GANSlider: How Users Control Generative Models for Images using Multiple Sliders with and without Feedforward Information

Hai Dang
hai.dang@uni-bayreuth.de
University of Bayreuth
Bayreuth, Germany

Lukas Mecke
lukas.mecke@uni-bw.de
Bundeswehr University Munich
Munich, Germany
LMU Munich
Munich, Germany

Daniel Buschek
daniel.buschek@uni-bayreuth.de
University of Bayreuth
Bayreuth, Germany

Figure 1: This paper compares different user interfaces with sliders for interactive control of a generative model for face images (StyleGAN2). We study different numbers of sliders and two designs: (a) Regular sliders and (b) Filmstrip sliders that provide feedforward information via preview images. Participants used these UIs in image reconstruction tasks to generate a given target images. The right part of the figure (c) shows one example of a resulting "exploration path" towards a target (for more examples see Appendix A).

ABSTRACT

We investigate how multiple sliders with and without feedforward visualizations influence users’ control of generative models. In an online study (N=138), we collected a dataset of people interacting with a generative adversarial network (StyleGAN2) in an image reconstruction task. We found that more control dimensions (sliders) significantly increase task difficulty and user actions. Visual feedforward partly mitigates this by enabling more goal-directed interaction. However, we found no evidence of faster or more accurate task performance. This indicates a tradeoff between feedforward detail and implied cognitive costs, such as attention. Moreover, we found that visualizations alone are not always sufficient for users to understand individual control dimensions. Our study quantifies fundamental UI design factors and resulting interaction behavior in this context, revealing opportunities for improvement in the UI design for interactive applications of generative models. We close by discussing design directions and further aspects.

CCS CONCEPTS
• Human-centered computing → Empirical studies in HCI; Graphical user interfaces; • Computing methodologies → Image manipulation.

KEYWORDS
interactive AI, generative adversarial network, image manipulation, user study, dataset

ACM Reference Format:
Hai Dang, Lukas Mecke, and Daniel Buschek. 2022. GANSlider: How Users Control Generative Models for Images using Multiple Sliders with and without Feedforward Information. In CHI Conference on Human Factors in Computing Systems (CHI '22), April 29-May 5, 2022, New Orleans, LA, USA. ACM, New York, NY, USA, 15 pages. https://doi.org/10.1145/3491102.3502141

1 INTRODUCTION

Artificial intelligence (AI) supported interactive tools are now being adopted by both expert and non-expert users alike. Especially generative machine learning (ML) models find their application in end user products where they enable users to generate realistic media. In this paper we focus on the use case of image generation,
such as seen in the recently introduced Smart Neural Filters in Photoshop [33]. These allow users to change semantic features of face portrait photos.

The underlying models are typically trained on large unlabeled image datasets to learn data representations useful for generation and manipulation of photos. This learned representation is called latent space and is often high-dimensional and not always interpretable by humans. However, there are techniques to facilitate the learning or extraction of disentangled dimensions [4, 12, 29], such that each one represents a (more) interpretable feature. For example, for faces these might be hair color, eye gaze direction, and so on.

End user products can invest in engineering efforts to achieve clearly interpretable dimensions (cf. the Photoshop example [33], GauGAN [21]). In contrast, such disentangled dimensions are not always readily available to (AI) researchers while developing new generative models. As a new way to handle this, researchers have worked on methods to explore and evaluate generative models via interaction [12, 30]. This often involves visualizing a model’s learned dimensions to judge their interpretability and quality. A popular method in (AI) research publications is to plot multiple images generated at different points along said dimensions (e.g. [12, 14, 15, 22]). Recently, such image grids have also been used interactively (e.g. [22, 43]).

Today, most user interfaces (UIs) for generative models use a set of regular sliders, in which each one is mapped to the control of one latent dimension. Such UIs have been used to enable interaction for model exploration and evaluation [12, 22, 30]. However, slider UIs themselves have not been at the focus of any empirical study in this context so far.

This motivates us to better understand the interaction patterns with sliders for the control of generative models for images. Concretely, we hypothesize that here the design of effective UIs is constrained by different factors: First, we investigate how the number of control dimensions (i.e. sliders) impacts the interaction. An increasing number of control dimensions corresponds to a larger latent image space that can be explored, and thus adds to the complexity of interactive tasks in that space. Currently, there is no guidance on the number of control dimensions to use in various settings, with numbers reported in related work ranging from 5 to 80 dimensions [12, 22, 30]. Second, we hypothesize that visual feedforward information in the UI may aid users in their decision-making when working with generative models (i.e. a preview of the outcome of performing an interaction). This motivates us to introduce and evaluate a “filmstrip” slider design, which shows multiple preview images at different points along the controlled dimension (Figure 1 b). This leads to the following two research questions that we examine in this paper:

**RQ1** How do different numbers of control dimensions (sliders) impact users’ interaction behaviour and reconstruction task performance with a generative image model?

**RQ2** How does added visual feedforward information (preview images) on the sliders impact users’ interaction behaviour and reconstruction task performance with a generative image model?

To answer these questions, we conducted a within-subject user study (N=138) in which each participant worked with \(1, 2, 3, 4, 5, 8, 10\) sliders of both types (Regular, Filmstrip). We used an image reconstruction task (cf. Figure 1) similar to Ross et al. [30]. We measured all interaction events plus subjective feedback.

Our results show that the number and type of sliders both significantly influence the interaction: More sliders lead to more interactions and add to the complexity of the task, which filmstrips partly mitigate. However, we found no evidence of faster or more accurate task performance with filmstrips. Furthermore, we observed that controlling generative models can already become challenging for up to ten sliders. While our results indicate that filmstrips alone are not always sufficient to interpret a model’s latent dimensions, they do lead to more goal-oriented user actions and were overall well-received by the participants. Furthermore, we found that it is crucial to look beyond performance measures such as speed and accuracy to evaluate UI designs in this context. Based on these results and the collected open feedback we discuss implications for UIs for generative models.

In summary, we contribute: (1) The first empirical evaluation of two fundamental UI design factors for interaction with generative models; involving (2) a new slider design with “filmstrip” previews as feedforward information; and (3) the resulting dataset and prototype, which we release to the community to facilitate further research.

## 2 BACKGROUND AND RELATED WORK

We structure this related work section into three parts: a motivation for interaction with generative models (Section 2.1), frontend (i.e. UI, HCI view – Section 2.2) and backend (i.e. modeling, AI view – Section 2.3).

### 2.1 Motivation for Studying Interaction with Generative Image Models

Our work is motivated by the growing relevance of interactive generative models in both research, industry and products (e.g. Artbreeder\(^2\), GauGAN [21], Photoshop [33], Figure 2 a). This trend is expected to continue, given the investment of major tech companies [32, 33, 41]. Recent research in Human Computer Interaction (HCI) and AI used generative models interactively as well (e.g. see [12, 24, 30] and Figure 2), including work on co-creativity and computational creativity (e.g. [27, 28]). The study by Ross et al. [30] is most closely related: They evaluated the interpretability of such models by letting people reconstruct a target image with sliders to control the model (Figure 2 e). We follow their approach and study image reconstruction with sliders. However, while their goal was to evaluate the models, our goal is to evaluate the slider UI. We see these goals as supporting each other since understanding user behaviour is crucial for further establishing interactive tasks as an evaluation method for AI: For instance, UIs for model comparisons need to be well-understood to avoid bias. Evaluation tasks should also elicit realistic behaviour, and in the context of interactive AI

\(^{1}\)Mockup by the authors, following the Photoshop UI shown in https://youtu.be/5jDi2-Gw8lQ; (b) https://youtu.be/jdTICDa_eAL; (c) https://youtu.be/0elW1tW8Npq; (d) https://youtu.be/5gkLDt6vlgB; (e) http://hreps.s3.amazonaws.com/quiz/manifest.html; all last accessed 01.12.2021.

\(^{2}\)https://www.artbreeder.com/, last accessed 01.12.2021.
Figure 2: Examples of the many slider and image grid UIs used in related work to interact with generative image models: (a) UI for editing face photos with the “Smart Portrait Filters” in Adobe’s Photoshop [33]; (b) UI used in the GANSpace paper [12] (sliders manipulate latent dimensions discovered via PCA); (c) UI used in the “Swapping Autoencoders” paper [22] (thumbnail grid; sliders on thumbnails change strength of the corresponding texture edits); (d) Automatically created image gallery for interactive GAN exploration (image grid without sliders) [43]; (e) slider UI used in a user study to evaluate model interpretability by interactive reconstruction [30]. In this paper, we examine a new combination of sliders and images for controlling generative models – “filmstrip sliders” (cf. Figure 1). Image sources: Screenshots from the related work’s videos/websites.

“researchers need to be cautious about their pragmatic decisions” [6]. So far, the regular slider UI is such a pragmatic choice for generative models for two reasons: First, slider design and use has not been studied in this context yet. Second, comparisons to alternative UI elements are missing. In this paper, we focus on the first aspect – better understanding the slider design and interaction behaviour.

2.2 Frontend/UI: User Interfaces for Generative Models

2.2.1 Slider UIs. The slider is the most commonly found UI element for interaction with generative models today. Figure 2 shows examples from research and industry. Typically, each slider maps to a shift along one latent dimension (e.g. Figure 2 a, b, c, e). These dimensions could be predetermined (e.g. in end user applications such as in Figure 2 a: “happiness”, "gaze", etc.) or open for discovery (e.g. in research contexts such as Figure 2 b and e). Sometimes, sliders are accompanied by images that visualize the dimension (e.g. Figure 2 c) and/or the overall outcome (e.g. Figure 2 a, b and e). However, interaction with sliders with and without images has not been systematically evaluated yet for generative models. Without this baseline, it is difficult to advance the UI design for this use case. This motivates us to investigate how well the basic slider design performs and how it might be improved with visuals.

2.2.2 Other UIs. 2D grids are another presentation for image generation models. For example, Zhang and Banovic [43] generate galleries to explore Generative Adversarial Networks (GANs) (Figure 2 d). This affords navigation such as selecting the next image on which to center the grid. Typically, grids map x/y axes to two directions in a model’s latent space, showing images at equidistant points along those. Non-interactive variants frequently appear in (AI) publications to visualize (1) latent spaces (e.g. [12]), (2) the impact of varying inputs and hyperparameters (e.g. [14, 22]), or (3) generated examples (e.g. [15]). Our filmstrip design explores a combination of sliders with such image concepts.

Further UI concepts edit image parts or aspects: Park et al. [22] enable structural/textural edits via thumbnails and sliders to control their strength (Figure 2 c). Others allow users to mark image areas to (not) be modified by the model [42], to guide the model [38, 44], or to specify semantic edits (e.g. add windows, remove chairs) [2]. In this paper, we focus on sliders for global image edits to analyze interactions in-depth. However, localized edits (e.g. brushing, pen tools) could be studied with similar methods in the future (e.g. logging interactions in local editing tasks).

2.2.3 Extending Sliders with Feedforward. Previews [31] and feedforward concepts [3, 7] inform users about the outcome of their actions before they complete them. The HCI literature includes related slider designs: Willett et al. [40] added visual “scents” to
navigate datasets, for example, with a slider with an added bar chart. Related, Tsandilas et al. [37] enabled users to draw sliders, with density plots added automatically along the drawn line. Similarly, Kwon et al. [18] added "rainbow" visualizations of data attributes along user-defined, non-linear axes of a scatterplot. Terry and Mynant [34] proposed "side views" – pop-ups that show visual previews of the states of a UI element to help users explore its functionality. Our filmstrip slider builds on these ideas of adding visual (preview) information to the slider line.

2.3 Backend/Modeling: Generative Models and Selecting Dimensions
ML/AI research has improved the quality of generated output and its scope of applications (e.g., text and images) with increasing model sizes [5] and refined training and architectures [13–15, 25]. Motivated by creating models that can be understood by humans, efforts were taken to make them more interpretable and to measure interpretability [30]. Here, the term disentanglement is used to describe how "clear cut" the dimensions of the learned data representations are and how well they match the underlying "true" factors [4, 29].

This is also important for interactive use: For example, for face images, an entangled dimension might change both hairstyle and skin tone, while a disentangled model might have learned these as two separate dimensions.

As described in Section 2.1, Ross et al. [30] compared models with varying degrees of disentanglement using an interactive task with one UI. We instead compare varying UI designs and thus chose one model, StyleGAN2 [15], trained on face images. This is motivated by exploring a task that goes beyond more abstract or simpler datasets (e.g., Sinelines, MNIST) [30].

To obtain interesting dimensions to be controlled in the UI, we can either facilitate learning disentangled representations (e.g., [4]) or "discover" meaningful concepts in a model: For our study, we used the GANSpace approach [12] to automatically select the dimensions from StyleGAN to be controlled via sliders in our study (Section 4.2.1), without manual labeling. Our motivation here is a middle ground between random (and thus likely meaningless) dimensions and fully "engineered" interpretable dimensions. The latter are important for end user applications (e.g., the Photoshop example in Figure 2 a) but cannot be readily expected in earlier stages (e.g., research and development). Moreover, related work has recently identified interaction as a key factor for evaluating generative models that are not perfectly disentangled [24, 30]. At the same time, the UI has not been in focus here yet, further motivating our study.

3 EXTENDING THE SLIDER UI WITH FILMSTRIPS
As one of our variables of interest, we examine the impact of adding further visual information to the sliders (see Figure 1). Here, we describe this UI concept in more detail.

3.1 Filmstrip Previews
In AI research, image strips/grids are widely used to present generative model results (e.g., [12, 14, 15, 22]). This is mostly non-interactive (e.g., paper figures). In HCI and information visualization, previews and feedforward concepts [3, 7, 31, 34, 40] support interaction and "what if" reasoning in tasks. Our filmstrip concept combines these experiences (Figure 1). We chose a fixed number of images for visual orientation along the underlying continuous control dimension. Concretely, we show five images per slider, as informed by a pretest with N=12 people, the available space on a regular desktop screen, and considering computational costs. Sliders ranges were set to [-5, 5].

In our pretest, we found this to be a good compromise between expressiveness and robustness, since, as typical for models such as StyleGAN, moving further along a dimension causes stronger changes but can eventually lead to visual artefacts (cf. [12]).

3.2 Linked Sliders
The output image of the generative model is the sum of all slider edits. If one slider changes the hair color, the color in all filmstrips has to be updated if we want the filmstrip on each slider to always show the concrete outcome of changing that slider. An alternative design might show a generalised visual representation per slider, such as a filmstrip with different hair colors (e.g., color swatches or a fixed face with different hair colors). However, this approach assumes that the dimensions have known and fixed interpretations. Thus we decided for the first option here. Accordingly, in our UI, moving one slider updates the filmstrip preview images of all sliders.

3.3 Side-by-Side Outcome View
We include an outcome view with two images ("Your Image" and "Target Image" in Figure 1), following related work, where people found this side-by-side view more helpful than overlays [30]. Beyond research studies, this design is also relevant for applications: For example, for image editing, one image could show the original and one the edited version.

3.4 Technical Implementation Aspects
The preview images are computationally costly because they require to run StyleGAN for all sliders after each interaction. To address this, we implemented the following update scheme: With each slider change event the client requests an update from the server. This also aborts all pending requests to avoid spending computation time on now outdated events. The server computes and sends back the image(s) or an empty response if no computing time is available. In case of an empty response, the client retries immediately and keeps the previous image until the update succeeds. This effectively realises that updates come as fast as possible for the available computing power and changing sliders is always possible (non-blocking UI). Concretely, a slider was greyed out as a whole while any of its images was updating. This was informed by preliminary testing, to clearly indicate outdated previews and ongoing computation, while also reducing the amount of UI "flickering" that this necessarily introduces. Moreover, the outcome image ("Your Image", Figure 1) had update priority.
4 USER STUDY

We conducted a user study to investigate how different numbers and types of sliders impact users’ interaction behaviour and reconstruction task performance with a generative image model.

4.1 Study Design

We designed a within-subject online study with two independent variables: the sliders’ Type (two levels: Regular and Filmstrip) and the Number of sliders (seven levels: 1, 2, 3, 4, 5, 8, 10; informed by pretests that showed 10 to be clearly challenging). As dependent variables, we computed interaction measures from logging data, and elicited feedback via questionnaires (Likert items and open questions).

4.2 Apparatus

4.2.1 Web System. We implemented a light server for message passing (flask) and a client (ReactJS). Besides the sliders (Figure 1), this frontend included a study consent form, task descriptions, done/skip buttons, and questionnaires.

The model ran on a multi-GPU instance on AWS Sagemaker. We used the StyleGAN2 model trained on the FFHQ dataset and applied the GANSpace approach (i.e. Principal Component Analysis, PCA, on StyleGAN’s w vectors, see details). Concretely, for a task with N sliders, we use this to extract the N top dimensions as ranked by PCA. We then map this ranking to the UI layout (i.e. first slider controls first principal component). We chose this ranked extraction approach as a balance between random control dimensions and manually selected or “engineered” ones (see Section 2.3).

In contrast to Ross et al. [30], we do not show numerical real-time feedback (e.g. remaining distance to target image) since they reported users sometimes used this distance as the only source of information to solve the task and thereby did not pay attention to the sliders.

4.2.2 Generation of the Image Reconstruction Tasks. StyleGAN2 is capable of generating “random” faces, which we use in this study. For each task, the starting face and target face are defined as follows: First, we choose a random point (i.e. a face) in StyleGAN2’s latent space. This is the starting image for the task shown with all sliders at the center (i.e. at 0). Second, we choose a random target offset for each slider. Since each slider corresponds to a direction in the latent space, these values define an offset in the latent space. Third, we shift the point by this offset and use StyleGAN2 to generate the target image. As an example, for a task with only one slider, we might roll an offset of “-2.2”. In this case, the task can be solved perfectly by moving the slider from its initial position (center) at zero to “-2.2” (towards the left).

We created a set of seven random faces for each participant. These faces were randomly assigned to each task for each slider variant, such that the seven tasks (i.e. numbers) for both slider variants used all seven faces, but in a different order. This approach was chosen to ensure these three aspects: (1) The study overall covers a wide range of model outputs (random faces across participants); (2) a potential influence of specific faces on task difficulty is balanced because for one participant the same faces appear in both slider variants; (3) it is still not possible for participants to know the correct slider configuration for a face when encountering it again in the second variant, as it appears with different target offsets (i.e. target slider values) and a different number of sliders.

4.2.3 Task Questionnaires. We used the NASA-TLX questionnaire to measure workload and four custom Likert statements (see titles in Figure 8). These were presented directly in the web system after each reconstruction task.

4.2.4 Final Questionnaire. A final questionnaire asked for open feedback: Do you have any final remarks on the interpretability of the different slider types? Is there anything you would add to the slider interface to improve it?, and Can you think of other use cases where the filmstrip slider interface would be helpful? These questions were not mandatory, to account for the case that participants had no feedback/ideas.

4.3 Participants

We recruited 12 participants for a pilot study and 156 for the main study, using Prolific. The study took 45 minutes on average and was compensated with £ 5.63 (Prolific uses £), following Prolific’s recommendation. After exclusions (e.g. incomplete or invalid attempts, such as not moving the sliders), we had N=138 participants for the analysis.

4.4 Procedure

4.4.1 Study Intro. In line with our institutional regulations and informed consent procedures, the first page explained the study, provided detailed information on data collection and privacy protection regulations, and further general study information (e.g. emphasizing that participants could end the study at any time). Before the first actual task, an introductory page allowed participants to try out single sliders of both variants.

4.4.2 Image Reconstruction Tasks. Each participant completed 14 image reconstruction tasks: They first completed one set of seven tasks corresponding to one slider Type before switching to the other one. This was counterbalanced (i.e. half of participants started with the seven tasks for Regular, the others with the seven tasks for Filmstrip).

The order of these seven tasks per slider variant was fixed with the Number of sliders increasing. This decision was informed by our prestudy, which revealed that tasks with higher slider numbers can be very challenging. In this way, a potential learning effect in our study is in favour of participants being able to solve the tasks with many sliders. Similar study designs with tasks of increasing interaction difficulty have been used successfully in related work [20].

4.4.3 Ending a Task. We did not use a time limit or a predefined similarity threshold for ending a task. Instead, people had two options to end a task: They could either indicate that they had successfully finished it (“done”) or that they wanted to “skip” it. We

---

3https://flask.palletsprojects.com/en/2.0.x/, last visited February 3, 2022
4https://reactjs.org/, last visited February 3, 2022
5https://aws.amazon.com/sagemaker/, last visited February 3, 2022
6www.prolific.co, last accessed 01.12.2021
did this to allow users to fully concentrate on solving the task to the best of their ability and assess their perceived success. Each task was followed by the questionnaires described in Section 4.2.3.

4.4.4 Ending the Study. The final questionnaire (Section 4.2.4) concluded the study with open feedback.

5 RESULTS

Here we report the results of our study. Where applicable, we report significance at $p < .05$, tested with R [26]. We use (generalised) linear mixed-effects models (LMMs, packages lme4 [1] and lmerTest [17]). These LMMs accounted for individual differences using random intercepts (for participant), and had Type and Number as fixed effects. For Likert (ordinal) data, we use Generalized Estimating Equations (GEEs) from the R package mltgee [35]. Where not stated otherwise, we exclude the data of tasks that participants marked as skipped (see Section 4.4.3).

5.1 Total Interactions

To analyse the number of interactions per task (Figure 3a) we counted a sequence of input events as one interaction if the user changed the same slider with at most 250 ms between any two events (i.e. one interaction = changing one slider with a continuous drag/move or a direct click). This was informed by measuring event frequencies when dragging in various browsers as well as analysing the histogram of logged inter-event times.

Descriptively (Figure 3a), users needed more interactions to solve tasks with more control dimensions, in particular for Regular. In contrast, interaction counts for Filmstrip did not increase beyond 4 dimensions. To test this effect, we fitted an LMM (Poisson family) on the interaction counts. The effect of Number was significant and positive ($\beta = .18, SE = .001, CI_{95\%} = [.18, .19], p < .0001$): Each additional slider was estimated by the model to significantly increase the number of interactions by 19% (computed as $\exp(\beta) = \exp(.18) = 1.19$). The effect of Type was significant and negative ($\beta = -.18, SE = .01, CI_{95\%} = [-.21, -.16], p < .0001$): Thus, using Filmstrip instead of Regular was estimated by the model to significantly reduce the number of interactions by 17% ($1 - \exp(-.18)$). The interaction of Number and Type was also significant and negative ($\beta = -.11, SE = .002, CI_{95\%} = [-.11, -.10], p < .0001$), confirming the visible trend in Figure 3a that the difference between the slider types grows with the number of control dimensions.

5.2 Control Dimension Switches (Slider Switches)

We counted a switch between control dimensions every time an input event modified another slider than the slider modified by the last event. Descriptively (Figure 3b), users switched more between control dimensions if more were available, which can be combinatorially expected. Filmstrip had generally fewer switches than Regular. An LMM (Poisson family) confirmed this picture: The model had Number as a significant positive predictor ($\beta = .24, SE = .004, CI_{95\%} = [.24, .25], p < .0001$). Thus, each additional slider was estimated by the model to significantly increase the number of switches by 27%, Type was also significant ($\beta = .08, SE = .04, CI_{95\%} = [.06, .09], p < .05$) and so was the interaction effect ($\beta = -.06, SE = .04, CI_{95\%} = [-.07, -.05], p < .05$), which is in line with the trend visible in Figure 3b: Switches increase more per control dimension for Regular than for Filmstrip.

5.3 Overshooting along Control Dimensions

We counted interactions that result in moving a slider across its target value (either in +/- direction). This measures "overshooting" of the target value of a control dimension in a task. Descriptively (Figure 3c), overshooting happened more often if users had more dimensions to deal with. Moreover, we observed more overshooting with Regular than Filmstrip. This is in line with the LMM (Poisson family), which had Number as a significant positive predictor ($\beta = .17, SE = .003, CI_{95\%} = [.16, .18], p < .0001$): Each additional control dimension was estimated by the model to significantly increase the number of overshooting actions by 23%. Type was significant and negative ($\beta = -.33, SE = .04, CI_{95\%} = [-.41, -.25], p < .0001$): Using Filmstrip instead of Regular was estimated by the model to significantly reduce the number of overshooting actions by 28%. The interaction was also significant ($\beta = -.11, SE = .006, CI_{95\%} = [-.13, -.10], p < .0001$): As seen in Figure 3c, overshooting actions increase more per control dimension for Regular than for Filmstrip.

5.4 Time to First Interaction

We analysed the time from the start of a task to the first interaction, which might be seen as an "orientation" time. Descriptively (Figure 3d), this time was rather stable across the number of dimensions for Regular and increasing for Filmstrip. Noticeable high values appear for tasks with one slider, explained by the fact that these were the first tasks with each slider type and people thus likely looked at the task description and "new" UI in more detail before starting. We fitted an LMM on this data yet found no statistically significant effects (also when excluding the first tasks).

5.5 Progress Patterns: Task Performance over the Course of Interaction

Here we analyse the distance between the current slider positions and the target slider positions over the course of a task. We normalize this by the number of sliders to enable comparisons across the tasks. Figure 4 plots these distances per percent of interactions in a task (i.e. 0% = first interaction; 100% = last interaction), to look at progress patterns independent of absolute task time or number of interactions. Progress is slower for tasks with more control dimensions (i.e. compare "slopes" across plots in Figure 4). Moreover, Filmstrip sliders tend to stay slightly closer to the targets throughout most interactions. The final distances (i.e. task accuracy) are examined in more detail in the next section.

A subtle but noteworthy pattern here is that Regular sliders move away from the target in the initial stages of a task. Closer examination of individual task logs indicates that this is because users initially move sliders seemingly randomly to grasp the effects of each control dimension. In contrast, the visual previews address this to the extent that this pattern is not visible for Filmstrip sliders.

5.6 Image Reconstruction Accuracy

We measured two distances to quantify users’ accuracy at the end of a task: (1) the distance between final slider positions and the task’s
target (i.e. “perfect”) slider positions; and (2) the distance between reconstruction and target image as measured by a face recognition model [23], as a proxy for visual difference. We fitted LMMs for both distances: NUMBER was a significant positive predictor in both (slider distance: $\beta=2.79$, SE=.05, CI95%=[2.69, 2.90], p<.0001; face distance: $\beta=.04$, SE=0.001, CI95%=[.04, .04], p<.0001), while TYPE was not significant for either. The interaction effect was negative for both distances yet only significant for the slider distance ($\beta=-.20$, SE=.08, CI95%=[-.35, -.05], p<.01). In summary, in line with the trends visible in Figure 4, people solved the tasks significantly less accurately for more control dimensions, and there is a trend that the filmstrip design overall slightly mitigated this decrease in accuracy.
5.7 Task Completion Success

People could end a task either by marking it as "done" or "skip" (Section 4.4.3). Figure 5a shows this data. An LMM (binomial family) had NUMBER as a significant negative predictor ($\beta=-.36$, SE=.04, CI95%=[-.44, -.28], p<.0001): Tasks with more control dimensions had a significantly lower chance of success. However, absolute rates of people’s indicated success were rather high. We did not find a significant effect of TYPE or interaction effect. Moreover, face recognition distances varied, indicating that they used the visual information to decide if the sliders; and (4) significantly harder decisions on which slider to use.

5.8 Task Completion Time

We measured task completion time (Figure 5b) from the start of a task to submitting it as "done". An LMM on this data (in ms) had NUMBER as a significant positive predictor ($\beta=22535$, SE=1497, CI95%=[19601, 25468], p<.0001): Tasks with more control dimensions took significantly longer. TYPE was a negative predictor (i.e. Filmstrip reducing times) but not significant. We also did not find a significant interaction effect.

5.9 Exploration Behaviour

We analyzed the interaction logs as sequences: Concretely, Figure 6 shows how often users transitioned between specific dimensions (e.g. row 1, column 3 = changing the 1st slider, then the 3rd). These plots reveal differing strategies per slider design: For Regular, people started at the top of the UI (i.e. slider 1, see starting probabilities in Figure 6) and tried out sliders one after the other (i.e. highest values just above the diagonals in Figure 6). They sometimes also went back up (i.e. rather high values just below the diagonals in Figure 6). This sequential pattern is far less pronounced for Filmstrip, in particular with increasing control dimensions. While people here also tend to start at the top of the UI, transitions are much more varied, indicating that they used the visual information to decide which slider to change next.

5.10 Task Perception and Subjective Feedback

Here we report on the results from the questionnaires and open feedback (see Section 4.2.3).

5.10.1 Task Load Index

Figure 7 shows participants’ NASA-TLX ratings, which we analyse on subscale level [10]: Concretely, the LMM analysis showed that NUMBER was a significant predictor for all NASA-TLX facets (mental demand: $\beta=1.08$, SE=.05, CI95%=[-.99, 1.17], p<.0001; physical demand: $\beta=.47$, SE=.04, CI95%=[.40, .53], p<.0001; effort $\beta=.88$, SE=.05, CI95%=[.79, .97], p<.0001; temporal demand: $\beta=.36$, SE=.04, CI95%=[.28, .43], p<.0001; performance: $\beta=-1.00$, SE=.06, CI95%=[-1.09, -.91], p<.0001; frustration: $\beta=.95$, SE=.05, CI95%=[.87, 1.04], p<.0001). Thus, people perceived tasks with more sliders as significantly more demanding and frustrating and as requiring significantly more effort. They also perceived their own task performance as significantly lower. Neither TYPE nor the interaction of NUMBER and TYPE was found as significant for any of the questions.

5.10.2 Likert Items per Task

Figure 8 shows the results of the Likert items after each task assessing the sliders’ interpretability, user confidence, and ease of interaction. Descriptively, tasks with more sliders received worse ratings and tasks with Filmstrip sliders received marginally better ones. The results from the GEE analysis match this picture: TYPE was a positive predictor, yet not significant, while NUMBER was a significant negative predictor for all questions. Concretely, the odds of giving a higher Likert rating decrease with an additional slider. They are estimated by the model as X times the odds without that slider (with X=..66 for Q1, .64 for Q2, .66 for Q3, and .65 for Q4, all p<.0001). This means that having more sliders results in a perception of: (1) significantly worse interpretability of individual sliders; (2) significantly lower confidence in one’s interactions; (3) significantly harder decisions on how far to adjust the sliders; and (4) significantly harder decisions on which slider to adjust next.

5.10.3 Open Feedback

The study concluded with three open questions (see Section 4.2.4). Two authors developed a codebook inductively and then coded all responses independently. All differences were resolved through discussion.
Starting prob.

To slider

From slider

Starting prob.

To slider

From slider

Figure 6: Overview of users’ transitions between different sliders during interaction. For each slider number and design, the matrix plot shows the transition probabilities of switching from one slider (row) to another (column) during interaction (i.e. rows sum to 1). This is non-trivial only for >2 sliders. The single row plots show the starting probabilities per slider in each task. See text for details.

Figure 7: Overview of user responses to NASA-TLX questionnaire. There are six dimensions. Overall, the perceived workload increases with increasing numbers of sliders. The perceived success decreases with increasing numbers of sliders.
Interpretability of the slider types: 51 people provided comments on this question. Many compared the sliders. For example, one person in favor of Filmstrip explained: "Sliders with photos stitched together were definitely better than those without. I enjoyed working with them and I had fun. Working with sliders without photos was very annoying and stressful." In contrast, another person said: "I believe the plain slider as opposed to the filmstrip slider was much easier to interpret as the user is able to focus on the main two images rather than getting distracted by the images within the filmstrip slider, this allows them I think to be more accurate and focused." Overall, Filmstrip was preferred here: 31% explicitly mentioned something positive about Filmstrip vs 6% about Regular; and 37% explicitly expressed a preference for Filmstrip vs 8% for Regular. Beyond such comparisons, further mentioned aspects included comments on: slider numbers (14%), mostly stating that more sliders make it more difficult; hard to interpret dimensions (12%); and performance, such as lags (8%).

Ideas for UI improvements: 78 participants responded to this question. Here, the top aspects were: adding slider labels (35%); improving performance (18%); and adding UI elements (17%), such as a reset or undo button or an option to save the current state. Further suggestions included enabling more fine-grained control (8%) and having more meaningful dimensions (6%). We further analyzed the aspects mentioned as potential labels for such systems: demographics (e.g., age, perceived gender, ethnicity), appearance (e.g., facial features like eyes, nose, mouth and hair, or accessories such as jewelry or glasses) and image properties (e.g., hue, saturation, contrast, brightness).

Potential other use cases: 57 people answered this question. The top aspects were: image editing (25%); criminology (26%); prediction (21%) such as on ageing, hairstyles, glasses or jewelry; and gaming (7%).

6 DISCUSSION

6.1 Measuring and Addressing the Costs of Dimensionality in Controlling Generative Models

As a key result, we provide the first quantification of interaction costs per control dimension for a generative model for images: Each control dimension, operationalised in the UI as a slider, is estimated to increase number of user actions towards a desired outcome by +19%. It also increases workload. More dimensions also make interaction paths towards the target image more complex, with an estimated +27% increase of switches between dimensions per additional slider. Ross et al. [30] recently shared the expectation that “interacting with all dimensions simultaneously may be overwhelming for models with many tens or hundreds of representation dimensions”. Our analyses and people’s feedback here indicate that this can become challenging already with about five to ten dimensions.

Based on these results, end user applications should carefully consider how many control dimensions to simultaneously show as sliders. Combined with people’s comments on interpretability and the Likert ratings, we recommend at most 3-5. This is likely a conservative estimate, in the sense that dimensions with a higher degree of interpretability [30] can be expected to impose lower interaction costs. In this light, our results provide an additional, interaction-centric motivation for work on interpretability: Reducing interaction costs for UIs with multiple control dimensions.

In contrast, research applications might need UI controls for many dimensions, such as for exploring a generative model in development. Here, our results motivate UI concepts that let people externalise their exploration of said (potentially many) dimensions. Beyond allowing for entering text labels [12, 30], our insights motivate exploring concepts from infovis and information retrieval (e.g., searching, reordering, ranking, filtering or selecting control dimensions). For example: (1) users could hide sliders in the UI if they deem them to be currently uninteresting; (2) users could group or merge sliders if they identify them as similar or more meaningful as a single interactive control; (3) or sliders could be reordered in the UI, either manually or automatically according to various (selectable) metrics.

6.2 Feedforward Information for Interactive Generative Models for Images

Here we discuss the observed benefits and challenges around feedforward information in this context.
6.2.1 Feedback Information Facilitates Selective and Strategic Control of Generative Models. A clear benefit of the examined slider design with visual previews is that it mitigates the costs of dimensionality described in the previous section: That is, with preview images on the sliders, the required number of interactions tapers off at about three control dimensions, instead of increasing further (Figure 3a). Similarly, the previews also reduce the number of slider switches (Figure 3b) and overshoots (Figure 3c). That is, they reduce patterns indicating uncertainty such as “jumping” back and forth between dimensions, and along dimensions, instead of setting them correctly once. Moreover, the previews facilitate strategies beyond simply going by the order of the sliders in the UI layout (Figure 6). Related, some people commented that the previews helped with interpretation, adjustments and avoiding “trial and error”.

To interpret this further, we can view image reconstruction as a search problem in which users have to find the target image within the part of the latent space that is interactively accessible through the sliders. In this view, adding a dimension expands the space exponentially (e.g. $n^d$ images for $d$ sliders with $n$ discrete values each). As our results show, users’ strategies allow them to avoid an exponential growth in their required actions: With regular sliders, users achieve linear growth, that is, adding a slider adds a roughly constant number of required interactions (Figure 3a). Visual feedback allows them to achieve a logarithmic pattern instead (i.e. diminishing costs per slider).

Overall, these findings support the conclusion that visual feedback information in the goal-directed control of a generative model for images leads to more selective and strategic decision-making throughout the interaction.

6.2.2 No Evidence for Improved Image Reconstruction Performance with Feedback. Our findings do not support the conclusion that the strategic benefits of the filmstrips described above result in faster or more accurate reconstruction: First, we did not find a significant effect on task completion times. A likely explanation is that users needed extra time to attend to the previews. Preview updates also had a short delay. Moreover, a few people commented that they felt distracted by the previews. Related, previews seemed to invite spending more time on orientation before the first interaction (Figure 3d) although this was not statistically significant.

Second, we could not find a significant effect on the final reconstruction accuracy: An explanation is that, for both slider designs, people found strategies to solve the tasks, and difficulty was rather mostly dependent on the number of control dimensions. This is supported by the interaction measures and patterns, revealing different strategies for the two slider types. While these strategies did not lead to significantly different perceived workload and performance (Figure 7 and Figure 8), the open feedback was clearly in favour of the filmstrip design (Section 5.10.3).

6.2.3 Summary and Ideas for Future Work. Overall, our takeaway is to use and further explore visual feedback for interactive control of generative models: While people can indeed solve image reconstruction tasks with blank sliders, the visual feedback information facilitates more goal-directed interactions. This is also subjectively perceived as such by many users, resulting in a positive and preferable user experience overall. Finally, as methodological guidance, researchers studying generative models via interaction need to be aware that the regular slider design mainly elicits a simple sequential user strategy (i.e. going through the dimensions as presented in the UI layout).

Future studies could explore further designs in comparison to our fundamental filmstrip design here. For example, further ideas motivated by our results and participants’ suggestions include showing only two images per slider (e.g. at min and max state) or “derivative” information (e.g. image showing difference between max and min state). Such designs could also be compared for models of varying disentanglement, effectively motivating a study that combines the key independent variables of this paper and those in the work by Ross et al. [30]. Moreover, sliders could be compared to different UI concepts in this context (e.g. image grids [43]).

6.3 Quantifying Interactions with Generative Models beyond Time and Accuracy

We found that it is crucial to study interaction with generative models beyond the typical HCI performance metrics of task time and accuracy: The two slider designs were similar in these measures despite drastic differences in users’ behaviour and strategies. These were only revealed by detailed interaction metrics (Figure 3, Figure 6). Recent related work has proposed performance measures for interaction with generative models [27, 30], namely completion rate and time, error AUC (a summary of what we plot over time in Figure 4), and self-reported difficulty. We contribute further metrics, including: number of interactions, number of switches between control dimensions and overshooting within dimensions, and starting/transition probabilities between control elements in the UI. Studies of interactive control of generative models have only recently appeared in the community and called for further explorations [27, 30, 43]. In this light, we hope these metrics provide timely methodological inspiration. To further facilitate reuse, we release the code to compute these metrics as well as our dataset as a point of comparison for future measurements.

6.4 Discovering Interpretations of the Control Dimensions

People were overall successful in completing the tasks but in the open feedback wished for explicit labeling of sliders: Here, we found demographics, appearance and image properties as the three main label categories (Section 5.10.3). This shows an interest in fine-grained control over several aspects of the image.

We conclude that visual feedback helps users to better predict which slider to adjust and how (Section 5.9). However, it is insufficient for in-depth understanding of the underlying dimensions. Using the terms of recent work on understanding of intelligent systems [9], previews mainly facilitated interaction knowledge: Users learned how to use the system effectively – without necessarily being able to explicitly explain it. Here, text labels may help yet require an interpretable model. Note how in the presence of labels previews could fill a new role: While labels would introduce the broad concept of a slider the previews would give an impression of the concrete impact. In other cases, or if labels are not available upfront (e.g. in research [12]), our results motivate a combination:
We studied a general user population here. Future studies could investigate specific groups (e.g. AI researchers). Preview images are computationally costly. We switched to a multi-GPU server after a pretest to handle this, and observed times for updating all previews of about 700 ms to 2500 ms, depending on the number of sliders. About 10% of all users commented on performance. We deem this acceptable for an online study in which we cannot control people’s internet connection and computing environment. When interpreting the results it should be taken into account that this might have influenced the comparisons of task times, perception and success. However, task times were still clearly dominated by the difficulty of tasks with more sliders, as evident from the increased number of actions (Figure 3), a trend towards slightly faster times with filmstrips (Figure 5b) and people’s feedback. Moreover, we found no significant differences between the designs in the NASA-TLX and success rates. Finally, our UI updating strategy (Section 3.4) ensured that the sliders were still usable during updates. Speed-ups might be achieved with decreasing model sizes or other optimisations. However, changing a studied model needs to be carefully considered in light of a study’s goals. The chosen dataset may also influence the image resolution required to visually discern thumbnails and thus indirectly influence the render speed of the system.

Generalisation of our results may be limited due to the dataset (faces), model (StyleGAN2), automatic extraction of dimensions (GANSpace) and UI concept (sliders). For example, distinguishing subtle changes may be easier for faces than cars, and handcrafted dimensions may be easier to interpret and control. However, we expect similar effects of the number of individually controlled dimensions and visual feedforward for other generative models with visual output. Future studies could examine such effects for other datasets (i.e. beyond faces), other media types and feedforward modalities (e.g. text, audio), and other models.

6.5 Limitations
We studied a general user population here. Future studies could investigate specific groups (e.g. AI researchers).

Preview images are computationally costly. We switched to a multi-GPU server after a pretest to handle this, and observed times for updating all previews of about 700 ms to 2500 ms, depending on the number of sliders. About 10% of all users commented on performance. We deem this acceptable for an online study in which we cannot control people’s internet connection and computing environment. When interpreting the results it should be taken into account that this might have influenced the comparisons of task times, perception and success. However, task times were still clearly dominated by the difficulty of tasks with more sliders, as evident from the increased number of actions (Figure 3), a trend towards slightly faster times with filmstrips (Figure 5b) and people’s feedback. Moreover, we found no significant differences between the designs in the NASA-TLX and success rates. Finally, our UI updating strategy (Section 3.4) ensured that the sliders were still usable during updates. Speed-ups might be achieved with decreasing model sizes or other optimisations. However, changing a studied model needs to be carefully considered in light of a study’s goals. The chosen dataset may also influence the image resolution required to visually discern thumbnails and thus indirectly influence the render speed of the system.

Generalisation of our results may be limited due to the dataset (faces), model (StyleGAN2), automatic extraction of dimensions (GANSpace) and UI concept (sliders). For example, distinguishing subtle changes may be easier for faces than cars, and handcrafted dimensions may be easier to interpret and control. However, we expect similar effects of the number of individually controlled dimensions and visual feedforward for other generative models with visual output. Future studies could examine such effects for other datasets (i.e. beyond faces), other media types and feedforward modalities (e.g. text, audio), and other models.

6.6 Broader Reflections
Generative models and their applications have been criticised for biases [39]. Our study adds the following insights: Matejka et al. [19] found that visual markers on sliders influence the result of simple value choices. We revealed a related effect for the control of generative models: Preview images change users’ strategies and therefore the outputs seen during interaction. In principle, it might thus be possible to design UI controls in a way that favours users’ exposition to certain outputs when interacting with the model. Moreover, related work shows evidence that visual slider midpoints are perceived as a conceptual center or most typical value [36]. Therefore, model output shown as previews on a slider might be implicitly presented as “normal” (center) or not (ends). Overall, our work highlights that applications of generative models need to look also beyond models to address bias: Careful design of their UI controls is also important.

For use cases with images in particular, our study also newly emphasises the influence of the input UI elements, complementing HCI literature that discusses bias in image outputs (e.g. in image search results [16]). Finally, generative models can also be used to reveal biases in other AI systems, by generating counterfactual inputs [8]: The related work here called for further human assessment of “[...] images that result from manipulating the latent space”. This in turn requires UIs such as the ones that we studied here. Together, these aspects motivate further studies at the intersection of HCI and AI on interaction with generative models.

7 CONCLUSION
We have investigated the impact of different numbers and types of sliders on users’ interaction behaviour and performance in image reconstruction tasks with a generative model. Overall, we found that exposing users to more control dimensions steeply increases the number and complexity of interactions. However, using the filmstrip slider variant mitigates the extent of this effect. These results also refine prior expectations in the literature [30] by showing that control of generative models can get very challenging even for up to ten sliders. Adding to the methodology in this context, we found that measures beyond task completion times and overall success rate are crucial to characterize the impact of different UI designs.

Our results challenge the HCI and AI research community to further investigate the UI design space for interactive generative models: While regular sliders are frequently used, there is still room for improvement. The filmstrip slider is one step in that direction. We make the collected interaction dataset and prototype publicly available to facilitate research towards the vision of empowering experts and non-experts alike to work with generative models:

https://osf.io/tze2x/

ACKNOWLEDGMENTS
We thank Christina Schneegass, Markus Klar, Pascal Knierim and Martin Zürn for their feedback on the manuscript. This project is funded by the Bavarian State Ministry of Science and the Arts and coordinated by the Bavarian Research Institute for Digital Transformation (bid).

REFERENCES
[1] Douglas Bates, Martin Mächler, Ben Bolker, and Steve Walker. 2015. Fitting Linear Mixed-Effects Models Using lme4. Journal of Statistical Software 67, 1 (2015), 1–48. https://doi.org/10.18637/jss.v067.i01
[2] David Bau, Hendrik Strobelt, William Peebles, Jonas Wulff, Bolei Zhou, Jun-Yan Zhu, and Antonio Torralba. 2019. Semantic Photo Manipulation with a Generative Image Prior. ACM Trans. Graph. 38, 4, Article 59 (July 2019), 11 pages. https://doi.org/10.1145/3306346.3302923
[3] Olivier Bau and Wendy E. Mackay. 2008. OctoPocus: A Dynamic Guide for Learning Gesture-Based Command Sets. In Proceedings of the 21st Annual ACM Symposium on User Interface Software and Technology (Monterey, CA, USA) (UIST ’08). Association for Computing Machinery, New York, NY, USA, 37–46. https://doi.org/10.1145/1449715.1449724
[4] Yoshua Bengio, Aaron Courville, and Pascal Vincent. 2013. Representation Learning: A Review and New Perspectives. IEEE Transactions on Pattern Analysis and Machine Intelligence 35, 8 (2013), 1798–1828. https://doi.org/10.1109/TPAMI.2013.50
[5] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Arvil Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Rudford, Ilya
Figure 9: Example of four different user exploration paths where users marked the task as done. The last image (red) marks the target image. The penultimate images show the final user edited images (blue). Each image represents the state after an edit. For more than 40 interactions we downsampled to 40 images for the sake of brevity of the visualization.
Figure 10: Example of two user exploration paths where users eventually indicated that they want to skip the task. The last image (red) marks the target image. The penultimate images show the final user edited images (blue). Each image represents the state after an edit. For more than 40 interactions we downsampled to 40 images for the sake of brevity of the visualization.