
Pragmatic Image Compression for Human-in-the-Loop Decision-Making

Siddharth Reddy, Anca D. Dragan, Sergey Levine
University of California, Berkeley
{sgr,anca,svlevine}@berkeley.edu

Abstract

Standard lossy image compression algorithms aim to preserve an image’s appearance, while minimizing the number of bits needed to transmit it. However, the amount of information actually needed by a user for downstream tasks – e.g., deciding which product to click on in a shopping website – is likely much lower. To achieve this lower bitrate, we would ideally only transmit the visual features that drive user behavior, while discarding details irrelevant to the user’s decisions. We approach this problem by training a compression model through human-in-the-loop learning as the user performs tasks with the compressed images. The key insight is to train the model to produce a compressed image that induces the user to take the same action that they would have taken had they seen the original image. To approximate the loss function for this model, we train a discriminator that tries to distinguish whether a user’s action was taken in response to the compressed image or the original. We evaluate our method through experiments with human participants on four tasks: reading handwritten digits, verifying photos of faces, browsing an online shopping catalogue, and playing a car racing video game. The results show that our method learns to match the user’s actions with and without compression at lower bitrates than baseline methods, and adapts the compression model to the user’s behavior: it preserves the digit number and randomizes handwriting style in the digit reading task, preserves hats and eyeglasses while randomizing faces in the photo verification task, preserves the perceived price of an item while randomizing its color and background in the online shopping task, and preserves upcoming bends in the road in the car racing game.

1 Introduction

Modern web platforms serve billions of images every day, and typically rely on lossy compression algorithms to store and transmit this data efficiently. Recent work on machine learning methods for lossy image compression [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11] improves upon standard methods like JPEG [12] by training neural networks to minimize the number of bits needed to generate high-fidelity reconstructions. In this paper, we explore the idea of compressing images to even smaller sizes by intentionally allowing reconstructions to deviate drastically from the visual appearance of their originals, and instead optimizing reconstructions for the specific, downstream tasks that the user wants to perform with them, such as video conferencing, online gaming, or remotely operating space robots [13].

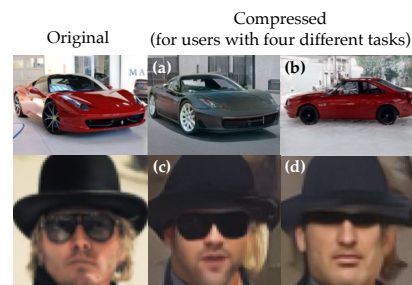


Figure 1: Images compressed 2-4x smaller than JPEG retain information for tasks like shopping for cars in a perceived price range (a), surveying car colors (b), and checking photos for eyeglasses (c) or hats (d).

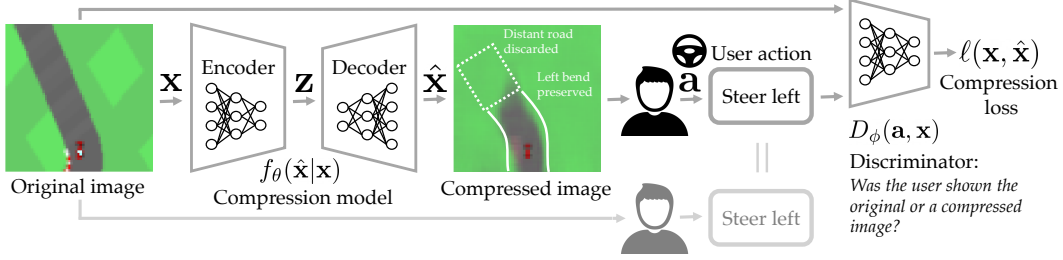


Figure 2: Given the original image x , we would like to generate a compressed image \hat{x} such that the user’s action a upon seeing the compressed image is similar to what it would have been had the user seen the original image instead. In a 2D top-down car racing video game, our compression model learns that, in order to match the user’s steering with and without compression, it must preserve bends, but can discard the road farther ahead.

Our main observation in this work is that, instead of optimizing the compression model for a task-agnostic *perceptual* similarity objective function, we can instead optimize the compression model for *functional* similarity: producing compressed images that, when shown to the user, induce the user to take the same actions that they would have taken had they observed the original, uncompressed images. We call this *Pragmatic Compression* (PICO), inspired by prior work on pragmatics [14, 15, 16] that characterizes the meaning of a message through the behavior it induces in a listener. PICO adapts compression to user behavior, enabling the user to perform their individually-desired tasks with compressed images instead of the original images. For example, consider two users with distinct tasks: one flying a quadcopter, and the other driving a ground robot. On a network with an extremely low bitrate, we would like the compressed video feed of the ground robot to preserve ground-level obstacles and terrain while discarding details about power lines and tree canopies, and the quadcopter feed to do the opposite.

To this end, we formulate compression as a human-in-the-loop learning problem, in which the compression model is represented as an encoder-decoder neural network that takes the original image as an input and outputs the compressed image. The user sees the compressed image, and takes an action to perform their desired task (see Figure 2). The main challenge in this work is designing a loss function for the compression model that evaluates the quality of the compressed image in the context of the original image and the user’s action. We do not assume knowledge of the user’s desired task, so we cannot directly evaluate the quality of the compressed image by evaluating the fitness of the user’s action upon seeing the compressed image. We also do not assume access to ground-truth action labels for the original images in the streaming setting, so we cannot compare the user’s action upon seeing the compressed image to some ground-truth action.

Instead, we define the loss function through adversarial learning. For example, consider a user browsing an online shopping catalogue, observing photos and clicking on appealing items. To collect positive and negative examples of user behavior, we simply randomize whether a user sees the original or compressed version of an image while they are shopping, and record their actions. We then train a discriminator to predict the likelihood that a user’s action was taken in response to the original rather than a compressed image, and train the compression model to maximize this predicted likelihood.

Our primary contribution is the PICO algorithm for human-in-the-loop learning of data compression models. We validate PICO through three user studies on Amazon Mechanical Turk, in which we train and evaluate our compression models on data from human participants. In the first study, we asked participants to read handwritten digits and identify the numbers – PICO learned to preserve the number and discard handwriting style (Figure 3). In the second study, we asked users to browse a car catalogue and select cars based on perceived price – PICO learned to preserve overall shape and sportiness while randomizing paint jobs and backgrounds (Figure 4). In the third study, we asked participants to verify photos of faces by checking if heads or eyes were covered – PICO learned to preserve hats and eyeglasses while randomizing faces (Figure 5). In all three studies, PICO obtained up to 2-4x lower bitrates than non-adaptive baseline methods. To show that PICO can be used in sequential decision-making problems, we also ran a user study with 12 participants who played a car racing video game – at a fixed bitrate, PICO learned to preserve bends in the road substantially better than a non-adaptive baseline method, enabling users to drive more safely (Figure 6).

2 Related Work

Prior work on learned lossy image compression focuses on overcoming various challenges in training neural networks on images [17], including amortized variable-rate compression [1, 4], end-to-end training with quantization [2, 5, 6], optimizing the rate-distortion trade-off [7, 8], optimizing perceptual quality [9, 10, 11], training hierarchical latent variable models [3], and sequential compression of videos [18, 19]. While these methods aim to generate visually-pleasing reconstructions that are perceptually similar to their originals, PICO focuses on preserving functional similarity. Hence, PICO can achieve substantially lower bitrates for specific downstream tasks (e.g., see Figure 3).

Prior work has studied human-in-the-loop learning in related contexts, including reinforcement learning of text summarization policies from user feedback [20] and automatic data visualization for decision support systems [21]. In the context of imitation learning, the idea of fitting a model of human behavior using generative adversarial networks [22] has also been explored [23]. PICO differs from [21, 23] in that it tackles image compression – an entirely different problem from decision support and imitation learning. In contrast to [20], which elicits user comparisons between different summaries of the same text, PICO can be used for sequential tasks like video games (see Section 5.3) where the user cannot be repeatedly queried with different compressed versions of the same image.

3 Pragmatic Compression

Generative models are typically used for sampling and representation learning, but they can also be used for compression [24, 25, 26, 27]. For example, variational autoencoders [28] are trained with a variational information bottleneck [29] that explicitly constrains the amount of information carried by their latent variables – hence, we can use a trained encoder to compress an image, and a trained decoder to reconstruct it from latent features [5, 30]. In contrast to compression methods that train such generative models to maximize the visual fidelity of the reconstruction, we formulate compression as a problem of *control*, including the downstream behavior of the user in the problem statement. First, the environment generates an image $\mathbf{x} \in \mathbb{R}^{w \times h \times c}$. Given the original image \mathbf{x} , the compression system generates a compressed image $\hat{\mathbf{x}} \in \mathbb{R}^{w \times h \times c}$ that can be represented using no more than n bits, where n is a hyperparameter. The user then observes the compressed image $\hat{\mathbf{x}}$ and samples an action $\mathbf{a} \sim \pi(\mathbf{a}|\hat{\mathbf{x}})$ from their unknown policy π . We do not assume access to the user’s utility function $U(\mathbf{x}, \mathbf{a})$ or a specification of their desired task. Our goal is to generate a compressed image $\hat{\mathbf{x}}$ that induces an action \mathbf{a} that maximizes the unknown utility $U(\mathbf{x}, \mathbf{a})$.

We approach this problem by generating a compressed image $\hat{\mathbf{x}}$ that induces the user to take the same action \mathbf{a} that they would have taken had they seen the original image \mathbf{x} instead. Let $f_\theta(\hat{\mathbf{x}}|\mathbf{x})$ denote a parametric model of our compression function, where θ are the model parameters (e.g., neural network weights). To train f_θ , we need a loss function that evaluates the difference between an original image \mathbf{x} and the output of the compression model $\hat{\mathbf{x}} \sim f_\theta(\hat{\mathbf{x}}|\mathbf{x})$. One approach is to use conditional generative adversarial networks [31] to train a discriminator $D(\hat{\mathbf{x}}, \mathbf{x})$ that tries to distinguish between original and compressed images, and train the compression model to generate compressed images $\hat{\mathbf{x}}$ that fool this discriminator, analogous to prior work on adversarial image compression [11]. However, this approach seeks to maximize the *perceptual* similarity of the original and compressed image, whereas we would like to maximize their *functional* similarity.

The key challenge for our method then is to train the discriminator $D(\hat{\mathbf{x}}, \mathbf{x})$ to detect differences between \mathbf{x} and $\hat{\mathbf{x}}$ that influence the user’s downstream action, while ignoring superficial differences between the images that do not affect the user’s action. We address this challenge by first training an action discriminator $D_\phi(\mathbf{a}, \mathbf{x})$ to predict whether the user saw the original or a compressed image before taking the action \mathbf{a} . This action discriminator D_ϕ captures differences in user behavior caused by compression, while ignoring visual differences between the original and compressed images. To construct a loss function that links the compressed images to these behavioral differences, we distill the action discriminator $D_\phi(\mathbf{a}, \mathbf{x})$ into an image discriminator $D_\psi(\hat{\mathbf{x}}, \mathbf{x})$.

3.1 Maximizing Functional Similarity of Images through Adversarial Learning

We formalize the idea of maximizing the functional similarity of the original \mathbf{x} and compressed image $\hat{\mathbf{x}}$ as follows. Let $T \in \{0, 1\}$ denote whether the user sees the original or a compressed image before taking an action: if $T = 1$, then $\hat{\mathbf{x}} \leftarrow \mathbf{x}$; else if $T = 0$, sample $\hat{\mathbf{x}} \sim f_\theta(\hat{\mathbf{x}}|\mathbf{x})$. We would like to train

Algorithm 1 Pragmatic Compression (PICO)

```
Initialize compression model  $f_\theta$ 
while true do
   $\mathbf{x} \sim p_{\text{env}}(\mathbf{x})$  ▷ environment generates original image
   $T \sim \text{Bernoulli}(0.5)$  ▷ randomly decide whether user sees compressed image or original
  if  $T = 1$  then  $\hat{\mathbf{x}} \leftarrow \mathbf{x}$  else  $\hat{\mathbf{x}} \sim f_\theta(\hat{\mathbf{x}}|\mathbf{x})$ 
   $\mathbf{a} \sim \pi(\mathbf{a}|\hat{\mathbf{x}})$  ▷ user takes action using unknown policy
   $\mathcal{D} \leftarrow \mathcal{D} \cup \{(T, \mathbf{x}, \hat{\mathbf{x}}, \mathbf{a})\}$ 
   $\phi \leftarrow \phi + \nabla_\phi \sum_{(T, \mathbf{x}, \hat{\mathbf{x}}, \mathbf{a}) \in \mathcal{D}} T \cdot \log D_\phi(\mathbf{a}, \mathbf{x}) + (1 - T) \cdot \log(1 - D_\phi(\mathbf{a}, \mathbf{x}))$  ▷ update action discrim.
   $\psi \leftarrow \psi - \nabla_\psi \sum_{(\mathbf{x}, \hat{\mathbf{x}}, \mathbf{a}) \in \mathcal{D}} D_{\text{KL}}(D_\phi(\mathbf{a}, \mathbf{x}) \parallel D_\psi(\hat{\mathbf{x}}, \mathbf{x}))$  ▷ update image discriminator
   $\theta \leftarrow \theta + \nabla_\theta \sum_{\mathbf{x} \in \mathcal{D}} \log D_\psi(f_\theta(\mathbf{x}), \mathbf{x})$  ▷ update compression model
```

the compression model to minimize the divergence of the user’s policy evaluated on the compressed image $\pi(\mathbf{a}|\hat{\mathbf{x}})$ from the policy evaluated on the original $\pi(\mathbf{a}|\mathbf{x})$,

$$\begin{aligned} \mathcal{L}(\theta) &= \mathbb{E}_{\mathbf{x}}[D(\pi(\mathbf{a}|\mathbf{x}) \parallel \mathbb{E}_{\hat{\mathbf{x}} \sim f_\theta(\hat{\mathbf{x}}|\mathbf{x})}[\pi(\mathbf{a}|\hat{\mathbf{x}})|\mathbf{x}])] \\ &= \mathbb{E}_{\mathbf{x}}[D(p(\mathbf{a}|\mathbf{x}, T = 1) \parallel p(\mathbf{a}|\mathbf{x}, T = 0; \theta))], \end{aligned} \quad (1)$$

where D is a divergence (e.g., the Jensen-Shannon divergence) – note that we are overloading D to denote a divergence in Equation 1, and to denote a discriminator elsewhere. Since the user’s policy π is unknown, we approximately minimize the loss in Equation 1 using conditional generative adversarial networks (GAN) [31], where the side information is the original image \mathbf{x} , the generator is the compression model $f_\theta(\hat{\mathbf{x}}|\mathbf{x})$, and the discriminator $D(\mathbf{a}, \mathbf{x})$ tries to discriminate the action \mathbf{a} that the user takes after seeing the generated image $\hat{\mathbf{x}}$.

To train the action discriminator, we need positive and negative examples of user behavior; in our case, examples of user behavior with and without compression. To collect these examples, we randomize whether the user sees the compressed image or the original before taking an action. Let $T \sim \text{Bernoulli}(0.5)$ represent this random assignment. When $T = 1$, the user sees the original \mathbf{x} and takes action \mathbf{a} , and we record $(\mathbf{x}, \hat{\mathbf{x}}, \mathbf{a})$ as a positive example of user behavior. When $T = 0$, the user sees the compressed image $\hat{\mathbf{x}}$ and takes action \mathbf{a} , and we record $(\mathbf{x}, \hat{\mathbf{x}}, \mathbf{a})$ as a negative example. Let \mathcal{D} denote the dataset of all recorded tuples $(T, \mathbf{x}, \hat{\mathbf{x}}, \mathbf{a})$. We train an action discriminator $D_\phi(\mathbf{a}, \mathbf{x})$ to predict the likelihood $p(T = 1|\mathbf{a}, \mathbf{x})$, using the standard binary cross-entropy loss and the training data \mathcal{D} . Note that this action discriminator is conditioned on the original image \mathbf{x} and the user action \mathbf{a} , but not the compressed image $\hat{\mathbf{x}}$ – this follows from our problem formulation in Equation 1, and ensures that the action discriminator captures differences in user behavior caused by compression, while ignoring differences between the original and compressed images that do not affect user behavior.

3.2 Distilling the Discriminator and Training the Compression Model

The action discriminator $D_\phi(\mathbf{a}, \mathbf{x})$ gives us a way to approximately evaluate the loss function in Equation 1. However, we cannot train the compression model $f_\theta(\hat{\mathbf{x}}|\mathbf{x})$ to optimize this loss directly, since D_ϕ does not take the compressed image $\hat{\mathbf{x}}$ as input. To address this issue, we distill the trained action discriminator $D_\phi(\mathbf{a}, \mathbf{x})$, which captures differences in user behavior caused by compression, into an image discriminator $D_\psi(\hat{\mathbf{x}}, \mathbf{x})$ that links the compressed images to these behavioral differences. In particular, we train D_ψ to approximate D_ϕ by optimizing the loss,

$$\ell(\psi) = \sum_{(\mathbf{x}, \hat{\mathbf{x}}, \mathbf{a}) \in \mathcal{D}} D_{\text{KL}}(D_\phi(\mathbf{a}, \mathbf{x}) \parallel D_\psi(\hat{\mathbf{x}}, \mathbf{x})). \quad (2)$$

Then, given the trained image discriminator D_ψ , we train the compression model using the standard GAN generator loss [22, 31],

$$\ell(\theta) = \sum_{\mathbf{x} \in \mathcal{D}} -\log D_\psi(f_\theta(\mathbf{x}), \mathbf{x}), \quad (3)$$

where $f_\theta(\mathbf{x})$ denotes $\mathbb{E}_{\hat{\mathbf{x}} \sim f_\theta(\hat{\mathbf{x}}|\mathbf{x})}[\hat{\mathbf{x}}|\mathbf{x}]$. Our complete pragmatic compression method is summarized in Algorithm 1. We randomly initialize the compression model f_θ . The environment samples an original image \mathbf{x} from an unknown distribution p_{env} . To decide whether the user sees the original or

compressed image, we sample a Bernoulli random variable T . After seeing the chosen image, the user samples an action \mathbf{a} from their unknown policy π . To update the action discriminator D_ϕ , we take a gradient step on the binary cross-entropy loss. To update the image discriminator D_ψ , we take a gradient step on the KL-divergence loss in Equation 2. To update the compression model f_θ , we take a gradient step on the GAN generator loss in Equation 3. See Appendix A.3 for details.

4 Structured Compression using Generative Models

One approach to representing the compression model f_θ could be to structure it as a variational autoencoder (VAE) [28], and train the VAE end to end on the adversarial loss function in Equation 3 instead of the standard reconstruction error loss. This approach is fully general, but requires training a separate model for each desired bitrate (which is determined by the β coefficient in the VAE training objective), and can require extensive exploration of the pixel output space before it discovers an effective compression model. To simplify variable-rate compression and exploration in our experiments, we forgo end-to-end training, and first train a generative model on a batch of images without the human in the loop by optimizing a task-agnostic perceptual loss, yielding an encoder and decoder such that $\mathbf{z} = \text{enc}(\mathbf{x})$ and $\hat{\mathbf{x}} = \text{dec}(\mathbf{z})$, where $\mathbf{z} \in \mathbb{R}^d$ is the latent embedding. Analogous to prior work on conditional image generation [32], we then train our compression model $f_\theta(\hat{\mathbf{z}}|\mathbf{z})$ to compress the latent embedding, instead of compressing the original pixels. We use a variety of different generative models in our experiments, including a β -VAE [33] for the handwritten digit identification experiments in Figure 3, a StyleGAN2 model [34] for the car shopping and survey experiments in Figure 4, an NVAE model [35] for the photo verification experiments in Figure 5, and a VAE for the car racing experiments in Figure 6. See Appendix A.4 for details.

Generative models like the VAE and StyleGAN2 tend to learn disentangled features – hence, instead of training f_θ to map directly to the latent space \mathbb{R}^d , we structure f_θ to output a vector of probabilities that determines which latent features are transmitted exactly between \mathbf{z} and $\hat{\mathbf{z}}$, and which other features are masked out and then reconstructed from the prior distribution. In particular, we structure $f_\theta : \mathbb{R}^d \mapsto [0, 1]^d$ to output a vector of mask probabilities $\mathbf{p} \in [0, 1]^d$ given the latent embedding $\mathbf{z} \in \mathbb{R}^d$. Then, given a hyperparameter $\lambda \in [0, 1]$ that controls the compression rate, we transmit the $\lfloor \lambda d \rfloor$ latent features i with the lowest mask probabilities p_i , and mask out the remaining $d - \lfloor \lambda d \rfloor$ features. We reconstruct the masked features by assuming that $\hat{\mathbf{z}}$ follows a multivariate normal distribution, and sampling the masked feature values from the conditional prior distribution given the transmitted feature values. See Appendix A.4 for details.

This design of the compression model f_θ simplifies variable-rate compression: at test time, we simply choose a value of λ that obtains the desired bitrate, without retraining the model. It also simplifies exploration: instead of exploring in pixel output space, we explore in the space of masks over latent features, which leverages the decoder to generate more realistic compressed images during the early stages of training. We can now also reduce the dimensionality of the image discriminator inputs: instead of training $D_\psi(\hat{\mathbf{x}}, \mathbf{x})$, we train $D_\psi(\mathbf{p}, \mathbf{x})$. In our experiments, we also leverage the low-dimensional mask output space to perform batch learning instead of online learning, which greatly simplifies our implementation of PICO with real users. See Appendix A.1 for additional discussion.

While these simplifications enable us to provide a proof of concept for pragmatic compression in this paper, we acknowledge that they do require both server and client to have a copy of a domain-specific (but task-agnostic) generative model. End-to-end training of the compression model would be a more general approach that does not involve learning and storing a separate generative model – this is a promising direction for future work, which we discuss in Section 6.

5 User Studies

In our experiments, we evaluate to what extent PICO can minimize the number of bits needed to transmit an image, while still preserving the image’s usefulness to users performing downstream tasks. We conduct user studies on Amazon Mechanical Turk, in which we ask human participants to complete three tasks at varying bitrates: reading handwritten digits from the MNIST dataset [36], verifying attributes of faces from the CelebA dataset [37], and browsing a shopping catalogue of cars from the LSUN Car dataset [38]. To study PICO’s performance on sequential decision-making

problems, we also run an experiment with 12 participants who play the Car Racing video game from OpenAI Gym [39] under a constraint on the bitrate of the video feed. In all experiments, we train our discriminators and compression model on 1000 negative examples and varying numbers of positive examples, and split PICO into two rounds of batch learning and evaluation (see Appendices A.1 and A.5). Appendix A discusses the implementation details.

5.1 Minimizing Bitrate by Maximizing User Action Agreement

We claim that PICO can learn to transmit only the features that users need to perform their tasks. Our first set of user studies seeks to answer **Q1**: does maximizing user action agreement enable PICO to obtain lower bitrates than baseline methods that do not take into account downstream user behavior? We would like to study this question in domains where we can measure the performance of various compression methods by computing the agreement between the user’s actions with and without compression – i.e., collecting action labels for the original images, and comparing the user’s actions upon seeing compressed versions of those images to the labels. As such, we run experiments on Amazon Mechanical Turk that focus on single-step decision-making settings where we can collect action labels for a fixed dataset of images: (a) identifying a handwritten digit, (b) clicking on an item in a shopping catalogue, and (c) verifying photos of faces. In (a), we instruct users to identify the number in the image within the range 0-9. In (b), to simulate the experience of browsing a catalogue on a budget, we instructed users to click on images of cars that they perceive to be worth less than \$20,000. In (c), we instruct users to check if the person’s eyes are covered (e.g., by eyeglasses) and click on one of two buttons labeled “covered” and “not covered”.

In all domains, we evaluate PICO by varying the bitrate and, at each bitrate, measuring the agreement of user actions upon seeing a compressed image with user actions upon seeing the original version of that image (see Appendix A.7 for details). As discussed in Section 4, PICO learns a compression model f_θ that, given a separate generative model, selects which latent features to transmit. Since the purpose of this experiment is to test the effect of user-adaptive compression in PICO, we compare to a non-adaptive baseline method that selects a uniform-random subset of features to transmit, but otherwise uses the same generative model as PICO – this enables us to conduct an apples-to-apples comparison that isolates the effect of training f_θ on user behavior data. We also compare to a baseline method that maximizes perceptual similarity by replacing the adversarial loss in Equation 3 of PICO with the mean absolute pixel difference $|\mathbf{x} - \hat{\mathbf{x}}|$. In simulation experiments, we found that this perceptual similarity baseline performed better than the non-adaptive baseline in the MNIST domain, but did not perform better in the other domains (see Appendix C), so we only test it in the MNIST user study. To provide a point of comparison to widely-used compression methods, we also compare to JPEG [12], where the quality parameter is set to the lowest value (1) in order to bring the bitrate as close as possible to the range obtained by PICO and the non-adaptive baseline. Though JPEG is no longer the state of the art, it enables us to roughly calibrate the results achieved by PICO as well as the non-adaptive and perceptual similarity baselines.

Figures 3, 4, and 5 show that, at low bitrates, PICO achieves substantially higher user action agreement than the non-adaptive baseline (orange vs. gray) and perceptual similarity baseline (orange vs. red). PICO also obtains much lower bitrates than the JPEG baseline (orange vs. teal), while maintaining higher agreement on CelebA, comparable agreement on MNIST, and lower agreement on LSUN Car. The samples in Figure 3 show that PICO learns to preserve digit numbers more often than the non-adaptive and perceptual similarity baselines, while randomizing handwriting

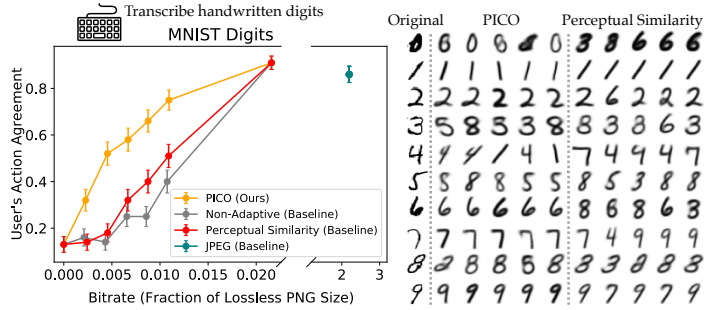


Figure 3: MNIST digit identification experiments that address **Q1**. When users are instructed to identify the digit number, PICO learns to preserve the digit number while randomizing handwriting style. The plots show user action agreement evaluated on 100 held-out images, with error bars representing standard error. The average lossless PNG file size is 0.3kB, and each image has dimensions 28x28x1. Each of the five columns in the two groups of compressed images represents a different sample from the stochastic compression model $f(\hat{\mathbf{x}}|\mathbf{x})$ at bitrate 0.011.

more often than the non-adaptive and perceptual similarity baselines, while randomizing handwriting

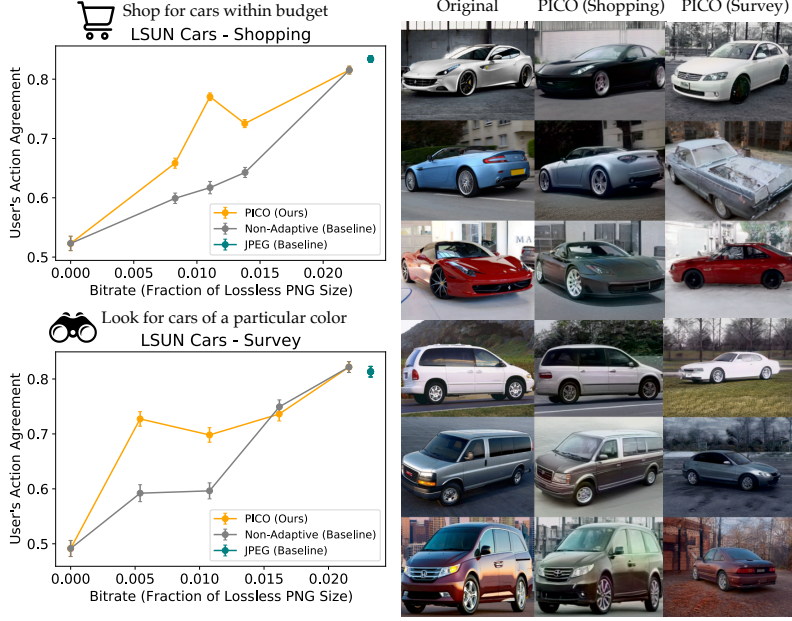


Figure 4: LSUN Car shopping experiment that addresses **Q1**, and survey experiment that addresses **Q2**. The plots show action agreement evaluated on 100 held-out images, with error bars representing standard error. The average lossless PNG file size is 247kB, and each image has dimensions 512x512x3. The shopping samples show that, when users are instructed to click on cars they perceive to be worth less than \$20,000, PICO learns to preserve the overall shape and sportiness of the car, while randomizing paint jobs, backgrounds, and other details that are irrelevant to the users’ perception of price. In contrast, when users are instead instructed to determine whether the car is “dark-colored” or “light-colored” for a survey task, PICO learns to preserve the car’s color while randomizing its pose. We intentionally show compressed image samples for a low bitrate (0.011) to highlight differences between the compression models learned for the two tasks.

style in order to satisfy the bitrate constraint. The samples in Figure 4 show that, for users performing the shopping task, PICO learns to preserve the overall shape and sportiness of the car, while randomizing paint jobs, backgrounds, and other details that are irrelevant to the user’s perception of the price of the car. The samples in Figure 5 show that, for users checking whether eyes are covered, PICO learns to preserve the presence of eyeglasses while randomizing hair color, faces, and other irrelevant details (see top row of samples). The dip in the orange curve in the car shopping plot may be due to the fact that increasing the bitrate preserves more of the encoded latent features, which, when combined with features sampled from the prior, can be out-of-distribution inputs to the StyleGAN2 decoder [40, 41], potentially leading to degraded image quality (see Appendix A.4 for details). Figures 9 and 10 in the appendix include more examples.

5.2 Adapting Compression to Different Downstream Tasks

The experiments in the previous section show that PICO can outperform a non-adaptive baseline method by transmitting only the features that users need to perform their tasks. Our second set of user studies investigates this mechanism further, by asking **Q2**: can PICO adapt the compression model to the specific needs of different downstream tasks in the same domain? To answer this question, we run an additional experiment in the CelebA domain from the previous section, in which users are instructed to check if the person’s head is covered (e.g., by a hat). We also run an additional experiment in the LSUN Car domain from the previous section, in which we simulate a survey task that asks users to ‘help a car dealership conduct market research’ by determining whether an observed car has a “dark-colored” or “light-colored” paint job.

Figure 5 shows that PICO adapted the compression model to the user’s particular task. In the experiment from the previous section, when users checked eyes, PICO learned to preserve the presence of eyeglasses while randomizing hair color, faces, and other irrelevant details (see top row of samples). On the other hand, when users checked for head coverings like hats and helmets, PICO

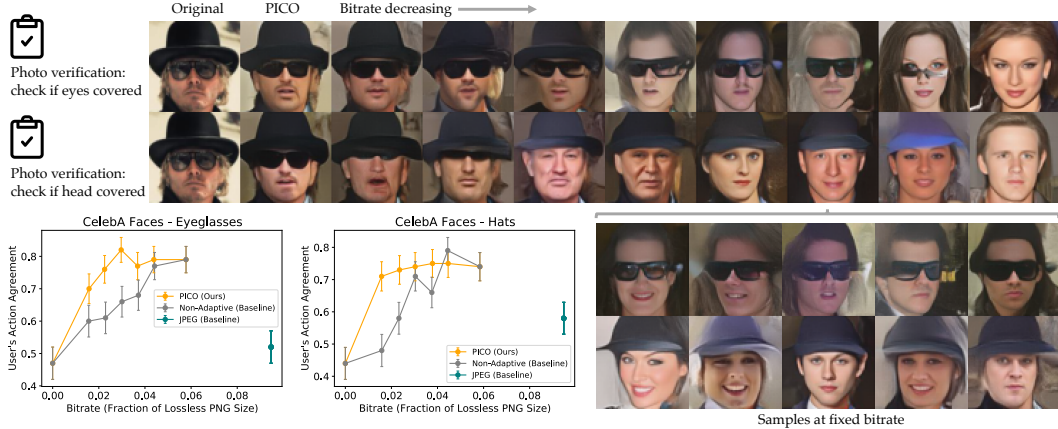


Figure 5: CelebA photo attribute verification experiments that address **Q1** and **Q2**. Depending on the instructions given to the user, PICO learns to either preserve hats or eyeglasses, while randomizing faces and other task-irrelevant details. The plots show action agreement evaluated on 100 held-out images, with error bars representing standard error. The average lossless PNG file size is 7.7kB, and each image has dimensions 64x64x3.

learned to preserve the presence of hats while randomizing eyes and other details (see second row of samples). The third and fourth rows of samples illustrate the fact that PICO learns a stochastic compression model $f_{\theta}(\hat{x}|\mathbf{x})$ from which we can draw multiple compressed samples \hat{x} for a given original \mathbf{x} . The fact that all the samples in the third row have eyeglasses but differ in other attributes like pose angle, and those in the fourth row all have hats while some are smiling and some are not, shows that even though the compression model is stochastic, it produces stable attributes when they are needed for the downstream task. Figure 9 in the appendix includes more qualitative examples. In addition to these photo verification results, the samples in Figure 4 illustrate substantial differences in the compression models learned for the car shopping and survey tasks. For users performing the shopping task, PICO learned to preserve perceived price while randomizing color. In contrast, for users performing the survey, PICO learned to preserve color while randomizing perceived price.

5.3 Compressing Observations for Sequential Decision-Making

Our third user study seeks to answer **Q3**: can PICO learn to compress image observations in the sequential decision-making setting? To answer this question, we run an experiment with 12 participants in which we ask users to play a 2D top-down car racing video game, while constraining the number of bits that can be used to transmit the image observation to the user at each timestep. We would like to measure the performance of PICO and the non-adaptive baseline by computing user action agreement, as in the previous sections. However, since images rarely re-occur in this video game, it is unlikely that we will have an action label for the exact pixels in any given observation. Instead, we measure the user’s progress along the road in the game – specifically, the fraction of new road patches visited during an episode. In these experiments, we fix the bitrate to 85 bits per step, which is well below the 170 bits per step required to transmit the full set of features for the 64x64x3 images. To simplify our experiments and ensure that they could be completed within the allotted 30 minutes per participant, we trained the PICO compression model on data from a pilot user, then evaluated the compression model’s performance with each of the 12 participants. Appendix A.7 describes the experimental setup in further detail.

Figure 6 shows that, at a fixed bitrate, PICO enables the user to perform substantially better on the driving task than the non-adaptive compression baseline (orange vs. gray), and comparably to a positive control in which we do not compress the image observations at all (orange vs. teal). The first and second film strips show that, when we use the non-adaptive compression baseline, there is a substantial difference between the originals and the compressed images. For example, even at the first timestep, the compressed image shows the road to be less tilted than it actually is, so in the next frame we see that the user has mistakenly driven forward and ended up in the grass instead of turning right to stay on the road. In contrast, the third and fourth film strips show that PICO has learned to preserve the angle of the road, while discarding the details of the road much farther ahead in order to satisfy the bitrate constraint. We ran a one-way repeated measures ANOVA on the road progress

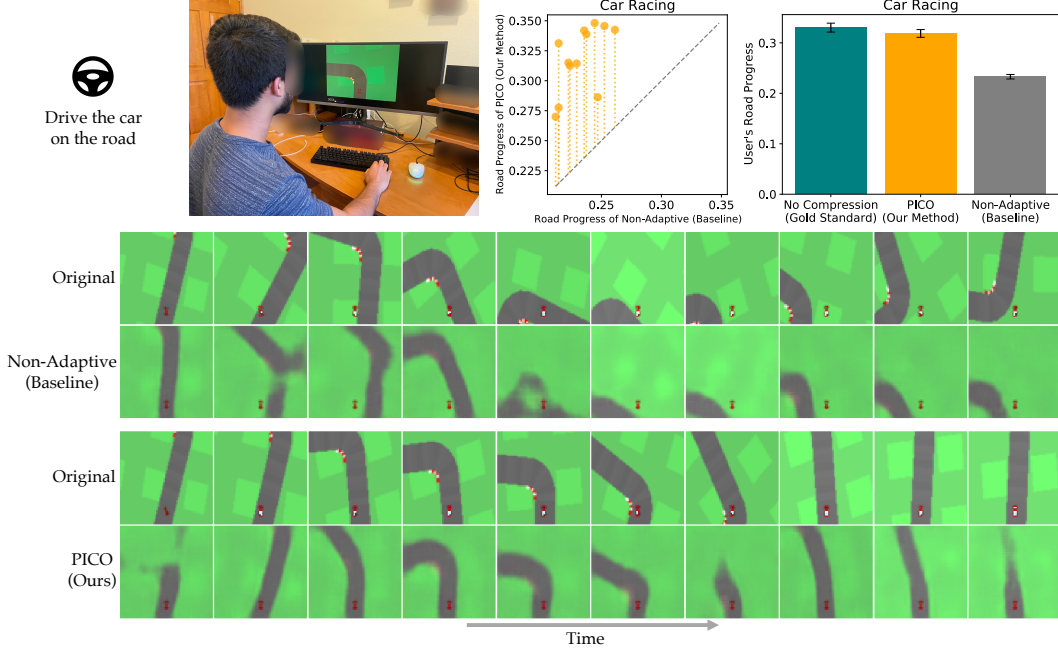


Figure 6: Car Racing game experiments that address **Q3**. The scatter plot shows that, for each of the 12 users (orange), road progress with PICO was substantially higher than with the non-adaptive compression baseline. The bar chart shows road progress averaged over all users, with error bars representing standard error.

metrics from the non-adaptive baseline and PICO conditions with the presence of PICO as a factor, and found that $f(1, 11) = 176.32, p < .0001$. The subjective evaluations in Table 1 in the appendix corroborate these results: users reported feeling higher situational awareness and ability to control the car with PICO compared to the non-adaptive baseline. After evaluating PICO, one user commented, “This environment was a lot easier. It felt more consistent. I felt like we had a mutual understanding of when I would turn and what it would show me to make me turn.” Appendix B discusses the results in more detail, and videos are available on the project website¹.

6 Discussion

We presented a proof of concept that, through human-in-the-loop learning, we can train models to communicate relevant information to users under network bandwidth constraints, without prior knowledge of the users’ desired tasks. Our experiments show that, for a variety of tasks with different kinds of images, pragmatic compression can reduce bitrates 2-4x compared to non-adaptive and perceptual similarity baseline methods, by optimizing reconstructions for functional similarity. Since we needed to carry out user studies with real human participants, we decided to limit the number of parameters trained during these experiments for the sake of efficiency, by using a pre-trained generative model as a starting point and only optimizing over the latent space of this model. This can be problematic when the generative model does not include task-relevant features in its latent space – e.g., the yellow sports car in rows 7-8 of Figure 10 in the appendix gets distorted when encoded into the StyleGAN2 latent space, even without any additional compression. An end-to-end version of PICO should in principle also be possible, but would likely require longer human-in-the-loop training sessions. This may, however, be practical for real-world web services and other applications, where users already continually interact with the system and A/B testing is standard practice. End-to-end training could also enable PICO to be applied to problems other than compression, such as image captioning for visually-impaired users, or audio visualization for hearing-impaired users [42] – such applications could also be enabled through continued improvements to generative models for video [43, 44], audio [45], and text [46, 47]. Another exciting area for future work is to apply pragmatic compression to a wider range of realistic applications, including video compression for robotic space

¹<https://sites.google.com/view/pragmatic-compression>

exploration [13], audio compression for hearing aids [48, 49], and spatial compression for virtual reality [50].

7 Acknowledgements

Thanks to members of the InterACT and RAIL labs at UC Berkeley for feedback on this project. This work was supported in part by AFOSR FA9550-17-1-0308, NSF NRI 1734633, GPU donations from NVIDIA, and the Berkeley Existential Risk Initiative.

References

- [1] George Toderici, Sean M O’Malley, Sung Jin Hwang, Damien Vincent, David Minnen, Shumeet Baluja, Michele Covell, and Rahul Sukthankar. Variable rate image compression with recurrent neural networks. *arXiv preprint arXiv:1511.06085*, 2015.
- [2] Johannes Ballé, Valero Laparra, and Eero P Simoncelli. End-to-end optimized image compression. *arXiv preprint arXiv:1611.01704*, 2016.
- [3] Karol Gregor, Frederic Besse, Danilo Jimenez Rezende, Ivo Danihelka, and Daan Wierstra. Towards conceptual compression. *arXiv preprint arXiv:1604.08772*, 2016.
- [4] George Toderici, Damien Vincent, Nick Johnston, Sung Jin Hwang, David Minnen, Joel Shor, and Michele Covell. Full resolution image compression with recurrent neural networks. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2017.
- [5] Lucas Theis, Wenzhe Shi, Andrew Cunningham, and Ferenc Huszár. Lossy image compression with compressive autoencoders. *arXiv preprint arXiv:1703.00395*, 2017.
- [6] Eirikur Agustsson, Fabian Mentzer, Michael Tschannen, Lukas Cavigelli, Radu Timofte, Luca Benini, and Luc Van Gool. Soft-to-hard vector quantization for end-to-end learning compressible representations. *arXiv preprint arXiv:1704.00648*, 2017.
- [7] Fabian Mentzer, Eirikur Agustsson, Michael Tschannen, Radu Timofte, and Luc Van Gool. Conditional probability models for deep image compression. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018.
- [8] Mu Li, Wangmeng Zuo, Shuhang Gu, Debin Zhao, and David Zhang. Learning convolutional networks for content-weighted image compression. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2018.
- [9] Michael Tschannen, Eirikur Agustsson, and Mario Lucic. Deep generative models for distribution-preserving lossy compression. In *Neural Information Processing Systems*, 2018.
- [10] Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2018.
- [11] Fabian Mentzer, George D Toderici, Michael Tschannen, and Eirikur Agustsson. High-fidelity generative image compression. *Neural Information Processing Systems*, 2020.
- [12] Gregory K Wallace. The JPEG still picture compression standard. *IEEE Transactions on Consumer Electronics*, 1992.
- [13] Terrence Fong, Jennifer Rochlis Zumbado, Nancy Currie, Andrew Mishkin, and David L Akin. Space telerobotics: unique challenges to human–robot collaboration in space. *Reviews of Human Factors and Ergonomics*, 2013.
- [14] Herbert P Grice. Logic and conversation. In *Speech acts*. 1975.
- [15] Dan Sperber and Deirdre Wilson. *Relevance: Communication and cognition*. 1986.

- [16] Michael Frank, Noah Goodman, Peter Lai, and Joshua Tenenbaum. Informative communication in word production and word learning. In *Proceedings of the annual meeting of the cognitive science society*, 2009.
- [17] J Jiang. Image compression with neural networks – a survey. *Signal Processing: Image Communication*, 1999.
- [18] Guo Lu, Wanli Ouyang, Dong Xu, Xiaoyun Zhang, Chunlei Cai, and Zhiyong Gao. DVC: An end-to-end deep video compression framework. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2019.
- [19] Salvator Lombardo, Jun Han, Christopher Schroers, and Stephan Mandt. Deep generative video compression. In *Neural Information Processing Systems*, 2019.
- [20] Nisan Stiennon, Long Ouyang, Jeff Wu, Daniel M Ziegler, Ryan Lowe, Chelsea Voss, Alec Radford, Dario Amodei, and Paul Christiano. Learning to summarize from human feedback. *arXiv preprint arXiv:2009.01325*, 2020.
- [21] Sophie Hilgard, Nir Rosenfeld, Mahzarin R Banaji, Jack Cao, and David C Parkes. Learning representations by humans, for humans. *arXiv preprint arXiv:1905.12686*, 2019.
- [22] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In *Neural Information Processing Systems*, 2014.
- [23] Jonathan Ho and Stefano Ermon. Generative adversarial imitation learning. In *Neural Information Processing Systems*, 2016.
- [24] Claude E Shannon. A mathematical theory of communication. *The Bell system technical journal*, 1948.
- [25] Brendan J Frey and Geoffrey E Hinton. Efficient stochastic source coding and an application to a Bayesian network source model. *Computer Journal*, 1997.
- [26] Guy E Blelloch. Introduction to data compression. 2001.
- [27] David JC MacKay. *Information theory, inference and learning algorithms*. 2003.
- [28] Diederik P Kingma and Max Welling. Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114*, 2013.
- [29] Alexander A Alemi, Ian Fischer, Joshua V Dillon, and Kevin Murphy. Deep variational information bottleneck. *arXiv preprint arXiv:1612.00410*, 2016.
- [30] James Townsend, Tom Bird, and David Barber. Practical lossless compression with latent variables using bits back coding. *arXiv preprint arXiv:1901.04866*, 2019.
- [31] Mehdi Mirza and Simon Osindero. Conditional generative adversarial nets. *arXiv preprint arXiv:1411.1784*, 2014.
- [32] Jesse Engel, Matthew Hoffman, and Adam Roberts. Latent constraints: Learning to generate conditionally from unconditional generative models. *arXiv preprint arXiv:1711.05772*, 2017.
- [33] Ricky TQ Chen, Xuechen Li, Roger B Grosse, and David K Duvenaud. Isolating sources of disentanglement in variational autoencoders. *Neural Information Processing Systems*, 2018.
- [34] Tero Karras, Samuli Laine, Miika Aittala, Janne Hellsten, Jaakko Lehtinen, and Timo Aila. Analyzing and improving the image quality of StyleGAN. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020.
- [35] Arash Vahdat and Jan Kautz. NVAE: A deep hierarchical variational autoencoder. *arXiv preprint arXiv:2007.03898*, 2020.
- [36] Yann LeCun. The MNIST database of handwritten digits, 1998.

- [37] Ziwei Liu, Ping Luo, Xiaogang Wang, and Xiaoou Tang. Deep learning face attributes in the wild. In *International Conference on Computer Vision (ICCV)*, December 2015.
- [38] Fisher Yu, Yinda Zhang, Shuran Song, Ari Seff, and Jianxiong Xiao. LSUN: Construction of a large-scale image dataset using deep learning with humans in the loop. *arXiv preprint arXiv:1506.03365*, 2015.
- [39] Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. OpenAI Gym. *arXiv preprint arXiv:1606.01540*, 2016.
- [40] Elad Richardson, Yuval Alaluf, Or Patashnik, Yotam Nitzan, Yaniv Azar, Stav Shapiro, and Daniel Cohen-Or. Encoding in style: a StyleGAN encoder for image-to-image translation. *arXiv preprint arXiv:2008.00951*, 2020.
- [41] Omer Tov, Yuval Alaluf, Yotam Nitzan, Or Patashnik, and Daniel Cohen-Or. Designing an encoder for StyleGAN image manipulation. *arXiv preprint arXiv:2102.02766*, 2021.
- [42] Yuchi Zhang, Willis Peng, Bastian Wandt, and Helge Rhodin. AudioViewer: Learning to visualize sound. *arXiv preprint arXiv:2012.13341*, 2020.
- [43] Jacob Walker, Ali Razavi, and Aäron van den Oord. Predicting video with VQVAE. *arXiv preprint arXiv:2103.01950*, 2021.
- [44] Wilson Yan, Yunzhi Zhang, Pieter Abbeel, and Aravind Srinivas. VideoGPT: Video generation using VQ-VAE and transformers. *arXiv preprint arXiv:2104.10157*, 2021.
- [45] Aaron van den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves, Nal Kalchbrenner, Andrew Senior, and Koray Kavukcuoglu. WaveNet: A generative model for raw audio. *arXiv preprint arXiv:1609.03499*, 2016.
- [46] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.
- [47] Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*, 2020.
- [48] Alex Armstrong, Chi Chung Lam, Shievanie Sabesan, and Nicholas A Lesica. The hearing aid dilemma: amplification, compression, and distortion of the neural code. *bioRxiv*, 2020.
- [49] Nasim Alamdari, Edward Lobarinas, and Nasser Kehtarnavaz. Personalization of hearing aid compression by human-in-the-loop deep reinforcement learning. *IEEE Access*, 2020.
- [50] Niels Christian Nilsson, Tabitha Peck, Gerd Bruder, Eri Hodgson, Stefania Serafin, Mary Whitton, Frank Steinicke, and Evan Suma Rosenberg. 15 years of research on redirected walking in immersive virtual environments. *IEEE Computer Graphics and Applications*, 2018.
- [51] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.
- [52] David Ha and Jürgen Schmidhuber. Recurrent world models facilitate policy evolution. *arXiv preprint arXiv:1809.01999*, 2018.

A Experimental Setup

Here, we discuss the implementation details of the experiments in Section 5. Source code is available at <https://github.com/rddy/pico>.

A.1 Batch Learning from Logged Compression Data

In our experiments, we found that initializing the compression model such that it outputs uniform-random mask probabilities, collecting a batch of 1000 tuples ($T = 1, \mathbf{x}, \hat{\mathbf{x}}, \mathbf{a}$) using this random compression model, and training the models D_ϕ , D_ψ , and f_θ to convergence on this data yielded a high-performing compression model f_θ . In other words, rather than alternating one step of data collection with one gradient step as in Algorithm 1, we used batch learning. The initial random compression model explored the structured output space of feature masks well enough to generate useful training data for our models, so we did not need to learn from on-policy data generated by partially-trained compression models. This approach illustrates how PICO can be practically deployed in real-world applications where other compression algorithms are already in use and have generated large amounts of offline data \mathcal{D} , and where online learning may be difficult to implement.

In the digit identification, car shopping and survey, and car racing experiments, we set the compression rate hyperparameter λ (see Section 4) to 0.5 during training. In the photo verification experiments, we set $\lambda = 0.25$ during training.

A.2 Measuring Bitrates

For the digit identification, car racing, and car shopping and survey experiments, we use the following procedure to measure compression rates. To estimate the prior distribution (introduced in Section 4), we fit a multivariate Gaussian distribution to the latent embeddings of the images in our training set. To measure the number of bits needed to encode a given latent embedding, we normalize the latent feature values to their z-scores, discretize the z-scores into bins of width 0.1, and sum the negated base-2 log-probabilities of the discretized values under the prior distribution. For the photo verification experiments, we use the base-2 KL-divergence between the latent posterior and prior in the NVAE model [35].

In the digit identification experiments in Figure 3, we sweep $\lambda \in \{0, 0.1, 0.2, 0.3, 0.4, 0.5, 1\}$ and measure the resulting bitrates (the hyperparameter λ is defined in Section 4). In the car shopping experiments in Figure 4, we sweep $\lambda \in \{0, 0.375, 0.5, 0.625, 1\}$. In the car survey experiments in Figure 4, we sweep $\lambda \in \{0, 0.25, 0.5, 0.75, 1\}$. In the photo verification experiments in Figure 5, we sweep $\lambda \in \{0, 0.25, 0.375, 0.5, 0.625, 0.75, 1\}$. In the car racing experiments in Figure 6, we set $\lambda = 0.5$.

A.3 Network Architectures and Training

We use stochastic gradient descent – in particular, Adam [51] – to perform the optimization steps in Algorithm 1.

In the car racing and digit identification experiments, we use a feedforward network with 2 layers of 256 units to represent the discriminators; to represent the compression model, the same architecture, but with 64 instead of 256 units. In the car shopping and survey experiments, we use the same architecture, but with 64 instead of 256 units, for the discriminators. In the photo verification experiment, we combine the convolutional network architecture from https://github.com/yzwxx/vae-celebA/blob/master/model_vae.py with 2 additional fully-connected layers of 256 units to represent the discriminators and the compression model.

A.4 Compressing Images using a Generative Model

Following up on the discussion in Section 4 about structuring the compression model $f_\theta(\hat{\mathbf{z}}|\mathbf{z})$, let $\hat{\mathbf{z}} = [\mathbf{z}_1 \mathbf{z}_2]$ denote the decomposition of $\hat{\mathbf{z}}$ into masked features \mathbf{z}_1 and transmitted features \mathbf{z}_2 . In the digit identification, photo verification, and car racing experiments, we set the masked features to

follow the distribution $\mathbf{z}_1 \sim \mathcal{N}(\bar{\boldsymbol{\mu}}, \bar{\boldsymbol{\Sigma}})$, where

$$\begin{aligned}\bar{\boldsymbol{\mu}} &= \boldsymbol{\mu}_1 + \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}(\mathbf{z}_2 - \boldsymbol{\mu}_2), \\ \bar{\boldsymbol{\Sigma}} &= \boldsymbol{\Sigma}_{11} - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\boldsymbol{\Sigma}_{21}.\end{aligned}$$

We estimate $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ empirically, from the data used to train the generative model. In the car racing experiments, at each timestep t , we set the prior mean $\boldsymbol{\mu}$ to the transmitted feature values at the previous timestep $t - 1$, and estimate the prior covariance $\boldsymbol{\Sigma}$ empirically from state transition data. In the car shopping and survey experiments, we sample the masked features from the StyleGAN2 prior – i.e., by feeding Gaussian noise input to the StyleGAN2 mapping network, and computing the intermediate latents \mathbf{w} .

To make exploration easier (see Section 4 for discussion), we reduce the dimensionality d of the mask output space by grouping together consecutive latent features. In the car racing experiments, we train a VAE with 32 latent features using prior methods [52], and reduce the dimensionality of the compression model’s output space from 32 to $d = 8$ by creating 8 groups of 4 latent features each – where group 1 contains latent features 1-4, group 2 contains features 5-8, etc. – and masking groups instead of masking individual features. In the car shopping experiments, we use a StyleGAN2 model with 16 style layers – trained on the LSUN Car dataset using prior methods [34] – and reduce the dimensionality to $d = 8$ by dividing the 16 style layers into 8 groups. In the car survey experiments, we reduce to $d = 4$ using the same method. To encode images into the StyleGAN2 latent space, we use the optimization-based projection method described in Section 5 of [34]. In the photo verification experiments, we use the NVAE model for CelebA 64x64 described in Table 6 of [35]. We always sample the latents in the second and third scales from the prior. For the latents in the first scale, we reduce the dimensionality of the mask output space from $d = 5 \cdot 8^2$ to $d = 8$ by applying the same mask to all 5 groups, and dividing the 64 latents into groups of 8. In the digit identification experiments, we use a β -VAE with 10 latent features, which we do not group together as in the other experiments.

In the digit identification, car shopping and survey, and car racing experiments, we use the latent embedding \mathbf{z} instead of the full image \mathbf{x} as input to the discriminators – i.e., we set $D_\phi(\mathbf{a}, \mathbf{x}) \leftarrow D_\phi(\mathbf{a}, \mathbf{z})$ and $D_\psi(\mathbf{p}, \mathbf{x}) \leftarrow D_\psi(\mathbf{p}, \mathbf{z})$.

A.5 Positive Examples for Discriminator Training

In the digit identification experiments, we treat 63,000 labeled images from the MNIST training set as positive examples of user behavior without compression. In the photo verification experiments, we do the same with 202,397 examples from the labeled CelebA training set – in particular, the Eyeglasses and Hat labels. In the car shopping experiments, we automatically label the Ferrari, Bugatti, McLaren, Aston Martin, Lamborghini, Spyker, and Porsche categories as unaffordable, and the Wagon, Minivan, and Van categories as affordable, discard images belonging to any other categories, and treat 1,507 of the remaining labeled images as positive examples. In the car survey experiments, we collect positive examples by eliciting 1,507 binary labels of “dark-colored” vs. “light-colored” on Amazon Mechanical Turk.

A.6 Prompts for Amazon Mechanical Turk Participants

For the photo verification experiment in Figure 5 in which users check if eyes are covered:

In this task, you will examine photos of people and check if their eyes are covered. Photos of people wearing eyeglasses or sunglasses should be classified as covered. Choose the appropriate label that best suits the image: ‘Eyes are not covered’ or ‘Eyes are covered’.

For the photo verification experiment in Figure 5 in which users check if heads are covered:

In this task, you will examine photos of people and check if their head is covered. Photos of people wearing hats or caps should be classified as covered. Choose the appropriate label that best suits the image: ‘Head is not covered’ or ‘Head is covered’.

For the car shopping experiments in Figure 4:

In this task, you will examine photos of cars and guess if they are affordable for someone with a budget of approximately \$20,000. Choose the appropriate label that best suits the image: 'Affordable' or 'Not affordable'.

For the car survey experiments in Figure 4:

In this task, you will examine photos of cars and determine if they are dark-colored (black, dark blue, dark red, etc.) or light-colored (white, silver, light red, yellow, etc.). Choose the appropriate label that best suits the image: 'Dark-colored car' or 'Light-colored car'.

For the handwritten digit identification experiments in Figure 3:

Choose the appropriate label that best suits the image: 0, 1, 2, 3, 4, 5, 6, 7, 8, or 9

A.7 Subject Allocation

Amazon Mechanical Turk experiments. In the car shopping and survey tasks, we assigned 10 users to label each of the 100 held-out images, in order to reduce the variance introduced by our intentionally-vague prompts (see previous section). For the other AMT experiments, we only assigned one user to each image, since we found that behavior did not vary substantially across users.

Car racing video game experiment. We recruited 10 male and 2 female participants, with an average age of 25. Each participant was provided with the rules of the game and played 5 practice episodes to familiarize themselves with the controls. To generate positive and negative examples for training the PICO discriminator, we had a pilot user play 10 episodes without compression and 15 episodes with a compression model that outputs uniform-random mask probabilities. Each of the 12 participants played in both experimental conditions: with the non-adaptive compression baseline, and with the trained compression model from PICO. To avoid the confounding effect of users learning to play the game better over time, we counterbalanced the order of the two conditions. Each condition lasted 15 episodes, with 100 timesteps (10 seconds) per episode.

B Subjective Evaluations in Car Racing Experiment

After evaluating the non-adaptive compression baseline:

It was quite hard to understand where the car/road were when the video got hazy by the end of the training, the delay felt less significant. I almost didn't notice it. I had difficulty figuring out what the environment wanted me to do when it would bend the road far ahead of me but not near me.

It was often hard to tell if the car was moving or not, and the road sometimes disappeared, which also made it hard to tell when steering was needed

Often the task wasn't too hard, but it was most challenging when the scene geometry would suddenly shift and I couldn't anticipate how to react with my controls.

After evaluating PICO:

It was a lot more predictable and the blur was very infrequent. The road did behave pretty unpredictably sometimes and I could not control

This environment was a lot easier. It felt more consistent. I felt like we had a mutual understanding of when I would turn and what it would show me to make me turn.

After model training much easier than before model training

This time around the task was a lot easier – the fact that the scene geometry changed more naturally, and the fact that the effects of any delayed actions were predictable, made it easier to decide how to steer

Table 1: Subjective Evaluations in the Car Racing User Study

| | <i>p</i> -value | Non-Adaptive | PICO |
|---|-----------------|--------------|-------------|
| I was able to keep the car on the road | < .0001 | 3.45 | 5.64 |
| I could anticipate the consequences of my steering actions | < .01 | 3.82 | 5.36 |
| I could tell when the car was about to go off road | < .01 | 3.55 | 5.36 |
| I could tell when I needed to steer to keep the car on the road | < .01 | 4.09 | 5.73 |
| I was often able to determine the car’s current position | < .001 | 4.00 | 5.82 |

Means reported for responses on a 7-point Likert scale, where 1 = Strongly Disagree, and 7 = Strongly Agree. *p*-values from a one-way repeated measures ANOVA with the use of PICO as a factor influencing responses.

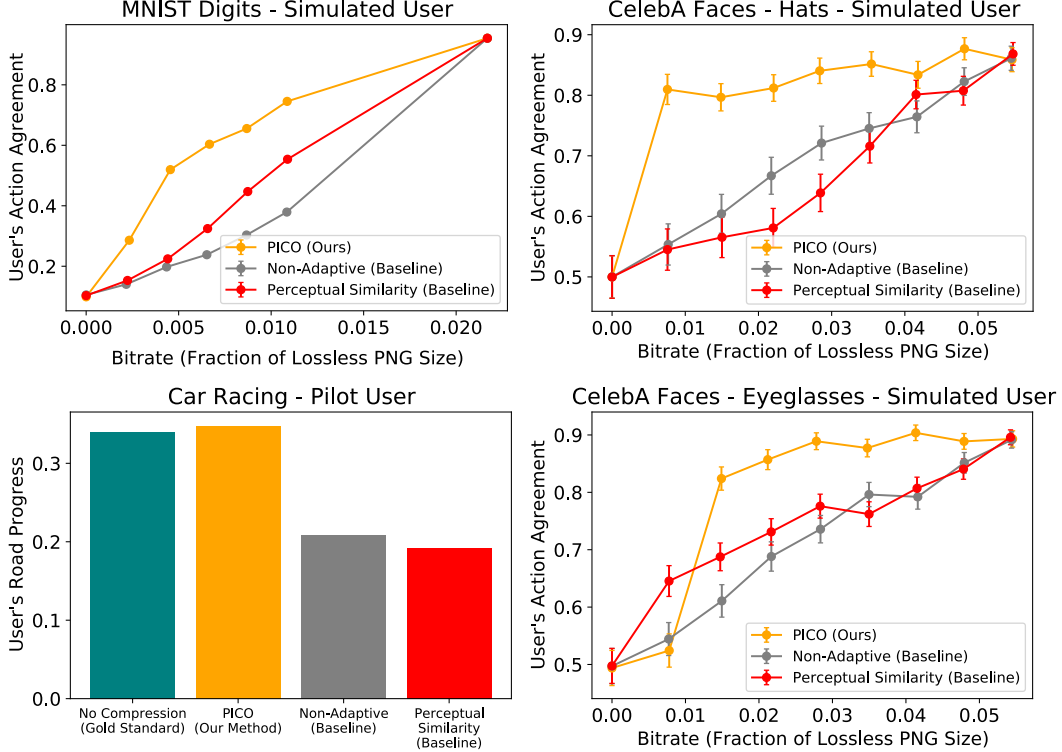


Figure 7: Experiments with simulated and pilot users show that PICO outperforms both baselines, and that the perceptual similarity baseline only performs better than the non-adaptive baseline on the digit identification task (top left).

C Simulation Experiments

To determine which baseline methods to compare with PICO in the user studies in Section 5, we ran preliminary experiments in which we simulated user behavior. In the digit identification and photo verification tasks, we simulated the user’s policy by training a classifier on labeled data (see Appendix A.5 for a description of the labeled data in each domain). In the car shopping, car surveying, and car racing tasks, we did not have enough labeled data to train a policy that qualitatively matched real user behavior. Hence, in the car racing task, we conducted a small-scale experiment with a single pilot user; and in the car shopping and surveying tasks, we perform a qualitative analysis of compressed image samples.

Figure 7 shows that PICO outperformed both the non-adaptive and perceptual similarity baselines in all domains. Furthermore, the perceptual similarity baseline only performed better than the non-adaptive baseline in the digit identification task; hence, our decision to omit the perceptual similarity baseline from the other user studies in Section 5. Figure 8 shows that, while PICO learns to preserve the perceived price of the car in the shopping task, and to preserve the color of the car in the survey task, the perceptual similarity baseline does not preserve either of the two features.

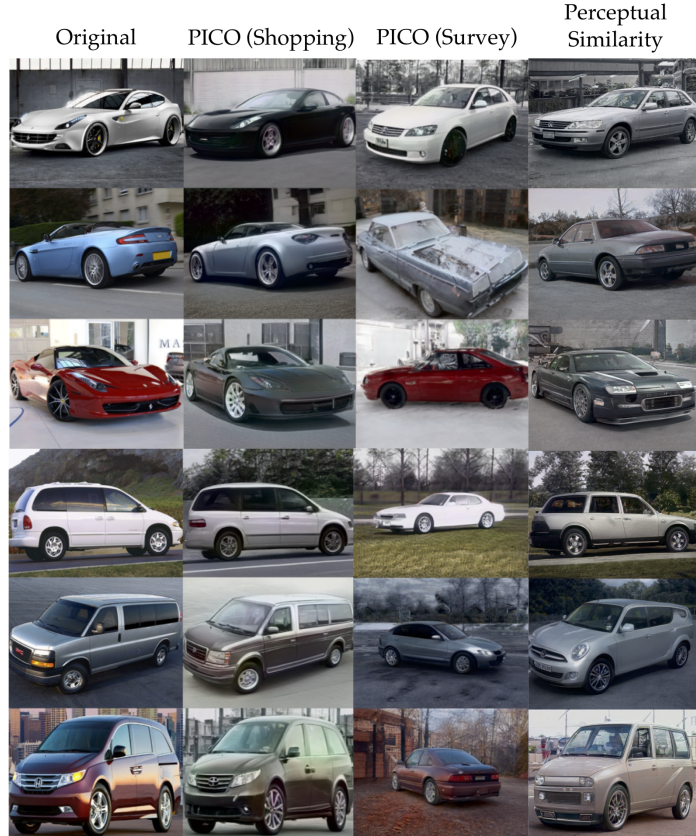


Figure 8: While PICO learns to preserve the perceived price of the car in the shopping task (second column), and to preserve the color of the car in the survey task (third column), the perceptual similarity baseline fails to preserve either of the two features (fourth column).

D Failure Cases

There are several ways in which PICO can fail to match the user’s actions with and without compression. For example, the latent embedding z produced by the pre-trained generative model (see Section 4) may lack the necessary features for performing the downstream task: the yellow sports car in rows 7-8 of Figure 10 gets distorted when encoded into the StyleGAN2 latent space, even without any additional compression. Another failure mode is for the latent features to be entangled, causing the structured mask output space of the compression model (see Section 4) to be insufficiently expressive for learning an effective compression policy: many of the compressed faces in Figure 9 are visually distorted, most likely because the true prior distribution over latent embeddings is not modeled accurately by a Gaussian (see Appendix A.4).

E Examples of Compression at Different Bitrates

Figures 9 and 10 show that PICO tends to preserve task-relevant features like digit number, eyeglasses and hats, and the price and color of a car, more often than the non-adaptive baseline, and especially at lower bitrates. As the bitrate decreases, PICO discards task-irrelevant features before discarding task-relevant features. At extremely low bitrates (e.g., zero), PICO gracefully degrades to sampling a random image from the pre-trained generative model (see the right-most columns in Figures 9 and 10), instead of, e.g., transmitting a heavily-distorted image with visual artifacts that make it difficult for the user to even attempt to perform their task.



Figure 9: Additional samples from the non-adaptive compression baseline and PICO drawn at varying bitrates. Left: digit identification experiments from Section 5.1 and Figure 3. Right: photo verification experiments from Section 5.2 and Figure 5.



Figure 10: Additional samples from the non-adaptive compression baseline and PICO drawn at varying bitrates, for the car shopping experiments in Section 5.1 and Figure 4.