
Emergence of Hidden Capabilities: Exploring Learning Dynamics in Concept Space

Core Francisco Park^{*1,2}, Maya Okawa^{*2,3}, Andrew Lee^{*4}

Ekdeep Singh Lubana^{*2,4}, Hidenori Tanaka^{*2,3}

¹Department of Physics, Harvard University, Cambridge, MA, USA

²CBS-NTT Program on Physics of Intelligence, Harvard University, Cambridge, MA, USA

³Physics & Informatics Laboratories, NTT Research, Inc., Sunnyvale, CA, USA

⁴EECS Department, University of Michigan, Ann Arbor, MI, USA

Abstract

Modern generative models demonstrate impressive capabilities, likely stemming from an ability to identify and manipulate abstract concepts underlying their training data. However, fundamental questions remain: what determines the concepts a model learns, the order in which it learns them, and its ability to manipulate those concepts? To address these questions, we propose analyzing a model’s learning dynamics via a framework we call the *concept space*, where each axis represents an independent concept underlying the data generating process. By characterizing learning dynamics in this space, we identify how the speed at which a concept is learned, and hence the order of concept learning, is controlled by properties of the data we term *concept signal*. Further, we observe moments of *sudden turns* in the direction of a model’s learning dynamics in concept space. Surprisingly, these points precisely correspond to the emergence of *hidden capabilities*, i.e., where latent interventions show the model possesses the capability to manipulate a concept, but these capabilities cannot yet be elicited via naive input prompting. While our results focus on synthetically defined toy datasets, we hypothesize a general claim on *emergence of hidden capabilities* may hold: generative models possess latent capabilities that emerge suddenly and consistently during training, though a model might not exhibit these capabilities under naive input prompting.

1 Introduction

Modern generative models, such as text-conditioned diffusion models, show unprecedented capabilities [1–8]. These abilities have led to use of such models in applications as valuable as training control policies for robotics [9–11] and models for weather forecasting [12], to as drastic as campaigning in democratic elections [13, 14]. Similar claims can be made for generative models of other modalities, e.g., large language models (LLMs) [15–18], speech and audio models [14, 19], or even systems designed for enabling scientific applications such as drug discovery [20, 21]. Arguably, acquiring such general capabilities requires for models to internalize the data-generating process and disentangle the concepts (aka latent variables or factors of variation) underlying it [22, 23]. Flexibly manipulating these concepts can then enable generation of novel samples that are entirely out-of-distribution (OOD) with respect to the ones used for training [24–28].

As shown in prior work, modern generative models do exhibit signs of disentangling concepts underlying the data generating process and learning of corresponding capabilities to manipulate said

^{*}Denotes equal contribution (see [detailed list](#)). Email: corefranciscopark@g.harvard.edu, ajyl@umich.edu, {mayaokawa, ekdeepclubana, hidenori_tanaka}@fas.harvard.edu

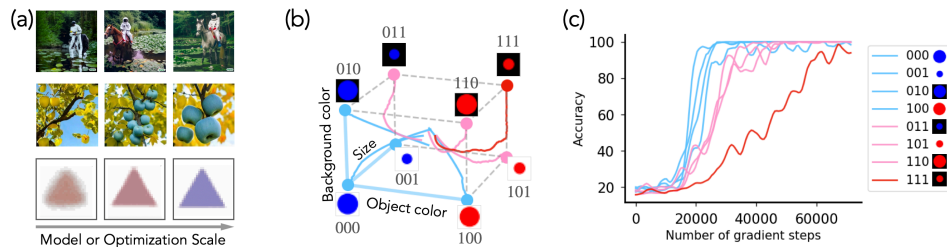


Figure 1: **Concept Learning Geometry underlies emergence.** (a) Top: A multimodal model learns to generate the concepts in the order of “astronaut”, “horse”, and finally “riding” as it scales up (adapted from Yu et al.[45]). Middle: “blue square apple” is generated in the order of “apple”, “blue”, and “square” (adapted from Li et al.[46]). Bottom: Despite its simplicity, our model trained on synthetic data shows *concept learning dynamics* where it first learns “shape” and then “color”. (b) Concept space is an abstract coordinate space where individual axes correspond to different concepts and a given point corresponds to a “concept class”, i.e., a predefined collection of concepts (e.g., large blue circles on bottom left corner). Traversal along axes of the concept space yield change in a specific property of the sample (e.g., going from large blue circle to large red circle along object color axis). Trajectories show a model’s dynamics in concept space for learning to generate classes shown in-distribution (blue nodes) versus out of distribution (pink / red nodes). As we show, dynamics in concept space are highly interpretable, enabling precise comments on which concepts the model learns first, why, and what order it follows. (c) Measuring how accurately a model generates samples from a given concept class, showing an order of concept learning: first background color is learned, then size, and then object color.

concepts [29–37]. At the same time, contemporary work has argued that models’ capabilities can be unreliable, arbitrarily failing for a given input and succeeding on another [38–44]. Thus, critical questions remain on how generative models acquire their capabilities (see Fig. 1): what determines whether the model will disentangle a concept and learn the capability to manipulate it; are all concepts and corresponding capabilities learned at the same time; and is there a structure to the order of concept learning such that, given insufficient time, the model learns capabilities to manipulate only a subset of concepts but not others?

This work. To address the questions above, we propose to analyze a model’s *learning dynamics at the granularity of concepts*. Since performing such an analysis on realistic, off-the-shelf datasets can be challenging, we develop synthetic toy datasets of 2D objects with different concepts (e.g., shape, size, color) that give us thorough control over the data-generating process and allow for an exhaustive characterization of the model’s learning dynamics (see Fig. 1). Our contributions are as follows.

- **Introducing Concept Space.** We propose to evaluate a model’s learning dynamics in the *concept space*—an abstract coordinate system whose axes correspond to specific concepts underlying the data-generating process. We instantiate a notion of underspecification in concept space and establish its effects on a model’s (in)ability to disentangle concepts.
- **Concept Signal Dictates Speed of Learning.** We find the speed at which a model disentangles a concept and learns the capability to manipulate it is dictated by the sensitivity of the data-generating process to changes in values of said concept—a quantity we call *concept signal*. We show concept signals shape the geometry of a learning trajectory and hence control the overall order of concept learning.
- **Sudden Transitions in Concept Learning.** We use analytical curves to explain the phenomenology of learning dynamics in concept space, showing the dynamics can be divided into two broad phases: **(P1)** learning of a *hidden capability*, whereby even if the model does not produce the desired output for a given input, there exist systematic latent interventions that lead the model to generate the desired output, and **(P2)** learning to generate the desired output from the input space.

Overall, while our results focus on a toy synthetic task and text-to-image diffusion models, we hypothesize a broader claim on *hidden emergence of latent capabilities* holds true: generative models possess latent capabilities that are learned suddenly and consistently during training, but these capabilities are not immediately apparent since prompting the model via the input space may not elicit them, hence hiding how “competent” the model actually is [47, 48]. Empirically, signs of “hidden capabilities” have already been shown in generative models at scale [45, 49–53], and our results help provide a formal framework to partially ground such results.

2 Related Work

Concept learning. The term concepts as used in this work is broadly equivalent to the notion of factors of variation from prior work on disentangled representation learning [23, 30, 54–61], and is motivated by use of the term in a similar sense in cognitive science [62–67]. The focus of literature on disentanglement has been to prove identifiability results, e.g., when will a generative model trained on a dataset learn to invert the data-generating process, hence identifying the latent variables, i.e., concepts, that underlie it. Given the success of modern generative models, we argue, despite impossibility results from prior work, these models are in fact learning to disentangle some, if not all, concepts. Precisely what guides which concepts are disentangled however requires studying the learning dynamics—the target of our work.

Interpretability. A growing line of papers demonstrate highly interpretable representations of intuitive concepts exist in generative models, especially LLMs [68–74]. Similar work in this vein in image diffusion models has found semantic representations in various components of the model [37, 52, 75–77]: e.g., existence of linear representations for concepts such as 3D depth or object versus background distinctions [78, 79]. These papers further bolster our argument, modern generative models are truly inverting the data-generating process and identifying the concepts underlying it.

Competence vs. performance. In cognitive science, a system’s competence on a task is often contrasted with its performance [47, 48, 80–83]: competence is the system’s *possession of a capability* (e.g., to converse in a language) and performance is system’s *use of that capability in concrete situations* [80]. For example, a bilingual person may generally converse in their primary language \mathcal{L} , despite possessing knowledge of another language \mathcal{L}' , unless it is crucial to use the latter—clearly, they are competent in both languages, but gauging their performance on \mathcal{L}' requires appropriately “prompting” them to use it. One can analogize this distinction with remarks on a neural network possessing a capability versus us being able to elicit it on predefined benchmarks and measure their performance [84–87]. For example, on the BigBench benchmark [88], LLMs were shown to have perform poorly on several tasks, but follow up work [89] showed mere chain-of-thought prompting [49, 50] leads to huge boosts on all tasks. This indicates the evaluated models were in fact “competent”, but inappropriate prompting led to undermining how “performant” they are.

3 Concept Space: A Framework for Analyzing Concept Learning Dynamics

We first formally introduce our framework of *concept spaces*. See Fig. 12 for a schematic. Motivated by a rich body of literature on disentangled representation learning [23, 30, 54–60], this framework allows us to systematically analyze how different concepts underlying the data generating process and corresponding capabilities to manipulate them are learned during training. We highlight that since our primary empirical focus in this paper will be an abstraction of text-to-image generative models, parts of the framework will be specifically instantiated with text-to-image generation tasks in mind. To this end, we note our model class of interest is a generative model F that is trained using conditioning information h to produce images y . For example, F may be instantiated using a diffusion model that uses embeddings h of textual descriptions of a scene to produce images y . We next define a *concept space*.

Definition 1. (Concept Space.) Consider an invertible data-generating process $\mathcal{G} : \mathcal{Z} \rightarrow \mathcal{X}$ that samples vectors $z \sim P(\mathcal{Z})$ from a vector space $\mathcal{Z} \subset \mathbb{R}^d$ and maps them to the observation space $\mathcal{X} \in \mathbb{R}^n$. We assume the sampling prior is factorizable, i.e., $P(z \in \mathcal{Z}) = \prod_{i=1}^d P(z_i)$, and individual dimensions of \mathcal{Z} correspond to semantically meaningful concepts. Then, a concept space \mathcal{S} is defined as the multidimensional space composed of all possible concept vectors z , i.e., $\mathcal{S} := \{z \mid z \sim P(\mathcal{Z})\}$

As an example, consider a concept space defined using three concepts, say, $z_1 = \text{shape}$, $z_2 = \text{size}$, and $z_3 = \text{color}$ that maps to a dataset of images with objects of different combinations of shapes, sizes, and colors (see Fig. 2). The assumption that concepts are independently distributed implies one can intervene on a given concept without affecting the other ones. For example, given a sample from the dataset above, the concept `color` in an image can be altered by changing the value of the relevant latent variable and mapping it to the image space via the data-generating process. Now, using a mixing function \mathcal{M} that yields conditioning information $h := \mathcal{M}(z)$, we can train a conditional generative model and define a notion of capabilities relevant to our work as follows.

Definition 2. (Capability.) A concept class \mathcal{C} denotes the set of concept vectors $z_{\mathcal{C}}$ such that a subset of dimensions of these vectors are fixed to predefined values. Classes \mathcal{C} and \mathcal{C}' are said to differ in the k^{th} concept if $\forall z \in z_{\mathcal{C}}$, there exists $z' \in z_{\mathcal{C}'}$ with $z[k] \neq z'[k]$ and $z[i] = z'[i]$ for $i \neq k$. We say a model possesses the “capability to alter the k^{th} concept” if for any class \mathcal{C} whose samples were seen during training, the model can produce samples from class \mathcal{C}' that differs from \mathcal{C} in the k^{th} concept.

Intuitively, the definition above comments on whether the model can flexibly manipulate concepts of classes seen during training to produce samples from classes that were not seen, i.e., classes that are entirely out-of-distribution. As an example, consider a concept space with shape, color, and size as concepts. If shape and color are fixed to `circle` and `blue` respectively, we get the class of `blue circles`; i.e., $\forall z \in z_{\text{blue circles}}$, the first and second dimension respectively take on values that correspond to the shape `circle` and color `blue`. Then, given a conditional diffusion model that was shown `blue circles` during training, we will say this model possesses the capability to alter the concept `color` if it can produce samples from concept classes with the same shape as `circles`, but different colors (e.g., `red` or `green circles`). Analyzing learning dynamics in the concept space will thus provide a direct lens into the model’s capabilities as they are acquired.

We also note that the definition above is not dependent on the precise manner via which the model is prompted to elicit an output, i.e., it need not be the case that the conditioning information h that is used for training the model is used to evaluate the model capability. In fact, in our experiments, we will try alternative protocols such as intervening on the latent representations to show that substantially before the model can be prompted using h to generate samples from an OOD concept class, it can generate samples from said class via such latent interventions. To this end, we also define a measure that assesses how much learning signal the data provides towards disentanglement of a concept, and hence learning of a capability to manipulate it.

Definition 3. (Concept Signal.) The concept signal σ_i for a concept z_i measures the sensitivity of the data-generating process to change in the value of a concept variable, i.e., $\sigma_i := |\partial \mathcal{G}(z) / \partial z_i|$.

Intuitively, if the training objective is factorized at the granularity of concepts, concept signal indicates how much the model would benefit from learning about a concept. For example, consider a diffusion model trained using the MSE loss with conditioning $h := z$ to predict the noise added to an image $\mathcal{G}(z)$. σ_i is then merely the component of the loss representing how much change in conditioning h yields changes in concept z_i , as it is represented in the image. Concept signal will thus serve as a crucial knob in our experiments to analyze learning dynamics in concept space and the order in which concepts are learned.

3.1 Experimental and Evaluation Setup

Before proceeding further, we discuss our experimental setup that concretely instantiates the formalization above. Our data-generating process is motivated by prior work on disentanglement [54–60] and involves concept classes defined by three concepts, each with two values: `color` = {`red`, `blue`}, `size` = {`large`, `small`}, and `shape` = {`circle`, `triangle`}. In Sec. 4.1 and Sec. 4.4, we use two attributes: `color` (with `red` labeled as 0 and `blue` as 1) and `size` (large labeled as 0 and small as 1). We generate a total of 2048 images for each class, with objects randomly positioned within each image. We train models on classes 00 (large red circles), 01 (large blue circles), and 10 (small red circles), shown as blue nodes in Fig. 2, and test using class 11 (small blue circles), shown as pink nodes, to evaluate a model’s ability to manipulate concepts and generalize OOD (see App. B.1 for further details). In Sec. 5, we will restrict to two attributes, `shape` = {`circle`, `triangle`} and `color` = {`red`, `blue`}, and study the effect of noisy conditioning, i.e., what happens when concepts are correlated in the conditioning information h due to some non-linear mixing

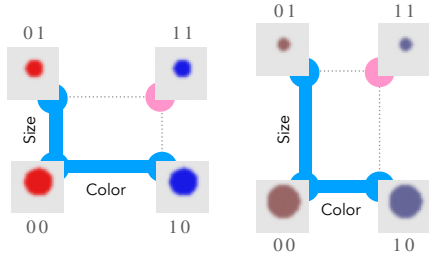


Figure 2: Concept spaces with different concept values see different concept signal. Consider a concept space comprised of concepts `size` and `color`. (Left) The color separation between the classes is stronger than the size separation, resulting in a stronger concept signal in the color dimension. (right) The size separation between the classes is stronger, thus resulting in a stronger signal for size.

function. For all experiments, we use a variational diffusion model [90] to generate $3 \times 32 \times 32$ images conditioned on vectors h (see App. B.2 for further training details).

Evaluation Metric. To assess whether a generated image matches the desired concept class without human intervention, we follow literature on disentangled representation learning [23, 30, 54, 55, 91–94] and train classifier probes for individual concepts using the diffusion model’s training data. The probe architecture involves a U-Net [95] followed by an average pooling layer and n MLP classification heads for the n concept variables. See App. B.2 for further details.

4 Learning Dynamics in Concept Space

4.1 Concept Signal Determines Learning Speed

We first demonstrate the utility of concept signal as a tool to gauge at what rate the model learns a concept and the capability to manipulate it. To this end, we develop controlled variants of our data-generating process by changing the level of concept signal of each concept and train diffusion models conditioned with the latent concept vector z on them. We primarily focus on concepts `color` and `size`, altering their concept signal by respectively adjusting the RGB contrast between red and blue and the size difference between large and small objects (see App. B.1 for details). We define the speed of learning each concept as inverse of the number of gradient steps required to reach 80% accuracy for class 11, i.e., the OOD class that requires learning the capability to manipulate concepts as seen during training. Results comparing different concept signals are shown in Fig. 3. For both `color` and `size`, we observe that *concept signal dictates the speed at which individual concepts are learned*. We also find that when different concepts have varying strengths of concept signals, this leads to differences in the learning speed for each concept.

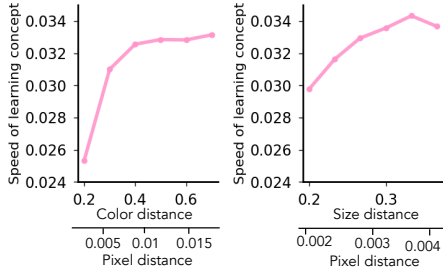


Figure 3: Concept signal determines learning speed. The speed of concept learning as an inverse of the time in gradient steps when the separation in color (left) and size (right) between different classes increases. Concept learning is faster when pixel differences among concept class and hence concepts are larger.

4.2 Concept Signal Governs Generalization Dynamics

We next examine the model’s learning dynamics in concept space under various levels of concept signal for the concepts `color` and `size`. For completeness, we evaluate a model’s ability to generalize

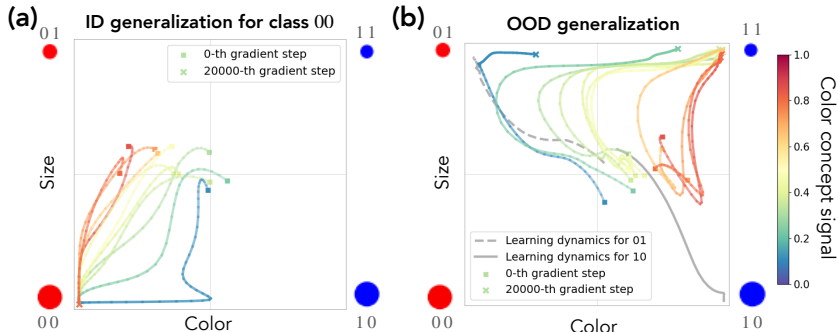


Figure 4: Concept signal governs generalization dynamics. (a) Learning dynamics in the concept space for in-distribution concept class 00 (bottom left). (b) Learning dynamics for out-of-distribution (OOD) concept class 11 (top right). We plot the accuracy for `color` on the x-axis and `size` on the y-axis. The $[0,1]$ normalized `color` concept signal level is color coded. Two trajectories for 01 and 10 are shown to illustrate *concept memorization*. See App. D.3 for uncertainties.

both in-distribution (ID) and OOD, but only the latter is deemed learning of a capability to manipulate a concept. Results are shown in Fig. 4, with panel (a) showing dynamics for learning to generate samples from ID class 00 and panel (b) showing dynamics for OOD class 11. Results on OOD generalization show *concept memorization*, which we define as the phenomenon where *the model’s generations on an OOD conditioning h are biased towards the training class that helps define the strongest concept signal*. For example, for the unseen conditioning 11, the generations are more alike 01 when the concept signal is stronger for size (e.g., blue curve in Fig. 4(b)) and alike 10 when the signal is stronger for color (e.g., red curve). Interestingly, we observe that for settings with high imbalance in concept signals, e.g., the blue curve in Fig. 4 (b), the endpoint of *concept memorization* is very biased towards one training class, here 01, delaying its out-of-distribution (OOD) generalization. For the learning trajectories of all classes, see Fig. 15 in App. D.2.

Broadly, our results imply that an early stopped text-to-image model can witness *concept memorization* and hence simply associate an unseen conditioning to the nearest concept class when asked to generate OOD samples (see Kang et al. [96] for a similar result in LLMs). However, given sufficient time, the model will disentangle concepts underlying the data-generating process and learn to generate entirely novel, OOD samples. For further evidence in this vein, we also confirm our results across more general scenarios, including with the real-world CelebA dataset (App. D.4) and using three concept variables: color, background color, and size (App. D.5).

4.3 Towards a Landscape Theory of Learning Dynamics

Fig. 4 indicates models undergo phases of understanding of concepts at different stages of training. In fact, an intriguing property of trajectories shown in Fig. 4 (b) is that there is a sudden turn in the learning dynamics from *concept memorization* to *OOD generalization* (e.g., see the top-left quadrant in Fig. 4 (b)). To investigate this further, we propose a minimal toy model that captures the geometry of model’s learning trajectories shown in that figure. Specifically, we use the following dynamics equation, $d(t) := \tilde{z} + (\hat{z} - \tilde{z}) \cdot \frac{1}{1+e^{-(t-\hat{t})}}$, where \hat{z} is the target point we want to get to and \tilde{z} is the initial, “biased” target. For example, consider the case with color and size concepts in Fig. 4 (b). The model’s generated samples are more alike class 01 and biased towards $(\tilde{z}_1, \tilde{z}_2) = (0, 1)$ when the size concept signal σ_2 is stronger than σ_1 ; and to 10, $(\tilde{z}_1, \tilde{z}_2) = (1, 0)$ when the color concept signal σ_1 is stronger than σ_2 . We define (\hat{z}_1, \hat{z}_2) as the target values or directions we want the learning to head towards (e.g., $(1, 1)$ for OOD generalization). Based on this framework, we can derive the following energy function.

$$\frac{dz}{dt} = -\nabla_{\mathbf{z}} L, \quad L(z_1, z_2) = \begin{cases} \frac{1}{2a} (d(t - \hat{t}_1) - z_1)^2 + \frac{a}{2} (1 - z_2)^2 & \text{if } \sigma_1 > \sigma_2, \\ \frac{1}{2a} (1 - z_1)^2 + \frac{a}{2} (d(t - \hat{t}_2) - z_2)^2 & \text{otherwise.} \end{cases} \quad (1)$$

Here, a is determined by the difference $|\sigma_1 - \sigma_2|$ and \hat{t}_1 and \hat{t}_2 denote the times when the model learns concepts z_1 and z_2 , respectively. Fig. 5 illustrates the simulated trajectories for classes 00 and 11, based on Eq. 1. Panels (a) and (b) correspond to classes 00 and 11, respectively. We define the actual target points (\hat{z}_1, \hat{z}_2) as $(0, 0)$ for class 00 and $(1, 1)$ for class 11. For the initial targets $(\tilde{z}_1, \tilde{z}_2)$, we set both values to $(0, 0)$ for class 00. For class 11, the targets are set to $(1, 0)$ when $\sigma_1 > \sigma_2$ and to $(0, 1)$ when $\sigma_1 < \sigma_2$. We find our toy model effectively captures the actual learning dynamics for both in-distribution (Fig. 3(b)) and out-of-distribution (OOD) concept classes (Fig. 3(c)). Notably, our simulation accurately replicates the two types of curves: clockwise (blue trajectory in Fig. 3(b)) and counterclockwise (red trajectory).

An important conclusion that follows from the results above is that the network’s learning dynamics can be precisely decomposed into two stages, hence yielding the sudden turns seen in trajectories in

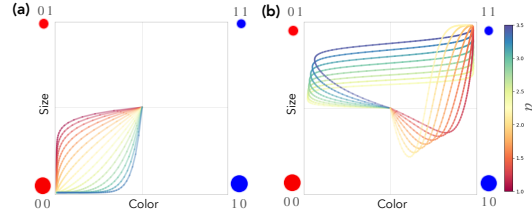


Figure 5: **A Phenomenological Model of Learning Dynamics in Concept Space.** Using Eq. 1, we simulate the learning trajectory for concept class 00 in panel (a) and the OOD class 11 in panel (b). Initially, target values are set at $(0, 1)$ or $(1, 0)$ based on the concept signal strengths for color or size, respectively. As the model progressively learns each concept, the target values gradually shift towards $(1, 1)$. This simple toy model accurately reproduces the observed curves in Fig. 3(c), which arise from *concept memorization*.

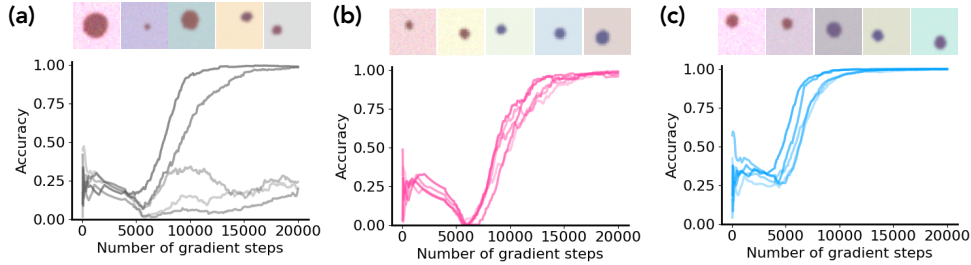


Figure 6: **Emergence of hidden capabilities.** We plot accuracy as a function of gradient steps for five different runs, using three different protocols for prompting the model to generate outputs for OOD concept classes. (a) The baseline, naive prompting protocol; (b) linear latent intervention, applied in the activation space; and (c) overprompting, akin to an intervention on the input space.

Fig. 4. We hypothesize there is a phase change underlying this decomposition and the model acquires the capability to alter concepts at this point of phase change. We investigate this next.

4.4 Sudden Transitions in Concept Learning Dynamics

The concept space visualization of learning dynamics observed in Fig. 4 (b) and our toy models analysis in Fig. 5 indicate that there exists a phase in which the model departs from concept memorization and disentangles each of the concepts, but still produces incorrect images. We claim that at the point of departure, the model has in fact already disentangled concepts underlying the data-generating process and acquired the relevant capabilities to manipulate them, hence yielding a change of direction in its learning trajectory. However, naive input prompting is insufficient to elicit these capabilities and generate samples from OOD classes, giving the impression the model is not yet “competent”. This then leads to the second phase in the learning dynamics, wherein an alignment between the input space and underlying concept representations is learned. We take the model corresponding to the second from left curve (the green curve) in Fig. 4 (b) to investigate this claim in detail. Specifically, given intermittent checkpoints along the model’s learning trajectory, we use the following two protocols for prompting the model to produce images corresponding to the class 11 (blue, small). See App. C for further details.

1. **Activation Space: Linear Latent Intervention.** Given conditioning vectors h , during inference we add or subtract components that correspond to specific concepts (e.g., h_{blue}).
2. **Input Space: Overprompting.** We simply enhance the color conditioning to values of higher magnitude, e.g. $(r, g, b) = (0.4, 0.4, 0.6)$ to $(0.3, 0.3, 0.7)$.

Fig. 6 shows the accuracy for five independent runs under: (a) naive input prompting, (b) linear latent interventions, and (c) overprompting. In Fig. 6 (a), we observe that some runs can produce samples from the target concept class (blue, small) with $\sim 100\%$ accuracy after around 8,000 gradient steps, while other runs fail to do so. However, in Fig. 6 (b, c), we find alternative protocols for prompting the model can *consistently* elicit the desired outputs much earlier than input prompting, e.g., at around as early as 6,000 gradient steps. *This indicates the model does possess the capability to alter concepts and generalize OOD!* Furthermore, we note that different protocols enable elicitation of the capability at approximately the same number of gradient steps, irrespective of the seed, and that this is precisely the point of sudden turn in the learning dynamics in Fig. 4! Interestingly, experiments with Classifier Free Guidance (CFG) [97] show that CFG only becomes effective after this transition (Fig. 21).

We further explore the second phase of learning in Appendix D.7 by patching the embedding module used for processing the conditioning information from the final checkpoint to an intermediate one. Our results show that when the final checkpoint does enable use of naive input prompting for eliciting a capability, the embedding module can be patched to an intermediate checkpoint and we can retrieve the desired output at approximately the same time that alternative prompting protocols start to work well. This suggests the second phase of learning primarily involves aligning the input space to intermediate representations that enable eliciting the model capabilities. Overall, our results above yield the following hypothesis.

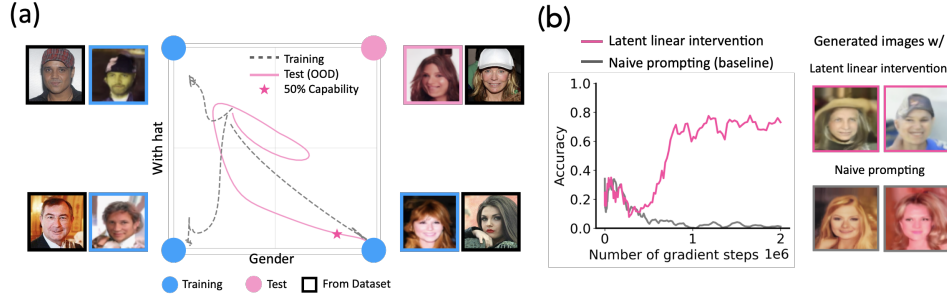


Figure 7: **Validating our Findings on CelebA.** (a) Concept space dynamics of generated images concepts Gender and With Hat. We find the generalization class (Female, With Hat) ends up near (Female, No Hat). (b) Compositional Generalization Accuracy when performing latent interventions vs. naive prompting. This rise of accuracy near 5×10^5 gradient steps clearly demonstrates that the model is *capable* of generalizing out-of-distribution, but is not *performant* when evaluated via naive prompting.

Hypothesis 1. (Emergence of Hidden Capabilities.) *Generative models possess hidden capabilities that are learned suddenly and consistently during training, but naive input prompting may not elicit these capabilities, hence hiding how “competent” the model actually is.*

4.5 Additional Results on Realistic Data

To provide further support for our hypothesis, we provide results in a more realistic and naturalistic data. Specifically, we use the CelebA dataset [98], which contains fine-grained attributes corresponding to concepts like Gender, With Hat, and Smiling, and analyze two settings.

- **Using concepts Gender and Smiling.** Results are in Fig. 18, where we find that concept learning dynamics discovered in the relatively simple setting in prior sections generalizes. We see that there is first a phase of concept memorization, wherein the model learns to generate images of (Female, Smiling). However, as training proceeds, there is a sudden turn in the learning dynamics and the model learns to generalize out-of-distribution.
- **Using concepts Gender and With Hat.** In this setting, given a compute budget of 2M gradient steps, we find that the model seem to never learn to generalize out-of-distribution (see Fig. 7). However, when we perform latent interventions on the model’s representations, we are able to force the model to produce images from the class (Female, With Hat). These results reiterate that the model is indeed *capable* of generalizing out-of-distribution, but is not *performant* when naively prompted.

5 Effect of Underspecification on Learning Dynamics in Concept Space

In the results above, we use conditioning information that perfectly specifies concepts underlying the data-generating process, i.e., $h = z$. In practice, however, instructions are underspecified and one can thus expect correlations between concepts in the conditioning information extracted from those instructions [99–103]. For example, images of a strawberry are often correlated with the color red (see Fig. 9(a)). Correspondingly, unless a text-to-image model is shown explicit data stating “red strawberry” or images of non-red strawberries, the model’s ability to disentangle the concept color from the concept strawberry may be impeded (see generations for “yellow strawberry” in Fig. 9). Motivated by this, we next investigate the effects of using underspecified conditioning information on a model’s ability to learn concepts and capabilities to manipulate them.

Experimental setup. The data generation and evaluation process follows the protocol described in Sec. 3.1. We select

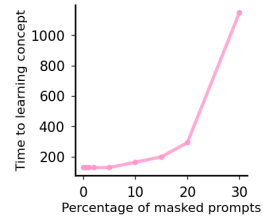


Figure 8: **Underspecification delays out-of-distribution (OOD) generalization.** The number of gradient steps required to reach accuracy above 0.8, as the percentage of masked prompts increases. A higher proportion of masked prompts slows down the speed of concept learning.

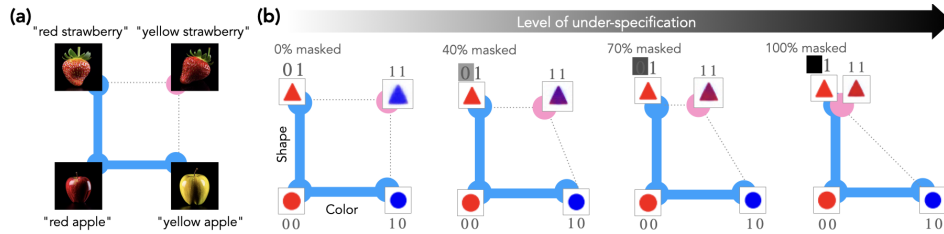


Figure 9: **Underspecification and Concept Learning.** (a) The state-of-the-art generative models [104] erroneously produces a red strawberry (top right corner) for the prompt “yellow strawberry”. (b) Without underspecification in the training data, a model F accurately learns the concepts of shape and color, successfully generalizes to the unseen node blue triangle (leftmost). As masks are applied to the prompt red triangle, concept signal for triangle increasingly starts to correlate with the concept red. This causes the output images to change from blue to purple as the level of masking increases (panels left to right). Eventually, the color dimension for triangle collapses, biasing the model towards generating solely red triangles (rightmost).

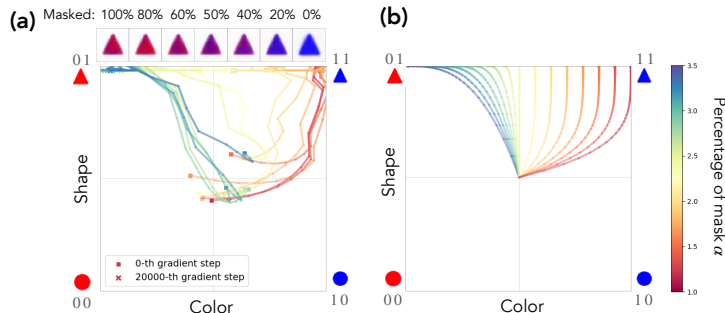


Figure 10: **Underspecification hinders out-of-distribution (OOD) generalization.** (a) The learning dynamics with varying levels of prompt masking, from 0% to 100%, and the generated images. At 0% masking (top right image), the model correctly produces an image of blue triangle from the prompt “blue triangle.” As the masking increases (from right to left), the images gradually shift towards the incorrect color, red. (b) The simulation of the learning dynamics under underspecification in concept space based on Eq. 2. Our toy model replicates a trained network’s learning dynamics.

color (red and blue) and shape (circle and triangle) as the concepts, drawing an analogy to the “yellow strawberry” example. To simulate underspecification, we randomly select training samples that have a specific combination of shape and color (e.g., “red triangle”). We then mask the token representing the color (“red”) and train the model on three concept classes $\{00, 01, 10\}$, represented by blue nodes in Fig. 9, with some prompts masked. We test using class 11 (pink node) with no prompts masked to see if the model can generalize OOD.

Underspecification Delays and Hinders OOD generalization. Fig. 8 shows how underspecification (masked prompts) affects the speed of concept learning. We see that as the percentage of masked prompts increases, the speed of learning a concept decreases, suggesting that underspecification leads to slower learning of concepts. Further, Fig. 10 (a) shows models’ learning dynamics in concept space at varying levels of underspecification. With 0% masking, the model accurately produces an image of blue triangle (see Fig. 9(b)). However, as the percentage of masking increases, the color of generated images shifts from blue to purple (middle), and finally red. This demonstrates that when prompts are masked, the model’s understanding of shape triangle becomes intertwined with color red; even when blue is specified in the prompt, the dynamics are biased towards red.

Toy Model of Learning Dynamics with Underspecification. When prompts are masked (i.e., underspecification occurs), target values for the concept variables are shifted: e.g., in our setup, with no mask applied, the target directions for the class 11 is $(1, 1)$. When the word “red” in “red triangle” is fully masked, the target shifts to $(0, 1)$. Assuming this shift is linear with respect to the percentage of masked prompts α , we can derive the following energy function.

$$\frac{dz}{dt} = -\nabla_{\mathbf{z}} L, \quad L(z_1, z_2) = ((1 - s\alpha) - z_1)^2 + (1 - z_2)^2. \quad (2)$$

In the above, parameter s represents the impact of underspecification. Fig. 10 (b) shows the simulation of model behavior in the concept space according to Eq. 2 ($s = 0.01$). As the masking level increases, the target directions shift from $z_2 = 1$ in the top right corner to $z_2 = 0$ in the top left corner. Our simulated dynamics thus match well with the model’s learning dynamics shown in Fig. 10 (a).

Influence of Underspecification on Emergence of Hidden Capabilities. Following Sec. 4.4, we also explore whether it is possible to elicit the desired outputs from a model trained with underspecified data. Fig. 11 shows the accuracy results over five runs (a) without using any prompting method, and (b) using over-prompting. In both scenarios, the percentage of masking is set at 50%. Results clearly demonstrate that with over-prompting, the model achieves 100% accuracy after approximately 1,000 gradient steps, whereas without over-prompting, it fails in three out of five runs even after 2,000 gradient steps. These findings confirm that capability can develop prior to observable behavior, even in cases of underspecification.

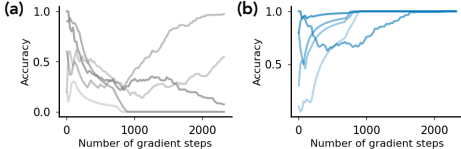


Figure 11: Underspecification and Hidden Capabilities. We use the over-prompting protocol from Sec. 4.4 to assess if the capabilities to enable OOD generalization are learned before naive input prompting. (a) Accuracy for OOD generalization across five different seed runs under naive prompting; (b) Accuracy under over-prompting, with a fixed masking percentage of 50%.

6 Discussion

Why study the concept space? One might ask why concept space could be useful beyond synthetic datasets. In Fig. 14, we show the loss, accuracy, and training trajectory in concept space of a model from Fig. 6. The moment during training when the model acquires the capability to manipulate `size` and `color` independently is not evident from either the loss or accuracy curve. However, in concept space, one can directly see the divergence of the trajectory from *concept memorization*. Benchmarking generative models is a challenging task, still often involving humans in the loop [105, 106]. Our concept space framework suggests that benchmarking core generalization capabilities can potentially be reduced to monitoring the learning trajectory in concept space. Moreover, this information can be used to develop better training schemes as discussed in Ren et al. [107].

Concept learning vs. grokking We make a distinction between the potentially delayed elicitation of capabilities in our model versus grokking [108]. The phenomenology of delayed increase in performance on the test set, as seen in Fig. 14, is shared. However, we deal with out-of-distribution evaluations, which is different from setups like modular arithmetic or polynomial regression in which grokking is usually studied [108–112]. Secondly, research on grokking using hidden progress measures indicates that the model gradually builds representations toward an ideal one [111, 113]; however, our results find that even at the level of latent representations, there is a sudden emergence whereby the model learns the capability to manipulate concepts underlying the data-generating process and generalize OOD.

Is concept learning a phase transition? In Sec. 4.4, we have demonstrated that before the capability to manipulate a concept is learned, the desired outputs cannot be generated regardless of the protocol used to prompt the model. Moreover, we showed that different protocols yield the desired outputs at the exact same time, which is also highly independent of model initialization (Fig. 6, Fig. 17). We thus hypothesize that: *Concept learning is a well-controlled phase transition in model capability. However, the ability to elicit this capability through predefined, single-input prompting can be delayed arbitrarily, depending on factors like the strength of the concept signal.*

Limitations One limitation of our work is that the compositional setup used in this study is rather simple. Real world concepts are often hierarchical [114, 115] or relational [116]. We also make assumptions that concepts are linearly embedded in the vector space \mathcal{Z} in Sec. 3. However, this assumption seems to be at least partially justified as seen in Sec. D.8. Another limitation is that the findings are mainly drawn from synthetic data. While we show that our findings generalize to realistic data to some extent, as seen in Sec 4.5, Fig. 18 and Fig. 7, further studies are needed to investigate how our findings apply to real data in general.

Acknowledgments and Disclosure of Funding

CFP and HT gratefully acknowledges the support of Aravinthan D.T. Samuel. CFP, MO, ESL and HT are supported by NTT Research under the CBS-NTT Physics of Intelligence program. ESL’s time at University of Michigan was partially supported by the National Science Foundation (IIS-2008151 and CNS-2211509). The computations in this paper were run on the FASRC cluster supported by the FAS Division of Science Research Computing Group at Harvard University. The authors thanks Zechen Zhang, Helena Casademunt, Carolina Cuesta-Lazaro, Shivam Raval, Yongyi Yang and Itamar Pres for useful discussions.

Contributions

Motivated by prior work from MO, ESL and HT [30], CFP and HT started investigating the order in which concepts are learned first by a diffusion model, leading to CFP identifying the notion of concept signal. This kickstarted the project. ESL and HT defined the formal setup (Sec. 3). ESL hypothesized the point of sudden turn marks the emergence of hidden abilities, hence defining the project narrative around competence versus performance. AL, CFP, and ESL led the hidden emergence section (Sec. 4.4), with AL contributing the latent and MLP intervention and CFP contributing the input space one. MO and HT collaborated on the landscape theory (Sec. 4.3), with inputs from CFP. MO and ESL collaborated on the underspecification picture of learning dynamics, with inputs from HT (Sec. 5). Paper writing and literature review were led by ESL, with several inputs from all authors. Visualizations were led by MO and HT, with several inputs from CFP. Experiments on CelebA learning dynamics were led by CFP and MO, and corresponding latent intervention were led by AL.

References

- [1] Bahjat Kawar, Shiran Zada, Oran Lang, Omer Tov, Huiwen Chang, Tali Dekel, Inbar Mosseri, and Michal Irani. Imagic: Text-based real image editing with diffusion models. *arXiv preprint arXiv:2210.09276*, 2022.
- [2] Tim Brooks, Bill Peebles, Connor Holmes, Will DePue, Yufei Guo, Li Jing, David Schnurr, Joe Taylor, Troy Luhman, Eric Luhman, Clarence Ng, Ricky Wang, and Aditya Ramesh. Video generation models as world simulators. 2024. URL <https://openai.com/research/video-generation-models-as-world-simulators>.
- [3] Dan Kondratyuk, Lijun Yu, Xiuye Gu, José Lezama, Jonathan Huang, Rachel Hornung, Hartwig Adam, Hassan Akbari, Yair Alon, Vighnesh Birodkar, et al. Videopoet: A large language model for zero-shot video generation. *arXiv preprint arXiv:2312.14125*, 2023.
- [4] Jonathan Ho, William Chan, Chitwan Saharia, Jay Whang, Ruiqi Gao, Alexey Gritsenko, Diederik P Kingma, Ben Poole, Mohammad Norouzi, David J Fleet, et al. Imagen video: High definition video generation with diffusion models. *arXiv preprint arXiv:2210.02303*, 2022.
- [5] Chitwan Saharia, Jonathan Ho, William Chan, Tim Salimans, David J Fleet, and Mohammad Norouzi. Image super-resolution via iterative refinement. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2022.
- [6] Ben Poole, Ajay Jain, Jonathan T Barron, and Ben Mildenhall. Dreamfusion: Text-to-3d using 2d diffusion. *arXiv preprint arXiv:2209.14988*, 2022.
- [7] Ruiqi Gao, Aleksander Holynski, Philipp Henzler, Arthur Brussee, Ricardo Martin-Brualla, Pratul Srinivasan, Jonathan T Barron, and Ben Poole. Cat3d: Create anything in 3d with multi-view diffusion models. *arXiv preprint arXiv:2405.10314*, 2024.
- [8] Ziyang Chen, Daniel Geng, and Andrew Owens. Images that sound: Composing images and sounds on a single canvas. *arXiv preprint arXiv:2405.12221*, 2024.
- [9] Yilun Du, Mengjiao Yang, Bo Dai, Hanjun Dai, Ofir Nachum, Joshua B Tenenbaum, Dale Schuurmans, and Pieter Abbeel. Learning universal policies via text-guided video generation. *arXiv e-prints*, pages arXiv–2302, 2023.

- [10] Yilun Du, Mengjiao Yang, Pete Florence, Fei Xia, Ayzaan Wahid, Brian Ichter, Pierre Sermanet, Tianhe Yu, Pieter Abbeel, Joshua B Tenenbaum, et al. Video language planning. *arXiv preprint arXiv:2310.10625*, 2023.
- [11] Jake Bruce, Michael Dennis, Ashley Edwards, Jack Parker-Holder, Yuge Shi, Edward Hughes, Matthew Lai, Aditi Mavalankar, Richie Steigerwald, Chris Apps, et al. Genie: Generative interactive environments. *arXiv preprint arXiv:2402.15391*, 2024.
- [12] Samar Khanna, Patrick Liu, Linqi Zhou, Chenlin Meng, Robin Rombach, Marshall Burke, David Lobell, and Stefano Ermon. Diffusionsat: A generative foundation model for satellite imagery. *arXiv preprint arXiv:2312.03606*, 2023.
- [13] Yan Zhuang (New York Times). *Imran Khan’s ‘Victory Speech’ From Jail Shows A.I.’s Peril and Promise*, 2024. <https://www.nytimes.com/2024/02/11/world/asia/imran-khan-artificial-intelligence-pakistan.html>.
- [14] Mark Sullivan (FastCompany). *AI deepfakes get very real as 2024 election season begins*, 2024. <https://www.fastcompany.com/91020077/ai-deepfakes-taylor-swift-joe-biden-2024-election>.
- [15] Sébastien Bubeck, Varun Chandrasekaran, Ronen Eldan, Johannes Gehrke, Eric Horvitz, Ece Kamar, Peter Lee, Yin Tat Lee, Yuanzhi Li, Scott Lundberg, et al. Sparks of artificial general intelligence: Early experiments with gpt-4. *arXiv preprint arXiv:2303.12712*, 2023.
- [16] Gemini Team. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context. Technical report, Google DeepMind, 2024. https://storage.googleapis.com/deepmind-media/gemini/gemini_v1_5_report.pdf.
- [17] OpenAI. GPT-4 System Card. Technical report, OpenAI, 2023. <https://cdn.openai.com/papers/gpt-4-system-card.pdf>.
- [18] Claude team. Introducing the next generation of Claude. Technical report, Anthropic AI, 2024. <https://www.anthropic.com/news/claude-3-family>.
- [19] Generative Media Team (Google Deepmind). *Generating audio for video*, 2024. <https://deepmind.google/discover/blog/generating-audio-for-video/>.
- [20] Shengchao Liu, Yanjing Li, Zhuoxinran Li, Anthony Gitter, Yutao Zhu, Jiarui Lu, Zhao Xu, Weili Nie, Arvind Ramanathan, Chaowei Xiao, et al. A text-guided protein design framework. *arXiv preprint arXiv:2302.04611*, 2023.
- [21] MIT News. *Speeding up drug discovery with diffusion generative models*, 2024. <https://news.mit.edu/2023/speeding-drug-discovery-with-diffusion-generative-models-diffdock-0331>.
- [22] Yoshua Bengio, Aaron Courville, and Pascal Vincent. Representation learning: A review and new perspectives. *IEEE transactions on pattern analysis and machine intelligence*, 35(8): 1798–1828, 2013.
- [23] Francesco Locatello, Stefan Bauer, Mario Lucic, Gunnar Raetsch, Sylvain Gelly, Bernhard Schölkopf, and Olivier Bachem. Challenging common assumptions in the unsupervised learning of disentangled representations. In *Proc. int. conf. on machine learning (ICML)*, 2019.
- [24] Jivat Neet Kaur, Emre Kiciman, and Amit Sharma. Modeling the data-generating process is necessary for out-of-distribution generalization. *arXiv preprint. arXiv:2206.07837*, 2022.
- [25] Liwei Jiang, Jena D Hwang, Chandra Bhagavatula, Ronan Le Bras, Jenny Liang, Jesse Dodge, Keisuke Sakaguchi, Maxwell Forbes, Jon Borchardt, Saadia Gabriel, et al. Can machines learn morality? the delphi experiment. *arXiv e-prints*, pages arXiv–2110, 2021.
- [26] Bernhard Schölkopf, Francesco Locatello, Stefan Bauer, Nan Rosemary Ke, Nal Kalchbrenner, Anirudh Goyal, and Yoshua Bengio. Towards causal representation learning. *arXiv preprint. arXiv:2102.11107*, 2021.

- [27] Jonas Peters, Dominik Janzing, and Bernhard Schölkopf. *Elements of causal inference: foundations and learning algorithms*. The MIT Press, 2017.
- [28] Jean Kaddour, Aengus Lynch, Qi Liu, Matt J Kusner, and Ricardo Silva. Causal machine learning: A survey and open problems. *arXiv preprint arXiv:2206.15475*, 2022.
- [29] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. Hierarchical text-conditional image generation with clip latents. *arXiv preprint arXiv:2204.06125*, 2022.
- [30] Maya Okawa, Ekdeep Singh Lubana, Robert P. Dick, and Hidenori Tanaka. Compositional abilities emerge multiplicatively: Exploring diffusion models on a synthetic task, 2024.
- [31] Hu Yu, Hao Luo, Fan Wang, and Feng Zhao. Uncovering the text embedding in text-to-image diffusion models. *arXiv preprint arXiv:2404.01154*, 2024.
- [32] Lingjing Kong, Guangyi Chen, Biwei Huang, Eric P Xing, Yuejie Chi, and Kun Zhang. Learning discrete concepts in latent hierarchical models. *arXiv preprint arXiv:2406.00519*, 2024.
- [33] Qiucheng Wu, Yujian Liu, Handong Zhao, Ajinkya Kale, Trung Bui, Tong Yu, Zhe Lin, Yang Zhang, and Shiyu Chang. Uncovering the disentanglement capability in text-to-image diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1900–1910, 2023.
- [34] Rohit Gandikota, Joanna Materzynska, Tingrui Zhou, Antonio Torralba, and David Bau. Concept sliders: Lora adaptors for precise control in diffusion models. *arXiv preprint arXiv:2311.12092*, 2023.
- [35] Nan Liu, Yilun Du, Shuang Li, Joshua B Tenenbaum, and Antonio Torralba. Unsupervised compositional concepts discovery with text-to-image generative models. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2085–2095, 2023.
- [36] Michel Besserve, Arash Mehrjou, Rémy Sun, and Bernhard Schölkopf. Counterfactuals uncover the modular structure of deep generative models. *arXiv preprint. arXiv:1812.03253*, 2018.
- [37] Zihao Wang, Lin Gui, Jeffrey Negrea, and Victor Veitch. Concept algebra for (score-based) text-controlled generative models. *Advances in Neural Information Processing Systems*, 36, 2024.
- [38] Vishaal Udandarao, Ameya Prabhu, Adhiraj Ghosh, Yash Sharma, Philip HS Torr, Adel Bibi, Samuel Albanie, and Matthias Bethge. No "zero-shot" without exponential data: Pretraining concept frequency determines multimodal model performance. *arXiv preprint arXiv:2404.04125*, 2024.
- [39] Colin Conwell and Tomer Ullman. Testing relational understanding in text-guided image generation. *arXiv preprint arXiv:2208.00005*, 2022.
- [40] Colin Conwell and Tomer Ullman. A comprehensive benchmark of human-like relational reasoning for text-to-image foundation models. In *ICLR 2023 Workshop on Mathematical and Empirical Understanding of Foundation Models*, 2023.
- [41] Evelina Leivada, Elliot Murphy, and Gary Marcus. Dall-e 2 fails to reliably capture common syntactic processes. *arXiv preprint arXiv:2210.12889*, 2022.
- [42] Tejas Gokhale, Hamid Palangi, Besmira Nushi, Vibhav Vineet, Eric Horvitz, Ece Kamar, Chitta Baral, and Yezhou Yang. Benchmarking spatial relationships in text-to-image generation. *arXiv preprint arXiv:2212.10015*, 2022.
- [43] Gautam Singh, Fei Deng, and Sungjin Ahn. Illiterate dall-e learns to compose. *arXiv preprint arXiv:2110.11405*, 2021.
- [44] Royi Rassin, Shauli Ravfogel, and Yoav Goldberg. Dalle-2 is seeing double: flaws in word-to-concept mapping in text2image models. *arXiv preprint arXiv:2210.10606*, 2022.

- [45] Jiahui Yu, Yuanzhong Xu, Jing Yu Koh, Thang Luong, Gunjan Baid, Zirui Wang, Vijay Vasudevan, Alexander Ku, Yinfei Yang, Burcu Karagol Ayan, et al. Scaling autoregressive models for content-rich text-to-image generation. *arXiv preprint arXiv:2206.10789*, 2022.
- [46] Hao Li, Yang Zou, Ying Wang, Orchid Majumder, Yusheng Xie, R Manmatha, Ashwin Swaminathan, Zhuowen Tu, Stefano Ermon, and Stefano Soatto. On the scalability of diffusion-based text-to-image generation. *arXiv preprint arXiv:2404.02883*, 2024.
- [47] Raphaël Millièvre and Cameron Buckner. A philosophical introduction to language models – part i: Continuity with classic debates, 2024.
- [48] Raphaël Millièvre and Cameron Buckner. A philosophical introduction to language models-part ii: The way forward. *arXiv preprint arXiv:2405.03207*, 2024.
- [49] Takeshi Kojima, Shixiang (Shane) Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. Large language models are zero-shot reasoners. In *Advances in Neural Information Processing Systems*, volume 35, 2022.
- [50] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Ed Chi, Quoc Le, and Denny Zhou. Chain of thought prompting elicits reasoning in large language models. *arXiv preprint arXiv:2201.11903*, 2022.
- [51] Evan Hubinger, Carson Denison, Jesse Mu, Mike Lambert, Meg Tong, Monte MacDiarmid, Tamera Lanham, Daniel M Ziegler, Tim Maxwell, Newton Cheng, et al. Sleeper agents: Training deceptive llms that persist through safety training. *arXiv preprint arXiv:2401.05566*, 2024.
- [52] Mingi Kwon, Jaeseok Jeong, and Youngjung Uh. Diffusion models already have a semantic latent space. In *The Eleventh International Conference on Learning Representations*, 2023. URL <https://openreview.net/forum?id=pd1P2eUBVfq>.
- [53] Sébastien Bubeck. Sparks of artificial general intelligence: Early experiments with GPT-4 (Talk), 2023. URL <https://www.youtube.com/watch?v=qBIk7-JPB2c>.
- [54] Hyunjik Kim and Andriy Mnih. Disentangling by factorising. In *International Conference on Machine Learning*, pages 2649–2658. PMLR, 2018.
- [55] Sjoerd Van Steenkiste, Francesco Locatello, Jürgen Schmidhuber, and Olivier Bachem. Are disentangled representations helpful for abstract visual reasoning? *Adv. in Neural Information Processing Systems (NeurIPS)*, 2019.
- [56] Aapo Hyvarinen and Hiroshi Morioka. Nonlinear ICA of temporally dependent stationary sources. In *Proc. Int. Conf. on Artificial Intelligence and Statistics (AISTATS)*, 2017.
- [57] Aapo Hyvarinen and Hiroshi Morioka. Unsupervised feature extraction by time-contrastive learning and nonlinear ica. *Adv. in Neural Information Processing Systems (NeurIPS)*, 2016.
- [58] Aapo Hyvarinen, Hiroaki Sasaki, and Richard Turner. Nonlinear ICA using auxiliary variables and generalized contrastive learning. In *The 22nd Int. Conf. on Artificial Intelligence and Statistics (AISTATS)*, 2019.
- [59] Julius Von Kügelgen, Yash Sharma, Luigi Gresele, Wieland Brendel, Bernhard Schölkopf, Michel Besserve, and Francesco Locatello. Self-supervised learning with data augmentations provably isolates content from style. *Adv. in Neural Information Processing Systems (NeurIPS)*, 2021.
- [60] Luigi Gresele, Julius Von Kügelgen, Vincent Stimper, Bernhard Schölkopf, and Michel Besserve. Independent mechanism analysis, a new concept? *Adv. in Neural Information Processing Systems (NeurIPS)*, 2021.
- [61] Yi Ren, Samuel Lavoie, Mikhail Galkin, Danica J. Sutherland, and Aaron Courville. Improving compositional generalization using iterated learning and simplicial embeddings, 2023. URL <https://arxiv.org/abs/2310.18777>.

- [62] Susan Carey. The origin of concepts. *Journal of Cognition and Development*, 1(1):37–41, 2000.
- [63] Susan Carey. Knowledge acquisition: Enrichment or conceptual change. *The epigenesis of mind: Essays on biology and cognition*, pages 257–291, 1991.
- [64] Susan Carey. The origin and evolution of everyday concepts. *Cognitive models of science*, 15: 89–128, 1992.
- [65] Susan Carey and Elizabeth Spelke. Domain-specific knowledge and conceptual change. *Mapping the mind: Domain specificity in cognition and culture*, 169:200, 1994.
- [66] Susan Carey. Bootstrapping & the origin of concepts. *Daedalus*, 133(1):59–68, 2004.
- [67] Susan Carey. Where our number concepts come from. *The Journal of philosophy*, 106(4):220, 2009.
- [68] Samuel Marks and Max Tegmark. The geometry of truth: Emergent linear structure in large language model representations of true/false datasets. *arXiv preprint arXiv:2310.06824*, 2023.
- [69] Samuel Marks, Can Rager, Eric J Michaud, Yonatan Belinkov, David Bau, and Aaron Mueller. Sparse feature circuits: Discovering and editing interpretable causal graphs in language models. *arXiv preprint arXiv:2403.19647*, 2024.
- [70] Wes Gurnee, Neel Nanda, Matthew Pauly, Katherine Harvey, Dmitrii Troitskii, and Dimitris Bertsimas. Finding neurons in a haystack: Case studies with sparse probing. *arXiv preprint arXiv:2305.01610*, 2023.
- [71] Wes Gurnee and Max Tegmark. Language models represent space and time. *arXiv preprint arXiv:2310.02207*, 2023.
- [72] Andy Ardit, Oscar Obeso, Aaquib Syed, Daniel Paleka, Nina Rimsky, Wes Gurnee, and Neel Nanda. Refusal in language models is mediated by a single direction. *arXiv preprint arXiv:2406.11717*, 2024.
- [73] Danny Halawi, Jean-Stanislas Denain, and Jacob Steinhardt. Overthinking the truth: Understanding how language models process false demonstrations. *arXiv preprint arXiv:2307.09476*, 2023.
- [74] Kiho Park, Yo Joong Choe, and Victor Veitch. The linear representation hypothesis and the geometry of large language models, 2024. URL <https://arxiv.org/abs/2311.03658>.
- [75] René Haas, Inbar Huberman-Spiegelglas, Rotem Mulayoff, and Tomer Michaeli. Discovering interpretable directions in the semantic latent space of diffusion models. *arXiv preprint arXiv:2303.11073*, 2023.
- [76] Yong-Hyun Park, Mingi Kwon, Junghyo Jo, and Youngjung Uh. Unsupervised discovery of semantic latent directions in diffusion models. *arXiv preprint arXiv:2302.12469*, 2023.
- [77] Samyadeep Basu, Keivan Rezaei, Ryan Rossi, Cherry Zhao, Vlad Morariu, Varun Manjunatha, and Soheil Feizi. On mechanistic knowledge localization in text-to-image generative models. *arXiv preprint arXiv:2405.01008*, 2024.
- [78] Yida Chen, Fernanda Viégas, and Martin Wattenberg. Beyond surface statistics: Scene representations in a latent diffusion model. *arXiv preprint arXiv:2306.05720*, 2023.
- [79] Mohamed El Banani, Amit Raj, Kevis-Kokitsi Maninis, Abhishek Kar, Yuanzhen Li, Michael Rubinstein, Deqing Sun, Leonidas Guibas, Justin Johnson, and Varun Jampani. Probing the 3d awareness of visual foundation models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 21795–21806, 2024.
- [80] Noam Chomsky. *Aspects of the Theory of Syntax*. Number 11. MIT press, 2014.
- [81] John Collins. Linguistic competence without knowledge of language. *Philosophy Compass*, 2(6):880–895, 2007.

- [82] Jill G De Villiers and Peter A De Villiers. Competence and performance in child language: Are children really competent to judge? *Journal of Child Language*, 1(1):11–22, 1974.
- [83] Gillian Brown, Kirsten Malmkjær, and John Williams. *Performance and competence in second language acquisition*. Cambridge university press, 1996.
- [84] METR. *Guidelines for Capabilities Elicitation*, 2024. <https://metr.github.io/autonomy-evals-guide/elicitation-protocol/>.
- [85] Ryan Greenblatt, Fabien Roger, Dmitrii Krasheninnikov, and David Krueger. Stress-testing capability elicitation with password-locked models. *arXiv preprint arXiv:2405.19550*, 2024.
- [86] Tom Davidson, Jean-Stanislas Denain, Pablo Villalobos, and Guillem Bas. Ai capabilities can be significantly improved without expensive retraining. *arXiv preprint arXiv:2312.07413*, 2023.
- [87] Stephen Casper, Carson Ezell, Charlotte Siegmann, Noam Kolt, Taylor Lynn Curtis, Benjamin Bucknall, Andreas Haupt, Kevin Wei, Jérémy Scheurer, Marius Hobbhahn, et al. Black-box access is insufficient for rigorous ai audits. In *The 2024 ACM Conference on Fairness, Accountability, and Transparency*, pages 2254–2272, 2024.
- [88] Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, et al. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models. *arXiv preprint arXiv:2206.04615*, 2022.
- [89] Mirac Suzgun, Nathan Scales, Nathanael Schärli, Sebastian Gehrmann, Yi Tay, Hyung Won Chung, Aakanksha Chowdhery, Quoc V Le, Ed H Chi, Denny Zhou, et al. Challenging big-bench tasks and whether chain-of-thought can solve them. *arXiv preprint arXiv:2210.09261*, 2022.
- [90] Diederik P. Kingma, Tim Salimans, Ben Poole, and Jonathan Ho. Variational diffusion models, 2023.
- [91] Irina Higgins, Loic Matthey, Arka Pal, Christopher Burgess, Xavier Glorot, Matthew Botvinick, Shakir Mohamed, and Alexander Lerchner. beta-vae: Learning basic visual concepts with a constrained variational framework. In *Proc. Int. Conf. on Learning Representations (ICLR)*, 2017.
- [92] Cian Eastwood and Christopher KI Williams. A framework for the quantitative evaluation of disentangled representations. In *International Conference on Learning Representations*, 2018.
- [93] Ricky TQ Chen, Xuechen Li, Roger B Grosse, and David K Duvenaud. Isolating sources of disentanglement in variational autoencoders. *Advances in neural information processing systems*, 31, 2018.
- [94] Abhishek Kumar, Prasanna Sattigeri, and Avinash Balakrishnan. Variational inference of disentangled latent concepts from unlabeled observations. *arXiv preprint arXiv:1711.00848*, 2017.
- [95] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation, 2015.
- [96] Katie Kang, Eric Wallace, Claire Tomlin, Aviral Kumar, and Sergey Levine. Unfamiliar fine-tuning examples control how language models hallucinate. *arXiv preprint arXiv:2403.05612*, 2024.
- [97] Jonathan Ho and Tim Salimans. Classifier-free diffusion guidance. *arXiv preprint arXiv:2207.12598*, 2022.
- [98] Ziwei Liu, Ping Luo, Xiaogang Wang, and Xiaoou Tang. Deep learning face attributes in the wild. In *Proceedings of International Conference on Computer Vision (ICCV)*, December 2015.

- [99] Ben Hutchinson, Jason Baldridge, and Vinodkumar Prabhakaran. Underspecification in scene description-to-depiction tasks, 2022.
- [100] Alexander D’Amour, Katherine Heller, Dan Moldovan, Ben Adlam, Babak Alipanahi, Alex Beutel, Christina Chen, Jonathan Deaton, Jacob Eisenstein, Matthew D Hoffman, et al. Underspecification presents challenges for credibility in modern machine learning. *Journal of Machine Learning Research*, 23(226):1–61, 2022.
- [101] Sandro Pezzelle. Dealing with semantic underspecification in multimodal nlp. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*.
- [102] Yingtian Tang, Yutaro Yamada, Yoyo Zhang, and Ilker Yildirim. When are lemons purple? the concept association bias of vision-language models. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, 2023.
- [103] Royi Rassin, Eran Hirsch, Daniel Glickman, Shauli Ravfogel, Yoav Goldberg, and Gal Chechik. Linguistic binding in diffusion models: Enhancing attribute correspondence through attention map alignment. In *Thirty-seventh Conference on Neural Information Processing Systems*, 2023. URL <https://openreview.net/forum?id=AOKU4nRw1W>.
- [104] Junsong Chen, Jincheng Yu, Chongjian Ge, Lewei Yao, Enze Xie, Yue Wu, Zhongdao Wang, James Kwok, Ping Luo, Huchuan Lu, and Zhenguo Li. Pixart- α : Fast training of diffusion transformer for photorealistic text-to-image synthesis, 2023.
- [105] Sharon Zhou, Mitchell L. Gordon, Ranjay Krishna, Austin Narcomey, Li Fei-Fei, and Michael S. Bernstein. Hype: A benchmark for human eye perceptual evaluation of generative models, 2019.
- [106] Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily Denton, Seyed Kamyar Seyed Ghasemipour, Burcu Karagol Ayan, S. Sara Mahdavi, Rapha Gontijo Lopes, Tim Salimans, Jonathan Ho, David J Fleet, and Mohammad Norouzi. Photorealistic text-to-image diffusion models with deep language understanding, 2022.
- [107] Yi Ren, Shangmin Guo, and Danica J. Sutherland. Better supervisory signals by observing learning paths, 2022. URL <https://arxiv.org/abs/2203.02485>.
- [108] Alethea Power, Yuri Burda, Harri Edwards, Igor Babuschkin, and Vedant Misra. Grokking: Generalization beyond overfitting on small algorithmic datasets. *arXiv preprint arXiv:2201.02177*, 2022.
- [109] Ziming Liu, Ouail Kitouni, Niklas S Nolte, Eric Michaud, Max Tegmark, and Mike Williams. Towards understanding grokking: An effective theory of representation learning. *Advances in Neural Information Processing Systems*, 35:34651–34663, 2022.
- [110] Ziming Liu, Eric J Michaud, and Max Tegmark. Omnigrok: Grokking beyond algorithmic data. In *The Eleventh International Conference on Learning Representations*, 2022.
- [111] Neel Nanda, Lawrence Chan, Tom Lieberum, Jess Smith, and Jacob Steinhardt. Progress measures for grokking via mechanistic interpretability, 2023.
- [112] Tanishq Kumar, Blake Bordelon, Samuel J Gershman, and Cengiz Pehlevan. Grokking as the transition from lazy to rich training dynamics. *arXiv preprint arXiv:2310.06110*, 2023.
- [113] Boaz Barak, Benjamin Edelman, Surbhi Goel, Sham Kakade, Eran Malach, and Cyril Zhang. Hidden progress in deep learning: Sgd learns parities near the computational limit. *Advances in Neural Information Processing Systems*, 35:21750–21764, 2022.
- [114] Blaž Zupan, Marko Bohanec, Janez Demšar, and Ivan Bratko. Learning by discovering concept hierarchies. *Artificial Intelligence*, 109(1-2):211–242, 1999.
- [115] Yangqing Jia, Joshua T Abbott, Joseph L Austerweil, Tom Griffiths, and Trevor Darrell. Visual concept learning: Combining machine vision and bayesian generalization on concept hierarchies. *Advances in Neural Information Processing Systems*, 26, 2013.

- [116] Martin Wattenberg and Fernanda B Viégas. Relational composition in neural networks: A survey and call to action. *arXiv preprint arXiv:2407.14662*, 2024.
- [117] Core Francisco Park, Victoria Ono, Nayantara Mudur, Yueying Ni, and Carolina Cuesta-Lazaro. Probabilistic reconstruction of dark matter fields from biased tracers using diffusion models, 2023.
- [118] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition, 2015.
- [119] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E. Hinton. Layer normalization, 2016.
- [120] Dan Hendrycks and Kevin Gimpel. Gaussian error linear units (gelus), 2023.
- [121] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need, 2023.
- [122] Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization, 2019.
- [123] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In *ICLR*, 2015.
- [124] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Köpf, Edward Yang, Zach DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library, 2019.
- [125] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pages 8748–8763. PMLR, 2021.
- [126] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models, 2022.

A Schematic for Concept Space

Fig. 12 illustrates the concept space framework discussed in Sec. 3.

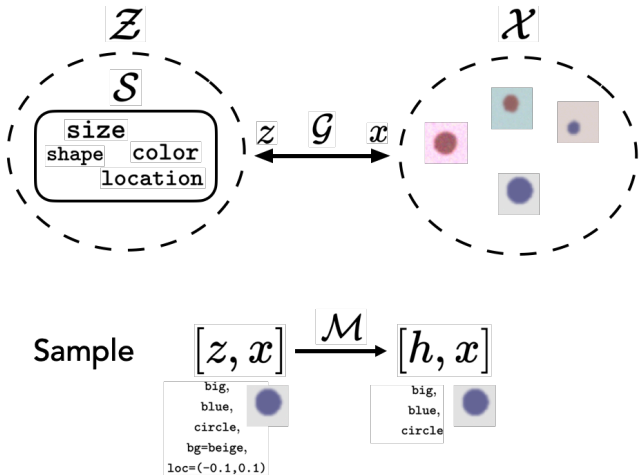


Figure 12: **The concept space framework.** \mathcal{G} is an invertible data-generating that maps process maps sampled vectors $z \sim P(\mathcal{Z})$ (where $\mathcal{Z} \subset \mathbb{R}^d$) to an observation $x \in \mathbb{R}^n$ (an image in this work). The concept space, $\mathcal{S} := \{z | z \sim P(\mathcal{Z})\}$, is defined as a space of all possible concept vectors generated from a compositional prior $P(\mathcal{Z})$. The mixing function \mathcal{M} masks some concept variables, the masked concept variables are thus underspecified.

B Experimental Details

B.1 Synthetic data

We design a data generation process (DGP) compatible with the concept space framework introduced in Sec. 3. Our full DGP has six concepts: $\text{shape}=\{\text{circle}, \text{triangle}\}$, x coordinate $\in \mathbb{R}$, y coordinate $\in \mathbb{R}$, $\text{color}=\{\text{red}, \text{blue}\}$, $\text{size}=\{\text{big}, \text{small}\}$, and background color $=\{\text{bright}, \text{dark}\}$. We generally explore only a subset of these at a given time in our experiments.

In Sec. 4, we fix $\text{shape}=\text{circle}$ and x coordinate, y coordinate, background color are masked out. Thus the conditioning vector h only specifies $\text{color}=\{\text{red}, \text{blue}\}$ and $\text{size}=\{\text{big}, \text{small}\}$. We sample both of these concept variables from a mixture of two uniform distributions, one component for each class (big, small) and (red, blue). Each value in each dimension is sampled from $\mathcal{U}(m^i - s, m^i + s)$, where m^i is the class dependent mean. For example, $\text{color}=\text{red}$ could be sampled from $\mathcal{U}(0.7, 0.9) \times \mathcal{U}(0.1, 0.3) \times \mathcal{U}(0.1, 0.3)$, where $m^0 = (0.8, 0.2, 0.2)$. For brevity, we name the four resulting classes “00”, “01”, “10”, and “11”, where the class “11” is kept as the unseen target to evaluate out-of-distribution (OOD) generalization. For each training run, the DGP was initialized with a set random seed and 2048 images were generated in each class.

In Sec. 5, we used two concept variables, shape and size . The training dataset included the classes “00”, “01”, and “10”. For evaluation, we used the class “11”. For each class, we generated a total of 1,000 images, each featuring objects of varying positions and sizes to ensure variability in our dataset.

In App. D.5, we add the concept variable background color $\in \mathbb{R}^3$ to have a three dimensional concept space of ($\text{color}, \text{size}, \text{background color}$). In this case our training data is composed of the classes (“000”, “001”, “010”, “100”) and the test classes are (“011”, “101”, “110”, “111”)

Our DGP is resolution agnostic, but we work with square images of 32x32 for fast experiments.

Adjusting concept signal To adjust concept signals, we vary the class dependent mean of the two components of the mixture distributions. For example a strong color concept signal is achieved by drawing $\text{color}=\text{red}$ from the mean $m^{\text{red}} = (0.9, 0.1, 0.1)$ and $\text{color}=\text{blue}$ from the mean $m^{\text{blue}} = (0.1, 0.1, 0.9)$ whereas a weak color concept signal can be drawn using $m^{\text{red}} = (0.6, 0.4, 0.4)$ and $m^{\text{blue}} = (0.4, 0.4, 0.6)$. We scale the standard deviation of each component by the same ratio the

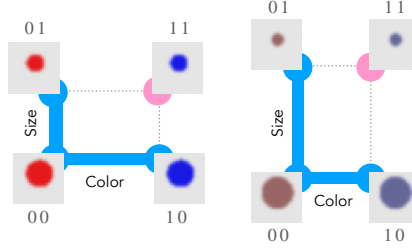


Figure 13: **Different distributions in concept values result in different concept signal.** (Left) The color separation between the classes is stronger than the size separations resulting in a stronger concept signal in the color dimension. (right) The size separation between the classes is stronger, thus resulting in a stronger concept signal in size

difference between the class means has been scaled. This latter is important to avoid the model’s natural interpolation or extrapolation abilities from confounding with the generalization dynamics.

Fig. 13 illustrates two datasets with varying concept signals. Fig. 13 (left) illustrates a case where the color concept signal is stronger than the size concept signal, while Fig. 13 (right) illustrates the inverse case where the size concept signal is stronger.

B.2 Model Details

Model Architecture We used a network architecture similar to the U-Net [95] used in Variational Diffusion Models [90]. We used the implementation publicly available in [117]. The architecture has 2 ResNet [118] blocks before each downsampling layer and a has self-attention layer in the bottleneck layer of the network. The U-Net has 64, 128, 256 channels at each resolution levels, an has a LayerNorm [119] and a GELU [120] activation. We used a sinusoidal timestep embedding [121] of 64 dimensions followed by a 2-layer MLP with hidden dimension 256 and a conditioning vector embedding using a 2-layer MLP with hidden dimensions 256 independent in every residual block.

Optimizer We use the AdamW [122] optimizer with learning rate 0.001 and weight decay 0.01 to optimize the parameters of our network. We train our networks for 20K gradient steps. We use the default values for the decay rates: $\beta_1 = 0.9$, $\beta_2 = 0.999$.

Classifier Free Guidance At training time we drop the conditioning to a -1.0 filled null vector ϕ with probability 0.2. This unconventional choice was made instead of the dropping it to the null vector since the null vector was near the interpolation limit of our model in the color subspace of the conditioning. The w_{cfg} parameter is used to estimate the noise in the diffusion process by: $\hat{\epsilon}_{t-1} = f_{\theta}(x_t|\phi) + w_{cfg} * (f_{\theta}(x_t|h) - f_{\theta}(x_t|\phi))$, where θ denotes parameters of the network f .

Diffusion Process Hyperparameters We used the continuous time variational diffusion model [90] in order to (i) keep the sampling step parameter T an inference time hyperparameter and (ii) to allow the model to the adjust its optimal noise schedule for these images, especially since our synthetic images are expected to be different in SNR from natural images. In particular, we initialize our network with $\gamma_i = -5.0$ and $\gamma_f = 10.0$ (see [90] for the definition of γ) and use a learned linear schedule of $\gamma(t)$. We use a reconstruction loss corresponding to a negative log likelihood from a standard normal with $\sigma = 10^{-3}$ centered at the data for the first step of the diffusion process.

Evaluation probe Details. We used a U-Net [95] backbone with 64 output channels followed by a max pooling layer and $n \times 1$ -layer MLP classifier for each of the n classes to estimate each concept of an image independently. We sample from the same data distribution but with maximal data diversity, i.e., with s_i values in App. B.1 maximized within the range allowing perfect classification (no overlap of z between classes). We sample 4096 images per class from the DGP and train the classifier for 10K gradient steps with AdamW [122] and achieve a 100% accuracy on the held out test set. At evaluation phase, we average the classifier softmax output over 5 data generation / model initialization seeds and 32 inference samples to construct the concept space representation of the generations.

Hyperparameter Search We conducted a hyperparameter search, testing batch sizes from 32 to 256, number of channels per layer from 64 to 512, learning rates between 10^{-4} and 10^{-3} , the number of steps in the diffusion process from 100 to 400, weight decay between 3×10^{-3} and 5×10^{-2} ,

and model weight initialization scale between $\mathcal{N}(0, 0.003)$ and $\mathcal{N}(0, 1)$. We also tried the Adam optimizer [123] with $\beta_1 = 0.9$, $\beta_2 = 0.99$, and weight decay of 10^{-5} . No qualitative change were found in our results.

Computational Details. We implement our models in PyTorch [124]. The diffusion model was trained on four Nvidia A100 GPUs and 64 CPUs for the data generating process. A standard model run (e.g., in Sec. 4.2) took ~ 20 minutes on a single NVIDIA A100 40GB GPU. The CelebA runs took ~ 24 hours on the same GPU. The full research required roughly 500 GPU hours, while the experiments in the paper would require roughly 100 GPU hours.

B.3 Code Availability

Our code is available at <https://github.com/cfpark00/concept-learning>.

C Details on Alternative Protocols for Eliciting Model Capabilities

Input Space: Overprompting. Our model is trained on a distribution of conditioning vectors centered around a class dependent mean: $p^i(z_j) = \mathcal{U}(m_j^i - s_j, m_j^i + s_j)$ for each class i . We prompt the model with conditioning vectors extrapolated in the direction $\vec{m}_1 - \vec{m}_0$. For instance, assuming the red conditioning was (0.6, 0.4, 0.4) and the blue conditioning was (0.4, 0.4, 0.6), we “prompt” the model with (0.2, 0.2, 0.8) for blue. In practice, we use 5 conditionings (0.4, 0.4, 0.6), (0.35, 0.35, 0.65), (0.25, 0.25, 0.75), (0.15, 0.15, 0.85), (0.05, 0.05, 0.95), and report the maximum joint accuracy.

Activation Space: Linear Latent Intervention. We demonstrate the ability to compose capabilities by manipulating the conditional vectors \vec{h} . Namely, we create a condition vector \vec{h}_i for a specific concept i by specifying a concept of interest (e.g., $\vec{h}_{\text{blue}} = M(z_{\text{blue}})$). During the forward pass, given \vec{h} , we can compute the component of each concept in \vec{h} by projecting onto a specific concept-condition vector (\vec{h}_{blue}). We can then enhance or reduce the component of each concept by scaling each of these projected components. In practice, we perform the following operation: $\vec{h}' = \vec{h} + \alpha \vec{h}_{\text{blue}} - \beta \vec{h}_{\text{large}}$, where α, β are hyperparameters. We sweep over [0.1, 1, 2, 4] for α and [0.1, 0.25, 0.5, 1] for β .

\vec{h}_{blue} is constructed by first deriving a blue direction in condition embedding space ($\vec{h}_{5,5,95}$) by embedding a concept vector ($\vec{z}_{5,5,95}$) where its RGB components are set to (0.05, 0.05, 0.95): $\vec{h}_{5,5,95} = M(\vec{z}_{5,5,95})$. We then project \vec{h} onto this direction to derive \vec{h}_{blue} . \vec{h}_{large} is generated similarly using $\vec{z}_{\text{size}=0.7}$. The model then generates an image conditioned on \vec{h}' .

D Additional Results

D.1 Loss and Accuracy versus Concept Space (Fig. 14)

In Fig. 14, we plot loss, accuracy, and OOD generalization trajectory in concept space of the models for a training run in Fig. 6. The time at which the model acquires a capability to manipulate the concept color is not evident from the loss or accuracy curves; however, in concept space, one can identify when the trajectory deviates from *concept memorization* and thus when the compositional ability has emerged. Benchmarking generative models is a challenging task, still often involving humans in the loop [105, 106]. Our concept space framework suggests that benchmarking out-of-distribution (OOD) generalization can potentially be reduced to monitoring the learning trajectory in concept space.

D.2 Additional trajectories of learning dynamics (Fig. 15)

Here we show all concept space trajectories for the experiments mentioned in Fig. 4 (a,b), for all classes and color concept signal levels. We find asymmetric behavior for the 01 class and the 10 class when adjusting the color concept signal level. The dynamics of the generations in the training set matches our intuitions of concept signal as discussed in the main text. At low color concept

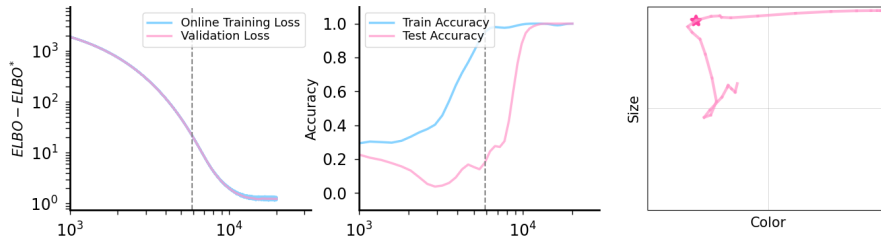


Figure 14: **Loss vs. accuracy vs. concept space.** (left) The training and validation loss on ID classes during training. (center) The accuracy on the training classes and the test (OOD generalization) class. (right) Concept space trajectory of the generalization class. Loss and accuracy do not always intuitively reflect what capabilities the model has acquired during training. However, as one can see in the rightmost panel, the point of sudden turn in concept space corresponds to when the capability has emerged, i.e., the moment when well defined prompting protocols can elicit the desired output from the model, which we indicate using the pink star (50% capability).

signal, we observe that the dynamics fit size first for both 00 and 10, and afterwards find their correct colors.

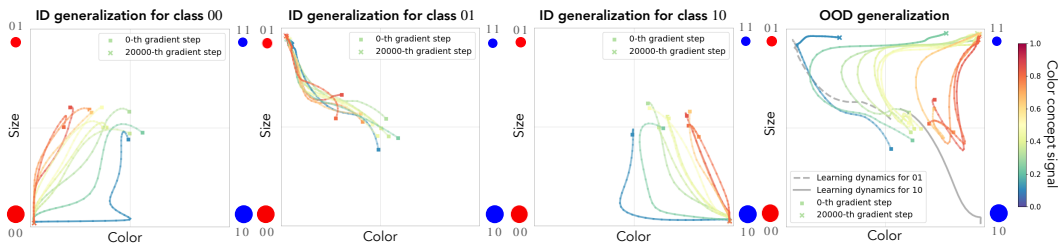


Figure 15: **Concept space dynamics for all classes (00, 01, 10, 11).** The experiment is identical as in Fig. 4. The $[0,1)$ normalized color concept signal is color coded in every trajectory. Two training data trajectories are shown in gray in the last panel to illustrate *concept memorization*.

D.3 Error Quantification (Fig. 16, Fig. 17)

We show the standard error of the mean (s.e.m.) of concept space trajectories of Fig. 4 and Fig. 15 in Fig. 16 (a). Fig. 16 (b) illustrates the 50% capability point across 4 different model initialization seeds. Fig. 16 (c) illustrates the 50% capability point across different color concept signal level. Overall, our results are consistent over random seeds and concept signal levels.

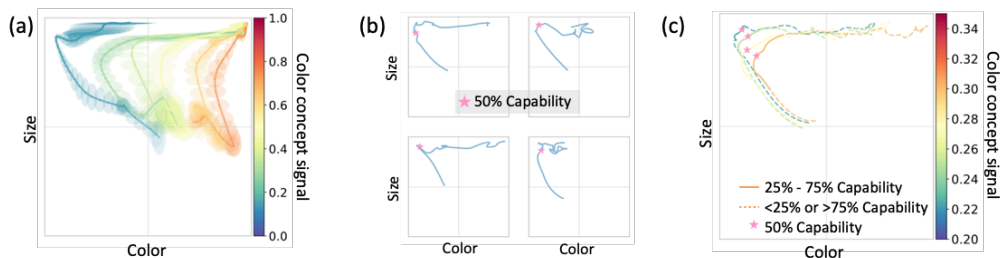


Figure 16: **Error quantification on concept space trajectories.** (a) Concept space trajectories and their standard error of the mean ($n=5$) for different concept signal levels. (b) Concept space trajectories for 4 different seeds. The pink stars denote the point of 50% capability. (c) Concept space trajectories for different color concept signal level. The stars again denote the 50% capability point and the 25% – 75% capability regions are in solid lines.

We show the standard deviation of compositional generalization accuracy for different prompting methods in Fig. 17. We find that the standard deviation is large for the naive prompting method, while linear latent interpolation and overprompting extract the hidden capability *robustly across seeds*, resulting in a small standard deviation.

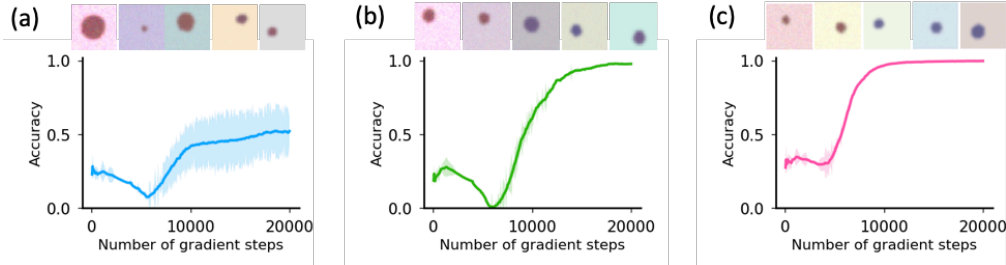


Figure 17: **Standard deviation of compositional generalization accuracy.** We show the compositional generalization accuracy and shade the 1σ region for (a) Naive prompting (b) Linear latent intervention (c) Overprompting

D.4 Additional Experiments with real data, CelebA (Fig. 18)

To assess our findings on a more realistic dataset, we ran experiments on the CelebA [98] dataset. The experiments in Fig. 7 and Fig. 18, share the same experiment hyperparameters, described below.

We selected the Female and Smiling features as the two concept dimensions to explore. This choice was motivated by the relatively balanced number of samples in all four classes (00=(Male, Not Smiling), 01=(Male, Smiling), 10=(Female, Not Smiling), 11=(Female, Smiling)), from which we randomly sampled 30K images in each class. To construct the concept space, we trained a fully convolutional network with a average pooling layer followed by a classification MLP head to classify the two attributes with independent cross entropy losses. (See B.2). We trained the classifier with the AdamW [122] optimizer with learning rate 10^{-3} and weight decay 10^{-5} for 10K gradient steps. The classifier achieved a final accuracy of respectively 95% and 97% on the held out validation set, which was 10% of the entire dataset.

We trained the same diffusion model (See App. B.2) from our synthetic experiments on 64x64 resized images from the classes (00, 01, 10) and assessed the out-of-distribution (OOD) generalization to 11. We used a color jitter of 0.1 for brightness, contrast and saturation and randomly flipped the images horizontally. As the class attributes are categorical, they were one hot encoded and concatenated to an input conditioning vector of 4 dimensions. The diffusion model was trained for 2×10^6 gradient steps with a batch size of 64 with the same optimizer as in the main experiments.

The concept space dynamics of generations from the in distribution conditioning and OOD conditioning are shown in Fig. 18. We find similar observations from the concept space trajectories as in our synthetic experiments. Initially, the images corresponding to the class 11 follows the concept space trajectory of 10, optimizing Female, which we intuitively expect to have a stronger concept signal, although it is intractable to compute since the DGP is unknown. Similar to our synthetic experiments, we see a transition in the concept space trajectory of the compositional class corresponding to the model disentangling the concepts. After this transition, concept learning begins but we observe a substantial bias towards the training distribution. We see a trade-off of moving in the right direction towards one concept degrades the other one similarly to the observations in Fig. 4 (b) for high color concept signal levels. The visual generations in Fig. 18 confirm that our findings are not merely a result of an ill-calibrated classifier model. However, in this case, we do not observe full out-of-distribution (OOD) generalization at 2M gradient steps. We expect this task of generating (Female, Smiling) is inherently harder than our synthetic setup. We note that the goal of this experiment is not to show good compositional generalization but it is more on confirming that our qualitative findings generalize to real data without touching the model or training method.

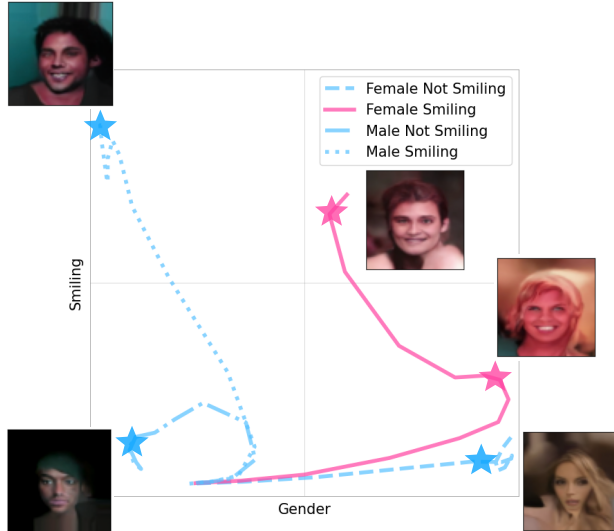


Figure 18: **Concept space dynamics with CelebA.** We train on the classes 00=(Male, NOT Smiling), 01=(Male, Smiling), 10=(Female, NOT Smiling) (plotted in blue) and test on the class 11=(Female, Smiling) (plotted in pink). We find similar observations as in Fig. 4.2, *concept memorization* and the resulting bias.

D.5 Experiments with 3D concept space (Fig. 19, Fig. 20)

To further verify our findings in Sec. 4, we explore a setup where the concept conditioning specifies three concepts: color, size and background color. Fig. 19 illustrates two example scenarios in which the concept signal in color and background color are varied, respectively resulting in cases of success and failure of OOD generalization by naive prompting. The length of edges of the cuboids represent their concept signal magnitude. In Fig. 19 (a), we see that the object color has a strong concept signal and this is reflected in the concept space trajectories as this direction being split first. In this case we see, similarly to the blue generalization curve in Fig. 4 (b) and Fig. 15 (rightmost panel), a slow generalization process for the compositional class 111. Again similarly to our findings in Sec. 4.2, we observe that the 011 class initially undergoes *concept memorization* for class 010, which shares the two stronger concept signals color and background color, and shows a transition where it suddenly curves out from this trajectory. In Fig. 19 (b), we see a case where out-of-distribution (OOD) generalization did not succeed within the given 80K gradient steps. In this case, we see two classes, 011 and 111, which didn’t reach the right compositional class via naive prompting. However, the concept space trajectories suggest that the *capability* to compositionally generalize background color has already emerged as visible from the sharp turns.

Fig. 20 quantifies the accuracy of each concept separately. Fig. 20 (a) shows that stronger concept signal accelerates the corresponding concept learning. Fig. 20 (b) shows that other concepts’ learning speed can vary, albeit smoothly, when changing a single concept signal while the corresponding concept is the most affected.

D.6 Experiments with classifier free guidance (Fig. 21)

An implication of our conclusions in Sec. 4.4 is that before the model has passed the transition point where the model has the *capability* to compose concepts, the model should not be able to generate small blue circles no matter how well “prompted”. Here, instead of prompting, we explore Classifier Free Guidance (CFG) [97] to see if our findings apply to a conditional diffusion model trained with CFG. In Fig. 21, we see that even the models with CFG show this transition from *concept memorization* to out-of-distribution (OOD) generalization. In a scenario where there isn’t a sharp acquisition of the capability to compositionally generalize, we would expect the sharp transition to disappear with CFG scale. However, as we observe in Fig. 21, the sharp turn in concept space still exists with CFG, perhaps even more pronounced than baseline experiments. These results suggest

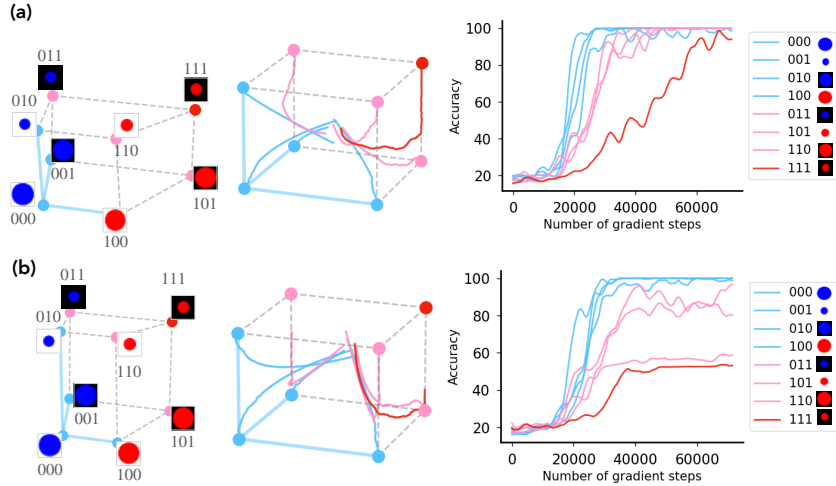


Figure 19: **Generalization dynamics in a 3 concept setting.** (a) Generalization dynamics when color carries the strongest concept signal. (b) Generalization dynamics when size carries the strongest concept signal. We observe sharp turns corresponding to learning background color, however, naive prompting cannot fully elicit compositional generalization.

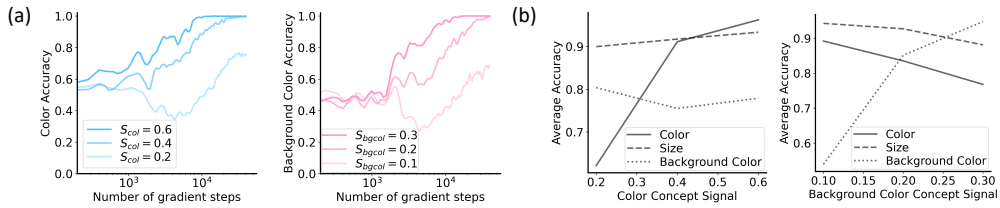


Figure 20: **Accuracy on individual concepts in a 3 concept setting.** a) We show the dynamics of color and background color accuracy during model training, depending on different concept signal levels b) We show the average accuracy until the end of training as a metric of learning speed for different concepts, as we change a single concept signal level.

that the acquisition of the compositional generalization ability is required for CFG to enhance OOD generalization.

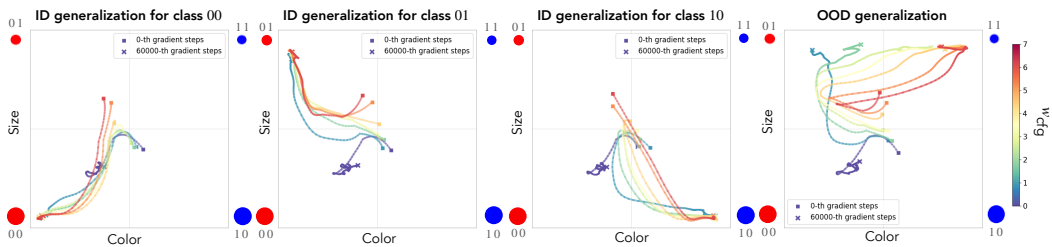


Figure 21: **Learning dynamics in Concept space for classifier-free Guidance** We show the learning dynamics in the concept space for all the classes (00, 01, 10, 11). The generalization task (rightmost) shows a sharp transition from *concept memorization* to OOD generalization independently of the classifier-free guidance scale.

D.7 Patching the embedding module (Fig. 22)

We test an additional elicitation method where we swap the conditioning vector (h)’s embedding module with that of the last checkpoint. An interpretation of this method is that the embedding module disentangles the concepts, i.e., generates a representation for each concept, while the U-Net [95] then

utilizes such representations. This would imply that the U-Net [95] learns how to utilize concept representations early during training, while many more gradient steps are needed for the concepts to be disentangled when naively prompted.

We test our approach on 5 random initialization seeds. Results are shown in Fig. 22. We find that for some seeds, we are able to elicit the target behavior at around the same time in which overprompting and linear interventions also elicit the target behavior; for other seeds, this is not the case. These results demonstrates that the role of the embedding module and the U-Net *might* be separated during training for some runs without an explicit term enhancing this separation of roles.

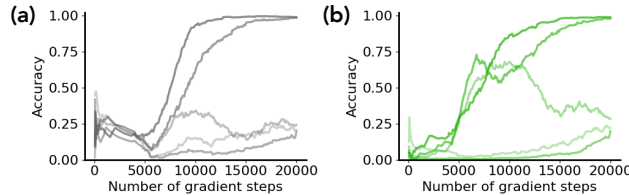


Figure 22: **Embedding patching.** We patch the embedding module (an MLP) used for transforming the conditioning information into an embedding that the model processes from the last checkpoint to intermediate checkpoints. Panel (a) shows the baseline accuracy for out-of-distribution (OOD) generalization across five different seed runs, while panel (b) shows accuracy achieved when the patched embedding module is used.

D.8 Proof of Concept Experiments with Frontier Models (Fig. 23)

We show simple proof of concept experiments on frontier models in Fig. 23. In Fig. 23 (a), we show that CLIP [125] already embeds text/images with compositional concepts in its vector space as a cube respecting the Hamming graph of concepts. In Fig. 23 (b), we show that simple over-prompting can enhance compositional generalization ability in Stable Diffusion v1.4 [126]. These experiments show that the assumptions we made to construct the concept space framework in Sec. 3 and the elicitation method we used work at least to some extent in frontier models.

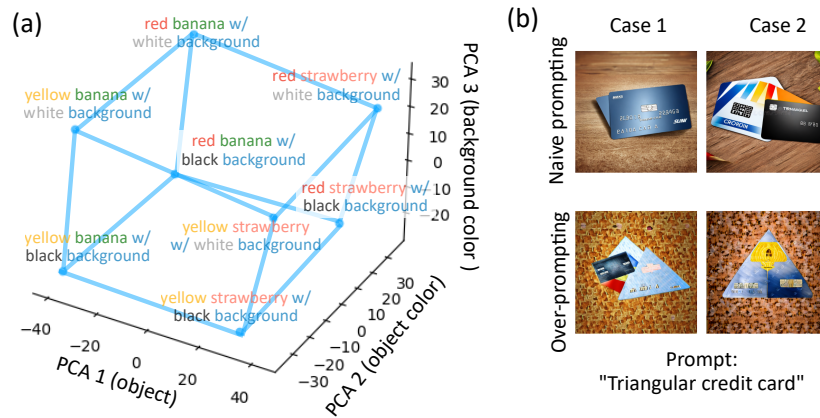


Figure 23: **Proof of concept experiments on frontier models** (a) CLIP [125] embeds compositional text/images as a concept cube in its vector space. (b) Simple over-prompting can enhance compositional generalization in Stable Diffusion v1.4 [126]

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [Yes]

Justification: Section 4.2, Section 4.4

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: Section 6

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory Assumptions and Proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [NA]

Justification:

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental Result Reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: Section B.1, Section B.2, Section C, Section B.3.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: Section B.3.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental Setting/Details

Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: Section B.1, Section B.2

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment Statistical Significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [No]

Justification: While we report some error bars and show multiple seeds when applicable, we did not test for statistical significance as most conclusions were qualitative.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).

- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments Compute Resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: Section B.2

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code Of Ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines?>

Answer: [Yes]

Justification:

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader Impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [NA]

Justification:

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.

- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification:

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [NA]

Justification:

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.

- If this information is not available online, the authors are encouraged to reach out to the asset’s creators.

13. **New Assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [NA]

Justification:

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and Research with Human Subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification:

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional Review Board (IRB) Approvals or Equivalent for Research with Human Subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification:

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.