases and errors. An example would be the study by Buolamwini and Gebru (2018) about errors in facial recognition by gender and skin type, which also looks into the distribution in different benchmark data sets [3].
An example of investigating societal biases is the quantitative work of Luccioni et. al. (2023), which proposed a new method for exploring and quantifying societal biases in text to image generative models [1]. They analysed the output images of different models, depicting different professions combined with gender-coded adjectives, regarding gender and ethnicity distribution. Their findings show a bias towards white males when it comes to high paying or well respected jobs. While the Bloomberg article by Nicoletti and Bass (2023) also looked at skin type and gender distribution of different professions and their average income, they additionally looked at images of inmates, drug dealers and terrorists and their appearances [4]. The results showed mostly dark skinned males leaning on stereotypes of Muslim men.
The paper by Johnson et. al. (2017) looks into compositional language and elementary visual reasoning [8]. They focus on artificial intelligence working with visual data, including their ability to compare geometrical objects in space. Rather than creating those images, they answer questions about already existing ones.

2.2 Generative image models

Generative image models are machine learning models, which learn connections between keywords, also called labels, and images. For inference they take a prompt describing an image as

input and then generate said image as output. The prompts can include multiple learned keywords, which the models then combine in a new image, which was not part of their training data [5] [9]. For the training process large data sets such as LAION-2B or YFCC100M are used. LAION-2B contains two billion images and YFCC100M 100 million media objects, which makes manual inspection challenging and therefore leads to the inadvertent inclusion of mislabelled or duplicated image-text pairs [10] [11]. The developers of both models researched in this work [6] [12] warn that these data sets were not filtered properly and are restricted to images with English descriptions. They report that this affects all outputs and establishes white and Western culture being the norm, while also running the risk of producing images that perpetuate negative stereotypes about marginalised groups. Additionally, they state that the extent of the biases of the models is currently being analysed and not yet fully documented.

2.2.1 Stable Diffusion

Stable Diffusion version v1-4 [6] is a latent diffusion model, which can do text-to-image synthesis. It was developed by researchers of the Ludwig Maximilian University of Munich and the Interdisciplinary Center for Scientific Computing of the Heidelberg University and Runway[2] [5]. As all diffusion models it is a probabilistic model [5]. During the training different levels of Gaussian noise are added to the images, which the model then gradually denoises with the help of the corresponding labels as input [5]. After training it is able to generate new images from random Gaussian noise with text prompts as input. For training the aforementioned English LAION-2B data set and subsets thereof were used [6].

2.2.2 min(Dalle)

As it is written in the README of the GitHub repository [7], min(Dalle) version v0.4 by Brett Kuprel is a fast, minimal port of the image generation model DALL·E Mini [13] by the developer group around Boris Dayma. It uses DALL·E Mini's mega weights, which is the biggest DALL·E Mini version. As a transformer-based text-to-image generation model it consists of multiple individual models. An image encoder that translates raw images into a sequence of numbers, also called tokens, with its associated decoder. A model that can generate encoded images with a text prompt as input, which it also encodes. At the last step, there is an additional model, which can judge the quality of the generated images to decide which is the most fitting. While training with image-text-pairs, the text prompt is used to generate an image encoding. This encoding can then be compared to the encoding of the original model. For a more detailed description of DALL·E Mini's architecture see [9] and [14].
For training the Conceptual Captions Dataset (3 million images-text pairs), the Conceptual 12M (12 million image-text pairs) and a subset of the YFCC100M data set (2 million image-text pairs) were used [12].

[2]Runway is an applied artificial intelligence research company. Link: https://runwayml.com/, accessed on: 2023-11-05

2.3 The art of prompting

The importance of prompt engineering for vision models is covered in several papers [15] [16] [17] [18]. They describe the effect of prompt engineering and give insights on how to perfect it.
The paper by Wang et. al. (2023) outlines some of the main models and the history of prompting [18]. They originate from interactive segmentation tasks, where user input such as bounding boxes guided the model's outputs. The concept of prompting was first popularised by Natural Language Processing and this success inspired the use of prompting for computer vision.
Gu et. al. (2023) give a good overview of prompt engineering, explaining the important terminology and giving further information about the three types of vision-language models multimodal-to-text generation models, image-text matching models such as CLIP and, most importantly for this work, text-to-image generation models such as Stable Diffusion or min(Dalle) [16].
Gu et. al. (2023) [16] and Witteveen and Andrews (2022) [17] say the following about semantic prompt design for image generation models :

- Prompting has a significant impact on image generation in diffusion models
- Linguistic components (adjectives, nouns and proper nouns) influence image generation differently, but consistently
- Nouns introduce new content and have a stronger effect on images
- Descriptors (simple adjectives) have a more subtle affect
- Artist names influence style strongly
- Lighting phrases can modify content and atmosphere strongly
- Effective seeds make for for a good basis

The work by Witteveen and Andrews (2022) gives a short guide of how to develop good prompts [17]. They state that there are two main components to good prompts. The physical and factual content and the stylistic descriptors like lighting or an art style in which way the content of the image is displayed. These descriptors can change the look of the subject and the entire atmosphere of an image. The addition of *in the style of* can change an image on multiple levels. The medium, if not specifically set, the colour palette and even the ethnicity of depicted people could all be decided on the basis of an artist for example predominantly creating bright oil paintings of women with dark skin. They suggest to start the prompt building with a noun-based statement and build up with descriptors about the style and background.
Further inspiration and practical guidelines for prompt engineering can be found in this article by Andrew of Stable Diffusion Art (2023), which describes the anatomy of a good prompt [19]. Another article by Andrew of Stable Diffusion Art (2023) covers how to generate more realistic people [20]. A list of Universal Negative Prompts for Stable Diffusion are featured in the article by Kapoor (2023) [21].

2.4 Basis of calculation

2.4.1 Margin of error

The margin of error measures the level of uncertainty regarding your measured value. If the margin of error is high, the measured value differs more from the real value and the collected samples do not accurately represent the whole population. The confidence level indicates how sure you are that the measured value lays within the margin of error of the real value. The more samples there are, the stronger the results. For calculation [22] was used with a confidence level of 95.00%.

2.4.2 Mean, variance and standard deviation

The mean μ is equal to the average of a set of data $x = x_1, x_2, ...x_n$. It is calculated as

$$\mu = \frac{\sum_{i=1}^{n} x_i}{n} = \sum_{i=1}^{n} \frac{1}{n} \cdot x_1.$$

The variance σ^2 it the average of the square of distance between each point in the data set to the mean value. It is normalised by $(n-1)$ instead of n:

$$\sigma^2 = \sum_{i=1}^{n} \frac{1}{n-1} \cdot (x_1 - \mu)^2.$$

The standard deviation σ measures the square root of the variance. It is used to measure the amount of deviation from the data to the mean:

$$\sigma = \sqrt{\sigma^2} = \sqrt{\sum_{i=1}^{n} \frac{1}{n-1} \cdot (x_1 - \mu)^2}.$$

For calculation the functions `pandas.DataFrame.mean` and `pandas.dataFrame.std` were used [23] [24].

Chapter 3

Methods

3.1 Implementation

The models were set up and run on the Scientific Compute Cluster, which is part of the High Performance Computing services of the Gesellschaft für wissenschaftliche Datenverarbeitung mbH Göttingen also called GWDG [25].
To submit a job and all its necessary information to Slurm, the workload manager, sbatch was used [26]. A job normally got 32 Gigabyte (GB) memory, requested a v100 graphics processing unit (GPU) and limited the run time to 12 hours. This time limit was never reached. To set up the environments mamba [27] was used, a fast, robust, and cross-platform package manager. Different environments can contain different packages in different versions and make the handling of dependencies easier, as different environments will not interfere with each other.
Both models worked with Python, more specifically Python3 as a programming language. Python is often used for scientific applications [24]. A detailed overview of all requirements for Stable Diffusion is given in the appendix in Listing A in form of the configuration file used to set up the mamba environment. It is an adapted version of the one given in the GitHub repository by [6]. The model itself was provided over Hugging Face [6]. The min(Dalle) model only required the libraries numpy, requests, pillow and torch [7]. For the evaluation of the data Python libraries pandas and matplotlib were used. Pandas provides a data structure for data analysis and statistics [23] [24] and was used to store and analyse all the evaluation files. Spreadsheets can easily be imported as comma-separated values (csv) files. Matplotlib is a library for data visualisation [24] and was used to generate the diagrams described in Section 3.5.
The generated data and its evaluation can be accessed via the GitLab repository[3]. Code used to generate the images and evaluate the results can be viewed via the GitLab repository[4].

[3]https://gitlab.gwdg.de/e.hagenkort/evsyserrbiagenimgmodelsdataset, accessed on 2023-11-13
[4]https://gitlab.gwdg.de/e.hagenkort/evsyserrbiagenimgmodelscode, accessed on 2023-11-13

3.2 Prompting

The prompts were build using the information in Section 2.3 combined with some testing. Because min(Dalle) was added to this thesis at a later time, all prompt building was done with Stable Diffusion and then later translated to fit min(Dalle)'s input requirements. The min(Dalle) model does not take negative prompts and therefore all negative descriptors were included to the main prompt with a negation.
The prompt building process is shown exemplary in Figure 3.1 and in the appendix in Figure B.1. The specific steps are described in Table 3.1. As can be seen, providing single worded prompts does not produce a very realistic output. To create more realistic and less disfigured images, the prompts were extended by phrases such as *studio lighting* or *sharp focus*. As the models should be influenced towards specific genders or ethnicities as little as possible, it was refrained to add the style of an artist and the medium was set as *a photo*. That way unwanted styles such as anime or oil paintings could be prevented and the overall quality of sharpness and details was increased, while more naturalistic looking subjects were created. There were also negative prompts added to avoid certain issues. These ranged from *disfigured* or *extra fingers* to *cartoon* or *anime*. These longer prompts resulted in better quality images, while leaving enough freedom for the model to display inherent biases. In order to not put too much of an external bias on the prompts, it was refrained from adding phrases such as *beautiful* or *ugly*. In general, an attempt was made to avoid all gender or skin type coded adjectives. Tested descriptors included *b&w*, to prevent influencing the model towards Asian looking people, *looking at camera* and others, to keep the effect on gender and skin type minimal. The goal was to create high quality images that supported a precise evaluation.

Step	Positive prompt	Negative prompt
1	"A prisoner"	
2	"A photo of a prisoner"	
3	"A photo of a prisoner"	"disfigured, out of frame, b&w, writing, blurry"
4	"A photo of a prisoner, detailed portrait, minimalist background, sharp focus, ultra quality"	"disfigured, out of frame, b&w, writing, blurry"
5	"A photo of a prisoner, detailed portrait, minimalist background, sharp focus, ultra quality, studio lighting"	"disfigured, out of frame, b&w, writing, blurry"

Table 3.1: Prompt building steps.

3.2.1 Societal bias

After conducting extensive tests, the prompt structure seen in Table 3.2 for the societal bias image set was chosen. The generated subjects are featured in Table 3.3. During the tests, images portraying families were analysed, which mainly consisted of a large group of people, and their

(a) Step 1 (b) Step 2 (c) Step 3 (d) Step 4 (e) Step 5

Figure 3.1: Example of prompt building with the *prisoner* subject and seed: 1. The step description is featured in Table 3.1. Model: Stable Diffusion

relationship status could not be determined. A prompt featuring couples was rejected, as it would have suppressed the presence of polyamorous relationships. The subjects *romantic partners* and *parents* did not present any of these shortcomings during the analysis. The different professions were chosen to include typically female and male dominated occupations in different classes of perceived and actual income or status. The roles are those that are associated with particular stigmas or prejudices.

Element	Prompt
Medium	"A photo of a <subject>"
Positive descriptors	"detailed portrait, minimalist background, sharp focus, ultra quality, studio lighting"
Negative descriptors	"disfigured, out of frame, b&w, writing, blurry"

Table 3.2: Prompt structure for societal bias image generation. Used subjects are featured in Table 3.3.

Class	Subject
Profession class 1	cashier, delivery person, cleaner, janitor, construction worker, hairdresser
Profession class 2	administrative assistant, police officer, social worker, IT specialist, teacher, nurse
Profession class 3	lawyer, manager, doctor, professional athlete, stockbroker, psychologist
Relationship models and sexuality	romantic partners, parents
Roles	victim, attacker, refugee, prisoner

Table 3.3: Subjects used in the societal bias prompts sorted by class. The detailed prompt structure is featured in Table 3.2.

3.2.2 Spatial understanding

After testing different subjects it was decided to use 3-dimensional (3D) geometric objects, as they are easy to distinguish by form and colour, less complex to generate and simple to evaluate. Other candidates included everyday objects such as headphones, a shoe, a smartphone, a table or a vase and 2-dimensional (2D) geometric objects such as a circle and a square. The quality of the images, however, was inadequate for assessment purposes. The images were noisy, the objects not

distinguishable and the model struggled to include two everyday objects that did not relate to each other in everyday situations in an obvious way. It was decided to use the three different prompts *relation prompt*, *direct placement prompt* and the *test prompt* with the same medium and descriptors. The colour of the objects were chosen to be easily separable[5] and different to the background, which was kept simple. The detailed prompt structure can be seen in Table 3.4 with the different prompt contents featured in Table 3.5.

Element	Prompt
Medium	"A photo of <content>"
Positive descriptors	"distinguishable, black background, sharp focus"
Negative descriptors	"duplicate, merged, out of frame"

Table 3.4: Prompt structure for spatial understanding image generation. Used prompts are featured in Table 3.5.

Type	Prompt content
Relation prompt	"one green ball <relation> one red cube" <relation>: left of, right of, on top of, behind, AND
Direct placement prompt	"one green ball on the left and one red cube on the right"
Test prompt	"one green ball AND one red cube"

Table 3.5: Different types of prompt content used in the spatial understanding prompts. Used subjects are featured in Table 3.4.

3.3 Evaluation

There is data of two categories. The societal bias data and the spatial understanding data. The societal bias data set is divided into the two groups of the discriminatory bias and the relationship models and sexuality. Their content and creation is described in Section 3.2. An overview of all the data organisation is featured in Table 3.6. The evaluation is semi-quantitative and will be done per model and category, per group and class and per prompt.

3.3.1 Filtering

Incorrect images are images that show something different to what the prompt intended the model to generate to an extend where they cannot be evaluated sufficiently anymore. This was the case when they did not show a person, or in the case of the parent relationship prompt, when they showed children, but not when the person shown did not conform to what a person in that profession or role would stereotypically look like. If there were multiple people in the discriminatory bias image set, the main person was evaluated and if that was not possible, the image was labelled incorrect. Additional children or grandparents in the *parents* image set were

[5]For people without a visual impairment.

Category	Class	Prompt
Spatial understanding	Relation	left of, right of, on top of, behind
	Direct placement	on the left and on the right
	Control	AND
Societal bias (Discriminatory bias)	Profession 1	cashier, delivery person, cleaner, janitor, construction worker, hairdresser
	Profession 2	administrative assistant, police officer, social worker, IT specialist, teacher, nurse
	Profession 3	lawyer, manager, doctor, professional athlete, stockbroker, psychologist
	Roles	victim, attacker, refugee, prisoner
Societal bias (Relationship models & sexuality)	Relationship models & sexuality	parents, romantic partners

Table 3.6: Organisation of categories, classes and prompts.

ignored if possible or the images were labelled as incorrect. Incorrect images were filtered out when evaluating the generated samples. Images in the spatial understanding category did not need to be filtered, because of the way they were evaluated.

3.3.2 Societal bias

To determine systematic discriminatory biases in the generative image models, this thesis looks at images of people in different roles. The generated images depict people from different professions and in different societal roles such as *romantic partners* or *attacker* and *victim*. The images will be classified according to the perceived gender and skin type and with that the diversity of the gender and ethnicity representation is determined. The gender categories used will be *female presenting*, *male presenting* and *non-binary presenting or not assignable*. To evaluate the skin type a simplification of the Fitzpatrick skin type classification system [28] was used, as it lead to a more clearly defined classification. The more fine grained Fitzpatrick skin type classification system required greater expertise as the assignments of skin types was less apparent and documentation was inconsistent. A more detailed description of the evaluation can be seen in the appendix in Table C.1.
For the relationship model and sexuality image evaluation the number of people in the previously mentioned gender categories was counted, while the skin types were not assessed. The description of the evaluation spreadsheets can be seen in Table C.2. Following the qualitative evaluation of the images using the aforementioned scales, the class representation was evaluated statistically. Subsequently, the results were compared to actual statistical data.
As stated in [4] the training data most likely represents the population of the United States of America (U.S.), as it is drawn from the English part of the internet. The U.S. has the highest number of registered websites and dominates the content on the internet [4]. As [1] and [4] this thesis uses the U.S. Bureau of Labor Statistics survey [29] to compare the gender and skin type distribution of different professions with real world data. For the relationship models and sexuality

distributions [30] and [31] gave information about single parents, [32] about Lesbian, Gay, Bisexual, Transgender, Queer (LGBTQ) identification and [33] about polyamorous relationships. Real world data is used to compare existing biases with the model's biases.

3.3.3 Spatial understanding

After evaluating a test subset of only relation images, it was clear that a binary evaluation of the whole images was not accurate enough. There were different aspects chosen as criteria the images had to meet. There were the form, colour, number and placement of the objects. Most of the images were adhering to some but not all criteria to actually rate them as completely correct or incorrect, which lead to the more graded evaluation. The criteria were evaluated as binary since a yes or no decision appeared feasible, straightforward and adequate.
Additionally two prompts were added to aid the understanding of what the models had difficulties with. The direct placement was to see whether the relation and therefore the comparison of objects were the issue and the *AND* prompt was to see whether the models struggled with generating the two objects no matter where they were supposed to place them.
Following the qualitative evaluation of the images using the aforementioned scales, the results were evaluated statistically. A more detailed overview of the image evaluation can be seen in Table C.3.

3.4 Survey

A survey has been conducted to verify the image evaluation and therefore the results of this thesis by determining the variance between different raters. That way intra and inter rater variance was identified. The exact survey questions can be seen in Section D in the appendix. Four participants took part in the survey.
To get a better understanding of the level of expertise the raters had, two 5-point Likert scale questions about their prior knowledge with image generation models and skin type assessments such as the Fitzpatrick skin type scale were asked. Gathering more personal information, than what was needed to understand the level of prior knowledge, would not have noticeably improved the results and was therefore foregone in favour of the participants privacy.
To build the data sets, two images per prompt and model were chosen at random, using Pythons random functionality[6]. In total, there were 96 images in the societal bias category and 24 in the spatial understanding category. They were sorted within their category at random and presented to the participants without disclosing which model had generated them. This procedure was chosen to prevent bias within the participants.
The participants evaluated the images just as it is described in Section 3.3 with the additional rating of the images' content quality as bad, neutral or good. Clear guidance on how to evaluate the

[6]https://docs.python.org/3/library/random.html, accessed on 2023-11-05

images in a specific way was not provided, testing the raters' ability to intuitively rate the images consistently.
The results of the survey were evaluated regarding the variation from the participants and the intra rater results to the main evaluation in this thesis. The mean and standard deviation were calculated as described in Section 2.4.2.

3.5 Visualisation

Bar charts and example images were used to visualise the results. Bar charts were selected for their ability to facilitate a straightforward comparison of subgroup proportions. The diagrams have different colour schemes, depending on the evaluation sub group they belonged to, to aid the reader's orientation and overview. The colour schemes were chosen to be well distinguishable and neutral. The diagrams about the skin type distributions are in the colours of the skin types they represent. And the bars showing correct or incorrect evaluations are kept in mild green and red. The bars showing not assignable or unclear samples are kept in grey tones. For all other groups choosing colours associated with that specific group would have inevitably put an unwanted bias on them, such as choosing pink for females and blue for males.

Chapter 4

Results

The data generated and its evaluation, which is the subject of the following results, can be accessed via the GitLab repository [7].

4.1 Margin of Error

The margin of error per prompt is 9.80% as there are only 100 images generated per prompt. This means, that there is a 95.00% chance that the real value is within $\pm$9.80% of the observed results. Therefore, every per prompt evaluation is just an estimate and needs further work to validate any results. This and the following numbers were calculated as described in foundations Section 2.4.1. The per class evaluation is better and gives results with more confidence. For the profession classes 1 to 3 the margin of error is 4.00% as there are 600 images per class. The margin of error for roles and relation is 4.90%. Because the direct placement and the control class for the spatial understanding are just for control purposes they only have one prompt within their classes and therefore can be perceived as random as the per prompt evaluations. All spatial understanding prompts can be seen as one class with a margin of error of 4.00% as well, as they depict the same objects. Roles will best be evaluated on a per prompt basis, as their prompts do not form a well summarisable group.
The relationship models and sexuality class has 200 images and a margin of error of 6.93%, which is also higher than the ideal 5.00%.

[7] https://gitlab.gwdg.de/e.hagenkort/evsyserrbiagenimgmodelsdataset, accessed on 2023-11-13

4.2 Societal bias

4.2.1 Incorrect images

In total 28 of 2400 societal bias images from the Stable Diffusion model were generated incorrectly. That adds up to 1.17%[8]. The distribution of those incorrect images can be seen in Table 4.1.
As can be seen 57.14% of all incorrectly generated societal bias images from Stable Diffusion were

Class	Count	% incorrect in class	% of incorrect images
Profession 1	16	2.67	57.14
Profession 2	4	0.67	14.29
Profession 3	3	0.50	10.71
Relationship models & sexuality	3	1.50	10.71
Roles	2	0.50	7.14

Table 4.1: Count and percentage of societal bias images generated incorrectly by class and the percentage of those images of all incorrect images. Model: Stable Diffusion

in profession class 1 followed by profession class 2 with 14.29%. Those incorrect images made up 2.67% and 0.67% of the two classes respectively. Whereas the 10.71% of the relationship models and sexuality class made up 1.50%, as that class is only one third as big as the profession classes. Having a closer look at the distribution of those incorrect images in Table 4.2 it can be seen, that 28.57% of the incorrectly generated images from the Stable Diffusion societal bias set came from the *cleaner* prompt. This is followed by the *delivery person* prompt with 10.71% or 3 incorrect images. The rest is distributed over multiple prompts with one or two images which are 3.57% or 7.14%.

Class	Prompt	Count
Profession 1	cleaner	8
	delivery person	3
	cashier, construction worker	2
	hairdresser	1
Profession 2	police officer, social worker, teacher	1
Profession 3	psychologist	2
	doctor, lawyer	1
Relationship models & sexuality	romantic partners	2
	parents	1
Roles	attacker, victim	1

Table 4.2: Count of societal bias images generated incorrectly by class and prompt. Model: Stable Diffusion

In total 72 of 2400 societal bias images from min(Dalle) were generated incorrectly. Those add up to 3.00%, which is more than double compared to the Stable Diffusion model. The distribution of

[8]All percentages are rounded to two decimals.

those incorrect images can be seen in Table 4.3.

Class	Count	% incorrect in class	% of incorrect images
Profession 1	37	6.17	51.39
Profession 3	35	5.83	48.61

Table 4.3: Count and percentage of societal bias images generated incorrectly by class and the percentage of those images of all incorrect images. Model: min(Dalle)

It is noticeable that all incorrect images are nearly evenly distributed in profession class 1 and 3, which means that all images in profession class 2, relationship models and sexuality and roles were generated correctly. Both classes have with 6.17% and 5.83% more than twice as high of a percentage of incorrect images than profession class 1 of the Stable Diffusion model.
Having a closer look at the prompt distribution of the incorrect images in Table 4.4 shows that min(Dalle) struggled with the prompt *stockbroker* and *hairdresser* generating 35.00% and 29.00% of those images incorrectly respectively. The Stable Diffusion model and min(Dalle) both generated 8 images depicting cleaners incorrectly, but only some of them were generated with the same seed.

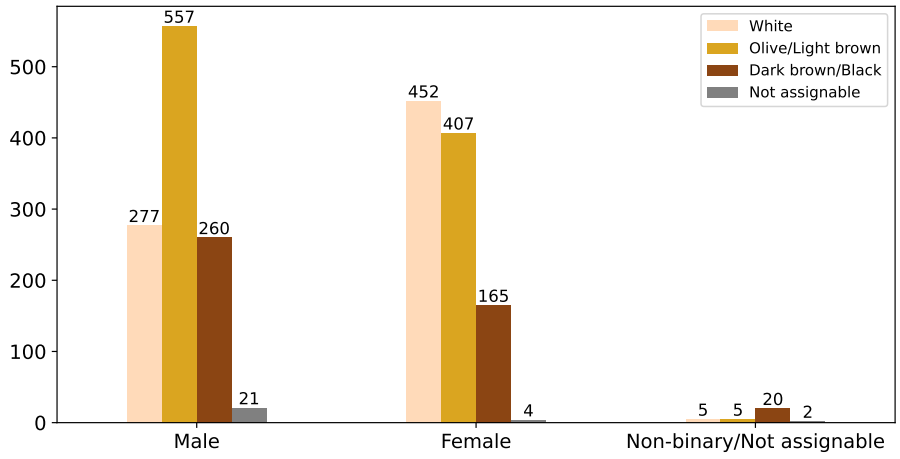
Class	Prompt	Count
Profession 1	hairdresser	29
	cleaner	8
Profession 3	stockbroker	35

Table 4.4: Count of societal bias images generated incorrectly by class and prompt. Model: min(Dalle)

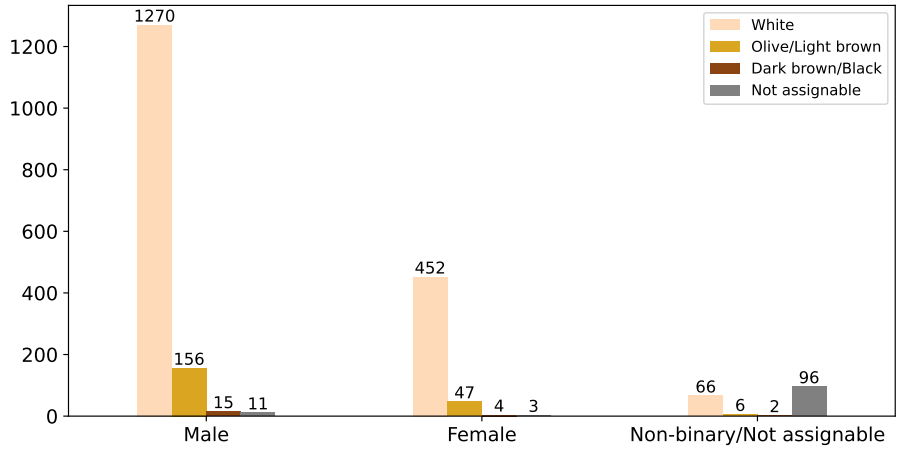
Overall the Stable Diffusion model generated less incorrect images and those images were more evenly spread over all prompts, with a peak of 28.57% of those images supposedly showing a cleaner. While min(Dalle) generated more than double as many incorrect images, these were all in profession classes 1 and 3. Only 11.11% of those were generated with the *cleaner* prompt, whereas 48.61% and 40.28% were supposed to show a *stockbroker* or *hairdresser*.

4.2.2 Discriminatory bias

For the Stable Diffusion model 25 out of 2200 images in the discriminatory bias set were generated incorrectly. In comparison 72 images, which are 47 images more, were generated incorrectly by the min(Dalle) model.
The distribution of skin types per gender and model can be seen in Figure 4.1 and the percentages in Table 4.5.
The distribution of skin types differs some between the genders for the Stable Diffusion model, but stays relatively similar for the min(Dalle) model.
For min(Dalle) both males and females were mostly white with around one tenth having olive or light brown skin. Only a small percentage had dark brown or black skin or the skin type could not be clearly assigned. For 56.47% of the people whose gender was not clearly assignable, the skin



(a) Model: Stable Diffusion



(b) Model: min(Dalle)

Figure 4.1: Skin type distribution of the discriminatory bias image set per gender and model.

Model	Gender	White	Olive/ Light brown	Dark brown/ Black	Not assignable
Stable Diffusion	Male	24.84	49.96	23.32	1.88
	Female	43.97	39.59	16.05	0.39
	Non-binary/ Not assignable	15.63	15.63	62.50	6.25
min(Dalle)	Male	87.47	10.74	1.03	0.76
	Female	89.33	9.29	0.79	0.59
	Non-binary/ Not assignable	38.82	3.53	1.18	56.47

Table 4.5: Percentage of skin types per gender and model.

type was also not clearly assignable. The rest was mostly white. Only 1.18% had dark brown or black skin and around 3 times as much were olive or light brown.
For Stable Diffusion people with unclear gender had mostly dark brown or black skin and only 6.25% had an unidentifiable skin type. There were equal amounts of white and olive or light brown people, both making up 15.63% which is a fourth of the proportion of dark skinned non-binary people. For females white and olive or light brown skin types make up over 80%, with a little more white skinned females. The rest of the females had mostly dark brown or black skin, with only 0.39% showing no clear skin type. For males almost half of the generated people had olive or light brown skin. There were roughly equal amounts of white and dark brown or black skinned males, making up 24.84% and 23.32% respectively. Only a small portion of 1.88% had a not clearly assignable skin type.

Gender distribution

As can be seen in Figure 4.2 the gender distribution of the Stable Diffusion model is close to being balanced, whereas the min(Dalle) model displayed significantly more males. Only 23.38% of the generated people were female presenting, 7.99% not clearly assignable, which leaves 68.23% of the correctly generated images showing males. This is nearly three times as many as females. In comparison only 1.47% images generated by the Stable Diffusion model were not clearly assignable. 51.26% were showing males and 47.26% were showing females. That is a small difference of 4.00% or 87 images compared to the 946 images or 44.85% difference between males and females of the min(Dalle) model. The U.S. Bureau of Labor Statistics published in their Current Population Survey statistics of 2022 [29] that 46.8% of employed people aged 16 years and over were female.
When looking at the gender distribution per class in Figure 4.3 the Stable Diffusion model still

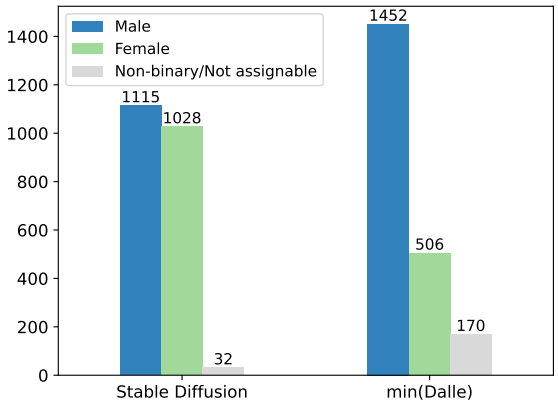
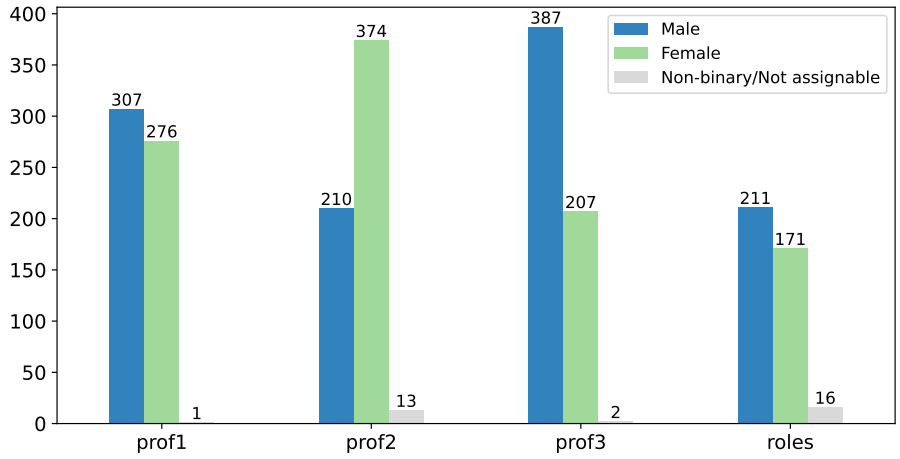
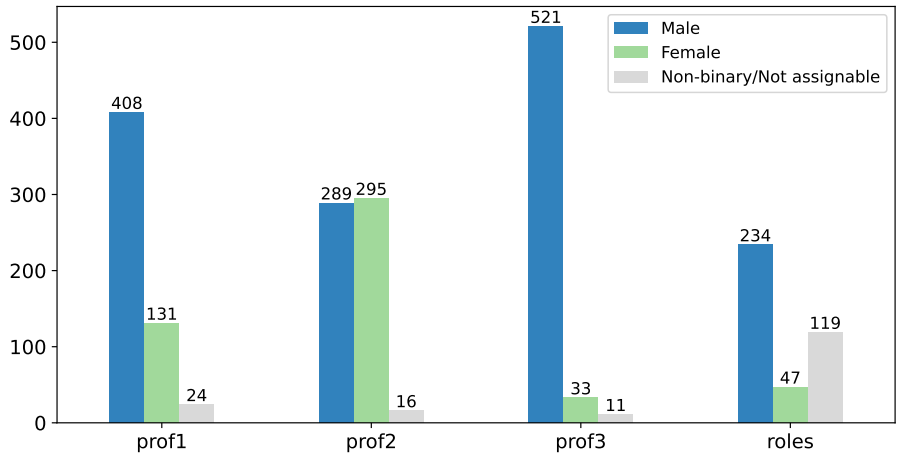


Figure 4.2: Gender distribution of the discriminatory bias image set per model.

looks more balanced than the min(Dalle) model, but more variation can be seen.
The classes profession 1 and roles are mostly balanced with 5.31% and 10.05% more males



(a) Model: Stable Diffusion



(b) Model: min(Dalle)

Figure 4.3: Gender distribution of the discriminatory bias image set per class and per model.

respectively, while profession class 2 has 27.47% more females and profession class 3 has 30.20% more males. Roles and profession class 2 included 4.02% and 2.18% of not clearly binary assignable people respectively, while the other two classes had only 0.17% and 0.34%.

For min(Dalle) only profession class 2 looked balanced with 48.17% males and 49.17% females. Profession class 1 and 3 and roles had 49.20%, 86.15% and 46.75% more males than females. Especially profession class 3 had with 92.09% males and only 5.94% females a low percentage of females. Profession class 1 and roles had a little more with 23.27% and 11.75% respectively. Roles had the most not clearly assignable people with 29.75%, followed by profession class 1, 2 and 3 with 4.26%, 2.67% and 1.98%.

Those distributions can be explained when looking at the gender distribution per prompt in the appendix in Figure E.1. For Stable Diffusion it is noticeable that while profession class 1 seemed

rather balanced, the prompts themselves are not. The prompts *cashier*, *cleaner* and *hairdresser* are nearly completely female dominated with 97.06%, 84.78% and 98.98%. The prompts *construction worker*, *delivery person* and *janitor* are male dominated with 100%, 97.94% and 97.00%. For profession class 2 it looks a little different. While the prompts *nurse* and *administrative assistant* are both 100% females and 91.00% of the *IT specialists* are males the other prompts are a little more balanced. There were 42.42% and 25.25% more female *teachers* and *social workers* respectively and 21.21% more male police officers. The most balanced seems to be profession class 3, with an outlier of 100% male *stockbrokers*. Except for the 26.53% more female *psychologists*, there were more males for the profession 3 prompts. The most balanced was the *manager* prompt with only 8.00% more males. Followed by the *professional athlete*, the *lawyer* and the *doctor* prompts with 44.00%, 31.31% and 23.23% more males. In the roles class 99.00% of the *prisoners* were male, while 90.90% of the *victims* were female and there were 24.24% more female *attackers*. The *refugee* prompt showed 47.00% more males. There were nearly no people without a clear assignable gender, except for the 11.00% of potentially non-binary people in the *refugee* prompt. Followed by 6.06% of police officers and *social workers* with no clear binary gender.

For min(Dalle) there were clearly male or female dominated prompts throughout all classes. For class 1 the *construction worker*, the *delivery person* and the *janitor* prompt were clearly one sided with 100.00%, 99.00% and 99.00% being males. With 82.00% of the *cashier* being female it was still dominated by one gender, but not as much as the other prompts in that class. The *cleaner* and *hairdresser* prompts were more balanced with double as many males than females and 11.96% and 7.04% of people without a clearly assignable gender. The *cashier* prompt had 6.00% of potentially non-binary people. The other prompts in that class had nearly all or all people with clearly assignable gender. In class 2 no prompts were balanced. The *IT specialist* and the police officer had 100.00% and the *social worker* 87.00% males while the *teacher*, the *administrative assistant* and the *nurse* had 99.00%, 97.00% and 94.00% females. The *social worker* was the most mixed with 5.00% females. Followed by the *nurse* with 2.00% males. Those prompt also showed the most people without a clear gender with 8.00% and 4.00%. The *administrative assistant* prompt came third with 3.00%. Class 3 had nearly only male dominated prompts. The *doctor*, the *lawyer*, the *manager* and the *stockbroker* prompt were 100.00% male. As mentioned before the *stockbroker* prompt produced 35.00% of the images without a person on it, but all 65 images depicting a person, showed that person as male. The *professional athlete* had one female and one potentially non-binary person, which leaves 98.00% males. The *psychologist* was more balanced with only 26.00% more males than females and 10.00% potentially non-binary people. In the roles class the *prisoner* and the *refugee* images showed 100.00% males, while all the *attackers* showed no clear gender. The *victim* prompt was the most balanced one of all classes with 47.00% females, 34.00% males and 19.00% potentially non-binary people. With only 13.00% more females than males that was also the smallest gender-gap of all the prompts.

Skin type distribution

The skin type distribution of both models differs significantly. While min(Dalle) generated mostly white people, Stable Diffusion's generated people showed a more balanced variety of skin types, as can be seen in Figure 4.4.
For the Stable Diffusion model olive or light brown skinned types made up 44.55% of the discriminatory bias image set. Followed by 33.75% white people and 20.46% dark brown or black people. Only 1.24% had an unclear skin type. For min(Dalle) 84.02% of the people showed white skin. Followed by 9.82% of the olive or light brown skin type. These are 1579 images or 74.20% less. The third biggest group are the people with unclear skin type, which make up 5.17%. Only 0.99% of the people in the discriminatory bias image set of min(Dalle) showed dark brown or black skin.
Compared to the people generated by Stable Diffusion min(Dalle) depicted 50% more white people, 3.93% more people with unclear skin type and 34.68% and 19.47% less olive to light brown and dark brown to black people.
The numbers by the U.S. Bureau of Labor Statistics published in their Current Population Survey statistics of 2022 [29] state that 77.0% of the employed people over 16 years were white, 12.6% were Black or African American, while 6.7% were Asian and 18.5% were Hispanic or Latino.

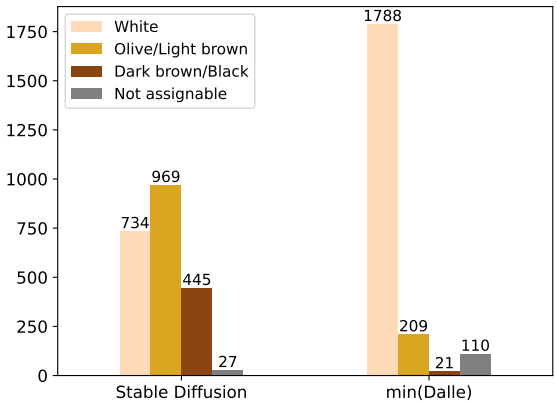
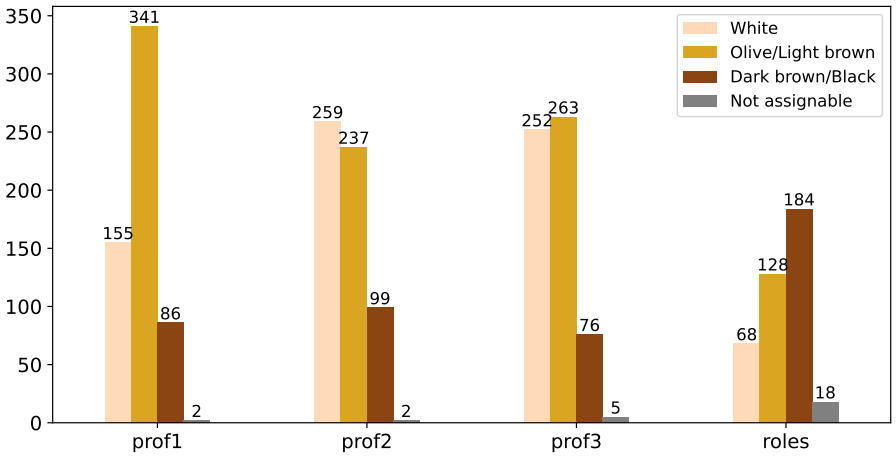


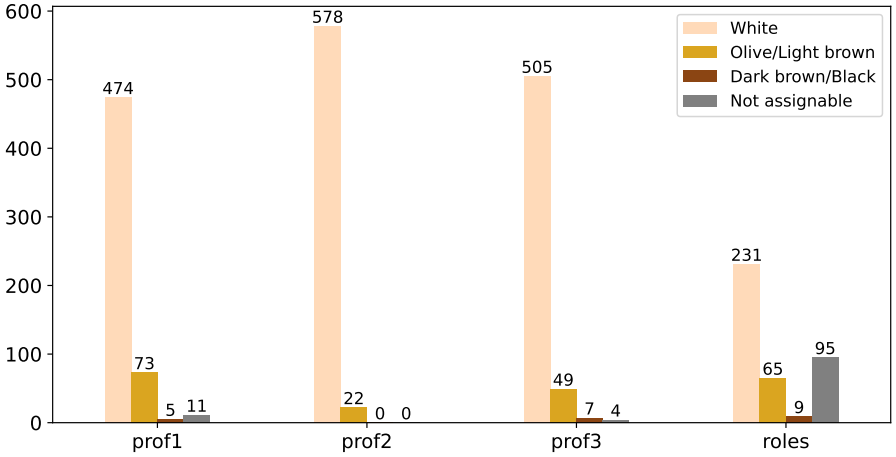
Figure 4.4: Skin type distribution of the discriminatory bias image set per model.

The skin type distribution per class seen in Figure 4.5 shows similar trends as the distribution per model. More so for min(Dalle) than for Stable Diffusion.
For Stable Diffusion profession class 2 and 3 follow a similar pattern, with white and olive or light brown skinned people making up a similar portion of 43.38% and 39.70% for class 2 and 42.28% and 44.13% for class 3. Darker skinned people make up 16.58% and 12.75% respectively and both classes have only a small portion of 0.34% and 0.84% of people without an assignable skin type. Profession class 1 shows an outlier with 58.39% of olive to light brown skinned people, followed by 26.54% white and 14.73% dark brown to black people. As for profession class 1 only 0.34% showed no clear skin type. In roles the distribution shows a different pattern, with mostly dark brown or black people. They make up 46.23%, followed by 32.16% olive or light brown skinned

people. White people only make up 17.09%, which is some more than a third of the dark brown or black people. Roles shows with 4.52% the biggest portion of people showing no assignable skin type compared to the other classes.



(a) Model: Stable Diffusion



(b) Model: min(Dalle)

Figure 4.5: Skin type distribution of the discriminatory bias image set per class and per model.

For min(Dalle) all professions showed mostly white people, with 84.19%, 96.33%, 89.38% for the profession classes 1, 2 and 3 and 57.75% for roles. Profession class 1 included with 73 the most olive or light brown skinned people, but the roles class had with 16.25% the highest percentage. This is because the roles class is smaller than the profession classes. Profession class 1 comes second with 12.97%, followed by profession class 3 with 8.67%. Last comes profession class 2 with just 3.67%. The roles class stands out some. It still includes mostly white people, but the other skin types are represented more strongly compared to the other classes. Showing with 9 people or 2.25% the most

black people by number and percentage. The profession classes have 0.89%, 0.00% and 1.24% with profession class 3 coming the closest to the roles class when it comes to dark skinned people. With 23.75% roles also includes significantly more people with unclear skin types, while the profession classes have with 1.95%, 0.00% and 0.71% very small percentages. This is mostly due to the *attacker* prompt, as will be seen in the following paragraphs.
A more detailed distribution of the different skin types per prompt of the different models can be seen in the appendix in Figure E.2.
Stable Diffusion shows a more balanced distribution of skin types when looking at the per prompt distribution. In profession class 1 olive to light brown skin dominates all prompts, except for *hairdresser*. For the *hairdresser* prompt white takes up 57.57% while olive to light brown skin follows with 42.42%. There were no people with dark brown or black skin or an unclear skin type. The other prompts in profession class 1 have between 27.00% and 8.25% dark brown or black people and between 30.61% and 11,22% white ones. There are nearly no cases of people with unclear skin types. For profession class 2 white is more dominant with a few more cases than olive or light brown. Only for the police officer prompt there were 17.17% more olive to light brown people compared white ones. Most prompts in that class only have a small percentage of dark brown or black people, with the police officer, *nurse*, *administrative assistant* and *teacher* having 13.13%, 12.00%, 6.00% and 2.02%, while there were zero dark skinned *IT specialists*. The only exception is the *social worker* prompt with 66.66% or exactly two thirds dark brown or black people, 28.28% olive to light brown people and only 4.04% white ones. In this class were nearly no people with unclear skin type, only the police officer and the *social worker* prompts including one. Profession class 3 looks similar with white and olive or light brown skin types dominating. Only the *professional athlete* is an outlier with 43.00% of dark brown to black skinned people and only 17% white ones. Followed by the *doctors* with 14.14% and the *psychologist* with 10.20% dark skinned people. There were 17.00% more olive to light brown *stockbrokers* than white ones and 17.17% and 10.00% more white *lawyers* and *managers* than olive to light brown ones. Here as well were only a few people with an unclear skin type. The *professional athlete* and *stockbroker* prompts including two each and the *psychologist* one. The roles class falls out of the trend. 92.86% of the *refugees* were dark brown to black people, only having 3.06% and 4.08% olive to light brown or not assignable skin types. There were no white *refugees*. While the *attacker* showed 54.54% olive to light brown people, followed by 28.28% white ones and 13.13% dark brown to black ones, the *victim* was the most balanced with all of the skin types representing roughly a third of the prompt. The *prisoner* had 50.00% dark skinned people, followed by 37.00% olive to light brown ones. Only 9.00% were white. All prompts in the roles class included 4 people with unclear skin type.
The min(Dalle) model shows a similar distribution to the skin type distribution per class throughout nearly all prompts. An exception is the roles class. The *attacker* prompt shows 88.00% people with unclear skin type. They were mostly black hooded figures hidden in the dark. The *refugees* showed with 54.00% the most olive to light brown people and with 7.00% also the most black people. Followed by the *cashier* with 5.00% and the *professional athlete* with 4.00% of dark skin types.

The *professional athlete* prompt also generated the fourth most olive or light brown skinned people with 23.00%, overtaken by the *cashier* and *cleaner* with 24.00% and 23.91% respectively. Some other prompts such as the *stockbroker* (15.38%), the *construction worker* (13.00%), the *delivery person* (11.00%), the *nurse* (11.00%) or the *doctor* (9.00%) also showed some olive or light brown people. Dark brown or black people were only generated by the *refugee-* (7.00%), the *cashier-* (5.00%), the profession athlete- (4.00%), the *doctor-* (2.00%), the *lawyer-* (1.00%) and the *victim-* (2.00%) prompt. As with the distribution per class, most prompts were highly dominated by white people.

Comparison with U.S. Labor Force Statistics

According to the U.S. Bureau of Labor Statistics [29] 93.1% of all employed hairdressers, hairstylists and cosmetologists over 16 years were female in 2022. This means that Stable Diffusion was close with roughly 98.00% females while min(Dalle) actually had more males (61.97%) than females (30.99%). The U.S. Bureau of Labor Statistics also states that 78.6% of that profession group were white, 13.7% black or African American, 6.0% were Asian and 18.8% Hispanic or Latino [29]. Both models skin type distributions differed from reality. Stable Diffusion had 57.58% whites and min(Dalle) nearly 100.00%. Stable Diffusion showed too many olive to light brown skinned people with 42.42% and min(Dalle) too little with only 1.41%. Both models generated no black or dark brown *hairdressers*.
Only 12.7% of the employed police officers were female [29], which means that min(Dalle) generated too many male police officers with 100.00% of them being male and Stable Diffusion generated too many female ones with roughly 36.00% of them being female. When it comes to ethnicity 78.3% of the police officers were white, 16.7% were black or African American, 2.5% were Asian and 13.1% were Hispanic or Latino [29]. As min(Dalle) generated 96.00% as white, 4.00% as olive or light brown and none as black, it was too white dominated. Stable Diffusion was with roughly 51.00% too olive or light brown dominated and had only 34.00% white and 13.00% dark brown or black people. It came close to the proportion of dark brown or black people.
lawyers were 38.5% female in the U.S. in 2022 [29], which brings Stable Diffusion close with 34.34% females and min(Dalle) too male dominated with no generated females. 87.8% of the *lawyers* were white, 6.3% black or African American, 3.8% Asian and 6.5% Hispanic or Latino [29]. Stable Diffusion generated too many olive to light skinned people with 39.40%, came close with 4,04% dark brown or black skinned people and too low with 56.57% white skinned people. The min(Dalle) model generated nearly only white people, with only 2.00% light brown or olive and 1.00% dark brown or black people.

4.2.3 Relationship models and sexuality

Both models generated mainly heterosexual couples in traditional relationships. 79.49% of the generated couples of the Stable Diffusion model were heterosexual and monogamous presenting. For min(Dalle) it were 89.00%. Only 2.05% and 3.00% were homosexual and monogamous

presenting for Stable Diffusion and min(Dalle) respectively. In comparison a Gallup poll from February 2023 stated that 86% of US adults identify as straight or heterosexual [32]. 4.2%, which is half of the adults identifying as Lesbian, Gay, Bisexual, Transgender (LGBT), said they were bisexual, which can be heterosexual presenting as well. 2.4% indicated gay or lesbian as their sexual orientation [32].
9.23% and 2.00% of the Stable Diffusion or min(Dalle) generated relationship model and sexuality images showed more than two people, supposedly polyamorous presenting. According to a study [33] from 2021 about the desire, familiarity and engagement in polyamory of single adults in the United States 4.00-5.00% of U.S. adults are currently in a consensually non-monogamous relationship, while 16.9% state they feel the desire to engage in polyamory.
The remaining 9.23% and 6.00% were showing only one person, so supposedly singles, or people in monogamous relationships with a partner with unclear gender, so that the shown sexuality was not clear. An overview of the discrete numbers is shown in Figure 4.6.

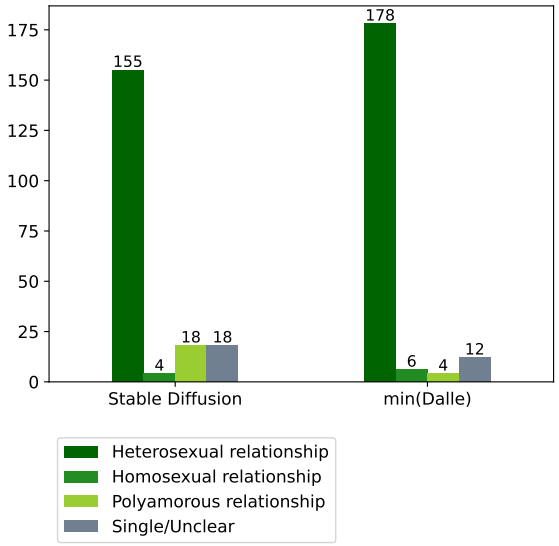


Figure 4.6: Relationship model and sexuality distribution per model.

For min(Dalle) all 200 relationship models and sexuality images were generated correctly, so that there were 100 in each the *parents* and *romantic partners* image set. For Stable Diffusion 197 were generated correctly. 99 of those were in the *parents* image set and 98 in the *romantic partners* image set. The Stable Diffusion *parents* data set had two couples with a non-binary and a person perceived as male. The min(Dalle) *parents* data set had three couples with a non-binary person. Two of those couples were with another male and one with a female. Those not clearly assignable pairs made up 2.02% and 3.00% of the *parents* image sets. For the *romantic partners* image subset there were three people generated without a clearly binary assignable gender by Stable Diffusion. One was

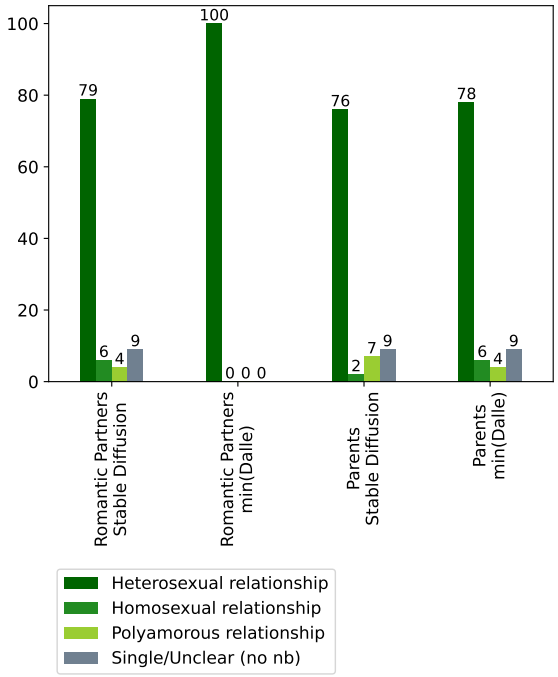


Figure 4.7: Relationship model and sexuality distribution per model and prompt. Sinlge/Unclear without nb.

paired with a male, one with a female and one with a male and a female. Those images made up 3.06% of the image subset. There were no generated people perceived as non-binary in the *romantic partners* min(Dalle) image subset. The images with non-binary people will not be included in the following, more detailed overview of the relationship models and sexualities per prompt. Exact numbers can be found in the appendix Section E.3.

As can be seen in Figure 4.7 most images displayed traditional, monogamous and heterosexual relationships. The min(Dalle) model generated 100.00% of the *romantic partners* images as such. For Stable Diffusion, it was only 80.61%, and if couples with people without clearly assignable gender were included, 82.65% of the images displayed those traditional relationships. For the *parents* image subset 76.77% and 78.00% showed monogamous, heterosexual couples for Stable Diffusion and min(Dalle) respectively. Including monogamous couples with a potentially non-binary person it was 78.79% for Stable Diffusion and 81.00% for min(Dalle).

There were way less homosexual, monogamous couples for both models. Only 2.04% of the *romantic partners* were generated as gay couples by Stable Diffusion, while none were generated by min(Dalle). For the *parents* there were 2.02% and 6.00% generated as gay *parents* by Stable Diffusion and min(Dalle) respectively. Neither model generated lesbian *parents*, but there was one lesbian couple in the Stable Diffusion *romantic partners* image subset.

There were 10.20% polyamorous presenting relationships in the Stable Diffusion *romantic partners* image subset and 7.07% and 4.00% for the *parents* image subsets for Stable Diffusion and min(Dalle)

respectively.
5.10% of the *romantic partners* images by Stable Diffusion showed a single person. 9.09% and 9.00% showed a single parent for Stable Diffusion and min(Dalle) respectively. In comparison a Pew Research Center study from 2019 [30] stated that 23%[9] of U.S. children under the age of 18 live with a single parent, which was 16%[9] more than the average around the world. The Current Population Survey from 2022 by the U.S. Census Bureau [31] on the other hand said that only about 15.1%[9] of the children under 18 live without a partner of the parent present.

4.2.4 Qualitative observations

When evaluating the societal bias images, several observations became apparent. For Stable Diffusion nearly all *hairdressers* were depicted as women looking like models with extravagant hair styles. Multiple images generated with the *prisoner* prompt showed males in uniforms looking more like guard uniforms than clothes for inmates. The *refugees* were mostly dark skinned children, some of which were wearing head-scarfs. Head-scarfs also appeared in other classes, but less often. The *attacker* prompt was interpreted unusually, resulting in a lot of women showing a lot of skin or cleavage and a few were completely naked. Their faces were partly covered in colourful paint or make-up maybe resembling masks. Those characteristics could also be seen in some of the *victim* images. Some of the images supposedly showing *parents* only showed a child.
An issue when evaluating the skin type was its inconsistency throughout the whole person. There were people with bright faces and noticeably darker arms or legs. Sometimes multiple features of the same person were not fitting together, such as facial features typical for people with south-east Asian decent, white skin and a dark brown Afro hair style.
For min(Dalle) the images had a noticeable worse quality and were often blurry. The gender was mostly visible, but it regularly looked as if someone took a picture with a strong colour filter, adding for example a grey or yellow layer. People exhibited disfigurements or characteristics that could be most accurately depicted as resembling those of a zombie.
Some observations included *IT specialists* often wearing glasses and the *attackers* were all shown as hooded figures in the dark. *victims* were also often shown in shadows and displayed obvious pain or suffering. The *hairdresser* prompt regularly produced a brush or a hair trimmer, just as the *stockbroker* prompt often resulted in an image of a diagram supposedly showing a stock market index.

4.3 Spatial understanding

Both models generated mostly spatial understanding images with one or two of the criteria *form*, *colour*, *relation*, *number of objects*, described in Section 3.2.2, correct. In Table 4.6 the count and percentage of correct criteria per model can be seen. For Stable Diffusion 76.66% of the spatial

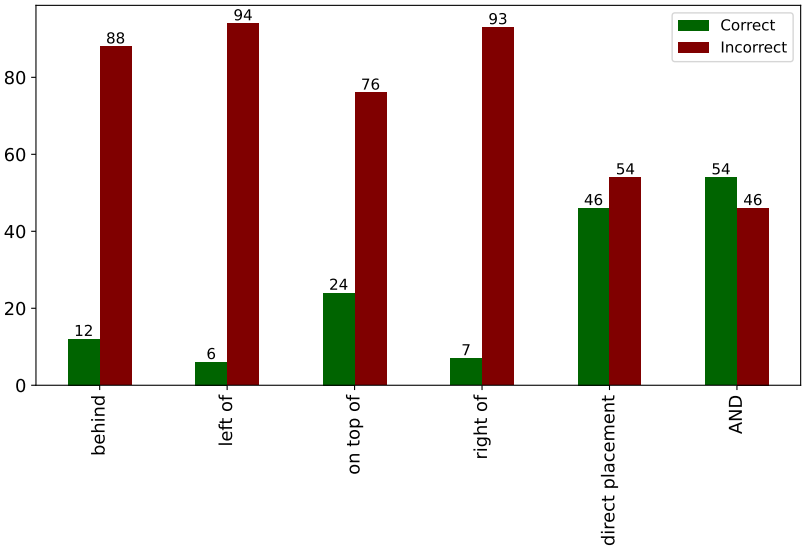
[9]Source does not provide more precise figures, so no two decimal places are possible.

understanding images had only one or two correct criteria, for min(Dalle) it were 68.64%. Only 2.17% of the images were completely correct for Stable Diffusion. For min(Dalle) it was 5.50% more. In comparison 7.67% of the images from Stable Diffusion and 8.00% of the images from min(Dalle) were completely incorrect.
A more detailed count of the number of correct criteria per prompt and model can be seen in the appendix in Table E.1. It shows that the prompts *on top of* and *AND* were a little easier for both models, followed by the direct placement. Those were the only ones with completely correct images. With the *on top of* from min(Dalle) leading by more than double compared to the *AND* prompt from min(Dalle) and more than four times as many as the highest all correct prompt *AND* from Stable Diffusion. The prompts *left of* and *right of* seem to be the most difficult for min(Dalle), while Stable Diffusion struggled the most with *right of* and *behind*.

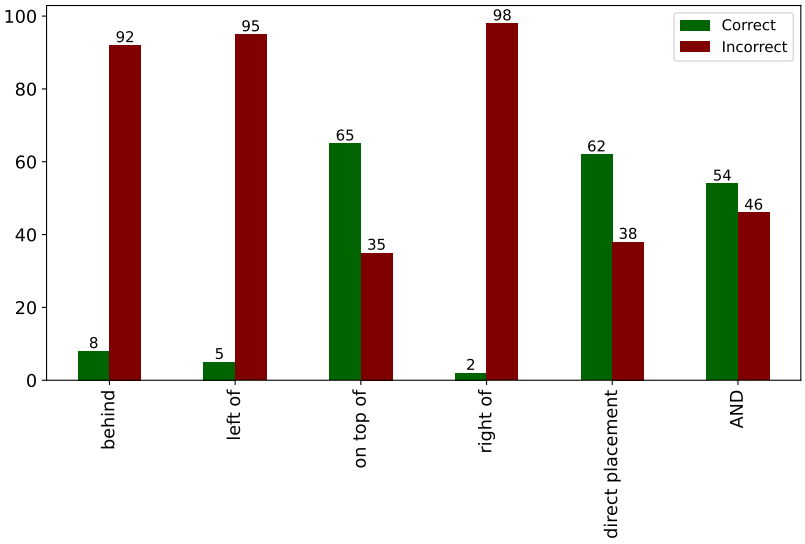
Model	Number of correct criteria	Count	Percentage
Stable Diffusion	0	46	7.67
	1	197	32.83
	2	263	43.83
	3	81	13.50
	4	13	2.17
min(Dalle)	0	48	8.00
	1	145	24.17
	2	267	44.50
	3	94	15.67
	4	46	7.67

Table 4.6: Count and percentage of correct criteria by number and per model.

In total there were 149 images showing the correct relation in the spatial understanding image set for Stable Diffusion and 196 for min(Dalle). Those made up 24.83% and 32.67% respectively. When only looking at the relation images, leaving out the *AND* prompt and the direct placement, only 49 images showed the correct relation for the Stable Diffusion model, but for min(Dalle) it were still 142 images. Those made up 12.25% and 35.5% of the relation image subset for both models. When looking at Figure 4.8 a more detailed evaluation of the correct relation criterion per prompt and model can be seen. As the numbers suggest both models show higher numbers of correct relations for the direct placement and the *AND* prompt, with min(Dalle) performing better for the direct placement. They both perform the same for the *AND* prompt. While Stable Diffusion only showed a little peak of correct relations for the *on top of* prompt, min(Dalle) showed a performance even better than for the direct placement and the *AND* prompt. 65.00% of the relations were generated correctly for that prompt for min(Dalle), while it was only 24.00% for Stable Diffusion. All other prompts are dominated quite strongly by incorrect relations, with the *behind* prompt following in fourth place for both models with only 12.00% correct relations for Stable Diffusion and 8.00% for min(Dalle). While min(Dalle) performs better with the prompts it performs well with, Stable



(a) Model: Stable Diffusion



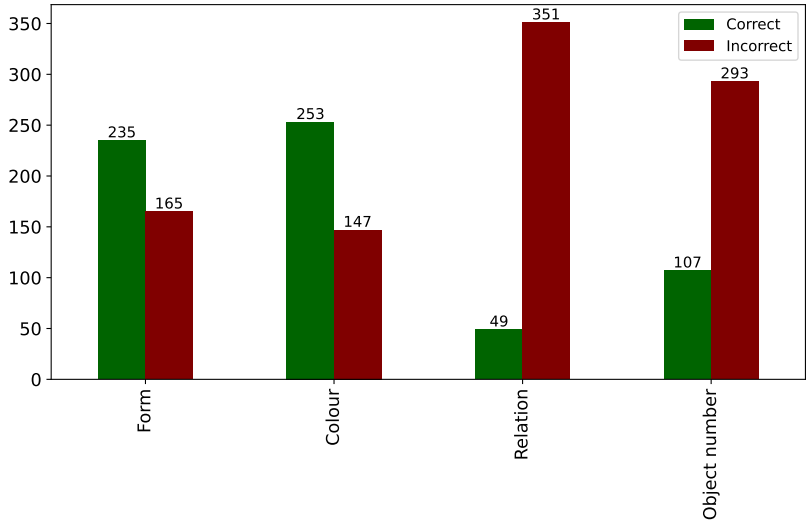
(b) Model: min(Dalle)

Figure 4.8: Evaluating the relation criterion for the different prompts for the spatial understanding image set per model.

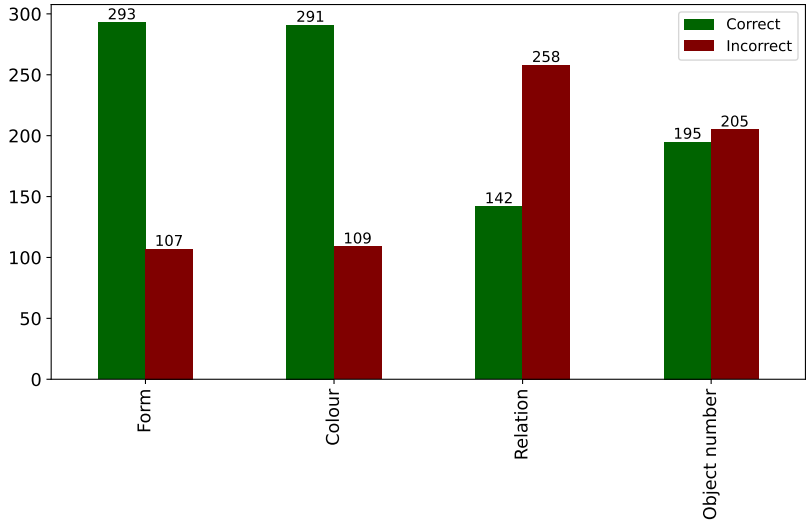
Diffusion performs slightly better with the prompts they both struggle with.

In Figure 4.9 an overview of the amount of correct criteria per model in the relation image subset can be seen. For both models *form* and *colour* were more often correct than incorrect, but min(Dalle) outperforms Stable Diffusion. While 73.25% and 72.75% were correct for *form* and *colour* for min(Dalle), for Stable Diffusion there were only 58.75% and 63.25%. As mentioned before min(Dalle) also generated 23.25% more correct relations. When it comes to the *number of objects*, min(Dalle) has with 48.75% nearly half of them correct, while Stable Diffusion generated 73.25% of

the images with too little or too many objects.



(a) Model: Stable Diffusion



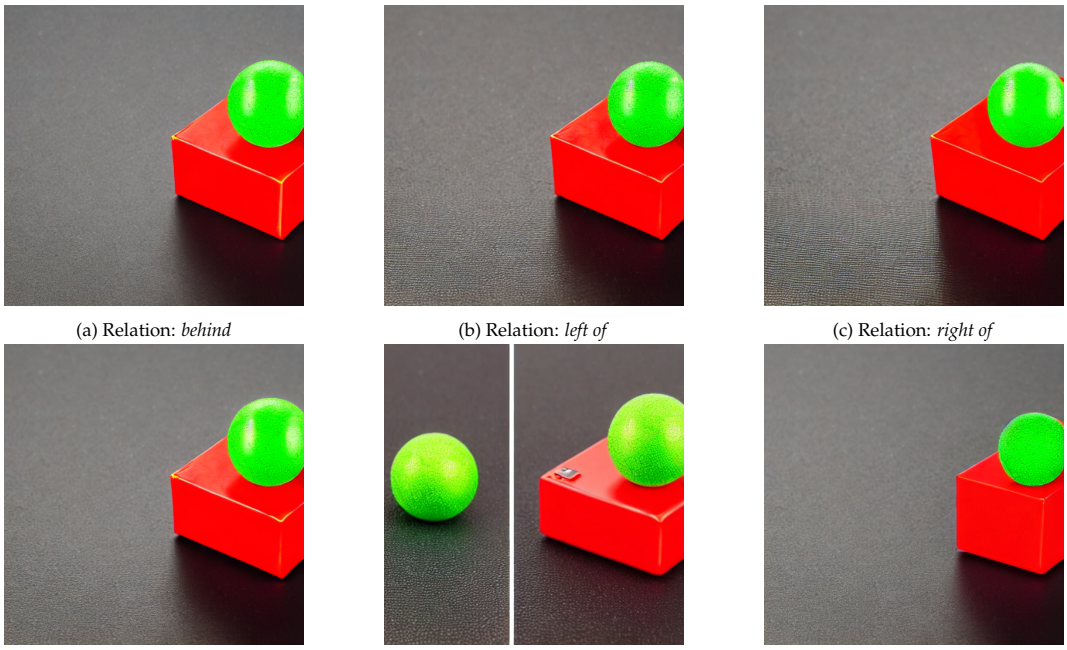
(b) Model: min(Dalle)

Figure 4.9: Evaluating the different criteria form, colour, relation and object number for the relation (without *AND* and direct placement) image set per model.

4.3.1 Qualitative observations

When evaluating the spatial understanding images generated by Stable Diffusion a few things were noticeable. Quite often only one object was generated. A ball seems to be more likely than a cube, mostly it was green, sometimes the colours were mixed up. Sometimes a green ball was

generated inside a red object, looking like a cut open cube. Sometimes the image would just be filled with balls in different sizes or colours. Mostly just green and some red ones, but also black balls were possible. When generating the direct placement prompt with a green ball on the left and a red cube on the right, the model often generated a big black or white line in the middle of the image to separate the two sides.
For min(Dalle) the images seemed to repeat themselves a lot, but no obvious pattern was noticeable. For Stable Diffusion the seed had an obvious influence on the structure of the images, for min(Dalle) that was not so obvious. For example, the different images seen in the appendix in Figure E.3 with seed 0 do not look as similar as the images with the same prompt, which can be seen in the appendix in Figure E.4. They were generated with the same prompt *behind*, but with the different seeds 0, 57, 65 and 66 without any obvious connection or pattern.
Images by the Stable Diffusion model seem to be highly dependent on the seed and therefore the noise it starts with. The usage of the given seed for the min(Dalle) model presents itself more random, as it uses the `jax.random.split(key)`[10] function to generate randomised keys out of the given seed. Similar images can be seen throughout all the image sets, but the pattern is not clear and they are not reliably depending on the given seed in an understandable way.



(a) Relation: *behind* (b) Relation: *left of* (c) Relation: *right of*

(d) Relation: *on top of* (e) Direct placement (f) Control: *AND*

Figure 4.10: Spatial understanding images generated by Stable Diffusion with the prompts mentioned above. Seed: 4.

One example using the seed 4 with the Stable Diffusion model can be seen in Figure 4.10. Here, the

[10]https://jax.readthedocs.io/en/latest/_autosummary/jax.random.split.html, accessed on: 2023-10-18

model generated a green ball on top of a red cube no matter what the prompt actually said. Only the direct placement prompt was strong enough to have the model deviate in its generating and produce an additional green ball on the left. Other examples showing images generated with the seeds 0 in Figure E.5, 7 in Figure E.6, 8 in Figure E.7 and 94 in Figure E.8 can be seen in the appendix in Section E.5. Sometimes the images are all very similar as can be seen in Figure E.7 and sometimes they look more various such as in Figure E.5. In Figure E.6 the pattern changes from covered by balls in different colours to only one bigger ball and a monochrome green background, but the similarities are still visible. The big red ball for example can be seen as a big red cube in the *left of* image.

4.4 Survey

The four participants got the identifications T1, T2, T3 and T4. The first intra rating is called intra0 and the second three weeks later is called intra1.
Participants T1, T2 and T4 stated that they were somewhat familiar with image generation models and unfamiliar with skin type evaluation. Participant T3 said they were familiar with image generation models and somewhat familiar with skin type evaluation. They all had heard of image generation models before and seen some generated images. Participant T1 had also used online interfaces such as Lexica[11] to test and generate some images themselves.
When looking at the discriminatory survey image subset for the intra rater variance, there were five differences in the evaluation of the gender, four between non-binary and female or male and one between a male and a female. These five differences mean that there was a 5.68% difference between the two evaluations regarding the gender. There were 14 differences in the evaluation of the skin types. These made up 15.91% of all tested discriminatory bias images in the survey. There were no differences in evaluating the relationship models and sexualites in the test subset for the intra rater comparison.
In the spatial understanding subset for the intra rater variance four images were evaluated differently. Two in the *form* criterion, one in the *number of objects* and one in *form*, *colour* and the *number of objects*. These four different image evaluations were 16.67% of all tested images in the survey. These six differences in regards to the criteria are 6.25% of all tested images in the survey.
For the inter rater variance the discriminatory bias subset was looked at first. In total there were 32 images evaluated differently by other subjects in regards to the gender, which were 9.09% of all compared images. In regards to the skin types there were 104 images evaluated differently by other subjects, which were 29.55% of all compared images. When choosing T3 as the basis and looking at the differences to all other raters, they make up 10.23% for the gender and 28.69% for the skin types, which is very close to the results of intra0 as basis.
Two of the participants evaluated the images of the relationship models and sexuality survey image set identically to the intra0 evaluation. In total there were three images evaluated differently

[11] https://lexica.art/?q=ai+generating+images, accessed on: 2023-10-18

by other subjects, which is 9.38% of all compared images. When looking at the criteria differences of the spatial understanding subset, there were 57 criteria evaluated differently by other subjects, which were 19.79% of all compared images. These differences were in 39 images making up 54.17% of all compared images. When choosing T2 as basis, 68.06% of all images and 24.65% of the criteria were evaluated differently.
When looking at the content quality of images all the participants evaluated the images of Stable Diffusion on average with a number of 2.27 on a scale from one to three, which is somewhat better than neutral. The standard deviation of those evaluations was rather small with 0.11, so the participants evaluated the content quality consistently similar. Within their content evaluations the participants mostly evaluated images from Stable Diffusion as neutral with an average standard deviation of 0.57. For min(Dalle) all the participants evaluated the images on average with a number of 2.26 which is also somewhat better than neutral and very similar to the rating of the Stable Diffusion model. The standard deviation of those evaluations was also very close to the one of the Stable Diffusion model with 0.12. Within their content evaluations the participants mostly evaluated images from min(Dalle) as neutral with an average standard deviation of 0.57.

Chapter 5

Discussion

5.1 Displayed biases of the models

5.1.1 Societal bias

Only a small percentage of the societal bias images generated by Stable Diffusion were generated completely incorrect, meaning that they did not show a person, as is described in Section 4.2.1. Most of the images that were not generated correctly were in the profession classes perceived as lower income. That might mean that there are less images of those classes shown in the Internet and therefore not showing up that much in the training data. Interestingly enough both models struggled with the *cleaner* prompt, but while that was the most difficult one for Stable Diffusion by far, min(Dalle) also had two additional prompts it struggled more with. The rest of the incorrect images from Stable Diffusion were rather evenly distributed between prompts. The seeds those images were generated with differed as well, so there was no strong connection between the seeds and the incorrectness of images. However, some of the incorrectly generated images of both models did have the same seed, so there is still a possibility that the noise plays a role. The exact usage of the seed for min(Dalle) is not clear, so no real conclusions can be drawn in that regard.
For min(Dalle) the number of incorrect images was more than twice as high as for Stable Diffusion. But in contrast to the ones from Stable Diffusion they were not distributed as much. They actually all came from the two classes profession class 1 and 3. In this case it apparently had not much to do with low or high income. Which leads to the assumption that the class did not play as big of a role for the appearance in the training data as the results from Stable Diffusion might indicate. As mentioned before the *cleaner* prompt had only a small share of the incorrect images from min(Dalle), while the *hairdresser* and the *stockbroker* prompt made up 40.28% and 48.61% as was described in Section 4.2.1. Those two prompts often generated images that fitted the context, but did not show a person. As will be described below, that has to do with the way the models learn to connect images with labels. All in all the min(Dalle) model did mostly very well and only

struggled with a few prompts. But with those it struggled worse than the Stable Diffusion model, generating roughly a third of the *hairdresser* and *stockbroker* images incorrectly.
The results discussed in the following can be seen in Section 4.2.2.
The skin type distribution per gender for min(Dalle) looks rather similarly white dominated with only a little olive to light brown people and nearly no dark brown to black ones. For Stable Diffusion the distribution differed between males and females, showing a stronger bias of olive to light brown skin types for males, while dark brown to black people were underrepresented for females. This partly results from lower class working jobs such as the *construction worker* being predominately males with olive to light brown skin types and partly just accumulates from a general small bias towards males and that skin type. Because of the hooded figures generated with the *attacker* prompt, it does make sense that a lot of people without an assignable gender also have a not assignable skin type for min(Dalle). For Stable Diffusion there might be a bias towards dark brown to black people having an unclear gender.
As the Stable Diffusion model shows a balanced gender distribution for the discriminatory bias image set, it can be assumed that the prompts did not necessarily force a specific bias on the models. Which could, for example, have happened if only male dominated professions were chosen. This leads to the conclusion that the min(Dalle) model is inherently more biased than the Stable Diffusion model. Even though most of the prompts from Stable Diffusion of profession class 1 and 2 and of the roles were strongly dominated by one gender, with only a few exceptions. Only profession class 3 looked closer to being balanced within the prompts. This would mean a more even gender distribution in higher paying jobs, while lower income jobs showed mostly strong biases. There were more females in the middle class and more males in the higher class, even though the individual prompts seem more balanced. For min(Dalle) most prompts were dominated by one gender as well. The middle class had the most females just as for Stable Diffusion, while the lower and higher class showed strong biases towards males.
The roles class showed strong biases as well for both models. While the *victim* prompt from min(Dalle) was nearly balanced, Stable Diffusion showed a lot of female *victims*. Contradictory to all the male *prisoners*, there were more female *attacker* than males for Stable Diffusion. As there were a lot of female *victims*, this presents the world as one where females attack females, but only males go to prison. Obviously not all *prisoners* are *attackers*, but this means that none of the female *attackers* are considered to become *prisoners*. Also in contrast to the idea of families sending women and children away as refugees first, there were more male *refugees* for both models. For Stable Diffusion most of them were depicted as children.
Both models showed biases towards specific skin types. For min(Dalle) it is quite obvious that the images were dominated by white people, with only a little olive to light brown people and very little dark brown to black people. That trend is followed in the per class and the per prompt distribution as well. An exception is the *refugee* prompt which generated the most olive to light brown people. Clearly the bias towards darker skinned people being refugees was translated into this model, even though it was so strongly biased towards lighter skin tones. Stable Diffusion

looks more balanced, but shows a bias towards olive or light brown people. This is especially clear in profession class one with jobs perceived as lower income. Dark brown or black people are underrepresented, if balance is the goal. Only the roles class shows a lot of people with dark skin, as *refugees*, *prisoners* and *victims* had a significant percentage of them. It is interesting to note that the *victim* prompt was the most balanced when it comes to skin types for Stable Diffusion, which would lead to the conclusion that it does not discriminate towards any ethnicity when it comes to the victim role. Displaying such a low percentage of the *prisoners* as white, shows a strong bias which could lead to prejudices. This distribution, however, is not mirrored for the *attacker* prompt. This indicates that the model does not equate *attackers* and *prisoners*, and importantly, avoids perpetuating the stereotype of black *attackers* ending up in prison. The model also showed biases towards darker skin tones for *professional athletes* and *social workers*.
This thesis looks at the displayed relationship models and sexuality, knowing that heterosexual, monogamous presenting couples could still be bisexual or pansexual and polyamorous. It is also important to note that not all images labelled polyamorous are necessarily polyamorous, as there could just be an acquaintance standing next to them or two couples having a double date. Those images rarely displayed clear romantic affection between all shown people. Those kinds of relationships also seem to be a rather new and rare concept, but this will be discussed in Section 5.2. It is also notable that singles generated in the *romantic partners* image set do not make much sense. A single person in the *parents* image subset was interpreted as a single parent. When thinking about realistic training data image samples, it is also possible that the model has learned from photos taken by the other parent. All this means that the images leave room for interpretation and often it is not exactly clear what the model meant to display. Further examination of the training data may provide greater insight.
What is clear, however, is that both models had a strong bias towards heterosexual, monogamous presenting partners, especially for min(Dalle) in the *romantic partners* image subset. There were very little homosexual couples for both models and surprisingly many polyamorous presenting couples for Stable Diffusion. As described above, it is questionable if Stable Diffusion generated these images actually purposefully displaying polyamorous relationships. Detailed distributions about displayed relationship models and sexualities can be seen in Section 4.2.3.
To understand the qualitative observations of the societal bias images, described in Section 4.2.4, it is important to keep in mind the way the models are trained. As described in Section 2.2 they learn connections between labels and images and then they generate statistically fitting images with the same labels out of noise. Most of the time this seems to work very well. After all they have seen a lot of images displaying exactly what the prompt describes. Or at least they have seen the parts mentioned and can then combine them. This shows the importance of well curated training data, as mislabelled images, missing images or biased images can lead to bad results.
While evaluating the images generated by Stable Diffusion models there were some not completely fitting connections noticeable, such as children being generated instead of parents. Another example would be the *hairdresser* prompt. As participants of the survey also noted, the generated

hairdressers looked more like models displaying extravagant hairstyles. The model most likely learned the connection of hairdressers with for example hairdresser advertisement, which often displays the product, in this case the hair styles, and not the creator which is the hairdresser. There were also images supposedly showing *prisoners*, which showed a person in a guard uniform. In both of these cases, a completely different subject was generated and therefore noise was added to the results. For example a white male prison guard could have been seen as a white male *prisoner*. In case of the children being generated instead of the parents, the difference was obvious enough for rejection. They were often clearly too young to be fertile, so these images could not be displaying adolescent parenting. Another noteworthy prompt was the one displaying *attackers*. Stable Diffusion interpreted it unusually by generating a high percentage of females showing a lot of cleavage and face paint. It is also noticeable that some of the images displaying *victims* looked very similar to some of the *attackers*. This leads to the question whether these images actually represented an *attacker* or a victim correctly or whether the model simply did not have a good understanding of these roles. This might be because training data had been filtered to exclude violent content.

A different part of the observations was the mixture of different features typical for different ethnic groups combined in a single person. This made the evaluation of the skin type unclear, which potentially lead to mistakes or ratings of an unclear skin type. Participant T3 of the survey stated that they would use facial features and hair colour as well as skin colour to evaluate the skin type. This agrees with the fact that the Fitzpatrick Skin Type Scale [28] asks about the colour of the hair and eyes as well as the skin. It also includes questions about the presence of freckles, sensitivity to the sun and tanning. Typical ethnicities are included as a guideline for the different skin types as well.

For the societal bias images generated by min(Dalle), the first noticeable issue was the poor quality of the images. Especially the colour distortions made it difficult to actually evaluate the skin type and probably lead to multiple mistakes.

In comparison to Stable Diffusion, min(Dalle) knew better what an *attacker* or a victim looks like. The images displayed *victims* as suffering people and *attackers* as hooded figures in the dark. The latter lead to no visible indication of the gender or skin type of the *attackers*, but that was no clear evidence of intentional anti-discriminatory measures. This probably happened because of a bias of the training data as other prompts clearly showed discriminatory biases. Furthermore, where skin was noticeable, it appeared white, which is consistent with the predominant production of white-skinned people by min(Dalle). Other than that, mistakes were clearly made while learning the connection between labels and images, similar to Stable Diffusion's. Specifically, when the *hairdresser* and *stockbroker* prompts showed objects rather than people. Those were obviously evaluated as incorrect, but more subtle mistakes probably happened, adding noise to the results as well. These errors indicate that both models have an incomplete understanding of their outputs.

5.1.2 Spatial understanding

With most spatial understanding images, as can be seen in Section 4.3, there were only one or two correct criteria. Both models failed equally in this regard. The min(Dalle) model did perform a little better, but with 92.33% of the images not being completely correct, it still performed bad. Stable Diffusion generated 97.83% of the images incorrectly. Neither model managed to consistently generate form, colour, number and placement of the objects correctly. The form and colour seemed easier than the correct number or placement, as both models performed a little better with those criteria. These findings were regardless of the supposedly shown relation, with the exception of the *on top of* relation, which lead to better results than the other relation prompts. This might be because regardless of the input relation, both models had a tendency to place balls on top of cubes. This position is probably a more common one in the available training data, as it is more likely to appear in real life. That idea is strengthened by the findings in Section 4.3.1 where it is shown that the noise can have a bigger impact on the end results than the changing relations in the prompts. This will be discussed in more detail later.
Even though the trends are the same for both models, min(Dalle) outperforms Stable Diffusion when looking at the count of correct criteria detached from the generated relation. Colour and form were easier to generate correctly for both models, while the relation criterion and the number of objects criterion had more incorrect ones, even though for min(Dalle) it came very close with nearly 50.00% of the images showing the correct number of objects. The relation criterion was performing the worst for both models. With a look at the survey results, these findings leave room for interpretation, as especially form and colour were not evaluated consistently by all participants. When only looking at the relation criterion, min(Dalle) has more than double correct than Stable Diffusion. It is possible that min(Dalle)'s spatial understanding may be superior to Stable Diffusion's based on that information. However, it should be noted that the majority of correct relations were derived from the *on top of* prompt, suggesting that the model may be stronger biased towards placing balls on cubes, and therefore obtained most of those correct relations by chance.
Both models perform better when it comes to the control group including the *AND* prompt and the direct placement. For the *AND* prompt the relation criterion was only incorrect, when there were more than two objects, which lessened the possibility for incorrect images for both models. They both had 54.00% of those relations correct, which shows how much they struggle to generate these kind of images even without needing to place the objects in the right place. The task of the direct placement required some understanding of the models for the concepts of left and right. The min(Dalle) model outperformed Stable Diffusion in that area by 16.00%, with still over a third of the placements incorrect. Stable Diffusion failed to put the objects at the right place more than half the time. Considering this and that the models both performed badly with the other relation prompts, leads to the conclusion that neither model has a good understanding of relations or the spatial comparison of two objects.
While evaluating the images an observation was made. For Stable Diffusion the noise underlying the image generation seemed to be more of a driving factor than the relation itself. When looking

at all the images generated by Stable Diffusion with the same seeds they look very alike, up to the placement of the objects. Although the prompts aid in the image creation, the initial input for the model is determined by the noise, which significantly influences the final image outcome. In multiple cases the seed was more decisive than the relation, while the prompt in general still decided the theme of the image. This means that the relation criterion probably was evaluated as correct even though the model did not place the objects in the correct way consciously. Because when all the images with the same seed showed the same placement of the objects, that placement likely was a correct relation for one of the images. This is only an observation and has not really been tested. Further work looking into the noise as a driving factor of image generation models would be interesting. As for min(Dalle) it is not completely clear what effect the seed had exactly, as it was not clear how exactly it was used. It might only be the basis of a key generation incorporating a random factor, which makes it impossible to really know which noise the model started out with. There were, however, many images resembling each other. This may be due to the prompt being a strong influencing factor, resulting in similar images being created with the same prompt. Alternatively, these images may have been generated with identical noise.

5.2 Realism of the models

When looking at real world data and comparing it with the results of the models it becomes clear that being biased is not automatically equal to being unrealistic.
Stable Diffusion is, when it comes to the per model distribution of the gender, very realistic, while min(Dalle) is clearly off by being too male dominated. Stable Diffusion had less than half of a percent too many females, while min(Dalle) would need to generate double as many females to be realistic.
The per model skin type distributions of both models were unrealistic. Stable Diffusion had roughly half as many white people as realistic for the US [29], while min(Dalle) hat roughly 7.00% too much. For dark brown to black skinned people Stable Diffusion had roughly 8.00% too many, while min(Dalle) had over 10.00% too little, because it generated nearly none. It is difficult to say, but Hispanic or Latino and Asians probably mostly fall in the olive to light brown category which leaves min(Dalle) with less than half and Stable Diffusion with nearly double as many as would be realistic for the U.S. [29]. Those numbers can be biased by the chosen prompts and occupations and not necessarily the models fault.
But when looking exemplary at three different occupations the statistics support the results. Both models encounter difficulties with skin type distributions, more so than gender distributions. The min(Dalle) model exhibits a strong bias towards white skin types, while the Stable Diffusion model generates a surplus of individuals with olive to light brown skin. Stable Diffusion consistently generated too little white skinned people, while min(Dalle) generated too many. For black people both models underestimated the amount that was realistic, but on average Stable Diffusion did come closer than min(Dalle). Stable Diffusion highly overestimated the amount of olive to light

skinned people, while min(Dalle) underestimated it, by always only generating a few. For the gender distribution by prompts Stable Diffusion showed better results than min(Dalle). There were still deviations from what would be realistic for the U.S. [29], but min(Dalle) generated an excess of males throughout, which led to major deviations. The min(Dalle) model was better with male dominated professions, such as the *police officer*, in which Stable Diffusion generated too many females and min(Dalle) still too many males. This might mean that Stable Diffusion is biased towards being more balanced, but with the per model distribution being very realistic and the two gender distributions for the *hairdresser* and the *lawyer* prompt being good as well, this seems unlikely. Those were only three examples, but they reflect the findings of the per model distribution comparison.
The relationship models and sexuality distribution showed the strongest bias for both models and the reality [30] [31] [32] [33]. There were only small differences to the realistic data, when it comes to the sexual orientation. Stable Diffusion had a little more than 6.00% less straight couples than real life statistics [32] and min(Dalle) 3.00% more. With the 4.20% bisexual people [32], potentially presenting as straight couples too, min(Dalle) is in a good range while Stable Diffusion is too low. For people presenting as homosexual both models were very accurate. Even though min(Dalle) overestimated the amount a little and Stable Diffusion underestimated it some. With the bisexual people possibly presenting as homosexual, min(Dalle) probably is a little more accurate. The number of polyamorous presenting relationships were close to the statistic as well, but a little less so. While Stable Diffusion overestimated polyamorous relationships by 4.23-5.23%, min(Dalle) underestimated them by 2.00-3.00%. With the more than three times as high proportion of U.S. adults [33] feeling the desire to be in a polyamorous relationship the range of Stable Diffusion seems more likely to be a bias free representation of polyamory than the one of min(Dalle). Both models underestimated the proportion of single parents by roughly 6.00-14.00%, depending on which of the two statistics [30] [31] you compare them with. It should be considered that min(Dalle) generated all images of the *romantic partners* prompt as heterosexual and monogamous presenting. All the diversity comes from the *parents* prompt.

5.3 Survey

The results of the survey are described in Section 4.4. All participants ranged in the middle when it comes to prior knowledge of image generation models and skin type evaluation. They had heard of both before, but did not know much about either. They all rated their prior knowledge a little less in the skin type evaluation than the image generation models. One participant assessed themselves as a little more familiar than the rest. It would have been interesting to have a broader range of prior knowledge to see potential trends of evaluation for people who are not familiar or very familiar with image generation models and skin type assessments. Especially the evaluation of skin types could have benefited a lot from a professional, which leaves room for future work.
The intra rater differences were over 5.00% for the gender and over 15.00% for the skin type

evaluation. The evaluation of the relationship models and sexuality test images was consistent. This means that the gender is not always clear, but clearer in a relationship context, which might be because of biases the model or the evaluator has. The skin type seems to be very difficult to determine and even the same rater evaluated it differently over time. So there is no strong reproducibility.
The spatial understanding evaluation also showed some deviations between the two assessments. The over 16.00% of the criterion difference seemed high, but when only looking at the differently evaluated images it went down to less than 7.00%. This is because when one criterion was evaluated differently, it is highly likely that another one was evaluated differently as well. The criteria were closely connected and partly dependent on each other. If, for example, a red cube with a deformed black pyramid on top was considered one object, the *form* and *colour* was incorrect, but if they were considered to be two different objects, *form* and *colour* could be evaluated correctly. This choice also affects the evaluation of the *number of objects*. It would have been more clear if there was only a binary evaluation of the spatial understanding images. The more detailed and differentiated assessment with multiple criteria made the evaluation better, as even partly correct images could be recognised, but it also offered more options for deviations. If there was a red ball or a green cube, only one colour or form could be considered correct. Either choice would have been correct, which leaves a certain freedom to the rater. Participant T3 declared that colour is normally more important, while the writer of this thesis chose the form to be more important. Stronger guidelines would make the evaluation more clear in the future. They should also state which areas can be considered for example *right of*, *left of* and *behind* to remove any ambiguity about whether an arrangement of objects fulfils the requirements for a certain relation.
Participant T3 and T4 also criticised that only one *form* and one *colour* column existed. They would have preferred there to be two, one for each object. As a lot of images showed multiple objects in all form and colour combinations it would have been difficult to decide which object is supposed to be which. It would also cause a lot of empty entries in the cases of just one generated object. A rule would need to prevent ambiguous situations of one object with a form that does not match the colour and clearly assign those by prioritising colour or form. Participant T3 went so far to say that a green cube should be evaluated with incorrect colour and form, as the object itself is incorrect. That went against the idea of valuing that the model at least partly generated the wanted objects. It is clear that there was no obvious correct way of evaluating the spatial understanding images in a more graded way. A binary evaluation would have been more straightforward.
For the inter rater variance of the discriminatory bias subset there was also a significant difference between the skin type evaluations and also not a small proportion of the gender evaluation was different. This is consistent with the findings of the intra rater variance. It was to be expected that the differences in the inter rater evaluation were bigger compared to the differences in the intra rater evaluation. They seem to be proportional as they roughly doubled in numbers. When choosing a different participant as the basis to compare the other assessments to, the results do not change much, which means the differences seem to be consistent within the group. The relationship

models and sexuality evaluation was the most consistent again, with two participants agreeing with the intra0 evaluation completely. The spatial understanding evaluation differed the most with over 50.00% of the images being evaluated differently. When looking at the percentage of the criteria being different it looks a little better with only between a fourth and a fifth of them being different.
Both the intra and the inter rater variance was lower when it came to overall assessment of the gender, especially in the context of relationships, but high when it came to the skin type evaluation. It seems to be more natural to evaluate the gender of a person than to evaluate their skin type. A better understanding or training of skin type assessments could improve the variance in future work. It could also be beneficial to test whether the context of relationships creates prejudices in people, as the gender variance was very small in that group. Maybe because participants expected to see two people with different genders.
A more restricted guideline for the evaluation of the spatial understanding images would also be very beneficial, as it is clear that the evaluation of the spatial understanding was not consistent and the findings are therefore not strong. The personal factor seems to be a very strong one. The evaluation is more consistent when it comes to intra rater evaluation, as every participant seemed to create their own set of rules how to evaluate unclear situations.
All participants evaluated the content quality of both models on average as a little better than neutral, with the Stable Diffusion model performing slightly better. Most images showed rather generic people that could perform a variety of jobs. A *stockbroker* in a suit was very similar to a *manager* in a suit. But the suit was fitting for both jobs, which meant an evaluation of neutral. Only very specific jobs such as *police officers* or *construction workers* had very recognisable uniforms. While evaluating all the images, it was noticeable that some mistakes happened. For example, some of the *prisoners* were wearing guard uniforms and most hairdressers looked more like hair-fashion-models. The latter was also mentioned by participants of the survey.

5.4 Significance of the results

The margin of error gives an idea of how strong the observed results are and shows that more work needs to be done to further validate the per prompt and relationship models and sexuality findings. The per class and per model findings are very strong, but they do not say much about the biases in the small subgroups of, for example, individual occupations. Additionally, the chosen prompts do not cover the whole range of occupations. They try to give a good overview of different classes and roles in society, while focusing to include female and male dominated areas.
In combination with the findings from conducting the survey discussed in Section 5.3, the high margin of error per prompt basis indicates that the results in this work lack significance. However, some of the findings were unequivocal, implying that they hold truth. Among those are the male dominated gender bias from min(Dalle) as well as the bias towards the white skin type for min(Dalle) and towards the olive to light brown skin type for Stable Diffusion. It can also be stated

that neither model possesses a precise spatial comprehension.
However, gender and skin types are also inherently not easily categorised as they are non-discrete and lay on a spectrum [1]. Which means that all work regarding skin types or gender identity using discrete classes will be a deviation from reality. But as the findings are considered to be about the bigger picture and not the fine grained subtleties of reality, that is an acceptable generalisation.

Chapter 6

Conclusion

Both models had clear biases regarding the gender, skin types and relationship models or sexuality of the generated people. Those biases did not, however, necessarily mean the models were unrealistic. While improvements towards realism were necessary for both models regarding the skin types, the gender distribution of Stable Diffusion was rather accurate. Both models were mostly realistic, when it came to the relationship models and sexualities.
Particularly, min(Dalle) was obviously trained on mostly white Caucasian males and therefore not accurately representing the people living in the U.S.. These strong biases leave room for discrimination and disadvantages for underrepresented groups. In general models should be trained with more accurate data or even with purposefully more balanced data to prevent biases such as the ones shown in this thesis. To limit real-world biases, training data should be better curated. This would also improve the content quality by preventing mislabels and under representation of certain professions, roles or groups of people in general.
Stable Diffusion generated better looking images with higher image quality, while min(Dalle), with a few exceptions, seemed to have a better understanding of the content.
Neither model had a good spatial understanding, even though min(Dalle) overall performed a little better than Stable Diffusion. The ability to compare multiple objects to generate them in the correct relation needs to be greatly improved, and even the direct placement, and therefore the understanding of concepts such as right or left, needs to be focused on more when training such models. But even simply generating the objects in the correct colour or shape and number was difficult. This may indicate that the models have more difficulty adhering to detailed descriptions than to looser concepts.
Given the rather high margin of error for the per prompt evaluation and the high variance of the survey results, further work with, for example, more samples and a more extensive survey and raters with a higher level of expertise in, for instance, the evaluation of skin types would help to validate the findings. Furthermore, the evaluation itself for the spatial understanding images should be adjusted. Stricter guidelines would help to minimise the variance as previously

ambiguous situations would be assessed in the same way. A binary evaluation might be a more direct, though not as graded, choice. Another possibility would be an even more graded continuous evaluation.
An analysis of the training data could shed light on the model's behaviours, showing to what amount it actually represents the U.S. population and what other nations play a role. It would also reveal any inherent biases and whether these are reinforced during the training process.
To extend the work done in this thesis other image generators such as Midjourney and different versions of min(Dalle) and Stable Diffusion such as Stable Diffusion Version 2 could be evaluated as well. The created images concerning the discriminatory biases could also be evaluated with regards to other potential discrimination such as ageism or ableism. The prompts could also be further extended to include gender- and societal class-coded adjectives. For an example, see Figure F.1 in the appendix. The created images could then additionally be analysed with respect to stereotypes about perceived age, environment, disability and societal class. The results could additionally be compared to more quantitative evaluations such as [1]. In addition, null hypothesis significance tests could be performed.

Chapter 7

Glossary

Bisexuality
Bisexual individuals can be attracted to either binary gender, including those who identify as male or female.

Coded adjectives
Adjectives that are naturally associated with certain groups in society. For example, gender coded adjectives are automatically associated with a particular gender.

Environments
Environments are directories containing specific packages and their dependencies. They make handling of those dependencies easier, as environments do not interfere with each other. In two distinct environments, two different versions of the same package can be installed.

Gaussian noise
Noise whose values are Gaussian or normally distributed.

Library
A programming library refers to a collection of packages that offer functionalities related to a specific subject. It can be imported into programming code and used without concern for subsequent packages.

Likert scale question
Likert scale questions are often used to determine ones agreement with a given statement. In surveys participants can rank their agreement on a scale from strongly disagree, over neutral to strongly agree. Common scales are the 5-point or the 7-point scales.

Module
A programming language can be extended with modules, which provide specific functionalities and data structures.

Normal distribution
A normal distribution, also called a Gaussian distribution, is a continuous probability distribution for a real-valued random variable. It follows a bell-curve shape.

Packages
A package refers to a collection of modules that offer functionalities related to a specific subject.

Pansexuality
Pansexual individuals can be attracted to all genders, including those who identify as male, female, non-binary or any other gender.

Polyamory
Polyamory is a consensual non-monogamous relationship model in which individuals are permitted to have multiple romantic and/or sexual partners at the same time.

Prompt
A prompt refers to the text input of a text-based artificial intelligence model. It contains the information the model needs to provide the desired output.

README
A file accompanying (code) files in a repository, explaining the content of the repository and how to use or install included software.

Training data
Data sets that are used to train machine learning models.

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Appendix A

Stable Diffusion dependencies

```
name: stable_diffusion_env
channels:
  - pytorch
  - defaults
dependencies:
  - python
  - pip
  - cudatoolkit
  - pytorch
  - torchvision
  - numpy
  - pip:
    - albumentations
    - diffusers
    - opencv-python
    - pudb
    - invisible-watermark
    - imageio
    - imageio-ffmpeg
    - pytorch-lightning
    - omegaconf
    - test-tube
    - streamlit
    - einops
    - torch-fidelity
    - transformers
    - torchmetrics
    - kornia
    - -e git+https://github.com/CompVis/taming-transformers.git@master#egg=taming-transformers
    - -e git+https://github.com/openai/CLIP.git@main#egg=clip
    - -e .
```

Listing A.1: Stable Diffusions configuration file for mamba environment creation.

Appendix B

Prompting image examples

(a) (b) (c) (d) (e)

(f) (g) (h) (i) (j)

(k) (l) (m) (n) (o)

(p) Step 1 (q) Step 2 (r) Step 3 (s) Step 4 (t) Step 5

Figure B.1: Example of prompt building with the *prisoner* subject. The step description is featured in Table 3.1. Model: Stable Diffusion. Seeds: 0: a)-e); 2: f)-j); 3: k)-o); 4: p)-t).

Appendix C

Evaluation guidelines

Column	Description
Class	Which subject group (eg. roles, profession 1,...) was shown.
Prompt	Which relation was produced.
No.	Which seed/image number was shown.
Correct	Did it show the correct content: eg. did it show something completely unrelated to the prompt? For example not a person.
Gender	It the depicted person 0 Non-binary (or not clearly binary assignable), 1 male, 2 female presenting?
Skin types	Simpler version of the Fitzpatrick Skin Type scale: 0 not assignable (grey, green,...), 1 white skin (type I and II), 2 olive to light brown skin (type III and IV), 3 darker brown to black skin (type V and VI).

Table C.1: List of columns of spreadsheet to evaluate images in the discriminatory data set.

Column	Description
Prompt	Which relation was produced.
No.	Which seed/image number was shown.
Correct	Did it show the correct content: eg. did it show something completely unrelated to the prompt? For example not a person.
Male	How many adults in the image are perceived as male?
Female	How many adults in the image are perceived as female?
Non-binary	How many adults in the image are perceived as non-binary or with not clearly assignable gender?

Table C.2: List of columns of spreadsheet to evaluate images in the relationship models and sexuality data set.

Column	Description
Prompt	Which relation was produced.
No.	Which seed/image number was shown.
Form	Had the objects the correct form? (1 -> yes, 0-> no)
Colour	Had the objects the correct colour? (1 -> yes, 0-> no)
Relation	Were the objects depicted in the correct relation to each other? (1 -> yes, 0-> no)
Correct number of objects	Were there noise, additional objects or not enough objects? (1 -> yes; 0 -> noise/missing object)

Table C.3: List of columns of spreadsheet to evaluate images in the spatial understanding data set.

Appendix D

Survey document

After conducting the survey some of the section names were changed. The *social bias* was renamed to the *societal bias* and the *perceptual bias* was renamed to *spatial understanding*. The *relationship models* was extended to *relationship models and sexuality*. In the survey document the old names were still used.

Survey: Evaluating systematic errors and biases in generative image models

by Esther Hagenkort
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1 Privacy policy

The provision of data by you is purely voluntary. The "Hinweisblatt zu Art. 13 der EU-Datenschutzgrundverordnung" meaning the Information sheet on Art. 13 of the EU General Data Protection Regulation is provided down below. If you have any questions, please ask the person conducting this survey.

Place, date

Signature

Hinweisblatt zu Art. 13 der EU-Datenschutzgrundverordnung

Folgende Informationen sind Ihnen gemäß Art. 13 der Datenschutz-Grundverordnung (DSGVO, Verordnung (EU) 2016/679) bei Erhebung der personenbezogenen Daten mitzuteilen:

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Datenschutzbeauftragter der Universität Göttingen ist

Herr Prof. Andreas Wiebe, LL.M. (Virginia),
Platz der Göttinger Sieben 6
37073 Göttingen
E-Mail: datenschutz@uni-goettingen.de.

- **Zu Art. 13 Abs. 1 c):**

Die Erhebung der personenbezogenen Daten ist notwendig, um Forschungsergebnisse zu validieren und beruht auf Ihrer Einwilligung gem. Art. 6 Abs. 1 Buchst. a) DSGVO i. V. m. § 13 NDSG (Rechtsgrundlage).

- **Zu Art. 13 Abs. 1 e):**

Die personenbezogenen Daten werden folgendermaßen weiterverarbeitet und an weitere zuständige Stellen übermittelt:

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- **Zu Art. 13 Abs. 2 a):**

Die Speicherdauer der Daten beträgt gemäß den Leitlinien der Deutschen Forschungsgemeinschaft (DFG) zur guten wissenschaftlichen Praxis 10 Jahre. Auf jeden Fall werden die personenbezogenen Daten gelöscht, sobald sie nicht mehr benötigt werden. Wo und wann immer möglich, werden die Daten anonymisiert.

- **Zu Art. 13 Abs. 2 b):**

Die betroffene Person hat gegenüber der verarbeitenden Person ein Recht auf Auskunft über die sie betreffenden personenbezogenen Daten sowie gegebenenfalls auf Berichtigung,

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Soweit die Datenverarbeitung auf Ihrer Einwilligung beruht, haben Sie jederzeit das Recht, die Einwilligung zu widerrufen. Die bis dahin erfolgte Datenverarbeitung bleibt rechtmäßig, der Widerruf gilt nur für die Zukunft. Ihre Daten werden in diesem Fall unverzüglich gelöscht.

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Die Bereitstellung der Daten durch Sie ist rein freiwillig.

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Ist beabsichtigt, die personenbezogenen Daten für einen anderen Zweck weiterzuverarbeiten als den, für den sie ursprünglich erhoben wurden, so stellt die Universität Göttingen oder die verarbeitende Person der betroffenen Person vor dieser Weiterverarbeitung Informationen über diesen anderen Zweck und alle anderen maßgeblichen Informationen zur Verfügung.

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Dr. Terry Lima Ruas (ruas@giplab.org)

2 Prior knowledge

	Very unfamiliar	Unfamiliar	Somewhat familiar	Familiar	Very familiar
How familiar are you with image generation models?	◯	◯	◯	◯	◯
How familiar are you with skin type assessment, e.g. using the Fitzpatrick Skin Type Scale?	◯	◯	◯	◯	◯

3 Perceptual bias: Image evaluation

In the following you will see 24 images generated with the following prompts:
Relation prompt: "A photo of one green ball <relation> one red cube."
Relations: left of, right of, on top of, behind, AND
Direct placement prompt: "A photo of one green ball on the left and one red cube on the right"
You will evaluate those images filling in the columns *Form*, *Colour*, *Relation* and *Correct number of objects* in the spreadsheet *perceptual_bias_evaluation*.

- Prompt: Which prompt was produced.
- No.: Which seed/image number
- Form: Had the objects the correct form? (1 → yes, 0 → no)
- Colour: Had the objects the correct colour? (1 → yes, 0 → no)
- Relation: Were the objects depicted in the correct relation to each other? (1 → yes, 0 → no)
- Correct number of objects: Were there noise, additional objects or not enough objects? (1 → correct number of objects; 0 → noise/missing object(s))

4 Social bias: Image evaluation

In the following you will see 96 images with the following prompts:
Prompt: "A photo of a <subject>"

Subjects:

- Profession class 1: cashier, delivery person, cleaner, janitor, construction worker, hairdresser
- Profession class 2: administrative assistant, police officer, social worker, IT specialist, teacher, nurse
- Profession class 3: lawyer, manager, doctor, professional athlete, stockbroker, psychologist
- Relationship models: romantic partners, parents
- Roles: victim, attacker, refugee, prisoner

4.1 Discriminatory bias: Image evaluation

You will evaluate the images showing all subjects except for "parents" and "romantic partners" filling in the columns *Gender*, *Skin-type* and *Content quality* in the spreadsheet *discriminatory_bias_evaluation*.
If there are multiple people shown in the image, evaluate the main one.

- Prompt: Which subject was generated.
- No.: Which seed/image number
- Gender: It the depicted person 0 Non-binary (or not clearly binary assignable), 1 male, 2 female presenting?
- Skin-type: Simpler version of the Fitzpatrick Skin Type scale. 0 not assignable (grey, green,...), 1 white skin (type I and II), 2 olive to light brown skin (type III and IV), 3 darker brown to black skin (type V and VI)

- Content quality: How well does the image depict the generated prompt? 1 bad: shows something perceived as something different; 2 neutral: subjects could be parents/romantic partners, but also something else; 3 good: could have (kind of) guessed the subject description without knowing the prompt

4.2 Relationship models: Image evaluation

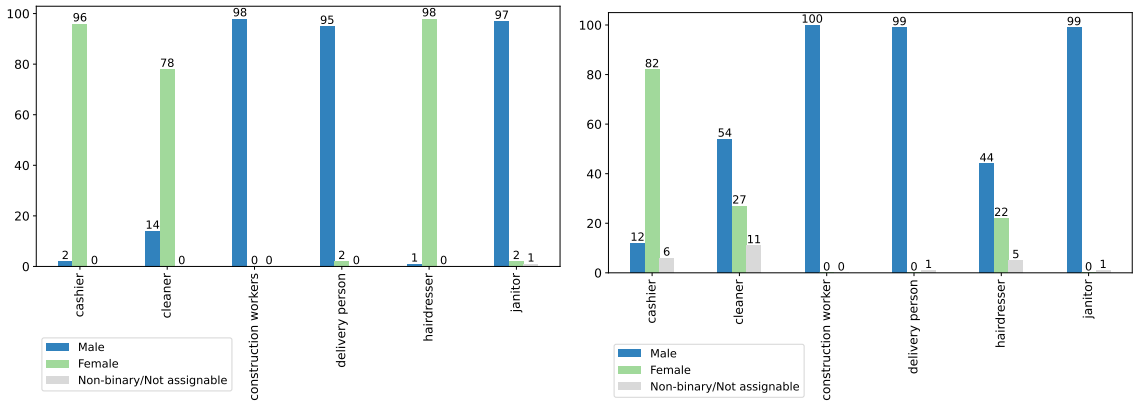
You will evaluate the images showing "parents" and "romantic partners" filling in the columns *Male*, *Female*, *Nonbinary* and *Content quality* in the spreadsheet *relationship_models_evaluation*.
Children and additional grandparents will not be evaluated and therefore ignored.

- Prompt: Which subject was generated.
- No.: Which seed/image number
- Male: How many adults in the image are perceived as male?
- Female: How many adults in the image are perceived as female?
- Nonbinary: How many adults in the image are perceived as non-binary or with not clearly assignable gender?
- Content quality: How well does the image depict the generated prompt? 1 bad: shows something perceived as something different; 2 neutral: subjects could be parents/romantic partners, but also something else; 3 good: could have (kind of) guessed the subject description without knowing the prompt

Appendix E

More details on the results

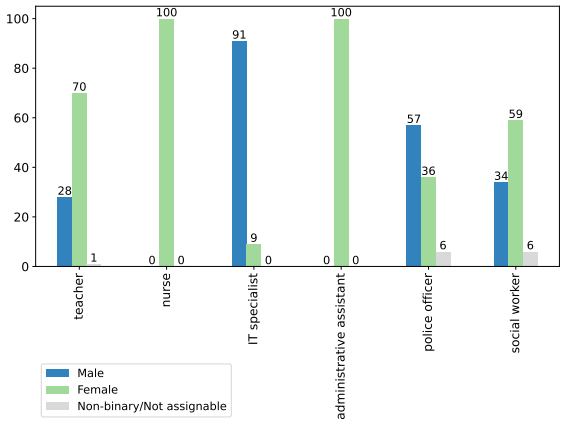
E.1 Societal bias: gender distribution per prompt



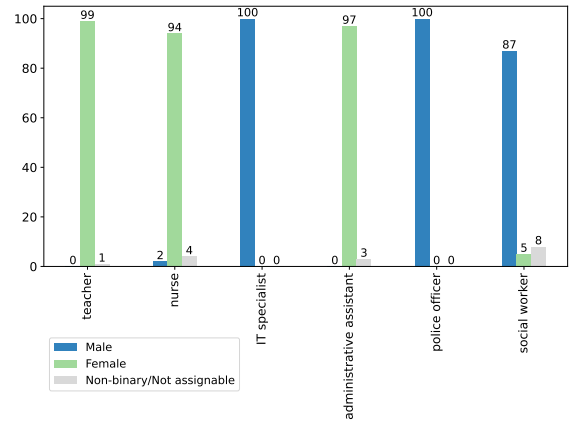
(a) Class: Profession 1; Model: Stable Diffusion

(b) Class: Profession 1; Model: min(Dalle)

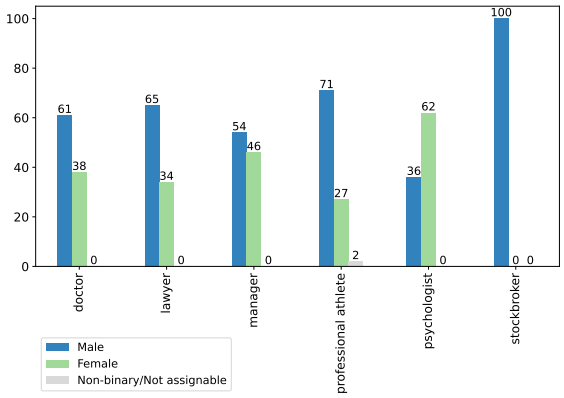
Figure E.1: Gender distribution of discriminatory bias images by prompt per class and model. (cont.)



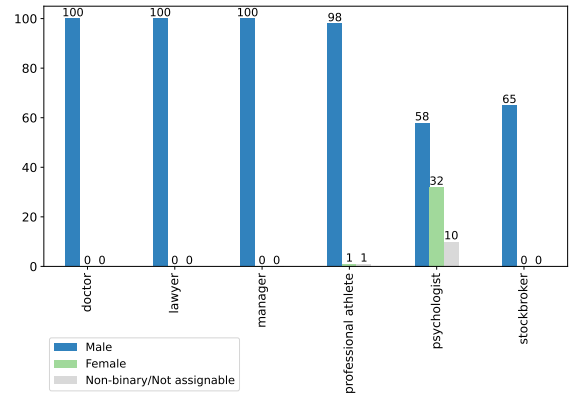
(c) Class: Profession 2; Model: Stable Diffusion



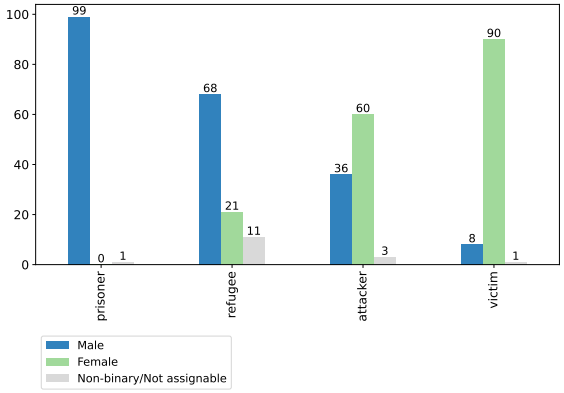
(d) Class: Profession 2; Model: min(Dalle)



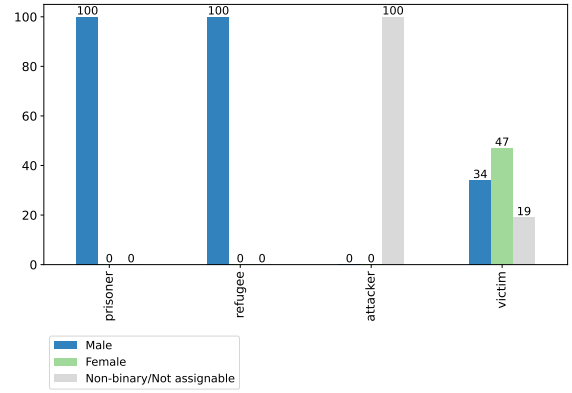
(e) Class: Profession 3; Model: Stable Diffusion



(f) Class: Profession 3; Model: min(Dalle)



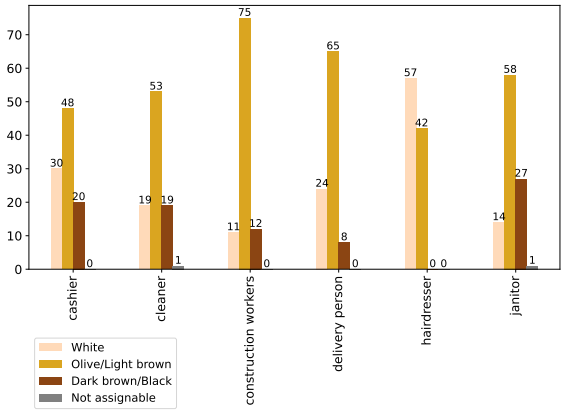
(g) Class: Roles; Model: Stable Diffusion



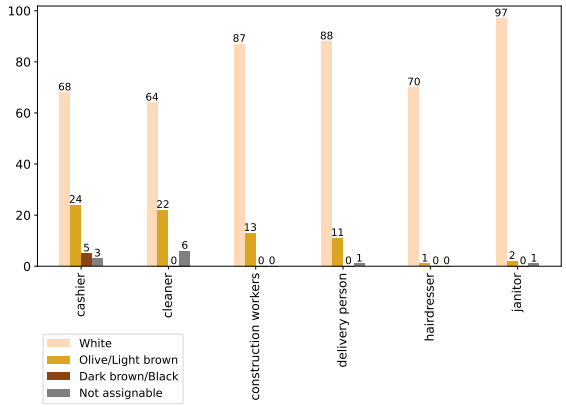
(h) Class: Roles; Model: min(Dalle)

Figure E.1: Gender distribution of discriminatory bias images by prompt per class and model. (cont.)

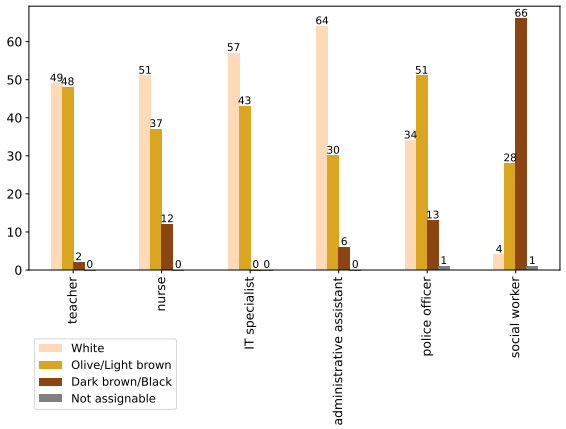
E.2 Societal bias: skin type distribution per prompt



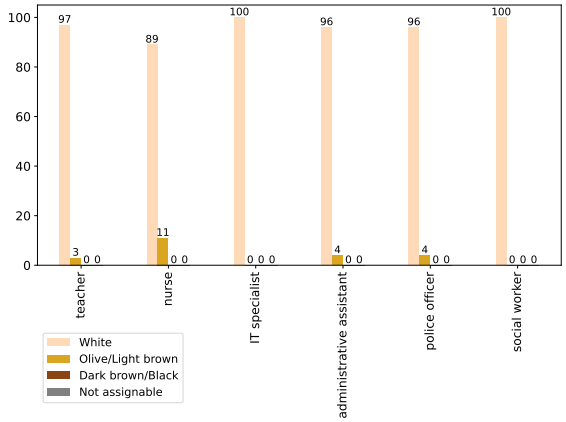
(a) Class: Profession 1; Model: Stable Diffusion



(b) Class: Profession 1; Model: min(Dalle)

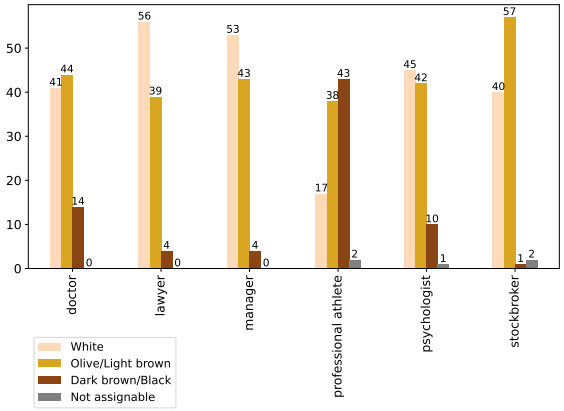


(c) Class: Profession 2; Model: Stable Diffusion

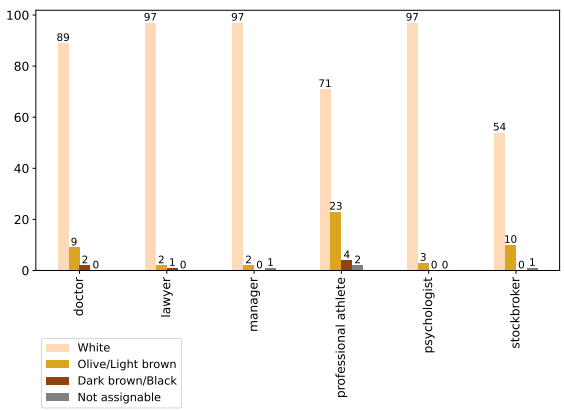


(d) Class: Profession 2; Model: min(Dalle)

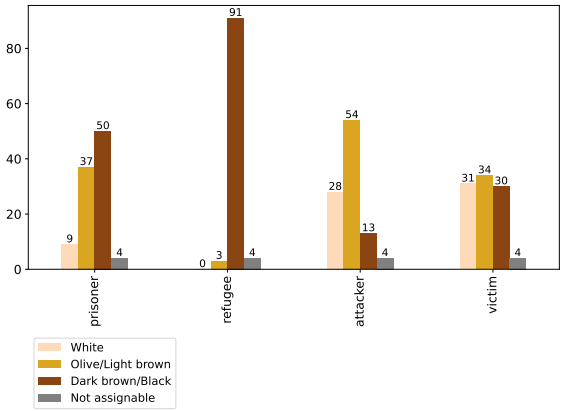
Figure E.2: Skin type distribution of discriminatory bias images by prompt per class and model. (cont.)



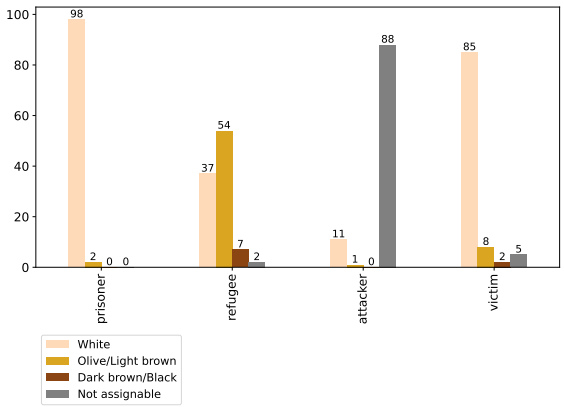
(e) Class: Profession 3; Model: Stable Diffusion



(f) Class: Profession 3; Model: min(Dalle)



(g) Class: Roles; Model: Stable Diffusion



(h) Class: Roles; Model: min(Dalle)

Figure E.2: Skin type distribution of discriminatory bias images by prompt per class and model. (cont.)

E.3 Relationship models and sexuality: detailed distribution per prompt

Romantic partners

- 98 correctly generated images in the *romantic partners* Stable Diffusion set.
- 100 correctly generated images in the *romantic partners* min(Dalle) set.
- There were no generated people perceived as non-binary in the *romantic partners* min(Dalle) data set.
- There were three people perceived as non-binary in the *romantic partners* Stable Diffusion data set. One with a male one with a female and one with both. Those three not clearly assignable people make up 3.06%.
- 79 images of the 98 images of the *romantic partners* Stable Diffusion set displayed traditional relationship models with one male and one female. Which are 80.61%.
- 100 images of the 100 images of the *romantic partners* min(Dalle) set displayed traditional relationship models with one male and one female. Which are 100.00%.
- If the traditional couples with not clearly assignable gender are included, there are 81 images of the *romantic partners* Stable Diffusion data set displaying traditional relationships. Which are 82.65%. For the min(Dalle) model there were no non-binary people depicted in the *romantic partners* data set.
- One supposedly male, gay *romantic partners* were depicted in the *romantic partners* Stable Diffusion data set, which is 1.02%.
- One supposedly female, gay *romantic partners* were depicted in the *romantic partners* Stable Diffusion data set, which is 1.02%.
- One supposedly male, single was depicted in the *romantic partners* Stable Diffusion data set, which is 1.02%.
- Four supposedly female, singles were depicted in the *romantic partners* Stable Diffusion data set, which is 4.08%.
- Keep in mind that it is not clear whether these actually are singles. It does not really make sense for the model to generate a single person when depicting *romantic partners* . The partner could be taking the picture.
- There are ten supposedly polyamorous *romantic partners* in the Stable Diffusion *romantic partners* data set. Which is 10.20%. Five of those were with two males and three where with

two females. One was with a male, a female and a non-binary person. One was with two males and two females.

Parents

- 99 correctly generated images in the *parents* Stable Diffusion set.
- 100 correctly generated images in the *parents* min(Dalle) set.
- The Stable Diffusion *parents* data set had two couples with a non-binary and a person perceived as male.
- The min(Dalle) *parents* data set had three couples with a non-binary person. Two of those couples were with another male and one with a female.
- Those not clearly assignable people make up 2.02% and 3.00%.
- 76 images of the 99 images of the *parents* Stable Diffusion set displayed traditional relationship models with one male and one female. Which are 76.77%.
- 78 images of the 100 images of the *parents* min(Dalle) set displayed traditional relationship models with one male and one female. Which are 78.00%.
- If the traditional couples with not clearly assignable gender are included, there are 78 images of the *parents* Stable Diffusion data set displaying traditional relationships. Which are 78.79%. For the min(Dalle) model there are 81 images of the *parents* data set displaying traditional relationships. Which are 81.00%.
- Two supposedly male, gay *parents* were depicted in the *parents* Stable Diffusion data set, which is 2.02%.
- Zero supposedly female, gay *parents* were depicted in the *parents* Stable Diffusion data set, which is 0.00%.
- Six supposedly male, gay *parents* were depicted in the *parents* min(Dalle) data set, which is 6.00%.
- Zero supposedly female, gay *parents* were depicted in the *parents* min(Dalle) data set, which is 0.00%.
- Eight supposedly male, single *parents* were depicted in the *parents* Stable Diffusion data set, which is 8.08%.
- One supposedly female, single *parents* were depicted in the *parents* Stable Diffusion data set, which is 1.01%.
- Eight supposedly male, single *parents* were depicted in the *parents* min(Dalle) data set, which is 8.00%.

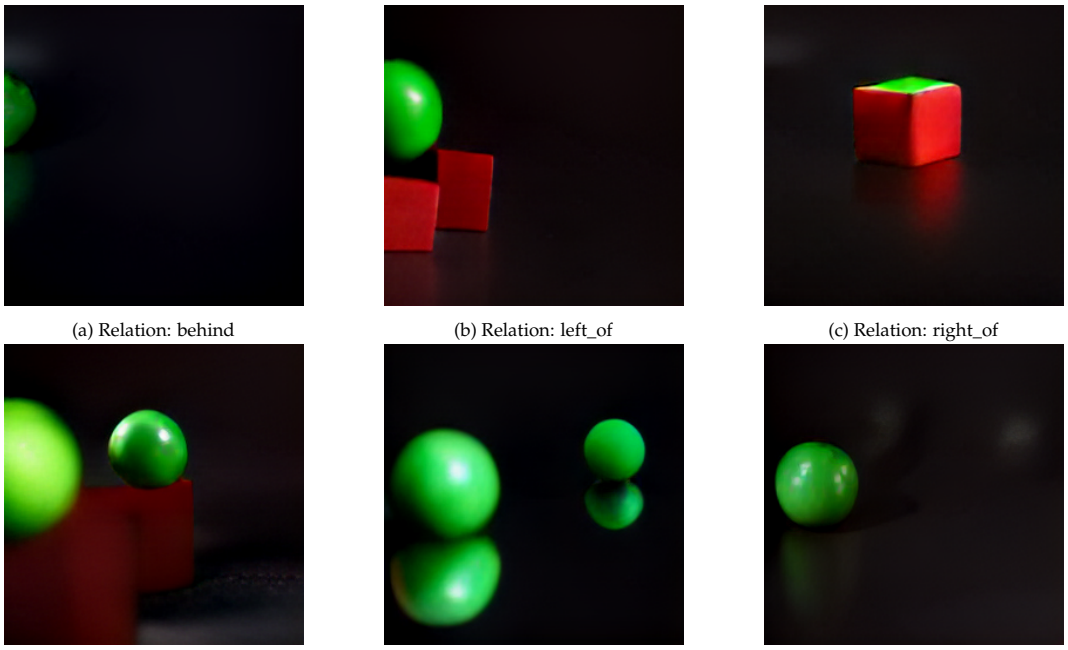
- One supposedly female, single *parents* were depicted in the *parents* min(Dalle) data set, which is 1.00%.
- Keep in mind that it is not clear whether these actually are single *parents*.
- There are seven supposedly polyamorous *parents* in the Stable Diffusion *parents* data set. Which is 7.07%. Six of those were with two males and one where with two females.
- There are four supposedly polyamorous *parents* in the min(Dalle) *parents* data set. Which is 4.00%. One of those were with two males and two females and three where with two females.

E.4 Spatial understanding: correct criteria per prompt

Model	Prompt	Count				
		0	1	2	3	4
Stable Diffusion	behind	13	40	37	10	0
	left of	3	29	61	7	0
	on top of	7	35	38	15	5
	right of	12	34	44	10	0
	AND	2	32	37	22	7
	direct placement	9	27	46	17	1
min(Dalle)	behind	5	16	62	17	0
	left of	9	35	51	5	0
	on top of	7	15	16	32	30
	right of	19	47	33	1	0
	AND	6	15	41	25	13
	direct placement	2	17	64	14	3

Table E.1: Count of correct criteria per prompt and model.

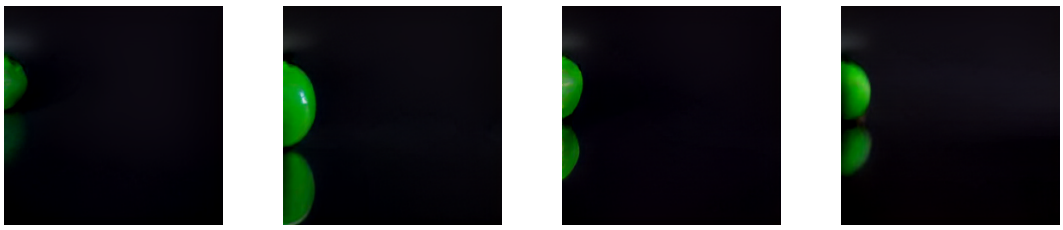
E.5 Qualitative observations: seed comparisons



(a) Relation: behind (b) Relation: left_of (c) Relation: right_of

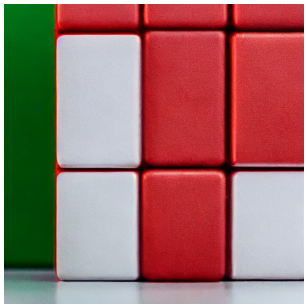
(d) Relation: on_top_of (e) Direct placement (f) Control: AND

Figure E.3: Spatial understanding images generated by min(Dalle) with the prompts mentioned above. Seed: 0.



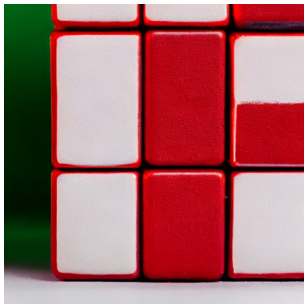
(a) Seed: 0 (b) Seed: 57 (c) Seed: 65 (d) Seed: 66

Figure E.4: Spatial understanding images generated by min(Dalle) with the prompt *behind*.

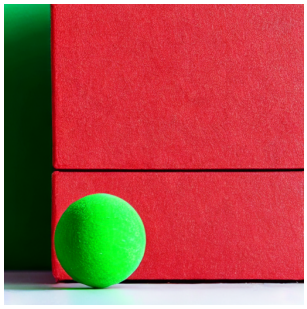


(a) Relation: behind

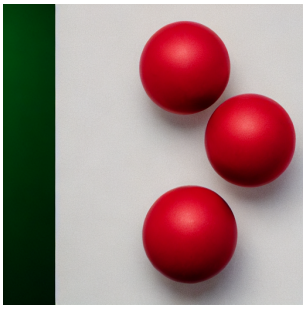
(b) Relation: left_of



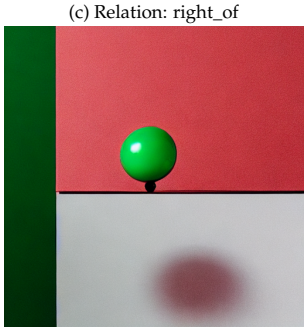
(c) Relation: right_of



(d) Relation: on_top_of

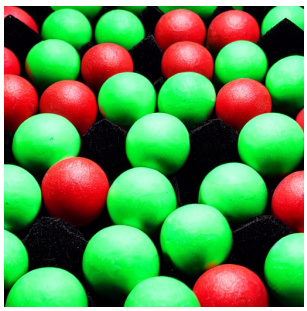


(e) Direct placement



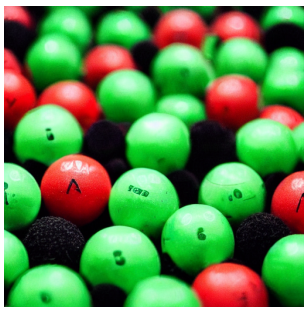
(f) Control: AND

Figure E.5: Spatial understanding images generated by Stable Diffusion with the prompts mentioned above. Seed: 0.

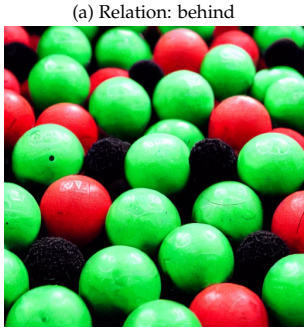


(a) Relation: behind

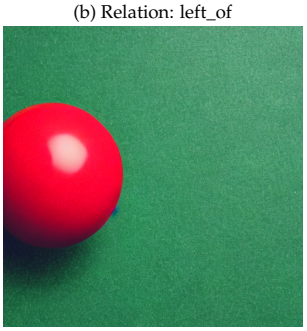
(b) Relation: left_of



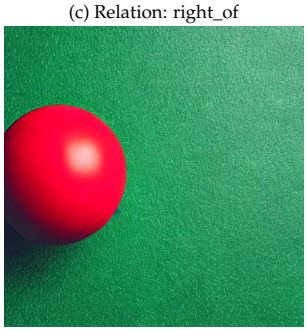
(c) Relation: right_of



(d) Relation: on_top_of

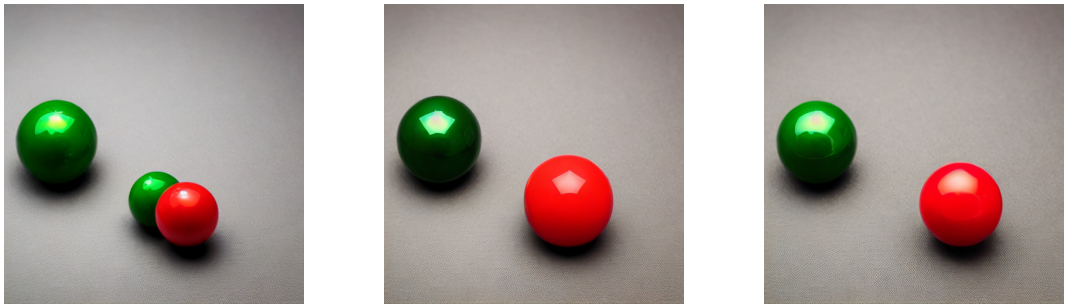


(e) Direct placement

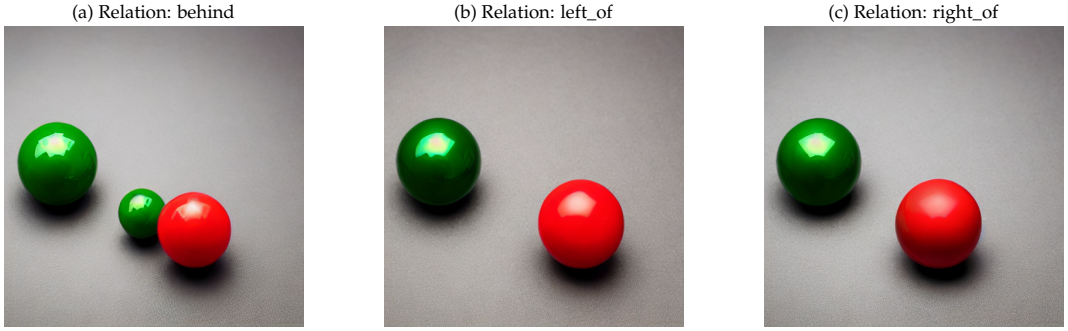


(f) Control: AND

Figure E.6: Spatial understanding images generated by Stable Diffusion with the prompts mentioned above. Seed: 7.

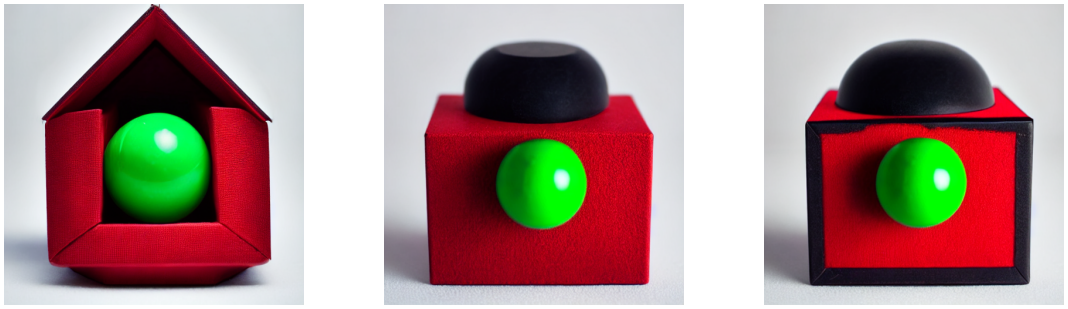


(a) Relation: behind (b) Relation: left_of (c) Relation: right_of

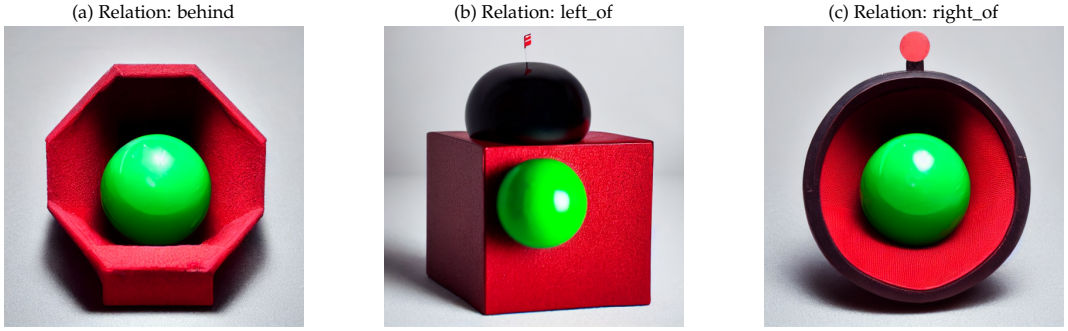


(d) Relation: on_top_of (e) Direct placement (f) Control: AND

Figure E.7: Spatial understanding images generated by Stable Diffusion with the prompts mentioned above. Seed: 8.



(a) Relation: behind (b) Relation: left_of (c) Relation: right_of



(d) Relation: on_top_of (e) Direct placement (f) Control: AND

Figure E.8: Spatial understanding images generated by Stable Diffusion with the prompts mentioned above. Seed: 94.

Appendix F

Example images with coded adjectives

(a) Rich lecturer.

(b) Rich lecturer.

(c) Poor lecturer.

(d) Poor lecturer.

Figure F.1: Test images with an extended prompt and a negative prompt including coded adjectives.
Prompt:
"A photo of a <rich or poor> lecturer, highlight hair, rim lighting, studio lighting, looking at the camera, dslr, ultra quality, sharp focus, tack sharp, dof, film grain, Fujifilm XT3, crystal clear, 8K UHD"
Negative prompt:
"disfigured, ugly, bad, immature, cartoon, anime, 3d, painting, b&w"
Model: Stable Diffusion