Hallucinating Pose-Compatible Scenes

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Abstract

What does human pose tell us about a scene? We propose a task to answer this question: given human pose as input, hallucinate a compatible scene. Subtle cues captured by human pose — action semantics, environment affordances, object interactions — provide surprising insight into which scenes are compatible. We present a large-scale generative adversarial network for pose-conditioned scene generation. We significantly scale the size and complexity of training data, curating a massive meta-dataset containing over 19 million frames of humans in everyday environments. We double the capacity of our model with respect to StyleGAN2 to handle such complex data, and design a pose conditioning mechanism that drives our model to learn the nuanced relationship between pose and scene. We leverage our trained model for various applications: hallucinating pose-compatible scene(s) with or without humans, visualizing incompatible scenes and poses, placing a person from one generated image into another scene, and animating pose. Our model produces diverse samples and outperforms pose-conditioned StyleGAN2 and Pix2Pix baselines in terms of accurate human placement (percent of correct keypoints) and image quality (Fréchet inception distance).

1. Introduction

Human pose can reveal a lot about a scene. For example, mime artists\footnote{For those unfamiliar with mime artists, here is a wonderful example performance: \url{https://youtu.be/FPMBV3rd_hI}} invoke vivid scenes in a viewer’s mind through pose and movement alone, despite performing on a bare stage. The viewer is able to imagine the invisible objects and scene elements because of the strong relationship between human poses and scenes learned through a lifetime of daily observations.

Psychologists have long been interested in understanding this symbiotic relationship between human and scene \cite{8, 28}. J.J. Gibson proposed the notion of affordances \cite{28}, which can be described as “opportunities for interactions” furnished by the environment. In computer vision, affordances have been used to provide a functional description of the scene. Given an image (or video), a number of approaches try to predict the likely human poses that these scenes afford \cite{18, 27, 33, 34}.

This work, on the other hand, considers the opposite problem: given a human pose as input, the goal is to hallucinate scene(s) that are compatible with that pose. Consider Figure 1. A push-up pose (top) places severe constraints on the space of compatible scenes: they must not only be semantically compatible (e.g., gym, exercise room), but also have compatible spatial affordances (enough floor space or appropriate equipment). Objects in the scene can afford interaction with the human (e.g., squishing down an exercise ball). Other poses might not appear as constraining, but even a simple standing pose (bottom) — head looking down, hands reaching in, legs occluded — is actually a strong indicator of a cooking scene, and signals that an object (e.g., countertop) must be present to occlude the legs.

Rather than explicitly model scene affordances and contextual compatibility, we employ a modern large-scale generative model (based on a souped-up StyleGAN2 \cite{48} architecture) to discover these relationships implicitly, from data. While GANs have performed well at capturing disentangled visual models in specialized scenarios (e.g., faces, churches, categories from ImageNet \cite{19}), they have not been demonstrated \textit{in situ}, on complex, real-world data across varying environments. Indeed, there is currently no single dataset...
available that captures the full scope of scene-pose interactions needed to learn our task.

We curate a massive meta-dataset of humans interacting with everyday environments, containing over 19 million frames. The complexity and scale of data is much higher than common GAN datasets, such as FFHQ [47] (70,000 face images) and ImageNet [19] (1.3M object images). With an appropriate pose conditioning mechanism, increased model capacity, and removal of style mixing, we are able to successfully train a pose-conditioned GAN on this highly complex data. Our model and meta-dataset mark substantial progress leveraging GANs in real-world settings containing humans and diverse environments. Through numerous visual experiments, we demonstrate our model’s emergent ability to capture affordances and contextual relationships between poses and scenes.

The remainder of the paper is organized as follows: Section 2 gives an overview of prior work, Section 3 describes the construction of our meta-dataset, Section 4 covers our Pose-compatible Scene GAN architecture and training, and Section 5 presents the experimental results and ablations.

2. Related Work

Scene and object affordances. Affordances [28] describe the possible uses of a given object or environment. A significant body of work learns scene affordances, such as where a person can stand or sit, from observing data of humans [17, 18, 25, 27, 32, 33, 42, 54, 77]. Overlapping areas of work focus on human interactions with objects [12, 29, 52, 80, 85] or synthesize human motion conditioned on an input scene [10, 53, 74]. We propose the reverse task of hallucinating a scene conditioned on pose.

Pose-conditioned human synthesis. There are a plethora of methods that take a source image (or video) of a human and a new pose and generate an image of the human in the new pose [3, 6, 16, 55, 58, 69, 76]. Although we too condition on pose, our goals are almost entirely opposite: we aim to generate novel scenes compatible with a given pose, whereas the above methods reuse the scene from the source image/video and only focus on reposing the person within that provided scene.

GANs for image synthesis. Introduced by Goodfellow et al. [31] a generative adversarial network (GAN) is an implicit generative model that learns to synthesize data samples by optimizing a minimax objective. The generator is tasked with fooling a discriminator, and the discriminator is tasked with differentiating real and generated samples. Modern GANs are capable of producing high quality images [9, 45, 47, 48]. Image translation [40, 76] utilizes conditional GANs [62] to translate from one domain to another. While our task is pose-conditional scene generation, we leverage benefits of modern unconditional GANs [48].

Visual disentanglement. Disentanglement methods attempt to separate out independent controllable attributes of images. This can be achieved with unsupervised and self-supervised methods [38, 41, 47, 66], or an auxiliary signal [30, 56]. Components of image samples can be added, removed and composed using pretrained GANs [7, 15]. Recent work has applied similar strategies to image translation models to compose style and content from different images [65]. The most related to us is the work of Ma et al. [59], who synthesize images of people, while independently controlling foreground, background, and pose. However, the focus is on generating humans in very tightly cropped images with simple backgrounds, rather than generating scenes with appropriate affordances.

Many disentanglement methods assume all images or image attributes can be combined (“mixed-n-matched”) with all others [30, 38, 41, 47, 56, 59, 65, 66]. In this work, we seek disentangled representations of pose, human appearance and scene, yet it is essential our model understand which scenes can or cannot be composed with which poses.

Contextual relationships. Many works leverage contextual relationships among objects and scenes [8] to improve vision models such as object recognition and semantic segmentation [21, 64, 67, 72]. Divvala et al. [21] explicitly enumerate (Table 1) a taxonomy of possible contextual information. In this paper we are specifically interested in contextual relationships between humans and their environments, and aim to recover them implicitly, from data.

3. Humans in Context Meta-dataset

To study the rich relationship between scenes and human poses requires large-scale data of people interacting with many different environments. Internet videos are a natu-
4. Pose-compatible Scene GAN

We design a conditional GAN [31, 62] to produce scenes compatible with human pose. Our network architectures are based on StyleGAN2 [48] and are depicted in Figure 3. Generating high quality pose-compatible scenes arises from simple yet important modifications: dual pose conditioning, removal of style mixing, and large-scale training.

4.1. Dual pose conditioning

The conditional generator $G$ and discriminator $D$ both utilize input pose via two mechanisms: keypoint heatmap conditioning, which specifies spatial placement of a human subject, and pose latent conditioning, which infers compatible scenes. To succeed at our task, humans must be positioned correctly and generated scenes must be compatible. Dual pose conditioning drives strong performance in both respects, and outperforms conditioning on either alone in our ablation experiment (Table 3). Furthermore, dual pose conditioning facilitates disentanglement by separating controls of scene and human pose. We leverage these separate controls for numerous applications: generating scenes without humans, visualizing incompatible scenes and poses, placing a person in a new scene, and animating pose.

Keypoint heatmaps. Let pose $p = (p_1, ..., p_K)$ denote 2D locations of the $K = 18$ human keypoints detected by OpenPose [11], and let $v = (v_1, ..., v_K)$ indicate visibility of each keypoint. Following the works of [3, 6, 69], our keypoint heatmaps $H(p)$ consist of radial basis function kernels centered at each keypoint. For heatmap $k \in \{1, ..., K\}$, the intensity at location $q$ is given by Equation 1. We concatenate heatmaps at each scale of the generator, and at the input of the discriminators.

$$H_{k,q}(p) = \begin{cases} \exp\left(-\frac{||q - p_k||^2}{2\sigma^2}\right) & \text{if } v_k = 1 \\ 0 & \text{otherwise} \end{cases}$$

Pose latent conditioning. To generate compatible scenes, we condition scene latent codes on the input pose. Akin to intermediate latents in StyleGAN2 [48], the scene latent code $w$ controls generation by modulating convolutional weights. To condition the latent code, pose locations and
visibility are flattened and mapped to a 512-dimensional input via a learned linear projection. A noise sample \( z \sim \mathcal{Z} \) is concatenated with the input vector and passed through a multi-layer perceptron (MLP) \( f_G \) to produce a scene latent code \( w \in \mathcal{W} \). Multiple plausible scenes can be generated by sampling different noise vectors \( z \) for the same pose. The discriminator learns a separate linear projection and MLP \( f_D \), and passes conditioning to the final layer.

4.2. Removal of style mixing

Style mixing regularization [47, 65] encourages disentanglement by randomly mixing intermediate latent codes during training. The technique assumes image attributes at each layer are compatible with all other image attributes (e.g. any face could have any color hair). This assumption is not true when composing scenes and humans, which we visually demonstrate through the incompatible scenes and poses in Figure 4. This motivates removing style mixing regularization during training, which improves results in our ablation experiments (Table 2).

4.3. Large-scale GAN training

Typical datasets used with StyleGAN2 (e.g. faces, bedrooms, churches [57, 81]) are relatively homogeneous. Increasing model capacity is a natural extension given the diversity and complexity of scene images in our dataset. We find that increasing the channel width of convolutional layers by \( 2 \times \) significantly improves our model. Prior work in scaling GANs from Brock et al. [9] found large minibatch sizes crucial to training stability. We therefore increase the minibatch size by \( 3 \times \) (from 40 to 120) when training a larger model. We ablate components of our model to clearly demonstrate improvements due to scale compared to other factors (Table 2).

4.4. Model details

We train all models at \( 128 \times 128 \) resolution with non-saturating logistic loss [31], path length [48] and \( R_1 \) [61] regularization, and exponential moving average of generator parameters [45]. We remove spatial noise maps in StyleGAN2 from all models to isolate control of the latent code. Our final model employs differentiable augmentation of both real and generated images [46, 84], and trains the discriminator on an additional fake example containing real images with mismatched labels [68].

5. Experiments

Our model hallucinates diverse, high quality images of scenes compatible with input pose. We generate scenes in isolation as well as scenes containing humans, and analyze our model through several visual experiments. Generating scene images is challenging due to the high complexity of data, and our model outperforms Pix2Pix and pose-conditioned StyleGAN2 baselines in terms of image quality and accurate human placement. We present characteristic success and failure results in Figure 5 and Figure 6. See the appendix for more results, including multiple pages of random uncurated samples.

5.1. Not all scenes and poses are compatible

It is essential that we model which scenes are compatible with which poses. A person cannot do a push-up in the middle of a horse, ride atop a kitchen countertop, or be occluded by thin air. These scenarios sound obviously false, yet could occur if the scene and human pose are incompatible. We visualize images generated with correctly and incorrectly paired scene latent codes and keypoint heatmaps in Figure 4. Correctly paired images are shown in blue on the diagonal — a person doing a pushup in a gym, riding a horse, cooking in a kitchen, and a baby leaning on a table. These exemplify interesting relationships between human pose and scene learned by our model. Other images mix scene latent codes with keypoint heatmaps from the wrong pose, often producing unrealistic images.

These examples of incompatible scenes and poses high-
Figure 5. **Success cases.** Our model learns complex scene-pose relationships. For each input pose, we show many hallucinated scenes, with and without a human. Diverse outputs include a person paddling a kayak (B), lifting a barbell in their hand (G), and playing the drums (M). Our model produces multiple plausible scenes for the same pose, providing insight into scenes with related affordances: in the same pose, a person may climb in an indoor gym or on a snowy ledge (F); a person can ride a horse, ride a bicycle, or ride a tractor (L). Please see the appendix for multiple pages of random results. *See example K for the first ever GAN-generated image of a person cleaning a toilet.*
Causes for failure include: partially generating objects, such as a bike (A); poor overall image quality (B); missing limbs without proper occluders (C); difficulty placing objects, such as a golf club, in a person’s hands (D); difficulty hallucinating an object on which to sit (E); overly repetitive textures (F); infeasible scenes, such as walking on water (G); and leaving behind a partial human when hallucinating the scene in isolation (H).

Our model hallucinates scenes with foreground objects, such as a drum kit or table, to occlude portions of the input pose which are not visible.

Any face can be given glasses, longer or shorter hair, or a darker or lighter skin tone and still remain a feasible image. This enables global disentanglement of attributes, and applications like style mixing, which combines different intermediate latent codes of any two samples (see Figure 3 of the original StyleGAN paper [47] for a wonderful example). The assumption of compatibility between all attribute pairs no longer holds for data of scenes with humans, which motivates conditioning scene latent codes on pose. Relatedly, we find that removing style mixing from training significantly improves performance (Table 2).

Portions of a human pose may be occluded by foreground objects, such as a piece of furniture. Scenes with occluders only afford particular human poses in order for the occluder and human to be compatible. In the reverse direction, provided a partially visible human pose, our model hallucinates scenes with foreground objects to occlude portions of the pose not visible. Figure 7 shows an example full body pose and output scenes (top). When legs are not visible in an otherwise identical pose, our model hallucinates objects (e.g., a drum kit or table) to occlude the legs.

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Sections 5.1 demonstrates why complete separation of pose and scene is undesirable. We can, however, disentangle human subjects from scenes when both are conditioned on the same pose. To achieve this, we optimize a scene latent code $w$ to compose two samples. To increase expressiveness of the latent space, we separately optimize the latent used at each scale of our model, similar to the $W^+$ space used in [1]. We minimize perceptual loss [43, 82] between person-only crops of the composition and first sample, obtained using the bounding box surrounding human pose; we also minimize perceptual loss between scene-only images of the composition and second sample, obtained by zeroing out keypoint heatmaps. Figure 8 shows results where people are placed in new scenes without changing human appearance. See the appendix for details.

Regions of low density in the data distribution are particularly challenging to model. Quality can be improved (at the loss of some diversity) by sampling from a truncated or shrunk distribution [4, 9, 24, 37, 51, 60]. Truncation in
1.00
0.75
0.50
0.25
0.00
(a) (b)

Figure 9. Scene clusters and truncation. We contrast truncation via (a) interpolation toward the mean of random latents, and (b) interpolation toward the mean of conditional latents. The left plot shows a t-SNE [73] visualization of scene latent codes. Gray points are 10,000 randomly sampled latents. Colored sets of points are each 1000 latent samples conditioned on the same pose. The formation of clusters signifies that different scene latents conditioned on the same pose are close to each other in the intermediate latent space. The dark gray point in the center is the mean of all random latents, and dark colored points are the mean latents for each pose. Beside each cluster is the input pose and image generated using the corresponding mean cluster latent. Conditional truncation (b) works significantly better than unconditional (a).

StyleGAN [47] interpolates intermediate latents $w$ toward the mean $\bar{w} = \mathbb{E}_{z \sim Z}[w]$ to shrink the sampling distribution. While this improves generation quality for StyleGAN trained on data such as faces, we note that our data is much more complex, and that the mean scene latent may be less meaningful than the mean face latent. Shown in part (a) of Figure 9, naively interpolating toward the mean scene latent produces a gray scene rather than improving quality.

In visualizing a t-SNE [73] plot of scene latents in Figure 9, we observe that latents sampled from different noise vectors $z$ yet conditioned on the same pose $p$ form clusters. We apply conditional truncation by interpolating a latent $w$ toward the conditional mean $\bar{w}_p = \mathbb{E}_{z \sim Z}[w|p]$, shifting the sample toward the cluster center. Shown in part (b) of Figure 9, conditional truncation works significantly better for our model. We apply conditional truncation $w' = \bar{w}_p + \psi(w - \bar{w}_p)$ of $\psi = 0.75$ to generated images throughout the paper.

5.5. Animating pose

The focus of our paper is hallucinating scene images compatible with a single pose. However, after training, our model is capable of animating pose in a stationary scene. In Figure 10 we demonstrate a sequence of images generated by fixing the scene and animating the human pose. The scene is inferred from only the first pose, and is limited to small human motion and stationary backgrounds.

Figure 10. Animating pose. In this example, we infer a scene based on the first pose in a sequence. We then animate pose by keeping the scene latent fixed and passing keypoint heatmaps for each subsequent pose.

5.6. Baseline metric comparisons

We measure numeric performance in two respects: how accurately human subjects are positioned, and how realistic generated scenes look.

**Accurate human positioning.** PCKh [5] measures the percent of correct pose keypoints (within a radius relative to the head size), where a higher percent is better. We use OpenPose [11] to extract poses from generated images for comparison with input poses. PCKh is computed on a held out test set, ensuring accurate placement of new poses not seen during training.

**Realistic scene images.** FID — Fréchet inception distance [36] — measures realism by comparing distributions of Inception network [71] features between the training dataset and generated images. Lower FID scores are better and correlate with higher quality, more realistic images.

To succeed at our task, a model must both put a human in the correct pose and generate a compatible scene. Table 1 compares our model with Pix2Pix and StyleGAN2 baselines on these metrics, demonstrating that our model achieves superior performance. Note that StyleGAN2 [48] is primarily an unconditional GAN. The public code release and follow-up work [46] support class-conditional generation. We refer to the version of our model with only pose latent conditioning as StyleGAN2, since it is the most straightforward extension of StyleGAN2 for our task.

5.7. Ablations

We present two ablation experiments. Table 2 enumerates changes relative to a pose-conditioned StyleGAN2 baseline, demonstrating the improvements gained by our simple yet important modifications. Table 3 compares three options for pose conditioning: latents only, keypoint heatmaps only, and dual conditioning of both. Keypoint heatmaps are necessary to accurately position a human in the scene, which is shown by a substantially higher PCKh.
Table 1. **Baseline metric comparisons.** We report PCKh (higher is better) as a measure of how accurately humans are positioned, and FID (lower is better) as a measure of how realistic generated scenes look. Our model outperforms Pix2Pix and pose-conditioned StyleGAN baselines on both metrics.

| Model                     | PCKh | FID  |
|---------------------------|------|------|
| Pix2Pix                   | 48.4 | 71.2 |
| StyleGAN2 (with pose latent conditioning) | 32.4 | 16.6 |
| Ours                      | 84.2 | 5.9  |

Table 2. **StyleGAN2 ablation.** We enumerate modifications relative to a pose-conditioned StyleGAN2 baseline. In particular, removing style mixing, conditioning on keypoint heatmaps, augmenting discriminator inputs and passing a fake mismatched example to the discriminator, and increasing model scale all contribute to our final model.

| Modification                  | PCKh | FID  |
|-------------------------------|------|------|
| StyleGAN2 (with pose latent conditioning) | 32.4 | 16.6 |
| + style mixing                | 36.4 | 11.6 |
| + keypoint heatmaps           | 79.8 | 12.2 |
| + augmentation, mismatch      | 80.7 | 12.1 |
| + large scale (Ours)          | 84.2 | 5.9  |

Table 3. **Pose conditioning ablation.** We contrast three options for pose conditioning: only conditioning the latent on pose, only conditioning on keypoint heatmaps, and dual conditioning of both latents and heatmaps. We conduct this ablation on the smaller version of our model. We find that keypoint heatmap conditioning is crucial for accurately placing a human (PCKh), whereas latent conditioning improves the quality of scene generation (FID). We condition with both mechanisms in our final model, which has the best metric trade-off, and enables separating control of human position and scene generation after training.

| Conditioning method | PCKh | FID  |
|---------------------|------|------|
| Latent only         | 36.4 | 11.6 |
| Heatmap only        | 79.7 | 15.1 |
| Both                | 79.8 | 12.2 |

Latent conditioning improves quality of generated scenes, which is shown by a lower FID score. We condition with both mechanisms — in addition to offering the best trade-off in metric performance, dual conditioning enables applications of disentanglement, such as generating scenes without humans or visualizing incompatible scenes and poses.

6. Discussion

**Limitations.** Our dataset and model only consider images with a single human subject. Dataset curation is limited by the performance of Keypoint R-CNN [35, 78] and OpenPose [11, 13] when filtering videos for humans. For training, we depend on OpenPose to correctly predict the conditioning pose. Our model does not consider human movement when inferring scenes (our experiments with temporal pose conditioning did not significantly improve the results).

**Societal impact.** Models which understand scene-human relationships may enable future vision and robotics systems to better help people by predicting human affordances and interactions. Scene generation may lead to more accessible and affordable content creation tools. There is some risk of this or future generative models being used to create fake and misleading content (though current GAN-generated images are easy to identify [75]). Our model also inherits any demographic bias present in the existing datasets used to source our training data. We believe the potential positive impacts and scientific contributions of this paper outweigh risk caused by our work.

**Conclusion.** In this paper, we present a new task: provided a human pose as input, hallucinate the possible scene(s) which are compatible with that input pose. Strong relationships between humans, objects and environments dictate which scenes afford a given pose. Many prior works study human affordances from the angle of predicting which poses are possible provided an input scene — we study the other side of the same coin, and hallucinate scenes that afford an input pose. We employ a large-scale GAN with appropriate pose conditioning to both correctly position humans and infer compatible scenes. To train our model, we curate the Humans in Context meta-dataset, which contains 19M video frames of people in a wide variety of everyday environments. We demonstrate the emergent ability of our model to capture affordance relationships between scenes and poses. This work marks a significant step toward using GANs to represent complex real-world environments. We hope it will motivate the broader research community to leverage modern generative approaches for scene understanding and modeling.

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A. Humans in Context Meta-dataset Details

Our dataset contains diverse footage of humans immersed in everyday environments. Each image is supplemented with pseudo-ground truth human pose obtained using OpenPose [11, 13]. The data is sourced from 10 existing human and action recognition datasets, with the numbers of clips and frames from each source dataset detailed in Table 4. Video footage provides a vast source of diverse human activity, and ensures all poses are represented, rather than only human poses photographers choose to capture in still images. For the MPII [5] dataset, which is primarily a still image dataset, we use short video clips of the frames preceding and following each image.

We filter out videos where either dimension is shorter than 256 pixels, and we resize remaining videos using Lanczos resampling [22] such that the smaller edge is exactly 256 pixels. We exclude videos with an average bitrate below 0.9 bits per pixel, or with a framerate that does not fall between (and cannot be subsampled to fall between) 23.9 fps and 30 fps. Videos are truncated to 3000 frames. Source datasets which provide pre-extracted frames only undergo quality filtering by spatial resolution.

Frames are then filtered to contain a single person using pretrained Keypoint R-CNN [35, 78] person detection. Person bounding boxes are detected for each frame, with a minimum accuracy of 95%, a minimum bounding box area of 1% of the total frame area, and non-maximum suppression of overlapping bounding boxes with an intersection over union greater than 0.3. With these thresholds, any frame with more than a single person detected is removed. Stricter thresholds are then applied to the remaining frames with a single person bounding box: a minimum accuracy of 98%, a minimum bounding box area of 4% of the total frame area, and a maximum bounding box area of 80% of the total frame area. These thresholds ensure with high accuracy that there is a single person present in the frame at a reasonable size. Frames are then cropped to a 256 × 256 resolution toward the average bounding box center for each contiguous segment of frames.

Pseudo-ground truth pose labels are computed for each frame using OpenPose [11, 13] keypoint prediction. We use the single-scale OpenPose version to compute 18 body keypoints. Similar to person detection, we use a relaxed total score threshold of 2.5 when filtering for multiple people, and a strict total score threshold of 10.0 when ensuring there is a single person. Each individual keypoint has a score threshold of 0.3, and keypoints below this threshold are marked as not visible in the frame. To avoid frames of just legs or torso, we only include frames where the keypoint at the base of the neck is visible, and where a total of at least 8 of 14 keypoints (excluding eyes and ears) are visible.

The final dataset only includes clips of at least 30 adjacent frames where each frame passed filtering. Note that multiple clips may be sourced from the same video, and that duplicate videos from different source datasets are possible.

B. Model Implementation Details

We train all models at 128 × 128 resolution. Many aspects of our model are borrowed directly from StyleGAN2 [48], including non-saturating logistic loss [31], equalized learning rates for all parameters [45], R1 regularization [61], path length regularization [48], and exponential moving average of generator parameters [45].

We use a learning rate of 2.5 × 10⁻³, an exponential moving average rate of β = 0.995, a moving average warmup of 150,000 steps, and R1 regularization strength of γ = 0.05. We remove spatial noise maps to isolate control over the scene to the latent code. We also remove style mixing regularization during training. Our final model was trained with a minibatch size of 120 on 10 × NVIDIA Quadro RTX GPUs, and for 1,000,000 steps. Ablations were trained with a batch size of 40 on 5 × NVIDIA GeForce RTX 2080 GPUs for 600,000 iterations. Multiple checkpoints were saved throughout training, and the checkpoint with the lowest FID score was used for all evaluation. The Pix2Pix baseline was trained for 10,000,000 iterations with a batch size of 40 on 5 × NVIDIA GeForce RTX 2080 GPUs.

B.1. Data augmentation

Data augmentation of both generated and real images just prior to the discriminator can improve robustness and prevent the discriminator from overfitting to the train dataset [46, 84]. Our augmentation parameters are largely based on [84]. Brightness is augmented by randomly offsetting intensity by a value uniformly sampled from −25% to +25%. Saturation is augmented by interpolating red, green and blue channels toward or away from the mean of all three at each pixel, with interpolation weights uniformly sampled from 0.0 to 2.0. Contrast is augmented by interpolating color values toward or away from the mean of all color values in an entire frame sequence, with interpolation weights uniformly sampled from 0.5 to 1.5. Horizontal flipping is applied with a 50% chance to all frames and poses in a sequence. Frames are scaled by a factor uniformly sampled from 0.8 to 1.25 and translated by an offset sampled uniformly from −12.5% to +12.5%. A random cutout, half the size of each dimension and randomly placed, is erased from each frame. Spatial transformations applied to frames are also applied to poses so that the frames and poses still correspond correctly. We briefly experimented with dropout augmentation of pose, but did not find it helpful. See Figure 11 for examples of our data augmentation.
Table 4. **Humans in Context source data.** Our dataset consists of video clips filtered from 10 existing human and action recognition datasets. High quality clips have sufficient bitrate, framerate and resolution. Person clips are those where pretrained person detection and pose prediction networks assert that a single person is present. In total we curate 229,595 clips and 19,503,700 frames.

| Source                  | # Video Clips | # Frames          |
|-------------------------|---------------|-------------------|
| HVU [20]                | Source        | 566,489           | 98,603,223       |
|                         | High Quality  | 353,174           | 56,074,418       |
|                         | Person        | 105,634           | 3,374,112        |
| Moments [63]            | Source        | 757,804           | 78,037,500       |
|                         | High Quality  | 653,368           | 2,428,079        |
|                         | Person        | 54,156            | 2,157,074        |
| Kinetics-700-2020 [14,49] | Source     | 620,119           | 5,738,042        |
|                         | High Quality  | 432,502           | 3,374,112        |
|                         | Person        | 26,911            | 76,112           |
| Charades [70]           | Source        | 9,848             | 2,157,074        |
|                         | High Quality  | 7,319             | 56,074,418       |
|                         | Person        | 16,967            | 3,374,112        |
| InstaVariety [44]       | Source        | 2,545             | 1,025,459        |
|                         | High Quality  | 2,449             | 352,498          |
|                         | Person        | 5,773             | 163,956          |
|Oops [23]                | Source        | 29,940            | 321,071          |
|                         | High Quality  | 27,953            | 730,211          |
|                         | Person        | 8,360             | 76,112           |
| MPII [5]                | Source        | 24,987            | 161,029          |
|                         | High Quality  | 24,980            | 76,112           |
|                         | Person        | 8,820             | 352,498          |
| VLOG-people [26]        | Source        | 663               | 1,025,459        |
|                         | High Quality  | 555               | 352,498          |
|                         | Person        | 1,261             | 163,956          |
| PennAction [83]         | Source        | 2,326             | 161,029          |
|                         | High Quality  | 2,221             | 76,112           |
|                         | Person        | 1,208             | 352,498          |
| YouTube-VOS [79]        | Source        | 4,519             | 613,441          |
|                         | High Quality  | 4,511             | 34,763           |
|                         | Person        | 505               | 19,503,700       |

Total 2,019,240 1,509,032 229,595 248,729,428 19,503,700

B.2. Mismatch discrimination

We force the discriminator to pay attention to pose conditioning by providing a mismatched real image with the incorrect pose conditioning as an additional fake example. For the mismatched fake example, the pose embedding and keypoint heatmaps both take pose from another sample in the minibatch. This training method was first introduced in text-to-image generation [68] but has not been widely used in the image or video translation literature; we found training with mismatch discrimination provides a slight improvement, forcing the discriminator to use conditioning. See Figure 12 for examples of the three types of input pairs provided to the discriminator.

B.3. Human disentanglement

Our generator can be used to place a human subject in a new scene, as we outline in Section 5.3 of the main paper. We accomplish this by optimizing for a latent code which produces a scene matching one image and a subject matching another. We separately optimize the latent code used at each scale of our model, which is similar to the $\mathcal{W}^+$ space [2] used for inversion (although slightly lower dimensional). We minimize perceptual loss [43, 82] between a subject-only crop of the first generated image and the composition. When generating subject-only images, we zero out the learned constant input to the StyleGAN2 generator [48], which we found helps isolate the subject from the background. The crop region is obtained from human pose. We also minimize perceptual loss between scene-only versions of the second generated image and composition image. We optimize for 1000 steps using the Adam optimizer [50] and a learning rate of 0.05.

C. Additional Results

Please see Figures 13 14 15 16 17 for random uncurated samples from our model.
Figure 13. Random samples.
Figure 14. Random samples.
Figure 15. Random samples.
Figure 16. Random samples.
Figure 17. Random samples.